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# Chapter 1

## Introduction

Information regarding the initial work-plan, deviations from it, work packages, gantt diagram...

## Chapter 2

# State of the art

In this section, Deep Learning and neural networks are briefly introduced. In addition to that, both the text-to-speech and sentiment analysis tasks are also introduced and discussed, including the challenges that they present as well as the classical and more modern techniques that tackle them, and how they have influenced the development of this project. By the end of this chapter, the core concepts necessary for the discussion of the work done in this publication will have been introduced to the reader.

### 2.1 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 give speech impaired people a voice to communicate with and it can also be used by non-sighted people by simulating more human-like interactions between them and the unanimated objects around them.

#### 2.1.1 Unit selection

Unit selection systems function by rendering a speech signal by concatenating waveform fragments from a large single-speaker database [12]. The outcome of this technique is highly natural-sounding speech signal since the fragments that are concatenated come from real speech 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 [13], as we are limited by the waveforms database in the first place. Each unit can also have an associate feature vector containing prosodic information such as pitch or formants.

It also has a high storage cost, since we need to have access to all of the waveform fragments to produce the speech signals.

$$asd \tag{2.1}$$

The best sequence of concatenated units is found by means of dynamic programming using the Viterbi algorithm minimizing the cost of concatenating consecutive units. The cost of concatenation is defined by [?]. Given a sequence of concatenated units  $u$ , the total cost of concatenation is given by:

### 2.1.2 Statistical Parametric Speech Synthesis

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

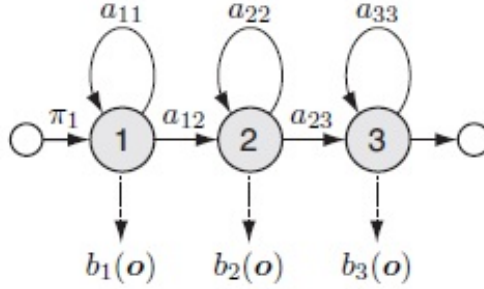


Figure 2.1: A 3-state left-to-right Hidden Markov Model.

As seen in Figure 2.1, 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 and  $\Pi$  are the initial state probabilities (spectral & excitation output parameters). HMMs are used as generative model since they provide a time-discrete series of observations from a distribution of the speech parameters. In contrast with unit selection, HMM based speech synthesis models offer a more compact representation than unit selection since they don't require a large database after the models have been trained.

Moreover, it 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 HMM parameters appropriately as describes in [19].

In the methodology chapter of this document, the concepts from this section will be revisited and explained more in-depth.

### 2.1.3 Recurrent Neural Network-based Speech Synthesis

Another approach to speech synthesis that is the one used in this project is using recurrent neural networks (RNNs) to process a sequence of linguistic features to 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 [6], this scheme consists of using neural networks to generate parametric speech in two stages: a duration model predict the duration of a phoneme, and an acoustic model to predict the spectral and excitation parameters for as many time steps as predicted by the duration model. Figure 2.3 shows the complete scheme of this approach.

### 2.1.4 Expressive

Summary of the bibliography of the approaches to expressive speech synthesis.

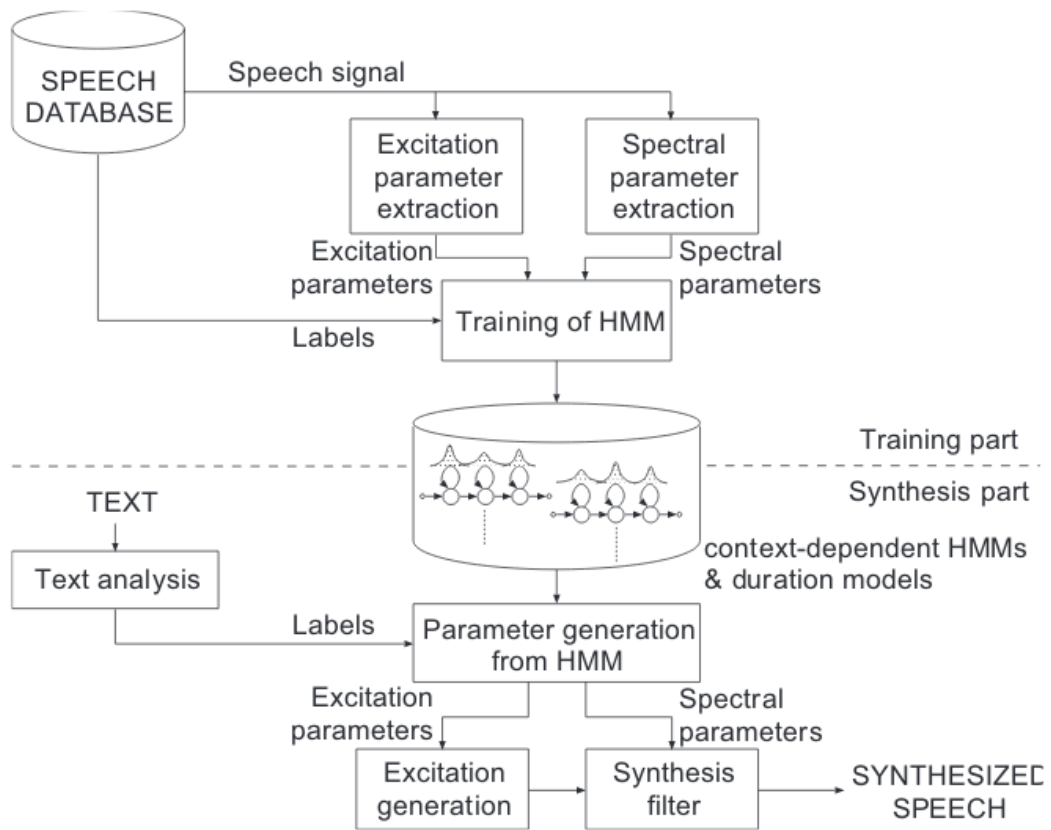


Figure 2.2: SPSS system based on HMMs.

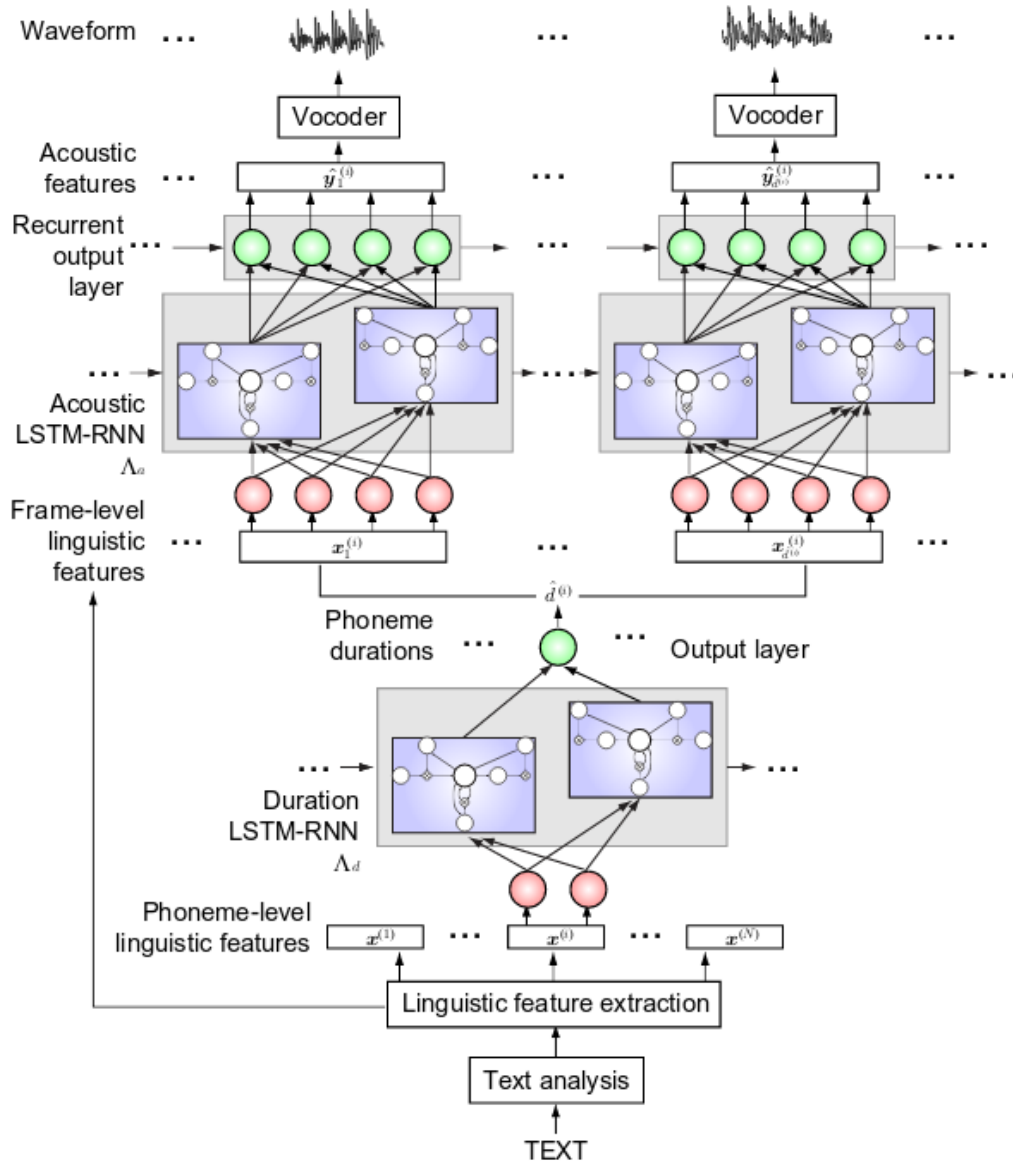


Figure 2.3: RNN-based SPSS scheme. Concepts such as LSTM that appear in the figure are covered at later section of this chapter.

## 2.2 Text classification for sentiment Analysis

## 2.3 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. [9]

[1] 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 them 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 as Imagenet [16] are being made publicly available. These datasets are often used as benchmarks and serve as points of reference to drive research and development forward.

In summary, one could describe Deep Learning as models capable of obtaining high level information from low level one, and the compute resources and databases that make training of these models possible.

### 2.3.1 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.

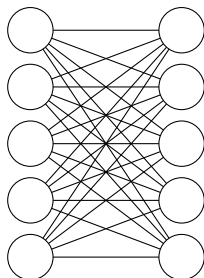


Figure 2.4: Neural network basic configuration. Each layer consists of a net of nodes which perform a linear operation of the inputs, before being fed to an activation function at the output and fed to the next layer.

DNNs are defined by stacking several layers of basic units called neurons. In each layer,



a linear operation takes place, where the inputs  $\mathbf{x} = \{1, x_1, x_2, \dots, x_N\}$  (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 (2.3) or a tanh) which introduces the non-linearities of the system and is differentiable (property that will be relevant for optimizing or training the weights). Equation 2.2 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  $\sigma$  is the activation function.

$$\mathbf{y}_i = \sigma(\mathbf{W}_i \cdot \mathbf{x}_i) \quad (2.2)$$

$$\sigma(x) = \frac{1}{1 + e^{-x}} \quad (2.3)$$

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 2.4 shows a neural network configuration.

### 2.3.2 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 the whether 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).

$$L(\mathbf{x}; \mathbf{w}) = \sum_{\mathbf{x}_k} L_i(\mathbf{x}_k) \quad (2.4)$$

$$w_i[n+1] = w_i[n] - \lambda \frac{\partial L(\mathbf{x}; \mathbf{w}[n])}{\partial w_i} \quad (2.5)$$

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 [10]). given a loss, we can find improve the performance of a model by translating the weight vector of the model in the direction of the gradient.

Equation 2.4 is a general 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 2.5). This technique is called stochastic gradient descent [4] (SGD).

Before updating the weights, the partial derivatives of the loss function are computed using the back-propagation algorithm [5]. For this we need to be able to compute the derivatives of both the loss function and the activation functions of the neurons.

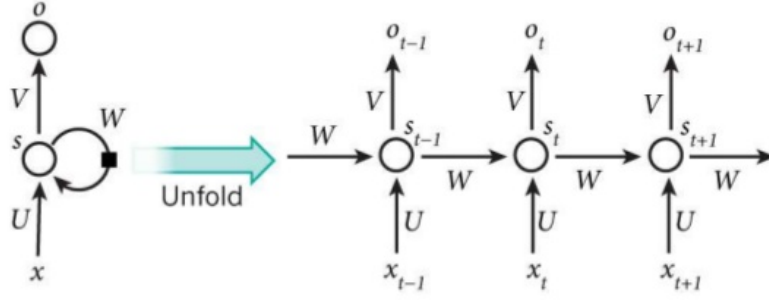


Figure 2.5: Unfolded RNN

After computing the derivatives, the norm of the gradient can be scaled by a factor called learning rate (expressed as  $\lambda$  in Equation 2.5) that can be used to speed-up or slow-down the convergence of the loss function during training. Other ways to improve this update are Adam [15] and Adadelata [18].

## 2.4 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:

$$\mathbf{y}_t = \sigma(\mathbf{W} \cdot \mathbf{x}_t + \mathbf{U}_t \cdot \mathbf{y}_{t-1}) \quad (2.6)$$

Where  $\mathbf{x}[n]$  is an input vector at the  $n$ -th timestep and  $\mathbf{U}_i$  is an additional set of trainable 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 [17] which is specific case of back-propagation where the errors are also back-propagation back in time in the same ways that they are propagated backwards from the outputs to the inputs of the network. If we expand 2.6 we get:

$$\mathbf{y}_t = \sigma(\mathbf{W} \cdot \mathbf{x}_t + \mathbf{U}_t \cdot \sigma(\mathbf{W} \cdot \mathbf{x}_{t-1} + \mathbf{U}_{t-1} \cdot \sigma(\dots \sigma(\dots) \dots))) \quad (2.7)$$

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, as described in [2], that occurs during training with 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.

### 2.4.1 Long Short-Term Memory (LSTM)

Long Short-Term Memory [11] 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 than are trained while optimizing the network to control the flow of information coming in and out of the cell. Figure 2.6

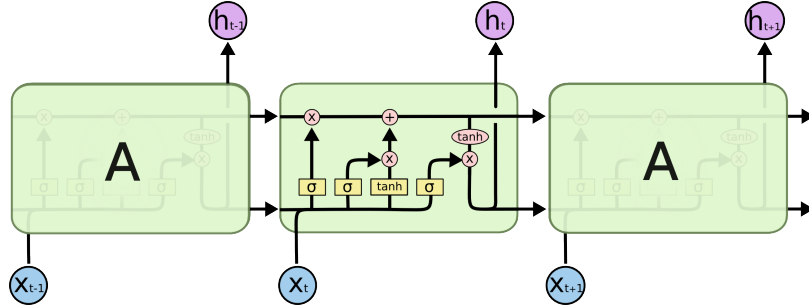


Figure 2.6: Diagram of a chain of LSTM units. The horizontal axis represents time and the vertical represents the RNN-LSTM at each timestep.  $X_t$  are the input vectors at the past, present and future timestep. The gating mechanism controls the flow of information that is input to the next state of the layer. This figure was taken from [?]

## Chapter 3

# Expressive Speech synthesis

### 3.1 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 [8] by using the Socrates Text-to-speech framework. This is a RNN-LSTM based model, which, as mentioned in section 2.1.3, contains a duration model and an acoustic model which are trained independently.



Figure 3.1: Baseline model

- 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 pervious model and the relative duration of the frame within the duration of the phoneme. The output of this model is also explained in the next section.

#### 3.1.1 Data preparation

The database that has been used for this project contains approximately 20 hours or several audiobooks along with the transcriptions. The data came from the Blizzard challenge [14] 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 database was because of its richness in expressive content. Table 3.1 shows some information about the audio files that we had.

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 3.1: Information about the Blizzard Challenge utterances.

### 3.1.2 Obtaining Acoustic features

As mentioned in section 2.1.3, 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 [7].

Every audio file is framed by means of a sliding window with a stride of 25 milliseconds. Ahocoder then processes each frame to produce a set of excitation and spectral parameters which are:

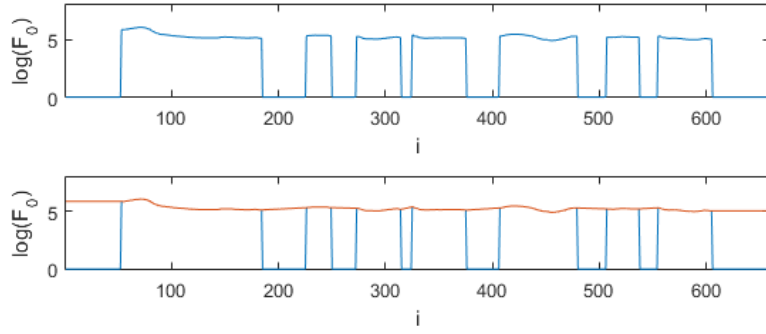
- Mel Frequency Cepstral Coefficients (MFCC) of order  $p = 39$ , which corresponds to 40 coefficients.
- Pitch contour ( $\log(F_0)$ ). Unvoiced frames correspond to  $F_0 = 0$  value of  $-\inf$  after the logarithm. Ahocoder outputs a value of  $-10^8$  when the frame is unvoiced.
- Maximum voiced frequency ( $f_v$ ). 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  $f_v$  or  $\log(f_0)$  outputs of Ahocoder.

The data is not used as it is, at the output of the Ahocoder. 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 [8]. The outputs of the Ahocoding process have been normalized so that they are bound between a minimum and a maximum value range. This range is chosen to be 0.01, 0.99 for better convergence properties. The normalization of the acoustic outputs is shown in equation 3.1

$$y = 0.01 + (0.99 - 0.01) \frac{y - y_{min}}{y_{max} - y_{min}} \quad (3.1)$$

This doesn't work for the  $\log(F_0)$  and  $f_v$  features since their high dynamic range will compress the values from the voiced frames too much. [8] solves it by keeping the values from the voiced frames and interpolating the values in the unvoiced regions as shown in Equation 3.2:

$$\log F_0^i = \log F_0^p + (\log F_0^n - \log F_0^p) \cdot \frac{i - p}{n - p} \quad (3.2)$$

Figure 3.2:  $F_0$  contour interpolation

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 3.2 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 layed out in the following manner in the training data tables:

```
<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 3.3: Training table used to train the acoustic model is stored in the server disk.

Which are the examples that are used to train the acoustic model. Some of the inputs are repeated depending on the duration of the phonemes. The linguistic features are explained in the next section.

### 3.1.3 Obtaining linguistic features

Each of the audio transcriptions is 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:

p1^p2\$-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)

Table 3.2 (continued)

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)
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
Table 3.2 (continued)	
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 3.2: Context-dependent 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|/C:0+0+2/D:NN.2/E:DT+1`1+5&0+3#0+1/F:NN.6/G:3.2/H:10=5`3=1|F/I:
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:
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/I:
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/I:
@`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/I:
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|F/I:
@`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=1|F/I:
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=1|F/I:
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=1|F/I:
```

Figure 3.4: Label representation of the phrase "the autobiography of a horse."

This label conversion is carried out with the aid of the Ogmios framework [3]. This program offers a collection of speech processing modules that are combined to perform a given task. For the case of this project, it is used to obtain this label representation and to predict the duration of each of the phonemes in the sentences from the Blizzard corpus. Figure 3.5 shows the steps that it takes to obtain this information:

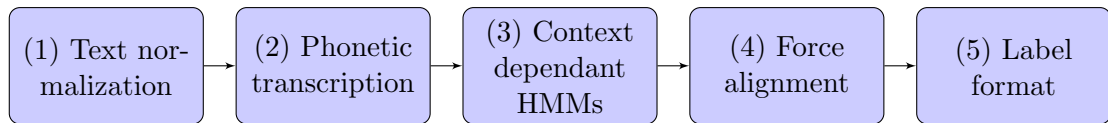


Figure 3.5: Ogmios modules used to predict phoneme duration.

1. The text normalization module converts numeric values, dates, etc to its corresponding text form.



2. The phonetic transcription module provides the pronunciation of the words.
3. The HMM module estimates a left-to-right HMM model for each of the phonemes (Figure 2.1) using the speech spectral parameters.
4. Given the phonemes of a sentence, it chains the HMM models and the most probable sequence of states is calculated using the Bitervi algorithm. With this information it can calculate the duration of each phoneme.
5. The phonetic transcriptions along with the duration predictions are converted to the label format from table ??.

This data also has to be normalized prior to training. The label format contains both categorical features and real features. The categorical information is 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  $\{A, B, C\}$ . Its one-hot encoding would be  $\{(1, 0, 0), (0, 1, 0), (0, 0, 1)\}$ .

The real features are normalized so that the mean equals zero and the standard deviation equals one. This is called z-norm and the operation is shown in 3.3.

$$z = \frac{x - \mu}{\sigma} \quad (3.3)$$

As for the predicted duration of each phoneme, rather than using the raw value and as previously mentioned, it is 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 [8]. Figure 3.6 contains the histogram of the raw predicted durations and the histogram after the log-compression operation.

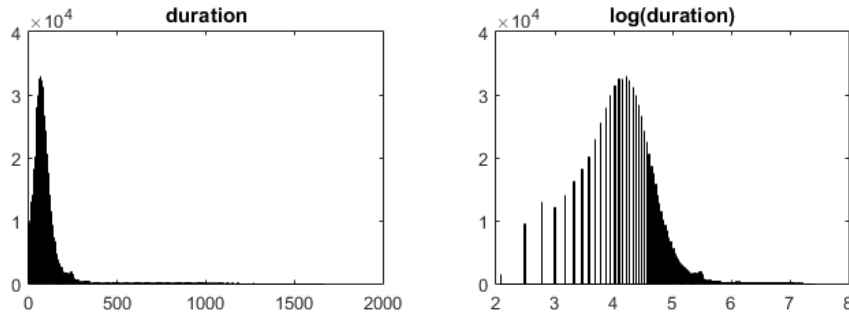


Figure 3.6: Histogram of the phoneme duration predictions by Ogmios.

Once we have ensembled the linguistic features, we discard of those who reference the past and only keep the ones tagged with an asterisk (\*). This is because the models are based on LSTM-RNN which are known to be good at modeling long term dependencies[11].

## 3.2 Expressive synthesis development

## 3.3 Sentiment analysis & embedding extraction task

Explain the two networks, the datasets used and how the data was prepared to be fed into the training process and how to obtain the expressive embeddings that will be used in the next section

## 3.4 Experiments

Explain the experiments that were carried out and whose subsequent evaluation and results are presented in the next chapter

## Chapter 4

# Evaluation & Results

This chapter shows the results from the different experiments and attempts to draw conclusions from them.

### 4.1 Objective evaluation

Training curves of the different stages of this project (accuracy & loss curves) as well as objective metrics from the work proposal document.

### 4.2 Subjective evaluation

Results from the subjective evaluation. Box plots comparing experiments.

## Chapter 5

# Budget

An approximation of the budget of this project, taking into account server uptime, weekly meetings, etc..

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