University of Amsterdam

MSc Artificial Intelligence
Master Thesis

Enriching Textual Data with Document Structure For Text Classification

by
Maarten de Jonge
10002109

January 6, 2019

42 EC
01 July 2017, 31 December 2017

Supervisor:	*Assessor:*
Dr Maarten Marx	Dr Maarten van Someren

Information and Language Processing Systems Group
Informatics Institute

Contents

Abstract

Proceedings of parliamentary debates are often published as unstructured PDF files, making them unsuitable for indexing into a database or querying for specific information. Digitizing them into a structured format is challenging; doing so manually is labor-intensive, doing so through a rule-based system is error-prone. Manually annotating a small number of documents can provide a training set that allows a convolutional neural network to accurately classify the elements that denote the structure of the document (e.g. the start of a new speech), using purely the textual content of the document. Adding a preprocessing step that clusters pieces of text based on the physical layout of the document improves the classification performance in a minor, but statistically significant way.

1 Introduction

A healthy democracy relies on a transparent political process that is open to the common populace

hier valt vast iets leuks te quoten van een politiek filosoof

. A common step towards achieving this is by publishing the proceedings of the parliament's debates, such as the *Bundestag* in Germany[1] or the *Tweede Kamer* in the Netherlands[2]. These proceedings can be useful in various ways, for example:

- Double-checking whether a certain politician's actions in the parliament are consistent with their public stance.
- Using them as a source of data for text analysis, such as classifying political ideology[1].
- Tracking the change in ideological leaning of a politician or party over time[2].

In each of these cases it would be hugely beneficial if the data was properly indexed. If you want to know John Doe's stance on immigration, you would ideally simply query a database for speeches by John Doe regarding the topic of immigration without having to manually skim over hundreds of documents to find the relevant speeches. It is unfortunate then that many of these debates are published solely in unstructured formats, such as PDF or plain text. Projects such as Political Mashup[3] handle this by writing systems to parse and then index these documents. The semantic information required for indexing is currently recovered using rule-based methods. In

[1]https://www.bundestag.de/protokolle
[2]https://www.tweedekamer.nl/kamerstukken
[3]http://search.politicalmashup.nl/about.html

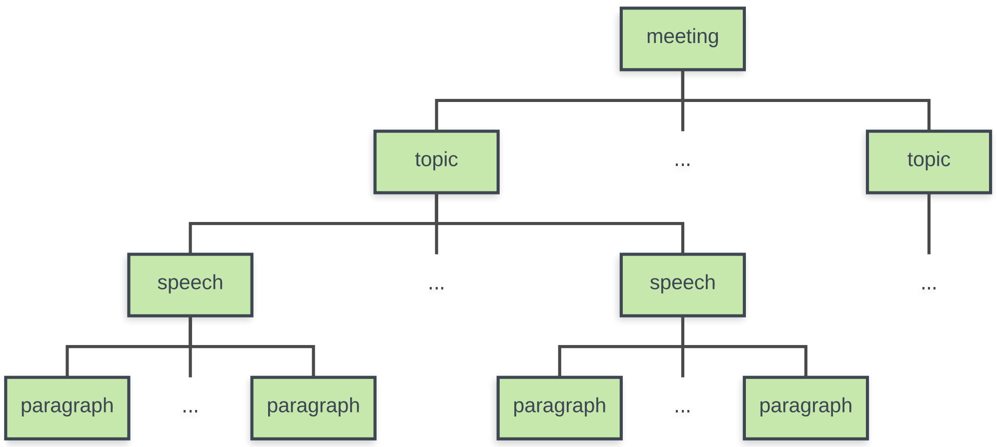


Figure 1: The structure of a parliamentary debate is that of a shallow tree.

the case of a PDF document, this is fairly challenging. The data often gets transcribed by a human typist, compiled to a PDF, and then goes back into a PDF decompiler for easier processing; this adds a lot of places where minor variations can occur in the output even though the document itself uses a consistent layout. Dealing with this in a rule-based system entails using either highly general rules that lead to a large probability of false positives, or a large amount of highly specific rules which can quickly lead to a spaghetti-like mess of special cases and is very fragile to unseen cases.

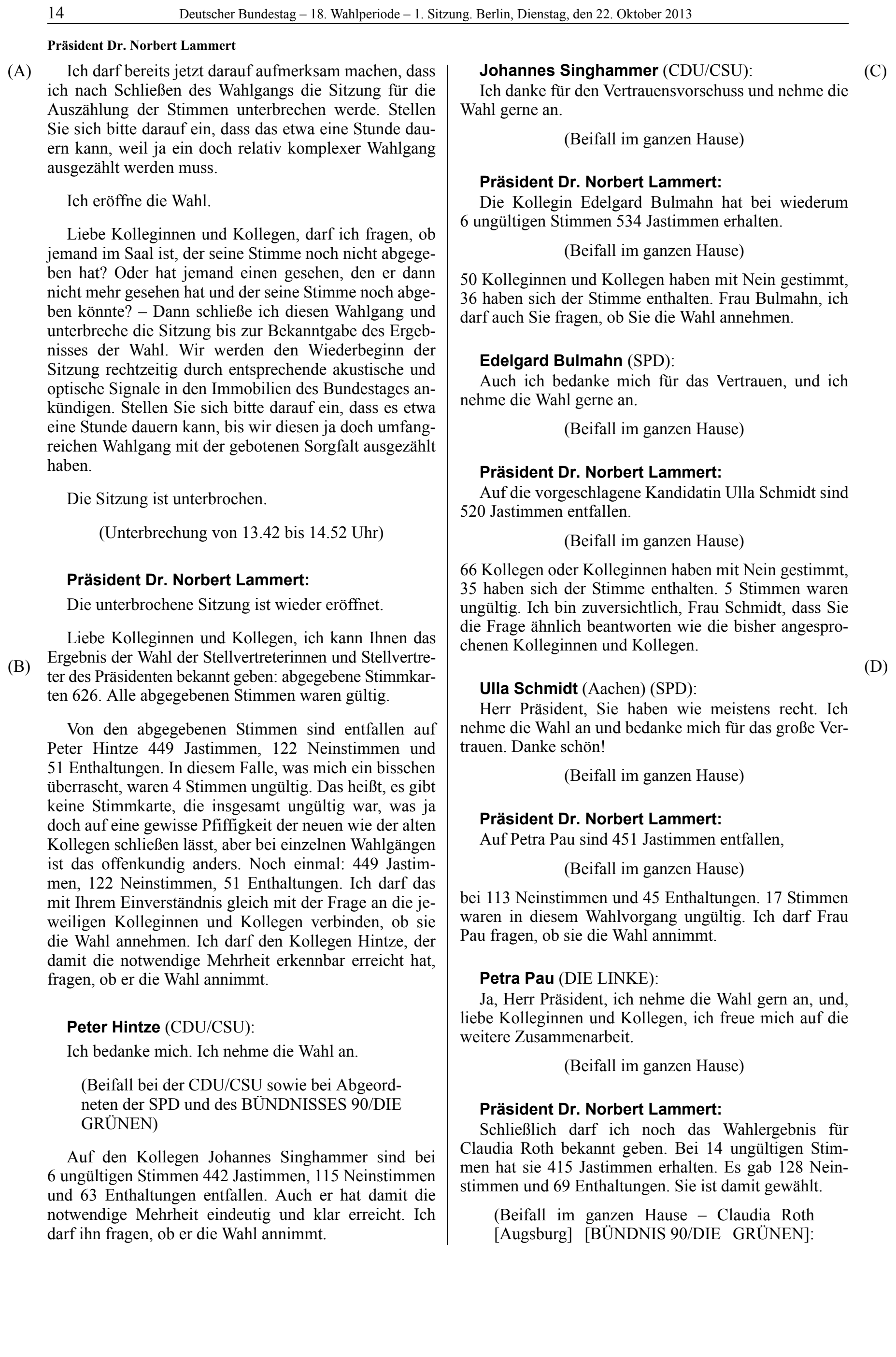
I propose that by using a small number of manually annotated documents as a dataset, a machine learning algorithm can learn to classify fragments of text in a way that allows it to segment a document into its constituent parts, while being more robust to noise than its rule-based counterpart. While the structure of a parliamentary debate is tree-shaped (a general example in shown in fig. 1), this tree is generally both shallow and very rigidly structured. As a result, simply classifying the positions in the text where a new structural element begins is enough to reconstruct the full tree given the domain knowledge about this particular set of documents; some variations can occur depending on the particular conventions used by the creator of the documents, for example in how speech interruptions by noisy colleagues are handled. After the document's layout has been extracted, it is a matter of obtaining each element's metadata (such as the speaker and their political affiliation for each speech element). This step is outside of the scope of this thesis.

The common ways to do sentence classification (e.g. convolutional neural networks [3], recurrent neural networks or the simpler bag-of-words models) operate on sentences in a vacuum, considering only their linguistic contents and ignoring any contextual information that might be contained in the layout in which the text might have been embedded. This is to be expected considering that most of the common datasets in this area really *are* just small bits of text in a vacuum; often-used datasets involve Twitter messages or short product reviews. In this case however, the sentences come from a document with a rich structure providing a lot of context. Anecdotally, as a human it is trivial to discern section headers in a document even when the document is in a foreign language; simply the fact that the section header might be printed in bold and centered rather than left-aligned gives it away. Incorporating this structural data into the learning process, using a clustering approach inspired by Klampfl *et al.* [4], will hopefully increase the performance of the system, either by simply scoring better on the used metrics, or perhaps more indirectly by requiring less data or training time to achieve the same score.

2 Problem Statement

The German parliament, called the *Bundestag*, publishes the proceedings of their meetings, as an effort to open up the political process to the common people. These proceedings have been continously published since the inception of the German Empire in 1871, when the parliament was called the *Reichstag*, up to 1942; publishing resumed after the conclusion of World War 2 with the inception of the Bundestag in 1949. Of course, the further back in the time you go,the more difficult the documents become to use. While the more recent documents are fully digital, documents prior to 1998 are scans of physical documents and require optical character recognition, which becomes even more problematic in the documents from the 1800s where a thick Gothic font is used. Figure 2 shows a sample page from one of these proceedings; the left column contains a continuation of a speech from the previous page as well as two moderately sized speeches, while the right column contains a large number of very short speeches. Figure 3 shows the same page seen in fig. 2, but with a number of regions of interest (manually) colored in. Unfortunately this data is only available in a PDF format, which in terms of internal representation is entirely unstructured. That means that none of the rich structure highlighted in fig. 3 is actually present in a computer-usable way.

The central problem in this thesis is the extraction of speeches from the documents, transforming each document into a structured series of speeches that can be serve as a useful entry point into further research. As a first step, the structural layout (as in fig. 3) will be extracted using unsupervised clustering algorithms. The textual contents of the document are then fed into supervised text classifier, where each piece of text is augmented with the corresponding layout information previously obtained. More details on



14 Deutscher Bundestag – 18. Wahlperiode – 1. Sitzung. Berlin, Dienstag, den 22. Oktober 2013

Präsident Dr. Norbert Lammert

(A) Ich darf bereits jetzt darauf aufmerksam machen, dass ich nach Schließen des Wahlgangs die Sitzung für die Auszählung der Stimmen unterbrechen werde. Stellen Sie sich bitte darauf ein, dass das etwa eine Stunde dauern kann, weil ja ein doch relativ komplexer Wahlgang ausgezählt werden muss.

Ich eröffne die Wahl.

Liebe Kolleginnen und Kollegen, darf ich fragen, ob jemand im Saal ist, der seine Stimme noch nicht abgegeben hat? Oder hat jemand einen gesehen, den er dann nicht mehr gesehen hat und der seine Stimme noch abgeben könnte? – Dann schließe ich diesen Wahlgang und unterbreche die Sitzung bis zur Bekanntgabe des Ergebnisses der Wahl. Wir werden den Wiederbeginn der Sitzung rechtzeitig durch entsprechende akustische und optische Signale in den Immobilien des Bundestages ankündigen. Stellen Sie sich bitte darauf ein, dass es etwa eine Stunde dauern kann, bis wir diesen ja doch umfangreichen Wahlgang mit der gebotenen Sorgfalt ausgezählt haben.

Die Sitzung ist unterbrochen.

(Unterbrechung von 13.42 bis 14.52 Uhr)

Präsident Dr. Norbert Lammert:
Die unterbrochene Sitzung ist wieder eröffnet.

(B) Liebe Kolleginnen und Kollegen, ich kann Ihnen das Ergebnis der Wahl der Stellvertreterinnen und Stellvertreter des Präsidenten bekannt geben: abgegebene Stimmkarten 626. Alle abgegebenen Stimmen waren gültig.

Von den abgegebenen Stimmen sind entfallen auf Peter Hintze 449 Jastimmen, 122 Neinstimmen und 51 Enthaltungen. In diesem Falle, was mich ein bisschen überrascht, waren 4 Stimmen ungültig. Das heißt, es gibt keine Stimmkarte, die insgesamt ungültig war, was ja doch auf eine gewisse Pfiffigkeit der neuen wie der alten Kollegen schließen lässt, aber bei einzelnen Wahlgängen ist das offenkundig anders. Noch einmal: 449 Jastimmen, 122 Neinstimmen, 51 Enthaltungen. Ich darf das mit Ihrem Einverständnis gleich mit der Frage an die jeweiligen Kolleginnen und Kollegen verbinden, ob sie die Wahl annehmen. Ich darf den Kollegen Hintze, der damit die notwendige Mehrheit erkennbar erreicht hat, fragen, ob er die Wahl annimmt.

Peter Hintze (CDU/CSU):
Ich bedanke mich. Ich nehme die Wahl an.

(Beifall bei der CDU/CSU sowie bei Abgeordneten der SPD und des BÜNDNISSES 90/DIE GRÜNEN)

Auf den Kollegen Johannes Singhammer sind bei 6 ungültigen Stimmen 442 Jastimmen, 115 Neinstimmen und 63 Enthaltungen entfallen. Auch er hat damit die notwendige Mehrheit eindeutig und klar erreicht. Ich darf ihn fragen, ob er die Wahl annimmt.

(C) **Johannes Singhammer** (CDU/CSU):
Ich danke für den Vertrauensvorschuss und nehme die Wahl gerne an.

(Beifall im ganzen Hause)

Präsident Dr. Norbert Lammert:
Die Kollegin Edelgard Bulmahn hat bei wiederum 6 ungültigen Stimmen 534 Jastimmen erhalten.

(Beifall im ganzen Hause)

50 Kolleginnen und Kollegen haben mit Nein gestimmt, 36 haben sich der Stimme enthalten. Frau Bulmahn, ich darf auch Sie fragen, ob Sie die Wahl annehmen.

Edelgard Bulmahn (SPD):
Auch ich bedanke mich für das Vertrauen, und ich nehme die Wahl gerne an.

(Beifall im ganzen Hause)

Präsident Dr. Norbert Lammert:
Auf die vorgeschlagene Kandidatin Ulla Schmidt sind 520 Jastimmen entfallen.

(Beifall im ganzen Hause)

66 Kollegen oder Kolleginnen haben mit Nein gestimmt, 35 haben sich der Stimme enthalten. 5 Stimmen waren ungültig. Ich bin zuversichtlich, Frau Schmidt, dass Sie die Frage ähnlich beantworten wie die bisher angesprochenen Kolleginnen und Kollegen.

(D) **Ulla Schmidt** (Aachen) (SPD):
Herr Präsident, Sie haben wie meistens recht. Ich nehme die Wahl an und bedanke mich für das große Vertrauen. Danke schön!

(Beifall im ganzen Hause)

Präsident Dr. Norbert Lammert:
Auf Petra Pau sind 451 Jastimmen entfallen,

(Beifall im ganzen Hause)

bei 113 Neinstimmen und 45 Enthaltungen. 17 Stimmen waren in diesem Wahlvorgang ungültig. Ich darf Frau Pau fragen, ob sie die Wahl annimmt.

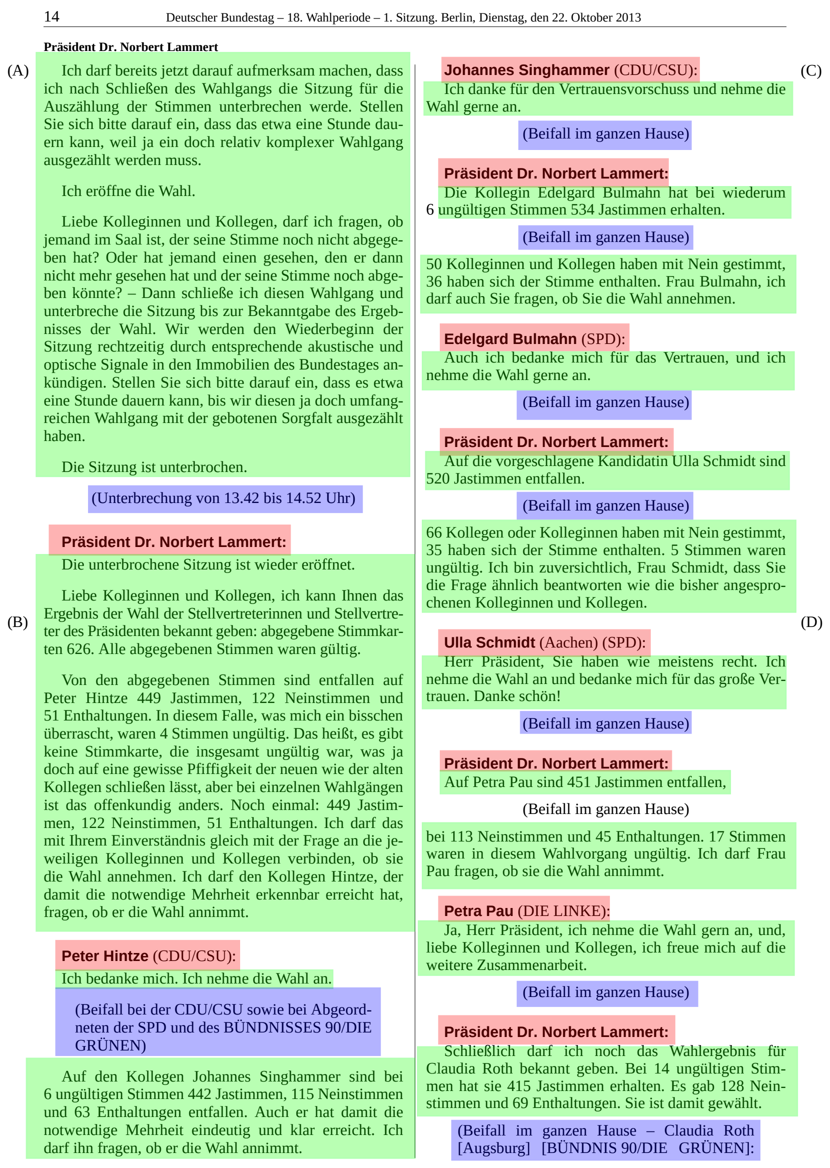
Petra Pau (DIE LINKE):
Ja, Herr Präsident, ich nehme die Wahl gern an, und, liebe Kolleginnen und Kollegen, ich freue mich auf die weitere Zusammenarbeit.

(Beifall im ganzen Hause)

Präsident Dr. Norbert Lammert:
Schließlich darf ich noch das Wahlergebnis für Claudia Roth bekannt geben. Bei 14 ungültigen Stimmen hat sie 415 Jastimmen erhalten. Es gab 128 Neinstimmen und 69 Enthaltungen. Sie ist damit gewählt.

(Beifall im ganzen Hause – Claudia Roth [Augsburg] [BÜNDNIS 90/DIE GRÜNEN]:

Figure 2: A sample page from one of the Bundestag proceedings.



14 Deutscher Bundestag – 18. Wahlperiode – 1. Sitzung. Berlin, Dienstag, den 22. Oktober 2013

Präsident Dr. Norbert Lammert

(A)

Ich darf bereits jetzt darauf aufmerksam machen, dass ich nach Schließen des Wahlgangs die Sitzung für die Auszählung der Stimmen unterbrechen werde. Stellen Sie sich bitte darauf ein, dass das etwa eine Stunde dauern kann, weil ja ein doch relativ komplexer Wahlgang ausgezählt werden muss.

Ich eröffne die Wahl.

Liebe Kolleginnen und Kollegen, darf ich fragen, ob jemand im Saal ist, der seine Stimme noch nicht abgegeben hat? Oder hat jemand einen gesehen, den er dann nicht mehr gesehen hat und der seine Stimme noch abgeben könnte? – Dann schließe ich diesen Wahlgang und unterbreche die Sitzung bis zur Bekanntgabe des Ergebnisses der Wahl. Wir werden den Wiederbeginn der Sitzung rechtzeitig durch entsprechende akustische und optische Signale in den Immobilien des Bundestages ankündigen. Stellen Sie sich bitte darauf ein, dass es etwa eine Stunde dauern kann, bis wir diesen ja doch umfangreichen Wahlgang mit der gebotenen Sorgfalt ausgezählt haben.

Die Sitzung ist unterbrochen.

(Unterbrechung von 13.42 bis 14.52 Uhr)

Präsident Dr. Norbert Lammert:

Die unterbrochene Sitzung ist wieder eröffnet.

(B)

Liebe Kolleginnen und Kollegen, ich kann Ihnen das Ergebnis der Wahl der Stellvertreterinnen und Stellvertreter des Präsidenten bekannt geben: abgegebene Stimmkarten 626. Alle abgegebenen Stimmen waren gültig.

Von den abgegebenen Stimmen sind entfallen auf Peter Hintze 449 Jastimmen, 122 Neinstimmen und 51 Enthaltungen. In diesem Falle, was mich ein bisschen überrascht, waren 4 Stimmen ungültig. Das heißt, es gibt keine Stimmkarte, die insgesamt ungültig war, was ja doch auf eine gewisse Pfiffigkeit der neuen wie der alten Kollegen schließen lässt, aber bei einzelnen Wahlgängen ist das offenkundig anders. Noch einmal: 449 Jastimmen, 122 Neinstimmen, 51 Enthaltungen. Ich darf das mit Ihrem Einverständnis gleich mit der Frage an die jeweiligen Kolleginnen und Kollegen verbinden, ob sie die Wahl annehmen. Ich darf den Kollegen Hintze, der damit die notwendige Mehrheit erkennbar erreicht hat, fragen, ob er die Wahl annimmt.

Peter Hintze (CDU/CSU):

Ich bedanke mich. Ich nehme die Wahl an.

(Beifall bei der CDU/CSU sowie bei Abgeordneten der SPD und des BÜNDNISSES 90/DIE GRÜNEN)

Auf den Kollegen Johannes Singhammer sind bei 6 ungültigen Stimmen 442 Jastimmen, 115 Neinstimmen und 63 Enthaltungen entfallen. Auch er hat damit die notwendige Mehrheit eindeutig und klar erreicht. Ich darf ihn fragen, ob er die Wahl annimmt.

Johannes Singhammer (CDU/CSU):

(C)

Ich danke für den Vertrauensvorschuss und nehme die Wahl gerne an.

(Beifall im ganzen Hause)

Präsident Dr. Norbert Lammert:

Die Kollegin Edelgard Bulmahn hat bei wiederum 6 ungültigen Stimmen 534 Jastimmen erhalten.

(Beifall im ganzen Hause)

50 Kolleginnen und Kollegen haben mit Nein gestimmt, 36 haben sich der Stimme enthalten. Frau Bulmahn, ich darf auch Sie fragen, ob Sie die Wahl annehmen.

Edelgard Bulmahn (SPD):

Auch ich bedanke mich für das Vertrauen, und ich nehme die Wahl gerne an.

(Beifall im ganzen Hause)

Präsident Dr. Norbert Lammert:

Auf die vorgeschlagene Kandidatin Ulla Schmidt sind 520 Jastimmen entfallen.

(Beifall im ganzen Hause)

66 Kollegen oder Kolleginnen haben mit Nein gestimmt, 35 haben sich der Stimme enthalten. 5 Stimmen waren ungültig. Ich bin zuversichtlich, Frau Schmidt, dass Sie die Frage ähnlich beantworten wie die bisher angesprochenen Kolleginnen und Kollegen.

(D)

Ulla Schmidt (Aachen) (SPD):

Herr Präsident, Sie haben wie meistens recht. Ich nehme die Wahl an und bedanke mich für das große Vertrauen. Danke schön!

(Beifall im ganzen Hause)

Präsident Dr. Norbert Lammert:

Auf Petra Pau sind 451 Jastimmen entfallen,

(Beifall im ganzen Hause)

bei 113 Neinstimmen und 45 Enthaltungen. 17 Stimmen waren in diesem Wahlvorgang ungültig. Ich darf Frau Pau fragen, ob sie die Wahl annimmt.

Petra Pau (DIE LINKE):

Ja, Herr Präsident, ich nehme die Wahl gern an, und, liebe Kolleginnen und Kollegen, ich freue mich auf die weitere Zusammenarbeit.

(Beifall im ganzen Hause)

Präsident Dr. Norbert Lammert:

Schließlich darf ich noch das Wahlergebnis für Claudia Roth bekannt geben. Bei 14 ungültigen Stimmen hat sie 415 Jastimmen erhalten. Es gab 128 Neinstimmen und 69 Enthaltungen. Sie ist damit gewählt.

(Beifall im ganzen Hause – Claudia Roth [Augsburg] [BÜNDNIS 90/DIE GRÜNEN]:

Figure 3: The same page as in Figure 2, hand-annotated with interesting regions that play a significant role in understanding the layout. The red regions are the headers the signify that someone is starting a speech, and contain information about who the speaker is. The blue regions are little interruptions (*Heiterkeits*), often signifying approval or displeasure (the regularly seen *Beifall* means applause). The green regions indicate plain blocks of text.

this process will be supplied in section 4.

As annotating data by hand is an expensive process, a big focus is on limiting the amount of required training data as much as possible; it would be preferable if the system was able to learn sufficiently from a handful (say, less than 5) of hand-annotated files.

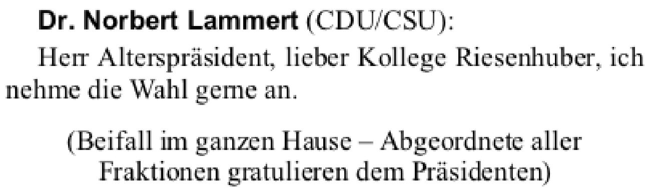
2.1 Dataset

The dataset contains 11 hand-annotated documents, comprising 2052 positive samples and 76,944 negative samples. The average document contains about 200 positive samples. Seeing as the source documents are PDF files, some transformations are needed to extract text from them in a way that is suitable for use as a machine learning dataset. This is not as trivial as it might seem, given that PDF files only contain instructions for drawing certain characters at certain coordinates, with no internal concept of paragraphs, lines or even words.

For the supervised portion of the system, the PDF files are transformed using the `pdftohtml` utility from the Poppler PDF rendering library[4]. This utility takes a PDF file and uses a number of heuristics to output lines of text occurring inside the file. In this context, a *line* refers to any number of characters that occur on the same height on a page while preserving reading order (which is relevant when dealing with documents that have a two-column layout) and is explicitly not the same as a sentence. These lines are output in an XML format which includes metadata on the geometry of the line (position and size) and its font. An example of a portion of text from the dataset and the corresponding XML output from `pdftohtml` is shown in fig. 4. Since this process is based on heuristics, it can and does go wrong; there are instances of mistakes such as a single line being broken up into multiple XML nodes, or lines of two side-by-side columns being taken as a single XML node. This is not terribly common (the frequency of such errors is perhaps one per file on average), but it does make the dataset inherently noisy and is one of the issues that rule-based systems have trouble with.

For the unsupervised clustering, the PDF files are taken directly as input and clustering is done using individual characters as the basic unit. This is just as easy as clustering on the lines produced by `pdftohtml`, but has the benefit of not being dependent on the imperfect line-extraction heuristics.

[4]https://poppler.freedesktop.org/


Dr. Norbert Lammert (CDU/CSU):

Herr Alterspräsident, lieber Kollege Riesenhuber, ich nehme die Wahl gerne an.

(Beifall im ganzen Hause – Abgeordnete aller Fraktionen gratulieren dem Präsidenten)

(a) A portion of the source PDF.

```
<text top="122" left="125" width="143" height="16" font="3">
    Dr. Norbert Lammert
</text>
<text top="122" left="269" width="83" height="17" font="4">
    (CDU/CSU):
</text>
<text top="142" left="125" width="328" height="17" font="4">
    Herr Alterspräsident, lieber Kollege Riesenhuber, ich
</text>
<text top="158" left="108" width="156" height="17" font="4">
    nehme die Wahl gerne an.
</text>
<text top="186" left="141" width="278" height="17" font="4">
    (Beifall im ganzen Hause  Abgeordnete aller
</text>
<text top="203" left="158" width="242" height="17" font="4">
    Fraktionen gratulieren dem Präsidenten)
</text>
```

(b) XML created by running `pdftohtml`, corresponding to the PDF excerpt in Figure 4a. The contents of the `text` elements are used as inputs for the classification algorithm; the layout data contained in the properties is not used, as a separate software pipeline is used for the unsupervised clustering.

Figure 4: A sample excerpt from a source PDF, along with its XML representation created by `pdftohtml`.

2.2 Research Question

A baseline model can be created by leaving out the clustering step, leaving us with two models:

1. A baseline model that classifies based on purely text
2. A model that classifies based on both text and layout information

There are two ways in which the second model can improve upon the baseline: either it performs better (using a metric such as the F1 score), or it requires less data to reach the same performance. This naturally leads to two research questions:

Research Question 1 *Does augmenting a text classification system with layout information obtained by unsupervised clustering of the input data improve the F1 score of the classifier?*

Research Question 2 *Does augmenting a text classification system with layout information obtained by unsupervised clustering of the input data allow the classifier to reach its peak performance using less input data?*

3 Related Work

The task handled in this thesis is in a way similar to that of wrapper induction, which is the process of inferring a *wrapper* (a program that extracts data into a usable form) from a web page. A fairly recent survey of the state of this field is done by Ferrara *et al.* [5], who note that a big problem is keeping up with the constantly changing nature of web pages. A novel approach to combat this is that of Gogar *et al.* [6]. They do wrapper induction by combining the textual content of a webpage with a screenshot of the rendered webpage in an effort to do wrapper induction on previously unseen web pages. The text is encoded in a way that maintains spatial information, a model they refer to as *Text Maps* or *Spatial bag of words.* The text maps and the screenshot are fed into separate convolutional networks, after which the output is combined for a final classification. In a test of extracting product names and prices from web pages, the system obtains very high score comparable to systems that do use site-specific initialization.

In terms of analyzing document structure, Klampfl *et al.* [4] introduce a method to analyze scientific articles, detecting blocks of text, labeling them (as e.g. section headers, tables or references) and determining the reading order — all in an unsupervised manner. The text block detection is done using a sequence of different clustering algorithms, while the labeling is done using a heuristic approach.

For text classification, various forms of convolutional neural networks are commonly used. The most basic architecture is described by Kim [3], where the input is tokenized and the tokens are embedded into a higher-dimensional representation before passing them to the convolutional neural network. Using this same architecture, Zhang & Wallace [7] perform additional exploration of the parameters and their effects on various datasets. Comparable results are achieved by Zhang *et al.* [8] by operating on the character-level rather than the word-level, bypassing the overhead of using word embedding (either in extra training time or in finding suitable pretrained embeddings) as well as freeing the researcher from having another layer in their network to tune. All the previously mentioned architectures use a single convolutional layer; this is contrary to current trends in computer vision, where popular models such as ResNet[9] go as deep as 152 layers. This difference is explored by Conneau *et al.* [10], who take a character-level CNN and show that adding more layers improves performance, before leveling out at 29 layers. They hypothesize that the difference in effective depth between computer vision and language processing might be due to the difference in datasets. The common ImageNet dataset used in computer vision deals with 1000 classes; in contrast, sentiment analysis datasets vary between 2 and 25 classes. In addition, they note that the deeper networks do require a larger amount of data to train.

4 Methodology

As described in section 2, the input data comes in the form of a series of PDF files. From this point on, there are two different systems acting on the data:

1. An unsupervised clustering step.
2. A supervised classifier.

The clustering step acts on the raw PDF file to segment it into blocks of text; these blocks are then clustered based on the shape of the blocks. This is described in detail in section 4.2. The second system is a supervised classification algorithm, consisting of two parts. First a convolutional neural network operates on lines of text to generate an intermediate representation, which is then combined with the output from the clustering step before being fed into a feed-forward neural network layer, which outputs the probability of each line of text being the start of a new speech. More details on this process are given in section 4.2. Figure 5 shows a high-level overview of the two systems and how they interact.

4.1 Unsupervised

The unsupervised algorithm detects and classifies blocks of text in the PDF file; Figure 6 shows an example of what a desired output could look like. This approach consists of two separate clustering steps, based on work by Klampfl

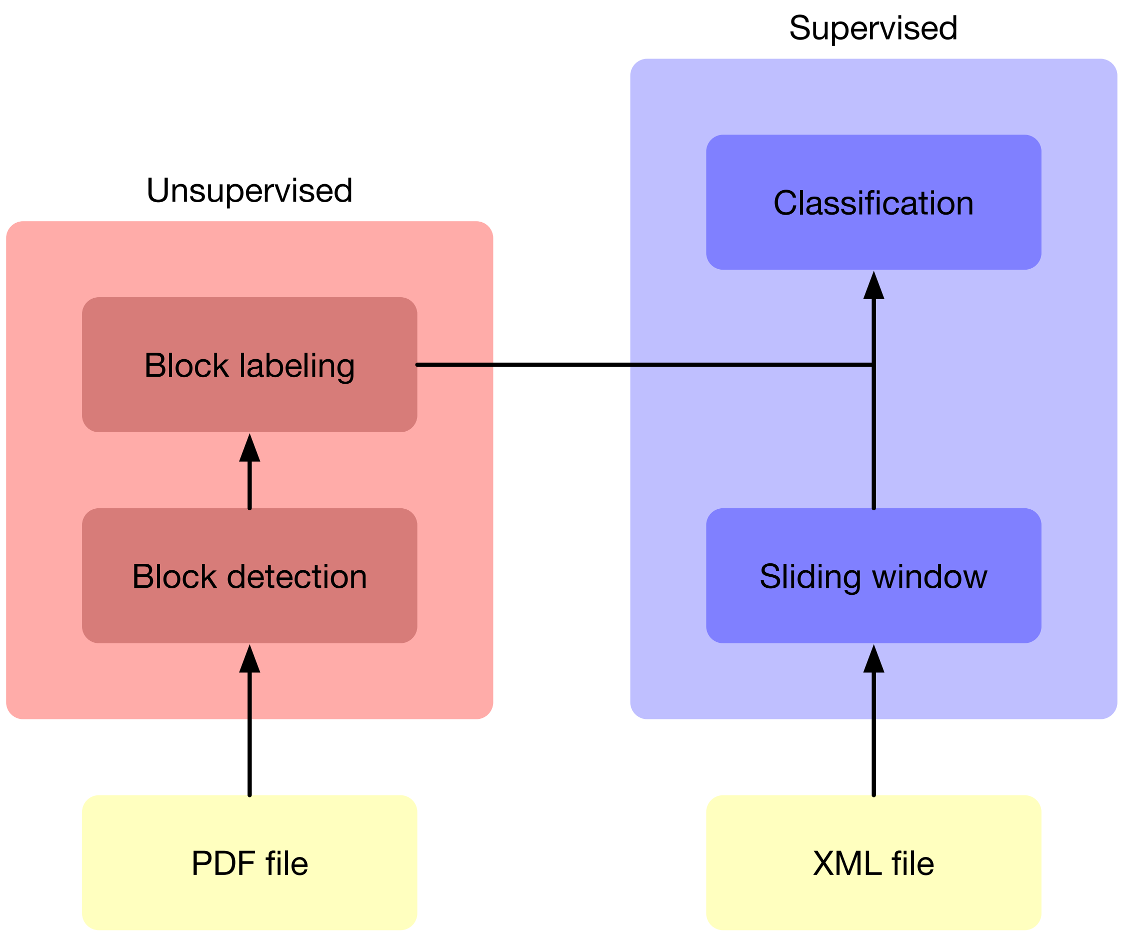
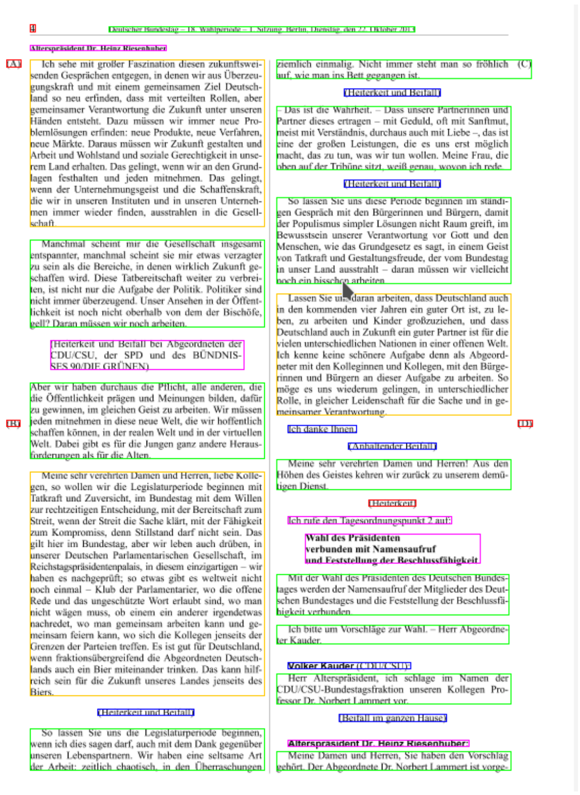


Figure 5: A high-level overview of the system. The unsupervised block augments the input to the classifier.

et al. [4]. First, individual characters (the fundamental objects available in a PDF file) are clustered together into blocks of semantically relevant text. These could be, for example, paragraphs, section headers or page decoration. By using the bounding boxes of the blocks, they can be clustered based on their shape and some additional metadata (e.g. occurrence of font types and sizes). The rest of this section will go into details on the two clustering steps.

4.1.1 Hierarchical Agglomerative Clustering

The first step is performed using hierarchical agglomerative clustering (HAC), an unsupervised bottom-up clustering algorithm that constructs a hierarchical tree of clusters (in this context referred to as a *dendrogram*). An example is shown in fig. 7. The algorithm iterates through the individual characters



4 Deutscher Bundestag – 18. Wahlperiode – 1. Sitzung. Berlin, Dienstag, den 22. Oktober 2013

Alterspräsident Dr. Heinz Riesenhuber

(A) Ich sehe mit großer Faszination diesen zukunftsweisenden Gesprächen entgegen, in denen wir aus Überzeugungskraft und mit einem gemeinsamen Ziel Deutschland so neu erfinden, dass mit verteilten Rollen, aber gemeinsamer Verantwortung die Zukunft unter unseren Händen entsteht. Dazu müssen wir immer neue Problemlösungen erfinden: neue Produkte, neue Verfahren, neue Märkte. Daraus müssen wir Zukunft gestalten und Arbeit und Wohlstand und soziale Gerechtigkeit in unserem Land erhalten. Das gelingt, wenn wir an den Grundlagen festhalten und jeden mitnehmen. Das gelingt, wenn der Unternehmungsgeist und die Schaffenskraft, die wir in unseren Instituten und in unseren Unternehmen immer wieder finden, ausstrahlen in die Gesellschaft.

Manchmal scheint mir die Gesellschaft insgesamt entspannter, manchmal scheint sie mir etwas verzagter zu sein als die Bereiche, in denen wirklich Zukunft geschaffen wird. Diese Tatbereitschaft weiter zu verbreiten, ist nicht nur die Aufgabe der Politik. Politiker sind nicht immer überzeugend. Unser Ansehen in der Öffentlichkeit ist noch nicht oberhalb von dem der Bischöfe, gell? Daran müssen wir noch arbeiten.

(Heiterkeit und Beifall bei Abgeordneten der CDU/CSU, der SPD und des BÜNDNISSES 90/DIE GRÜNEN)

Aber wir haben durchaus die Pflicht, alle anderen, die die Öffentlichkeit prägen und Meinungen bilden, dafür zu gewinnen, im gleichen Geist zu arbeiten. Wir müssen (B) jeden mitnehmen in diese neue Welt, die wir hoffentlich schaffen können, in der realen Welt und in der virtuellen Welt. Dabei gibt es für die Jungen ganz andere Herausforderungen als für die Alten.

Meine sehr verehrten Damen und Herren, liebe Kollegen, so wollen wir die Legislaturperiode beginnen mit Tatkraft und Zuversicht, im Bundestag mit dem Willen zur rechtzeitigen Entscheidung, mit der Bereitschaft zum Streit, wenn der Streit die Sache klärt, mit der Fähigkeit zum Kompromiss, denn Stillstand darf nicht sein. Das gilt hier im Bundestag, aber wir leben auch drüben, in unserer Deutschen Parlamentarischen Gesellschaft, im Reichstagspräsidentenpalais, in diesem einzigartigen – wir haben es nachgeprüft; so etwas gibt es weltweit nicht noch einmal – Klub der Parlamentarier, wo die offene Rede und das ungeschützte Wort erlaubt sind, wo man nicht wägen muss, ob einem ein anderer irgendetwas nachredet, wo man gemeinsam arbeiten kann und gemeinsam feiern kann, wo sich die Kollegen jenseits der Grenzen der Parteien treffen. Es ist gut für Deutschland, wenn fraktionsübergreifend die Abgeordneten Deutschlands auch ein Bier miteinander trinken. Das kann hilfreich sein für die Zukunft unseres Landes jenseits des Biers.

(Heiterkeit und Beifall)

So lassen Sie uns die Legislaturperiode beginnen, wenn ich dies sagen darf, auch mit dem Dank gegenüber unseren Lebenspartnern. Wir haben eine seltsame Art der Arbeit: zeitlich chaotisch, in den Überraschungen ziemlich einmalig. Nicht immer steht man so fröhlich (C) auf, wie man ins Bett gegangen ist.

(Heiterkeit und Beifall)

– Das ist die Wahrheit. – Dass unsere Partnerinnen und Partner dieses ertragen – mit Geduld, oft mit Sanftmut, meist mit Verständnis, durchaus auch mit Liebe –, das ist eine der großen Leistungen, die es uns erst möglich macht, das zu tun, was wir tun wollen. Meine Frau, die oben auf der Tribüne sitzt, weiß genau, wovon ich rede.

(Heiterkeit und Beifall)

So lassen Sie uns diese Periode beginnen im ständigen Gespräch mit den Bürgerinnen und Bürgern, damit der Populismus simpler Lösungen nicht Raum greift, im Bewusstsein unserer Verantwortung vor Gott und den Menschen, wie das Grundgesetz es sagt, in einem Geist von Tatkraft und Gestaltungsfreude, der vom Bundestag in unser Land ausstrahlt – daran müssen wir vielleicht noch ein bisschen arbeiten.

Lassen Sie uns daran arbeiten, dass Deutschland auch in den kommenden vier Jahren ein guter Ort ist, zu leben, zu arbeiten und Kinder großzuziehen, und dass Deutschland auch in Zukunft ein guter Partner ist für die vielen unterschiedlichen Nationen in einer offenen Welt. Ich kenne keine schönere Aufgabe denn als Abgeordneter mit den Kolleginnen und Kollegen, mit den Bürgerinnen und Bürgern an dieser Aufgabe zu arbeiten. So möge es uns wiederum gelingen, in unterschiedlicher Rolle, in gleicher Leidenschaft für die Sache und in gemeinsamer Verantwortung.

Ich danke Ihnen. (D)

(Anhaltender Beifall)

Meine sehr verehrten Damen und Herren! Aus den Höhen des Geistes kehren wir zurück zu unserem demütigen Dienst.

(Heiterkeit)

Ich rufe den Tagesordnungspunkt 2 auf:

Wahl des Präsidenten
verbunden mit Namensaufruf
und Feststellung der Beschlussfähigkeit

Mit der Wahl des Präsidenten des Deutschen Bundestages werden der Namensaufruf der Mitglieder des Deutschen Bundestages und die Feststellung der Beschlussfähigkeit verbunden.

Ich bitte um Vorschläge zur Wahl. – Herr Abgeordneter Kauder.

Volker Kauder (CDU/CSU):

Herr Alterspräsident, ich schlage im Namen der CDU/CSU-Bundestagsfraktion unseren Kollegen Professor Dr. Norbert Lammert vor.

(Beifall im ganzen Hause)

Alterspräsident Dr. Heinz Riesenhuber:

Meine Damen und Herren, Sie haben den Vorschlag gehört. Der Abgeordnete Dr. Norbert Lammert ist vorge-

Figure 6: An example of clustered blocks of text. Blocks with the same outline color belong to the same cluster.

from the PDF files, successively grouping the two closest clusters (the initial inputs being regarded as clusters of one element) together until only a single cluster remains. This process involves two parameters:

1. A distance function between two characters.
2. A distance function between two clusters of characters.

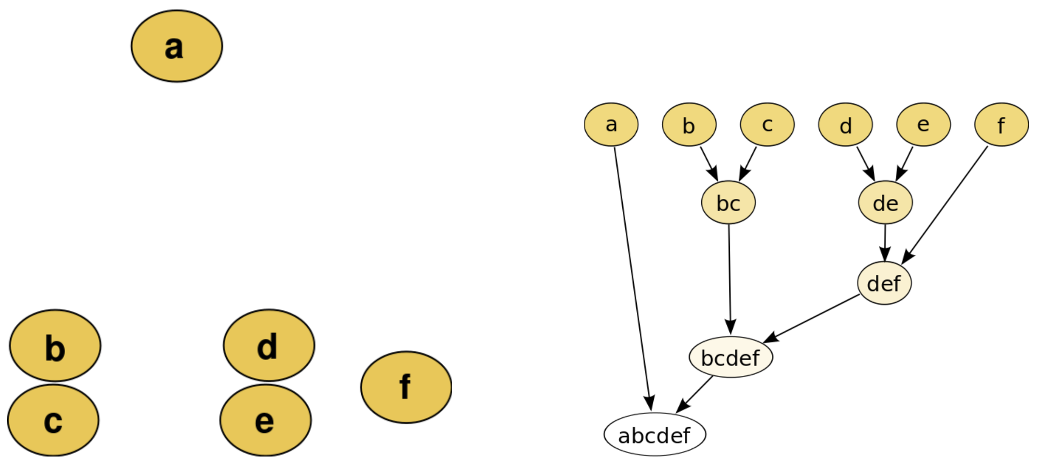
The first parameter is trivially chosen to be the Euclidean distance between the coordinates of the two characters. The second parameter is called the *linkage* and has several common options, the most basic of which are:

- Single-linkage: The distance between clusters is based on the closest two elements:

$$d(A, B) = \min\{d(a, b) : a \in A, b \in B\}$$

- Maximum-linkage: The distance between clusters is based on the furthest two elements:

$$d(A, B) = \max\{d(a, b) : a \in A, b \in B\}$$



(a) Before (b) After

Figure 7: An example of hierarchical agglomerative clustering, where the nodes are clustered by distance.

- Average-linkage: The distance between clusters is based on the average distance of its elements:

$$d(A,B) = \frac{1}{|A||B|} \sum_{a \in A} \sum_{b \in B} d(a,b)$$

More involved linkage criteria exist, such as the Ward method which minimizes the variance within clusters. Although these more complex methods would generally be favored, in this context single-linkage is actually the best option[4]. This is due to its tendency to form long, thin clusters; this mirrors the nature of text, in particular words and sentences (which are just long, thin strings of letters and words respectively). As an additional bonus, it is the most computationally efficient method. While the general time complexity for HAC is in $\mathcal{O}(n^3)$, clever algorithms exist for single-linkage clustering that fall in $\mathcal{O}(n^2)$ [11], making it far more usable on larger datasets.

After the dendrogram is constructed, it has to be cut at some level to obtain the desired blocks of text. Clustering can optionally be rerun using the newly found clusters as basic elements. This way, the document can incrementally be clustered from characters into words, words into lines, and finally lines into paragraphs. Both the level at which to cut the tree and the number of times to recluster are to be manually tuned based on the particular set of documents.

4.1.2 Clustering

The blocks that were found in the previous step are then clustered according to their similarity based on the following metrics:

- Width of the block
- Height of the block
- The most common font occurring in the block
- The size of the most common font occurring in the block

This is implemented two different ways, with their performance to be compared later on. The first method is the familiar K-Means clustering algorithm, which works as follows:

1. Randomly initialize k cluster centroids.
2. Assign each observation to its nearest centroid.
3. Recompute each centroid to be the mean of all of its assigned observations.
4. Repeat steps 2 and 3 until the assignments stop changing.

After the algorithm has converged, the clustering is defined by each observation's nearest cluster centroid; with k clusters, each observation is assigned a k-dimensional one-hot vector.

4.1.3 Dirichlet Process Clustering

K-Means clustering can be generalized to a *mixture of Gaussians* model. Whereas K-Means clustering defines each cluster by a centroid and assigns each sample to the nearest centroid, a mixture of Gaussians — as the name implies — instead defines each cluster by a Gaussian distribution; each sample then gets assigned a probability of belonging to each cluster. This adds a degree of uncertainty to the representation, which is lost in K-Means' hard assignments. While this already improves upon K-Means by increasing the amount of information encoded in the representation, it still requires a suitable value for the number of distributions, analogous to the K in K-Means clustering. In this case, this is a rather unintuitive parameter; there is no way to figure out a suitable value without experimenting with a range of values. Fortunately, this parameter can be eliminated by using an infinite mixture model. As the name implies, an infinite mixture model is similar to a Gaussian mixture model, except using an infinite amount of distributions, thereby removing the most significant parameter.

The core component of this infinite mixture model is a *Dirichlet process*. This is conceptually similar to the well-known Dirichlet distribution, with one key difference. Whereas the Dirichlet distribution generates discrete probability distributions with a finite amount of possible values, the Dirichlet process generates distributions with an infinite amount of possible values. There are a number of methods to sample from a Dirichlet process, most commonly the *stick-breaking process*, *Pólya urn scheme* or the *Chinese restaurant process*[12].

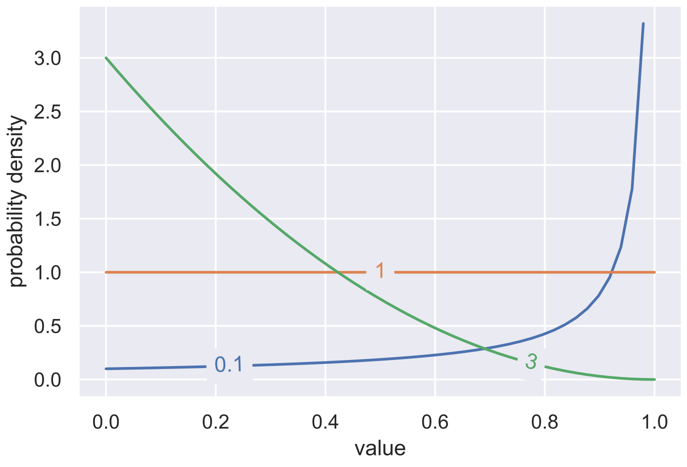


Figure 8: The probability density function of Beta$(1, \alpha)$ for various values of α. As the value of α increases, the most likely values of the distribution shift towards zero.

In this case, the stick-breaking process was used. Using this process, the probability w_k of a sample being assigned to the k'th distribution is given by

$$w_k = \beta_k \cdot \prod_{i=1}^{k-1} (1 - \beta_i)\,, \tag{1}$$

where β_k is a random variable drawn from the distribution Beta$(1, \alpha)$. Since the Beta distribution is defined on the interval $[0, 1]$, the β_k values can be considered as portions of a unit-length stick. When the first cluster is assigned to, a piece of size β_k is broken off of this unit-length stick. On subsequent assignments, the new sample is either assigned to an existing cluster with a probability proportional to the length of that cluster's portion of the stick, or a new cluster is assigned to. In the latter case, the new cluster gets a β_k-sized portion of the remains of the stick. This way, cluster assignments tend towards a long-tailed distribution. The α parameter in the prior distribution Beta$(1, \alpha)$ is called the weight-concentration parameter. Figure 8 shows the probability density function for various values of α. For lower values of α, big portions of the stick are likely to be broken off, concentrating the cluster assignments into a small amount of clusters; conversely, higher values of α lead to smaller portions and more diversity in the cluster assignments.

The tendency to continuously decrease the probability of assigning to a new cluster is a key factor in using Dirichlet process clustering in practice. Since at a certain point the probability of a new cluster being assigned becomes practically zero, it is sufficient to implement this using a finite "large enough" number of clusters, after which the clusters with very low probabilities can be pruned. This is illustrated with a simple example in fig. 9. Note that because of the Bayesian nature of the algorithm, even though the prior favors a long-tail distribution, it has no problem creating equally likely clusters if the data demands it.

The samples generated from each cluster are assumed to come from a Gaussian distribution; the rest of the probabilistic model mostly consists of run-of- the-mill priors, without much semantic meaning to them and differing between different implementations of the algorithm. In this case an implementation from Scikit-Learn[13] was used, whose probabilistic model and subsequent derivation of the inference algorithm can be found online[5].

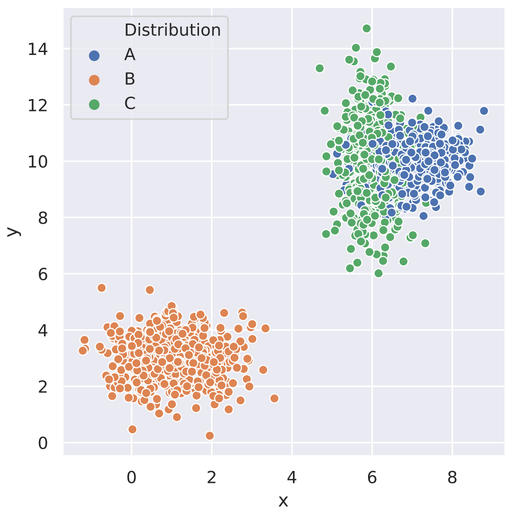
4.2 Supervised

After the data is augmented by the previously described clustering algorithms, it's fed into a convolutional neural network for classification. Since the documents have a dual column layout (meaning each line of text is pretty short) and classification is based on the lines from the document, a sliding window is used to supply more context. The window consists of a variable amount of lines before and after the main line, which is the one supplying the label (whether or not the line starts a new speech). This sliding window is then used as input to a neural network, consisting of a convolutional part followed by a feed-forward neural network. The convolutional part is applied to the sliding window and outputs an intermediate representation, which is concatenated to the clustering distribution obtained previously (in the case of the mixture model, this is the actual probability distribution over each cluster; in the K-Means case, it is a one-hot vector). This combined vector, containing semantic information from the convolutional layer and layout information from the clustering step, is then fed into the feed-forward network to obtain the final classification. There are two different models, differing in their convolutional layer:

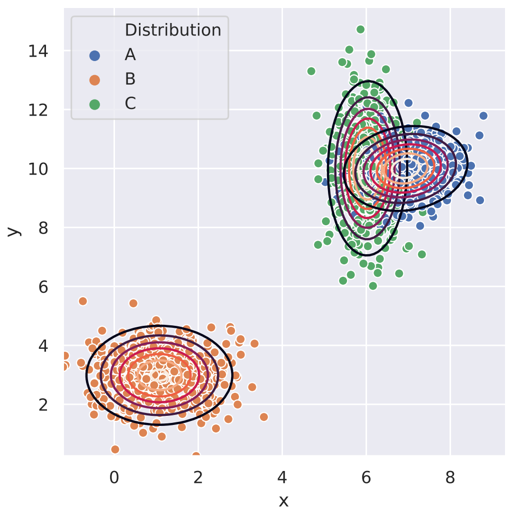
- WordCNN: A shallow word-based architecture[3], where the text is tokenized such that each token is either a word or a single punctuation mark (for example, "Hello-!" would produce the tokens "Hello", "-" and "!").
- CharCNN: A character-based architecture[8]. This is a deeper network, that operates on the raw characters without using an embedding layer.

The WordCNN and CharCNN models are described in tables 1a and 1b; the feed-forward neural network common to both models in described in table 1c. A high-level overview of how the different parts of the system fit together is shown in fig. 5.

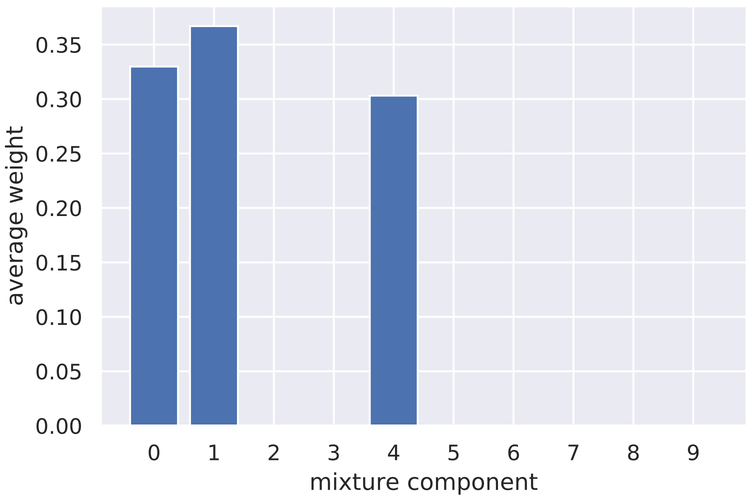
[5]http://scikit-learn.org/stable/modules/dp-derivation.html



(a)



(b)



(c)

Figure 9: Dirichlet Process mixture model clustering with a prior of ten mixture components, performed on 1500 samples drawn from three different bivariate normal distributions (fig. 9a). The distributions found by the clustering algorithm are drawn in fig. 9b. As shown by averaging the component weights of each sample's assignment (fig. 9c), the Dirichlet Process correctly assigned to just three mixture components, despite its prior of ten components.

Layer	Type	Filters	Size	Pooling
1	Embedding	-	100	-
2	Conv	99	$3, 5, 7$	1-max

(a) The convolutional part of the WordCNN models consists of an embedding layer to embed the tokens into a higher-dimensional space, followed by a single convolutional layer. The convolutional layer uses 33 filters of each of three different sizes, with a stride of 1. The filters are concatenated for a total of 99 filters, with 1-max pooling applied to each filter such that the final output is a 99-dimensional vector.

Layer	Filters	Size	Pooling
1	256	7	3
2	256	7	3
3	256	3	-
4	256	3	-
5	256	3	-
6	256	3	3

(b) The convolutional part of the CharCNN model is a relatively deeply layered sequence of convolutions. Each convolution is followed by a ReLU activation function. The convolutions have a stride of 1, while the pooling layers are non-overlapping with a stride of 3.

Layer	Output Size	Activation	Dropout
1	1024	ReLU	0.5
2	1024	ReLU	0.5
3	1	Sigmoid	None

(c) Both architectures go through this feed-forward neural network with 3 layers.

Table 1: The layouts of the neural networks. Table (a) corresponds to the convolutional part of the WordCNN model while Table (b) similarly corresponds to the CharCNN model; Table (c) describes the feed-forward neural network common to both models.

The network is trained for 100 epochs, stopping early once no significant improvement has been made on a small validation set for 10 epochs in a row. The optimization process is done using the Adadelta[14] algorithm, with binary cross-entropy as the loss function and the training data delivered in batches of 50 samples. Regularization is done through a combination of dropout[15] and an upper limit on the L2 norm of each weight vector[16]. Further explanation on the use of convolutional neural networks is given in section 4.2.1, and details on the optimization process and the regularization methods are provided in section 4.2.2 and section 4.2.3 respectively.

4.2.1 Convolutional Neural Networks

Although convolutional neural networks (CNNs) are more closely associated with computer vision, they are also widely used for text classification, offering results competitive with recurrent neural networks[17] at greater speed due

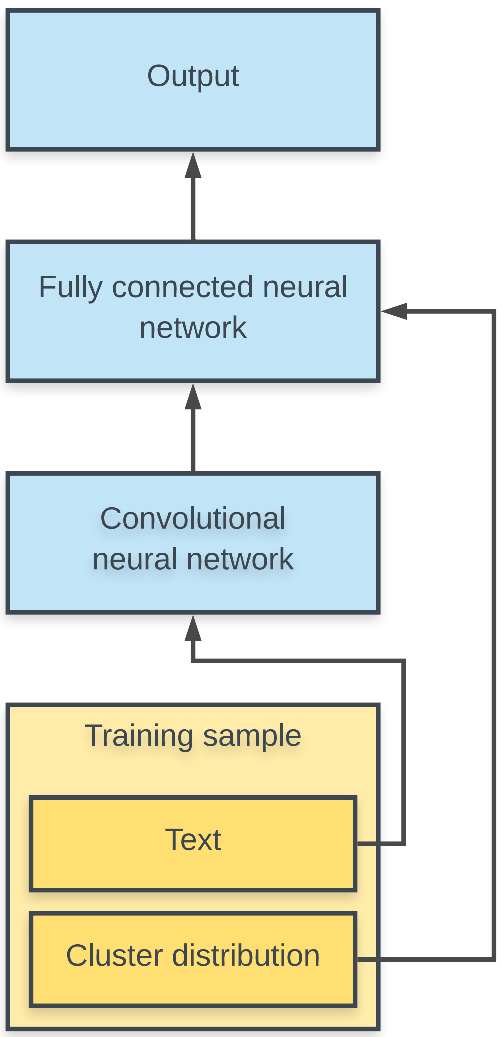


Figure 10: The layout of the supervised portion of the system. The input data contains text and a cluster type assigned by the unsupervised portion. The text gets put into a convolutional neural network, the output of which is fed together with the cluster type into a feed-forward neural network. The sigmoid function is applied to the output of this final neural network to obtain the classification.

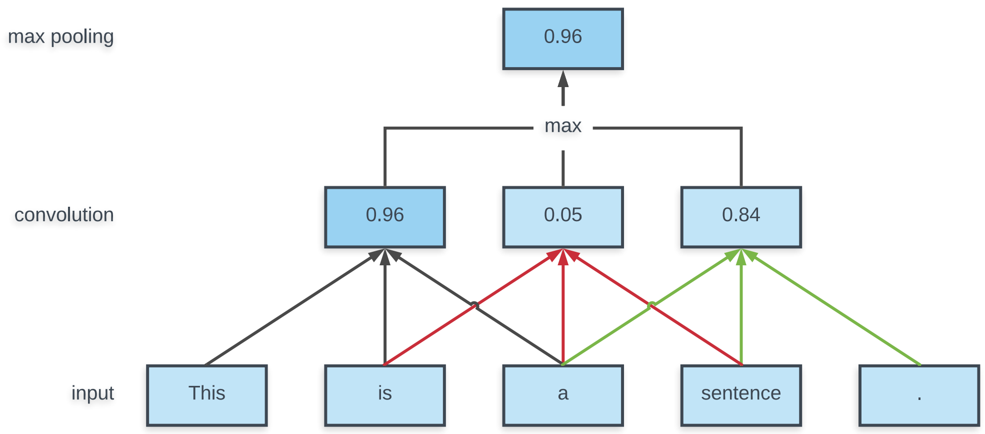


Figure 11: A simplified convolutional neural network with one filter and max pooling.

to the more parallel nature of CNNs[18].

Convolutional neural networks (CNNs) work by taking a number of filters of a specified size and convolving these over the input data. A simplified example using one filter is shown in fig. 11. In this example, the input text is convolved with a filter with a width of 3 and a stride of 1 — that is, each application of the filter considers three subsequent input elements, after which the window is shifted one space to the right. This filter is essentially a small neural network mapping three items to one output value, whose weights are reused for each application of the filter. Reusing the weights in this way (weight sharing) prevents the number of parameters in the network from spiraling out of control [19]. After the application of this convolution layer, the responses of the filter form a new sequence of roughly the same size as the input (minus a few due to missing the edges). The next step is to downsample this sequence by means of a *max pooling* layer, which maps all values within a window to the maximum value amongst those values. While superficially similar to a convolution, this step generally does not involve overlap, instead either setting the stride to the same value as the window size (usually 2) or reducing the entire sequence to 1 value (1-max pooling). The reason for this is twofold:

1. It downsamples the data, reducing the amount of parameters required further on in the network.

2. It adds translation invariance to the feature detected by this filter. The example filter of fig. 11 reacts strongly to the first three words. Without the pooling layer, changing the location of these words in the input would similarly change the location of the high activation in the intermediate representation. The more aggressively the pooling is

applied, the higher the degree of invariance; using 1-max pooling, the representation is fully translation invariant.

This combination of convolution followed by pooling can be repeated multiple times as desired or until there is only a single value left as output from the filter. Finally, the outputs of all filters are concatenated and fed into a regular neural network.

While CNN architectures in computer vision are generally very deep, they tend to be very shallow in natural language processing; commonly just a single convolution followed by 1-max pooling [7].

4.2.2 Optimization process

Optimization is done using the Adadelta update rule[14]. This is easiest to explain by starting with the basic mini-batch stochastic gradient descent algorithm (SGD). At each iteration t, the network parameters θ are updated based on some calculated difference:

$$\theta_{t+1} = \theta_t - \Delta\theta_t \,. \tag{2}$$

The difference between optimization algorithms is how $\Delta\theta$ is calculated. With SGD, it is simply

$$\Delta\theta_t = \mu \nabla_{\theta_t} \mathcal{L}(\theta_t) \,, \tag{3}$$

where $\mathcal{L}$ is the loss function (in this case, the binary cross entropy between the predicted labels and the true labels), and μ is an arbitrary learning rate between 0 and 1. This learning rate is a tricky parameter to set; too low and learning will take ages, too high and the network will fail to converge because the steps taken are too big. One way to improve this is by using the Adagrad[20] algorithm. While SGD uses a single learning rate for the entire parameter vector, Adagrad (which stands for "adaptive gradient") adapts the learning rate for each individual parameter; frequently updated parameters get a lower learning rate, while less frequently updated parameters are updated with a higher learning rate. This is done by simply dividing the learning rate with the L2 norm of the sum of all previous gradients:

$$g_t = \nabla_{\theta_t} \mathcal{L}(\theta_t) \tag{4}$$

$$\Delta\theta_t = \frac{\mu}{\sqrt{\sum_{\mathcal{T}=1}^{t} g_{\mathcal{T}}^2}} g_t \,. \tag{5}$$

This has been found to work very well, in particular in natural language processing and computer vision where features are often sparse, but it has two drawbacks:

1. A suitable value for the global learning rate μ has to be manually provided.

2. Since the learning rate is rescaled using a monotonically increasing sum of previous gradient magnitudes, the learning rate will converge to zero.

Adadelta nullifies these drawbacks by eliminating the global learning rate and restricting the accumulation of gradients to a window of recent updates. First of all, the sum over all previous gradients is replaced by an exponentially decaying average of the squared gradients, referred to as $E[g^2]$:

$$E[g^2]_t = \rho E[g^2]_{t-1} + (1-\rho) g_t^2 \,. \tag{6}$$

Here ρ is a constant representing the rate of decay; this decaying sum serves as a more efficient approximation of an actual window of past gradients, which would require far more memory to store (considering both the huge number of parameters in a neural network and the memory constraints of running on a GPU). Substituting this into the Adagrad algorithm gives us:

$$\begin{align} \Delta\theta_t &= \frac{\mu}{\sqrt{E[g^2]_t}} g_t \tag{7} \\ &= \frac{\mu}{RMS[g]_t} g_t \,. \tag{8} \end{align}$$

The quantity $\sqrt{E[g^2]_t}$ is called the *root mean square* of g, which occurs often enough in optimization algorithms that it is often abbreviated as $RMS[g]$. As a final step, the learning rate μ is eliminated by replacing it with a decaying average of the previous gradient updates, similar to eq. (6):

$$\Delta\theta_t = \frac{RMS[\theta]_{t-1}}{RMS[g]_t} g_t \,. \tag{9}$$

4.2.3 Regularization

The main regularization method in use is the popular dropout[15] method; at training time, each node in the neural network has a probability p of outputting zero (i.e. the node being “disabled”). As a result, nodes cannot rely on the output of any other node being present, preventing co-adaptation and as a result reducing the probability of overfitting on the training data. When running the network in evaluation mode, all nodes are active and the outputs are rescaled by a factor of $1-p$ to account for the now higher activation values.

One of the key elements in dropout’s effectiveness is related to model combination. It is commonly known that for any machine learning classifier, including neural networks, performance can be improved by training a large number of slightly different classifiers (either trained on different subsets of the data or using different parameters) and taking the average of their outputs. For neural networks in particular, this is prohibitively expensive; they take a long time to train, and using subsets of the training data negates one of their key advantages, being that they scale so well with additional training data. Using dropout, every combination of nodes disabled by dropout could be considered a unique neural network architecture, making dropout act as a computationally cheap approximation to averaging multiple networks.

In addition to dropout, a maximum L2 norm is imposed on each node's incoming weight vector. If the weight vector's L2 norm exceeds this limit, it is rescaled so that its new norm is equal to the maximum allowed norm; otherwise the weight vector is left alone:

$$\mathbf{w} = \begin{cases} \mathbf{w} & \text{if } ||\mathbf{w}||^2 \leq n \\ n\frac{\mathbf{w}}{||\mathbf{w}||^2} & \text{otherwise} \end{cases} \tag{10}$$

This differs from the more common L2-regularization — where the combined L2 norm of all weight vectors is added to the loss function — in that the weights are not being continuously pushed towards zero, making it a milder form of regularization that allows for a bit more complexity in the model.

5 Evaluation

To recap the previous sections, we are dealing with two models here:

- "WordCNN", a convolutional neural network operating on tokenized words and punctuation,
- "CharCNN", a convolutional neural network operating on tokenized characters,

as well as three variations for each model:

- No clustering.
- The data is augmented with K-Means clustering.
- The data is augmented with clustering through an infinite Gaussian mixture model.

These variations will be referred to as "Baseline", "K-Means" and "GMM " respectively. Although K-fold cross validation is a common way of comparing the performance of different, there are two reasons why it isn't used in these experiments:

- One of the more interesting variables in this context is the size of the training set, but with cross validation it is directly tied to the number of folds (e.g. with a dataset of 1000 samples and 10 folds, each fold would have a training set of 100 samples).
- The training set and the test set are sampled from the same pool of data. In our case, we want the training set and the test set to be sampled from different electoral periods, because:

  - A change of electoral period means at least a partial change in parliamentary members, which reduces the ability of the model to overfit on their names.
  - Although older documents use the same layout as newer ones, the PDF files were generated using different software (electoral period 13 started in 1994 and was the first period to use truly digital documents — older documents are scanned versions of printed paper). Since PDF decompilation is already a flaky process, this results in the PDF decompiler making different mistakes than it does on the newer documents. This is a big problem for rule-based systems, but hopefully the probabilistic nature of neural networks makes them more robust to this issue.

Therefore, a variation of cross validation is used instead. There is a pool of training data consisting of documents from the 18th electoral period of the *Bundestag*, and a test set containing documents from the electoral periods 13 to 17. For 10 iterations, k samples are pulled from the pool of training data. Each of the three models is trained on these samples and then tested on the full test set.

5.1 Results

The results of the main experiments are shown in fig. 12. A number of things are immediately noticeable:

- With a context window of size 1 (i.e. only a single line of text), results are particularly bad. Adding the subsequent line of text (a window size of 2) increases performance significantly, but additional increases lead to diminishing returns and eventual regression in performance.
- The CharCNN model scales better with the size of the dataset than the TokenCNN model; in each case except for the smallest window size, TokenCNN has a much flatter curve. It outperforms CharCNN at low dataset sizes, but in most cases CharCNN manages to edge out a bit of extra performance at 2400 and 3000 samples.
- GMM clustering performs equal to or better than the baseline in almost every case; in some cases the GMM curve is clearly above the baseline curve, in others they are close enough that their confidence interval overlaps. K-Means clustering is a little bit harder to pin down, but in many cases seems to fall in between the baseline and GMM clustering.

It is risky to readily draw conclusions from this data, as the variance between cross validation runs is high relative to the difference in F1 score between the models. Although significance testing (by means of of P scores) can be a useful tool in scenarios like this, their power with is relatively

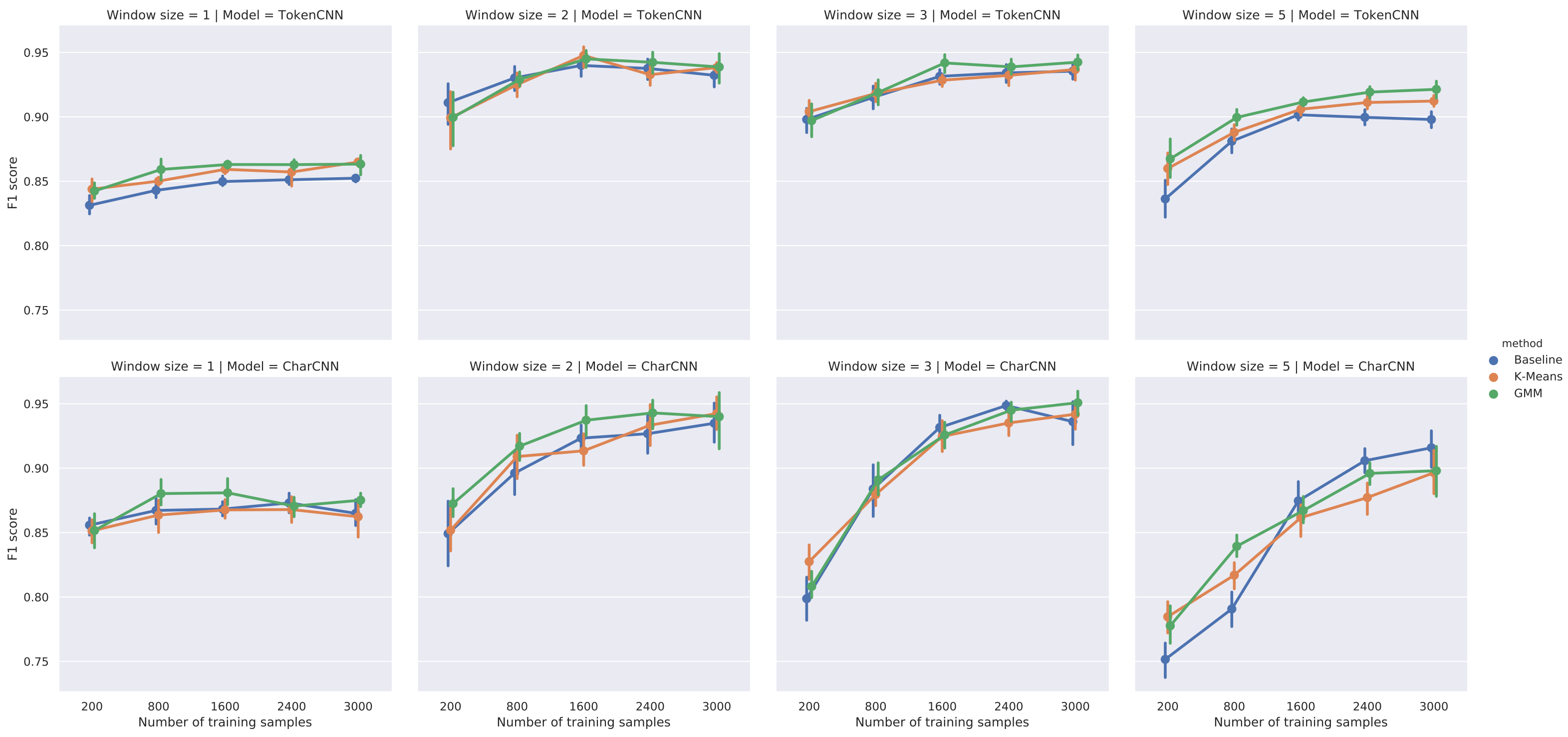


Figure 12: A number of point plots showing the F1 scores of the experiments, averaged over 10 cross validation runs. The error bars indicate the 95% confidence interval, meaning that the true mean has a 95% chance of lying within the shown interval. The number of training samples is varied on the x-axis; the left column shows the TokenCNN model, the right column the CharCNN model. The rows correspond to the size of the context window. The three clustering methods are displayed within the same graph.

low with the low sample size of 10 combined with the small difference in scores. Increasing the number of cross validation folds would have been a solution, although at significant cost in both time and electricity; instead, the discriminative power can be increased by coalescing the results at different parameter configurations. This is shown in table 2a for all parameters, and in table 2b for a well-performing subset of parameters. This paints a much clearer picture. In table 2a, the TokenCNN model is significantly improved by both forms of clustering, while the CharCNN does not appear to benefit from adding K-Means clustering. In this overall case, the TokenCNN also outperforms the CharCNN, mostly because of the inclusion of the low amounts of training data which the CharCNN model struggles with.

Restricting our view to the better performing parameter settings in table 2b, a couple of things change. First of all, K-Means clustering does

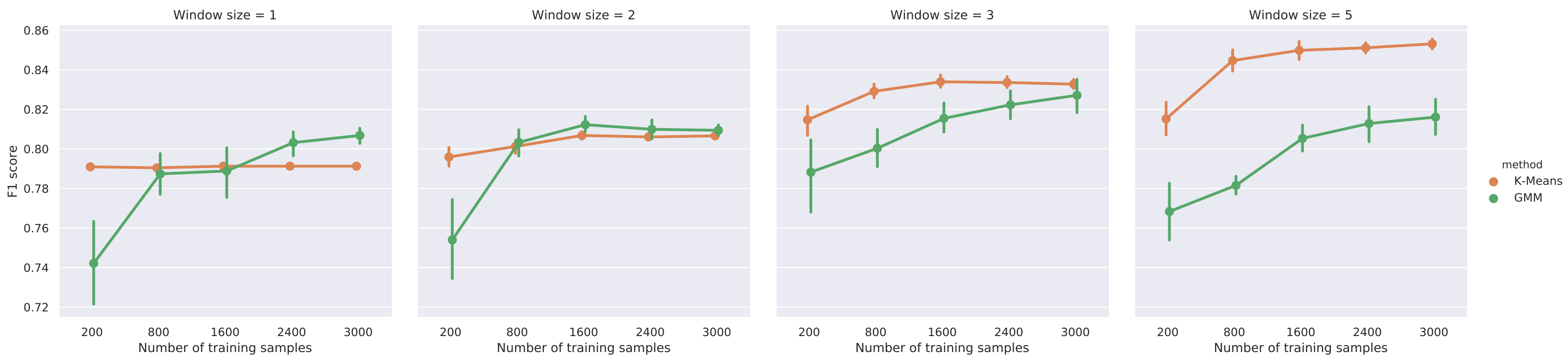


Figure 13: This figure is similar to fig. 12, except when trained on *only* the clustering data, with the textual data being discarded.

not appear to improve the scores for either model. GMM clustering is still a significant improvement when applied to the TokenCNN. When applied to the CharCNN, the score is still quite a bit higher, although it loses its significance in a statistical sense. Additionally, CharCNN now wins out over TokenCNN with a slight margin.

5.2 Discriminative power of clustering

Now that it is somewhat established that GMM clustering outperforms K-Means clustering, it might be interesting to look at their differences in greater detail. We have already compared the baseline (only text) with the augmented models (text and clustering); why not add something of an inverse baseline that is trained using only the clustering data? The results of this experiment are shown in fig. 13, and they contain some surprises. While the previous experiments seemed to imply that adding GMM clustering improved the F1 scores more than adding K-Means clustering did, here we actually see K-Means on its own significantly out-perform GMM at larger window sizes. In fact, K-Means seems to scale very well with increased window sizes, while the GMM performance is rather constant. In addition, K-Means suffers far less when lowering the number of training samples to 200. Lastly, their performance is surprisingly good. The peak F1 score of around 0.85 is not all that far removed from the baseline scores of roughly 0.94, considering the amount of information lost when discarding the text.

	TokenCNN		CharCNN	
Method	Mean	P	Mean	P
Baseline	0.895	-	0.880	-
K-Means	0.901	2.55×10^{-5}	0.880	0.81
GMM	0.905	6.12×10^{-13}	0.888	1.16×10^{-4}

(a) The values in this table are taken from all window sizes and all dataset sizes.

	TokenCNN		CharCNN	
Method	Mean	P	Mean	P
Baseline	0.935	-	0.937	-
K-Means	0.935	0.96	0.938	0.72
GMM	0.941	0.03	0.945	0.12

(b) The values in this table are taken from the best performing subset of the parameters, with the number of training samples being 2400 and 3000 and the size of the context window set to 1 or 2.

Table 2: The results averaged over all tested parameters. The P column shows the P value comparing each model to the baseline, using a paired Student's t-test over the full cross validation output. The P value is based on the null hypothesis that neither model improves on the baseline. Using the common $P \leq 0.05$ cutoff for rejecting the null hypothesis, any P value below 0.05 would be grounds to consider the model to perform differently from the baseline. Since each model's mean score is equal to or higher than the baseline score, in this case we can fortunately take "differently" to mean "better".

6 Conclusion

As stated earlier in section 2.2, the addition of clustering information was intended to either improve the peak scores or reduce the required amount of training data for similar scores. In addition to this main research question, two different neural network models were compared: TokenCNN, a model that operates at the word level, and CharCNN, a model that operates at the character level. Finally, clustering was implemented using a basic K-Means algorithm as well as a more involved Gaussian mixture model.

With regards to the two neural network models, it all boils down to the amount of available training data. At lower amounts, TokenCNN greatly outperforms its character-based counterpart; starting from around 2400 training samples, CharCNN catches up and achieves slightly better scores. Between the two clustering models, the mixture model simply outperforms

K-Means clustering in every scenario.

Coming back to the main research question, the conclusion is cautiously positive, if underwhelming. Comparing the baseline to Gaussian mixture model clustering, table 2b shows an increase in F1 score of 0.06 (P = 0.03) for the TokenCNN model and an increase of 0.07 (P = 0.12) for the CharCNN. While these are not massive improvements, the addition of GMM does appear to improve the F1 score. On the other hand, K-Means clustering adds nothing to the score.

Regarding the second research question about data efficiency, there is no difference beyond what is implied by the previous paragraph. Since the GMM-augmented model generally outperforms the baseline, it is trivial that there are cases where the augmented F1 score with little data is equal to the baseline F1 score when using more data. In fig. 12 however, both models tend to follow the same curve with respect to the number of training samples, flattening out somewhere around 2400-3000 training samples. Since the models scale similarly with increased samples and reach their peak performance around the same amount, in practice one would aim for a similarly sized dataset regardless of whether or not GMM augmentation is being used. In that sense, it seems fair to conclude that there are no benefits regarding data efficiency.

6.1 Discussion

In this thesis I proposed a method for adding layout information to a standard text classifier and showed that it slightly increases the classifier's performance. This could be considered somewhat of a proof of concept, as there are a number of other potential benefits that were unexplored. For instance, document layouts are largely invariant to the document's language or subject; I have little experience with both German and with politics, but I had no problem understanding how the Bundestag documents from the dataset were laid out. This suggests that the clustered layouts might respond very well to transfer learning, i.e. training on one dataset, then reusing the trained network for another dataset after training on a very small amount of documents from that new dataset.

Taking a step back, the reason that the document layout was described using clustering algorithms was purely convenience; it was easy to implement and integrates well with a neural network classifier. There might be more specialized algorithms that represent the layout in an even more informative way, which would hopefully amplify the increased performance seen here. In fact, before properly starting on this thesis my ambition was to segment the documents using only the layout, outperforming any classifier relying on the document's text. Although I did not succeed in that regard, I still feel like it is possible, and I hope to see it done some day.

References

1. Iyyer, M., Enns, P., Boyd-Graber, J. & Resnik, P. *Political ideology detection using recursive neural networks* in *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)* **1** (2014), 1113–1122.
2. Gross, J. H., Acree, B., Sim, Y. & Smith, N. A. Testing the Etch-a-Sketch Hypothesis: A Computational Analysis of Mitt Romney's Ideological Makeover During the 2012 Primary vs. General Elections (2013).
3. Kim, Y. *Convolutional Neural Networks for Sentence Classification* in *EMNLP* (2014).
4. Klampfl, S., Granitzer, M., Jack, K. & Kern, R. Unsupervised document structure analysis of digital scientific articles. *International Journal on Digital Libraries* **14,** 83–99 (2014).
5. Ferrara, E., Meo, P. D., Fiumara, G. & Baumgartner, R. Web Data Extraction, Applications and Techniques: A Survey. *Knowl.-Based Syst.* **70,** 301–323 (2014).
6. Gogar, T., Hubacek, O. & Sedivy, J. *Deep Neural Networks for Web Page Information Extraction* in *Artificial Intelligence Applications and Innovations* (eds Iliadis, L. & Maglogiannis, I.) (Springer International Publishing, Cham, 2016), 154–163. ISBN: 978-3-319-44944-9.
7. Zhang, Y. & Wallace, B. C. *A Sensitivity Analysis of (and Practitioners' Guide to) Convolutional Neural Networks for Sentence Classification* in *IJCNLP* (2017).
8. Zhang, X., Zhao, J. & LeCun, Y. *Character-level convolutional networks for text classification* in *Advances in neural information processing systems* (2015), 649–657.
9. He, K., Zhang, X., Ren, S. & Sun, J. Deep Residual Learning for Image Recognition. *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR),* 770–778 (2016).
10. Conneau, A., Schwenk, H., Barrault, L. & LeCun, Y. Very Deep Convolutional Networks for Natural Language Processing. *CoRR* **abs/1606.01781** (2016).
11. Sibson, R. SLINK: an optimally efficient algorithm for the single-link cluster method. *The computer journal* **16,** 30–34 (1973).

12. Frigyik, B. A., Kapila, A. & Gupta, M. R. Introduction to the Dirichlet distribution and related processes. *Department of Electrical Engineering, University of Washignton, UWEETR-2010-0006* (2010).

13. Pedregosa, F. *et al.* Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research* **12,** 2825–2830 (2011).

14. Zeiler, M. D. ADADELTA: An Adaptive Learning Rate Method. *CoRR* **abs/1212.5701** (2012).

15. Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I. & Salakhutdinov, R. Dropout: A simple way to prevent neural networks from overfitting. *The Journal of Machine Learning Research* **15,** 1929–1958 (2014).

16. Hinton, G. E., Srivastava, N., Krizhevsky, A., Sutskever, I. & Salakhutdinov, R. Improving neural networks by preventing co-adaptation of feature detectors. *CoRR* **abs/1207.0580** (2012).

17. Yin, W., Kann, K., Yu, M. & Schütze, H. Comparative Study of CNN and RNN for Natural Language Processing. *CoRR* **abs/1702.01923** (2017).

18. Gehring, J., Auli, M., Grangier, D., Yarats, D. & Dauphin, Y. *Convolutional Sequence to Sequence Learning* in *ICML* (2017).

19. LeCun, Y., Bengio, Y., *et al.* Convolutional networks for images, speech, and time series. *The handbook of brain theory and neural networks* **3361,** 1995 (1995).

20. Duchi, J., Hazan, E. & Singer, Y. Adaptive subgradient methods for online learning and stochastic optimization. *Journal of Machine Learning Research* **12,** 2121–2159 (2011).