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Paragraph and Word Embeddings for Expressive Speech Synthesis

Degree's Thesis
Audiovisual Systems Engineering

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Abstract

This project attempts to enhance the features of a statistical parametric speech synthesis (SPSS) system based on long short-term memory recurrent neural networks (RNN-LSTM) in order to be able to perform better with an expressive corpus. We used the Blizzard Challenge [21] text-to-speech corpus to train the speech synthesis. This corpus was chosen because of its richness in expressive content.

The first part of of the project was to develop a baseline speech sythesizer from [26]. This architecture is based on RNN-LSTMs where the inputs are a vector of linguistic features and the output are speech parameters that are fed to a vocoder (we used Ahocoder [11] for this project) to reconstruct the waveform from the synthesized speech.

The second part of the project was to develop a sentiment analysis classifier based on convolutional neural networks (CNN), that predicts how good or bad a given sentence is. This classifier was trained with a dataset from the Stanford sentiment treebank [29], which consists of movie reviews.

To obtain the expressive features that would allow for expressive speech to be synthesized, another CNN was trained using the Blizzard corpus to adapt the domain of the sentiment analysis network to the one from the synthesized speech. In the end, we use the activations from one of the layers from the sentiment analysis network as expressive embeddings and use them as inputs for the speech synthesizer.

Various experiments have been carried out to find the set of expressive features that give the best objective and subjective results (including a baseline) by means of an evaluation done by TODO volunteers.

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Chapter 1

State of the art

This chapter gives a brief introduction to the background of this project. The first thing that is discussed is classical methods of speech synthesis, as well as a brief mention of deep learning methods used in this particular task.

Next there is a brief introduction to Deep Learning and deep architectures (both definition and training) a field that is applied to this project. By the end of this chapter, the necessary background will have been introduced for its application in the next chapter.

1.1 Speech synthesis

Speech synthesis is the process of generating a synthetic speech signal, emulating that of a real human being. More specifically, this project focuses on synthesizing the signal given text level information. That means, mapping a piece of text to the sounds a human would make to utter said text, and it has to be possible to generate any text that is given to the system.

Speech synthesis has many applications, from medical to recreational. These systems can be used to help speech impaired people and it can also be used to design more human-like interactions objects.

1.1.1 Unit selection

Unit selection systems render a speech signal by concatenating waveform fragments from a large single-speaker database [17]. The outcome of this technique is highly natural-sounding speech since the fragments that are concatenated come from real waveforms. However, while this system is good at producing natural sounding speech, it lacks the flexibility to produce new speaker sounds or vary the speaking style, as described in [19], since we are limited by the waveforms database. Each unit also has an associated feature vector containing prosodic information such as pitch and formants.

To choose the best sequence of concatenated units, a cost of concatenation is defined [?] given a sequence of units $u_1^N = \{u_1, u_2, ..., u_N\}$ and their corresponding prosodic vectors p_1^N:

$$C_T^p = C_T^p(u_1^N) = \sum_{i=1}^{N} C_p(p_t, p_i) \tag{1.1}$$

$$C_T^c = C_T^c(u_1^N) = \sum_{i=2}^{N} C_c(u_{i-1}, u_i) \tag{1.2}$$

Where C_p is a function that measures the cost of using a specific feature vector (for example if the units have matching formants and pitch) to match a given target p_t and C_c is the cost of concatenation of two consecutive units (for example a unit ends with the same pitch level that the next one starts with). Finding the best sequence of units is done by using the Viterbi algorithm to minimize the total concatenation cost:

$$u_1^N = \underset{u_1^N}{argmax} \left\{ \rho \cdot C_T^p(u_1^N) + (1 - \rho) \cdot C_T^c(u_1^N) \right\} \tag{1.3}$$

$$0 \leq \rho \leq 1 \tag{1.4}$$

Where ρ is a weighting term that can be used to pay more attention to the targets that to the concatenation, or vice versa.

1.1.2 Statistical Parametric Speech Synthesis

In statistical-parametric speech synthesis (SPSS) a set of spectral and excitation parameters are extracted from a speech corpus from where a set of statistical generative models (typically a hidden Markov model or HMM) are trained to model the them for use in speech synthesis.

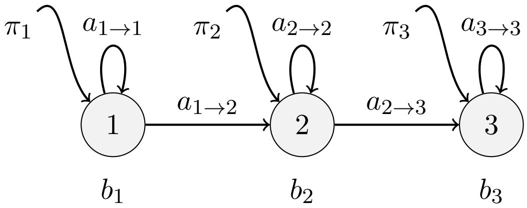


Figure 1.1: A 3-state left-to-right Hidden Markov Model.

As seen in Figure 1.1, a HMM is a finite state machine that can be described by the tuple $\lambda = \langle A, B, \Pi \rangle$ where A are the state transition probabilities, B are the output distributions on each state (spectral & excitation output parameters) and Π are the initial state probabilities. HMMs provide a time-discrete series of observations from a distribution of the speech parameters. In contrast with unit selection, SPSS models offer a more compact representation than unit selection since they don't require a large database after the models have been trained.

Moreover, SPSS also overcomes the limitation of only being limited to one speaker, since we can easily modify the speaker characteristics and speaking styles by transforming the model parameters appropriately as describes in [36] and [**?**].

1.1.3 Recurrent Neural Network-based Speech Synthesis

Another approach to speech synthesis more closely related to this project, is using recurrent neural networks (RNNs) to process a sequence of linguistic features and predict the same excitation and spectral parameters from SPSS.

RNNs are covered in more detail in a later section of this chapter. As describes by [8], this scheme consists of using neural networks to generate parametric speech in two stages:

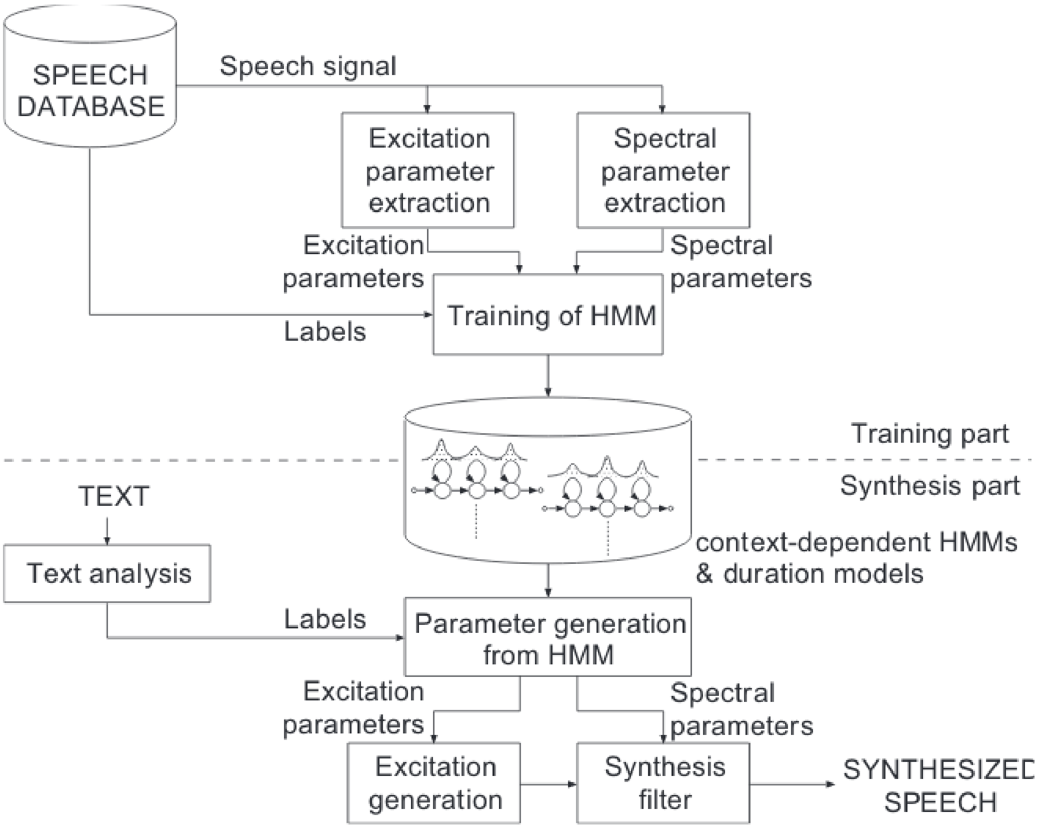


Figure 1.2: SPSS system based on HMMs. This scheme corresponds to the HTS framework [36].

a duration model that predicts the duration of a phoneme in a sentence, and an acoustic model to predict the spectral and excitation parameters for as many time steps as predicted by the duration model. Figure 1.3 shows the complete scheme of this approach.

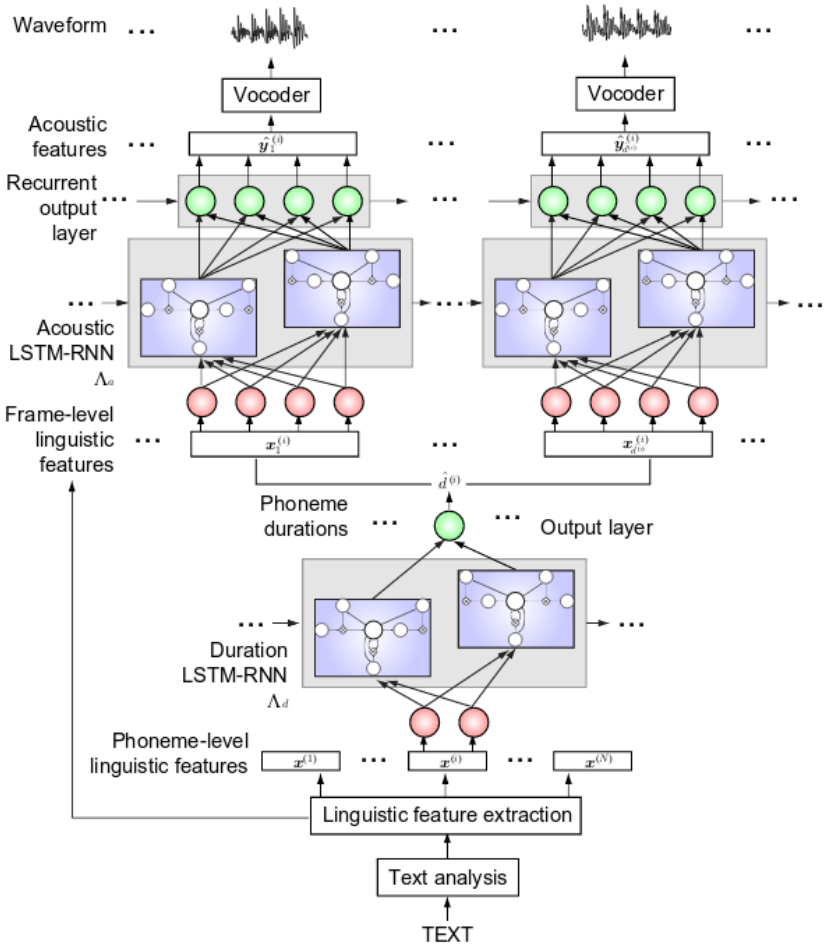


Figure 1.3: RNN-based SPSS scheme. Concepts such as LSTM that appear in the figure are covered at later section of this chapter. The figure is originally from [8]

1.1.4 Expressive speech synthesis

The techniques from the previous sections for doing speech synthesis typically only offer a single speaking style that is independent of the message that is being transmitted. In [6] and [13] a prosodic target is modeled in order to synthesize a text with different types of emotions using a unit selection systems and pitch prediction to modify the prosodic content of the speech.

More recently, [18] uses deep neural networks (more on this in the following sections) to predict acoustic features of expressive speech from semantic vector space representations. The results can be used to enhance the inputs of speech synthesis systems by modeling the expressiveness of a corpus in SPSS systems, which in contrast with [6] and [13], the synthesis would adapt to the semantic content of the message.

1.2 Text classification for sentiment Analysis

Text classification is a task in natural language processing [9] (NLP) where a text is assigned a given label automatically. A classic model used for text classification is bag of words [31] (BOW), where a piece of text is assumed to be a sequence of words picked at random from a specific set. In the topic of text classification, classifying text using BOW would involve predicting the set the text belongs to (for example, a SPAM email contains specific words common to all SPAM emails, or a positive text may contain words that are different from a negative text).

More recently, more modern techniques such as deep learning have been used to improve the accuracy of these systems. In [37] text is treated as a signal an processed using Convolutional neural networks (more on this in the next sections) and [20] uses vector representations of words (word embeddings [14]) to classify text.

1.3 Deep Learning

In recent years, deep structured learning, or more commonly called deep learning is a set of techniques that has risen in popularity and established itself as a new area of machine learning among the scientific and research communities. [12]

[2] discussed the limitations of shallow architectures and provided a theoretical basis to the advantages of deeper ones. But it has only been in recent years that such architectures have been able to be put into production with ever-growing popularity thanks to compute technologies being every time more available and affordable to consumers.

With deep learning architectures, it is possible to learn complex non-linear representations from large amounts of data. Raw data can be processed and turned into several levels of higher level representations to make it possible to reason about it and make tasks such as classification easier and more effective.

In addition to more compute power, large datasets that can take advantage of deep models such Imagenet [27] are being made publicly available. These datasets are often used as benchmarks and serve as points of reference to drive research and development forward.

1.3.1 Deep Neural Networks

In Deep Learning, a common architecture is the so called Deep Neural Network (DNN), which is an artificial neural network with a large number of hidden layers. The desire to decomposing a signal into higher levels of abstraction drives such neural networks configurations, and since more layers require more trainable parameters, large amounts of training data are also needed to train them.

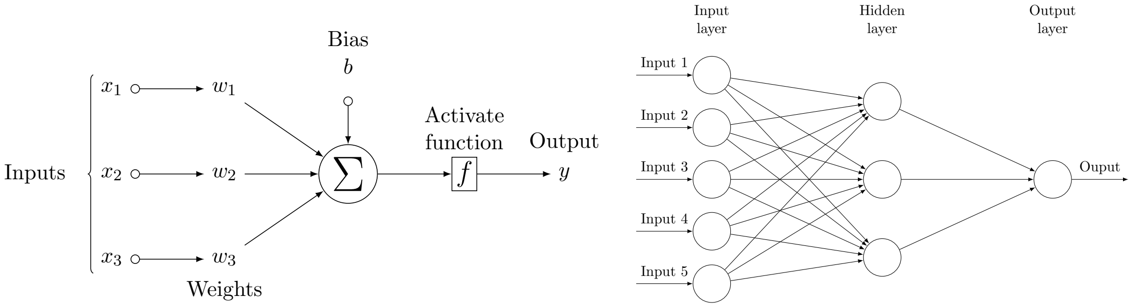


Figure 1.4: Basic neuron (left) and neural network configuration (right).

DNNs are defined by stacking several layers of basic units called neurons. In each layer, a linear operation takes place, where the inputs $\mathbf{x} = \{1, x_1, x_2, ..., x_N\}$ (1 is for a bias term) are linearly combined by a set of weights that are characteristic of each layer. The output of this linear operation is fed to a non-linear activation function (such as a sigmoid (1.6) or a tanh) which introduces the non-linearities of the system. Equation 1.5 shows the operation that takes place in the i-th layer, where $\mathbf{W_i}$ is the matrix of weights, $\mathbf{x_i}$ is the input vector of the layer, $\mathbf{y_i}$ is the output vector and σ is the activation function.

$$\mathbf{y_i} = \sigma\left(\mathbf{W_i} \cdot \mathbf{x_i}\right) \tag{1.5}$$

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{1.6}$$

The outputs of this activation function are fed to the next layer of neurons until the last layer of a network, typically a softmax activation function for classification tasks or linear operation in regression ones. Figure 1.4 shows a neural network configuration.

1.3.2 Optimization

Optimizing, or training, a DNN is the process of finding the best possible set of weights that accomplish the best results in a given task. A task that DNNs are used for is classification, where a label is assigned to each input vector (predicting wether an image is from a cat or a dog) and also regression (predicting the expected cost of a property given the land size and proximity to the coast).

To optimize the network a cost or loss function is defined to measure the error of the predictions (such as the root mean square error or the cross-entropy error [15]). given a loss, we can improve the performance of a model by translating the weight vector in the direction of the gradient.

$$L(\mathbf{x};\mathbf{w}) = \sum_{\mathbf{x}_k} L(\mathbf{x_k}) \tag{1.7}$$

$$w_i[n+1] = w_i[n] - \lambda \frac{\partial L(\mathbf{x};\mathbf{w}[n])}{\partial w_i} \tag{1.8}$$

Equation 1.7 is a loss function, computed by adding the errors of a batch of vectors of a dataset. These vectors are the examples from where the network learns. The size of the batch is usually fixed and smaller than the total size of the dataset, and is used to perform an iteration in the weight update process (Equation 1.8). This technique is called stochastic gradient descent [5] (SGD).

Before updating the weights, the partial derivatives of the loss function are computed using the back-propagation algorithm [7]. For this we need to be able to compute the derivatives of both the loss function and the activation functions of the neurons, and the update is performed like in Equation 1.8.

The norm of the gradient can be scaled by a factor called learning rate (expressed as λ in Equation 1.8) to speed-up or slow-down the convergence of the loss function during training. Ways to improve this weight updates are Adam [22] and Adadelta [35].

1.4 Recurrent networks

Recurrent neural networks (RNN) are a special type of architecture capable of modeling sequences, where the outputs of a hidden layer are fed back to the inputs of the same layer. This feedback loop introduces a state in the neurons and the output of the layers can be rewritten as:

$$\mathbf{y_t} = \sigma\left(\mathbf{W}\cdot\mathbf{x_t} + \mathbf{U}\cdot\mathbf{y_{t-1}}\right) \tag{1.9}$$

Where $\mathbf{x_t}$ is an input vector at the t-th timestep and $\mathbf{U}$ is an additional matrix of tranable weights. Because of the introduction of a neuron state, RNNs can model various types of sequential data (predict the next frame of a video given the N first, translate a sequence of words to another a different language, predict the duration of each of the phonemes in a sequence, etc...).

Recurrent networks can still be trained efficiently by using back-propagation through time [32] which is specific case of back-propagation where the errors are also back-propagation back in time. If we expand 1.9 we get:

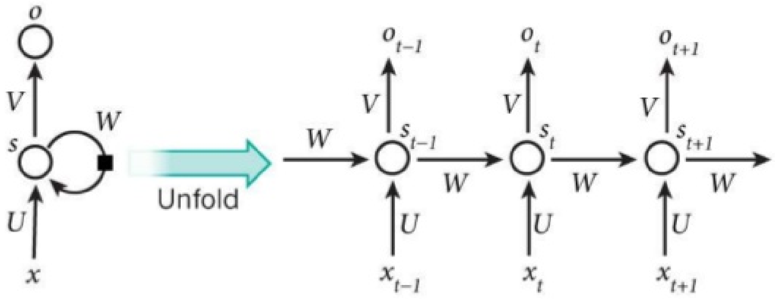


Figure 1.5: Unfolded RNN

$$\mathbf{y_t} = \sigma\left(\mathbf{W} \cdot \mathbf{x_t} + \mathbf{U} \cdot \sigma\left(\mathbf{W} \cdot \mathbf{x_{t-1}} + \mathbf{U} \cdot \sigma\left(\cdots \sigma\left(\cdots\right) \cdots\right)\right)\right) \tag{1.10}$$

The recursive multiplication of U_t make RNNs a special case of DNNs, where the repeated multiplications can cause the gradients to become too small or too big by the time they reach the inputs of the network when doing back-propagation. This is due to the vanishing or exploding gradient problem [3] that occurs in SGD.

To mitigate this problem in RNNs, we can use specially designed recurrent neurons such as Long Short-Term Memory as opposed to regular RNNs.

1.4.1 Long Short-Term Memory (LSTM)

Long Short-Term Memory [16] or LSTM are a special kind of recurrent unit that deals with the aforementioned problem of the vanishing gradient. This cell works by introducing gating mechanism operated by soft switches trained while optimizing the network that control the flow of information coming in and out of the cell.

1.5 Convolutional Neural Networks

As seen in Equation 1.5, a neuron activation depends on all the output activation of the previous layer. Convolutional neural networks (CNN) are a type of architecture that contain a type of hidden layers called Convolutional layers. These architectures have proven to be very effective in computer vision applications but they are also used with success in NLP tasks [37].

Rather than combining all the outputs of the previous layer, CNN neurons only focus on the activations of a fixed number of neurons from the previous layer [23]. While each neuron focuses on a different set of inputs, the total number is fixed and the weights are shared among the activations of the layer. Because of this, we can think of these layers as having an associated kernel that is used to filter the previous layer by means of a convolution to produce a feature map in the layer. The number of feature maps is a parameter of the convolutional layer.

Chapter 2

Expressive Speech synthesis

This chapter explains how the project was developed. The methodologies and technologies that were used during this project are also discussed.

2.1 Baseline development

The first stage of this project was to develop a baseline speech synthesizer. This model is used as a reference when comparing the results of the subsequent experiments explained in later sections of this chapter. The architecture is based on the work done by [?] by using the Socrates Text-to-speech framework, which is based on the Keras deep learning library. This is a RNN-LSTM based model, which, as mentioned in section 1.1.3, contains a duration model and an acoustic model which are trained independently.

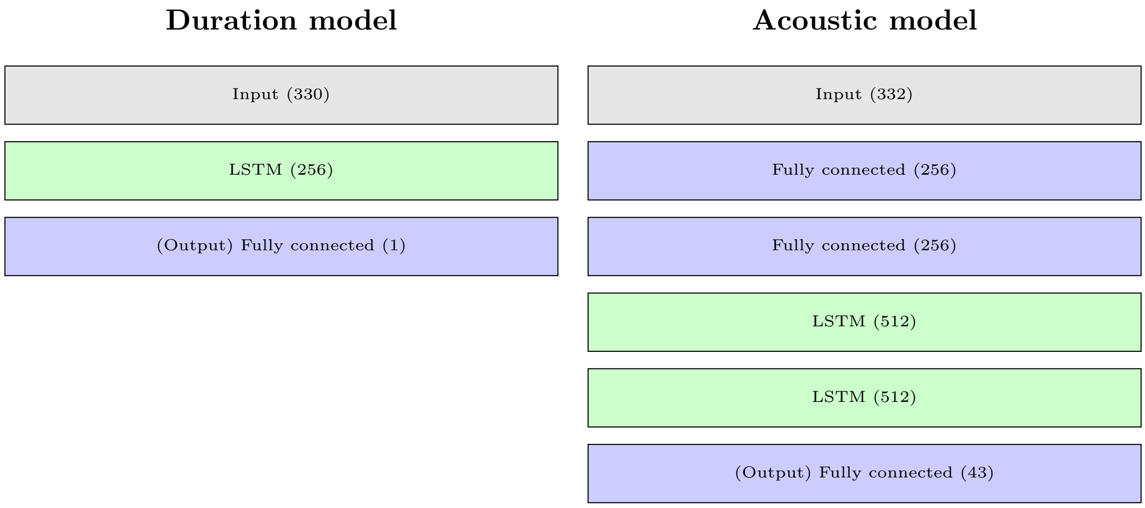


Figure 2.1: Baseline models.

- The duration model predicts the duration of a phoneme. This model takes a vector of linguistic features with information about the phoneme and its context and outputs a single value that is the log-compressed duration of the phoneme (this log-compression is explained in the data preparation section).

- The acoustic model predicts the excitation and spectral parameters of a frame of speech. The input of this system is the same vector of linguistic features, the normalized duration of the predicted value from the previous model and the relative position of the frame within the duration of the phoneme. The output of this model is also explained in the next section.

2.1.1 Data preparation

The corpus that has been used for this project contains approximately 20 hours or several audiobooks along with the transcripts. The data came from the Blizzard challenge [21] and is already segmented at the utterance level, removing the need to align the whole audio stream with the raw text data. The reason we chose this corpus is because of its richness in expressive content. Table 2.1 shows some information about the audio files that we get from it.

Metric	Value
Sampling rate (Hz)	16000
Bit depth (bits)	16
Channels	mono
Length (seconds mean)	7.23
Length (seconds std)	4.52
Speakers	1

Table 2.1: Information about the Blizzard Challenge utterances.

2.1.2 Obtaining Acoustic features

As mentioned in section 1.1.3, this RNN based speech synthesizer is a SPSS case and as such it doesn't output the waveforms directly but the excitation and spectral parameters before they are reconstructed by a vocoder. The vocoder that we used is Ahocoder [11].

Every audio file is framed by means of a sliding window with a stride of 5 milliseconds. Ahocoder then processes each frame to produce a set of excitation and spectral parameters which are:

- Mel Frequency Cepstral Coefficients (MFCC) of order $p = 39$, which corresponds to 40 coefficients.

- Pitch contour ($log(F_0)$). Unvoiced frames correspond to $F_0 = 0$ value of $-\inf$ after the logarithm. Ahocoder outputs a value of -10^8 when the frame is unvoiced.

- Maximum voiced frequency (fv), This value is 0 when a frame is unvoiced.

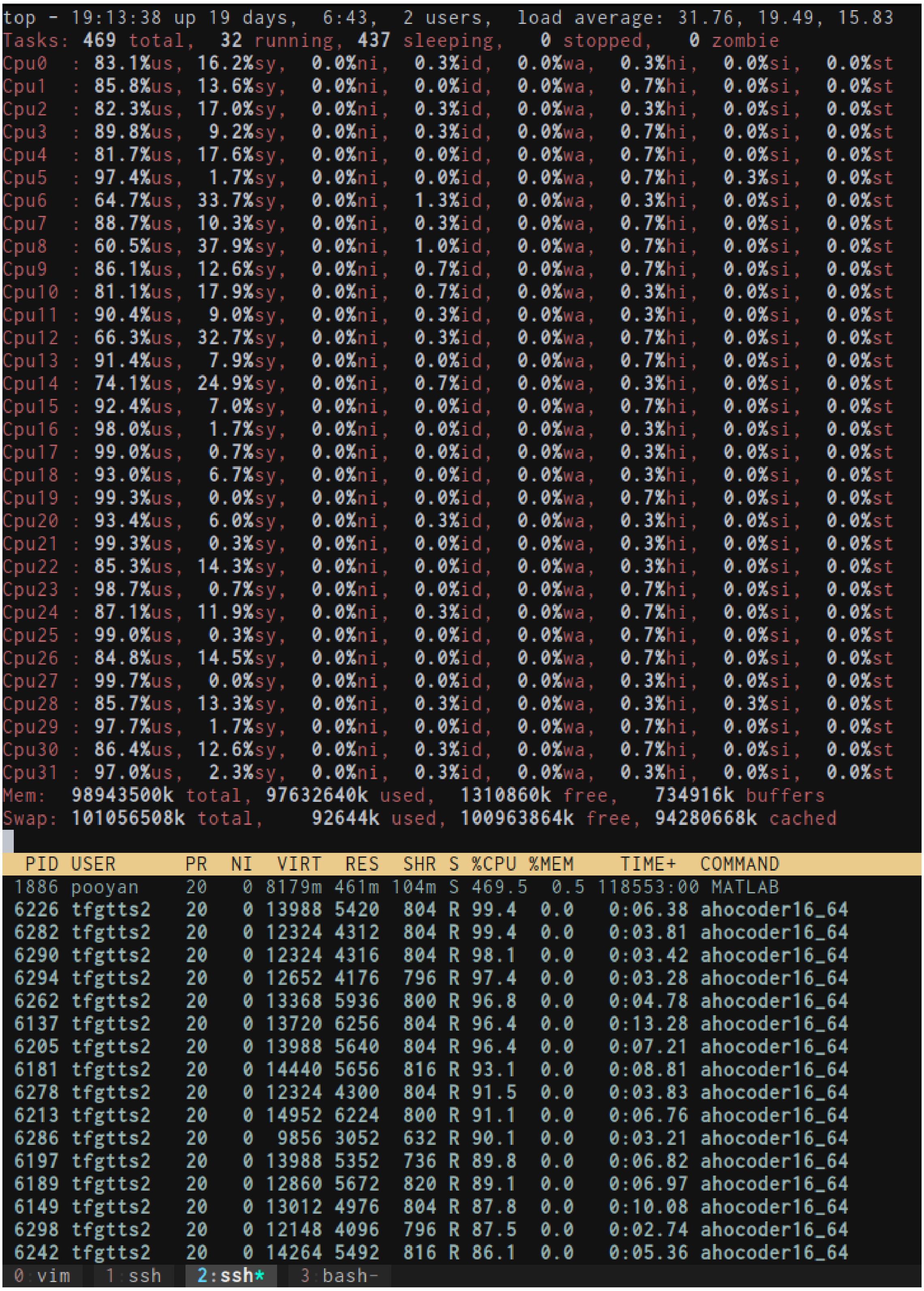
- Voiced/Unvoiced (UV) flag. This value indicates if a given frame of audio corresponds to a voiced or unvoiced sound and can be obtained using the fv or $log(f0)$ outputs of Ahocoder. This flag is not directly output by the Ahocoder.

To perform this data extraction from the Blizzard corpus, the Python and Bash scripting languages were used to parallelize the whole process. The basic unit of work of this step is to spawn an Ahocoder decoder process with the path of the file, and save the speech parameters that it generates to disk. Because this operation is single threaded, and because of the large amount of data that we had in the Blizzard Challenge dataset (20 hours of speech), this process was parallelized in order to fully utilize the computing resources of the server. This involved writing two scripts:

- **split_names.py** is a Python script that takes a list of files (All the filenames from the Blizzard corpus) and splits it into smaller chunks.

- **process_ahocode.sh** is a Bash script that reads a list of files and processes each of them through Ahocode and saves the speech parameters to the disk.

The filenames of the corpus was split into 30 chunks (the server has 32 CPUs) using the **split_names.py** script and each of the chunks was processed by **process_ahocode.sh**. Using this method inspired by [26] this whole data preparation process was accomplished in less than one hour fully utilizing the system resources as seen in Figure 2.2.



```
top - 19:13:38 up 19 days,  6:43,  2 users,  load average: 31.76, 19.49, 15.83
Tasks: 469 total,  32 running, 437 sleeping,   0 stopped,   0 zombie
Cpu0  : 83.1%us, 16.2%sy,  0.0%ni,  0.3%id,  0.0%wa,  0.3%hi,  0.0%si,  0.0%st
Cpu1  : 85.8%us, 13.6%sy,  0.0%ni,  0.0%id,  0.0%wa,  0.7%hi,  0.0%si,  0.0%st
Cpu2  : 82.3%us, 17.0%sy,  0.0%ni,  0.3%id,  0.0%wa,  0.3%hi,  0.0%si,  0.0%st
Cpu3  : 89.8%us,  9.2%sy,  0.0%ni,  0.3%id,  0.0%wa,  0.7%hi,  0.0%si,  0.0%st
Cpu4  : 81.7%us, 17.6%sy,  0.0%ni,  0.0%id,  0.0%wa,  0.7%hi,  0.0%si,  0.0%st
Cpu5  : 97.4%us,  1.7%sy,  0.0%ni,  0.0%id,  0.0%wa,  0.7%hi,  0.3%si,  0.0%st
Cpu6  : 64.7%us, 33.7%sy,  0.0%ni,  1.3%id,  0.0%wa,  0.3%hi,  0.0%si,  0.0%st
Cpu7  : 88.7%us, 10.3%sy,  0.0%ni,  0.3%id,  0.0%wa,  0.7%hi,  0.0%si,  0.0%st
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Cpu10 : 81.1%us, 17.9%sy,  0.0%ni,  0.7%id,  0.0%wa,  0.3%hi,  0.0%si,  0.0%st
Cpu11 : 90.4%us,  9.0%sy,  0.0%ni,  0.3%id,  0.0%wa,  0.3%hi,  0.0%si,  0.0%st
Cpu12 : 66.3%us, 32.7%sy,  0.0%ni,  0.3%id,  0.0%wa,  0.7%hi,  0.0%si,  0.0%st
Cpu13 : 91.4%us,  7.9%sy,  0.0%ni,  0.0%id,  0.0%wa,  0.7%hi,  0.0%si,  0.0%st
Cpu14 : 74.1%us, 24.9%sy,  0.0%ni,  0.7%id,  0.0%wa,  0.3%hi,  0.0%si,  0.0%st
Cpu15 : 92.4%us,  7.0%sy,  0.0%ni,  0.0%id,  0.0%wa,  0.7%hi,  0.0%si,  0.0%st
Cpu16 : 98.0%us,  1.7%sy,  0.0%ni,  0.0%id,  0.0%wa,  0.3%hi,  0.0%si,  0.0%st
Cpu17 : 99.0%us,  0.7%sy,  0.0%ni,  0.0%id,  0.0%wa,  0.3%hi,  0.0%si,  0.0%st
Cpu18 : 93.0%us,  6.7%sy,  0.0%ni,  0.0%id,  0.0%wa,  0.3%hi,  0.0%si,  0.0%st
Cpu19 : 99.3%us,  0.0%sy,  0.0%ni,  0.0%id,  0.0%wa,  0.7%hi,  0.0%si,  0.0%st
Cpu20 : 93.4%us,  6.0%sy,  0.0%ni,  0.3%id,  0.0%wa,  0.3%hi,  0.0%si,  0.0%st
Cpu21 : 99.3%us,  0.3%sy,  0.0%ni,  0.0%id,  0.0%wa,  0.3%hi,  0.0%si,  0.0%st
Cpu22 : 85.3%us, 14.3%sy,  0.0%ni,  0.0%id,  0.0%wa,  0.3%hi,  0.0%si,  0.0%st
Cpu23 : 98.7%us,  0.7%sy,  0.0%ni,  0.0%id,  0.0%wa,  0.7%hi,  0.0%si,  0.0%st
Cpu24 : 87.1%us, 11.9%sy,  0.0%ni,  0.3%id,  0.0%wa,  0.7%hi,  0.0%si,  0.0%st
Cpu25 : 99.0%us,  0.3%sy,  0.0%ni,  0.0%id,  0.0%wa,  0.7%hi,  0.0%si,  0.0%st
Cpu26 : 84.8%us, 14.5%sy,  0.0%ni,  0.0%id,  0.0%wa,  0.7%hi,  0.0%si,  0.0%st
Cpu27 : 99.7%us,  0.0%sy,  0.0%ni,  0.0%id,  0.0%wa,  0.3%hi,  0.0%si,  0.0%st
Cpu28 : 85.7%us, 13.3%sy,  0.0%ni,  0.3%id,  0.0%wa,  0.3%hi,  0.3%si,  0.0%st
Cpu29 : 97.7%us,  1.7%sy,  0.0%ni,  0.0%id,  0.0%wa,  0.7%hi,  0.0%si,  0.0%st
Cpu30 : 86.4%us, 12.6%sy,  0.0%ni,  0.3%id,  0.0%wa,  0.7%hi,  0.0%si,  0.0%st
Cpu31 : 97.0%us,  2.3%sy,  0.0%ni,  0.3%id,  0.0%wa,  0.3%hi,  0.0%si,  0.0%st
Mem:  98943500k total, 97632640k used,  1310860k free,   734916k buffers
Swap: 101056508k total,    92644k used, 100963864k free, 94280668k cached

  PID USER      PR  NI  VIRT  RES  SHR S %CPU %MEM    TIME+  COMMAND
 1886 pooyan    20   0 8179m 461m 104m S 469.5  0.5 118553:00 MATLAB
 6226 tfgtts2   20   0 13988 5420  804 R 99.4  0.0   0:06.38 ahocoder16_64
 6282 tfgtts2   20   0 12324 4312  804 R 99.4  0.0   0:03.81 ahocoder16_64
 6290 tfgtts2   20   0 12324 4316  804 R 98.1  0.0   0:03.42 ahocoder16_64
 6294 tfgtts2   20   0 12652 4176  796 R 97.4  0.0   0:03.28 ahocoder16_64
 6262 tfgtts2   20   0 13368 5936  800 R 96.8  0.0   0:04.78 ahocoder16_64
 6137 tfgtts2   20   0 13720 6256  804 R 96.4  0.0   0:13.28 ahocoder16_64
 6205 tfgtts2   20   0 13988 5640  804 R 96.4  0.0   0:07.21 ahocoder16_64
 6181 tfgtts2   20   0 14440 5656  816 R 93.1  0.0   0:08.81 ahocoder16_64
 6278 tfgtts2   20   0 12324 4300  804 R 91.5  0.0   0:03.83 ahocoder16_64
 6213 tfgtts2   20   0 14952 6224  800 R 91.1  0.0   0:06.76 ahocoder16_64
 6286 tfgtts2   20   0  9856 3052  632 R 90.1  0.0   0:03.21 ahocoder16_64
 6197 tfgtts2   20   0 13988 5352  736 R 89.8  0.0   0:06.82 ahocoder16_64
 6189 tfgtts2   20   0 12860 5672  820 R 89.1  0.0   0:06.97 ahocoder16_64
 6149 tfgtts2   20   0 13012 4976  804 R 87.8  0.0   0:10.08 ahocoder16_64
 6298 tfgtts2   20   0 12148 4096  796 R 87.5  0.0   0:02.74 ahocoder16_64
 6242 tfgtts2   20   0 14264 5492  816 R 86.1  0.0   0:05.36 ahocoder16_64
 0:vim   1:ssh   2:ssh*   3:bash-
```

Figure 2.2: Full utilization of system resources by Ahocoder. Memory and CPU usage are close to their limits.

2.1.3 Acoustic feature normalization

The data is not used as it is output by the Ahocoder directly. These acoustic predictors are normalized before they are used to train the acoustic model for a good behavior of the back-propagation algorithm, as discussed in [26].

The outputs of the Ahocoding process ($MFCC$, $log(f_0)$ and f_v) was normalized so that the speech parameters are bound between a minimum and a maximum value range. This range is chosen to be $0.01, 0.99$. The normalization of the acoustic outputs is shown in equation 2.1

$$\hat{y} = 0.01 + (0.99 - 0.01)\frac{y - y_{min}}{y_{max} - y_{min}} \tag{2.1}$$

This doesn't work for the $log(F_0)$ features however, since their high dynamic range would compress the values from the viced frames too much. [26] solves it by keeping the values from the voiced frames and interpolating the values in the unvoiced regions as shown in Equation 2.2:

$$logF_0^i = logF_0^p + (logF_0^n - logF_0^p) \cdot \frac{i - p}{n - p} \tag{2.2}$$

Where n is the next voiced frame's frame index, F_0^n is the next voiced frame's first value, p is the previous voiced value's frame index, F_0^p is the previous voiced value and F_0^i is the i-th new interpolated value to be replaced in the original output of the Ahocoding process (Figure 2.3 has an example of this interpolation). We can then use the UV flag to recover the original format after denormalization and reconstruct the waveform.

These acoustic features are used to train the acoustic model of the system. The data is structured for training as a series of input-output vector pairs laid out in the following manner in the training data tables:

Which are the examples that are used to train the acoustic model. Some of the inputs are

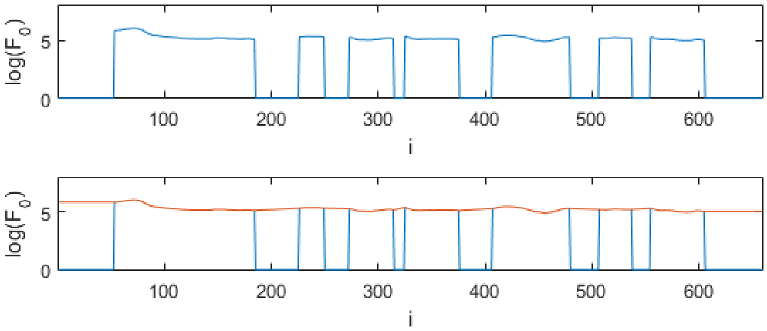


Figure 2.3: F_0 contour interpolation

```
<linguistic features 1, duration 1> <acoustic features 1>
<linguistic features 1, duration 1> <acoustic features 2>
<linguistic features 1, duration 1> <acoustic features 3>
<linguistic features 2, duration 2> <acoustic features 4>
<linguistic features 2, duration 2> <acoustic features 5>
<linguistic features 2, duration 2> <acoustic features 6>
<linguistic features 2, duration 2> <acoustic features 7>
<linguistic features 3, duration 3> <acoustic features 8>
<linguistic features 3, duration 3> <acoustic features 9>
...
```

Figure 2.4: Training table used to train the acoustic model is stored in the server disk.

repeated depending on the duration of the phonemes (the linguistic features are explained in the next section). To create these tables, another python script **gen_aco_tables.py** was written for the project. This script reads a list of files corresponding to the single sentences from the Blizzard corpus and does the following:

1. Reads the file of acoustic features (explained in the next section) containing both the phonetic segmentation and the phoneme durations.

2. Reads the corresponding acoustic features from Ahocoder (obtained in the previous section) and writes a line containing: the vector of linguistic features, the log normalized duration of the phoneme, the relative position of the ahocoder window within the current phoneme, and the vector of acoustic features ($MFCC$, $log(f_0)$, f_v and UV). This line in repeated for as many windows the phoneme lasts (modifying the relative duration value every line). At the end there might be a remainder duration error because the number of windows the phoneme lasts might not be an integer number. This

remainder is carried to the next phoneme.

3. Once all the data has been collected, the values are normalized and written to disk for use in Socrates.

We execute this script for both the training data, the test data and the validation data. These can be done in parallel but it is not as critical as obtaining the acoustic parameters.

2.1.4 Obtaining linguistic features

Each of the audio transcriptions was transformed into a lower level phonetic representation called Label that contains a set of both real and categorical descriptors with information about each phoneme and its context within a sentence. Table **??** contains a description of the values that are included in this representation.

When a phoneme is converted into a Label, it has the following format:

p1ˆp2$−$p3$+$p4$=$p5˜p6_p7/A:a1_a2_a3/B:b1−b2−b3˜b4−b5&b6−b7#b8−b9$b10 . . .
−b11!b12−b13;b14−b15|b16/C:c1+c2+c3/D:d1_d2/E:e1+e2˜e3+e4&e5+e6#e7+e8 . . .
/F:f1_f2/G:g1_g2/H:h1=h2˜h3=h4|h4/I:i1_i2/J:j1+j2−j3

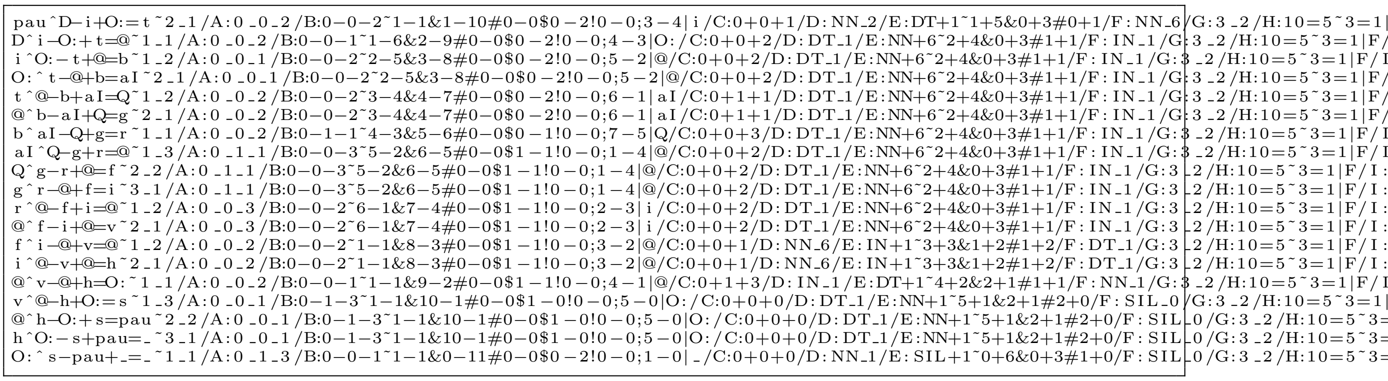
label format	
Symbol	Description
p1	phoneme identity before the previous phoneme
p2	previous phoneme identity
p3*	current phoneme identity
p4*	next phoneme identity
p5*	the phoneme after the next phoneme identity
p6*	position of the current phoneme identity in the current syllable (forward)
p7*	position of the current phoneme identity in the current syllable (backward)
a1	whether the previous syllable is stressed or not (0; not, 1: yes)
a2	whether the previous syllable is accented or not (0; not, 1: yes)
a3	number of phonemes in the previous syllable
b1*	whether the current syllable stressed or not (0: not, 1: yes)
b2*	whether the current syllable accented or not (0: not, 1: yes)
b3*	the number of phonemes in the current syllable
b4*	position of the current syllable in the current word (forward)

Table 2.2 (continued)

b5*	position of the current syllable in the current word (backward)
b6*	position of the current syllable in the current phrase(forward)
b7*	position of the current syllable in the current phrase(backward)
b8*	number of stressed syllables before the current syllable in the current phrase
b9*	number of stressed syllables after the current syllable in the current phrase
b10*	number of accented syllables before the current syllable in the current phrase
b11*	number of accented syllables after the current syllable in the current phrase
b12*	number of syllables from the previous stressed syllable to the current syllable
b13*	number of syllables from the current syllable to the next stressed syllable
b14*	number of syllables from the previous accented syllable to the current syllable
b15*	number of syllables from the current syllable to the next accented syllable
b16*	name of the vowel of the current syllable
c1*	whether the next syllable stressed or not (0: not, 1:yes)
c2*	whether the next syllable accented or not (0: not, 1:yes)
c3*	the number of phonemes in the next syllable
d1	gpos (guess part-of-speech) of the previous word
d2	number of syllables in the previous word
e1*	gpos (guess part-of-speech) of the current word
e2*	number of syllables in the current word
e3*	position of current word in the current phrase (forward)
e4*	position of current word in the current phrase (backward)
e5*	number of content words before the current word in the current phrase
e6*	number of content words after the current word in the current phrase
e7*	number of words from the previous content word to the current word
e8*	number of words from the current word to the next content word
f1*	gpos (guess part-of-speech) of the next word
f2	number of syllables in the previous word
g1	number of syllables in the previous phrase
g2	number of words in the previous phrase
h1*	number of syllables in the current phrase
h2*	number of words in the current phrase
h3*	position of the current phrase in utterance (forward)
h4*	position of the current phrase in utterance (backward)
h5*	Phrase modality (question, exclamation, etc.)
i1*	number of syllables in the next phrase
i2	number of words in the previous phrase
j1*	number of syllables in this utterance
j2*	number of words in this utterance
j3*	number of phrases in this utterance

Table 2.2: Label format.

A full example of this conversion is shown in ??:



```
pau^D-i+O:=t~2_1/A:0_0_2/B:0-0-2~1-1&1-10#0-0$0-2!0-0;3-4|i/C:0+0+1/D:NN_2/E:DT+1~1+5&0+3#0+1/F:NN_6/G:3_2/H:10=5~3=1|
D^i-O:+t=@~1_1/A:0_0_2/B:0-0-1~1-6&2-9#0-0$0-2!0-0;4-3|O:/C:0+0+2/D:DT_1/E:NN+6~2+4&0+3#1+1/F:IN_1/G:3_2/H:10=5~3=1|F/
i^O:-t+@=b~1_2/A:0_0_1/B:0-0-2~2-5&3-8#0-0$0-2!0-0;5-2|@/C:0+0+2/D:DT_1/E:NN+6~2+4&0+3#1+1/F:IN_1/G:3_2/H:10=5~3=1|F/I
O:^t-@+b=aI~2_1/A:0_0_1/B:0-0-2~2-5&3-8#0-0$0-2!0-0;5-2|@/C:0+0+2/D:DT_1/E:NN+6~2+4&0+3#1+1/F:IN_1/G:3_2/H:10=5~3=1|F/
t^@-b+aI=Q~1_2/A:0_0_2/B:0-0-2~3-4&4-7#0-0$0-2!0-0;6-1|aI/C:0+1+1/D:DT_1/E:NN+6~2+4&0+3#1+1/F:IN_1/G:3_2/H:10=5~3=1|F/
@^b-aI+Q=g~2_1/A:0_0_2/B:0-0-2~3-4&4-7#0-0$0-2!0-0;6-1|aI/C:0+1+1/D:DT_1/E:NN+6~2+4&0+3#1+1/F:IN_1/G:3_2/H:10=5~3=1|F/
b^aI-Q+g=r~1_1/A:0_0_2/B:0-1-1~4-3&5-6#0-0$0-1!0-0;7-5|Q/C:0+0+3/D:DT_1/E:NN+6~2+4&0+3#1+1/F:IN_1/G:3_2/H:10=5~3=1|F/I
aI^Q-g+r=@~1_3/A:0_1_1/B:0-0-3~5-2&6-5#0-0$1-1!0-0;1-4|@/C:0+0+2/D:DT_1/E:NN+6~2+4&0+3#1+1/F:IN_1/G:3_2/H:10=5~3=1|F/I
Q^g-r+@=f~2_2/A:0_1_1/B:0-0-3~5-2&6-5#0-0$1-1!0-0;1-4|@/C:0+0+2/D:DT_1/E:NN+6~2+4&0+3#1+1/F:IN_1/G:3_2/H:10=5~3=1|F/I:
g^r-@+f=i~3_1/A:0_1_1/B:0-0-3~5-2&6-5#0-0$1-1!0-0;1-4|@/C:0+0+2/D:DT_1/E:NN+6~2+4&0+3#1+1/F:IN_1/G:3_2/H:10=5~3=1|F/I:
r^@-f+i=@~1_2/A:0_0_3/B:0-0-2~6-1&7-4#0-0$1-1!0-0;2-3|i/C:0+0+2/D:DT_1/E:NN+6~2+4&0+3#1+1/F:IN_1/G:3_2/H:10=5~3=1|F/I:
@^f-i+@=v~2_1/A:0_0_3/B:0-0-2~6-1&7-4#0-0$1-1!0-0;2-3|i/C:0+0+2/D:DT_1/E:NN+6~2+4&0+3#1+1/F:IN_1/G:3_2/H:10=5~3=1|F/I:
f^i-@+v=@~1_2/A:0_0_2/B:0-0-2~1-1&8-3#0-0$1-1!0-0;3-2|@/C:0+0+1/D:NN_6/E:IN+1~3+3&1+2#1+2/F:DT_1/G:3_2/H:10=5~3=1|F/I:
i^@-v+@=h~2_1/A:0_0_2/B:0-0-2~1-1&8-3#0-0$1-1!0-0;3-2|@/C:0+0+1/D:NN_6/E:IN+1~3+3&1+2#1+2/F:DT_1/G:3_2/H:10=5~3=1|F/I:
@^v-@+h=O:~1_1/A:0_0_2/B:0-0-1~1-1&9-2#0-0$1-1!0-0;4-1|@/C:0+1+3/D:IN_1/E:DT+1~4+2&2+1#1+1/F:NN_1/G:3_2/H:10=5~3=1|F/I
v^@-h+O:=s~1_3/A:0_0_1/B:0-1-3~1-1&10-1#0-0$1-0!0-0;5-0|O:/C:0+0+0/D:DT_1/E:NN+1~5+1&2+1#2+0/F:SIL_0/G:3_2/H:10=5~3=1|
@^h-O:+s=pau~2_2/A:0_0_1/B:0-1-3~1-1&10-1#0-0$1-0!0-0;5-0|O:/C:0+0+0/D:DT_1/E:NN+1~5+1&2+1#2+0/F:SIL_0/G:3_2/H:10=5~3=
h^O:-s+pau=_~3_1/A:0_0_1/B:0-1-3~1-1&10-1#0-0$1-0!0-0;5-0|O:/C:0+0+0/D:DT_1/E:NN+1~5+1&2+1#2+0/F:SIL_0/G:3_2/H:10=5~3=
O:^s-pau+_=_~1_1/A:0_1_3/B:0-0-1~1-1&0-11#0-0$0-2!0-0;1-0|_/C:0+0+0/D:NN_1/E:SIL+1~0+6&0+3#1+0/F:SIL_0/G:3_2/H:10=5~3=
```

Figure 2.5: Label representation of the phrase ”the autobiography of a horse.”

To obtain the Labels of the Blizzard corpus, first the sentences were phonetically segmented. This process was done using the Ramses and Ogmios [4] software. The whole process was mostly automated following a guide:

1. The text files are converted to their phonetic representation. Speech parameters are also computed from the audio files from where a codebook created and quantized.

2. The next step estimates a HMM for every phonem using the speech parameters. Using these HMM models and the phonetic transcriptions, a force alignment is performed to find the transitions of the phonemes and the internal pauses and silences in the sentences using the Viterbi algorithm.

3. Next it creates a diphone transcription [24] of the sentences and estimates an HMM of them.

4. Finally, a force alignment is performed again to ontain the diphone transitions and compute the duration of each phoneme.

5. A script from the server is called to convert the outputs from the Ogmios program to the Label representation with the phoneme durations.

2.1.5 Linguistic features normalization

The linguistic features, also had to be normalized prior to training. As seen previously, the label format contains both categorical features and real features. The categorical information was encoded so that all categories are orthogonal to each other by using a one-hot encoding. As a small example of a one-hot encoding, consider the three categories $\{A, B, C\}$. The one-hot encoding for the three categories is $\{(1, 0, 0), (0, 1, 0), (0, 0, 1)\}$.

The real features from the acoustic features are normalized so that the mean equals zero and the standard deviation equals one for each of them. This operation is called z-norm and it is shown in 2.3.

$$z = \frac{x - \mu}{\sigma} \tag{2.3}$$

The predicted duration of each phoneme was log-compressed to avoid having a long-tailed distribution that can distort the training of the model when using the Mean Square Error (ME) minimization as discussed in [?]. Figure 2.6 contains the histogram of the raw predicted durations and the histogram after the log-compression operation. This operation was performed by simply taking the natural logarithm of the stored phoneme durations:

$$\hat{d} = log(d) \tag{2.4}$$

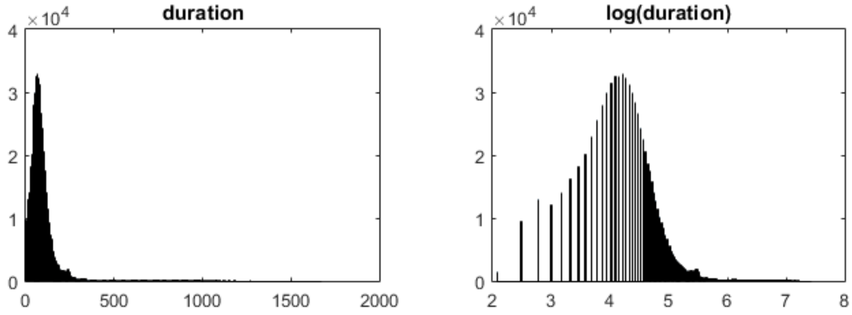


Figure 2.6: Histogram of the phoneme duration predictions by Ogmios.

Once we have obtained the linguistic features, we discard of those who reference the past and only keep the ones tagged with an asterisk $(*)$ in Table [?]. This is because the models are based on LSTM-RNN which are known to be good at modeling long term dependencies[16].

2.1.6 Baseline training

As mentioned before, the system is developed within the Socrates Test-to-speech framework. In the version that was used, this program allows us to define the full architecture in a plain-text configuration file. In this file we specify the number of layers, inputs parameters, the paths where the training, test and validation data are stored in the disk, and the path where to store the intermediate files that the framework generates during training (network weights, loss curves and cached information). An example of configuration file is shown in Figure ??.

```
[[tts_core]]
name=”labdecode_core”

[[tts_core]]
name=”dur_rnn_core”
topology=”baseline/dur_rnn_core-eng.cfg”
dur_stats=”model/73/dur/dur.stats.test”
train_table=”../tables/duration/baseline/train.dur”
test_table=”../tables/duration/baseline/test.dur”
valid_table=”../tables/duration/baseline/valid.dur”
loss_path=”baseline/loss_curves/”
tables_cache_path=”baseline/tables_cache”

[[tts_core]]
name=”dur2aco_norm_core”
dur_stats=”model/73/dur/dur.stats.test”

[[tts_core]]
name=”aco_rnn_core”
dur_stats=”model/73/aco/dur.stats.test”
aco_stats=”model/73/aco/aco.stats.test”
train_table=”../tables/acoustic/baseline/train.aco”
test_table=”../tables/acoustic/baseline/test.aco”
valid_table=”../tables/acoustic/baseline/valid.aco”
topology=”baseline/aco_rnn_core-eng.cfg”
tables_cache_path=”baseline/tables_cache”
loss_path=”baseline/loss_curves/”

[[tts_core]]
name=”ahodecode_core
```

Figure 2.7: Configuration example for the baseline system. Some options have been omitted.

In this example, we specify that this model is composed of five modules, called cores within the framework. Each of these cores perform the following actions

1. **labdecode_core** decodes the label format from Section 2.1.4 and converts it to the input that the model expects (converts the categories to one-hot and normalizes the numeric values)

2. **dur_rnn_core** predicts the duration of the phoneme that was provided from the previous core.

3. **dur2aco_norm_core** denormalizes the predicted duration and generates the input features that are feed to the acoustic model. It also adds the durations and relative durations as mentioned at the beginning of this chapter.

4. **aco_rnn_core** predicts the acoustic features explained in Section 2.1.2.

5. **ahodecode_core** takes the output from the previous core, formats the data to be input to the Ahodecoder, and produces a WAVE file containing the synthesized speech.

6. **ahodecode_core** takes the output from the previous core, formats the data to be input to the Ahodecoder, and produces a WAVE file containing the synthesized speech.

The configuration file also has access to the ”stats” of the features that contain the minimum and maximum values so that the compression from 2.1 can be undone.

As mentioned previously, the Blizzard Challenge dataset contains roughly twenty hours of speech data. Due to complications loading the data into memory using the framework, we had to cut the total amount down to 30% to train the acoustic model. Newer releases of this framework deal with this problem so it can handle the full corpus data.

2.2 Expressive synthesis development

The baseline system has been explained. Once we had the system up and running it was time to introduce the modifications that would allow for expressive speech to be modeled by the system. The way this is done in this project is by introducing a new set of features as inputs to the system (both the duration and acoustic model). These are known as the embeddings that encapsulate the information about the way a given sentence is supposed to be synthesized like, given its semantic content. In this section we describe the process of obtaining these new features. Other than these new inputs, the developed system shares the same architecture from the baseline system.

2.2.1 Sentiment analysis & embedding extraction task

Once the baseline system was developed, the additions to the initial system were developed. These involve obtaining the expressive paragraph embeddings that would allow for the modeling of the expressiveness of the speech signal. We used sentiment analysis to capture the expressive information of the Blizzard Challenge dataset that was used in the baseline system. Because the sentences on this dataset are not made for sentiment analysis task, they lack the information to train a text classification system. To perform this text classification task, we used the Stanford sentiment treebank dataset [29]. An example of a tagged sentence from this dataset is shown in figure ??.

```
(2 (3 (3 Effective) (2 but)) (1 (1 too-tepid) (2 biopic)))

Tag Sentence
2   Effective but too-tepid biopic
2   Effective but
3   Effective
2   but
1   too-tepid biopic
1   too-tepid
2   biopic
```

Figure 2.8: Example of sentence tree corresponding to the sentence ”Effective but too-tepid biopic”

Each of the nodes on the tree is tagged in a scale from 0 to 4, 0 meaning very negative and 4 being a very positive text. Each sub-sentence was tagged down to the single words of the sentence. We used this dataset to train a CNN-based classifier similar to [20]. This architecture is shown in Figure ??.

- The first layer is an embedding layer. Each word is transformed into a low dimensional

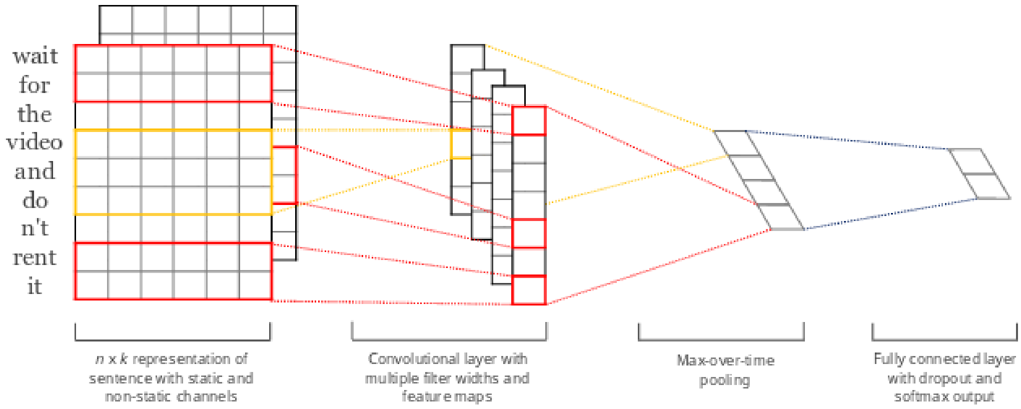

wait
for
the
video
and
do
n't
rent
it
n x k representation of sentence with static and non-static channels
Convolutional layer with multiple filter widths and feature maps
Max-over-time pooling
Fully connected layer with dropout and softmax output

Figure 2.9: Text classification architecture. The figure is originally from [20]

(300) representation. This step converts a sentence into a signal suitable for the next convolutional layer. The embedding layer consists of a N*300 matrix where N is the size of the vocabulary and the n-th vector column corresponds to the embedding of the n-th word in the vocabulary.

- A convolutional layer with filters of sizes 3, 4 and 5 with 100 feature maps each.
- A max-over-time pooling operation [10], where we select the maximum value from each of the feature maps.
- A Fully connected layer with softmax activations that give the output of the classification task. This layer is regularized using the dropout method with dropout probability of 0.5 [30] and the weights of this network are constrained using l2 regularization.

We choose the max-over-time pooling layer activations as the additional inputs added to the baseline synthesizer model. There is an issue with using the Stanford treebank dataset to train this classifier to obtain features for the synthesizer. Because the dataset is based on movie reviews, the text domain doesn't belong to the same from the Blizzard challenge data that we use to train the synthesizer models, therefore, the text classifier network has to be adapted. The following section explains the methodology that was followed in order to attempt to achieve this task.

2.2.2 Network domain adaptation

To perform the domain adaptation we do the same classification task on a different architecture using the Blizzard challenge data. This network makes the prediction with the audio files as inputs. As explained before, this dataset is not prepared for text classification therefore they lack the class tags needed. We obtain these by using the network from the previous section after it has been trained using the Stanford sentiment treebank dataset. In [1] they train a waveform classifier using unlabeled audio files and a pre-trained network to obtain them. We perform the same task using audio and text data instead.

This task is performed in two steps:

1. We train the audio based network by using the text network to obtain the labels. Because the labels that we obtain for the Blizzard sentences are probabilities, we optimize the network using KL-divergence using standard back-propagation [1].

2. After a fixed number of iterations, we fine tune [34] the text network by using labels obtained from the audio network. The two networks take turns to perform a back-propagation pass. Because the state of the weight of each network is constantly changing, we intend to leak information about the audio files into the text network.

2.2.3 Training embeddings extraction and expressive synthesis

Sentiment analysis task

In order to train the embedding extraction, the Keras deep learning framework was used to define the two networks. First, the data had to be processed in order to train the system. As shown in Figure ??, the sentences in the Stanford sentiment treebank are provided by a tree representation. Each of these trees were traversed in order to collect all the sentences and sub-sentences of the dataset. Figure 2.10 shows the distribution of sentence lengths:

To train this sentiment analysis task, we use all the sentences from the training dataset that are ≥ 3 in length (words). The test data however, only contains the root nodes of the

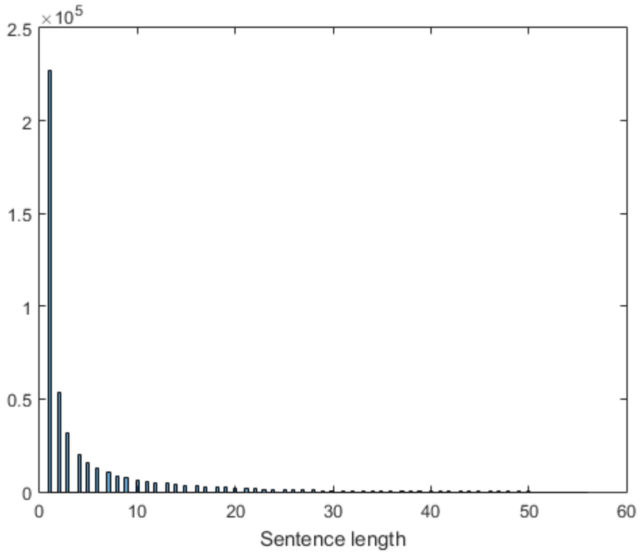


Figure 2.10: Distribution of sentence lengths in the Stanford sentiment treebank dataset.

sentences like they do in [20] and in the original paper from the dataset.

Domain adaptation task

	conv	pool	conv	pool	conv	pool	conv	conf	conv
Feature maps	32	32	64	64	128	128	256	512	5
Filter size	64	8	32	8	16	8	8	4	5
Stride	2	2	2	2	4	2	4	1	1

Table 2.3: CNN used to process the Blizzard waveforms.

Once the sentiment analysis task is done, the same network has to be adapter for the aforementioned reasons. To perform this task, we define a CNN from Table 2.3. The reason for choosing a CNN architecture as opposed to a different one such a DNN is because of the high dimensionality of the input. As aforementioned, this network takes whole waveforms from the Blizzard corpus. Convolutional layers have less trainable parameters since the number only depends on the size of the filters and the number of feature maps. This network also contains pooling layers which reduce the dimensionality of the input [28] and PReLU activations [33] which are activations with trainable parameters. We then use the following methodology:

1. The audio network is trained using the Blizzard challenge WAVE files. The label of a file is obtained by using the sentiment analysis network with the transcript. Perform a

fixed number of back propagation passes to initialize the weights of the network. From this point, the networks will take turns in performing back-propagation steps.

2. We perform a back-propagation in the text network using a batch of sentences from the Blizzard corpus. The labels are obtained like in step 1 using audio network to obtain the labels.

3. We perform a back-propagation in the audio network using a batch of wave files from the Blizzard corpus. Again, use the text network to obtain the labels.

4. repeat step 2 for a fixed number of iterations.

2.2.4 Training the expressive speech synthesizer

Once the expressive embeddings are extracted for every sentence in the Blizzard Challenge corpus, we include the new inputs to both the duration and the acoustic model from the baseline system. This is specified in a new Socrates configuration file. Every linguistic feature vector that is input to the system includes the additional features that correspond to the full sentence the given phonemes belong to. After that, the process of training the models is the same that was followed in the baseline system.

One last processing step is to normalize the embeddings by compressing them between the $[0, 1]$ range.

2.3 Experiments

In order to test the performance of the model, we have performed a series of experiments involving different input configurations of the speech synthesizer models. This experiments are the ones that are shown in the next chapter of this document.

1. Baseline system (only linguistic features from 2.1.4)

2. Text embeddings taken from the sentiment analysis network without doing adaptation

step.

3. Text embeddings but with the adaptation step.

4. Train the system using only word embeddings from Glove.

Chapter 3

Evaluation & Results

In this chapter it is explained how the evaluation of each of the systems was developed and carried out with the experiments listed at the end of the previous chapter.

3.1 Sentiment analysis evaluation

As mentioned previously, the semtniment analysis task was trained using a dataset from Stanford. To perform this task we used the same test and train splits used in [29] which is the same from [20]. During training, both the loss and the accuracy of this classification task were recorded but only the loss is used in back-propagation.

The loss function was choosen among the ones available in the Keras framework to be the categorical cross-entropy [15] and the optimizer was Adadelta [35]. The batch size was set to 50 to stay as close as possible to the experiments in [20].

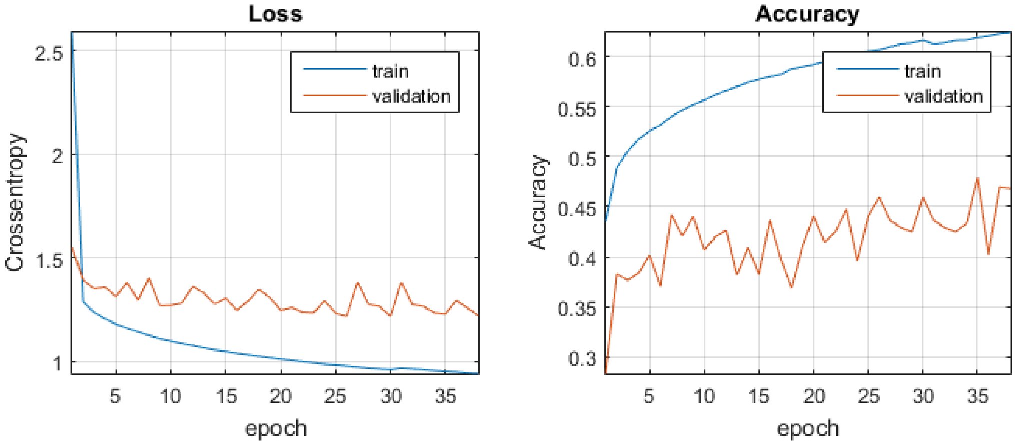


Figure 3.1: Training and validation curves of the sentiment analysis task.

3.2 Speech synthesis evaluation

This section contains both the objective and subjective evaluation results and how they were performed.

3.2.1 Objective evaluation

To perform the objective evaluation the Socrates framework keeps track of the loss evolution during the training. At the end of each batch, it saves the batch loss and at the end of each epoch, the validation data is used to obtain the validation loss of the models.

The metric that are computed by Socrates are the root mean square error (RMSE) for the duration predictions, mel cepstral distortion [25] (MCE) for the MFCC predictions, RMSE for the F_0 predictions and accuracy (%) for the UV flag.

	Duration	MFCC	F_0	UV
Random weights	152.75	22.35	58.50	34.31
Baseline	49.17	7.18	37.67	95.32
Expressive embeddings	51.76	7.35	41.46	94.72
Adapted embeddings	49.37	7.18	37.67	66.28

Table 3.1: Objective metrics.

Both the duration and acoustic models were trained minimizing the mean square error (MSE) using the Adam [22] optimizer.

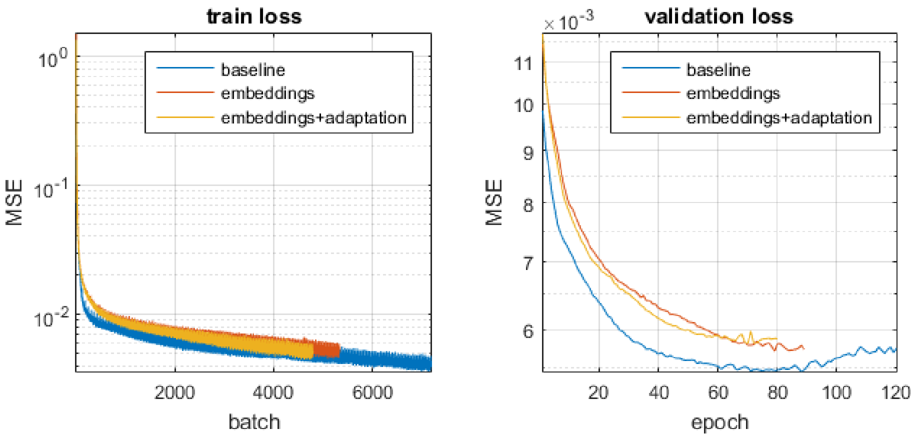


Figure 3.2: Duration model's training curves

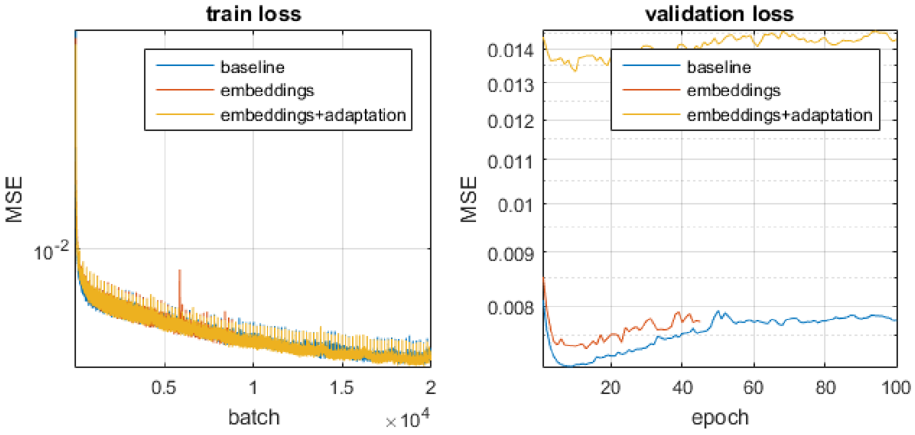


Figure 3.3: Acoustic model's training curves

3.2.2 Subjective evaluation

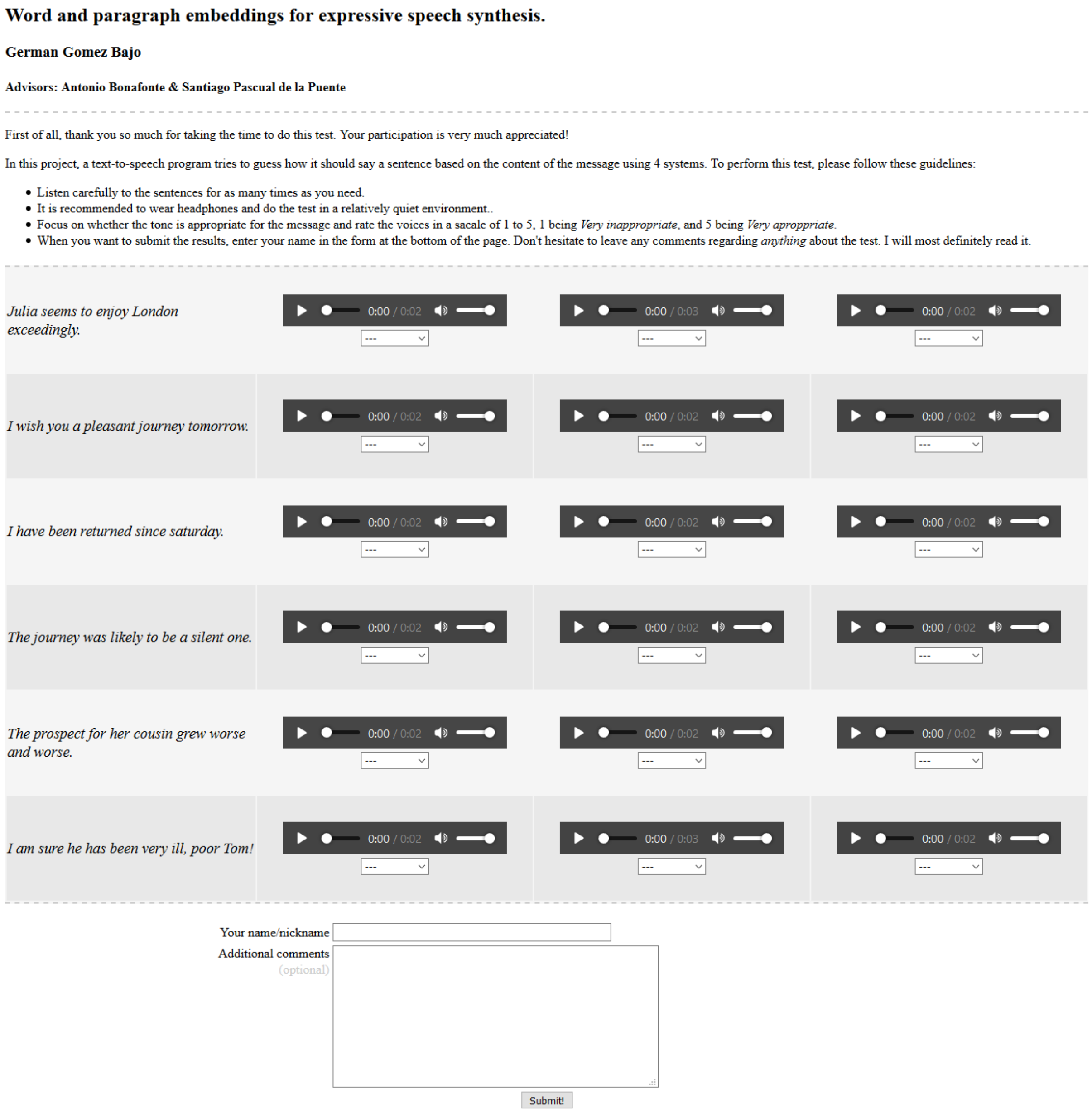
To perform the subjective evaluation, six sentences were chosen from the test split from the Blizzard corpus. To choose the sentences, all the transcripts from the corpus were processed with the sentiment analysis classifier from Section 2.2.1 and a score was computed for each of them:

$$s = 2 \cdot p_{nn} + \cdot p_n - \cdot p_p - 2 \cdot p_{pp} \tag{3.1}$$

Where p_{nn} is the probability of the sentence being *very negative*, p_n is the probability of being *negative*, p_p is the probability of the sentence being *positive* and p_{pp} is the probability of being *very positive*. The probability of a sentence being *neutral* is not used in the score.

The scored sentences were sorted in a list and two were picked from the top (as negative sentences), two from the bottom (positive sentences) and two from the middle (neutral sentences).

A web based application was developed with the selected audio files obtained from the systems from Section 2.3 and volunteers were asked to rate how appropriate the voices were in a scale from one to five, one being *very unappropriate* and five being *very appropriate*. The results were saved in an SQL database in the server side of the application.



Word and paragraph embeddings for expressive speech synthesis.

German Gomez Bajo

Advisors: Antonio Bonafonte & Santiago Pascual de la Puente

First of all, thank you so much for taking the time to do this test. Your participation is very much appreciated!

In this project, a text-to-speech program tries to guess how it should say a sentence based on the content of the message using 4 systems. To perform this test, please follow these guidelines:

- Listen carefully to the sentences for as many times as you need.
- It is recommended to wear headphones and do the test in a relatively quiet environment..
- Focus on whether the tone is appropriate for the message and rate the voices in a sacale of 1 to 5, 1 being *Very inappropriate*, and 5 being *Very aproppriate*.
- When you want to submit the results, enter your name in the form at the bottom of the page. Don't hesitate to leave any comments regarding *anything* about the test. I will most definitely read it.

Julia seems to enjoy London exceedingly.	0:00 / 0:02 ---	0:00 / 0:03 ---	0:00 / 0:02 ---
I wish you a pleasant journey tomorrow.	0:00 / 0:02 ---	0:00 / 0:02 ---	0:00 / 0:02 ---
I have been returned since saturday.	0:00 / 0:02 ---	0:00 / 0:02 ---	0:00 / 0:02 ---
The journey was likely to be a silent one.	0:00 / 0:02 ---	0:00 / 0:02 ---	0:00 / 0:02 ---
The prospect for her cousin grew worse and worse.	0:00 / 0:02 ---	0:00 / 0:02 ---	0:00 / 0:02 ---
I am sure he has been very ill, poor Tom!	0:00 / 0:02 ---	0:00 / 0:03 ---	0:00 / 0:02 ---

Your name/nickname

Additional comments
(optional)

Submit!

Figure 3.4: Screenshot of the subjective evaluation's web application.

Chapter 4

Budget

An approxmation of the budget of this project, taking into account server uptime, weekly mettings, etc..

Chapter 5

Conclusions

Chapter 6

Annex

6.1 SA keras summary

Result of calling the summary method on the keras model.

```
----------------------------------------------------------------------------------------------------
Layer (type)                     Output Shape          Param #     Connected to
====================================================================================================
input_1 (InputLayer)             (None, 128)           0
----------------------------------------------------------------------------------------------------
input_2 (InputLayer)             (None, 128)           0
----------------------------------------------------------------------------------------------------
embedding_1 (Embedding)          (None, 128, 300)      120000300   input_1[0][0]
----------------------------------------------------------------------------------------------------
embedding_2 (Embedding)          (None, 128, 300)      0           input_2[0][0]
----------------------------------------------------------------------------------------------------
convolution1d_1 (Convolution1D)  (None, 126, 82)       73882       embedding_1[0][0]
----------------------------------------------------------------------------------------------------
convolution1d_2 (Convolution1D)  (None, 126, 82)       73882       embedding_2[0][0]
----------------------------------------------------------------------------------------------------
convolution1d_3 (Convolution1D)  (None, 125, 82)       98482       embedding_1[0][0]
----------------------------------------------------------------------------------------------------
convolution1d_4 (Convolution1D)  (None, 125, 82)       98482       embedding_2[0][0]
----------------------------------------------------------------------------------------------------
convolution1d_5 (Convolution1D)  (None, 124, 82)       123082      embedding_1[0][0]
----------------------------------------------------------------------------------------------------
convolution1d_6 (Convolution1D)  (None, 124, 82)       123082      embedding_2[0][0]
----------------------------------------------------------------------------------------------------
activation_1 (Activation)        (None, 126, 82)       0           convolution1d_1[0][0]
----------------------------------------------------------------------------------------------------
activation_2 (Activation)        (None, 126, 82)       0           convolution1d_2[0][0]
----------------------------------------------------------------------------------------------------
activation_3 (Activation)        (None, 125, 82)       0           convolution1d_3[0][0]
----------------------------------------------------------------------------------------------------
activation_4 (Activation)        (None, 125, 82)       0           convolution1d_4[0][0]
----------------------------------------------------------------------------------------------------
activation_5 (Activation)        (None, 124, 82)       0           convolution1d_5[0][0]
----------------------------------------------------------------------------------------------------
activation_6 (Activation)        (None, 124, 82)       0           convolution1d_6[0][0]
----------------------------------------------------------------------------------------------------
merge_1 (Merge)                  (None, 126, 164)      0           activation_1[0][0]
                                                                   activation_2[0][0]
----------------------------------------------------------------------------------------------------
merge_2 (Merge)                  (None, 125, 164)      0           activation_3[0][0]
                                                                   activation_4[0][0]
----------------------------------------------------------------------------------------------------
merge_3 (Merge)                  (None, 124, 164)      0           activation_5[0][0]
                                                                   activation_6[0][0]
----------------------------------------------------------------------------------------------------
globalmaxpooling1d_1 (GlobalMaxPo(None, 164)           0           merge_1[0][0]
----------------------------------------------------------------------------------------------------
globalmaxpooling1d_2 (GlobalMaxPo(None, 164)           0           merge_2[0][0]
----------------------------------------------------------------------------------------------------
globalmaxpooling1d_3 (GlobalMaxPo(None, 164)           0           merge_3[0][0]
----------------------------------------------------------------------------------------------------
merge_4 (Merge)                  (None, 492)           0           globalmaxpooling1d_1[0][0]
                                                                   globalmaxpooling1d_2[0][0]
                                                                   globalmaxpooling1d_3[0][0]
----------------------------------------------------------------------------------------------------
dropout_1 (Dropout)              (None, 492)           0           merge_4[0][0]
----------------------------------------------------------------------------------------------------
dense_1 (Dense)                  (None, 5)             2465        dropout_1[0][0]
----------------------------------------------------------------------------------------------------
activation_7 (Activation)        (None, 5)             0           dense_1[0][0]
====================================================================================================
Total params: 120593657
----------------------------------------------------------------------------------------------------
```

6.2 Audio keras summary

Result of calling the summary method on the keras model.

```
____________________________________________________________________________________________________
Layer (type)                     Output Shape          Param #     Connected to
====================================================================================================
input_1 (InputLayer)             (None, 160000, 1)     0
____________________________________________________________________________________________________
convolution1d_1 (Convolution1D)  (None, 80000, 32)     2080        input_1[0][0]
____________________________________________________________________________________________________
batchnormalization_1 (BatchNormal(None, 80000, 32)     64          convolution1d_1[0][0]
____________________________________________________________________________________________________
prelu_1 (PReLU)                  (None, 80000, 32)     2560000     batchnormalization_1[0][0]
____________________________________________________________________________________________________
maxpooling1d_1 (MaxPooling1D)    (None, 10000, 32)     0           prelu_1[0][0]
____________________________________________________________________________________________________
convolution1d_2 (Convolution1D)  (None, 5000, 64)      65600       maxpooling1d_1[0][0]
____________________________________________________________________________________________________
batchnormalization_2 (BatchNormal(None, 5000, 64)      128         convolution1d_2[0][0]
____________________________________________________________________________________________________
prelu_2 (PReLU)                  (None, 5000, 64)      320000      batchnormalization_2[0][0]
____________________________________________________________________________________________________
maxpooling1d_2 (MaxPooling1D)    (None, 625, 64)       0           prelu_2[0][0]
____________________________________________________________________________________________________
convolution1d_3 (Convolution1D)  (None, 157, 128)      131200      maxpooling1d_2[0][0]
____________________________________________________________________________________________________
batchnormalization_3 (BatchNormal(None, 157, 128)      256         convolution1d_3[0][0]
____________________________________________________________________________________________________
prelu_3 (PReLU)                  (None, 157, 128)      20096       batchnormalization_3[0][0]
____________________________________________________________________________________________________
maxpooling1d_3 (MaxPooling1D)    (None, 19, 128)       0           prelu_3[0][0]
____________________________________________________________________________________________________
convolution1d_4 (Convolution1D)  (None, 5, 256)        262400      maxpooling1d_3[0][0]
____________________________________________________________________________________________________
batchnormalization_4 (BatchNormal(None, 5, 256)        512         convolution1d_4[0][0]
____________________________________________________________________________________________________
prelu_4 (PReLU)                  (None, 5, 256)        1280        batchnormalization_4[0][0]
____________________________________________________________________________________________________
convolution1d_5 (Convolution1D)  (None, 5, 512)        524800      prelu_4[0][0]
____________________________________________________________________________________________________
batchnormalization_5 (BatchNormal(None, 5, 512)        1024        convolution1d_5[0][0]
____________________________________________________________________________________________________
prelu_5 (PReLU)                  (None, 5, 512)        2560        batchnormalization_5[0][0]
____________________________________________________________________________________________________
convolution1d_6 (Convolution1D)  (None, 1, 5)          12805       prelu_5[0][0]
____________________________________________________________________________________________________
batchnormalization_6 (BatchNormal(None, 1, 5)          10          convolution1d_6[0][0]
____________________________________________________________________________________________________
prelu_6 (PReLU)                  (None, 1, 5)          5           batchnormalization_6[0][0]
____________________________________________________________________________________________________
flatten_1 (Flatten)              (None, 5)             0           prelu_6[0][0]
____________________________________________________________________________________________________
activation_1 (Activation)        (None, 5)             0           flatten_1[0][0]
====================================================================================================
Total params: 3904820
____________________________________________________________________________________________________
```

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