Latent Variable Models and Signal Separation

Class 9. 29 Sep 2011

The Engineer and the Musician

Once upon a time a rich potentate discovered a previously unknown recording of a beautiful piece of music. Unfortunately it was badly damaged.

He greatly wanted to find out what it would sound like if it were not.

So he hired an engineer and a musician to solve the problem.

The Engineer and the Musician

The engineer worked for many years. He spent much money and published many papers.

Finally he had a somewhat scratchy restoration of the music.

The musician listened to the music carefully for a day, transcribed it, broke out his trusty keyboard and replicated the music.

The Prize

Who do you think won the princess?

Sounds – an example

- A sequence of notes
- Chords from the same notes
- A piece of music from the same (and a few additional) notes

Sounds – an example

- A sequence of sounds
- A proper speech utterance from the same sounds
Template Sounds Combine to Form a Signal

- The individual component sounds "combine" to form the final complex sounds that we perceive
  - Notes form music
  - Phoneme-like structures combine in utterances
  - Component sounds – notes, phonemes – too are complex

- Sound in general is composed of such "building blocks" or themes
  - Our definition of a building block: the entire structure occurs repeatedly in the process of forming the signal

- Goal: To learn these building blocks automatically, from analysis of data

Urns and balls

- An urn has many balls
- Each ball has a number marked on it
  - Multiple balls may have the same number
- A "picker" draws balls at random...
- This is a multinomial

Signal Separation with the Urn model

- What does the probability of drawing balls from Urns have to do with sounds?
  - Or Images?

- We shall see..

The representation

- We represent signals spectrographically
  - Sequence of magnitude spectral vectors estimated from (overlapping) segments of signal
  - Computed using the short-time Fourier transform
  - Note: Only retaining the magnitude of the STFT for our operations
  - We will, however need the phase later for conversion to a signal

A Multinomial Model for Spectras

- A magnitude spectral vector obtained from a DFT represents spectral magnitude against discrete frequencies
  - This may be viewed as a histogram of draws from a multinomial

A more complex model

- A "picker" has multiple urns
- In each draw he first selects an urn, and then a ball from the urn
  - Overall probability of drawing $/f$ is a mixture multinomial
    - Since several multinomials (urns) are combined
    - Two aspects – the probability with which he selects any urn, and the probability of frequencies with the urns

- The balls are marked with discrete frequency indices from the DFT

- We shall see...
The Picker Generates a Spectrogram

- The picker has a fixed set of Urns
  - Each urn has a different probability distribution over $f$
- He draws the spectrum for the first frame
  - In which he selects urns according to some probability $P_0(z)$
- Then draws the spectrum for the second frame
  - In which he selects urns according to some probability $P_1(z)$
- And so on, until he has constructed the entire spectrogram
By fragmentation

- The URNS are the same for every frame.
  - These are the component multinomials or bases for the source that generated the signal.
- The only difference between frames is the probability with which he selects the urns.

Frame-specific spectral distribution:

\[ p(f) = \sum \pi_i p_i(f | z) \]

Source-specific bases

Simple EM solution

- Except bases are learned from all frames.
  - The Picker Generates a Spectrogram

Spectral View of Component Multinomials

- Each component multinomial (urn) is actually a normalized histogram over frequencies \( P(f | z) \)
  - I.e. a spectrum
- Component multinomials represent latent spectral structures (bases) for the given sound source.
  - The spectrum for every analysis frame is explained as an additive combination of these latent spectral structures.

Spectral View of Component Multinomials

- By “learning” the mixture multinomial model for any sound source we “discover” these latent spectral structures for the source.
- The model can be learnt from spectrograms of a small amount of audio from the source using the EM algorithm.

EM learning of bases

- Initialize bases
  - \( P(f | z) \) for all \( z \), for all \( f \)
  - Must decide on the number of urns.
- For each frame
  - Initialize \( P_t(z) \)

Learning the Bases

- Simple EM solution
  - Except bases are learned from all frames.

Learning Structures

- \( P(f | z) \)
- From Bach’s Fugue in Gmin
- The “Basis” distribution


Component Multinomials represent latent spectral structures (bases) for the given sound source.
Given Bases Find Composition

- Iterative process:
  - Compute a posteriori probability of the zth topic for each frequency f in the t-th spectrum
    \[ P(z | f, t) = \frac{P(f, z | t) P(z | t)}{\sum_{z'} P(f, z' | t) P(z' | t)} \]
  - Update mixture weight of zth basis
    \[ P(z | t) = \frac{\sum_{f} P(f, z | t) P(z | f, t) N_t(f)}{\sum_{z'} \sum_{f} P(f, z' | t) P(z' | f, t) N_t(f)} \]

Bag of Frequencies vs. Bag of Spectrograms
- The PLCA model described is a “bag of frequencies” model
  - Similar to “bag of words”
- Composes spectrogram one frame at a time
  - Contribution of bases to a frame does not affect other frames
- Random Variables:
  - Frequency
  - Possibly also the total number of draws in a frame

Bag of Frequencies PLCA model
- Bases are simple distributions over frequencies
- Manner of selection of urns/components varies from analysis frame to analysis frame

Bag of Spectrograms PLCA Model
- Compose the entire spectrogram all at once
  - One pot has a distribution over frequencies: these are our bases
  - The second has a distribution over time
- Each draw:
  - Select a superpot
  - Draw “F” from frequency pot
  - Draw “T” from time pot
  - Increment histogram at (T,F)

The bag of spectrograms
- Drawing procedure
  - Fundamentally equivalent to bag of frequencies model
    - With some minor differences in estimation

Estimating the bag of spectrograms
- EM update rules
  - Can learn all parameters
  - Can learn P(T|Z) and P(Z) only given P(f|Z)
  - Can learn only P(Z)
Bag of frequencies vs. bag of spectrograms
- Fundamentally equivalent
- Difference in estimation
  - Bag of spectrograms: For a given total \( N \) and \( P(Z) \), the total "energy" assigned to a basis is determined
    - increasing its energy at one time will necessarily decrease its energy elsewhere
    - No such constraint for bag of frequencies
    - More unconstrained
  - Can also be used to assign temporal patterns for components
- Bag of frequencies more amenable to imposition of a priori distributions
- Bag of spectrograms a more natural fit for other models

The PLCA Tensor Model
- The bag of spectrograms can be extended to multivariate data
- EM update rules are essentially identical to bivariate case

How meaningful are these structures
- If bases capture data structure they must
  - Allow prediction of data
    - Hearing only the low-frequency components of a note, we can still know the note
    - Which means we can predict its higher frequencies
  - Be resolvable in complex sounds
    - Must be able to pull them out of complex mixtures
      - Denoising
      - Signal Separation from Monaural Recordings

The musician vs. the signal processor
- Some badly damaged music is given to a signal processing whiz and a musician
  - They must “repair” it. What do they do?
- Signal processing:
  - Invents many complex algorithms
  - Writes proposals for government grants
  - Spends $1000,000
  - Develops an algorithm that results in less scratchy sounding music
- Musician:
  - Listens to the music and transcribes it
  - Plays it out on his keyboard/piano

Prediction
- Bandwidth Expansion
  - Problem: A given speech signal only has frequencies in the 300Hz-3.5Khz range
    - Telephone quality speech
  - Can we estimate the rest of the frequencies
    - The full basis is known
    - The presence of the basis is identified from the observation of a part of it
    - The obscured remaining spectral pattern can be guessed

Bandwidth Expansion
- The picker has drawn the histograms for every frame in the signal
Bandwidth Expansion

- The picker has drawn the histograms for every frame in the signal

Bandwidth Expansion

- The picker has drawn the histograms for every frame in the signal

However, we are only able to observe the number of draws of some frequencies and not the others. We must estimate the number of draws of the unseen frequencies.

Bandwidth Expansion

- The picker has drawn the histograms for every frame in the signal

Bandwidth Expansion: Step 1 – Learning

- From a collection of full-bandwidth training data that are similar to the bandwidth-reduced data, learn spectral bases
  - Using the procedure described earlier

Bandwidth Expansion: Step 2 – Estimation

- Using only the observed frequencies in the bandwidth-reduced data, estimate mixture weights for the bases learned in step 1.
Step 2
- Iterative process:
  - Compute a posteriori probability of the zth urn for the speaker for each f:
    \[ P(f|z) = \frac{P(z|f)P(f)}{\sum_z P(z|f)P(f)} \]
  - Compute mixture weight of zth urn for each frame f:
    \[ P(z) = \sum f P(z|f)S(f) \]
  - P(f|z) was obtained from training data and will not be reestimated

Predicting from P(f): Simplified Example
- A single Urn with only red and blue balls
- Given that out an unknown number of draws, exactly m were red, how many were blue?
- One Simple solution:
  - Total number of draws N = m / P(red)
  - The number of tails drawn = N*P(blue)
- Actual multinomial solution is only slightly more complex

Estimating unobserved frequencies
- Expected value of the number of draws:
  \[ \hat{N}_f = \frac{\sum f S(f)}{\sum f P(f)} \]
- Estimated spectrum in unobserved frequencies:
  \[ \hat{S}(f) = \hat{N}_f P(f) \]

Step 3 and Step 4
- Compose the complete probability distribution for each frame, using the mixture weights estimated in Step 2:
  \[ P(f) = \sum z P(z|f)P(f|z) \]
- Note that we are using mixture weights estimated from the reduced set of observed frequencies
  - This also gives us estimates of the probabilities of the unobserved frequencies
- Use the complete probability distribution P(f) to predict the unobserved frequencies!

The inverse multinomial
- Given P(Z) for all bases
- Observed n_1, n_2 .. n_k
- What is n_{k+1}, n_{k+2}...
  \[ P(n_1, n_2, \ldots) = \frac{n_k^{N_k} \ldots n_1^{N_1}}{\prod n_i} \]
  - N_i is the total number of observed counts
  - n_1 + n_2 + ...
  - P_n is the total probability of observed events
  - P(f_1) + P(f_2) + ...

Overall Solution
- Learn the “urns” for the signal source from broadband training data
- For each frame of the reduced bandwidth test utterance, find mixture weights for the urns
  - Ignore (marginalize) the unseen frequencies
- Given the complete mixture multinomial distribution for each frame, estimate spectrum (histogram) at unseen frequencies
A spectrum is a histogram of frequencies called out.

The caller selects a picker at random.

Each sound source is represented by its own picker and urns.

We must "fill in" the hole in the image.

To obtain the one to the right,

Easy to do – as explained.

Some frequency components are missing (left panel).

We know the bases $P(f|z)$.

But not the mixture weights for any particular spectral frame.

We must "fill in" the hole in the image.

To obtain the one to the right.

Easy to do – as explained.

The problem:

Multiples sources are producing sound simultaneously.

The combined signals are recorded over a single microphone.

The goal is to selectively separate out the signal for a target source in the mixture.

Or at least to enhance the signals from a selected source.

Each source has its own "bases".

In each frame:

- Each source draws from its own collection of bases to compose a spectrum.
- Bases are selected with a frame specific mixture weight.
- The overall spectrum is a mixture of the spectra of individual sources.
- I.e. a histogram combining draws from both sources.

Underlying model: Spectra are histograms over frequencies.

Goal: Estimate number of draws from each source.

The probability distribution for the mixed signal is a linear combination of the distribution of the individual sources.

The individual distributions are mixture multinomials.

And the urns are known.

Separating the sources.

$$P(f) = P(z_1)P(f|z_1) + P(z_2)P(f|z_2)$$

$$P(f) = \sum_z P(z|f)P(f|z_1) + \sum_z P(z|f)P(f|z_2)$$
Separating the sources

- Goal: Estimate number of draws from each source
  - The probability distribution for the mixed signal is a linear combination of the distribution of the individual sources
  - The individual distributions are mixture multinomials
  - And the urns are known

\[
P(f) = P(s_1)P(f|s_1) + P(s_2)P(f|s_2)
\]

Algorithm

- For each frame:
  - Initialize \( P_t(s) \)
    - The fraction of balls obtained from source \( s \)
    - Alternately, the fraction of energy in that frame from source \( s \)
  - Initialize \( P_z(t|s) \)
    - The mixture weights of the urns in frame \( t \) for source \( s \)
  - Reestimate the above two iteratively
  - Note: \( P(f|z,s) \) is not frame dependent
    - It is also not re-estimated
    - Since it is assumed to have been learned from separately obtained unmixed training data for the source

Reestimation

- The reestimate of source weights is simply the proportion of all balls that was attributed to the sources

\[
P(s) = \sum \frac{P(z|s)f}{P(f|z,s)}S(f)
\]

- The reestimate of mixture weights is the proportion of all balls attributed to each urn

\[
P(z|i) = \sum \frac{P(z|s)f}{P(f|z,s)}S(f)
\]
Separating the Sources

For each frame:

- **Given**
  - $S_t(f)$ – The spectrum at frequency $f$ of the mixed signal

- **Estimate**
  - $S_i(f)$ – The spectrum of the separated signal for the $i$-th source at frequency $f$

A simple maximum a posteriori estimator

$$\hat{S}_i(f) = S_i(f) \sum_z P(z, s | f)$$

If we have only have bases for one source?

- Only the bases for one of the two sources is given
- Or, more generally, for $N-1$ of $N$ sources

$$P(f | z, s) = P(z | s) P(f | z, s) + P(z_2) P(f | z_2)$$

Partial information: bases for one source unknown

- $P(f | z, s)$ must be initialized for the additional source
- Estimation procedure now estimates bases along with mixture weights and source probabilities
  - From the mixed signal itself
  - The final separation is done as before

Iterative algorithm

- **Iterative process:**
  - Compute a posteriori probability of the combination of speaker $s$ and the $z$-th urn for the speaker for each $f$

$$P(z, s | f) = \frac{P(z | s) P(f | z, s)}{\sum_{z'} P(z' | s) P(f | z', s)}$$

- Compute the a priori weight of speaker $s$ and mixture

$$P(z) = \sum_z P(z | s) S(z | s)$$

- Compute unknown bases

$$\hat{S}_i(f) = S_i(f) \sum_z P(z, s | f)$$
Separating Mixed Signals: Examples

- "Raise my rent" by David Gilmour
- Background music "bases" learnt from 5-seconds of music-only segments within the song
- Lead guitar "bases" learnt from the rest of the song
- Norah Jones singing "Sunrise"
- A more difficult problem: Original audio clipped!

Where it works

- When the spectral structures of the two sound sources are distinct
  - Don’t look much like one another
  - E.g. Vocals and music
  - E.g. Lead guitar and music
- Not as effective when the sources are similar
  - Voice on voice

Separate overlapping speech

- Bases for both speakers learnt from 5 second recordings of individual speakers
- Shows improvement of about 5dB in Speaker-to-Speaker ratio for both speakers
- Improvements are worse for same-gender mixtures

How about non-speech data

- We can use the same model to represent other data
- Images:
  - Every face in a collection is a histogram
  - Each histogram is composed from a mixture of a fixed number of multinomials
    - All faces are composed from the same multinomials, but the manner in which the multinomials are selected differs from face to face
  - Each component multinomial is also an image
    - And can be learned from a collection of faces
  - Component multinomials are observed to be parts of faces