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Travel Time Prediction

A Comparison Study on a common Data Set

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Abstract

Intelligent transportation systems are information and communication technology solutions in the transportation sector. Systems for predicting travel time are examples of such systems. Intelligent transportation systems are becoming an increasingly larger part of modern society and may contribute to improve traffic efficiency and safety. Accurate and reliable information is crucial for these types of systems, which is why conducting research in this area is important.

A great variety of approaches to travel time prediction are reported in the literature. Two categories of machine learning approaches that are employed in the traffic domain are ensemble learning and online learning. These two approaches are used in order to provide accurate and reliable information. Ensemble learning approaches combine predictions from a set of baselines in order to achieve higher prediction accuracy, whilst online learning methods are capable of adapting to changes in the underlying data set. As the approaches reported in the literature are tested on different data sets, it is difficult to compare their prediction accuracy. In order to do a fair comparison, this work investigates the methods' performance using a common data set. Two experiments are conducted, one comparing state of the art ensemble learning approaches, and the other comparing state of the art online learning approaches.

The ensemble learning approaches investigated in this study are bagging, boosting, lasso, and a fuzzy rule based system. These ensemble learning methods are also compared to a simple average of the baselines' predictions. The online learning methods investigated are online-delayed extended Kalman filter and local online kernel ridge regression.

The results indicate that there is no method that consistently outperforms the other methods in either of the two experiments. Among the ensemble learning methods, using lasso and fuzzy rule based system results in prediction errors with the lowest deviation, whilst bagging is the method with least bias. Additionally, bagging seems to follow the actual travel times better than the other methods. As for the online learning methods, using online-delayed extended Kalman filter results in prediction errors with the lowest deviation, whilst local online kernel ridge regression has lowest bias.

Sammendrag

Intelligente transportsystemer er løsninger som bruker informasjons- og kommunikasjonsteknologi i transportsektoren. Systemer som predikerer reisetid er eksempler på slike systemer. Intelligente transportsystemer blir en stadig større del av det moderne samfunnet, og kan bidra til forbedret trafikkavvikling og -sikkerhet. Nøyaktig og pålitelig informasjon er avgjørende for slike systemer, og det er derfor viktig å drive forskning innenfor dette feltet.

Det er rapportert et stort utvalg av metoder for å predikere reisetid i litteraturen. To maskinlæringskategorier som er brukt i trafikkdomenet er ensemble learning og online learning. Metoder innenfor disse to kategoriene er brukt for å gi nøyaktig og pålitelig informasjon. Ensemble learning metoder kombinerer prediksjoner fra et sett med modeller for å oppnå høyere prediksjonsnøyaktighet, mens online learning metoder evner å tilpasse seg endringer i det underliggende datasettet. Metodene som er beskrevet i litteraturen er testet på ulike datasett. Dette gjør det vanskelig å sammenlikne prediksjonsnøyaktigheten deres. For å kunne gjøre en rettfærdig sammenlikning, undersøker dette studiet ytelsen til metodene på et felles datasett. To eksperimenter er utført, hvor det ene sammenlikner ensemble learning metoder, og det andre sammenlikner online learning metoder.

Ensemble learning metodene som undersøkes i dette studiet er bagging, boosting, lasso og et fuzzy ruled based system. Disse ensemble learning metodene sammenliknes også med et enkelt gjennomsnitt av prediksjonene fra de underliggende modellene. Online learning metodene som undersøkes er online-delayed extended Kalman filter og local online kernel ridge regression.

Resultatene tyder på at ingen av metodene gjør det konsekvent bedre enn de andre, i noen av eksperimentene. Blant ensemble learning metodene, har lasso og fuzzy rule based system prediksjonsfeil med lavest avvik, mens bagging er metoden med minst bias. Selv om ingen av ensemble learning metodene gjør det best på tvers av alle ytelsesmålene, ser bagging ut til å følge den faktiske reisetiden bedre enn de andre metodene. Når det gjelder online learning metodene, har online-delayed extended Kalman filter prediksjonsfeil med lavest avvik, mens local online kernel ridge regression har minst bias.

Preface

This work is conducted as part of the authors' Master's degree at NTNU, and is an extension of the work done in Øien Lunde and Wolff [2014]. Sections 1.1, 2.1 and 2.2 in this report are repeated from Øien Lunde and Wolff [2014].

Emil Øien Lunde, Thomas Wolff
Trondheim, May 28, 2015

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ANN Artificial Neural Network.....	8
EC2 Amazon Elastic Computing Cloud.....	44
EKF Extended Kalman Filter.....	14
FRBS Fuzzy Rule Based System.....	14
k-NN k-Nearest Neighbors.....	8
LOKRR Local Online Kernel Ridge Regression.....	15
MAE Mean Absolute Error.....	32
NPRA Norwegian Public Roads Administration.....	10
RMSE Root Mean Squared Error.....	31
SVM Support Vector Machine.....	8

Chapter 1

Introduction

Section 1.1 introduces the concept of intelligent transportation systems and conceptual approaches to travel time prediction. Note that Section 1.1 is repeated from Øien Lunde and Wolff [2014, p. 1-4]. Section 1.2 describes the goal of this study, and states the research questions this work sets out to answer. Section 1.3 describes the research method employed and Section 1.4 summarizes this work's contributions. Finally, Section 1.5 describes the structure of the rest of the paper.

1.1 Background and Motivation

This section gives an overview of intelligent transportation systems, and introduces conceptual approaches to estimating or predicting traffic variables.

1.1.1 Intelligent Transportation Systems

Intelligent transportation systems is a term describing systems and services in the transportation sector using information and communication technology [Norwegian Public Roads Administration, 2007]. Intelligent transportation systems are often highly complex, consisting of multiple levels of hardware and software each responsible for performing different tasks. To collect road data, multiple sources such as cameras, loop detectors, and GPS devices are used. Since road networks span thousands of square kilometers, the distributed systems responsible for collecting and transmitting this data need to be capable of dealing with events such as faulty detectors and lost connections between transmission devices. Additionally, data is collected continuously, producing large amounts of raw data. The systems responsible for processing this data need to be very efficient to keep up with the incoming data streams whilst being able to extract useful information

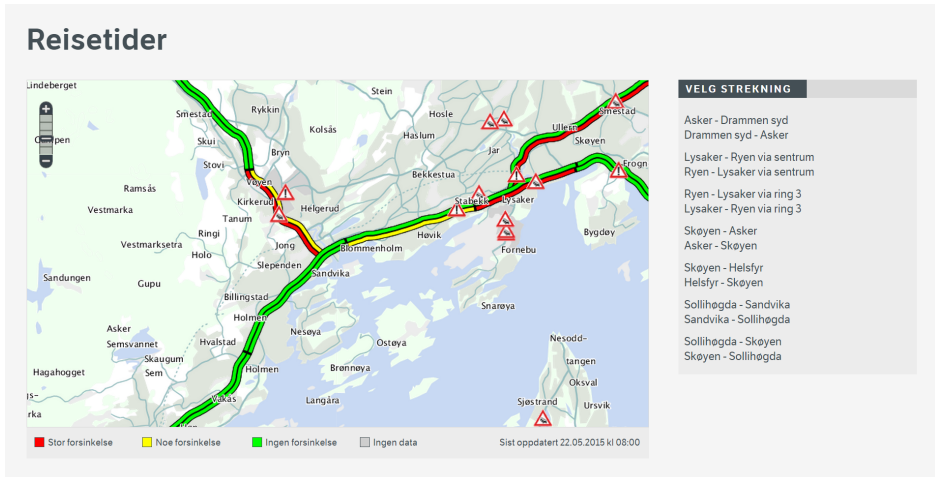


Figure 1.1: Screenshot from www.reisetider.no¹

from big data sets. Finally, the extracted information needs to be distributed to the end users, such as traffic control centers or website users, requiring good quality of service in terms of availability.

The Norwegian Public Roads Administration's system for providing drivers with travel time information is an example of an intelligent transportation system. The Norwegian Public Roads Administration collects travel times from automatic vehicle identification systems on selected roads. This data is processed in order to remove incorrect travel times, for example caused by vehicles stopping in between two detectors. Then, based on the observed data, the system is able to compute expected travel times. The procedure taken to compute these expected travel times is described in more detail in Section 2.1.5. The travel time information is finally made available to drivers through a website², illustrated in Figure 1.1. The roads illustrated on the website are colored in green, yellow or red indicating whether there is no delay, some delay or a large delay on the corresponding road, respectively. The map also displays notifications concerning special circumstances that may affect the traffic, such as a traffic accident or road construction work. The same type of information, e.g. delays and driving conditions, may also be distributed through electronic road signs as illustrated in Figure 1.2.

Aside from the challenges involving a highly complex distributed system, what makes intelligent transportation systems interesting are their environmen-

¹<http://www.reisetider.no/reisetid/omrade.html?omrade=1>, May 22, 2015

²www.reisetider.no

³Source: Norwegian Public Roads Administration's archive



Figure 1.2: Example of an electronic road sign³

tal and economical benefits. Moreover, such systems can potentially increase traffic safety. Commission of the European Communities [2001] stated that intelligent transportation systems have the potential to reduce travel times by up to 20%, whilst network capacity can be increased by 5 – 10%. If this is achieved, CO₂ emissions and transportation costs can be significantly reduced. The impact of intelligent transportation systems on traffic safety has been estimated to reduce rear-end collisions by 10 – 15% because of advanced information and control strategies. Furthermore, automatic incident detection systems, making managing emergency situations easier, have increased survival rates when accidents occur.

In terms of increasing traffic efficiency, providing drivers with expected travel times is a common approach. Travel time is a variable most commuters can relate to. Based on the travel time, it is easy to deduct what the current traffic situation is. This makes it a suitable variable to use in traffic information systems. A survey, reported in Chung et al. [2004], suggests that 78% of drivers are willing to change their departure time or take a different route if they are informed about delays. This indicates that providing commuters with traffic information is a useful tool for efficiently distributing traffic in the road network. Another area where travel time information is useful is trip planning, which requires predicting what travel times will be in the future. Transportation companies rely on this information to optimize their routes, potentially reducing costs and increasing efficiency.

1.1.2 Estimating or Predicting Traffic Variables

The traffic domain is highly complex as it is affected by a great variety of factors. These include aspects such as human behaviour and interaction, how signalized intersections are programmed, and weather conditions. Many of these factors are non-deterministic, which makes them difficult to predict. Consider the example of cars driving on a road section with a signalized intersection. The fact that the amount of time spent waiting for a green light is different for individual vehicles may lead to different travel times, even though the traffic density is constant. Other factors like human interactions and traffic accidents are also difficult to predict. The relationships between these factors and how they affect traffic conditions are highly complex, making it difficult to incorporate all of them into a single model. Analytical models, such as models based on macroscopic traffic flow theory, are therefore limited in their capability of making accurate predictions about traffic conditions.

Another approach to predicting traffic conditions is using data driven approaches. The benefit one can draw from these methods is that they do not focus on using the semantics of the data to express relationships between the variables in the data set. Instead, data driven methods attempt to discover patterns in the data by looking at many examples. This makes them suitable for modelling complex domains, such as the traffic domain.

Machine learning is an example of a data driven method which estimates the true function that maps inputs to outputs in the underlying domain. In the case of traffic, this can be to find a function that captures the relationship between previous and future travel times.

Researchers are constantly attempting to find ways of improving the prediction accuracy of machine learning models. Russell and Norvig [2010] state that one possible approach is to use ensemble learning. In short, ensemble learning combines predictions from several models to make a single prediction. This technique is described in more detail in Section 2.1.2.

Traditionally, machine learning techniques used to predict travel times have been based on using historical data. Over time, as changes in the underlying data set occur, their models may become outdated and their prediction accuracies deteriorate. Online learning methods are able to incorporate the most recent data in their models. This makes them very adaptable, a desirable property for systems deployed in the real-world. Online learning is described in more detail in Section 2.1.3.⁴

A structured literature review investigating in what degree ensemble learning and online learning are employed in the traffic domain is presented in Øien Lunde

⁴Thus far, the text in this section is repeated from Øien Lunde and Wolff [2014, p. 1-4] with some minor modifications. The text that follows in the rest of this section should be considered new and not a part of Øien Lunde and Wolff [2014].

and Wolff [2014]. The authors report that various studies investigating ensemble learning and online learning in the traffic domain are conducted. The results of these studies demonstrate that ensemble learning provides higher prediction accuracy compared to its baseline methods. Additionally, online methods are proven to be better at adapting to changes in the underlying data set. However, the structured literature review does not reveal any studies that compare the proposed techniques on a common data set. This makes it difficult to determine which methods perform best.

In order to gain knowledge as to how the different techniques compare to each other, this work sets out to conduct experiments that measure the methods' performance on a common data set. Although this research is conducted in collaboration with the Norwegian Public Roads Administration, the focus in this work is on comparing the methods from an artificial intelligence research perspective. However, the results may also be used to give guidelines to the Norwegian Public Roads Administration as to which technique(s) may be integrated in their own systems.

1.2 Goals and Research Questions

Goal To find the most accurate ensemble and online learning technique(s), among the ones reported in Øien Lunde and Wolff [2014], for predicting travel times for a given road section.

In order to achieve this goal, this work attempts to answer the two following research questions:

Research Question 1 Given a set of baseline methods, which ensemble learning technique yields the best prediction accuracy?

Research Question 2 Which online learning technique yields the best prediction accuracy?

1.3 Research Method

This work employs a comparison study methodology in an attempt to reach the research goal described in Section 1.2. In a comparison study, the performance of one or more methods is assessed through the means of some performance measure. The performance measure is used as a basis for comparing the methods and may also be used to compare the performance of the methods with an existing standard that solves the same problem [Cohen and Howe, 1988]. This way, one can identify whether or not the proposed methods provide any improvements to the existing

solutions. In this comparison study, several experiments are designed, each suited to produce results that may give answers to one or more of the research questions stated in Section 1.2. By examining the results of the experiments, and evaluating the performance of the different approaches, the authors hope to answer these research questions.

1.4 Contributions

This work's contribution is two-fold. First, this study compares state of the art ensemble learning and online learning techniques on a common data set. Second, local online kernel ridge regression is employed on a data set with individual travel times, in contrast to the original approach where five minute aggregated data is used.

1.5 Thesis Structure

Chapter 2 gives an introduction to important concepts used throughout this paper and presents the motivation for selecting the methods investigated in this study. Chapter 3 provides a more detailed description of the methods that are investigated. Chapter 4 describes the experiments conducted in this study and presents the experimental results. An evaluation and discussion of the results, along with a conclusion and suggestions for future work, are presented in Chapter 5.

Chapter 2

Background Theory and Motivation

This chapter covers relevant background theory and presents the literature review. In Section 2.1, key terminology used throughout this paper is described. Section 2.2 describes how the literature review was conducted. Note that sections 2.1 and 2.2 are repeated from Øien Lunde and Wolff [2014, p. 7-10] and Øien Lunde and Wolff [2014, p. 10-12], respectively, with some minor modifications. Section 2.3 presents the findings of the literature review and motivates the use of the techniques investigated in this research.

2.1 Background Theory

In this section, relevant concepts for predicting travel times are introduced. Machine learning is described in Section 2.1.1. Two important machine learning concepts referred to in this study are then introduced. Section 2.1.2 describes ensemble learning, whilst Section 2.1.3 presents online learning. Section 2.1.4 covers traffic data collection and describes some important variables used in traffic modeling. The solution for travel time estimation in use at the Norwegian Public Roads Administration as of 2015 is covered in Section 2.1.5.

2.1.1 Machine Learning

Machine learning is a term used in computer science covering methods for learning computers different tasks by investigating data. Mitchell [1997] defines machine learning as:

A computer program is said to **learn** from experience E with respect to some class of tasks T and performance measure P , if its performance at tasks in T , as measured by P , improves with experience E .

Given many data points of the form (\mathbf{x}, y) , where \mathbf{x} is a input vector of features and y is the corresponding output value, the goal of machine learning is to estimate the true function $F(\mathbf{x})$ that maps input vectors \mathbf{x} to output values y . This estimated function $M(\mathbf{x})$ is called a model of the true function. Given a new input vector \mathbf{x}_{new} , whose output value is not known, this model can be used to predict the output $y_{\mathbf{x}_{new}}$.

2.1.2 Ensemble Learning

Basic machine learning methods, like Support Vector Machine (SVM) [Cortes and Vapnik, 1995], k-Nearest Neighbors (k-NN) and Artificial Neural Network (ANN), use a single model to make predictions. Single model learners have proven to make accurate predictions, but even higher accuracy can still be achieved. The idea behind ensemble learning is to combine several predictions in to a single prediction. Consider an ensemble of five classification predictions, where majority voting is used. For the ensemble's prediction to be incorrect, at least three of those five predictions have to be incorrect [Russell and Norvig, 2010]. This is the motivation behind the approach. An ensemble of learners that collectively make a prediction is more likely to be correct, especially if the learners in the ensemble have different bias with regards to the training data. By having a low correlation between the errors, it is less likely that all of the learners are mistaken at the same time. The ensemble is able to mask the weakness of each individual learner, thus increasing prediction accuracy.

2.1.3 Online Learning

Online learning is a machine learning approach where the underlying model is trained incrementally on the most recent data. As soon as new data becomes available, the error of the model is computed by comparing its output with the actual value. Next, the model is adjusted in order to reduce this error. By constantly adjusting the model it is able to adapt to changes in the data set that happen over time. In the case of travel time prediction, the model is updated as soon as new travel time information becomes available. This allows the model to adapt to changes in traffic conditions such as new lanes being added to a road section causing a decrease in congestion, or tolls on one road leading to a change in traffic volume.

2.1.4 Traffic Domain

This section introduces two common variables used to express the state of traffic, travel time and traffic flow, and approaches used to measure traffic variables. In addition to travel time and traffic flow, other commonly used traffic variables are point speed, section speed and density. However, these variables are not used in this study, and therefore not covered in this section. This section is based on Haugen and Aakre [2014].

Travel Time

Travel time is defined as the time it takes to drive from point a to point b . It can be expressed as:

$$t = t_b - t_a \quad (2.1)$$

where t is travel time, t_a is the point in time where the vehicle passed point a , and t_b is the point in time where the vehicle passed point b .

Traffic Flow

Traffic flow is defined as the number of cars passing through a certain point on the road per unit time. It can be expressed as:

$$q = \frac{n}{T} \quad (2.2)$$

where q is traffic flow, n is the number of cars, and T is time. Traffic flow is commonly given in vehicles per hour.

Collecting Traffic Data

There are several approaches to collecting traffic data. This section covers the most commonly used approaches.

Inductive loop detectors are loops of electrical wire integrated in the road. Electrical current runs through the wire, creating a magnetic field. When a car passes through the loop, a controller can register this because the car changes the magnetic field. Inductive loop detectors can measure several variables such as traffic flow and car length. Since inductive loop detectors are installed in pairs, a few meters apart from each other, speed can also be measured.

Using piezoelectric wires is another approach to collecting traffic data. These wires emit an electrical signal when compressed. This way a controller can register when cars run over it. Piezoelectric wires can be used to measure variables such as traffic flow, speed, the number of axles on a car and the weight per axle.

Radars are also used to collect traffic data. They can measure traffic flow, speed, and classify cars by their lengths.

Although their main task is to validate the payment of cars driving on toll roads, AutoPASS tags can be used to collect travel time data as well. AutoPASS tags are installed in many cars, and sits in the top of the windshield. These tags enable identification of individual vehicles, such that travel times between two measurement points can be registered.

2.1.5 Current Solution at the Norwegian Public Roads Administration

The Norwegian Public Roads Administration (NPRA) are responsible for collecting traffic data on roads in Norway. They use detectors in the road, such as loop detectors and piezoelectric cables, to detect passing vehicles. Additionally, many cars in Norway are equipped with electronic devices, called AutoPASS tags, used for automatic toll payments. Measurements from AutoPASS tags are what the NPRA use today to estimate the current travel times on road sections in Norway. The current solution provides commuters with up-to-date travel time information based on travel times collected from the last five minutes. These measurements are used as input to the algorithm described in Wahl and Haugen [2005]. In this algorithm, individual travel times are placed in groups of one-minute intervals, e.g. the travel times 25:00 and 25:59 are placed in the 25 minute group. The estimated travel time is computed based on the interval with the most registered travel times and its neighboring intervals. A weighted average of the travel times of these intervals is the final estimated travel time.

2.2 Structured Literature Review Protocol

This section gives an overview of the structured literature review process employed in this study. This process follows the guidelines reported in Kofod-Petersen [2014]. A more extensive and detailed description of the process can be found in Appendix A.

To find relevant literature, a search string that covers the main aspects of this research is developed. This search string is used to retrieve articles from two search engines: IEEEXplore¹ and Engineering Village². As most of the retrieved literature is irrelevant to this study, a screening process to filter out this literature

¹<http://ieeexplore.ieee.org/search/advsearch.jsp?expression-builder>, September 24, 2014

²<http://www.engineeringvillage.com/search/expert.url?CID=expertsearch>, September 24, 2014

is employed. This is done in a top-down approach, first filtering the articles by title, second by abstract, and finally by full text.

The first two filtering steps are used to ensure that the articles included further in the screening process are in the right domain, and that the work exhibits solutions that are relevant to this study. To decide which articles are relevant, inclusion criteria regarding the contents of the titles and abstracts are developed. An example of an inclusion criterion is: "The title indicates that the article predicts, estimates or models road traffic variables, e.g. traffic flow, speed, congestion or travel time". This criterion ensures that articles regarding estimation or prediction of traffic variables are included, as they are of high relevance to this study. Another example of an inclusion criterion is: "The article describes a solution that can easily be extended or adapted to fit our research". By employing this inclusion criterion, articles that present solutions that can be adapted to our problem are included. After evaluating each article based on every criteria for title and abstract, the most irrelevant literature is filtered out.

The last step in the screening process is to assess the quality of the work presented in the different articles. During the quality assessment, questions such as "Is the method/algorithm thoroughly explained?" and "Does the test evidence support the findings presented?" have to be answered to identify the good research. The articles are given a score in the range from 0 to 1 for each quality assessment question. To ensure a certain quality, only articles with a total score above a set threshold is included in the state of the art review.

2.3 Motivation

The structured literature review presented in Øien Lunde and Wolff [2014] reports several ensemble learning techniques employed in the traffic domain, ranging from simple linear combinations to more complicated non-linear schemes. It also reports several online learning techniques used for making predictions in the traffic domain. This section presents the key findings in the structured literature review, and motivates using the methods investigated further in this research.

2.3.1 Inclusion Criteria

To ensure that there is enough time to thoroughly evaluate the methods, only a small selection of the techniques described in Øien Lunde and Wolff [2014] can be included in the experiments in this study. Therefore, a set of inclusion criteria are developed to narrow down the number of methods being tested. These criteria are:

Inclusion Criterion 1 The paper employs an ensemble learning technique or

an online learning technique.

and

Inclusion Criterion 2 The technique described in the paper is available through an open source implementation or is sufficiently explained in order to be implemented.

and

Inclusion Criterion 3 The paper focuses on improving prediction accuracy.

Since this research sets out to compare ensemble learning techniques as well as online learning techniques, it is essential that the proposed approach in a paper falls into one of these two categories. This is reflected by Inclusion Criterion 1. Furthermore, it is an absolute necessity that the methods being tested do not require much implementation, as the main focus in this work is on comparing methods, not spending time implementing them. Inclusion Criterion 2 ensures that only papers presenting methods requiring a minimum of implementation is included. As several papers presented in Øien Lunde and Wolff [2014] focus on other aspects of travel time prediction than prediction accuracy, like computational cost, Inclusion Criterion 3 is present to ensure that the main focus of the proposed method is increasing prediction accuracy.

Of all the papers resulting from the structured literature review in Øien Lunde and Wolff [2014], only those employing ensemble learning or online learning techniques are candidates for the experiments in this study due to Inclusion Criterion 1. Four of these candidate techniques did not satisfy Inclusion Criterion 2 and Inclusion Criterion 3. Zhu and Shen [2012] describes a technique that makes use of the notion of traffic regimes. As the authors do not give an accurate definition of the different traffic regimes used in their work, the paper does not satisfy Inclusion Criterion 2, and is therefore not included. The approach described in van Hinsbergen et al. [2009] is not included as the paper focuses on reducing computational cost, and thus does not satisfy Inclusion Criterion 3. Wu et al. [2012] describes a solution consisting of two parts, one for predicting normal traffic conditions, and another for handling abnormal traffic conditions. As the approach for setting the thresholds for what is considered normal and abnormal traffic conditions is not explained, the paper does not satisfy Inclusion Criterion 2, and is not further investigated in this work. Although Lu [2012] satisfies all the inclusion criteria, it is not included in the experiments. The proposed method's results are compared to a primitive baseline, which makes it difficult to determine how it compares to established methods such as ANN. This uncertainty about the proposed method's performance makes it unjustifiable to spend time implementing.

2.3.2 Methods

The motivation for including the methods used in the experiments in this study is explained in the following sections.

Bagging

Sun [2009] investigates whether or not using a multitask learner will improve upon using a simple task learner when predicting traffic flow. Additionally, the authors look at the effect of using an ensemble of multitask learners compared to just a single multitask learner. In contrast to single task learners, which predict one variable at a time, multitask learners make predictions for several variables simultaneously. The motivation for using multitask learners is that they may incorporate more information during training because the different learning tasks share some common properties. The method they use for combining predictions from their ensemble of multitask learners is called bagging, which is described in more detail in Section 3.1.1. The results from the experiments conducted in Sun [2009] illustrate that bagging may improve prediction accuracy compared to using just one model to make predictions.

Boosting

All though not present in any of the papers reported in the structured literature review in Øien Lunde and Wolff [2014], boosting is included in this study. Boosting is one of the most common ensemble learning techniques [Russell and Norvig, 2010] and is hence included due to completeness. Section 3.1.2 explains boosting in more detail.

Lasso

Bagging combines its baseline models by simply computing an average. This means that the baselines are combined without regards to their performance. Another approach is to assign a weight to each model in the ensemble, representing its contribution to the ensemble's output. The idea behind using a weighted average is that the weights can be computed based on each model's prediction error, thus allowing the ensemble to adjust for errors in each model. This can help improve the overall performance of the ensemble, e.g. by making the best performing models more prominent.

In Li et al. [2014] three different weighting schemes are explored, namely least squares, ridge regression and lasso [Tibshirani, 1996; Efron et al., 2004; Hastie et al., 2009]. Their results indicate that the weighting schemes increase prediction accuracy compared to the best performing baseline model. The strength of lasso compared to the other weighting schemes is that it can automatically perform

model selection, by assigning zero weight to some models, thus outputting a weighted average of only the best performing models. This feature, i.e. being able to automatically select the appropriate baseline models, makes lasso an interesting approach. The weighting schemes tested in Li et al. [2014] are not compared to a simple average or to any other ensemble approaches. Although demonstrating the effectiveness of combining predictions with a weighted average, the research does not indicate whether this approach is preferable to any other ensemble approach. The lasso technique is described in more detail in Section 3.1.3.

Fuzzy Rule Based System

Stathopoulos et al. [2008] argues that the optimal relationships between the baseline models in an ensemble are not necessarily linear, which is why a Fuzzy Rule Based System (FRBS) [Bellman and Zadeh, 1970] capable of representing non-linear relationships between baseline models is proposed in Stathopoulos et al. [2008].

In general, an FRBS works by explicitly defining a set of rules that convert inputs to an output. Since these rules are explicitly defined, one is able to incorporate expert knowledge and represent relationships between models that are impossible to represent by linearly combining them. FRBSs are explained in more detail in Section 3.1.4.

The contribution of Stathopoulos et al. [2008] is somewhat similar to Li et al. [2014]. The experimental results demonstrate that the FRBS ensemble outperforms the best performing baseline in terms of prediction accuracy, but none of their experiments compare the proposed method to any other ensemble approaches. Because the FRBS approach exhibits some interesting features, more specifically its ability to represent non-linear relationships and to incorporate expert knowledge, it is included in this comparison study.

Online Extended Kalman Filter

So far, the methods described focus on how to combine predictions from an ensemble of models into one, hopefully more accurate, prediction. The other branch of methods that the structured literature review in Øien Lunde and Wolff [2014] reports, are methods capable of updating its underlying model each time new observations arrive. These methods are often called online methods or incremental methods because they learn from one observation at a time and continually update their model during the prediction phase. In contrast, offline methods first learn, then they predict.

Van Lint [2008] presents an online method for predicting travel time using the Extended Kalman Filter (EKF) approach for training the weights of an ANN.

Van Lint makes the assumption that the weights in the ANN perform a random walk along some high-dimensional path, and that the ANN makes a non-linear observation of those weights when making a prediction. The EKF works in an iterative fashion, updating its state vector and variance estimate each time step. This makes it suitable for online learning. A more detailed description of the method can be found in Section 3.2.1.

The results reported in Van Lint [2008] demonstrate that the online EKF algorithm does not perform as good as an offline trained model. However, it has the benefit of being online, which makes it more attractive for use in a real time system. Offline methods are limited to the data it is exposed to during training. This makes it hard for offline methods to predict outcomes for situations it has never seen before. Online methods, on the other hand, updates its model continuously as new observations arrive. This way it is capable of adapting its model to the changes in the underlying data that happen over time. This leads to a more adaptive model that does not get outdated if there is a change in the underlying data.

Local Online Kernel Ridge Regression

Haworth et al. [2014] presents a novel online learning approach for travel time prediction called Local Online Kernel Ridge Regression (LOKRR). The approach is based on creating multiple kernels, each corresponding to a specific time interval of the day, using ridge regression to predict travel times based on historical data. One of the most significant drawbacks with using a single kernel to represent the entire data set is that the amount of information it can incorporate is limited due to computational complexity. This makes it difficult to capture properties such as seasonal variations in the traffic data. LOKRR aims to deal with this limitation. Since each kernel in LOKRR only needs to incorporate data from a certain time of day, more historical data can be used in each kernel. This makes it easier to detect cyclic patterns, such as rush hours, in the data. Additionally, the parameters of each kernel can be tuned individually. This enables each kernel to adapt to its underlying data distribution more effectively, thus increasing prediction accuracy. Another important feature in LOKRR is that it uses a sliding window approach to update the kernels with the most recent data, enabling it to adapt to changes in the data. A detailed description of LOKRR can be found in Section 3.2.2.

The advantages of LOKRR are demonstrated in the experiments presented in Haworth et al. [2014]. LOKRR outperforms a support vector machine and an artificial neural network for certain prediction horizons in addition to providing better prediction accuracy during non-recurrent congestion scenarios.

Chapter 3

Models and Architecture

To give a theoretical backdrop for the rest of this work, this chapter explains the methods used in this comparison study in more detail. Section 3.1 explains the ensemble learning techniques bagging, boosting, lasso, and fuzzy rule based system. Section 3.2 explains the online extended Kalman filter, and local online kernel ridge regression.

3.1 Ensemble Learning

This section describes the different ensemble learning approaches used in this study. All these approaches have in common that they combine the predictions of a set of baseline members. Figure 3.1 illustrates this process where the same data set is available to all K baselines, and K individual predictions are generated from these baselines. The ensemble learning method combines these predictions in some way into a final prediction.

3.1.1 Bagging

Bagging is an ensemble learning technique introduced in Breiman [1996]. Although the technique is actually more concerned with how the models in the ensemble are trained than how the models are combined, it is considered an ensemble learning algorithm. During the bagging training phase, the K different models are trained on individual subsets of the original training data. The subsets are sampled uniformly with replacement from the training data. When making a prediction from the ensemble, the mean of the predictions from the individual members of the ensemble is used for regression problems, and majority voting is used for classification problems.

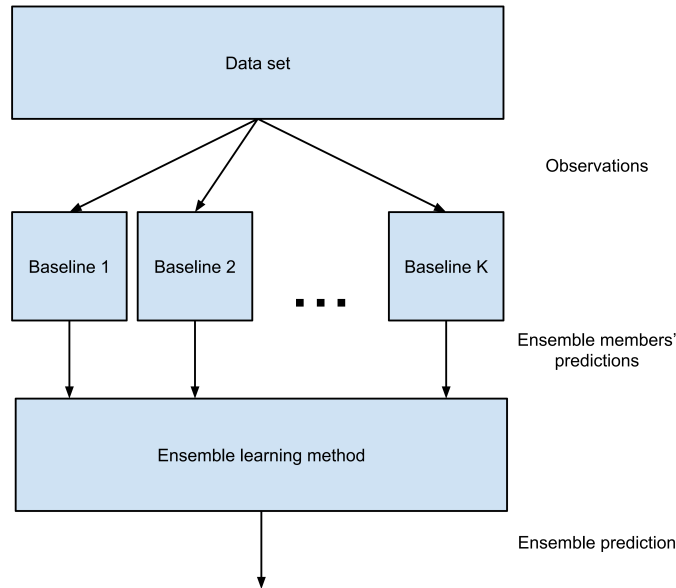


Figure 3.1: Ensemble Learning Process

It is important to note that the members of a bagging ensemble are all of the same type, e.g. all models are artificial neural networks, or all models are k-nearest neighbors models. Bagging's ability to improve the baselines' performance is affected by which machine learning approach is used as baseline. Machine learning approaches can be divided into two groups, stable and unstable learners. A machine learning method is referred to as stable if a change in the training set makes little to no change in the learned model. However, a machine learning method is referred to as unstable if a change in the training set makes large changes in the learned model. Breiman [1996] explains that bagging may work well for ensembles of machine learning methods that are unstable. However, one has little to gain from using bagging when the ensemble consists of machine learning methods that are stable. The motivation for using unstable learners in bagging is due to the fact that using unstable learners increases the probability of generating models having different bias. Recall from Section 2.1.2 that having baselines with different bias increases the ensemble's probability of making an accurate prediction.

3.1.2 Boosting

Boosting is one of the most common ensemble learning techniques [Russell and Norvig, 2010]. Like bagging, boosting re-samples the training data to construct an ensemble of models. However, the sampling technique in boosting is different from the one used in bagging. In boosting, each training example is given a weight. This weight corresponds to the importance of the example, and is initialized to 1 for all examples, meaning that each example is equally important. The training examples for the first model in the ensemble are drawn from this uniform distribution of weights.

During training, the first model will correctly classify some examples, while other examples will be misclassified. For regression problems, there will be a resulting prediction error in contrast to the correct-incorrect case for classification. Before constructing the next model in the ensemble, the weights for each example in the training data are updated, increasing the weights of the misclassified examples, and reducing the weights of the correctly classified examples. For regression problems, the weights are updated according to how large the prediction error is compared to the largest prediction error among all examples [Drucker, 1997]. This way, the misclassified examples are given higher importance, and have a higher probability of being sampled by the next model in the ensemble. The idea is that the models are getting better at classifying these examples, and that the ensemble is collectively predicting more accurately.

This iterative process continues until K models are constructed, where K is a parameter to the boosting algorithm. When making predictions, a weighted majority vote from the models in the ensemble is used. The weight of each model is proportional to the number of correctly classified examples it has predicted during training, or how low the prediction error is for regression problems.

3.1.3 Lasso Ensemble

Both bagging and boosting include all models in the ensemble when making the final collective prediction. The motivation behind using lasso is to only include the best performing models. Lasso creates a prediction by computing a weighted average of its baselines' predictions. The baselines' weights are set in an attempt to minimize the difference between the predicted and actual travel times across all training examples. Due to the approach taken to optimize these weights, lasso has the property that it may exclude the worst performing baseline models.

The experiment described in Li et al. [2014] uses sensors along a road to register traffic data at N locations for T time steps. This data forms a matrix $\mathbf{F} \in \mathbb{R}^{N \times T}$ of recent traffic observations. Consider an ensemble of K models, whose task is to make predictions about traffic variables at these N locations for each time step. Each model k makes its prediction $g_n^t(k)$ for location n at time t .

This forms a matrix of predictions $\mathbf{G}_k \in \mathbb{R}^{N \times T}$. The models' predictions are put together in a vector $\mathbf{G} = [\mathbf{G}_1, \mathbf{G}_2, \dots, \mathbf{G}_K]$. The ensemble's collective prediction h_n^t for location n at time t is a weighted average of the member's predictions:

$$h_n^t = \sum_{k=1}^K w_k g_n^t(k) \quad (3.1)$$

where w_k is the weight corresponding to model k . The ensemble's predictions for all N locations for all T time steps forms a matrix \mathbf{H} , and is given by $\mathbf{H} = \mathbf{G}\mathbf{W}$, where $\mathbf{W} = [w_1, w_2, \dots, w_K]$. Different \mathbf{W} will result in different predictions, and in turn different prediction accuracies. How do we find the optimal set of weights $\hat{\mathbf{W}}$?

One of the proposed solutions in Li et al. [2014] to this question is to use lasso ensemble [Tibshirani, 1996; Efron et al., 2004; Hastie et al., 2009]. In this approach, the optimal set of weights is given by solving the following equation:

$$\hat{\mathbf{W}} = \arg \min_{\mathbf{W}} \|\mathbf{F} - \mathbf{G}\mathbf{W}\|_2^2 + \lambda \|\mathbf{W}\|_1 \quad (3.2)$$

where $\|\mathbf{F} - \mathbf{G}\mathbf{W}\|_2^2$ is the l_2 norm of the least squares solution, $\|\mathbf{W}\|_1$ is the l_1 norm of the weights, and λ is a regularization term controlling the importance of the l_1 norm of the weights. Li et al. [2014] explains that having this l_1 regularization of the weights leads to a sparse solution, corresponding to many weights being zero. This means that only some of the models are included when making the final prediction. This is advantageous as the lasso ensemble technique selects the best performing models in the ensemble, and accumulates their prediction into the ensemble's final prediction. Li et al. [2014] explains that having a broad range of models in combination with the lasso ensemble approach may produce good results as large parts of the parameter space is thus covered, and the best performing of them is included in the final prediction.

The baseline models used in this work's lasso ensemble are SVM, k-NN, ANN and Kalman filter. These four methods are chosen as baselines as they are reported in Sjøfjell et al. [2013] as commonly used methods in the traffic literature. Figure 3.2 demonstrates the architecture of the lasso ensemble.

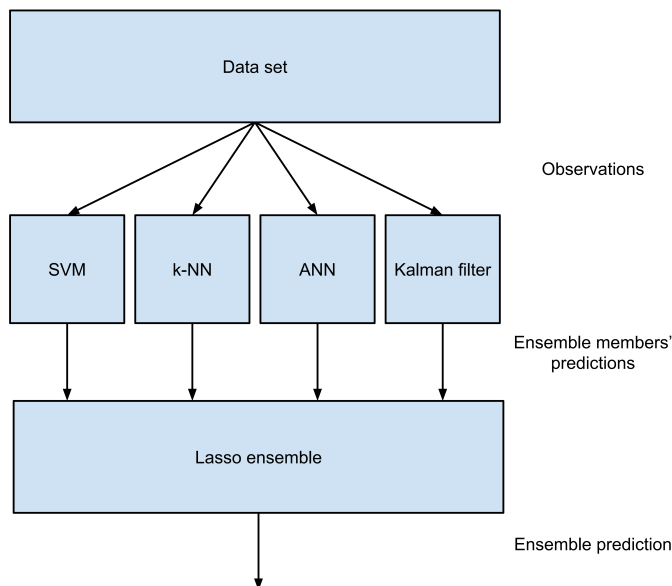


Figure 3.2: Lasso ensemble process

3.1.4 Fuzzy Rule Based System

An FRBS is a machine learning approach where a set of rules define its behaviour. These rules can either be manually created, thus enabling the ability to incorporate expert knowledge, or automatically created based on a data set. In terms of using an FRBS to predict travel time, the rules can constitute a mapping from a set of baselines' predictions into a single prediction. Consequently, an FRBS is capable of capturing non-linear relationships between the baselines' predictions and the ensemble's output. An FRBS consists of a fuzzyfication stage, an inference system, and a defuzzyfication stage.

The fuzzyfication stage assigns input values to fuzzy sets. Fuzzy sets are sets whose elements have degrees of membership. What degree of membership an input is given to a fuzzy set is defined by a membership function. Basically what a membership function does is that it returns a probability that some value is a member of a fuzzy set. Imagine a system predicting people's weight based on their height. Two possible fuzzy sets describing a persons height are *short* and *tall*. E.g. the height 185 cm can be assigned the degrees 0.2 and 0.8 to *short* and *tall*, respectively. This situation is illustrated in Figure 3.3.

The inference system is used to generate outputs based on the fuzzyfied input. It consists of a number of if-then rules, referred to as the rule base, that define

what to do when some condition is satisfied. The rule base basically constitutes a complete mapping from all possible inputs to outputs. In the example FRBS described above, a rule could be "If a person is *tall* then that person is *heavy*". In contrast to typical black-box approaches such as artificial neural networks, the behaviour of an FRBS can easily be interpreted because its behaviour is explicitly described in the rule base.

The responsibility of the defuzzification stage is to convert the values representing membership degrees returned by the inference system into one single output. For example converting membership degrees of *heavy* and *light* into kilograms.

Stathopoulos et al. [2008] employs an FRBS to combine forecasts from two different models predicting traffic flow: ANN and Kalman filter. The traffic flows are mapped to the fuzzy sets *low*, *medium* and *high*. The FRBS consists of two different rule bases, each preferring one of the models over the other, as seen in Table 3.1. When predicting traffic flow at time $t + 1$, the rule base giving priority to the best performing model at time t is selected. The output from the rule base is then converted back to a traffic flow value using the center of gravity algorithm [Takagi and Sugeno, 1985]. The center of gravity defuzzification rule works by first cutting the triangular membership functions at the computed degree of membership. This forms a trapezoid for each function. Next, these trapezoids are combined into one polygon. Then, the center of gravity of this polygon is computed, and the first component of the center of gravity point is used as the defuzzified value. An illustration of the center of gravity defuzzification rule is presented in 3.4. The FRBS used in this study follows the same approach as described in Stathopoulos et al. [2008], and the structure of the FRBS is illustrated in Figure 3.5.

3.2 Online Learning

This section describes the two online learning approaches used in this study, online EKF and LOKRR.

3.2.1 Online Extended Kalman Filter

The Kalman filter approach is used in signal processing to filter out noise in an input signal, in order to reconstruct a smoothed estimate of the original signal. The idea in Van Lint [2008] is to view the weights in an ANN as a signal, and apply the Kalman filter to update its weights. As the weights in the ANN are updated each time a new observation is available, the approach is considered to be online. To explain the online EKF, this section starts by explaining the Kalman filter and its extension, EKF. Next, this section explains how the EKF

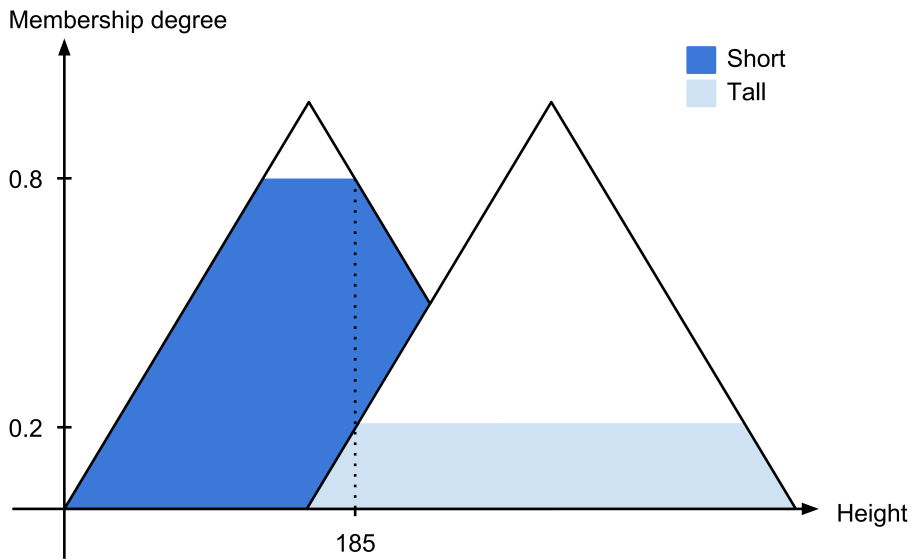


Figure 3.3: Example of membership functions

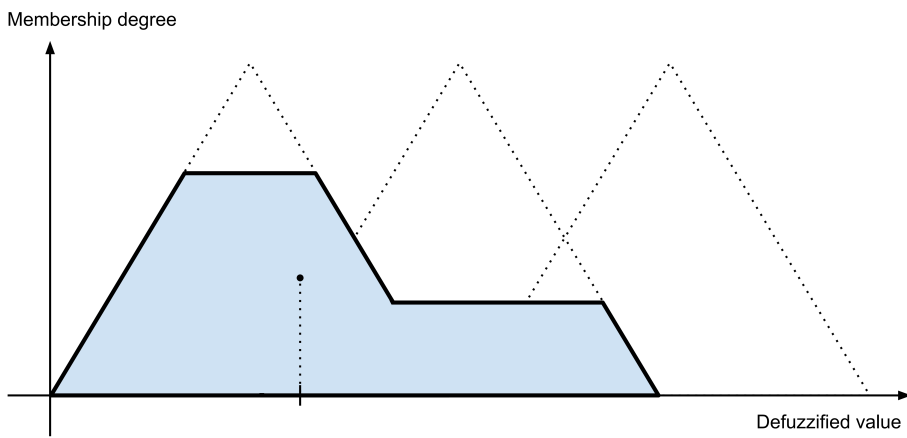


Figure 3.4: Center of gravity defuzzification rule

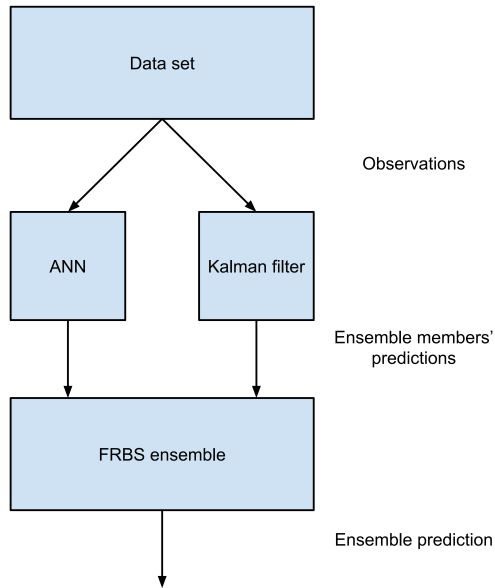


Figure 3.5: FRBS ensemble process

IF predicted flow of model A is LOW AND predicted flow of model B is LOW, THEN flow at time $t + 1$ is LOW
IF predicted flow of model A is LOW AND predicted flow of model B is NOT LOW, THEN flow at time $t + 1$ is LOW
IF predicted flow of model A is MEDIUM AND predicted flow of model B is MEDIUM, THEN flow at time $t + 1$ is MEDIUM
IF predicted flow of model A is MEDIUM AND predicted flow of model B is NOT MEDIUM, THEN flow at time $t + 1$ is MEDIUM
IF predicted flow of model A is HIGH AND predicted flow of model B is HIGH, THEN flow at time $t + 1$ is HIGH
IF predicted flow of model A is HIGH AND predicted flow of model B is NOT HIGH, THEN flow at time $t + 1$ is HIGH

Table 3.1: Rule base used in Stathopoulos et al. [2008].

can be used for training the weights of an ANN, and how the online-delayed EKF and censored EKF conduct this training in an incremental fashion.

Kalman Filter

The Kalman filter is an approach for making estimations about some state vector \mathbf{x}_t at time t from noisy observations $[\mathbf{z}_0, \mathbf{z}_1, \dots, \mathbf{z}_{t-1}, \mathbf{z}_t]$ from time $t = 0$ to time t . It is assumed that there is a linear relationship between the state vector \mathbf{x}_t at time t and the state vector \mathbf{x}_{t+1} at time $t+1$. Additionally, it is assumed that the process evolves with some uncertainty, and that this uncertainty can be modelled as a term following a zero mean Gaussian distribution. These assumptions yield the basis for the transition model, describing the relationship between successive states in the system, which can be expressed by the following equation:

$$\mathbf{x}_{t+1} = \mathbf{F}\mathbf{x}_t + \mathbf{B}\mathbf{u}_t + \epsilon_{process} \quad (3.3)$$

where \mathbf{x}_{t+1} is the state vector at time $t+1$, \mathbf{x}_t is the state vector at time t , \mathbf{F} is a matrix that represents the relationship between the variables in the state vector at time t and $t+1$, \mathbf{B} is a matrix that represents the effect that the input \mathbf{u}_t , given to the system at time t , has on the state vector. $\epsilon_{process}$ is the error term that represents the uncertainty with which the system evolves. $\epsilon_{process}$ follows a zero mean Gaussian distribution which has covariance matrix \mathbf{Q} .

It is further assumed in the Kalman filter that the state vector \mathbf{x}_t can not be observed directly. One can only gain insight to the state vector through observations of related variables in observation vector \mathbf{z}_t . It is assumed that there is a linear relationship between the unobservable state vector \mathbf{x}_t and the observation vector \mathbf{z}_t . It is also assumed that the observations are noisy, which means that there is some uncertainty related to the observations. This uncertainty is assumed to follow a zero mean Gaussian distribution. Putting this together, the observation model, describing the relationship between observations and the state vector, can be expressed by the following equation:

$$\mathbf{z}_t = \mathbf{H}\mathbf{x}_t + \epsilon_{observation} \quad (3.4)$$

where \mathbf{z}_t is the observation at time t , \mathbf{x}_t is the state vector at time t , \mathbf{H} is a matrix that represents the relationship between the observations and the state vector. $\epsilon_{observation}$ represents the uncertainty related to the observation, following a zero mean Gaussian distribution with covariance matrix \mathbf{R} .

The Kalman filter approach provides the following equations for making predictions about the system in question:

$$\hat{\mathbf{x}}_{t|t-1} = \mathbf{F}\hat{\mathbf{x}}_{t-1|t-1} + \mathbf{B}\mathbf{u}_t \quad (3.5)$$

$$\mathbf{P}_{t|t-1} = \mathbf{F}\mathbf{P}_{t-1|t-1}\mathbf{F}^T + \mathbf{Q} \quad (3.6)$$

where $\hat{\mathbf{x}}_{t|t-1}$ is the prediction of the state vector at time t given observations up to time $t = t - 1$, $\hat{\mathbf{x}}_{t-1|t-1}$ is the estimate of the state vector at time $t - 1$ given observations up to time $t = t - 1$. $\mathbf{P}_{t|t-1}$ is the covariance matrix of $\hat{\mathbf{x}}_{t|t-1}$, representing the uncertainty related to the prediction made, $\mathbf{P}_{t-1|t-1}$ is the covariance matrix representing the uncertainty from the previous iteration.

After making an observation \mathbf{z}_t at time t , the Kalman filter approach provides the following equations for updating the estimation of the state vector and its uncertainty:

$$\hat{\mathbf{x}}_{t|t} = \hat{\mathbf{x}}_{t|t-1} + \mathbf{K}(\mathbf{z}_t - \mathbf{H}\hat{\mathbf{x}}_{t|t-1}) \quad (3.7)$$

$$\mathbf{P}_{t|t} = \mathbf{P}_{t|t-1} - \mathbf{K}\mathbf{H}\mathbf{P}_{t|t-1} \quad (3.8)$$

where $\hat{\mathbf{x}}_{t|t}$ is the updated estimate for the state vector, $\hat{\mathbf{x}}_{t|t-1}$ is the predicted state vector, \mathbf{K} is the Kalman gain matrix which is given by the following expression:

$$\mathbf{K} = \mathbf{P}_{t|t-1}\mathbf{H}^T(\mathbf{H}\mathbf{P}_{t|t-1}\mathbf{H}^T + \mathbf{R})^{-1} \quad (3.9)$$

The Kalman filter operates in an iterative fashion, starting with an initial state vector $\mathbf{x}_{t=0}$ and a corresponding covariance matrix $\mathbf{P}_{t=0}$ at time $t = 0$. Then it makes a prediction for the state vector $\hat{\mathbf{x}}_{t=1|t=0}$ and its uncertainty $\mathbf{P}_{t=1|t=0}$ for time $t = 1$. Next, it makes an observation $\mathbf{z}_{t=1}$ at time $t = 1$ providing the basis for updating the state vector $\hat{\mathbf{x}}_{t=1|t=1}$ and its uncertainty $\mathbf{P}_{t=1|t=1}$ for time $t = 1$. Now the process starts over again, making a prediction for the next time step, doing an observation, updating the state vector etc.

Extended Kalman Filter

The Kalman filter approach described above assumes that the relationship between successive states, and the relationship between observations and state vector, are linear. However, this may not be sufficient to model all systems and processes. The EKF generalizes the ideas from the Kalman filter and does not assume that these relationships are linear. Allowing non-linear relationships in the model yields the following transition and observation model equations:

$$\mathbf{x}_{t+1} = f(\mathbf{x}_t, \mathbf{u}_t) + \epsilon_{process} \quad (3.10)$$

$$\mathbf{z}_t = g(\mathbf{x}_t) + \epsilon_{\text{observation}} \quad (3.11)$$

where f and g are arbitrary continuous, differentiable functions.

Since the transition and observation models are changed in the EKF, the prediction and update equations have to be updated to reflect this non-linear relationship. The prediction equations for the EKF can be expressed as:

$$\mathbf{x}_{t|t-1} = f(\mathbf{x}_{t-1|t-1}, \mathbf{u}_t) \quad (3.12)$$

$$\mathbf{P}_{t|t-1} = \mathbf{J}_f \mathbf{P}_{t-1|t-1} \mathbf{J}_f^T + \mathbf{Q} \quad (3.13)$$

where \mathbf{J}_f is the Jacobian of function f .

The update equations for the EKF can be expressed as:

$$\hat{\mathbf{x}}_{t|t} = \hat{\mathbf{x}}_{t|t-1} + \mathbf{K}(\mathbf{z}_t - g(\hat{\mathbf{x}}_{t|t-1})) \quad (3.14)$$

$$\mathbf{P}_{t|t} = \mathbf{P}_{t|t-1} - \mathbf{K} \mathbf{J}_g \mathbf{P}_{t|t-1} \quad (3.15)$$

where the Kalman gain matrix is expressed as:

$$\mathbf{K} = \mathbf{P} \mathbf{J}_g^T (\mathbf{J}_g \mathbf{P} \mathbf{J}_g^T + \mathbf{R})^{-1} \quad (3.16)$$

and \mathbf{J}_g is the Jacobian of function g .

Artificial Neural Network Weight Training

The above explanations of the Kalman filter and the EKF are general and not written to be specific to any problem, process or system. This section explains how the EKF can be applied for training the weights in an ANN.

An ANN consists of several layers of neurons. Each neuron outputs a signal which is generated by applying a function, often a non-linear sigmoid shaped function, to a weighted sum of its input signals. A common structure of an ANN is having an input layer, one or more hidden layers, and an output layer. The neurons are connected to each other with weighted edges, propagating signals from inputs to outputs. During training, the network is exposed to a set of input-output pairs. The network propagates the input signals through the network, and the output signal from the output neuron is compared to the correct output in the input-output pair. Then the weights are adjusted to make the difference

between the network's output and the correct output as small as possible across all training examples.

The outputs of the network can be seen as a non-linear function of the input signals to the network and the weights in the network. The idea presented in Van Lint [2008] is that one can consider the weights in an artificial neural network to perform a random walk along a high-dimensional path. These weights constitute the state vector, and the artificial neural network is assumed to make a non-linear observation of the weights through the network's outputs. This state space definition can be expressed as:

$$\begin{cases} \theta_t = \theta_{t-1} + \mathbf{r}_t, \mathbf{r}_t \sim \mathcal{N}(0, R_t) \\ y_t = G(\mathbf{x}_t, \theta_t) \end{cases} \quad (3.17)$$

where θ_t represents the weights at time t , θ_{t-1} represents the weights at time $t - 1$, \mathbf{r}_t represents the uncertainty with which the weights evolve, and $G(\mathbf{x}_t, \theta_t)$ represents the mapping from inputs to outputs in the ANN. Given this state-space definition, one can apply the EKF equations explained in Section 3.2.1 to update the weights in the artificial neural network in an incremental fashion.

Online-Delayed Extended Kalman Filter

A common setting for prediction tasks is to make a prediction $\hat{\mathbf{y}}_t$ based on an input \mathbf{x}_t at time t , observe the correct output \mathbf{y}_t , and update the model given the prediction error $\epsilon = \hat{\mathbf{y}}_t - \mathbf{y}_t$. This approach is applicable for many problems. However, it assumes that at the time that the prediction $\hat{\mathbf{y}}_t$ is made, the correct output \mathbf{y}_t is available. For many problems this is true, but this is not the case for travel time prediction. Imagine predicting travel times for a road section stretching from point A to point B . When a vehicle arrives at point A at time t_A , one wants to make a prediction \hat{y}_{AB} for how long it will take for that vehicle to arrive at point B , given the current traffic flow, traffic density and vehicle speeds \mathbf{x}_{t_A} . Making the prediction is straight forward, the input values \mathbf{x}_{t_A} are fed into the model, and a prediction \hat{y}_{AB} is given as output. However, the model cannot correct for the prediction error $\epsilon = \hat{y}_{AB} - y_{AB}$ until the actual travel time y_{AB} spent driving from point A to point B is available. This travel time is available at time $t = t_A + y_{AB}$. This is the approach taken in online-delayed EKF, where a prediction is made when a vehicle enters the road section, and the model is updated when the actual travel time for that vehicle is available. As the name indicates, this approach yields a model that is delayed. The weights of the artificial neural network is not updated until the realized travel time is available, which may be an arbitrary long time, especially during congestion. This makes the model lag behind the traffic situation.

Censored Extended Kalman Filter

To reduce the delay of when the model is updated, Van Lint [2008] proposes an approach that makes use of a *censored* observation of the realized travel time. Imagine a vehicle when it has just passed point B, lets call this point in time p . This vehicle entered the road section at some time m and spent d_m seconds driving from point A to point B, where $m = p - d_m$. Consider all vehicles starting at some time k where $m < k < p$ for which no realized travel time is available yet. Van Lint [2008] suggests that a *censored* observation of the travel time d_k is $d_k^* = p - k$. This censored observation of the actual travel time can be used as a lower bound estimate for the actual travel time during training, and the model can be updated at an earlier time p instead of being updated at time $k + d_k$ which is at a later point in time. This may lead to a model that reflects the traffic situation better than online-delayed EKF. This effect is best seen during the time when congestion is building up. In online-delayed EKF, as the travel times increase, it takes increasingly longer time until the model is updated. However, in censored EKF, the censored observations for these travel times provide an increasingly more accurate estimate of the actual travel time, and the model is updated incrementally as more censored observations become available. This leads to a model that better reflects the current traffic situation, and may lead to higher prediction accuracy.

3.2.2 Local Online Kernel Ridge Regression

In Haworth et al. [2014] a novel approach for travel time prediction is introduced, namely LOKRR. The approach is based on dividing the day into five minute intervals, and creating a travel time prediction model for each interval. This is done in order to capture traffic conditions that are local to a specific time of the day. As new observations become available, the travel time prediction model responsible for that specific time of day is updated. Consequently, the approach is considered online. The approach is based on using kernel ridge regression to generate a prediction for a data point as follows:

$$g(\mathbf{x}) = \mathbf{y}'(\mathbf{K} + \lambda \mathbf{I}_n)^{-1} \mathbf{k} \quad (3.18)$$

In Equation 3.18, \mathbf{x} is a new observation, \mathbf{K} is a kernelized version of matrix \mathbf{X} , which is a $n \times p$ matrix with n observations of p variables, \mathbf{y} is a vector of size n where element i corresponds to the true value for observation i in \mathbf{X} , λ is the regularization parameter, and \mathbf{k} is a vector of size n where element i is the value of a kernel function between the new observation \mathbf{x} and row i in \mathbf{X} .

The kernel function used in Haworth et al. [2014] is the Gaussian radial basis function kernel:

$$\mathbf{G}(\mathbf{x}, \mathbf{z}) = \exp\left(-\frac{\|\mathbf{x} - \mathbf{z}\|^2}{2\sigma^2}\right) \quad (3.19)$$

\mathbf{K} is generated by computing the value of Equation 3.19 between every pair of observations in \mathbf{X} . $\|\mathbf{x} - \mathbf{z}\|^2$ is the squared Euclidean distance between vectors \mathbf{x} and \mathbf{z} , whilst σ is the kernel bandwidth parameter controlling the smoothness of the function.

The idea in LOKRR is to divide the day into five minute intervals. For each interval, a data set containing observations of travel times during that specific interval for the last N days is created. This data set is what is referred to as the \mathbf{X} matrix in Equation 3.18. A kernel is created for each interval by computing the \mathbf{K} matrix based on \mathbf{X} . By creating a kernel for each interval, LOKRR is better able to capture subtle differences in traffic patterns that are local to specific times of the day. If one single big kernel was used for the entire data set, these local differences would be a lot more difficult to detect.

Haworth et al. argue that recurring events such as congestion during rush hours do not necessarily happen at exactly the same time every single day, which is why each kernel also contains data from its neighboring intervals. For a kernel responsible for interval t , its \mathbf{X} matrix contains data from interval $t-w$ to interval $t+w$, where w is the window size. This is done to create a buffer for when events can happen, whilst still being detectable by a single kernel.

To generate a travel time prediction for an observation \mathbf{x} at time t , LOKRR uses the kernel responsible for interval i containing time t to calculate Equation 3.18. As soon as the true travel time is observed, all the kernels responsible for an interval in the range $[i-w, i+w]$ update their \mathbf{X} matrix. This means that \mathbf{K} and \mathbf{K}^{-1} also need to be updated. Doing this every time a new travel time is realized is computationally expensive. Therefore, a method that significantly reduces the computation time by computing the inverse of \mathbf{K} at time $t+1$ based on the inverse at time t is used. The method is described in detail in Haworth et al. [2014, p. 156].

Chapter 4

Experiments and Results

This chapter presents the experiments performed in this study along with their results. Section 4.1 describes the intent of each experiment and how they are conducted. Section 4.2 explains the experimental setup, describing the data set, and model parameters. Section 4.3 describes the environment in which the experiments are run. Section 4.4 presents the results of the experiments.

4.1 Experimental Plan

This section introduces the different measures that are used to evaluate the performance of the approaches investigated in this study, in addition to describing the two experiments that are conducted.

4.1.1 Performance Metrics

The two performance metrics presented below are chosen because they are extensively used in the literature when comparing predicted values to observed values. They are measures representing the performance of a model using a single number, making it easy to compare the models to each other.

The first performance metric used is Root Mean Squared Error (RMSE), which is expressed as:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{t=N} (\hat{y}_t - y_t)^2}{N}} \quad (4.1)$$

where \hat{y}_t is the predicted value, y_t is the observed value and N is the number of observations.

Although RMSE is a commonly used error metric, it should be noted that one of the most prominent drawbacks with the RMSE comes from the fact that it squares the difference between predicted values and observed values. Large errors are therefore weighted exponentially more than small errors, making the RMSE sensitive to extreme values.

The other performance metric used is Mean Absolute Error (MAE), which is expressed as:

$$MAE = \frac{1}{N} \sum_{i=1}^n |\hat{y}_t - y_t| \quad (4.2)$$

where \hat{y}_t is the predicted value, y_t is the observed value and N is the number of observations.

As both RMSE and MAE are measures of the difference between the predicted and actual values, accurate predictions will result in low RMSE and MAE values. Therefore, minimizing RMSE and MAE is desirable.

4.1.2 Experiment 1 - Ensemble Learning

Experiment 1 is conducted in an attempt to answer Research Question 1, which relates to the prediction accuracy of each ensemble learning method described in Section 3.1. The outline of Experiment 1 is presented below, and Research Question 1 is repeated for convenience.

Outline Use predictions from a set of baselines to construct the ensemble learning methods bagging, boosting, lasso, and FRBS. Compare the ensembles to each other, and a simple average of the baselines' predictions, with respect to prediction accuracy.

Research Question 1 Given a set of baseline methods, which ensemble learning technique yields the best prediction accuracy?

Baseline Models

The first step in this experiment is to tune the parameters of the baseline methods SVM, k-NN, ANN and Kalman filter. This parameter tuning is performed on a designated part of the data set. A grid of possible parameters for each baseline is constructed, and a separate model for each combination of parameters is trained using k-fold cross-validation. For each baseline, the set of parameters that produce the lowest RMSE during the grid search is used in Experiment 1.

The baseline models are trained on a separate part of the data set with the parameters obtained from the parameter tuning step, and are used to make predictions for the rest of the data set.

Ensemble models

The next part of the experiment consists of training the ensemble learning models. The predictions from the baselines are divided into a training and a testing set for the ensemble learning techniques. Lasso and FRBS use the training set to tune their parameters and then make predictions for the testing set. Bagging and boosting differ from lasso and FRBS in terms of how they are constructed. Instead of constructing a model based on predictions from the same set of baselines as lasso and FRBS, they are concerned with constructing multiple versions of one type of baseline model. In order to give bagging and boosting a fair basis for comparison, their baselines are built on the same data set as the baselines used in lasso and FRBS. In addition, a naive ensemble learning approach taking the average of the baselines' predictions is constructed. The simple average of the baselines' predictions is included to give a basis for comparison to the other ensemble learning approaches.

In order to evaluate the performance of the ensemble methods in terms of prediction accuracy, their performance metrics and the properties of their error distributions are inspected. Additionally, hypothesis testing is conducted to investigate whether or not the potential differences between the methods are significant.

4.1.3 Experiment 2 - Online Learning

Experiment 2 sets out to give an answer to Research Question 2, which is concerned with finding the best performing online learning technique among the ones described in Section 3.2. The outline of Experiment 2 is presented below, and Research Question 2 is repeated for convenience.

Outline Train online-delayed EKF and LOKRR on a common data set and compare the two approaches with respect to prediction accuracy.

Research Question 2 Which online learning technique yields the best prediction accuracy?

Section 3.2.1 explains two ways of using the EKF to train an ANN in an online fashion, namely online-delayed EKF and censored EKF. Implementing the censored EKF approach is more time consuming than implementing the online-delayed EKF. Van Lint [2008] reports that using the censored EKF in favor of the online-delayed EKF only results in a slight improvement of prediction accuracy. Because the censored EKF approach requires more time to implement, and only offers a slight improvement over online-delayed EKF, it is decided to only investigate the latter approach in this study.

Parameters for the two online learning approaches online-delayed EKF and LOKRR are tuned using a designated part of the data set. The approach taken to tune the parameters of online-delayed EKF and LOKRR is similar to the one taken to tune the parameters of the baselines in Experiment 1. A grid of possible parameters is constructed, and a model for each combination of parameters is trained. The performance of each model is assessed using RMSE, and the model with best performance is chosen to be used in the next step of the experiment. This model is then used to make predictions, and learn when observations become available, for the rest of the data set.

In order to evaluate the performance of the online learning methods in terms of prediction accuracy, their performance metrics and the properties their error distributions are inspected. Additionally, hypothesis testing is conducted to investigate whether or not the potential differences between the methods are significant.

4.2 Experimental Setup

This section describes how the experiments are set up, including the data set and parameter tuning for the baselines, ensemble learning approaches and online learning approaches.

4.2.1 Data Description

The data used in the experiments in this study is collected by the NPRA from highway E39 between Dusavik and Bogafjell in Rogaland, Norway. The route is illustrated in green in Figure 4.1. There are in total five measurement points along this route, illustrated as black lines across the road in Figure 4.1. Data from two consecutive points, Tjensvoll and Auglendshøyden, along this route is used in the experiments. The stretch is 4.6 km long, and the data is collected in the southbound direction between January 29, 2015 and March 31, 2015. The road section is highlighted in red in Figure 4.1.

The data set consists of two input variables and one output variable. The two input variables used are mean travel time the last five minutes, and traffic flow at the entry point the last five minutes. The value of each variable is computed at the time a vehicle enters the road section. The output variable in the data set is the realized travel time for the vehicle. The data is collected by registering IDs from AutoPASS tags in vehicles driving along this road section. Travel times are derived by computing the time difference between the registration of the same AutoPASS identification number at the two points. The mean travel times are

¹<http://www.reisetider.no/reisetid/omrade.html?omrade=4>, April 19, 2015



Figure 4.1: Map showing the route where the data is collected from.¹

trivial to compute once the travel times are registered. Traffic flow is derived from counting the number of vehicles passing the first registration point. The data set consists of 247 074 observations, and the first ten rows of the data set are shown in Table 4.1.

A plot of all individual travel times and five minute mean of all travel times for January 29, 2015 can be seen in Figure 4.2 and Figure 4.3, respectively. A plot of the traffic flow based on all vehicles for the same day is displayed in Figure 4.4. By inspecting the travel times plotted in Figure 4.2 it can be seen that a considerable amount of outliers are present in the data set. These are seen as dots lying far above the travel times representative for the current traffic situation. The outliers may represent commuters stopping along the road section to fill gas or to run other errands. In order to train models on observations in the data set that are representative for the actual traffic situation, an attempt to remove outliers is conducted. All rows in the data set having a travel time outside the range $[\mu - 3\sigma, \mu + 3\sigma]$ are removed, where μ is the mean of the travel times in the data set and σ is the standard deviation of the travel times in the data set. The data set where outliers are removed is used in Experiment 1.

In real time systems, where online approaches may be used, removing outliers from the data set is not as straight forward as the approach described above. A global threshold for removing outliers will not suffice, as changes to the data set can happen over time, and the same threshold will not always lead to correct

removals. One can imagine using a more local approach to remove outliers, where travel times above some weighted sum of the x previous travel times are not fed to the online learning method. However, such an attempt to remove outliers is not performed in this work, and the online learning approaches in Experiment 2 are trained using the unprocessed data set.

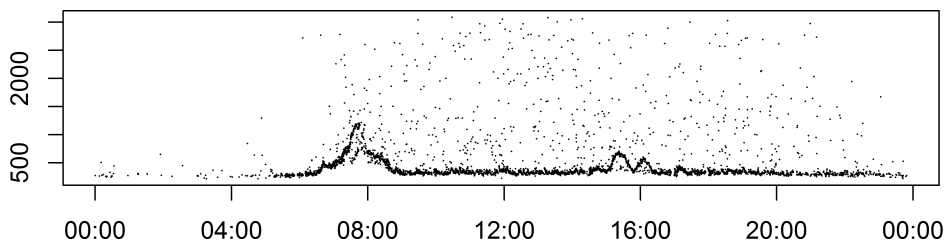


Figure 4.2: Plot of all travel times from January 29, 2015

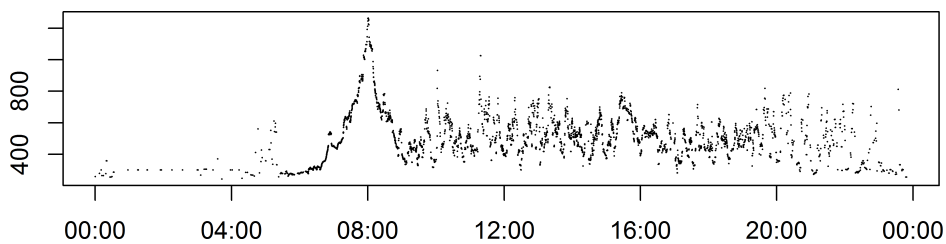


Figure 4.3: Plot of five minute mean of all travel times from January 29, 2015

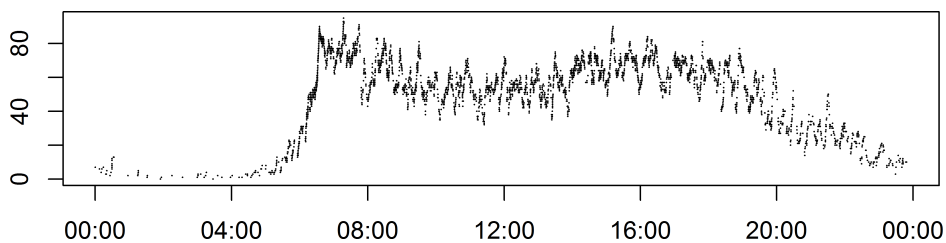


Figure 4.4: Plot of traffic flow based on all vehicles from January 29, 2015

Date and time	Mean travel time	Traffic Flow	Travel Time
2015-01-29 00:01:25	298.67	4	242
2015-01-29 00:05:14	690	6	1111
2015-01-29 00:07:05	386.67	6	243
2015-01-29 00:11:55	243	4	241
2015-01-29 00:27:43	1111	2	639
2015-01-29 00:28:25	1111	3	223
2015-01-29 00:35:34	223	3	292
2015-01-29 00:37:27	300	3	249
2015-01-29 00:39:47	639	6	335
2015-01-29 00:40:11	639	8	302

Table 4.1: Example rows from the data set

4.2.2 Baselines

This section describes each baseline method used in Experiment 1. The process applied to every baseline is presented in the first section below, whilst specific details about each baseline is given in the following sections.

Overview

The baseline methods used in Experiment 1 are implemented in R [R Core Team, 2014]. Parameter tuning and training for SVM, k-NN and ANN is done through the library `caret` [Kuhn et al., 2015], which is a library meant to make the process of constructing predictive models in R easier. In this work, `caret` is used as a layer between the authors code in R and the respective implementations of the baseline methods. `caret` provides structures for setting the grid for which parameters are to be searched among, and returns the model with parameters providing the best performance in terms of RMSE. Tuning and training of the Kalman filter is done with the R library `d1m` [Petris, 2010].

The baselines use the data set were outliers are removed. In order to find the best set of parameters for each baseline, 10-fold cross-validation on data from January 29, 2015 to February 1, 2015 is used. Each baseline is then trained with the best set of parameters on data from February 5, 2015 to February 25, 2015. The resulting models are then used to generate predictions from February 26, 2015 to March 31, 2015.

Support Vector Machine

The SVM implementation used in this work is from the R library `kernlab` [Karatzoglou et al., 2004]. When using SVMs one can choose among several kernel functions. To determine which kernel to use in the SVM of Experiment 1, a preliminary experiment comparing the RMSE of SVM models using linear, polynomial and radial basis kernel functions is conducted. The training data for these models are observations from January 29, 2015 to February 1, 2015. The testing data, for which the RMSE is computed, is from February 2, 2015 to February 4, 2015. For each kernel, a grid of possible parameter values is searched in order to find the best set of parameters. The SVM with a radial basis kernel function produced the lowest RMSE, and is therefore selected to be used in Experiment 1. Among the parameter values tested in the grid search for the radial basis function SVM models, the parameters $\sigma = 4.1451$ and $C = 2^{-1}$ produced the best performing model, and is the one used in Experiment 1. For a more detailed description of the parameter search for SVM, please see Appendix B.1.

k-Nearest Neighbors

The k-NN implementation used in this work is from the R library `kkn` [Schliep and Hechenbichler, 2014]. The parameters that are possible to tune in `kkn` are k , distance measure and kernel. The k parameter controls how many neighbors to extract from the instances present in the data set when making predictions. The distance measure parameter controls how the distance between two points in the data set is computed. The kernel parameter controls how to weight the values of the k neighbors based on their distance. In order to find a good set of parameters for the weighted k-NN algorithm a grid search is performed. Based on the results from the grid search, the following parameters lead to the lowest RMSE: $k = 50$, distance measure = 1 (Euclidean) and kernel = Rank. Please see Appendix B.1 for a more comprehensive description of the grid search process.

Artificial Neural Network

The ANN implementation used in Experiment 1 is from the R library `nnet` [Venables and Ripley, 2002]. The `nnet` library provides functions for creating and training feed forward ANNs with a single hidden layer. The parameters being tuned for the ANN is the number of hidden nodes in the network and the weight decay parameter. The parameters producing the lowest RMSE are: number of hidden nodes = 16 and decay = 1×10^{-4} . Please see Appendix B.1 for a more elaborate description of the parameters, and a table presenting the results for each combination of parameters.

Kalman Filter

`d1m`, which is an R library providing functions for defining dynamic linear models of various types, is used to perform the Kalman filter predictions in Experiment 1. The actual travel times of the data set form a time series, and it is assumed that this time series of travel times can be modelled using a first order linear model with the following state space formulation:

$$\begin{cases} y_t = \theta_t + v_t, v_t \sim \mathcal{N}(0, V_t) \\ \theta_t = \theta_{t-1} + w_t, w_t \sim \mathcal{N}(0, W_t) \end{cases} \quad (4.3)$$

where y_t is the observed travel time at time t , θ_t is the *actual* travel time at time t , which is assumed to be unobservable, v_t is the observation noise and w_t is the process noise. Both v_t and w_t are assumed to follow a zero mean Gaussian distribution with covariance matrices V_t and W_t , respectively.

The parameters that are tuned for this model are the covariance matrices V_t and W_t . Since y_t and θ_t are univariate, matrices V_t and W_t are 1×1 matrices, and only one value per covariance matrix is tuned. V_t and W_t are set to 47 939 and 122, respectively. In order to give a complete definition of the dynamic linear model, an initial estimate of $y_{t=0}$ and its variance $\sigma_{t=0}$ has to be provided. This is set to be the mean and standard deviation of the training observations, which are 242 and 255, respectively. A detailed description of the parameter tuning process can be found in Appendix B.1.

4.2.3 Ensemble Learning Methods

The setup of each ensemble method used in Experiment 1 is presented in this section. The general procedure is described in the first section below, whilst specific details concerning the setup of each ensemble method can be found in the following sections.

Overview

Bagging and boosting train multiple SVMs on the same data set used to train the baselines described in Section 4.2.2, which consists of data from February 5, 2015 to February 25, 2015. These SVMs then generate predictions on data from February 26, 2015 to March 31, 2015.

Lasso and FRBS use the predictions of the baselines described in Section 4.2.2 as input. Lasso is tuned and trained on predictions made by the four baselines from February 26, 2015 to March 18, 2015. Lasso's predictions are generated based on the predictions of the four baselines from March 19, 2015 to March 31, 2015. Due to the computational complexity of FRBS, only one week of data

from February 26, 2015 to March 4, 2015 is used to search for the best set of parameters. As the rules in the FRBS are manually created, no training phase is necessary. Predictions by FRBS are generated from March 5, 2015 to March 31, 2015.

Bagging

The bagging method is implemented in R. There are two parameters that must be specified for bagging: the number of learners K to use in the ensemble, and the number of observations N to sample for each learner. In Experiment 1, K is set to 25, and N is set to the number of training examples in the training set. An SVM model with the parameters of the best performing model from the parameter tuning step for SVM reported in Section 4.2.2 is used, i.e. an SVM model with a Gaussian radial basis function as kernel, $\sigma = 4.1451$ and $C = 2^{-1}$.

Boosting

In order to investigate the effects of boosting, the AdaBoost algorithm [Freund and Schapire, 1997] is used. An implementation of the AdaBoost.r2 algorithm [Drucker, 1997], which is a version of the AdaBoost algorithm for regression problems, is found in the Python library `scikit-learn` [Pedregosa et al., 2011]. Of the baseline methods used in this work, the only method that is both implemented in `scikit-learn` and supports weighting of training examples is SVM. It is therefore used as the baseline in the boosting ensemble in Experiment 1. An SVM model with the same parameters as the one used in bagging is also used for the boosting approach. The only parameter provided to the AdaBoost algorithm is the number of learners K to use in the ensemble, which is set to 25 in Experiment 1.

Lasso Ensemble

The implementation of the lasso method from the R library `elasticnet` [Zou and Hastie, 2012] is used in Experiment 1. The `elasticnet` library provides functions for defining elastic nets, of which the lasso method is a special case. Recall from Equation 3.2 in Section 3.1.3 that the optimal weights in lasso is given by solving the following equation:

$$\hat{\mathbf{W}} = \arg \min_{\mathbf{W}} \|\mathbf{F} - \mathbf{GW}\|_2^2 + \lambda \|\mathbf{W}\|_1$$

where λ is a parameter of the Lasso method. `caret` provides functionality for optimizing this λ parameter through a grid search, where RMSE is used to assess the performance of a given λ value. A λ value of 1 resulted in the lowest RMSE,

<p>IF ANN is <i>low</i> and KF is <i>low</i> THEN output is <i>low</i> IF ANN is <i>low</i> and KF is <i>not low</i> THEN output is <i>low</i> IF ANN is <i>medium</i> and KF is <i>medium</i> THEN output is <i>medium</i> IF ANN is <i>medium</i> and KF is <i>not medium</i> THEN output is <i>medium</i> IF ANN is <i>high</i> and KF is <i>high</i> THEN output is <i>high</i> IF ANN is <i>high</i> and KF is <i>not high</i> THEN output is <i>high</i></p>

Table 4.2: Rule base preferring ANN over Kalman filter (KF)

<p>IF KF is <i>low</i> and ANN is <i>low</i> THEN output is <i>low</i> IF KF is <i>low</i> and ANN is <i>not low</i> THEN output is <i>low</i> IF KF is <i>medium</i> and ANN is <i>medium</i> THEN output is <i>medium</i> IF KF is <i>medium</i> and ANN is <i>not medium</i> THEN output is <i>medium</i> IF KF is <i>high</i> and ANN is <i>high</i> THEN output is <i>high</i> IF KF is <i>high</i> and ANN is <i>not high</i> THEN output is <i>high</i></p>

Table 4.3: Rule base preferring Kalman filter (KF) over ANN

and is the one used in Experiment 1. More details concerning the parameter tuning of lasso can be found in Appendix B.2.

Fuzzy Rule Based System

The R library `frbs` [Riza et al., 2015] is used to generate an FRBS based on the approach described in Stathopoulos et al. [2008]. The input to the FRBS is a data set containing predictions from the ANN and the Kalman filter described in Section 4.2.2. Following the approach described in Stathopoulos et al. [2008], two different rule bases, each preferring one of the two baselines, are used. The rule base preferring ANN is displayed in Table 4.2, whilst the rule base preferring Kalman filter is illustrated in Table 4.3. The travel time predictions from the baselines are mapped with triangular membership functions to three fuzzy sets: *low*, *medium*, and *high*. Data from February 26, 2015 to March 4, 2015 is used to optimize the membership function parameters. The final membership parameters are presented in Table 4.4 and Table 4.5. The value b defines the peak of the triangle, whilst the values a and c define the left and right boundary of the triangle, respectively. Please refer to Appendix B.2 for more details with regards to the FRBS setup.

	low	medium	high
a	204.5799	292.2150	298.0683
b	287.4319	313.9751	1111.8725
c	302.5835	404.7539	1448.2825

Table 4.4: Membership function parameters for FRBS preferring ANN

	low	medium	high
a	164.3251	240.4815	272.8217
b	328.2455	344.3591	968.0878
c	332.7156	1039.4697	1700.2693

Table 4.5: Membership function parameters for FRBS preferring Kalman filter

4.2.4 Online Learning Methods

This section presents the setup of the online methods used in Experiment 2. First, the general approach is described. Second, specific details for the individual methods are presented in their respective sections.

Overview

The online learning methods are tuned and trained on two weeks of data from January 29, 2015 to February 11, 2015. The first week is used to build the models with a certain set of parameters, whilst the second week is used to calculate the RMSE of the predictions done during that week. Since the methods are online, the data in the second week is also used to update the models whilst making predictions. The parameters that lead to the lowest RMSE during parameter tuning is used in the final model. Predictions are generated from February 12, 2015 to March 31, 2015. No outliers are removed in the data set used in Experiment 2.

Online-Delayed Extended Kalman Filter

An implementation of the EKF [Cao, a] and using this EKF to train a feed-forward ANN [Cao, b] is found in Matlab [MATLAB, 2014] on the Matlab Central File Exchange². Recall from Equation 3.17 in Section 3.2.1 that the state space definition that is assumed for the EKF can be expressed as follows:

$$\begin{cases} \theta_t = \theta_{t-1} + \mathbf{r}_t, \mathbf{r}_t \sim \mathcal{N}(0, R_t) \\ y_t = G(\mathbf{x}_t, \theta_t) \end{cases}$$

²<http://www.mathworks.com/matlabcentral/fileexchange/>, May 21, 2015

where θ_t represents the weights in the feed-forward ANN at time t , \mathbf{r}_t is the noise with which the weights are assumed to evolve, and G represents the mapping performed by the ANN from inputs \mathbf{x}_t to output y_t given weights θ_t .

Recall from Section 3.2.1 that an initial estimate of the state vector $\mathbf{x}_{t=0}$, its covariance matrix $\mathbf{P}_{t=0}$, process noise covariance matrix \mathbf{Q} , and observation noise covariance matrix \mathbf{R} has to be defined in order to run the EKF. Due to the way EKF is used in the experiments in this study, an initial estimate of the weights θ_{initial} has to be provided. The approach described in Van Lint [2008] is that the weights θ_{initial} are initialized using the Nguyen-Widrow method [Nguyen and Widrow, 1990]. In Van Lint [2008], the weights' covariance matrix $\mathbf{P}_{\text{initial}}$ is initialized to a diagonal matrix with large values, reflecting that it is assumed that the weights are independent, and that there is a large uncertainty regarding the initial guess of the weights. These are also the approaches taken in this work, and the value along the diagonal of θ_{initial} is set to 10 000.

As Van Lint [2008] does not describe how the covariance matrices \mathbf{Q} and \mathbf{R} are set, a parameter tuning step is performed to find reasonable values for \mathbf{Q} and \mathbf{R} , in addition finding to the number of nodes in the hidden layer in the feed-forward ANN. The covariance matrix \mathbf{Q} is assumed to be a diagonal matrix, once more reflecting that the weights are independent, such that the only value being searched for regarding \mathbf{Q} in the parameter tuning step, is the value q along the diagonal of \mathbf{Q} : $\mathbf{Q} = q \times \mathbf{I}$. As the output y_t consists of a single value, namely the travel time, the covariance matrix \mathbf{R} of the observation noise is a single element r reflecting the noise related to the observations that the ANN makes of the weights.

The parameters that produced the lowest RMSE during the tuning process are: $q = 0.1$, $r = 750$, number of hidden nodes = 1. Please see Appendix B.3 for more details on the parameter tuning process.

Local Online Kernel Ridge Regression

To the best of the authors knowledge, no open source implementation of LOKRR exists. Therefore, an implementation of LOKRR is developed in Python [Rossum, 1995]. The parameters of LOKRR are tuned on the same data set as in online-delayed EKF. For each pair of parameter values, the kernels are trained, i.e. the inverse of the regularized kernel matrix is calculated, on the first week of data. The predictions are made on the second week of data. The observations in the test set are also used to update the kernels to simulate how LOKRR would normally work. The \mathbf{X} matrix is reset to contain only the training data before every run with new parameters. This way the best pair of parameters are found for each kernel.

The recommendations, presented in Haworth et al. [2014], for finding possible parameter values for the kernel bandwidth σ and the regularization constant λ

are followed. The approach recommended in the article for finding possible λ values is based on Exterkate [2013]. First, the R^2 of an ordinary least squares fit of \mathbf{y} on \mathbf{X} is found. Then λ_0 is determined as $\lambda_0 = 1/\phi_0$, where $\phi_0 = R^2/(1 - R^2)$. The recommended values for λ are $\{1/8\lambda_0, 1/4\lambda_0, 1/2\lambda_0, \lambda_0, 2\lambda_0\}$. The recommended approach for finding possible σ parameters is based on the observation that optimal values of σ lie in the range between the 0.1 and 0.9 quantiles of the pairwise euclidean distance between the points in the kernel [Caputo et al., 2002]. The 0.25, 0.5 and 0.75 quantiles are used as possible values for σ . Due to the amount of data being smaller during the night, the data set used for LOKRR only contains observations from 06:00 to 21:00. Additionally, the window size is set to 1. This is done to reduce the computational complexity. A more detailed description of the LOKRR implementation can be found in Appendix B.3.

4.3 Environment

The experiments described in Section 4.1 are run in two environments, an Ubuntu 14.04 server at Amazon Elastic Computing Cloud (EC2)³ and a laptop computer. The Ubuntu server is running on a EC2 instance of type m3.xlarge⁴, which has a Intel Xeon E5-2670 v2 (Ivy Bridge) processor⁵ @ 2.5 GHz and 15 GiB of RAM. The laptop computer is a Samsung ATIV Book 9 Plus NP940X3G running Windows 8.1 with an Intel Core i7-4500U Processor @ 1.8 GHz⁶ and 8 GiB of RAM. The Ubuntu server is used to run all experiments, with the exception of the online-delayed EKF which is run in Matlab on the laptop computer.

4.4 Experimental Results

This section presents the results of Experiment 1 and Experiment 2 in the form of tables showing RMSE and MAE across all examples in the testing set.

Table 4.6 displays the performance metrics for bagging, boosting, lasso, FRBS and a simple average of the baselines' predictions. The performance metrics in Table 4.6 are computed based on predictions and actual travel times from March 19, 2015 to March 31, 2015 as this is the largest span of dates that all models have made predictions for. This is done in order to give all methods an equal basis for comparison.

³<http://aws.amazon.com/ec2/>, May 21, 2015

⁴<http://aws.amazon.com/ec2/instance-types/>, May 21, 2015

⁵http://ark.intel.com/products/75275/Intel-Xeon-Processor-E5-2670-v2-25M-Cache-2_50-GHz, May 21, 2015

⁶http://ark.intel.com/products/75460/Intel-Core-i7-4500U-Processor-4M-Cache-up-to-3_00-GHz, May 21, 2015

Model	RMSE	MAE
Bagging	231.87	93.883
Boosting	233.36	165.57
Lasso	167.09	95.920
FRBS	167.71	94.003
Average	215.69	98.346

Table 4.6: Performance metrics for ensemble approaches

Table 4.7 shows performance metrics values computed from actual travel times and predictions from online-delayed EKF and LOKRR. The performance metric values are computed based on predictions and actual travel times from February 12, 2015 to March 31, 2015.

Model	RMSE	MAE
Online-delayed EKF	427.19	230.55
LOKRR	476.18	233.53

Table 4.7: Performance metrics for online-delayed EKF and LOKRR

Chapter 5

Evaluation and Conclusion

Section 5.1 presents an evaluation of the results presented in Section 4.4. Section 5.2 offers a more detailed discussion, presenting possible explanations for the results. Section 5.3 draws the final conclusions based on the evaluation and discussion. Section 5.4 summarizes the contributions of this work, and Section 5.5 suggest possible directions for future work.

5.1 Evaluation

This section evaluates the experimental results presented in Section 4.4, and forms the basis for the statistical inference employed in this evaluation.

5.1.1 Overview

Figure 5.1 and Figure 5.2 display plots and tables showing sample median, sample mean and sample deviation of the error distributions of the predictions from the ensemble learning and online learning approaches, respectively. The error is computed by subtracting the actual travel time from the predicted travel time. Before performing any statistical inference regarding these distributions, it is important to know whether or not they can be assumed to be normally distributed. The distribution of the error affects which properties of the distributions that should be compared, and which hypothesis tests can be employed. Some of the characteristics of the normal distribution are that it is symmetrical about its mean μ ; the first derivative is positive for all $x < \mu$ and negative for all $x > \mu$; and the mean, median and mode are the same value. By considering the density plots, it can be seen that none of these properties are satisfied by the error distributions. This indicates that the errors of the different methods do not follow

Model	A	p
Bagging	8945.0	3.7×10^{-24}
Boosting	8875.1	3.7×10^{-24}
Lasso	6413.8	3.7×10^{-24}
FRBS	5400.5	3.7×10^{-24}
Average ensemble	8124.1	3.7×10^{-24}
Online-delayed EKF	29300	3.7×10^{-24}
LOKRR	21771	3.7×10^{-24}

Table 5.1: Result of Anderson-Darling normality test

a normal distribution.

To further investigate this assumption, the Anderson-Darling test [Anderson and Darling, 1952] is employed to check for normality. The Anderson-Darling test investigates whether or not a given distribution follows a normal distribution. Its null hypothesis is that the distribution follows a normal distribution, and the alternative hypothesis is that the given distribution is not normally distributed. The Anderson-Darling test statistic and the corresponding p-value for each methods' error distribution is displayed in Table 5.1. The Anderson-Darling test is based on 50 381 samples for the ensemble learning approaches, and 176 953 samples for the online learning approaches. The results of the Anderson-Darling test indicate, on a 0.05 significance level, that none of the error distributions follow a normal distribution. Based on the inspection of the error distributions, and the results of the Anderson-Darling test, it is assumed that none of the errors are normally distributed.

5.1.2 Experiment 1 - Ensemble Learning

In order to investigate Research Question 1, which is repeated below for convenience, a comparison between all the different ensemble methods is conducted. First, this section compares the performance metrics of the different ensemble learning approaches. Second, the plots of the error distributions are evaluated. Finally, the results from the non-parametric significance tests are reported.

Research Question 1 Given a set of baseline methods, which ensemble learning technique yields the best prediction accuracy?

Performance metrics

The results from Experiment 1 indicate that lasso has the lowest RMSE of all the ensemble learning approaches. However, it is only slightly lower than the RMSE

Model	Sample median	Sample mean	Sample deviation
Bagging	3.3645	-59.036	224.23
Boosting	127.34	55.521	226.66
Lasso	44.158	2.7922	167.07
FRBS	38.944	-4.6371	167.64
Average	20.313	-47.314	210.44

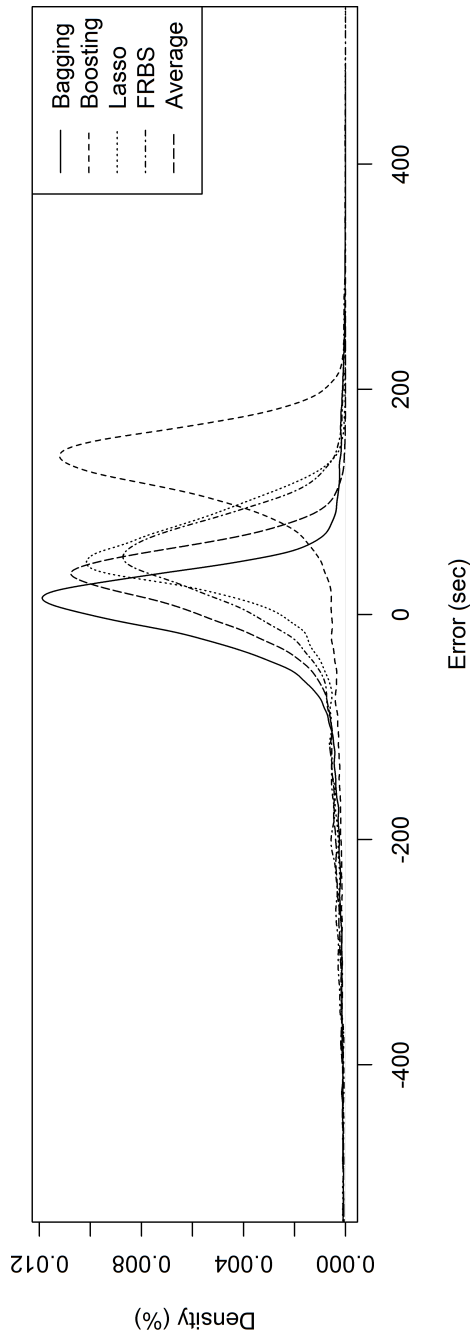
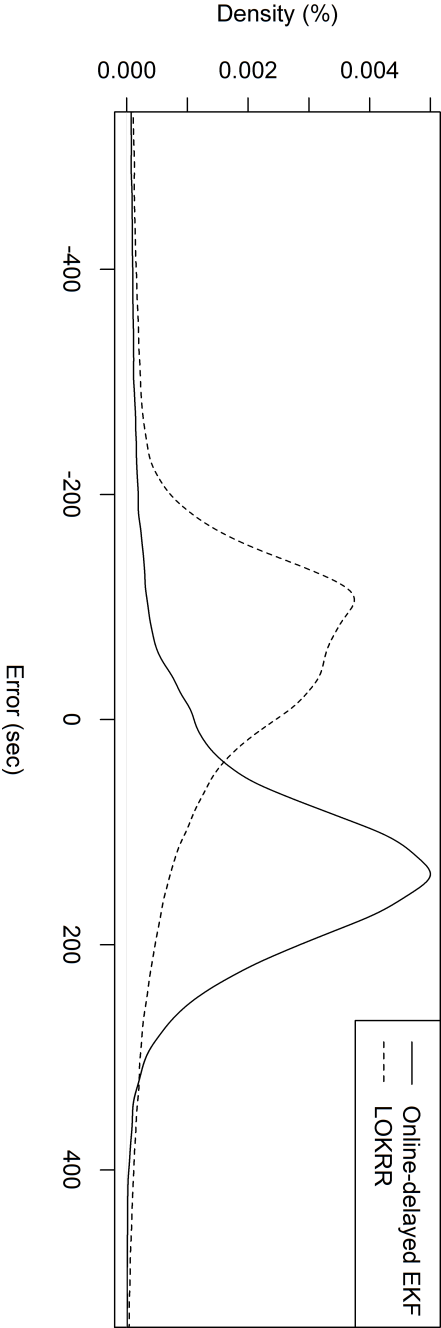


Figure 5.1: Density of errors from the ensemble learning approaches



Model	Sample median	Sample mean	Sample deviation
Online-delayed EKF	117.26	-3.9720	427.17
LOKRR	-69.816	-153.40	450.80

Figure 5.2: Density of errors from the online learning approaches

of FRBS. Bagging, boosting and average have considerably higher RMSE values than lasso and FRBS.

Comparing the MAE for the different models forms a slightly different picture. The most noticeable difference comparing the MAE values in contrast to the RMSE values, is that bagging has the lowest value among the ensemble learning approaches. Lasso, FRBS and the average have MAE values close to that of bagging. However, boosting's MAE is considerably higher than the MAE values of the other ensemble methods.

The results presented above do not agree upon which method is most accurate in terms of both RMSE and MAE. Consequently, the performance metrics alone may not be sufficient to support any conclusions as to which ensemble learning approach provides the best prediction accuracy. The density plots presented in Figure 5.1 contain a lot of information a single performance metric is unable to represent. Therefore, a detailed examination of the error distributions follows.

Error distributions

Due to the non-normality assumption of the error distributions, the sample mean of an error distribution is not a representative value for where the majority of the mass of the distribution is located. Figure C.5 to Figure C.9 in Appendix C illustrate the individual error distributions for the ensemble learning methods. The sample means of the distributions are affected by the long tails present in the error distributions, and are offset in the direction of the most prominent tail. Two measures that are more capable of representing the location of the majority of the error distributions' mass are the sample median and sample mode, as these are not as affected by the tails present in the error distributions as the sample mean. The sample median is chosen as a basis for comparison here because it is convenient to use in non-parametric significance tests.

From the error distributions, presented in Figure 5.1, it can be seen that bagging has a sample median close to zero. This might indicate that bagging is close to unbiased when predicting travel times. Based on the sample median of the error distributions it appears as though average, FRBS, lasso and boosting are biased towards overestimating travel times.

Furthermore, there are noticeable differences between the distributions' sample deviation. Lasso and FRBS have sample deviations that are considerably lower than the sample deviations of average, bagging and boosting. Bagging, boosting and the average have long tails towards the left. This can be seen in Figure C.5, Figure C.6 and Figure C.9 in Appendix C, respectively. This indicates that in rare cases the models heavily underestimate the travel time. Both lasso and FRBS have long tails on both sides, indicating that they occasionally greatly overestimate or greatly underestimate the travel time.

In order to investigate whether the observed differences between the sample medians of the different models are significant, statistical significance testing should be employed. Usually, the alternative hypotheses in significance tests are expressed as $\text{mean}_A < \text{mean}_B$. This poses a problem in this case, as the distributions contain negative errors, which leads to incorrect orderings. Comparing an error of -100 to an error of $+1$ would prefer the error of -100 . This is undesirable because it is a larger error, only in the negative direction. For this reason, plots of the distribution of absolute errors are used as basis for making the alternative hypotheses.

Figure 5.3 displays plots and a table showing the sample medians of the distributions of the absolute errors of the ensemble learning approaches. Table 5.2 ranks the ensemble learning approaches, from best to worst, based on how close their sample medians are to zero, i.e. based on their bias. The closer the sample median is to zero, the lower the bias. As bagging seems to have the lowest bias of the ensemble learning approaches, it given the highest rank. This ranking forms the basis for the hypotheses that a method has lower sample median than all of the methods having a lower rank than itself. To further investigate whether or not these hypotheses are supported by the data, statistical significance testing is employed.

Method	Rank
Bagging	1st
Average	2nd
FRBS	3rd
Lasso	4th
Boosting	5th

Table 5.2: Ranking based on the approaches' bias. Lower bias results in lower rank.

Hypothesis Testing

Based on the assumption that the errors do not follow a normal distribution, non-parametric significance testing is used to test the hypotheses described above. In non-parametric significance testing, the test variable used is the sample median. This is in contrast to parametric significance testing, where the sample mean is used.

When doing significance testing on a group of related hypotheses, the probability of making type 1 errors increases as the number of hypotheses increases. This probability is referred to as the familywise error rate, and the concept of increased probability of making type 1 errors when the number of hypotheses

Model	Sample median
Bagging	26.658
Boosting	136.14
Lasso	58.973
FRBS	58.218
Average	40.617

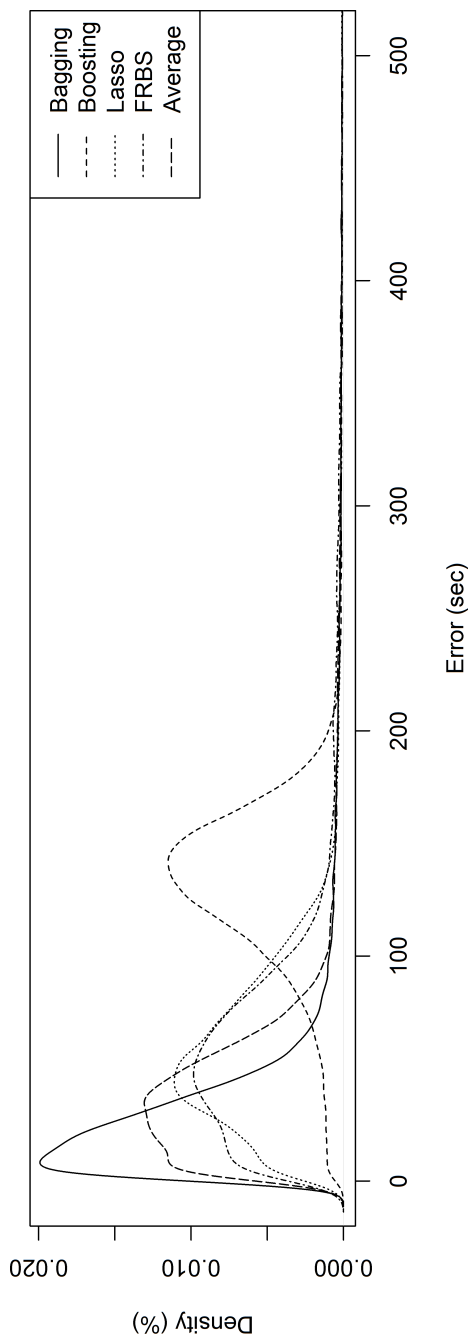


Figure 5.3: Density of absolute errors from the ensemble learning approaches

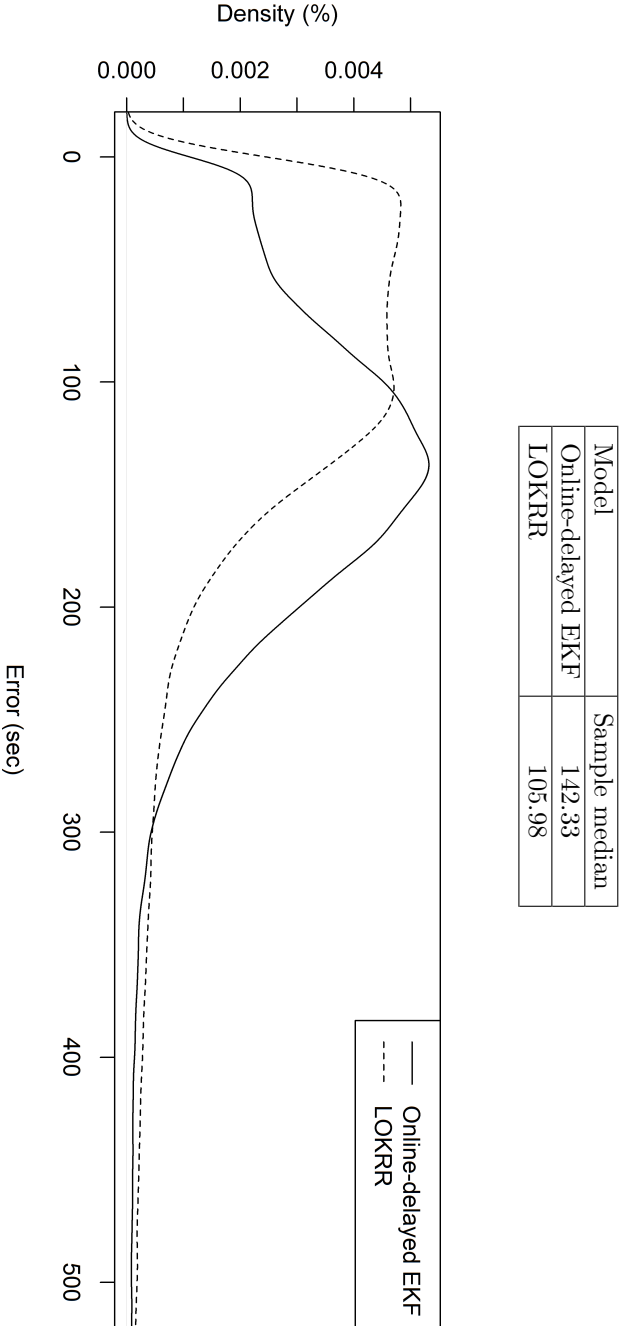


Figure 5.4: Density of absolute errors from the online learning approaches

increases is known as the multiplicity effect [Salzberg, 1997]. Trawinski et al. [2012] suggests using the approach described in García and Herrera [2008] to control the familywise error rate, when comparing more than two machine learning regression models. The approach uses the Friedman test [Friedman, 1937], which works by assigning a rank to each model. For every prediction made during testing, the model with the lowest error is assigned the lowest rank and the model with the highest error is assigned the highest rank. The average rank is computed for each model across all predictions. The Friedman test indicates whether any of the rankings are significantly different from each other. However, it does not identify the specific pairs of models that differ. Consequently, one or more post-hoc procedures are needed to determine which pairs of models that are significantly different. Note that these procedures do not test whether or not the differences in sample medians are significant. Rather, their test statistic is based on the differences in Friedman rank.

The post-hoc procedures used in García and Herrera [2008] are Nemenyi [Nemenyi, 1962], Holm [Holm, 1979], Shaffer [Shaffer, 1986], and Bergmann-Hommel [Bergmann and Hommel, 1988]. These procedures perform two-sided hypothesis tests, and can therefore only establish whether or not there is a significant difference in Friedman rank between a pair of models. In the cases where a significant difference can be established, the rank from the Friedman test indicates which of the two models is considered best, where lower rank is better.

This study follows the approach recommended in Trawinski et al. [2012]. The Friedman test and post-hoc procedures are conducted using an open source program available on the web page¹ for the research group Soft Computing and Intelligent Information Systems at the University of Granada, Spain. The software is written in Java [Gosling et al., 2013] and follows the procedure reported in García and Herrera [2008]. It is important to note that the program assumes the input to be prediction accuracies. Since the performance of the methods investigated in this study are assessed with error metrics, the inverse of the absolute error is given as input to the program.

The Friedman test is run using 50 381 observations of inverse absolute errors from the five ensemble learning approaches. The result of running the Friedman test indicates, on a 0.05 significance level, that there is a significant difference in performance between the ensemble learning approaches. The ranking resulting from the Friedman test is displayed in Table 5.3. As the Friedman test indicates a significant difference between the ensemble learning approaches, post-hoc procedures are employed to determine for which pairs of algorithms the difference is significant. The adjusted p-values resulting from running the different post-hoc procedures are illustrated in Table 5.4, where the approach highlighted with bold font is the one with lowest rank in the Friedman test. The post-hoc procedures

¹<http://sci2s.ugr.es/sicidm/#ten>, May 21, 2015

are unanimous in their decisions to reject all the null hypotheses with a significance level of 0.05. The results indicate that bagging has a significantly lower Friedman rank than all the other ensemble approaches in this study. Furthermore, the Friedman rank of average is significantly lower than that of boosting, lasso and FRBS. The test also reveals that the Friedman rank of FRBS is significantly lower than the Friedman rank of lasso, whilst both lasso and FRBS have a significantly lower Friedman rank than boosting.

Algorithm	Friedman rank	Rank position
Bagging	2.1884	1st
Average	2.4067	2nd
Lasso	2.9801	3rd
FRBS	3.0291	4th
Boosting	4.3957	5th

Table 5.3: Friedman ranking

5.1.3 Experiment 2 - Online Learning

In order to investigate Research Question 2, which is repeated below for convenience, a comparison of the two online learning approaches is conducted. First, the performance metrics of online-delayed EKF and LOKRR are compared. Second, the error distributions of the two online methods are examined. Finally, statistical significance testing is employed.

Research Question 2 Which online learning technique yields the best prediction accuracy?

The results from Experiment 2 indicate that the online-delayed EKF has a noticeably lower RMSE than LOKRR. Online-delayed EKF also has the lowest MAE. In contrast to the RMSE values, the MAE values do not differ considerably from each other.

Figure 5.2 displays plots and a table showing sample median, sample mean and sample deviation of the error distributions of online-delayed EKF and LOKRR. Online-delayed EKF has a sample median of 117.26, whilst LOKRR has a sample median of -69.816 . This might indicate that the two methods have different bias towards predicting travel time, where online-delayed EKF tends to overestimate the travel time and LOKRR tends to underestimate the travel time. Figure C.10 and Figure C.11 in Appendix C illustrate the error distributions individually for online-delayed EKF and LOKRR, respectively. Looking at the tails of error distributions for the two methods, it can be seen that LOKRR's

Algorithms	Nemenyi	Holm	Shaffer	Bergmann-Hommel
Bagging vs. boosting	0.0	0.0	0.0	4.9×10^{-324}
Boosting vs. average	0.0	0.0	0.0	4.9×10^{-324}
Boosting vs. lasso	0.0	0.0	0.0	4.9×10^{-324}
Boosting vs. FRBS	0.0	0.0	0.0	4.9×10^{-324}
Bagging vs. FRBS	0.0	0.0	0.0	4.9×10^{-324}
Bagging vs. lasso	0.0	0.0	0.0	4.9×10^{-324}
FRBS vs. average	0.0	0.0	0.0	4.9×10^{-324}
Lasso vs. average	0.0	0.0	0.0	4.9×10^{-324}
Bagging vs. average	1.8022×10^{-105}	3.6044×10^{-106}	3.6044×10^{-106}	3.6044×10^{-106}
Lasso vs. FRBS	8.6857×10^{-6}	8.6857×10^{-7}	8.6857×10^{-7}	8.6857×10^{-7}

Table 5.4: Post-hoc procedure results

Alternative hypothesis	V	p
LOKRR < Online-delayed EKF	632 913 330	2.2×10^{-16}

Table 5.5: Result of Wilcoxon sign-rank test

right tail is noticeably longer than that of online-delayed EKF. However, both approaches have similarly long tails towards the left. This indicates that both methods greatly underestimate the travel time in some cases, whilst LOKRR also occasionally heavily overestimates the travel time. Online-delayed EKF has a sample deviation of 427.17, and LOKRR has a sample deviation of 450.80. The sample deviations do not differ to the same extent as the sample medians of the two methods.

Following the same approach as with the ensemble learning techniques, the sample medians of the absolute errors of online-delayed EKF and LOKRR are compared. The distributions of the absolute errors and a table showing sample medians for the two online learning approaches are displayed in Figure 5.4. This plot suggest that the sample median of LOKRR is lower than the sample median of online-delayed EKF. In order to investigate whether the differences between the two sample medians are significant, a statistical significance test is employed.

Section 5.1.2 explains the multiplicity effect that arises when performing hypothesis testing including more than two hypotheses. In Experiment 2, only two models are tested for significant difference, and the multiplicity effect is therefore not prominent. A paired non-parametric significance test is thus sufficient to evaluate the results from Experiment 2. More specifically, the Wilcoxon signed rank test [Wilcoxon, 1945] is employed. The null hypothesis is that the sample medians of the two distributions of online-delayed EKF and LOKRR are equal. The alternative hypothesis is that the sample median of LOKRR is lower than the sample median of online-delayed EKF. The Wilcoxon signed rank test statistic and corresponding p-value can be seen in Table 5.5. The result is based on 176 953 samples, and indicate, on a 0.05 significance level, that LOKRR’s sample median is significantly lower than that of online-delayed EKF.

5.2 Discussion

This section offers a discussion of the results from the experiments.

5.2.1 Error Distributions

Figures C.1 to C.11 in Appendix C illustrate the error distributions of the baselines, ensemble learning approaches and the online learning approaches. It can be seen from these figures that the error distributions have long tails. These tails may be explained by the presence of outliers in the data set. The traffic flow and mean travel time during the last five minutes for those vehicles having an abnormally large travel time might be the same as vehicles having a normal travel time. When the methods make predictions for the vehicles having an extreme travel time, they will have seen the normal case more times, and therefore predict that the current vehicle will have a normal travel time. However, due to this vehicle stopping along the road section, the resulting travel time is much larger than normal, and an extreme error occurs. This will both affect the tails of the error distributions, and the performance metrics, especially the RMSE.

5.2.2 Experiment 1 - Ensemble Learning

Figure 5.5 to Figure 5.9 illustrate the actual travel time and predicted travel times for the ensemble learning approaches on March 19, 2015. This date is chosen as it exemplifies and is representative for the methods' performance on the other days. Based on Figure 5.5, bagging seems to be able to accurately predict the peaks in travel time during the morning and afternoon. The figure also indicates that bagging is unbiased in its predictions, because its predictions are neither considerably above nor noticeably below the actual travel times. Lasso's predictions, which is displayed in Figure 5.6, performs similar to bagging during the morning rush hour. However, lasso is unable to predict the afternoon congestion as accurately as bagging. It is also interesting to note that lasso's predictions contain more noise than bagging's predictions. During training, lasso assigns weights to the baselines that minimize the expression in Equation 3.2. By minimizing this expression, the resulting weights generate predictions that are as close to the actual travel times as possible, across all observations. When outliers are present in the data set, lasso will adapt to these observations as well. This might explain why noise is present in lasso's predictions. Figure 5.7 indicates that FRBS is unable to predict the peaks in travel time. However, FRBS is able to provide accurate predictions during normal traffic conditions. The predictions of FRBS also contain some noise. However, the noise in FRBS's predictions seems to have an upper bound. If the inference stage in FRBS assigns a membership degree of zero to the fuzzy sets *low* and *medium*, and a non-zero membership

degree to *high*, the defuzzified output of the FRBS will be the b-parameter of the membership function representing *high*. Because the membership degree of the fuzzy set *high* is the only non-zero value, the membership function representing *high* will be the only membership function considered in the center of gravity algorithm. This will form a trapezoid, and the center of gravity of that trapezoid thus corresponds to the b-parameter of the *high* membership function. This might explain why the predictions of FRBS have an upper bound. The average, which is displayed in Figure 5.8, also performs similar to bagging. However, the average is not capable of predicting the peak in travel time during the afternoon. Figure 5.9 clearly illustrates that boosting tends to overestimate the travel time. It also illustrates that boosting is unable to predict the morning and afternoon rush hour.

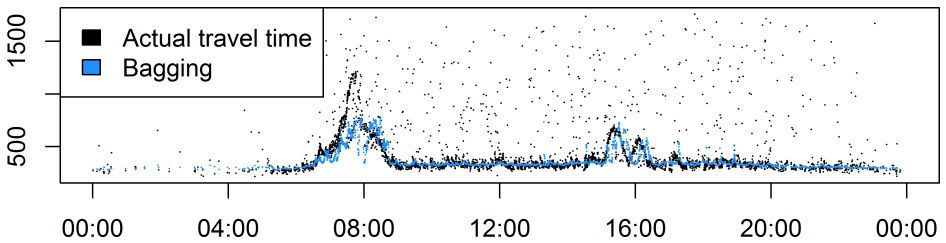


Figure 5.5: Predictions from bagging and actual travel time on March 19, 2015

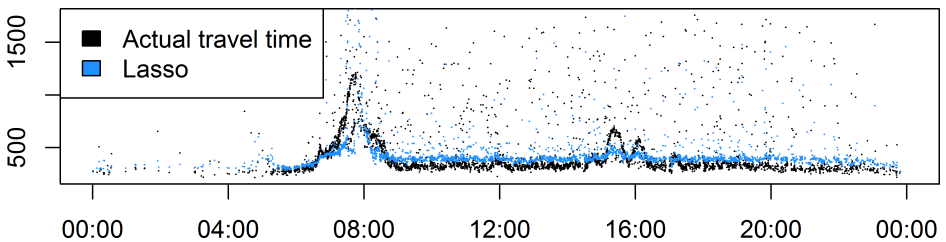


Figure 5.6: Predictions from lasso and actual travel time on March 19, 2015

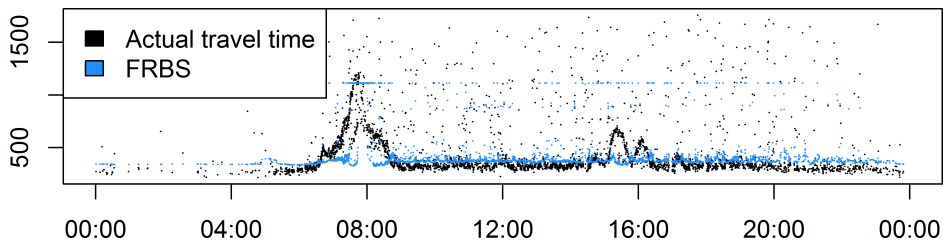


Figure 5.7: Predictions from FRBS and actual travel time on March 19, 2015

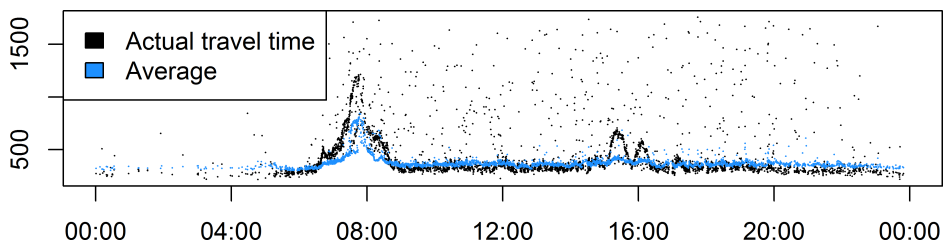


Figure 5.8: Predictions from average and actual travel time on March 19, 2015

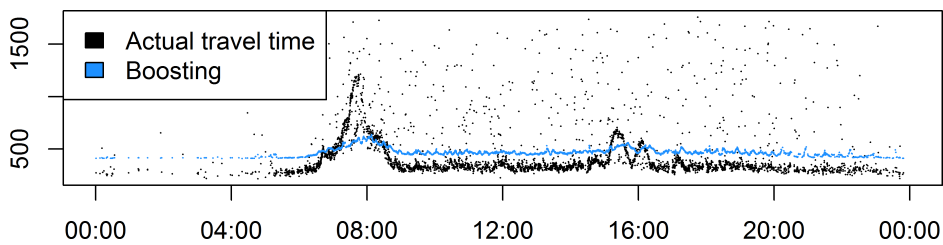


Figure 5.9: Predictions from boosting and actual travel time on March 19, 2015

One thing that is noticeable from the results in Experiment 1, is that there does not seem to be a strong positive correlation between which method is considered best in terms of sample median, RMSE and MAE. Bagging is the method with the lowest MAE and has the sample median closest to zero, but has the second highest RMSE. Lasso is the method with the lowest RMSE, whilst at the same time having an MAE value close to that of bagging. FRBS has a RMSE value close to that of lasso. The fact that bagging has the lowest MAE and lowest sample median whilst also having the second highest RMSE, might indicate that bagging makes predictions being closer to the actual travel time more often than

lasso. This is also indicated by the result of the Friedman test where bagging has the best Friedman rank. Even though bagging has lower MAE and sample median than lasso, lasso has considerably lower RMSE than bagging. Since RMSE is sensitive to large errors, this might indicate that in those rare cases where their errors are very large, bagging's errors are larger than those of lasso.

Both lasso and FRBS are optimized in terms of RMSE, i.e. they combine the predictions of their baselines in order to reduce the RMSE as much as possible. This might explain why lasso and FRBS achieve lower RMSE than the other approaches. When they optimize their performance in terms of RMSE during training, they will most likely be the ones performing best in terms of RMSE during testing as well, as long as they do not overfit the training data.

Bagging's approach, on the other hand, is entirely different. It trains multiple baselines on a random subset of the training data and then combines them by taking the average over all predictions. It makes no attempt to decrease the RMSE, but instead achieves the lowest median of the ensemble approaches. In theory, the strength of bagging is that it can even out the differences in bias between its underlying baselines by averaging their predictions. However, in Experiment 1, this does not seem to be the reason why bagging achieves a low sample median. All the sample medians of the baselines used in bagging are centered around 3, which can be seen in Table C.1 in Appendix C. Consequently, when bagging averages the predictions from its baselines, bagging's sample median is also approximately three.

Recall from Section 4.2.3 that the implementation of boosting for regression models provided in `scikit-learn` is used in Experiment 1. The only method of the four baselines used in this study, that is both implemented in `scikit-learn` and supports weighting of training examples is SVM. This puts a restriction on the baseline being used in boosting, as SVM is the only baseline available. In order to compare bagging and boosting on a fair basis, SVM is also chosen as the baseline in bagging. The use of SVM as baseline may have lead to suboptimal performance for bagging. Section 3.1.1 explains that bagging may work well with unstable learners. However, there is little to gain from bagging when using stable learners. SVMs are stable learners [Sammut and Webb, 2010] and are therefore unlikely to get completely different bias when trained on slightly different data. This might explain why all the underlying baselines in bagging are very similar, even though they have been trained on different subsets of the training set. Consequently, when using SVMs as baselines for bagging, this study does not realize bagging's full potential as an ensemble learner. This makes it difficult to conclude whether any of the other ensemble learners are better than bagging.

The fact that bagging may work well with unstable learners relates to the fact that ensemble learners work best when its baselines have different bias. By

inspecting figures C.1 to C.4 in Appendix C, it can be seen that k-NN, ANN and Kalman filter have sample medians of 23.463, 26.541 and 49.394, respectively, whilst SVM has a sample median of -31.633 . This might indicate that k-NN and ANN have similar bias towards slightly overestimating the travel time, whilst Kalman filter overestimates the travel time even more. In contrast, SVM has a bias towards underestimating the travel time. Including even more baselines, or baselines with greater diversity in terms of bias could potentially lead to even better performance for the ensemble learning approaches. This might also result in a bigger difference in performance between lasso and the average. Imagine having one baseline performing considerably worse than the other baselines in the ensemble. In this situation, lasso may be able to exclude this baseline from its ensemble and thus have better performance than the average, which includes all baselines in the ensemble independent of their performance.

Boosting performs considerably worse than the other methods in terms of sample median and MAE. Its sample median of 127.43 illustrates a considerable bias towards overestimating the travel time. Additionally, boosting comes out as the worst performing approach in terms of RMSE and Friedman ranking. During training, boosting is set to use a maximum of 25 baselines in order to form a fair basis for comparison with bagging. In `scikit-learn` the boosting algorithm stops if it achieves perfect fit on the training data. In Experiment 1, boosting ends up with five baselines. The fact that boosting has the opportunity to use 25 baselines, but only use five, indicates that it achieves perfect fit on the training data, and its poor performance might be due to overfitting the training set. Although the results for boosting in this study are not promising, it does not mean it is not a viable ensemble learning approach for travel time prediction.

The fact that the sample median of the average ensemble is farther away from zero than bagging suggests that the average ensemble has a stronger bias towards overestimating travel times than bagging. However, the average ensemble has a sample median closer to zero than lasso, FRBS and boosting, which indicates that the average ensemble has a weaker bias than the mentioned approaches. The average ensemble's MAE value is considerably lower than that of boosting, and close to those of bagging, lasso and FRBS, albeit higher than the three latter methods. The average ensemble's RMSE and sample deviation illustrates that its predictions might have larger deviations than those of lasso and FRBS. These results illustrates that even a simple approach like taking the average of the baselines' predictions may be a viable approach to constructing an ensemble.

As the different performance metrics and other criteria for comparison do not agree on which method is best, it is interesting to explore their interpretation and importance. The RMSE is tightly coupled with the sample deviation, as their computations are carried out in a similar fashion. Therefore, both RMSE and sample deviation can be seen as measures of variation in the predictions

of a method. The median, on the other hand, is more representative for the model's bias and is a good indicator for what an expected error is. Similarly, the MAE is a measure indicating what a typical absolute error is. Therefore it is not surprising that the approach with the lowest sample median also has the lowest MAE. Additionally, it is also expected that the method with the lowest RMSE also has the lowest sample deviation.

Since these measures represent different properties, what measure to consider when deciding what model is best depends on what properties are most important. Presented with two methods A and B, where method A has low bias, but large deviation; and method B has larger bias, but smaller deviation, which method is most desirable? Method B will in most cases either overestimate or underestimate travel times, depending on the direction of the bias. This is not the case for method A since it is unbiased, but its errors will fluctuate more than method B because of its higher deviation. It is simpler to correct for method B's bias than it is to correct for method A's varying errors. One can, in theory, correct for method B's bias by adding or subtracting a constant to its prediction, depending on the direction of its bias. In terms of predicting travel time, having consistent predictions is important. One can imagine commuters having more confidence in a travel time prediction system if its predictions are consistent. However, it is also important to have accurate predictions, meaning that the travel time predictions are as close to the actual travel time as possible. If a bias is present in a prediction model, it may be better having a bias towards overestimating travel time than underestimating it. Commuters might be more pleased using less time than predicted in contrast to using longer time than predicted. In total, both accurate predictions and consistent predictions are desirable properties for a travel time prediction system.

To summarize the results, there is no ensemble approach among the ones investigated in this study that clearly outperforms the other methods on all measures. This makes it difficult to conclude which ensemble learning technique has the best prediction accuracy.

5.2.3 Experiment 2 - Online Learning

Based on the performance metrics alone, online-delayed EKF appear to be better than LOKRR. However, based on the error distribution plots and the significance tests regarding the sample medians, LOKRR's sample median seem to be lower than the sample median of online-delayed EKF. The fact that online-delayed EKF has lower RMSE and MAE than LOKRR, might be explained by that online-delayed EKF does not have as extreme errors as LOKRR, and in this way does not get punished as much through the performance metrics. At the same time, LOKRR has an absolute error distribution with lower sample median than

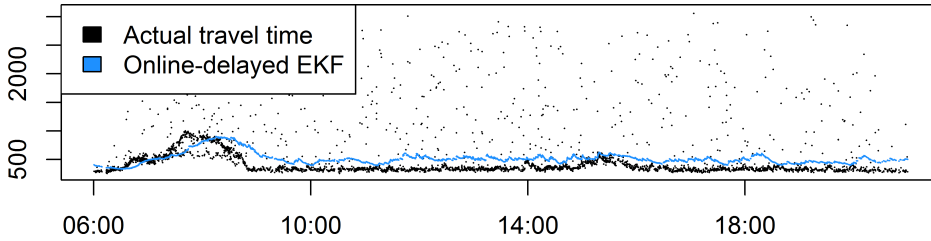


Figure 5.10: Predictions from online-delayed EKF and actual travel time on March 4, 2015

online-delayed EKF. A possible explanation for this is that in majority, LOKRR makes predictions being closer to the actual travel time than online-delayed EKF, and thus makes less biased predictions than online-delayed EKF.

Note that the performance metrics and sample deviations of the two online learning approaches are considerably higher than those of the ensemble approaches. This relates to the fact that the online learning approaches have learned from and made predictions for a data set where no attempt to remove outliers is made. Having outliers in the data set leads to higher prediction errors, and consequently the performance metrics of the online approaches have higher values. In contrast, the ensemble learning approaches have used a data set where outliers have been removed to some degree. Additionally, the offline learners can look at data more than once and therefore have a better chance of discovering patterns in the data. However, the focus of this study is not to compare online learners with offline learners. What is important is to assess the performance of them as online learners and to compare them to each other.

In Figure 5.10 and Figure 5.11 the predictions from online-delayed EKF and LOKRR on March 4, 2015 are plotted, respectively. Online-delayed EKF tends to overestimate the travel times. This can be seen in Figure 5.10, where the online-delayed EKF predictions tend to lie above the actual travel time during normal traffic conditions. LOKRR, on the other hand, tends to underestimate the travel times as its predictions tend to lie below the actual travel times. It can be seen in Figure 5.11 that the predictions from LOKRR vary greatly from one prediction to the next. In contrast to LOKRR, online-delayed EKF's predictions do not fluctuate a lot. Online-delayed EKF seems to be able to follow the curve of the true travel time, albeit with a delay.

In theory, the strength of online learning approaches is their ability to adapt to abnormal traffic scenarios, i.e. scenarios that are not present in the training set. Figure 5.12 and Figure 5.13 illustrate actual travel times and predictions from online-delayed EKF and LOKRR on March 13, 2015, respectively. The afternoon

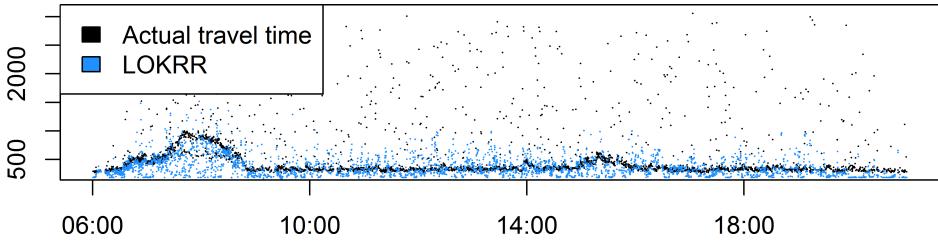


Figure 5.11: Predictions from LOKRR and actual travel time on March 4, 2015

peak on this date is considerably higher than usual. In order to investigate how well the two online learning approaches predict this peak, their predictions are inspected.

Interestingly, LOKRR is unable to detect the increase in travel time at all. One possible explanation for LOKRR’s inability to detect this peak is that it is an instance based approach. Each kernel contains data which approximately covers the past week. If this data does not contain any abnormally high travel times, the kernel is unable to predict that such travel times can happen. Figure C.12 to Figure C.18 in Appendix C illustrate actual travel times and LOKRR’s predictions in the week leading up to March 13, 2015. The travel times during this week reveals that no similar peaks in travel times occurred. It is also interesting to note that the abnormally high travel times observed during the afternoon on March 13 do not seem to affect the predicted travel times the following day. This can be seen in Figure C.19 and Figure C.20 in Appendix, which illustrate actual travel times and LOKRR’s predictions during March 14, 2015 and March 15, 2015, respectively.

The online-delayed EKF is better able to detect that there is a peak in travel times. However, there is a considerable latency between when the congestion builds up and the online-delayed EKF is able to detect the increase. Similarly, the online-delayed EKF is slow to detect the decrease in travel time. Consequently, the online-delayed EKF predicts a peak in travel time when the traffic is almost back to normal. Recall from Section 3.2.1 that this behaviour is due to the fact that online-delayed EKF does not update its weights until the travel times are realized. This is most noticeable when congestion is building up. As the travel times increase, it takes increasingly longer time until the travel times are realized.

In the original paper [Haworth et al., 2014], LOKRR uses five minute aggregated travel time data. However, in this study the kernels contain individual observations. This leads to several challenges.

First of all, using individual travel times heavily limits how far back in time one can keep data. In Haworth et al. [2014], the kernels consisted of observations

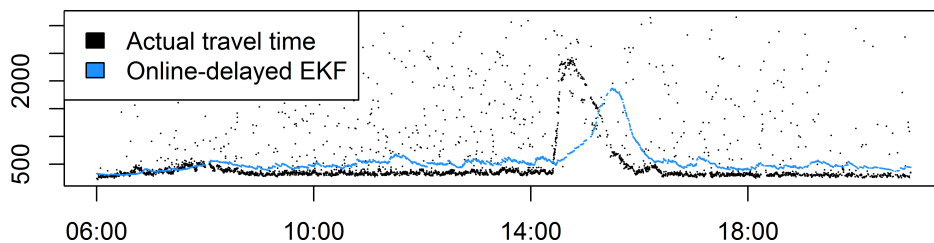


Figure 5.12: Predictions from online-delayed EKF and actual travel time on March 13, 2015

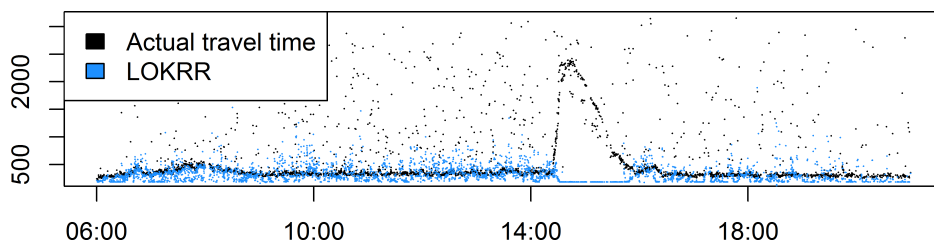


Figure 5.13: Predictions from LOKRR and actual travel time on March 13, 2015

from the 80 previous days. Including a window size of 3, this leads to each kernel containing 560 observations. In this study, the biggest kernel contained 698 observations. However, this only comprised a week of data with a window size of 1. One week of data might not be enough to detect cyclic patterns. Additionally, the limited window size further decreases the kernels' ability to detect cyclic patterns, since it is unlikely that events such as rush hours occurs at the same exact five minute interval every day.

Secondly, the kernels end up with different amounts of data. The traffic flow during the morning and afternoon rush hours far exceed the traffic flow at 8 PM. Kernels responsible for periods of the day with less traffic have less data to base their predictions on, which is expected to lead to lower prediction accuracy. This could be solved by setting a limit to how much data each kernel could contain. However, that would mean that the kernels responsible for intervals with less traffic would contain data further back in time than kernels responsible for periods of the day with heavy traffic. Whether or not that is a desirable property should be considered.

It may be unfair to employ LOKRR on a type of data set that it is not designed for and the implications using individual travel times have for LOKRR make it difficult to compare it to online-delayed EKF or any other online learner.

5.2.4 Limitations

Section 5.2.2 and Section 5.2.3 presents some limitations to this work. Additional limitations are presented in this section.

The methods investigated in this study are data driven approaches. which are inherently affected by the data they operate on. Consequently, the data pre-processing step will affect the final results both in terms of the trained models and the performance metrics. Figure 4.2 display all travel times registered for January 29, 2015. The figure clearly illustrates the presence of vehicles with abnormally high travel times, which is seen as dots high above the line illustrating the normal travel time. An attempt to remove such outliers is performed. However, more sophisticated schemes may be employed. When the methods are evaluated based on RMSE, the approaches that best adapt to the outliers may appear better than those who are unable to adapt to outliers. This may suggest the use of other performance metrics than RMSE when outliers are present in the data set. However, it may also indicate that having a greater focus on removing outliers from the data set is important in order to decrease the effect that outliers have on the performance metrics.

Another aspect affecting the method's performance is the amount of training data that they are provided with. Having more training data increases the probability that the methods generalize better on the test set. In order for the methods to perform well on the test set, their training set has to contain enough data to include all the different scenarios in the test set. The data set used in the experiments is collected from one specific road section within a limited range of time. This makes it difficult to detect cyclic patterns with a frequency greater than the data set's range. Additionally, the data set does not contain a lot of variations in travel time and noticeable congestion does not occur very often. Because the methods investigated in this study are based on this data, the degree of differences between the methods one can observe may be limited. Using a larger data set from a road section with greater variety in traffic conditions may reveal greater and other differences between the methods.

The methods are also affected by their parameters. In this study relatively small amounts of data is used for parameter tuning. Additionally, the parameter search is fairly simple. Larger grids could have been employed to begin with, and several steps of using finer grids could have been used to optimize the parameters even further. Some methods are more sensitive to their parameters than others and it is possible that placing more emphasis on the parameter tuning step could have lead to different results.

5.3 Conclusion

This study sets out to compare state of the art ensemble learning and online learning solutions in order to find the best performing methods in terms of prediction accuracy. More specifically, the ensemble learning methods that are investigated are bagging, boosting, lasso, FRBS and a simple average of the baselines' predictions. The online learning methods that are investigated are online-delayed extended Kalman filter and local online kernel ridge regression. The methods are trained and tested on a common data set in an attempt to answer the following research questions:

Research Question 1 Given a set of baseline methods, which ensemble learning technique yields the best prediction accuracy?

Research Question 2 Which online learning technique yields the best prediction accuracy?

The results of the experiments indicate that lasso and fuzzy rule based system are the best methods in terms of root mean squared error, whilst bagging is best in terms of mean average error, and has least bias in its predictions. Boosting performs consistently worse than all the other methods. However, no method performs consistently better than all other methods across all performance metrics. This makes it difficult to conclude which ensemble learning technique yields the best prediction accuracy in terms of the performance metrics. However, based on plots of the predicted and actual travel times, there is a difference in terms of how well the approaches are able to follow the evolution of the travel times. Bagging seems to do this more accurately than the other ensemble learning methods.

In regards to online learning, online-delayed extended Kalman filter is the best performing method in terms of root mean squared error and mean absolute error. However, local online kernel ridge regression has least bias in its predictions. During an event with unexpectedly high travel times, online-delayed extended Kalman filter is able to adapt to the changing traffic situation considerably better than local online kernel ridge regression. However, the results make it difficult to conclude which online learning technique yields the best prediction accuracy.

To summarize, this study compares state of the art ensemble learning and online learning approaches on a common data set. Based on the experimental results, a conclusion as to which approaches provide the most accurate predictions can not be made.

5.4 Contributions

This work's contribution is two-fold. First, this study compares state of the art ensemble learning and online learning techniques on a common data set. Second, local online kernel ridge regression is employed on a data set with individual travel times, in contrast to the original approach where five minute aggregated data is used.

5.5 Future Work

As mentioned in Section 5.2.2, bagging is used with support vector machines as baselines, which is considered a stable learner. As there is little to gain from using bagging with a stable learner, a suggestion for future work is to repeat Experiment 1 where bagging is used with an unstable baseline, such as an artificial neural network, in order to investigate whether or not this leads to better performance for bagging.

In Experiment 1, the fuzzy rule based system ensemble uses two baselines, artificial neural network and Kalman filter. In contrast, the lasso ensemble uses four baselines, support vector machine, k-nearest neighbors, artificial neural network and Kalman filter. It would be interesting to investigate how the fuzzy rule based system ensemble performs using the same baselines as the lasso ensemble, in order to compare the two ensemble learning approaches on an equal basis. Furthermore, the fuzzy rule based system used in Experiment 1 uses manually created rules. Investigating whether or not using automatically generated rules will capture different relationships between the baselines in the ensemble is another suggestion for future work.

In this work, only two online learning approaches are tested. In order to further investigate which online learning method provides best prediction accuracy, other approaches should be considered. The method described in Wu et al. [2012] is based on handling abnormal traffic conditions by employing separate learners for normal and abnormal traffic conditions. It would be interesting to further investigate and compare the proposed method to the online-delayed extended Kalman filter and local online kernel ridge regression.

There are more aspects to travel time prediction methods than their performance relative to some performance metric. The overall RMSE of a method does not necessarily represent its usefulness for to users, e.g. a traffic control center. Being able to accurately predict the sudden increases and drops in travel time might be a more desirable property than having a low overall RMSE. Being able to predict these significant increases and decreases in travel times may be of large benefit for traffic control centers. This may help them to detect congestion as it starts to build up. This is beneficial as they can use this information to route

traffic, and by doing so limit the degree of congestion. However, comparing such a property among a set of methods is difficult. Inspecting predictions for specific scenarios leads to subjective opinions on what method is best. Future work may be to create a numeric performance metric that represents this quality in a method. Having a numerical measure means that this property can be compared across different methods in an objective manner.

The goal of this study is to compare state of the art travel time prediction approaches in order to find the best approach in terms of prediction accuracy. In the future it might be beneficial to develop a set of benchmark data sets that novel approaches can be tested on. This may make it easier to compare the performance of different approaches on a fair basis as they are evaluated on the same data set.

The methods investigated in this study are evaluated based on data that are used in the current solution at the Norwegian Public Roads Administration. Therefore, it is interesting to investigate whether or not the solutions employed in this study offer any improvements to the current solution at Norwegian Public Roads Administration's solution. Comparing these methods is a possible direction for future work.

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Appendices

A Structured Literature Review Protocol

This section describes in detail how the structured literature review was conducted. Two search engines were used: IEEEXplore² and Engineering Village³.

A.1 Specifying the Search Term

When doing a structured literature review, it is necessary to have a search string that represents the subjects of interest. Having this search string serves two purposes: it makes it possible to reproduce the search results given the archive(s) used. In addition it captures the different aspects of the research, and therefore yields a reduced number of results, hopefully with the relevant literature.

The search string is built up using three groups of terms. The different terms contained in one group are synonyms, have the same semantics or cover similar concepts. The terms in one group are joined using the logical OR operator, and each group is joined using the logical AND operator. In this way the search string is meant to yield the research that is the intersection of the different groups. The search string used is:

(“prediction” OR “forecasting” OR “estimation”)

AND

(“travel time” OR “transit time” OR “driving time” OR “traffic flow” OR “congestion”)

AND

(“ensemble learning” OR “machine learning” OR “artificial intelligence”)

By examining this search string one can identify three aspects that this research focuses on: prediction or estimation of traffic variables using ensemble learning or machine learning in general.

A.2 Search Results

The search was conducted on the 24th of September, 2014. Engineering Village returned 670 results and IEEE returned 477 results. Because many of the articles are unlikely to be suitable for this research, a filtering process is employed to narrow down the number of articles being read in its entirety.

The filtering process consists of three stages: filtering by title, filtering by abstract and finally filtering by full text. In this way irrelevant literature is filtered out as early in the process as possible. The next sections explains in more detail how the filtering stages are executed.

²<http://ieeexplore.ieee.org/search/advsearch.jsp?expression-builder>

³<http://www.engineeringvillage.com/search/expert.url?CID=expertsearch>

A.3 Filtering by Title

This stage filters the articles by looking at their title. In this way articles that obviously do not concern the current research are excluded, and do not go further in the filtering process. An article is included if its title indicate that it:

Inclusion Criterion 1 Is about Intelligent Transportation Systems

or

Inclusion Criterion 2 Is about ensemble learning

or

Inclusion Criterion 3 Predicts, estimates or models road traffic variables, e.g. traffic flow, speed, congestion or travel time.

Inclusion criterion 1 ensures that articles in the ITS domain are included. These articles are valuable to this research, as they can give insight to the domain in general and contributes to the pool of knowledge in the area. By using inclusion criterion 2 articles about ensemble learning are included. The reason that research done on ensemble learning in the ITS domain is interesting, is that it that an ad hoc search prior to this literature review showed that ensemble learning is a possible direction to go in to achieve more accurate predictions [Russell and Norvig, 2010]. Inclusion criterion 3 ensures that research done on predicting or estimating traffic variables no matter what method that is employed is included. After filtering the articles by these three criteria, 401 articles remained in total.

A.4 Filtering by Abstract

After filtering the articles by title, a more thorough approach has to be employed to identify the valuable articles. For an article to be included in the last filtering stage, its abstract has to indicate one or more of the following:

Inclusion Criterion 1 The main focus of the article is using AI method(s) to predict travel time, traffic flow, speed or congestion.

Inclusion Criterion 2 That the article gives insight to which data sources that are relevant in the ITS domain.

Inclusion Criterion 3 The article gives insight to how data aggregation or pre-processing impacts prediction or estimation of travel time, traffic flow, speed of congestion.

Inclusion Criterion 4 That the article solves a problem using ensemble learning.

Inclusion Criterion 5 The article describe a solution that can easily be extended or adapted to fit our research.

Since investigating what machine learning techniques that have been used to predict traffic variables is of interest, inclusion criterion 1 is employed to include articles that would be relevant in that regard.

Preliminary discussions with the NPRA revealed that it would be interesting to use several data sources in the prototype system to increase prediction accuracy. Inclusion criterion 2 ensures that articles that can give insight to what data sources that are relevant to use is included.

There is an ongoing discussion at the NPRA about how to aggregate the data, and how the aggregation method affects the estimation of traffic variables. Currently, the most common technique used for travel times at the NPRA is to use an average of the travel times the last five minutes. Inclusion criterion 3 ensures that any literature that touches upon this issue is included.

As stated in the previous section, ensemble learning is one of the main focuses in this research and inclusion criterion 4 ensures that research that have employed ensemble learning to solve a problem is included.

If there is work that is done in the ITS domain whose solution can be extended or adapted to predicting travel time, we can draw knowledge from their findings. Inclusion criterion 5 ensures that such research is included.

Employing these filtering criteria yielded 294 articles. Given that this work is conducted by two students for a specialization project, it is infeasible due to time limitations, to read 294 articles in the last stage of the process. In order to further reduce the number of articles, a ranking system is developed. The ranking system consists of ten criteria by which the articles are rated. Each criterion is given an integer weight, and the total score of each article is the sum of all the weights that article has received for each criterion. The criteria, with the corresponding weights shown in parentheses, are as follows:

Ranking Criterion 1 The article is poorly written (-5)

Ranking Criterion 2 The article has empirical results (+3)

Ranking Criterion 3 The work concerns predicting travel time (+2)

Ranking Criterion 4 The models used are based on travel times for road sections, not GPS data etc. (+2)

Ranking Criterion 5 The work concerns short term prediction (+1)

Ranking Criterion 6 The work concerns urban/signalized roads (+1)

Ranking Criterion 7 The work employs online learning (+1)

Ranking Criterion 8 The work predicts traffic variables for public transport (-1)

Ranking Criterion 9 The work employs ensemble learning (+4)

Ranking Criterion 10 The work uses multiple data sources (+1)

Because of the previous stages of the filtering process, all the articles given as input to this stage have a certain degree of relevance, and this stage is meant to find the most relevant amongst them. As indicated by the weight of ranking criterion 2, the fact that the articles base their findings on empirical results are important, as this increases the credibility and reproducibility of their work. Ranking criterion 9 shows that articles concerned with ensemble learning are also favorable because they give insight to the one of the main topics in our study. Articles that are poorly written are given a big penalty, as seen by ranking criterion 1, as this makes them hard to read and time is wasted. The rest of the criteria correspond to features that would be beneficial to this research, but not essential.

After ranking all 294 articles using the aforementioned ten criteria, the total scores were in the range [-5, 10]. A threshold of 6 was set, where articles with a score of 6 or higher are included. This yielded 54 articles, a reasonable number of articles to read for two people. The number of articles was further reduced due to duplicates being removed and that some full texts were not available. The final number of articles entering the full text filtering was 36, and can be found in Table A.2 and Table A.3. It can be seen in from the tables that all articles with a total score of 6 or better have empirical results, and most of them predict travel time in addition to having other interesting features like using online learning or employing short term prediction. From Table A.2 and Table A.3 we can also see that articles that do not predict travel time can be included, as long as they have enough other interesting features.

A.5 Filtering by Full Text

In this final filtering stage the goal is to assess the quality of the work done in the remaining articles. In order to do this, another ranking system is developed where each article is evaluated using the following seven quality criteria [Kofod-Petersen, 2014]:

Quality Criterion 1 Are system or algorithmic design decisions justified?

Quality Criterion 2 Is the method/algorithm thoroughly explained?

Quality Criterion 3 Is the experimental procedure thoroughly explained and reproducible?

Quality Criterion 4 Is it clearly stated in the study which other algorithms the study's algorithm(s) have been compared with?

Quality Criterion 5 Are the performance metrics used in the study explained and justified?

Quality Criterion 6 Are the test results thoroughly analysed?

Quality Criterion 7 Does the test evidence support the findings presented?

Six of the above quality criteria are taken directly from [Kofod-Petersen, 2014]. Question 2 is added because it is important that the methods described are reproducible. Each question is given a weighted answer: yes (1), in some degree (0.5) and no (0).

To ensure that the different questions were interpreted in the same way by both students reading the articles, a calibration round was done on 8 of the articles where both students read and evaluated all 8 of them. After agreeing on how the questions should be interpreted, the remaining 30 articles were divided equally and read separately.

After assessing all articles, their score were in the range [2.5, 7]. As this range shows, not all articles had the same level of quality. To ensure a certain level of quality for the articles that are going to be included as our final references, a threshold of 5 is set, where articles with score higher than or equal to this threshold is included as references in our state of the art review. The final articles are shown in Table A.1.

Final Articles	
Ensemble	[Sun, 2009] [Li et al., 2014] [Zhu and Shen, 2012] [Stathopoulos et al., 2008] [van Hinsbergen et al., 2009]
Online	[Liu et al., 2006a] [Liu et al., 2006b] [Van Lint, 2008] [Haworth et al., 2014] [Lu, 2012] [Wu et al., 2012]
Hybrid Approach	[Hofleitner et al., 2012]
Vehicle Infrastructure Integration	[Ma et al., 2012]
Other	[Park et al., 2014] [Bouillet et al., 2013] [Dharia and Adeli, 2003] [Nikovski et al., 2005] [Tam and Lam, 2007] [Vanajakshi and Rilett, 2007] [Mu et al., 2013]

Table A.1: Articles resulting from the structured literature review

Title	RC1	RC2	RC3	RC4	RC5	RC6	RC7	RC8	RC9	RC10	Total Score
Li et al. [2009]	0	3	2	0	0	0	1	0	4	0	10
Ma et al. [2012]	0	3	2	2	0	0	1	0	0	1	9
Rossi et al. [2012]	0	3	2	0	0	0	0	0	4	0	9
van Himsbergen et al. [2009]	0	3	2	0	0	0	0	0	4	0	9
Zhu [2011]	0	3	0	0	1	0	0	0	4	0	8
Yang et al. [2012]	0	3	0	0	1	0	0	0	4	0	8
Zhu and Shen [2012]	0	3	0	0	1	0	0	0	4	0	8
Chen and Chen [2007]	0	3	0	0	1	0	0	0	4	0	8
Wu et al. [2012]	0	3	0	0	0	0	1	0	4	0	8
Tam and Lam [2007]	0	3	2	2	1	0	0	0	0	0	8
Sun [2009]	0	3	0	0	0	0	0	0	4	0	7
Mu et al. [2013]	0	3	2	0	1	0	0	0	0	1	7
Mak et al. [2009]	0	3	2	0	0	1	0	0	0	1	7
Li et al. [2014]	0	3	0	0	0	0	0	0	4	0	7
Liu et al. [2006a]	0	3	2	0	1	1	0	0	0	0	7
Zheng and van Zuylen [2013]	0	3	2	0	0	1	0	0	0	1	7
Chen and Zhang [2005]	0	3	0	0	0	0	0	0	4	0	7
Deb Nath et al. [2010]	0	3	2	2	0	0	0	0	0	0	7
Dembczynski et al. [2013]	0	3	2	2	0	0	0	0	0	0	7
Yao et al. [2001]	0	3	0	0	0	0	0	0	4	0	7

Table A.2: Articles included in the quality screening process, part I

Title	RC1	RC2	RC3	RC4	RC5	RC6	RC7	RC8	RC9	RC10	Total Score
Bouillet et al. [2013]	0	3	2	0	0	0	1	0	0	1	7
Park et al. [2014]	0	3	0	2	1	0	0	0	0	1	7
Hofeimer et al. [2012]	0	3	2	0	0	1	0	0	0	0	6
Bajwa et al. [2003]	0	3	2	0	1	0	0	0	0	0	6
Dharia and Adeli [2003]	0	3	2	0	0	0	0	0	0	1	6
Zhu et al. [2009]	0	3	2	0	0	1	0	0	0	0	6
Wang and Poslad [2013]	0	3	2	1	0	0	0	0	0	0	6
Yanaajakshi and Rilett [2007]	0	3	2	0	1	0	0	0	0	0	6
Ohra et al. [1997]	0	3	2	0	0	0	1	0	0	0	6
Van Lint [2008]	0	3	2	0	0	0	1	0	0	0	6
Hao et al. [2008]	0	3	2	0	0	1	0	0	0	0	6
Haworth et al. [2014]	0	3	2	0	0	1	0	0	0	0	6
Stathopoulos et al. [2008]	0	3	0	0	1	1	1	0	0	0	6
Lu [2012]	0	3	2	0	0	0	1	0	0	0	6
Lin et al. [2006b]	0	3	2	0	0	1	0	0	0	0	6
Nikovski et al. [2005]	0	3	2	0	1	0	0	0	0	0	6

Table A.3: Articles included in the quality screening process, part II

B Experimental Setup Protocol

B.1 Baselines

This section contains descriptions of each baseline method used in Experiment 1: Support Vector Machine (SVM), k-nearest neighbor (k-NN), Artificial Neural Network (ANN) and Kalman filter. Information about the process applied to every baseline is given in Overview, whilst specific details about each baseline is given in their respective sections.

Overview

The implementation of the baseline methods used in Experiment 1 is done in R [R Core Team, 2014]. Parameter tuning and training for support vector machine, k-nearest neighbors and artificial neural network is done through the library `caret` [Kuhn et al., 2015], which is a library meant to make the process of constructing predictive models easier in R. In this work, `caret` is used as a layer between the authors code in R and the respective implementations of the baseline methods. `caret` provides structures for setting the grid for which parameters are to be searched among, and returns the model with parameters resulting the best performance in terms of RMSE. Tuning and training of the Kalman filter is done with the R library `d1m` [Petris, 2010].

The baselines use the data set were outliers have been removed. In order to find the best set of parameters for each baseline, 10-fold cross-validation on data from January 29, 2015 to February 1, 2015 is used. Each baseline is then trained with the best set of parameters on data from February 5, 2015 to February 25, 2015. The resulting models are then used to generate predictions from February 26, 2015 to March 31, 2015.

Support Vector Machine

The SVM implementation used in this work is from the R library `kernlab` [Karatzoglou et al., 2004]. When using SVMs there is a choice among several kernel functions to use. To determine which kernel to use in the SVM of Experiment 1, a preliminary experiment comparing the RMSE of SVM models using a linear, polynomial and radial basis kernel functions was conducted. In addition to experimenting with different kernel functions, a grid of parameters is searched for each kernel function in order to find the parameters to be used for the best performing kernel.

For the linear kernel the only parameter to optimize is the cost parameter C . For the polynomial kernel there are three parameters to optimize: the degree of the polynomial *degree*, the cost parameter C and the scale parameter *scale*.

C	RMSE
2^{-5}	0.1594510
2^{-1}	0.1594400
2	0.1594396
2^5	0.1594387
2^{10}	0.1604016
2^{15}	0.1843528

Table B.1: Parameter tuning for Linear SVM

For the radial basis function kernel there are two parameters to optimize: σ and the cost parameter C . Tables B.1, B.2 and B.4 presents the range of parameters used during the parameter tuning of the SVM models using a linear, polynomial and radial basis function kernel functions, respectively. Table B.3 summarizes the results from the different degrees used in polynomial kernel function.

Table B.5 summarizes the results of running the best performing models for each kernel type on the test set. The SVM with a radial basis function kernel function yielded the lowest RMSE of 243.3726 and was therefore selected to be used in Experiment 1. Among the parameter values tested in the grid search for the radial basis function SVM models, the parameters $\sigma = 4.1451371$ and $C = 2^{-1}$ yielded the best performing model, and is the one used in Experiment 1.

k-Nearest Neighbors

The k-NN implementation used in this work is from the R library `kknn` [Schliep and Hechenbichler, 2014]. The parameters that are possible to tune in `kknn` are k , distance measure and kernel. The k parameter controls how many neighbors to extract from the instances present in the data set when making predictions. The distance measure parameter controls how the distance between two points in the data set is computed. The kernel parameter controls how to weight the values of the k neighbors based on their distance. In order to find a good set of parameters for the weighted k-NN algorithm a grid search was performed.

The distance parameter is more specifically the parameter used to calculate the Minkowski distance between two points. In the grid search the values 1 and 2 were selected to use the Manhattan and Euclidean distance, respectively. The kernel is a function representing the distribution of the underlying data set. Since k-NN does not require any training, testing for a large number of combinations is possible. Therefore all the available kernel functions in the `kknn` library were tested. Small k values makes k-NN sensitive to noise in the data, but makes it easier to distinguish different traffic scenarios from each other. Choosing large k

C	Scale	RMSE
2^{-5}	0.001	0.1678236
2^{-1}	0.001	0.1603247
2	0.001	0.1596821
2^5	0.001	0.1594829
2^{10}	0.001	0.1594655
2^{15}	0.001	0.1602348
2^{-5}	0.010	0.1607862
2^{-1}	0.010	0.1595467
2	0.010	0.1594870
2^5	0.010	0.1594715
2^{10}	0.010	0.1594667
2^{15}	0.010	0.1590753
2^{-5}	0.100	0.1596038
2^{-1}	0.100	0.1594786
2	0.100	0.1594710
2^5	0.100	0.1594700
2^{10}	0.100	0.1594310
2^{15}	0.100	0.2060724

C	Scale	RMSE
2^{-5}	0.001	0.1648976
2^{-1}	0.001	0.1597790
2	0.001	0.1591884
2^5	0.001	0.1577153
2^{10}	0.001	0.1572685
2^{15}	0.001	0.1576086
2^{-5}	0.010	0.1595339
2^{-1}	0.010	0.1575453
2	0.010	0.1573096
2^5	0.010	0.1572620
2^{10}	0.010	0.1572505
2^{15}	0.010	0.1570599
2^{-5}	0.100	0.1573271
2^{-1}	0.100	0.1572610
2	0.100	0.1572575
2^5	0.100	0.1572554
2^{10}	0.100	0.1573637
2^{15}	0.100	0.1835173

First degree polynomial

C	Scale	RMSE
2^{-5}	0.001	0.1632949
2^{-1}	0.001	0.1594510
2	0.001	0.1586526
2^5	0.001	0.1573733
2^{10}	0.001	0.1569685
2^{15}	0.001	0.1564797
2^{-5}	0.010	0.1586273
2^{-1}	0.010	0.1571663
2	0.010	0.1568624
2^5	0.010	0.1565607
2^{10}	0.010	0.1565122
2^{15}	0.010	0.1628453
2^{-5}	0.100	0.1566293
2^{-1}	0.100	0.1565251
2	0.100	0.1565129
2^5	0.100	0.1565076
2^{10}	0.100	0.1576626
2^{15}	0.100	0.1660079

Second degree polynomial

Third degree polynomial

Table B.2: Parameter tuning for Polynomial SVM

Degree	C	Scale	RMSE
1	2^{15}	0.010	0.1590753
2	2^{15}	0.010	0.1570599
3	2^{15}	0.001	0.1564797

Table B.3: Summary of best performing parameters per degree for Polynomial SVM

σ	C	RMSE
0.1005521	2^{-5}	0.1560983
0.1005521	2^{-1}	0.1558789
0.1005521	2	0.1558185
0.1005521	2^5	0.1556929
0.1005521	2^{10}	0.1557148
0.1005521	2^{15}	0.1565749
0.5023972	2^{-5}	0.1558294
0.5023972	2^{-1}	0.1556032
0.5023972	2	0.1555518
0.5023972	2^5	0.1554235
0.5023972	2^{10}	0.1554382
0.5023972	2^{15}	0.1575169
4.1451371	2^{-5}	0.1560392
4.1451371	2^{-1}	0.1549082
4.1451371	2	0.1549102
4.1451371	2^5	0.1552377
4.1451371	2^{10}	0.1564157
4.1451371	2^{15}	0.1647936

Table B.4: Parameter tuning for Radial SVM

Kernel	Parameters	RMSE
Linear	$C = 2^5$	248.3869
Polynomial	Degree = 3, $C = 2^{15}$, Scale = 0.001	243.3781
Radial Basis Function	Sigma = 4.1451371, $C = 2^{-1}$	243.3726

Table B.5: Summary of the best performing SVM models per kernel type

values reduce the algorithms sensitivity to noise, but reduces its ability to detect special cases. Tables B.6 and B.7 shows the parameters tested for each kernel type. Notice that the best performing set of parameters per kernel is highlighted with bold font. Table B.8 lists the best performing set of parameters for each kernel, and enhances the best performing set of parameters across all parameters with bold font. The following parameters yielded the lowest RMSE of 0.1501901: $k = 50$, distance measure = 1 (Euclidean) and kernel = Rank.

Artificial Neural Network

The ANN implementation used in Experiment 1 is from the R library `nnet` [Venables and Ripley, 2002]. The `nnet` library provides functions for creating and training feed forward ANNs with a single hidden layer. The parameters being tuned for the ANN is the number of hidden nodes in the network and the weight decay parameter. Table B.9 presents the different values tested during the parameter tuning for ANN, and the resulting RMSE for each combination of parameters. The parameters yielding lowest RMSE of 0.1497285 was: number of hidden nodes = 16 and decay = 1×10^{-4} , highlighted with bold font in Table B.9.

Kalman Filter

`d1m` is a R library providing functions for defining dynamic linear models of various types, which is used to perform the Kalman filter predictions in Experiment 1. The actual travel times of the data set forms a time series, and it is assumed that this time series of travel times can be modelled using a first order linear model with the following state space formulation:

$$\begin{cases} y_t = \theta_t + v_t, v_t \sim \mathcal{N}(0, V_t) \\ \theta_t = \theta_{t-1} + w_t, w_t \sim \mathcal{N}(0, W_t) \end{cases} \quad (1)$$

where y_t is the observed travel time at time t , θ_t is the *actual* travel time at time t , which is assumed to be unobservable, v_t is the observation noise and w_t is the process noise. Both v_t and w_t are assumed to follow a zero mean Gaussian distribution with covariance matrices V_t and W_t , respectively.

The parameters that are tuned for this model are the covariance matrices V_t and W_t . This is done through a grid search using maximum likelihood estimation. The `d1m` library provides a function for finding the set of parameters α having the highest probability given a set of observations x . The optimal set of parameters $\hat{\alpha}$ is found through searching through a grid of possible α values, and choosing the one maximizing the log-likelihood of α given the observations x . The observations

Kmax	Distance	RMSE
3	1	0.1703484
3	2	0.1701785
5	1	0.1610623
5	2	0.1613434
7	1	0.1575735
7	2	0.1577541
10	1	0.1546021
10	2	0.1547042
20	1	0.1517638
20	2	0.1517947
50	1	0.1502186
50	2	0.1502300

Kmax	Distance	RMSE
3	1	0.1761805
3	2	0.1761574
5	1	0.1653235
5	2	0.1654804
7	1	0.1603163
7	2	0.1603996
10	1	0.1566807
10	2	0.1567659
20	1	0.1525314
20	2	0.1525958
50	1	0.1502085
50	2	0.1502746

Rectangular

Kmax	Distance	RMSE
3	1	0.1781971
3	2	0.1786599
5	1	0.1669801
5	2	0.1680861
7	1	0.1614506
7	2	0.1624606
10	1	0.1574673
10	2	0.1581775
20	1	0.1531711
20	2	0.1536536
50	1	0.1503567
50	2	0.1506450

Optimal

Kmax	Distance	RMSE
3	1	0.1764503
3	2	0.1769599
5	1	0.1651597
5	2	0.1663247
7	1	0.1600756
7	2	0.1610494
10	1	0.1564606
10	2	0.1571335
20	1	0.1527153
20	2	0.1531223
50	1	0.1502012
50	2	0.1504361

Triangular

Kmax	Distance	RMSE
3	1	0.1837144
3	2	0.1842058
5	1	0.1728479
5	2	0.1739973
7	1	0.1660075
7	2	0.1675166
10	1	0.1608040
10	2	0.1620943
20	1	0.1549380
20	2	0.1558122
50	1	0.1512792
50	2	0.1519595

Epanechnikov

Kmax	Distance	RMSE
3	1	0.1770035
3	2	0.1775128
5	1	0.1657162
5	2	0.1668814
7	1	0.1604792
7	2	0.1614875
10	1	0.1567521
10	2	0.1574551
20	1	0.1528490
20	2	0.1532873
50	1	0.1502529
50	2	0.1505107

Triweight

Cos

Table B.6: k-NN Parameter Tuning Results pt. 1

Kmax	Distance	RMSE
3	1	0.1837840
3	2	0.1836059
5	1	0.1781395
5	2	0.1781810
7	1	0.1755044
7	2	0.1754793
10	1	0.1733839
10	2	0.1732052
20	1	0.1703310
20	2	0.1700676
50	1	0.1675241
50	2	0.1671295

Kmax	Distance	RMSE
3	1	0.1709502
3	2	0.1708552
5	1	0.1620715
5	2	0.1624392
7	1	0.1583586
7	2	0.1587008
10	1	0.1555217
10	2	0.1557561
20	1	0.1524583
20	2	0.1526986
50	1	0.1504290
50	2	0.1506819

Inv

Gaussian

Kmax	Distance	RMSE
3	1	0.1734786
3	2	0.1733456
5	1	0.1640946
5	2	0.1642367
7	1	0.1596231
7	2	0.1597906
10	1	0.1562839
10	2	0.1563961
20	1	0.1524152
20	2	0.1524823
50	1	0.1501901
50	2	0.1502636

Rank

Table B.7: k-NN Parameter Tuning Results pt. 2

Kmax	Distance	Kernel	RMSE
50	1	Rectangular	0.1502186
50	1	Optimal	0.1502085
50	1	Triangular	0.1503567
50	1	Epanechnikov	0.1502012
50	1	Triweight	0.1512792
50	1	Cos	0.1502529
50	2	Inv	0.1671295
50	1	Gaussian	0.1504290
50	1	Rank	0.1501901

Table B.8: Summary of best performing parameters per kernel for k-NN

Number of hidden nodes	Weight Decay	RMSE
1	0	0.2270246
1	1×10^{-4}	0.1504067
1	1×10^{-1}	0.1513350
2	0	0.2270246
2	1×10^{-4}	0.1580870
2	1×10^{-1}	0.1509677
4	0	0.2192657
4	1×10^{-4}	0.1498524
4	1×10^{-1}	0.1509192
8	0	0.2111320
8	1×10^{-4}	0.1499537
8	1×10^{-1}	0.1510321
16	0	0.2195452
16	1×10^{-4}	0.1497285
16	1×10^{-1}	0.1510171

Table B.9: Parameter tuning for ANN

that are given to find these parameters is the same set of training data that the other baseline models are given.

$$\hat{\alpha} = \max_{\alpha} \mathcal{L}(\alpha|x)$$

Since y_t and θ_t are univariate, matrices V_t and W_t are 1×1 matrices, and only one value per covariance matrix is tuned. V_t and W_t are set to 47939 and 122, respectively. In order to give a complete definition of the dynamic linear model, an initial estimate of $y_{t=0}$ and its variance $\sigma_{t=0}$ has to be provided. This is set to be the mean and standard deviation of the training observations, which are 242 and 255, respectively.

B.2 Ensemble Learning Methods

The setup of each ensemble method used in Experiment 1 is presented in this section. The general procedure is described in Overview, whilst specific details concerning the setup of each ensemble method can be found in their respective sections.

Overview

Bagging and boosting train multiple SVMs on the same data set as the baselines described in Section 4.2.2. Data from February 5, 2015 to February 25, 2015 and generate predictions on data from February 26, 2015 to March 31, 2015. Due to the computational complexity of training SVMs, no parameter tuning is conducted for bagging and boosting.

Lasso and Fuzzy Rule Based System (FRBS) use the predictions of the baselines described in Section 4.2.2 as input. Lasso is tuned and trained on data from February 26, 2015 to March 18, 2015 and uses data from March 19, 2015 to March 31, 2015 to generate predictions. Due to the computational complexity of FRBS, only one week of data from February 26, 2015 to March 4, 2015 is used to search for the best set of parameters. As the rules in the FRBS are manually created, no training phase is necessary. Predictions are generated from March 5, 2015 to March 31, 2015.

Bagging

The bagging method is implemented in R. There are two parameters that must be specified when doing bagging of a baseline learner: the number of learners K to use in the ensemble, and the number of samples N to do for each learner. In Experiment 1, K is set to 25, and N is set to the number of training examples in the training set. A SVM model with the parameters of the best performing

model from the parameter tuning step for SVM reported in Section B.1 is used, i.e. a SVM model with a Gaussian radial basis function as kernel, $\sigma = 4.1451371$ and $C = 2^{-1}$.

Boosting

In order to test the effects of boosting, the AdaBoost [Freund and Schapire, 1997] algorithm is used. An implementation of the AdaBoost.r2 algorithm [Drucker, 1997], which is a version of the AdaBoost algorithm for regression problems, is found in the Python library `scikit-learn` [Pedregosa et al., 2011]. Of the baseline methods used in this work, the only one that is supported in `scikit-learn` is SVM, and is therefore the baseline used for the boosting ensemble in Experiment 1. A SVM model with the same parameters as the one reported in Section B.2 is used for the Boosting approach. The only parameter provided to the AdaBoost algorithm is the number of learners K to use in the ensemble, which is set to 25 in Experiment 1.

Lasso Ensemble

The implementation of the lasso method is taken from the R library `elasticnet` Zou and Hastie [2012]. The `elasticnet` library provides functions for defining elastic nets, of which the lasso method is a special case. Recall from Section 3.1.3 that the optimal weights in lasso is given by solving the following equation:

$$\hat{\mathbf{W}} = \arg \min_{\mathbf{W}} \|\mathbf{F} - \mathbf{GW}\|_2^2 + \lambda \|\mathbf{W}\|_1$$

where λ is a parameter of the lasso method. `caret` provides functionality for optimizing this λ parameter through a grid search, where RMSE is used to assess the performance of a given λ value. `elasticnet`, which `caret` uses to perform the lasso approach, requires that this λ value is controlled by specifying a fraction f which represents how much the weight regularization term contributes to the sum relative to the norm of the full least squares solution. A search grid of values from 0.05 up to 1 in steps of 0.05 is used in the parameter tuning step for lasso. Table B.10 summarizes the performance for the different fraction values tested during the parameter tuning step. Having the fraction parameter set to 1 resulted in the lowest RMSE of 169.4987, and is the parameter used in Experiment 1.

Fraction	RMSE
0.05	228.9219
0.10	220.7864
0.15	213.0905
0.20	205.8835
0.25	199.2188
0.30	193.1524
0.35	187.7423
0.40	183.0462
0.45	179.1200
0.50	176.0145
0.55	173.7729
0.60	172.4239
0.65	171.6533
0.70	170.9984
0.75	170.4612
0.80	170.0428
0.85	169.7440
0.90	169.5771
0.95	169.5259
1.00	169.4987

Table B.10: Parameter tuning for Lasso Ensemble

Fuzzy Rule Based System

The R library `frbs` [Riza et al., 2015] is used to generate a FRBS based on Stathopoulos et al. [2008]. The input to the FRBS is a data set containing predictions from the artificial neural network and the Kalman filter described above. As in Stathopoulos et al. [2008], two different rule bases, each preferring one of the two baselines, are used. The rule base preferring ANN is displayed in Table B.11. The rule base preferring Kalman filter is similar, except that it gives priority to the Kalman filter’s predictions. The travel time predictions from the baselines are mapped with triangular membership functions to three fuzzy sets; low, medium, and high. The values of the membership functions are optimized with the `constrOptim` function in the `stats` library [R Core Team, 2015], in which the Nelder-Mead [Nelder and Mead, 1965] algorithm is used to search for an optimal set of parameters bounded by the constraints shown in Table B.12. Data from February 26, 2015 to March 4, 2015 is used to tune the FRBS. The final set of membership function parameters for each rule base can be found in Table B.13 and Table B.14, and illustrations of the membership functions are

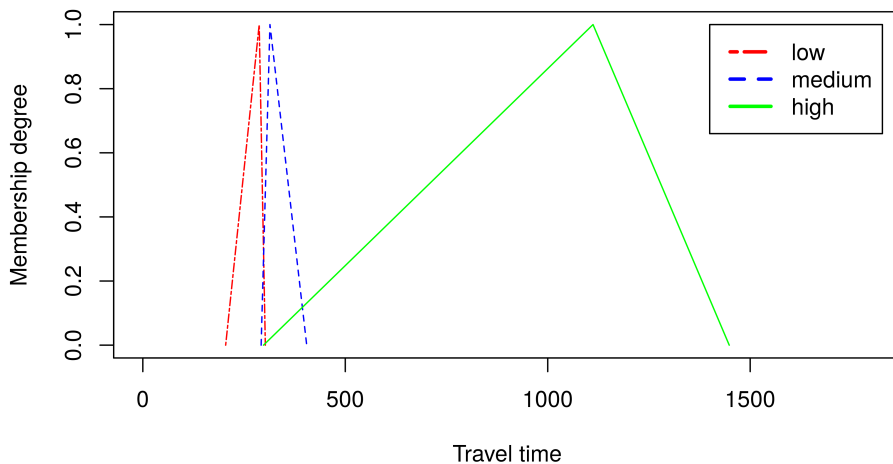


Figure B.1: Illustration of membership functions for FRBS preferring ANN

given in Figure B.1 and Figure B.2.

B.3 Online Learning Methods

This section presents the setup of the online methods used in Experiment 2. The general approach is described in Overview, whilst specific details for the individual methods are presented in their respective sections.

<p>IF ANN is <i>low</i> and KF is <i>low</i> THEN output is <i>low</i> IF ANN is <i>low</i> and KF is <i>not low</i> THEN output is <i>low</i> IF ANN is <i>medium</i> and KF is <i>medium</i> THEN output is <i>medium</i> IF ANN is <i>medium</i> and KF is <i>not medium</i> THEN output is <i>medium</i> IF ANN is <i>high</i> and KF is <i>high</i> THEN output is <i>high</i> IF ANN is <i>high</i> and KF is <i>not high</i> THEN output is <i>high</i></p>

Table B.11: Rule base preferring ANN over Kalman filter (KF)

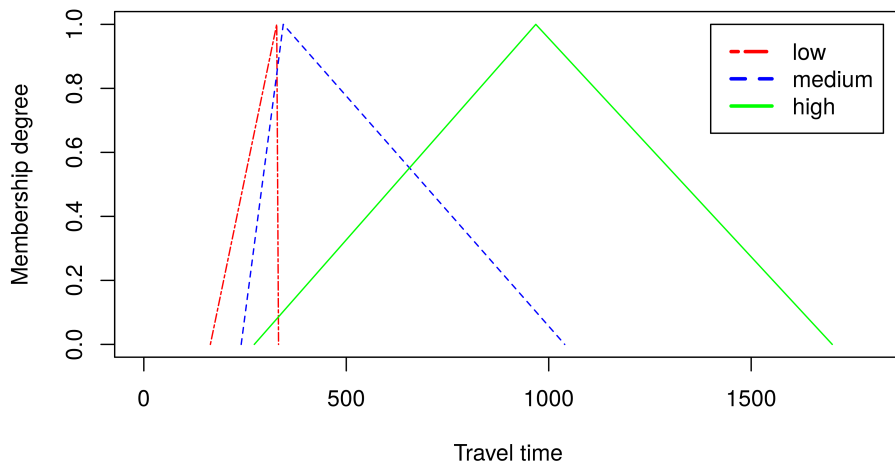


Figure B.2: Illustration of membership functions for FRBS preferring Kalman filter

low_a	\geq	min
low_b	\geq	low_a
low_c	\geq	low_b
low_c	\geq	$medium_a$
$medium_a$	\geq	low_a
$medium_b$	\geq	$medium_a$
$medium_c$	\geq	$medium_b$
$medium_c$	\geq	$high_a$
$high_a$	\geq	$medium_a$
$high_b$	\geq	$high_a$
$high_c$	\geq	$high_b$
$high_c$	\leq	max

Table B.12: Constraints for the parameters of the membership functions

	low	medium	high
a	204.5799	292.2150	298.0683
b	287.4319	313.9751	1111.8725
c	302.5835	404.7539	1448.2825

Table B.13: Membership function parameters for FRBS preferring ANN

	low	medium	high
a	164.3251	240.4815	272.8217
b	328.2455	344.3591	968.0878
c	332.7156	1039.4697	1700.2693

Table B.14: Membership function parameters for FRBS preferring Kalman Filter

Overview

The online learning methods are tuned and trained on two weeks of data from January 29, 2015 to February 11, 2015. The first week is used to build the models with a certain set of parameters, whilst the second week is used to calculate the RMSE of the predictions done during that week. Since the methods are online, the data in the second week is also used to update the models whilst making predictions. The model built on the set of parameters that lead to the lowest RMSE is used to generate predictions from February 12, 2015 to March 13, 2015. The data set used is not preprocessed, i.e. no outliers are removed.

Online-Delayed Extended Kalman Filter

An implementation of the Extended Kalman Filter (EKF) [Cao, a] and using this EKF to train a feed-forward ANN [Cao, b] is found in Matlab [MATLAB, 2014] on the Matlab Central File Exchange⁴. The state space definition that is assumed can be expressed as follows:

$$\begin{cases} y_t = G(\mathbf{x}_t, \theta_t) \\ \theta_t = \theta_{t-1} + r_t, r_t \sim \mathcal{N}(0, R_t) \end{cases} \quad (2)$$

where θ_t is the weights in the feed-forward ANN at time t , r_t is the noise with which the weights are assumed to evolve, and G represents the mapping performed by the ANN from inputs \mathbf{x}_t to output y_t given weights θ_t . That is, the weights are assumed to follow a random walk, and the ANN does a noisy observation of the weights through its outputs. In the experiments performed in

⁴<http://www.mathworks.com/matlabcentral/fileexchange/>

this study, the input vectors input_t consists of the mean travel time the previous five minutes and traffic volume the previous five minutes. The target values target_t for the output of the ANN is the actual travel time for each vehicle.

$$\begin{aligned}\text{input}_t &= [\text{mean travel time, traffic volume}] \\ \text{target}_t &= \text{actual travel time}\end{aligned}$$

Recall from Section 3.2.1 that an initial estimate of the state vector $\mathbf{x}_{t=0}$, its covariance matrix $\mathbf{P}_{t=0}$, process noise covariance matrix \mathbf{Q} , and observation noise covariance matrix \mathbf{R} has to be defined in order to run the EKF. For the way EKF is used in the experiments in this study, this means that an initial estimate of the weights θ_{initial} has to be provided. The approach described in Van Lint [2008] is that the weights θ_{initial} are initialized using the Nguyen-Widrow method [Nguyen and Widrow, 1990]. In Van Lint [2008], the weights' covariance matrix $\mathbf{P}_{\text{initial}}$ is initialized to a diagonal matrix with large values, reflecting that it is assumed that the weights are independent, and that there is a large uncertainty connected to the initial guess of the weights. These are also the approaches taken in this work, and the value along the diagonal of θ_{initial} is set to 10 000.

As Van Lint [2008] does not describe how the covariance matrices \mathbf{Q} and \mathbf{R} is set, a parameter tuning step is performed to find reasonable values for \mathbf{Q} and \mathbf{R} , in addition to the number of nodes in the hidden layer in the feed-forward ANN. The covariance matrix \mathbf{Q} is assumed to be a diagonal matrix, once more reflecting that the weights are independent, such that the only value being search for regarding \mathbf{Q} in the parameter tuning step, is the value q along the diagonal of \mathbf{Q} .

$$\mathbf{Q} = q \times \mathbf{I}$$

As the output y_t consists of a single value, namely the travel time, the covariance matrix \mathbf{R} of the observation noise is a single element r reflecting the noise related to the observations that the ANN does of the weights.

The parameter tuning for online-delayed EKF is run on two weeks of data from January 19, 2015 to February 11, 2015. Given a set of parameters the online-delayed EKF is trained on the first week of data from January 19, 2015 to February 4, 2015. Next, the model is used to train on the second week of data from Februar 5, 2015 to February 11, 2015, and the predictions made during this final training phase is used as a basis for computing the RMSE for that combination of parameters. The parameters yielding the lowest RMSE on the test set is the ones used for the online-delayed EKF model in Experiment 2.

Table B.15 illustrates the values for each parameter that is evaluated during the parameter tuning. All combinations of the parameters is evaluated. As this leads to 192 combinations, only the combination yielding lowest RMSE is

q	r	Number of hidden nodes
0.1	10	1
0.01	25	2
0.001	50	4
0.0001	100	8
	250	16
	500	32
	750	
	1000	

Table B.15: Values tested during parameter tuning for Online-Delayed Extended Kalman Filter

repeated here: $q = 0.1$, $r = 750$, number of hidden nodes = 1. This set of parameters yielded a RMSE = 406.42. The RMSEs during the parameter tuning was in the range [406.42, 735.13]. Notice that the RMSE of this parameter tuning step lies within another range than the ones resulting from the parameter tuning for the baselines in Experiment 1. This is due to the fact that the RMSE values reported from the parameter tuning for the baselines in Experiment 1 are computed using normalized travel times. This is not the case for online-delayed EKF, where the RMSE is computed on non-normalized values.

Local Online Kernel Ridge Regression

To find optimal parameters for each kernel two weeks of data from January 29, 2015 to February 11, 2015 was used. The first week was used to train the kernels on different parameter values and the last week was used to make predictions. For each pair of parameter values, the kernel was trained (i.e. the inverse of the regularized kernel matrix was calculated) on the first week of data and predictions were made on the second week of data. The observations in the test set were also used to update the kernel to simulate how Local Online Kernel Ridge Regression (LOKRR) would normally work. The \mathbf{X} matrix was reset to contain only the training data before every run with new parameters. This way the best pair of parameters could be found for each kernel. The recommendations for finding possible parameter values for σ and λ presented in the article were followed. The approach the authors recommend for finding possible λ values is based on Exterkate [2013]. First, the R^2 of an ordinary least squares fit of \mathbf{y} on \mathbf{X} is found. Then λ_0 is determined as $\lambda_0 = 1/\phi_0$, where $\phi_0 = R^2/(1 - R^2)$. The recommended values for λ is $\{1/8\lambda_0, 1/4\lambda_0, 1/2\lambda_0, \lambda_0, 2\lambda_0\}$. The recommended approach for finding possible σ parameters is based on that optimal values of σ lie in the range between the 0.1 and 0.9 quantiles of the pairwise euclidean distance

between the points in the kernel [Caputo et al., 2002]. The 0.25, 0.5 and 0.75 quantiles were used as possible values for σ .

No open source implementation of LOKRR was found, so a n implementation of LOKRR was developed in Python [Rossum, 1995] from scratch. Several issues were encountered during this process.

Data Set 1 contains individual travel times as opposed to Haworth et al.'s experiments with five minute aggregated data. Since the amount of traffic is a lot bigger during the day than during the night, the kernels in our LOKRR implementation ended up with different sizes. An upper bound on how much data one kernel could contain was not set, but the method was slightly changed for kernels with little data. In the article the kernel sizes are kept static, meaning a data point is removed from the kernel as soon as a new point is added. For kernels with number of observations below some threshold (200) a decision was made not to remove the oldest observation. This way kernels responsible for intervals with low traffic were aloud to grow also during the testing and verification stages. Otherwise the kernels responsible for intervals with low traffic would be limited by the amount of observations in the training set. By adding this functionality kernels with less than 200 observations during the training period could keep data further back in time than the other kernels when new observations were made. This was done in hope of increasing prediction accuracy.

It was also discovered that the regularized kernel matrix sometimes ended up with a determinant of zero, in which case an inverse can not be found. To avoid getting an error during run time when attempting to calculate the inverse of a singular matrix, a check was added to check if adding a new point would cause a determinant of zero in the regularized kernel matrix. In those cases the point was not added to the kernel. This means that some observations may have been skipped by LOKRR during the testing and verification stage.

During parameter tuning two other issues were encountered. In cases where a kernel only has two points in its \mathbf{X} matrix, the R squared of an ordinary least squares fit of \mathbf{y} on \mathbf{X} equals 1. This causes division by zero when calculating ϕ . Kernels with a high percentage of similar observations also caused problems when selecting parameter values for σ . Similar observations means that the euclidean distance between them is zero. This led to one or more of the possible σ values to become zero, which again caused division by zero when calculating the kernel matrix. These two issues seemed to occur during intervals at night with few observations in the kernels. Therefore a decision was made to only consider intervals with a significant amount of traffic such that the probability of these events happening was minimized. The data set used for LOKRR contained observations from 06:00 to 21:00. Additionally, the window size is set to 1. This is done to reduce the computational complexity.

C Experimental Results

Baseline	Sample median
1	3.3158
2	3.3944
3	3.2888
4	3.5681
5	3.409
6	3.3392
7	3.2783
8	3.2737
9	3.3757
10	3.3157
11	3.3435
12	3.3958
13	3.0521
14	3.0536
15	3.2123
16	3.0686
17	3.2234
18	3.2264
19	3.6155
20	3.2237
21	3.1358
22	3.3673
23	3.2151
24	2.998
25	3.5768

Table C.1: Sample medians of bagging baselines

$\bar{x} = -102.9802$ $s = 209.52$
 $Md = -31.6325$ $Mo = -12.5852$

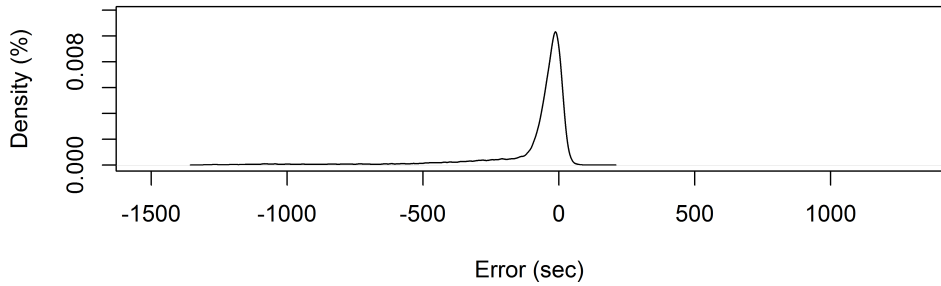


Figure C.1: Density of errors from SVM

$\bar{x} = -42.7118$ $s = 214.17$
 $Md = 23.4627$ $Mo = 50.8276$

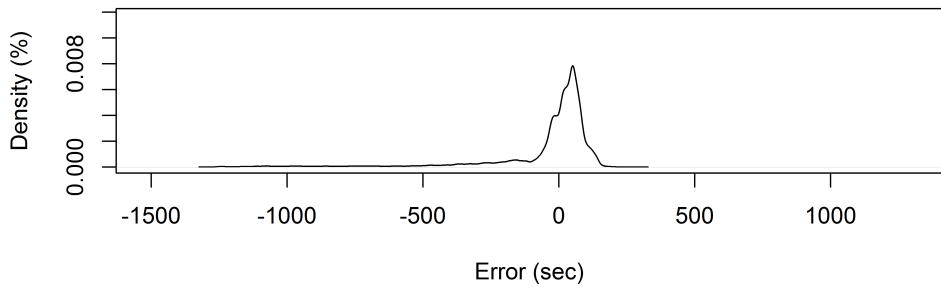


Figure C.2: Density of errors from k-NN

$\bar{x} = -43.5735$ $s = 212.07$
 $Md = 26.5412$ $Mo = 44.9849$

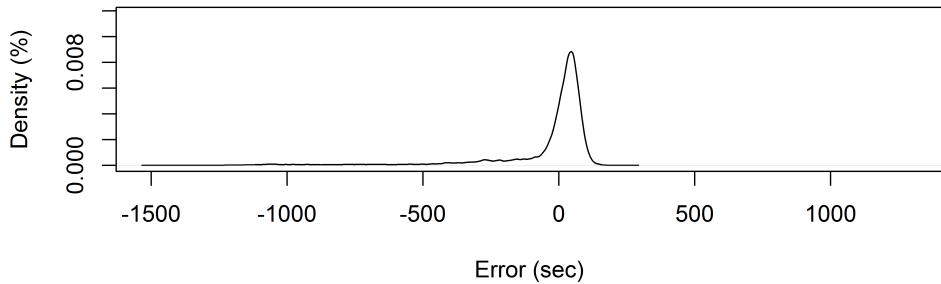


Figure C.3: Density of errors from ANN

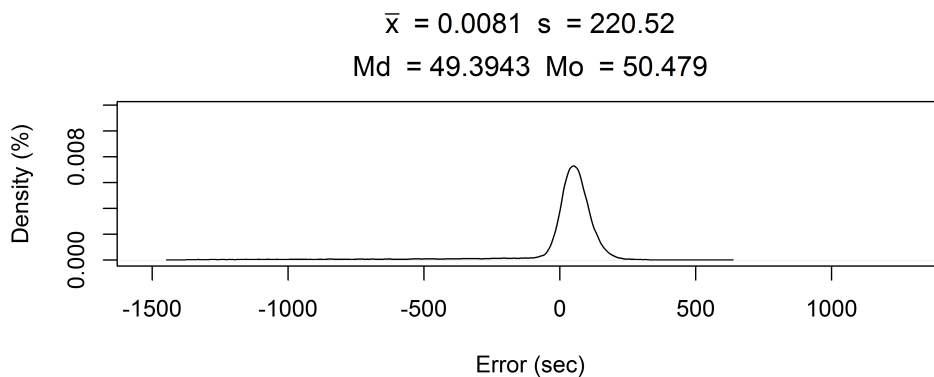


Figure C.4: Density of errors from Kalman filter

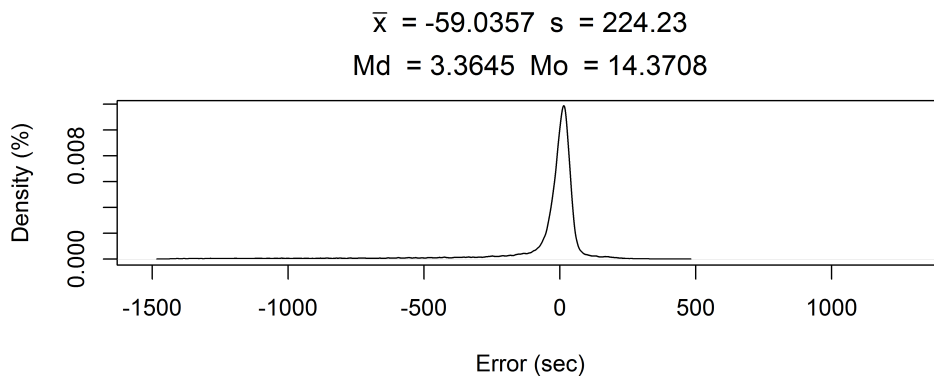


Figure C.5: Density of errors from bagging

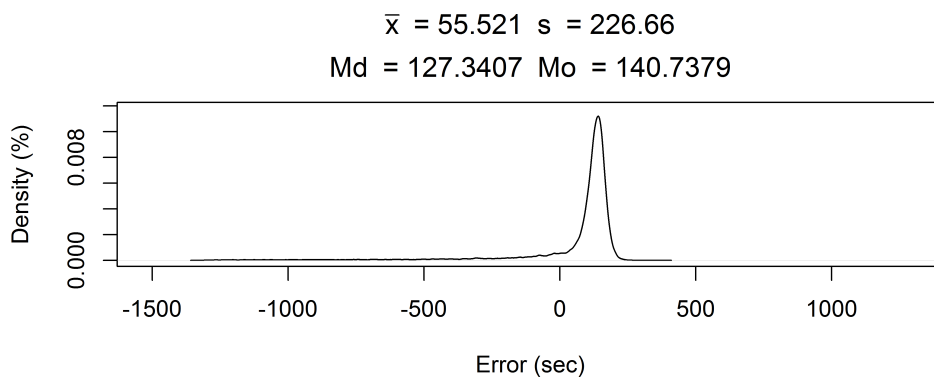


Figure C.6: Density of errors from boosting

$\bar{x} = 2.7922$ $s = 167.07$
 $Md = 44.1579$ $Mo = 45.868$

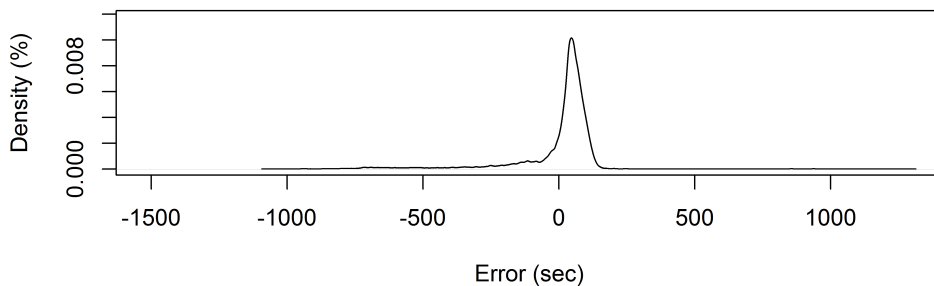


Figure C.7: Density of errors from lasso

$\bar{x} = -4.6371$ $s = 167.64$
 $Md = 38.9437$ $Mo = 50.8357$

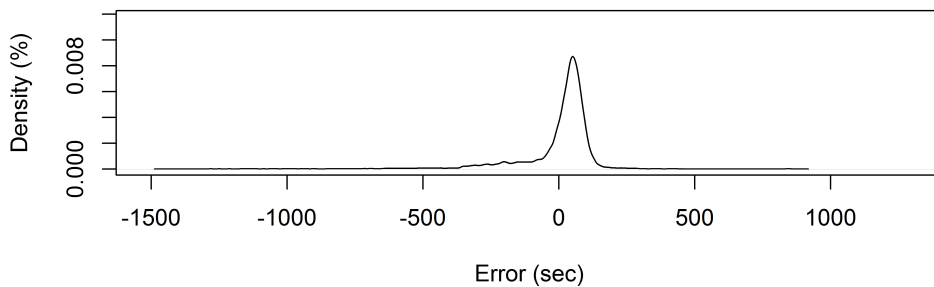


Figure C.8: Density of errors from FRBS

$\bar{x} = -47.3143$ $s = 210.44$
 $Md = 20.3134$ $Mo = 36.2406$

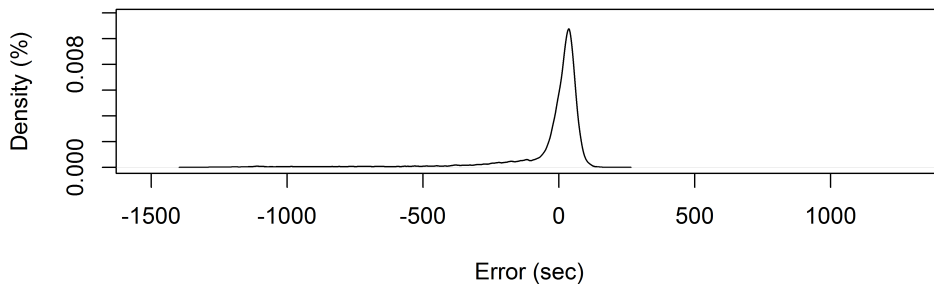


Figure C.9: Density of errors from average

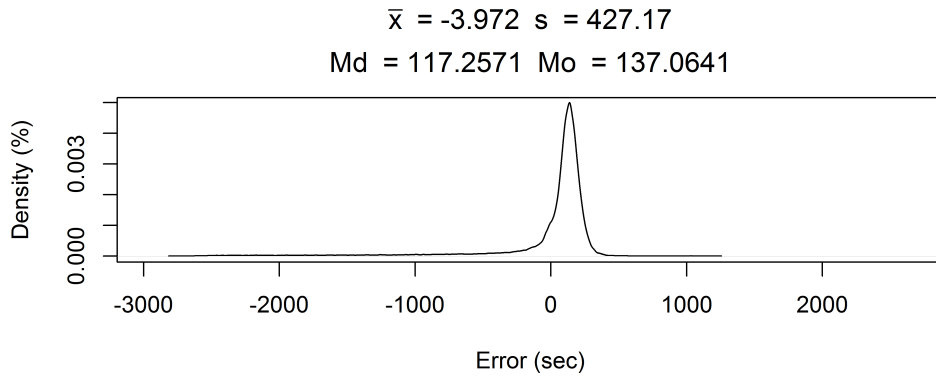


Figure C.10: Density of errors from online-delayed EKF

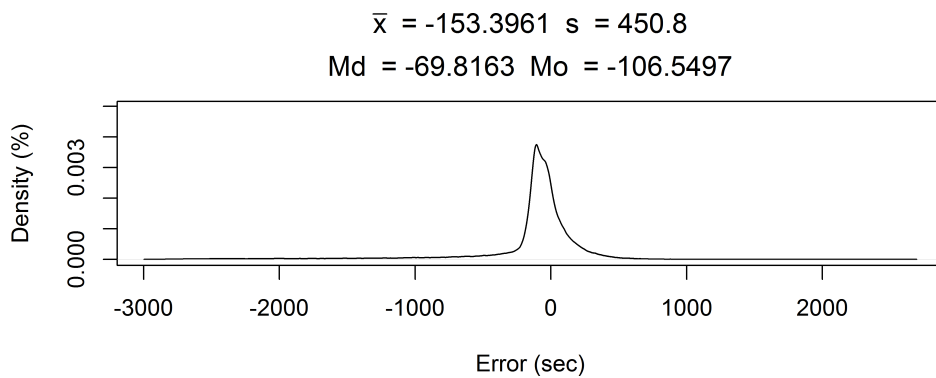


Figure C.11: Density of errors from LOKRR

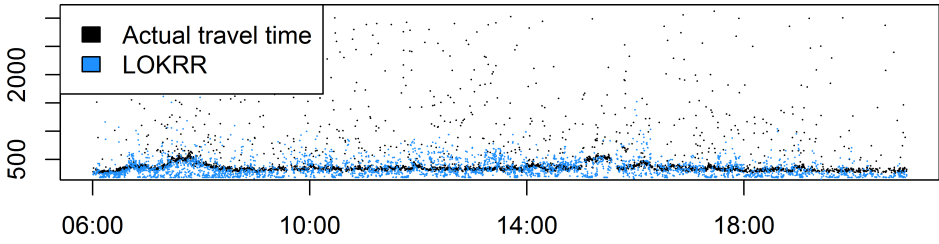


Figure C.12: Predictions from LOKRR and actual travel time on March 6, 2015

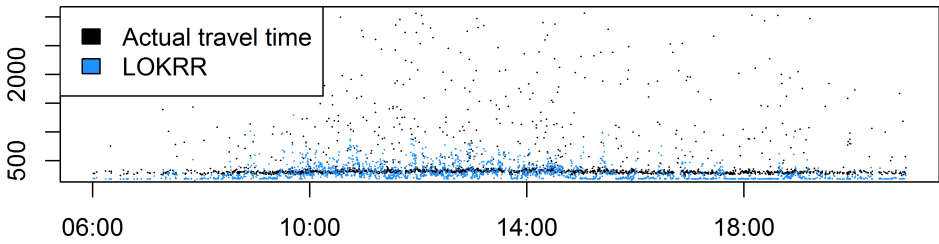


Figure C.13: Predictions from LOKRR and actual travel time on March 7, 2015

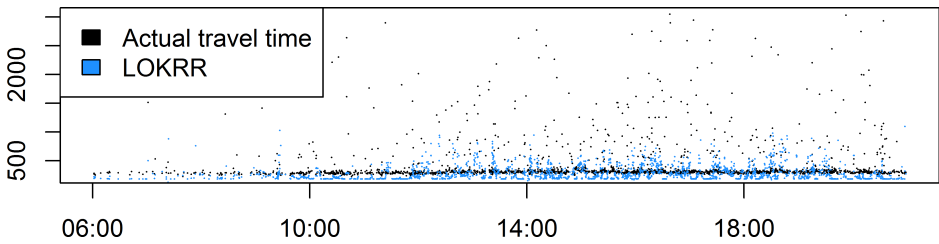


Figure C.14: Predictions from LOKRR and actual travel time on March 8, 2015

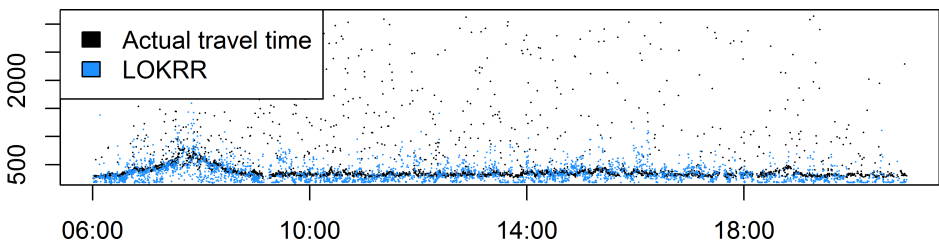


Figure C.15: Predictions from LOKRR and actual travel time on March 9, 2015

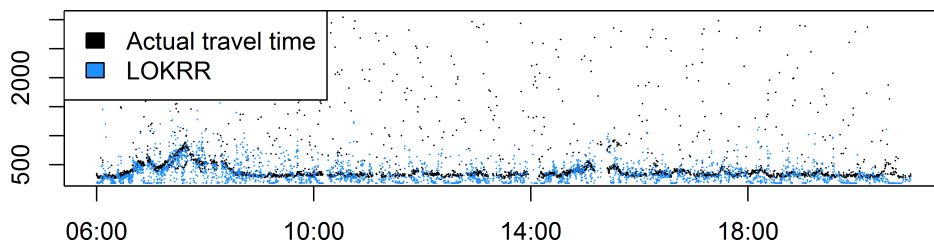


Figure C.16: Predictions from LOKRR and actual travel time on March 10, 2015

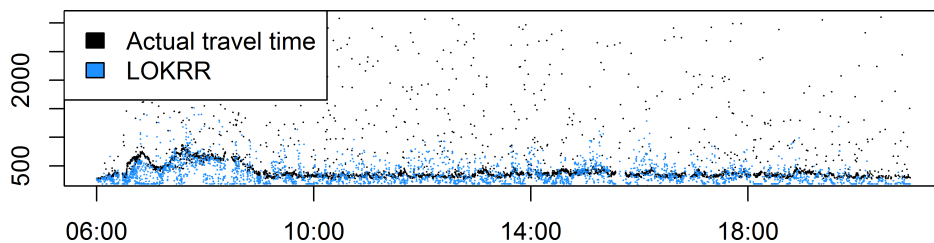


Figure C.17: Predictions from LOKRR and actual travel time on March 11, 2015

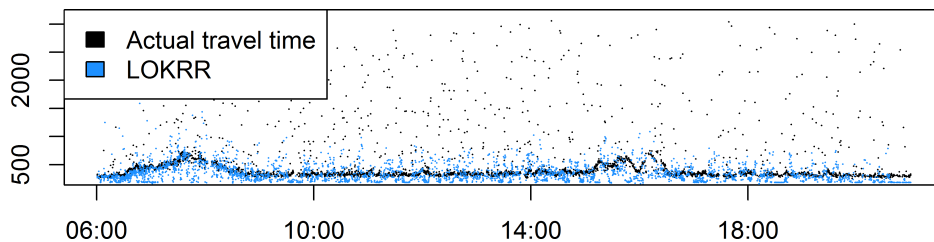


Figure C.18: Predictions from LOKRR and actual travel time on March 12, 2015

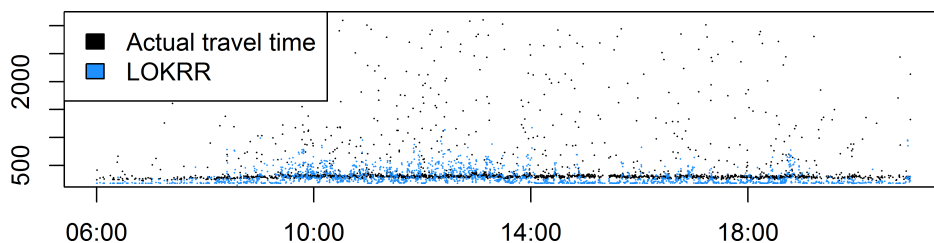


Figure C.19: Predictions from LOKRR and actual travel time on March 14, 2015

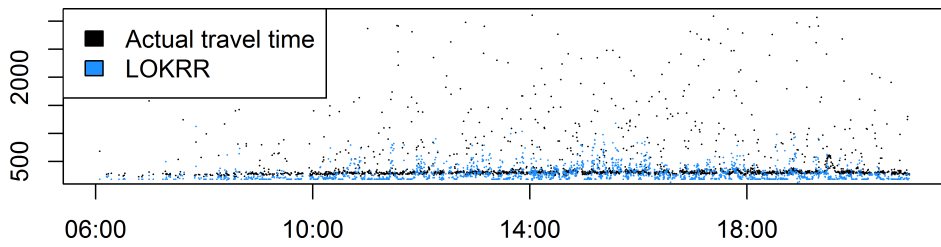


Figure C.20: Predictions from LOKRR and actual travel time on March 15, 2015