Blind Source Separation

Abstract

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Chapter 1

Introduction

One of the many truly remarkable facet of human intelligence is our ability to *sub-conciously* process the enormous amounts of information picked up by our sensory organs at any given moment in time. It is worthwhile emphasizing the fact that this is a sub-concious process, and that it takes only very little effort on the part of the subject[1]. As mundane and everyday as this process may seem then, one would expect it to be a very trivial problem. However, the fact is quite the opposite: vast amount of effort has been undertaken in assimilating this process in computers; some progress has been made, but we have still a long way to go in reaching the end of human level performance in these tasks.

In this report we are to focus on a particular subset of such filtering tasks; we are to consider audio data[2]. Furthermore we will focus on a particular problem known as *blind source separation* (BSS). The textbook example of BSS is the *cocktail party problem* which can be states as follows. At a fashionable cocktail party, you are standing with fellow guests in one of several cliques, and there are several conversations going on in the room in addition to there being played music in the background. In this situation, you are receiving a large number of auditory stimuli, but still you have no problem of following the conversation in which you are parttaking.

How is it that you are able to solve this problem so well? The human auditory system has several clues to rely on: firstly, we are more prone to pick up louder signals which are the voices of the people in our proximity. Secondly, we learn quickly to recognize features such as the pitch and loudness of the voices of those with whom you are engaged in a conversation.

Perhaps equally important to the auditory concepts, in this setting you do not only use auditory clues in the signal processing task – there are also several other context dependent pieces of information used, which in princi-

[1] One can only imagine the durdgery of life if it were not!

[2] It should be noted that many of the methods described here have been successfully applied to visual data as well.

ple means that we are not really doing truly *blind* source separation. If you are discussing the various merits of different classification algorithms you are able to follow along that conversation because you know what type of information content such a discussion should have. By means of knowing such content, the brain complements the auditory system in two ways. Firstly, you can effortlessly ignore those behind you talking about the last episode of Paradise Hotel, and secondly, the brain assists the auditory system by filling in "blanks" if there is some word you don't hear. Finally, we also use visual clues as a complement to auditory functions[3].

Given the vast amount of information we adopt as complements to the auditory system, it is perhaps no wonder that implementing this iltering operation separately in a computer system is challenging. In this report we will look at some approaches to this problem. In the remainder of this chapter, we will state the blind source separation problem in the mathematical notation we will be using throughout this report, and provide an overview over some of the methods we will explore. Chapters 3-**??** discuss three particular methods in greater detail and explores their qualities by considering their performance on actual examples.

1.1 Formal Problem Statement

We now provide a notation leading to a mathematical statement of the blind source separation (BSS) problem. We let $\boldsymbol{S}(t) \in \mathbf{R}^n$ for $t > 0, n > 0$ denote the signals generated by n sources. Similarly, let $\boldsymbol{X}(t) \in \mathbf{R}^m$ for $t > 0, n > 0$ the observed sensor readings resulting from the emitted signals. A *mixing model* $f(\boldsymbol{S}, t)$ defines the relationship between source and observed signal:

$$\boldsymbol{X} = f(\boldsymbol{S}, t) \tag{1.1}$$

As only the observed value $\boldsymbol{X}$ is known, we need to determine the inverse $f^{-1}(\boldsymbol{S}, t)$, that is, the *unmixing model*.

1.1.1 Single Sensor Blind Source Separation

A particular instance of the BSS problem, is the single sensor blind source separation (SSBSS) problem, to which we will devote particular attention. In the SSBSS problem, we have one or more source signals, but the observed signal $\boldsymbol{X}(t)$ is a scalar. This introduces problems as this instance does not lend itself to solutions by means of the "standard" methods we consider in the standard BSS problem. Chapter 5 is devoted to the SSBSS problem.

[3]The best example of this is those with hearing impairments being able to read lips.

1.1.2 A Linear Mixing Model

The simplest mixing model is a noiseless, stationary linear mixing model. The stationarity assumption means that the mixing model does not change as a function of time, so the t argument in Equation 1.1 can be omitted. With T measurements, N sources, and M sensors, this model can be defined as:

$$\boldsymbol{X} = \boldsymbol{A}\boldsymbol{S} \tag{1.2}$$

With $X \in \mathbf{R}^{N\times T}$, $\boldsymbol{A} \in \mathbf{R}^{N\times M}$ and $\boldsymbol{S} \in \mathbf{R}^{M\times T}$. The problem of determining the unmixing model now consists of computing the inverse $\boldsymbol{W} = \boldsymbol{A}^{-1}$, so that the original signal:

$$\boldsymbol{S} = \boldsymbol{W}\boldsymbol{X} \tag{1.3}$$

can be recovered. This is to say that the estimate of the original signal j at time t is computed as the jth row of $\boldsymbol{W}$ times the tth column of X.

From Equation 1.2, we can see that the blind source separation problem, even in the simplest case, is ill-poised, as we are trying to determine $M \times T + N \times M$ parameters (both $\boldsymbol{A}$ and $\boldsymbol{S}$) given only $N \times T$ ($\boldsymbol{X}$). This implies that we need to impose some kind of assumptions on the nature of the data. These assumptions, often called the *generative model*, state something about the nature of the signals and how they are mixed. As will be made apparent later, which assumptions are made, gives rise to different solution approaches. For the purpose of this study, we will be quite restrictive in what assumptions we are willing make, hence the term *blind* source separation. The type of assumptions made are primarily related to statistical properties of the sources. The textbook assumptions are uncorrelated and independendent sources, leading to the PCA and ICA solutions, respectively[4].

1.2 Overview

In the next chapters we will be looking at a few different algorithms for solving various instances of the BSS problem. Each algorithm has its own merits depending to a large extent on the assumptions we make about the data. Here we present a brief overview.

Principal component analysis (PCA) (Chapter 3) and independent component analysis (ICA) (Chapter 4) are the textbook approaches to blind source separation. These methods work well for analysing time-domain data. Many extensions to the ICA framework have been proposed, notable among

[4]Under the assumptions that the number of observations are greater than or equal to the number of sources.

them are short-term and spectral domain ICA which allow for separating underdetermined systems (fewer observed signals than sources).

In single source or single sensor we review two approaches proposed by Roweis (REF). The common denominator behind these methods is the use of latent variables representing the sources. The first approach uses represents each sources by a Gaussian mixture model (GMM) where each component of the GMM is an multi-dimensional Gaussian distribution over a discretized short-term spectrum. A theoretical weakness of this approach is that it does not account for the time-dynamics of the signals. Roweis therefore proposes an extended hidden markov approach to this model where the latent variables follow a stochastic process.

Chapter 2

Literature Review

The blind source separation problem refers to the process of recovering one or more signals that have been mixed in some unknown manner and possibly also contamined by noise. Without any assumptions on the mixing process, this problem is ill-poised. In practice therefore, all BSS methods rely on some stylized fact about the nature of the signals and/or the mixing process. It is therefore useful to dichotomize BSS methods by these assumptions.

Arguably, two of the most important facts characterizing a mixing process, are its temporal dynamics and the number of degrees of freedom. The first point refers to whether the nature of the mixing process changes over time, that is if the mixing matrix at time $t+k$ is different from that at time t for $k > 0$. The number of degrees of freedom is the same concept as in linear algebra - the connection is apparent by seeing the mixing process as a system of linear equations. If m is the number of observed signals and n the number of sources, the system is said to be *underdetermined* if $m < n$ and conversely *overdetermined* if $m > n$.

We can also differentiate between method based on the nature of input data. Early BSS research often considered the case of $n = m$, which allows one to work with data in the time domain. For undetermined systems, it is commonplace to work with some transformation of the data, which in the case of audio data a time-frequency representation. Common methods include the *short-term Fourier transform* and the *wavelet transform*.

The organization of this study is as follows. Section 2.1 will briefly summarize the literature review process, which is further documented by the underlying research protocol given in Appendix 2.4. Section 2.2 is a short description of the different techniques and methodologies found, summarised in section 2.3.

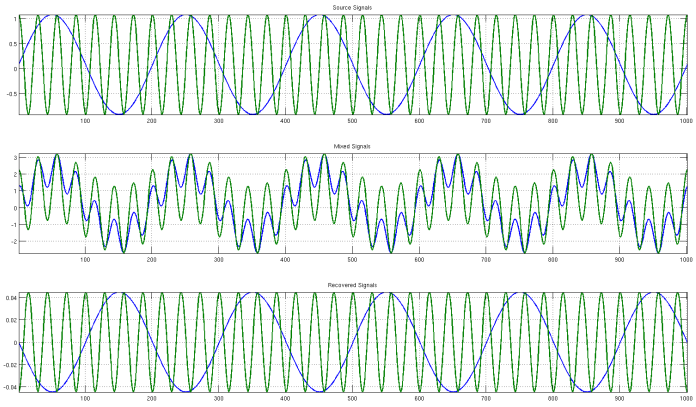

Figure 2.1: Stationary linear mixing process and separation.

2.1 Literature Review Process

The literature review process was conducted by manually searching searching the listed databases for published articles containing the predefined search terms. The table below shows the amount of results presented to us when using the more general of our search terms. Since the search terms we had defined gave us a large amount of results, we prioritized newer papers over older ones as per the Appendix 2.4.

Search term	**CiteSeerX**	**Google Scholar**	**SpringerLink**
blind source separation	292581	698000	13143
blind audio source separation	28612	26000	1072
single channel blind source separation	275543	78600	5024

Table 2.1: Magnitude of hits on the most general terms

Searching the database CiteSeerX with the terms *ica blind source separation*, *single mixture blind source separation* and *spectral blind source separation* returned the papers[2][4].

Using the search term *hidden markov source separation* on the Google Scholar database returned papers [7] [11], while the term *independent component analysis* returned papers[1] [6]. The term *single channel source separation independent component analysis* returned [8]

After screening the results against the different criteria set in appendix 2.4, these papers were brought on for further consideration.

Title	Author	Published
Independent Component Analysis: a new concept?	Comon, P.	1994
An information maximization approach to blind separation and blind deconvolution	Bell, A.J. and Sejnowski, T.J.	1995
A Context-Sensitive Generalization of ICA	Pearlmutter, B. A. and Parra, L. C.	1996
Independent Component Analysis	Hyvärinen, A.	2001
Blind One-Microphone Speech Separation: A Spectral Learning Approach	Bach, F.R. and Jordan, M.I.	2004
Fast and Robust Fixed-Point Algorithms for Independent Component Analysis	Hyvärinen, A.	1999
One Mincrophone Source Separation	Roweis, Sam T.	2001
Source separation using single channel ICA	Davies, M.E. and James, C.J.	2007
Multidimensional Independent Component Analysis	Cardoso, J. L.	1998
Source Separation From Single-Channel Recordings by Combining Empirical-Mode Decomposition and Independent Component Analysis	Mijovic, B. De Vos, M., Gligorijevic, I., Taelman, J. and Van Huffel, S.	2010
Hidden Markov model decomposition of speech and noise	Varga, A. P., and R. K. Moore	1990

2.2 Literature Overview

2.2.1 Independent Component Analysis

Among the most common approaches to blind source separation is independent component analysis (ICA). Common definitions of ICA use either the maximization of independence or minimization of mutual information between the source signals[1]. Formally, we can state the ICA problem in terms of a generative model of the observed signals $\mathbf{x}$, and the unknown a mixing matrix $\mathbf{W}$ and source signals $\mathbf{s}$:

$$\mathbf{x} = \mathbf{W}\mathbf{s} \tag{2.1}$$

[1]It should be noted that while this text presents ICA in terms of blind source separation, the method is applicable to a wide array of machine learning problems including dimension reduction, classification, and de-noising.

The AIM of the ICA process is to estimate the inverse mixing process along with the original signals.

The classical reference on ICA is [1], where the method of minimization of mutual information between sources is presented. [1] also presents an analysis of the ambiguities and limitations of ICA, hereunder the permutation of sources, scaling and non-gaussianity.

There are several equivalent statements of ICA, which yields different interpretations and computational models. [2] proposes minimizing mutual information between sources, as measured by *differential entropy*. In this implementation a feed-forward neural network structure is proposed. Other approaches include conventional maximum likelihood ([3]) and maximization of non-gausianity as measured by excess kurtosis. A popular approach is the FastICA algorithm ([6]) that minimizes mutual information expressed by *negentropy* by a fixed point method.

The classic studies on ICA focus to a large extent on developing the formal framework for ICA, and examples are largely centered on time domain analysis in systems of an equal number of sensors and sources[2]. ICA has however been extended to underdetermined systems and the extreme case of single sensor systems.

Many of these extensions are to a lesser extent changes to the previously known algorithms; rather they involve transforming the observed signals from the time domain to some other basis, the most common of which are the frequency domain (Fourier transform), the time-frequency domain (short-term Fourier transform) and the wavelet domain. Compared to the time domain, the two latter are redundant representations, but they transform the data so as to be suited for ICA. [10] surveys variations on ICA as applied to single channel recordings, hereunder single channel ICA (SCICA) and wavelet ICA (WICA), in addition to proposing an algorithm that combines ICA with empirical mode decompostion (EMD). EMD decomposes a signal into independent components in the spectral domain and can be viewed as similar to STFT.

The abovementioned approaches represent a select set of common approaches to the BSS problem. Other approaches rely to a larger extent on direct application of knowledge about the human auditory system. As an example [5] focuses on the problem on single channel speech separation in the spectral domain by means of feature maps where the features roughly corresponds to "audible" features such as common onset, pitch, timbre and so forth.

[2]For a much more thorough survey on the classical literature on ICA, see [4].

2.2.2 Hidden Markov Model Decomposition of Speech and Noise

One of the earlier examples of using hidden Markov models for speech separation, are presented by A.P. Varga and R.K. Moore [11]. The approach described in this paper attempts to obtain the best estimate likelihood of an input observation conditioned on a particular state of the model and given the knowledge available about the contaminating noise. This is achieved with the use of parallel hidden Markov models, one for each of the components in the mixture signal to be decomposed. Given a two-component signal, the output generated from the model can be modelled as:

$$ObservationalProbability = P(Observation|Hmm_1 \otimes Hmm_2) \tag{2.2}$$

Recognition is carried out by extending the normal Viterbi equation to include the components desired to be decomposed:

$$P_t(i,j) = \max_{u,v} P_{t-1}(u,v) a1_{u,i} a2_{v,j} b1_i \otimes b2_j(O_t)^3 \tag{2.3}$$

By using this form of the Viterbi algorithm, this framework is able to simultaneously recognise different components of a mixture. It should be noted that this approach may be computationally difficult as the state search space grows in dimension for each component added. Utilizing the fact that components rarely overlap in a certain frequency band, evaluation of the observation probability is approximated by:

$$\begin{aligned} b1_i \otimes b2_j(O_t) &= P(max(O1_t, O2_t|i,j)) \\ &= C(O1_t, \mu 1_i, \sigma 1_i^2) N(O2_t, \mu 2_j, \sigma 2_j^2) + C(O2_t, \mu 2_i, \sigma 2_i^2) N(O1_t, \mu 1_j, \sigma 1_j^2)^4 \end{aligned} \tag{2.4}$$

Initialization of the system consisted of supervised training on components, here being spoken numbers and noise. Utilizing a previously published algorithm for connected word recognition, the system was able to correctly classify speech contaminated with noise in the range -21 to + 15 dB.

[3] $P_t(i,j)$ is the probability at time t of the first component being in state i and the second component in state j. $a1_{u,i}$ is the tranitional probability for the first component, likewise $a2_{v,j}$ is the transitional probability for the second component. $b1_i \otimes b2_j(O_t)$ is the observation probability

[4] $C(O_t, \mu, \sigma)$ is the cumulative probability of all observation levels less than O_t coming from a Normal distribution with mean μ and variance σ^2. Similarly $N(O_t, \mu, \sigma^2)$ is the probability of observation O_t coming from a Normal distribution with mean μ and variance σ^2.

2.2.3 Factoral Hidden Markov Models

The Hidden Markov modelling has been around since the late 1960s. Roweis[7] proposes a technique called refiltering, where the idea is to separate sources in a mixed or corrupted recording. This is achieved through non stationary masking of the different frequency sub-bands from the target recording. Different sources may be isolated in the recording by changing the masking parameters. Using regularities in the spectrogram produced by a recording, it is possible to set the masking parameters, eg. common onset and offset.

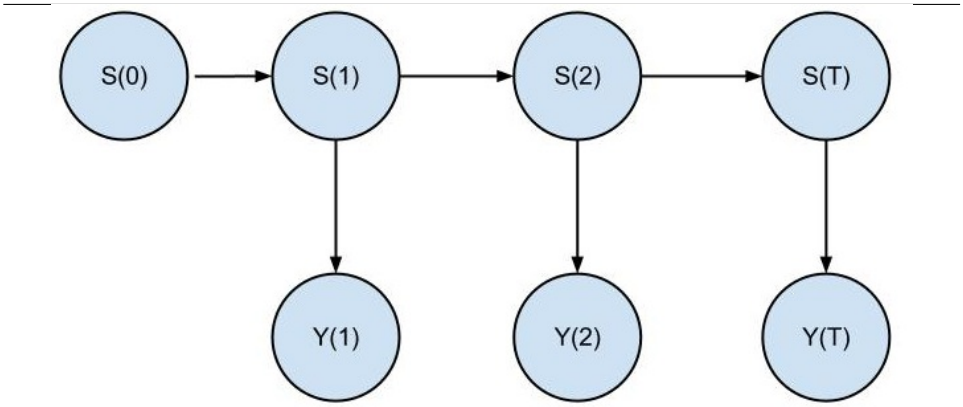

Figure 2.2: Hidden Markov Model

Training speaker dependent HMMs on isolated data from the sources to be separated, these models are then combined together in an architecture called factorial-max HMMs. The different HMMs evolve independently and for each observation vector produced at time t by each HMM, the elementwise maximum is chosen to create an observation. This is because the log magnitude spectrogram of a mixture of sources is very similar to the elementwise maximum of the individual spectrograms[5]. Separation is performed by setting the various masking signals to 1 or 0, depending on the observation vector at time t for frequency band i.

The full generative model is given in Equations 2.5 - 2.7.

$$p(x_t = j|x_{t-1} = i) = T_{ij} \tag{2.5}$$

$$p(z_t = j|z_{t-1} = i) = U_{ij} \tag{2.6}$$

$$p(y_t|x_t, z_t) = N(max[a_{x_t}, b_{z_t}], R) \tag{2.7}$$

[5]This example was performed on two speakers. a_{x_t} is the observation vector for speaker x at time t, likewise is b_{z_t} the observation vector for speaker z at time t

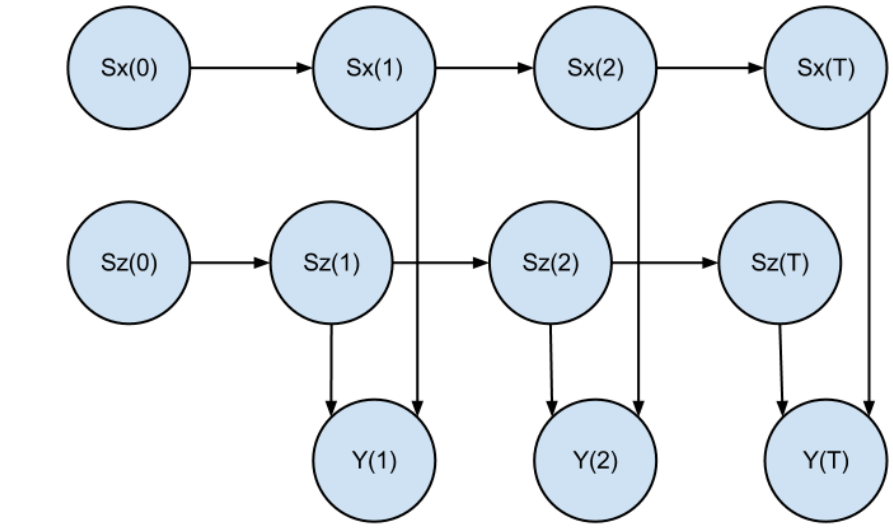

Figure 2.3: Factorial Hidden Markov Model

2.3 Conclusion

In this survey we have provided an overview over some techniques in blind source separation. Early work on blind source separation focused to a large extent on time domain ICA. In extending the BSS problem to multiple sources, the classical ICA method has been augmented by adopting different signal representations, where the time-frequency domain is particularly common. Different methods have also been introduced, some borrowing from the human auditory system attempting to hard-code domain specific knowledge. Others adopt different algorithms; one important example here being hidden markov models (HMMs). This is a very flexible approach to BSS as it allows for non-stationary mixing, and relaxes many of the stringent assumptions of classical ICA.

2.4 Research Agenda

The aim of this study is to systematically review current technology for blind source separation (BSS), with particular emphasis on the particular subproblem of single channel blind source separation (SCBSS); that is, the recovery of several source signals from one observed signals.

2.4.1 Background

The blind source separation problem consists transforming a set of observed signals that has undergone some particular mixing process back to the orig-

inal unobserved signals. The "blind" part of the problem refers to the fact that the nature of the mixing process is unknown. From original research on the blind source separation problem, focus has shifted from the case where with as many, or more recording channels than original sources, to the case of fewer channels than original sources. An important subproblem that we wish to focus on is where we have only one recording and attempt to recover multiple sources.

Our approach is two-fold: firstly we wish to look at studies about the performance of current single channel separation methods. Secondly, we wish to gain a broader overview over the state of research on BSS.

2.4.2 Research Questions

1. What are the different variations on the blind source separation problem, in particular as pertains to audio data.

2. Which methodologies and algorithms are applied to the different variations of the blind source separation problem as identified in Question 1.

3. What are the theoretical properties of the techniques identified in Question 2, and what assumptions do they make about the nature of the sources and the mixing process?

4. What empirical evidence is there to document the performance of the techniques identified in Question 2 as applied to the problems identified in Question 1?

2.4.3 Search Strategy

In reviewing the BSS literature we conduct a search of the below databases based on a set of keywords listed below. To filter the results we introduce a set of criteria to judge the relevance and quality of the results.

Databases

- SpringerLink
- CiteSeerX
- Google Scholar

List of Search Terms

blind source separation, single channel blind source separation, single mixture blind source separation, hidden markov blind source, single microphone

blind source separation, blind source separation review, blind source separation survey, pca blind source separation, ica blind source separation, principal component analysis blind source separation, independent component analysis blind source separation.

Inclusion and Quality Criteria

We wish to study how various methods and/or approaches by which blind source problem is solved, which constraints are imposed by these methods, and how well a BSS system based on these ideas perform on real-life data. To filter out the most important studies to this end, we adopt the following criteria.

Inclusion Criteria

1. The main concern of the study is the BSS problem.
2. The algorithmic design decisions in the study must be justified.
3. The study describes a reproducible algorithm/method.
4. The study focuses on blind source separation of auditory signals.

Quality Criteria

1. The study presents empirical results.
2. More recent studies are preferred.
3. The described test data set is reproducible.
4. The study should present novel theoretical approaches/methodologies OR empirical results about previously known methods.
5. Literature reviews should discuss single channel blind source separation.
6. The study should describe which other algorithms/methods the proposed solution can be compared with and the performance measure used in comparison.

Chapter 3

Principal Component Analysis

Principal component analysis [12] (PCA) is a eigenvector-based, non-probabilistic technique that uses orthogonal projection to represent data in a lower dimensional subspace spanned by the k first eigenvectors of the covariance matrix. The eigenvectors form an orthogonal basis for the data such that a projection onto the eigenvectors will decorrelate the data. In the next section we will derive this result by maximizing the variance of an axis of projection.

PCA is useful in several applications, hereunder visualization and detection of so-called *latent variables*. The principal components (PCs) are the basis of the subspace onto which the data is projected, and are such that the variance explained by each component is maximized; that is, the first PC explains a higher proportion of variance than the second PC and so forth. We can therefore, by retaining only the first few components acheive a representation of the data containing the most of the variance exhibited by the assumption that the PCs accounting for the smallest portion of variance are noise.

The next sections presents PCA from two different but equivalent perspectives; Secion 3.1 presents some intuition behind PCA and how we use projections to reduce dimensionality[1] in data so as to make it simple to capture the distinctive features of the phenomenon we are interested in. We then proceed more analytically, first solving for the direction of maximal variation using the method of Lagrange multipliers, and subsequently by singular value decomposition. The latter is the more computationally efficient, and the rationale for this approach is easy to see once the first perspective is known. We then proceed to looking at how PCA can be applied

[1] It should be noted that while in many applications of PCA, dimenension reduction is the main aim, in direct applications of PCA to source separation, we are more interested in the fact that the projected data is uncorrelated.

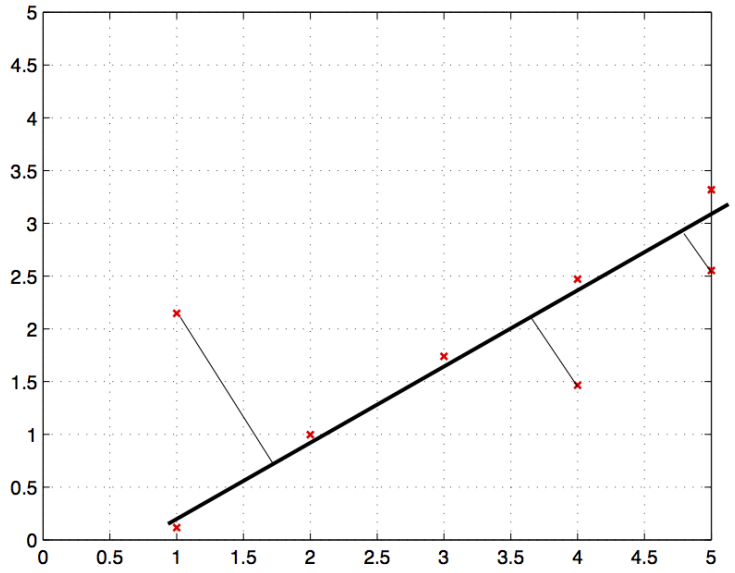

Figure 3.1: After projecting the data onto the dark line, little variation left in the dataset.

to the blind source problem and how the assumptions made about the data affect the results of a real-world mixing case.

3.1 Intuition

Consider the two dimensional dataset of Figures 3.1-3.2. We now want to find a new *one-dimensional* representation for this data that captures the most of the variation in this data. Figures 3.1-3.2 illustrate two attempts at doing this by drawing twostraight lines through the set of points. Notice the difference between the two lines; as the line in Figure 3.1 runs almost perfectly through the points, there are only three points that differ significantly from the others which lie almost on the line. As for the line in Figure 3.2, we can distinguish between most of the points by virtue of their distance from the line[2].

Now we want to introduce some terminology so we may extend our intuition to more complex (and realistic cases). In the example above, each of our original data points are *vectors* $\mathbf{v}_i$ in two dimensional Euclidean space $\mathbb{R}^2$. The dimensionality reduction operation is here a projection $T : \mathbb{R}^2 \to \mathbb{R}$. In the general case of PCA we are interested in finding such projections

[2] While we may not guarantee that this particular line will serve as well with future points, we can at least say it does a good job with the limited sample we have.

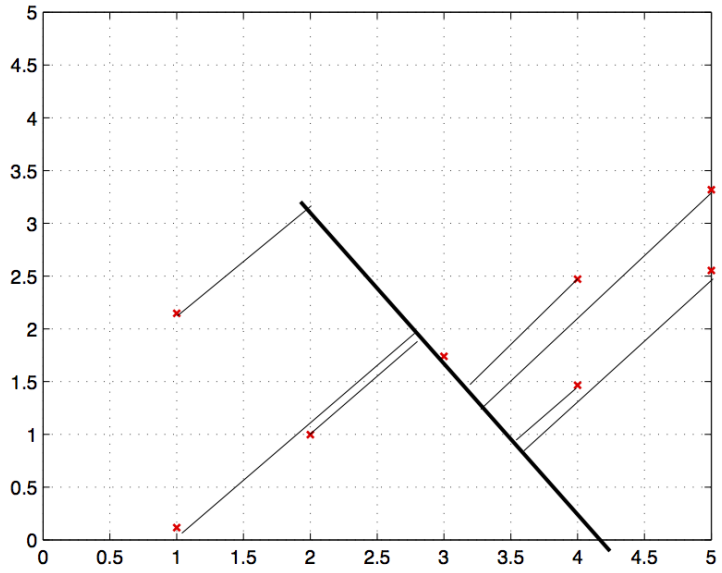

Figure 3.2: Projecting the data onto the dark line we reduce dimensionality while keeping a large portion of the variation characterizing the data.

$T : \mathbb{R}^m \to V$ to maximize the variance of the data projected onto a lower dimensional vector space V.

We characterize a vector space V by its *basis* $B = \{\mathbf{u}_1, ..., \mathbf{u}_N\}$, which is a set of vectors such that any vector $\mathbf{v} \in V$ can be expressed as a linear combination of B. The projection operation discussed above can be thought of as a change of basis. In the context of Figure 3.2 the new basis may be a vector $\mathbf{u} = (1, -1)^T$. $\mathbf{u}$ would then correspond to a unit vector in the direction of the dark line. For any point $\mathbf{x}_i = (x_i^{(1)}, x_i^{(2)})^T$, the only operation we need to express it in the new basis is computing the dot product $\mathbf{u} \cdot \mathbf{x}_i$.

In the next sections we will formalize these ideas and look at how we actually compute the bases B so as to find the axis of maximum variability for a given dimensionality.

3.2 Formal Statement

In this section we review the PCA problem as a constrained maximization problem. We seek to maximize the variance of the projected data by means of the method of Lagrange multipliers.

Let $\boldsymbol{x}_i \in \mathbf{R}^n$ denote the i'th observation of a dataset of m observations. We now want to project our data onto a vector $\boldsymbol{u}$ in $\mathbb{R}^n$ so as to maximize the variance of the resulting projection $\sum_{i=1}^{m} \boldsymbol{x}_i^T \boldsymbol{u}$ subject to the constraint

$|\boldsymbol{u}| = 1$. Under the assumption that $\boldsymbol{X}$ is standardized to zero mean and unit variance, the Lagrangian is then given by Equation 3.1:

$$\begin{aligned}
\mathcal{L}(u, \lambda) &= \tfrac{1}{m} \textstyle\sum_{i=1}^{m} (\boldsymbol{x}_i^T \boldsymbol{u})^2 - \lambda(\boldsymbol{u}^T \boldsymbol{u} - 1) \\
&= \tfrac{1}{m} \textstyle\sum_{i=1}^{m} (\boldsymbol{u}^T \boldsymbol{x}_i)^T (\boldsymbol{x}_i^T \boldsymbol{u}) - \lambda(\boldsymbol{u}^T \boldsymbol{u} - 1) \\
&= \tfrac{1}{m} \textstyle\sum_{i=1}^{m} \boldsymbol{u}^T (\boldsymbol{x}_i \boldsymbol{x}_i^T) u - \lambda(\boldsymbol{u}^T \boldsymbol{u} - 1) \\
&= \tfrac{1}{m} u^T \textstyle\sum_{i=1}^{m} (\boldsymbol{x}_i \boldsymbol{x}_i^T) \boldsymbol{u} - \lambda(\boldsymbol{u}^T \boldsymbol{u} - 1) \\
&= \tfrac{1}{m} \boldsymbol{u}^T \boldsymbol{\Sigma} \boldsymbol{u} - \lambda(\boldsymbol{u}^T \boldsymbol{u} - 1)
\end{aligned} \tag{3.1}$$

Here, $\boldsymbol{\Sigma} = \sum_{i=1}^{m} \boldsymbol{x}_i \boldsymbol{x}_i^T$ is the covariance matrix. Setting the gradient of 3.1 equal to zero yields Equation 3.2:

$$\nabla_u \mathcal{L}(\boldsymbol{u}, \lambda) = \boldsymbol{\Sigma} \boldsymbol{u} - \lambda \boldsymbol{u} = 0 \tag{3.2}$$

Equation 3.2 shows that the direction of maximum variance u, which we will refer to as the first principal component, is the first eigenvector of the covariance matrix of the dataset. By similar means it can be shown that the second eigenvector points in the direction of largest variance *orthogonal* to the first eigenvector and so forth. Finally it is worth noting that the portion of the total variance explained by a principal component is proportional to its associated eigenvalue.

3.2.1 Singular Value Decomposition

For a high dimensional dataset (e.g. $n = 10,000$), which is frequently the case working with for instance image or video data, the covariance matrix will have $10,000 \times 10,000 = 100,000,000$ entries, which is computationally untractable. Hence, PCA is usually implemented in terms of *singular value decomposition* (SVD). For an $m \times n$ matrix $\boldsymbol{X}$, the SVD is a factorization such that:

$$\boldsymbol{X} = \boldsymbol{U} \boldsymbol{S} \boldsymbol{V}^T \tag{3.3}$$

Here, $\boldsymbol{U} \in \mathbb{R}^{m \times m}$, $\boldsymbol{S} \in \mathbb{R}^{m \times n}$, and $\boldsymbol{U} \in \mathbb{R}^{n \times n}$. The SVD relates to the eigenvalue problem (Equation 3.2) as follows:

- The columns of $\boldsymbol{U}$ form the projections of $\boldsymbol{X}$ onto the eigenvectors $\boldsymbol{V}$.
- The entries s_{ii} on the leading diagonal of $\boldsymbol{S}$ are the eigenvalues of $\boldsymbol{\Sigma} = \boldsymbol{X}^T \boldsymbol{X}$.
- The top k columns of $\boldsymbol{V}$ are the top k eigenvectors of $\Sigma = \boldsymbol{X}^T \boldsymbol{X}$

Most statistics libraries provide SVD functionalities that are highly optimized, hence we will not cover algorithms for computing the SVD here[3].

We will not go into the derivation of this result as SVD is covered in most textbooks on linear algebra or basic numerical mathematics (see for instance REF). Rather, we will proceed to show how PCA can be applied to BSS, and what assumptions it requires us to make about the data.

3.3 PCA Application to Blind Source Separation

We have so far looked at PCA as a method of transforming data from N-dimensional Euclidean space onto a set of *principal components* which is the basis of a new vector space $\boldsymbol{V}$. A key property of $\boldsymbol{V}$ is that the data is now linearly uncorrelated. This is in turn the key idea to take into account in blind source separation.

The top graph of Figure 3.3 shows two periodic signals s_1 and s_2 contaminated by an additive Gaussian white noise with standard deviation $\sigma = .2$.

$$\begin{aligned} s_1 = &\quad \sin(\pi x) \quad 0 < x < 5 \\ s_2 = &\quad \cos(7\pi x) \quad 0 < x < 5 \end{aligned} \tag{3.4}$$

The signals are subsequently mixed, as shown in the middle part of Figure 3.3 by the matrix:

$$\boldsymbol{A} = \begin{bmatrix} \cos\alpha & -\sin\alpha \\ \sin\alpha & \cos\alpha \end{bmatrix} \tag{3.5}$$

where $\alpha = \pi/4$. Here the mixing matrix $\boldsymbol{A}$ corresponds to a rotation operator that will rotate the data by α radians in counterclockwise direction.

The lower part of Figure 3.3 shows the recovered signal[4].

- Example where it works - why
- Example where it fails - why

[3] In MATLAB, we can perform SVD using the `svd` statement: `[u,S,v] = svd(X)`.

[4] The estimated unmixing matrix here is $\hat{W} = \hat{A}^{-1} = \begin{bmatrix} .7071 & .7071 \\ -.7071 & .7071 \end{bmatrix}$ which is, as expected, the inverse of A for the value of α above.

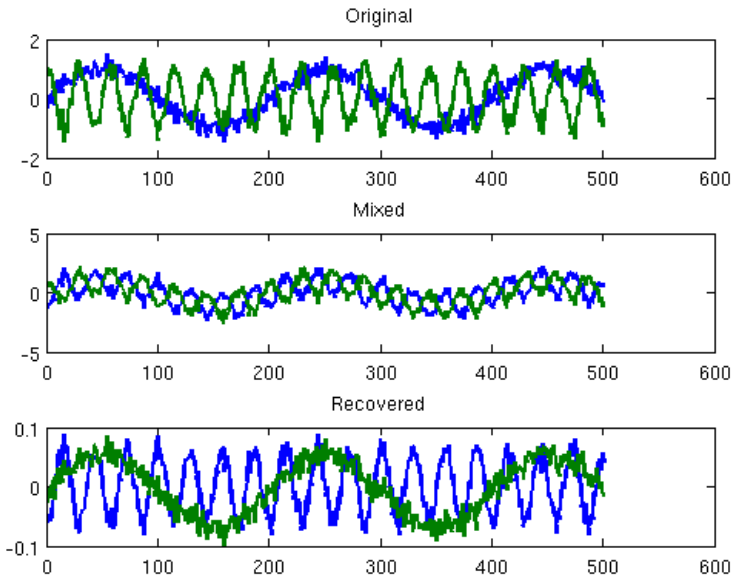

Figure 3.3: PCA Source Separation.

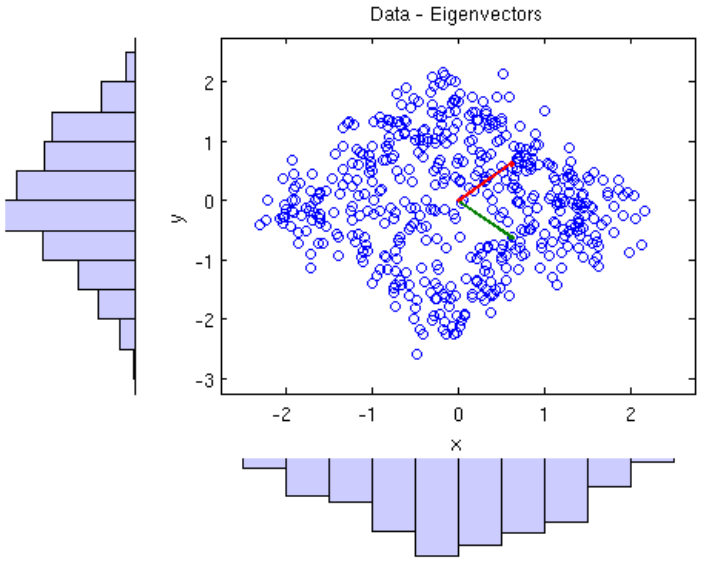

Figure 3.4: Standardized data points vs eigenvectors.

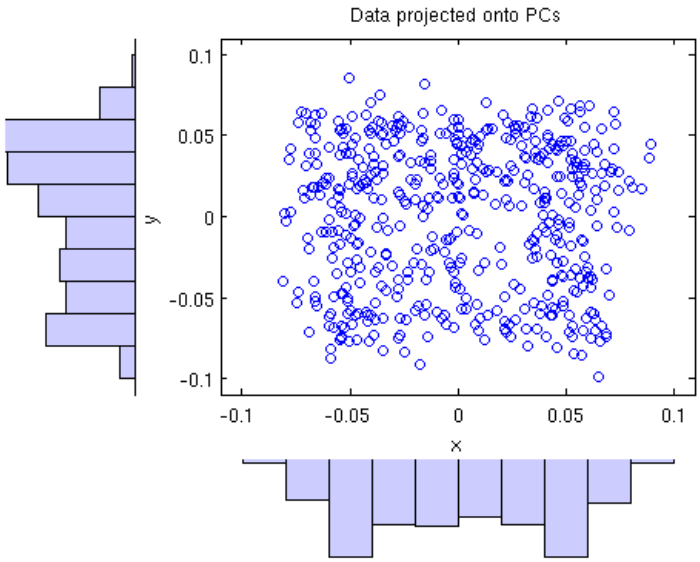

Figure 3.5: Standardized data projected onto eigenvectors.

Chapter 4

Independent Component Analysis

PCA finds the basis of a subspace in which the variance is maximized in the direction of the basis vectors and the covariance between the data is zero. ICA seeks to find basis vectors that are statistically independent, which is a stronger property than simply being uncorrelated as independence implies uncorrelatedness, while the opposite is not true. Like PCA, we can interpret ICA as an optimization problem, but in contrast to PCA, ICA does not have a general closed form solution, so a numerical optimization method is usually applied in computing the ICA transform.

This chapter is structured as follows. First we give a brief overview over different approcahes to ICA in Section 4.1. We then consider some limitations of the ICA model in Section 4.2, with particular emphasis on the non-gaussianity constraint, which is important with respect to the types of data we can analyze using ICA. Section 4.3 goes into the maximum likelihood approach to ICA in further detail, and derives a gradient descent learning rule for independent components analysis. As it turns out, this gradient rule is similar to the learning rules proposed under the different frameworks discussed in Section 4.1. Finally, Section **??** illustrated ICA with a few blind source separation problems.

4.1 Equivalent Statements of ICA

ICA can be derived by several different approaches representing slightly different interpretations of the same problem. Among these are maximum differential entropy (REFFFF), maximum kurtosis (REF) and maximum likelihood ([13]). In this section we provide a brief overview over the two first, while we go in more detail on the maximum likelihood method in subsequent sections.

4.1.1 Kurtosis Maximization

The kurtosis β_X of a random variable X is defined as the fourth moment around the mean μ_X:

$$\beta_X = \frac{\mathbb{E}[(X - \mu_X)^4]}{\mathbb{E}[(X - \mu_X)^2]^2} \tag{4.1}$$

If we standardize our data to zero mean and unit variance, we see that the above simplifies to $\mathbb{E}(X^4)$. Often times, we are interested in comparing a distributions to the normal distribution by means of kurtosis, which leads to the definition of *excess kurtosis*, $\gamma = \beta - 3$, where the -3 term is necessary to make the kurtosis of the normal distribution zero.

We now consider the problem $\boldsymbol{x} = \boldsymbol{A}\boldsymbol{x}$ and let $\boldsymbol{W} = \boldsymbol{A}^{-1}$. Setting $\hat{\boldsymbol{s}} = \boldsymbol{W}^T\boldsymbol{x}$, and $\boldsymbol{z} = \boldsymbol{A}^T\boldsymbol{W}$, we can substitute into the equation for $\hat{\boldsymbol{s}}$:

$$\hat{\boldsymbol{s}} = \boldsymbol{W}^T\boldsymbol{x} = \boldsymbol{W}^T\boldsymbol{A}\boldsymbol{s} = \boldsymbol{z}\boldsymbol{s} \tag{4.2}$$

We now rely on the following property of kurtosis $\gamma(ax_1 + bx_2) = a^4\gamma(x_1) + b^4\gamma(x_2)$, and note that as $\boldsymbol{z}$ is a square matrix of the same dimension as the mixing matrix[1], $\boldsymbol{z}\boldsymbol{s}$ is of the same dimension as the as the input. The kurtosis of the estimate $\hat{\boldsymbol{s}}$ is the weighted product of the columns of $\boldsymbol{z}\boldsymbol{s}$:

$$\gamma(\hat{\boldsymbol{s}}) = \gamma(\boldsymbol{z}\boldsymbol{s}) = \sum_{i=1}^{N} \boldsymbol{z}_i^4 \gamma(\boldsymbol{s}_i) \tag{4.3}$$

(Equation 4.3) lends itself easily to standard optimization procedures to maximize kurtosis so as to produce the independent components:

$$\boldsymbol{s}_i = \arg\max_{s_i} \sum_{i=1}^{N} \boldsymbol{z}_i^4 \gamma(\boldsymbol{s}_i) \tag{4.4}$$

Kurtosis maximization is of the most common approaches to ICA and is discussed in greater detail in REFERANSER!!!.

4.1.2 Maximum Mutual Information

4.2 Limitations of the ICA Model

ICA imposes a few critical assumptions about the nature of the sources and the extentent to which they can be recovered. In short, these are:

- *Signal ordering*: We cannot recover the correct order of the signals.
- *Scaling*. Recovered signals may be scaled arbitrarily.

[1] We assume that there is an equal number of sources as observables.

- *Gaussianity.* We cannot recover Gaussian sources.

As in PCA, we cannot recover the original ordering of the signals; i.e. the rows of the source matrix $\boldsymbol{S}$ may be swapped in the resulting $\hat{\boldsymbol{S}}$. Furthermore, the correct scaling of the source compents, including their sign cannot be recovered. This can be seen in that $\boldsymbol{X} = \boldsymbol{AS} = (.5\boldsymbol{A})(2\boldsymbol{S})$.

The final limitation of ICA is that the source signals must be non-Gaussian. To see why this must hold, we rely on the fact that the multivariate gaussian distribution is rotationally symmetric. Furthermore, to fully recover the sources, we must be able to "undo" any rotation caused by applying the mixing operator. To see the effect of an applying a rotation operator to a sine wave, consider the example in Section 3.3.

Consider a single observation $\boldsymbol{x} = \boldsymbol{x}(t) = \boldsymbol{As}(t) = \boldsymbol{As}$. The covariance matrix of $\boldsymbol{x} = \boldsymbol{As}$ is:

$$\mathbb{E}(\boldsymbol{x}\boldsymbol{x}^T) = \mathbb{E}((\boldsymbol{As})(\boldsymbol{As})^T) = \mathbb{E}(\boldsymbol{A}\boldsymbol{s}\boldsymbol{s}^T\boldsymbol{A}^T) = \boldsymbol{A}\boldsymbol{A}^T \tag{4.5}$$

Now, let $\boldsymbol{R}$ be a rotation operator and $\boldsymbol{A'} = \boldsymbol{AR}$. We consider mixing $\boldsymbol{s}$ by $\boldsymbol{A'}$ instead. The covariance matrix of $\boldsymbol{x'} = \boldsymbol{A's}$ is:

$$\begin{aligned} \mathbb{E}(\boldsymbol{x'}\boldsymbol{x'}^T) &= \mathbb{E}((\boldsymbol{A's})(\boldsymbol{A's})^T) \\ &= \mathbb{E}(\boldsymbol{A'}\boldsymbol{s}\boldsymbol{s}^T\boldsymbol{A'}^T) \\ &= \mathbb{E}(\boldsymbol{AR}\boldsymbol{s}\boldsymbol{s}^T(\boldsymbol{AR})^T) \\ &= \boldsymbol{A}\boldsymbol{R}\boldsymbol{R}^T\boldsymbol{A}^T \\ &= \boldsymbol{A}\boldsymbol{A}^T \end{aligned} \tag{4.6}$$

Hence, we see that both $\boldsymbol{s}$ and $\boldsymbol{s'}$ come from the same Gaussian distribution $\boldsymbol{\Phi}(0, \boldsymbol{A}\boldsymbol{A}^T)$. This means that the recovered data may be rotated by an arbitrary rotation matrix $\boldsymbol{R}$, which as discussed above, provides little information about the sources.

4.3 Maximum Likelihood ICA in the Linear Mixing Model

INTRO BS....

Consider the value of a single source s_i at a given instant in time, and let $p_s(s_i)$ be the probability density function for source i. Assuming the sources are independent the joint distribution of all the n sources is given by the product of the marginal distributions of each source:

$$p_s(s) = \Pi_{i=1}^n p_s(s_i) \tag{4.7}$$

Recalling our notation for the unmixing model:

$$\boldsymbol{A}^{-1} = \boldsymbol{W} = \begin{bmatrix} \boldsymbol{w}_1^T \\ \boldsymbol{w}_2^T \\ ... \\ \boldsymbol{w}_n^T \end{bmatrix} \tag{4.8}$$

We can substitute for s_i in (Equation 4.7), to obtain the following expression for the joint distribution[2].

$$p(s) = \Pi_{i=1}^{n} p_s(\boldsymbol{w}_i^T \boldsymbol{x}) \cdot |\boldsymbol{W}| \tag{4.9}$$

Under maximum likelihood estimation, we want to find the $\boldsymbol{W}$ that is most likely given our dataset $\boldsymbol{X} = [\boldsymbol{x}_1, \boldsymbol{x}_2, ..., \boldsymbol{x}_T]$, ie.

$$\boldsymbol{W}^* = \arg\max_{\boldsymbol{W}} \mathbb{P}(\boldsymbol{W}|\boldsymbol{X}) \tag{4.10}$$

By straight forward application of Bayes' rule, we can rewrite the probability in (Equation 4.10) as:

$$\mathbb{P}(\boldsymbol{W}|\boldsymbol{X}) = \frac{\mathbb{P}(\boldsymbol{X}|\boldsymbol{W})\mathbb{P}(\boldsymbol{W})}{\mathbb{P}(\boldsymbol{X})} \propto \mathbb{P}(\boldsymbol{X}|\boldsymbol{W}) \tag{4.11}$$

From (Equation 4.11), we can set up the maximum likelohood function:

$$\begin{aligned} l(W) &= \log \mathbb{P}(\boldsymbol{X}|\boldsymbol{W}) \\ &= \Sigma_{t=1}^{T} \log p_s(\boldsymbol{W}\boldsymbol{X}) + \log |\boldsymbol{W}| \\ &= \Sigma_{t=1}^{T} \Sigma_{i=1}^{N} \log p_s(\boldsymbol{w}_i^T \boldsymbol{x}(t) + \log |\boldsymbol{W}| \end{aligned} \tag{4.12}$$

The final step is to determine the marginal distributions p_s of the sources. A common, but not necessary assumption is to let all the sources have the same distribution. As gaussian marginals are precluded by the assumptions of our model, we need to choose an alternative distribution for s. Typically, the distribution is specified in terms of the cumulative density function $P_s(s)$. Standard choices here include the sigmoid $P_s(s) = \frac{1}{1+e^{-s}}$ and hyperbolic tangent ($P_s(s) = \tanh(s)$).

4.3.1 A Gradient Descent Rule for ICA

Given the log likelihood function of Equation 4.12, we will now discuss how this can be maxmimized by gradient descent. The gradient descent method has an intuitive appeal, and lends itself easily to a computer implementation along the lines of the pseudocode Figure **??**.

Gradient descent is an iterative optimization method where local extrema are found by taking steps proportional to the gradient of the function

[2]Here the determinant term results from the rule for linear transformations of probability densities.

at a given point. The algorithm may be seeded randomly or initialized by domain knowledge of the optimization problem at hand. Normally, the step size of the algorithm is decremented as the algorithm converges, which is expressed through the learning rate $\alpha(n)$ which is a function of the current of iteration count n. We can state this as the following update rule:

$$x_{n+} = x_n + \alpha(n)\nabla F(x_n) \tag{4.13}$$

The rule in (Equation 4.13 is iterated until convergence is reached. This is typically measured by the difference $|x_{n+1} - x_n$ or in terms of the number of iterations passed as in Figure 4.1.

In the particular case of objective functions that are the sum of a large number of terms it is often convenient to apply a modified version of gradient descent known as stochastic gradient descent, where only a randomly selected subset of the terms are computed in evalutating the gradient. Of the most important applications of this rule is of course the maximization of log likelihood functions.

```
% Variables:
X % Mixed sources
a % learning rate
w % unmixing matrix

for i = 1:nIter
  s = randomSubset(X)
  w = w + a*(1-2*(1/exp(-s))*s')*w;
```

Figure 4.1: Pseudocode for ML ICA by stochastic block gradient descent.

To conclude this section, we review the gradient descent algorithm of Figure 4.1. Here, we assume the data is distributed according to a sigmoid cdf f. By inserting substituting this into (Equation 4.12) and differentiating, we get the following update rule:

$$\mathbf{W}_{n+1} = \mathbf{W}_n + \alpha(1 - 2 * f(\mathbf{W}\mathbf{X})\mathbf{X}^T + (\mathbf{W}^T)^{-1}) \tag{4.14}$$

For a more sophisticated ICA algorithm, we refer to Hyvarinen's FastICA [REF].

4.4 BSS by ICA

Here we also observe that the sign of the original speech signal is reversed in the bottom right recovered signal

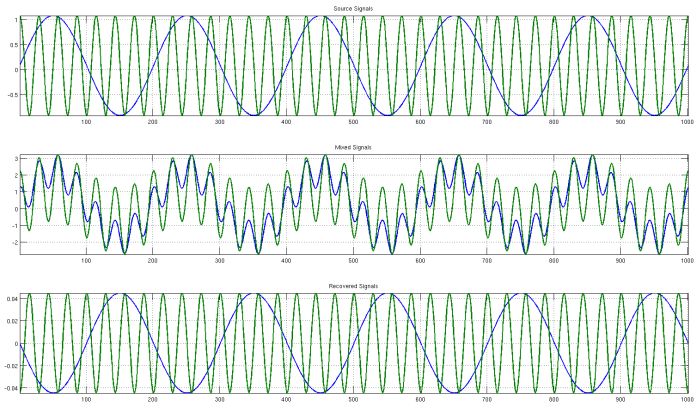

Figure 4.2: ICA on a 2×2 BSS problem. Note the "sign reversal" for the blue sine wave (cf. Section 4.2).

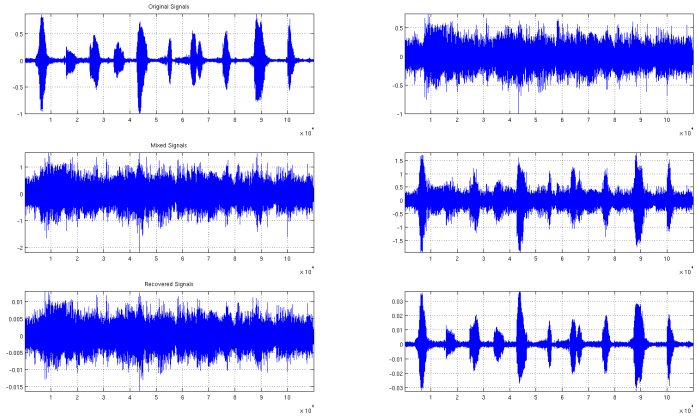

Figure 4.3: Separating a speech signal (top left) from background music (top right) by ICA.

Chapter 5

Single Sensor Blind Source Separation

Single sensor BSS[1] is a particularly important case of the underdetermined BSS problem where the observed signal consists of only a scalar value at any point in time as if the source signals were recorded a sole microphone. This presents us with particular challenges, and we often need to make further assumptions about the data generating process – i.e. we need a more complex generative model.

In this chapter we present a solution to the single sensor BSS problem proposed by Roweis (XXXX)[**?**] that relies on a latent variable model (mixture of gaussians). This metod has two phases; a training phase where the mixture models are estimated one clean recordings of each source. The subsequent inference phase where mixed signals are separated rely on two important ideas: an approximation for determining which source is active at a given time, and an efficient pruning method to reduce the computational cost of the model.

This chapter is structured as follows. Section 5.1 provides an introduction to the time-frequency domain signal representation which is common in most single channel audio separation models. Section 5.2 discusses the logmax property that is fundamental to the inference algorithm. Section 5.3 introduces the key ideas of this chapter. First we review mixture models in general terms before we look at estimating and doing inference in the particular latent variable model at hand. Finally, we briefly discuss an extended hidden markov model proposed by Roweis, before we illustrate the method with a few simple examples in Section 5.5.

[1] Also called single channel BSS.

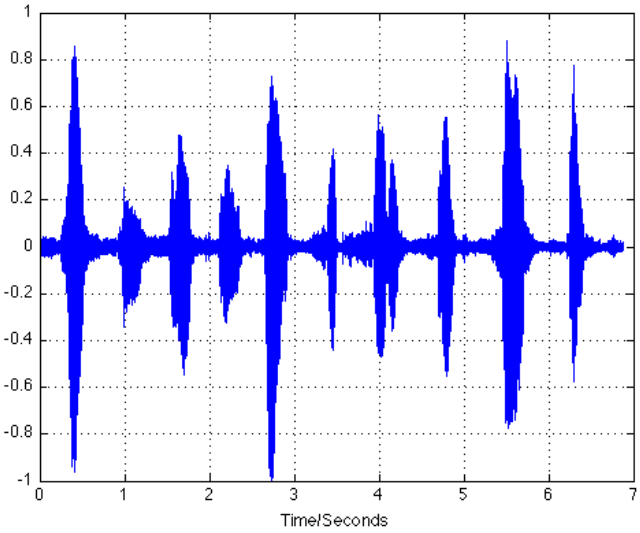

Figure 5.1: Time domain representation of a male voice counting from one to ten.

5.1 Time Frequency Signal Representation

A time frequency representation (TFR) is a redundant signal representation in comparison to a simple time domain representation that contains only the amplitude values at given point in time. As seen in for instance Figure REF, sound signals are often non-stationary, which indicates that a windowed or short-term analysis is appropriate.

In working with underdetermined blind source separation, we rely on a redundant signal representation in the time-frequency domain, rather than the standard representations in the time domain. Time-frequency representation is advantageous in comparison with a pure spectral representation as the latter contains no information on when different components of a signal occur in time. While many different time-frequency representations exist, our presentation relies on the *short-term Fourier transform* (STFT).

The time-frequency representation, often called a *spectrogram* produced by the STFT maps the energies in various parts of the spectrum over the timespan of the signal. For a low amplitude portion of the signal will have its energy concentrated in the upper part of the spectrogram and vice versa. This is illustrated in Figure XX.

Equation 5.1 defines the discrete time STFT for the nth segment (which is centered around m):

$$\text{STFT}\{x[n]\}(m,\omega) = X(m,\omega) = \sum_{n=-\infty}^{\infty} x[n]\omega[n-m]e^{-i\omega n} \tag{5.1}$$

Here, ω is a zero centered window function, typically uniform or gaussian. The window determines which part of the signal x is to be included in the spectrogram near m. In practice, the STFT is computed using the fast fourier transform (FFT). To better allow for visualization of the STFT, which is a complex number, the spectrogram is defined as the squared magnitude of the STFD (Equation 5.2).

$$\text{spectrogram}\{x[n]\}(m,\omega) = |X(m,\omega)|^2 \tag{5.2}$$

Figure **??** shows a spectrogram represented as a colormap. Here, the abscissa and ordinate of a point represent time and frequency respectively, while the spectral intensity at the is color coded with red representing high energy.

5.2 Log Max Approximation

An important observation underlying the inference model discussed in this chapter is the following. If two signals $s_1(t)$ and $s_2(t)$ are mixed *additively* in the time domain so that $x(t) = s_1(t) + s_2(t)$, then the mixture log spectrogram $\log F(x)$ is almost equal to the element-wise maximum of the source log spectrograms, that is $\log(F(s_1) + F(s_2)) \simeq \max(\log(F(s_1)) + \log(F(s_2))$. The relationship is illustrated in Figure **??**.

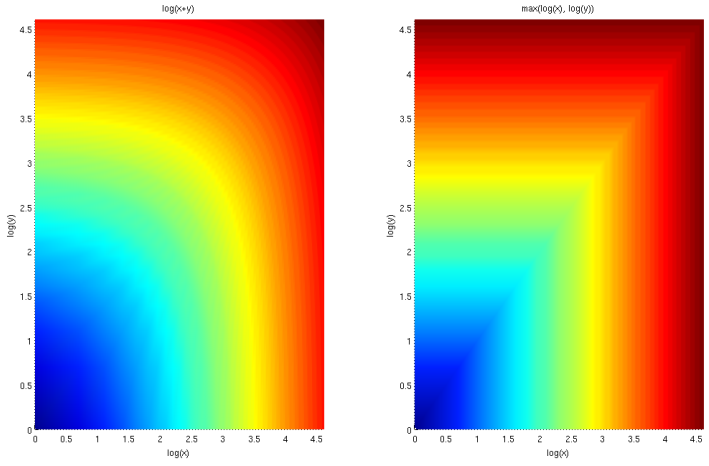

Figure 5.2: Log-max approximation.

There is a simple intuition behind this approximation; in the spectral domain, a signal is characterized by how energy is distributed over different frequency bands, and particular sounds have a "signature" according to which frequencies have the highest energies. Hence, if we allow for the assumption that the signals are more or less independent, *different* signals are likely to have different energy distributions at a given point in time. We should also not that the use of logarithms is important here as it accentuates the differences between signals.

5.3 Latent Variable BSS

While we are essentially dealing with a *two-level latent variable model*, we follow Roweis' terminology, adopting the term *factoral-max vector quantizer* or MAXVQ for this class of models. This will also provide a ground for discussing the complexity issues of traditional inference methods as pertains to factorial BSS models, and a proposed solution to these problems.

We start by looking at gaussian mxiture models in general terms in Section 5.3.1. We then turn to specifying the latent variable model of BSS and briefly describe the estimation procedure for this model in Section 5.3.2 before we conclude the theoretical part of this chapter by looking at inference, first by standard methods, and subsequently by a more efficient pruning algorithm.

5.3.1 Gaussian Mixture Models

A gaussian mixture model (GMM) is latent variable model that gives a tractable representation of high-dimensional probability distribution. Let Z be a multinomial random variable taking on values $z \in \{1, 2, 3, ..., N\}$ and $\{X_i\}$, $i \in \{1, 2, 3, ..., N\}$ be a set of (multivariate) Gaussian random variables. If X and Z har the joint distribution (5.3) then we say X and Z has a gaussian mixture distribution:

$$\mathbb{P}(X, Z) = \mathbb{P}(X|Z)P(Z) = \sum_{i=1}^{N} \Phi(X_i, \mu_i, \mathbf{\Sigma}_i) Mn_N(Z) \tag{5.3}$$

Here, $\Phi(X, \mu, \mathbf{\Sigma})$ denotes X having a gaussian distribution with expectation vector μ and covariance matrix $\mathbf{\Sigma}$), and $Mn_N(Z)$ denotes Z having an N-valued multinomial distribution.

A common interpretretation of the gaussian mixture model is for Z to represent a latent or hidden variable describing the state of a system, while X is some observable quantity depending on the state of the system.

Figure 5.3 illustrates a mixture of gaussians distribution with two components where the component an observation is drawn from is marked by

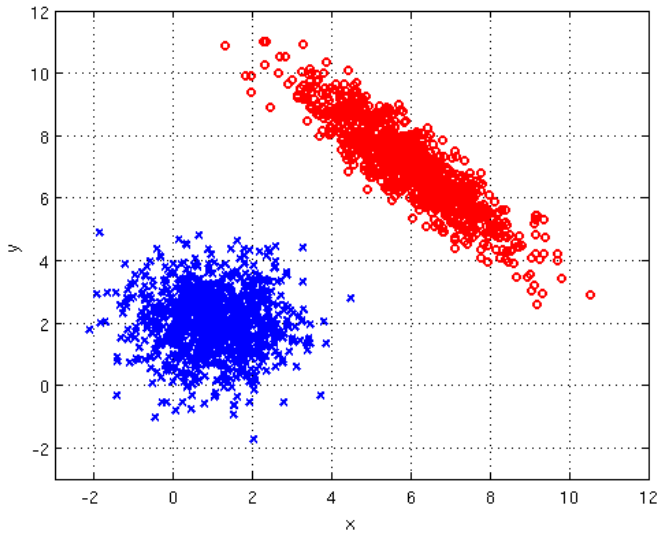

Figure 5.3: A mixture of gaussians distribution with two components.

red circles and blue crosses. Here the two components represent two different bivariate distributions with separate means and covariance matrices. A common assumption reducing the computational complexity is to estimate a shared covariance matrix for all components.

When speaking of a *latent* variable, we refer to the fact that we as observers of a stochastic process do not know whether an observation x is generated from the "red" or the "blue" distribution. It is as if an "invisible hand" selects one of the two distributions and then generates a random number accordingly.

5.3.2 Generative Model

Let $\mathcal{Q} = \{q_1, q_2, .., q_M\}$ denote the set of speakers[2], and Q be a multinomial random variable over $\mathcal{Q}$, $\mathcal{Z}_m = \{z_1^m, z_2^m, .., z_N^m\}$ be the set of states for the latent variable Z^m for source m. Finally, we let $\boldsymbol{X}(t) = (x_1, x_2, ..., x_D)$ be an *observed* D-dimensional frequency vector. The generative model for a given frequency band d is then:

$$\begin{aligned} &\mathbf{P}(q) = Mn_M(q) \\ &\mathbf{P}(z|q) = Mn_N^q(z) \\ &z_{max}^d = \max_m z_{md} \\ &\mathbf{P}(x_d|z) = \Phi(x^d|z_{max}^d, \sigma) \end{aligned} \tag{5.4}$$

where $Mn_M(\cdot)$ refers to an M-valued multinomial distribution, and

[2]For simplicity, we assume $M = 2$.

$\Phi(\cdot|\mu, \Sigma)$ the normal distribution. The idea can be expressed as follows: *Each source m selects a latent variable z which in turn produces an intensity vector $\mathbf{x}_m$ according to the distribution $\mathbb{P}(\mathbf{x}|z)$. The final output $\mathbf{x}$ is the elementwise maximum over all vectors $\{\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_M\}$.*

The model is trained in an unsupervised manner by estimating a gaussian mixture to a training dataset where sources are separated. More recently, attempts have been made at estimation directly on mixed signals [REFERANSE]. The canonical training method used in these models is the expectation maximization (EM) algorithm as described in appendix [[[REF]]].

5.3.3 Estimation Procedure - The EM Algorithm

TODO!

5.3.4 A Generic Inference Procedure

Having estimated the gaussian mixture models corresponding to each one of our sources, we turn to the problem of recovering the set of orignial signals from the mixture spectrogram $\boldsymbol{S}_{mix}$. Our algorithm in this section is based on Roweis (REF MAXVQ), but in this step we will ignore the branch-and-bound procedure, and instead do the inference steps based only on the GMMs.

The approach is an iterative method. Since we make no assumptions on the temporal dynamics of our signals, we can perform a inference step-by-step, considering each column of the spectrogram independently. We adopt the following notation: let $\boldsymbol{\Phi}_1 = \{\mu_1^1, ..., \mu_1^N, \Sigma_1\}$ and $\boldsymbol{\Phi}_2 = \{\mu_2^1, ..., \mu_2^M, \Sigma_2\}$ denote the GMMs (assuming equal covariance matrices for all components of each GMM).

Given a single column vector $\boldsymbol{X}$ of the spectrogram, we find the most likely component for each GMM:

$$\begin{aligned} \mu_1^* &= \arg\max_i \mathbb{P}(\mu_1^i|\boldsymbol{X}, \Sigma_1) \\ \mu_2^* &= \arg\max_i \mathbb{P}(\mu_2^i|\boldsymbol{X}, \Sigma_2) \end{aligned}$$

As usual, we apply Bayes' rule in estimating the probabilities:

$$\mathbb{P}(\mu_k^i|\boldsymbol{X}, \Sigma_k) \propto \mathbb{P}(\boldsymbol{X}|\mu_k^i, \Sigma_k) \tag{5.5}$$

for each GMM component k. Given that the all our mixture components have a multivariate normal distribution, it is simple to show that the following[3] holds true for the right hand side of (Equation 5.5).

$$\mathbb{P}(\boldsymbol{X}|\mu_k^i, \Sigma_1) \propto (\boldsymbol{X} - \mu_k^i)^T \Sigma_k^{-1} (\boldsymbol{X} - \mu_k^i) \tag{5.6}$$

[3]We can interpret (Equation 5.6) geometrically as selecting the nearest component to the observed data under the *Mahalanobis* metric.

Knowing most likely components of each source given the observed data, we subsequently turn to computing the *masking signal* for each frequency band, ie. for each element of $\boldsymbol{X}$. This masking signal is computed for every source i, and takes the value 1 if source i is the maximum over all sources at the given frequency band/timestep pair and zero otherwise.

5.3.5 An Improved Pruning Method for MAXVQ Inference

The purpose of the inference part of the model is computing the most likely sequence of source/gmm component combinations given the observed data. In the previous section we discussed a naïve method for doing this that applies standard machine learning principles. For large datasets, this method quickly becomes computationally intractible.

To amend this problem reducing time complexity of the inference procedure, Roweis [[xxx]] describes a branch-and-bound methodbased on estimating an upper bound on the log likelihood of the latent variables given the observed data.

For source/latent variable combination (m, k), given each observation vector, $\mathbf{x}$, we compute the following bound.

$$B_{m,k} = -\frac{1}{2}\sum_{d} \max(x^d - v_m^d, 0)^2 - \frac{D}{2}\log|D| - \log \pi_m \tag{5.7}$$

Next, let $z_m^* = \arg\min B_{m,k}$, and let l^* be the log likelihood associated with z_m^*. For all sources m, we eliminate latent variables k such that $B_{mk} < l^*$. For the remaining source/latent variable combinations, we evalutate the log likelihood by the model specified in 5.4. If a new lower bound is discovered, we reiterate the pruning procedure over the remaining source/-component combinations with the new bound, otherwise, we compute log likelihoods until all remaining are evaluated.

5.4 Factorial Hidden Markov Model for BSS

We will now describe the factoral HMM for blind source separation as put forward by Roweis in a two signal setting. We adopt the following notation: for each timestep $t \in \{1, 2, 3, ..., T\}$, $\mathbf{X}_t$ denotes the M-dimensional spectral vector of power spectral intensities over the finite set of frequency values $\mathcal{F}$. We note that while the set of frequencies are discrete, the intensities x_{it} are real-valued, hence we adopt a real valued emission model, as discussed later.

The FHMM is essentially a supervised learning method, and the learning process consists in estimating a separate HMM based on separate (clean) recordings of the particular source. That is to say, the learning part consists entirely in learning a probability model of each source.

```
% Variables:
gmms         % List of GMM(comp_1,...,comp_N)
spectrogram  % d x T matrix
bounds       % List of best bound for
             % (source m / speaker k)
masks        % Mask matrix of dimension d x T x 2.
             % Entry corresponds to active
             % (source/component)
minIdx       % index of best component
             % for each source
for t = 1:T
  X = spectrogram(t)

  % Initial bound estimate
  bounds = list()
  for m = 1:length(gmms)
    for k = 1:NComponents(gmms(m))
      bounds(m,k) = computeBound(X, gmms(m,k))

  % Max log likelihood for each source
  for m = 1:length(gmms)
    minIdx(m) = argmin(bounds(m))
    l0(m) = logLikelihood(bounds(m,minIdx(m)))

  % Reduction
  while length(bounds) > 0
    for m = 1:length(gmms)
      for k = 1:NComponents(gmms{m})
        if bounds(m,k) < l0
          % Delete observation from list
          bounds = bounds - bounds(m,k)
        else
          l1 = logLikelihood(bounds(m,k))
          if l1 < l0
          l0 = l1

  % Set masks
  for i = 1:d
    sourceIdx = argmin(l0(d))
    masks(d,t) = (sourceIdx, minIdx(sourceIdx))
```

Figure 5.4: Pseudocode for MAXVQ algorithm.

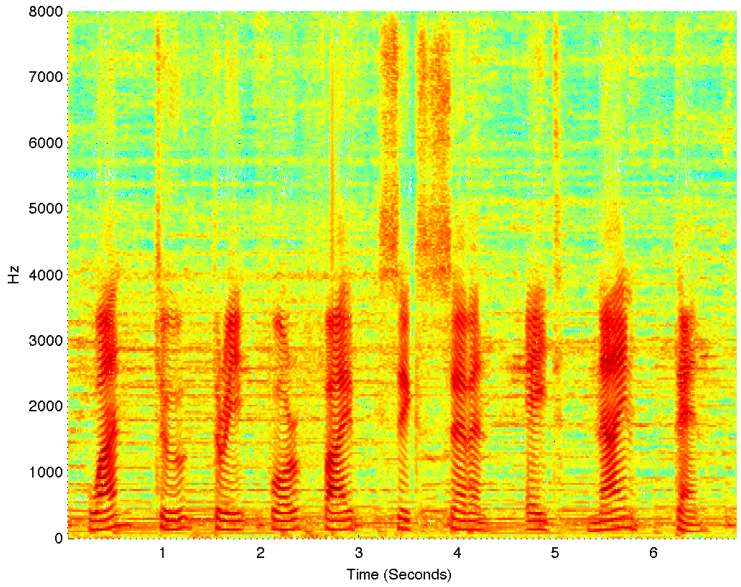

Figure 5.5: Spectrogram of male voice counting from one to ten.

For a given source, the training phase then consists in training a HMM with a discrete (latent) state space $\mathcal{Z}$, and a continuous emission distribution $\mathbf{P}(\mathbf{X}|\mathbf{Z})$. The emissions model will produce intensity vectors $\mathbf{X}_t$ as described in the preceding paragraph.

5.4.1 Initialization

The factoral hidden markov model consists of one HMM per speaker which is trained on separate non-mixed training data for each source.

The initialization of the FHMM training consists in estimating the emission probabilities $P(X|Z)$ (see figure, lag figur). While Roweis operates with a finite state model for the latent variables, the observable variables are real valued intensities. This indicates that a mixture model may be appropriate in the inital estimate of the emission model (vis til andre artikler med samme greier).

We follow Roweis in estimating a Gaussian mixture model with a single shared covariance matrix $\mathbf{\Sigma}$. For a spectrogram with N frequency bands, our approach is to estimate a GMM with k N-dimensional components or latent variables. The mean vector $\mu_i \in \mathbb{R}^N$ for each component i represents the expected intensity (power spectral density value) in each frequency band given that the system is in state i. The pair $(\{\mu_i\}, \Sigma)$ then forms the initial parametrization of the emissions model.

5.4.2 Separation

Next, consider the problem of recovering the orignial sources[4] $\mathbf{S} = \{S_1, S_2\}$ given the observed sequence $\{\mathbf{Y}(t)\}$, $t \in \{1, 2, 3, ..., T\}$ which we take to be spectral vectors as discussed above. As before, we let $z_k(t)$, $i \in \{1, 2\}$ denote the value of the latent variable for each HMM.

A key question in the separation process is how the observable signal generated by full FHMM relates to the observable values for each of the underlying HMMs. This question adresses a property of the *data generating model*, and must reflect properties of the physical system we are trying to model. In the case of auditory signals, Roweis argues for model whereby the observed value equals the maximum value of the observable values $\mathbf{X}_k(t)$ of the underlying HMMs with an additive gaussian noise:

$$\mathbf{Y}(t) = \Phi(\{\mathbf{X}_1(t), \mathbf{X}_2(t)\}^+, \Sigma) \tag{5.8}$$

For a further discussion on the rationale behind the log-max approximation, see [REFERANSER].

5.5 Results

[4]For simplicity, we will here frame the problem in terms of two sources.

Chapter 6

Conclusion

todo.

Appendix A

Mathematical Concepts

In this appendix we will provide a brief background on some of the mathematical notions that are central to understanding the methods used in this report.

A.1 Linear Algebra

In this section we will define a few important concepts that are necessary. These concepts are particularly important for understanding PCA, but are also relevant in the analysis of markov models. With stationary transition probabilities, the steady state distribution of the system is the solution to the eigenvector-eigenvalue problem.

The Eigenvector - Eigenvalue Problem

Singular Value Decomposition

A.2 Statistics and Optimization

A large portion of machine learning relies on statistical methods; the methods considered in this report being no exception. As the learning problems having relevance in practical life are often far too complex to describe by analytic formulae, we therefore often need mathematical methods to find models that have the best fit to the observed data.

In this section, we therefore consider one very important method for finding "optimal" parameters in a given model; the maximum likelihood method which is presented in Section A.2.1. We then proceed to show how to actually solve the resulting maximzation in Section A.2.2.

A.2.1 Maximum Likelihood Estimation

ML estimation is a method for determining the parameters of a statistical model by setting the parameters so as to maximize the *likelihood* of observing the actual data under the given model. Denoting $f(\boldsymbol{X}|\boldsymbol{\Theta})$ the probability distribution of $\boldsymbol{X} = \{x_1, x_2, ..., x_n\}$ with parameters $\boldsymbol{\Theta} = \{\theta_1, \theta_2, ..., \theta_m\}$, the maximum likelihood estimate of Θ solves EquationA.1

$$\arg\max_{\Theta} f(\boldsymbol{X}|\boldsymbol{\Theta}) \tag{A.1}$$

An important case is if the x_i are i.i.d., where the joint density is the product of the marginal densities. This means we can write the likelihood function f as Equation A.2.

$$f(\boldsymbol{X}|\boldsymbol{\Theta}) = \prod_{i=1}^{n} f(x_i|\Theta) \tag{A.2}$$

The solution to an optimzation problem is the same under any monotone transformation. Therefore it is often times useful to deal with the log-likelihood function instead of f directly.

A.2.2 Mathematical Optimization

Gradient Descent

A.3 Spectral Analysis

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