Using Independent Component Analysis for Blind Source Separation

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1. Introduction

The "Cocktail Party Problem" is classic problem in the fields of speech recognition and natural language processing. This problem refers the human brain's remarkable ability to focus auditory attention on a single source while filtering out others in a noisy setting such as a party room. Training a machine to same task requires blind source separation (BSS), the separation of a set of sources signals from a set of mixed signals.

In this project, we perform blind source separation on a given set of audio signals that we mixed randomly. We use Independent Component Analysis (ICA), an algorithm designed to separate multivariate signal into additive components. The algorithm works on the assumption that the source signals are non-Gaussian and that therefore the mixed Gaussian signals are separable into their statistically independent source components through minimization of mutual information and maximization of non-Gaussianity.

2. Methods

Mathematical Foundation

We assume that our original source signals arise from a sigmoid shaped cumulative distribution function of the following form:

$$g(s) = \frac{1}{1+e^{-}s} \tag{1}$$

Then, given that the mixed signals, *X*, can be unmixed into the source signals, *S*, by the unmixing matrix, *W*, as follows:

$$S = WX \tag{2}$$

The source signals can then be extracted by determining the matrix *W*. This matrix can be iteratively determined using stochastic gradient descent (SGD) in which we seek to maximize the following log-likelihood function for *W*.

$$l(W) = \sum_{i=1}^{m}(\sum_{j=1}^{m} log[g'(w_j^T x^{(i)}] + log(W)) \tag{3}$$

In maximizing the log-likelihood function, we maximize the negentropy which in turn minimizes the mutual information between the signals. The SGD algorithm iterates on the values of *W*, which is randomly initialized, until it converges using the following iteration:

$$\Delta W = \eta((tI + (1-2Z)x^T + (W^T)^{-1} \tag{4}$$

where η is a small learning rate and Z is the CDF defined in (1).

3. Results

Plots

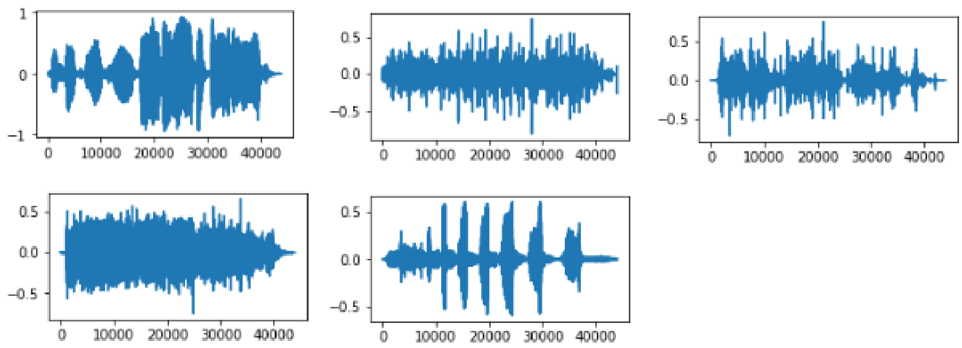

Figure 1: Source Signals

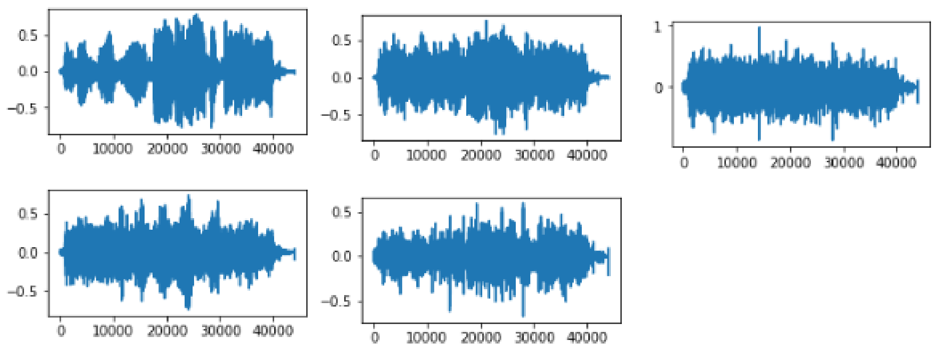

Figure 2: Mixed Signals

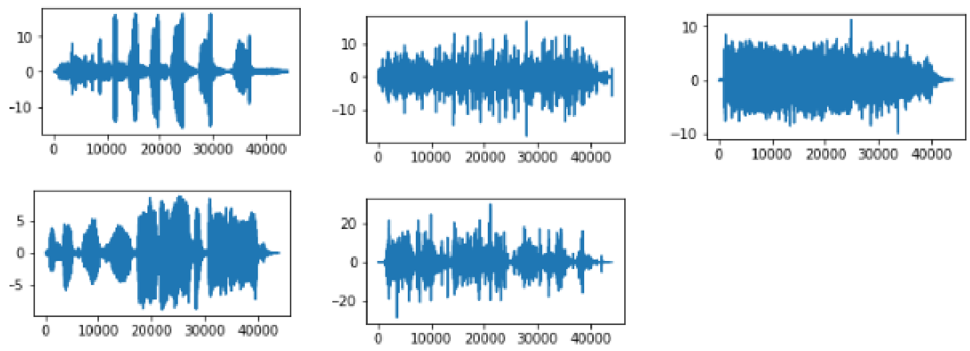

Figure 3: Recovered Signals

Figure 1 plots each of the five source signals against time. Figure 2 is a plot of the signals mixed using a randomly generated transformation matrix, *A.* Lastly, Figure 3 is plot of the recovered signals using the methodology described in the methods section. Using trial and error and experimentation, we determined the optimal learning rate=5e-7. Visually, the plots in Figure 3 look strikingly similar the original plots in Figure 1 suggesting a high correlation.

Correlation

Utilizing the np.corrcoef() function we obtained the correlations between each of the five recovered signals and their corresponding original source signals. They tabulated below:

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[0.99993796, 0.99996491, 0.99986743, 0.99993835, 0.9999279 ]
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The found correlations, each greater than 99.99%, confirm the high fidelity in the results of the ICA algorithm that was visually apparent from the plots.

4. Summary

The results of this project demonstrate that ICA provides an efficient method for blind source separation given that the sources are Gaussian and independent. The technique seeks to minimize the mutual information contained between the sources which can be quantified using the negentropy. In this project, we were able to recover the original sources with a 99.99% accuracy after adjusting the learning rate. In general, smaller learning rates provide higher accuracy by prevent overshoot but add significant computational time.