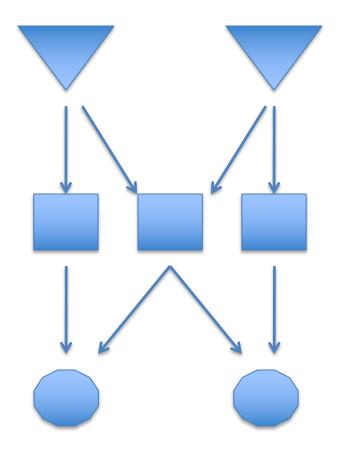
02458 Cognitive Modeling

Natural world statistics

A modest proposal

- The perceptual system is optimized to represent information relevant for survival
 - The dynamic range of neurons match the dynamic range of stimuli
 - Independent image components (e.g. objects) are coded in independent channel
- Testable hypothesis
 - If we know the statistics of natural images



objects

correlation

sensors

decorrelation

representation

Joint (pixel) probabilities

- Images are parameterized as vectors of pixels
 - For each color channel
 - For now, we just look at luminance (b/w)
- How do we parameterize P(I)?
 - As a joint probability $P(I_1, I_2, ..., I_N)$
 - Pixels are not independent $P(I_1,I_2)^{\sim}=P(I_1)(I_2)$
 - How do we describe dependence?

Covariance

- Variance: $E((x-\mu_x)^2) \cong E((x-\bar{x})^2)$
- Covariance: $E((x-\mu_y)(y-\mu_y)) \cong E((x-\overline{x})(y-\overline{y}))$
- For independent variables:

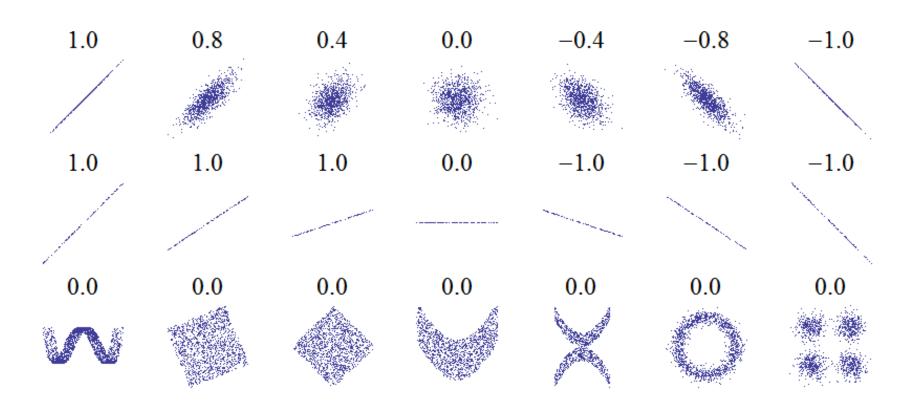
$$E((x-\overline{x})(y-\overline{y})) = \sum_{i,j} P(x_i, y_j)(x_i - \overline{x})(y_j - \overline{y}) =$$

$$\sum_{i,j} P(x_i) P(y_j)(x_i - \overline{x})(y_j - \overline{y}) = \sum_i P(x_i)(x_i - \overline{x}) \sum_j P(y_j)(y_j - \overline{y}) =$$

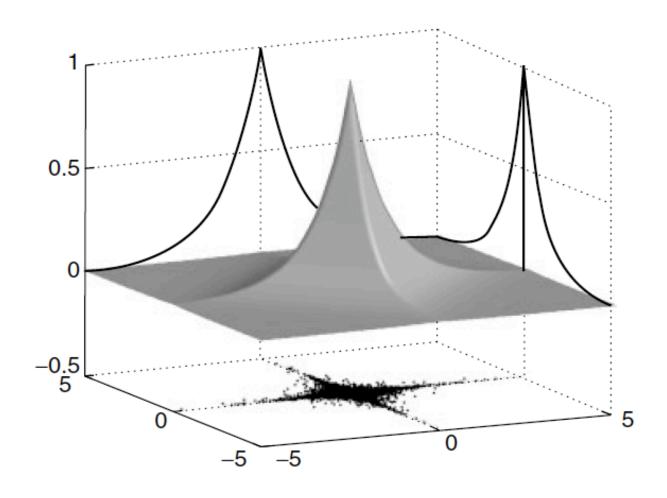
$$\left(\sum_i P(x_i)x_i - \overline{x}\sum_i P(x_i)\right)\left(\sum_i P(y_i)y_i - \overline{y}\sum_i P(y_i)\right) =$$

$$(\overline{x} - \overline{x})(\overline{y} - \overline{y}) = 0$$

Covariance does not imply independence

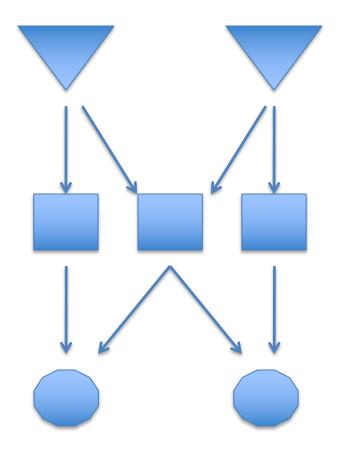


Natural statistics are not Gaussian



Natural statistics are sparse

- Sparseness means
 - Frequent, Low amplitude events
 - Infrequent, high amplitude events
- Sparseness is approximately
 - The fourth moment, kurtosis, $E((x-\mu)^4)$
- Sparseness implies structure
 - Gaussian distribution implies randomness



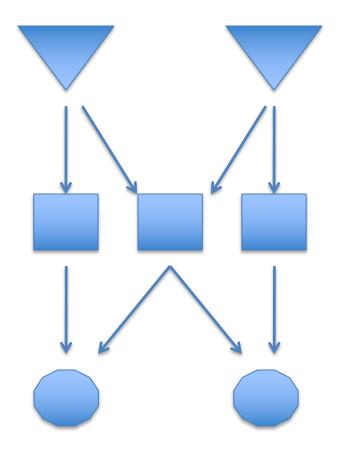
objects

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sensors

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representation



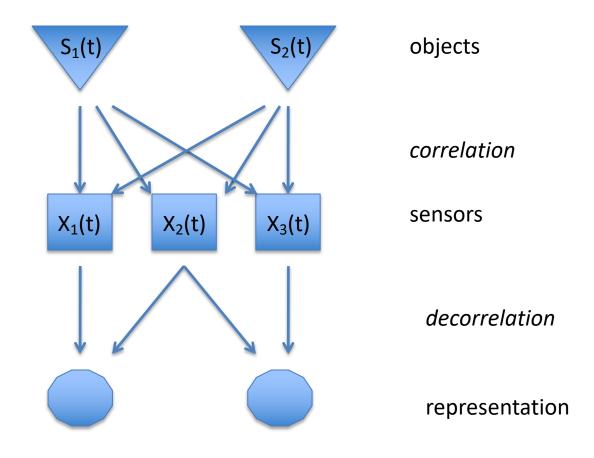
objects

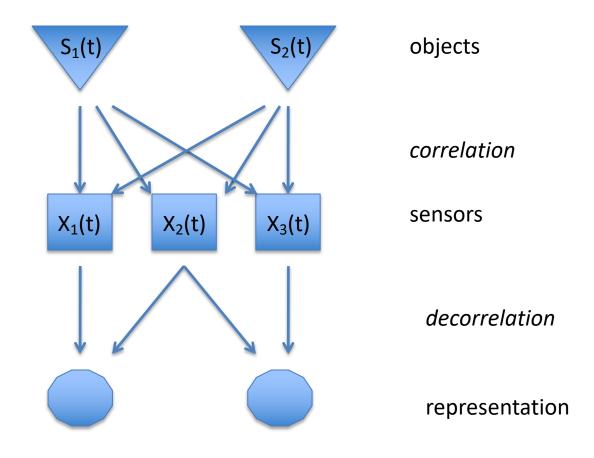
correlation

sensors

decorrelation

representation





$$x_{1}(t) = a_{11}s_{1}(t) + a_{12}s_{2}(t) + a_{13}s_{3}(t)$$

$$x_{2}(t) = a_{21}s_{1}(t) + a_{22}s_{2}(t) + a_{23}s_{3}(t)$$

$$x_{3}(t) = a_{31}s_{1}(t) + a_{32}s_{2}(t) + a_{33}s_{3}(t)$$

$$\updownarrow$$

$$\overline{x}(t) = \overline{a}_{1}s_{1}(t) + \overline{a}_{2}s_{2}(t) + \overline{a}_{3}s_{3}(t)$$

$$\updownarrow$$

The problem:

Knowing the sensor activation x(t)

We need to find the stimulus/signal s(t)

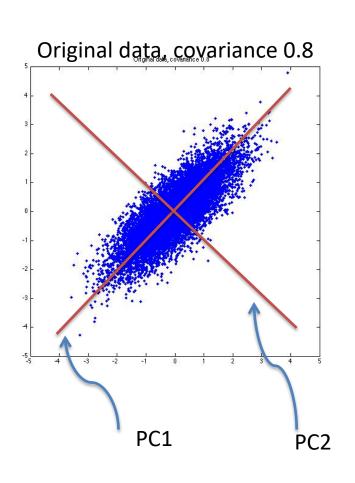
AND

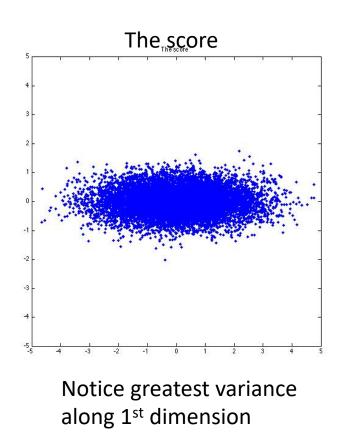
The weights / mixing matrix A

$$\begin{bmatrix} x_1(t) \\ x_2(t) \\ x_3(t) \end{bmatrix} = \begin{bmatrix} \overline{a}_1 & \overline{a}_2 & \overline{a}_3 \end{bmatrix} \begin{bmatrix} s_1(t) \\ s_2(t) \\ s_3(t) \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} s_1(t) \\ s_2(t) \\ s_3(t) \end{bmatrix}$$

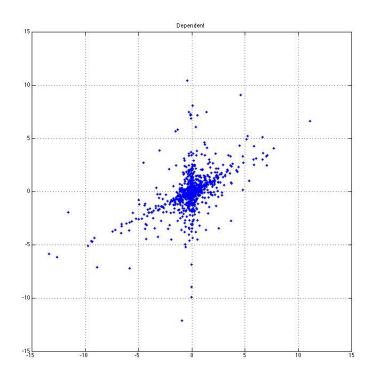
$$X = AS$$

Principal component analysis (PCA)

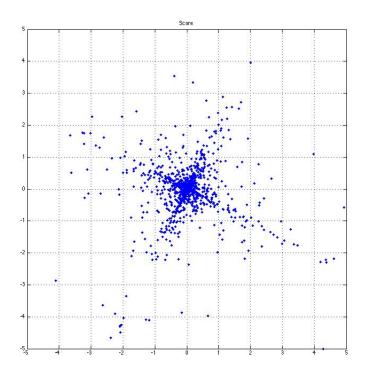




Principal component analysis (PCA)



Non-Gaussian dependent joint distribution

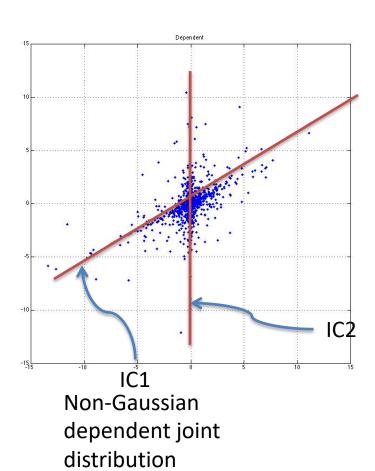


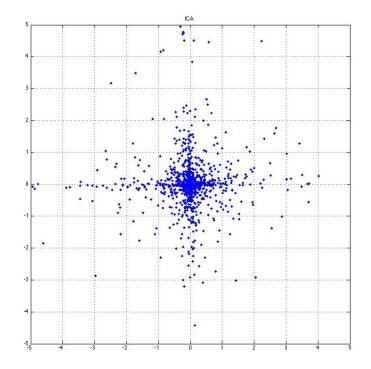
The PCA score is still dependent "Rays" radiate from origo in directions not following the axis

Need for something else

- PCA minimizes covariance / maximize variance
 - Assuming orthogonality
- We need to minimizes dependence / maximize sparseness
 - Without assuming orthogonality
- Independent Component Analysis
 - Maximizing kurtosis on non-orthogonal components

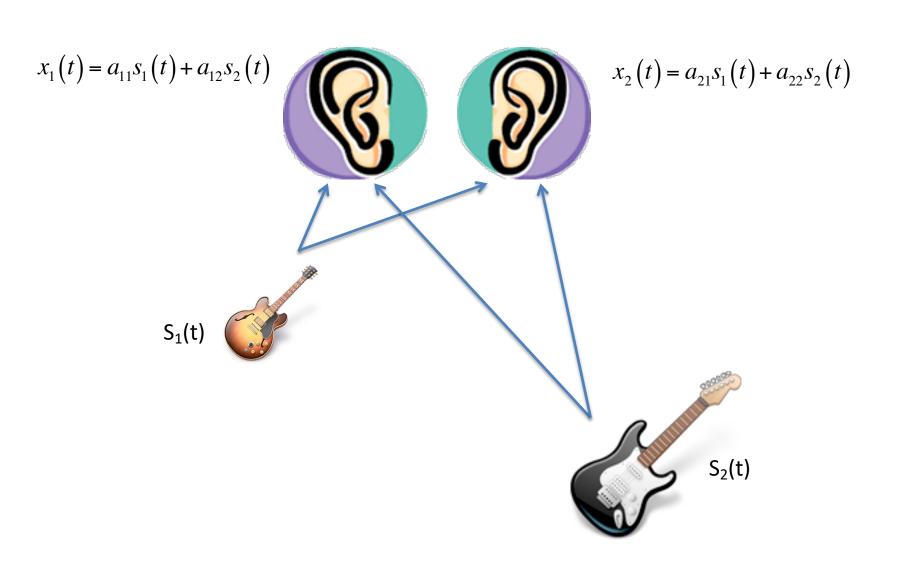
Independent component analysis (ICA)

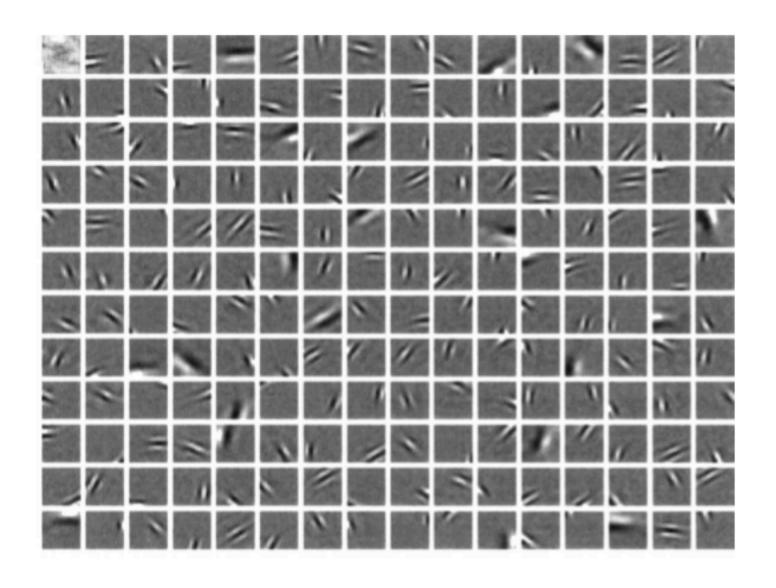




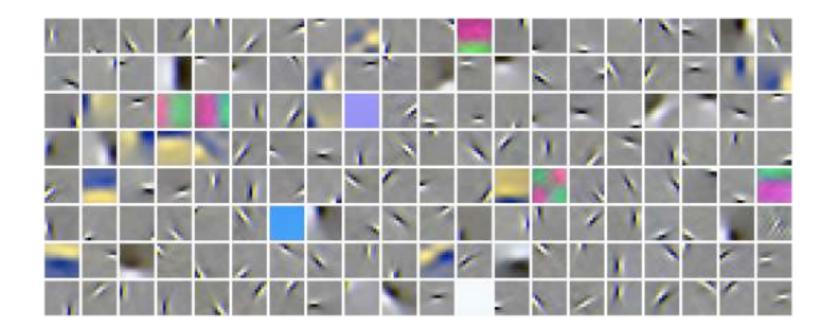
The ICA score is independent "Rays" radiate from origo in directions following the axis

The cocktail party effect

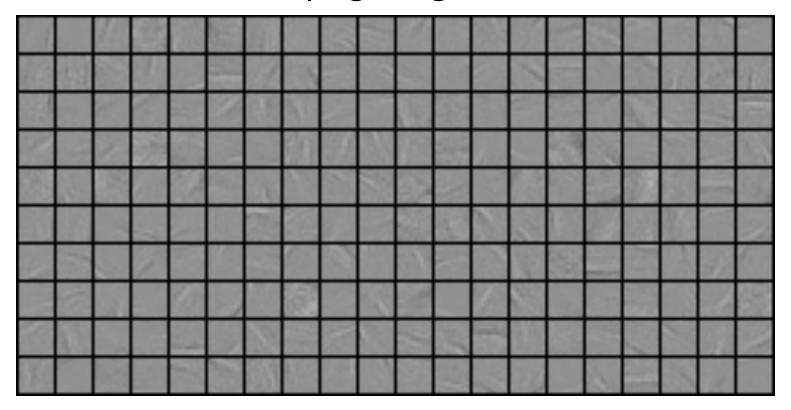




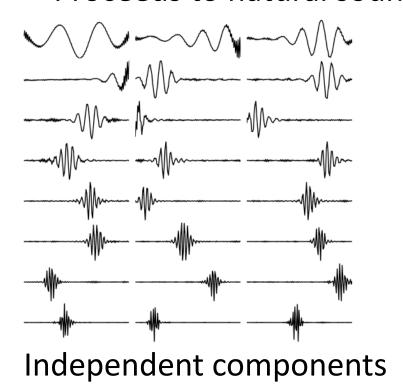
- Hoyer and Hyvärinen, 2000
 - Extends to color (and stereo) images

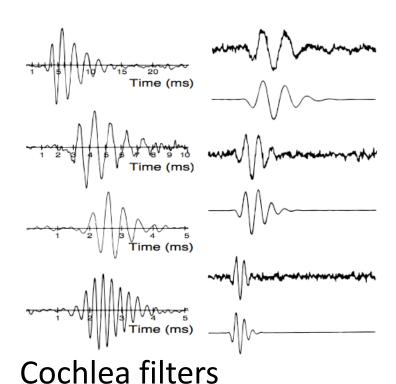


- Olshausen, 2000
 - Extends time-varying images

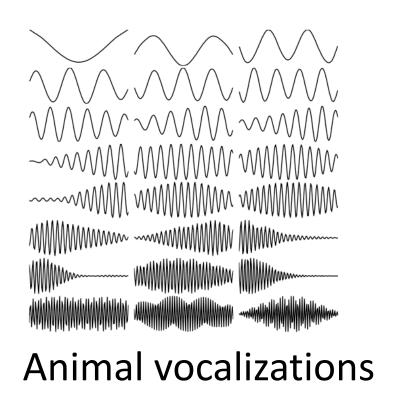


- Lewicki, 2002
 - Proceeds to natural sounds





Including different auditory stimulus domains



Human speech

Why stop with perception?

- What about higher order scene components?
 - Objects, identity, etc.

What about concepts?

Text

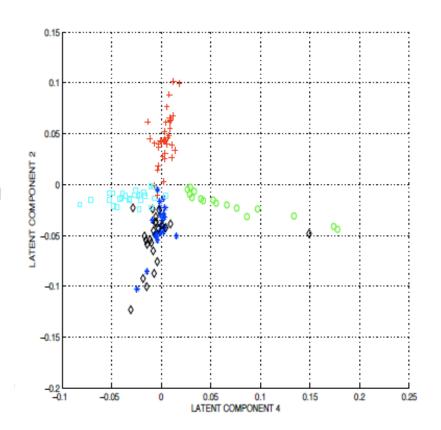
- Term/document matrix
 - Each document is a vector in term-space
 - But take away stop terms like and, if, or, a
- Latent Semantic Analysis
 - PCA on the term/document matrix
 - What are the principal axes?

Text

- Term/document matrix
 - Each document is a vector in term-space
 - But take away stop terms like and, if, or, a
- Latent Semantic Analysis
 - PCA on the term/document matrix
 - What are the principal axes?
 - Topics, themes or genres

Text

- Plotting the score reveals
 - Rays
 - Correspondence with human labels



Music

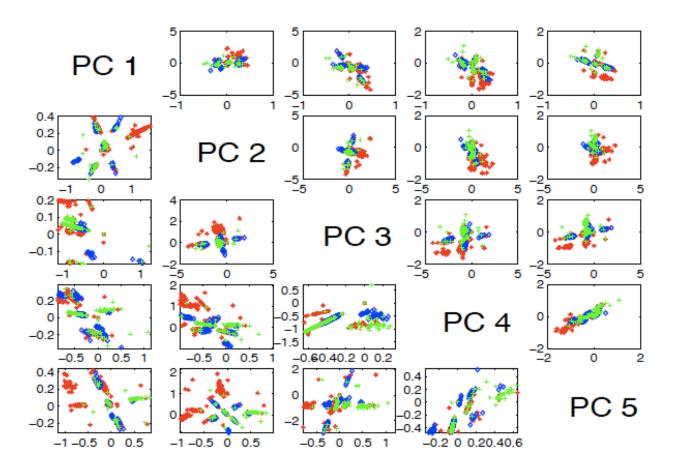
- Song/sound sample matrix
 - Sound sample is vectorized
 - Mel-frequency cepstral coefficients (MFCCs)
 - What are the principal components?

Music

- Song/sound sample matrix
 - Sound sample is vectorized
 - Mel-frequency cepstral coefficients (MFCCs)
 - What are the independent components?
 - Similar sounding music, genres

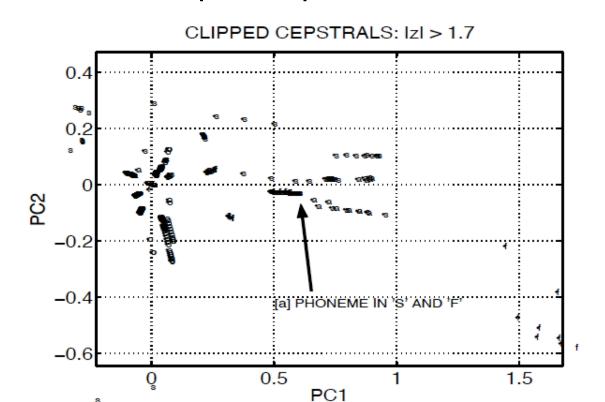
Music

Comparing the rays with human classifications



Speech

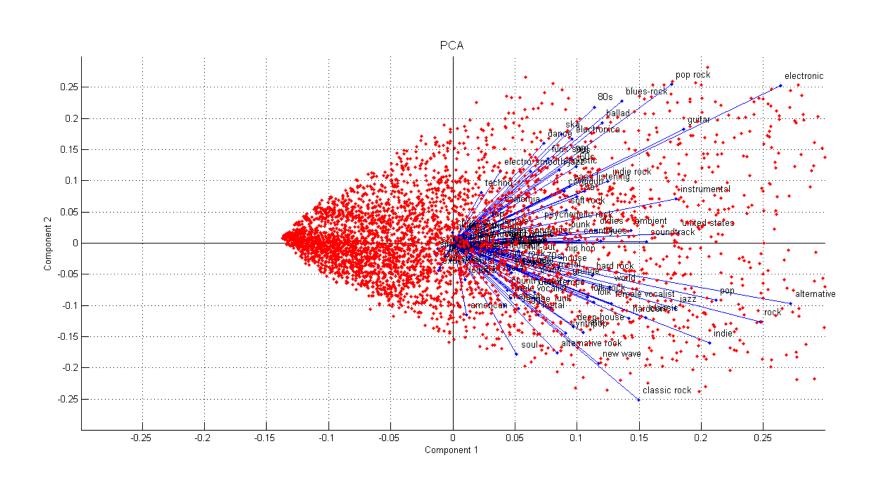
- Speech sample matrix
 - If sampled on the right time scale, speech samples should be equal to phonemes



Tag-based music analysis

- Echonest is a music data base
- Gets labels/tags on tunes from blogs (and other)
- Last FM is a web based music provider
 - Allows users to tag tunes
 - Share a large set of tag counts
- Document / term <-> tune/ tag term

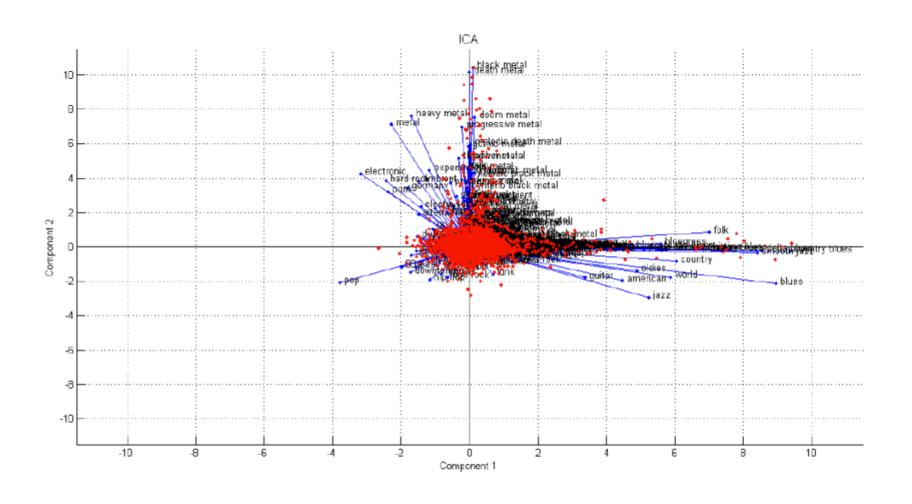
PCA based analysis of tune-tag matrix



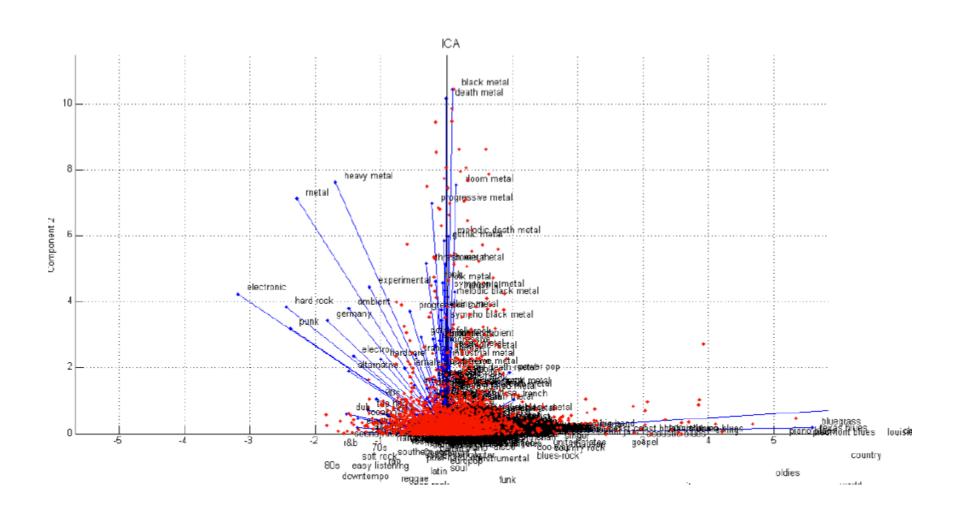
PCA based analysis of tune-tag matrix

Component 1		Component 3			
'e lectronic'	[0.2930]	'jazz'	[-0.2569]		
'rock'	[0.2702]	'punk'	[0.2564]		
'pop rock'	[0.2477]	'alternative'	[0.2412]		
'pop'	[0.2206]	'metal'	[0.2332]		
'classic rock'	[0.1894]	'rock'	[0.2326]		
'alternative rock'	[0.1814]	'alternative rock'	[0.2214]		
Component 2		Component 4	Component 4		
'electronic'	[-0.2512]	'hip hop'	[-0.3920]		
'blues'	[0.2481]	'rap'	[-0.2747]		
'hip hop'	[-0.2172]	'ambient'	[0.2547]		
'techno'	[-0.2064]	'folk'	[0.2391]		
'electro'	[-0.2059]	'reggae'	[-0.2021]		
'house' [-0.1808]		'soul'	[-0.1930]		
	-				

ICA based analysis of tune-tag matrix



ICA based analysis of tune-tag matrix



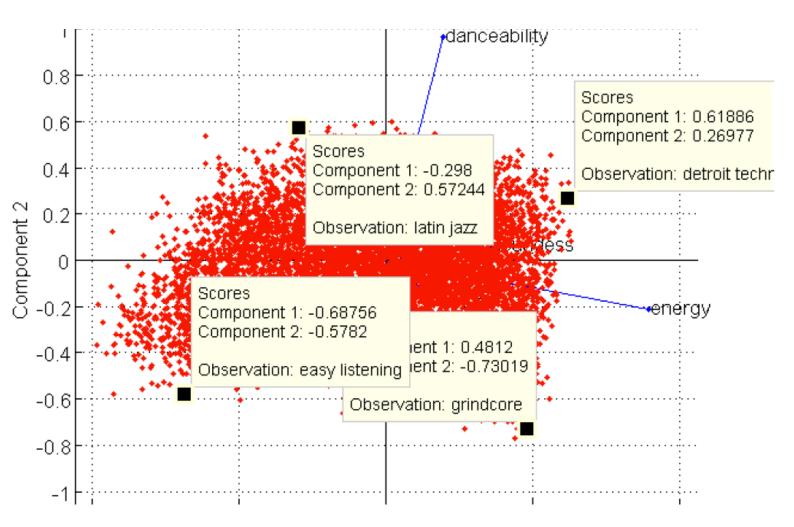
ICA based analysis of tune-tag matrix

Component 1		Compo	Component 3		Component 4	
'progressive house'	[-13.0420]	'metalcore'	[9.7857]	'country blues'	[-11.2841]	
'trance'	[-11.6010]	'hardcore'	[9.0779]	'delta blues'	[-10.3246]	
'progressive trance'	[-10.5130]	'metal'	[8.6138]	'blues'	[-10.0484]	
'techno'	[-10.3755]	'screamo'	[8.5570]	'chicago blues'	[-9.4272]	
'tech house'	[-10.3539]	'emo'	[8.5221]	'smooth jazz'	[-8.0635]	
'house'	[-9.8672]	'alternative metal'	[8.2246]	'louisiana blues'	[-7.5511]	
Component 5		Compo	Component 9		Component 10	
'country'	[-11.1097]	'black metal'	[-10.3062]	'downtempo'	[-7.1691]	
'classic country'	[-10.3586]	'death metal'	[-10.0929]	'easy listening'	[-6.6198]	
'oldies'	[-8.1613]	'doom metal'	[-7.9393]	'acid jazz'	[-6.5100]	
'honky tonk'	[-7.6438]	'metal'	[-7.8662]	'trip hop'	[-6.4428]	
'country rock'	[-7.2752]	'heavy metal'	[-7.8264]	'future jazz'	[-6.2716]	
'world'	[-7.2509]	'progressive	[-7.2647]	'disco'	[-6.1470]	
		metal'				
Component 12		Сотро	nent 19	Component 33		
'roots reggae'	[-10.0137]	'ccm'	[-14.2041]	'rap'	[-10.3298]	
'dancehall'	[-9.9293]	'christian'	[-12.5425]	'gangster rap'	[-8.8597]	
'dub'	[-8.8466]	'gospel'	[-10.0297]	'hip hop'	[-8.0857]	
'reggae'	[-8.6909]	'contemporary	[-7.4200]	'hardcore rap'	[-6.9934]	
'lovers rock'	[-8.4640]	christian'		'new york'	[-6.7396]	
'ska'	[-6.8764]	'christian rock'	[-6.4889]	'east coast rap'	[-6.6330]	
		'worship music'	[-4.3180]			
	I		I			

Acoustical features of tunes

- Echonest also provides acoustical features
 - Energy (loudness variation)
 - Danceability (beat strength and consistency)
 - Tempo (BPM)
 - Loudness (overall)

PCA based analysis of acoustical features



Now to the exercises...