Article Duplicates

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Summary (English)

The goal of this thesis is create is to document my work with implementing a working prototype of using algorithms to find article duplicates in a large corpus of articles. I will describe how the article inflow is currently working and how Infomedia plans on implementing my work in this inflow.

I will look at various algorithms for text comparison, and look into the possibility of creating my own or tweak an existing algorithm to better suit the needs for this thesis.

Finally I will create a summary of the work done, problems I have come upon and what the future of the project will be.

Summary (Danish)

Målet for denne afhandling er at dokumentere mit arbejde med at finde artikel duplikater, i et større artikel corpus, ved brug af algoritmer. Jeg vil beskrive hvordan Infomedias artikel inflow virker nu, og hvordan Infomedia planlægger at bruge mit arbejde i fremtiden.

Jeg vil undersøge forskellige tekstsammenlignings algoritmer, og undersøge muligheden for at lave min egen algoritme, eller modificere en eksisterende algoritme til at bedre udføre det arbejde jeg laver i denne opgave.

Til sidst vil jeg gennemgå det arbejde jeg har lavet, hvilke problemer jeg løb ind i og hvad fremtiden for projektet vil være.

Preface

This thesis was prepared at the department of Informatics and Mathematical Modelling at the Technical University of Denmark in fulfilment of the requirements for acquiring an B.Eng. in Informatics.
The project is equal to 20 ECTS points.

This thesis is protected by confidentiality. No information from this thesis can be handed off to any party without signed permission.

All excerpts from articles are owned by the respective authors / papers.

The thesis deals with the issue of finding articles that are duplicates in a large corpus of articles. This is done using various algorithms and is implemented in C#.

The thesis consists of ...

Lyngby, 09-June-2014

Not Real

Brian Lynnerup Pedersen

Acknowledgements

I would like to thank my supervisors from DTU, Inge Li Gørtz and Philip Bille, for the help they provided to my project. Also I would like to thank my company Infomedia, for letting me do my project with them, in particular my project leader Klaus Wenzel Jørgensen and Rene Madsen.

Contents

Chapter 1

Introduction

As mentioned above, I have done this thesis for the company I work for, Infomedia[1]. I have been working for them since my fourth semester at DTU (march 2012), while studying as an IT engineer (B.Eng.). Infomedia is in short a company that deals with news monitoring.

Infomedia is the result of a fusion between Berlingske Avisdata and Polinfo in 2002, which means that Infomedia is partly owned by JP/Politikens Hus[2] and Berlingske Media[3]. It is a company with around 150 employees, of which 107 is contract employees and the rest is student aides in the various departments. Infomedia has various departments, which includes an economy, sales, analysis and an IT department amongst others.
I am employed in the IT department (*PIT - Product Innovation and Technology)* as a student programmer (student aide).

Infomedia deals with news monitoring, which means that we have an inflow of articles[4] from various newspapers, news sites, television and radio media, which we then monitor for content that is of interest to our clients. This can be a client that wishes to know when their firm is mentioned in the press or

[1] www.infomedia.dk

[2] www.jppol.dk

[3] www.berlingskemedia.dk

[4] Articles are sent to Infomedia daily, this can be more than 40,000 articles per day.

a product they are using, if that is being mentioned. Currently (while writing this thesis) the upcoming EP[5] election is going on, and politicians are using the monitoring service from Infomedia to track how they are doing in the media Infomedia[Alb14]. Infomedia had a free for all news monitoring of the EP election, meaning that all interested could sign up for a getting a daily (weekdays) news monitoring mail from Infomedia, containing the top stories about the EP election. Amongst other things a candidate visibility monitoring was created[Inf14]. Infomedia have also begun monitoring social media. Infomedia sells various solutions to clients, so they can get the kind of media monitoring they want.

One of the things that Infomedia tries to do, is that we want to present our clients with a fast overview of the articles in which terms[6], that trigger our news monitoring, appear. Many local newspapers are today owned by bigger media houses (like the owners of Infomedia) and as such, they will feature a lot of the articles that have also been printed in the "mother paper". This will make the same (or roughly the same[7]) article appear many times in news monitoring. In an effort to make the list of articles presented to the clients, easy to look at, and preventing a client having to read the "same" article many times, Infomedia has a wish to cluster article duplicates. Infomedia can then present the client with a list of articles and in that list have further sub lists that contains duplicates of the original aritcle[8]. This also have an economic factor as clients are charged per article read.

Another issue, is the issue of copyrights and when the same article will appear in different media, but without content given from the author of that article. An example that is often happening is that news telegrams from Reuters[9] or Ritzau[10] is published in a newspaper, but without the source indication. All news media are of course interested in knowing when their material is being published in competing media. This how ever can be tricky business, as official rules on the matter is incredible fuzzy.

[5] EP - European Parliament.

[6] A term is, in short, a word or a combination of words. For the rest of my thesis a term will however only be a single word.

[7] Articles can be slightly edited in order to make them fit into the layout of the various papers.

[8] Or the longest article rather, as this will tend to contain the most information.

[9] `www.reuters.com`

[10] `www.ritzau.dk`

1.1 Thesis Statement

I will in this thesis try and look into various ways of identifying article duplicates (or articles that have a lot of text in common) within a test corpus[11] of articles, by using algorithms. The long term goal for Infomedia is having this being implemented in the inflow of articles, and having a look back functionality so that we can group duplicates not just for one day, but for a longer period of time.

1.2 Limitation

Due to the time constraints, this will be done as prototype. I will show through testing how the algorithms works, and analyse their results. These results will then be evaluated and I will comment on these findings.

[11] A days worth of articles from 10/31/2013 - totalling 22.787 articles.

Chapter 2

General - Terms and Rules

I will in this chapter cover the essentials of the expressions and terms used throughout this thesis.

2.1 Terms

As there is a lot of terms used in this thesis, a short introduction to the most used are in order.

- **Article:** For this thesis, a digital document containing the contents of a piece of news. Could originate from papers, magazines, TV or other forms of media. For this thesis a document corresponds to an article. Articles are in their electronic form stored at Infomedia as XML files, I will throughout this thesis only deal with the part of the XML files that contains data of value to me in this assignment. This being *Tags* (see below), *Headline*, *Sub headline* and *Article Text*.

- **Corpus:** From Latin meaning *body*. In this thesis that describes the test set of articles being used a test set throughout my thesis.

- **Monitoring:** In relation to the news monitoring (news surveillance) that Infomedia does, is the act of collecting news that holds information of value to our customers.
- **Tag:** Used in Ontology[1] to create words that describes the contents of an article.
- **Term:** Basically a word. A term will be something that can be searched for.

2.2 Matching

I will in this thesis talk about false and true positives and negatives. A match will mean that two articles to some extend have the same content.

- **False Positive:** When an algorithm wrongfully identifies two articles as a match.
- **False Negative:** When an algorithm wrongfully identifies two articles as not being a match, when in fact they are a match.
- **True Positive:** When an algorithm correctly identifies two articles as a match.
- **True Negative:** When an algorithm correctly identifies two articles as not being a match.

2.3 Duplicates

In this thesis I will often use the term 'duplicates' or 'match' about article comparisons. A duplication (match) can be an article that has been taken directly from a news feed and posted in a newspaper. Many local newspapers is owned by larger newspapers, and they will often receive articles from their owning paper. They will then print this in their own paper. Sometimes they will only use parts of the article and this will also be considered a duplicate for this thesis. As such duplication in this thesis is a way of describing how similar two articles are, rather than saying different papers are doing conscious fraud. That is a matter for another thesis.

[1] http://en.wikipedia.org/wiki/Ontology_(information_science)

2.3.1 Topic Matching

When looking at article matching, there is also the possibility of having articles score pretty well by the algorithms because they are dealing with the same topic. There are cases where the article have been heavily modified, and then there would be no basis to talk about duplication, then one could talk about topic matching. The article no longer contains the same phrases, but deals with the same topic. Of course two articles could describe the same topic, but never have been related to begin with. I will not try and dissect whether this is the case, only try and indicate when I find two articles that are dealing with the same topic, and mark them as such.

2.3.2 Copyright

It is hard to talking about duplicating without talking about copyrights. Although this thesis will not delve into whether something is duplicated as a part of a copyright infringement, it seems only reasonable to give a moment to talk about what a copyright is, and how it would affect duplication.

I feel that this quote is fulfilling as to explaining the concept of *'copyright'*, even if it is talking about a case that is ongoing in USA at the time, and copyright rules can vary from nation to nation.

> A copyright is basically a legal protection for an original expression on a fixed medium. So a song on a record, words on a page, ballet steps written down, and paint on a canvas are all copyrightable things. A phone book is not copyrightable (it's not original). A copyright only protects the expression and not the underlying idea. Marvel does not have a corner on men in mechanical suits who fight crime – they only have the particular expression of that idea in Iron Man comic books.
>
> Confused? That's okay. Copyrights are pretty complex things. A lot of what can be copyrighted is figured out in court when people fight over it. The basic test that the court will pose in this case is "is the expression original? Does the potentially infringing work actually borrow from the original expression?" [Lin14]

So the whole concept is extremely fuzzy, and often the infringement part will have to be settled in court. In the recent years that have been a lot of debate in which university educated people have become accused of plagiarism in relation to their doctoral or master thesis[2,3]. A hard topic to deal with in a fixed way, and to top it off, there is also the notion of *"fair use"*[4]. Although there is no real fair use paragraph in Danish law, we instead have *'låneregler'*[5].

In the world that Infomedia is dealing with, articles are also a target of duplication, and a lot of effort have begun being invested into this, as it can be a question about a lot of money if you fail to protect your copyrighted material. So the motivation in finding article duplicates can be two sided. First off, it creates a better overview for Infomedia's customers, secondly newspapers are very interested in finding out if their material is being used, unlicensed, in other media.

Hvornår er en artikel et duplikat (korte artikler (breaking news), hvornår er to artikler "tilstrækkeligt" forskellige?) blah about copyright rules in Denmark...

[2] http://www.theguardian.com/world/2011/feb/16/german-defence-minister-plagiarism-accusation

[3] http://www.nytimes.com/2012/04/03/world/europe/hungarian-president-pal-schmitt-resigns-amid-plagiarism-scandal.html?_r=0

[4] http://www.umuc.edu/library/libhow/copyright.cfm#fairuse_definition

[5] http://da.wikipedia.org/wiki/Fair_use

Chapter 3

Analysis

This chapter describes the considerations taken in picking an algorithm, as well as what is already implemented at Infomedia.

3.1 Algorithms in General

Before any sort of work can be done, one must consider various algorithm to work with. There are several text matching algorithms available for free on the Internet, and if one has the money for it, there are companies that can develop a specialized algorithm for you. As I do not have a lot of money (and paying for someone else, to do an algorithm for me, kind of defeats the purpose of this whole thesis) I have gone with the first option and found a free basic algorithm on the Internet, as well as contemplated to create my own algorithm from scratch.

3.1.1 Requirements Analysis

The algorithms should be able to live up to the following demands:

- The algorithm should be able to work with text.
- Performance is of secondary importance, but should have good accuracy (performance $<$ accuracy).
- The algorithm shall be able to return a score based on how identical two articles are.
- The algorithm should be focus on doing one thing only (not try to do several forms of text comparisons).
- The algorithm shall be available in an open source, or free to use, licence.

3.2 Initial Considerations

Infomedia already have an algorithm implemented in the inflow to make a rough comparison of the articles coming in. How ever, the thought is that a combination of several algorithms would provide a better and more granular view of the articles as they are being compared. A new algorithm should be one that was specialized in text matching. It should also be an algorithm that would work in different manner than what Infomedia already have implemented[1], as having two algorithms that work in more or less the same fashion would not produce results of much interest.

As the current implementation is rather fast, it could prove useful to have the algorithm that is already implemented, do the initial rough split of matches and no matches, and then have a slower (but more thorough) algorithm look at the *interesting* article comparisons. Initially I have looked at two algorithms to fill this need, *Longest Common Substring* and *Semaphore Tag Matching* - an algorithm I would make from scratch.

3.2.1 System Architecture

As mentioned the various algorithms should work in different ways, meaning they should have various ways. This is to ensure a balanced image of how much an article comparison is actually a match. The thought is, that instead of having a few algorithm having to have many focus areas. It is better to have many that only focus on one thing, then combine their scores into a broad representation of how similar two articles is.

[1] More on the algorithm already implemented in the next section.

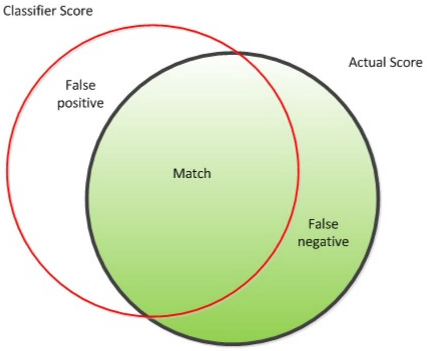


Figure 3.1: Variation between how a single algorithm might score an article comparison, and how the actual score should be[ML14].

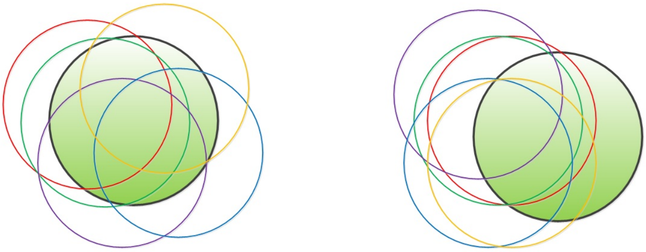


Figure 3.2: **Left:** A balanced score, obtained by using several algorithm with different focus areas. **Right:** An unbalanced score, obtained by using several algorithms with the same focus area[ML14].

The essential thing in this, is to ensure that the various algorithms works in different ways. If one were to use many algorithms that all focused on the same way of doing text comparisons, the results would not provide that broad image of scores that is wanted for a more accurate score representation.

The idea is that the algorithms should do 99.9% of the work in identifying article duplicates, and then have the last 0.1% be verified by humans. This is already how things are working at Infomedia, but only with one algorithm at the moment. My work will the be the first algorithm to do a check of the work done by the already implemented algorithm. This will hopefully narrow the field of possible article duplicates that has to be verified by human eyes.

The system would then ideally work as follows.

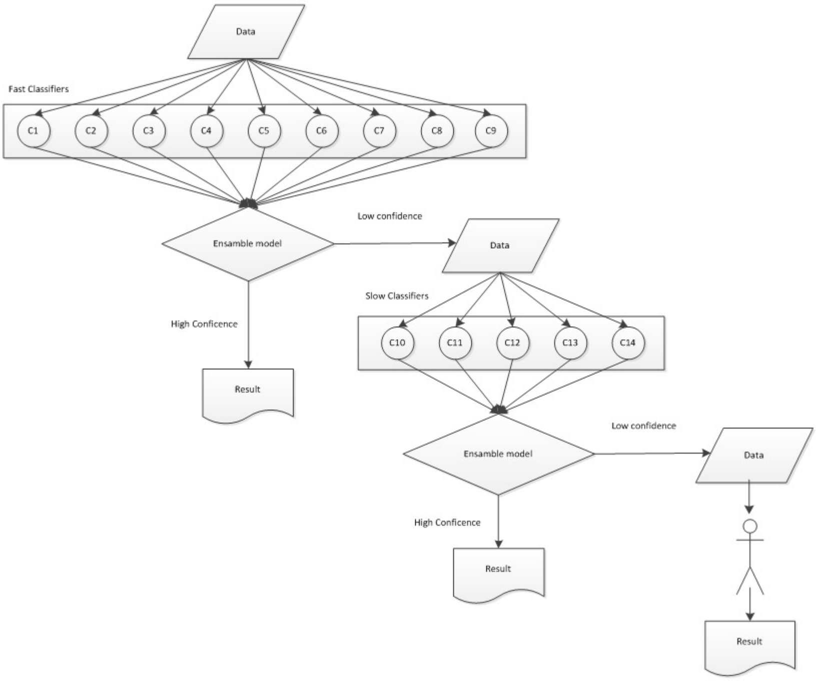


Figure 3.3: System Architecture, with many algorithms doing text analysis[ML14].

When data (articles) arrives in the inflow, a number of fast algorithms would then do the rough split of the comparisons. All of these comparisons would then receive scores, that would then be evaluated through the ensemble model. If the scores leaves no doubt (is over a given threshold) that the article comparison is a match, the comparison would stored as a match. If the scores of the comparisons leaves some degree of doubt as to whether a comparison is a match or not (the scores being between a set of thresholds), the comparisons are then passed on to the slower algorithms, that then in turn would evaluate the comparisons. If these algorithms find that the comparison is a match, it would be stored as such. If there is still some doubt to whether it is a match or not, the articles would then finally be sent for human evaluation. The task of my thesis is to create a secondary algorithm (one of the slower ones) to evaluate the results given from the faster (and already implemented) algorithm.

3.3 Algorithms Used

Term Frequency - Inverse Document Frequency[Wik14b] (Cosine), generates a vector from each document. **I will not cover this algorithm in detail, as I have not done any work on it, only used some of the methods in it for my thesis.** This is the algorithm already implemented in the inflow today (a modified version of it, that is based on the Vector Space Model[2]). Each word in every article is added to a *word map* which contains all the words of all articles in the corpus being checked (which also is used to create the document vector). The word map is used to generate a weight of each word (a word occurring in many articles will have less weight than a word that is only present in a few articles). Each word generates a bit of the articles total vector, a word that occurs in all documents will have a very short vector, a more rare word will have a longer (and therefore weigh heavier) in the article vector.

Once the word map is created, the articles are then scored. The way that this is done, is that the algorithm compares two article's vectors with each other and then returns a score based on the cosine angle between the two article vectors. This is done one article comparison at a time (although done with parallel coding to speed up the process). As the word map is generated each time the algorithm is run, the word map can (and probably will) differ from each run (if the corpus of articles are being changed). Infomedia is therefore talking about implementing this bit differently, and building a constant word map, that only gets updated with each run, not overwritten. This will ensure that common words will always have a short vector.

The algorithm then returns a list of article comparisons (based on a threshold set by the user), with article ID[3] and scores. So each comparison has the ID of *"article 1"* and *"article 2"* and their score (the angle between the two vectors, in a multidimensional universe). The closer the score is to the value 1.0 the more similar are two articles. A score of 0.0 indicates that two articles has nothing in common (according to this algorithm, I will discuss this point in the next paragraph), whereas a score of 1.0 indicates two perfectly identical articles (according to this algorithm). This algorithm and it has a good O-notation (O(log N)).

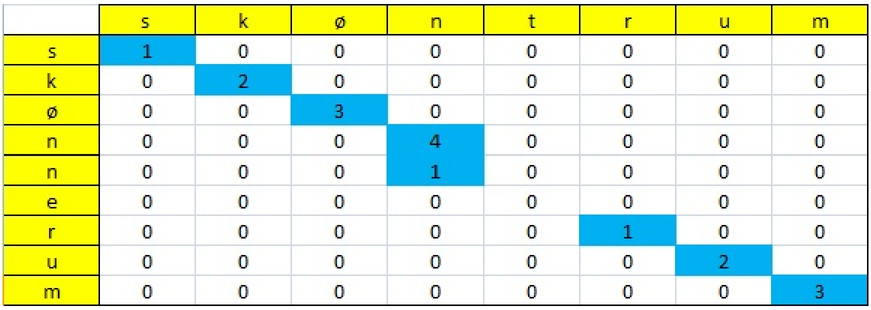
Problem: This string comparison is very sensitive to articles containing many of the same words, for instance "A man walks his dog in the park" and "A dog walks his man in the park" would result in returning a cosine value of 1.0, due to the way the algorithm works. The two strings are clearly different, but the

[2] `http://en.wikipedia.org/wiki/Vector_space_model`

[3] Each article has their own unique ID.

words in each string is the same, therefore the Cosine algorithm will find them to be identical. This problem is very unlikely to yield false positives.

Longest Common Substring (LCS), compares documents in pairs. A general implementation would be to have a list of documents and then compare a document to every other document in the list. The algorithm will then return the length of the longest common substring. By default the LCS algorithm[Wik14a] checks the contents of a string character by character against another string. When initialized, the algorithm creates an double array and each time a match is found (when two identical characters are found ('a' and 'a' for instance)) the algorithm marks that in the array by adding a number. It then checks if this substring is longer than what has previous been found, if so, it discards the old substring and keeps the newly found.



	s	k	ø	n	t	r	u	m
s	1	0	0	0	0	0	0	0
k	0	2	0	0	0	0	0	0
ø	0	0	3	0	0	0	0	0
n	0	0	0	4	0	0	0	0
n	0	0	0	1	0	0	0	0
e	0	0	0	0	0	0	0	0
r	0	0	0	0	0	1	0	0
u	0	0	0	0	0	0	2	0
m	0	0	0	0	0	0	0	3

Figure 3.4: An example of how two words are compared in LCS. The fields in yellow are the two words broken into characters ('Skøntrum' and 'Skønnerum'). The fields in blue indicates when LCS finds a match, the number indicates the length of the substring. In this case, LCS finds three sub strings:'skøn', 'n' and 'rum', the longest of the three is the first, and this will be the result that LCS returns to the user.

I will use the basic implementation of this algorithm in my thesis, I will then try and modify it to work better in context with finding article duplicates, instead of just the longest common substring.

Problem: This algorithm is very prone to fail in cases where there have been made alterations to the article in question. A word change in the middle of one of two otherwise identical articles will result in a 50 % match. If the article in question have been obfuscated with many changed words, the LCS will be extremely short. This is a high risk problem, as article duplication will often involve changing words. This algorithm is also substantially slower than the Cosine algorithm, having an O-notation of O(n*m). Ideally this algorithm is therefore best used on a selection of articles, rather than on the entire corpus.

3.4 Optimizing Performance

3.4.1 Stop Words

Stop word[4] removal would improve running time (performance) of both algorithms, and would pose little threat of causing either algorithm to fail (finding false positives). The exception to this could be very short articles (like breaking news articles[5]), that only contains common words, like "Man walks away". Depending on the stop word list, this article could end up being *null*[6]. We can safely (with respects to the previously addressed problem) remove stop words, as they don't provide any *semantic*[7] value to the text.

3.4.1.1 Cosine

For the cosine algorithm removal of stop words would improve performance, by reducing the size of the *Magnitude Vector.*

3.4.1.2 LCS

In regards to the LCS algorithm, the performance would also be improved, as the algorithm wouldn't need to traverse as many characters. This would reduce the length of the longest common substring, but it would be unlikely that it would affect the outcome of the algorithm, as stop words are rarely changed when duplicating articles.

3.4.2 Stemming

Stemming[8] Stemming is the act of conjugating a word to the base form (Danish: *'Grundform'*). It is done in order to reduce the amount of noise in a text. Words will then be conjugated and instead of having the same word represented

[4] `http://en.wikipedia.org/wiki/Stop_words`

[5] Breaking News articles is a thing of the 2000s. With the spread of media onto the Internet, an article is no longer a static printed piece of news in a paper. News can be published instantly on the web, and then updated as information are received. How ever, Breaking News articles can still be printed in the paper article with only little text attached to it.

[6] An article with no text data.

[7] `http://en.wikipedia.org/wiki/Semantics`

[8] `http://en.wikipedia.org/wiki/Stemming`

several time in different conjugations they will all be noted as the same word. Stemming does not ruin the semantic content of the text.

3.4.2.1 Cosine

Stemming improves the performance of the cosine algorithm as this will reduce the number of words in the *vector space*. As words would be reduced to their base form (Danish:*Grundform*), words used several times, but with different endings would be counted as the same word. When using weighed evaluation this would actually improve performance to some extend. It can have a slight impact of the Cosine algorithm. This is because that without stemming the same word can occur several times in a text in different conjugations, and thus each conjugation would have a larger vector than when the conjugations are all counted as the same word. This impact will be minimal because the rare words are still occurring less often than normal words (stop words).

3.4.2.2 LCS

Stemming would not improve the performance of the LCS algorithm by much. As this algorithm matches characters one by one, it would make little difference if the words are stemmed or not. As the 'Grundform' is the shortest form of a word in Danish, it will make a slight difference, but this is hardly worth noting.

3.5 Semaphore Tagging

Another way of finding duplicates is by looking at each articles semaphore tags. When Infomedia receives articles in the inflow, these articles are enriched with *Semaphore Tags*[9]. A tag also has relations to other tags. A politician would be tagged with politics, political party, other people in politics that are in some way associated with that person. The tag is also enriched with a score, that is based on the relevance for that tag in that given article. So if a politician is the main focus of an article, the name of that politician is high than if the article deals with something that the politician only have a remote connection to. Each

[9] Semaphore tags are tags that describes the contents of the article, an article about financial fraud would contain the tag *Economic Crime*. These tags are created by the Infomedia Ontology (`http://en.wikipedia.org/wiki/Ontology_(information_science)`) team. They are creating rules for when a certain word (or words) appear in certain context, then an article will be tagged with a certain semaphore tag.

article then gets a number of tags based on what terms are found in the article. A way of finding article duplicates could be through creating an algorithm that would check a pair of articles with their respective semaphore tags.

3.5.1 Cons to Semaphore

As these tags are more of a general indicator to an articles' contents than an actual text matching algorithm, it will provide very little value as a stand alone implementation. Each article will only contain tags for the terms, for which the ontology team has created semantic rules for. If 100 articles all contained various doings of a minister (picking up the children, going to meetings, being involved in a crisis) many of the same tags would be present in the 100 articles, this could be the ministers name, political party and other general tags that are linked to this minister. It would therefore be hard to decipher much information that could truly and uniquely link two articles together just by doing this. However this could be used to enhance another algorithm (for instance one of the two mentioned above). If the articles compared contains the same tags, they are likely to have some sort of relevance to each other, and if the tags also have matching scores, that would strengthen the possibility of a match. I will not look any further into implementing this algorithm in this thesis, as this approach is difficult in providing a definite result.

3.6 Text Preparation

To reduce the chance of the algorithms failing in detecting duplicates, the text should be 'normalized'. As there are quite a few pitfalls in text analysis, one should try and take as many precautions as possible. A common source of error is common spelling errors, I will not check my article for spelling errors. These can have a rather big impact on the LCS algorithm. However as all text editors today have spell checking, this will be a tiny error source.

As the focus of this thesis have been on proving the thesis statement, there has been done no text preparation other than what is already implemented.

Another problem with text analysis is localized spelling. An example of this can be the Swedish town of Malmö. The issue here being the 'ö' letter which is in the Swedish alphabet. This town's name can be spelled in a few different ways.

- Malmö (Swedish spelling)

- Malmø (Danish and Norwegian spelling)
- Malmo (English spelling)
- Malmoe (Phonetic spelling of the 'ö' character)

The same article could be in different newspapers, but with different spelling of the word. All words, or rather words containing special characters (non English characters) should therefore be normalized. In this case, the character 'ö' could be normalized into the letter 'o'. The phonetic spelling of the 'ö' character is highly unlikely to occur, as the normalized way of spelling 'Malmö' in languages without the 'ö' vowel, would be the third option. There is a lot of issues in this regard. This could be words or characters in a non Latin alphabet (Cyrillic, Arabic, Greek letters used in SI references or others). For this thesis, there is few non Danish texts or words in the test corpus, so it will have little influence. I will in this thesis not normalize text, but accept that minor deviance in scores can occur due to this.

Another good choice in text preparations is to lower case and remove all non alpha numerical characters. This can be advantageous for instance when looking at the name of the current Danish prime minister, Helle Thorning-Schmidt. As the hyphen can often be forgotten the last name can easily be misspelled. Removing the hyphen and replacing it with a blank space character would improve the accuracy of the algorithms.

Stemming is another good way of normalizing text, I have already covered this topic in a previous section, and will not cover this more in detail here.

Stop words will reduce the number of words in an article, and with less words, there are less error margin in terms of spelling errors, also less words in the article text means less words that has to be analysed. As stop words have little meaning when trying to figure out if two articles match, it is a good idea to remove these in order to improve performance.

Unfortunately due to the time limit of this thesis, I will not be able to look into any of text the preparations mentioned, but wanted to describe what should be kept in mind, when implementing this project into Infomedia's inflow.

Finally it is important that all files are stored with the same encoding[10], as different encoding could cause havoc in the systems ability to read the text in the files. This is already done in the system, so I will not worry about this factor in my thesis.

[10] http://en.wikipedia.org/wiki/Character_encoding

3.7 Technology

As the inflow system at Infomedia is created in C$^\sharp$, it is the easy (and logical) choice to create my work in C$^\sharp$ as well. This would help integrating my work into the existing systems without too much trouble. I am using Visual Studio 2013 and .NET version 4.5 for my code development, which is provided to me by Infomedia. I am using Infomedias Team Foundation Server (TFS) for version control.

Chapter 4

Implementation

This chapter deals with the description of implementing and modifying the LCS.

For this thesis there was created a test project in the Infomedia TFS where I could do my work. This was so that I would not mess up Infomedia's inflow while trying to make the algorithms work correctly.

4.1 Basic LCS Implementation

First off the Cosine algorithm was implemented in said test project. There was no changes to that implementation, it was implemented to work as it currently does in our inflow. Doing this, would make testing the LCS implementation show what results would be returned once this was in production. After that the basic implementation of LCS was implemented.

Then the basic LCS algorithm was implemented in the project, to be used for further development. It is taken without modifications from the wikibooks site [Wik14a].

```
public int LongestCommonSubstring(string str1,
         string str2)
{
    if (String.IsNullOrEmpty(str1)
        || String.IsNullOrEmpty(str2))
    return 0;

        int[,] num = new int[str1.Length, str2.Length];
        int maxlen = 0;

    for (int i = 0; i < str1.Length; i++)
        {
        for (int j = 0; j < str2.Length; j++)
        {
                if (str1[i] != str2[j])
                num[i, j] = 0;
            else
            {
                if ((i == 0) || (j == 0))
                        num[i, j] = 1;
                else
                    num[i, j] = 1 + num[i - 1, j - 1];

                    if (num[i, j] > maxlen)
                    {
                        maxlen = num[i, j];
                        }
                }
        }
        }
    return maxlen;
}
```

Listing 4.1: Basic LCS implementation in C♯

The LCS method works by taking in two strings as arguments and then comparing them character by character (see figure 3.4. First off the algorithm checks to see if either of the string arguments are either *null* or *Empty*, which basically means that it makes a check for if either argument either was not set when calling the method or that either string was without any content. Because if this is the case, then the returning value will be 0, and there is no need to do any further work. The method then creates two arrays, one for each of the strings. It then tries to match the first character of the first array with all characters of the second array, marking any matches with a number. The number is given by checking the value in the double array on step back diagonally (see figure

3.4), if it is the first time a match was found, that number will be stored as the length of the longest common substring. When ever another match is found, the algorithm then checks to see if the length (number in the [i, j] space of the array) are bigger than the length of the current longest common substring. If this is the case, the newly found max length is then stored. After having checked all places in the [i, j] array, the algorithm then returns the length of the longest common substring.

This implementation can easily be modified to return the content of the longest common substring (all the chars in that String)[1].

This works really well for finding substrings that can have been obfuscated in long lines of text. How ever in this thesis, the main objective is to find substrings of plain words rather than finding bits and pieces.

When comparing two articles with the LCS, the algorithm finds a lot of substrings, but only keeps the longest by default

The next step was to modify the LCS algorithm to make it suit the needs of this thesis. When looking at article duplicates, it makes more sense to look for entire words rather than single characters. This is because when an article is duplicated, any obfuscation or alteration would be done by cutting out sections of the article or moving sections around or adding new sections.

4.2 Modification of LCS - String Comparison

As hinted both in the text of the last section and also in figure 5.1, the next step was to modify LCS to compare whole words (string) instead of single letters (char). There are of course pros and cons to this approach. One of the pros would be that we could improve the performance of the algorithm. If we assume that the average word length is roughly five characters long[2], that means that comparing articles on a character by character basis increases the number of comparisons by a factor of 25 as compared to doing it word by word. This will therefore mean we can get a rather big performance boost, and when talking about an inflow that just for my test corpus contains 22800 articles, but can be as many as 40000 articles daily, this factor will make quite the impact. Another pro is that we are looking for word duplication, not for sentences ob-

[1] `http://en.wikibooks.org/wiki/Algorithm_Implementation/Strings/Longest_common_substring#Retrieve_the_Longest_Substring`

[2] `http://www.wolframalpha.com/input/?i=average+english+word+length` - although it is for English words, it is most likely not that different from Danish.

fuscated within other sentences, therefore we do not really need to look at single characters.

On the cons side is the fact that if we are looking for words rather than single characters the algorithm becomes more prone to spelling errors. If the word *'doomsday device'* was included in an article and in an article that is a duplicate of that article was a spelling error *'doomday device'*, this would cause the character based substring to be slightly longer than than the words based substring. The character based substring would return *'sday device'* whereas the word based substring would only contain *'device'*. This can be an issue within texts that have many spelling error, but that case is highly unlikely to appear in the articles this thesis is dealing with, as one would assume that journalists are pretty okay with correct spelling (and also has spelling checking on their text programs).

So even though modifying LCS to compare words with words rather than characters, can return incorrect results, the likely hood of this being a substantial error source is negligible.

4.2.1 Issue With Word (String) Comparisons

The issue with comparing words rather than single characters in data science, is that the way comparison is done with data types, which is not as easy as when a human would do text comparison. For a human, reading and comparing two list of single letters, would be substantially slower than comparing two lists of words. This is based on how we recognize both single letters and words. A computer does things in a completely different way.
The basic implementation of LCS compares chars with chars, a char being a primitive data type in most modern objective oriented programming languages (Java, C$^\sharp$, Objective C, C++ and so on). Comparing primitives is a simple operation, just checking their values. The modification being implemented here would compare Strings with Strings, a String being of data type *'object'* in object oriented languages. A String is internally a list of chars, that makes up the whole String, so comparing a String object with another String object is basically doing a char comparison (with some minor differences, such as String comparison also checks the length of the Strings).

However, in a future implementation of the modified version of LCS, one could transform the Strings into an int (one could use the word map generated by the Cosine algorithm for this), so that each word gets it's own int value, comparing the words as int values would be much faster than both the String and char comparison. This is because an int is a primitive, like the char, and instead of having to check a lot of chars for each "word", there would only be a need to check a single int value for each word. This would improve the overall performance of LCS dramatically (approximately by a factor 25, by applying the same theory as above, each word on average being five characters long) as the list of words (int) would be substantially shorter than the lists of chars. The conversion of String to int could be done in the text preparation phase (see Section 3.6).

Due to the fact that I did not contemplate this until late in the work process, there have been no time to implement a String to int conversion in the LCS modification.

For testing purposes it is nicer and easier to read text split up into words rather than text split in chars, so that is a feature of the String comparison modification of LCS.

So even though it adds no immediate performance boost, this is both a step on the way and helping hand in terms of evaluating the results from LCS.

4.3 Collection of Substrings

Another modification to the LCS that would help finding article duplicates would be to make LCS create a collection of substrings. The benefits of this would to some extend help eliminate the error prone ways of LCS. If looking at two articles that would be considered a perfect match (same length, same article text), except for the word in middle of the text in one of the articles. If this have been changed, misspelled or forgotten, this would cause the basic implementation of LCS to return that the length of the longest common substring would be just under 50% of the article's length. How ever, if we create a collection of substring we can in part work around this issue. Then we would find two substrings, one before the middle word (that is missing or in other way not present in the same form as in the other article) and one after the middle word. Our combination of substrings would then return a length that is close to 100% of the article length (all words minus the missing word).

When doing this modification one should consider using a threshold that indicates the minimum length a substring should have in order to be included. There will inevitably be a lot of short matches (single words, white spaces, two words that are often in same context and so on) when comparing articles with the LCS. So an effective threshold would be one that filters away the noise, but it not so high that important (in terms of finding duplicates) sentences are filtered out. For this thesis the threshold have been set to four, meaning that all substrings consisting of four or more words are being stored as a result.

When creating the collection of substrings their lengths will be added and compared to the total length, thus creating a hopefully more correct image of whether two articles match or not.

```
public Dictionary<String, String>
 LongestCommonSubstring(List<String> str1,
  List<String> str2, int threshold)
    {
          if (str1.Count == 0 || str2.Count == 0)
              throw new Exception
              ("One␣or␣both␣documents␣was␣empty.");

      int[,] num = new int[str1.Count, str2.Count];

      var combined = new Dictionary<string, string>();

      for (int i = 0; i < str1.Count; i++)
      {
         for (int j = 0; j < str2.Count; j++)
         {
            if (str1[i] != str2[j])
                num[i, j] = 0;
            else
            {
              if ((i == 0) || (j == 0))
                  num[i, j] = 1;
              else
                  num[i, j] = 1 + num[i - 1, j - 1];

              if (num[i, j] >= threshold)
              {
                // Find the start index
                // of the current substring
                String index =
                ((i - num[i, j]) +
                ",␣" + (j - num[i, j]));

                String insert = "";
                // Do we already have this key stored?
                if (!combined.ContainsKey(index))
                {
                    var words = new List<String>();
                    for (int x = 3; x > 0; x--)
                    {
                        words.Add(str1[i - x]);
                    }
                    foreach (String word in words)
                        insert += word + "␣";
                    insert += str1[i] + "␣";
                    combined.Add(index, insert);
                }
                else
                {
                    String valueStore = combined[index];
                    valueStore += str1[i] + "␣";
                    combined[index] = valueStore;
                }
              }
            }
          }
        }
      return combined;
  }
```

Listing 4.2: Modified version of LCS

We can see from listing above, that the LCS works largely in the same way as before. How ever there are (naturally) some changes. The first being we no longer just check to see if the current substring is longer than the current longest common substring. As part of the method arguments we now provide the algorithm with a threshold, this threshold is what we are now evaluating our substrings against. When ever a match is found between two words we then mark the match in the double array as done in the basic LCS implementation. The value of the marked space will then be evaluated against the threshold. If the value is greater than or equal to the threshold value, we want to to store that substring. This is done using a dictionary. The key of the dictionary is the combination of values of i and j combined with a *','*. The key has to be a unique value, which is the reason for adding the comma. This also have the added bonus of making it easier to read for humans, when trying to read the results from the algorithm.

First off the algorithm checks if the [i, j] value (the key in the dictionary) is already in the dictionary, if so, it adds the String content to the value part of the key. If not, it then adds the key and adds the value of the [i, j] space we are looking at and the value of the three previous (diagonally back) values. For each value we add a white space. Again this makes it easier to read, but also, the longest common substring found in the basic LCS implementation would count white spaces as well. The way that the modified LCS is called by the program, it is given two lists of Strings, with only the actual words of the articles, the white spaces are removed. The algorithm then adds white spaces after each word to have a result that matches the basic LCS better.

Once all the words have been matched, the algorithm then returns *result* which then contains all substrings found with a length greater or equal to the given threshold.

4.4 Post Processing

Once all articles in the test corpus (or the selected articles) have been processed through the algorithms and scored, the results and the articles was stored in a data type (see figure 4.1), *AdvancedComparisonResult*, and then that was stored in a list of the same type. This list would then be processed through other methods for creating visual representations of the results.

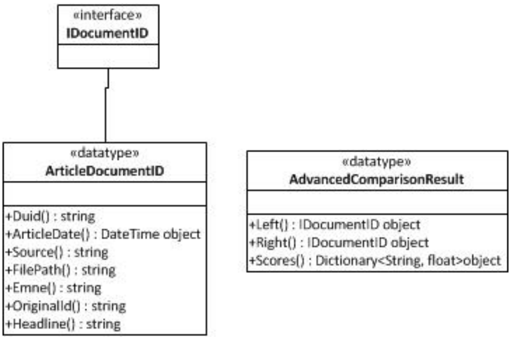


Figure 4.1: The data types used to store article information and information about article comparisons.

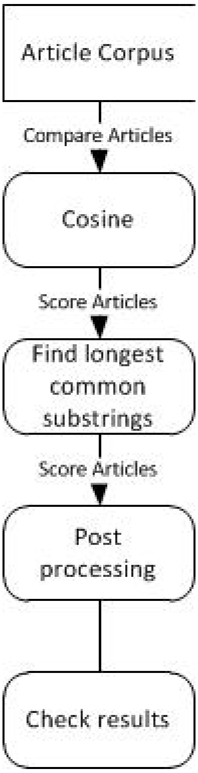


Figure 4.2: Flow chart for the implemented system.

Chapter 5

Test

This chapter describes the tests that was done to make sure the implementation of LCS was working correctly. Also various tests was done on the test corpus using the Cosine algorithm.

During the test segment, there was a focus on mainly four sources (their article content), those being *Jyllands Posten (JP), Politiken (POL), JV.dk (JV) and http://folkebladetlemvig.dk/ (FL).* There is various reasons for picking those four. Jyllands Posten and Politiken are nation wide papers, and some of the most read in Denmark. As such, they have big budgets, big staffs and can afford doing a lot of journalistic work of their own. They could often deal with the same topics, can use the same news agencies (such as Reuters), but would often have a lot of unique material (at least that is the theory to be tested). jv.dk and folkebladetlemvig.dk are both local papers, meaning they they are only published in parts of the country. This means they to a larger extend deals with local happenings and news. They will have less focus on international material. As a small paper they will have small budgets, smaller staff and may not have the journalistic manpower to do much ground breaking, in-depth journalistic work. Also these papers are often distributed freely (their on line content may be protected by a payment wall) in the local area, and as such, their main revenue is adds sales. These adds will take up a lot of space in these papers, allowing for less news articles that in the bigger news papers. Finally a reason for picking these two sources in particular is that they are both owned

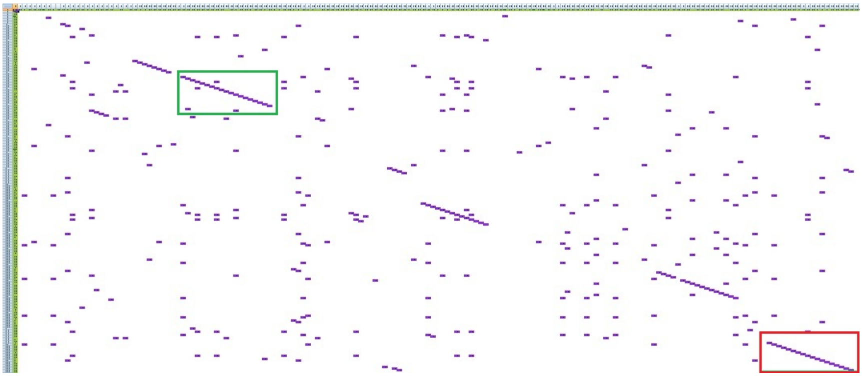


Figure 5.1: Diagram showing the result of two articles being compared by using LCS, and plotted in Excels. See Appendix A.1 for bigger image. The green and red boxes indicates longest common substrings found.

by Belingske Media, and they do therefore make a good case for testing how much (if any) material is shared between media.

After doing the various implementations of the algorithms, testing was made to verify the correctness of these implementations. This interweaves with the sections of the previous chapter.

5.1 Test of the basic LCS

As the final stage of the system implemented, to deal with the article duplication, there is a part that deals with post processing (see figure 4.2). This post processing mainly deals with setting up data in reader friendly way. This involves printing results to an Excel spreadsheet. Plotting the results of the LCS to a spreadsheet helps to illustrate how LCS works, and what results are being found.

An example of this type of plot can be seen in figure 5.1. The leftmost column (in green) is one article split into words, the topmost row (also in green) is another article split into words (in the basic LCS implementation the articles would be split in characters as seen in figure 3.4). All the purple boxes indicates where a match has been found, a diagonal line indicates a row (substring) of matches. The longest one would be the *'Longest Common Substring'* and the length of that would be returned by the algorithm. In the example from Figure 5.1 there

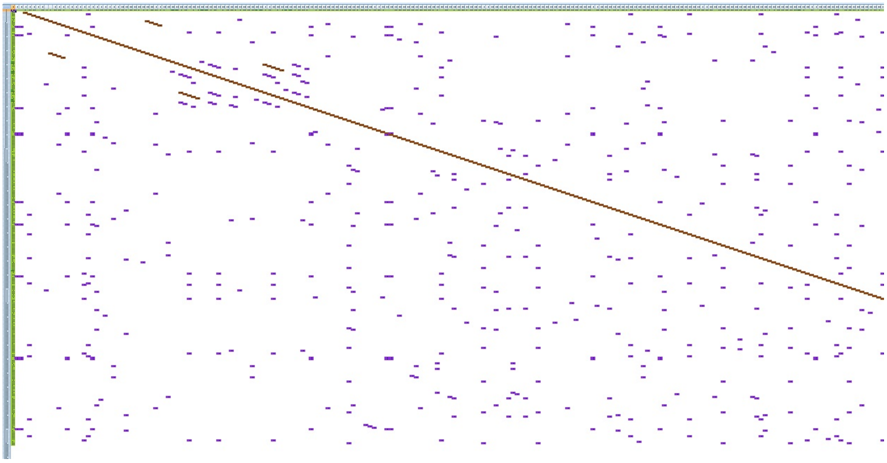


Figure 5.2: Diagram showing a part of an almost perfect match (the article along the y-axis is slightly longer than the article along the x-axis). The long brown diagonal line indicates the longest common substring found.

are two substrings of equal length (each having a length of 19 words (in the basic LCS the length would the number of characters, including white spaces)), how ever as LCS only returns the length of a single longest common substring (the longest found) and the second one (marked in the red box) is same length, LCS returns the length of the first (marked in the green box) substring. Again, as this example is made out of words rather than characters, the result could vary in case of counting actual characters, but for demonstration purposes the figure explains the idea.

In the case of a perfect match (require both articles to be of the exact same length). A line along the diagonal will be drawn. Of course the nature of representing all text in a horizontal way, distorts the image somewhat, as this makes the x-axis seem shorter than the y-axis even though the two might be of equal length.

So, what does this image tell us? Well, for starters it shows us how LCS works. It helps us see how many words the two articles have in common, and it also helps us get an overview of how similar the two articles are, in terms of being duplicated. This was the goal of implementing the LCS in the first place.

In Figure 5.2 there is two articles that are almost 100% identical, the articles are from JV and FL. One of the articles [Win13a] is slightly shorter than the other article [Win13b]. The on line content of the second article is protected by a payment wall, the article content can be found in Appendix B B.1. What is a added bonus of these two articles is that not only are they clearly duplicates, they are also written by the same author, *Johan Winther*, who happens to be a journalist working for Berlingske Tidne[1] as per 2014-05-22. This supports the thesis that the local papers, are fed news from their owning papers, to print in their own papers. This can be out of various reasons, one could be that the owning paper would have covered a story of nation wide importance, but with a special local importance. In this case, the articles deals with the company Danfoss, which is a big company in southern Jutland, and therefore has a big significance for the ares which is covered by the two local papers (JV covers southern Jutland, and FL covers the mid-west-northern part of Jutland).

5.2 Test of the Modified LCS

Once the modified version of LCS was implemented, the post processing underwent some changes to support this. The Excel printing was modified to colour the longest common substrings found, that was longer than the given threshold. All substrings that match that criteria is coloured in brown in the following. After doing some testing with the threshold, a threshold of four was selected. That value seemed to include most important sentences in terms of finding duplicates, without including too much text. Whether we remove stop words or not, should be considered when setting the threshold. Stop words are the easiest to remove or alter when modifying text, as they add little meaning to the overall topic of the text. With efficient stop removal, only key (or more significant) words will remain. These are in much higher degree a pointer to the similarity of two texts.

As seen in figure 5.3 the addition of substring collection significantly alters the result from what we would have gotten, had we only been using the basic LCS implementation. Judging from this diagram the two articles obviously have a lot in common. To tell if the article really have something in common it is needed to take a look at their content. The best way of doing this is by reading it the old fashion way, with your own eyes. All of the verification done in a prototype is expected to be done this way, once the users are satisfied (through repeated manual verification) that no or only very few errors would bypass the algorithms, then the verification would be left to the algorithms (as per figure 3.3).

[1] `http://www.b.dk/redaktionen/johan-winther`

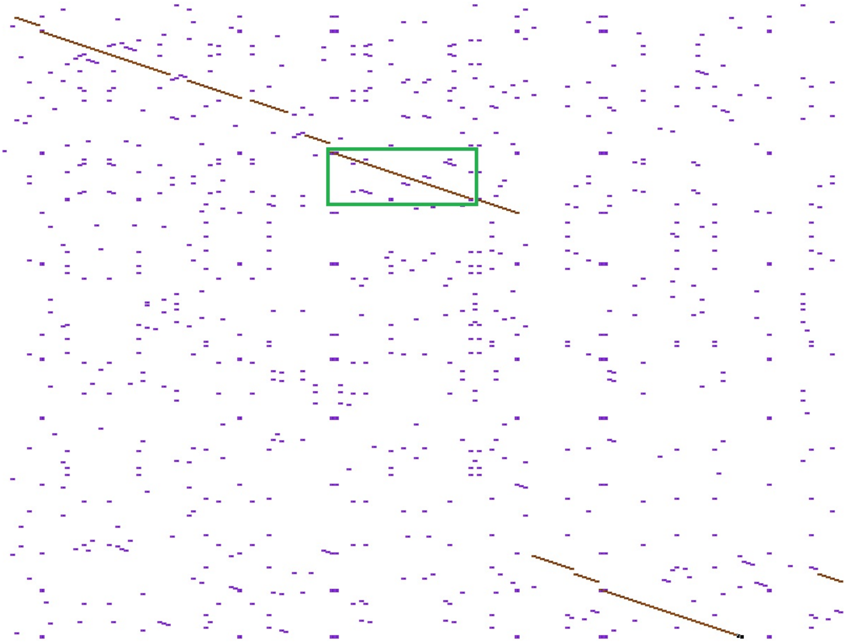


Figure 5.3: The result of having a collection of substrings). All substrings with a minimum length equal or grater to the threshold, have been coloured brown. All substrings that is short than this, is coloured in purple. If only the longest substring had been returned as the result, only the substring (marked by the brown line) in the green box would have been returned.

5.3 Fractile Distribution of Corpus

The way that Consine is implemented in the inflow now, is by scoring article comparisons based on the angle between the article's vectors. This score then indicates (to some extend) how alike two articles are. The score ranges from 0.0 to 1.0. In the inflow, Infomedia simply stores all comparisons with a score above 0.6, these articles can then be verified (this is where LCS will come in handy). For this thesis however, we will compare all articles and then use the LCS on those with a Cosine score above a certain threshold. A Cosine score above 0.9 indicates, with a high degree of certainty, that the two articles being compared are practical identical (there can be modifications to this statement, will be discussed later). A certain Cosine score would therefore qualify for a comparison being automatically accepted as identical, articles below that score and down to a lower threshold would then have to controlled by human eyes. So we would like the LCS to do some of work for the humans by further cutting down the field of possible duplicates. The idea of the Cosine algorithm doing the initial splitting of article comparisons and then letting the somewhat slower LCS algorithm look into the comparisons which are uncertain in relation to being duplicates raises the following question, how many article comparisons are we looking at? For this a test of the test corpus would be made in order to give a visual representation of the task ahead.

Before setting out on the task of comparing all articles in the test corpus, a minor test was made initially. The Cosine algorithm was put to work with scoring all articles from BERL and POL sources in the test corpus, storing the results in fractiles(by intervals of 0.1), and then printing them to an Excel spreadsheet.

As seen in figure 5.4, the vast majority of the article comparison are in the lowest fractile (0.0-0.1 Cosine score), and makes it really hard to use the pie chart for any sort of informative source. The scores are distributed as seen in table 5.1.

So in order to get a more informative view, removing the lowest fractile (comparisons scoring below 0.1 with the Cosine algorithm) will provide a better view (see figure 5.5). Please note that the value given in the various of the sections of the pie chart, is the minimum value of the fractile in question and percentage of comparisons in that fractile. The fractile named '0,9' is the fractile containing all comparisons that scored between 1.0 and 0.9(included).

To double check the test result, and also to test the thesis that JV and FL do share a significant number of articles, a fractile distribution graph was made for those two sources 5.6.

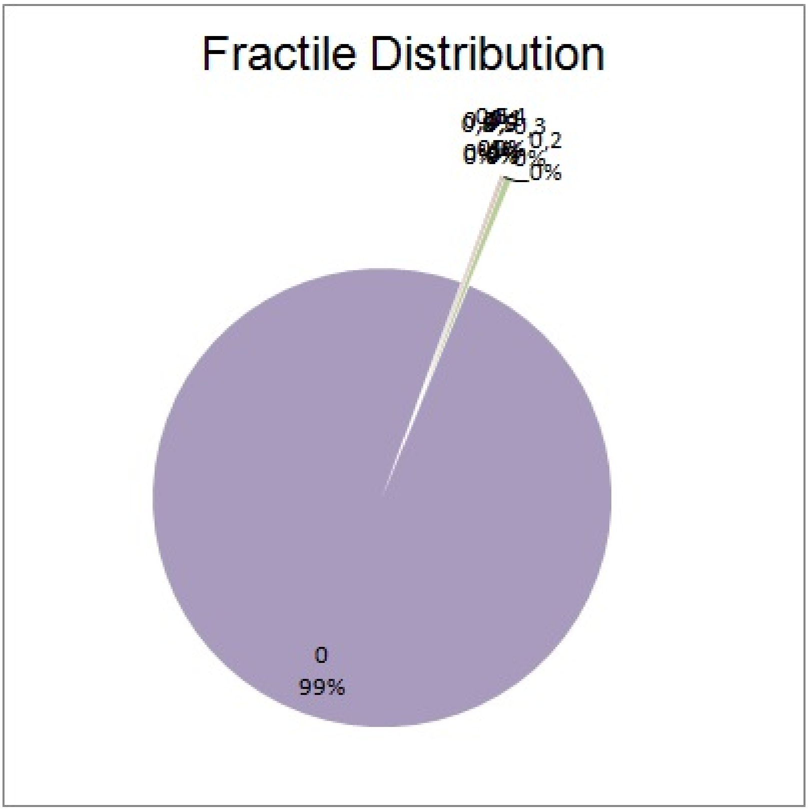


Figure 5.4: The result of running Cosine on all articles in the JP and POL sources (File: "fractile noise.xlsx").

Cosine Score (x)	Number of Comparisons
$x \leq 1.0 \bigwedge x \geq 0.9$	2
$x < 0.9 \bigwedge x \geq 0.8$	1
$x < 0.8 \bigwedge x \geq 0.7$	0
$x < 0.7 \bigwedge x \geq 0.6$	1
$x < 0.6 \bigwedge x \geq 0.5$	2
$x < 0.5 \bigwedge x \geq 0.4$	8
$x < 0.4 \bigwedge x \geq 0.3$	9
$x < 0.3 \bigwedge x \geq 0.2$	17
$x < 0.2 \bigwedge x \geq 0.1$	98
$x < 0.1 \bigwedge x \geq 0.0$	21608
Total Comparisons	21746

Table 5.1: Fractile distribution of article comparisons for JP and POL.

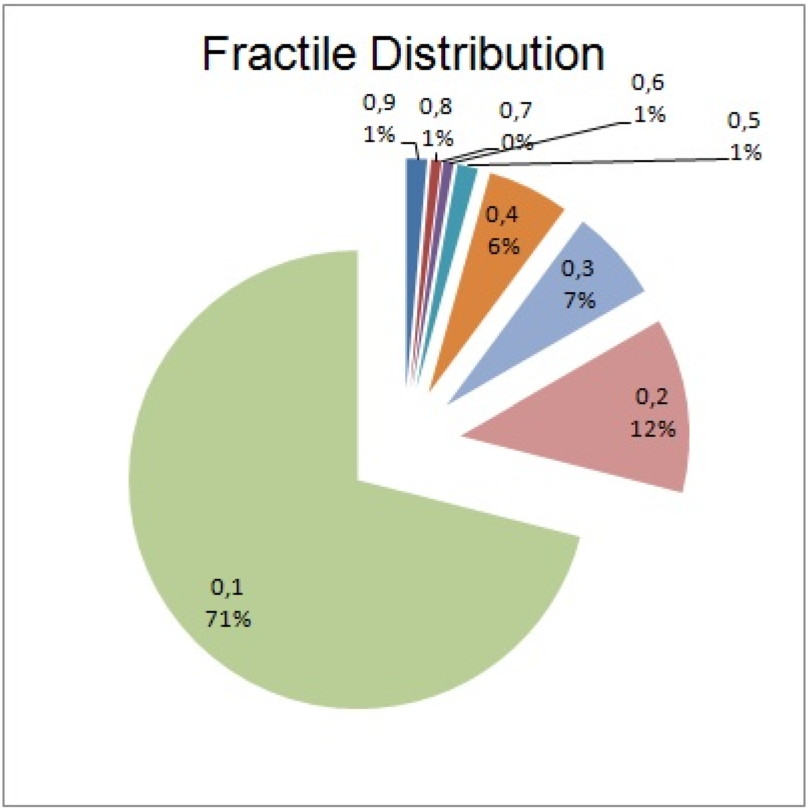


Figure 5.5: Fractile distribution (JP and POL articles) with the comparisons scoring lower than 0.1 in the Cosine comparison removed.

Cosine Score (x)	Number of Comparisons
$x \leq 1.0 \bigwedge x \geq 0.9$	102
$x < 0.9 \bigwedge x \geq 0.8$	1
$x < 0.8 \bigwedge x \geq 0.7$	1
$x < 0.7 \bigwedge x \geq 0.6$	7
$x < 0.6 \bigwedge x \geq 0.5$	6
$x < 0.5 \bigwedge x \geq 0.4$	10
$x < 0.4 \bigwedge x \geq 0.3$	42
$x < 0.3 \bigwedge x \geq 0.2$	99
$x < 0.2 \bigwedge x \geq 0.1$	1342
$x < 0.1 \bigwedge x \geq 0.0$	53017
Total Comparisons	54627

Table 5.2: Fractile distribution of article comparisons for JV and FL.

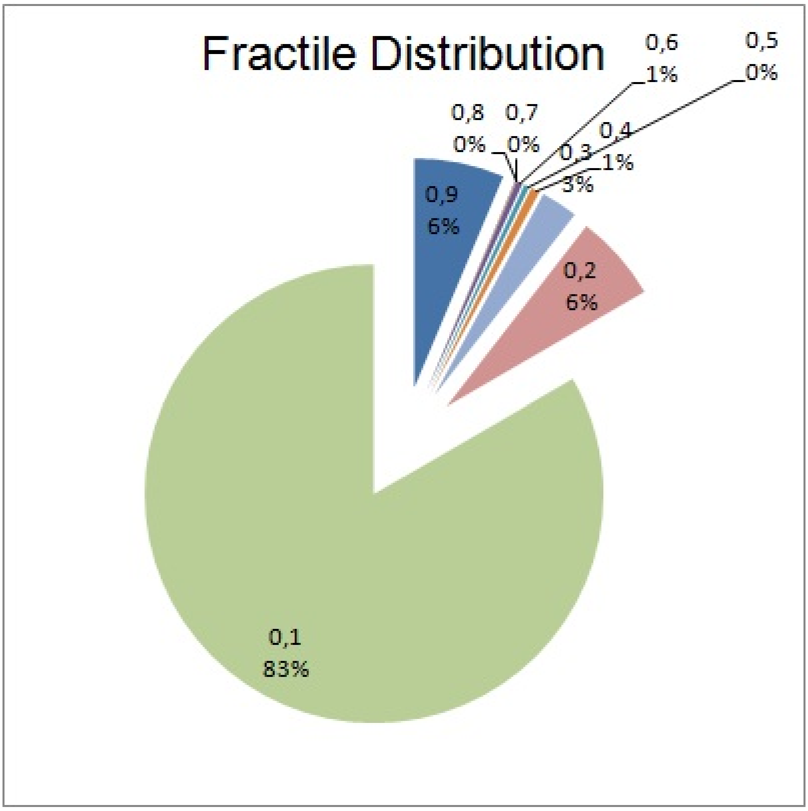


Figure 5.6: Fractile distribution (JV and FL articles) with the comparisons scoring lower than 0.1 in the Cosine comparison removed.

Cosine Score (x)	Number of Comparisons
$x \leq 1.0 \bigwedge x \geq 0.9$	61107
$x < 0.9 \bigwedge x \geq 0.8$	5168
$x < 0.8 \bigwedge x \geq 0.7$	15090
$x < 0.7 \bigwedge x \geq 0.6$	20443
$x < 0.6 \bigwedge x \geq 0.5$	22472
$x < 0.5 \bigwedge x \geq 0.4$	51945
$x < 0.4 \bigwedge x \geq 0.3$	132699
$x < 0.3 \bigwedge x \geq 0.2$	286529
$x < 0.2 \bigwedge x \geq 0.1$	1001151
$x < 0.1 \bigwedge x \geq 0.0$	247311986
Total Comparisons	248908590

Table 5.3: Fractile distribution for all files compared in Cosine.

Once again we see a large amount of comparisons in the 0.1-0.2 fractile 5.6, it being a great deal bigger (83% versus the 71% in figure 5.5 in the 0.1-0.2 fractile). We do however also see a bigger amount of comparisons in the top fractile (0.9-1.0) which would indicate that these two sources actually share quite a few articles, and also have more articles in common than JP and POL.

As a final test, to get the big picture of the task ahead, a test was performed for all articles in the test corpus (File: "symmetric all files fractiles.xlsx"). When running the Cosine algorithm, it is given three parameters the two first being the files to be compared, the third being a list that will contains the comparison score along with the articles information. Cosine starts with making a check of the two file sets, if they are the same, it will do a triangle comparison. This means we only have to check half the number of possible comparisons - minus the diagonal. This is handy if we want to do a comparison on a single set of articles. If you want to compare the articles from two days (or some other time frame), the algorithm will do an asymmetrical comparison, meaning that all possible comparisons are made - minus the diagonal, as checking an article with itself is trivial.

The scores of the final test are distributed as follows (the fractile below 0.1 have been included in this table, it accounts for 99% of the total number of comparisons) in table 5.3.

As table 5.3 shows, there is a massive amount of comparisons in the lowest fractile (close to quarter of a billion comparisons, the total number of comparisons above that is approximately 1,6 million comparisons (1,596,604 comparisons).

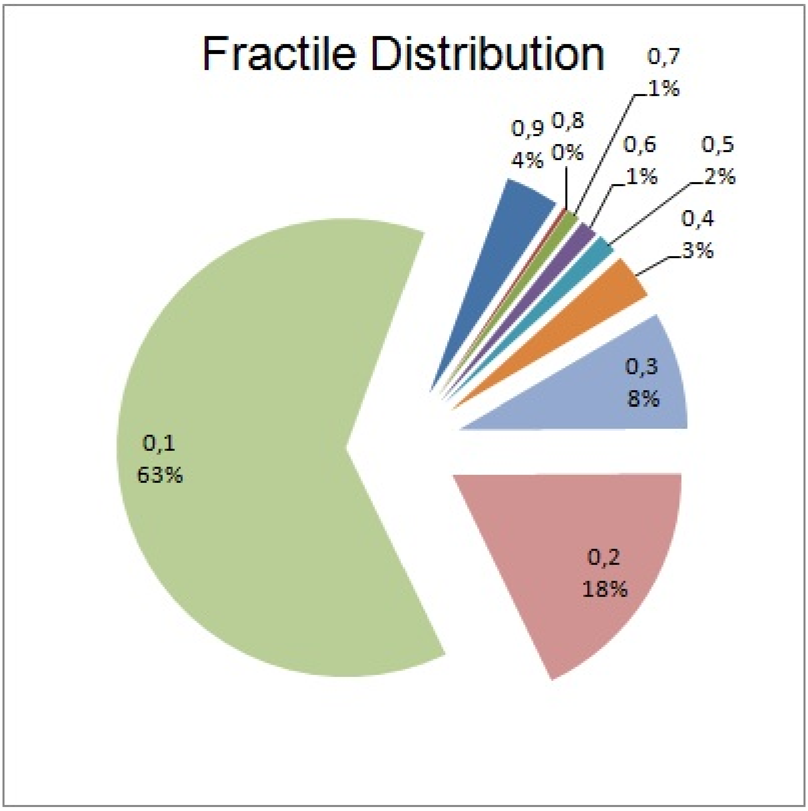


Figure 5.7: Cosine comparison of all files in the test corpus. The fractile below 0.1 have been left out, to create a better view of the comparison distribution (File: "symmetric all files fractiles.xlsx").

After doing these test, it would seem like the various parts of the project is working as planned, and it is now time to evaluate the results produced by running the program.

CHAPTER 6

Evaluation

This chapter deals with evaluating the results from the program when scoring article comparisons.

After having done tests to verify that the implementation of the algorithms worked correctly, it is now time to analyse the output.

6.1 Scores

The Cosine algorithm returns a score that is in fact an angle, where as the LCS algorithm returns a score that is based on the length of a string. As such these are hardly comparable in a one to one basis. If we modify the score of the LCS to not say something about the length of the substring(s), but tell us in percent how long the string is compared to the article is, it will produce a result that relates to the amount of text the two articles being compared have in common. This being said we still need to consider that the percentage value is relative to the length of the length of the article. We do therefore need to do a percentage calculation for both article's length. For better comparison of the Cosine and LCS score in the Excel graphs, the LCS percentage score is divided by 100 (even though comparing the scores is not really a decent indicator, it helps giving a better overview of the graphs).

So, a Cosine score of 1.0 means that the two article vectors are identical, same length and no angle between them. A LCS score of 1.0 means that the longest common substring's length is 100% of the article's length. So each score will have to be evaluated on their own premisses, as a Cosine score of 0.5 is not 50% identical. The Cosine score tells us something about how many special words that two articles have in common, where are the LCS tells us about the amount of text that is shared between the two articles.

6.2 Limiting the Number of Comparisons by Cosine Score

As discussed in the last chapter (see section 5.3) there is many comparisons in the lowest fractile of the article comparisons. Although dismissing them right of the bat can be seen as hasty, the chance of comparisons scoring below 0.3 having much in common would be unlikely. This is because comparisons that score very low in the Cosine algorithm either have very little in common in terms of special words (as common words will have very little impact on the vector) or the article is very short and again, with few special words (we will see an example of this later on). However, an article with no special words that is very short, is very rare and few in between. We will however see examples of such articles later on.

For the sake of proving anything in this thesis how ever, and as the chance of getting useful results from comparisons with low Cosine scores are slim and the number of comparisons having to be humanly checked are massive in numbers should we check all comparisons, I will for the rest of this thesis, disregard all comparisons with a cosine score lower than 0.3.

6.3 What the Scores Tell

First off we need to realize what the different scores is telling us on their own. The cosine score will give an indication of how similar two articles are in regards to the words being used, but will not tell us anything in regards to what the article is actually saying in regards to the structure of sentences (see section 3.3). By it's own, Cosine will tell us more about if the comparisons have the same topic that actually the same sentences.

The modified LCS is an indication of how big a percentage of text in relation to article length that an article have in common with another article. The LCS score will therefore tell us a lot about how much actual text a comparison shares.

6.4 Score Analysis

In figure 5.3 we see a part of the LCS result of two articles being compared with each other. A long each axis we have an article (topmost row and leftmost column - not visible on image). The purple squares shows where a word match have been found, and a diagonal row of coloured squares indicate several words in concession have been found. If squares are coloured in purple, it means that the substring found is too short, if the squares are in brown the substring is equal to or greater than the threshold set for accepting substrings.

In the figure we see that the two articles start off with having a lot in common, then around two thirds into figure there is a huge gap along the x-axis, but it is largely unbroken along the y axis. So if judging the result by looking at this image we can establish two things.

- The two articles have a lot of text in common, but the article along the x-axis is substantially longer than the article along the y-axis.
- The article along the y-axis is an excerpt of the article along the x-axis.

So when looking at this plot, we can tell if an article comparison is a duplicate, a excerpt or if there is no real match between two articles. To validate this fully it is needed to read the article text, to make sure the combination of substrings is not just a collection of random words, that are aligned in the same way without any relation.

In the following when looking at LCS comparison of articles, they are plotted like this in Excel.

6.5 Analysis of Comparisons

In the following is described the evaluation of the scores produced by matching the four sources (JP being matched with POL and JV being matched with FL).

6.5.1 JP and POL Comparison

First off, the sources POL and JP was compared in the program. The results of this was then plotted in Excel (File: JPPOL.xlsx). The data columns are:

- **Left Id / Right Id:** The article Ids of the comparison. These are used to find the articles, when checking their content manually.
- **Cosine Score:** The Cosine score for the comparison.
- **LCS Score:** The unmodified LCS score. This is included for comparison with the modified LCS score. It is a percentage score off the longest of the two articles in the comparison.
- **Combined Score Max:** The score from the modified LCS. This is a percentage score off the longest of the two articles in the comparison.
- **Combined Score Min:** The score from the modified LCS. This is a percentage score off the shortest of the two articles in the comparison.
- **Long Length:** The length of the longest article in characters.
- **Short Length:** The length of the shortest article in characters.
- **Match Group:** The match group the comparison have been placed into by the program (this will be explained later).
- **Adjusted Score:** The score modification after applying score weighing (this will also be explained later).

Originally only the LCS score based off the longest article was included and used for evaluating the results. It did become clear after the first few tests, that this would not suffice. If we looked at two articles, one being substantially longer than the other, but the shortest being a 100% excerpt of the longest, we could end up in a case where the article comparison would score very low because the LCS (and the Cosine for that matter) would be very low. We could then end up discarding this comparison as a "no match" because the scores was too low. How ever if we looked at the LCS score based off the length of the shortest article, we would get a completely different image. Then we could actually detect that the shortest article was in fact a excerpt, by seeing that it's LCS score would be 100%. We will therefore have to look into the length of the articles as well, in order to fully say something about how much of a match a comparison is (this will be brought up again later).

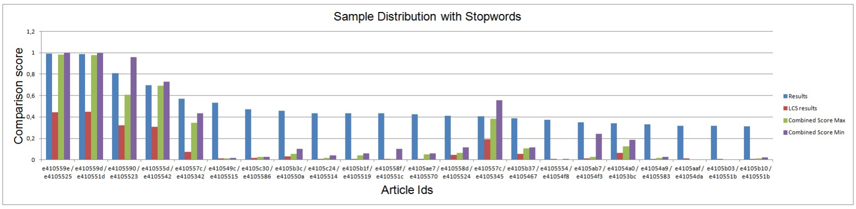


Figure 6.1: Comparison scores for the JP and POL sources (see appendix D for bigger image or File: JPPOL.xlsx).

Finally there are three graphs. The first is *'Sample Distribution with Stopwords'*. This shows in a column diagram the comparisons different scores. As mentioned earlier we cannot compare the Cosine score with the LCS score on a one to one basis. However this does indicate something about general relations.

Figure 6.1 shows the effect of having the modified LCS to collect all substrings longer than a given threshold. It also shows the necessity of having to evaluate the LCS score with both the length of the longest and the shortest article length as there can be quite a big difference in the scores.

Below that graph is two graphs side by side. The first shows the Cosine score plotted with the modified LCS score based off the longest article. The second graph shows the same, but this time the red dots is showing the Cosine and modified LCS score based off the shortest article.

The graphs in figure 6.2 and 6.3 was created in order to get a better overview of how the scores was distributed.

When evaluating the figure 6.1 we can start with looking at the first two collections of scores (comparisons *e410559e / e4105525* and *e410559d / e410551d*). Both comparisons have high scores in all columns. We note that the basic LCS scores around half as high as the scores for the two modified LCS scores. For the rest of this thesis I will disregard the scores produced by the basic LCS, as it holds no meaningful data when trying to find article duplicates. The length of the four articles in the comparisons is around the same length, meaning both of the LCS scores is more or less equally high.

<INDSÆT BILLEDE AF MATCHES!>S

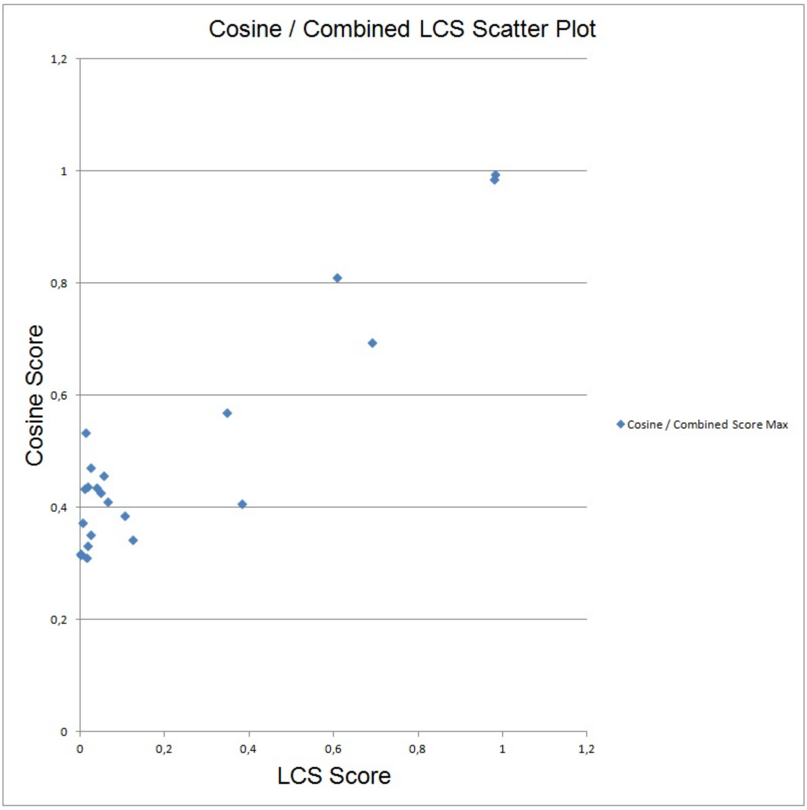


Figure 6.2: A plot showing the Cosine / LCS score (based of the longest article length in the comparison).

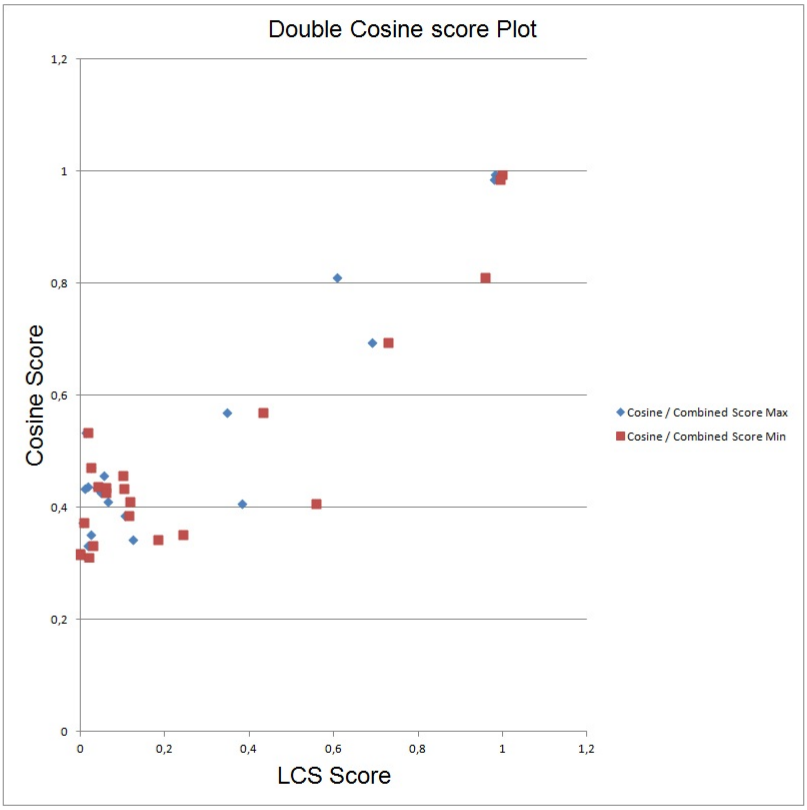


Figure 6.3: A plot showing the Cosine / LCS score (based off the longest article length - the blue dots) and the Cosine / LCS score (based off the shortest article length - the red squares).

6.6 Weighing the Scores

In combination the two sets of scores can draw us a more detailed picture, one that to a higher degree of confidence call tell about any relations between two articles. To try and break scores into something that is able to be defined, the following enums have been created, and called *'Match Groups'*:

- **Match:** The comparison is to a high degree a perfect match, meaning that the two articles being compared have a lot of text in common, scores high with the algorithms and is somewhat similar in length.
- **Partial Match:** This label would be a applied to a comparison, where only parts of the articles are shared, or that one article is a good deal shorter than the other, but scores highly in LCS. It would be considered an article excerpt.
- **Same Content:** For comparisons with relative high Cosine scores, but somewhat low LCS scores, we can sometimes talk about the articles deal with the same topic, but without sharing much text.
- **Low Score Match:** Applying this label to a comparison would indicate that either one or both article are very short in length, can have a relative high Cosine score, but will have a high LCS score. It will indicate that the comparison most have a lot in common, but will maybe not contain much article text of much value.
- **No Match:** When both algorithms scores low for a comparison, there is grounds to dismiss the comparison as a match. The articles will not have many sentences or special words in common.

The following table was created in order to try and give some weight to the scores. This could then be used in the program for score evaluation. The weight would be a factor that could be multiplied to the scores the algorithms produced in order to emphasize the result. These score weightings is based of tests that was done during the project.

The table 6.1 would be an immediate indication how related two articles are, but we do also need to take another parameter into account, this being the length of the articles. A perfect match comparisons would occur when two articles of the same length and scoring close to 1.0 in both algorithms, but if two articles have a big difference in length that could affect the algorithm scores in a way that might not apply the right label when placing a comparison in a match group. The following enums was created to try and categorize articles by their length:

	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.0	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
0.1	0.01	0.01	0.01	0.01	0.01	0.01	0.05	0.2	0.4	0.6	0.8
0.2	0.01	0.01	0.05	0.1	0.1	0.1	0.3	0.5	0.6	0.8	0.85
0.3	0.01	0.05	0.1	0.1	0.1	0.2	0.4	0.55	0.7	0.85	0.9
0.4	0.01	0.05	0.1	0.1	0.1	0.2	0.4	0.6	0.75	0.85	0.95
0.5	0.01	0.05	0.1	0.2	0.3	0.4	0.5	0.65	0.8	0.9	1.0
0.6	0.01	0.07	0.1	0.2	0.4	0.5	0.6	0.7	0.85	0.9	1.0
0.7	0.01	0.1	0.2	0.4	0.4	0.5	0.7	0.8	0.9	1.0	1.0
0.8	0.01	0.1	0.4	0.6	0.7	0.8	0.8	0.9	1.0	1.0	1.0
0.9	0.01	0.1	0.7	0.7	0.8	0.8	0.9	1.0	1.0	1.0	1.0
1.0	0.05	0.2	0.8	0.8	0.9	0.9	1.0	1.0	1.0	1.0	1.0

Table 6.1: Score weights. The cosine score is the top most row and LCS score is the leftmost x axis. The weights indicates to what extend that articles have something in common. A low score would mean that the combination of Cosine and LCS score indicates that there is a low chance of any relation between the articles, a high score would mean the opposite. (File: Score Weight.xlsx)

Very Short	$x < 300$
Short	$x \geq 300 \bigwedge x < 500$
Medium	$x \geq 500 \bigwedge x < 800$
Long	$x \geq 800 \bigwedge x < 1200$
Very Long	$x \geq 1200$

Table 6.2: Enums describing article length. X is the length of the article in characters and the values it is being compared with is the article length.

Appendix A

Test Diagrams

This appendix is full of stuff ... add more

Document from Infomedia about the general Vector Spaced Search.
Thesis document from Inge
Links to Wikipedia
The algorithm course book..
Example XML document (article) - to show what the XML documents look like.

An example of comparing two articles with LCS.

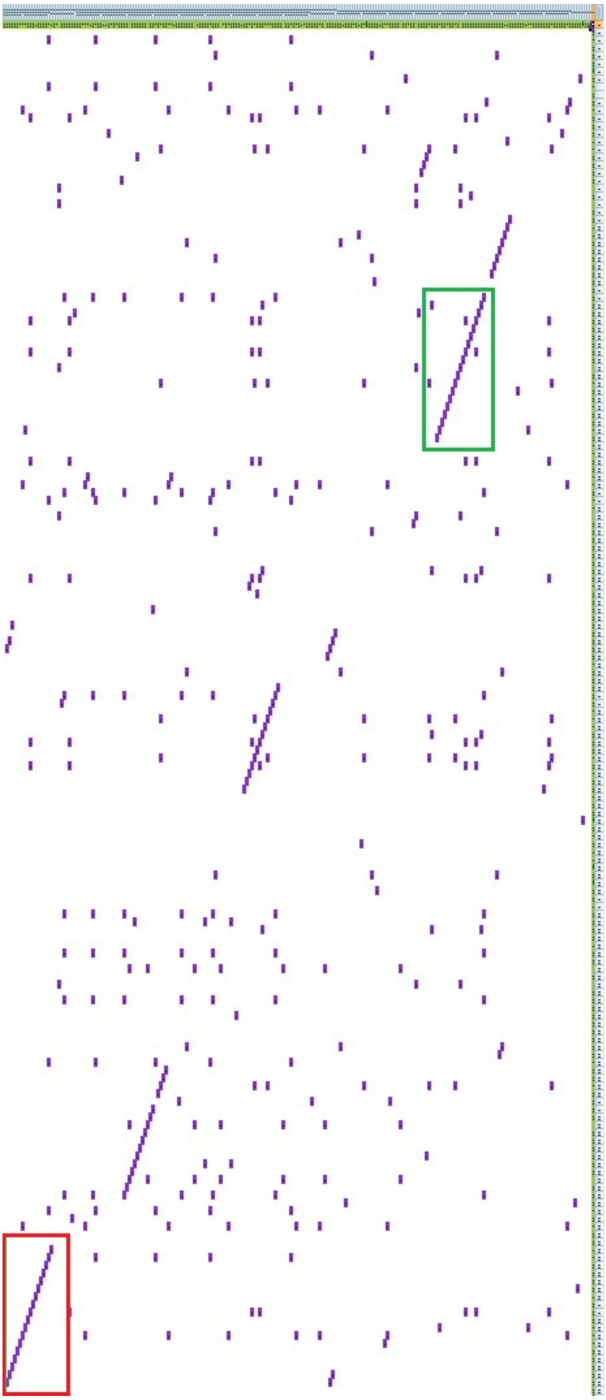


Figure A.1: Diagram showing the result of two article being compared by using LCS.

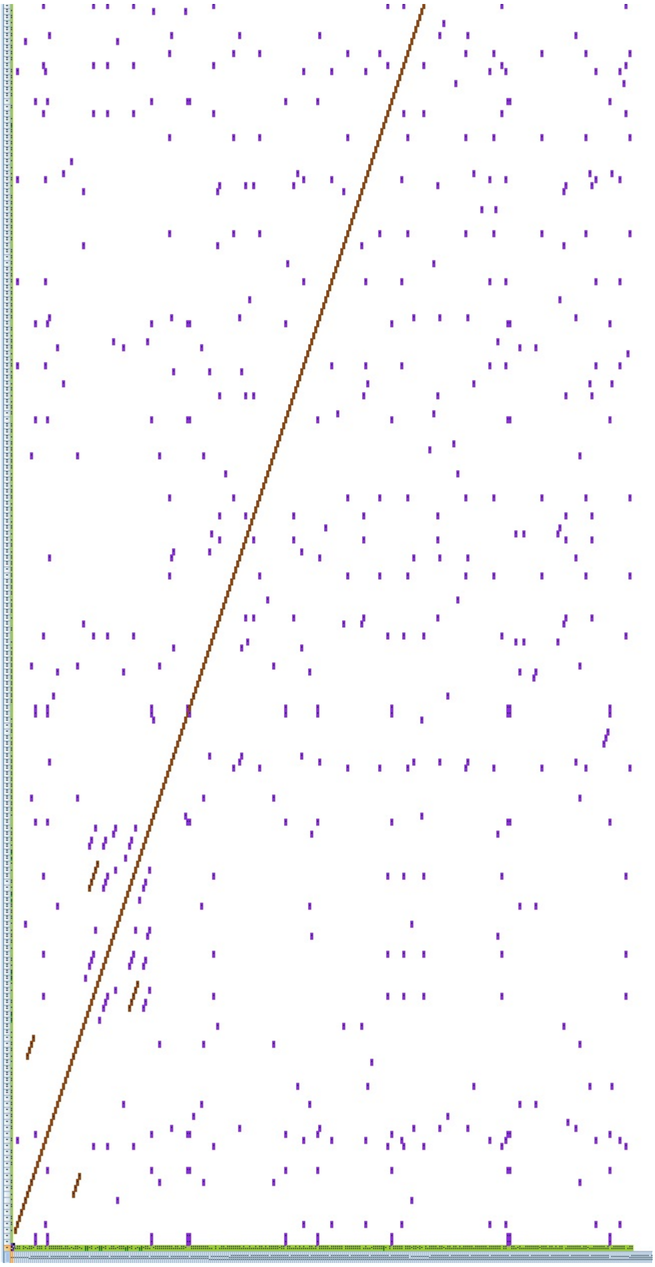


Figure A.2: Diagram showing part of the result from running LCS on two articles that are almost a perfect match.

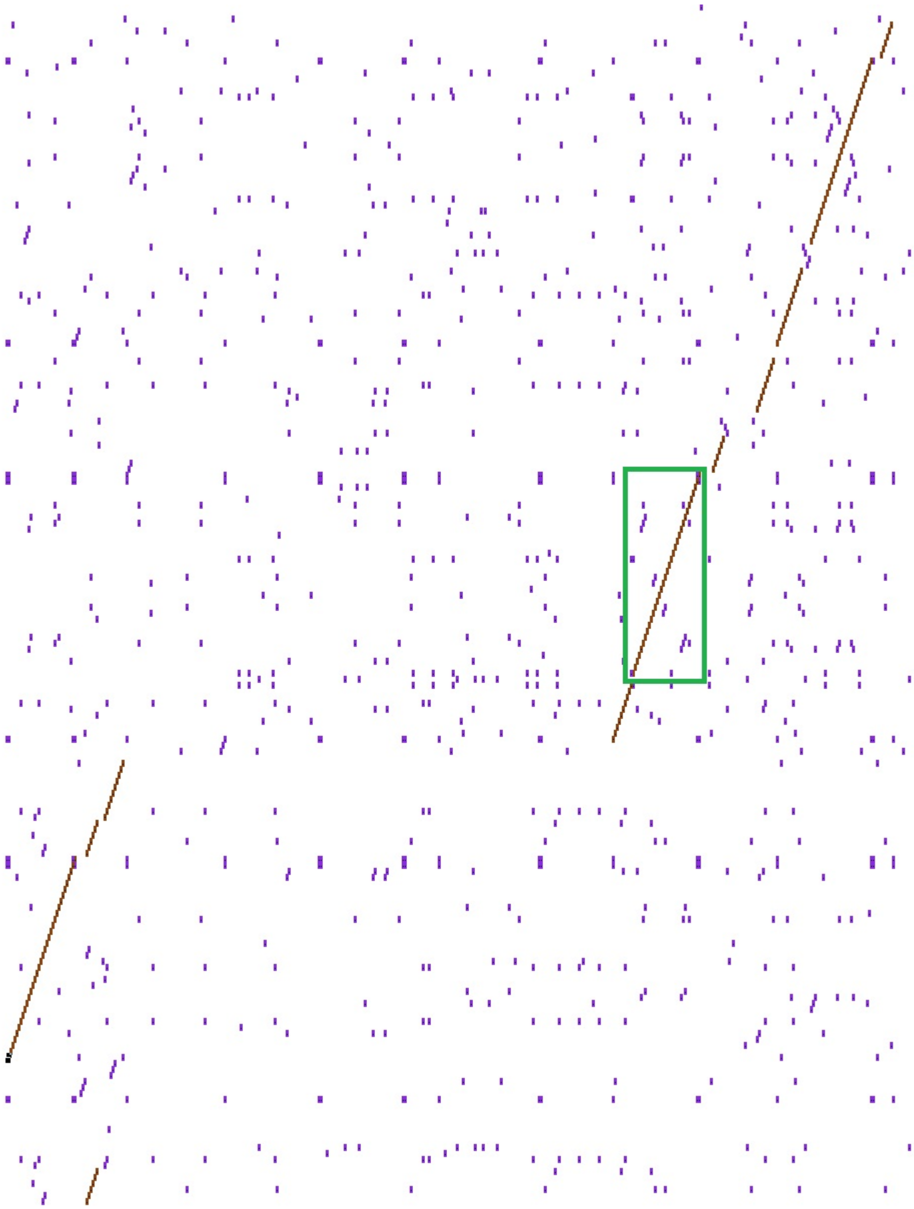


Figure A.3: Diagram showing part of the result of running LCS on two articles and marking up all substrings with a length larger than three words.

APPENDIX B

Article Content

B.1 Danfoss fastholder stabil forretning

Termostatkæmpen Danfoss holder sit indtjeningsniveau, mens omsætningen falder en smule. Ingen store dramaer i Danfoss. Det kunne være overskriften på selskabets regnskab for årets første ni måneder. Omsætningen falder en smule fra til 25.528 mio. kroner i år mod 25.985 mio. kroner i samme periode sidste år, mens indtjeningen lander på 2.938 mio. kroner i år mod 2.952 mio. kroner sidste år. Med andre ord en stabil forretning uden overraskelser, og det er koncernchef Niels B. Christiansen tilfreds med. »Takket være vores strategiske fokus på en stærk kerneforretning er vi i stand til at opveje både et kollapset europæisk solcellemarked og faldende valutakurser. Det er tilfredsstillende, at vi har formået at tilpasse os og levere så stærkt et resultat trods en generelt lav markedsvækst,« siger han. Selskabet anfører samtidig, at korrigeret for valutaeffekt er Danfoss' samlede omsætning på sidste års niveau. Det europæiske solcellekollaps har ellers ramt Danfoss hårdt, da selskabet producerer invertere til solcelleanlæg. Og solcellemarkedet var blandt de direkte årsager til, at Danfoss for tre måneder siden skar ned og fyrede 69 medarbejdere i Danmark. Den største vækst oplever Danfoss i Rusland og Brasilien, mens det kinesiske marked følger med i lavere tempo. Generelt forventer selskabet dog, at det globale marked vil være præget af lav vækst »et stykke tid endnu«. Og det åbner op for flere opkøb udover de seneste køb af Danfoss Turbocor og de sidste aktier i Sauer-Danfoss. »Derfor kigger vi meget på, om vi kan styrke forretningen gennem fokus på nye markeder og opkøb - såvel af nye teknologier som virksomheder. Vi har styrken til at kunne finansiere sådanne opkøb. Det giver en stor handlefrihed og mulighed for at forbedre Danfoss' position yderligere,« forklarer Niels B. Christiansen. For hele året venter Danfoss »beskeden vækst« i omsætning og indtjening. Danfoss' koncernchef Niels B. Christiansen venter "beskeden vækst" i år".

B.2 Danfoss fastholder stabil forretning - w/o Stop Words

Termostatkæmpen Danfoss holder indtjeningsniveau, omsætningen falder smule. Ingen dramaer Danfoss. Det overskriften selskabets regnskab årets måneder. Omsætningen falder smule 25.528 mio. kroner 25.985 mio. kroner år, indtjeningen lander 2.938 mio. kroner 2.952 mio. kroner år. Med stabil forretning overraskelser, koncernchef Niels B. Christiansen tilfreds med. Takket strategiske fokus kerneforretning opveje kollapset solcellemarked faldende valutakurser. Det tilfredsstillende, formået tilpasse levere stærkt trods generelt markedsvækst, han. Selskabet anfører samtidig, korrigeret valutaeffekt Danfoss' samlede omsætning års niveau. Det europæiske solcellekollaps ellers ramt Danfoss hårdt, selskabet producerer invertere solcelleanlæg. Og solcellemarkedet blandt årsager til, Danfoss måneder skar fyrede 69 medarbejdere Danmark. Den største vækst oplever Danfoss Rusland Brasilien, kinesiske følger lavere tempo. Generelt forventer selskabet dog, globale præget vækst endnu. Og åbner opkøb udover seneste køb Danfoss Turbocor aktier Sauer-Danfoss. Derfor kigger på, styrke forretningen gennem fokus markeder opkøb - såvel teknologier virksomheder. Vi styrken finansiere sådanne opkøb. Det giver handlefrihed forbedre Danfoss' position yderligere, forklarer Niels B. Christiansen. For året venter Danfoss »beskeden vækst« omsætning indtjening. Danfoss' koncernchef Niels B. Christiansen venter beskeden vækst år.

Appendix C

Data Diagrams

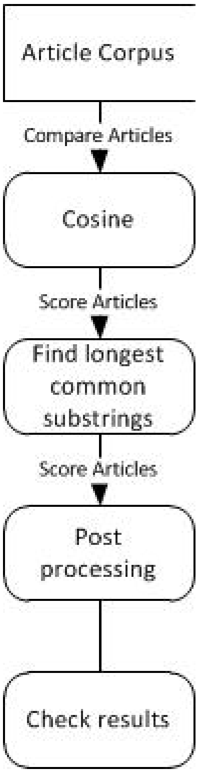


Figure C.1: Diagram of the data flow in the system.

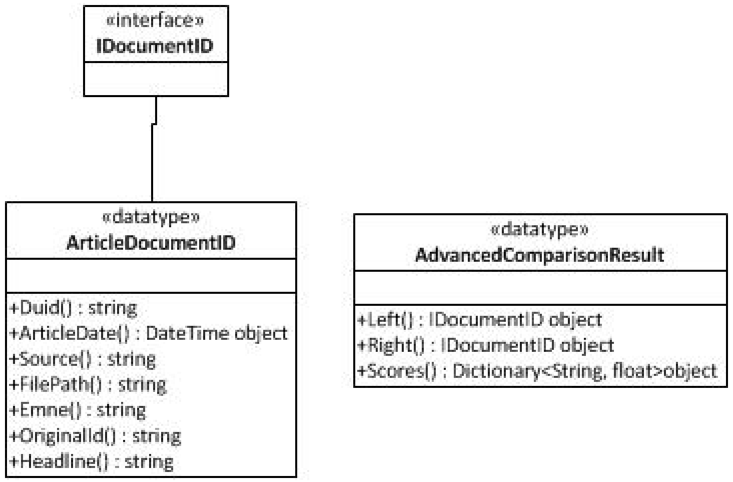
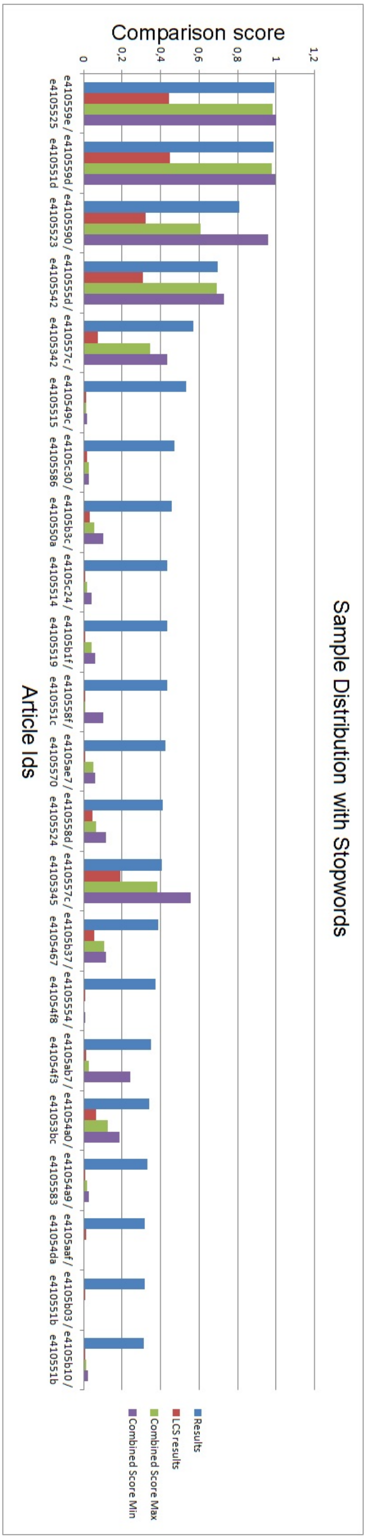


Figure C.2: The general data types used in this project to store information about articles and their scores.

Appendix D

Evaluation Diagrams

This contains the diagrams used in the Evaluation chapter.


Sample Distribution with Stopwords
Comparison score
0
0,2
0,4
0,6
0,8
1
1,2
e410559e / e4105525
e410559d / e410551d
e4105590 / e4105523
e410555d / e4105542
e410557c / e4105342
e410549c / e4105515
e4105c30 / e4105586
e4105b3c / e410550a
e4105c24 / e4105514
e4105b1f / e4105519
e410558f / e410551c
e4105ae7 / e4105570
e410558d / e4105524
e410557c / e4105345
e4105b37 / e4105467
e4105554 / e41054f8
e4105ab7 / e41054f3
e41054a0 / e41053bc
e41054a9 / e4105583
e4105aaf / e41054da
e4105b03 / e410551b
e4105b10 / e410551b
Article Ids
Results
LCS results
Combined Score Max
Combined Score Min

Bibliography

[Alb14] Rikke Albrechtsen. Messerschmidt: Ja-partierne taler vælgerne efter munden. http://www.altinget.dk/eu/artikel/messerschmidt-ja-partierne-taler-vaelgerne-efter-munden, 2014. Accessed: 2014-05-20.

[Inf14] Infomedia. Top 10: Kandidaternes synlighed i medierne. http://www.infomedia.dk/viden-indsigt/europaparlamentsvalg-og-patentdomstolsafstemning-kandidaternes-synlighed-i-medierne, 2014. Accessed: 2014-05-20.

[Lin14] Douglas Linn. Understanding the wizards v. hex lawsuit (in plain english), 2014.

[ML14] René Madsen and Niels Buus Lassen. Ensemble classifiers. 2014.

[Wik14a] Wikipedia. Algorithm implementation/strings/longest common substring. http://en.wikibooks.org/w/index.php?title=Algorithm_Implementation/Strings/Longest_common_substring&action=history, 2014. Accessed: 2014-05-20.

[Wik14b] Wikipedia. tf-idf. http://en.wikipedia.org/wiki/Tf-idf, 2014. Accessed: 2014-05-20.

[Win13a] Johan Winther. Danfoss fastholder stabil forretning. http://www.jv.dk/artikel/1633979:Business--Danfoss-fastholder-stabil-forretning, note = Accessed: 2014-05-20, 2013.

[Win13b] Johan Winther. Danfoss fastholder stabil forretning. *folkebladetlemvig.dk*, 2013. Online content protected by payment wall, article text included in Appendix B.