NTNU – Trondheim
Norwegian University of
Science and Technology

Financial Information Extraction and Visualization

Jan Rybak

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Supervisor:	Kjetil Nørvåg, IDI
Co-supervisor:	Krisztian Balog, IDI
	Richard Lipka, University of West Bohemia

Norwegian University of Science and Technology
Department of Computer and Information Science

Abstract

Our society became very information oriented in the recent two decades and every year the amount of digital data more than doubles. However, our ability to effectively process the data and extract useful and relevant information is limited.

In the scope of this thesis we are addressing two challenges, automated information extraction and its comprehensible visualization. The first part is concerned with identification of possibly interesting financial data from newspaper articles and their extraction. We are proposing a new approach to recognize named entities using DBpedia, we are identifying financial relations and extracting monetary data. Next, to communicate obtained information clearly, a tool for visualizing the financial cost of recognized entities is introduced. As we developed an advanced system, which helps people to reinforce their finance-related knowledge, we believe that the thesis's objective was met.

Preface

This report presents my Master thesis. The work has been carried out at the Department of Computer and Information Science, Faculty of Information Technology, Mathematics, and Electrical Engineering at NTNU. The work has been supervised by Dr. Kjetil Nørvåg, and co-supervised by Dr. Krisztian Balog, and researcher at the University of West Bohemia Dr. Richard Lipka.

This thesis would not have been possible without the support of many people. I would like to express my sincere thanks to Kjetil, Kristýna, Krisztian, Richard and Tárik. Finally, I am forever indebted to my parents for their endless love and support.

Pilsen, June 7, 2013
Jan Rybák

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Chapter 1

Introduction

1.1 Background

During the recent decades our society became information-oriented. Enormous amount of data is being produced every single second. The amount is so huge that we are not able to process it all and use it effectively. In 2010 the size of the Internet was estimated to be approximately 500 billion gigabytes. To give you an idea, that is the equivalent of a stack of books stretching from the Earth to Pluto ten times[1]. But not all the information is uploaded to the Internet. According to Bounie and Gille [7] the world generated 14.7 exabytes of new information in 2008, nearly triple the volume of information in 2003.

"We remember what we understand; we understand only what we pay attention to; we pay attention to what we want." - Edward Bolles -

For us, information consumers, the most difficult task is no longer to acquire the data, but to filter out all the irrelevant and unclear data that we don't need. In such situation it is very easy to lose our objectivity and general perspective. This phenomenon is called 'information overload' or 'info obesity' and the main causes are [2]:

- a rapidly increasing rate of new information being produced,
- the ease of duplication and transmission of data across the Internet,
- an increase in the available channels of incoming information.

[1] http://www.guardian.co.uk/business/2009/may/18/digital-content-expansion
[2] Information overload: http://en.wikipedia.org/wiki/Information_overload

The major implications and challenges that the information overload brings are:

- contradictions and inaccuracies in available information,
- a lack of methods for comparing and processing various kinds of information,
- the fact that the pieces of information are unrelated or do not have any overall structure to reveal their relationships.

Particularly, the last two points in the list above are crucial for this thesis. If there is no way to compare various pieces of information, it is impossible to realize its context. And without any context the information is meaningless.

Most of us are absorbing a huge amount of information every single day, it does not matter if the sources of it are newspapers, Internet, television or something else. We are used to hear news mentioning big financial numbers like billions or trillions of dollars but only a handful of us can really imagine such enormous sums of money. This is mostly caused by the fact that we are not dealing with that kind of money on a daily basis. It is difficult for us to relate quickly, for example, state's budget to the price of a new car.
And even if we are masters in comparing numbers, there is a second aspect associated with big numbers - their memorability. Unfortunately due to their abstract nature, numbers are one of the hardest things to remember. After some time it is not that easy to remember correctly at least the order of magnitude of big sums.

It is nearly impossible to focus only on the important information that reaches our senses, filter out all the noise, and remember everything. On the other hand this is the only way how to gain undistorted knowledge. In the thesis we are proposing a solution how to extract financial data, let user pick only the important and relevant pieces of information and put them into comparison. The goal of our tool is to motivate users to explore seemingly unrelated financial data and see "the big picture" in it.

1.2 Motivation

The first impulse that made us think about the comparison of financial data from various domains was a talk called 'The beauty of data visualization' given by David McCandless at TED conference[3] in 2010. He presents a treemap-style chart called 'The $Billion Dollar o-Gram' [4] where he compares various costs, subjects of these costs and motivation behind it. Even though the data he shows are publicly known, it is the comparison that makes all the magic. When you can visually compare different costs, big numbers are becoming less abstract.

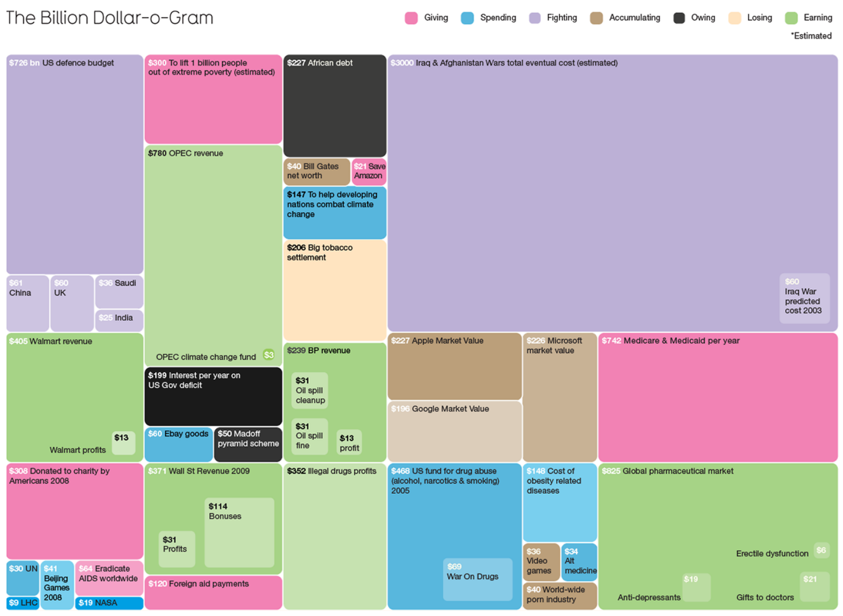


Figure 1.1: Billion Dollar o-Gram by David McCandless

David McCandless scraped all the data for his visualization manually. We are aware of the big potential in retrieving the data automatically or semiautomatically by means of natural language processing. Such an approach might bring new possibilities like manipulation with a vast amount of input data, interactivity, inclusion of temporal aspect of the data, etc.

[3] http://www.ted.com/talks/david_mccandless_the_beauty_of_data_visualization.html
[4] http://www.informationisbeautiful.net/visualizations/the-billion-dollar-o-gram-2009/

1.3 Project Goals

In this thesis we would like to develop a system that will be able to analyze plain text written in natural language, to extract financial data from the unstructured sources and visualize them in the most appropriate form for the user. The application should help people to access financial data, to turn it into information and most importantly to offer a tool to gain knowledge from the information. The term *financial data* means a triplet of data in the following format:

```
SUBJECT + RELATION + COST
E.g.: Google Inc. + earned + $ 37,000,000,000 USD
```

The subject, in other words the originator of financial information, might be e.g. a company, a person, a project or something else which is, somehow, connected with the cost. The interesting feature of the cost is its relation to the subject. To mention just a few examples, it can be revenue, loss, debt, expenses, share, etc.

1.4 Data Acquisition

Gathering the data is the first and foremost task which all the following steps directly depend on. To bring an interesting story to light, we first need relevant data. As mentioned in the introduction, the Internet offers nearly inexhaustible source of information, however, there is an disadvantage in its heterogeneity. This is the main reason why we have decided to extract the information from texts written in natural language. There is a whole field of science occupied with extracting useful information from large data sets or databases formally known as data mining [18].

Even though the system should be able to process any kind of plain text, we think that news articles are very suitable source of data. As we aim to develop an application for ordinary people, it is desirable to work with popular information channels such as The New York Times newspaper[5] or similar.

[5] http://www.nytimes.com/

1.5 Communicating information

"The visualization of information gains its importance for its ability to help us 'see' things not previously understood in abstract data." - Ben Fry -

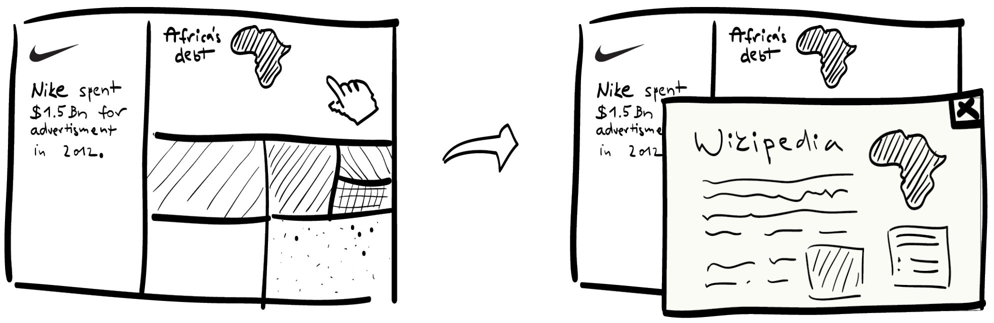


Figure 1.2: Mock-up of our visualization

Once we turned the data into information (data triplets), all the effort will be concentrated on comprehensible communication of the results to the user. Even if people are given the right figures, it doesn't necessarily mean that they can realize their meaning. It is the comparison and the relation to the context that play the important role.

Information visualization is a flourishing discipline that has become very popular in the recent years [10]. Graphical presentation of the data shows relationships much more clearly, the user can find patterns in data very quickly and it is also a more attractive form of data presentation than plain tables.

James J. Thomas and Kristin A. Cook stated the following about information visualization: *"Visual representations and interaction techniques take advantage of the human eye's broad bandwidth pathway into the mind to allow users to see, explore, and understand large amounts of information at once. Information visualization focused on the creation of approaches for conveying abstract information in intuitive ways."*[50]

1.6 Process

This thesis is composed of two main parts - information extraction and information visualization. In this section we would like to briefly describe individual steps that are covered by these comprehensive terms.

1. **Data acquisition**
   Feeding the system with input data - English plain text.
2. **Filtering**
   Selection of relevant articles, i.e. those which contain only financial information (number+currency).
3. **Subject extraction**
   Finding the originator of the financial information.
4. **Relation extraction**
   Identification of the relation between the subject and the cost.
5. **Storing**
   Storing the data triplets (Subject + Relation + Cost).
6. **Correction / Selection**
   Verification of the output by a human and selection of the data to be presented.
7. **Visualization**
   Graphical representation of the result.
8. **Interaction**
   User interaction with the presented results (manipulation, additional information, ...).

Part I

Information Extraction

Chapter 2

State-of-the-Art

Before we start describing the process of realization, we will give a fundamental overview in the field of natural language processing while emphasizing the information extraction. In this chapter, we also provide description of Linked Data publication concept which is closely related to the way we store and visualize extracted data.

2.1 Introduction

Information extraction (IE) is a specific discipline of natural language processing (NLP), a subfield of artificial intelligence, which has been a rich subject of research. IE systems are used for transforming unstructured information (such as Web) into machine-readable structures (such as relational database). The main goal of IE is to extract predefined types of data and relations from a single document. Typical types of entities that we are searching for include names of organizations, people or locations, but generally IE does not necessarily have to be domainspecific [55]. Recognition of desired information is a non-trivial task and significant number of techniques have been developed over the last few decades.

2.2 Historical Background

The serious beginnings of IE are strongly related to the series of Message Understanding Conferences (MUCs) held from 1987 to 1998. The main task of these competition-oriented conferences was to fill predefined templates with very specific pieces of information such as details about terrorist events in Latin America. These information bits were, after recognition, filled into exactly fitting slots of a prepared template (e.g. perpetrator, victim, date, location, etc.)[22].

Conferences such as MUCs set pattern matching approach of IE as a trend of the time. Basic, but very important concepts such as IE system evaluation techniques (recall, precision), named entitiy, word sense disambiguation, coreference, and many more, were introduced due to these conferences.

Another important challenge which influenced IE research was Automatic Content Extraction program [31] . The main objective of the program was identification of entities, relations, and the events in the natural language.

2.3 Definitions of Information Extraction

As the information extraction has been heavily researched for a long time, many definitions of the actual term 'Information Extraction' appeared in various papers. Formulations of these definitions are influenced mostly by the state-of-art techniques of the time. We can see the evolution in this particular field just by reading the following definitions.

"IE systems extract domain-specific information from natural language text. The domain and types of information to be extracted must be defined in advance. IE systems often focus on object identification, such as references to people, places, companies, and physical objects. [...] Domain-specific extraction patterns (or something similar) are used to identify relevant information." [40] - Riloff and Lorenzen -

"[...] isolates relevant text fragments, extracts relevant information from the fragments, and then pieces together the targeted information in a coherent frame-

work. [...] The goal of information extraction research is to build systems that find and link relevant information while ignoring extraneous and irrelevant information." [14] - Cowie and Lehnert -

"Information extraction is the identification, and consequent or concurrent classification and structuring into semantic classes, of specific information found in unstructured data sources, such as natural language text, making the information more suitable for information processing tasks." [29] - Moens -

2.3.1 Information Extraction or Document Retrieval

The terms Information Extraction (IE) and Information Retrieval (IR) or even Document Retrieval (DR) are often confused. IR is the activity of identifying and obtaining possibly relevant documents containing desired information from large document collections such as Web or a database. Document Retrieval is a specialized type of IR which is concerned with retrieval mainly from text-based documents. We can describe current Web search engines as Document Retrieval systems.

In their book [41], Russell and Norvig expressed the difference between information extraction and retrieval by the following sentence:

"Information extraction systems are mid-way between information retrieval systems and full-text parsers, in that they need to do more than consider a document as a bag of words, but less than completely analyze every sentence." [41]

2.4 Information Extraction Approaches

In this section we give thorough introduction to the main IE approaches. A nice survey of Web-focused IE systems is given in [9].

2.4.1 Information Units in IE

The first target elements of IE in the time of MUCs were names of people, organizations and locations together with temporal and numeric entries. Such mentions in a text are typically described as *entities* and, as expressed in [21], may take form of

- **names** (”Tim Berners-Lee”),
- **noun phrases headed by common nouns** (”the queen”),
- and **pronouns** (”it”).

The task of *named entity recognition* (NER) is covered in Section 2.5.

The next step in IE is the recognition of relationship which is defined over two or more entities. Example of such relationship between two entities can be ”is the father of” which is expressing the family relationship between a father and his son. Section 2.6 takes a closer look at Relation Extraction (RE) techniques. Higher-order structures such as *ontologies* or tables are also being extracted. Since we are using an ontology both for NER and RE purposes, there is Section 2.8 related to this topic.

2.4.2 Division of IE Techniques

According to Sarawagi [44] we can divide IE techniques into different groups by aspects stated below.

Hand-coded vs. Learning-based

The most straightforward approach for IE system implementation is to use handwritten rules. These rules used to extract a specific kind of information are usually composed by a domain expert (human) in the form of regular expressions. It is necessary that the person, who is preparing extraction rules, has a good knowledge of the IE system itself, so he or she is able to create robust rules. The preparation of such collection of rules is an expensive and tedious process, particularly for broad range domains. Knowledge-engineering approach was adopted mostly in the early IE systems because of its easier implementation.

More recent systems take advantage of machine learning model with limited amount of human input needed (supervised learning). Domain specific parts of training text must be manually annotated by a domain expert. Then, these data serve as a seed for training algorithm and the result is used to extract specific information from different data sets. We can see the process of learning as an attempt to obtain the rules automatically from the text itself. The majority of data is changing dynamically in time and retraining IE system seems to be easier than managing rule-based system up to date.

Rule-based vs. Probabilistic

Another aspect of IE systems division is whether extraction method is based on hard predicates (rules) or statistical analysis. Statistical learning methods are more robust to noise and variation in unstructured text [11]. Its advantage is also considerably lower need for human interaction when developing IE system for broad-range domains.

2.4.3 Rule-Based Methods

Rule-based approach, sometimes called *Language Engineering*, is a model relying on the theory of grammars and finite-state automata. In the rule-based systems we have to specify a pattern (i.e. rule, template) for every kind of information we want to extract. In the simplest cases, these patterns can be described by regular expressions, in more advanced cases some other tools might be used (e.g. rule language in GATE called JAPE).

Behavior of rule-based systems is driven by the following formula:

$$\begin{tikzcd}
\textbf{Search for pattern match} \arrow[d] & \\
\textbf{Pattern(s) is/are recognized} \arrow[r] & \textbf{Action} \arrow[ul]
\end{tikzcd}$$

Patterns can be recognized by lexical features of the matching token itself or by its context.

Features of the given token might be for example:

- Actual string of the token.
- Part-of-speech category of the token or other specific feature of the token.
- Annotations from previous steps of NLP (e.g. category assigned by Gazetteers[1], NER).

Listing 2.1: Pattern example in JAPE format (using POS of the token)

```
Rule: AdjectiveTagger
(
  {Token.category == "JJ"}
) : Adjective
```

If it is the context that identifies the token, than we are usually using a prefix and/or suffix to describe the target (see Listing 2.2).

Listing 2.2: Pattern example in JAPE format (using currency suffix to identify the token)

```
Rule: MyCurrencyCategory
Priority: 100
(
  {Number}
  ({SpaceToken})*
  (  {Lookup.majorType == "currency_unit",
      Lookup.minorType == "post_amount"}
  ):cur
): label
-->
:label.MONEY= {type="Money", value= :label.Number.value, currency=
    :cur@string}
```

Information Extraction systems usually comprise of many patterns and it may happen that more than one pattern fits the rule, such situation is called a conflict. That is why we need to define some policy that chooses the most suitable pattern in case of a conflict.

[1] list of named entities such as names, places or organisations

Classical approaches to resolve conflicts are:

- **Implicit** - e.g., longest matching pattern
- **Explicit** - assigning each pattern an explicit priority (Example: Listing 2.3)

These methods can be combined for the case of two patterns covering text of the same length; then the rule with higher priority is then applied.

Listing 2.3: Use of priority attribute.

```
Rule: PrefixCurrencyTagger
Priority: 100
```

Pattern Learning

Manual creation of patterns is a tedious and error-prone process, not speaking of the need for domain experts. This situation has encouraged many researchers to explore the problem of pattern learning methods. This specific application of *Machine Learning* usually requires input in the form of manually annotated data which is called a *training data set*. In the following section we describe the probabilistic approach to IE which is the core theory behind the pattern learning.

2.4.4 Probabilistic Approach

In case we need to extract information from noisy or not well-structured data, the rule-based systems do not perform very well. The main disadvantage of the finite-state systems is their inability to capture more complex language patterns in an easy way. Probabilistic approach is seeking *language models*, i.e., models describing the probability distribution of language expressions (e.g. words).

Classifiers

The classification problem is addressing the task of deciding if a data item $x \in X$ on the input belongs to one of predefined classes $c \in C$. For example, given the word ”perfectly” we have to tell to which syntactic category in $C = \{adjective, noun, verb, ...\}$ it belongs with the highest probability. We can also see the process of classification as assigning labels of different classes to data provided on the input. The unit which performs this labeling is denoted as the *classifier*. We distinguish *binary* and *n-ary classifiers*, depending on how many labels they are working with.

A trainable classifier is able to learn classification patterns and operate on any input, including previously unseen data. In NLP a technique called *supervised learning* is very popular. As the name suggests, the training algorithm requires manually labeled data for learning.

A typical classification task depends on a set of *features* which are describing the data item. For word-like units called *tokens* such features can be organized in the following groups:

- **Lexical Features** - e.g., word's surface form, etc.
- **Part-of-Speech Features** - lexical category of the word
- **Orthographic Features** - such as its capitalization form, the presence of special symbol, etc.
- **Dictionary Lookup Features** - if the word matches with a word in dictionary.

Learning Models

Many different learning algorithms are available for classifiers. The main difference among them is whether the input values are classified as conditionally independent. One of the most widely used models in NLP which is based on conditional probability, is the **Maximum Entropy Model**. The probability of assigning label c to data item x is given by

$$p(c|x) = \frac{1}{Z} exp \sum_{j=0}^{N} w_j h_j \tag{2.1}$$

where Z is a normalizing constant, h_j is the value of i^{th} *indicator function*, and w_j is the weight assigned to indicator function j by the training process. Each indicator function is a combination of a particular class label c and a particular feature of data item x. [21]

Other popular models, in detail explained in [25], are

- **Naïve Bayes Model** - input values are considered to be conditionally independent in this model. It is modeling the joint probability $p(c, \vec{x})$ of the imput values $\vec{x}$ and the class variable c.
- **Hidden Markov Models** - HMM is extension to NBM for sequential data.
- **Conditional Random Fields** - discriminative (conditional) model suitable for sequential data. It builds on the top of Maximum Entropy Model and also models the conditional probability $p(c|x)$.

2.5 Named Entity Recognition

Named entity recognition (NER) is the task of detection and classification of *proper nouns* such as names of people, organizations or locations. During the MUCs [1], it became clear that the ability to identify names is essential for information extraction. Nowadays, NER is an essential part for many NLP systems and from the initial set of 3 defined named entities introduced by *MUC-6* [1] it has grown up to couple of hundreds [47].

Example

Johnie Walker was named CTO of IBM Inc. in 1999. Two years later he started working for Yahoo.

$\downarrow$ *annotation*

[Johnie Walker]$^{\textbf{person}}$ *was named CTO of [IBM Inc.]*$^{\textbf{org}}$ *in 1999. Two years later he started working for [Yahoo]*$^{\textbf{org}}$.

NER Approaches

Many approaches to recognize named entities in text have been explored so far. In the recent years a lot of effort was invested in statistical methods based on ML techniques. However, grammar-based methods and methods using list lookup are still being used. Overview of existing methods and NER systems can be found in [49], [30].

2.6 Relation Detection

The aim of our system and many others is, besides other things, to detect semantic relation between extracted entities because the relationship may not be known in advance. The ability to identify relations in NLP is an essential step for language understanding. Let us first define the term *relation*:

Definition of relation:

Let X and Y be nonempty sets. A binary relation (or just relation) from X to Y is a subset

$$R \subseteq X \times Y.$$

If (x,y) $\in$ R, we say that x is R-related to y, denoted xRy.

Expressed by basic language, a binary relation in NLP context can be seen as an information describing some action between two entities. We can describe such relation by *triples* - relation type and two arguments.

Most of the systems focus on binary relations, however, there are some which are addressing the problem of *n-ary* relations. One of the proposed methods to detect *n-ary* relations is to decompose them into a set of binary relations [26].

Example of relations:

Company A was acquired by B. $\rightarrow$ *acquiredBy(Company A, B)*

Person X paid \$40. $\rightarrow$ *paid(Person X, \$40)*

John is from Prague. $\rightarrow$ *IsFrom(John, Prague)*

"Whereas entities refer to a sequence of words in the source and can be expressed as annotations on the source, relationships are not annotations on a subset of words.

Instead they express the associations between two separate text snippets representing the entities."[44]

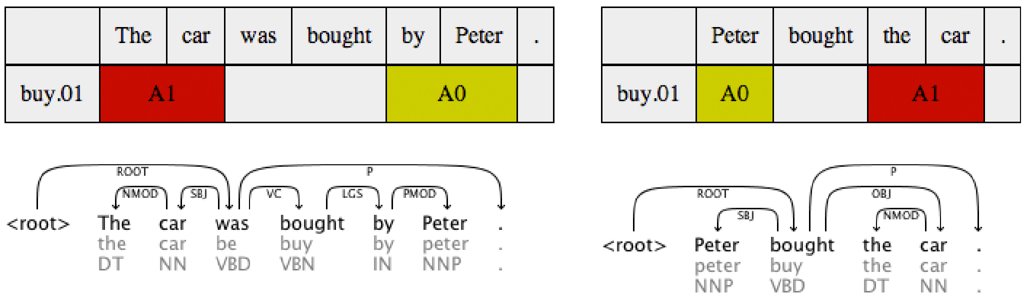
2.6.1 Challenges

Sunita Sarawagi is describing two scenarios of relationship extraction:

- predicting the relationship between a given entity pair,
- extracting entity pairs given a relationship type,

and in his paper [44] gives thorough overview of various RE approaches including *Feature-based Methods* and *Kernel-based Methods*.

2.6.2 Semantic Role Labeling



	The	car	was	bought	by	Peter	.
buy.01	🟥 A1	🟥			🟨 A0	🟨	

	Peter	bought	the	car	.
buy.01	🟨 A0		🟥 A1	🟥	

Figure 2.1: SRL representation of two sentences.

Semantic Role Labeling (SRL) is addressing the problem of automatic detection of *semantic roles* (see Section 2.6.2). Its goal is to identify semantic arguments of the predicate and assign roles that indicate for example the *Agent, Patient, Instrument*, or more specific roles such as the *Buyer, Seller*, etc. SRL is a very useful method for information extraction systems because of its ability to extract semantic roles independently on the sentence structure. For instance, these two sentences are equal in terms of semantic roles:

The car was bought by Peter.

Peter bought the car.

Semantic Roles

Semantic roles (also known as thematic roles) describe the relationship between the main verb in a clause and its arguments (participants). There is an important difference between semantic roles (agent, instrument, etc.) and grammatical relations (subject, object, etc.). While the grammatical relations are relations between words in a sentence, the semantic roles describe the actual relations that the participants play in a situation described by the sentence.

Table 2.1: Difference between grammatical relations and semantic roles.

Sentence	*Subject*	*Object*	*Agent*	*Recipient*
Google bought YouTube for $1.65 billion.	Google	Youtube	Google	Youtube
YouTube was bought by Google for $1.65 billion.	Youtube	Google	Google	Youtube

Typical semantic roles [2]

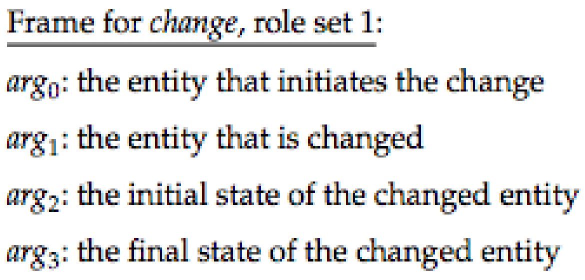
- **Agent** The 'doer' or instigator of the action denoted by the predicate.
- **Patient** The 'undergoer' of the action or event denoted by the predicate.
- **Theme** The entity that is moved by the action or event denoted by the predicate.
- **Experiencer** The living entity that experiences the action or event denoted by the predicate.
- **Goal** The location or entity in the direction of which something moves.
- **Benefactive** The entity that benefits from the action or event denoted by the predicate.
- **Source** The location or entity from which something moves.
- **Instrument** The medium by which the action or event denoted by the predicate is carried out.

[2] Source: http://elies.rediris.es/elies11/cap5111.htm

- **Locative** The specification of the place where the action or event denoted by the predicate in situated.

Process of Semantic Role Labeling

Semantic Role Labeling is the process of annotating sentence constituents with their semantic roles. Semantic roles are usually annotated with labels provided by a role set (for example see Fig. 2.2).



Frame for *change*, role set 1:

arg_0: the entity that initiates the change

arg_1: the entity that is changed

arg_2: the initial state of the changed entity

arg_3: the final state of the changed entity

Figure 2.2: Example of a role set from NomBank.

Example sentence:

`Google bought YouTube in October for $1.65 billion.`

Example annotation:

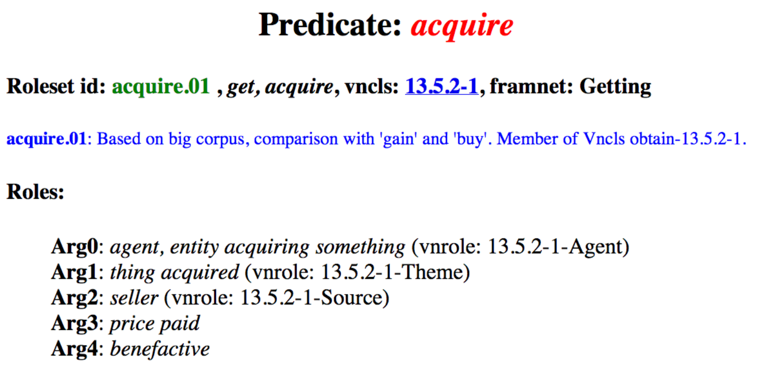
[$_{A0}$ Google] [$_{Predicate}$ bought] [$_{A1}$ YouTube] [$_{AM-TMP}$ in October] [$_{A3}$ for $1.65 billion].

PropBank

PropBank[3] is a corpus in which the arguments of each predicate are annotated with their semantic roles in relation to the predicate [34]. Argument structure of every single verb is described in the so-called *semantic frame*. One particular predicate can have distinct meanings in different contexts. PropBank differentiate predicates with the same surface form but different semantic role by suffixing the predicate name with a unique number.

[3]http://verbs.colorado.edu/propbank/

List of all semantic frames in PropBank can be found at http://verbs.colorado.edu/propbank/framesets-english/.



Predicate: *acquire*

Roleset id: acquire.01 , *get, acquire*, vncls: 13.5.2-1, framnet: Getting

acquire.01: Based on big corpus, comparison with 'gain' and 'buy'. Member of Vncls obtain-13.5.2-1.

Roles:

Arg0: *agent, entity acquiring something* (vnrole: 13.5.2-1-Agent)
Arg1: *thing acquired* (vnrole: 13.5.2-1-Theme)
Arg2: *seller* (vnrole: 13.5.2-1-Source)
Arg3: *price paid*
Arg4: *benefactive*

Figure 2.3: Example of an entry in PropBank for predicate `acquire.01`.

2.7 Pre-processing

The result of information extraction crucially depends on several operations which are usually described as pre-processing steps. Considering that our application's input is raw text in natural language, there is a need to recognize individual linguistic units such as words and sentences, to annotate named entities and filter out only the relevant content for further phases of IE.

Each part of pre-processing has to be as reliable and precise as possible because errors could cascade since the earliest stage and degrade overall results.

2.7.1 Tokenization

Tokenization is a process of splitting up input text into so called tokens. Usually these tokens denote words, numbers, symbols (currency) and punctuation. Tokenization can be also referred to as word segmentation.

Difficulty of tokenization depends on analyzed language. To give an example, European languages (e.g. English, Norwegian, Czech, etc.) have clear word boundaries given by space mark delimiters and therefor the task of segmentation is not as difficult as for some other languages, Chinese for instance [52].

2.7.2 Sentence Segmentation

Sentence segmentation can be described as a task of sentence boundary detection. In the majority of languages sentences are divided by punctuation marks. This observation can lead to the premature idea that plain identification of these marks is a sufficient technique of sentence boundaries recognition. In fact, the problem of sentence segmentation is much more complex. Exactly the same marks denoting the end of a sentence could be part of, for example, abbreviation or name (13 a.m., Prof.,). According to Liberman and Church [12], 47 % of periods in the Wall Street Journal delimit abbreviations.

Comprehensive overview of tokenization and segmentation problems is given by David D. Palmer in *Text Pre-processing* chapter of *Handbook of Natural Language Processing* book [33].

2.7.3 Part of Speech Tagging

Words exist in many different syntactic variations. Part of speech tagger assigns a grammatical category to every single processed word. A fixed set of part-of-speech tags (such as noun, verb, adjective, etc.) was established in well-known Brown and Penn treebank corpora. These part-of-speech tag sets contain conventional tags, such as ”verb”, as well as more detailed variations capturing, for example, different tenses of verbs (see Table 2.2). For information, the Brown tag set contains 179 tags.

Table 2.2: Example of Brown corpus part-of-speech tags [2].

Part-of-speech	*Tag*	*Part-of-speech*	*Tag*
adjective	ADJ	**pronoun**	PRO
adverb	ADV	**preposition**	P
conjunction	CNJ	**the word** *to*	TO
determiner	DET	**interjection**	UH
existential	EX	**verb**	V
modal verb	MOD	**past tense**	VD
noun	N	**present participle**	VG
proper noun	NP	**past participle**	VN
number	NUM	**wh determiner**	WH

2.8 Ontology

An ontology has been described by Noy & McGuiness [32] with the following words:

> *"Ontology is a common vocabulary for researchers who need to share information in a domain . It includes machine-interpretable definitions of basic concepts in the domain and relations among them."*

As mentioned above, ontologies are usually domain-specific. Pieces of information are organized into categories and subcategories (classes). This taxonomic hierarchy should follow the real concept of things and should capture relations among them. Objects are usually expressed by nouns, relations by verbs.

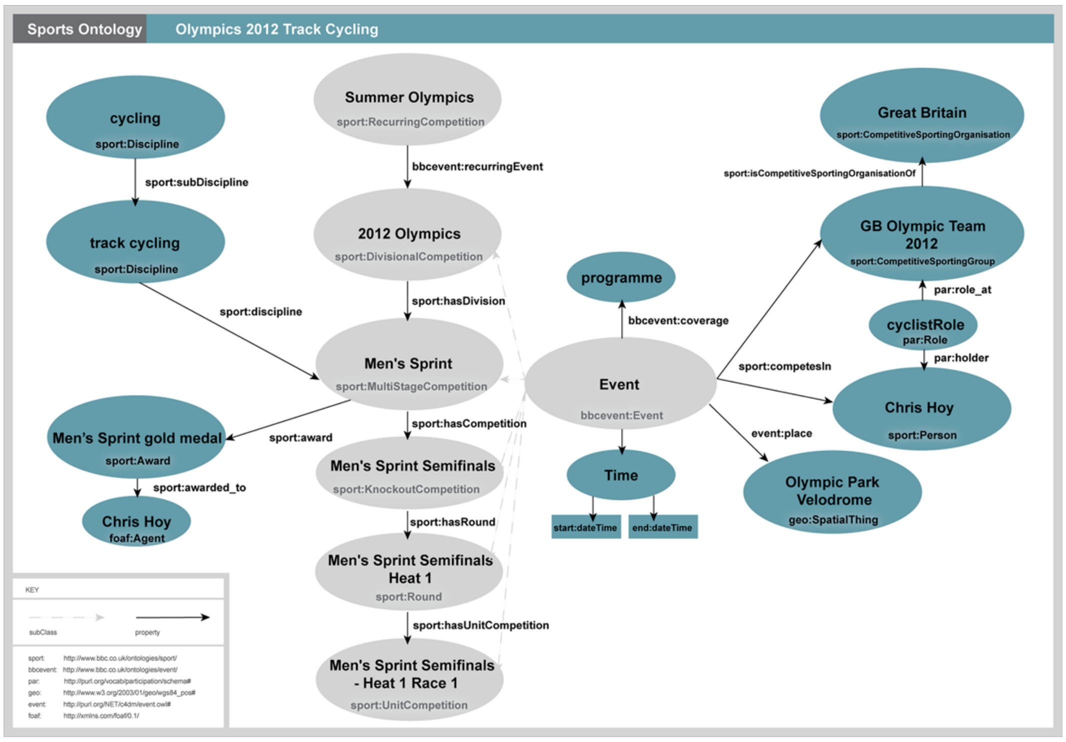


Figure 2.4: Example of an ontology - Sports Ontology. (Source: BBC)

Classes

Classes describe groups of items with the same qualities.

Development Approaches

Ontology can be visualized as a graph where the root node is the most general class and leaves are the most specific items. According to [32], there are three approaches in defining the class hierarchy:

Top-Down development
First we try to define the most general concepts, such as 'Car' if we want to create an ontology for cars.

Bottom-Up development
We start from the very specific class instances, such as 'BMW E61 M5 Touring' and later we create a superclass that covers several leaves in our graph, e.g. 'BMW', 'European cars', etc.

Combination of these two approaches
We are generalizing and specializing on the fly. First we create the most important classes and later we add up their instances or superclasses.

Ontology-based information extraction

Recently, new methods of information extraction using ontologies [53] have emerged and they are gaining even more attention nowadays when huge knowledge bases such as DBpedia or FactForge[4] exists. The approach called Ontology-based information extraction (OBIE) makes use of ontologies for the document tagging process. Definition of OBIE given by Wimalasuriya and Dou [53] states the following sentence: *"A system that processes unstructured or semi-structured natural language text through a mechanism guided by ontologies to extract certain types of information and presents the output using ontologies."*

There are OBIE systems generating the ontology autonomously [54]. The ontology to be used in our system should be defined or at least revised manually by domain experts to ensure its precision.

[4]http://ldsr.ontotext.com/

2.9 Linked Data

Linked Data is a concept whose objective is to interconnect related data published on the Web. In [3] this term was described with the following words: *"Linked Data is simply about using the Web to create typed links between data from different sources"*. This approach brings more possibilities to the current Web by providing data with URI identifiers, which makes them accessible and sharable. Linked Data structure can be seen as a graph. Each information is represented by RDF statement described bellow.

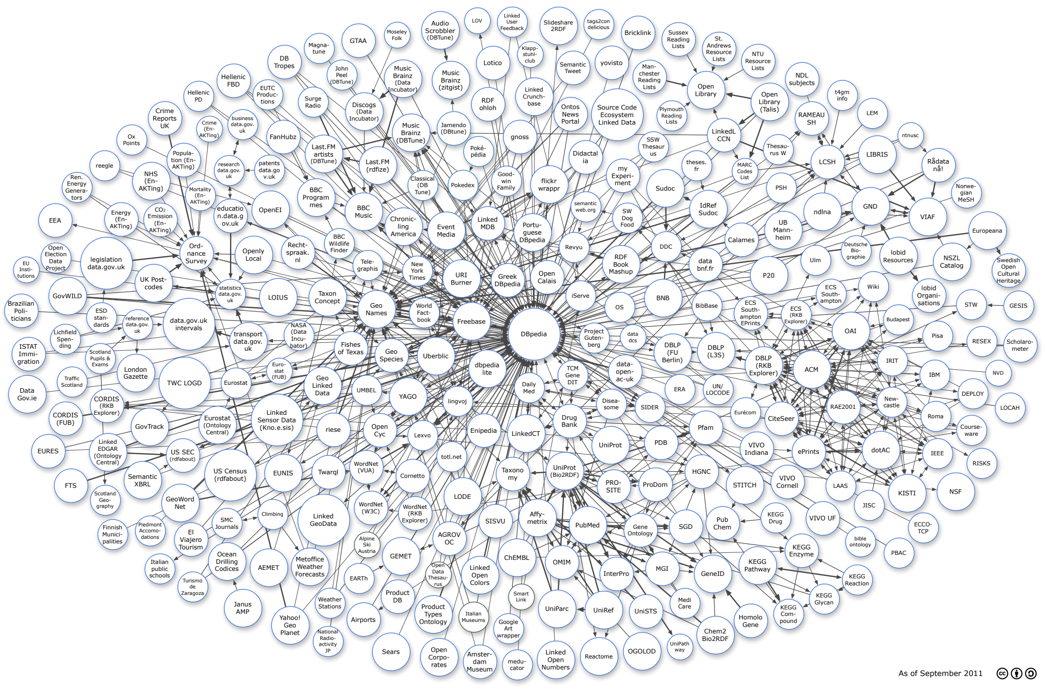


Figure 2.5: Linking Open Data cloud diagram, by Richard Cyganiak and Anja Jentzsch. http://lod-cloud.net/. Linked Data format data sets.

2.9.1 RDF

Resource Description Framework[5] (RDF) is a model representing data as a graph. It was specified by W3C[6]. As was already mentioned, RDF consists of statements.

[5]http://www.w3.org/RDF/
[6]World Wide Web Consortium: http://www.w3.org/

Each statement is defined by a triple: *subject*, *predicate* and *object* [3]. Entities are represented as nodes in the graph and relationships between them as edges [24].

2.9.2 SPARQL

SPARQL (Simple Protocol And RDF Query Language) is a query language designed to manipulate data in RDF storages. In the W3C documentation for SPARQL is written: *"Most forms of SPARQL query contain a set of triple patterns called a basic graph pattern. Triple patterns are like RDF triples except that each of the subject, predicate and object may be a variable. A basic graph pattern matches a subgraph of the RDF data when RDF terms from that subgraph may be substituted for the variables and the result is RDF graph equivalent to the subgraph."* [36].

2.9.3 DBpedia

"DBpedia is one of the more famous pieces of it (Linked Data Project)."[35] - Sir Tim Berners-Lee -

It is a knowledge base extracted out of Wikipedia and converted into structured, machine-readable format (RDF[7]). The DBpedia data set currently describes over 3.7 million items (in English) including more than 400 000 persons, 500 000 places and 170 000 organizations [28].

[7]Resource Description Framework: http://www.w3.org/RDF/

Chapter 3

Realization

In this chapter we will describe the realization part of the information extraction phase. We will present our ideas, suggested approaches and important implementation details. We also provide overview of the technology that we have used and architecture of the whole system. Our system was given a name - *VISUE* which is further divided into *VISUE Extraction* and *VISUE Visualization*.

3.1 Goal of the Application

The goal of the extraction phase can be summarized as follows: The application should accept files containing text in natural language (English). It should identify information containing utterance about money (with some numerical value) and should try to extract this information including the subject of the financial cost. Of course, when the information is extracted, there is a natural need to store acquired information in a convenient way, therefore this should be also considered.

The second part of the thesis is dedicated to visualization of data obtained in the extraction phase.

3.2 Technology

3.2.1 Programming Language and Development Environment

The selection of the most suitable programming language was significantly influenced by the choice of a toolkit for natural language processing (described in the following section). Except of this factor, the strongest reasons for using Java Programming Language (Java) are:

Object oriented aspect This feature is , besides other things, useful for the extensibility of the application and offers means for rapid prototyping.

Platform independency Platform independency is perhaps the reason why Java is so widely used for NLP purposes. It allows to port a ready-made application to different environments without giving much effort.

Java 7 was used as the main programming language for the final application. In some cases we used Python but it was mainly for experimenting[1] with data corpus. The application was written in Eclipse development environment. We chose Git as the version control system. Our repositories are hosted on GitHub (public code) and Assembla (private code). Parts that required server were deployed to Apache Tomcat 7.

3.2.2 Overview of NLP Frameworks

IE toolkits offer scalable and robust NLP tools which can be easily integrated in the final IE system. The integration of analytic components is referred as NLP pipeline. Selection of the framework was, most of all, driven by the degree of use in current state-of-the-art extraction systems, by the support of modules and, last but not least, by the quality of documentation/community activity. Extensive list of NLP toolkits can be found on Wikipedia[2].

[1] Repository with our helper functions: https://github.com/jendarybak/NYTC-Helpers
[2] http://en.wikipedia.org/wiki/Natural_language_processing_toolkits

Two final candidates were:

Apache OpenNLP The Apache OpenNLP library[3] is a machine learning based framework for natural language processing written in Java. Same as GATE, it supports variety of NLP tasks such as tokenization, sentence detection, part-of-speech tagging, chunking, parsing, named entity extraction and coreference resolution.

GATE - General Architecture for Text Engineering GATE is an open-source modular NLP tool whose architecture is defined by specialized components. Development of new components is encouraged and supported by the community and defined by the interface. List of available components can be found on the official webpage[4]. However, from our own experience, we would recommend searching in GATE's discussion forum if the component with desired functionality is not in the list.

We decided to use GATE for its extensibility. Apache OpenNLP can be, if necessary, run in GATE as a component. A comparison of these two systems can be found in [42].

[3]http://opennlp.apache.org
[4]http://gate.ac.uk/

3.3 Architecture

3.3.1 Pipeline Architecture

The whole system can be viewed as a set of interconnected components that are organized in a way that the output from one part is the input to another. This kind of modular architecture brings the advantage of component interchangeability which also means better flexibility.

The pipeline is displayed and described in the figure below:

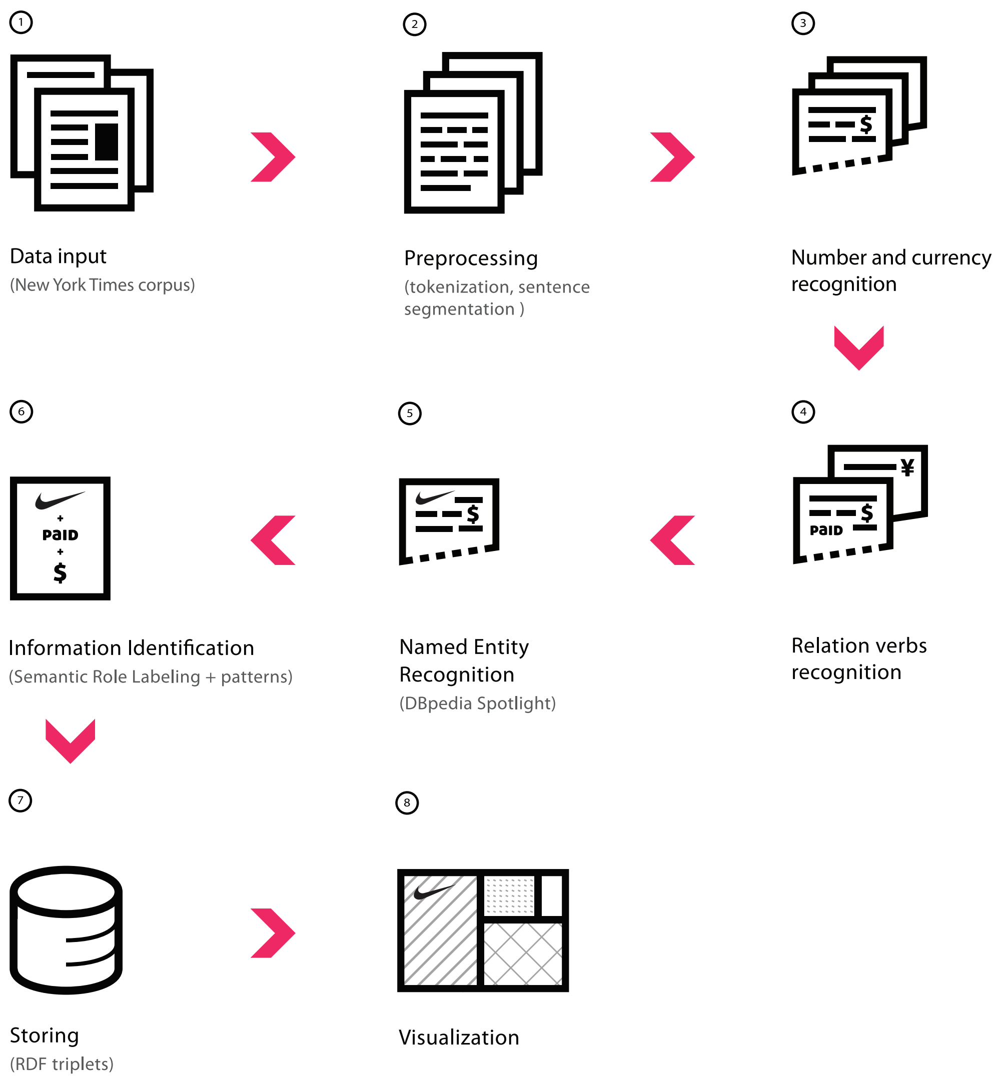

1
Data input
(New York Times corpus)
2
Preprocessing
(tokenization, sentence segmentation)
3
Number and currency recognition
4
Relation verbs recognition
5
Named Entity Recognition
(DBpedia Spotlight)
6
Information Identification
(Semantic Role Labeling + patterns)
PAID
7
Storing
(RDF triplets)
8
Visualization

Figure 3.1: Pipeline architecture of the system

1. **Data input**

   As described in the Section 3.4, data are provided by user in the form of The New York Times Corpus files. Each article is pre-processed in the step no.2.

2. **Pre-processing steps**

   Pre-processing is a part of nearly every NLP system. In our application we utilize tokenization and sentence segmentation. Due to noun phrase chunking (Section 3.7.2) there was the need to include part-of-speech recognition as well.

3. **Number and currency recognition**

   The recognition of finance-related information, as defined in the scope of this thesis, crucially depends on our ability to identify monetary information (number with currency). This step works at a sentence level and detailed description can be found in Section 3.5.

4. **Relation verbs recognition**

   We created an ontology of finance-related verbs. Such verb might be promising indicator of a relation describing financial cost of some entity. All sentences containing monetary information are being examined for the presence of financial verb. Ontology creation and tagging process is further described in Section 3.6.

5. **Originator Recognition**

   Originator Recognition is the part where possible subjects of the cost, in this thesis called *originators*, are marked. To put it simply, we considered only those subjects which have an entry in Wikipedia. Our approach is explained in Section 3.7.

6. **Information Identification**

   Putting all the previous steps together gives us a range of possible information parts (money, relations, originators). In this stage we tried to find related pieces of information with a method called Semantic Role Labeling (Section 3.8.1).

6. Information Extraction

The final step of the actual extraction is identification of triples *"originator - hasValue - cost"* and extraction in RDF format. This process is described in Section 3.8.2.

7. Storing

The triples are stored in an RDF storage (Section 3.9).

8. Visualization

The second part of the thesis deals with data visualization.

3.4 Data

Our system is capable of processing free text. However, because of many advantages it brings, we had decided to use *The New York Times Corpus* as the source of data. We build a wrapper for parsing XML files of the corpus which exploits metadata described bellow.

3.4.1 New York Times corpus

In 2008 the New York Times newspapers released a corpus - The New York Times Corpus (NYTC) - containing articles from the period of 1987 - 2007. These articles are mostly provided with metadata and manually summarized and tagged content. The total sum of articles in this corpus is close to 1.8 million [43].

The corpus includes [43]:

- More than 1.8 million articles (excluding wire services articles that appeared during the covered period).
- More than 650,000 manually written article summaries.
- More than 1,500,000 articles manually tagged by library scientists with tags drawn from a normalized indexing vocabulary of people, organizations, locations and topic descriptors.

- More than 275,000 algorithmically-tagged articles that have been hand verified by the online production staff at nytimes.com.
- Java tools for parsing corpus documents from .xml into a memory resident object.

This collection contains over 650,000 article-summary pairs which may prove to be useful in the development and evaluation of algorithms for automated document summarization. Also, over 1.5 million documents have at least one tag. Articles are tagged for persons, places, organizations, titles and topics using a controlled vocabulary that is applied consistently across articles."[43]

More details about the corpus can be obtained from the official catalogue web page[5] of the NYTC, where the information in this section comes from, or from the corpus manual[6].

Advantages

- Size of the corpus.
- The corpus contains meta data including e.g., category of the article, date, url, keywords.
- Timespan of the corpus - temporal aspect.
- Possibility of interlinking with NYT articles published on-line.

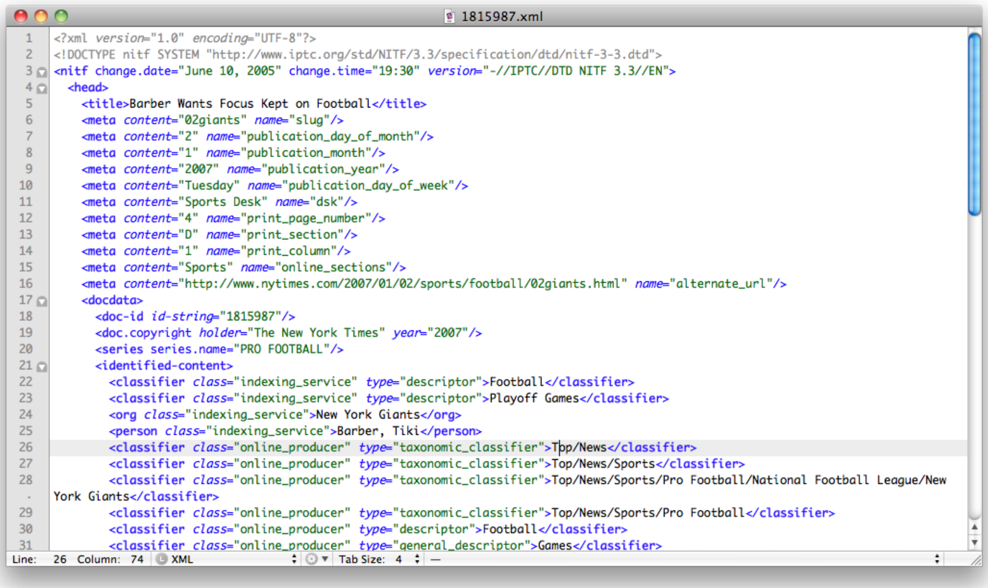
Disadvantages

- Corpus does not contain up to date articles.

[5]urlhttp://www.ldc.upenn.edu/Catalog/catalogEntry.jsp?catalogId=LDC2008T19
[6]urlhttp://www.ldc.upenn.edu/Catalog/docs/LDC2008T19/new_york_times_annotated_corpus.pdf

Structure

The New York Times Annotated Corpus is provided as a collection of XML documents that conform to version 3.3 of the News Industry Text Format (NITF) specification. An example of one modified corpus file is a part of the accompanying CD.



```
<?xml version="1.0" encoding="UTF-8"?>
<!DOCTYPE nitf SYSTEM "http://www.iptc.org/std/NITF/3.3/specification/dtd/nitf-3-3.dtd">
<nitf change.date="June 10, 2005" change.time="19:30" version="-//IPTC//DTD NITF 3.3//EN">
  <head>
    <title>Barber Wants Focus Kept on Football</title>
    <meta content="02giants" name="slug"/>
    <meta content="2" name="publication_day_of_month"/>
    <meta content="1" name="publication_month"/>
    <meta content="2007" name="publication_year"/>
    <meta content="Tuesday" name="publication_day_of_week"/>
    <meta content="Sports Desk" name="dsk"/>
    <meta content="4" name="print_page_number"/>
    <meta content="D" name="print_section"/>
    <meta content="1" name="print_column"/>
    <meta content="Sports" name="online_sections"/>
    <meta content="http://www.nytimes.com/2007/01/02/sports/football/02giants.html" name="alternate_url"/>
    <docdata>
      <doc-id id-string="1815987"/>
      <doc.copyright holder="The New York Times" year="2007"/>
      <series series.name="PRO FOOTBALL"/>
      <identified-content>
        <classifier class="indexing_service" type="descriptor">Football</classifier>
        <classifier class="indexing_service" type="descriptor">Playoff Games</classifier>
        <org class="indexing_service">New York Giants</org>
        <person class="indexing_service">Barber, Tiki</person>
        <classifier class="online_producer" type="taxonomic_classifier">Top/News</classifier>
        <classifier class="online_producer" type="taxonomic_classifier">Top/News/Sports</classifier>
        <classifier class="online_producer" type="taxonomic_classifier">Top/News/Sports/Pro Football/National Football League/New
York Giants</classifier>
        <classifier class="online_producer" type="taxonomic_classifier">Top/News/Sports/Pro Football</classifier>
        <classifier class="online_producer" type="descriptor">Football</classifier>
        <classifier class="online_producer" type="general_descriptor">Games</classifier>
```

Figure 3.2: Example of a file from The New York Times Corpus

3.4.2 Twitter Data

Twitter[7] messages, so called *tweets*, could be ideal candidates for information extraction by our system. There are several reasons why we think so. First of all, Twitter is truly popular and many news channels are using this service to spread out messages condensed into 140 characters. The length limitation is forcing authors to be factual and to express the important information preferably in one sentence. No co-reference resolution is therefore needed.

The availability of the data is another crucial factor. Twitter provides API that is with some limitations publicly available. Last but not least, selection of topic-

[7]Social network, url: http://www.twitter.com

s/tweets is up to the user and can be influenced by subscribing to various Twitter channels. Although we experimented with Twitter data, we were too busy with processing NYTC so that we are not able to publish any representable results with Twitter data at the moment.

3.5 Monetary Information Recognition

In the majority of financial articles every mention about money consists of two parts - **amount** and **currency**. Therefore finding a number and a currency symbol as a prefix or a suffix to it apparently gives us a piece of monetary information.

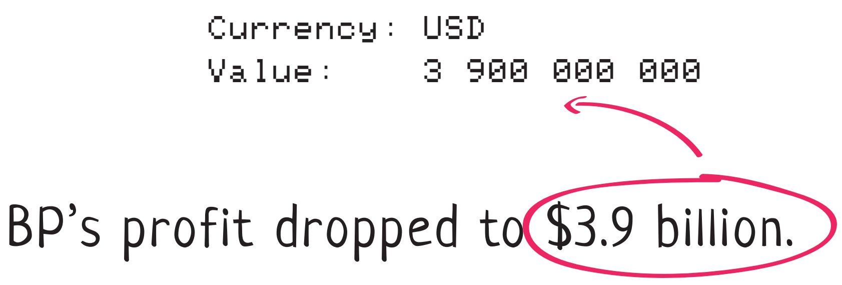
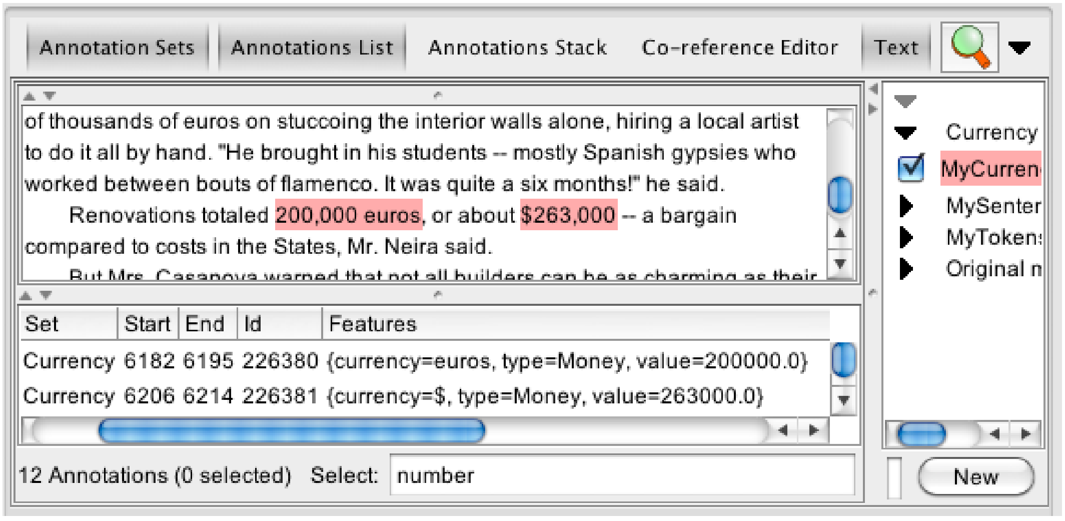


Figure 3.3: Monetary information recognition

In the next two sections we will describe extraction of numbers and currency symbols. Let's now assume that these two key elements have been already identified. A simple grammar in JAPE format shown in listing 3.1 is able to annotate the pair as a 'money data' and assign normalized financial amount and currency identifier to the annotation (see Figure 3.4).



of thousands of euros on stuccoing the interior walls alone, hiring a local artist to do it all by hand. "He brought in his students -- mostly Spanish gypsies who worked between bouts of flamenco. It was quite a six months!" he said.
Renovations totaled 200,000 euros, or about $263,000 -- a bargain compared to costs in the States, Mr. Neira said.

Set	Start	End	Id	Features
Currency	6182	6195	226380	{currency=euros, type=Money, value=200000.0}
Currency	6206	6214	226381	{currency=$, type=Money, value=263000.0}

12 Annotations (0 selected) Select: number

Figure 3.4: Annotated and normalized money data in GATE

Listing 3.1: Grammar in JAPE format (currency.jape)

```
Phase: myCurrencyPhase

Input: Number Token SpaceToken Lookup
Options: control = appelt

Rule: MyCurrencyCategory
Priority: 100
(
  {Number} ({SpaceToken})*
  ({Lookup.majorType == "currency_unit",
    Lookup.minorType == "post_amount"}):cur
  |
  ({Lookup.majorType == "currency_unit",
    Lookup.minorType == "pre_amount"}):cur
  ({SpaceToken})* {Number}

): label
-->
:label.MyCurrency = {type = "Money",
                     value = :label.Number.value,
                     currency = :cur@string}
```

3.5.1 Number Recognition

GATE in the standard implementation comes with a plugin which is capable of number recognition and tagging. The plugin is called *Tagger_Numbers*[15]. It needs the text to be tokenized and sentences to be segmented in advance. The plugin works on the rule-based principle where regular expression patterns are defined for numbers in numerical notation and gazetteer lists are used to recognize numbers in word form notation. After identification of either digits or numeral words, its numerical value is computed and assigned as a feature of the tag.

There were cases when the tagger failed. This was caused mostly by headline style of many news sources. It is common to use the following notation for large amounts:

- Would You Pay **$329K** for this Phone?
- Here's what **$100M** gets you in NY.
- Dell and Virgin Media in **$20bn** deals
- World's biggest economies face **$7.6T** debt.
- According to Henry's calculations, **$6.3tn** of assets is owned by only 92,000 people.!

When one writes digits in combination with word-format numbers, usually there is a white space in between. That does not apply when using abbreviations mentioned before.

- John Paulson gives **$100 million** to Central Park.
- John Paulson gives **$100M** to Central Park.

We have solved these issues firstly by augmenting gazetteer lists with possible abbreviations and secondly by changing settings of the plugin so that it attempts to find numbers even within words. Plugin gives satisfactory results after the modification.

Names of Large Numbers

We would like to point out that there are differences in names of "large numbers" in British and American English. Since we are using the New York Times corpus whose origin is American, it is logical to parse numbers according to the *short scale*[8] notation used in the United States. Example of differences in the short and the long scale is listed in the table3.1.

[8]Comprehensive overview of large number notations can be found here:http://en.wikipedia.org/wiki/Names_of_large_numbers

Table 3.1: Short (American) and Long (European) scale notation for large numbers.

Name	*Short scale value*	*Long scale value*
Million	10^6	10^6
Milliard	-	10^9
Billion	10^9	10^{12}
Trillion	10^{12}	10^{18}

3.5.2 Currency Recognition

Testing Data from The New York Times Annotated Corpus

Since there is no testing dataset for currency recognition problem available, we had to prepare our own. Initial idea was to manually search for monetary information in The New York Times Annotated Corpus, extract only those relevant articles which contains numerical financial data and populate XML files with the following structure:

Listing 3.2: Testing data example

```
<TestDataItem id="83">
    <Sentence>
        <string>The global prime brokerage business generates
        $8 billion to $10 billion a year, according to an estimate
        by the Vodia Group, a consulting firm for the financial
        services industry.</string>
        <value currency="dollar">8000000000</value>
        <value currency="dollar">10000000000</value>
    </Sentence>
    <Source>
        <year>2007</year>
        <month>01</month>
        <day>02</day>
        <filename>1815975.xml</filename>
    </Source>
</TestDataItem>
```

id Unique identification number of each dataset item.

string Original sentence containing monetary expression.

currency Currency of the monetary expression. In the example above it is not clear what kind of dollar (CAD, USD, etc.) is mentioned in the sentence, therefore general label 'dollar' is used.

currency value Normalized numerical value.

year/month/day Publication date of the article.

filename Name of the XML file containing the sentence in The New York Times Annotated Corpus.

Testing Data from Various Sources

However, we found out that the notation of currency expressions in the corpus is mostly following the same pattern:

```
'$' + number + (million | billion | trillion).
```

Variety of the testing data was no longer expanding with increasing number of testing sentences. In order to obtain dataset which can satisfy testing of currency extraction from general text sources, we had to consider sentences from various sources.

Example of monetary notations from The New York Times Annotated Corpus:

- $250
- $5,000
- $2.3 million
- $24 million
- $2 billion
- $3,693,101.49

Example of monetary notations from random webpages:

- $4.655
- 200 USD
- £1.55bn
- $700m
- $1tn
- $16,066,241,407,385.80
- EUR1350
- ¥8,871.4 bn
- 200 Japanese yen
- GBP 400,000-600,000

Currency Recognition in GATE

Our system is using gazetteer to identify and annotate entity names. Currency units and symbols has to be reliably recognized, otherwise the monetary information would be ignored in the following phases of IE. We included all possible currency units, symbols and notations into gazetteer lists for currency prefixes and postfixes (`currency_prefix.lst, currency_unit.lst`). A tag format for labeling a currency unit has the following syntax:

```
Lookup.majorType == "currency_unit" .
```

Example of variability of notations for *Euro* (€):

- EUR 3.14
- 3.14 EUR
- € 3,14
- 3,14 euros
- 1 euro

3.6 Relation Extraction

Finding a text snippet that contains a piece of monetary information indicates with high probability that the content is finance-related. However, the task is to process only those sentences that give us interesting information about a value of some subject. Such piece of information can be described as a relation between the subject and the cost of it (monetary information that we have already extracted). In human language relations are expressed by (linking) verbs and subjects are denoted by nouns (noun groups). This leaves us with the fact that we need to find finance-related verbs (relations) and identify the object/subject of the relation. In other words, we want to know who or what is the originator/agent of a transaction.

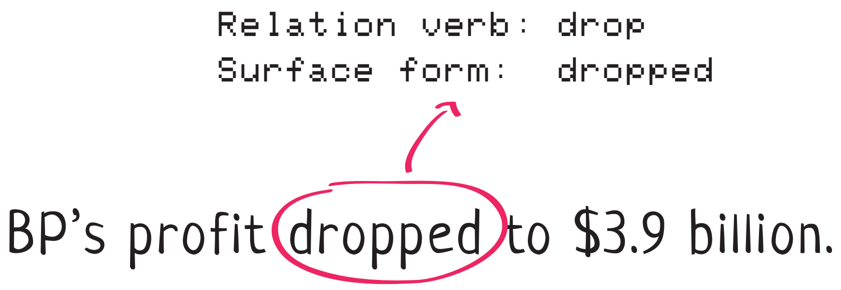


Figure 3.5: Financial verb contained in the ontology is recognized.

We decided to organize the list of finance-related verbs in the form of an ontology that can be utilized later on, if needed. The reason for ontology creation is that its structure brings in information about the hierarchy of the verbs (i.e. relations), which can be important for further process of extraction.

3.6.1 Ontology

Financial Relations Ontology

Our system is considered for the operation in relatively narrow domain - financial information in news articles. If we consider that there is a limited amount of possible relation types in the field and that ontologies can be scaled easily, thus utilizing an ontology to hold information about financial relations can give good extraction results.

We searched for an existing ontology of relations appearing in financial context but we did not succeed in finding one which would suit our needs. There are either ontologies dedicated only to financial terminology[9] or relation ontologies that are too general[10]. This was the reason why we created the ontology by ourselves.

Financial Relations Ontology Creation

According to the previously mentioned approaches (see Section 2.8), we used the combination of Top-Down and Bottom-Up development methods. We established two main classes as the most important criterion for further division:

”INTERACT”

- a relation requiring two participants (originator and recipient); an object of some value is the reason of this interaction.

”HAVE VALUE”

- a relation expressing financial value of an object.

We applied the following algorithm:

1. We extracted a sample set of finance-related sentences from NYT corpus.
2. In every sentence we manually looked up relations among monetary information, subject and object and made a list of corresponding verbs.
3. We found and appended synonyms of previously acquired verbs in the list.
4. We made 2 main classes (”Interact”, ”Have value”).
5. We grouped verbs with similar meaning and similar hypernym [11].
6. We made a superclass from the given hypernym.
7. If there were two hypernyms with similar meaning, we merged them into one class.

[9] http://fadyart.com/

[10] http://www.obofoundry.org/ro/

[11] Hypernym - a word that is more generic than a given word

8. We repeated steps 5) and 6) for all verbs until we reached one of the main classes.
9. We manually revised placement of few verbs.

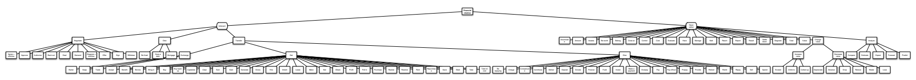


Figure 3.6: Financial relationships ontology.

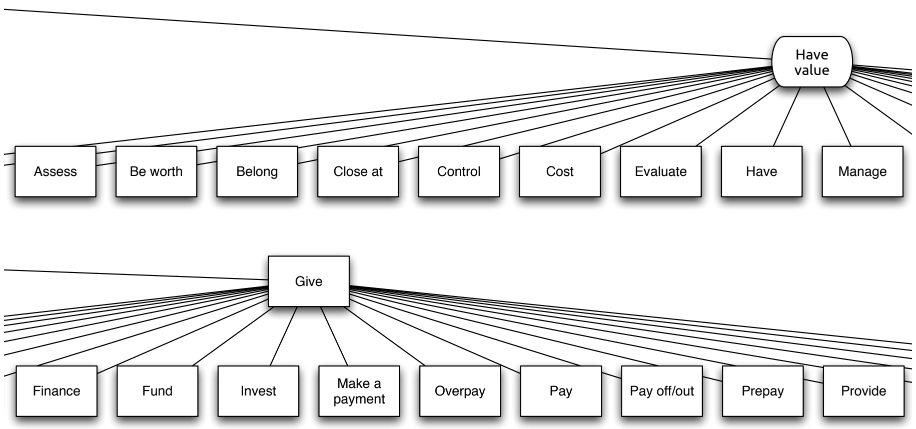


Figure 3.7: Detail of financial relationships ontology.

For acquisition of synonyms, hypernyms and hyponyms a large lexical database of English called WordNet[12] was used.

Ontology Tagging

There is a specialized plugin for ontology tagging in GATE. However, due to its relatively small size we decided to convert the ontology to gazetteer list and use GATE transducer component to annotate financial verbs in the text. The reason for this step was the improved speed of annotation.

[12] http://wordnet.princeton.edu/

3.7 Originator Recognition

Once we are able to recognize a text snippet containing monetary information and relation verb of our interest, we need to find out what does this information relate to. In other words, who or what is the originator/actor of a transaction. First step is to recognize all possible noun groups that might be in the relation with the financial verb. After that it is necessary to select one candidate which is actually in the relationship with the verb and the cost. The aim is to extract popular pieces of information from well known news sources that is why we are primarily focused on generally known originators. In addition, we attempt to link extracted originators with publicly available datasets such as DBPedia[13]. This feature allows users to instantly gain more knowledge on the topic.

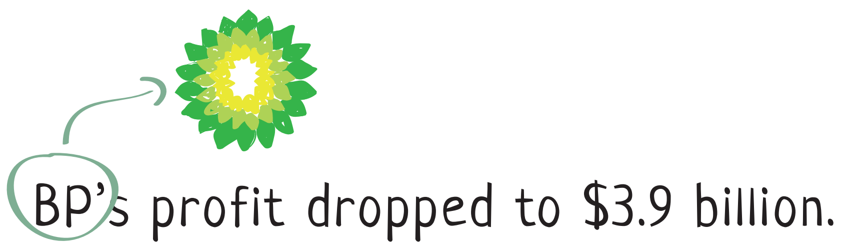


Figure 3.8: Example of originator (named entity) identification.

3.7.1 DBpedia

Wikipedia is a well-known source of quality information which is being edited by thousands of volunteers. We believe that considering Wikipedia articles as a set of admissible originators is a good heuristics how to separate possibly interesting pieces of information. Moreover, it gives us the possibility to link the originator with a Wikipedia article and thus offer relevant background information about the topic. This approach, i.e., using Wikipedia as a source of named entities, is described in detail in [5].

[13]http://dbpedia.org/

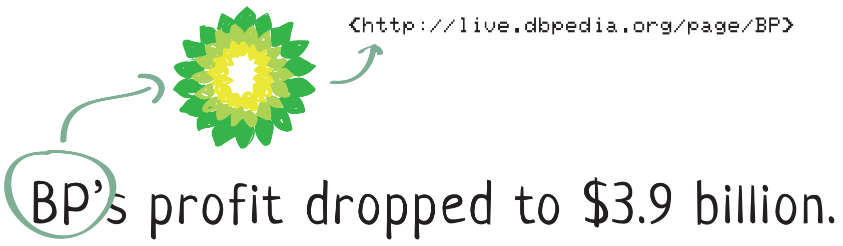

<http://live.dbpedia.org/page/BP>
BP's profit dropped to $3.9 billion.

Figure 3.9: Entities linked with DBpedia.

Extracting all information from Wikipedia pages would be tedious process. Fortunately there is a very convenient alternative called DBpedia which is described in Section 2.9.3.

NER - Named Entity Recognition

In the overview of state-of-the-art in NLP, we mentioned several methods used for named entity recognition. In the system we gave preference to NER utilizing the ontology and the data set of DBpedia that we mentioned above.

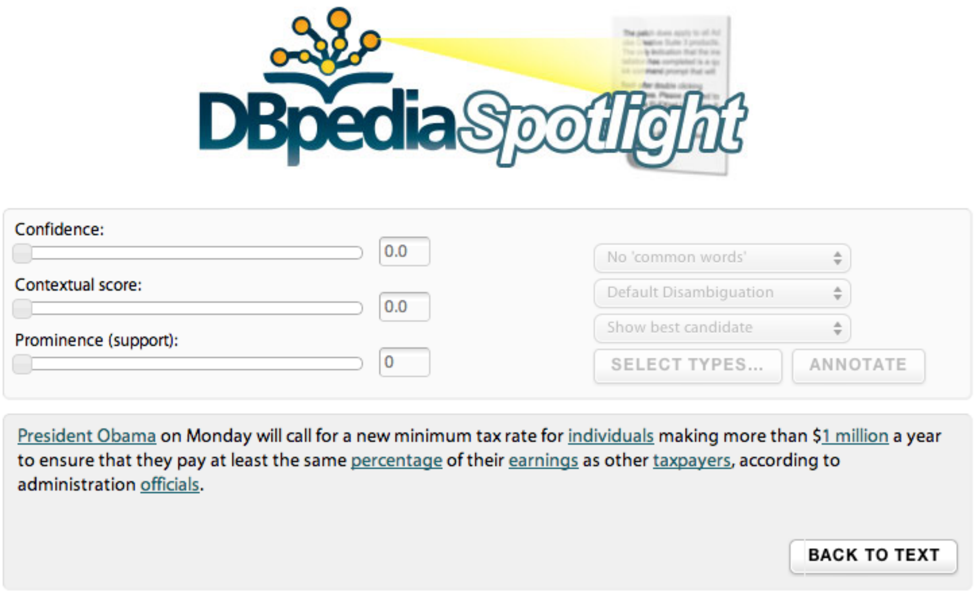
The main advantage of such approach is the constant growth of the named entities database with no extra effort from our side. In addition, it is possible to effectively influence the results of the whole system in the very beginning of the extraction process. By limiting number of the named entities in the text, the number of sentences for further processing can be proportionally reduced. As we describe in the following section, we can write custom queries to obtain arbitrary set of DBpedia items. These queries are written in RDF query language called SPARQL and can be arbitrarily specific. If desired, we can list for example just athletes who are older than 25 years, IT companies from Europe or countries belonging to G8. However, in our application we specified more general concepts to be annotated such as persons[14], organizations[15] and places[16].

The main challenge of the named entities recognition is ambiguity in annotated data. There are entities that can have several meanings in the given form

[14] RDF label: "dbpedia-ont:Person"
[15] RDF label: "dbpedia-ont:Organisation"
[16] RDF label: "dbpedia-ont:Place"

but without considering the context, like humans do, there is no way how to automatically choose the correct one (*e.g. Apple - is it a fruit or a company?*). Damljanovic and Bontcheva[16] have recently developed a disambiguation method which improved F-measure of NER from 0.24 to 0.82. This method uses context of the particular entity and various similarity metrics described in the paper. Inspired by the disambiguation improvement we have decided to include context-aware method of NER in the application.

DBpedia Spotlight



President Obama on Monday will call for a new minimum tax rate for individuals making more than $1 million a year to ensure that they pay at least the same percentage of their earnings as other taxpayers, according to administration officials.

Figure 3.10: DBpedia Spotlight online demo.

DBpedia Spotlight[17] is an open-source tool for annotating text with DBpedia resources. It is able to recognize entities from DBpedia in a text and simultaneously link these entities with the knowledge base. *"DBpedia Spotlight allows users to configure the annotations to their specific needs through the DBpedia Ontology and quality measures such as prominence, topical pertinence, contextual ambiguity and disambiguation confidence"*[27].

[17]http://github.com/dbpedia-spotlight/

As mentioned before, the main advantage of DBpedia Spotlight is its ability to influence the ambiguity of NER. In default settings DBpedia Spotlight performs annotation with all DBpedia Ontology categories, that is more than 270 classes (not only people, organizations and places). On the other hand, it is possible to restrict annotation to instances of particular classes and subclasses, alternatively used as fine-grained SPARQL queries to constrain the set of classes to annotate. The system is highly customizable and can be set up in a way which exactly reflects our needs.

Custom configuration of DBpedia Spotlight

Resource Set to Annotate User can provide a list of allowed (whitelist) or forbidden (blacklist) resources to annotate. Classes are provided by DBpedia Ontology. For more specific domain restriction SPARQL queries are available.

Resource Prominence To avoid annotation of rather rare and uninformative resources the support parameter can be used. This parameter denotes how many times a resource is referenced in Wikipedia (so called backlinks).

Topic Pertinence The topical relevance indicates how close a paragraph is to a DBpedia resource's context. This is measured by similarity score on the scale 0-1 (0 being unrelated, 1 totally relevant).

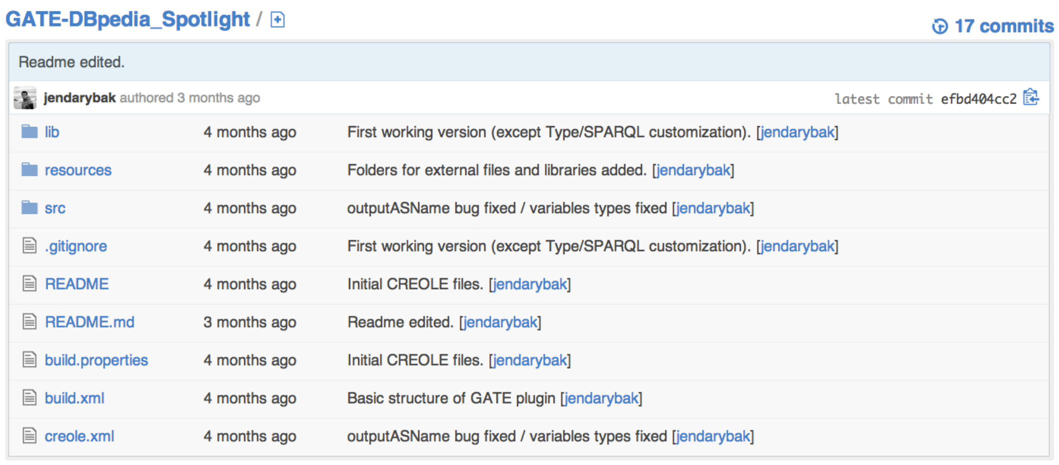
Contextual Ambiguity If there is more than one candidate with high topical pertinence in the given context, the contextual ambiguity is counted as the relative difference in topic score between the first two candidates.

Disambiguation Confidence This parameter is defined by the user and combines previously mentioned factors - topic relevance and context ambiguity. Its value is ranging from 0 to 1 and a higher threshold results in omitting incorrect annotations at the risk of loosing some correct annotations.

GATE Module

In order to use DBpedia Spotlight's annotations we had to create a GATE module for this purpose. DBpedia Spotlight offers RESTful[18] and SOAP[19] web services for the annotation and disambiguation processes with the possibility to set all the supported parameters. Returned results can be obtained in several formats including XML, JSON, HTML, etc. Our module currently works with XML format and supports all possible parameters of DBpedia Spotlight.

We made the plugin available to public[20] on GitHub [21]. Up to date instructions to install and run the module can be found on the repository webpage or in `README` file. Directory structure of the plugin is depicted in Figure 3.11.



GATE-DBpedia_Spotlight /

17 commits

Readme edited.

jendarybak authored 3 months ago — latest commit efbd404cc2

lib	4 months ago	First working version (except Type/SPARQL customization). [jendarybak]
resources	4 months ago	Folders for external files and libraries added. [jendarybak]
src	4 months ago	outputASName bug fixed / variables types fixed [jendarybak]
.gitignore	4 months ago	First working version (except Type/SPARQL customization). [jendarybak]
README	4 months ago	Initial CREOLE files. [jendarybak]
README.md	3 months ago	Readme edited. [jendarybak]
build.properties	4 months ago	Initial CREOLE files. [jendarybak]
build.xml	4 months ago	Basic structure of GATE plugin [jendarybak]
creole.xml	4 months ago	outputASName bug fixed / variables types fixed [jendarybak]

Figure 3.11: Directory structure of DBpedia Spotlight Tagger on Git.

[18]Representational State Transfer
[19]Simple Object Access Protocol
[20]http://github.com/jendarybak/GATE-DBpedia_Spotlight
[21]GIT repository: http://github.com/

Functionality of the plugin can be described by the following pseudocode:

Listing 3.3: Annotation process in DBpedia Spotlight Tagger

```
initialize the component;
read and check validity of input arguments;
read contents of the input document;
prepare HTTP request (POST);
send HTTP request to DBPedia Spotlight server;
receive XML answer A;
parse XML;

for (each entity in A) {
  extract arguments of the entity;  // e.g. URI, surface form, etc.
  annotate corresponding text in the input document with the
      arguments;
}
```

Large Knowledge Base (LKB) Gazetteer in GATE

We used DBpedia Spotlight's RESTful web service with its disambiguation capability. Therefor, the final results of our system are more precise, but time consuming. If it is the case that the speed is prioritized over precision, we propose a solution using gazetteers with lists of DBpedia resources.

One of the plugins implemented in GATE is the ontology-based gazetteer called LKB Gazetteer. At the time of plugin initialization, a connection to remote ontology is established, prepared queries are sent and a new gazetteer list is generated from the result. After the lookup, URIs are assigned to entities in the text.

We prepared queries to retrieve list of people, organizations and places. These lists are loaded every time GATE is launched and are therefore up to date with DBpedia (Wikipedia).

Querying DBpedia

DBpedia is based on Linked Data principles [3] and RDF data model, therefore accessing the knowledge base is very easy. To query the DBpedia data set a public SPARQL endpoint[22] is offered. SPARQL is a query language designed to manipulate data stored in RDF format. By writing SPARQL query we can obtain a list of items in arbitrary Wikipedia category. ”SPARQL is able to query by triple patterns, conjunctions, disjunctions, and optional patterns.” [37]

Example (query to show all organizations):

Listing 3.4: SPARQL query which lists organizations.

```
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>

SELECT ?Name ?Org ?Cls
FROM <http://www.ontotext.com/disable-sameAs>
WHERE {
    ?Org a ?Cls ; rdfs:label ?Name .
    FILTER (lang(?Name) = "en")
    FILTER (?Cls = <http://dbpedia.org/ontology/Organisation>)
}
```

[22] http://dbpedia.org/sparql

3.7.2 Noun Phrase Chunking

Chunking is a technique used to divide sentences into its constituent parts which do not overlap and are syntactically correlated. Noun Phrase Chunking is a special case whose task is the identification of noun groups.

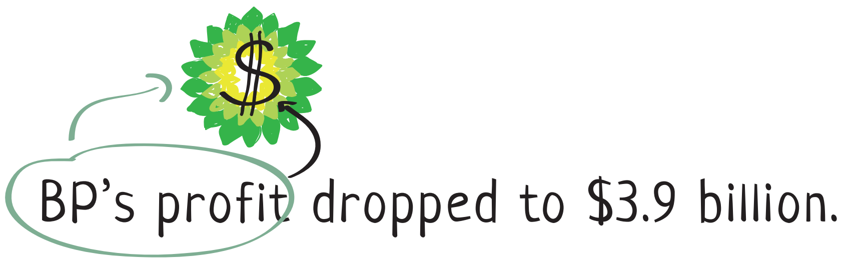


Figure 3.12: Example of noun phrase chunking.

Our idea was to use this technique to expand previously recognized named entities. Considering named entities as sufficient expressions for the action originators can in fact result in misleading information (see example bellow):

Example:
The entire **United States** ad market *is worth* about *$286 billion*.
The entire **United States ad market** *is worth* about *$286 billion*.

Approach

Because Machine Learning methods of noun phrase chunking are arguably on the uptrend and their results are significantly better compared to pattern recognition methods, we have opted for the statistical approach. We adapted this technique to our needs by combination with regular expressions. The standard part of GATE system is Ramshaw and Marcus BaseNP chunker[39] and we decided to use this one.

Process of extended noun chunk identification:

1. Assign POS tags to all words in the corpora.
2. Label all noun chunks with the tagger.
3. Remove label from chunks that do not contain any named entity (pers., org. , loc.).
4. Expand the label according to regular expression so that it covers all noun chunks connected by prepositions.

Even though this solution was working well, we decided to omit this part from the final system because it became redundant after implementing Semantic Role Labeling.

3.7.3 Part of Speech Tagging (POS)

Part of Speech Tagging is a process of assigning lexical category (verb, noun, etc.) and syntactic labels (gerund, possessive pronoun, etc.) to each word in a sentence or a document. We are using these tags for the purposes of noun phrase chunking. Semantic role tagger is also using part-of-speech tags but it is utilizing its own tagger. We rely on Mark Hepple's Brill-style POS tagger[23] which is a standard part of GATE framework. Since the whole system is modular, in case of need, the replacement for another implementation does not take much effort.

3.7.4 Extension of Noun Phrases using Regular Expressions

As mentioned above, noun chunks are non-overlapping phrases. In the case of two or more noun chunks connected by a preposition, it is very likely that we can consider the whole connection of phrases as the originator of some action. That is why we prepared regular expression rules to expand the label in such cases.

Example for location noun chunks:

Listing 3.5: Noun chunk extension with Regular Expressions

```
Rule: originatorExtraction
Priority: 100
(
  (
    (
      (
        {NounChunk, Token.kind != "number"}
        ({SpaceToken})?
        ({Token.category == "IN"} {SpaceToken})
      ?)*

      (
        {NounChunk contains LOCATION}
        ({NounChunk})
      ?)
    ):OrigLoc
  )
)
-->
:origLoc.Originator = {type="Location"}
```

3.8 Information Identification and Extraction

In the previous sections, our approaches to identification of monetary information, financial verbs and named entities in a text were described. Since there is no guarantee that all sentences contain only one piece of monetary information, one financial verb and one named entity and that there is necessarily a relationship to each other, we had to find a solution to identify and extract only those parts that belong to each other. First, we were thinking about applying custom methods of machine learning on this problem, but we found more appropriate solution in the technique called Semantic Role Labeling.

3.8.1 Semantic Role Labeling

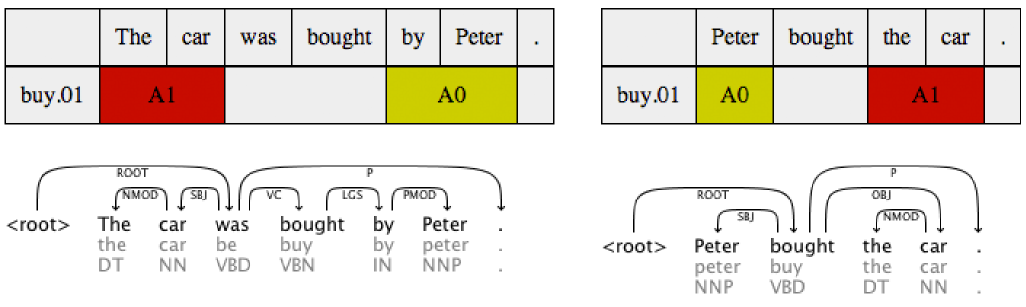

The car was bought by Peter .
buy.01 A1 A0
Peter bought the car .
buy.01 A0 A1
ROOT NMOD SBJ P VC LGS PMOD
<root> The car was bought by Peter .
the car be buy by peter .
DT NN VBD VBN IN NNP .
ROOT SBJ P OBJ NMOD
<root> Peter bought the car .
peter buy the car .
NNP VBD DT NN .

Figure 3.13: SRL representation of two sentences.

MATE Tools

For the purpose of SRL we used a state-of-the-art semantic role labeler developed by Anders Björkelund, Love Hafdell, and Pierre Nugues [4]. According to [4] the SRL module achieves an average labeled semantic *F1* of *80.90* when trained and tested on the English corpus of *CoNLL 2009*[23]. There are more SRL systems with comparable results available such as *Illinois Semantic Role Labeler*[38] or *SENNA*[13]. The one we decided to use offered the best combination of results quality, memory performance, suitability for GATE implementation and ease of installation/usage.

[23]http://ufal.mff.cuni.cz/conll2009-st/

The SRL system is data-driven and therefore dependent on trained models. Models for English, Chinese, Spanish and German are provided on project's website[24]. The application is running as a HTTP server that accepts a text snippet as the input and provides three format types for the output:

1. **HTML**

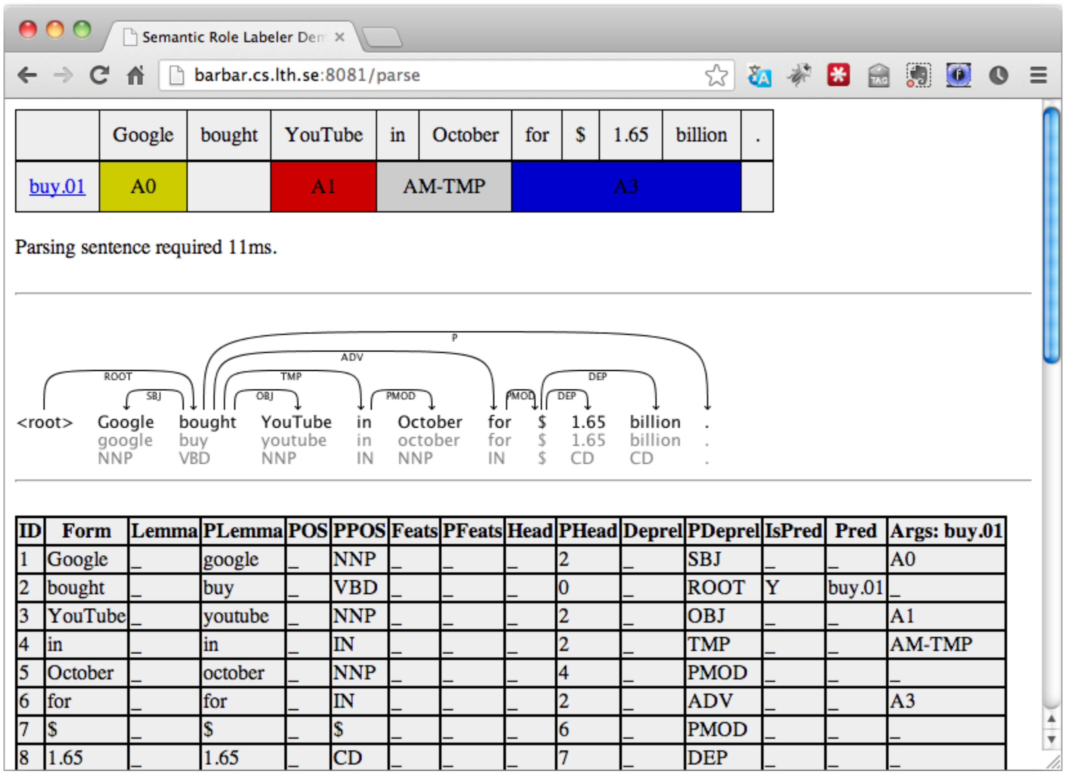
   Returns a webpage with a table formatted according to CoNLL-2009 data format, arguments visualization and arguments dependency graph (fig. 3.14).

2. **Raw text**

   Returns plain text document in CoNLL-2009 data format.

3. **RDF/N3**

   Returns data in RDF/N3 format.



	Google	bought	YouTube	in	October	for	$	1.65	billion	.
buy.01	A0		A1	AM-TMP		A3				

Parsing sentence required 11ms.

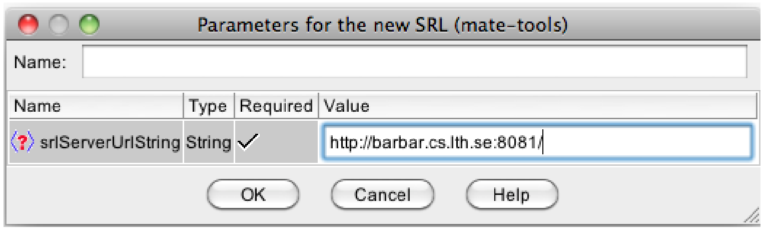
ID	Form	Lemma	PLemma	POS	PPOS	Feats	PFeats	Head	PHead	Deprel	PDeprel	IsPred	Pred	Args: buy.01
1	Google	_	google	_	NNP	_	_	_	2	_	SBJ	_	_	A0
2	bought	_	buy	_	VBD	_	_	_	0	_	ROOT	Y	buy.01	_
3	YouTube	_	youtube	_	NNP	_	_	_	2	_	OBJ	_	_	A1
4	in	_	in	_	IN	_	_	_	2	_	TMP	_	_	AM-TMP
5	October	_	october	_	NNP	_	_	_	4	_	PMOD	_	_	_
6	for	_	for	_	IN	_	_	_	2	_	ADV	_	_	A3
7	$	_	$	_	$	_	_	_	6	_	PMOD	_	_	_
8	1.65	_	1.65	_	CD	_	_	_	7	_	DEP	_	_	_

Figure 3.14: Example of SRL web interface.

[24]https://code.google.com/p/mate-tools/downloads/list

GATE Module

At the time of writing this thesis there was no SRL module available as a plugin for GATE and that is why we decided to implement MATE Tools module and make it public on GitHub[25]. Contrary to DBpedia Spotlight module, this plugin does not require any additional parameters except of the SRL server address (fig 3.15).

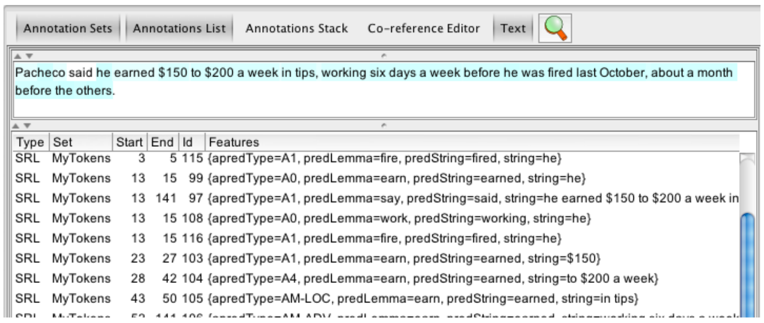


Name:

Name	Type	Required	Value
srlServerUrlString	String	✓	http://barbar.cs.lth.se:8081/

Figure 3.15: SRL module in GATE.

The module sends a sentence to the SRL server, which is listening on a specified address, and receives an answer in CoNLL-2009 format. We had to create a parser of the CoNLL-2009 format that is able to recognize predicates and read their arguments. All recognized arguments for each predicate are annotated in the GATE file. Later on, in the triple extraction phase, only the finance-related predicates are considered and extracted.



Pacheco said he earned $150 to $200 a week in tips, working six days a week before he was fired last October, about a month before the others.

Type	Set	Start	End	Id	Features
SRL	MyTokens	3	5	115	{apredType=A1, predLemma=fire, predString=fired, string=he}
SRL	MyTokens	13	15	99	{apredType=A0, predLemma=earn, predString=earned, string=he}
SRL	MyTokens	13	141	97	{apredType=A1, predLemma=say, predString=said, string=he earned $150 to $200 a week in
SRL	MyTokens	13	15	108	{apredType=A0, predLemma=work, predString=working, string=he}
SRL	MyTokens	13	15	116	{apredType=A1, predLemma=fire, predString=fired, string=he}
SRL	MyTokens	23	27	103	{apredType=A1, predLemma=earn, predString=earned, string=$150}
SRL	MyTokens	28	42	104	{apredType=A4, predLemma=earn, predString=earned, string=to $200 a week}
SRL	MyTokens	43	50	105	{apredType=AM-LOC, predLemma=earn, predString=earned, string=in tips}

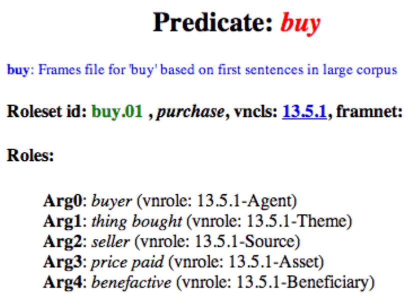
Figure 3.16: SRL annotation in GATE.

[25]SRL module for GATE is available at: https://github.com/jendarybak/GATE-SRL

3.8.2 Extraction of Related Triples

At this point, we have only those sentences which meet our requirements to be good candidates for information extraction, i.e. sentences containing a DBpedia entity, monetary information and a finance-related verb. We have also identified semantic roles of predicate's arguments. The key questions now are whether the money reference is related to the verb and whether the DBpedia entity describes participants of the financial transaction.

With the help of the PropBank role sets, it is possible to identify which arguments should describe the *agent*, *commodity*, and *financial value* of the commodity. Let's have a look at the following role set for the predicate `buy.01` (Fig. 3.17).



Predicate: *buy*

buy: Frames file for 'buy' based on first sentences in large corpus

Roleset id: buy.01 , *purchase*, vncls: 13.5.1, framnet:

Roles:

Arg0: *buyer* (vnrole: 13.5.1-Agent)
Arg1: *thing bought* (vnrole: 13.5.1-Theme)
Arg2: *seller* (vnrole: 13.5.1-Source)
Arg3: *price paid* (vnrole: 13.5.1-Asset)
Arg4: *benefactive* (vnrole: 13.5.1-Beneficiary)

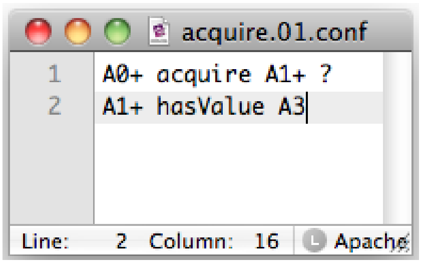
Figure 3.17: Role set for predicate `buy.01`.

In the output XML file (see Appendix A) you can see that the predicate is identified by its role set and lemma. All arguments have an attribute called `apredType` which denotes their semantic role. If there is a DBpedia entity contained in the argument, a `spotlight` child element is created to carry information about it. The same applies to monetary information, just the element is called `finance` .

Extraction Patterns

We created a system of patterns for specification of the predicate and arguments that we want to extract as a triple. For each predicate there is one configuration file (fig. 3.18) which holds one triple pattern per line.

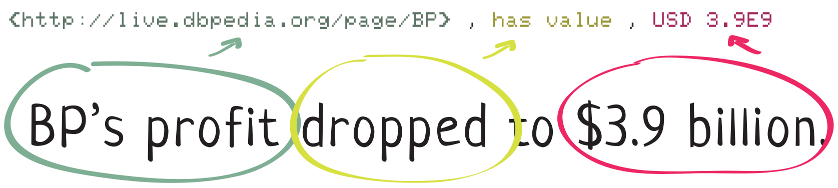
Writing a question mark ('?') behind the triple pattern signifies that the triple can be skipped if there are no matching arguments. User can define whether a DBpedia entity is required in the particular argument by simply writing a plus sign ('+') after the argument's label. Relation called `hasValue` has special meaning because the argument which follows this keyword must contain financial information, otherwise no triples are extracted.



```
A0+ acquire A1+ ?
A1+ hasValue A3
```

Figure 3.18: Example of extraction pattern for predicate acquire.01

3.9 Information Storage



<http://live.dbpedia.org/page/BP> , has value , USD 3.9E9
BP's profit dropped to $3.9 billion.

Figure 3.19: Information represented as an RDF triplet.

We decided to store acquired information in the form of RDF triples. This format is theoretically described in section 2.9.1. The reason to use RDFs for storage and operation with data instead of, for instance, relational database is simple - the data can be easily shared as Linked Data. Another benefit it brings is the possibility of interlinking our data with, for example, data from Wikipedia.

3.9.1 RDF Triples

Turtle format

Turtle (Terse RDF Triple Language) is one of many RDF syntaxes. We decided to use this format because it is more readable than the others. Another aspect is its compatibility with many RDF storages, especially with Sesame, the one we are using. Complete grammar of the Turtle syntax can be found at the official W3C specification web page [17]. Turtle supports three RDF term types:

- URI references
- Literals
- Blank nodes

In our application we use all of them. Worth mentioning is the concept of blank nodes. It is extremely useful when a unique identifier is needed. Following syntax (`_:inf`) will ensure the assignment of a unique id to every single piece of information:

Listing 3.6: Blank node in Turtle

```
_:inf rdf:type inf:information .
_:inf rel:file "1730066.xml" .
_:inf xsd:date "2006−01−07"^^xsd:date .
_:inf rel:sentence "Hilton said that it was acquiring ... for $5
    billion.".
```

XML to Turtle conversion

We implemented the process of triple statement retrieval (described in 3.8.2) in an application called `TurtleTransformer` . This application takes two arguments - a folder with the extraction patterns and a folder with extracted XML files. Each XML file represents, among other things, one predicate and its arguments. This application identifies the argument and provided there is a corresponding extraction pattern, an RDF triplet is composed and saved.

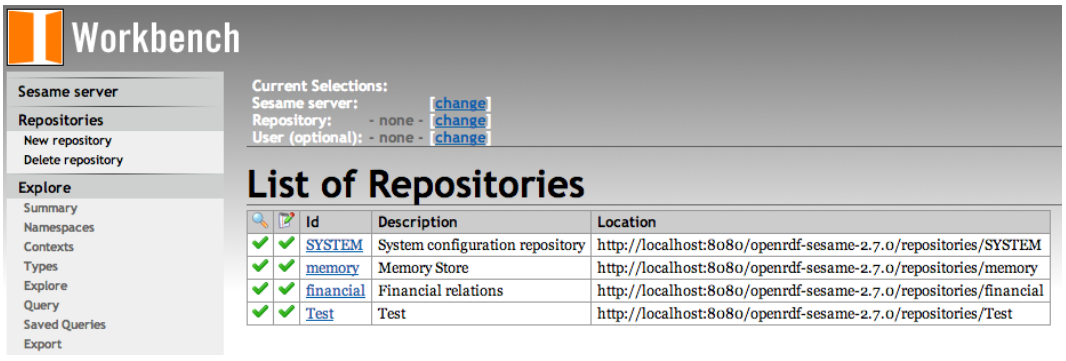
Example of RDF output (Sony's acquisition of CBS Records)

Listing 3.7: RDF output

```
@prefix rel: <http://www.rybak.in/schemas/relationship/> .
@prefix ent: <http://www.rybak.in/schemas/entities/> .
@prefix money: <http://www.rybak.in/schemas/money/> .

ent:Sony rel:stringValue "Sony" .
ent:Sony rel:seeAlso <http://dbpedia.org/resource/Sony> .
ent:CBS_Records rel:stringValue "CBS Records" .
ent:CBS_Records rel:seeAlso <http://dbpedia.org/resource/CBS_
    Records> .
ent:Sony rel:acquire ent:CBS_Records .

ent:CBS_Records rel:stringValue "CBS Records" .
ent:CBS_Records rel:hasValue ent:USD_3−4E12 .

ent:USD_3−4E12 rel:currency ent:USD .
ent:USD_3−4E12 rel:nominalValue 3.4E12 .
```

3.9.2 RDF Storage

We use Sesame 2.7.0[26] as the RDF framework for the storage and querying. Our decision for this selection was based mainly on the wide range of supported RDF formats (Turtle, N-Triples, RDF/XML, etc.), easy-to-use API and simple installation process (deployment to Apache Tomcat).

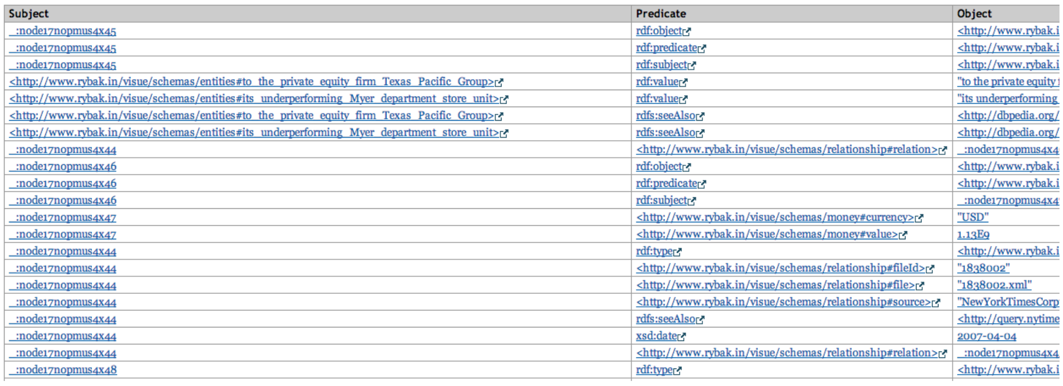


Current Selections:
Sesame server: [change]
Repository: - none - [change]
User (optional): - none - [change]

List of Repositories

		Id	Description	Location
✓	✓	SYSTEM	System configuration repository	http://localhost:8080/openrdf-sesame-2.7.0/repositories/SYSTEM
✓	✓	memory	Memory Store	http://localhost:8080/openrdf-sesame-2.7.0/repositories/memory
✓	✓	financial	Financial relations	http://localhost:8080/openrdf-sesame-2.7.0/repositories/financial
✓	✓	Test	Test	http://localhost:8080/openrdf-sesame-2.7.0/repositories/Test

Figure 3.20: Sesame Web Interface



Subject	Predicate	Object
_:node17nopmus4x45	rdf:object	<http://www.rybak.i
_:node17nopmus4x45	rdf:predicate	<http://www.rybak.i
_:node17nopmus4x45	rdf:subject	<http://www.rybak.i
<http://www.rybak.in/visue/schemas/entities#to_the_private_equity_firm_Texas_Pacific_Group>	rdf:value	"to the private equity f
<http://www.rybak.in/visue/schemas/entities#its_underperforming_Myer_department_store_unit>	rdf:value	"its underperforming
<http://www.rybak.in/visue/schemas/entities#to_the_private_equity_firm_Texas_Pacific_Group>	rdfs:seeAlso	<http://dbpedia.org/
<http://www.rybak.in/visue/schemas/entities#its_underperforming_Myer_department_store_unit>	rdfs:seeAlso	<http://dbpedia.org/
_:node17nopmus4x44	<http://www.rybak.in/visue/schemas/relationship#relation>	_:node17nopmus4x4
_:node17nopmus4x46	rdf:object	<http://www.rybak.i
_:node17nopmus4x46	rdf:predicate	<http://www.rybak.i
_:node17nopmus4x46	rdf:subject	_:node17nopmus4x4
_:node17nopmus4x47	<http://www.rybak.in/visue/schemas/money#currency>	"USD"
_:node17nopmus4x47	<http://www.rybak.in/visue/schemas/money#value>	1.13E9
_:node17nopmus4x44	rdf:type	<http://www.rybak.i
_:node17nopmus4x44	<http://www.rybak.in/visue/schemas/relationship#fileId>	"1838002"
_:node17nopmus4x44	<http://www.rybak.in/visue/schemas/relationship#file>	"1838002.xml"
_:node17nopmus4x44	<http://www.rybak.in/visue/schemas/relationship#source>	"NewYorkTimesCorp
_:node17nopmus4x44	rdfs:seeAlso	<http://query.nytime
_:node17nopmus4x44	xsd:date	2007-04-04
_:node17nopmus4x44	<http://www.rybak.in/visue/schemas/relationship#relation>	_:node17nopmus4x4
_:node17nopmus4x48	rdf:type	<http://www.rybak.i

Figure 3.21: RDF repository

3.9.3 RDF Triple uploader

To avoid the tedious manual work of RDF uploading, we prepared a simple program, which connects to the Sesame RDF storage and uploads all RDF files from a specified folder automatically.

[26]http://www.openrdf.org/

Chapter 4

Evaluation

4.1 Evaluation Data

In our experimental setup we processed New York Times articles from the year 2006. The total number of articles published that year is 87429. We used a limited ontology of finance-related verbs, which contains the 25 most essential predicates describing a financial activity (acquire, buy, sell, pay, etc.).

4.2 Evaluation Metrics

Our methodology of the extraction evaluation is based on the commonly used measures for information retrieval performance. *Precision* is in the scope of this thesis understood as a number of relevant information triples in the result set. By the term relevant we mean a triple, which fulfills the following criteria:

1. **Financial value**
   Both the currency and numerical value are correct and standardized.
2. **DBpedia entity**
   The originator of the financial cost contains one or more DBpedia entities, which are relevant to the subject.
3. **Originator phrase**
   The name of the originator does not necessarily have to be one or two words long. Nevertheless, phrases containing words with no relevance to the subject are considered incorrect.

4. RDF triple

The RDF triple file has to be in a valid form and has to represent the information correctly.

Formula used for precision evaluation looks as follows:

$$(P)recision = \frac{|\text{relevant information triples}|}{|\text{all information triples extracted}|} \tag{4.1}$$

4.3 Evaluation results

4.3.1 Precision

We manually evaluated 112 randomly picked information triples[1] and the resulting precision was 48,21%. This may seem like a poor performance, but in general, 94,64% of the triples carried meaningful information. Most of the errors were caused by the wrong assignment of DBpedia entity. Bellow we provide an analysis of error causes:

Table 4.1: Sources of inaccuracy in extraction of triples.

Preprocessing	*Money identification*	*DBpedia entity*	*Semantic Labeling*	*Triple extraction*
2.94%	**1.47%**	**80.88%**	**11.76%**	**2.94%**

To illustrate an example of incorrect result, let's have a look at the following triple:

Subject:	all-wool king-size mattress
Relation:	has value
Cost:	USD 2000
DBpedia:	http://dbpedia.org/resource/Elvis_Presley

Except of the entity assignment by DBpedia Spotlight, the information is correct. Nevertheless, it is clear that the mattress in this sentence is not called king-size because of Elvis Presley.

[1]This sample can be viewed at http://rybak.in/visue-evaluation/

4.3.2 Recall

Our application is meant to be precision-oriented. The recall can be improved by extending the ontology of financial relations. Instead of manual (and extremely time-consuming) evaluation of recall, we decided to measure number of sentences in every single step of the extraction process. We don't know the exact number of sentences in the unprocessed corpus, but our estimation is 150 000 - 200 000 sentences. However, we can use the number of sentences containing monetary information as a reference number, since the money recognizer is reliable part with high recall.

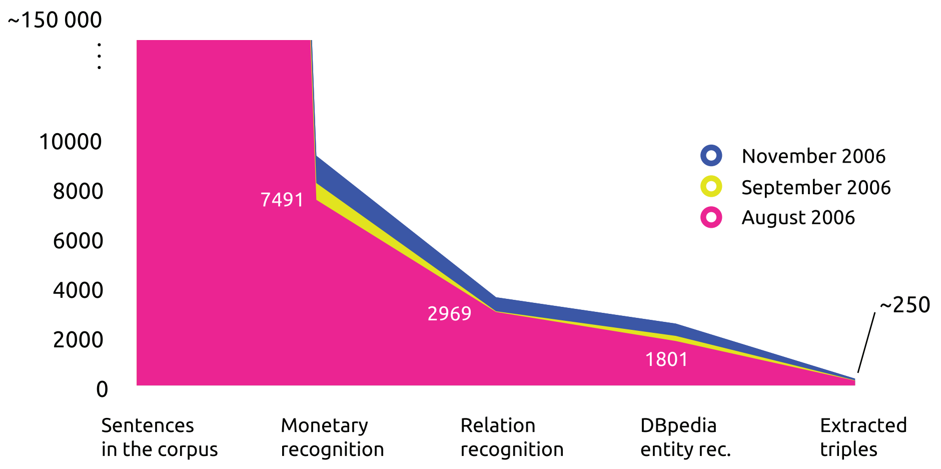


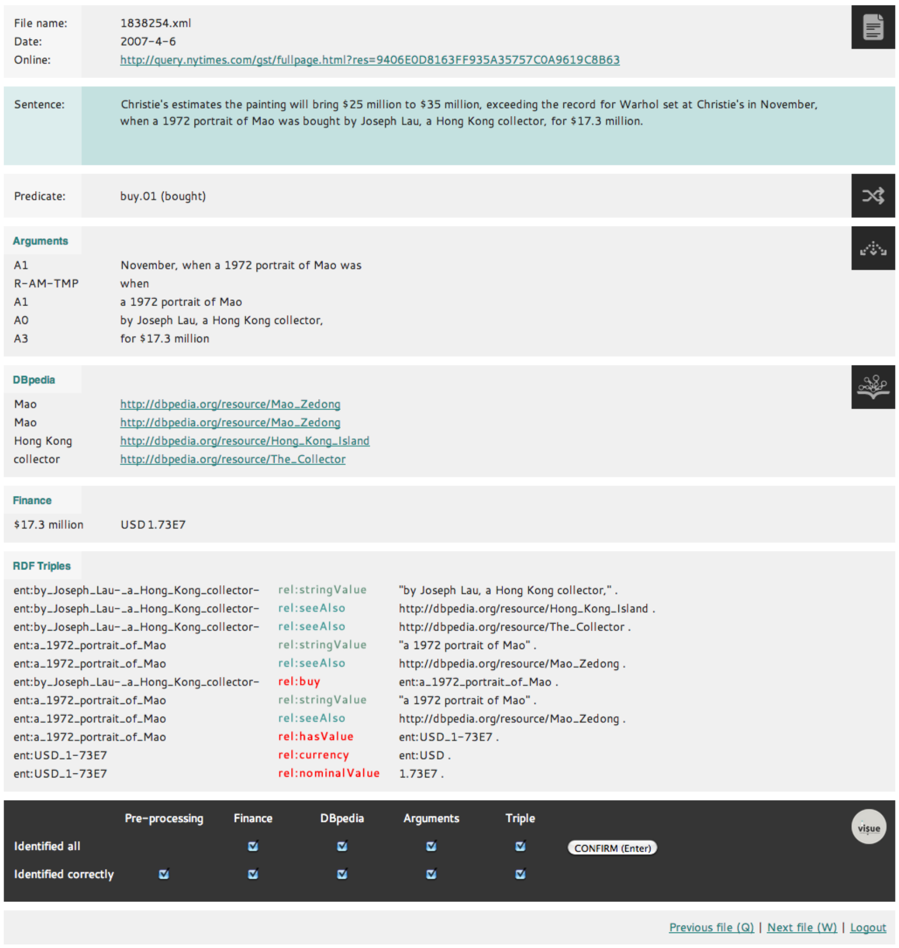
Figure 4.1: Distribution of sentences in subsequent phases of the extraction.

Table 4.2: Number of sentences in each phase of the extraction (year 2006).

Month	*Money identification*	*Financial relations rec.*	*DBpedia*	*Extracted triples*
November	**9 276**	**3 560**	**2 496**	**272**
September	**8 177**	**3 001**	**2 004**	**204**
August	**7 491**	**2 969**	**1 801**	**195**

4.4 Evaluation Interface

As the evaluation process requires manuall work, we prepared an interactive webpage which makes this process much easier - we call it VISUE Evaluation Tool[2]. This webpages loads extraction XML files together with the final RDF triples and shows them in a convenient way to the evaluator. All steps of the extraction phase can be marked as correctly/incorrectly processed. Results are collected in our database and further examined. For faster navigation there is a set of keyboard shortcuts that are listed in the application manual. This tool was developed in PHP, HTML, CSS, JavaScript (jQuery) and MySQL database.



File name:	1838254.xml
Date:	2007-4-6
Online:	http://query.nytimes.com/gst/fullpage.html?res=9406E0D8163FF935A35757C0A9619C8B63
Sentence:	Christie's estimates the painting will bring $25 million to $35 million, exceeding the record for Warhol set at Christie's in November, when a 1972 portrait of Mao was bought by Joseph Lau, a Hong Kong collector, for $17.3 million.
Predicate:	buy.01 (bought)

Arguments

A1	November, when a 1972 portrait of Mao was
R-AM-TMP	when
A1	a 1972 portrait of Mao
A0	by Joseph Lau, a Hong Kong collector,
A3	for $17.3 million

DBpedia

Mao	http://dbpedia.org/resource/Mao_Zedong
Mao	http://dbpedia.org/resource/Mao_Zedong
Hong Kong	http://dbpedia.org/resource/Hong_Kong_Island
collector	http://dbpedia.org/resource/The_Collector

Finance

$17.3 million	USD 1.73E7

RDF Triples

```
ent:by_Joseph_Lau-_a_Hong_Kong_collector-   rel:stringValue    "by Joseph Lau, a Hong Kong collector," .
ent:by_Joseph_Lau-_a_Hong_Kong_collector-   rel:seeAlso        http://dbpedia.org/resource/Hong_Kong_Island .
ent:by_Joseph_Lau-_a_Hong_Kong_collector-   rel:seeAlso        http://dbpedia.org/resource/The_Collector .
ent:a_1972_portrait_of_Mao                  rel:stringValue    "a 1972 portrait of Mao" .
ent:a_1972_portrait_of_Mao                  rel:seeAlso        http://dbpedia.org/resource/Mao_Zedong .
ent:by_Joseph_Lau-_a_Hong_Kong_collector-   rel:buy            ent:a_1972_portrait_of_Mao .
ent:a_1972_portrait_of_Mao                  rel:stringValue    "a 1972 portrait of Mao" .
ent:a_1972_portrait_of_Mao                  rel:seeAlso        http://dbpedia.org/resource/Mao_Zedong .
ent:a_1972_portrait_of_Mao                  rel:hasValue       ent:USD_1-73E7 .
ent:USD_1-73E7                              rel:currency       ent:USD .
ent:USD_1-73E7                              rel:nominalValue   1.73E7 .
```

	Pre-processing	Finance	DBpedia	Arguments	Triple
Identified all		✓	✓	✓	✓
Identified correctly	✓	✓	✓	✓	✓

Figure 4.2: VISUE Evaluation tool.

[2]http://www.rybak.in/visue-evaluation/

Part II

Information Visualization

Chapter 5

Background

5.1 Introduction

"The purpose of computing is insight, not numbers." - Richard Hamming -

Information visualization is a study of abstract data representation through the use of interactive visual interfaces. Its main purpose is simply to reinforce human cognition, make understanding of complex structures hidden in data easier and, perhaps, provide us with a decision-making tool.

The human vision is a very convenient channel for processing large amounts of data because from all our senses it has the largest bandwidth. It is said that our brain receives around 80% of all information from visual cues [46]. This makes the visual representation a suitable aid for external cognition, as described in [45].

Information visualization is a complex field, which builds on information theory, computer science, statistics, human-computer interaction, graphic design and many other areas of research. It has emerged from the need to get an insight into huge volumes of data, which we have to face more and more often. With the rise of computer era, it is now possible to include advanced forms of interaction and data manipulation into visual presentation. That, with no doubt, helps us to perceive phenomena or patterns in data.

5.2 History

Visual representation of data as such is not a new invention; it has been used for many centuries. However, visualization as a matter of scientific research is relatively new, it dates back to mid-80s.

William Playfair

One of the most influential persons in the field of visualization, widely held to be the father of data graphics [20], is William Playfair (1759-1823). He is believed to be the inventor of the most popular means of data visualization today: the line graph (Fig. 5.1) and the pie chart. Sometimes he is also credited to be the first one to use the bar chart, but two earlier pioneers - Nicole Oresme in 14th century and Joseph Priestley in 18th century - verifiably used the similar method to express quantitative information.

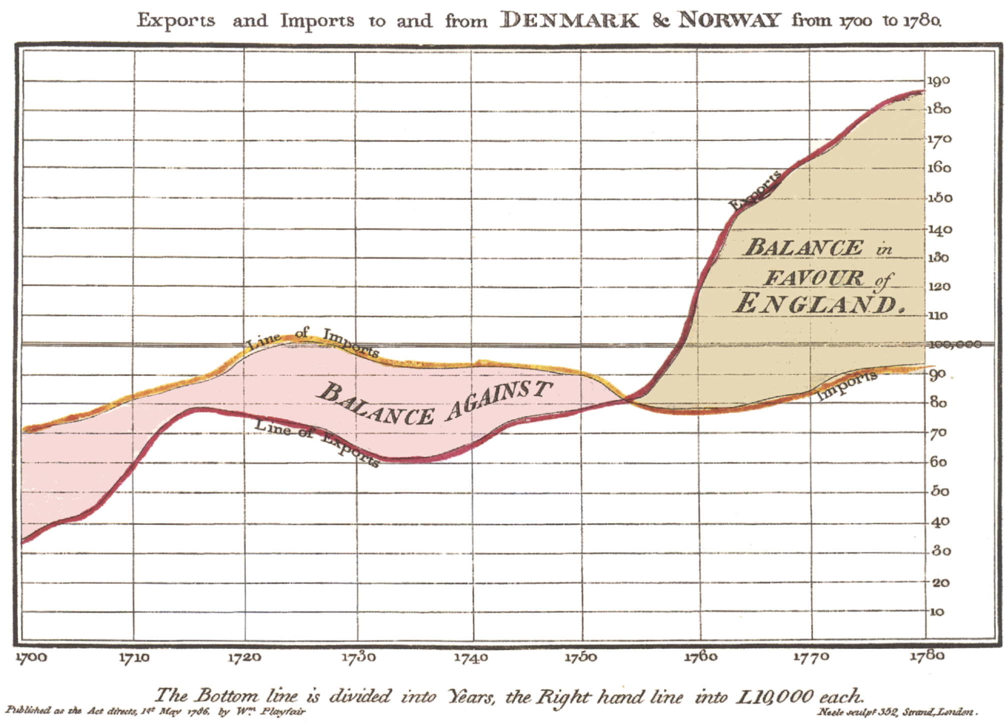


Figure 5.1: Playfair's trade-balance time-series chart (Commercial and Political Atlas, 1786) (Source: Wikipedia)

Charles Joseph Minard

Another very innovative graphical presentation of data is a flow map depicting Napoleon's march into Russia in 1812 designed by Charles Joseph Minard (1781-1870). This graph very clearly reveals the successive loss of French Army soldiers, which at some points correlates with the weather temperature. The visualization portrays several variables at once:

- the geographical position of the army with respect to the date
- the size of the army and successive loss of men
- the direction that the army was traveling
- the weather temperature

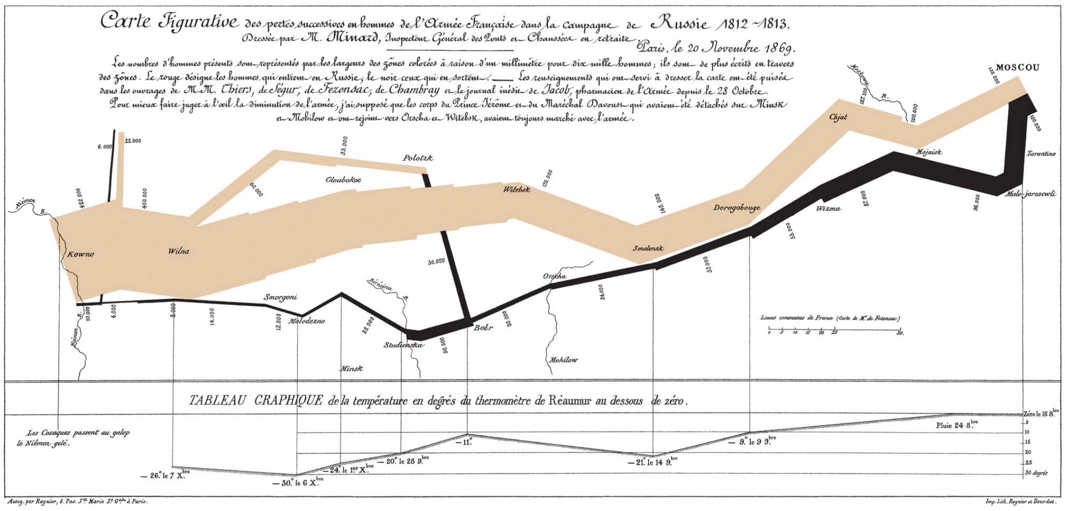

Carte Figurative des pertes successives en hommes de l'Armée Française dans la campagne de Russie 1812-1813.
Dressée par M. Minard, Inspecteur Général des Ponts et Chaussées en retraite.
Paris, le 20 Novembre 1869.
MOSCOU
Kowno
Wilna
Polotzk
Witebsk
Smolensk
Dorogobouge
Wixma
Chjat
Mojaisk
Tarantino
Malo-jarosewli
Smorgoni
Molodexno
Studienska
Botr
Minsk
Mohilow
Orscha
Gloubokoe
TABLEAU GRAPHIQUE de la température en degrés du thermomètre de Réaumur au dessous de zéro.
Les Cosaques passent au galop le Niémen gelé.
— 26° le 7 X.bre
— 30° le 6 X.bre
— 24° le 1er X.bre
— 20° le 28 9.bre
— 11°
— 21° le 14 9.bre
— 9° le 9 9.bre
Pluie 24 8.bre
Zéro le 18 8.bre

Figure 5.2: Charles Minard's flow map of Napoleon's March (1869) (Source: Wikipedia)

Despite its age, this visualization was described as *"probably the best statistical graphic ever drawn"* by a contemporary guru in the field - Edward Tufte[1].

[1] http://www.edwardtufte.com/tufte/posters

Chapter 6

Visualization Methods

Understanding the nature of data that we want to visualize is absolutely essential for the right choice of the visualization method. In the scope of this thesis we analyse financial costs and thus we are interested in the methods of quantitative information presentation. From the graphical and human perception point of view this matter was thoroughly examined in Edward Tufte's book called *Visual Display of Quantitative Information* [51]. For a recent overview of visualization techniques and concepts we would recommend to peruse the book *Data Points: Visualization That Means Something* [56] by Nathan Yau.

In this section, we give introduction to basic visualization concepts. Although we examined suitability of more visualization methods, we will limit our explanation just to the treemap layout (Section 6.2) which we actually applied in the final application.

6.1 Process

Nathan Yau [56] describes the process of data exploration for the purpose of visualization (see Figure 6.1) as a consequence of answering the following questions in the given order:

1. What kind of data are we dealing with?
2. What do we want to know about the data?
3. Which method should we use to visualize it?
4. Are we getting the desired outcome from the visualization?

If the result does not reflect our initial ideas, we should consider improving one of the steps of the whole process. For instance, if we want to implement chronological ordering of data while there is no temporal information in the source data set, we have to improve the process of data acquisition. Otherwise, we would have to reconcile to leaving this feature out.

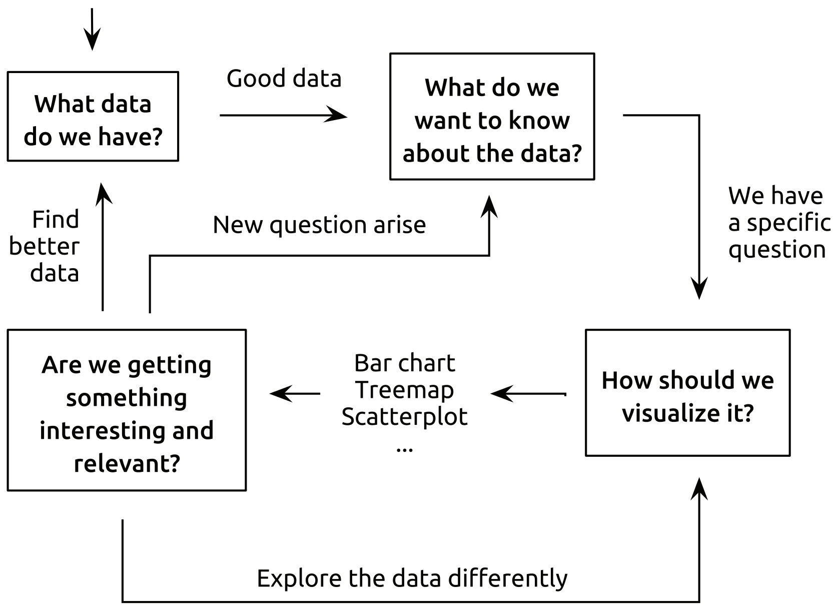

What data do we have?
Good data
What do we want to know about the data?
We have a specific question
Find better data
New question arise
How should we visualize it?
Bar chart
Treemap
Scatterplot
...
Are we getting something interesting and relevant?
Explore the data differently

Figure 6.1: Iterative process of the data exploration for the visualization purpose introduced by Nathan Yau (Source: [56]).

6.2 Treemap

The treemap is a form of visualization intended to represent large sets of quantitative data using a planar space-filling approach [48]. Its target field are usually hierarchically organized (tree-structured) data sets. This method was originally designed in 1990s by Ben Shneiderman[1] to show files and their sizes on a hard drive [48]. Nowadays its usage is widely diversified.

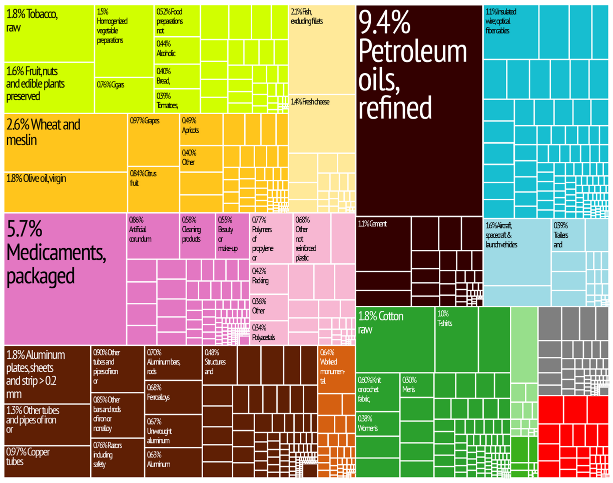


Figure 6.2: Treemap depicting Greece's product exports. (Source: Wikipedia)

The main principle lies in dividing the main visualization area into rectangles. The area of the rectangles proportionally corresponds to some quantifiable quality of data, for example a financial cost of the particular data item. If there are nested items (child nodes), they are visualized by further segmentation of the subarea (the parent's node area). Another dimension of the data can be encoded by assigning the node a background color. This is often used to express an affiliation to various categories. The obvious advantage of treemaps is their capability to use visualization space efficiently (100% coverage of the area).

[1] http://www.cs.umd.edu/hcil/treemap-history/

6.2.1 Layout Algorithms

The area-segmentation (tiling) algorithm ([48], [8]) is a very important aspect of the treemap method itself. Various ways exist to layout the rectangles. The final visual perception, which can be called *readability*, is strongly dependent on choosing the suitable one. A common metrics to evaluate the readability of the map is the aspect ratio r of rectangles R. The best possible algorithm is expected to produce map's average ratio close to 1 (square):

$$\forall r \in R, \frac{max(width(r), height(r))}{min(width(r), height(r))} \approx 1 \tag{6.1}$$

The overview of the most important algorithms is given in [19]. We present two methods important for this thesis.

Slice and Dice

Slice and Dice is the original implementation [48] of the treemap visualization method. For each level of the hierarchy the layout alternates between horizontal and vertical rectangles. The advantage of this algorithm is that it preserves the order of the elements and its performance, since only one traversal through the tree is needed, is *O(n)*. Though, the main drawback is that the average ratio is very high and the final treemap contains many thin rectangles.

Squarified Layout

The problem that this method is addressing is: how to recursively tile an area into rectangles, so that their aspect ratio is as close to 1 as possible? As mentioned by the authors of the algorithm - Bruls, Huizing and Wijk - there is a very large set of possible tessellations that makes this problem NP-hard [8]. Nevertheless, we seek for good enough solution, not the optimal one.

In simple terms, the goal of this algorithm is to create square-like rectangles for sibling items from one level, which makes it easier to fit items in in the second iteration. The algorithm starts by deciding whether the first division has to be in the horizontal or vertical direction - it depends which side of the initial rectangle is longer. Assuming that the horizontal side is longer, the first item is fitted to the left part of a given area and the aspect ratio is computed. Next, the second rectangle is added above the first one, which modifies its aspect ratio. If the ratio is closer to 1, another item is added above the previous two. If the ratio is worse, the last added item is removed and aligned to the right side. The algorithm is depicted in the Figure 6.3 [8] and described by a pseudo-code (Listing 6.1) from [19].

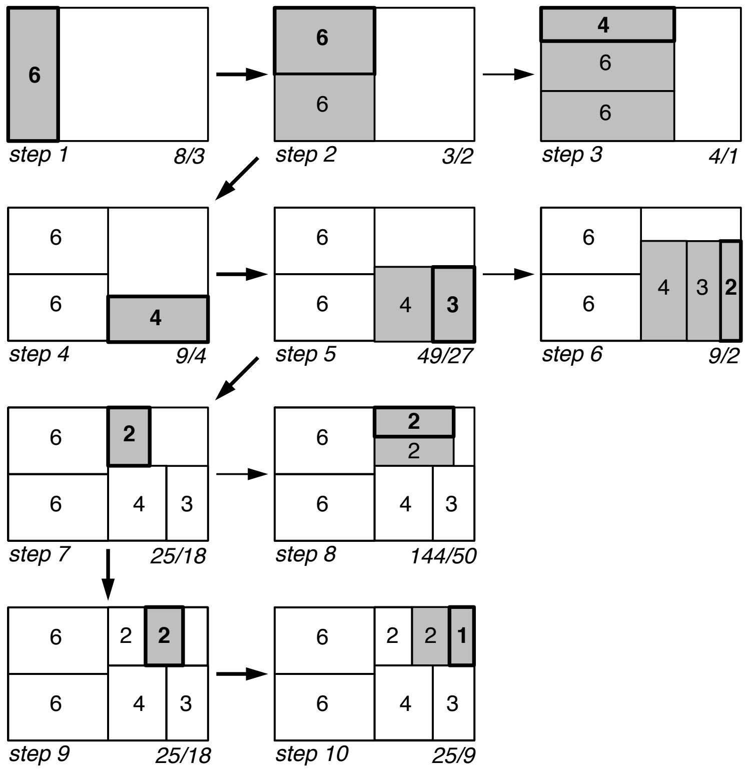


Figure 6.3: Squarified Layout area segmentation (Source: [8]).

Squarified Layout advantages:

- Square items are easy to read.
- Square items are better for area comparison.
- Number of pixels used for the border (if > 0) is proportional to the item's area.

Listing 6.1: Squarified Layout pseudo-code

```
squarify(Queue nodes) {
  Queue currentRow;
  nodes.sort(); // Sort on size

  while {nodes.length > 0) {
    Item current := nodes.dequeue();
    if (worst(currentRow + current) < worst(currentRow))
    currentRow.enqueue(current);
    else {
      layoutRow(currentRow);
      currentRow.clear();
      currentRow.enqueue(current);
    }
  }

  foreach (Item node in nodes)
  squarify(node.children);
}
```

Chapter 7

Realization

We decided to implement the visualization part of the thesis as a web application. We believe that it is the most straightforward option to make it accessible for the general public. The application structure and technologies used are described in the following sections.

7.1 Architecture

Our interactive visualization is a stand-alone web application, in other words, it is not interconnected with the extraction system (except of the data storage). The main benefit of this approach is the universality of the application - provided that we keep a defined format of input data, it does not matter how the data are acquired.

Architecture of the system is depicted on the following figure:

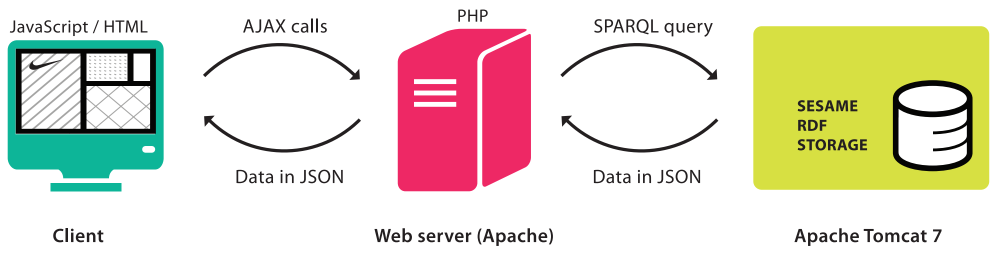


Figure 7.1: Architecture of the visualization system

7.2 Technology

The static part of the application is written in HTML5 and CSS3 which is today's standard. The application logic is mostly implemented in JavaScript while utilizing many libraries with the latest version of `jQuery` at the first place. In addition to that we use `accounting.js` [1] for money formatting, `tablesorter` [2] for sorting table columns, `FileSaver.js` [3] for saving exported files in the browser and `seed-random.js` [4] to implement the function of random number generation according to a given seed value.

We found a suitable framework for data visualization, `D3.js` , which we describe more in section 7.2.2. During the implementation we ran into a problem with the *Same Origin Policy* (SOP). This security concept prevents scripts from one domain (origin) to interact with a resource from the second one. In our case, it protected our JavaScript from accessing RDF storage and receiving data directly. As we did not want to rely on the fact, that the RDF storage has to be running in the same domain as the visualization application, we bypassed this obstacle by creating a PHP proxy script (`loadJSON.php`).

7.2.1 SPARQL

As mentioned above, the application receives data from RDF storage[5]. When a user specifies search parameters and submits the form, a SPARQL query is constructed on the client side and sent over HTTP to the RDF storage endpoint. The user is not disturbed by the page being reloaded, because we use asynchronous Ajax calls. Once the request is sent, the application is expecting results in the form of a *JSON*[6] file.

[1] http://josscrowcroft.github.io/accounting.js/
[2] http://tablesorter.com/
[3] https://github.com/eligrey/FileSaver.js
[4] http://davidbau.com/encode/seedrandom.js
[5] Sesame 2.7.0.
[6] JavaScript Object Notation

Listing 7.1: Simplified example of the SPARQL query with maximal cost filter set to 1000.

```
...prefixes...

SELECT DISTINCT ?id ?date ?currency ?cost ?url
WHERE {
?id rdf:type inf:information .
?id xsd:date ?date .
?id rdfs:seeAlso ?url .

?id rel:relation ?rel .
?rel rdf:predicate pred:hasValue .
?rel rdf:object ?object .

?rel rdf:subject ?money .
?money money:value ?cost .

FILTER(?cost <= 1000)
}
```

7.2.2 Data-Driven Documents (D3.js)

`D3.js` [7] is a very popular open-source JavaScript library for data visualization. It was designed and written by Mike Bostock [6] during his PhD studies at Stanford Visualization Group[8]. `D3.js` is a framework based on *Document Object Model* (DOM) which solves efficient manipulation of documents based on data [6], as expressed by its author on the project webpage:

"D3 allows you to bind arbitrary data to a Document Object Model (DOM), and then apply data-driven transformations to the document. For example, you can use D3 to generate an HTML table from an array of numbers. Or, use the same data to create an interactive SVG bar chart with smooth transitions and interaction."

The importance of `D3.js` for our application lies in the variety of predefined visualization methods, in its smooth interaction processing and its performance.

[7] http://d3js.org/
[8] http://vis.stanford.edu/

7.3 Interface

In the scope of the following sections, we would like to describe application's interface together with implementation details. Our goal was to design a system, which is easy to navigate and intuitive even for novice users. The initial page is depicted on figure 7.2.

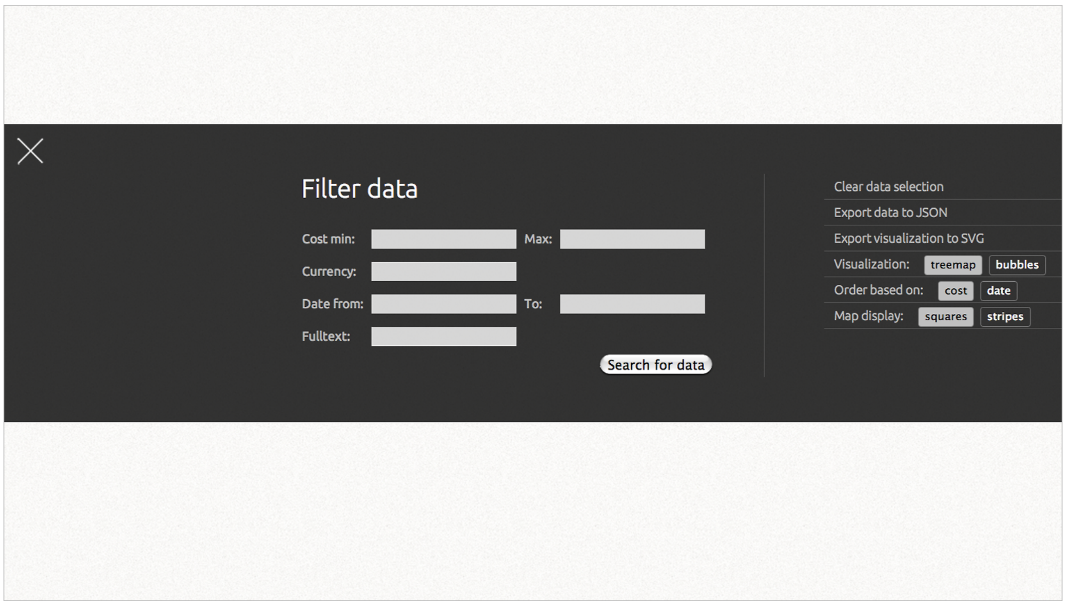


Figure 7.2: Initial page of the application.

7.4 Data Selection

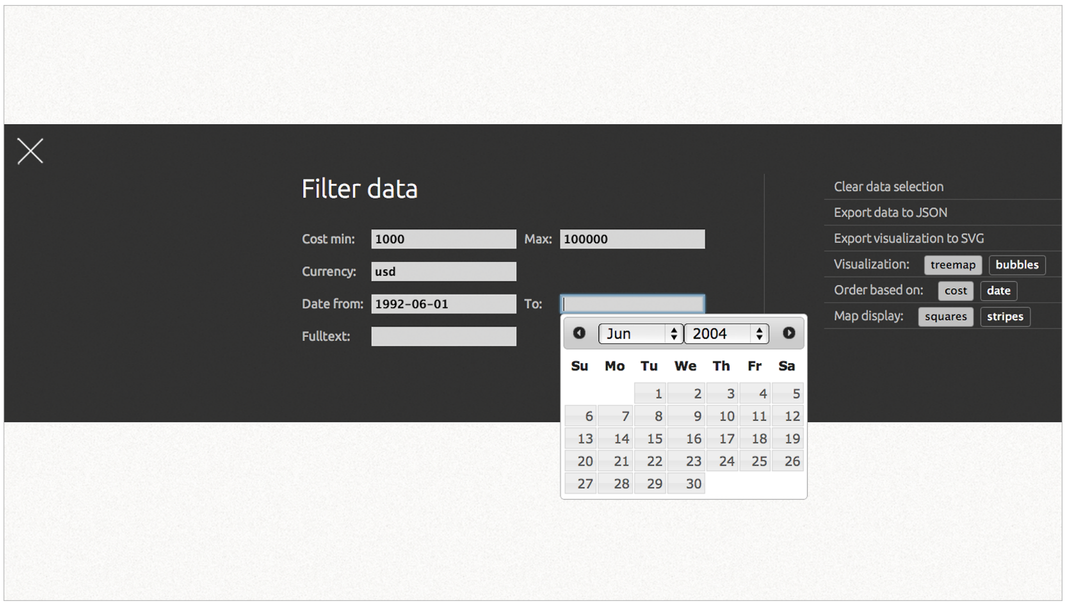
The first step that the user has to take is data selection. The user can influence the data returned from the RDF storage by specification of the following parameters:

Cost range The minimal and maximal financial amounts to be considered.

Currency The currency code (USD, EUR, etc.).

Date range Only information published within the date range will be presented.

Fulltext Only entities with a given keyword in their names are returned.



Filter data

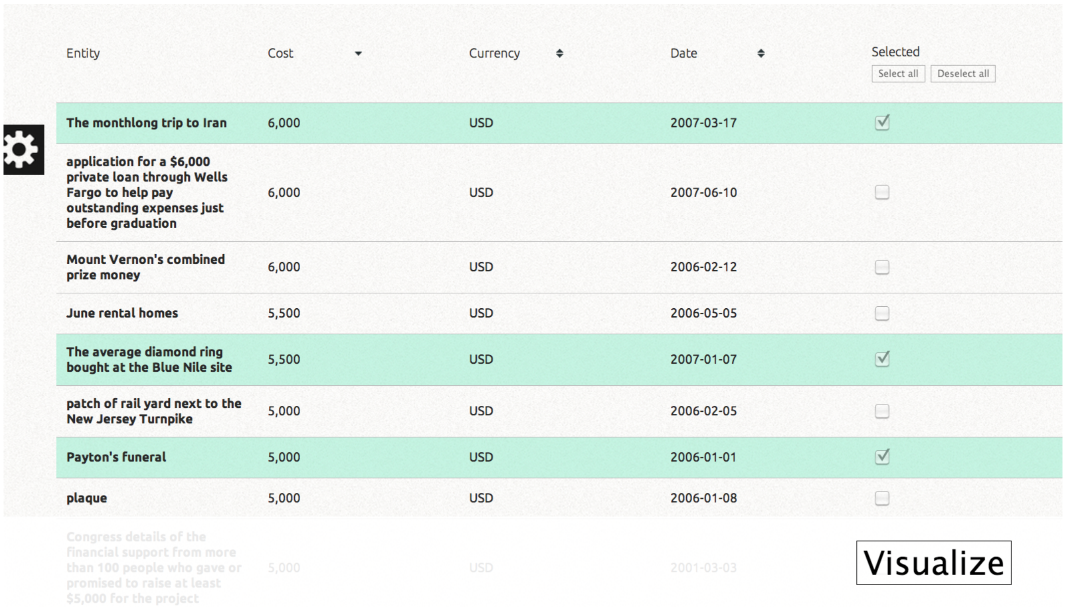
Cost min:	1000	Max:	100000
Currency:	usd		
Date from:	1992-06-01	To:	
Fulltext:			

Su	Mo	Tu	We	Th	Fr	Sa
		1	2	3	4	5
6	7	8	9	10	11	12
13	14	15	16	17	18	19
20	21	22	23	24	25	26
27	28	29	30			

Jun
2004
Clear data selection
Export data to JSON
Export visualization to SVG
Visualization: treemap bubbles
Order based on: cost date
Map display: squares stripes

Figure 7.3: User is encouraged to search in data by specifying search parameters.

After successful data search, the menu hides to the left side and the user is provided with tabular data reflecting his searching preferences (Fig 7.4). By clicking on a row, the corresponding data item is marked for visualizing and its back-

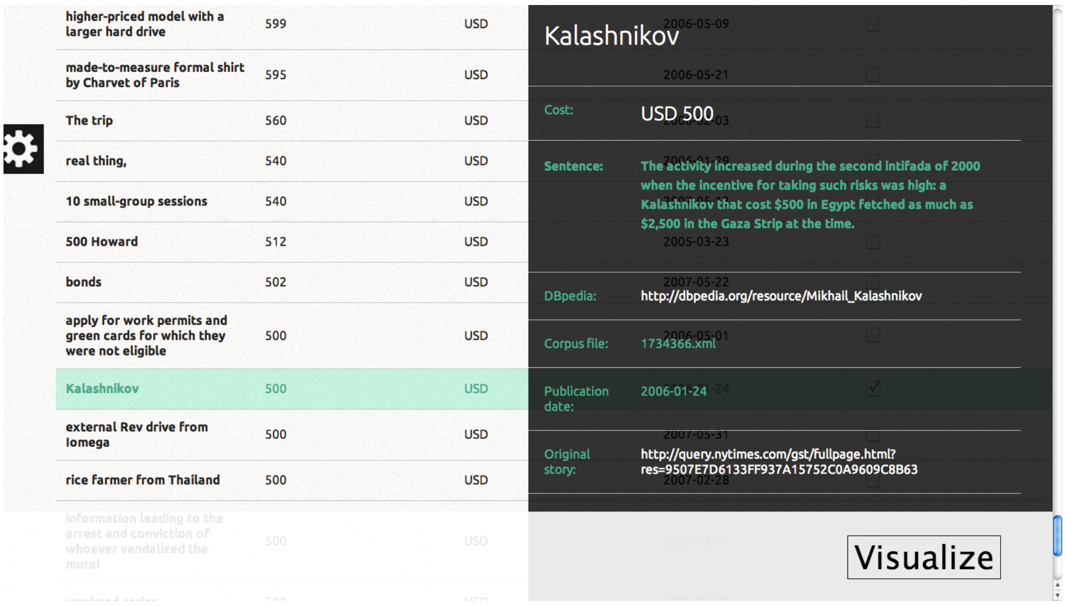


Entity	Cost	Currency	Date	Selected
The monthlong trip to Iran	6,000	USD	2007-03-17	✓
application for a $6,000 private loan through Wells Fargo to help pay outstanding expenses just before graduation	6,000	USD	2007-06-10	☐
Mount Vernon's combined prize money	6,000	USD	2006-02-12	☐
June rental homes	5,500	USD	2006-05-05	☐
The average diamond ring bought at the Blue Nile site	5,500	USD	2007-01-07	✓
patch of rail yard next to the New Jersey Turnpike	5,000	USD	2006-02-05	☐
Payton's funeral	5,000	USD	2006-01-01	✓
plaque	5,000	USD	2006-01-08	☐
Congress details of the financial support from more than 100 people who gave or promised to raise at least $5,000 for the project	5,000	USD	2001-03-03	

Figure 7.4: Selection of items for visualization.

ground color turns green. Repeating the same action removes the item from the selection. The user can select, or alternatively deselect, all items using the relevant button on the page.

For better understanding of the information in each table row, the user can navigate the mouse cursor over the entity name and the information box where additional details will appear (Fig 7.5).



higher-priced model with a larger hard drive	599	USD
made-to-measure formal shirt by Charvet of Paris	595	USD
The trip	560	USD
real thing,	540	USD
10 small-group sessions	540	USD
500 Howard	512	USD
bonds	502	USD
apply for work permits and green cards for which they were not eligible	500	USD
Kalashnikov	500	USD
external Rev drive from Iomega	500	USD
rice farmer from Thailand	500	USD
information leading to the arrest and conviction of whoever vandalized the mural	500	USD

Kalashnikov

Cost:	USD 500
Sentence:	The activity increased during the second intifada of 2000 when the incentive for taking such risks was high: a Kalashnikov that cost $500 in Egypt fetched as much as $2,500 in the Gaza Strip at the time.
DBpedia:	http://dbpedia.org/resource/Mikhail_Kalashnikov
Corpus file:	1734366.xml
Publication date:	2006-01-24
Original story:	http://query.nytimes.com/gst/fullpage.html?res=9507E7D6133FF937A15752C0A9609C8B63

Figure 7.5: Information box with details about the particular data item.

Confirming the data selection by pushing the **"Visualize"** button transforms the interface into fullscreen data visualization. An icon for menu/settings is always present on the browser's left side. In order to open the menu, the user has to click on the icon (Fig. 7.7).

7.5 Visualization Methods

Treemap Layout

The implicit visualization method is the treemap based on squarified algorithm (Section 6.2.1) with descending cost order. Since we do not use categorization of data, no special meaning is assigned to the color. Its value is based on a random number. Our visualization is build on top of `d3.layout.treemap()` layout implementation in `D3.js` .

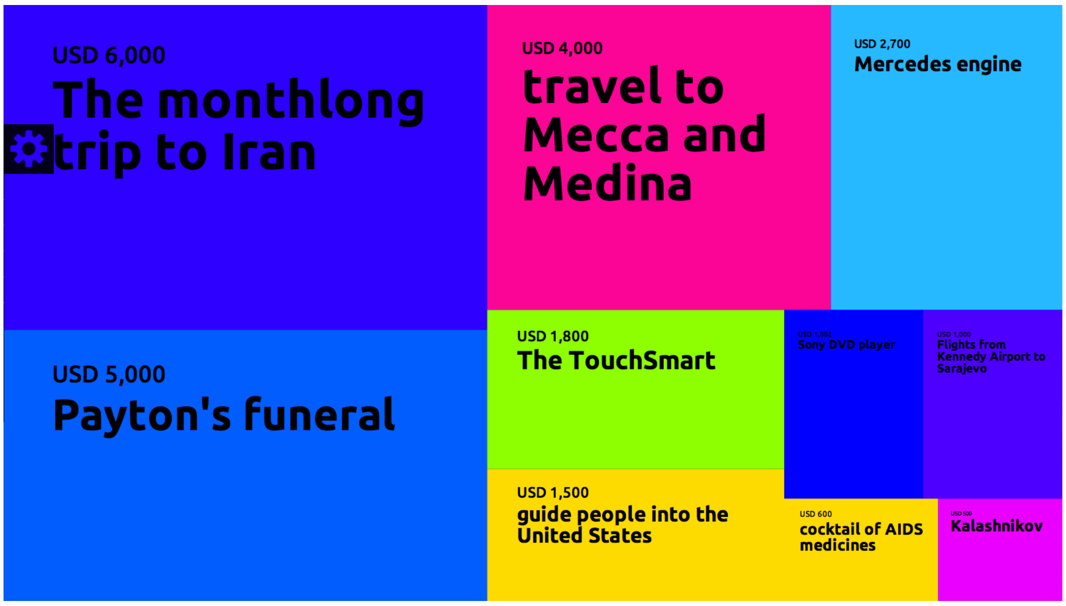
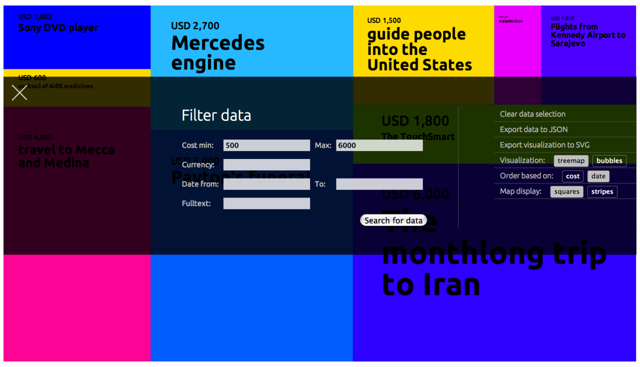


Figure 7.6: Implicit visualization - treemap with ordering by cost.



Filter data

Cost min: 500 Max: 6000
Currency:
Date from: To:
Fulltext:

Visualization: treemap bubbles
Order based on: cost date
Map display: squares stripes

Figure 7.7: Visualization method/settings can be modified in the menu.

Data items in the treemap can be also ordered by date of information publication. The oldest information is positioned in the top left corner and the most recent one is in the bottom right corner (see Figure 7.8).

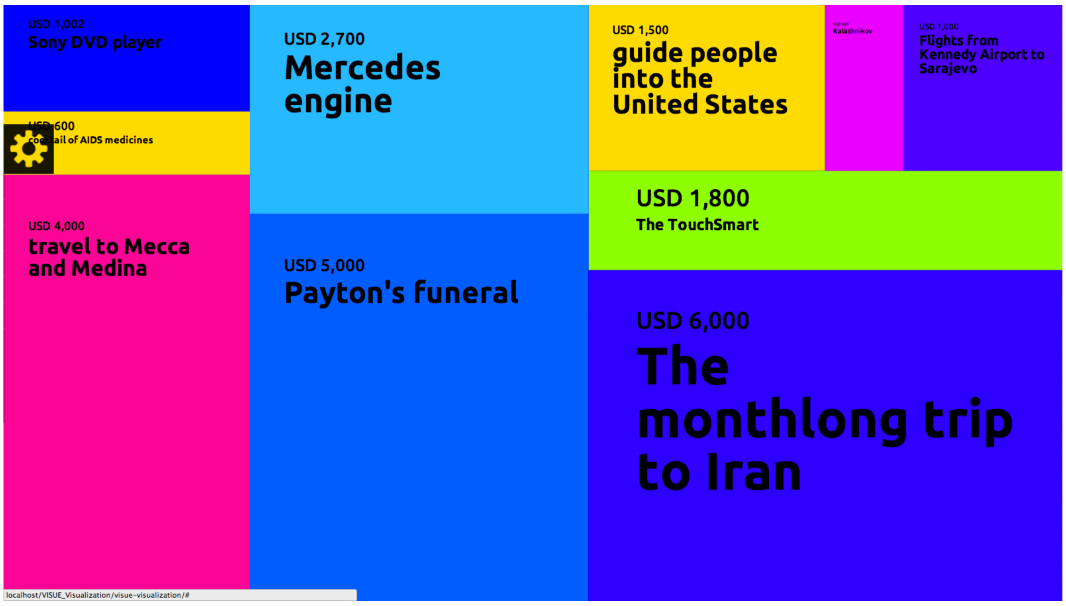

USD 1,002
Sony DVD player
USD 600
cocktail of AIDS medicines
USD 4,000
travel to Mecca and Medina
USD 2,700
Mercedes engine
USD 5,000
Payton's funeral
USD 1,500
guide people into the United States
Kalashnikov
USD 1,000
Flights from Kennedy Airport to Sarajevo
USD 1,800
The TouchSmart
USD 6,000
The monthlong trip to Iran
localhost/VISUE_Visualization/visue-visualization/#

Figure 7.8: Treemap with chronological ordering.

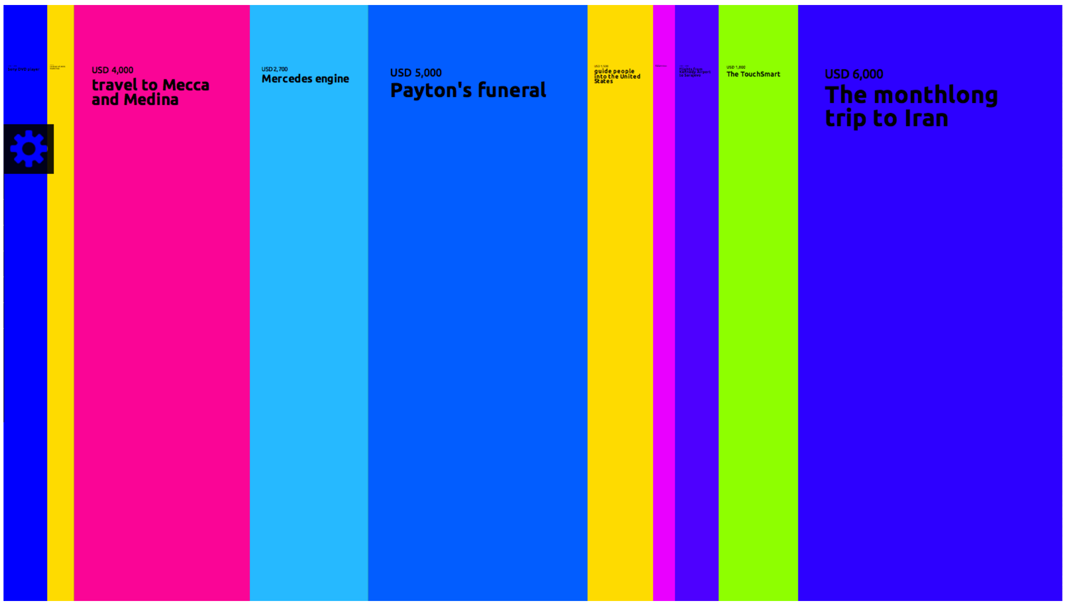


Figure 7.9: Treemap using dice algorithm is convenient when ordering by date.

However, for the chronological ordering the slice-dice algorithm is more suitable. Each piece of information occupies one vertical line and the global overview is much clearer. This mode is labeled as **”stripes”** in the menu.

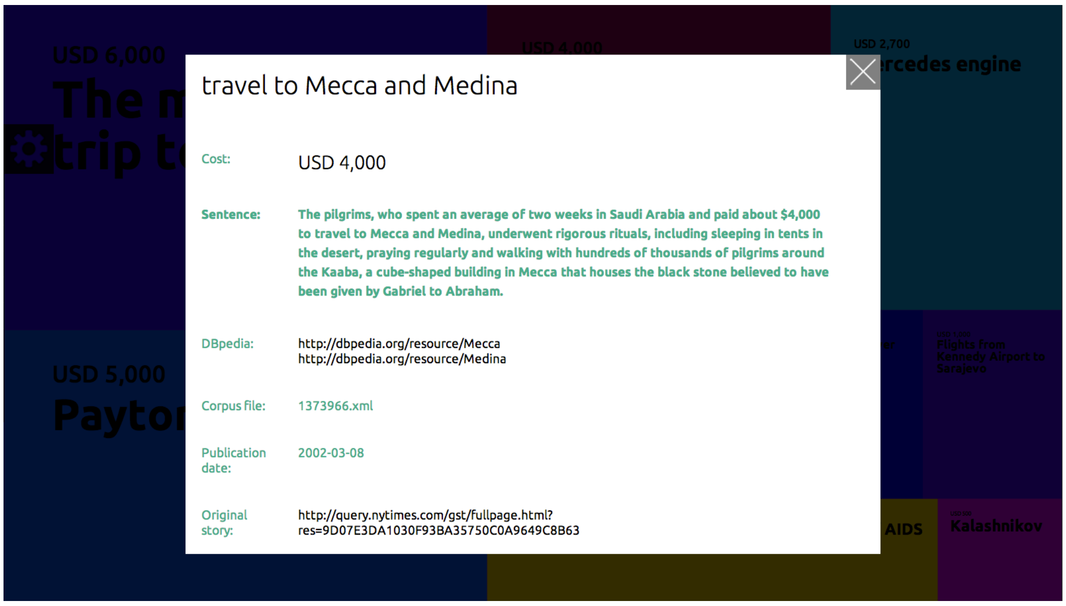
Circle Pack Layout

In addition to the treemap layout, our application offers visualization using circles with different radii. The size of each circle corresponds with the entity cost and its position is given by the type of ordering - by the date or the cost. Examples (Figure 7.11, 7.12) are depicted on the following page.

7.6 Interactivity

We included several possibilities of interactivity. Zooming is activated when scrolling the mouse wheel and dragging when user holds the left mouse button and moves it. These features are helpful especially when the differences among item costs are significant.

Another very important feature is the box with detailed information about an entity. It is displayed upon clicking on the data item (Fig. 7.10).



travel to Mecca and Medina

Cost: USD 4,000

Sentence: The pilgrims, who spent an average of two weeks in Saudi Arabia and paid about $4,000 to travel to Mecca and Medina, underwent rigorous rituals, including sleeping in tents in the desert, praying regularly and walking with hundreds of thousands of pilgrims around the Kaaba, a cube-shaped building in Mecca that houses the black stone believed to have been given by Gabriel to Abraham.

DBpedia: http://dbpedia.org/resource/Mecca
http://dbpedia.org/resource/Medina

Corpus file: 1373966.xml

Publication date: 2002-03-08

Original story: http://query.nytimes.com/gst/fullpage.html?res=9D07E3DA1030F93BA35750C0A9649C8B63

Figure 7.10: Detailed information is shown when user clicks on a data item.

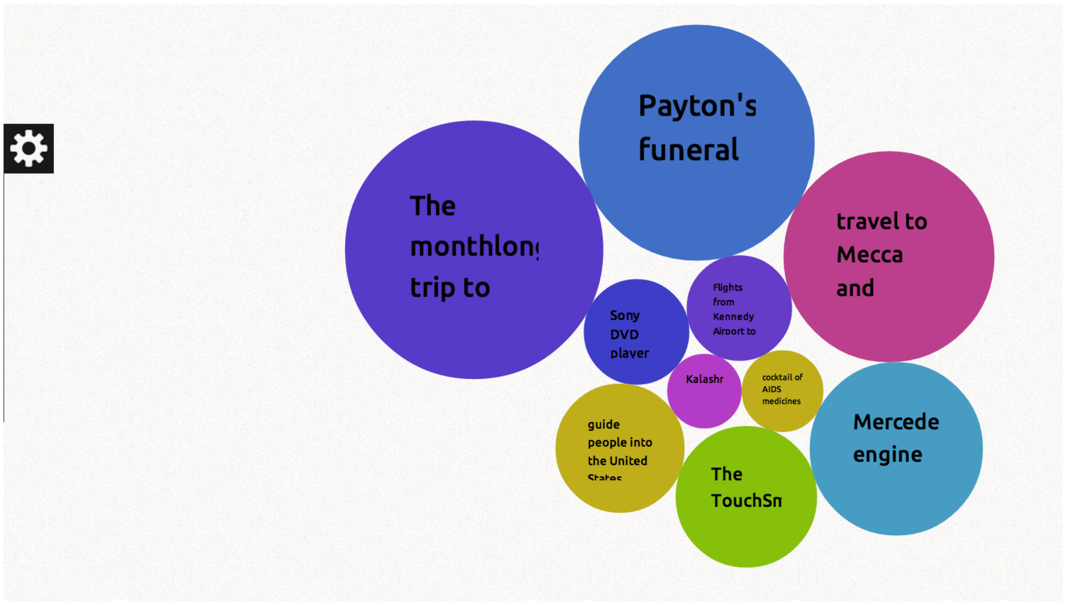


Figure 7.11: Circle Pack Layout and data ordered by cost.

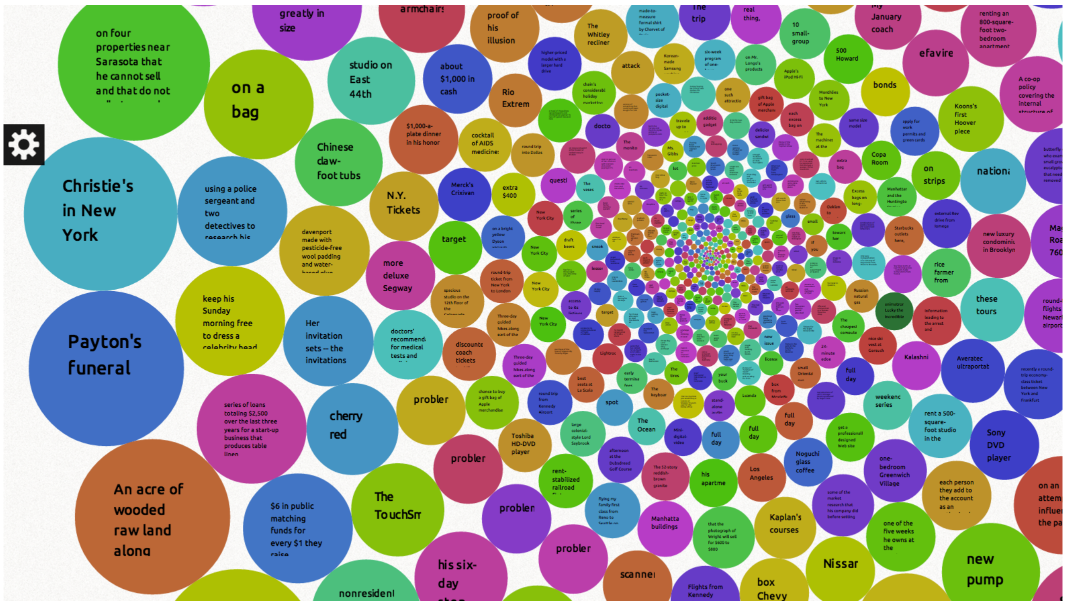


Figure 7.12: Circle Pack Layout presenting large amount of data.

7.7 Data Format and Export

Supported file formats for data export are:

- **JSON**
- **SVG**

The JSON format exported has the same structure as the JSON file processed in our application.

Listing 7.2: Simplified example of JSON processed in the application.

```
{
   "name":"VISUE-Data",
   "results":{
      "bindings":[
         {
            "id":       {"value":"node17plbpkc6x7531"},
            "object_value": {"value":"Atari collection"},
            "cost":     {"value":"30000.0"},
            "currency": {"value":"USD"},
            "date":     {"value":"2007-06-15"},
            "dbp":      {"value":"http://dbpedia.org/.../Atari"},
            "file":     {"value":"1854539.xml"},
            "url":      {"value":"http://query.nytimes.com/..."},
            "sentence": {"value":"But that does mean that the Atari
                 ..."}
         },
     ...
     ]
   }
}
```

Chapter 8

Conclusion and Future Work

8.1 Conclusion

The subject of this thesis was motivated by the following question:

Can we build a system that will be able to automatically extract and visualize costs of various interesting things?

And the simple answer is yes. We have built an information extraction system, which is processing a text in natural language. We proposed a solution to identify potentially interesting pieces of information. It is based on two main ideas. Firstly, the popular newspapers, such as The New York Times, are relevant source of information for this purpose and secondly, the entities with an article on Wikipedia are widely known and perhaps interesting. We created an ontology of finance-related verbs that help us with the relationship recognition. The "proof of concept" was successfully implemented and tested.

In the second part of the thesis we focused on the presentation of the extracted data. According to the assignment, we studied and implemented the treemap layout, which is a very convenient way of visualizing quantitative data. In addition, we included some useful features such as data filtering or the second visualization method utilizing circles of various radii to express the subject's cost.

We can conclude that the objective of this thesis was fulfilled. It is worth noting that we contributed to the GATE framework by providing previously unimplemented modules for the semantic role labelling and the DBpedia entity labelling. In the section about the future work we present some ideas how the current system can be enhanced.

8.2 Future Work

Several suggestions for the improvements of the system have emerged during the work on the thesis. The development of the current version was challenging and time-consuming so that we were not able to implement the enhancements stated bellow. However, we believe that any of them would add up to the overall quality and/or usability.

8.2.1 Information Extraction part

Coreference resolution

Since many sentences are introduced by a pronoun referring to the subject of previous sentence, this method would substantially increase the number of correctly extracted triples.

Entity linking

We suppose that by using machine-learning based methods for linking the subject's name with a DBpedia entity would produce more precise results.

Twitter data input

As we discussed in Section 3.4.2, data from Twitter (tweets) could be very promising source of the text input. They contain complete information in 140 characters and it is easy to select just the profiles providing some relevant news.

DBpedia Spotlight recognition by the whole article

Due to the long processing times of DBpedia Spotlight tool we are processing just single sentences containing financial information. If we were able to process the whole articles, the entity disambiguation would be more accurate.

8.2.2 Visualization

Linked Data filtering

Data filtering based on the entity type (person, company, etc.) would be a very useful feature in the visualization.

Finance flow visualization

With enough data processed by our system, it would be possible to visualize financial flows between individual entities. For instance, being able to see money spent and earned by Google company could be interesting.

Data categorization

Graphical objects could be colored by their affiliation to various categories (time range, predicate type, location, etc.).

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Appendix A

Extraction XML File

Listing A.1: Arguments assigned to the predicate 'buy.01' in an output XML

```
<extractionResult>
  <sentence>Google bought YouTube in October for $1.65 billion.</
      sentence>
  <extractedData>
    <predicate roleSet="buy.01" lemma="buy">bought</predicate>
    <arguments>
      <argument apredType="A0" s="0" e="6">
        <string>Google</string>
        <spotlight>
          <entity uri="http://dbpedia.org/resource/Google" s="0" e
              ="6">Google</entity>
        </spotlight>
      </argument>
      <argument apredType="A1" s="14" e="21">
        <string>YouTube</string>
        <spotlight>
          <entity uri="http://dbpedia.org/resource/YouTube" s="14"
              e="21">YouTube</entity>
        </spotlight>
      </argument>
      <argument apredType="AM-TMP" s="22" e="32">
        <string>in October</string>
      </argument>
      <argument apredType="A3" s="33" e="50">
        <string>for $1.65 billion</string>
        <finance>
```

```
          <money currency="USD" value="1.65E12">$1.65 billion</
              money>
        </finance>
      </argument>
    </arguments>
  </extractedData>
</extractionResult>
```

Appendix B

User Manual

In this section we will describe how to install and run programs developed in the scope of this thesis.

B.1 Visue Extraction Tool

The main application for the extraction is a console program written in Java, that is why Java Runtime Environment has to be present on the destination system. We included executable **jar** file, so there is no need to compile it. This application requires two external tools to be running:

DBpedia Spotlight

DBpedia Spotlight[1] is essential for named entity annotation. DBpedia Spotlight server can run either locally or remotely. This software can be used under the terms of the Apache Licence, 2.0.

Mate Tools - Semantic Role Labelling

Another inseparable part of the application is SRL tool. Latest version can be found on the enclosed CD. We have prepared all the configuration files, therefore running `run_http_server.sh` script should start the server at `http://localhost:8072/parse` .

Our application is started by the following command:

```
java -jar Visue.jar
```

[1] https://github.com/dbpedia-spotlight/dbpedia-spotlight

Supported arguments are:

`-i` , `--inputDir`
: Path to the directory with input files. If this argument is not provided, default directory is considered as the source folder. Default directory is: `app_root_folder/documents/input`

`-o` , `--outputDir`
: Path to the directory with the results of the extraction are stored. Default directory is: `app_root_folder/documents/extraction_results` .

`-ds` , `--dbpediaSpotlight`
: This arguments expects an address of the DBpedia Server. Default value is DBpedia demo address at `http://spotlight.dbpedia.org/rest/annotate/` .

`-srl` , `--semanticRoleLabeling`
: This parameter serves for setting the address of Semantic Role Labeling server.

B.2 Sesame RDF Uploader

This application is used for uploading extracted RDF files to the RDF storage (Sesame). We strongly recommend to use the latest version (currently: `openrdf-sesame-2.7.0`) of the storage, because there were serious problems with SPARQL queries in the previous versions.

The application is started by the following command:

```
java -jar RdfUploader.jar
```

and accepts these arguments:

`-a` , `--address`
: The address of the repository server.

`-r` , `--repository`
: The identifier (name) of the repository.

`-i ,--inputFolder`
: Folder, where the input RDF files are expected. By default, this is `app_root_folder/rdf/`

B.3 Visualization

As was already mentioned, the visualization is implemented as a web application. It requires a web server supporting PHP programming language. Since this application is obtaining data from an RDF storage, there has to be one on disposal and its address has to be specified in the file `loadJSON.php` .

Running demo can be seen at: http://rybak.in/visue/.

B.4 RDF storage

We have good experience with the latest release of Sesame RDF storage[2]. It requires Apache Tomcat 7 and as long as there is no need for storing data in database, no installation or configuration is required.

[2] http://www.openrdf.org/

Appendix C

Digital Attachments

This thesis is accompanied with an archive file containing the source codes, example data and third-party software.

Hierarchy of the DVD:

```
/
├── Code
│   ├── SesameRdfUploader ........ Tool for uploading RDF triples to storage.
│   ├── VisueEvaluationTool ............... Tool evaluating extraction results.
│   ├── VisueExtraction .................. Information Extraction application.
│   └── VisueVisualization ..................... Visualization web application.
├── ExtractedData ......................... Examples of extraction results.
│   ├── RDF
│   └── XML
├── New York Times Corpus Example . . Modified version of a file from NYTC.
├── Ontology ............................ Ontology of finance-related verbs
├── Thesis ....................................... Source files of this thesis.
└── Third Party Software
    ├── Sesame RDF storage ..................... RDF storage - version 2.7.0.
    └── SRL-MateTools ............................ Pre-configured SRL tool.
```

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