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Bachelor thesis

Better accuracy of automatic lecture transcriptions by using context information from lecture material

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1 Introduction

Scannability is crucial for academic research: you have to be able to quickly evaluate the usefulness of a given resource by skimming the content and looking for the parts that are specifically relevant to the task at hand.

The medium in which those resources are available is very centered on textual representation. Recorded spoken content, hereinafter called *speech media* (recorded audio- or audiovisual media that mainly consist of spoken language) doesn't make it possible to scan its contents. You are "stabbing in the dark" when looking for something specific in a medium like this and have to consume it like a linear narrative.

This means that although lectures and conference talks are a central element to science they are much more challenging and tedious to use for scholarly activities.

Being able to (a) efficiently search and (b) look at the temporal distribution of important keywords in a visually dense way would increase the usefulness of speech media for study and research immensely.

One approach to accomplish these goals is to utilize Automatic Speech Recognition (ASR) in order to transcribe speech to text and also get timing information for the recognized words. We then derive information about the density of given words at a given point of time in the talk, which in turn allows to compute word occurence density maxima. This opens up possibilities for compact visual representation of the interesting keywords, thus allowing the user to scan.

The main challenge when using ASR for this task is the recognition accuracy of task specific vocabulary and terminology. Most of them are not included in available language models, or they are included with very low probabilities, as the language models are broad and generic so as to optimize accuracy over a wide topic spectrum. But if they are not included in the language model there is no chance of recognition.

So the usefulness of applying ASR with a generic language model to the problem is very small, as the intersection of interesting keywords with those technical terms that can not be recognized is very big.

The central goal of this thesis is to explore an approach to overcome this problem. This approach consists of using textual material from lecture slides or other notes to generate a lecture-specific language model. This is then interpolated with a generic language model. Finally the results are compared with the 'baseline' accuracy of the generic model using appropriate metrics.

1.1 Research questions

The research questions I[1] want to investigate in this thesis can be formulated as follows:

(1) When we apply ASR to university lectures, what is the advantage of using an approach that consists of creating a lecture-specific language model and interpolating it with a generic language model, given that we are interested in improving the recognition accuracy of *interesting keywords* for the sake of searchability and scannability?

(2) What metric is useful for quantifying this advantage?

A secondary question is: How can we *use* the results from our approach to provide graphical interfaces for improving the user's ability to search and scan the given speech medium? The exploration of this question will not be at the center of this thesis, but it will provide practical motivation for the results of our approach.

1.2 Structure

The structure of this thesis is as follows: I will start by giving an overview of the scientific work done in ASR, explaining fundamental speech recognition concepts and discussing the most prevalent approaches. I will then present the chosen test data, which consists of lectures from the openly available *Open Yale Courses*[2], and explain selection criteria. This will be followed by a description of the LM-Interpolation approach, explaining general concepts and implementation. I will then discuss suitable metrics for evaluation and analyze the results. Finally I will explore an interface prototype for dense visual representation of keyword distributions over the timeline of a lecture. I will close by recapitulating the results of the thesis and summarizing possible extension points.

[1] I will mostly use the first person singular when introducing the next step or action in this thesis, whereas I will mostly use the first person plural when I want to involve the reader into the development of thoughts.

[2] Website: http://oyc.yale.edu/

2 Scientific background

2.1 The field of Automatic Speech Recognition

Automatic Speech Recognition (ASR) can be defined as an “independent, machine-based process of decoding and transcribing oral speech”, where a “typical ASR system receives acoustic input from a speaker through a microphone, analyzes it using some pattern, model, or algorithm, and produces an output, usually in the form of a text” (Lai, Karat, & Yankelovich, 2008).

Rabiner & Juang (1993) date the first research on ASR back to the early 1950s, when Bell Labs built a system for single-speaker digit recognition. Since then the field has seen three major approaches, which Marquard (2012) calls the *acoustic-phonetic approach*, the *statistical pattern-recognition approach* and the *artificial intelligence approach*.

The acoustic-phonetic approach aimed to identify phonetic features of speech such as vowels or consonants directly through their acoustic properties and then to build up words based on these constituent elements.

The statistical pattern-recognition approach measures features of the acoustic signal and compares these to existing patterns from a range of reference sources to produce similarity scores by using a search process; patterns are taken from multiple sources such as acoustic and language models.

Artificial intelligence approaches are mainly differentiated by being integrative, combining multiple types of knowledge sources. While the former approach uses fixed input features, AI approaches establish them by *learning*. A key technology here is the use of deep neural networks and other deep learning approaches (Hinton et al., 2012), which has been an active area of research in the last decade.

The most prevalent approach today is the statistical pattern-recognition approach, as it produces results with much higher accuracy compared to the acoustic-phonetic approach. The use of Hidden Markov Models (HMM) has been playing a key role in this approach, as it allows recognizers to use a statistical model of a given pattern rather than a fixed representation. This is also the paradigm used as the foundation of our approach.

2.2 Dimensions of speech recognition

There are three dimensions which serve to classify different applications of speech recognition (Marquard, 2012):

(1) **Dependent vs. independent**. Dependent recognition systems are developed to be used by one speaker. They are easier to develop and more accurate, but not flexible. Independent systems in contrast are developed

to be used by *any* speaker of a particular language or dialect, i.e speakers of North American English (NAE). Independent systems have lower accuracy but better flexibility. **Adaptive** systems lie between these poles, they are able to adapt to a particular speaker through training.

(2) **Small vs. large vocabulary**. Small vocabularies contain only up to a few hundred words and might be modeled by an explicit grammar, whereas large vocabularies contain tens of thousands of words so as to be able to model general purpose spoken language over a variety of subject areas.

(3) **Continuous vs. isolated speech**. Isolated speech consists of single words that are spoken with pauses in between them, whereas continuous speech consists of words that are spoken in a connected way. Continuous speech is significantly more difficult to recognize, as it is (a) more difficult to find the start and end of words and (b) the pronunciation of words changes in relation to their surrounding words.

With these three dimensions we can for example classify the application areas command and control systems, dictation and lecture transcription (Marquard, 2012):

Table 1: Three application areas

Application	Speaker	Vocabulary	Duration
Dictation	Dependent	Large	Connected
Command and control system	Independent	Small	Isolated
Lecture transcription	Independent/Adaptive	Large	Connected

The task of automatic lecture transcription can thus be characterized as speaker-independent (SI) large-vocabulary continuous speech recognition (LVCSR).

2.3 Concepts

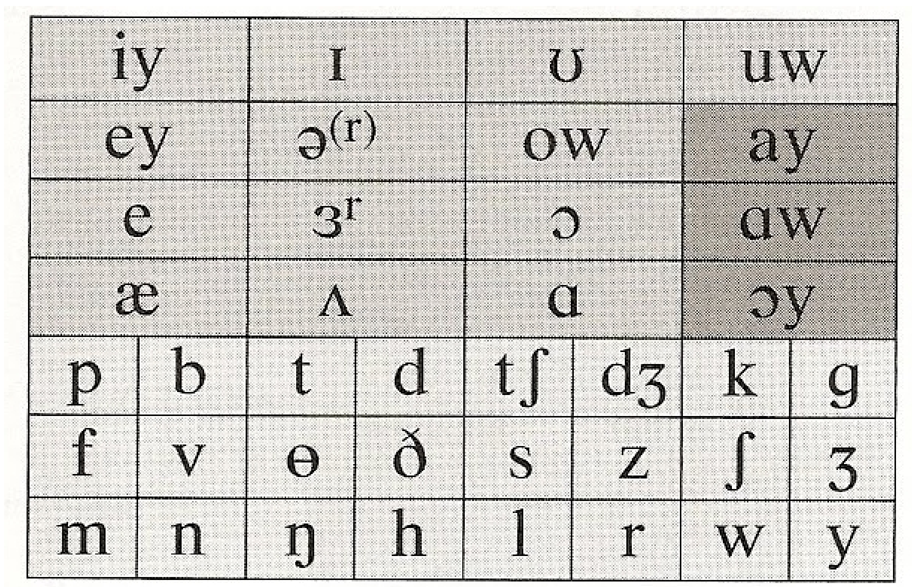
Speech recognition in the *statistical pattern-recognition approach* paradigm has these major concepts that are necessary for its understanding:

- phonemes
- phonetic dictionaries
- search
- acoustic models (AM)
- language models (LM)

2.3.1 Phonemes

A *phoneme* is “the smallest contrastive linguistic unit which may bring about a change of meaning” (Cruttenden, 2014, p. 43). Phonemes are the smallest unit of sound in speech which are combined to form words. The word *sun* for example can be represented by the phonemes `/s/`, `/u/` and `/n/`, the world *sum* differs only in the last phoneme, but the words have different meaning – hence `/m/` and `/n/` are different phonemes.

A language with a specific accent can be described by the set of phonemes that it consists of. Figure 1 shows the phonemes that are used in North American English, using symbols from the International Phonetic Alphabet (IPA).



iy		ɪ		ʊ		uw	
ey		ə(r)		ow		ay	
e		ɜr		ɔ		ɑw	
æ		ʌ		ɑ		ɔy	
p	b	t	d	tʃ	dʒ	k	g
f	v	θ	ð	s	z	ʃ	ʒ
m	n	ŋ	h	l	r	w	y

Figure 1: Phonemes in NAE

To be able to use phonemes in software an ASCII representation is more suitable. The standard for General American English is the *Arpabet*. Here each phoneme is mapped to one or two capital letters. The digits `0`, `1` and `2` signify stress markers: no stress, primary and secondary stress respectively.

2.3.2 Phonetic dictionaries

Phonetic dictionaries map words to one or more versions of phoneme sequences.

A phonetic representation of a word is specified manually based on the knowledge of how written words *actually sound* when spoken.

An excerpt from the CMU EN-US Pronouncing Dictionary (*cmudict-en-us.dict*, 2015) looks like this (phonemes are given in Arpabet representation):

```
...
abdollah AE B D AA L AH
abdomen AE B D OW M AH N
abdomen(2) AE B D AH M AH N
abdominal AE B D AA M AH N AH L
abdominal(2) AH B D AA M AH N AH L
...
```

The dictionary has 133.425 entries. Generally only words that are in the phonetic dictionary being used can be recognized during speech recognition. *Grapheme*[3]-*to-Phoneme converters* (G2P) however make it possible to get phoneme sequence hypotheses for arbitrary words (i.e arbitrary sequences of graphemes). While these results are on average less accurate than manually created variants, they play a vital role in texts with many technical terms as these are often not included in phonetic dictionaries.

2.3.3 Search

Search is the basic abstraction that lies at the center of the speech recognition process, which is called the *decoding phase*. The recognition process is implemented as a search algorithm on a directed search graph. This graph is constructed by taking different information dimensions into account: typically an acoustic model, a language model and phonetic dictionary. An example graph is shown in Figure 2[4]. Here words (from a language model) are shown in rectangles, phonemes (from a phonetic dictionary) as dark circles and audio input features as white circles (from an acoustic model). The general search space topology and phonetic context size is dependent on the specific algorithm used.

2.3.4 Acoustic models

An acoustic model (AM) describes the relation between an audio signal and the probability that this signal represents a given phoneme.

Acoustic models are created by *training* them on a *corpus* of audio recordings and matching transcripts. When being used in the context of speaker-independent recognition, these models are trained with a variety of speakers that represent a broad spectrum of the language/accent that the acoustic model should represent.

[3] A grapheme is "the smallest unit used in describing the writing system of a language" (Florian, 1996). Some languages have strong correspondences between phonemes and graphemes, this is not a necessary relationship however – the English word "debt" for example has the grapheme `<b>`, which is not represented by a corresponding sound.

[4] The graph is taken from Walker et al. (2004).

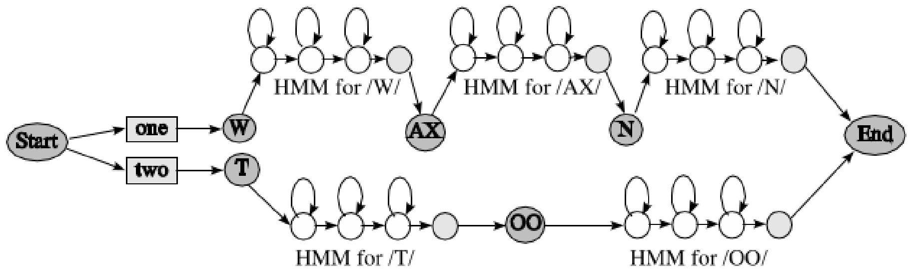


Figure 2: Search graph with example words “one” and “two”

During the decoding phase the acoustic model and a phonetic dictionary are used to match sequences of small audio “slices” to possible phonemes and those phonemes to possible word sequence hypotheses.

However, acoustic models alone are not sufficient for speech recognition as they do not have the “higher-level” linguistic information necessary to distinguish e.g. between homonyms and similar-sounding phrases such as “wreck a nice beach” and “recognize speech” (Marquard, 2012, p. 11). This information is provided by *language models*.

2.3.5 Language Models

Language models (LM) guide and constrain the search process that a speech recognition system performs by assigning probabilities to sequences of words. The basic premise, called Markov assumption, is that the overall probability of a sentence with the words $w_1, ..., w_n$ can be approximated as follows:

$$P(w_1, ..., w_n) = \prod_{i=1}^{m} P(w_i \mid w_1, ...w_{i-1})$$

This assumption says that an approximate probability of a given word can be calculated only by looking at the last n - 1 prior words. This property significantly decreases statistical complexity and thus makes it computationally feasible.

An example approximation with a bigram model for the sentence “I saw the red house” represented as $P(\text{I, saw, the, red, house})$ would look like

$$P(\text{I} \mid \langle s \rangle) \cdot P(\text{saw} \mid \text{I}) \cdot P(\text{the} \mid \text{saw}) \cdot P(\text{red} \mid \text{the}) \cdot P(\text{house} \mid \text{red}) \cdot P(\langle s \rangle \mid \text{house})$$

The most commonly used form of language models are *n-gram language models*. In the context of a language model an *n-gram* is a sequence of n words. 1-grams are called *unigrams*, 2-grams are called *bigrams* and 3-grams are called *trigrams*. An *n-gram language model* maps a set of *n-grams* to probabilities that they occur in a given piece of text.

N-gram language models do not need to be constrained to one type of n-gram; the *Generic US English Language Model* (*cmusphinx-5.0-en-us.lm*, 2015) from CMUSphinx we will use as the baseline for our approach consists of 1-, 2, and 3-grams, for example.

Language models are trained by applying statistical methods on a text corpus. Analogous to acoustic models, generic language models use huge text corpora with a broad variety of topics. It is however possible to train language models on small and specialized text corpora, which is the central technical foundation for the approach discussed in this thesis.

After this introduction of the central concepts of speech recognition in the statistical pattern-recognition approach we now have the necessary knowledge framework for looking at the scientific work done on ASR for lecture transcription.

2.4 Work done on ASR for lecture transcription

I will now give an overview of the scientific work done on lecture transcription, using Marquard (2012) as a guiding reference.

The research for speech recognition on lectures can be partitioned into two general approaches: generalization approaches and specialization approaches.

2.4.1 Generalization approaches

Generalization approaches try to create models that capture common characteristics of lectures. Those characteristics include highly spontaneous presentation style and "strong coarticulation effects, non-grammatical constructions, hesitations, repetitions, and filled pauses" (Yamazaki, Iwano, Shinoda, Furui, & Yokota, 2007). Glass, Hazen, Hetherington, & Wang (2004) note the "colloquial nature" of lectures as well as the "poor planning at the sentence level [and] higher structural levels".

The generalization approach has been applied on the acoustic model level: Cettolo, Brugnara, & Federico (2004) have examined adapting a generic acoustic model to account for spontaneous speech phenomena ("filler sounds").

While a subfield of ASR called "speaker diarization" tries to account for the interactivity between lecturers and students by identifying multiple speakers, most research treats lectures as single speaker events with the audience as background noise.

Generalization approaches at the language model level try to model common linguistic traits of the lecture genre (this can be called the *macro level*). Kato, Nanjo, & Kawahara (2000) investigate topic-independent language modeling by creating a large corpus of text from lecture transcripts and panel discussions and then removing topic-specific keywords.[5]

2.4.2 Specialization approaches

Specialization approaches try to use context specific to a single lecture (*meso level*) or parts of a single lecture (*micro level*[6]).

Methods used for creating LMs from context information can be categorized into two approaches: direct usage of lecture slides and notes for the creation of LMs versus usage of "derived" data from these materials. Deriving data by using keywords found in slides, using them as web search query terms and using the found documents as the basis for LM creation is explored in Munteanu, Penn, & Baecker (2007), Kawahara, Nemoto, & Akita (2008) and Marquard (2012).

Using the whole text from lecture slides has been explored by Yamazaki et al. (2007). They compare the meso level with the micro level by dynamically adapting the LM to the speech corresponding to a particular slide. Kawahara et al. (2008) also examine dynamic local slide-by-slide adaption and compare it to global topic adaption using Probabilistic Latent Semantic Analysis (PLSA)[7] and web text collection, concluding that the latter performs worse than the former because of a "worse orientation to topic words".

2.4.3 Conclusion

In our approach, we use the textual data from available lecture material to create a lecture-specific language model. As such it can be classified as a specialization approach with exclusive direct use of the lecture material. Specifically, it does not try to extend the material corpus by using derived data; it neither tries to consider the *micro level*, which would imply to look at parts of a single lecture.

After having located our approach against the backdrop of the different approaches currently explored by the scientific community, I will now continue to present the test data used.

[5] In a second step they combine this generalization technique with a specialization technique by adapting the resulting LM with a lecture-specific language model by using preprint papers of a given lecture.

[6] The three levels are taken from Marquard (2012).

[7] Latent Semantic Analysis is an approach to document comparison and retrieval which relies on a numeric analysis of word frequency and proximity.

3 Test data

The test data I will use for evaluating our approach are from *Open Yale Courses*[8], which is a selection of openly available lectures from Yale University. It consists of 42 courses from 25 departments, all in English. Each course has about 20-25 sessions that have an average length of 50 minutes. Each lecture is provided with good quality audio and video recordings, precise manual transcripts[9] and lecture material when available. Unfortunately only about 20% of the lectures have lecture notes or slides and most materials from the natural and formal science departments (physics, astronomics, mathematics) consist of hand-written notes, making them unsuitable for our approach, as a necessary step is automatically preprocessing digital text, whereas handwritten notes would require manual transcription first[10]. A more promising approach for lectures with these kind of materials would be using textual content from text books recommended for the course – this however is beyond the scope we have defined for our approach (exclusive, direct usage of textual data present in the material for the specific given lecture).

The main selection criterion in choosing the talks was topical diversity, the challenge being that the majority of talks with computer-parsable notes was from the humanities.

The following lectures were chosen: (Department, Course, Lecture Number - Title, abbreviation)

- *Biomedical Engineering*: Frontiers of Biomedical Engineering, 1 - What is Biomedical Engineering? (`biomed-eng-1`)
- *Environmental Studies*: Environmental Politics and Law, 8 - Chemically Dependent Agriculture (`environmental-8`)
- *Geology & Geophysics*: The atmosphere, the ocean, and environmental change, 8 - Horizontal transport (`geology-8`)
- *Philosopy*: Philosophy and the science of human nature, 8 - Flourishing and Detachment (`human-nature-8`)
- *Psychology*: Introduction to Psychology, 14 - What Motivates Us: Sex (`psy-14`)
- *Psychology*: Introduction to Psychology, 5 - What Is It Like to Be a Baby: The Development of Thought (`psy-5`)

[8] http://oyc.yale.edu/

[9] The transcripts do not include filler words, as they are optimized for readability.

[10] OCR would probably not be an option in this case as the notes are often in a highly idiosyncratic format.

3.1 Material overview

The available material is very heterogeneous. I will now give an overview with excerpts which will serve as a basis for examining at a later point if the quality and quantity of the supplied material is correlated with the performance of our approach.

`geology-8` supplies a 2-page excercise sheet.

> "Mars has a radius of 3.39 x 10^6 m and a surface gravity of 3.73 ms^{-2}. Calculate the escape velocity for Mars and the typical speed of a CO2 molecule (assume T = 250 K). How can Mars retain its CO2 atmosphere? (Hint: the molecular weight of carbon dioxide is 44. Use the formulae given in class.) [...]"

`biomed-eng-1` provides a 7-page glossary of technical terms.

> "[...] active transport - the transport of molecules in an energetically unfavorable direction across a membrane coupled to the hydrolysis of ATP or other source of energy
>
> ATP (adenosine 5'-triphosphate) - a nucleotide that is the most important molecule for capturing and transferring free energy in cells. Hydrolysis of each of the two high-energy phosphoanhydride bonds in ATP is accompanied by a large free-energy change ("G) of 7 kcal/mole
>
> aquaporin – a water channel protein which allows water molecules to cross the cell membrane much more rapidly than through the phospholipid bilayer [...]"

`human-nature-8` provides reading assignments for four books with short summaries each.

> "[A] Epictetus, The Handbook
>
> Background information about the Stoic philosopher Epictetus (c. 50-130 CE) and his famous work Encheiridion (The Handbook) appears in Nicholas White's introduction to our translation. White has also added footnotes that explain points of potential confusion.
>
> As the title indicates, The Handbook is intended as a tidy introduction to a more complex philosophical outlook. It is written in an accessible and engaging style.
>
> The Stoic movement originated around 300 BCE and flourished for over five hundred years. The Stoics believed that the external world is deterministic: its state at any time is completely determined by its

prior states. So, they maintained, it is pointless to wish for things to be different because to do so is to wish for something impossible. A wise person would, therefore, accept whatever befalls them without desiring that things go otherwise – hence the English word 'stoic.'

Passages to focus on/passages to skim

I encourage you to read the text in full, at a steady reading pace. [. . .]"

`psy-14/5` and `enviromental-8` provide ~10-page slides with a typical amount of text.

3.2 Conclusion

Only about 20% of the courses have lecture material at all; of these only about 20% actually have typical "slides" – the rest provides other heterogenous kinds of material. While it cannot be inferred from this dataset that this is a general condition, it nevertheless shows a clear "real-world" disadvantage of an approach necessarily relying on lecture materials. We will look at the impact of the varying quality and quantity in the analysis later on.

4 The LM-Interpolation approach

I will now describe the LM-Interpolation approach. The high level overview is as follows: we will use the open source speech recognition framework Sphinx 4[11] as the software for performing speech recognition. Sphinx 4 has a modular architecture which allows specifying components of the whole process per configuration. It provides multiple implementations of LMs[12], the default one being an n-gram model.

It also provides an `InterpolatedLanguageModel`[13] (ILM) which allows to specify multiple LMs and weights and to interpolate the probabilities for a given n-gram from all models' probabilities ($p = w_1 * p_1 + w_2 * p_2 + \ldots$ where w_n are the weights ($\sum_{i=1}^{n}(w_i) = 1$) and p_i is the probability for a given n-gram in LM_i).

The purpose of the ILM in our approach is to factor in the importance of keywords. These keywords have to be supplied in the form of an n-gram language model. For this we extract text content from the lecture material, preprocess it and create an n-gram LM from the resulting corpus. Sphinx 4 is then run (a) with a generic English n-gram LM only and (b) with the ILM configured to use the generic English LM and the material language model in a specified weighting. Finally the two resulting transcriptions are compared with a selection of metrics.

In the ILM implementation the probability of a missing n-gram is equal to 0. This means that n-grams not existing in the material LM but existing in the generic English model will have 50% of their original probability for a 50/50 weighting. As this probability reduction is uniform for all generic words it does not have an impact on the results: the probability comparison outcomes will be the same, just with lower input values.

As an example, the 1-gram *sex* has a probability of 2.82% in the material LM of `psy-14`, but a probability of 0.012% in the generic English LM.[14] When using interpolation with a 50/50 weighting, the result is $2.82\% \cdot 0.5 + 0.012\% \cdot 0.5 = 1.416\%$, which is an increase by the factor ~117 over the generic probability.

I will now give an overview of the Sphinx 4 architecture, followed by a description of the implementation of the approach.

4.1 Sphinx 4 architecture

The overall architecture of Sphinx 4 as shown in Figure 3 is comprised of three primary modules: the *FrontEnd*, the *Decoder* and the *Linguist*.[15] The *FrontEnd*

[11] Homepage: http://cmusphinx.sourceforge.net/wiki/sphinx4:webhome
[12] Overview: http://cmusphinx.sourceforge.net/doc/sphinx4/edu/cmu/sphinx/linguist/language/ngram/LanguageModel.html
[13] Javadoc: http://cmusphinx.sourceforge.net/doc/sphinx4/edu/cmu/sphinx/linguist/language/ngram/InterpolatedLanguageModel.html
[14] (*cmusphinx-5.0-en-us.lm*, 2015)
[15] The following description is based on Walker et al. (2004).

takes one or more input signals and parameterizes them into a sequence of *Features*. The *Linguist* takes any type of standard language model, pronunciation information from a phonetic *Dictionary* and information from one or more sets of *AcousticModels*, generating a *Search Graph*. The *SearchManager* in the *Decoder* uses *Features* from the *FrontEnd* to perform decoding. Each of the components (written in italics) are interfaces for which the actual implementation can be configured at runtime.

4.1.1 FrontEnd

The *FrontEnd* parameterizes an *Input* signal into a sequence of output *Features*. This process is realized as one or multiple chains that can run in parallel, permitting simultaneous computation of different types of parameters from the same or different input signals.

4.1.2 Linguist

The *Linguist* encapsulates the details of generating a *SearchGraph* used by the *SearchManager* in the *Decoder*. It consists of the *LanguageModel*, the *Dictionary* and the *AcousticModel*.

LanguageModel implementations can typically be categorized into graph-driven grammars and n-gram models. The latter are primarily differentiated by their usage parameters (e.g. small vs. very big LMs; input formats).

Dictionary provides the pronunciations for words found in the *LanguageModel*. A G2P Model can be specified in the configuration which will statistically model missing entries in the dictionary.

The *AcousticModel* provides a mapping between a phoneme and an HMM that can be scored against incoming *Features* provided by the *FrontEnd*, also taking word-contextual information into account.

4.1.3 SearchGraph

The primary data structure in the decoding phase is the *SearchGraph*. It is a directed graph whose nodes are *SearchStates* that are either *emitting* or *non-emitting*. *Emitting* nodes can be scored against an incoming acoustic feature, while *non-emitting* nodes represent higher-level linguistic constructs such as words and phonemes that are not directly scored against these features.

4.1.4 Decoder

The *Decoder* uses *Features* from the *FrontEnd* by using a *SearchManager* that controls the *Linguist's SearchGraph* to generate *Result* hypotheses. The *Decoder* tells the *SearchManager* to recognize a set of *Feature* frames. At each step, the *SearchManager* creates a *Result* object that contains all paths that "reached a final non-emitting state".

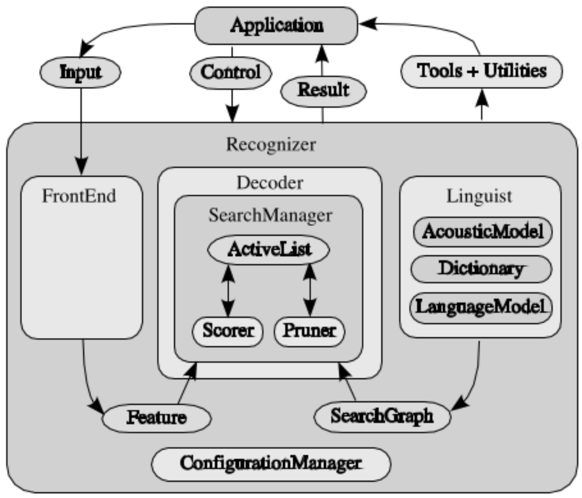


Figure 3: Sphinx 4 architecture

4.2 Implementation

The transformation from input audio, lecture material and reference transcription files to recognition and analysis results can be seen as a pipeline. The necessary tasks involve

(a) *logistics and infrastructure*, i.e. setting up directory structure for a test run, moving files, providing wrapper interfaces to facilitate Sphinx 4 calls with the right configuration
(b) *input file preprocessing*, i.e. converting audio to the format needed by Sphinx 4, converting the reference transcript to a suitable text-only format, perform PDF-to-text conversion on lecture material and text manipulation to optimize the textual data for language model creation
(c) *analysis* tools, i.e. scripts that automate the calulation of metrics
(d) *visualization* tools that provide a graphical representation of the results and metrics

This pipeline is implemented with a collection of standalone command line tools and a set of shell and Python scripts[16].

[16]The source code is available here: https://github.com/jonathanewerner/bachelor/tree/master/bin

The tasks are the following, in chronological order:

1. **Prepare the input**
   - The audio file is converted into Sphinx 4 compatible format (16khz, 16bit mono little-endian).
   - A testcase folder with a given shortname (e.g. `psy-15`) is created in the `results`-directory[17] of the source code repository.
   - The reference transcript, the material (PDF format is required) and the converted audio file are moved into a `resources` subfolder of the testcase folder.

2. **Create a material LM from lecture material**
   - `pdftohtml -i -xml` is applied on the given material PDF. The XML output representation then becomes the input for `pdfreflow`[18]. Compared to the tool `pdftotext` the combination of these 2 tools preserves paragraphs correctly, whereas `pdftotext` represents each line break in the input PDF as a new paragraph in the output text file. This is a significant disadvantage for the LM creation step, as in this case a newline in the input file constitutes the semantic "end of sentence" – so that a sentence split into 4 lines by `pdftotext` would count as 4 sentences in the LM.
   - The HTML output from `pdfreflow` is filtered by taking only relevant HTML-tags such as `<p>`'s (paragraphs) and `<blockquote>`'s, further improving the content-to-noise ratio.
   - The resulting text is then preprocessed for optimal compatibility with the LM creation tool by removing punctuation and superfluous whitespace[19].
   - The resulting corpus then becomes the input for `estimate-ngram`, an LM creation tool from the MIT Language Modeling Toolkit[20] (MITLMT). This tool finally outputs a LM file. The language model contains 1-, 2-, and 3-grams and is later used as input to Sphinx 4.

   For clarification intermediate results from this step follow as an example. They are taken from the test case `psy-5`[21]. Figure 4 shows an example slide.

   When using `pdftotext` the result for the given slide is as follows:

[17] https://github.com/jonathanewerner/bachelor/tree/master/results

[18] pdftohtml (http://pdftohtml.sourceforge.net/) and pdfreflow (http://sourceforge.net/projects/pdfreflow/) are open source linux command line utilities

[19] I use a combination of command line text processing (sed) and a perl script from Stephen Marquard here.

[20] https://code.google.com/p/mitlm/wiki/EstimateNgram

[21] "Introduction to Psychology, 5 - What Is It Like to Be a Baby: The Development of Thought"

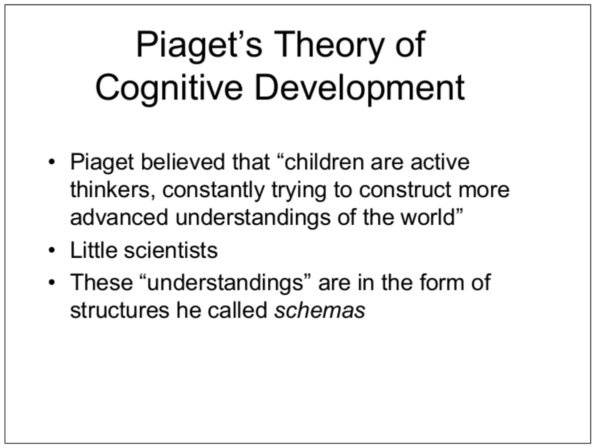


Figure 4: Slide from lecture `psy-5`

```
Piaget's Theory of
Cognitive Development
• Piaget believed that "children are active
thinkers, constantly trying to construct more
advanced understandings of the world"
• Little scientists
• These "understandings" are in the form of
structures he called schemas
```

Notice how each newline in the slide maps to a newline in the output. When using the combination of `pdftohtml` and `pdfreflow` the result looks like this:

```
<p class="p9">Piaget's Theory of
Cognitive Development </p>
<p class="p10">•  Piaget believed that "children are active
thinkers, constantly trying to construct more
advanced understandings of the world" </p>
<blockquote class="b9">•  Little scientists </blockquote>
<p class="p10">•  These "understandings" are in the form of
structures he called <i>schemas</i> </p>
```

Notice how a paragraph is captured in a `<p>`-tag. This allows to extract a sentence as one line in the corpus. After applying the preprocessing described above the final corpus for the slide looks like this (where ".." marks a line continuation):

```
piagets theory of cognitive development
```

```
piaget believed that children are active thinkers constantly
.. trying to construct more advanced understandings of the world
little scientists
these understandings are in the form of structures he called schemas
```

Finally running the MITLMTK script `estimate-ngram -text slides.corpus.txt -write-lm model.lm` results in the LM file used as the material LM file in the `InterpolatedLanguageModel` Sphinx 4 configuration besides the general english LM (*cmusphinx-5.0-en-us.lm*, 2015).

3. **Convert transcript to reference corpus**

   The transcript from Open Yale is supplied as HTML. We apply processing steps to transform it to a corpus ready to be consumed by the analysis tool (no punctuation, all lowercase). As these are just specific to the format chosen by Open Yale Courses, the details are omitted, as they are of no general relevance.

4. **Run Sphinx 4 in baseline and interpolated mode**

   `bin/sphinx-interpolated.py`[22] supplies a wrapper for interfacing with Sphinx 4. The Java API of Sphinx 4 is exposed for command line usage by a JAR package which bundles the Sphinx 4 libraries and a small `Main` class. This class uses command line arguments supplied by `bin/sphinx-interpolated.py` to correctly configure Sphinx 4 and start the actual recognition.

   Each testcase folder has a configuration file which specifies the models to be used by the test run:

```
{
  "acousticModelPath": "en-new/cmusphinx-en-us-5.2",
  "dictionaryPath": "en-new/cmudict-en-us.dict",

  "languageModelPath": "en-new/cmusphinx-5.0-en-us.lm",
  "keywordModelPath": "model.lm",
  "g2pModelPath": "en-new/en_us_nostress/model.fst.ser",

  "resultsFolder": "biomed-eng-1"
}
```

   `bin/sphinx-interpolated.py` interprets the "global" models relative to the repository root folder `models`, the `resultsFolder` relative to the root folder `results` and the `keywordModelPath` relative to the `resultsFolder`. It then supplies the absolute paths to the JAR. It also supplies absolute

[22] https://github.com/jonathanewerner/bachelor/blob/master/bin/sphinx-interpolated.py

output file paths for the transcription result and transcription word timing results.

For the interpolation run, the following part from the Sphinx 4 config is relevant:

```
<component name="interpolatedLanguageModel"
           type="edu.cmu.sphinx.linguist.language.ngram.InterpolatedLanguageModel">
  <propertylist name="languageModels">
    <item>simpleNGramModel</item>
    <item>simpleNGramModelKeywords</item>
  </propertylist>
  <propertylist name="languageModelWeights">
    <item>0.5</item>
    <item>0.5</item>
  </propertylist>
</component>

<component name="simpleNGramModelKeywords"
           type="edu.cmu.sphinx.linguist.language.ngram.SimpleNGramModel">
           <property name="location" value="file://{{keywordLm}}"/>
  <property name="dictionary" value="dictionary"/>
  <property name="maxDepth" value="3"/>
  <property name="unigramWeight" value=".7"/>
</component>

<component name="simpleNGramModel"
  type="edu.cmu.sphinx.linguist.language.ngram.SimpleNGramModel">
  <property name="location" value="file://{{lm}}"/>
  <property name="dictionary" value="dictionary"/>
  <property name="maxDepth" value="3"/>
  <property name="unigramWeight" value=".7"/>
</component>
```

For each run this config file is (a) copied to a `tmp/`-file and (b) `{{keywordLm}}` and `{{lm}}` are substituted by the absolute paths of the files provided in the test run's `config.json`.

This setup ensures reproducible results, as the environment of a given testcase is exactly specified (as long as the same binaries and script versions are assumed).

`bin/sphinx-interpolated.py` can now be used to run the baseline and/or interpolated version.

5. **Analyze and compare the results**

   Finally the results from the two recognition runs are analyzed and compared by running `bin/hotword-analyze <testcase folder name>`. This does two things: (a) run comparison and metrics generation and (b) keyword visualization.

5.1 *Run comparison and metrics generation*

This first calls `bin/wer.py`[23] on each run, which will calculate the WER and show a summary of substituted (SUB), inserted (INS) and deleted (DEL) words when comparing the reference (REF) to the hypothesis (HYP):

```
OP  | REF     | HYP
INS | ****    | this
INS | ****    | is
INS | ****    | that
OK  | this    | this
OK  | is      | is
OK  | a       | a
OK  | course  | course
SUB | a       | that
SUB | version | aversion
OK  | of      | of
OK  | which   | which
SUB | i've    | i
OK  | taught  | taught
INS | ****    | him
...
...
{'Sub': 1230, 'Ins': 674, 'WER': 0.316, 'Del': 324, 'Cor': 5492}
```

In a second step it compares the two WER result files with `bin/compare-wer.py`.

The result is an HTML file which shows (a) a comparison table with the columns *reference word*, *baseline hypothesis* and *interpolated hypothesis* and (b) various statistical measures which will be explored later. The table (shown in Figure 5) represents correctly recognized words in green color and incorrect words in red. It also marks words that have improved in the interpolated version with a green border and words that have worsened with a red border.

5.2 *Keyword visualization*

Data from the reference and the recognition results is compiled into a format suitable for consumption by a visualization module, which will be discussed in Chapter 6.

[23] `wer.py` has been adapted from http://progfruits.blogspot.de/2014/02/word-error-rate-wer-and-word.html

Reference	baseline	interpolated
this	this	this
is	is	is
a	a	a
course	course	course
a	that	ab
version	aversion	version
of	of	of
which	which	which
i've	i	i
taught	taught	taught
almost	almost	almost
every	every	every
year	year	year
for	for	for
the	the	the
last	last	last
twenty	the	the
years	years	years
and	and	added
it	it	a

Figure 5: WER comparison

All intermediate steps from the pipeline are represented as files in the testcase folder. Table 2 gives an overview of the files created by each pipeline step.

Table 2: File results of a testcase run

File	Description
Step 1: Prepare the input	
resources/audio.mp3	original audio
resources/audio.wav	converted audio
resources/slides.pdf	lecture material
resources/transcript.html	lecture transcript
config.json	run configuration
Step 2: Create a material LM	
slides.corpus.txt	lecture material corpus
model.lm	material LM
Step 3: Convert reference to corpus	
reference.corpus.txt	reference transcription corpus
reference_wordcounts.json	reference transcription word counts[24]
Step 4: Run Sphinx 4	
sphinx_log_baseline.txt	Sphinx 4 logging output
sphinx_log_interpolated.txt	
sphinx_result_baseline.txt	Sphinx 4 transcription
sphinx_result_interpolated.txt	
sphinx_word_times_baseline.txt	Sphinx 4 word times
sphinx_word_times_interpolated.txt	
Step 5.1: WER comparison / metrics generation	
results.json	run metrics in json format[25]
wer_baseline.txt	WER table / metrics
wer_interpolated.txt	
wer_comparison.html	rich WER comparison + metrics
Step 5.2: Keyword visualization	
cloud_baseline.json	data representation for visualization
cloud_interpolated.json	

[24] They are needed for the visualization later.
[25] This eases parsability for aggregating multiple testcase results later.

5 Analysis

I will now discuss how to evaluate the usefulness of the LM-Interpolation approach in light of the goal to improve recognition accuracy of interesting keywords.

5.1 Approaching a good metric

Our goal is to find a metric that describes if and how much the interpolated version improves upon the baseline version. The “canonical” metric used to evaluate speech recognition performance is called *Word Error Rate* (WER), which is derived from taking the Levenstein distance at the word level between a reference transcript and the recognition result. WER is calculated as:

$$WER = \frac{S + D + I}{N}$$

where

- S is the number of substitutions
- D is the number of deletions
- I is the number of insertions
- N is the number of words in the reference ($N = S + D + C$, where C is the number of correct words)

Levensthein alignment circumvents the problem that the reference and the recognition result get “out of sync” when words are inserted or removed.

The problem of using WER for our purposes is twofold: (a) It does not help to answer the question of how much our approach improves the accuracy of keywords; it only pertains to *all* words, including non-keywords such as determiners or pronouns. And (b) it penalizes *insertions*. But insertions are not relevant to the question of how many of the keywords from the reference transcript have been detected. Insertions only matter when we are interested in the *sentence integrity* of the result transcript. In our case, we do not care if there are superfluous words *between* correctly recognized keywords[26].

These considerations lead to the conclusion that a first improvement over regular *WER* would be to just look at the *detection rate* of words, where detection rate describes the proportion of words from a transcript that have been correctly recognized. This can be expressed by using WER in a first step in order to get the benefit of word synchronization and then filtering out insertions in a second

[26] Although there might be cases of technical terms that are compound words – in that case an insertion in between the compound word would be problematic. Detection of this edge case is however beyond the scope of our analysis.

step. It is not necessary to filter out deletions as these can be interpreted as non-detected words.

A further improvement consists in just considering the words which are part of the material corpus. By just taking the words that we used to create the material corpus for our interpolated LM we can precisely evaluate the improvement effect of this change. However, this is still not perfect. The lecture material corpus includes a substantial amount of words that would not be classified as "keywords": filler words and very common words. One approach to sort them out is subtracting a set of top x most common words (top_X *words*) from this list. The resulting metric can then be parameterized on the given x. This is an idea that Marquard uses when he proposes the metric "Ranked Word Correct Rate" (RWCR-n):

> "RWCR-n is defined as the Word Correct Rate for all words in the document which are not found in the first n words in a given general English word dictionary with words ranked from most to least frequent." (Marquard, 2012, p. 71)

5.1.1 Lemmas

When searching for a specific term the user is interested in the *lemma*[27] for a given word: when he wants to find occurences of "child" in the given lecture, occurences of "children" would also be relevant. This implies two things: (a) when looking at the "atomic" level of improvements and degradations it is more relevant to have lemmas as atoms and not words; and (b) the exact matching (a hypothesis word is only "correct" if it exactly matches the reference word) should be "loosened" to also mark hypothesis words as correct if their lemmatized version matches the reference.

The same principle holds for the top_X words: we only want to capture words for which the *lemma* is not in the top_X words.

5.1.2 Definition of KWDR-x and WDR

We can distill these concerns into a definition of a metric called *Key Word Detection Rate* (*KWDR-x*) where a keyword is defined as the lemma of a word occuring in a given lemmatized lecture material corpus, given that this lemma is not present in the top_X list of most common words of the given language. A keyword is *detected* when it is *lemma-equal*[28] to the corresponding word in the reference; if it has been substituted or deleted, it is *not detected*.

[27] A lemma, also called "headword", is the canonical form of a word that is chosen by convention to represent a group of lexemes that refer to the same meaning. A typical use would be the key of a dictionary entry.

[28] Two words are defined as *lemma-equal* when their lemmatized versions are equal. The words "children" and "child" are lemma-equal.

The *Word Detection Rate* (*WDR*) is analogously defined as the rate of detected words, where a word is *detected* when it is lemma-equal to its reference.

The value of x has to be determined empirically: how many of the top_X words should be filtered out? There has to be a balance between not accidentally excluding keywords (i.e "sex" is in the top_{500} words, but is a central keyword in lecture `psy-14`) and filtering out enough filler words.

After experimenting with some values I chose $x = 500$ for my measurements. It is hard to find a less ad hoc approach to determine the "best" x, as there is no "meta"-metric that would assess how well a given x captures the goal of accurately describing the detection accuracy of keywords; it necessarily is a "best guess". $x = 500$ was chosen by looking at the relationship of x to $\Delta KWDR$ (the improvement in KWDR-500) in an example lecture, as shown in Figure 6. For values of x below ~200 the growth of improvement is explained by the gradual removal of filler words from the set of keywords. The recognition accuracy of filler words is not improved by our approach which is why they prevent the accuracy improvement of actual keywords to be visible. Above ~200 this factor is ruled out and the chosen x value has only miniscule influence on the resulting KWDR.

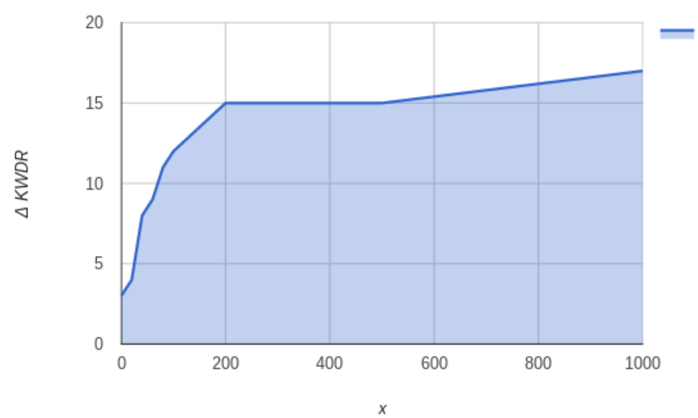


Figure 6: Relation of x to $\Delta KWDR$, compiled by running the analysis on lecture `geology-8` with the x-values 0, 20, 40, 60, 80, 100, 200, 300, 400, 500 and 1000.

This strategy, while depending on choosing an "ad hoc" value, was sufficient to validate our approach because it was possible to manually evaluate the metric's "precision" by observing the resulting word sets. Another approach would have been to take the *tf-idf* (Term Frequency - Inverse Document Frequency) as a criterion for "keyword-ness" of words. *tf-idf* computes the "relevance" of a word in the context of a document by taking into account the occurences of the word in the document offset by the word's frequency in a broader corpus. This way common words are rated lower although they occur frequently in the given document. As such there is no need for the arbitrary aspect of choosing a value of x and the negative side effect of accidentally excluding a keyword (which can be called the *false-negative rate*). On the other hand there would be the need to choose a threshold *tf-idf* score which would have to be reached for inclusion into the keyword set. Alternatively the words could be sorted by *tf-idf* score and the top_x words of this list could be taken. While also relying on an ad-hoc value, this approach could be superior as it classification of keywordness would not be binary but gradual, so that presumably only the "best", most "interesting" keywords would be selected.

5.1.3 Metrics overview

The following metrics are evaluated, including secondary or derived metrics:

- W: Number of tokens (all instances of words) in the reference
- W_{unique}: Number of types (unique words) in the reference
- $W(M)$: Number of tokens in the material corpus
- $W(M)_{unique}$: Number of types in the material corpus
- KW: Number of keyword tokens
- KW_{unique}: Number of keyword types
- $WER_{A|B}$: Word Error Rate of baseline (A) / interpolated version (B)
- $WDR_{A|B}$: Word Detection Rate of baseline (A) / interpolated version (B)
- $KWDR_{A|B}$: KWDR = KWDR-500 for brevity = Keyword Detection Rate with $x = 500$ of baseline (A) / interpolated version (B)
- $W_{worse|improved}$: Proportion of worsened/improved words
- $KW_{worse|improved}$: Proportion of worsened/improved keywords
- $W_{worse|improved}(K)$: Proportion of worsened/improved words that are keywords
- E: $W_{improved}(K) - W_{worse}(K)$: A percentage score for "effectiveness" of version B

5.1.4 Example calculation

The use of all metrics can be exemplarily demonstrated on the lecture `human-nature-8`: The lecture has 5342 words overall, of which 333 are keywords. When looking at the general WDR, run A and B both have a score of 58%. This can be "split up" by looking at $W_{worse|improved}$, which is 4% each, meaning that 4% (223/5342) of the words have been improved from run A to B, but 4% (221/5342) of them have been worsened, which sums up to 0% difference in WDR.

Secondly, the KWDR of A is 47% (156/333 keywords) versus 62% for B (212/333 keywords). This improvement of 15% can analogously be explained by looking at $KW_{worse|improved}$: when looking at the 333 keywords, 2% (7/333) of them have been worsened, while 17% (58/333) have been improved. $17 - 2 = 15\%$ explains the improvement from 47% to 62%.

The last metric of $W_{worse|improved}(K)$ looks at the overall worsened/improved words and informs about the proportion of words that were keywords. As mentioned, W_{worse} is 4% (221 of the overall 5342 words have been worsened). What is the proportion of keywords in this number? Analogously, what is the proportion of keywords when looking at the overall improved words? This metric is key in identifying the *effectiveness* (E) of our approach: the $W_{improved}(K)$ value answers the question of how well our approach is targeted towards improving the words we are interested in, the $W_{worse}(K)$ value answers the question of how big the "side effect" of worsening keywords is. In the example $W_{worse}(K)$ is 3% (7/221) and $W_{improved}(K)$ is 26% (58/223). This is great: of the 221 overall worsened words only **7** were relevant in light of our goals. In essence, we can interpret $W_{improved}(K) - W_{worse}(K)$ as an **effectiveness score**. We can say that our example has an effectiveness of $26 - 3 = 23\%$. An effectiveness of 100% would mean that *all* words that were improved had been keywords and *none* of the worsened words had been keywords.

5.2 Implementation of measurements calculation

Measurements are calculated automatically by `bin/wer.py` and `bin/compare-wer.py`. I will now outline some relevant implementation details.

`bin/wer.py` performs a typical WER calculation algorithm. This is run on version A (baseline) and B (interpolated). The results become the input for `bin/compare-wer.py`. The top_{500} words are taken from the *Corpus of Contemporary American English*[29]. The lemmatization of words is done by the `lemmatize` function of `nltk.stem.wordnet.WordNetLemmatize`.

The KWDR of A and B is then calculated by iterating over both WER results with insertions filtered out.

Each iteration operates on a tuple of (reference word, hypothesis A, hypothesis B).

1. For both hypotheses it checks if the reference word is *lemma-equal* to the hypothesis word; if that is not the case, the reference word is put in a "wrong words" bin (one bin for A and B each).
2. If both hypotheses are correct, the next iteration is performed.
3. Else: if A is correct and B is wrong, the reference is put into the "worsened" bin; the other way, round it is put into the "improved" bin.

[29] http://www.wordfrequency.info/free.asp

4. Finally, if a hypothesis is wrong *and* it is a keyword[30], the reference is put into the "wrong keyword" bin (also one for each run).

After the iterations are finished, the mentioned metrics are calculated by simple calculation of the proportions, taking into account the size of the resulting bins and overall measurements (like reference word count).

As side effects, the bin contents as well as the calculated metrics are exported to HTML and JSON for further manual inspection resp. result aggregation.

5.2.1 Example

The steps of this process can be made clearer by running through a small example. The following toy data set serves as input:

- Material corpus: [axons the people psychology is rewarding][31]
- Reference transcript: "Axons are firing to stimulate people's minds." (This gets preprocessed to "axons are firing to stimulate peoples minds" in a previous step.)
- Top_x words: [i are it is the people people's]
- The WER results for A:

```
OP  | REF       | HYP
sub | axons     | accent
ok  | are       | are
ins | ****      | very
sub | firing    | tiring
ok  | to        | to
ok  | stimulate | stimulate
sub | peoples   | people
ok  | minds     | minds
{'Ins': 1, 'Cor': 4, 'WER': 0.571, 'Del': 0, 'Sub': 3}
```

- The WER results for B:

```
OP  | REF       | HYP
sub | axons     | axon
ok  | are       | are
ins | ****      | very
sub | firing    | tiring
```

[30]It is a keyword if its lemma is in the lemmatized, top_x-words excluded material corpus.

[31]Imagine this being taken from sparse slides with bullet points.

```
ok  | to        | to
ok  | stimulate | stimulate
sub | peoples   | people
sub | minds     | may
{'Sub': 4, 'Ins': 1, 'Del': 0, 'Cor': 3, 'WER': 0.714}
```

The inputs are transformed to the following forms (removed words displayed as "**-removed**"; changed words as **-old +new**):

- Lemmatized material corpus: [**+axon -axons** the people psychology is rewarding]
- Lemmatized top_x words: [i are it is the people **-people's**]
- Lemmatized material corpus minus lemmatized top_x words ("keywords"): [axon **-the -people** psychology **-is** rewarding]

For the demonstration the following pseudo code conventions and abbreviations are used:

- (a, b, c) = (1, 2, 3) is a destructuring assignment, binding a to 1, b to 2, c to 3
- `ref` refers to the reference word, `hypA|B` to the hypothesis from version A/B
- l(word) refers to the lemmatized version of a given word
- `->` is equivalent to "thus"
- bin names:
  - wrong words from run X: `wrongX`
  - wrong keywords from run A: `wrongKW_X`

The KWDR algorithm performs with the following intermediate steps:

- **Step 0**: (`ref`, `hypA`, `hypB`) = (axons, accent, axon)
  - l(`ref`) != l(`hypA`) -> add `ref` to `wrongA`
  - l(`ref`) == l(`hypB`) -> do nothing (explanation: axon == axon)
  - `hypA` was wrong, `hypB` was correct -> add `hypB` to `improved`
  - `hypA` was wrong and a keyword -> add `ref` to `wrongKW_A`
  - `wrongA`: `[axons]`
  - `wrongB`: `[ ]`
  - `wrongKW_A`: `[axons]`
  - `wrongKW_B`: `[ ]`
  - `improved`: `[axons]`
  - `worsened`: `[ ]`
- **Step 1**: (`ref`, `hypA`, `hypB`) = (are, are, are)

- l(`ref`) == l(`hypA`) -> do nothing
  - l(`ref`) == l(`hypB`) -> do nothing
  - both are correct -> next iteration

- **Step 2**: (`ref`, `hypA`, `hypB`) = (firing, tiring, tiring)[32]
  - l(`ref`) != l(`hypA`) -> add `ref` to `wrongA`
  - l(`ref`) != l(`hypA`) -> add `ref` to `wrongB`
  - `wrongA`: `[axons, firing]`
  - `wrongB`: `[firing]`
  - `wrongKW_A`: `[axons]`
  - `wrongKW_B`: `[ ]`
  - `improved`: `[axons]`
  - `worsened`: `[ ]`

- **Step 3/4**: (`ref`, `hypA`, `hypB`) = (to, to, to) / (stimulate, stimulate, stimulate)
  - l(`ref`) == l(`hypA`) -> do nothing
  - l(`ref`) == l(`hypB`) -> do nothing
  - both are correct -> next iteration

- **Step 5**: (`ref`, `hypA`, `hypB`) = (peoples, people, people)
  - l(`ref`) == l(`hypA`) -> do nothing (explanation: people == people)
  - l(`ref`) == l(`hypB`) -> do nothing (same explanation)
  - both are correct -> next iteration

- **Step 6**: (`ref`, `hypA`, `hypB`) = (minds, minds, may)
  - l(`ref`) == l(`hypA`) -> do nothing
  - l(`ref`) == l(`hypB`) -> add `ref` to `wrongB`
  - `wrongA`: `[axons, firing]`
  - `wrongB`: `[firing, minds]`
  - `wrongKW_A`: `[axons]`
  - `wrongKW_B`: `[ ]`
  - `improved`: `[axons]`
  - `worsened`: `[minds]`

Results:

- `wrongA`: `[axons, firing]`
- `wrongB`: `[firing, minds]`
- `wrongKW_A`: `[axons]`
- `wrongKW_B`: `[ ]`
- `improved`: `[axons]`
- `worsened`: `[minds]`

[32] Notice how the inserted row (marked with "INS" in the WER output) has been skipped).

General/derived metrics:

- W (count of tokens in reference): 7 ("axons are firing to stimulate peoples minds")
- W_{unique} (count of types in reference): 7
- $W(M)$ (count of tokens in the material corpus): 5 ("the people psychology is rewarding")
- $W(M)_{unique}$ (count of types in the material corpus): 5
- KW (count of keyword tokens in reference): 1 ([axon])
- KW_{unique} (count of keyword types in reference): 1
- `worsenedKW`: all from `worsened` where the word is in KW -> `[ ]`
- `improvedKW`: all from `improved` where the word is in KW -> `[axons]`

With these results we can calculate all metrics:

- $WDR_A = 1 - \frac{|wrongA|}{W} = 1 - \frac{2}{7} = \ 71\%$
- $WDR_B = 1 - \frac{|wrongB|}{W} = 1 - \frac{2}{7} = \ 71\%$
- $W_{improved} = \frac{|improved|}{W} = \frac{1}{7} = \ 14\%$
- $W_{worsened} = \frac{|worsened|}{W} = \frac{1}{7} = \ 14\%$
- $KWDR_A = 1 - \frac{|wrongKW_A|}{KW} = 1 - \frac{1}{1} = 0\%$
- $KWDR_B = 1 - \frac{|wrongKW_B|}{KW} = 1 - \frac{0}{1} = 100\%$
- $KW_{improved} = \frac{|improvedKW|}{KW} = \frac{1}{1} = 100\%$
- $KW_{worsened} = \frac{|worsenedKW|}{KW} = \frac{0}{1} = 0\%$
- $W_{improved}(K) = \frac{|improvedKW|}{|improved|} = \frac{1}{1} = 100\%$
- $W_{worsened}(K) = \frac{|worsenedKW|}{|worsened|} = \frac{0}{1} = 0\%$
- $E = KW_{improved}(K) - KW_{worsened}(K) = 100\%$

These metrics are more accessible when we look at the HTML output from `compare-wer.py` as shown in Figure 7.

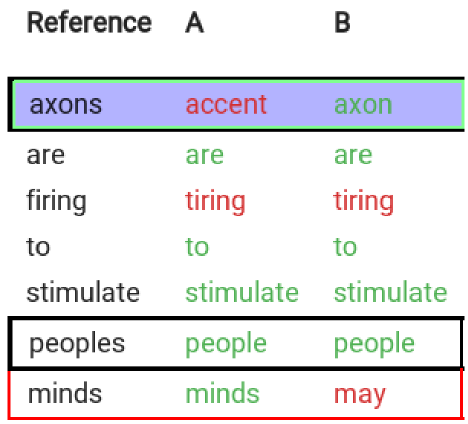


Figure 7: Visualization. Blue background: keyword. Green border: improved word. Red border: worsened word. Black border: lemmatization has changed a word.

5.3 LM interpolation weighting

It has been mentioned above that the weighting between the generic and material LM can be specified. I experimented with different weights and compared the outcome concerning $\Delta KWDR$ and ΔWER[33]. My assumption was that a higher weight for the material LM would result in a higher $\Delta KWDR$, as keywords would have a higher probability of "winning" a decision during the search process as their computed probabilities would outweigh those of "regular" words. But in turn the general WER would be higher as the probability of false-positive results on regular words would increase.

This assumption was confirmed by performing different interpolated runs on lecture `human-nature-8` with a varying weighting for the material corpus LM as shown in Table 3.

Table 3: Different interpolation runs on lecture `human-nature-8`

Weight of material LM in %	25	50	75	95
$\Delta KWDR$	13	15	18	18
ΔWER	1.2	0.4	-0.6	-5.0

It can be seen that the WER decreases when the weight of the material LM exceeds 50%. While the amount of test data would have to be extended to

[33] Δ refers to the improvement from version A to B.

draw definitive conclusions, these results seem reasonable on first sight. For all following test runs I chose a 50/50 weighting as a compromise between both values, although it could be argued that a value nearer to 75% would make more sense in order to maximize $\Delta KWDR$. For an *application* of our approach the optimal weighting should be empirically determined with more extensive testing; this was beyond the scope of this thesis, however.

5.4 Results

The results for the test lectures described above (Chapter 3) are shown in Table 5 (Δ referring to the improvement from version A to B, as mentioned above). The lectures are represented with numbers as shown in Table 4.

Table 4: Number to lecture mapping

#	Course	Lecture	Short name	Material
1	Philosophy and the science of human nature	Flourishing and Detachment	`human-nature-8`	reading assignments
2	Environmental Politics and Law	Chemically Dependent Agriculture	`environmental-8`	slides
3	Introduction to Psychology	What Motivates Us: Sex	`psy-14`	slides
4	Introduction to Psychology	What Is It Like to Be a Baby: The Development of Thought	`psy-5`	slides
5	Frontiers of Biomedical Engineering	What is Biomedical Engineering?	`biomed-eng-1`	glossary of technical terms
6	The atmosphere the ocean and environmental change	Horizontal transport	`geology-8`	two-page excercise sheet

Table 5: Summary of all relevant metrics (all but first block in %)

Lecture	1	2	3	4	5	6	Mean
W	5342	7233	7618	7142	7046	6024	6734
W_{unique}	1247	1592	1525	1323	1196	925	1301
$W(M)$[34]	1124	913	1314	697	3671	425	1357
$W(M)_{unique}$	446	519	486	359	974	212	499
KW	333	715	974	607	518	314	577
KW_{unique}	104	183	212	133	145	59	139
WER_A	52	46	39	42	32	46	42.3
WER_B	52	44	38	42	32	47	42.5
ΔWER	**0**	**2**	**1**	**0**	**0**	**-1**	**0.3**
WDR_A	58	70	66	63	78	60	65.6
WDR_B	58	70	66	63	78	60	65.6
$W_{improved}$	4	4	5	5	3	4	4.2
W_{worse}	4	4	5	5	3	5	4.3
ΔWDR	**0**	**0**	**0**	**0**	**0**	**0**	**0.0**
$KWDR_A$[35]	47	66	67	60	68	60	61.3
$KWDR_B$	62	82	83	81	83	78	78.2
$KW_{improved}$	17	16	17	22	16	20	18.0
KW_{worse}	2	1	1	0	1	1	1.0
$\Delta KWDR$	**15**	**15**	**16**	**22**	**15**	**18**	**16.8**
$W_{improved}(K)$	26	39	41	40	44	26	36.0
$W_{worse}(K)$	3	2	2	0	2	1	1.7
E	**23**	**37**	**39**	**40**	**42**	**25**	**35.0**

[34] W(M): The count of tokens in the material corpus.

[35] KWDR means KWDR-500 for brevity if not noted otherwise.

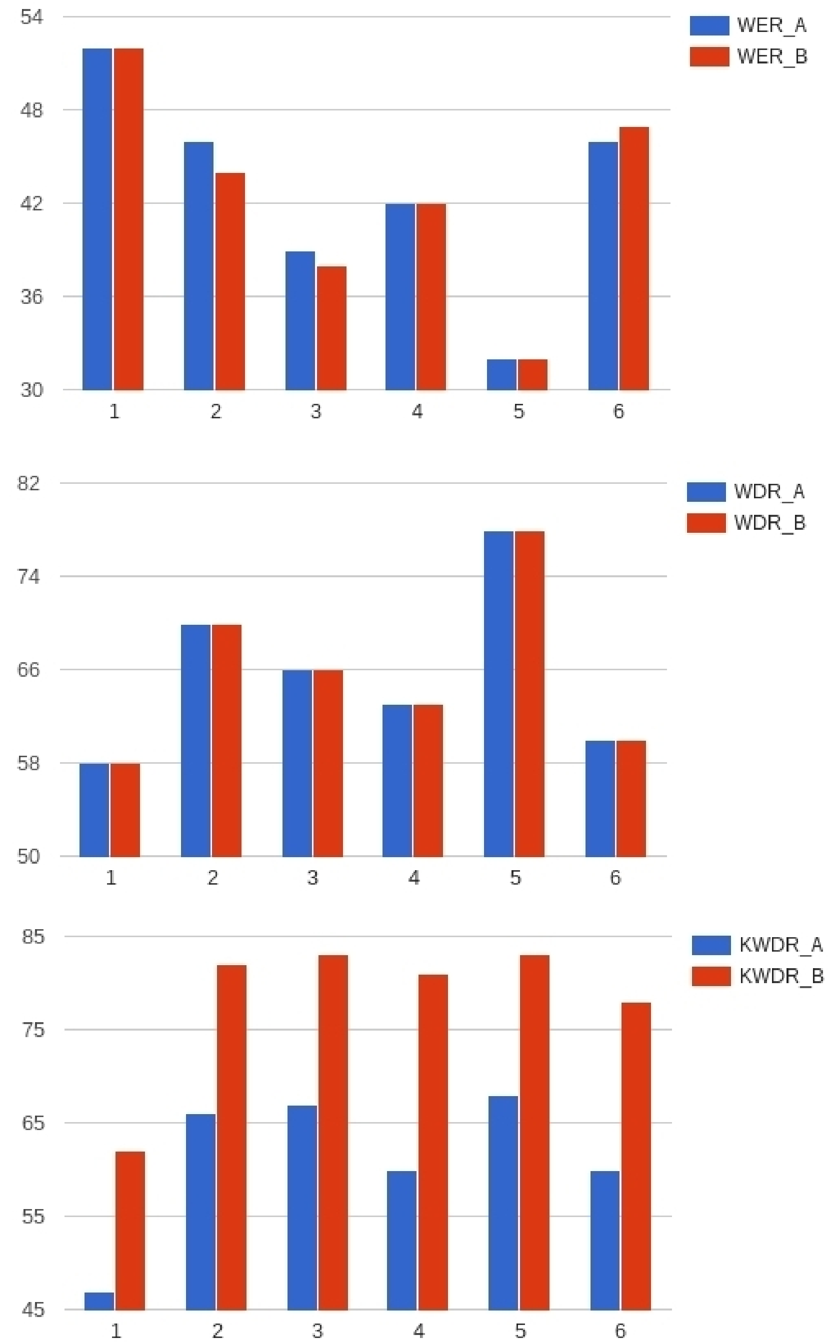


Figure 8: Diagrams showing the changes in WER, DWR and KWDR for run A and B

5.5 Interpretation

Several things are notable. The WDR as well as $W_{improved}$ and W_{worse} hardly change at all, the differences being only zero-digit absolute amounts. It is interesting to note that the results are unambiguous in this respect; it is also unexpected that $W_{improved}$ and W_{worse} always cancel each other out completely.

Assessing the $\Delta KWDR$ presents the challenge that no comparison is available that uses exactly the same metric. However it is possible to "fuzzily" compare the performance by looking at metrics based on similar concepts.

The above mentioned metric RWCR-n used by Marquard (2012) is comparable, as it also uses the concept of filtering out the top_n most frequent words; it differs insofar as it does not take the lemmatized word version as its atomic unit. That being said, the average improvement in RWCR-10k over 13 lectures also taken from Open Yale Courses is 9.0%, while their average WER increases by 0.8%.

Kawahara et al. (2008) use a metric called "Keyword Detection Rate", where keywords are defined as content words (nouns and verbs excluding numbers and pronouns) that appear in the slide text. They then compute the f-measure (the "mean of the recall rate of keywords included in utterances and the precision of keywords detected in ASR results."). They report improvements of 7.5% and 3.0% (for two test sets) in detection rate over the baseline accuracy, while the improvement in WER is 2.2% and 1.3% over the baseline respectively[36].

Miranda, Neto, & Black (2013) do not use a custom metric and report a WER improvement of 3.6%, when interpolating the LM with slide text contents; they achieve an improvement of 5.9% WER when using their proposed method of integrating the speech input with synchronized slide content.

While comparing WER performance has the already discussed disadvantage of low relevance to the defined evaluation goals and the non-standardized spectrum of custom metrics makes an objective comparison of the different approaches impossible, it yet gives an impression of how our approach's performance relates to other work: the $\Delta KWDR$ of 16.8% seems like a good indicator that our approach is a viable solution for the goal of improving speech recognition for searchability and scannability. Additionally, the *effectiveness score* demonstrates that the approach nearly does not worsen keywords at all and 36% of the improved words are actually keywords (the mean of $W_{improved}(K)$).

In general, the low variance of results over the various subject areas with their very different types of provided materials is also suprising: the variance σ^2 over $\Delta KWDR$ is 6.47, the standard deviation 2.54. This intuitively means that the values 15, 15, 16, 22, 15, 18 are quite near to their mean 16.8; only one outlier (22) can be seen. 22 is the result from to the lecture `psy-5`. The other psychology lecture `psy-15` however has a result of 16. Both lectures have lecture material of the same sort and also have the same speaker. Thus the outlier can not be explained by "superior" material or speaker style.

[36] The mentioned results refer to the combined method of global and local adaptation.

The results seem to suggest that the form and supposed "quality" of material (e.g. excercise sheet versus lecture slides) does not correlate with the improvement in KWDR. When looking at the quantity, we can see no positive correlation between $W(M)$ and $\Delta KWDR$. The glossary material from `biomed-eng-1` contains 3671 tokens and 974 types, it however has a $\Delta KWDR$ of 15; `geology-8`'s exercise sheet has the smallest $W(M)$ of 425 but the second highest $\Delta KWDR$ of 18.

The initial assumption that it would be harder to recognize lectures from the natural and formal sciences, based on the "naive" presumption that it would be impossible to recognize words like "adenosine 5'-triphosphate", seems to be invalid as well – apparently the combination of preprocessing, G2P and adapted weighting in the LM makes it possible to detect complicated technical terms like this as well.

5.5.1 Qualitative assessment

While representing the performance of our approach with a set of metrics allows (at least internal) comparability of results, it cannot convey a holistic impression of what would actually change for a user of a hypothetic speech media search/scan interface when data is used that is generated with our approach versus the baseline approach.

This impression can be given by looking at the following detailed results of the run on the `biomed-eng-1` lecture.

Normal words improved (*(word, count)*)

> (of, 8) (that, 7) (the, 6) (or, 6) (and, 5) (a, 5) (in, 4) (to, 4) (is, 4) (it, 3) (course, 3) (into, 2) (an, 2) (your, 2) (from, 2) (than, 2) (one, 2) (those, 2) (this, 2) (talk, 2) (bridge, 1) (set, 1) (don't, 1) (some, 1) (are, 1) (annoying, 1) (really, 1) (again, 1) (there's, 1) (would, 1) (it's, 1) (there, 1) (how, 1) (version, 1) (we're, 1) (which, 1) (you, 1) (more, 1) (week, 1) (be, 1) (students, 1) (free, 1) (i've, 1) (with, 1) (by, 1) (distance, 1) (about, 1) (like, 1) (well, 1) (infectious, 1) (yale, 1) (very, 1) (where, 1) (engineers, 1)

Normal words worse:

> (and, 15) (a, 10) (so, 9) (you, 8) (the, 8) (it, 7) (have, 6) (to, 5) (they're, 4) (of, 4) (that, 4) (are, 3) (can, 3) (be, 3) (we, 3) (on, 3) (at, 3) (in, 3) (how, 3) (online, 3) (that's, 3) (day, 2) (we'll, 2) (see, 2) (our, 2) (for, 2) (genes, 2) (could, 2) (it's, 2) (one, 2) (there, 2) (we're, 2) (but, 2) (is, 2) (as, 2) (if, 2) (two, 2) (principle, 2) (concept, 1) (office, 1) (years, 1) (london, 1) (go, 1) (just, 1) (had, 1) (easy, 1) (bridge, 1) (somebody, 1) (increased, 1) (very, 1) (familiar, 1) (safe, 1) (i've, 1) (every, 1) (they, 1) (now, 1) (organ, 1) (did, 1) (doctor's, 1) (because, 1) (old, 1) (some, 1) (really, 1) (what, 1) (said, 1) (lots, 1) (vessels, 1) (health, 1) (approach, 1) (patient, 1) (here, 1) (come, 1) (about, 1) (bow, 1) (or, 1) (cancer, 1) (point, 1) (period, 1) (long,

1) (apply, 1) (city, 1) (would, 1) (leading, 1) (three, 1) (been, 1) (their, 1) (way, 1) (was, 1) (tell, 1) (life, 1) (buy, 1) (posted, 1) (physician, 1) (these, 1) (say, 1) (us, 1) (patient's, 1) (thin, 1) (were, 1) (heart, 1) (an, 1) (heard, 1) (get, 1) (other, 1) (details, 1) (week, 1) (kinds, 1) (i, 1) (mechanical, 1)

KW improved:

(biomedical, 35) (dna, 7) (cells, 7) (engineering, 6) (biochemistry, 3) (cell, 3) (polymer, 2) (graph, 2) (gibbs, 2) (certain, 1) (energy, 1) (site, 1) (occur, 1) (plot, 1) (due, 1) (specifically, 1) (membrane, 1) (answer, 1) (has, 1) (higher, 1) (drugs, 1) (molecule, 1) (known, 1) (post, 1) (polymers, 1) (disease, 1) (order, 1)

KW worse:

(cells, 1) (maintain, 1) (beyond, 1) (genetic, 1) (due, 1)

Two things are notable: (a) the "exchange" of filler words between version A to B, which is of no interest for searching and scanning; and (b) interesting keywords that have a substantial number of occurrences that were not found before, while the amount of worsened keywords is tiny. This is the important "qualitative", high-level conclusion: the approach allows users to find technical terms in speech media which they were not able to find before and it works consistently over a broad spectrum of topics.

6 Visualization for scannability

We have shown that the LM-Interpolation approach is a viable tool for improving accuracy of keyword detection when performing ASR on university lectures. The output data of our system are words with meta information: their associated timing and the fact that they are a keyword or not. How can this information be further used in order to help a user with the task of scanning and searching through a given lecture? While it is technically possible to use the whole transcript and present the user an interface were the transcript is time-aligned with the lecture, that presentation is problematic as the *WER* of the transcript has not been improved and reading comprehension for texts with WERs above 30% is too low.

A better approach would be to focus the interface exclusively on the keywords in such a way that the provided timing meta information is transformed into a dense visual representation, thus making scanning possible. The user should be able to see the distribution of topics during the timeline of the lecture at a glance.

To this end I have developed a prototype implementation of such an interface[37]. It features two views: the first one is a list of word timelines (Figure 9). A word timeline shows the distribution of occurences of a given word over the time of the lecture. An occurence is displayed as a dot; clicking the dot positions the corresponding lecture audio at the time the word is spoken. The timelines are vertically sorted by count of word occurences. For analytical purposes the interface also shows the count of recognized occurences in relation to the actual count of occurences in the reference transcript, seen next to the word. It also overlays a graph which shows the *word density* at a given point of time. The density function is calculated by performing a Gaussian Kernel Density Estimation (KDE) algorithm on the array of time positions for a given word. The red dots are local maxima of the function[38], so that a word can have multiple maxima. The information about maxima is being used primarily in the second view.

The second view (Figure 10) is a *word cloud* with "semantic axes", compared to regular word cloud visualizations where the axes do not have meaning. The x-axis still is the time-axis of the lecture and the y-axis still is the keyword frequency. The central feature of this cloud is that it can show *multiple instances* of one keyword – one instance for each local maximum. The word instance is on the same point on the x-axis as the corresponding local maximum. The timeline for a word can be shown by clicking on it. The example shows "brain"

[37] The source code is available at https://github.com/jonathanewerner/bachelor/tree/master/viz. The prototype is implemented with web technology (Javascript, interactive SVGs, React.js, CSS) with the goal of easing possible integration into existing web video portals.

[38] The local maxima are computed with the `scipy.signal.argrelextrema` function from the python `scipy` package and had some mildly surprising results, which were of no relevance for the interface prototyping task however.

Figure 9: Word timelines

in the activated state; the timeline shows up below the cloud. One can see the two instances of "brain" being horizontally aligned with the two local maxima below[39]. Clicking on the word also transports the audio to the position of the word next to the given local maximum. The font size of this word W is computed by counting the word occurrences for which holds that the nearest local maximum is the maximum associated with word W. Additionally multiple instances of one keyword have the same color to further aid scanning by allowing the brain to pre-attentively process the representation.

This view allows a user to immediately scan the distribution of topics during the whole lecture. If particularly interested in the parts about the brain, he/she might click on "brain", be immediately transported to the relevant audio position and additionally have a more in-depth view in the bottom timeline below the cloud, allowing him/here to intuitively grasp how long the relevant part might be, maybe flicking around by clicking on other instances of the word in the timeline.

You could imagine integrating this interface as a semi-transparent overlay view on a video player, for example on platforms like lecture2go[40], the lecture video streaming platform used by the University of Hamburg. When using a system that integrates many lectures in one database like this, it would also be possible to not only link to keyword instances in the same lecture but also on a broader scope, e.g the whole course or even other relevant courses and lectures. Another

[39] It is obvious here that the first local maximum for the word should rather be at about 30-40% of the word's timeline, but that could be optimized.

[40] lecture2go.uni-hamburg.de

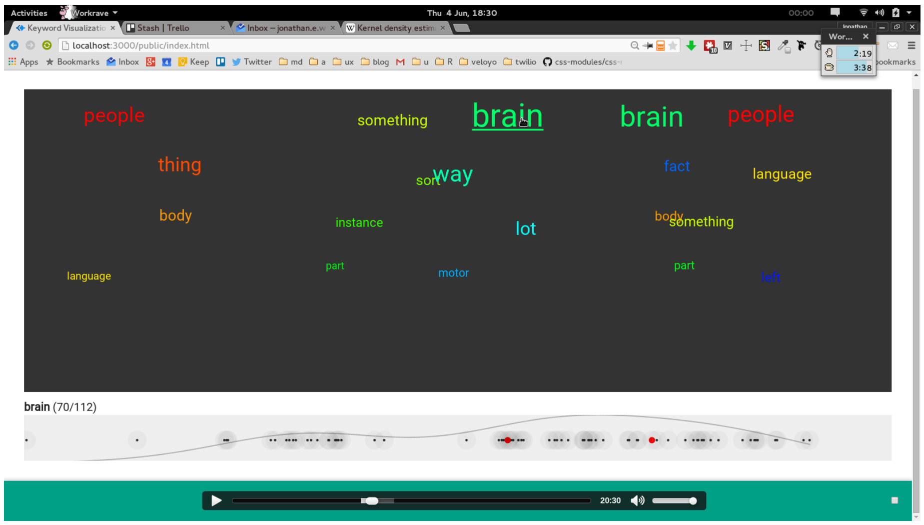


Figure 10: Word cloud

interesting extension point would be to integrate human intelligence by allowing to review/score the quality of keyword instances. This would allow filtering out false-positives and emphasize the keyword instances that students find helpful.

7 Conclusion

The primary question of the present thesis was: given that we are interested in improving speech recognition accuracy of keywords in university lectures, what is the advantage of creating a lecture-specific LM and interpolating it with a generic model and how can we measure this improvement? A secondary question was: how can we use the results of this approach to provide graphical interfaces for improving the user's ability to search and scan a given speech medium?

The strategy for answering the primary question consisted in first explaining the basic concepts of speech recognition and its scientific history in order to locate our approach in relation to other research and paradigms. We stated that our approach follows the statistical pattern-recognition paradigm. This paradigm sees ASR as the process of measuring features in the acoustic signal and then performing a search process using these features to find hypotheses using different sources, in particular acoustic and language models. Its use of fixed input features distinguishes it from *integrative approaches* which dynamically learn the input features.

We furthermore established that lecture transcription can be classified as *speaker-independent large-vocabulary continuous speech recognition* (SI-LVCSR).

After explaining the fundamental speech recognition concepts of phonemes, phonetic dictionaries, search as well as acoustic and language models, we presented an overview of the scientific work done on lecture transcription. Here we distinguished generalization and specialization approaches. While the former try to capture general characteristics of lectures – for example by adapting acoustic models to account for "filler sounds" which are very common in lectures – the latter try to use context specific to a single lecture (*meso* level) or even parts of a single lecture (*micro* level). Furthermore, methods using lecture material such as slides can be differentiated into two groups: those that only use the information existent in the material itself and those that use "derived" data such as Wikipedia articles crawled by using words from the material as search queries. Our approach can thus be categorized as a specialization approach operating on the *meso* level, only using immediately available data for the material corpus.

In the next step we looked at the 6 lectures from Open Yale Courses that were used as test data, displaying the heterogenity in quantity and style of each lecture material. We noted that only 20% of the available lectures have lecture material at all, and only 20% of these have typical "slides", which posed the question if material types such as excercise sheets or reading assignments have a detrimental effect on the recognition performance.

Our next step was to consider the implementation of the LM-Interpolation approach. We introduced the general architecture of the *Sphinx 4 Framework* used as the basis for performing speech recognition and explained the *InterpolatedLanguageModel* component. This component makes it possible to specify multiple LMs with associated weights in order to faciliate the interpolation of probabilities for a given n-gram. We then described the tool pipeline used to perform recognition and analysis with a baseline and an interpolated run. An important part in converting the material PDF to a corpus was to ensure that the conversion result exhibited no superfluous newlines as these would be represented as sentence boundaries in the resulting material LM, which would have been an unintended side effect. The intermediate steps and testcase results are saved in a subfolder of the `results` folder of the repository, allowing subsequent inspection of all steps.

This was followed by analyzing the results. The *Keyword Detection Rate* (KWDR-x) metric was developed to capture the improvement of the interpolated approach with respect to the formulated research goal of improving *keyword* recognition. Central modifications to the canonical *WER* consisted in ignoring word insertions, taking *lemmas* as the atomic unit and using the material corpus as an inclusive and the top_X most common words as an exclusive filter. The results showed an average improvement in KWDR of 16.8%, while WER did not change significantly. This result was compared with the results of other works. While there is no common metric but the WER to objectively compare results and WER has the disadvantage of low relevance to the evaluation goals as discussed above, the overall impression was that the measured improvement was quite high and at least serves to validate the usefulness of the explored approach. It could also be concluded that the supposed "quality" and quantity of the lecture material did not correlate with the amount of improvement.

Finally we explored the secondary research question of how to make use of the results for providing graphical interfaces that improve the user experience when searching and scanning a given speech medium. We noted that providing a full text display does not make sense for transcription results with a WER above 30% as the reading comprehension is too low at such a rate. An alternative was explored by presenting an interface prototype that displays a combination of word timelines and a word cloud with "semantic axes", allowing the user to immediately grasp the overall distribution of keywords during the timeline of a lecture.

7.1 Improvements and extensions

There are several possible improvements and extensions that were beyond the scope of the present thesis. The primary one would be to extend the system to work with different languages. For this thesis, English was chosen as the only language, primarily because no database with equivalent test cases like the ones provided by Open Yale Courses was available for other languages. The combination of quality reference transcriptions and provided lecture materials is unique, unfortunately. Also, the manual transcription of a lecture is very time consuming. Integrating multilinguality into the pipeline would also be no small task, as preprocessing and lemmatization is language-specific and suitable equivalent multilanguage tools would have to be found.

As already mentioned above, the approach of filtering out top_X words could possibly be solved more elegantly by using *tf/idf* to compute "keyword-ness" of words; this would help eliminate the cases where keywords that are part of the top_X words are filtered out.

More extensive empirical evaluation should be performed on the interpolation weights in order to achieve reliable results concerning the relationship of weights to $\Delta KWDR$ and ΔWER. While this has not been the primary focus of our evaluation, it is of importance for applications, as they could choose a weighting according to their focus on sentence integrity: an application not displaying full text would likely choose a high value for the material corpus' weight; accordingly an application actually showing full text would likely choose a weighting which does at least not diminish general recognition performance.

An further interesting experiment would be extending the material LM by performing *delemmatization* on the material corpus before creating the LM, where delemmatization means extrapolating all possible inflected forms from a given word. With our approach, spoken inflected forms of a keyword would not be recognized if only another inflection can be found in the material. This could potentially further improve keyword recognition accuracy. The challenge here seems to be finding tools that can automatically perform this task. This is especially complex for languages like German that have many complex compound words and irregular inflections. A starting point however would be performing "naive" delemmatization by for example adding the character "s" to english singular nouns ("car" would then become "cars"). An open question here would be how to integrate these inflected forms into the material corpus so that they would still be placed in the right context: given the corpus "A car is red", should the resulting corpus look like "A car is red `\n` cars" or rather "A car is red `\n` A cars is red"? The second would introduce a grammatical error, but coarsely retain the context of "car" and "red", whereas the first example would not retain it but also would not introduce a grammatical error. Of course "Cars are red" would be optimal, but it is questionable if this level of "intelligence" would be achievable given the complexity and non-grammaticality of spontaneous speech, especially in the context of lectures.

Concerning the fact that the definition of KWDR excludes the penalization of *insertions* it can be argued that while insertions are generally not relevant for the keyword detection rate, there actually *are* cases were they are relevant: namely the case when a *keyword is inserted*, as this leads to false-positive results. Thus it would be beneficial to first analyze if and how often this happens and secondly to adapt the metric to account for these cases.

Finally, it would be interesting to do user studies on the visualization prototype: would users actually use an interface like the proposed one for searching and scanning speech media? Would an integration of "human factors" like scoring for keyword instances be used and how could a suitable user-friedly interface look like? The association of lecture-specific keyword content to a broader context like the whole course content or even other courses leads to the the question of how this idea could impact the whole field of education if deployed and used widely – you could imagine a whole new paradigm of lecturing that shifts from the linear-narrative form to a networked, interconnected form, where a student watching lecture videos can effortlessly jump to previous points in time *during the whole course* where a necessary concept had been initially introduced, or jumps to relevant other courses, deepening his understanding "in free form" akin to what we are now used to when browsing the internet.

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Eidesstattliche Erklärung

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