GIPFA: Generating IPA Pronunciation from Audio

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Abstract
Transcribing spoken audio samples into International Phonetic Alphabet (IPA) has long been reserved for experts. In this study, we examine the use of an Artificial Neural Network (ANN) model to automatically extract the IPA phonemic pronunciation of a word based on its audio pronunciation, hence its name Generating IPA Pronunciation From Audio (GIPFA). Based on the French Wikimedia dictionary, we trained our model which then correctly predicted 75% of the IPA pronunciations tested. Interestingly, by studying inference errors, the model made it possible to highlight possible errors in the dataset as well as identifying the closest phonemes in French.

Keywords: Audio; Transcription; Phonemes; Artificial Neural Network; Dataset

1. Introduction

Some dictionaries like Wiktionary offer both listening to words spoken by real users and reading phonemic pronunciations in the form of the International Phonetic Alphabet (IPA).

However, in the case of the French Wiktionary, the phonemic IPA transcripts are subject to a small percentage of errors. Several reasons can explain these errors. First, Wiktionary contributors may not be IPA experts; second, even IPA experts sometimes may make careless mistakes; third, the audio may be inconsistent because it is generally recorded independently without taking IPA pronunciation into account, which can lead to important discrepancies; fourth, some sounds like /o/ and /ɔ/ may be very close to each other and can depend on the speaker.

This article examines whether such errors could be avoided by using a Natural Language Processing (NLP) tool to automatically extract phonemic IPA pronunciation from audio pronunciation.

To this purpose, we made use of Automatic Speech Recognition (ASR) which has already been the subject of in-depth studies. In particular, many recent implementation approaches have successfully used a deep Artificial Neural Network (ANN) as in Han et al. (2020) and Das et al. (2019), hence our choice to design a new ANN called Generating IPA Pronunciation From Audio (GIPFA). In order to train and test it, we also assembled a new experimental dataset based on 80400 samples from the French Wiktionary.

Despite a dataset containing an unknown percentage of erroneous data samples, our GIPFA model succeeded in providing reasonable accuracy. Although it failed to replace IPA experts, it nevertheless proved to be particularly useful in identifying the biggest errors in the dataset.

2. Methodology

In order to predict the IPA pronunciation of a word, two main steps were necessary: identifying a relevant dataset and designing an ANN model capable of inferring an IPA pronunciation from an audio pronunciation.
Table 1: Dataset

| Word       | Audio filename           | IPA pronunciation |
|------------|--------------------------|-------------------|
| bonjour    | LL-Q150 (fra)-LoquaxFR-bonjour.wav | bʒuin             |

2.1 Dataset

Our dataset came from a Wikimedia dump[^1] containing all pages and articles of the French Wiktionary. In this dump, each page generally contains three essential features: one word along with \( n \) main [IPA] pronunciations and \( m \) examples of audio pronunciations recorded by several speakers.

- A word is a text string containing Unicode characters. The word terminology has to be taken in the broad sense as a Wiktionary word contains common names, proper names words, abbreviations, numbers and even sayings. Although our ANN did not use it, we kept the word in our dataset for debugging purposes, in order to have the possibility to find back the Wiktionary page containing the pronunciations.

- An audio pronunciation refers to an audio file generally recorded in a Waveform Audio File (WAV) format containing the pronounced word. Wiktionary pages can contain one or more audio pronunciations for the same word. When an audio file is generated with LinguaLibre (LL)[^2] software, it benefits from three useful features: the audio file is under the Creative Commons sharing license[^3]; the file can be fetched from Wikimedia Commons[^4] based on its audio filename; the audio filename also contains a label representing a user name which can be used to identify audio files generated by users.

- An [IPA] pronunciation is a text string containing IPA symbols. For learning purposes, each audio pronunciation of a word should ideally be associated to a single [IPA] pronunciation transcribing this precise audio content; a ranking of the most common pronunciations might also be calculated and indicated in the page describing the word. However, most words have a single [IPA] pronunciation (i.e. \( n = 1 \)) even when multiple audio pronunciations are available. Although some words have multiple [IPA] pronunciations (e.g. coût), a Wiktionary page rarely indicates which of these pronunciations corresponds to an audio file.

For our purpose, we restricted our dataset to samples containing:

- Words of the French Wiktionary[^5]
- French words, given that each Wiktionary describes words of several languages;
- Words with a single [IPA] pronunciation, given that multiple [IPA] per audio sample introduce ambiguities;

[^1]: https://dumps.wikimedia.org/frwiktionary/20200501/
[^2]: https://lingualibre.org
[^3]: https://creativecommons.org/licenses/by-sa/4.0/
[^4]: https://commons.wikimedia.org/
[^5]: https://fr.wiktionary.org/
• **IPA** pronunciation containing symbols making part of the 37 traditional French phonemes (i.e. 'i', 'e', 'ê', 'a', 'â', 'o', 'u', 'y', 'Ô', 'œ', 'œ', 'ã', 'ã', 'ë', 'ê', 'û', 'ü', 'w', 'p', 'k', 't', 'b', 'd', 'g', 'f', 's', 's', 'Z', 'l', 'K', 'M', 'N');

• **IPA** pronunciation containing less than 20 phonemes, in order to keep our [ANN](#) model reasonable in size regarding our resources;

• Audio files recorded with [LL](#) in order to easily fetch audio files.

We also discarded 9 symbols that appear as optional in the [IPA](#) pronunciation of the French Wiktionary ('〜', '(', ')', '－', '、' and '・', '(', ')', '-').

The resulting dataset contained 80200 samples from 102 different speakers. As depicted in Table 1, each sample contained three features: a word, an audio filename and an [IPA](#) pronunciation.

In addition, we also pre-processed the [WAV](#) files to have a fix length of 2 seconds, and then converted them into an [Mel-Frequency Cepstral Coefficients (MFCC)](#) format so that they could serve as direct inputs into our model. Although processing audio files under a [WAV](#) format would be possible as in [Sainath et al.](#), it requires significant RAM memory, hence our choice to transpose them into a [MFCC](#) format, as usually performed in many studies like in [Alcaraz Meseguer](#) and [Nahid et al.](#).

### 2.2 Experiments

#### 2.2.1 Model architecture

![Figure 1: The GIPFA ANN model used for transcribing audio samples into IPA samples.](#)

We modeled our [GIPFA](#) ANN as depicted in Figure 1. It contains typical components found in many [ANN](#) models used for [ASR](#). However, given that we only had to translate a single word per sample, we did not use any Transformer component ([Vaswani et al.](#)). Each audio input sample [MFCC](#) data) first traversed a stack of two [Conv1D](#) layers to extract the shape of the MFCC data; followed by two [LSTM](#) filters ([Hochreiter & Schmidhuber](#)) to extract temporal sequences; and finally followed by a linear layer in order to allow a [CTC](#) loss calculation ([Graves](#)). We did not allow the succession of two identical phonemes because this is rare in French words. In addition, we used an [AdamW](#) optimizer ([Loshchilov & Hutter](#)) with a learning rate of $1 \times 10^{-4}$.

#### 2.2.2 Hyperparameters

We used Ray Tune ([Moritz et al.](#)) for fine-tuning our hyperparameters with respect to accuracy results. It led us to identify a set of best values among a larger set of experimented values as summarized in Table 2. The resulting model contained 9 609 558
trainable parameters. Slight variations in the best values did not lead to significant improvement. Although it is believed that wider network may have lead to better results (Nakkiran et al., 2019), we limited our model to these 10M parameters due to our limited computing resources.

| Hyperparameter      | Tested values | Best value |
|---------------------|---------------|------------|
| mfcc_coefficients   | 40            | 40         |
| conv1d_activ        | none, relu    | relu       |
| conv1d_layers       | 0, 1, 2, 3    | 2          |
| conv1d_units        | 32, 64, 128   | 128        |
| conv1d_bn           | False, True   | True       |
| lstm_layers         | 0, 1, 2       | 2          |
| lstm_units          | 128, 256, 512 | 512        |
| lstm_dropout        | 0.1, 0.25, 0.5| 0.5        |
| lstm_bidir          | False, True   | True       |
| lstm_bn             | False, True   | True       |
| optimizer           | Adam, AdamW   | AdamW      |
| lr                  | 1e-3, 1e-4    | 1e-4       |

Table 2: GIPFA hyperparameters values

2.2.3 Training

For the training step, we used 79,326 samples distributor over 3966 batches of 20 samples (3927 training batches and 39 evaluation batches). During a pre-processing step, all audio samples were standardized with a the mean (−11.48) and standard deviation (80.30) pre-observed on the dataset.

Before each run, the data samples were randomly shuffled. Each training run took approximately 10 epochs of 3 minutes each on a single GPU (GeForce RTX 2080, 8 GB).

2.2.4 Test

For the testing step, we used 1000 unseen samples to evaluate the performances of the GIPFA ANN.

2.2.5 Accuracy

Since solving the translation problem requires correct inference of the entire IPA pronunciation, we simply set for each tested sample an accuracy of 1 when our model predicted an IPA pronunciation equal to the tested target IPA pronunciation, or 0 otherwise. After each training run, we then calculated the average accuracy across all samples (i.e. average accuracy between 0.0 and 1.0).
We performed 11 runs (with one training step and one test step for each) to allow reasonable confidence in the average accuracy results. We finally computed a mean accuracy and the associated standard deviation (std) on the 11 tests.

Since the dataset had not been studied further, there was unfortunately no baseline reference to challenge our results.

### 2.2.6 Enlightenment on errors

To our knowledge, no study has examined the exactness and coherence of the audio files and IPA pronunciations of the French Wiktionary, meaning that the dataset may contain errors, making it difficult to assess whether a prediction error comes from the dataset or from the ANN.

In order to obtain more in-depth information on errors, we therefore also calculated three other metrics related to the 80000 samples in the dataset:

- **At the word level**
  - *Edit distance error*: the Levenshtein distance between the predicted IPA pronunciation and the target IPA pronunciation, in order to estimate how far the prediction was from the target.

- **At the phoneme level**
  - *Average phoneme accuracy*: the percentage of correct translations for each phoneme;
  - *Error pair percentage*: Since each of the 37 target phonemes can be incorrectly translated as one of the other 36 phonemes, the results can contain up to 37 * 36 categories of error pairs. To assess the representativeness of each pair, we calculated its number of occurrences divided by the total number of phonemic errors.

The code is available on Github.[6](https://github.com/marxav/gipfa)

### 3. Results

In this section, we describe two different results: first, the accuracy of the model; then a more detailed observation of errors at the phoneme level and at the word level.

#### 3.1 Accuracy

Table 3 presents the accuracy results which were consistent across the 11 runs; our GIPFA ANN model successfully predicted around 75 IPA pronunciations out 100 audio samples.

Correctly inferred pronunciations had a mean length of 7.51 whereas incorrectly inferred pronunciations had a mean length of 8.65 thus indicating a slightly higher probability of error as the length of the IPA pronunciation increased.

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[6] Code available at [https://github.com/marxav/gipfa](https://github.com/marxav/gipfa)
### Table 3: Pronunciation accuracy

| Training samples | Tested samples | Pronunciation accuracy (mean) | Pronunciation accuracy (std) |
|------------------|----------------|-------------------------------|-----------------------------|
| 79326            | 1000           | 0.75                          | 0.02                        |

Table 3: Pronunciation accuracy

### 3.2 Insights on the errors

Performing inferences on 80000 samples of the dataset allowed to better understand the reasons for the errors.

#### 3.2.1 Phoneme Accuracy

Table 4 reports the translation accuracy of each phoneme. One phoneme (/ɑ/) had poor accuracy (less than 50%), five phonemes (/o/, /η/, /ʌ/œ/, /η/ and /œ/) had moderate accuracy (between 65% and 89%) while the remaining thirty-one phonemes had high accuracy (over 90%).

![Confusion Matrix](image)

To better observe the details, we also detailed these phoneme translation errors in a confusion matrix as shown in Figure 2. Each row in the matrix represented a target phoneme while each column represented the distribution of predicted phonemes. For instance, it turned out that the target phoneme /ɛ/ was 6% of the time predicted as /e/, 92% as /ɛ/
| Target phoneme | Correct  | Incorrect | Average translation accuracy |
|----------------|----------|-----------|-----------------------------|
| a              | 392      | 605       | 0.39                        |
| o              | 4.615    | 2485      | 0.65                        |
| η              | 40       | 17        | 0.70                        |
| ø              | 241      | 89        | 0.73                        |
| m              | 697      | 110       | 0.86                        |
| œ              | 2459     | 301       | 0.89                        |
| η              | 1185     | 113       | 0.91                        |
| ε              | 15 859   | 1472      | 0.92                        |
| ø              | 7918     | 732       | 0.92                        |
| g              | 5911     | 427       | 0.93                        |
| o              | 2587     | 169       | 0.94                        |
| e              | 18 655   | 1074      | 0.95                        |
| w              | 30 018   | 1608      | 0.95                        |
| v              | 4357     | 159       | 0.96                        |
| u              | 7469     | 282       | 0.96                        |
| ê              | 6712     | 250       | 0.96                        |
| j              | 4527     | 192       | 0.96                        |
| b              | 12 753   | 434       | 0.97                        |
| n              | 13 165   | 472       | 0.97                        |
| p              | 14 845   | 464       | 0.97                        |
| l              | 23 181   | 684       | 0.97                        |
| ŋ              | 13 704   | 226       | 0.98                        |
| f              | 9632     | 225       | 0.98                        |
| y              | 8235     | 183       | 0.98                        |
| z              | 7730     | 146       | 0.98                        |
| i              | 34 772   | 664       | 0.98                        |
| d              | 15 975   | 323       | 0.98                        |
| k              | 23 159   | 503       | 0.98                        |
| f              | 4407     | 92        | 0.98                        |
| a              | 44 575   | 707       | 0.98                        |
| m              | 17 334   | 313       | 0.98                        |
| ñ              | 47 221   | 799       | 0.98                        |
| ʒ              | 5552     | 137       | 0.98                        |
| t              | 29 691   | 713       | 0.98                        |
| ʒ              | 9258     | 129       | 0.99                        |
| s              | 30 018   | 400       | 0.99                        |

Table 4: Average accuracy of each phoneme

and 1% /a/. Notable outliers were four large numbers outside the diagonal: 58% of /a/ seemed poorly predicted as an /a/; 31% of /o/ as /o/; 21% of /œ/ as /ê/; and 11% of /ŋ/ as /g/. It turned out that, like humans, the ANN had difficulties in differentiating near elementary sounds.
3.2.2 Error pair percentage

Table 5 represents the proportion of the error associated with each phoneme pair compared to the total errors of all pairs of phonemes. Interestingly, only three pairs of phonemes generated 31% of all errors: (/ο/, /ɔ/) (15% of all errors), (/ε/, /ɛ/) (12% of all errors) and (/α/, /ɑ/) (4% of all errors).

| Target phoneme | Predicted Percentage of phoneme | all errors |
|----------------|---------------------------------|------------|
| o              | o                               | 12.03%     |
| e              | ε                               | 6.51%      |
| e              | e                               | 5.46%      |
| a              | a                               | 3.16%      |
| o              | o                               | 3.07%      |
| t              | d                               | 1.25%      |
| ε              | a                               | 1.04%      |
| a              | α                               | 0.83%      |

Table 5: Most encountered error pairs

3.2.3 Word-level distance error

Table 6 reports a small mean Levenshtein distance and gives assurance that there is strong consistency between the audio content and the [IPA] pronunciation for the samples in the dataset studied.

| Computed Levenshtein distance |
|-------------------------------|
| samples | mean, std |
| 80000   | 0.31, 0.66 |

Table 6: Levenshtein distance

Table 6 reports a small mean Levenshtein distance and gives assurance that there is strong consistency between the audio content and the [IPA] pronunciation for the samples in the dataset studied.

However, Table 7 focuses on the most extreme outliers by reporting the 10 samples with the highest Levenshtein distance. Upon investigation, it was found that all these 10 samples contained either an error in the audio sample (e.g. bad word spoken or no word spoken at all) or an error in the target [IPA] pronunciation, which meant that all these errors were in the dataset itself. These results therefore suggest that data samples whose pronunciations have a high Levenshtein distance probably contain an error.

Additional work would be required to identify the best threshold distance to identify possible errors in the dataset.
4. Discussion and Conclusion

Previous work has documented the effectiveness of the ANN model for ASR. However, most studies have focused on the direct translation of audio samples into words.

In this study, we focused instead on the translation of audio samples into phonemes. We first proposed an ANN predicting with 75% accuracy the French pronunciations of the French Wiktionary.

Since to our knowledge no existing work has been done on this specific task and dataset, there was no basis for comparison or assurance as to the accuracy and consistency of the data.

We have shown that the translations of certain phonemes were more problematic since some phonemes are close elementary sounds (/o/ and /a/, /ɛ/ and /e/, /ɑ/ and /a/) and thus difficult to be distinguished. Future work may consider carefully checking the audio samples and IPA pronunciations containing these close phonemes, which would in turn enhance the efficiency of the ANN. In addition, future work could also involve synthesized audio examples and use them as additional samples to reinforce training data.

However, we have also shown that the Levenshtein distance between our GIPFA prediction and the target (as it exists in the dataset and therefore in the Wiktionary) can highlight the most suspect samples in the dataset. Such results therefore suggest that our GIPFA ANN would be a valuable tool to help verify the consistency of the Wiktionary regarding pronunciation.

Therefore, integrating it into a tool like LL should be useful in order to suggest an IPA transcription. It could even be used to suggest an IPA transcription associated with each recorded audio sample, since having one IPA transcription per audio file should further improve the performances of the ANN.

Finally, we believe this method should be applicable to other languages provided that a sufficient number of training samples are available.
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