

Urban Sound classification

Statistical methods for machine learning
experimental project report

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Contents

1	Introduction	2
2	Feature extraction	3
2.1	Dataset structure	3
2.2	First dataset	4
2.3	Extended dataset	4
3	Model definition	6
3.1	Neural network structure	6
3.2	Initial training set results	7
3.3	Hyperparameter tuning	8
4	Results and final remarks	10
4.1	Test set results	10
4.2	Future works	10

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1 Introduction

The goal of this project is to build a neural network to classify audio files from the *UrbanSound8k* dataset [?].

This dataset contains audio divided in ten classes, each one representing a different type of city sound, for instance, we can find *car horns*, *dogs barking*, *sirens*, etc. A deeper discussion about the dataset is made at Subsection 2.1 on the following page.

The presented methodology is composed of three main parts. The first step is to extract relevant features from audio files, this is discussed on Section 2 on the next page.

The next step consists in composing and refining a neural network to classify the data obtained from the feature extraction phase. This part is discussed in Section 3 on page 6.

Lastly, results from the classification, namely accuracy and standard deviation among test sets, and possible future works are presented in Section 4 on page 10.

Project structure The project folder is structured as follows:

- *src*: this contains the source code for the project. Each sub-folder contains code for a specific part of the processing. In particular, the *data* folder holds classes to extract features and to manage the dataset, the *model* folder contains the class to create the Neural Network, then *utils* stores utility functions to measure performances;
- *data*: here data is stored, there is a *processed* and *raw* sub-folders, where the first stores computed datasets and the second original data;
- *models*: trained models are saved here;
- *notebooks*: the folder contains the Jupyter notebooks used in the project, where code from *src* is practically used.

The code is written in *Python* [?].

2 Feature extraction

This Section presents the original dataset structure and the steps followed to create training and test sets from it.

Note that the models mentioned in this section are three layers *multilayer perceptron* with a reasonable number of neurons, trained for 100 epochs with default parameters for the *Stochastic Gradient Descent optimizer*. [?] [?]

The accuracy on the training is computed with a *cross-validation* approach. [?] Details about models and validation techniques used in the project can be found at Section 3 on page 6.

2.1 Dataset structure

The dataset contains ten folds of audio samples, each one about four seconds long. The samples are divided in ten classes.

From the total of ten folds, the number one, two, three, four and six are taken as a training set, the others are each one a test set. For this reason the following count about class numerosity considers only the five training folds.

Class name	Number of samples
air conditioner	500
car horn	208
children playing	500
dog bark	500
drilling	500
engine idling	517
gun shot	190
jackhammer	548
siren	536
street music	500

The table shows a clear class imbalance. In particular, the classes *car horn* and *gun shot* are not as numerous as the others. This can lead to poor performances on these two categories, it is therefore taken into consideration with training.

The following table shows the number of samples in the training set and the various test sets.

Dataset	Number of samples
Training set	4499
Test set 5	936
Test set 7	838
Test set 8	806
Test set 9	816
Test set 10	837

All the operations on the datasets are performed with *Pandas* library. [?]

2.2 First dataset

Choosing the features to extract was challenging due to the inexperience working on audio files, thus some *research* on what features to choose was necessary [?].

To extract information from audio files *Librosa* was used. [?] The library provides many methods to choose from, to keep it simple, for the first try with this dataset, the extracted features are these three ones:

1. *Mel-frequency cepstral coefficients*;
2. *Chromagram*;
3. *Root-mean-square*.

Each feature consists of an array of arrays containing measurements. A series of functions were applied to each sub-array and results were concatenated in a final feature vector. The functions applied are *minimum*, *maximum*, *mean* and *median* from the *Numpy* library [?].

This approach resulted in 132 components feature vectors.

Parallelizing feature extraction Extracting the three features listed above is really intensive but the task is easily parallelizable, in fact, each file is independent from one another.

For this purpose *Dask* was used to speed up the computation, and extract features from audio files in a multi-processing fashion. [?]

Feature scaling After testing some Neural Networks on the first dataset the results were not promising. One of the reasons is the big difference in ranges among feature vector components.

To mitigate this effect a *StandardScaler* from *scikit learn* was applied [?]. The result is a dataset where each feature has more or less a distribution centered in zero with unit variance. This lead to an improvement on the results using the same model as before.

2.3 Extended dataset

Results using the three features named in the previous Subsection are promising but not enough, thus, to improve results on the training set, new audio characteristics are extracted, namely:

1. *Zero-crossing rate*;
2. *Roll-off frequency*;
3. *Spectral flux onset strength*.

As before, *minimum*, *maximum*, *mean* and *median* are applied to each feature vector and results are concatenated, resulting in 12 new features for each audio file. Scaling yield to promising results on the first dataset, so the same approach is applied to the extended one.

After testing a network on the new training set results improved once again.

Feature selection Adding new features can lead to better results in the end but they all need to be useful to the model, so the extended dataset was subject of some experiments with feature selection, in particular *PCA* algorithm from scikit learn was applied [?].

The main idea is to select a reduced number of features from the total, without losing information. This approach often leads to better results, as useless features are discarded.

After some experiments with the number of features to select, 120 out of 144 were selected. This led to a small improvement on the training set.

3 Model definition

This Section starts by presenting how the networks used on the training set are structured. The second Subsection gives an overview of the performances on the different training sets, lastly, the Hyperparameter tuning phase is described.

3.1 Neural network structure

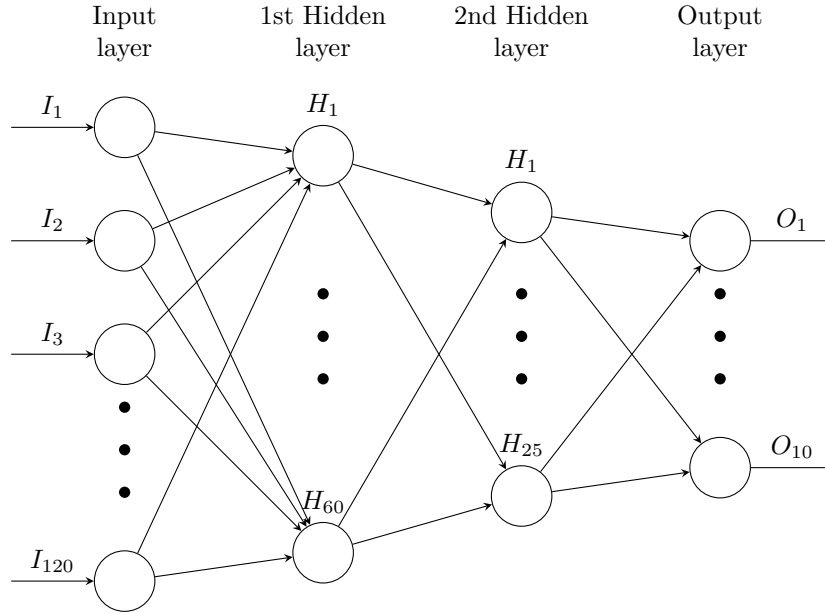
The starting point for the neural network structure was a reasonable network in terms of hidden neurons to prevent over-fitting, indeed a high number of units in the hidden layers would end up in learning too much from the dataset, leading to poor performances on the test sets.

For this reason, the rule of thumb followed to decide hidden neurons quantity is the following:

$$\#hidden\ neurons = \frac{2}{3} \#input\ neurons + \#output\ neurons$$

The next step is to decide the hidden layer number. To respect the number of hidden neurons, two hidden layers were considered. A higher number of layers would mean having a real small number of neurons per layer.

To give reference, this is the model used on the PCA training set, mentioned at the end of Subsection 2.3 on page 4, with 120 input features.



The activation function for the input and hidden layers is a *Relu* and the output one uses a *Softmax* to have classification probabilities among classes. [?] [?]

The loss used is the *Sparse Categorical Crossentropy loss* as it is suited for this kind of problems. [?]

To build the actual model *Tensorflow* and *Keras* library are used. [?] [?]

As discussed in the previous Section, models with this logic for construction were tested on the four training sets to choose the one to tune the final network on.

3.2 Initial training set results

Section 2 on page 3 talked about the four different training sets obtained from the dataset and, without going into details, stated that there was continuous improvement. We now give a more detailed look on training performance.

Note that all the random seeds used by Tensorflow were fixed to make results reproducible.

Class imbalance To deal with the minority of some classes, balancing techniques should be applied when fitting the model. One of the possible approaches, and the one followed here, is to assign class weights.

The main idea is to penalize errors made on not well represented classes, to account for their minority. To compute class weights, the *compute class weights* function from sklearn was used. [?]

The following are the computed quantities for the dataset classes:

Class name	Number of samples	Class weight
air conditioner	500	0.8998
car horn	208	2.1629
children playing	500	0.8998
dog bark	500	0.8998
drilling	500	0.8998
engine idling	517	0.8702
gun shot	190	2.3678
jackhammer	548	0.8209
siren	536	0.8393
street music	500	0.8998

As expected, the less numerous classes have higher class weight than the rest.

Stratified cross-validation To estimate performance on the training set stratified cross-validation with five folds was used. Basically the dataset is divided into five parts and a model is repeatedly trained on four and tested on one, all while considering class distribution, indeed, the original distribution of the classes is maintained in the splits. [?]

The stratified approach is required, as there is class imbalance on the training

set. The mean accuracy on the test folds gives a hint about the model performance. For this step the *Stratified KFold* class from scikit learn was used. [?]

Results For each presented training set, a model was defined with the structure presented at the beginning of this Section, and these are the results:

Training set	Mean accuracy	St. deviation
132 features unscaled	0.1138	0.0039
132 features scaled	0.5743	0.0324
144 features scaled	0.6079	0.0486
120 features reduced with PCA	0.6143	0.0481

There is a great improvement after scaling the training set, after that small refinements were made. As accuracy is the best on the last dataset, this was the one selected to perform the Hyperparameter tuning.

3.3 Hyperparameter tuning

Choosing the training set with PCA applied led to the best results with cross validation. Although the model was reasonable, it can not be the final one, as many parameters were left on their default value, for instance, learning rate and momentum of the optimizer were left untouched.

The main goal now is to experiments with different model parameters to find the best one.

Grid and Random search comparison Two of the most commonly used strategies in Hyperparameter optimization are *Grid* and *Random Search* [?].

In both cases we define ranges of parameters to test different combinations, for instance, fixed the number of neurons, one could try to find the best combination of learning rate and momentum that optimize accuracy on the training set.

While similar, the two methodologies differs in the amount of exploration they do. The Grid search try all the possible combinations of parameters, while the Random approach fixes a number of iterations and picks an arbitrary combination each time.

Obviously the first one is more computationally expensive than the second, if we fix a small amount of possible iterations, but in theory it finds a better result than going the random route. Nonetheless the Grid Search can led to over-fitting, and in practice Random Search in preferred.

Random search Starting from the model introduced in the previous Subsection, parameters are tweaked to find a better one.

Note that class weights are still considered and the models are evaluated again with a stratified cross-validation. The optimizer used is the Stochastic Gradient Descent. The considered ranges for parameters for this run are:

1. *Neurons*: first and last layers stay the same, while the two hidden layers are tested with a number of neurons respectively equals to:

$$60 + 2i \text{ and } 25 + 2j, \text{ with } i, j \in \{-2, -1, 0, 1, 2\}$$

2. *Learning rate*: 0.001, 0.01, 0.1, 0.5;
3. *Momentum*: 0.0, 0.01, 0.1, 1.

An early stopper is used on the fit with 100 *epochs*, *batch size* is fixed at 32. The total possible models are 400, but the search was performed with 100 iterations in total.

The best model found is the following:

- *Neurons*: 120 for input, 62 for the first hidden layer, 27 for the second, and 10 for output;
- *Momentum*: 0.0;
- *Learning rate*: 0.1.

Comparing the initial model with the one found now, a small improvement can be seen in accuracy despite a worse standard deviation:

Model	Mean accuracy	St. deviation
Initial model	0.6143	0.0481
Random search result	0.6297	0.0530

This is the final model found, therefore it is the one evaluated on the test sets.

4 Results and final remarks

This last Section shows the results obtained on the different test sets and possible improvements.

4.1 Test set results

As stated on the first Section, the five test sets are made out of the folds number five, seven, eight, nine and ten. Evaluating the model found by the Random Search on the test sets gives the following results:

Test set	Accuracy
Fold 5	0.6496
Fold 7	0.6169
Fold 8	0.7395
Fold 9	0.6789
Fold 10	0.6774

Finally, the mean accuracy and standard deviation for the test sets are:

Mean accuracy	Standard deviation
0.6724	0.0403

4.2 Future works

The results on the test sets are promising, but there is definitely room for improvement.

Indeed, a more refined training set creation can be made, by exploiting more features from the Librosa library, testing different type of scalers and experimenting with different feature selection techniques.

Finally, the models used in the project are simple, more complex Neural Networks with Convolutional layers could learn more from the training set and improve performances on test.