Final Project

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1 Introduction

The database is a set of noisy recordings, which have poor quality for further usage. So it make sense to improve them. In order to remove the noise, we propose to use online dictionary learning.

2 Problem Statement

We used a python library known as librosa to import our audio[1]. The audio recordings found in our test set had a sampling rate of 22050. This meant that every second of audio held approximately 22,000 numbers to represent it. For this reason, down sampling became necessary. Although some sacrifice in audio quality was necessary, we were able to reduce the sampling rate to 5,000, which made our calculations more feasible. The 5,000 points per second was still computationally intensive, but we found that we could break each second into X millisecond windows to ease computation further without sacrificing much quality. We found that a window size of 50 points or $50/5{,}000 = 1/100$ second windows worked well for our dataset.

3 Algorithm

3.1 Data Preparation

Initializing the $\boldsymbol{A}_0 \in \mathbb{R}^{k \times k}$ and $\boldsymbol{B}_0 \in \mathbb{R}^{m \times k}$ as $\vec{\boldsymbol{0}}$
k is atoms number and m is the dictionary size.

3.2 Sparse Coding

When each x_t come, using LARS[2] to calculate

$$\alpha_t \triangleq \underset{\alpha \in R^k}{\arg\min} \frac{1}{2 \cdot k} \|\boldsymbol{x}_t - \boldsymbol{D}_{t-1}\alpha\|_2^2 + \lambda\|\alpha\|_1$$

where $\boldsymbol{x} \in \mathbb{R}^m, \boldsymbol{D} \in \mathbb{R}^{m \times k}$ and $t \leq T$(maximum number of iterations)
Then updating $\boldsymbol{A}, \boldsymbol{B}$ by

$$\boldsymbol{A}_t \leftarrow \boldsymbol{A}_{t-1} + \alpha_t \alpha_t^T$$

$$\boldsymbol{B}_t \leftarrow \boldsymbol{B}_{t-1} + \boldsymbol{x}_t \alpha_t^T$$

3.3 Dictionary Update

$$\boldsymbol{D}_t \triangleq \arg\min_{\boldsymbol{D} \in C} \frac{1}{t} \sum \frac{1}{2} \|\boldsymbol{x}_i - \boldsymbol{D}\alpha_i\|_2^2 + \lambda \|\alpha\|_1$$

Where $C \triangleq \boldsymbol{D} \in \mathbb{R}^{m \times k}$ s.t. $\forall j = 1, ..., k, \boldsymbol{d}_j^T \boldsymbol{d}_j \leq 1$ to ensure the convex.
Using block-coordinate descent to update dictionary Extracting columns of $\boldsymbol{A}$ and $\boldsymbol{B}$

$$\boldsymbol{A} = [\boldsymbol{a}_1, ..., \boldsymbol{a}_k] \in \mathbb{R}^{k \times k}$$

$$\boldsymbol{B} = [\boldsymbol{b}_1, ..., \boldsymbol{b}_k] \in \mathbb{R}^{k \times k}$$

for each column from $j = 1 \Rightarrow k$

$$\boldsymbol{u_j} \leftarrow \frac{1}{A[j,j]}(\boldsymbol{b}_j - \boldsymbol{D}\boldsymbol{a}_j) + \boldsymbol{d}_j$$

$$\boldsymbol{d}_j \leftarrow \frac{1}{\max(\|\boldsymbol{u}_j\|_2, 1)} \boldsymbol{u}_j$$

return $\boldsymbol{D}$ for next iteration

4 Experiments

The Original and Downsampled figures are as follows.
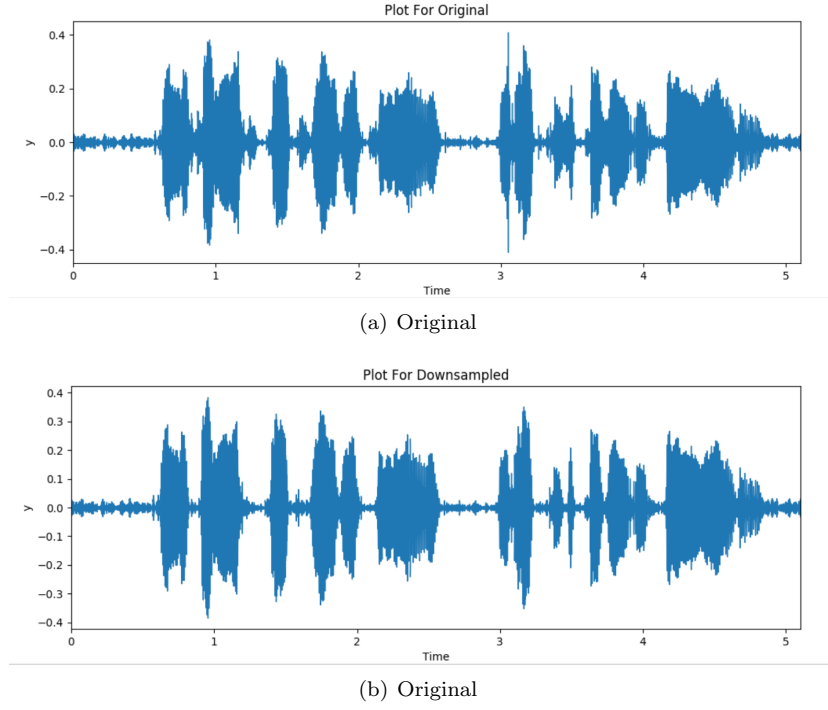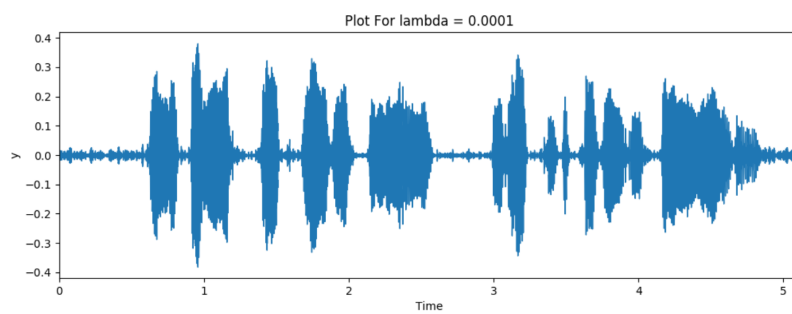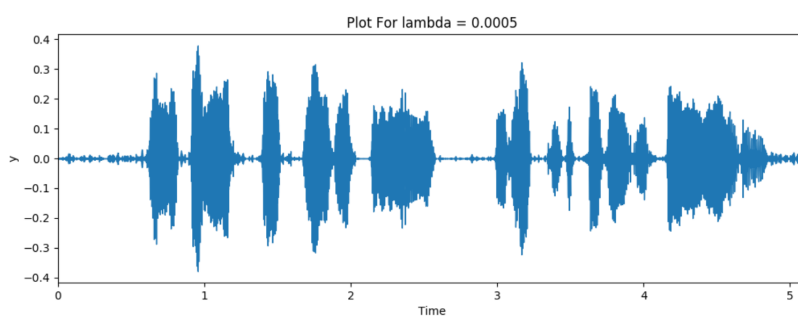
(a) Original
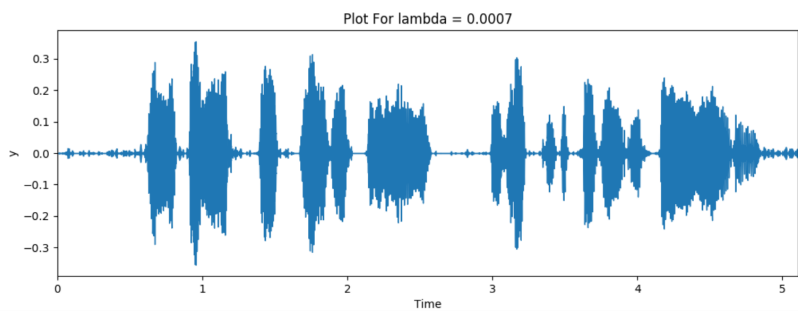

(b) Original

Figure 1: Original and Downsampled

We choose $k = 500$ and $m = 50$ for the online dictionary learning step and the result generated by different λ are presented in Figure 2.
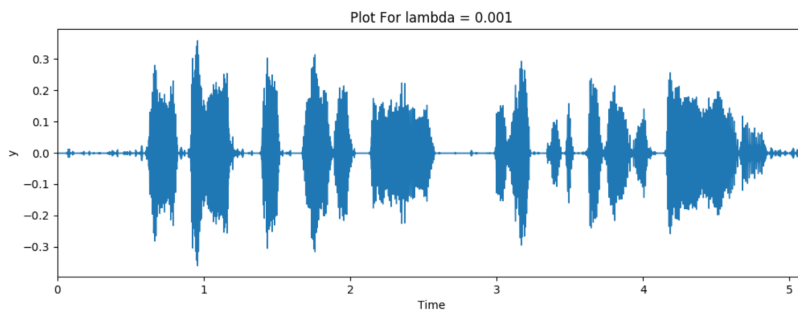
(a) $\lambda = 0.0001$

(b) $\lambda = 0.0005$

(c) $\lambda = 0.0007$

(d) $\lambda = 0.001$

Figure 2: Output

References

[1] Cassia Valentini-Botinhao, Xin Wang, Shinji Takaki, and Junichi Yamagishi. Speech enhancement for a noise-robust text-to-speech synthesis system using deep recurrent neural networks. In *Interspeech*, pages 352–356, 2016.

[2] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.

[3] Julien Mairal, Francis Bach, Jean Ponce, and Guillermo Sapiro. Online learning for matrix factorization and sparse coding. *Journal of Machine Learning Research*, 11(Jan):19–60, 2010.

[4] Brian McFee, Colin Raffel, Dawen Liang, Daniel PW Ellis, Matt McVicar, Eric Battenberg, and Oriol Nieto. librosa: Audio and music signal analysis in python. In *Proceedings of the 14th python in science conference*, pages 18–25, 2015.