Karlsruhe Institute of Technology

Online Neural Network-based Language Identification

Master's Thesis of

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I declare that I have developed and written the enclosed thesis completely by myself, and have not used sources or means without declaration in the text.

Karlsruhe, 12th of May, 2017

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(Daniel H. Draper)

Abstract

Zusammenfassung

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1. Introduction

Language Identification (LID) describes the classification task of differentiating between spoken speech in different languages and being able to correctly classify which speech-segments consists of which language. Neural Networks refer to Artificial Neural Network's, a Machine Learning approach to classification tasks employed greatly throughout all sciences and especially in computer science and tasks concerned with the processing of spoken speech. This thesis tries to find a low-latency, fast, or "online", approach to Language Identification using the classification method of neural networks.

The work done in this thesis uses the Janus Recognition Toolkit (jrtk)[1], an Automatic Speech Recognition toolkit developed in joint cooperation by the KIT and CMU. The jrtk offers a tcl/tk[2] script-based environment for the development of Automatic Speech Recognition systems, therefore source code in this thesis will consist of tcl/tk scripts with (some) janus-specific commands. The jrtk and tcl/tk are further explained in sec. 3.1.

1.1. Motivation

Automatic Speech Recognition (ASR) is used in many applications and devices today, especially in the rise of handheld mobile devices like smart-phones and tablets. It has progressed quickly in the last five years and has found commercial success. Famous examples include Google[3]'s "Ok, Google" and Apple[4]'s Siri. Which both include voice search[FHBM08] and a form of voice control, that even is extensible in the case of Google and Android e.g[bAO14]. Many other applications have emerged, including spoken language translation[5], especially relevant for this thesis in the realm of Lecture Translation[MNN+16] .

The task of Language Identification can be applied in all of those fields, as Automatic Speech Recognition is mostly trained on one language and therefore requires a totally different setup of classifiers per language, making a manual change of language previous to recognition necessary. Robust and low-latency language identification would eliminate the need for this.

LID would be especially applicable in the realm Spoken language translation, as used for example in the European Parliament where already components of ASR and Machine Translation are employed and are being actively developed in the TC-STAR inititative[6], e.g as in[VMH+05], and LID would further be able to automate these translation tasks.

[1] Janus Recognition Toolkit: `http://isl.anthropomatik.kit.edu/cmu-kit/english/1406.php`
[2] Tcl/tk: `https://www.tcl.tk/`
[3] Google: `www.google.com`
[4] Apple: `www.apple.com`
[5] IWSLT: `iwslt.org`
[6] TC-STAR: `tcstar.org`

This thesis will focus mostly on the KIT's lecture Translator[7] as the system trained was implemented for it. We believe our results are general enough to be transferable to other applications with small implementation-specific changes.

1.2. Overview

The following chapter gives an introductory view of the applications of Language Identification, and introduces the tasks this thesis tries to solve. Afterwards we give preliminary theoretical explanations and definitions, including an introduction to Neural Networks in Sec. 3.2. The next chapter describes the experimental setup used in this thesis, including the data corpusses and feature preprocessing done on raw audio files.

Chapters 4 and 5 describe our results that were accomplished by trying out different Network Structures and geometries in chapter 4 as well as different smoothing mechanisms on top of the direct neuronal output layer of the network in chapter 5. This is followed by the final summary of our work and an outlook onto future work improving upon these results.

[7] Lecture Translator: `https://lecture-translator.kit.edu`

2. Related Work

This chapter introduces related and previous works in the realm of language identification and how their approaches differ from the ones employed in the following chapters.

3. Fundamentals

The following chapter will define and explain terms and concepts used throughout this thesis, as to make understanding of the following chapters easier.

3.1. Janus Recognition Toolkit (jrtk)

The Janus Recognition Toolkit (jrtk) also known as just “Janus” is a general-purpose speech recognition toolkit developed in joint cooperation by both the Carnegie Mellon University Interactive Systems Lab and the Karlsruhe Institute of Technology Interactive Systems Lab [LWL+97]. Part of janus and the jrtk are a speech-to-speech translation system which includes Janus-SR the speech recognition component, the main part of janus used in this thesis.

Developed to be flexible and extensible, the jrtk can be seen as a programmable shell with janus functionality being accessible through objects in the tcl/tk scripting language. It features the IBIS decoder, that uses Hidden Markov Models for acoustic modeling in general, although in this thesis we used a neural network as our speech recognizer to generate the input features required by our Language ID network.

This thesis makes extensive use of the jrtk’s and tcl/tk’s scripting capabilities to be able to pre-process speech audio files for further use by our experimental setup. It also uses tcl/tk scripts and it’s janus API functionality in the development of our smoothing and evaluation scripts as can be seen in Ch. 6.

3.2. Neural Networks

Artificial Neural Networks today are used in many different fields: from image recognition/face recognition in [LGTB97] to Natural Language Processing in [CW08] and, as relevant to this thesis, to Speech Recognition and very successfully as in [HDY+12]. It has also been used in the realm of Language Identification, which will be described in Sec. **??**. This section will provide fundamental knowledge of how neural networks work and how to train them, to make the understanding of later chapters easier for the reader. The information in this section is based mostly on [HN04], [GBC16] and [Nie15]

3.2.1. General Setup

Neural Networks are based on collections of small ”neural units“ working together in tandem. The neuron’s behavior can be loosely linked to the brain’s axons. Each neuron is connected with others and a neuron is ”stimulated“ by input on these connections and then

decides on its own activation, or stimulation, by using a summation, or threshold, function with a certain limit to decide if the neuron ”fires“ and its own activation is propagated through the network to adjacent units. By changing weigths and activation thresholds in the network its output changes, therefore the possible adjustable parameter set Θ for a neural network includes all the weights for all neurons as well as all thresholds for the activation functions in each neuron.

3.2.2. Artificial Neuron

An artificial neuron, or perceptron in its most basic form, is a mathematical function that consists of four parameters that can be adjusted independently from each other:

- w_i the input weights for all inputs
- Σ the transfer function for summation of the weighted inputs
- φ the activation function that calculates the output value y_k basend on the transfer input and the threshold
- θ the threshold which defines when the neuron activates.

This means an artificial neuron with output y_k is the function 3.1. Many of these neurons coupled together (via the output of a neuron on a previous layer becoming the input for one on the current layer), make an Artificial Neural Network as used in this thesis. A schematic drawing of this can be seen in Fig. 3.2.2.

$$y_k = \varphi(\sum_{j=0}^{m} w_{kj} x_j) - \theta_j \tag{3.1}$$

Figure 3.1.: A schematic drawing of a Neuron and it’s parameters

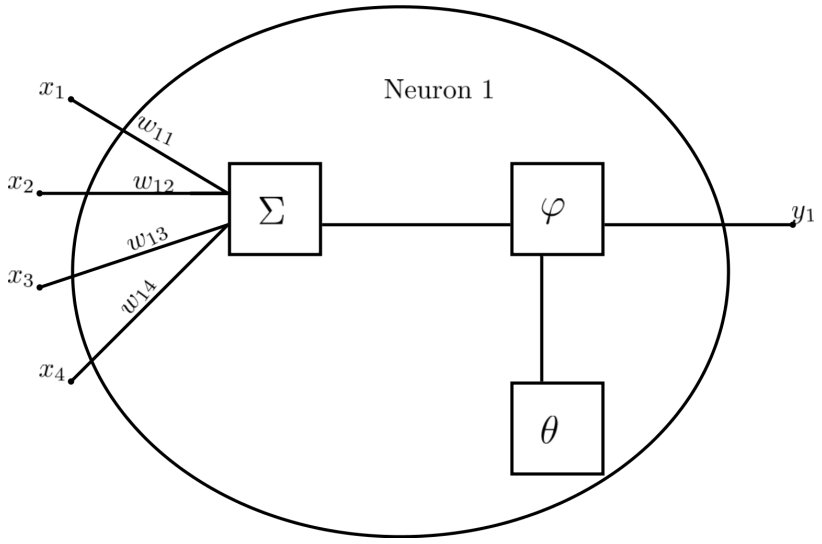
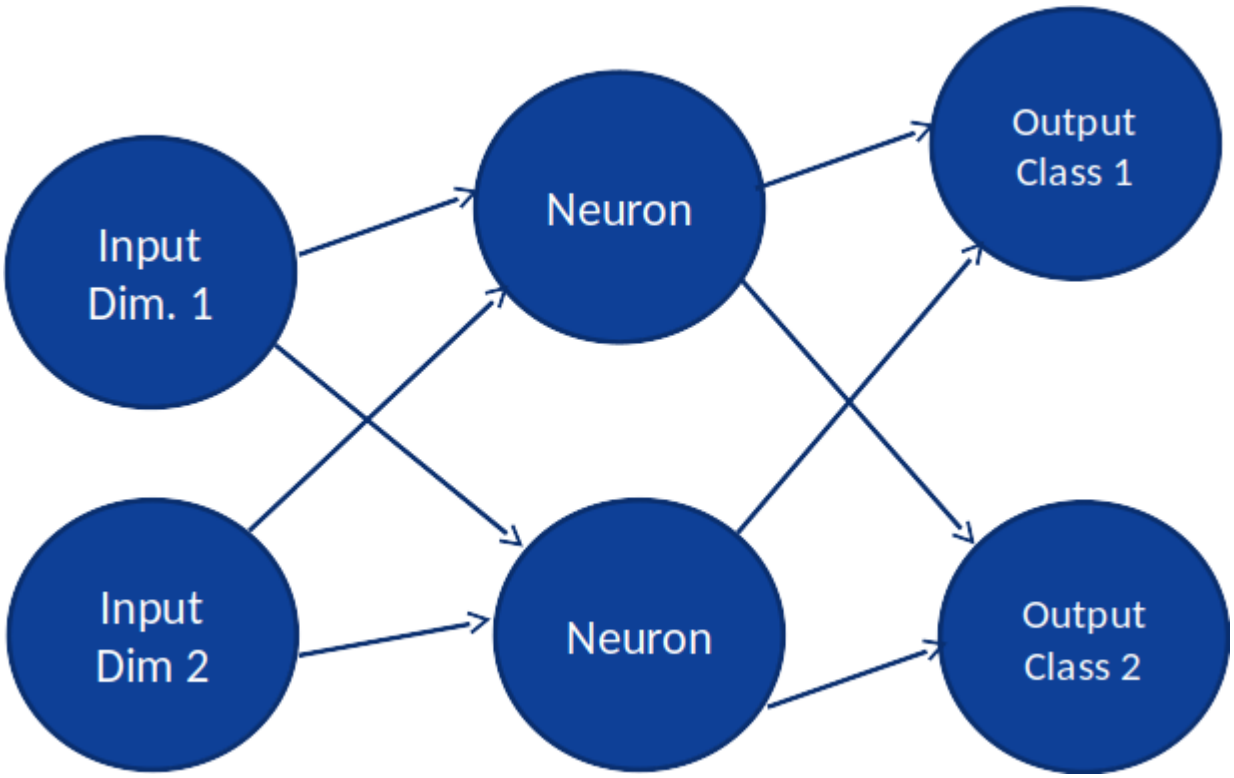


Figure 3.2.: A schematic drawing of a neural network



3.2.3. General Network Setup

A basic neural network consists of three layers: the input, a hidden layer of neurons and the output layer. Hereby, the output layer consists of as many neurons as classes that the network is trying to classify against and the one with the highest activation after entering input, is the classification output of the net. A basic, fully-connected (referring to the connections between neurons, so fully-connected means each neuron is connected to each possible other neuron) net can be seen in Fig. 3.2.3.

3.2.4. Network Types

3.2.4.1. Feed-Forward Neural Networks

A basic (non-deep) *Feed-Forward Neural Network* consists of three layers: the input, a hidden layer of neurons and the output layer. Feed-Forward refers to the fact, in opposition to *Recurrent Neural Networks*, that connections between the neural units are not cyclic.

In such a basic network, the output layer consists of as many neurons as classes that the network is trying to classify against and the neuron with the highest activation after entering input, is the classification output of the net.

3.2.4.2. Deep Feed-Forward Neural Networks

Deep Feed-Forward Neural Networks, DNNs, the net-type most used in this thesis, refer to Networks that have more than one hidden layer between input and output, but still feature non-cyclic connections between neurons. DNNs have a better performance than single-hidden-layer-networks in general, but require different techniques for training.

A common description of this phenomen is, that each hidden layer increases the level of abstraction the network can manage. E.g, in image processing, if the first layer recognizes a color in a certain pixel, then the next layer can infer more abstract characteristics from the output of the first layer. For example, after knowing a certain pixel is dark the next layer can derive that area might be the eye in a picture of a face, etc. This obviously makes more complicated classification tasks possible but also makes learning algorithms more difficult.

3.2.4.3. Deep Recurrent Neural Networks

Deep Recurrent Neural Networks, RNNs, refer to neural networks that are DNN's but cyclic connections are allowed. This means the network can have temporal behavior, so its performance changes dynamically over time, when the state of later neurons changes and affects the neurons in previous layers.

3.2.5. Learning

The interesting part about Neural Networks is their ability to learn from data and improve their own performance. Improving performance in this case means that by adjusting the available parameters of the neurons part of the network, we minimize a cost function that describes the difference between an optimal output and the actual output.

A Network can be seen to be an approximation of a function f^*. So, a network trying to classify an input x into a class y approximates:

$$y = f^*(x) \tag{3.2}$$

Then one run of the Network with parameter set Θ gives the mapping $y = f(x; \Theta)$ and we are trying to minimize our cost function of $C = f^* - f$ by adjusting the set of parameters in Θ each run.

Three basic approaches exist for training a network:

- *Supervised Training*, where the optimal output for input train data is known. This means, the train data has been pre-classified by a "teacher". This is the method we use in this thesis and further explained below.
- *Reinforcement Training*, where the optimal input for train data is not known prior to training, but the environment gives the net feedback about its own output and good output is "reinforced" while bad output is discouraged.

- *Unsupervised Training*, where nothing is known about the environment and the net (often) just tries to learn the probabilistic distribution of the data.

3.2.5.1. Sampling

Data for training is generally split into three sets: the training set with a size of about 80% of the total available data which is then used for the training, the development set with a size of about 10% used for evaluation of the net and adjusting different parameters without "distorting" the last test set which also has a size of around 10% and is used for final "clean" validation of the net performance.

Sampling is most commonly, as in this thesis, done using the

3.2.5.2. Supervised Training

Supervised Training refers to training where the optimal output for the training data is known, so a classification of the train data exists prior to training. This makes calculation of the Cost function as defined in the previous section relatively easy, as we define C as the actual difference in output of the current net with current parameter set Θ compared to the teacher-defined classification/labeling.

Mean Squared Error Function One way to calculate the difference between the net and the teacher-classification is by using the mean squared error, as is used in the training of nets in this thesis. If t is the expected output and $f(x;\Theta)$ is the actual predicted output and M the number of output neurons/classes, we define the Mean Squared Error (MSE) as:

$$E = 1/2 \sum_{j=1}^{M} (f(x;\Theta) - t)^2 \tag{3.3}$$

Stochastic Gradient Descent The goal of course is to minimize the MSE as defined above by adjusting parameters for each neuron and layer (including weights to output neurons) to change the predicted output of the net. This is done by adjusting the weights in direction of the falling gradient for each weight.

$$w_{i+1} = w_i - \eta \nabla E(f(x;w),t) = w_i - \eta \nabla 1/2 \sum_{j=1}^{M} (f(x;w) - t)^2 \tag{3.4}$$

This method is called the "Gradient Descent", with η being the "Learning Rate", the freely adjustable speed at which the network changes and therefore learns. As calculation of this gradient for every sample in the training data set is expensive, a stochastic approach is used where only a small number of samples is used each iteration to calculate the gradient, as the relation between the change of the mean error and the value of samples is not linear. Therefore the calculation of the Stochastic Gradient Descent" (SGD) is enough to estimate the real required parameter-changes.

Backpropagation While the SGD is used to calculate each iterative weight according to the falling gradient, the Backpropagation algorithm is used to calculate each weight from the total output of the net and its input. If we have neural network output vector (all output neurons together) t_i, input vector (all input dimensions together) x_i and current weights w_i we can calculate w_{i+1} by calculating the SGD on the function $w \longrightarrow E(w, x_i), y_i)$.

With preceding definitions we can summarize the training algorithm of a DNN as follows:

```
1  w_0 := rand()
2   do
3      forEach train-sample s
4         f(x;w_i) = neural-net-output(w_i,s) // Actual calculation using each
              neurons output -> Forward pass
5         t = pre-classification(s)
6         Error = E(f(x;w_i),t)
7          w_{i+1} := w_i - η∇E(f(x;w),t) = w_i - η∇1/2 Σ_{j=1}^{M} (f(x;w) - t)^2  //For all Weights and
               layers -> Backwards pass
8         w := w_{i+1}
9    if (ΔE <= Threshold) break
10 return Net
```

Listing 3.1: Pseudo Code to show the Backpropagation/SGD algorithm in Action

4. Experimental Setup

This chapter lays out the experimental setup used in this thesis. While Language Identification is applicable in many different scenarios, here the focus lies on trying to establish a low-latency online approach for recognizing the spoken language in a university-lecture environment. Because finding a suitable test setup for online data retrieval is hard, the data used was cut to short lengths to make an evaluation as to correctness of the recognition possible in an ”online-like” scenario.

This means that the output of the net is evaluated after short samples of speech and therefore can be seen as indicative of online performance of the net in the lecture translator.

This chapter introduces our experimental setup as well as the data sets the experiments were conducted on.

4.1. General Setup

Many different tools exist for deep learning, the most acclaimed being Tensorflow [AAB+16], DL4J/ND4j[1] and Theano [BBB+11]. Pre-existing work on Language Identification, or rather Language Feature Vector Extraction using a LID Network in [MSW16], used a python wrapper around Theano for training, that was developed by Jonas Gehring [Geh12]. This thesis continues the use of this wrapper for the training of our DNNs. The basic layout of the network used and improved upon by this thesis were input vectors from a multilingual ASR net, further explained in Sec. 4.5.1, which we used to generate Bottleneck Features with 966 coefficients. The LID network introduced in the following chapters then uses these BNF vectors to classify the audio input into a language. Different Network Structures and types (DNNs/RNNs) were used that will be further explained in Ch. 5.

As detl does not provide support for RNNs we used Lasagne [2], another wrapper around theano, as the framework for our RNN training.

4.2. Euronews 2014

The first data set used, was retrieved from Euronews [3] 2014. Euronews is a TV channel that is broadcast in 13 different languages simultaneously both on TV and over the Web and is semi-automatically transcribed. The data corpus includes 10 languages (Arabian, German, Spanish, French, Italian, Polish, Portuguese, Russian, Turkish and English) with around 72 hours of data per language provided overall, meaning the corpus had a total

[1] DL4J: `https://deeplearning4j.org/index.html`

[2] Lasagne: `https://lasagne.readthedocs.io/en/latest/`

[3] Euronews: http://www.euronews.com/

length of around 720 hours of audio data. This data was taken both from online video and recordings of the transmissions as described in [Gre14].

For the purposes of this work we then broke this corpus down further into a more manageable size as to make the feedback-cycle faster, while still keeping the corpus big enough to make results comparable to performance with the full corpus. Later, we then used the full data set to compare results between the smaller and bigger sets.

The corpus was broken down to a per-speaker-basis based on its automatic transcriptions. From this data we took a sample of a random 10.000 speakers, while making sure the total length of samples for each language were roughly the same. Details of this breakdown can be seen in table 4.2.

Language	Number of Speakers	Combined Length
Arabian	1055	16.76 h
German	928	18.80 h
Spanish	932	18.78 h
French	1016	18.67 h
Italian	935	19.00 h
Polish	1229	18.30 h
Portuguese	1062	16.19 h
Russian	958	18.66 h
Turkish	957	18.61 h
English	928	18.54 h
Overall	10000	182.31 h

Table 4.1.: The euronews corpus speaker breakdown used for most experiments with total utterances length.

Set	Number of Speakers	Combined Length
Train	8000	149.76 h
Development	1000	19.46 h
Test	1000	19.29 h

Table 4.2.: The Euronews corpus breakdown into the three data sets.

The speaker list was then split into three smaller datasets: the train set, development set and test set using the common Simple Random Sampling. The sizes were 80% allocated to the train set, and 10% for both the development and test set. Table 4.2 shows the split data for the three sets.

We also had a second Euronews Corpus available that was much larger. This was used to confirm intuition that a larger data corpus leads to better results which can be seen in Sec. 5.5. The breakdown of the large corpus' data is listed in Table 4.2

Language	Number of Speakers	Combined Length
Arabian	4401	51.13 h
German	4436	73.21 h
Spanish	4464	75.71 h
French	4434	68.14 h
Italian	4464	77.22 h
Polish	2625	33.15 h
Portuguese	4430	49.07 h
Russian	4418	72.23 h
Turkish	4385	70.42 h
English	4511	72.76 h
Overall	42568	643.04 h

Table 4.3.: The big Euronews corpus speaker breakdown with total utterances length.

4.3. Lecture Data

As part of the development of the KIT's Lecture Translator, German lectures at the KIT were recorded and annotated. This is described in [SKM+12]. This thesis then uses parts of this German corpus as well as newer recordings done at the KIT of English lectures with the same setup, English academic talks given at InterACT - 25[4], as well as French talks done at the DGA's [5] yearly academic conference on speech recognition.

This lecture data was then used in two different ways: Firstly, to evaluate the 10-Language trained Euronews-Net(s) to see how it would fare in a lecture-environment as part of the KIT's lecture translator by scaling the output down to the 3 available languages. Secondly to train a second net and further try out the findings about the net setup and net evaluation, as found with the Euronews corpus.

The breakdown of speakers and length can be seen in Table 4.3. As the main work was done on the Euronews corpus this data corpus is considerarbly smaller and was mostly just used as a proof-of-concept for a possible integration of a LID-Net into the Lecture Translator.

Language	Number of Speakers	Combined Length
German	8	16.22 h
French	30	8.25 h
English	27	10.78 h
Overall	65	35.25 h

Table 4.4.: The Lecture Data corpus speaker breakdown with total utterances length.

[4]InterACT 25: `http://www.interact25.org/`
[5]DGA: `http://www.defense.gouv.fr/dga`

4.4. European Parliament

As another form ofevaluation we used recordings of the Europen Parliament speeches that are freely available online [6]. The video recordings come with the simultaneous translations into all the official languages of the EU-countries. This includes seven of the languages also available on Euronews, namely German, English, French, Spanish, Italian, Polish and Portuguese. We extracted the seven audio tracks embedded in the recordings with ffmpeg [7].

We used the small corpus to evaluate performance of our Lecture Data as well as Euronews trained nets on this data, as well as improve capabilities of our networks with fine-tuning using the euronews data, of which results can be seen in the following chapter.

As each parliament discussion includes the same audio tracks, the length of all the languages in the set is the same, with each being 3.6 hours.

4.5. Feature Preprocessing

This chapter deals with the feature preprocessing used to form normal speech into feature vectors to be understood by neural networks. The setup used is based on the standard capabilities of the Janus Recognition Toolkit. It is then run through a six layer Automatic Speech Recognition network that was pre-trained on 10 languages. The 2nd last layer of the ASR net is a Bottleneck feature layer, where the feature vectors are extracted and then used as input for the trained Language Identification Network. The following sections describe this Feature Preprocessing for data as well as the first ASR network used to create the BNF features the LID net requires. Our experiments used stacked context frames with a context of 33 frames, with a spread (so the difference between each context frame included) of 3, giving us a stacked feature vector of 11 different frames.

Experiments with other context values showed worse result, as can be seen in the next chapter in Tab. **??**, so we kept the 33 frame context for all the nets explored.

This data is then written to “pfiles” that are then used to train the network using detl, the framework introduced above, or, in the case of RNNs, lasagne.

4.5.1. Feature Access

The experiments were all done with audio files in the pcm or wav format that were loaded by janus directly with a sampling rate of 16000.

4.5.2. Feature Description

The extracted ADC features from the audio files are then used for further preprocessing. We first use a standard Mel filter bank to extract only the necessary coefficients from the ADC0 feature.

[6] EU-Parliament plenary speeches: `http://www.europarl.europa.eu/ep-live/en/plenary/`
[7] ffmpeg:`https://ffmpeg.org/`

First a spectrum is applied to the ADC0 Feature, therefore calculating the Fast Fourier Transformation of the Digitalized Signal. We then also calculate the tone features of the audio signal by merg

4.5.3. ASR BNF network

5. LID Network Structure and Results

This chapter describes the actual Language Identification Neural Network trained as well as the results of different network/data setups used. Most network experiments in the Network Geometry, meaning the number of hidden layers as well as the layout of the neurons in these layers were tried using the Euronews corpus. Results from this corpus were then transferred over to the other corpusses, meaning that the network layout that worked best for Euronews was then adjusted for the lecture data but otherwise the geometry was kept intact.

5.1. Basic Setup

The first experimental net setup consisted of 5 layers of denoising auto-encoders with each 1000 nodes, aside from the input layer using the 966 feature frames that were output by the BNF layer of the asr net, and a tanh activation function using the mean squared error as the loss function.

The neural net was then trained using mini batches of size 2m and a learning Rate of 0.01. The pretrained net was then retrained with a 1000 neuron to 10 coefficient output to get to our 10 Languages as classes to classify against. In the basic setup this was trained using a learning rate of 1 and the exit condition of a minimum change of 0.005 / 0.0001 for the training/validation data respectively.

The beginning benchmark to improve upon was then set to the frame-based validation/-train error of 0.23 / 0.27 respectively, while of course understanding that non-training per-sample data would most likely have worse results at first than the frame-based validation error calculated on training data.

The following section describes different network layouts and changes we made to the training of the neural network and the improvements we managed to make upon our initial result.

5.2. Improving Network Layout

Different experiments were undertaken with the network layout. This includes a 6 hidden layer pre-training as well as changes in the geometry. The differences in the frame-based errors can be seen summarized in Table 5.2.

Decreasing Learning Rate Setting the learning rate of the output layer training to 0.1 instead of the default 1, gave us the first increase in frame-based recognition rates, improving it from an error of 0.274 for the base setup to an error rate of only 0.256, giving an improvement of almost 2%.

Adding a 6th hidden layer Adding another 1000 neuron hidden layer did not lead to an increase in recognition compares to the version using a lower learning rate and rather gave us an decrease of about 2%, meaning a error rate of 0.275 compared to the 0.256 for the lower learning rate version.

"Tree" net structure The biggest increase was achieved by changing the geometry of the net from 5 layers with each 1000 neurons to one of each layer having 200 less neurons of the previous one giving us a net definition of:

```
'!make da 966,tanh:1000 loss=mse' \
  '!make da 1000:800' \
  '!make da 800:600' \
  '!make da 600:400' \
  '!make da 400:200' \
```

This setup improved error rates from 0.256 down to 0.245, a decrease of 1.2 %.

Adding another 6th hidden layer onto this structure to give a net definition of (tanh being the activation function, mse the loss function of the mean squared error and make da the command for detl to add another hidden layer):

```
'!make da 966,tanh:1200 loss=mse' \
  '!make da 1200:1000' \
  '!make da 1000:800' \
  '!make da 800:600' \
  '!make da 600:400' \
  '!make da 400:200' \
```

further improved the results, yielding an error rate of only 0.241, perfoming another 0.4 % better than the 5-layer tree-structure.

An explanation for the better performance of the tree structure could be, that the farther the layer is removed from the input, it works on recognizing more "abstract" patterns, and less of the more abstract classes exist than of basic patterns. E.g. the first layer decides on the values of one certain frequency of the input what language is more likely, with the second layer then taking into account a whole range of frequencies (of which less exist) to further differentiate.

Adding a much larger number of hidden layers into this tree structure did not improve results, as a 10-hidden-layer version with the setup of

```
 '!make da 966,tanh:2000 loss=mse' \
  '!make da 2000:1800' \
  '!make da 1800:1600' \
  '!make da 1600:1400' \
  '!make da 1400:1200' \
  '!make da 1200:1000' \
  '!make da 1000:800' \
  '!make da 800:600' \
```

```
'!make da 600:400' \
'!make da 400:200' \
```

performed not at all featuring an error rate of 90 %, meaning the net is not classifying at all anymore.

As deeper hidden layers will take longer/more data to train correctly (as the changes have to propagate through the earlier layers first), our setup did most likely not include enough data for the training of these nets. Another explanation coould be the spreading of information in the input 966 features onto the 2000 neurons of the first hidden layer added wrong coefficients.

Net Structure	**Train Error**	**Validation Error**
Basic (5 layers 1000 Neurons)	0.226	0.285
6-Layers (1000 Neurons)	0.234	0.276
Reduced Learning Rate	0.273	0.266
Tree Structure (5 layers 1000...200 neurons)	0.221	0.245
Tree Structure (5 layers 1000...200 neurons) and reduced Learning Rate	0.245	0.235
Tree Structure (6 layers 1200...200 neurons)	0.211	0.242
Tree Structure (10 layers 2000...200 neurons)	0.899	0.910
Best	0.211	0.242

Table 5.1.: Results of the different net structures on the Euronews corpus. Frame-based errors on train/validation set.

5.3. Finetuning

As a further experiment, we used the pre-trained nets of the stacked hidden layers of our lecture and euronews data and finetuned them with the cross-set of Euronews/Lecture-Data respectively. This was done by loading net-parameters from pre-training and training the final output layer with a low learning rate of 0.1 (1/10th of the learning rate we used in the normal setup to make meaningful learning possible while fine-tuning) using the cross-set. It had the expected result of improving cross-set results for both nets while making the results with the own data set a little worse, which can be seen in Table **??** for both-fine-tuning attempts.

5.4. Combining Lecture Data and Euronews

By combining both the lecture data and euronews corpusses, we produced improved results that can be seen in Tab ref:tab:resultsConcat. This was to be expected just from the amount of train data almost doubling for the 3 lecture data-languages. However the results provided a surprise, in that they did not improve upon lecture-data finetuning results.

6. Smoothing and Evaluation

While frame-based error rates on the training/validation sets were already sufficiently good from the LID networks, this of course is not a reliable indicator of real-world online performance, so the development setup consisted of (for each data corpus) a development set of speakers whose samples were run through the LID setup (Feature Preprocessing Sec. 4.5 → ASR BNF extraction Sec. 4.5.3 → LID network Sec. 5). The following smoothing approaches were applied in an ”online” fashion, meaning it was made sure they can be calculated “on-the-fly” while new data is still coming in.

6.1. Basic Test Filter

The first filter tried was a basic 5-Frame smoothing: It saves the value of the last direct outputs and only outputs a language if the last 5 direct outputs would have been the same. It also includes a filtering based on the actual output of the language ID neuron, only counting outputs higher than that. This of course means that the approach requires a 5 frame ($\approx 50ms$) “warm-up” time, which still would make it usable in an online environment. It did however provide no improvement over the bare network output.

See Lst. 6.1 for the corresponding tcl/tk code for this basic filtering approach. The test setup used then goes through the entire development set of samples and counts the correctly/wrongly classified samples. This means that an extra amount of smoothing is included, but results should still be sufficiently general to be able to infer properties of employed filters, as they all include this extra smoothing. Table **??** shows a comparison of the basic filter with a bare setup only outputting the direct output of the LID net. Fig. **??** shows a comparison of the length of samples and the amount of correctly classified samples of this length for the LID net with the best evaluation results, the 6-layered geometry-adjusted lower learning rate net (See Sec. **??**)

```
1  proc filter{} {
2      #setting up variables
3       for {set i 0} {$i < 10} {incr i} {
4          set totalM($i) 0
5      }
6      set lastFrameID -1
7      set counter 0
8      set currentOutput -1
9      #Going through whole sample frame by frame in output layer of nn
           called nnBNF-> can be changed to work on continuously incoming
           data easily
10     for {set i 0} { $i < [featureSetLID frameN nnBNF]} {incr i} {
11         #we find the current output of the net
```

```
12          set maxFrame [lindex [lsort -decreasing -real [featureSetLID
                frame nnBNF $i]] 0]
13          set maxFrameID [lsearch -real [featureSetLID frame nnBNF $i]
                $maxFrame]
14          #Actual Filtering: Only count if last 4 frames were also
                classified to be this language
15          if {$maxFrameID != $lastFrameID} {
16              set lastFrameID $maxFrameID
17              set counter 0
18          #Also filter for the actual output of the neuron
19          } elseif {$maxFrame >= 0.61} {
20              incr counter
21              if {$counter >= 5} {
22                  set currentOutput $maxFrameID
23              }
24          }
25          #setting total classification amounts for current sample
26          if {$currentOutput != -1} {
27                set totalM($currentOutput) [expr {[set totalM(
                      $currentOutput)] + 1}]
28          }
29      }
30      set maxOverall -1
31      set maxID -1
32      #Now get the output for the whole sample (smoothing
33      for {set i 0} {$i < 10} {incr i} {
34          if {[set totalM($i)] > $maxOverall} {
35              set maxOverall [set totalM($i)]
36              set maxID $i
37          }
38      }
39      #print out the total classification for the entire sample
40      puts -nonewline "Overall we have classified as: "
41      #help function to print language name not id.
42      puts [getName $maxID]
43      return $maxID
44  }
```

Listing 6.1: Most basic filter employed to smooth output

6.2. Advanced Test Filter

The advanced test filter is based on the jrtk's *FILTER* capability. It automatically takes a defined amount of frames and calculates the weighted arithmetic mean with predefined weights for incoming audio. First tries were done using a basic filter setup of:

```
filter          nnFILTER   nnBNF  {-2 {1 2 3 2 1}}
```

Herein the context is 2 frames on each side of the current frame (the first parameter) with weights 1, 2 , 3 , 2 , 1 for the 5 frames respectively. It however offered no improvement of results, rather a decline in total correctness so different filter approaches were tried:

```
filter          nnFILTERREAL nnBNF {-5 {1 2 3 4 5 6 5 4 3 2 1}}
```

which however did not provide a furhter increase in correctness. The full tcl code for this can be found in the Appendix.

6.3. Difference Test Filter

As a next approach, the difference between the two most likely outputs was taken into account. We filtered the direct output by only changing from the previous output, if the difference (which we implied to be the amount of "sureness" the net had when determining the language) was bigger than 0.1.

This however, did not lead to an improvement in the robustness of the classification on the development set even with this small threshold, but rather an immense decline. The reason possibly being that the output of the 2nd most likely neuron is not going to differ from the maximum output on many language pairs: E.g. French/Italian, Russian/Polish, Italian/Portuguese, even if the net predicts one over the other as the difference between the languages is also relatively "small". E.g as presented in [CM05], the difference between English and French is small as the "linguistic score" is relatively high with 2.5.

The full tcl code of this filter can be found in the appendix . The evaluation results can be seen in Tab. **??**

6.4. Counting Filter

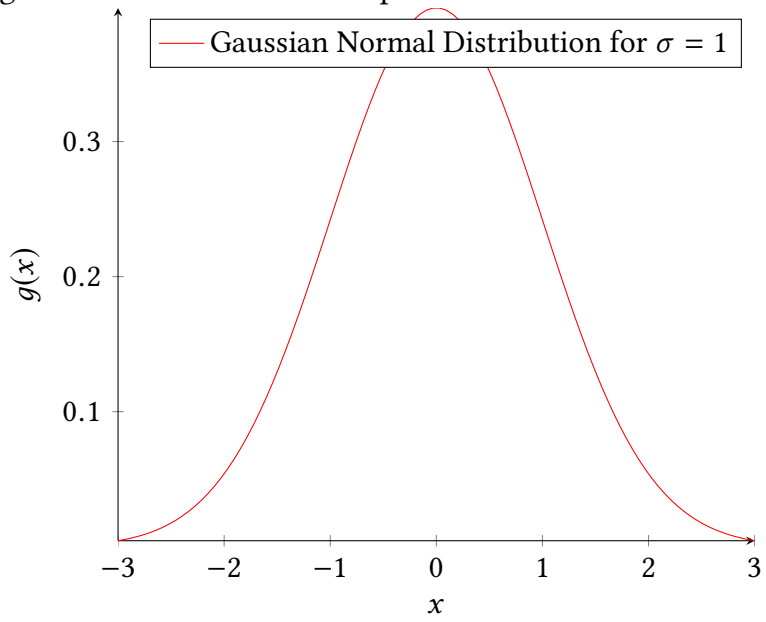
This filter included a counting of the occurence of a certain net output in a frame-range, and then outputting the ID of the language that was recognized the most in that frame-range. The first try was done using a frame-range of 10, later increased to 50, however both filters showed no improvement, but kept very close to the direct output of the net results, meaning that likely this was an improvement for longer samples but decreased accuracy in smaller samples as the output was likely to jump around anyways. The full code of this filter can be found in the Appendix.

6.5. Two-Language Setup

Table **??** shows the result produced by using the LID Euronews net for 10 languages on different combinations of 2 languages (namely french/italian and english/german). In this case we ignore the output of the net if it doesn't equal one of the two languages and instead keep the previous output intact in this case. This, as intuition predicted, gave a big boost in the recognition rate, bringing the rate up to 85 % for the two languages combined, an improvement of more than 10 % in correctness compared to the basic approach in Sec. 6.1.

6.6. Gaussian Smoothing Filter

Since most of the smoothing techniques tried out showed no significant improvement we decided to try a gaussian filter as well. Gaussian filters have shown great success in the realm of image processing in the form of canny edge detectors. A one-dimensional gaussian filter returns a response that is akin to the form of a normal distribution:



To calculate the Gaussian Filter Response, one needs a Gaussian Kernel with a Window-Size. While in general the gaussian filter has an infinite window size, choosing a fixed window size can approximate the gaussian well. In this discrete case σ, the standard deviation of the gaussian, can be approximated with N the size of the window:

$$\sigma = \sqrt{\frac{N}{2\pi}} \tag{6.1}$$

With σ, the gaussian function for point x can be calculated as:

$$g(x) = \frac{1}{\sqrt{2\pi}\sigma} * e^{-\frac{x^2}{2\sigma^2}} \tag{6.2}$$

Once the gaussian function is calculated for the window, the convolution of the data points with the gaussian kernel is performed ,resulting in smoothed over coefficients of the LID net output. The maximum smoothed coefficient is then chosen and the corresponding language is output, which gave us definite improvements over not smoothing the net output at all. In tcl the relevant code part can be seen in 6.2, in which we presume the window size to mean the number of points we take into account on both sides of the origin, while normally this number is the window size - 1.

```
1    #Windowsize definition
2    set ws 5
3    set sigma [expr sqrt($ws/(2*[Pi]))]
4    #calculate gauss kernel
```

```
5     for {set k 0} {$k <= $ws} {incr k} {
6         set gauss($k) [expr (1/(sqrt(2*[Pi])*$sigma)) * ([E] ** - (( $k
              ** 2)/ (2 * $sigma ** 2)))]
7     }
8     #For each frame
9     for {set i 0} { $i < [featureSetLID frameN nnBNF]} {incr i} {
10        for {set j 0} {$j < 10} {incr j} {
11            set values($j) [lindex [featureSetLID frame nnBNF $i] $j]
12            set curValue 0
13            #go from $i - $ws to $i + $ws
14            for {set k [expr -$ws]} {$k < $ws} {incr k} {
15                #Only use the current value if it actually exists
16                if {[expr $i + $k] >= 0 && [expr $i + $k] < [
                      featureSetLID frameN nnBNF]} {
17                    set cur [lindex [featureSetLID frame nnBNF [expr $i
                          + $k]] $j]
18                    #get correct index for gauss kernel, as we only
                          calculated once above for symmetric function
19                    if {$k < 0} {
20                        set curIdx [expr -$k]
21                    } else {
22                        set curIdx $k
23                    }
24                    #running sum of all previous values in the window
                          convoluted with the gaussian kernel.
25                    set curValue [expr $curValue + $cur * [set gauss(
                          $curIdx)]]
26                }
27            }
28            #save the value for current language coefficient
29            set values($j) $curValue
30        }
31        #Find maximum on smoothed values
32        set max -1
33        set maxID -1
34        for {set j 0} {$j < 10} {incr j} {
35            if {[set values($j)] > $max} {
36                set max [set values($j)]
37                set maxID $j
38            }
39        }
40        #Set the output as the Language with Max. coefficient.
41        set currentOutput $maxID
42    }
```

Listing 6.2: Gaussian Smoothing Filter as implemented in tcl/tk for the jrtk

We tried different window sizes of which the result can be seen in Tab. **??**.

6.7. Lecture Data

Of course, all the nets were tested against the lecture data corpus, as this is the closest to an actual possible integration into the KIT's lecture Translator. These results for different net setups are summarized in Tab. ??.

7. Conclusion

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A. Appendix

In this Appendix we present images, complete source code listings as well as a Glossary at the end.