Emotion detection from sound. Project report

December 28, 2019

by Alena Churakova

1 Introduction

1.1 Domain background

Much of the natural language understanding by a machine is based on study of text. This project focuses on recognition of emotions from the sound of human speech. Researchers recognize the importance of teaching machines to recognize human emotions, which can be used to adapt machine's action appropriately [1]. The rise of virtual personal assistants shows people willingness to interact with machines by voice. Analysis of tone in addition to the text information has a potential to make the interactions more natural, pleasant and effective.

1.2 Problem statement

A sentence with a neutral meaning, e.g. "This is a dog", carries factual content. Depending on the context and a person's attitude. The same sentence can be pronounced with happiness in the voice by a child who was secretly hoping their parents get a puppy a birthday present. A burglar, on the contrary, would likelier say it with fear.

The task is to recognise emotions from the audial signals of human speech, without involvement of text analysis. A model developed in this project can be useful in an application where a machine changes its action based on emotion detection, e.g. encourage the conversation partner when detecting sadness.

1.3 Evaluation metrics

In a described example scenario of changing machine's actions based on the detected emotion, an accurate prediction brings value of appropriate reaction by a machine. This motivates to use accuracy as an evaluation metric from the application/business perspective. Given a balanced dataset, this metric seems appropriate from a methodological perspective as well.

[1] Maghilnan S and Rajesh Kumar M. Sentiment Analysis on Speaker Specific Speech Data https://arxiv.org/pdf/1802.06209.pdf

2 Development

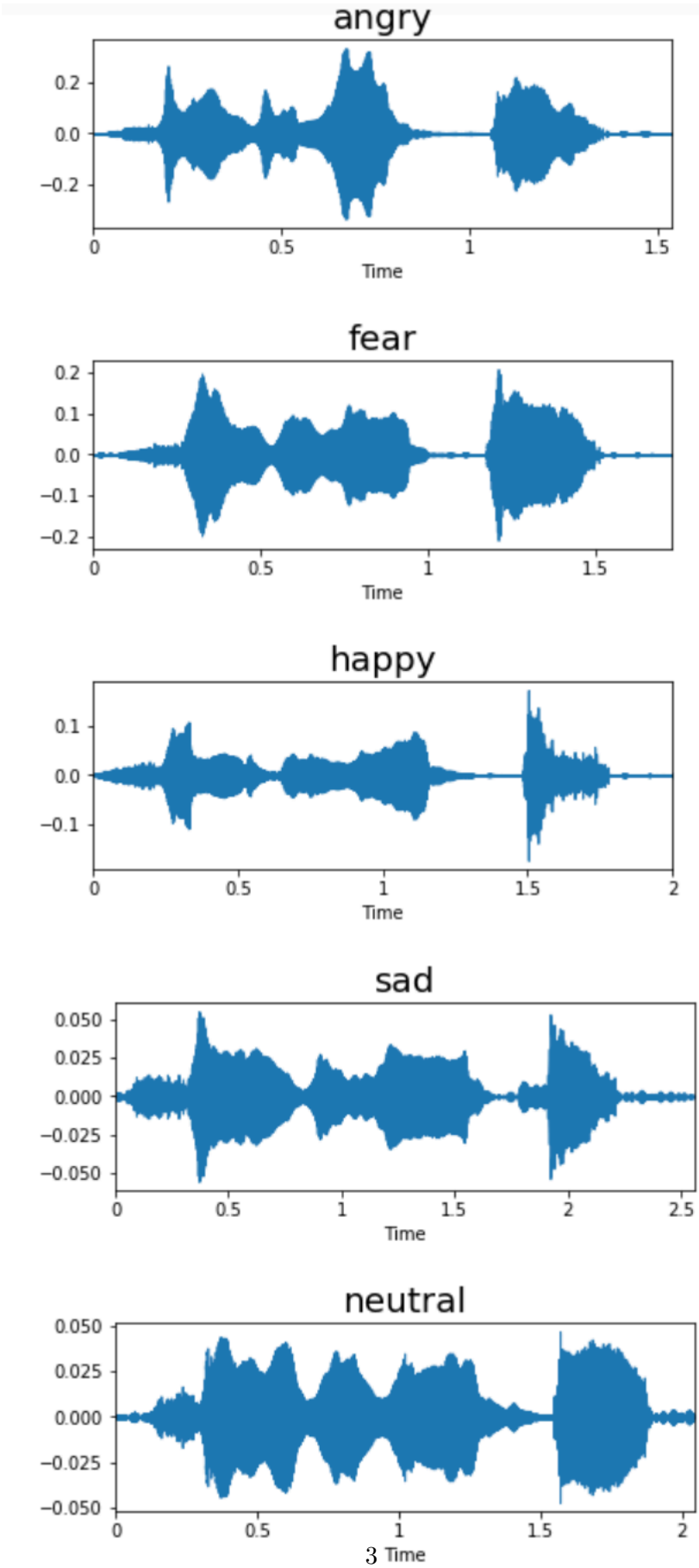
2.1 Data exploration

As outlined in the project proposal, the Toronto emotional speech set (TESS)[2] was used. It consists of short audiofiles (.wav format) recorded by two actors of different ages. Labels in the analysed dataset name emotions. Having heared multiple audio files, it became clear that a human would misclassify some of them. This happens because labels depend on interpretation of the speaker and overall, emotions labelling is difficult for people, let alone doing it from the voice.

This project concentrated on a few expressions - sad, happy, fear, angry and neutral. The dataset is balanced and the total number of files in each category is 400.

Visual inspection of audio represented as a time-series with the amplitude on the y-axis does not reveal large differences between emotions. This is likely be due to fact that audio files have a strict pattern 'Say the word _'.

[2]Dupuis, Kate and Pichora-Fuller, M. Kathleen (2010). Toronto emotional speech set (TESS) https://tspace.library.utoronto.ca/handle/1807/24487


angry
0.2
0.0
−0.2
0
0.5
1
1.5
Time
fear
0.2
0.1
0.0
−0.1
−0.2
0
0.5
1
1.5
Time
happy
0.1
0.0
−0.1
0
0.5
1
1.5
2
Time
sad
0.050
0.025
0.000
−0.025
−0.050
0
0.5
1
1.5
2
2.5
Time
neutral
0.050
0.025
0.000
−0.025
−0.050
0
0.5
1
1.5
2
Time

2.2 Pre-processing and feature engineering

In comparison to working with tabular data that might be used in machine learning directly, features should be extracted from sound files. As a preparatory step for feature engineering and training, metadata about audio files was created. Information for the metadata are extracted from file names that have a following pattern: talker_word_emotion.wav, e.g. OAF_back_angry.wav. Attributes currently used in the following steps are file name and class label (emotion).

Metadata examples:

filename	file_id	speaker	word	label
OAF_back_angry.wav	1	OAF	back	angry
OAF_back_fear.wav	3	OAF	back	fear
OAF_back_happy.wav	4	OAF	back	happy
OAF_back_neutral.wav	5	OAF	back	neutral
OAF_back_sad.wav	7	OAF	back	sad

Mel-Frequency Cepstral Coefficients (MFCC) is a well established feature for audio files that takes advantage of multiple ideas in sound preprocessing (overlapping windows, fast Fourier transforms, etc).[3] Despite being invented in the 70s, it is still often named state-of-the-art in articles on audio processing.[ˆ10]

The number of extracted coefficients in MFCC describe different number of sound aspects and various numbers were evaluated during the project. The modelling section below presents the influence of the number of extracted coefficients on the model perfomance.

2.3 Modelling

2.3.1 Benchmark

A no-model (random) prediction for a classification task could serve as a benchmark for all modelling approaches. With five categories (sad, happy, fear, angry, neutral) and a balanced data set, a baseline accuracy would be appx. 20%.

2.3.2 Approach

TESS data for five emotions was split to train (2/3) and test (1/3) with stratification. In addition, I recorded a few files myself, imitating different emotions. These were used for plausibility check after the final model was selected, in order to avoid influence of some picularities of the TESS dataset.

Deep learning approach suits the multi-class classification in the speech domain and will be followed in this project. This project utilized the *keras* framework with the *TensorFlow* backend for its

[3] Mendels, Gideon. How to apply machine learning and deep learning methods to audio analysis https://towardsdatascience.com/how-to-apply-machine-learning-and-deep-learning-methods-to-audio-analysis-615e286fcbbc

simplicity in use combined with robustness and integration with later AWS SageMaker model deployment. In particular, various architectures of Multilayer Perceptron (MLP) with different number of MFCCs (column one in the table below) were compared to the no-model benchmark performance in terms of accuracy. My guiding principle: a parsimonious model is prefered, however, it should be able to learn the complexities of the imput well enought. Performance above 85-90% could be considered sufficient.

Notes on models with their respective architectures:

Model 1

A ridiculously simple model that aims at verifying that there is nothing strange going on with the train and test data. It includes an input layer and a single fully-connected layer with two neurons and a ReLU activation function and an output layer with a softmax activation function.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_58 (Dense)             (None, 2)                 102
_________________________________________________________________
dense_59 (Dense)             (None, 5)                 15
=================================================================
Total params: 117
Trainable params: 117
Non-trainable params: 0
```

Model 2

Type of the activation fuctions as in model 1. The number of neurons in the hidden layer equals to the number of MFCCs (13, 20, 30, 40, or 50 respectively). A drop out layer is added to prevent overfitting. The architecture below depics the version with 50 MFCCs.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_60 (Dense)             (None, 50)                2550
_________________________________________________________________
dropout_29 (Dropout)         (None, 50)                0
_________________________________________________________________
dense_61 (Dense)             (None, 5)                 255
=================================================================
Total params: 2,805
Trainable params: 2,805
Non-trainable params: 0
```

Model 3

Increased number of neurons in a hidden layer (128) compared to in model 2. Dropout layer.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_62 (Dense)             (None, 128)               6528
_________________________________________________________________
dropout_30 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_63 (Dense)             (None, 5)                 645
=================================================================
Total params: 7,173
Trainable params: 7,173
Non-trainable params: 0
```

Model 4

Even higher number of neurons in a hidden layer (256). Dropout layer.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_64 (Dense)             (None, 256)               13056
_________________________________________________________________
dropout_31 (Dropout)         (None, 256)               0
_________________________________________________________________
dense_65 (Dense)             (None, 5)                 1285
=================================================================
Total params: 14,341
Trainable params: 14,341
Non-trainable params: 0
```

Model 5

Additional hidden with the same number of neurons then the first one (). layer Dropout layer after each hidden layer.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_66 (Dense)             (None, 256)               13056
_________________________________________________________________
dropout_32 (Dropout)         (None, 256)               0
_________________________________________________________________
dense_67 (Dense)             (None, 256)               65792
_________________________________________________________________
dropout_33 (Dropout)         (None, 256)               0
_________________________________________________________________
dense_68 (Dense)             (None, 5)                 1285
=================================================================
Total params: 80,133
Trainable params: 80,133
Non-trainable params: 0
```

The learning process was configure in the same way for all models: Adam optimizer, categorical crossentropy loss function and accuracy as an evaluation metric.

2.3.3 Results

Overview of the accuracy on the test dataset:

MFCCs	Benchmark (theory)	Model 1	Model 2	Model 3	Model 4	Model 5
13	0.2	0.2	0.28	0.73	0.81	0.44
20	0.2	0.2	0.39	0.88	0.94	0.32
30	0.2	0.2	0.65	0.96	0.95	0.62
40	0.2	0.24	0.91	0.98	0.97	0.80
50	0.2	0.2	0.94	0.97	0.99	0.95

Main observations from the experiments with combinations of feature engineering and modelling:

- As intended, Model 1 can be interpreted as a practical benchmark. With the accuracy of 20% it perfoms exactly as a no-model benchmark.
- In general, performance of Models 2 to 5 increases with larger number of MFCCs. As number of extracted coefficients rises, there is a danger that the amount of data would become unsufficient for their estimation. Which in term would deteriorate generalizability of the model.
- There should be a balance between number of inputs and network complexity. For example, Model 5 performs poorly with low number of MFCCa. Overall, as more parsimonious models are prefered, considering no advantages in terms of performance by Model 5, it is not selected as a final model.
- There seem to be no large performance gains between Model 3 and 4, especially with higher MFCCs, therefore Model 3 is preferred.
- Model 2 performs well starting from quite high number of MFCCs, while Model 3 does so on much lower number of dimensions. This gives a preference to Model 3 with 30 MFCCs.
- Model 3 with 30 MFCCs was selected as the final model for deployment for the sum of reasons presented above. According to the confusion matrix below (actual values as rows and predicted as columns), the model classified some of the neutral expressions as sad (quite plausible and could be misclassified by a human), and predicted some happy and fearful expressions as angry.

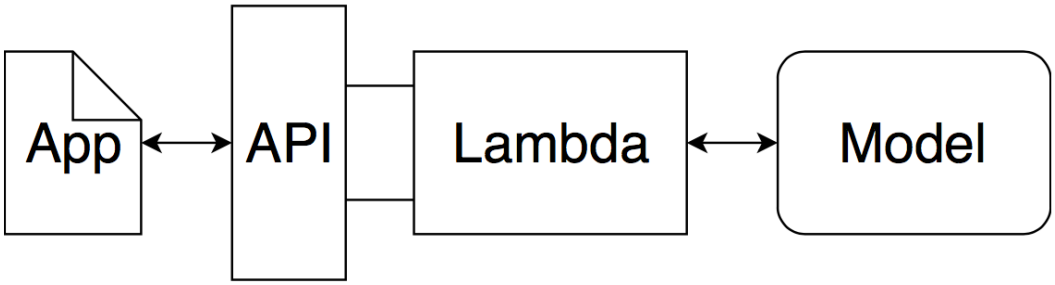
col_0 / row_0	sad	happy	angry	fear	neutral
sad	132	0	0	0	0
happy	0	123	8	0	1
angry	0	4	124	3	1
fear	0	0	3	129	0
neutral	13	0	0	0	119

The validation of the selected model on the self recorded files demonstrated correct prediction for all three files. This is not representive in terms of numbers, but was used as a plausibility check that the model works on an audio file not belonging to the test and train sets. This last step in development bilds a bridge to model deployment and serving in the next section.

3 Deployment and Serving

The productionizing of the solution includes model deployment and making prediction.

As described in the previous section, a keras model was trained. This project included a deployment of a keras model on AWS SageMaker and serving predictions via an app. The general overall serving architecture [4] is presented below:



Subsection belows describe different aspects of achieving the target architecture: model deployment, making predictions, Lambda function, API gateway and web app.

An AWS blogpost about deployment of a keras model on SageMaker [5] gave me a good general idea how to proceed. First, I changed the training approach to save model in a format enabling deployment on SageMaker. The blogpost described a workaround to deploy a model, by using *sagemaker.tensorflow.model.TensorFlowModel* and simulating its creation with an empty *train.py* file. As I discovered from the Sagemaker documentation, there is now a better way to deploy directly from model artifacts with *sagemaker.tensorflow.serving.Model* [6]. Importantly, the specification of the *framework_version* parameter aligns the TensorFlow version of the trained model with the version of the serving model. Otherwise, an error was thrown. In my case, inclusion of the *framework_version='2.0.0'* was necesary, because the model was trained with TensorFlow 2.0.

An end user is interested in the emotion label. e.g. *happy*. My approach during the prototype stage was to call *.predict_classes()* on the model to get a class represented by an integer and then transform it back to string labels with *.inverse_transform()* of the created *LabelEncoder()*.

A model deployed in SageMaker has no method *.predict_classes()*, but only a *.predict()* method that outputs probabilities for all classes. This method correspons to the *.predict()* on a local model.

[4] Udacity github repository https://github.com/udacity/sagemaker-deployment/blob/master/Project/Web%20App%20Diagram.svg

[5] Priya Ponnapalli (2019). Deploy trained Keras or TensorFlow models using Amazon SageMaker https://aws.amazon.com/blogs/machine-learning/deploy-trained-keras-or-tensorflow-models-using-amazon-sagemaker/

[6] Sagemaker Documentation. Deploying directly from model artifacts https://sagemaker.readthedocs.io/en/stable/using_tf.html#de directly-from-model-artifacts

A class with a maximum probabilitz value is predicted. For example, 0.53587806 is the maximum among (0.01964708, 0.03498399, 0.53587806, 0.01071843, 0.39877242) and the class 2 is predicted. With the help of a mapping dictionary, the class to is transformed to *happy*.

This logic developed for transforming probability predition into labels was applied in the **Lambda** function that receives MFCCs from the web app, invokes the prediction endpoint, receives the probability prediction for all classes from the endpoint and tranforms it to the emotion class predition.

A public **API** to access the deployed model was created using Amazon API Gateway. It that triggers the Lambda function described above.

The predictions can be served to users via a **web app**. The *Submit* button from the first screenshot below makes a POST request to the API assessing the deployed model. An example of a prediction can be seen on the second screenshot below.

4 Further work

Improvements could be done in various aspects of the project: data, feature engineering, modelling, and web app.

- **Data**: Extend list of emotions from the used TESS dataset.
- **Data**: Add data from another datasets containing emotion labels, e.g. consider RAVDESS Emotional song audio [7].
- **Feature engineering**: Experiment with other features extracted from sound, an overview could be found in the Audio Features chapter [8].

[7] Zenodo. RAVDESS Emotional song audio https://www.kaggle.com/uwrfkaggler/ravdess-emotional-song-audio
[8] Theodoros Giannakopoulos and Aggelos Pikrakis (2014). Introduction to Audio Analysis

- **Modelling**: Further experiments with MLPs, e.g. with optimizers or activation fuctions.
- **Modelling**: Experiment with other deep learning architectures, e.g. ones presented in a recent article [9] that reviews state-of-the-art deep learning techics for audio processing.
- **Web app**: improve the user interface by providing a possibility to record or upload an audio spippet for emotion detection.

[9] Hendrik Purwins, Bo Li, Tuomas Virtanen, Jan Schlüter, Shuo-yiin Chang, Tara Sainath (2019). Deep Learning for Audio Signal Processing. https://arxiv.org/abs/1905.00078