Probabilistic Modeling of Speech

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2015-3-11, Beckman, UIUC

What is this talk about?

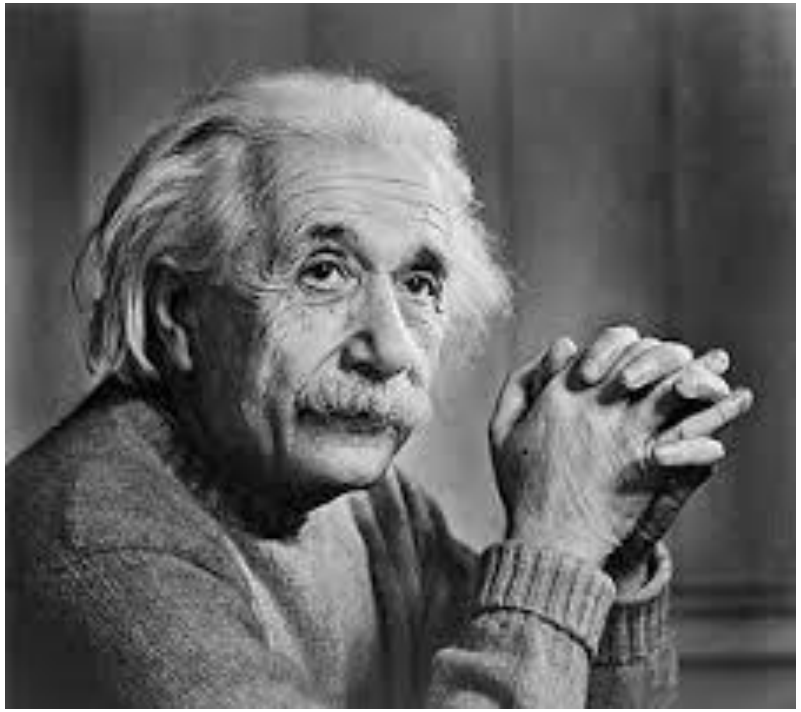
- Brief introduction to SPMI lab

- Motivation
- Bayesian HMM modeling of speech, ICASSP 2007.
- Variational nonparametric Bayesian HMM, ICASSP 2010.
- NMF modeling of voice in song, and a monaural voice and accompaniment separation system, ICASSP 2011.
- Probabilistic Acoustic Tube (PAT) Model, AISTATS 2012, ICASSP 2014.

Overview of SPMI Lab

- Setup the lab, since 2003.
- 2 master and 2 ph.d. students (Current), 7 master students (Graduated).
- Research interests
  - Speech Signal and Information Processing
    - Speech recognition and understanding (LVCSR - Mandarin, English)
    - Source separation
    - Speaker recognition
    - Natural language processing
    - Microphone array
  - Statistical Machine Intelligence
    - Construct probabilistic models of the studied phenomenon using human knowledge and machine learning algorithms;
    - Find efficient ways of implementing probabilistic inference with those models.

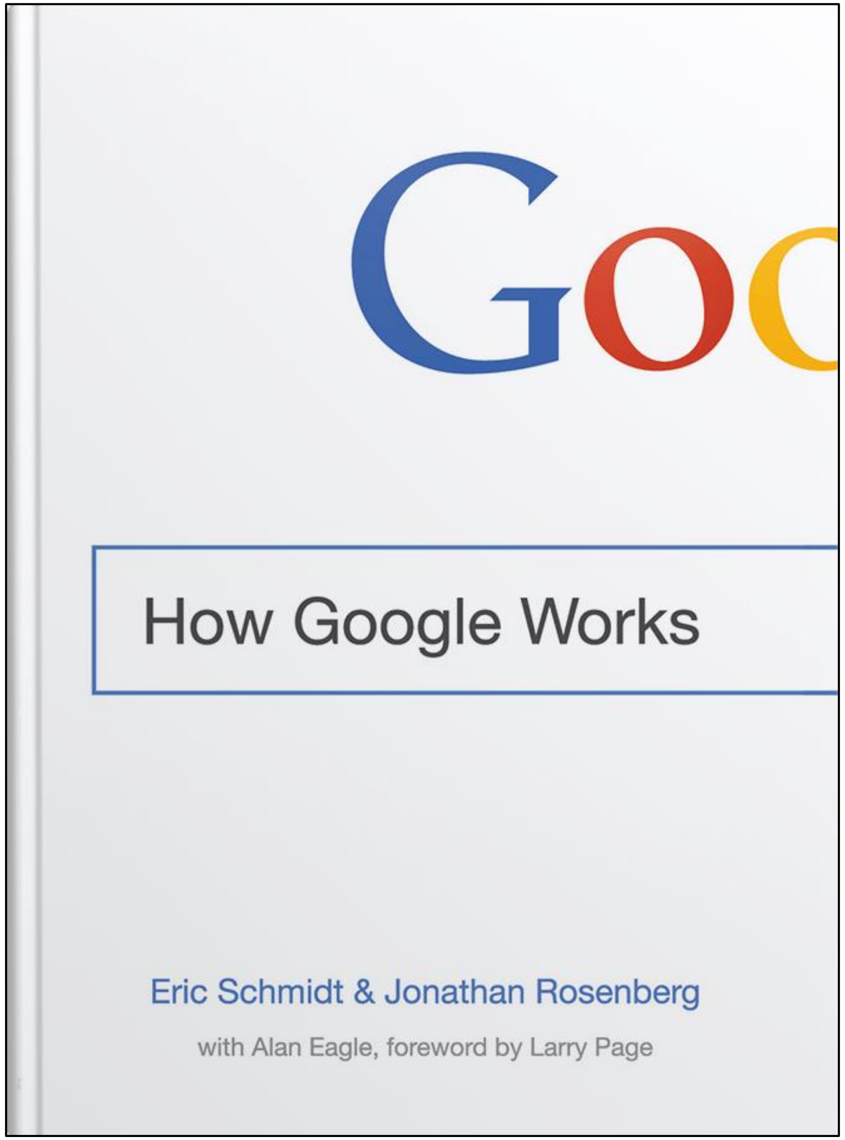
Motivation



As far as the laws of mathematics refer to reality, they are not certain;
and as far as they are certain, they do not refer to reality.

—— Albert Einstein

Motivation



… to think from first principles and real-world physics rather than having to accept the prevailing "wisdom."

—— Larry Page

Motivation - Probabilistic Modeling of Speech

- Dealing with uncertainty + Thinking from physics

- Most speech processing tasks (e.g. pitch estimation, speech recognition, source separation and so on) require a probabilistic model of speech.
- The more scientific the model is, the better we can do for speech processing.

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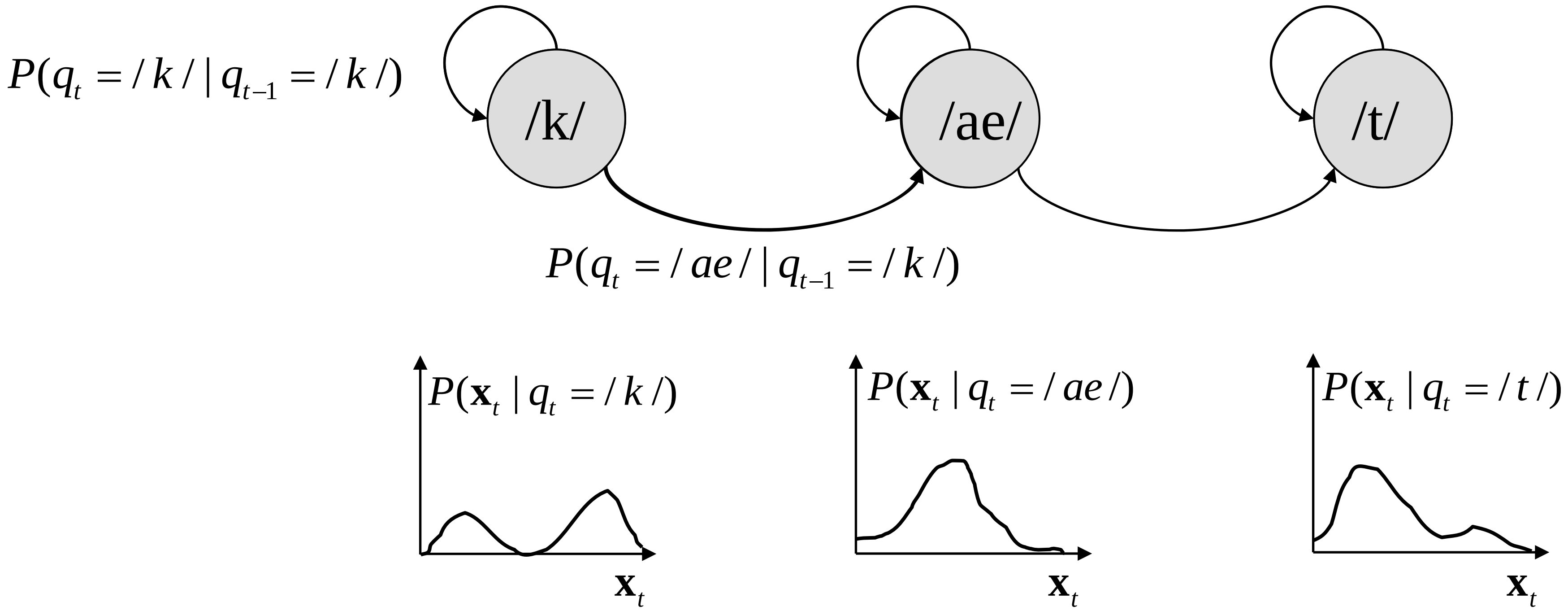
HMM based Acoustic Model

$$P(\vec{\mathbf{x}},\vec{q}) = P(q_0)P(\mathbf{x_0} \mid q_0)\prod_{t=1}^{T} P(q_t \mid q_{t-1})P(\mathbf{x_t} \mid q_t)$$

Feature Vector Sequence

Phone Sequence



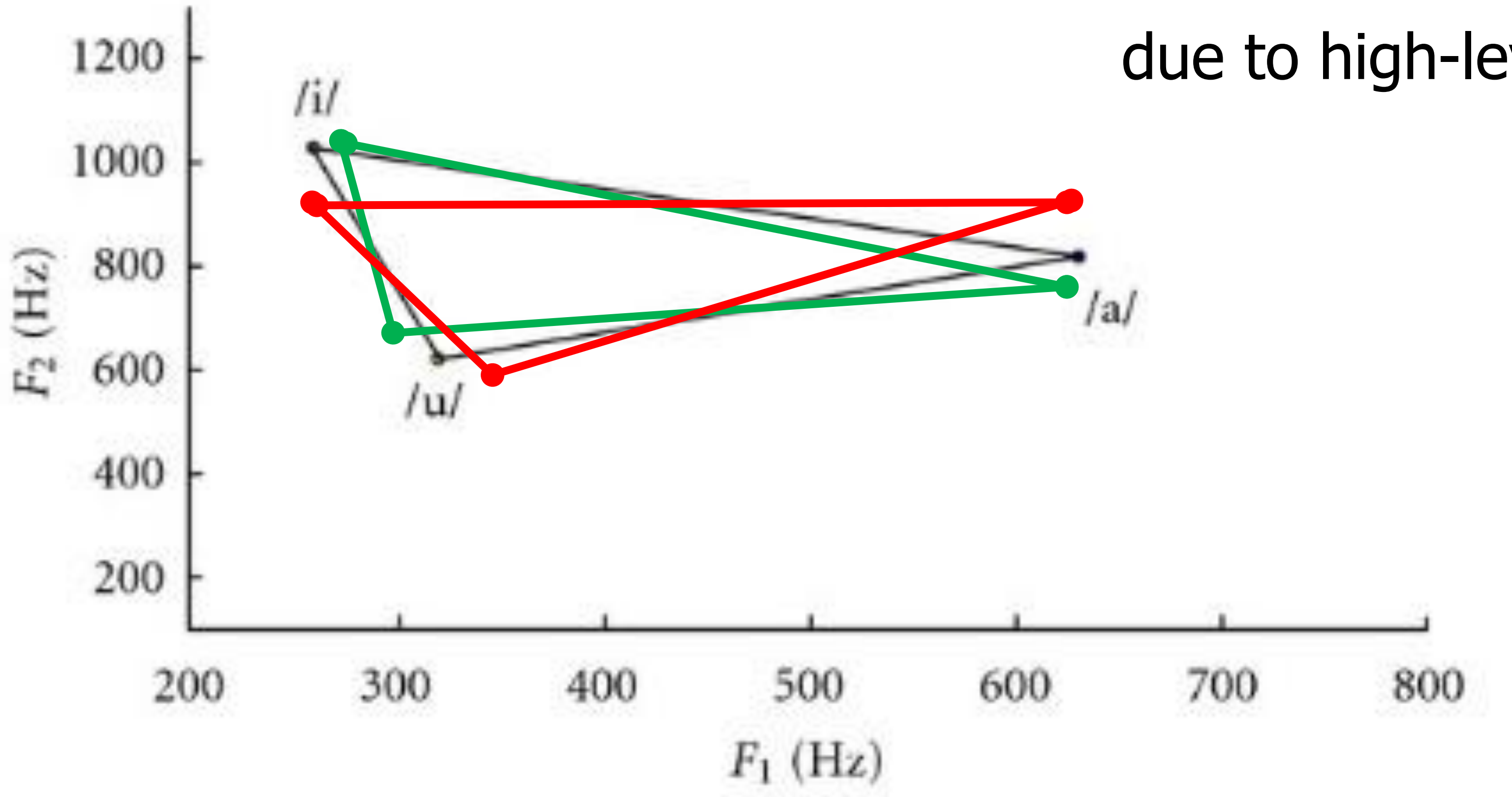
$\mathbf{x}_t$ is the Front-End Feature at time t

Correlation between different sounds

3000 states * 32 gaussians in R^{39}

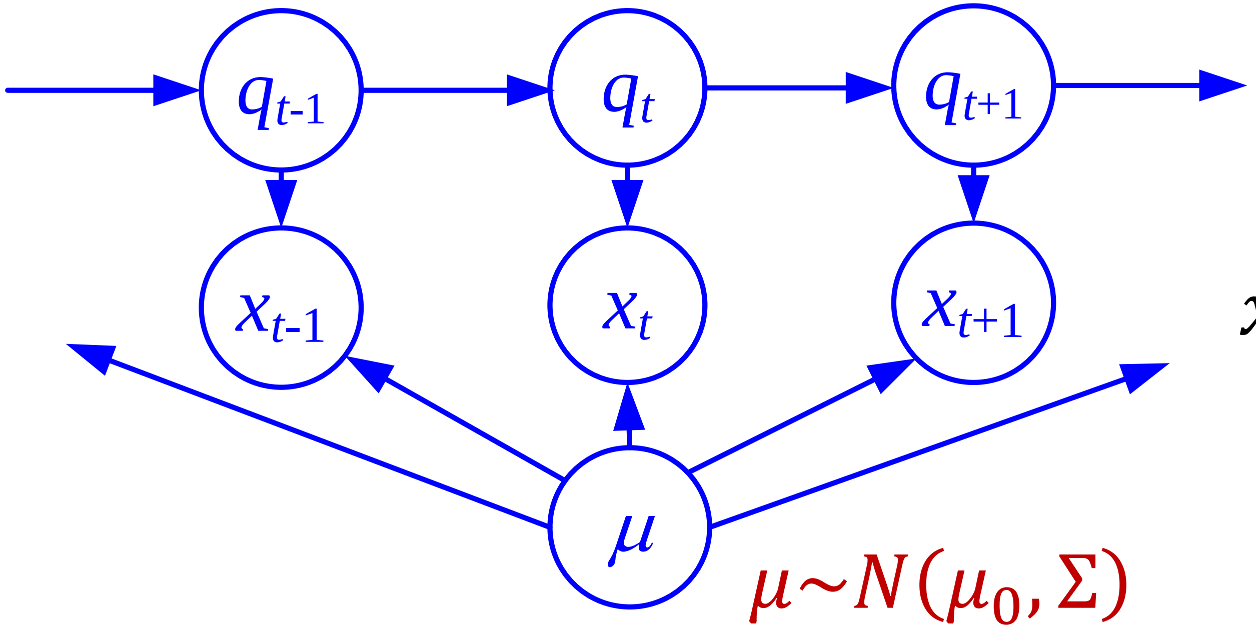
3 states * 1 gaussian in R^{2}

Correlation between the Gaussian means of different sounds due to high-level factors (e.g. speaker).



Bayesian HMM modeling of speech

Bayesian Network Representation of the Generative Model of Speech, incorporating the Supervector Variable μ.



$$x_t | q_t = i \sim N(\mu_i, C_i)$$

$$\mu \sim N(\mu_0, \Sigma)$$

- Use Variational EM algorithm to learn $\Theta = \{\mu_0, \Sigma, \{C_i\}\}$.
- Use ICM to adapt and recognize

$$\max_{q_1 \cdots q_T} p(q_1 \cdots q_T | x_1 \cdots x_T, \mu, \Theta), \max_{\mu} p(\mu | x_1 \cdots x_T, q_1 \cdots q_T, \Theta).$$

Experimental Results – ICASSP 2007

- OGI Numbers: 30-word vocabulary
- 39-dim feature : (12 MFCCs, Energy)+Δ+ΔΔ
- 26 monophone + sil + pause, each modeled by 3 states.

Word Error Rates

Mixture num per state		1	2	4
Baseline		20.86	16.85	13.34
Speaker adaptation	MLLR	20.71	16.79	13.25
	MAP	20.75	16.83	13.32
	MLLR+EV	20.79	16.27	12.59
	EM+EV	**18.42**	**15.76**	**12.44**
Utterance adaptation	MLLR	20.71	16.80	13.29
	MAP	20.75	16.86	13.24
	MLLR+EV	20.81	16.62	13.20
	EM+EV	**18.31**	**15.20**	**11.97**

i-vector in speaker recognition (2010)

Motivation to the next work

When applying HMMs, how many states should we use, and how the states are connected ?

Can we infer the state-transition structure from data ?

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Variational Nonparametric Bayesian HMM

Differences from other existing nonparametric Bayesian HMM

iHMM: Beal, Ghahramani, Rasmussen, “The infinite hidden Markov model,” NIPS 2002.

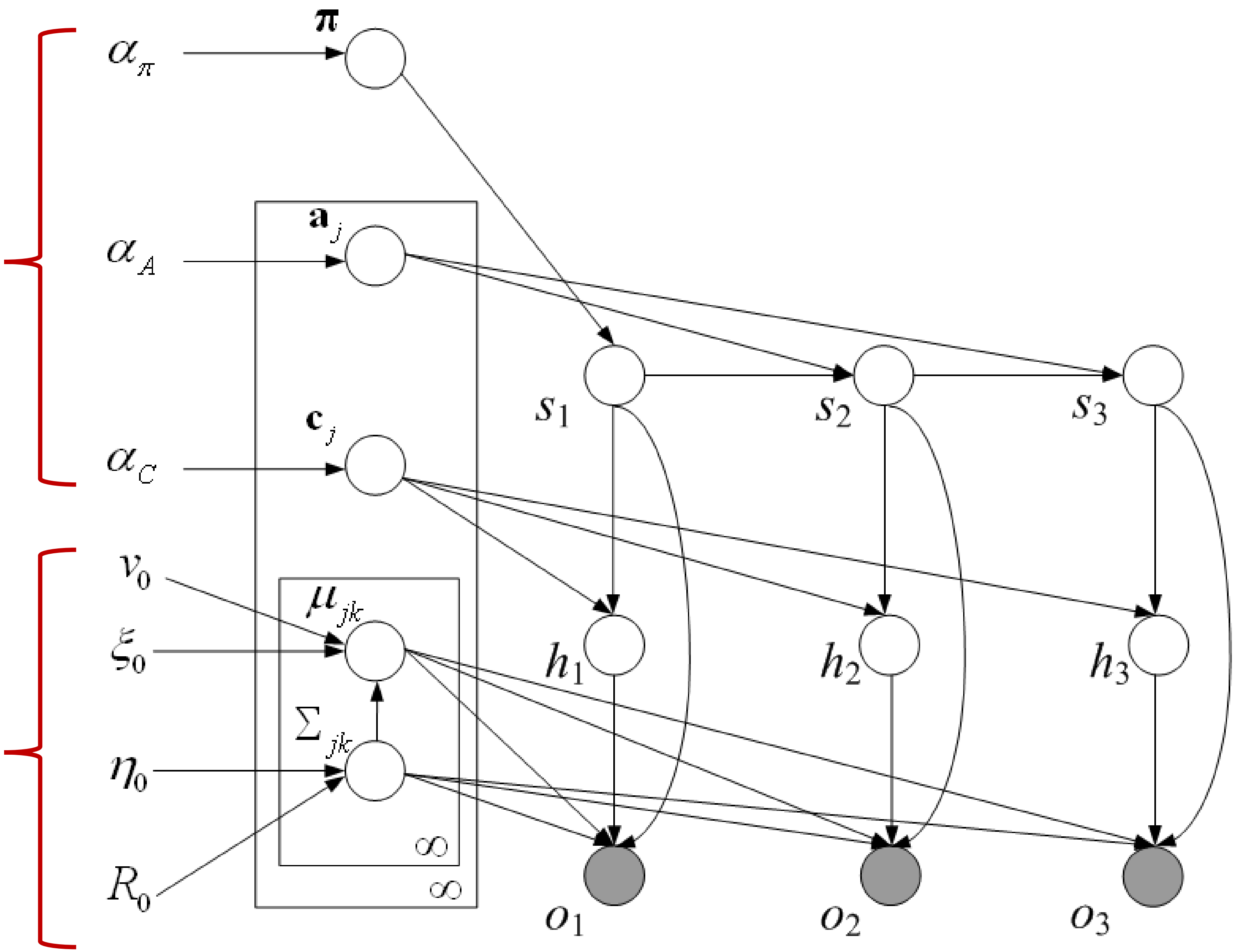
HDP-HMM: Teh, Jordan, Beal, Blei, “Hierarchical Dirichlet processes,” JASA 2006.

1	iHMM and HDP-HMM employ sampling based inference.	We apply the efficient variational inference for the NBHMM.
2	iHMM deals only with discrete observations.	NBHMM supports continuous observations via (infinite) Gaussian mixtures.
3	The transition distribution in iHMM and HDP-HMM is generated from HDP	In the NBHMM, directly created from a stickbreaking construction, simpler

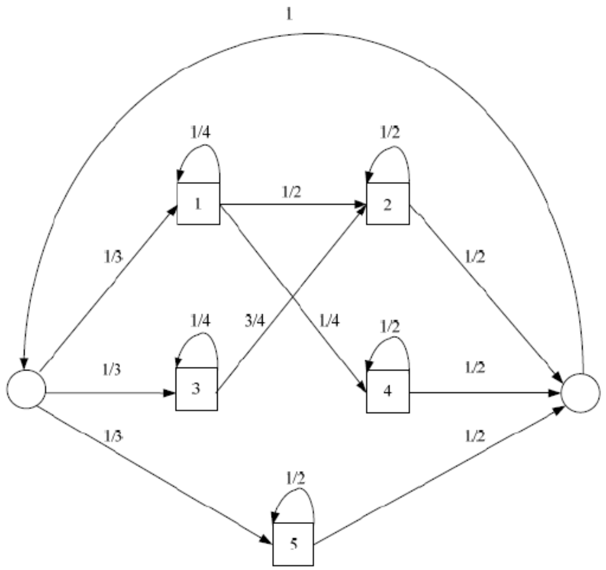
Graphical Model of the Nonparametric Bayesian HMM

A stickbreaking construction of Dirichlet Process prior for the infinite-length multinomial distributions

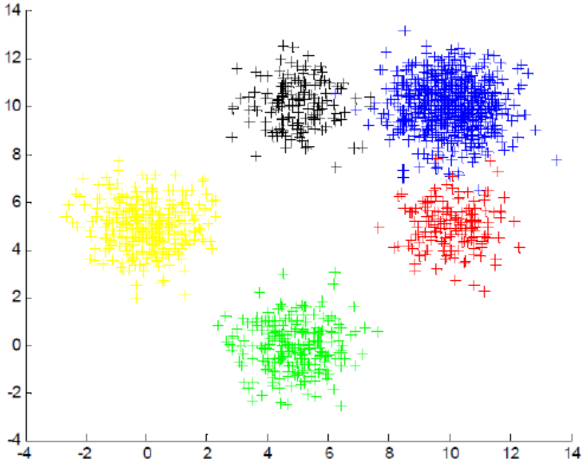
Gaussian-Gamma prior for the Gaussian means and variances



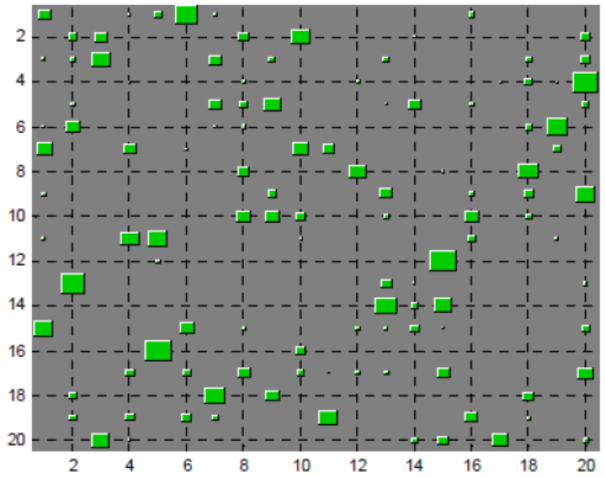
Experimental Results



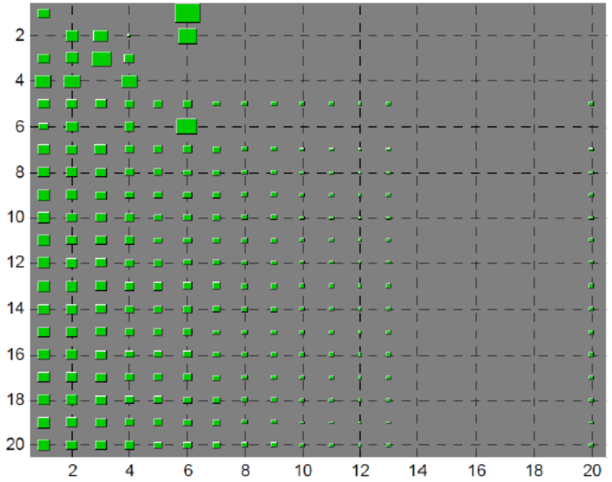
(a) Synthetic Markov machine.



(b) Synthetic observations



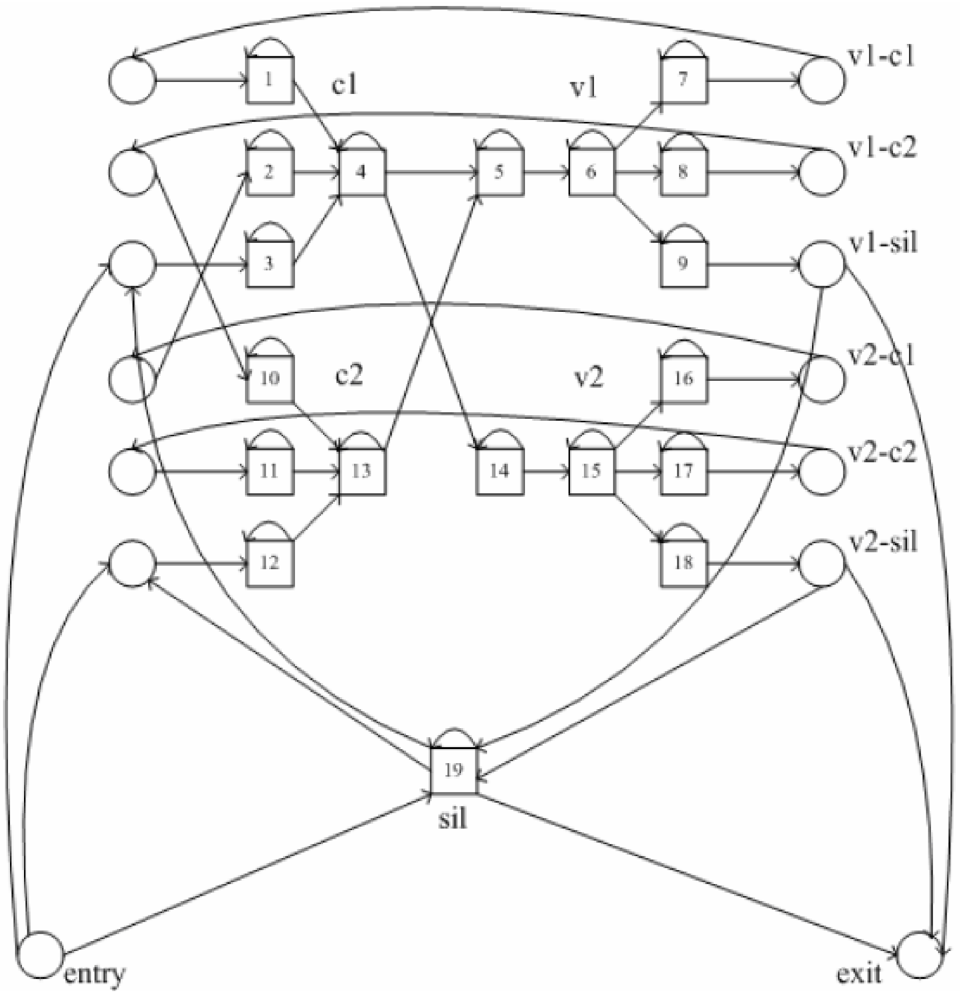
(c) Hinton graph for classical HMM



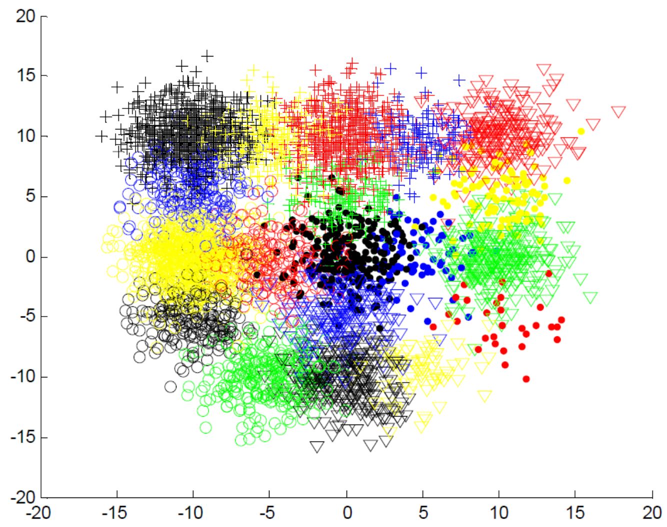
(d) Hinton graph for NBHMM

- A toy example of continuous speech recognition which uses four phonetic states (no.1-4) plus a silence state (no. 5).
- The data contains 50 chains, and the length of each chain is 20.
- The classical HMM with the size of state-space N = 20.
- The NBHMM with the truncation level L = 20.

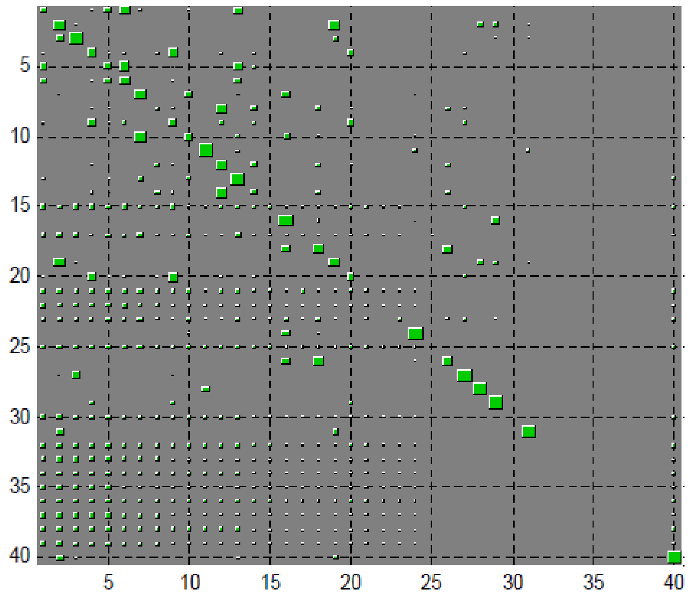
Experimental Results



A “triphone” structure



Synthetic observations



Hinton graph for NBHMM

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Introduction

- **Block diagram of voice/accompaniment separation systems**

Mixed Signal → Melody extraction → Time-frequency masking → Voice & Accompaniment

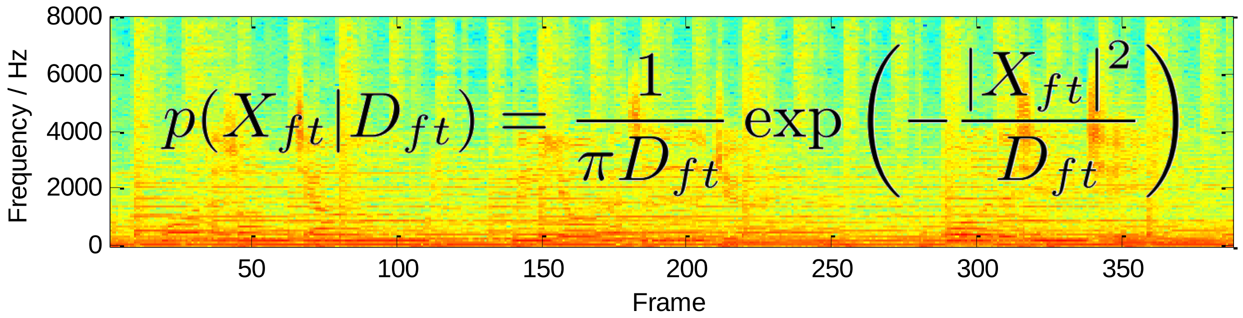
- **Various implementations**

	Melody extraction	**T-F masking**
D.L.Wang [IEEE ASLP 2007]	HMM	Hard
Hsu(1) [IEEE ASLP 2010]	Dressler (Neither HMM nor NMF)	Hard
Hsu(2) [ISMIR 2009]	**HMM**	
Virtanen [ISCA 2008]	HMM	NMF Soft
Durrieu [ICASSP 2009]	NMF	**NMF Soft**
Ours	**HMM**	**NMF Soft**

Flaw

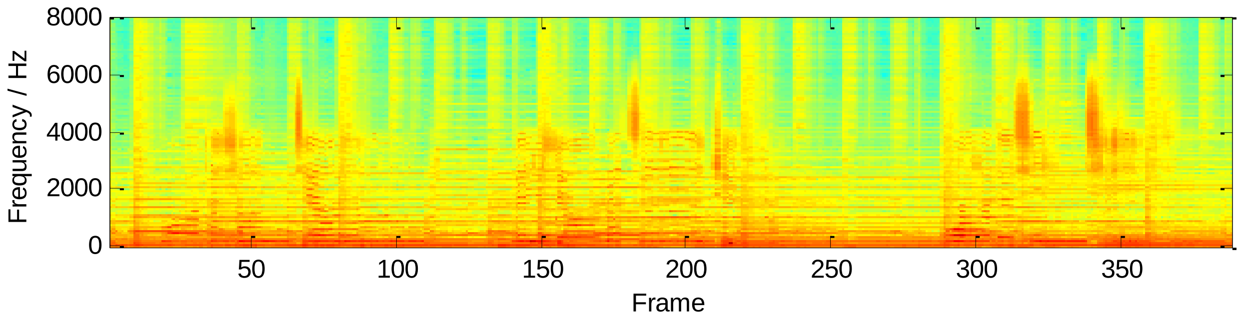
NMF based Acoustic Model

- **Observed spectogram *X*** as a stochastic process



$$p(X_{ft}|D_{ft}) = \frac{1}{\pi D_{ft}} \exp\left(-\frac{|X_{ft}|^2}{D_{ft}}\right)$$

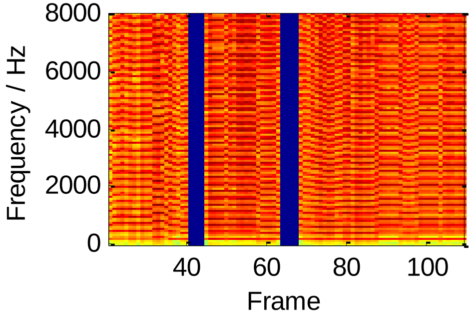
- **Power spectrogram *D*** as its variance parameters



- Main task: Estimate ***D*** with NMF constraints to maximize $p(\boldsymbol{X}|\boldsymbol{D})$

NMF based Acoustic Model

Glottal excitation



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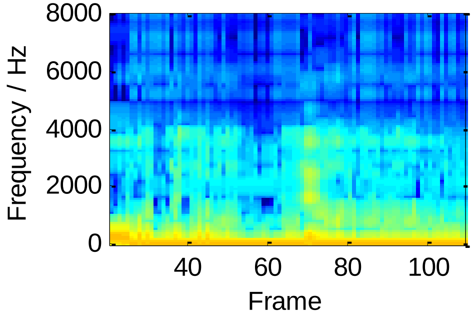
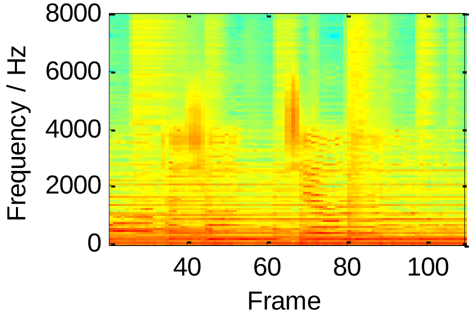
Vocal tract



$$\boldsymbol{D} = \underbrace{(\boldsymbol{B}_F \boldsymbol{A}_F) .* (\boldsymbol{B}_K \boldsymbol{A}_K)}_{\boldsymbol{D}_V} + \underbrace{(\boldsymbol{B}_M \boldsymbol{A}_M)}_{\boldsymbol{D}_M}$$



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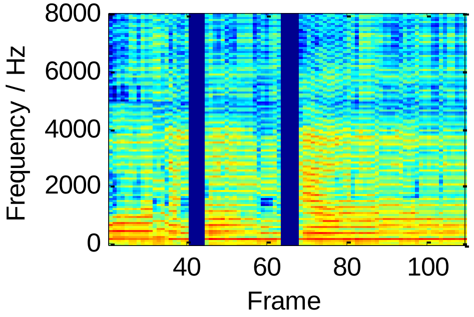

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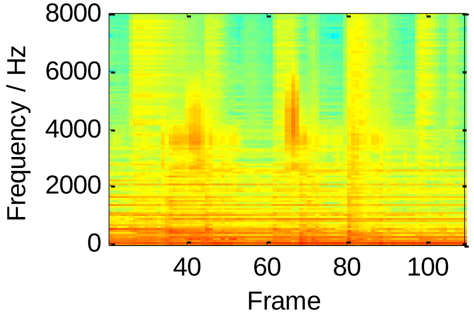
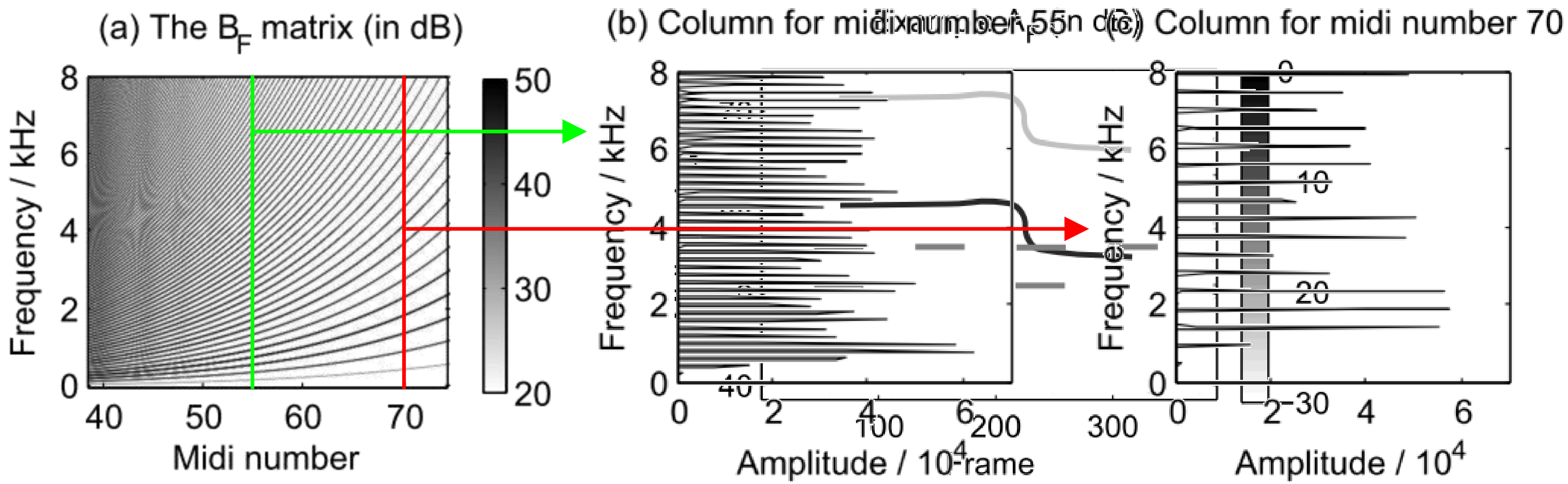


NMF based Acoustic Model

Glottal excitation　　Vocal tract　　Music

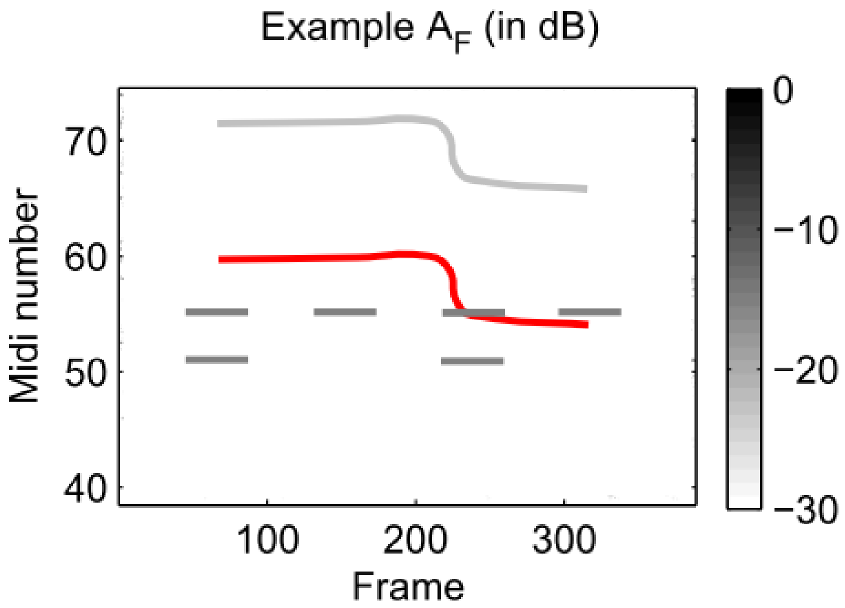
$$\boldsymbol{D} = \underbrace{(\boldsymbol{B}_F \boldsymbol{A}_F) .* (\boldsymbol{B}_K \boldsymbol{A}_K)}_{\boldsymbol{D}_V} + \underbrace{(\boldsymbol{B}_M \boldsymbol{A}_M)}_{\boldsymbol{D}_M}$$

- ***B*** matrices are "codebooks"
- ***A*** matrices are linear combination coefficients



NMF-based melody extraction and separation

- Fix B_F, estimate $\Theta = \{A_F, B_K, A_K, B_M, A_M\}$ under max likelihood
- Find the strong continuous pitch trajectory on A_F , using DP

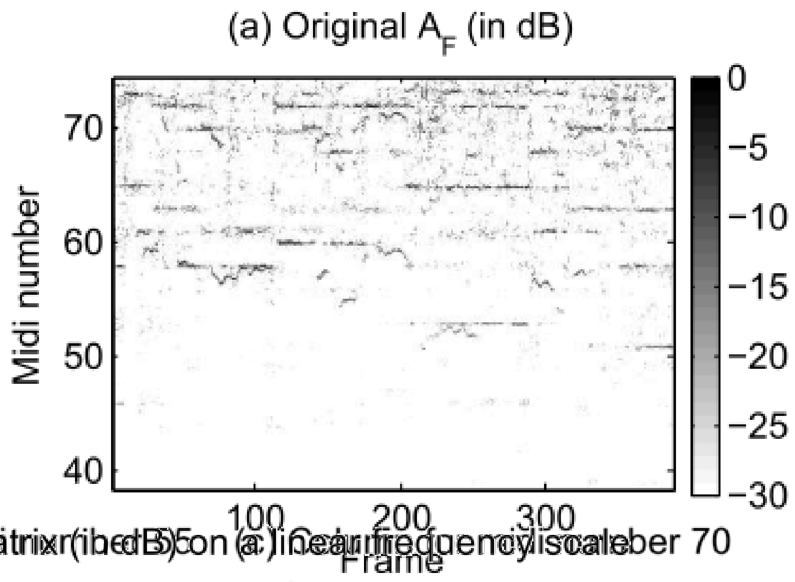


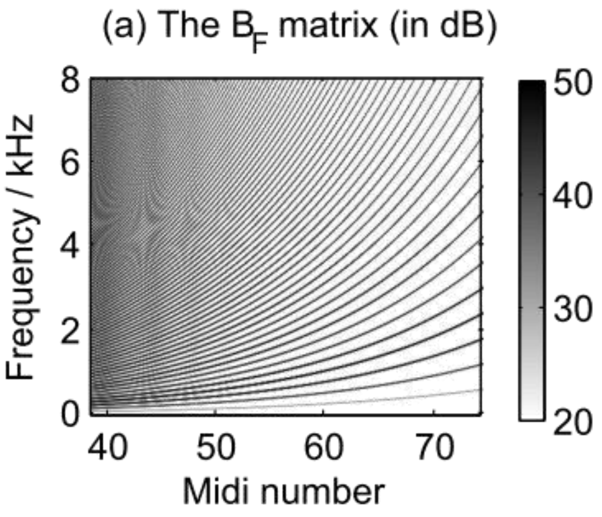
- Fix B_F and A_F , Re-estimate and Soft masking

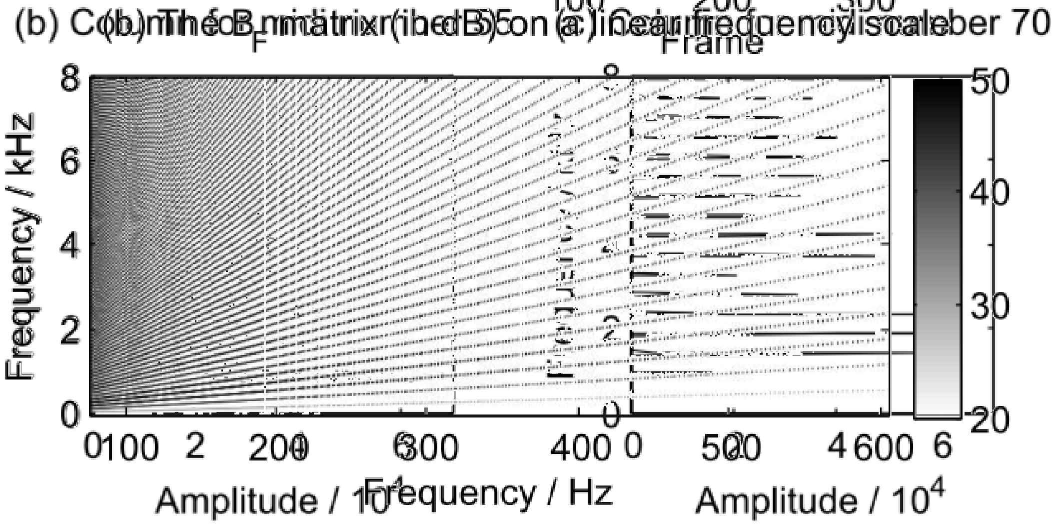
$$\hat{\boldsymbol{X}}_V = \frac{\boldsymbol{D}_V}{\boldsymbol{D}_V + \boldsymbol{D}_M}\boldsymbol{X} \qquad \hat{\boldsymbol{X}}_M = \frac{\boldsymbol{D}_M}{\boldsymbol{D}_V + \boldsymbol{D}_M}\boldsymbol{X}$$

Flaw of NMF-based melody extraction

- **Imbalance in A_F**
- **Two causes:**
  - Non-linearity of midi number scale
  - Columns of B_F unnormalized

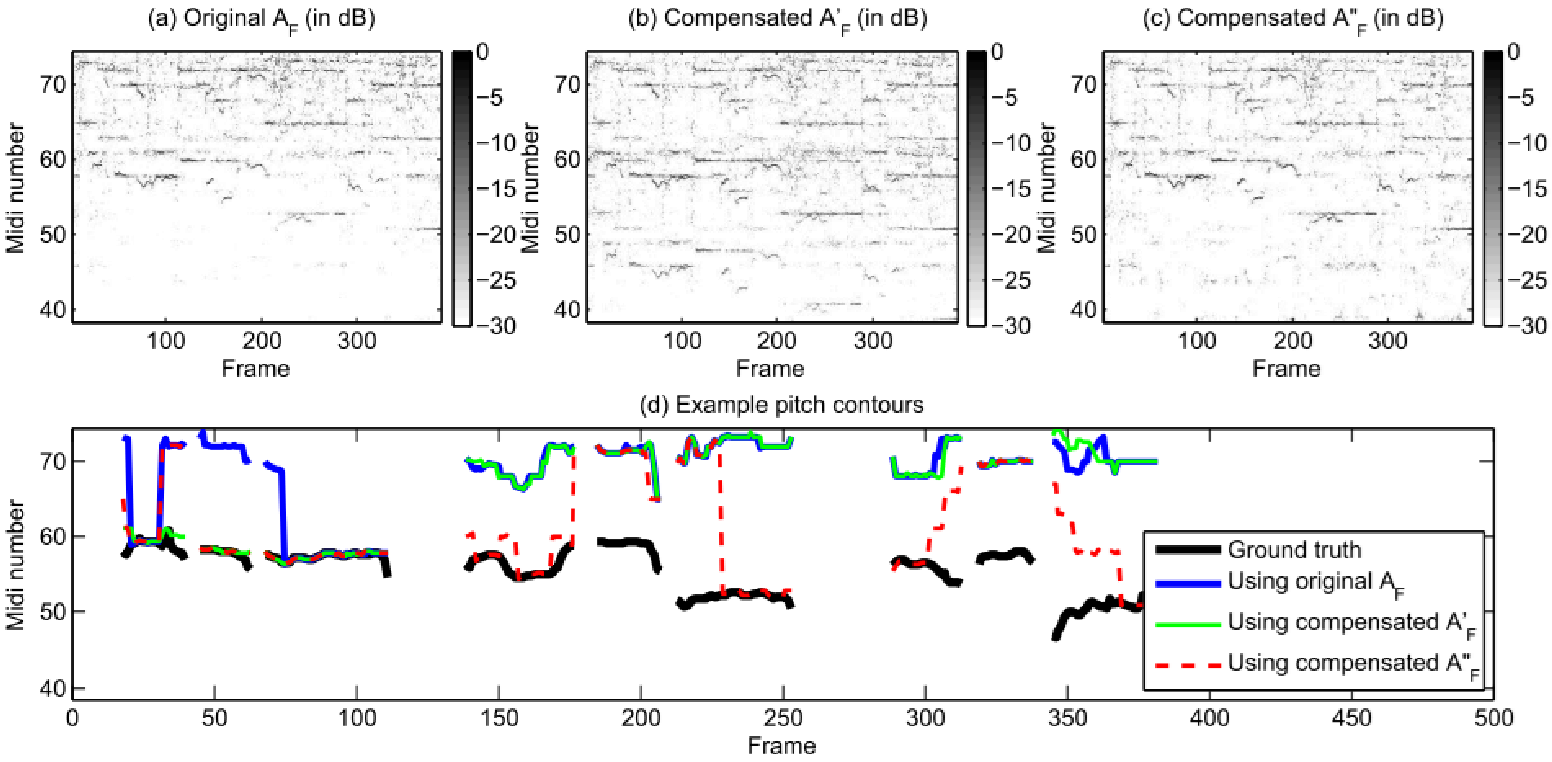






Flaw of NMF melody extraction

- Durrieu's compensation: $(\boldsymbol{A}'_F)_{n,t} = (\boldsymbol{A}_F)_{n,t} + 0.5(\boldsymbol{A}_F)_{n+12,t}$
- Our compensation: $(\boldsymbol{A}''_F)_{n,t} = (\boldsymbol{A}_F)_{n,t} \cdot \frac{1}{f'(n)} \cdot \sum_i (\boldsymbol{B}_F)_{i,n}$
- Compensation cannot eliminate imbalance!



Experimental Results

Mixing ratio	H1 system			Our system	
	Ideal masks	Annot. pitch	Extr. pitch	Annot. pitch	Extr. pitch
-5 dB	10.62	7.5	-0.5	10.34	4.03
0 dB	8.36	6.0	0.9	8.70	5.31
5 dB	5.82	3.0	0.2	6.53	4.09

Table 1. Comparison of Hsu's SDR gains (in dB) on the MIR-1K database for the H1 system (cited from [2]) and our system

Clip	Original		Durrieu		Our system	
	Voice	Acc.	Voice	Acc.	Voice	Acc.
Bearlin	-5.37	5.37	6.2	11.6	3.44	8.76
Tamy	0.51	-0.51	11.5	11.0	4.17	3.66
Bent	0.01	-0.01	5.5	5.6	8.46	8.45
Chevalier	-6.79	6.79	1.5	8.3	2.72	9.50
Love	0.28	-0.28	8.6	8.4	5.17	4.89
Matter	-4.72	4.72	8.0	12.7	4.52	9.24

Table 2. Comparison of Durrieu's SDRs (in dB) for voice and accompaniment on Durrieu's database for Durrieu's system using compensated A'_F (cited from Durrieu's website) and our system

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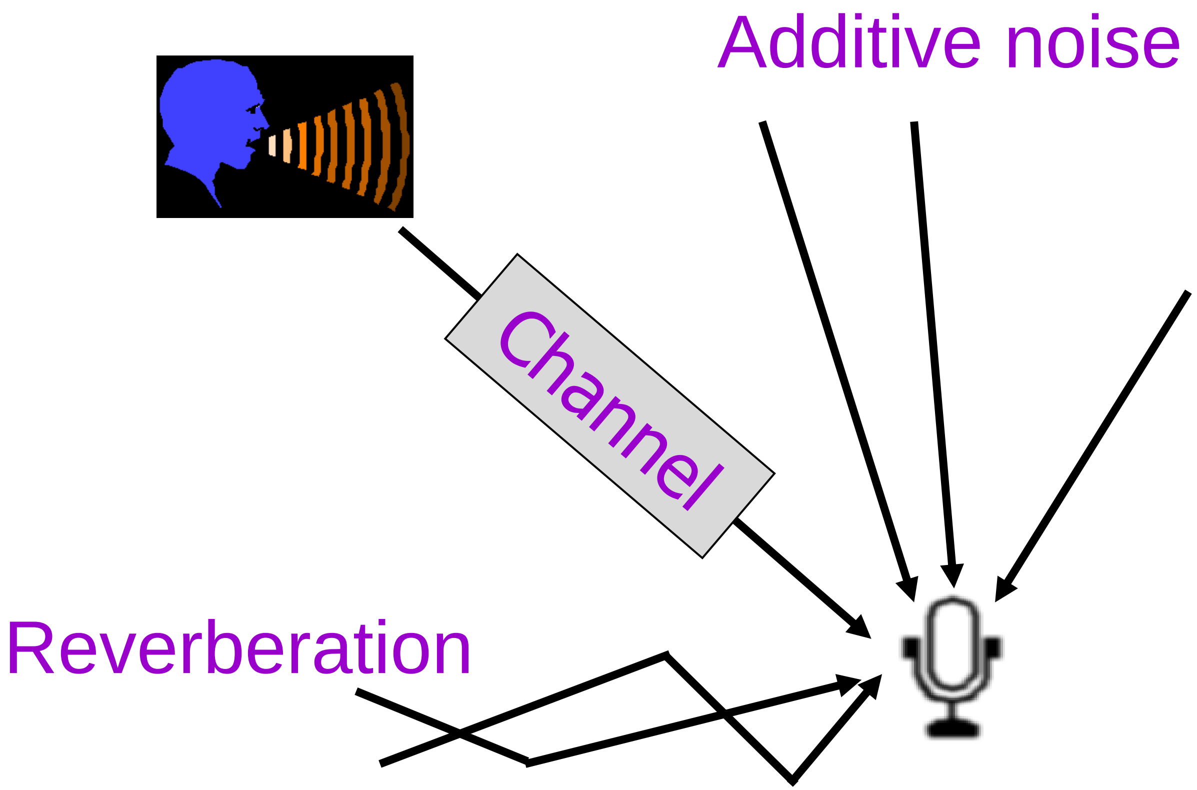
Grand Challenge

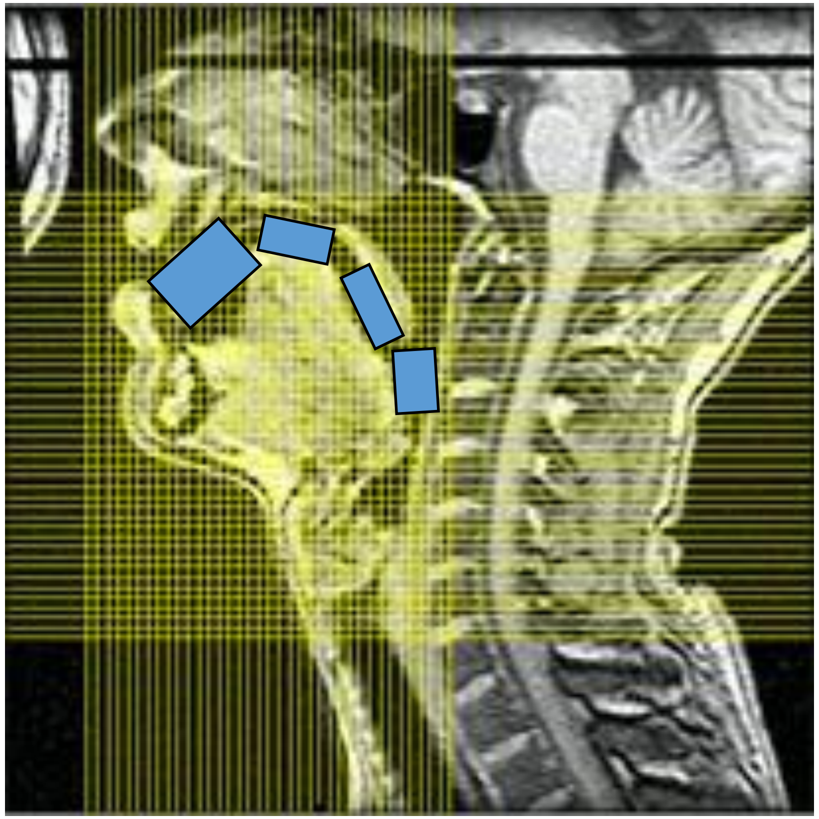
Make Intelligent Machines That Can Hear,
Especially In Complex Acoustic Environment Like Cocktail Party.

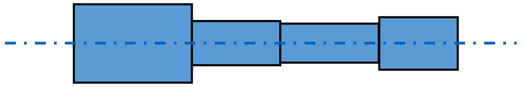


Motivation

What is the basic physical model of speech production ?

—— The Acoustic Tube Model, a.k.a Source-Filter Model.





Motivation

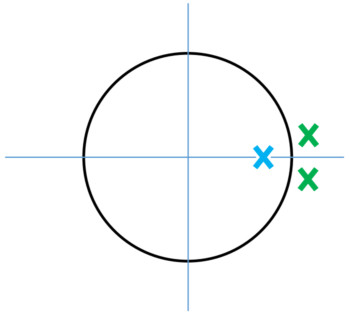
Are there any generative models of speech?

Motivation

- Most of them are actually generative models of the speech features (e.g. Magnitude, Correlogram, Cepstrum).
- Only a few directly model the spectrogram (Reyes-Gomez et al. 2005, Bach and Jordan 2005, Kameoka et al. 2006, Hershey et al. 2010).
- None of them fully respect the physical acoustic tube model
  - Pitch, Glottal source, Vocal tract response, Aspiration noise, Phase
- Drawback: Speech analysis is incomplete, inaccurate or even incorrect.
  - Chicken and egg effect;
  - Vocal tract estimate (e.g. LPC and MFCC) corrupted by spectral tilt.

PAT Model

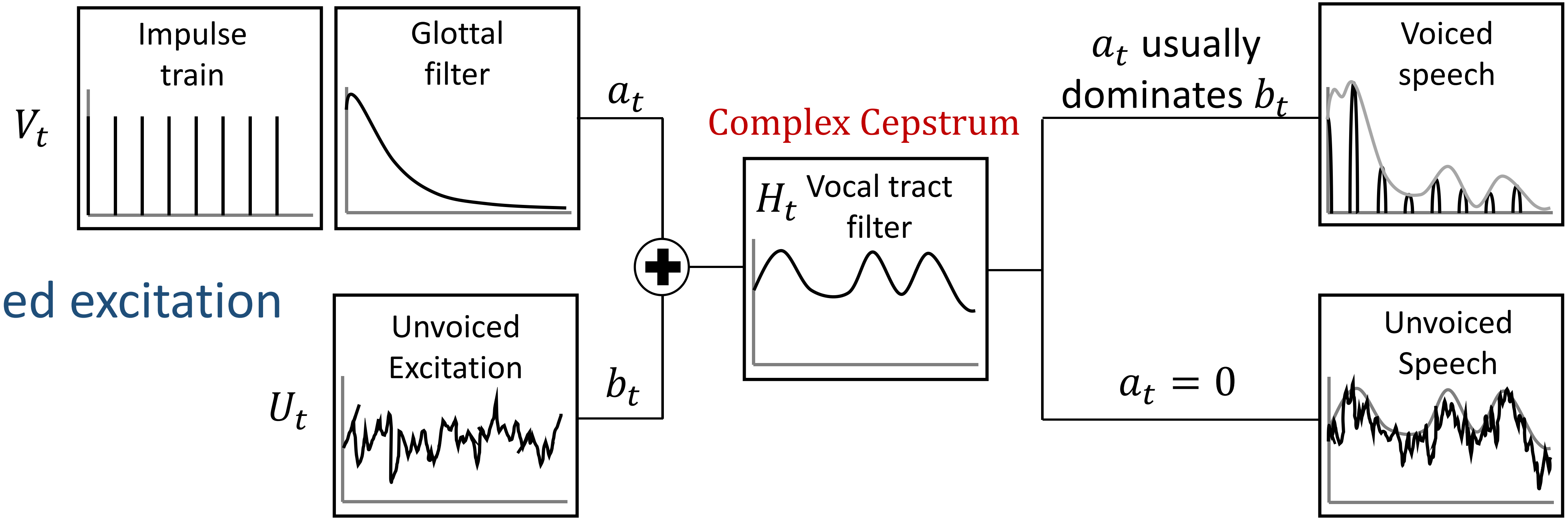
$$S_t(\omega) = [a_t V_t(\omega) + b_t U(\omega)] H_t(\omega) \circledast W_t(\omega) + N_t(\omega)$$



Voiced excitation

$$V_t(\omega) = G_t(\omega) e^{-j\omega\tau_t} \sum_k \delta(\omega - k\omega_{0t})$$

Unvoiced excitation



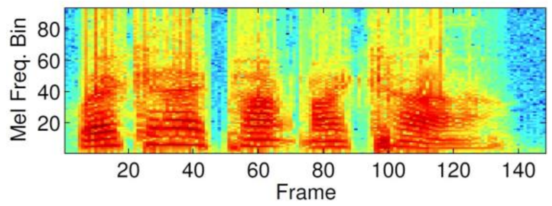
Highlight of PAT

- PAT is based on the fundamental physics of speech production.

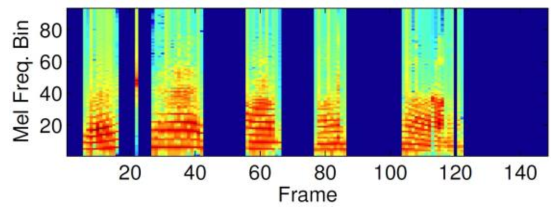
- A **probabilistic generative model** that **jointly** considers all important speech parameters;
- Incorporates **breathiness** and **glottal source**;
- Incorporates **phase modeling** and so completely defines a probabilistic model for the complex spectrum of speech;
- **Makes U/V states a continuum** by introducing voiced amplitude and unvoiced amplitude, which is closer to the nature of speech.

Experimental Results

Voiced Reconstruction

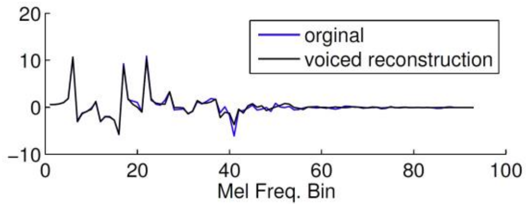


Original Spectrogram

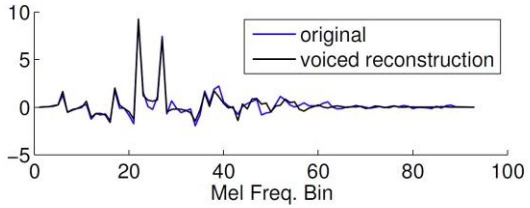


Voiced Reconstruct

Voiced Reconstruction – Single Frame

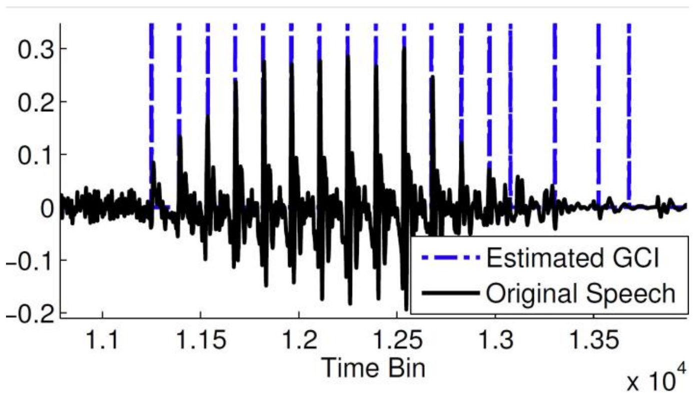


Real Spectrum

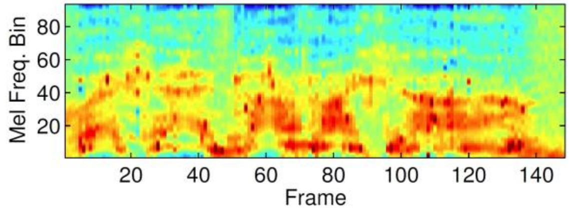


Imaginary Spectrum

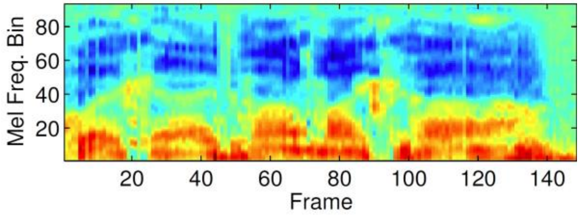
GCI Location Estimation



Vocal Tract Filter Estimation

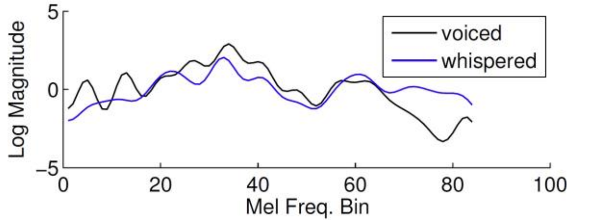


PAT2

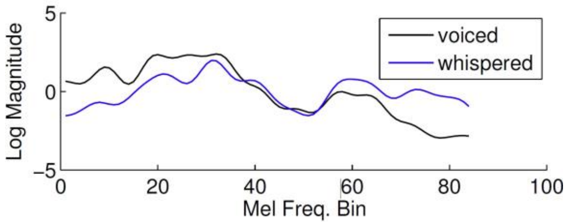


MFCC

Voiced vs Whispered



PAT2



MFCC

Summary - Probabilistic Modeling of Speech

- PAT: On the way …
- One of the reviewers comments "to my knowledge the most complete attempt on developing a true generative model for speech".

- Bayesian HMM modeling of speech, ICASSP 2007

  -> Put a prior over model parameters to account for high-level factors (e.g. the speaker, utterance style).

- Variational nonparametric Bayesian HMM, ICASSP 2010

  -> Discover the state-transition structure according to data.

- NMF modeling of voice, ICASSP 2011

  -> feasible

Thanks:

Jun Luo, Nan Ding, Yun Wang, Yang Zhang, Mark Hasegawa-Johnson.

Thanks for your attention !