Contents

CHAPTER 1

Introduction

1.1 Motivation

I was motivated to write a Phd thesis because I did not want to work directly after finishing my study

1.2 Organization

This thesis is organized as follows, ...

CHAPTER 2

Background

The aim of this work is to create a model that predicts if an article comment or a forum post can be classified as "persuasive" or "non-persuasive". We'll first give general definitions about persuasion and argumentation, and how the corpus was annotated. Then, the tool that was used to perform the classfication, DKPro Text Classification Framework, will be introduced and its functionnalities will be explained. Finally we'll discuss about the algorithm used and the metrics to evaluate our model.

2.1 Argumentation

2.1.1 General Definitions

2.1.2 Persuasion

2.1.3 Persuasion 2.0

2.2 NLP and the DKPro Framework

2.2.1 Natural Language Processing

2.2.2 UIMA

DKPro stands for *Darmstadt Knowledge Processing* [3] and it's a software suite for NLP based on the Apache UIMA Framework. UIMA are software systems that analyse large volumes of unstructured information in order to discover knowledge that is relevant to an end user. An example UIMA application might ingest plain text and identify entities, such as persons, places, organizations; or relations, such as works-for or located-at:

The real power of UIMA is its Analysis Engines (AE) which basically analyse a document and record descriptive attributes. Those descriptive attributes will form the docu-

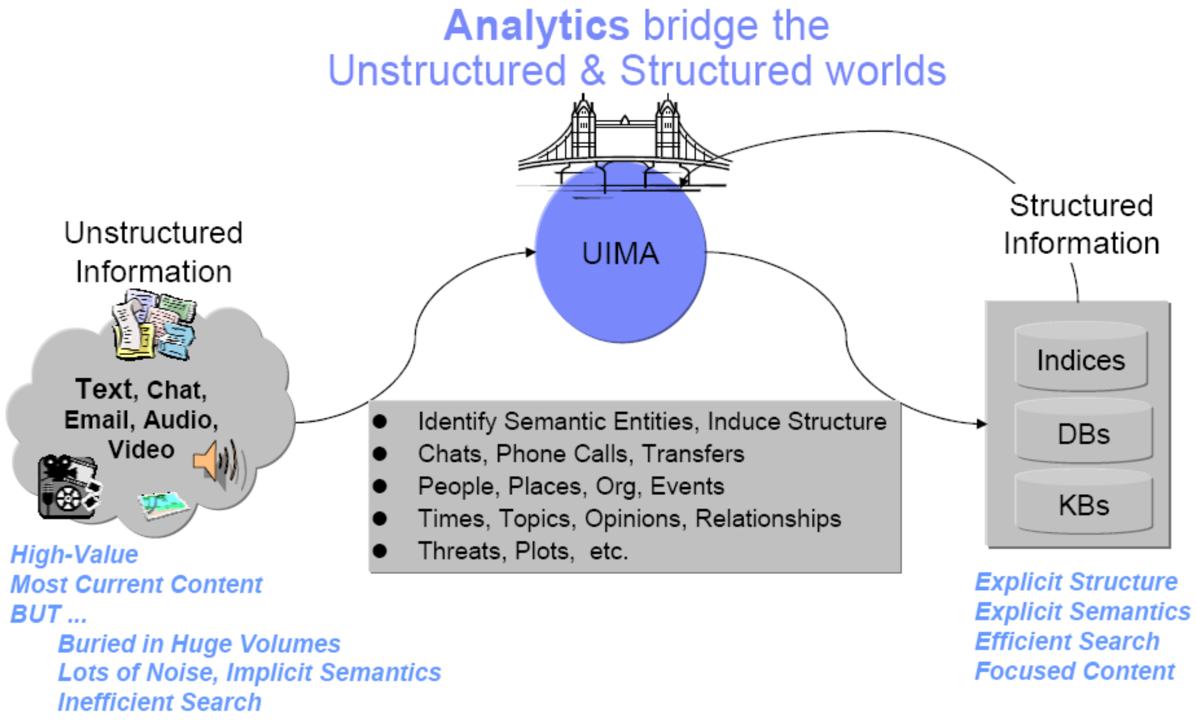


Figure 2.1: UIMA: Order unstructured data, from UIMA website [1]

ment's metadata that will be used for further analysis (such as Text Classification in our case).

GIVE EXAMPLES OF AE HERE AND DKPRO PROC PIPILINE AND CAS ?

Thus, the DKPRo software use UIMA's AE in order to collect structured information about textual data.

2.2.3 DKPro Core

Many NLP tools are already freely available in the NLP research community. DKPro Core [2] provides UIMA components wrapping these tools (and some original tools) so they can be used interchangeably in UIMA processing pipelines. The provided components wrap a constantly growing set of stand-of-the-art NLP tools and also include several original components written Java covering a wide range of tasks including: tokenization/segmentation, compound splitting, stemming, part-of-speech tagging, lemmatization, constituency parsing, dependency parsing, named entity recognition, coreference resolution, language identification, spelling correction, grammar checking, and support for reading and writing various file and corpus formats.

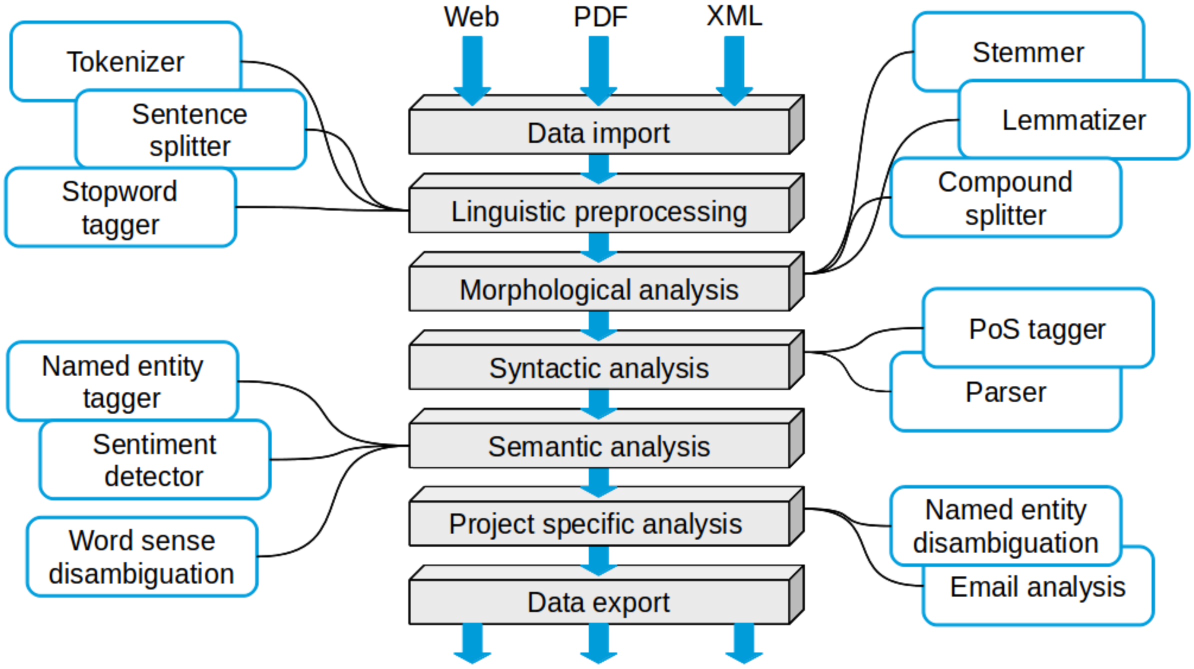


Figure 2.2: DKPro Core Pipeline

Core has several annotators either developed in-house or wrapped[1] from the state-of-the-art NLP libraries. Here is a non exhaustive list:

- **Stanford NLP** - segmentation, la lemmatisation, part of speech...
- **OpenNLP** - machine learning based toolkit for the processing of natural language text: tokenization, sentence segmentation, part-of-speech tagging, named entity extraction, chunking, parsing, and coreference resolution.
- **CleanNLP** - robust NLP components implemented in Java for part-of-speech tagging, dependency parsing, semantic role labelling...

2.2.4 DKPro Text Classification

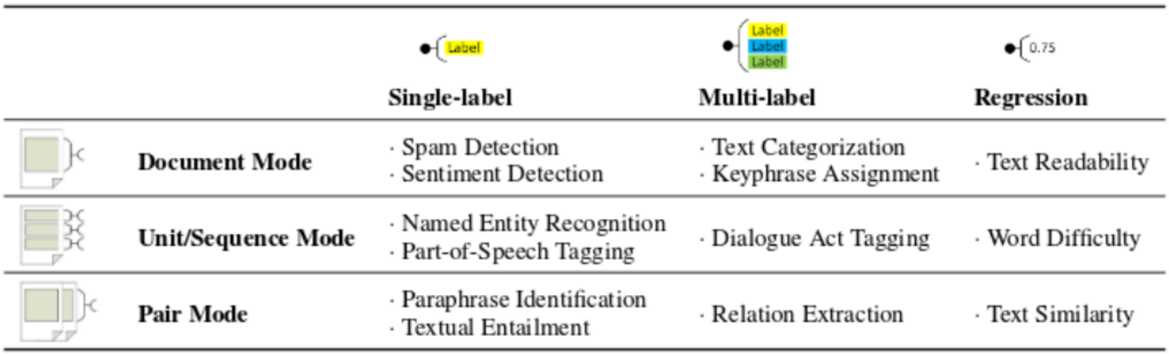
The aim of DKPro TC (commonly called TC) is to allow the user to apply machine learning algorithms easily on the extracted annotations. This framework was built in order to execute the following tasks:

- Supervised learning Classification. The user should provide annotated textual data.
- Can work atomically on text (word, sentence, paragraph) or on pairs of documents.
- Can perform single-label classification, multi-label classification and regression. DEFS

[1] A wrapper function is a subroutine in a software library or a computer program whose main purpose is to call a second subroutine or a system call with little or no additional computation. Source: Wikipedia

Concerning the algorithms used, TC relies on Weka[2] (*Waikato Environment for Knowledge Analysis*). Developed by the Waikato University in New Zealand, Weka is an open-source Data Mining software written in Java, which makes available to its users not only Machine Learning algorithms but also processing features (attribute selections and transformations) and a user interface with visualization tools. Regularly updated, Weka is one of the main state-of-the-art data mining software used in research.

Weka is integrated to TC thank to one major component: the **feature**. In the code, the feature is usually a class that computes a certain value (ex: length of a post, number of adjectives in a text, ect...) using the annotation provided by the DKPro pipeline. Features can be implemented by polymorphism from the mother-class *FeatureExtractorResource_ImplBase*. The results are then saved in an *ARFF* [3] file, which corresponds to Weka's format files.


Label
Label
Label
Label
0.75

	Single-label	Multi-label	Regression
Document Mode	· Spam Detection · Sentiment Detection	· Text Categorization · Keyphrase Assignment	· Text Readability
Unit/Sequence Mode	· Named Entity Recognition · Part-of-Speech Tagging	· Dialogue Act Tagging	· Word Difficulty
Pair Mode	· Paraphrase Identification · Textual Entailment	· Relation Extraction	· Text Similarity

Figure 2.3: The different usages of DKPro TC

In a nutshell, TC adds 4 more steps to DKPro Core:

- A step where the data are labelled, since we're doing supervised learning. In practice, the label information is extracted my a function of the reader ??WHERE do we define reader ?
- Extraction of the features from the annotations.
- Data Processing and Cross Validation ??DEF
- Report of the results (Accuracy, Macro F-Measure, ect...)

The TC developers give regularly some helpful tutorials on their website[4].

License and usage
While most DKPro TC modules are available under the Apache Software License (ASL) version 2, there are a few modules that depend on external libraries and are thus licensed under the General Public Licence (GPL).

[2] http://www.cs.waikato.ac.nz/ml/weka/

[3] An ARFF (Attribute-Relation File Format) file is an ASCII text file that describes a list of instances sharing a set of attributes.

[4] https://code.google.com/p/dkpro-tc/wiki/DemoExperiments

The SVN[5] commits of the different modules are available through Google code and the integration of new functionalities in a project is made possible by Maven (appendix B). It's also possible to use DKPro TC with Groovy which is an object-oriented programming language for the Java platform and destined to be run on a server.

[5] Apache Subversion (often abbreviated SVN, after the command name svn) is a software versioning and revision control system distributed as free software under the Apache License.

CHAPTER 3

The Research Work

In this part, we'll see how the theoretical knowledge in Argumentation Theory and NLP presented were applied to a concrete case study. We'll first see the types of textual data we have, how they were annotated for the supervised learning task and then how features were engineered to perform an automatic classification.

3.1 Text Corpus

The data set used for this study was originally composed of 990 text files. They contain forum posts or articles about 6 different domains related to education, that provoke debate in the American society:

- **homeschooling**: It's the education of children outside the formal settings of public or private schools and is usually undertaken directly by parents or tutors.
- **redshirting**: The practice of postponing entrance into kindergarten of age-eligible children in order to allow extra time for socioemotional, intellectual, or physical growth.
- **prayer in schools**: Debate about whether or not a public school should allow and allocate time and buildings for religious practices.
- **public vs private schools**: Which kind of school offers the best education.
- **mainstreaming**: In the context of education, it's the practice of educating students with special needs in regular classes during specific time periods based on their skills.
- **single sex education**: The practice of conducting education where male and female students attend separate classes or in separate buildings or schools.

The meta-information for each text (id, type of post, domain) is given my the name of the file in itself such as follow:

174_P2_artcomment_homeschooling.txt

$\frac{\text{Text}}{1}\frac{\text{Text}}{2}\frac{\text{Text}}{3}$??FIND A WAY TO DO IT THIS WAY

Later in the internship, I started to use *XMI* files[1] that contain more information about the post or comment in itself such as the author, the date, ect... ??Annexe with how xmi looks like ?

3.1.1 Manual Annotation

As mentioned before, the classification we want to perform is a supervised learning problem since it wants to imitate the human decision on judging if a post is persuasive or not. An annotation guideline was written by Ivan Habernal [4] in order for the annotators to understand the task. In this section, we'll discuss about the general ideas of this guideline.

3.1.1.1 Sources of the data

The textual data that will be used for the studies come from to kind of online sources:
artcomment: Article Comments, reactions to online articles
forumpost: Forum Posts, posts in online debates

3.1.1.2 Categories in Persuasion

The task: Distinguish, whether the comment is persuasive regarding the discussed topic. The key question to answer is: *Does the author intend to convince us clearly about his/her attitude or opinion towards the topic?* If the answer is yes, we classify the comment as persuasive. There are two main categories in this task, namely P1:Persuasive and P2:Non-persuasive. The second category is further divided into more categories, that basically cover the various phenomena that may be encountered in the data.

However, It is not necessary to categorize the data exactly into one of the categories under P2:Non-persuasive. For example, a particular text may be both off-topic and out-of-context; in that case, choose either of these categories.
Remember: we are mainly interested in finding the P1:Persuasive documents that represent on-topic texts with intentions to persuade and convince the readers.

Quick overview of possible distinct categories:
P1: Persuasive
P2: Non-persuasive
   P2.1: Out-of-context or reaction to other comment
   P2.3: Off-topic
   P2.4: Personal worries
   P2.5: Story-sharing without intentions to persuade
   P2.7: Impossible to decide about persuasiveness without deep background knowledge

While the annotation phase, the annotators were charged of determining if a text was in

[1] The XML Metadata Interchange (XMI) is an Object Management Group (OMG) standard for exchanging metadata information via Extensible Markup Language (XML).

the P1 class and if not they had to specify to which of the seven P2 subclasses it belongs to.

3.1.1.3 Examples

Clearly belongs to P1

#2013 (forumpost, single-sex-education) School should be co-ed. Some children are awkward with others of their own gender. For example, certain girls who are tom-boys might not be comfortable in a room full of girls. The mixed genders are preparing kids for the real world, where things are not segregated.

In #2013, the author states that schools should not be single-sex, also provides reasons why he/she thinks so.

Problematic P1 case

This section discusses some examples that were marked as P1 by two annotators but as P2 by a third annotator. We will explain, where the third annotator made an error.

#300 (artcomment, homeschooling) This is not representative of most homeschoolers. This is a very, very small minority. Lets compare that to entire schools in the public school system that cater their teaching to make sure their kids pass the standardized tests so they can keep funding, meanwhile the kids cant understand concepts that arent covered on the tests.

I was homeschooled in Texas, where there is no government oversight of homeschooling. I graduated high school at age 16 with 24 college credits under my belt, was accepted into every university I applied to (all the major schools in Texas), and graduated college in three years at age 19 after being on the Deans List every semester except one. Neither of my parents has a college degree and would not be deemed "qualified" to teach me. Somehow I didnt just make it, I thrived. Parental involvement works.

The second paragraph in #300 contains a statement "parental involvement works", which is clearly in favor of homeschooling.

P2.1: Non-persuasive, out-of-context or reaction to other comment

#3245 (artcomment, public-private-schools) Why are they bad, they still pay taxes but dont use the service so there is more money for the system to use on fixing its issues. Even when everyone is doing everything they can to fix something does not mean it will be fixed.

In #3245, without any context, we can only roughly guess what the author is writing about.

P2.3: Non-persuasive, off-topic

#2049 (artcomment, single-sex-education) Single-sex education. A poem./ Dearest people, the people/ always arguing and full of hate,/ why oh why should we ever/ turn out this way? Single-sex,/ co-educational, why does it matter?/ Girls, boys, everyone;/ WE CANNOT REMAIN LIKE THIS/ do you hear me?

P2.4: Non-persuasive, personal worries

#5024 (artcomment, redshirting) Oh boy. . . oh my little (but very tall) girl. Ive chosen to put her into a second year of preschool next year (5 days instead of 3) because I feel that's what is right for her. She's a late October baby, but I'm not sure she's ready for kindergarten. But I worry. Will she be the giant of her class every year? Will there be an opportunity to skip her a grade? She's quite bright, but socially still a little awkward. I don't feel I'm "holding her back", yet if she has brand new twin sisters arriving in July, should I totally turn her world upside down and ship her off to another school with mostly older kids? I'm torn (and totally on the fence) both ways. I want her to excel academically, but I don't want to throw too many changes at her at once. I'm with you, Erica. I'm torn, and I chose the now unpopular "redshirting", but not so she can be a hockey superstar. . . :) I just thought this was a better pace for her. In ten years, I'm sure the "experts" will be telling me I should have held her back, because all the young kids are struggling. . . You can't win.

In #5024, the author only expresses her worries about her child, but she neither takes stance on the topic nor argues about that.

P2.5: Non-persuasive, story-sharing without intentions to persuade

#5030 (artcomment, redshirting) Born in November, my youngest sister was among the oldest children in her peer group until she skipped a grade (I believe she skipped grade one but it may have been grade two). My other sister, also born in November and two years older, showed my youngest sister her homework and my youngest sister proved such a quick learner the teacher had no choice but to recommend she be moved up. Shes still achieving plenty and has never been intimidated by anyone older. She has a competitive drive and enjoys pushing herself forward.

The purpose of #5030 was to share the story without taking stance towards the topic or persuading others (the story of her sister skipping a grade and doing well could is also too far from the redshirting topic).

P2.7: Non-persuasive, impossible to decide about persuasiveness without deep back-ground knowledge

#164 (artcomment, homeschooling): Child abuse in the name of religious freedom. Just like parents who refuse medical treatment for their children. It makes me wish there was a hell.

In #164, without knowing the context that homeschooling and religion education are somehow related issues in some communities, it is not possible to decide about persuasiveness of this document.

3.1.1.4 Annotation Process

Three annotators were charged of labelling the data as P1 and P2 (if P2, he was asked to specify the subclass). For every annotations, the annotator could write a comment about why he thinks the text can be considered as persuasive or not. This comment can be useful especially if there's a conflict among the 3 annotators.

Once the annotations are performed, a discussion takes place with the annotators in order to solve issues and conflict annotations. If all annotators agree on the class (P1 or P2) of a text, the class will be set as the *gold label* of this text. But if after the discussion, there's still a conflict, the text will be labelled according to majority.

To evaluate how well were the annotations, we compare statistical metrics that are described in appendix C such as Recall, Precision, Accuracy and Macro F_1 measure. The comparison will be performed on 4 scenario:

- A_1 **vs** A_2
- A_1 **vs** A_3
- A_2 **vs** A_3
- 3 Annotators **vs** Gold data

A_1, A_2, A_3 stand for Annotator number 1, 2 and 3.

3.1.1.5 Results of the Manual Annotations

We measure the performances of the annotations on 3 batches of text data, and we aggregate the results:

				Persuasive			Non-Persuasive		
	Docs	Macro F_1	Acc.	P	R	F_1	P	R	F_1
Batch 1									
A1	100	0.879	0.880	0.942	0.845	0.891	0.813	0.929	0.867
A2	100	0.895	0.900	0.875	0.966	0.918	0.944	0.810	0.872
A3	100	0.849	0.850	0.922	0.810	0.862	0.776	0.905	0.835
Batch 2									
A1	200	0.855	0.855	0.909	0.792	0.847	0.813	0.919	0.863
A2	200	0.910	0.910	0.919	0.901	0.910	0.901	0.919	0.910
A3	200	0.874	0.875	0.839	0.931	0.883	0.920	0.818	0.866
Batch 3									
A1	509	0.927	0.927	0.953	0.906	0.929	0.902	0.950	0.926
A2	502	0.879	0.884	0.836	0.986	0.905	0.977	0.757	0.853
A3	511	0.907	0.908	0.977	0.835	0.900	0.857	0.981	0.915
All data									
A1	809	0.904	0.904	0.942	0.871	0.905	0.867	0.940	0.902
A2	802	0.890	0.893	0.858	0.964	0.908	0.948	0.807	0.872
A3	811	0.893	0.893	0.929	0.855	0.890	0.861	0.932	0.895

Table 3.1: Human performance on *gold data persuasive.*

??help: Find a way to say the results are good that's why we want to do a text classification.

3.1.2 Corpus Statistics

Now that we have the *gold labels* for the texts, we can sum the relevant information in a table: ??Find a ways for the color and the size

		redshirting	prayer-in-schools	homeschooling	single-sex-education	mai
P1	artcomment	24	60	64	17	1
	forumpost	14	17	22	9	9
	all	38	77	86	26	10
P2	artcomment	15	43	93	16	2
	forumpost	15	23	45	8	17
	all	30	66	138	24	19
P1 + P2	Total	68	143	224	50	29
	Percentage	6.9	14.4	22.6	5.1	2.9

3.1.3 Conflict Annotations

??Mention the conflict annotations + some statistics

3.2 Feature Engineering

Now that we have all our data annotated, we have to extract relevant information from it in order to perform the classification. The problem of identifying persuasion in a text is a relatively new question in NLP and we don't have any straightforward methodology to find relevant features. Thus, we'll implement the NLP standard features that are used widely in other sub-fields of language processing and then we'll use the state-of-the-art features discovered in Argumentation Mining. A lot of modules of DKPro helped us to create our features but we had to extend somehow the software for certain functionalities that were not in DKPro Core and TC (for example the *Sentiment Analysis*).

3.2.1 Lexical Features

The adjective lexical refers to the words and the vocabulary of a corpus. This part will deal with the extraction of meaningful features related to words, sentences, tokens[2], punctuations, ect...

3.2.1.1 Tokens N-Grams

In NLP, an n-gram is a contiguous sequence of n (with n integer) items from a given sequence of text or speech. As a result of, tokens n-grams are sequences of tokens from

[2] Tokenization is the process of breaking a stream of text up into words, phrases, symbols, or other meaningful elements called tokens.

a text (*Note:* For more information about units in linguistics such as words, tokens, lemma and stemma, have a look at appendix D). The study of n-grams distribution in a corpus is an ancient technique [5] in language processing and it's usage is common in the field.

In this study, we use a DKPro available feature that extracts the 10.000 most common 1,2 and 3-grams in all the corpus and returns for each text a 10000-dimensional binary vector. Each vector element corresponds to one of the 10000 extracted n-gram, its value is 1 the text contains the n-grams, 0 otherwise.

To better understand this feature, let's take a simple example. We consider that the set of 1-grams contains 10 elements such as follow:

$$E = \{2, 1990, a, born, dog, Frankfurt, in, I, was, zoo\}$$

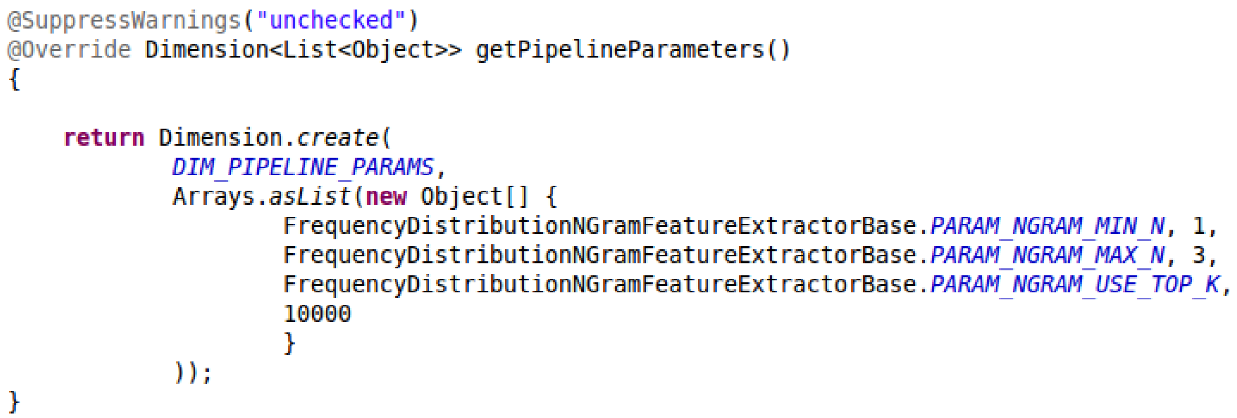
If the text input is:

```
I was born in 1990
```

DKPro will return the following binary 10-dimensional vector:

2	1990	a	born	dog	Frankfurt	in	I	was	zoo
0	1	0	1	0	0	1	1	1	0

As mentioned before, this feature is already implemented in DKPro and it's easy to use it in a pipeline.



```
@SuppressWarnings("unchecked")
@Override Dimension<List<Object>> getPipelineParameters()
{

    return Dimension.create(
            DIM_PIPELINE_PARAMS,
            Arrays.asList(new Object[] {
                    FrequencyDistributionNGramFeatureExtractorBase.PARAM_NGRAM_MIN_N, 1,
                    FrequencyDistributionNGramFeatureExtractorBase.PARAM_NGRAM_MAX_N, 3,
                    FrequencyDistributionNGramFeatureExtractorBase.PARAM_NGRAM_USE_TOP_K,
                    10000
                    }
            ));
}
```

Figure 3.1: NGram Feature in DKPro Java code

As displayed on 3.1, the n-gram feature extractor takes three parameters: *PARAM_NGRAM_MIN_N* for the minimal value of n, *PARAM_NGRAM_MAX_N* for the maximal value of n and *PARAM_NGRAM_USE_TOP_K* which is the number of common n-grams retained. Since we want the 10.000 most common 1,2 and 3-grams, the parameters are set such as follow:

```
PARAM_NGRAM_MIN_N = 1

PARAM_NGRAM_MAX_N = 3
```

```
PARAM_NGRAM_USE_TOP_K = 1
```

APPENDIX A

DKPro Core Overview

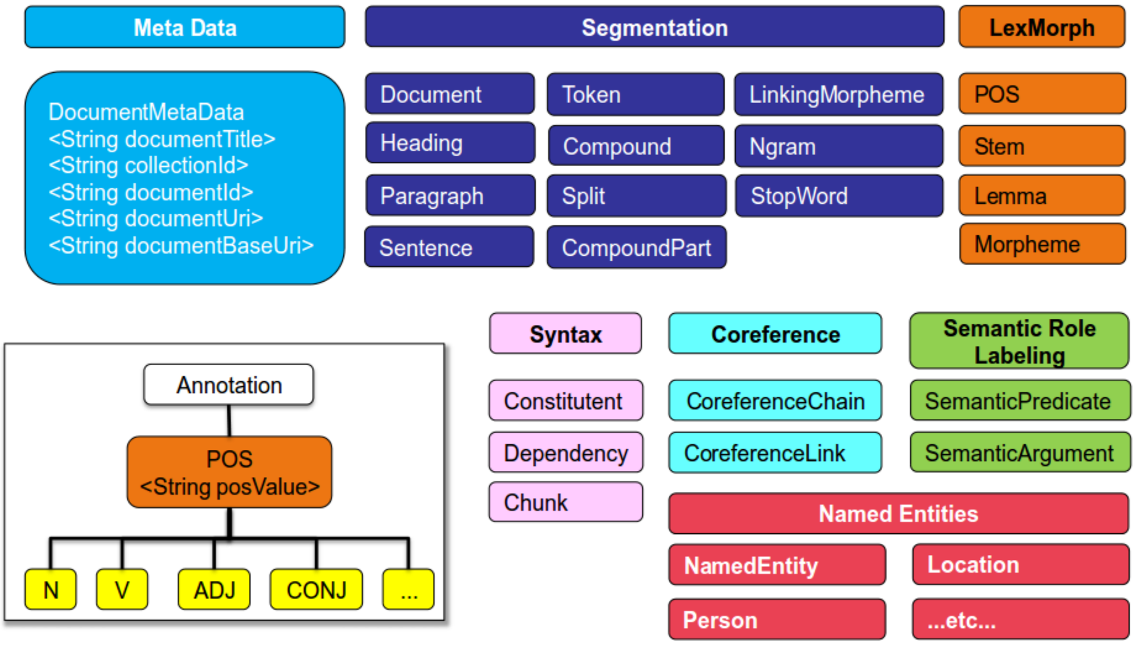


Figure A.1: DKPro Type System

APPENDIX B

Maven

TODO: Explain the functionalities of Maven.

APPENDIX C

Statistical Analysis of Binary Classification

TODO: TP, FP, R, P, Accuracy, F-mes, ect...

APPENDIX D

Units of linguistic morphology

TODO: Words, Tokens, Lemma, Stemma

Glossary

gold data Bla bla. 11

supervised learning Supervised learning is the machine learning task of inferring a function from labelled training data. 4

token Tokenization is the process of breaking a stream of text up into words, phrases, symbols, or other meaningful elements called tokens.. 12

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