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Audio Analysis of an African Violin

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Report submitted in partial fulfilment of the requirements of the module
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Electrical and Electronic Engineering at Stellenbosch University.

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I would like to thank my dog, Muffin. I also would like to thank the inventor of the incubator; without him/her, I would not be here. Finally, I would like to thank Dr Herman Kamper for this amazing report template.



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Abstract

English

The English abstract.

Afrikaans

Die Afrikaanse uittreksel.

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Nomenclature

Variables and functions

$p(x)$	Probability density function with respect to variable x .
$P(A)$	Probability of event A occurring.
ε	The Bayes error.
ε_u	The Bhattacharyya bound.
B	The Bhattacharyya distance.
s	An HMM state. A subscript is used to refer to a particular state, e.g. s_i refers to the i^{th} state of an HMM.
\mathbf{S}	A set of HMM states.
\mathbf{F}	A set of frames.
\mathbf{o}_f	Observation (feature) vector associated with frame f .
$\gamma_s(\mathbf{o}_f)$	A posteriori probability of the observation vector \mathbf{o}_f being generated by HMM state s .
μ	Statistical mean vector.
Σ	Statistical covariance matrix.
$L(\mathbf{S})$	Log likelihood of the set of HMM states \mathbf{S} generating the training set observation vectors assigned to the states in that set.
$\mathcal{N}(\mathbf{x} \mu, \Sigma)$	Multivariate Gaussian PDF with mean μ and covariance matrix Σ .
a_{ij}	The probability of a transition from HMM state s_i to state s_j .
N	Total number of frames or number of tokens, depending on the context.
D	Number of deletion errors.
I	Number of insertion errors.
S	Number of substitution errors.

Acronyms and abbreviations

AE	Afrikaans English
AID	accent identification
ASR	automatic speech recognition
AST	African Speech Technology
CE	Cape Flats English
DCD	dialect-context-dependent
DNN	deep neural network
G2P	grapheme-to-phoneme
GMM	Gaussian mixture model
HMM	hidden Markov model
HTK	Hidden Markov Model Toolkit
IE	Indian South African English
IPA	International Phonetic Alphabet
LM	language model
LMS	language model scaling factor
MFCC	Mel-frequency cepstral coefficient
MLLR	maximum likelihood linear regression
OOV	out-of-vocabulary
PD	pronunciation dictionary
PDF	probability density function
SAE	South African English
SAMPA	Speech Assessment Methods Phonetic Alphabet

Chapter 1

Introduction

The last few years have seen great advances in speech recognition. Much of this progress is due to the resurgence of neural networks; most speech systems now rely on deep neural networks (DNNs) with millions of parameters [1, 2]. However, as the complexity of these models has grown, so has their reliance on labelled training data. Currently, system development requires large corpora of transcribed speech audio data, texts for language modelling, and pronunciation dictionaries. Despite speech applications becoming available in more languages, it is hard to imagine that resource collection at the required scale would be possible for all 7000 languages spoken in the world today.

I really like apples. [3]

1.1. Background

This is some section with two table in it: Table 1.1 and Table 1.2.

Table 1.1: Performance of the unconstrained segmental Bayesian model on TIDigits1 over iterations in which the reference set is refined.

Metric	1	2	3	4	5
WER (%)	35.4	23.5	21.5	21.2	22.9
Average cluster purity (%)	86.5	89.7	89.2	88.5	86.6
Word boundary F -score (%)	70.6	72.2	71.8	70.9	69.4
Clusters covering 90% of data	20	13	13	13	13

Table 1.2: A table with an example of using multiple columns.

Model	Accuracy (%)		
	Intermediate	Output	Bitrate
Baseline	27.5	26.4	116
VQ-VAE	26.0	22.1	190
CatVAE	28.7	24.3	215

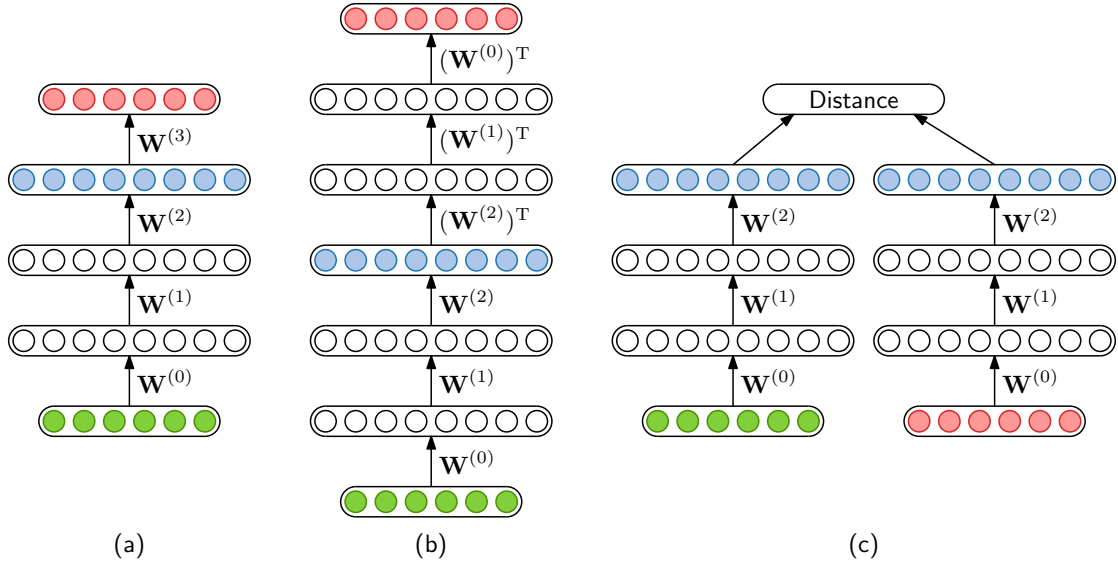


Figure 1.1: (a) The cAE as used in this chapter. The encoding layer (blue) is chosen based on performance on a development set. (b) The cAE with symmetrical tied weights. The encoding from the middle layer (blue) is always used. (c) The siamese DNN. The cosine distance between aligned frames (green and red) is either minimized or maximized depending on whether the frames belong to the same (discovered) word or not. A cAE can be seen as a type of DNN [1].

This is a new page, showing what the page headings looks like, and showing how to refer to a figure like Figure 1.1.

The following is an example of an equation:

$$P(\mathbf{z}|\boldsymbol{\alpha}) = \int_{\boldsymbol{\pi}} P(\mathbf{z}|\boldsymbol{\pi}) p(\boldsymbol{\pi}|\boldsymbol{\alpha}) d\boldsymbol{\pi} = \int_{\boldsymbol{\pi}} \prod_{k=1}^K \pi_k^{N_k} \frac{1}{B(\boldsymbol{\alpha})} \prod_{k=1}^K \pi_k^{\alpha_k-1} d\boldsymbol{\pi} \quad (1.1)$$

which you can subsequently refer to as (1.1) or Equation 1.1. But make sure to consistently use the one or the other (and not mix the two ways of referring to equations).

1.2. Problem Statement

1.3. Objective

1.4. Summary of Work

1.5. Scope

1.6. Roadmap

Chapter 2

Literature Review

Chapter 3

Method

Here is the frequency table we were talking about. You may need it at some stage to discuss results :-). Once you have your classification system, we'll look closely at all the ones that are different and we may need this to explain the difference. Please remember to stick with your files to the naming convention, so that we can identify the violins at the end.

General name structure: ViolinCodeNoteRepetition

Violin code: conventional (C), factory (F) and African (A) numbered consecutively

Note: G3, D4, A4, E5, E6 (I think Gerhard named the first few files wrong, please change the numbers to the correct ones)

Repetition of note: 1, 2, 3, 4, 5

3.1. Data Collection

Recordings made...

The wav files are named as follows: A = African violin C = Conventional violin F = Factory-made violin

Followed by note name: A5, D5, E5, G5, E6 or Adagio (piece)

So for example: A2-A5-001.wav is the note A5 played on an African violin

The equipment setup is:

Microphone: Sennheiser MKH 8020 (Omnidirectional) Position: 500mm above violin (end of fingerboard) Preamplifier: Sound Devices Mixpre 10t @ 30dB gain Sampling: 24 bits, 96 kHz

To get going, why not see if you can get the spectral analysis files I sent you working on these new recordings. As a sanity check, the spectra for the corresponding note of the African violin in these and the previous recordings should be very similar.

3.2. Data Preparation

Audacity

Chapter 4

Detailed Design

Chapter 5

Results

Chapter 6

Summary and Conclusion

Bibliography

- [1] G. E. Dahl, D. Yu, L. Deng, and A. Acero, “Context-dependent pre-trained deep neural networks for large-vocabulary speech recognition,” *IEEE Trans. Audio, Speech, Language Process.*, vol. 20, no. 1, pp. 30–42, 2012.
- [2] G. Hinton, L. Deng, D. Yu, G. E. Dahl, A.-R. Mohamed, N. Jaitly, A. Senior, V. Vanhoucke, P. Nguyen, T. N. Sainath, and B. Kingsbury, “Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups,” *IEEE Signal Process. Mag.*, vol. 29, no. 6, pp. 82–97, 2012.
- [3] M. Meincken, G. Roux, and T. Niesler, “An african violin – the feasibility of using indigenous wood from southern africa as tonewood.” *Afr J Sci.* 2021;117(11/12), Art.#11175, <https://doi.org/10.17159/sajs.2021/11175>, 2021.

Appendix A

Project Planning Schedule

This is an appendix.

Appendix B

Outcomes Compliance

This is another appendix.