### Vowel Tuner

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NLP M2

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## Outline

- Introduction
- 2 Methodology
- 3 Application
- Results and Discussion
- Conclusion and Future work

### Introduction



Introduction •000

### Our idea

Introduction

#### Aim

Help language learners improve their pronunciation of French vowels

#### Idea

Make a web application that can identify a vowel spoken by the user, and provide personalized feedback.

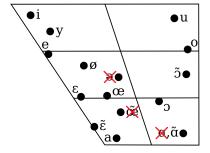
- Speaking is one of the tougher skills to master in terms of language learning [1]
- Many learners superimpose the phonetic inventory of their L1 onto L2 (phonetic substitution) [2]
- Comprehensibility can be increased if learners are made aware of phonetic boundaries in their target language.

Introduction

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$$/\alpha/\rightarrow/a/$$
  
"pâte" = "patte"

- $/ \ni / \to / \emptyset / \text{or} / \infty /$ "sur ce" /syʁsø/
  "prenait" /pʁœnɛ/[3]
- $/\tilde{e}/ \rightarrow /\tilde{\epsilon}/$ "brun" = "brin"[4]





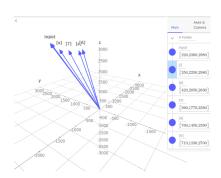






### Input:

- Formants
  - F1 openness
  - F2 frontness
  - F3 lip rounding
  - F4 nasality/paranasality
- Reference formants



## Reference approach

### Input:

Introduction

- Formants
  - F1 openness
  - F2 frontness
  - F3 lip rounding
  - F4 nasality/paranasality
- Reference formants

#### Prediction:

- Closest vowel in formant space
- Per-formant weight
- Improved using standard deviation

Bad results (<38% accuracy), difficult to finding good reference formants

 $\rightarrow$  Quickly abandoned



## Linguistic approach

### Input:

- Formants F1-F4
- Phonetic context
- Speaker gender

#### Classifiers:

- Decision Trees
- K neighbors
- Multinomial Logistic Regression
- Random Forests
- Multilayer Perceptron
- Extra Trees
- Bagging
- Stacking



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## Neural Approach

Introduction

- From audio to mel-spectrogram
- Images normalized and re-scaled
- Fed into CNN
- Softmax probability of each vowel
- Vowel with highest probability is chosen

## Vowel Extraction

Problem: The user says an entire word

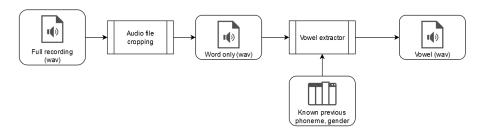


Figure: Vowel Extraction pipeline

### Datasets

- An informal corpus, recorded in real-life conditions, 8 students (6 male and 2 female), of which 5 native French speakers and 3 non-native learners.
- A subset of the InterFra corpus<sup>1</sup>, 2 non-native speakers, 2 native speakers, 225 vowels.
- The All Vowels corpus, native French speakers (34 female and 33 male speakers), 5,755 vowels.
- A testing corpus, French speakers in testing conditions, 900 vowels (see later)

## **Application**

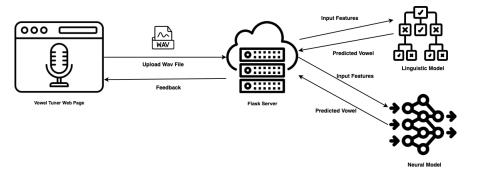


Figure: Vowel Tuner Application Diagram



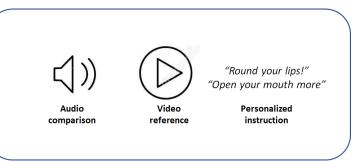
## Demo

# Demo time!



### Feedback

#### Feedback in three forms:



## Personalized feedback

Each vowel was tagged with four attributes:

- Openness
- Frontness
- Lip-rounding
- Nasality

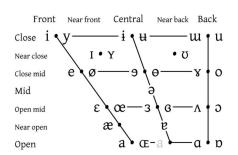


Figure: IPA vowel chart, courtesy of the International Phonetic Association.





## Linguistic classifier

Classifier	Accuracy	
Decision trees	74.25%	
K neighbors	79.40%	
Logistic regression	77.51%	
Multilayer perceptron	81.30%	
Extra trees	82.93%	
Random forest	82.93%	
Bagging	81.03%	
Stacking	80.22%	

Table: Test set accuracy of various classifiers on the All Vowels dataset

## Neural approach

Introduction

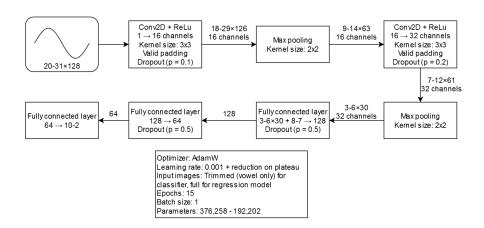


Figure: Best architecture for the neural classifier (left) and vowel extractor (right)

## Neural approach

#### Vowel extractor:

- Total MSE: 0.69371
- 17/356 noticeable errors
- 2 significant ones

#### Neural classifier:

Accuracy: 94.5946%



## **Human Evaluation**

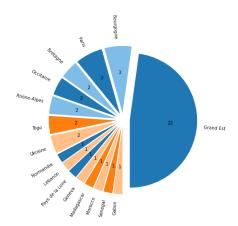


Figure: The origin of the 46 speakers (27 f, 19 m) who tested the system.



## Overall results

Accuracy	Male speakers	Female speakers	All speakers
Neural model	50.00%	53.59%	51.56%
Linguistic model	60.39%	77.69%	67.89%

Table: Accuracy of the models depending on the speaker's gender.

## Per vowel accuracy

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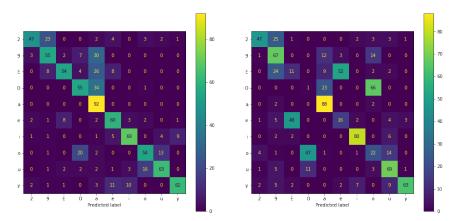


Figure: Confusion matrix of the linguistic (left) and the neural (right) model.



### Conclusion and Future work



## Conclusion

Introduction

#### **Neural model:**

Better in theory (94.59%), worse in real life (51.56%).

### Linguistic model:

Better in real life (67.89 %), worse in theory (82.93%).

#### Problems of neural model:

- Not noise robust
- Trained on homogeneous input

### Problems with linguistic model:

- Performance cap?
- Doesn't leverage confidence much



### Future work

Introduction

### Improvements:

- Better sound level detection
- More training data (e.g. from app users)
- Improve NN robustness (data augmentation with noise)
- ullet Gender input o types of voices

#### **Extensions:**

- Include nasal vowels
- Custom feedback based on the user's native language
- Include consonants
- Add more varieties of French



Merci! /merei/

- [1] Jessica S Miller. Teaching french pronunciation with phonetics in a college-level beginner french course. NECTFL Review, 69:47-68, 2012.
- Nancy F Chen and Haizhou Li. Computer-assisted pronunciation training: From pronunciation scoring towards spoken language learning. In 2016 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA), pages 1–7. IEEE, 2016.
- Bernard Rochet. Douglas c. walker. pronunciation of canadian french. ottawa: University of ottawa press. 1984. pp. xxii 185. \$15.00 (softcover). Canadian Journal of Linguistics/Revue canadienne de linguistique, 32(1):101–107, 1987.
- [4] Zsuzsanna Fagyal, Douglas Kibbee, and Frederic Jenkins. French: A Linguistic Introduction. Cambridge University Press, 2006.

## Accuracy per vowel

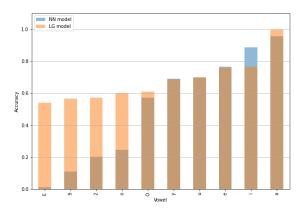


Figure: Accuracy of the neural (NN) and linguistic (LG) models for each true vowel in the dataset.

### Model confidence

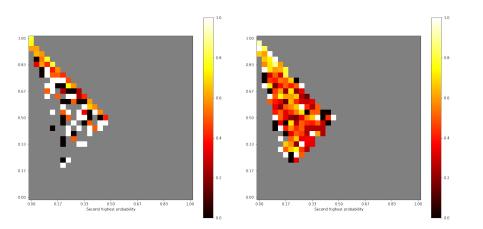


Figure: Accuracy of the linguistic (left) and neural (right) models depending on the value of the highest and second-highest probability returned.