

# Urban sound classification

Francesco Tomaselli

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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.

## 2 Feature extraction

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

The training set consists of the first four folds plus the sixth, the other folds create five different test sets.

### 2.1 First dataset

Choosing the features to extract was difficult as I did not have prior experience working with audio.

The *Librosa* library provides many feature to choose from, for my first try with this dataset I kept it simple by opting for these three ones:

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

Each feature consists of an array of arrays containing measurements. I applied a series of functions to each sub-array and then concatenated the results in a final feature vector. The functions applied are *minimum*, *maximum*, *mean* and *median*.

This approach resulted in 132 components feature vectors.

**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.

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To mitigate this effect scaling was applied to the dataset. This lead to an improvement on the results using the same model as before.

The scaler trained on the training set was then used to scale the five different tests sets.

## 2.2 Extended dataset

To improve results on the test sets new features were added to the dataset, namely:

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

After applying the same four functions to these three new arrays, a total of 12 new features were added to the dataset. Also, as scaling yield to promising results, the same scaler was used on this new dataset.

After testing a really simple network on the new dataset results improved once again.

**PCA** Scaling lead to important improvements on the first dataset, so I decided to try the PCA to select the most important features from the extended one.

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## 3 Model definition

### 3.1 Neural network structure

### 3.2 Hyperparameter tuning

## 4 Results

### 4.1 First dataset

### 4.2 Extended dataset

## 5 Final remarks