Lars Kai Hansen
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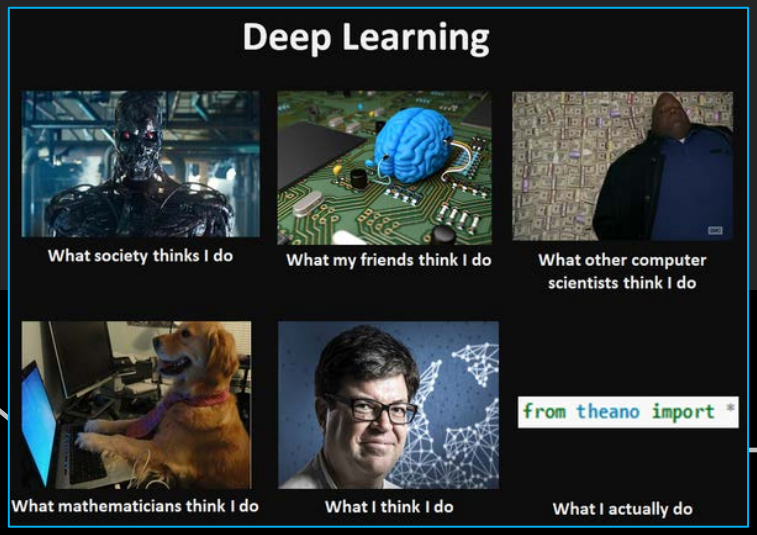
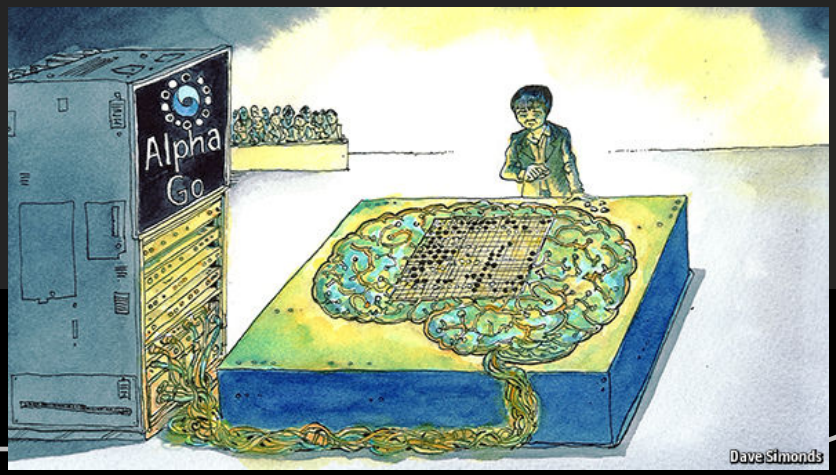
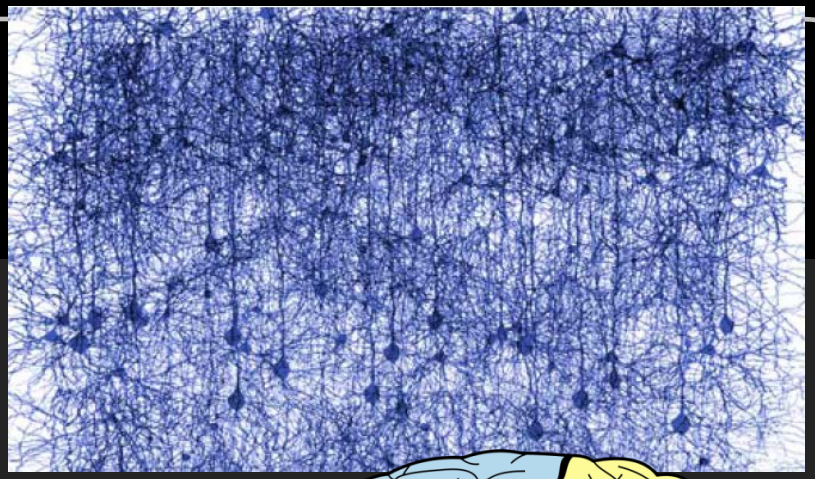
Sensing the deep structure of signals





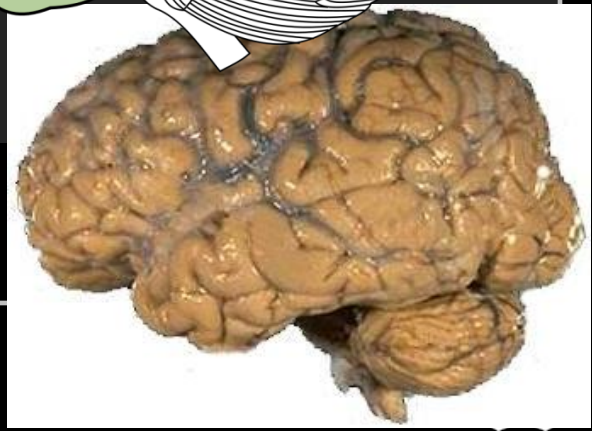
the brain design

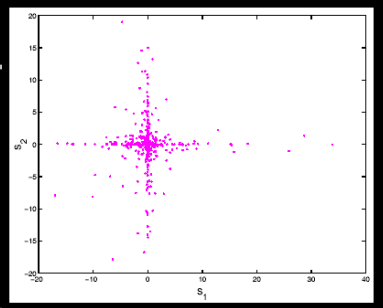


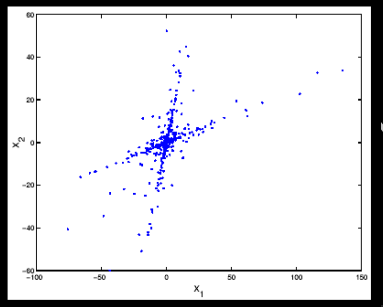
Three design principles

i) Division of labor
Centers for vision, hearing, smell etc
ii) Neural networks of simple computers
iii) Learning – adaptivity -plasticity

But how does this structure represent / index the world, how does is rank importance? etc etc







Outline

What is deep structure?

- Cognitive components and attention modeling
- Ecology of audio signals

Is structure is determined by the environment: Statistics/ physics / mechanisms?

Uniqueness of perception in the brain &
Uniqueness in deep neural networks

What about higher order cognition, social cognition?

things...?

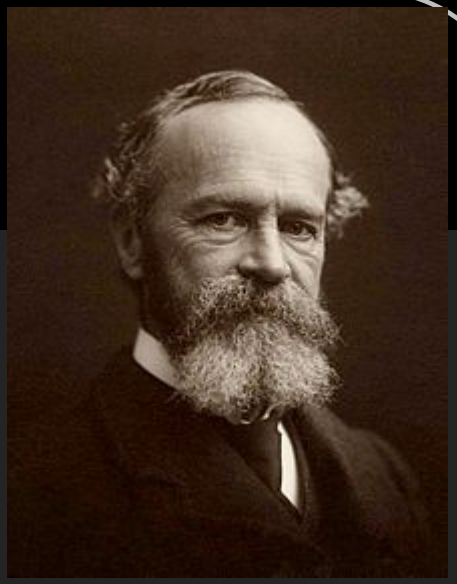
Attention & human optimality

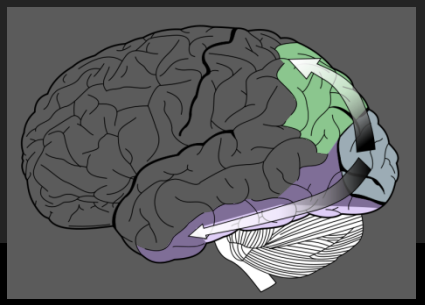
"... the withdrawal from some things
in order to deal effectively with others"

William James (1890)

"... To behave adaptively in a complex world, an animal must select, from the wealth of information available to it, the information that is most relevant at any point in time. This information is then evaluated in working memory, where it can be analyzed in detail, decisions about that information can be made, and plans for action can be elaborated. The mechanisms of attention are responsible for selecting the information that gains access to working memory."

Eric I. Knudsen (2007)





W. James, *The Principles of Psychology, Vol. 1, Dover Publications,* 1880/1950.
E.I. Knudsen, "Fundamental Components of Attention," *Annual Review of Neuroscience, vol. 30, no. 1, pp. 57–78, 2007.*

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Deep structure needed to predict the future

Processing in the brain is based on extremely well-informed / optimized representations and mechanisms –

A key issue is selective attention...

Fundamental question

What can you attend to?

or...

What is an object / chunk of information?

Cognitive component analysis ...what we can attend to

- The **object / chunk** is a key notion in cognitive psychology
  - ...number of objects in short time memory, objects ”race to short term memory”

Miller, G.A. (1956), The Magical Number Seven, Plus or Minus Two: Some Limits on our Capacity for Processing Information. Psychological Review, 63, 81-97

Bundesen, C., Habekost, T. and Kyllingsbæk, S., 2005. A neural theory of visual attention: bridging cognition and neurophysiology. Psychological review, 112(2), p.291).

  - Miller: “..we are not very definite about what constitutes a chunk of information.“
  - A pragmatic definition of an object could be: **An object is a signal source with independent behavior in a given environment** (..imagined?)

- Theoretical issues: The relation between supervised and un-supervised learning. Related to the discussion of the utility of unlabeled examples in supervised learning and fast/one sample learning...

- Practical Issues: Can we predict which digital media components a user will pay attention to? -a key challenge for cognitive systems.

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Cognitive compatibility

Unsupervised Learning

Hidden variable

$$p(\mathbf{s} \mid \mathbf{x}, \mathbf{w}_u) \propto p(\mathbf{x} \mid \mathbf{s}, \mathbf{w}_u) p(\mathbf{s} \mid \mathbf{w}_u)$$

"Cognitive event": Data, sound, image, behavior

Supervised learning

$$p(\mathbf{y} \mid \mathbf{x}, \mathbf{w}_s)$$

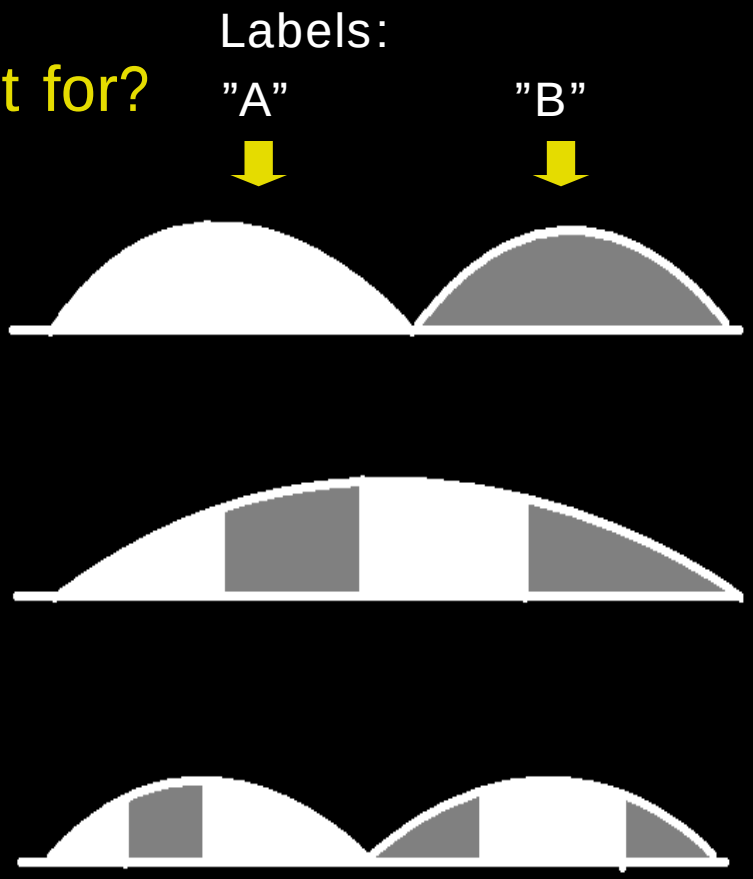
"Cognitive" label, i.e. provided by a human observer

How well do these learned representations match: s = y ?

Which domains are COCA relevant for?

- If ”statistical structure” in the relevant feature space is well aligned with the label structure we expect high **cognitive compatibility**
- Unsupervised-then-supervised learning –aka *pre-training*- can explain “learning from one example”

The Good,
the Bad,
and the Ugly…



Vector space representation

- Abstract representation - can be used for all digital media
- A “cognitive event” is represented as a point in a high-dimensional ”feature space” – document similarity ~ spatial proximity in a given metric

- Text: Term/keyword histogram, N-grams
- Image: Color histogram, texture measures
- Video: Object coordinates (tracking), active appearance models
- Sound: Spectral coefficients, mel cepstral coefficients, gamma tone filters

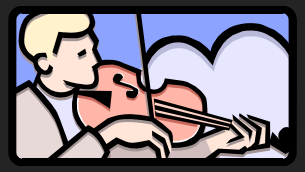
Contexts can be identified by their feature associations (= Latent semantics)

S. Deerwester et al. *Indexing by latent semantic analysis*.
Journal of the American Society for Information Science, 41(6), 391-407, (1990)

The independent component hypothesis

- Challenge: Presence of multiple agents/contexts
- Need to ”blindly” separate source signals = learn contexts
- ICA, NMF, tensor factorization provides (almost) unique solutions to...

$$x(\mathit{feature}, \mathit{time}) = \sum_k A(\mathit{feature}, k)\ s(k, \mathit{time})$$



Linear mixing generative model ICA - "Synthesis" simplistic model incorporating sparsity and independence

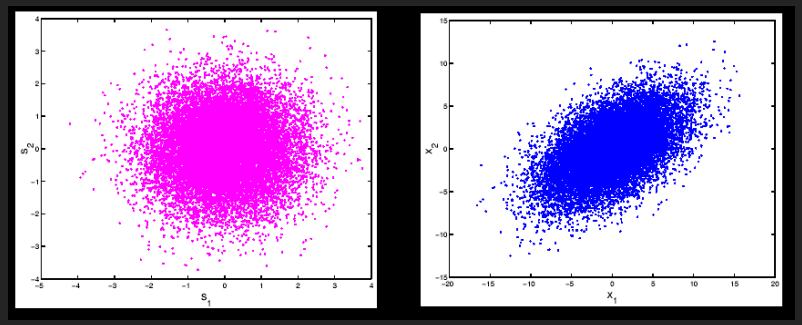
Space-time matrix

Component's "where"

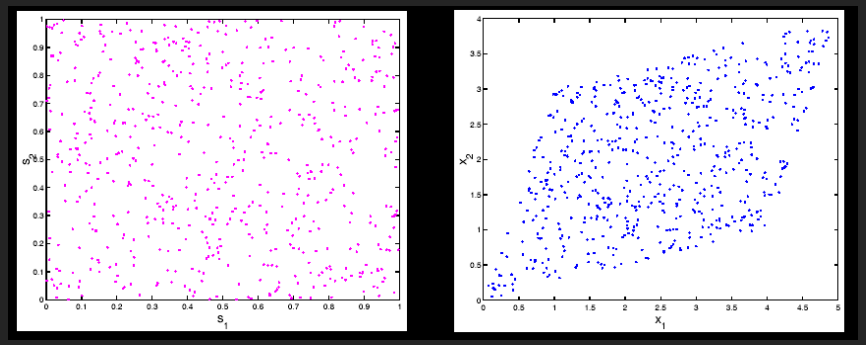
Vector of "what"

$$x(loc, time) = \sum_k A(loc, k)\ s(k, time)$$

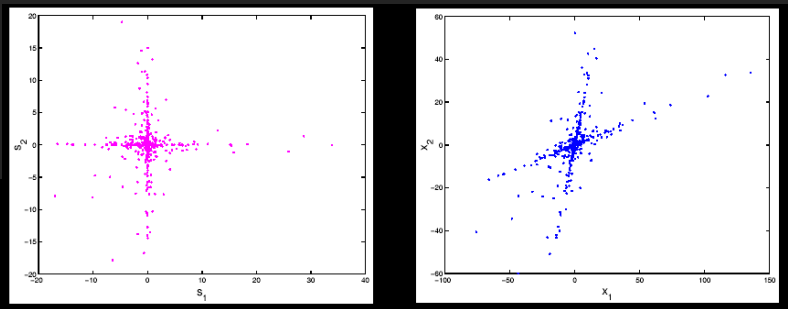
Normal sources



Dense sources



Sparse sources

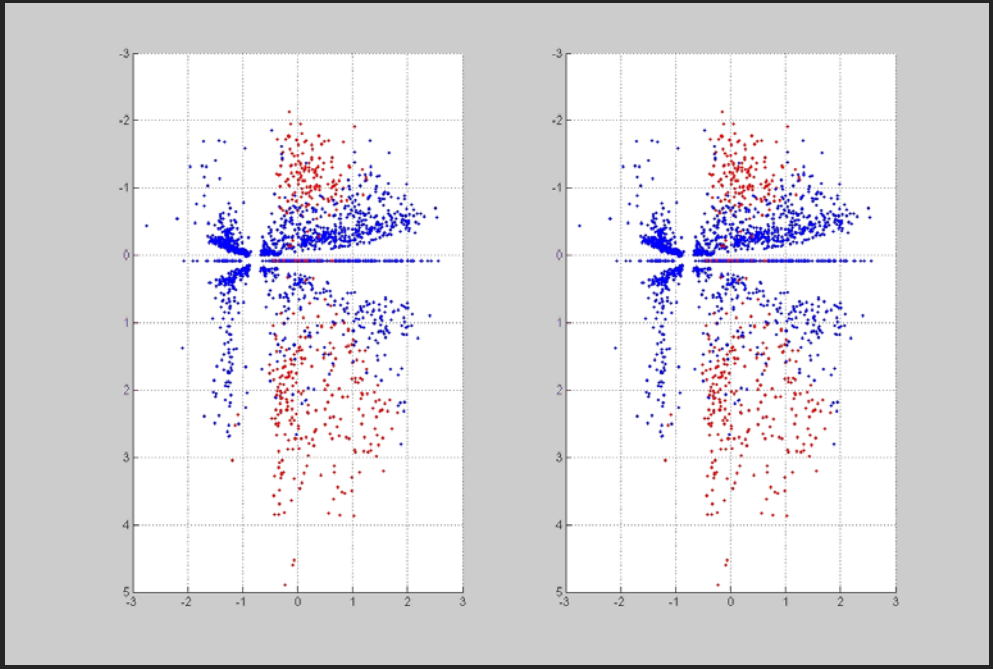


Protocol for comparing supervised and unsupervised learning

- Use the “unsupervised-then-supervised” scheme to implement a classifier:
  - Train the unsupervised scheme, eg., ICA
  - Freeze the ICA representation (A matrix)
  - Train a simple (e.g. Naïve Bayes) classifier using the features obtained in unsupervised learning Use
- Compare with supervised classifier
  - Error rates of the two systems
  - Compare posterior probabilities

Phoneme classification

Nasal vs oral: ”Esprit project ROARS” (Alinat et al., 1993)



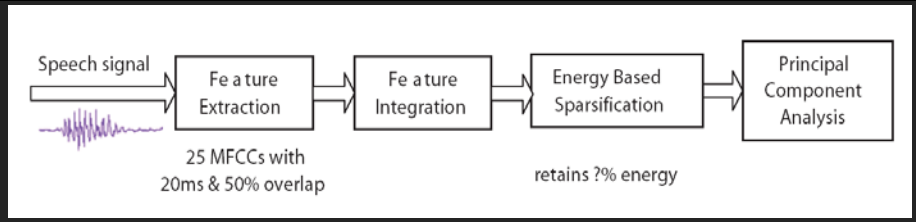
Binary classification

Error rates: **0.23** (sup.), **0.22** (unsup.)

Bitrates: **0.48** (sup.), **0.39** (unsup.)

Cognitive components of speech

- Basic representation: Mel weigthed cepstral coefficients (MFCCs)
- Modeling at different time scales 20 msec – 1000 msec



- Phonemes
- Gender
- Speaker identity

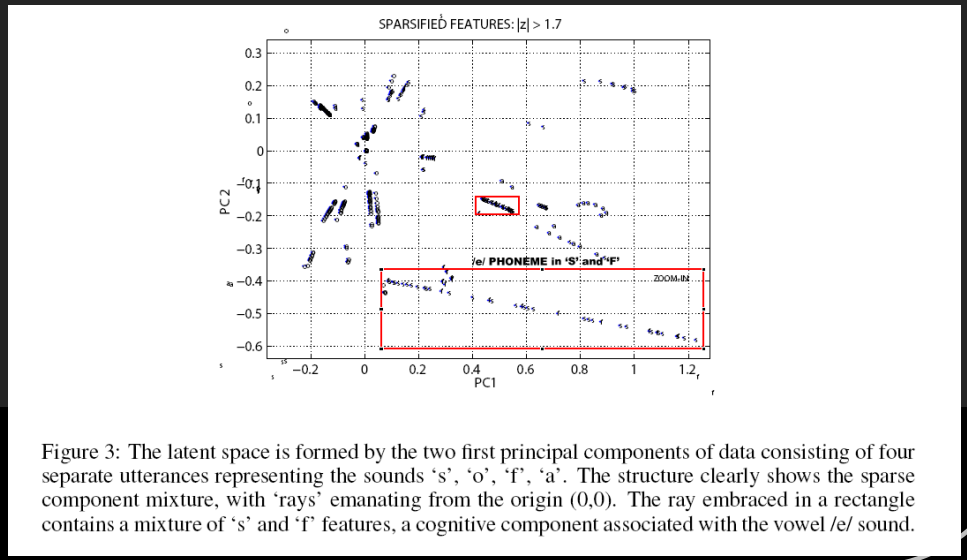
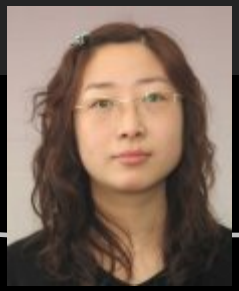
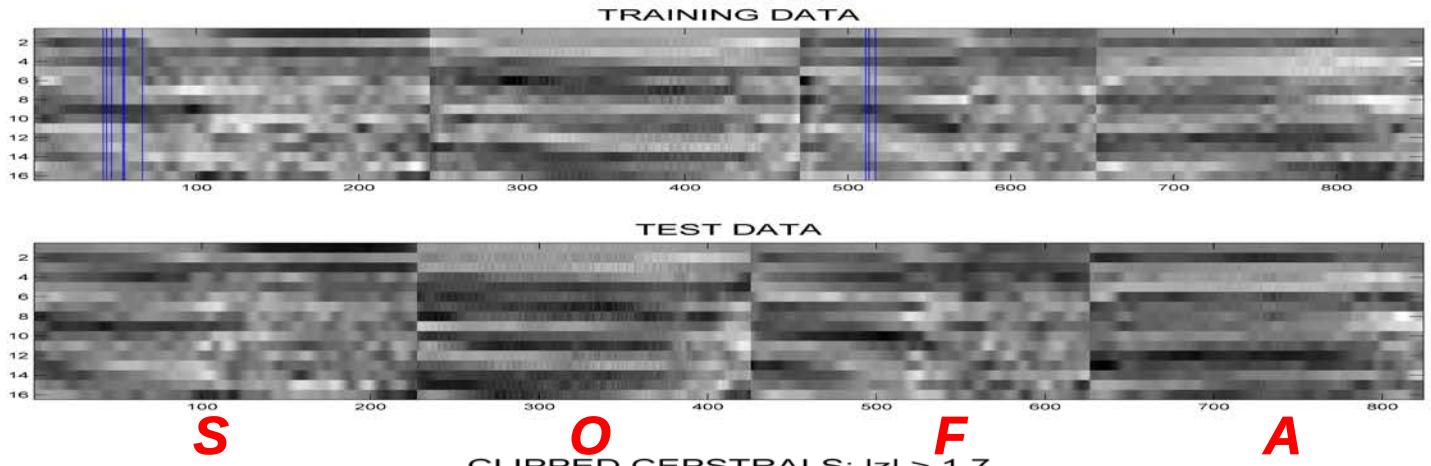


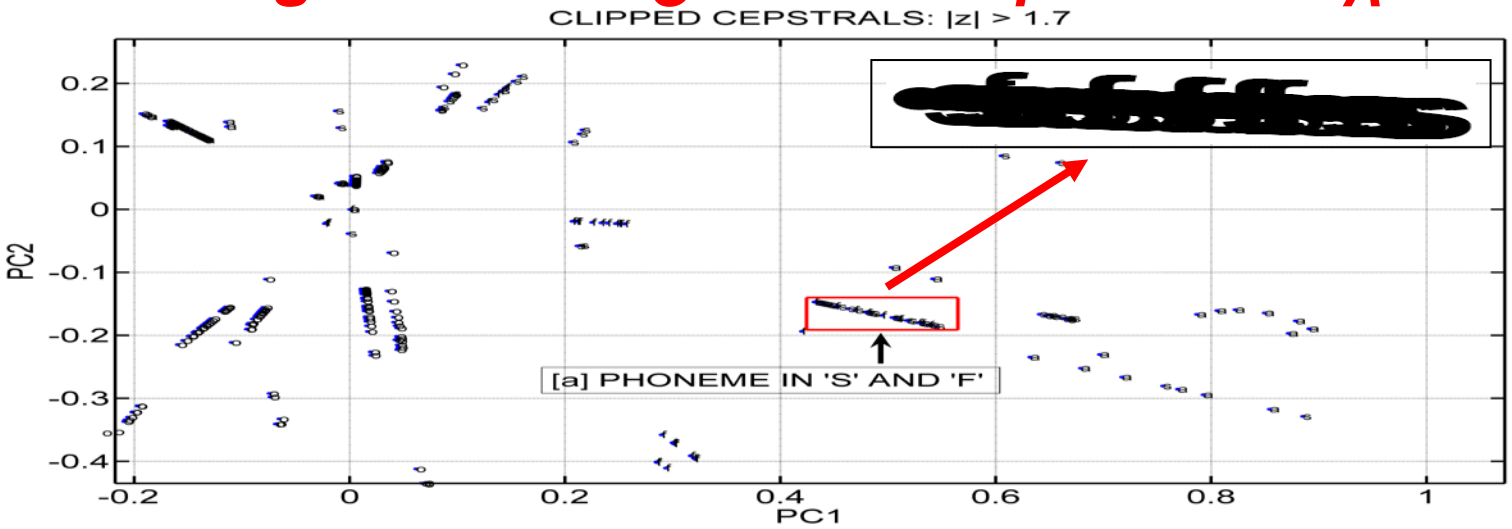
Figure 3: The latent space is formed by the two first principal components of data consisting of four separate utterances representing the sounds 's', 'o', 'f', 'a'. The structure clearly shows the sparse component mixture, with 'rays' emanating from the origin (0,0). The ray embraced in a rectangle contains a mixture of 's' and 'f' features, a cognitive component associated with the vowel /e/ sound.



Co-worker: Ling Feng

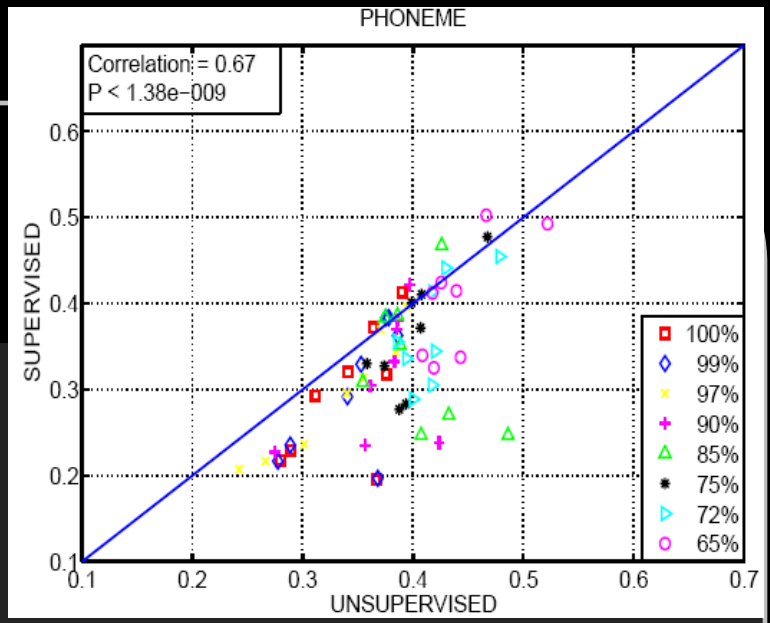
Mel weighted cepstral coeff. (MFCC)

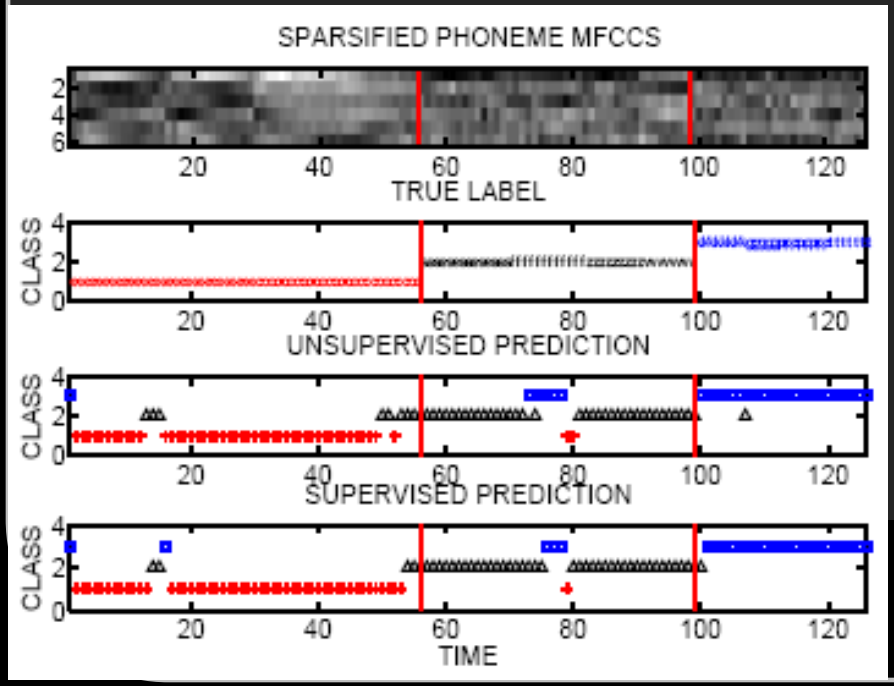




Error rate comparison

For the given time scales and thresholds, data locate around $y = x$, and the correlation coefficient $\rho = 0.67$, $p < 1.38e{-}09$.

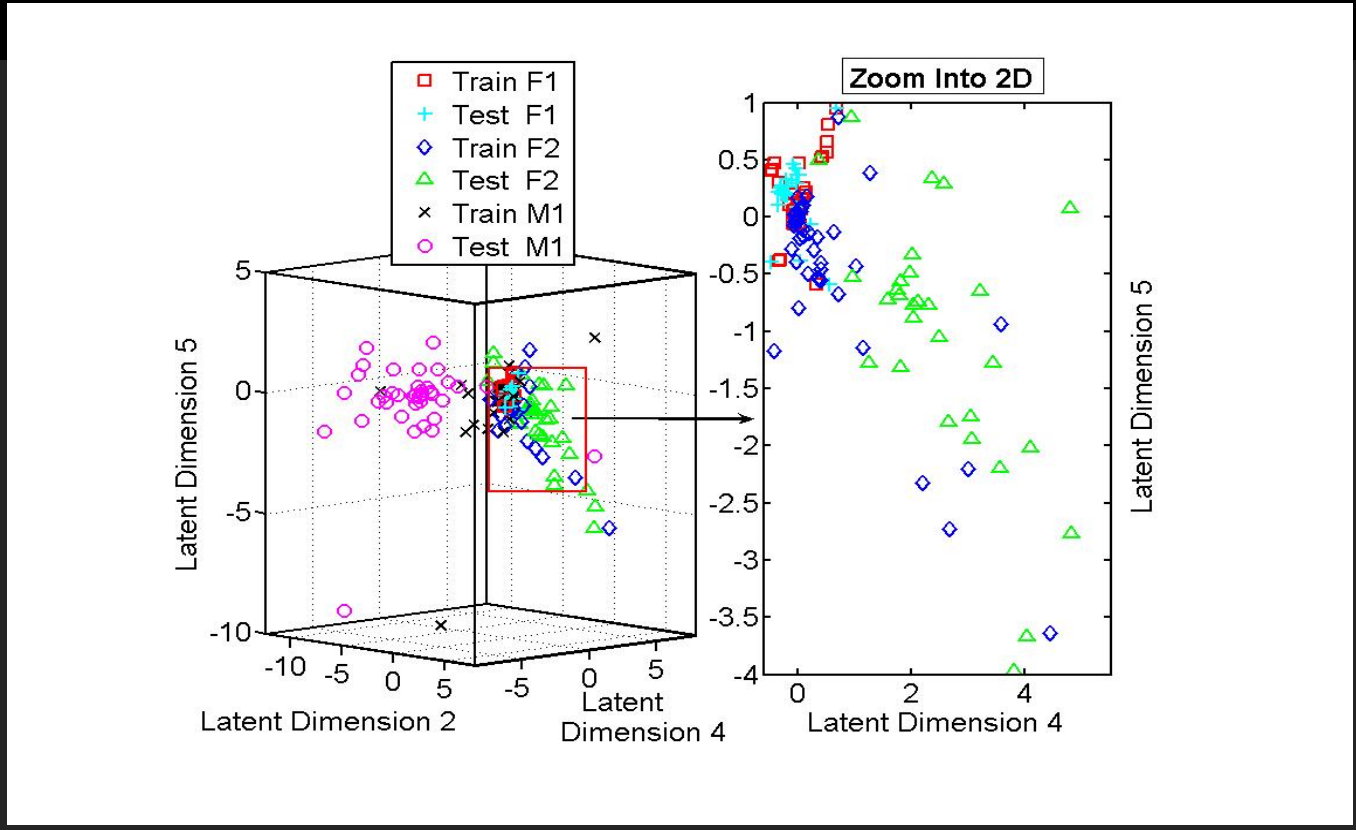




Sample-to-sample correlation

- Three groups: vowels eh, ow; fricatives s, z, f, v; and stops k, g, p, t.
- 25-d MFCCs; EBS to keep 99% energy; PCA reduces dimension to 6.
- Two models had a similar pattern of making correct predictions and mistakes, and the percentage of matching between supervised and unsupervised learning was 91%.

Longer time scales



Time integrated (1000ms) MFCC's: text independent speaker recognition....

Feng & Hansen (CIMCA, 2005)

Error rate correlations for super/unsupervised learning for different cognitive time scales and events

Challenged by degree of sparsity and time averaging

Gender, Identity, Heigth etc are the Audio Gist vars

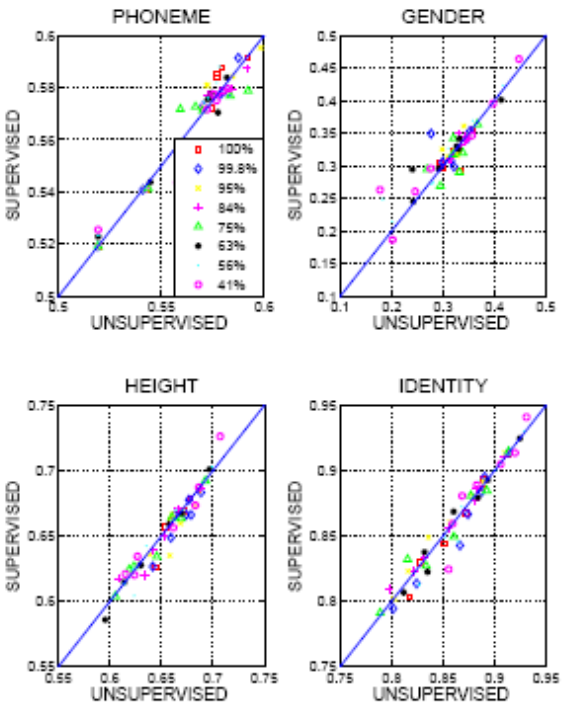


Fig. 4. Figure shows test error rates of both supervised and unsupervised learning on four topics: phonemes, gender, height and identity. Solid lines indicate $y = x$ in the coordinate systems. All data located along this line, meaning high correlation between supervised and unsupervised learning.

LETTER
doi:10.1038/nature11020

Selective cortical representation of attended speaker in multi-talker speech perception

Nima Mesgarani[1] & Edward F. Chang[1]

Human brain mechanisms Attention in speech mixtures

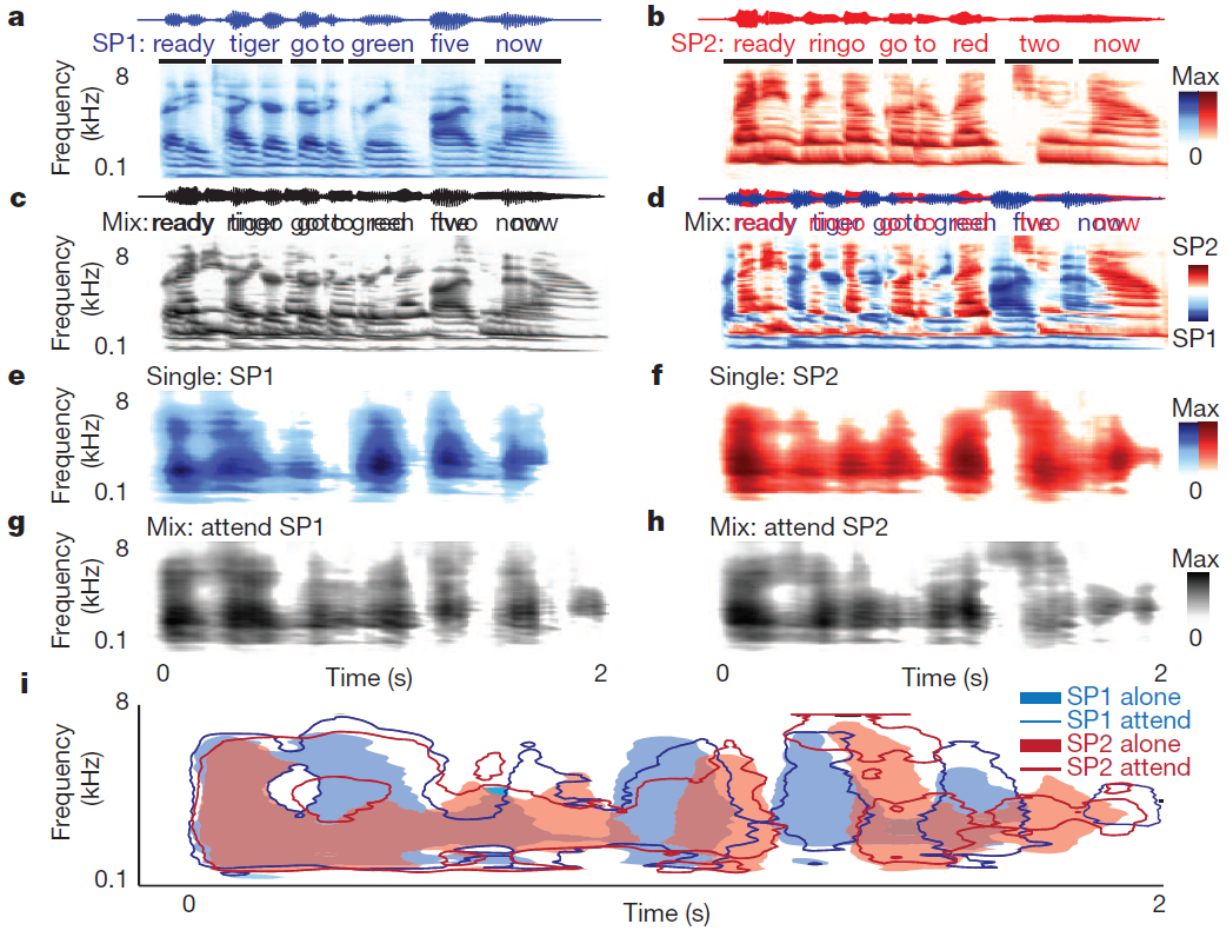
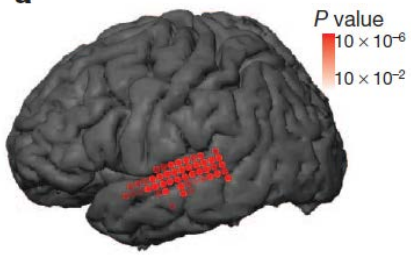


Figure 1 | Acoustic and neural reconstructed spectrograms for speech from a single speaker or a mixture of speakers. **a**, **b**, Example acoustic waveform and auditory spectrograms of speaker one (male; **a**) and speaker two (female; **b**). **c**, Waveform and spectrogram of the mixture of the two shows highly overlapping energy distributions. **d**, Difference spectrogram highlights the mixture regions where speaker one (blue) or two (red) has more acoustic energy. **e**, **f**, Neural-population-based stimulus reconstruction of speaker one (**e**) and speaker two (**f**) alone shows similar spectrotemporal features as the original spectrograms in **a** and **b**. **g**, **h**, The reconstructed spectrograms from the same mixture sound when attending to either speaker one (**g**) or two (**h**) highly resemble the single speaker reconstructions, shown in **e** and **f**, respectively. **i**, Overlay of the maximum energy spectrograms in

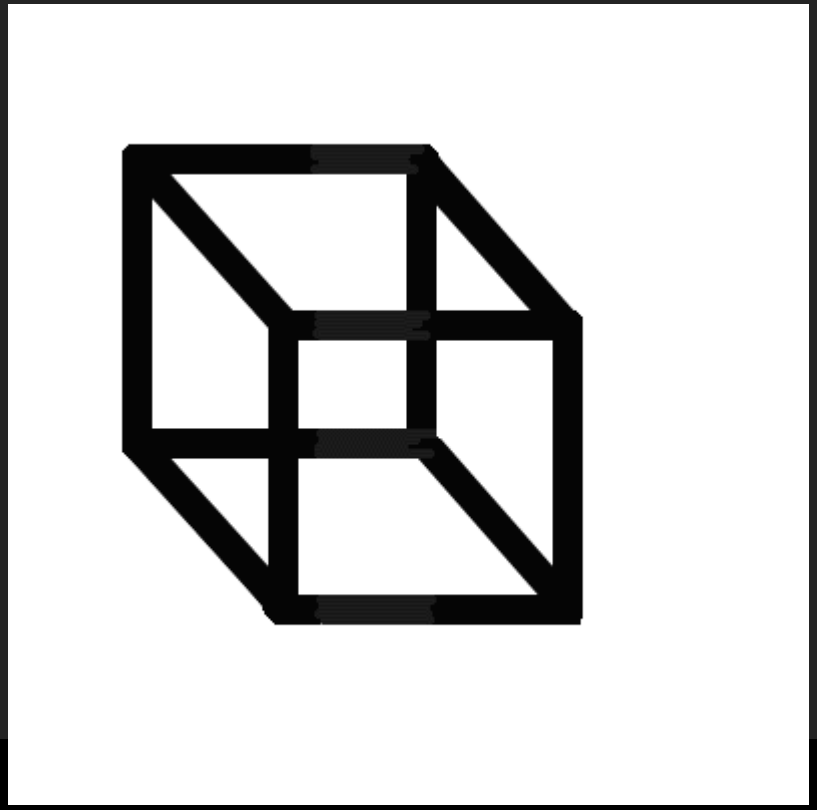


Uniqueness of representations?

Modern society's deep specialization requires efficient shared representations

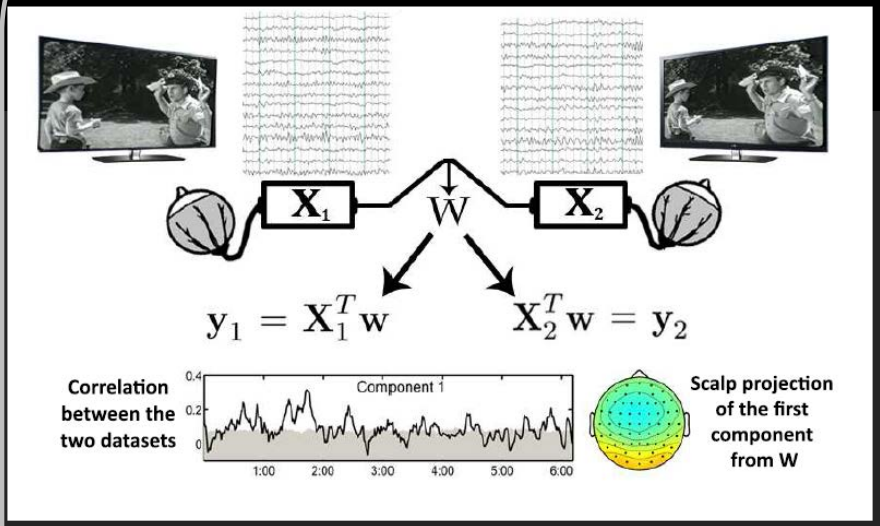
You know what I mean - right?

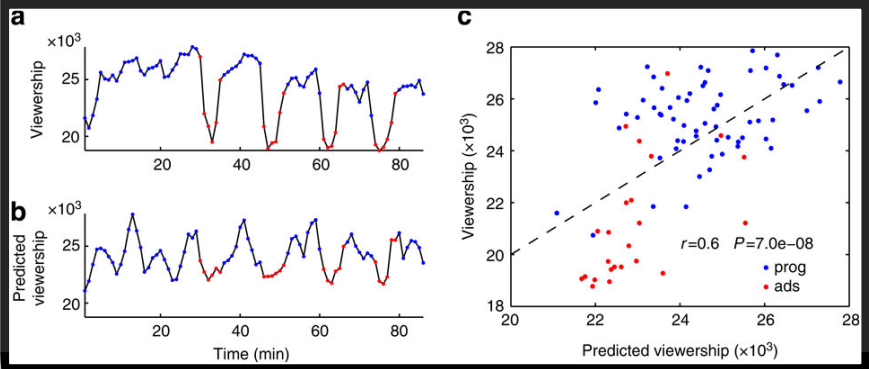
Does machine learning also develop shared representations and if so - why?

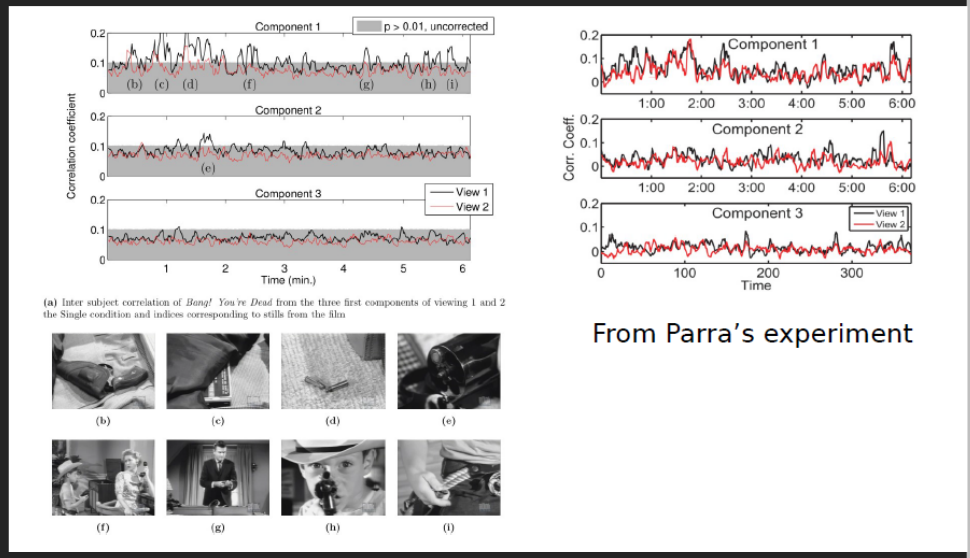


http://wisebytes.net/illusions/necker.php

Universality of attention to digital media



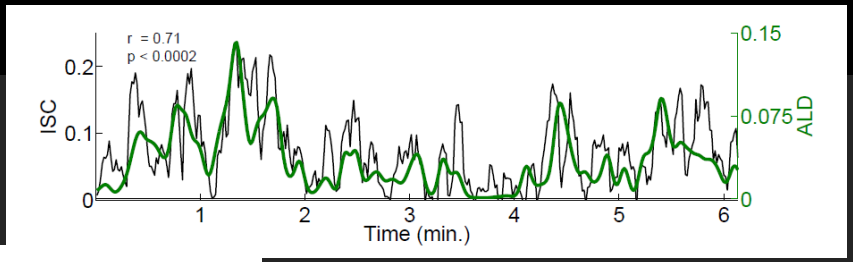




JP Dmochowski, P Sajda, J Dias, LC Parra, "Correlated components of ongoing EEG point to emotionally laden attention -a possible marker of engagement?" Frontiers of Human Neuroscience, 6:112, 2012.
JP Dmochowski, MA. Bezdek, BP. Abelson, JS. Johnson, EH Schumacher, LC Parra, "Audience preferences are predicted by temporal reliability of neural processing", Nature Communications 5:4567, 2014.
AT Poulsen, S, Kamronn, J Dmochowski, LC Parra, LK, Hansen:. "Measuring engagement in a classroom: Synchronised neural recordings during a video presentation". *arXiv preprint arXiv:1604.03019 (2016)*.

What is the joint attention signal?

Driven by early visual response
hich is modulated by attention...



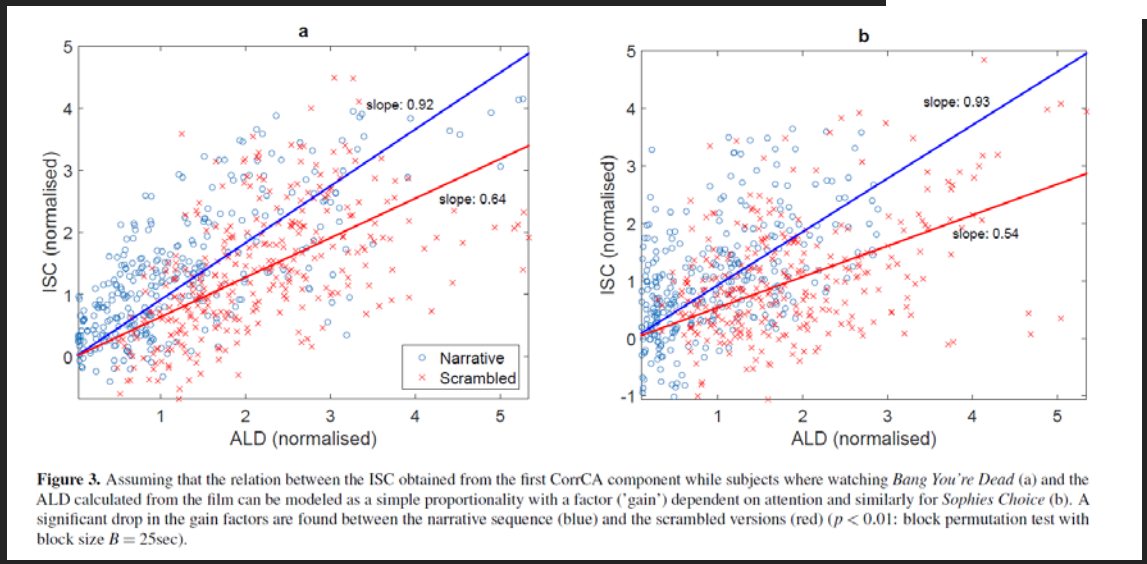
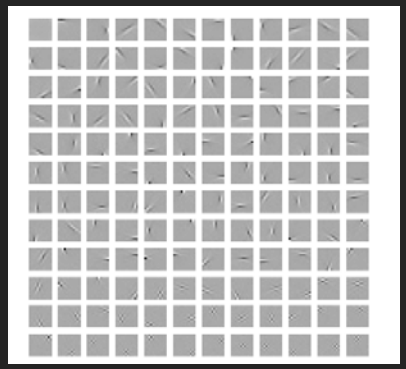


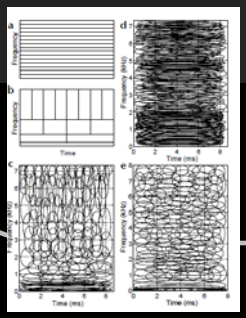
Figure 3. Assuming that the relation between the ISC obtained from the first CorrCA component while subjects where watching *Bang You're Dead* (a) and the ALD calculated from the film can be modeled as a simple proportionality with a factor ('gain') dependent on attention and similarly for *Sophies Choice* (b). A significant drop in the gain factors are found between the narrative sequence (blue) and the scrambled versions (red) ($p < 0.01$: block permutation test with block size $B = 25$sec).

Real-time feasible in (sub)-groups,
correlate with computed saliency...

Hiliard et al. Sensory gain control (amplification) as a mechanism of selective attention
Phil.Trans. R. Soc. Lond. B (1998) 353, 1257^1270

Optimal representations?





Important for engineering proxies for human information processing...
Cf. efficient coding of ”context-to-action” mapping

Deep networks

Reducing the Dimensionality of Data with Neural Networks

G. E. Hinton* and R. R. Salakhutdinov

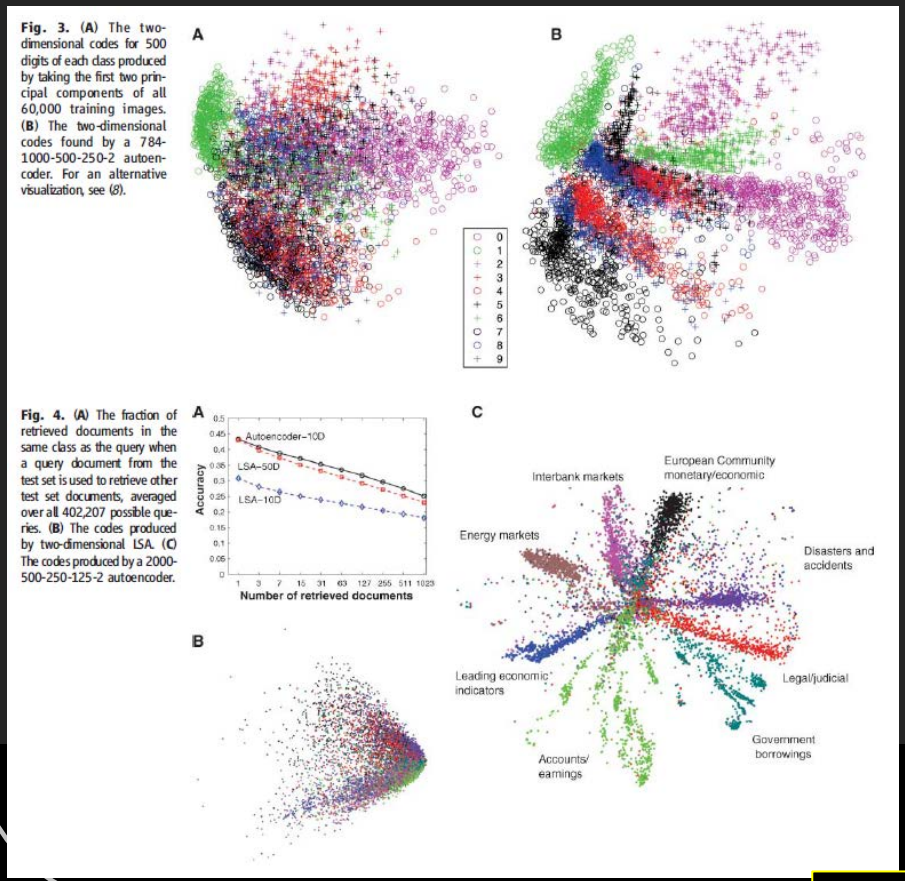


Fig. 3. (A) The two-dimensional codes for 500 digits of each class produced by taking the first two principal components of all 60,000 training images. (B) The two-dimensional codes found by a 784-1000-500-250-2 autoencoder. For an alternative visualization, see (8).

Fig. 4. (A) The fraction of retrieved documents in the same class as the query when a query document from the test set is used to retrieve other test set documents, averaged over all 402,207 possible queries. (B) The codes produced by two-dimensional LSA. (C) The codes produced by a 2000-500-250-125-2 autoencoder.

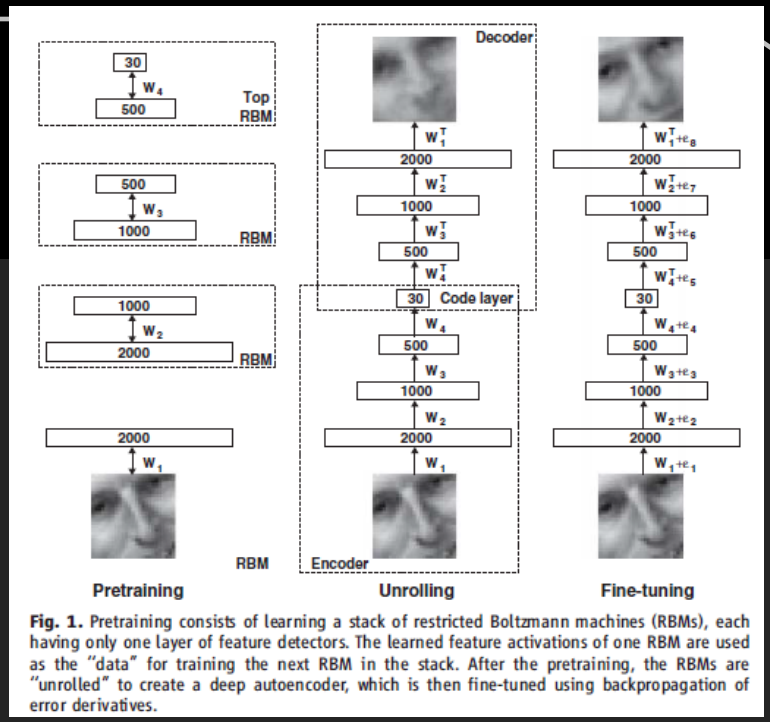
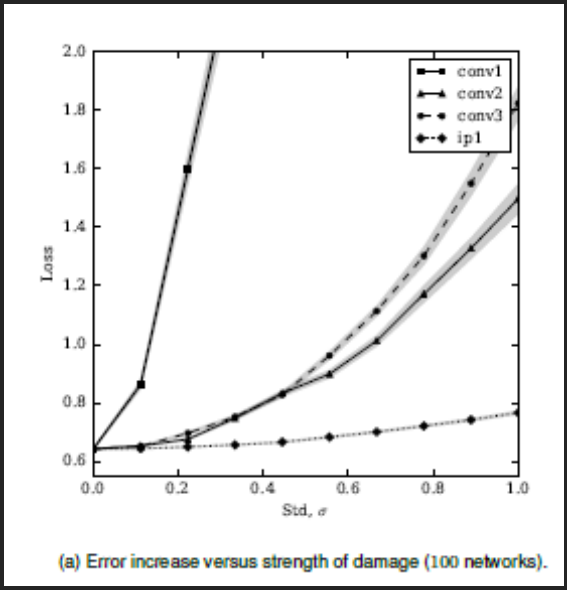


Fig. 1. Pretraining consists of learning a stack of restricted Boltzmann machines (RBMs), each having only one layer of feature detectors. The learned feature activations of one RBM are used as the "data" for training the next RBM in the stack. After the pretraining, the RBMs are "unrolled" to create a deep autoencoder, which is then fine-tuned using backpropagation of error derivatives.

Hinton, Geoffrey E., and Ruslan R. Salakhutdinov. "Reducing the dimensionality of data with neural networks." *Science* 313, no. 5786 (2006): 504-507.

How well determined are the representations by ecology… sensitivity analysis



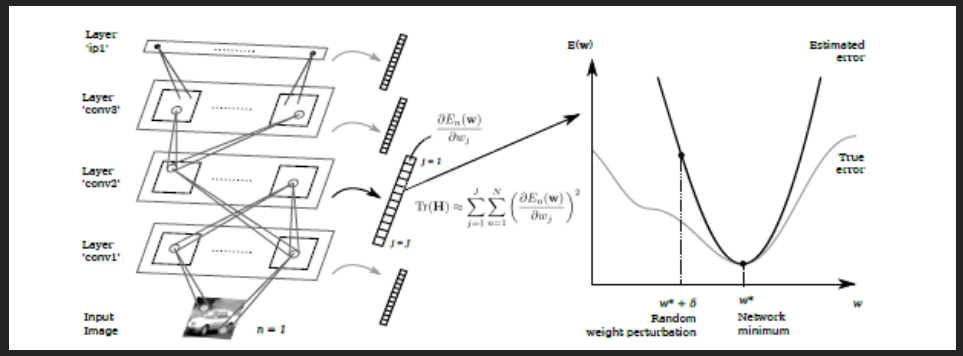
(a) Error increase versus strength of damage (100 networks).

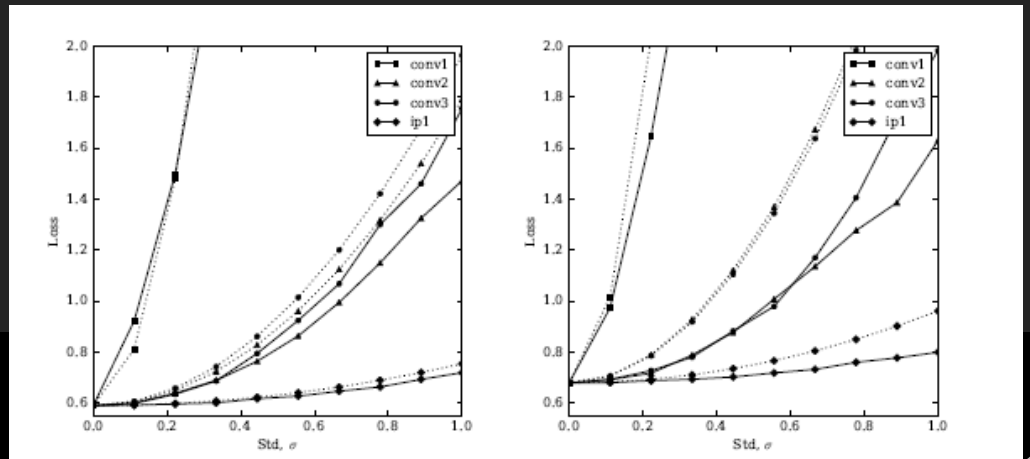
RJ Aaskov, LK Hansen "On the resilience of deep neural networks to weight damage." *In review* (2016)

On the resilience of deep neural networks to weight damage

Rasmus Jessen Aaskov
Dept. of Applied Mathematics and Computer Science
Technical University of Denmark

Lars Kai Hansen
Dept. of Applied Mathematics and Computer Science
Technical University of Denmark





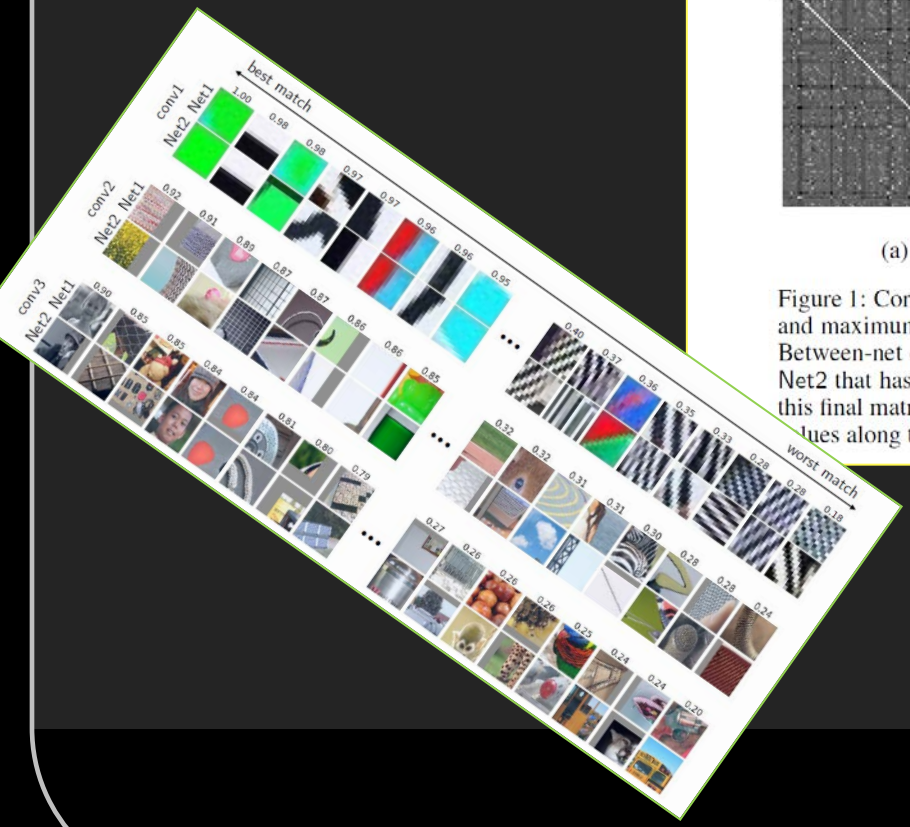
(a) Example of a well performing network (20.25% final test error rate). (b) Example of a network with poor performance (23.71% final test error rate).

Figure 3. Two examples of how our method for estimating loss behaves in different cases. In both figures, the average loss of a repeated damage experiment and our estimated expected loss is shown for each of the individual layers. The expected loss is illustrated as a dotted line with distinctive markers for each layer.

Published as a conference paper at ICLR 2016

CONVERGENT LEARNING: DO DIFFERENT NEURAL NETWORKS LEARN THE SAME REPRESENTATIONS?

Yixuan Li[1]*, Jason Yosinski[1]*, Jeff Clune[2], Hod Lipson[3], & John Hopcroft[1]



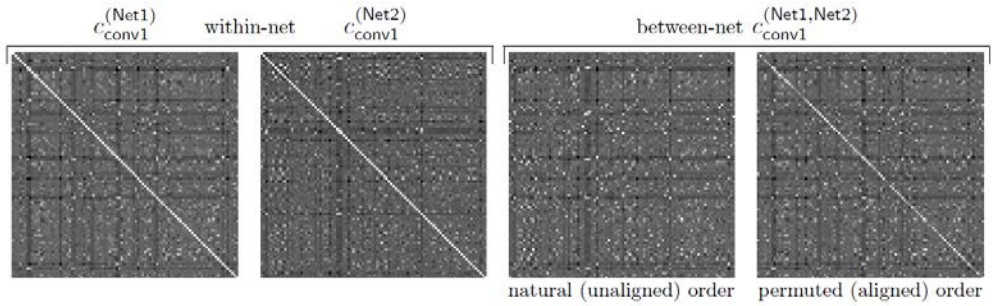
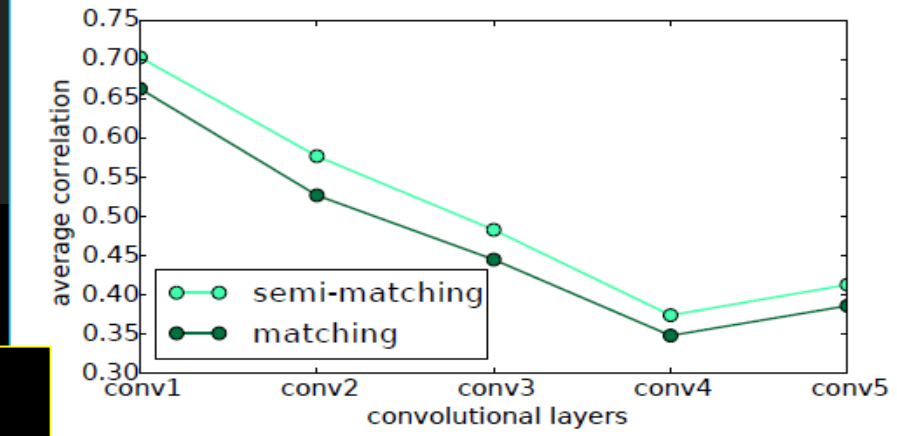
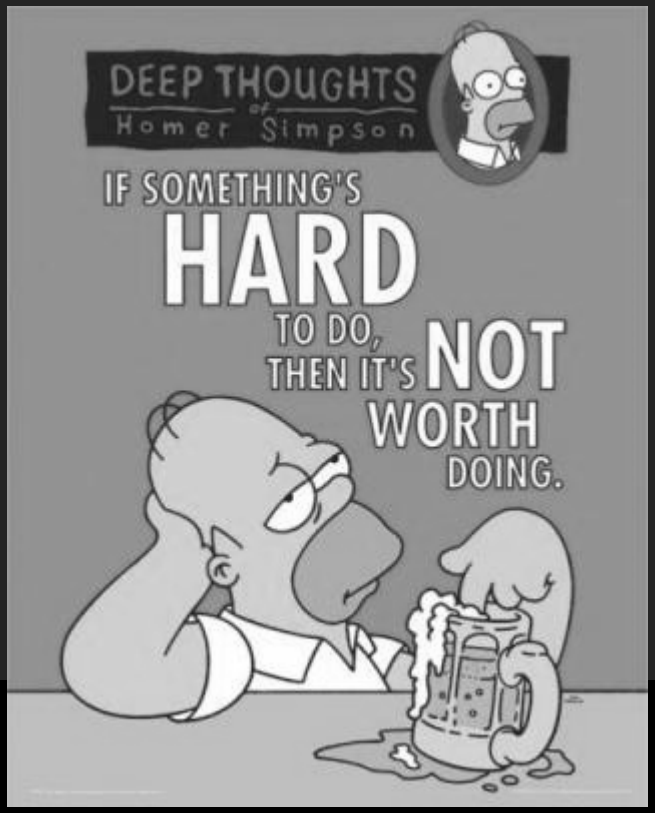


Figure 1: Correlation matrices for the conv1 layer, displayed as images with minimum value at black and maximum at white. **(a,b)** Within-net correlation matrices for Net1 and Net2, respectively. **(c)** Between-net correlation for Net1 vs. Net2. **(d)** Between-net correlation for Net1 vs. a version of Net2 that has been permuted to approximate Net1's feature order. The partially white diagonal of this final matrix shows the extent to which the alignment is successful; see Figure 3 for a plot of the values along this diagonal and further discussion.



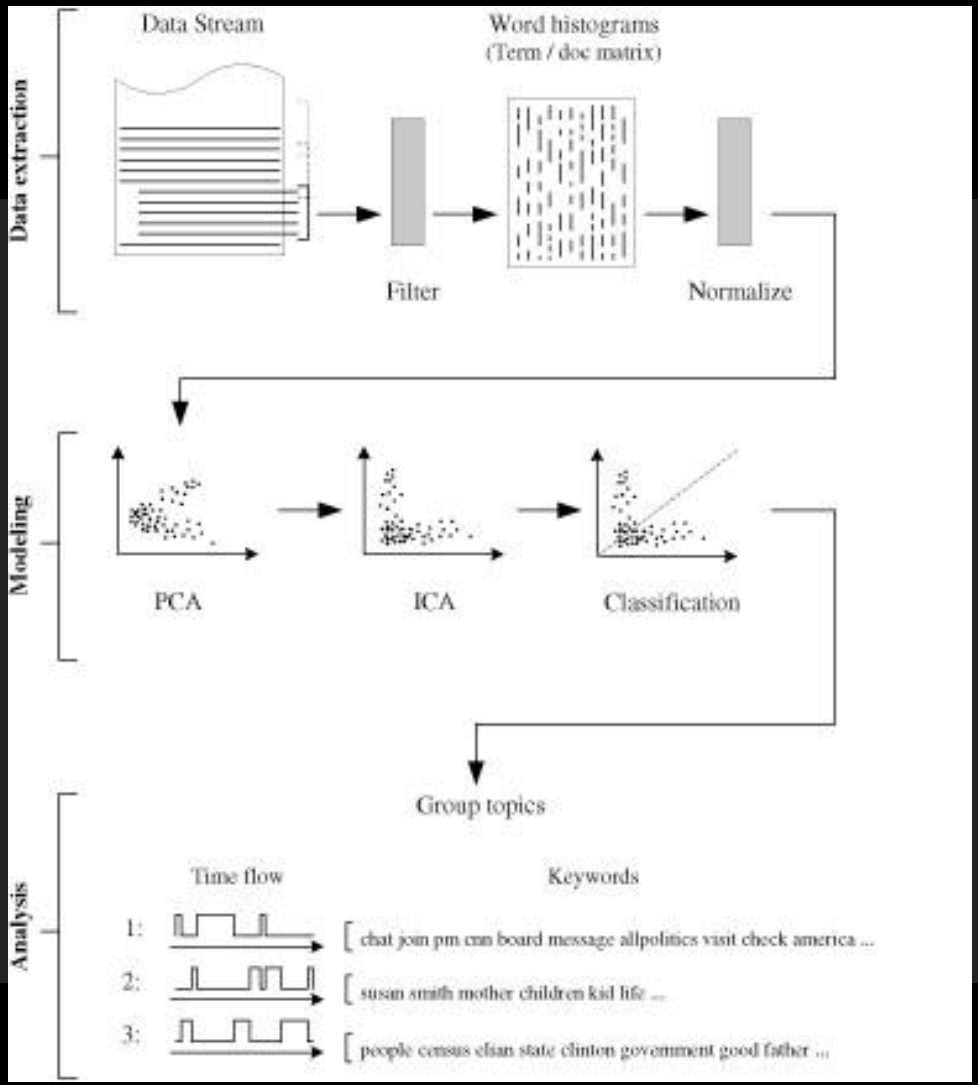
L, Yixuan, J Yosinski, J Clune, H Lipson, J Hopcroft. "Convergent Learning: Do different neural networks learn the same representations?." *arXiv preprint arXiv:1511.07543* (2015)

What about “higher order” cognition?



Independent contexts in document databases

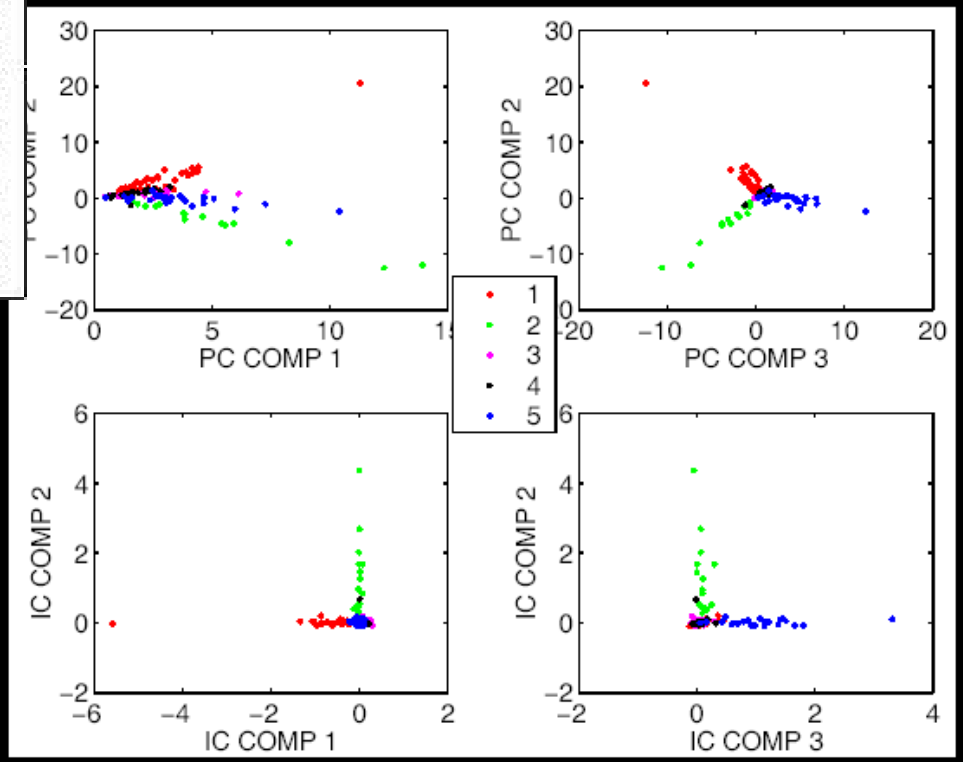
- x(j,t) is the occurence of the j'th word in the t'th document.
- s(k,t) quantifies how much the k'th context is expressed in t'th document.
- A(j,k) quantifies the typical importance of the j'th word in the k'th context



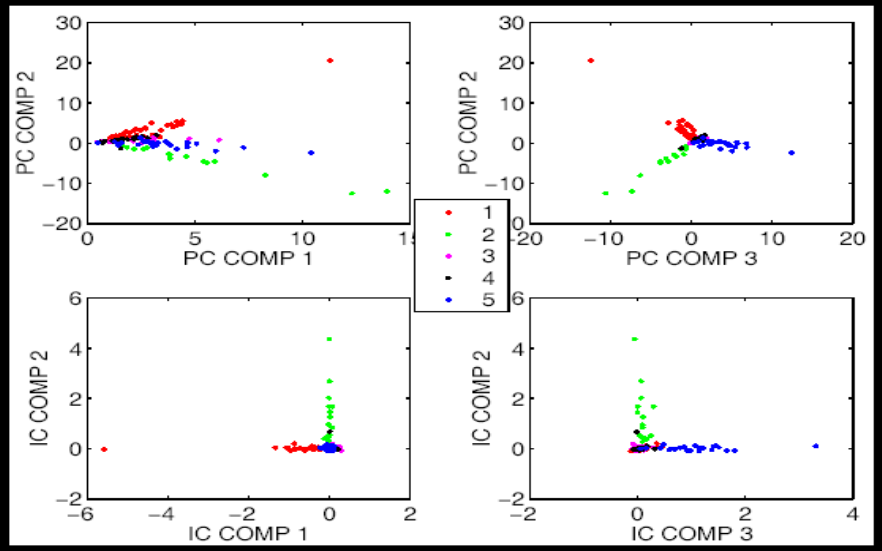
ICA in text
Isbell and Viola (1999)
Kolenda, Hansen, (2000)

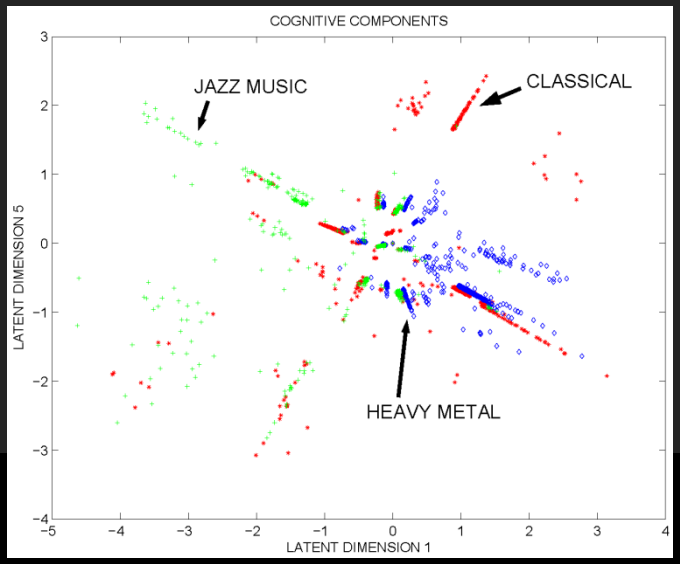
PCA vs ICA document scatterplots

Terms	Documents								
	c1	c2	c3	c4	c5	m1	m2	m3	m4
computer	1	1	0	0	0	0	0	0	0
EPS	0	0	1	1	0	0	0	0	0
human	1	0	0	1	0	0	0	0	0
interface	1	0	1	0	0	0	0	0	0
response	0	1	0	0	1	0	0	0	0
system	0	1	1	2	0	0	0	0	0
time	0	1	0	0	1	0	0	0	0
user	0	1	1	0	1	0	0	0	0
graph	0	0	0	0	0	0	1	1	1
minors	0	0	0	0	0	0	0	1	1
survey	0	1	0	0	0	0	0	0	1
trees	0	0	0	0	0	1	1	1	0



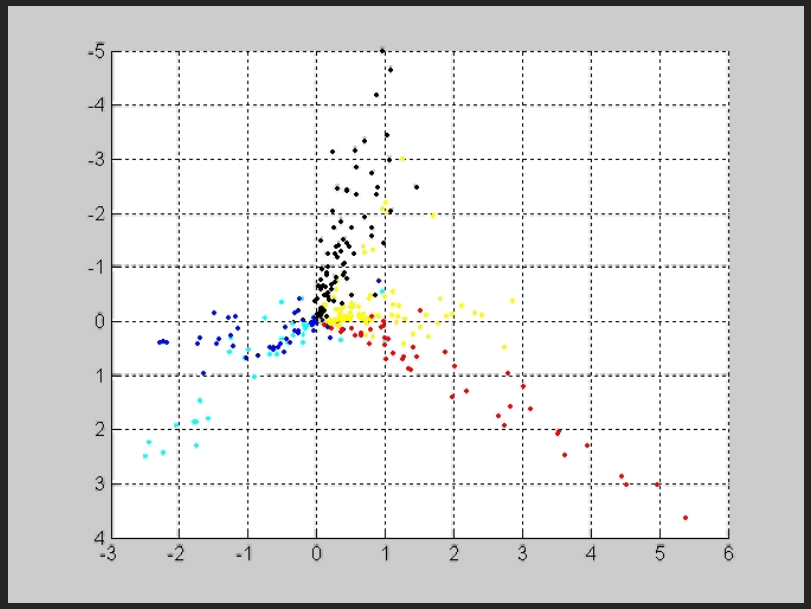
Linear mixture of independent agents in term-document scatterplots





Linear mixture of independent contexts observed in short time features (mel-ceptrum) in a music database.

Social networks: Linear mixtures of independent communities?

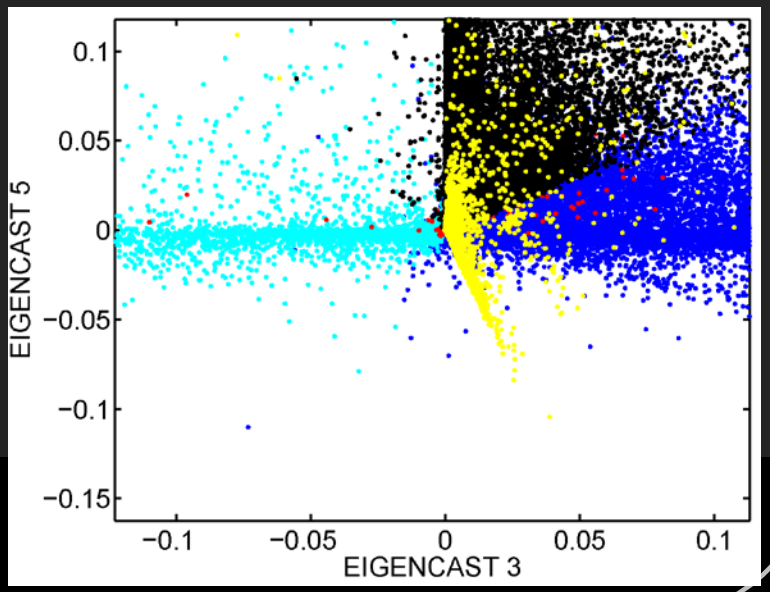


Genre patterns in expert's opinion on similar music artists

(AMG400, Courtesy D. Ellis)

"Movie actor network"
- A collaborative small world network

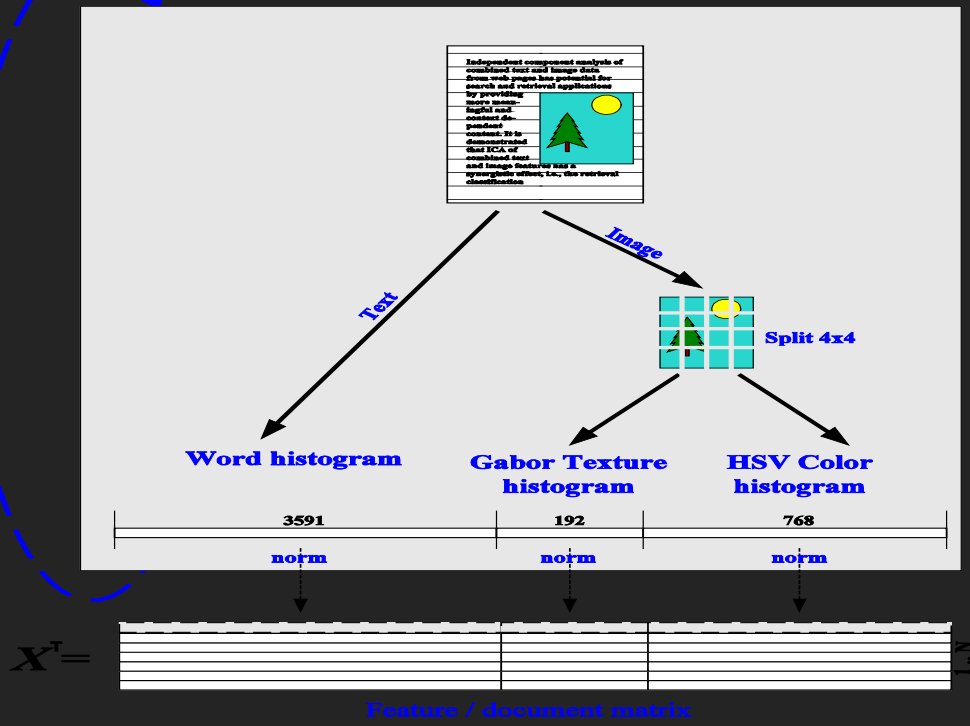
128.000 movies
380.000 actors



DTU

Independent contexts in multi-media

- Organizing webpages in categories
- Labels obtained from Yahoo's directory
- Features: Text, color, and texture subsets of MPEG image features



L.K. Hansen, J. Larsen and T. Kolenda "On Independent Component Analysis for Multimedia Signals". In L. Guan et al.: *Multimedia Image and Video Processing*, CRC Press, Ch. 7, pp. 175-199, 2000.

Coworkers: Thomas Kolenda, Jan Larsen

Performance of the system trained by associating unsupervised independent components with labels – generalization based on Yahoo cathegories

Modality	Classification Error
Color	23.0%
Texture	18.0%
Texture/Color	11.5%
Text	5.7%
Combined (texture/color/text)	2.8%

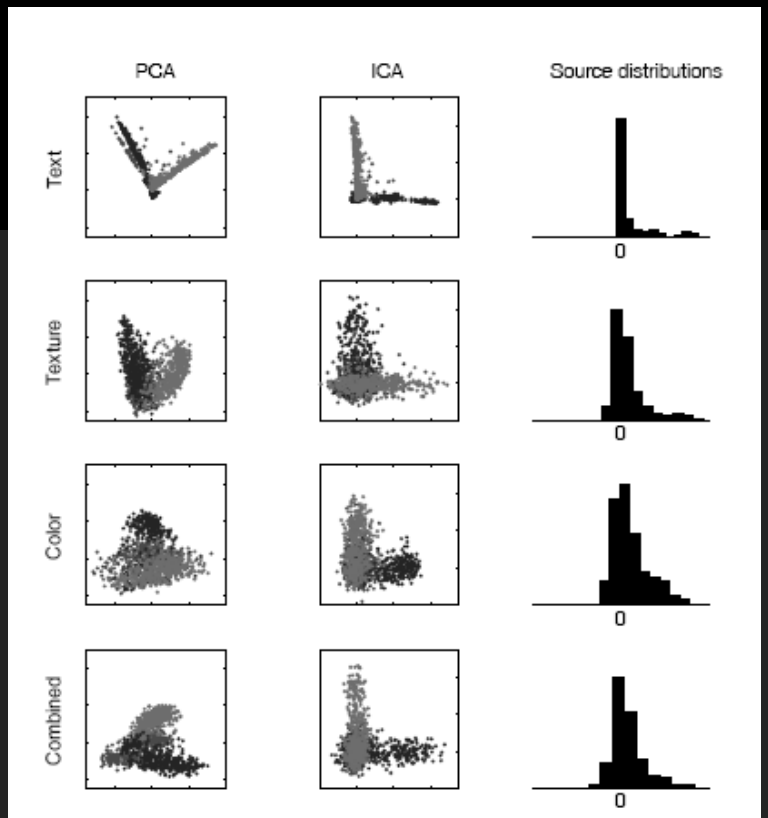
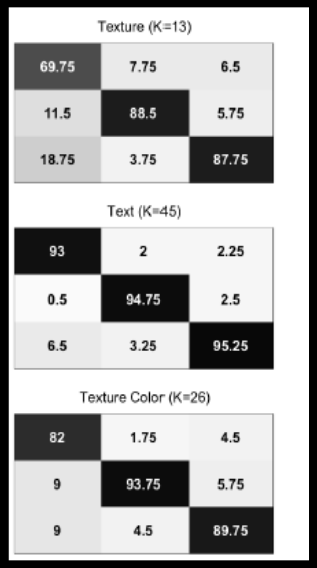


Fig. 3. Scatterplots of the text and image multimedia data, projected to a two-dimensional subspace found by PCA. Grey value of points corresponds to the three classes considered, see Fig. 4. The ray like structure strongly suggest an ICA interpretation, however, the relevance of this representation can only be determined by a subsequent inspection of the recovered source signals. As we will see in section 4.6, it turns out that there is an interesting alignment of the source signals and a manual labeling of the multimedia documents.



Texture (K=13)

69.75	7.75	6.5
11.5	88.5	5.75
18.75	3.75	87.75

Color (K=16)

70.75	3.75	10
12	81.5	11.25
17.25	14.75	78.75

Text (K=45)

93	2	2.25
0.5	94.75	2.5
6.5	3.25	95.25

Combined errorrate: 2.8%

Single best errorrate: 5.7%

Texture Color (K=26)

82	1.75	4.5
9	93.75	5.75
9	4.5	89.75

Texture Color Text (K=26)

98.25	0.25	0.75
0.75	98	3.75
1	1.75	95.5

ht guard

CASTSEARCH - CONTEXT BASED SPEECH DOCUMENT RETRIEVAL

Lasse Lohilahti Mølgaard, Kasper Winther Jørgensen, and Lars Kai Hansen

Informatics and Mathematical Modelling
Technical University of Denmark Richard Petersens Plads
Building 321, DK-2800 Kongens Lyngby, Denmark

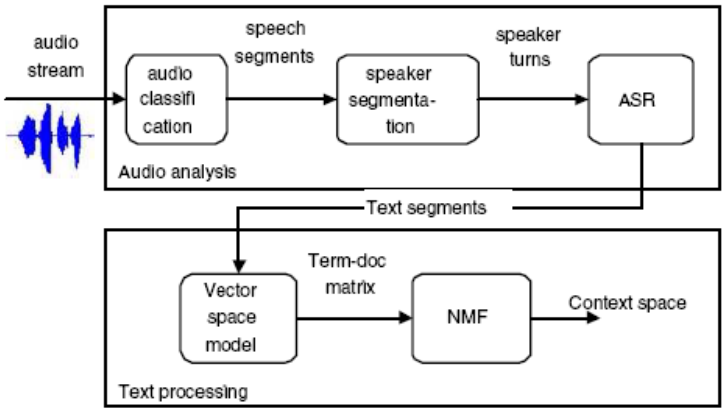
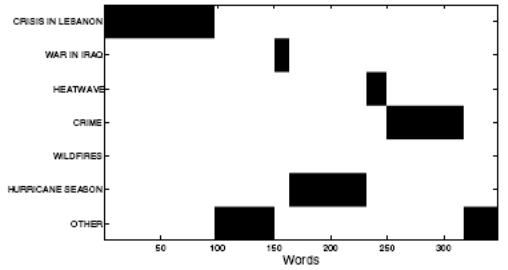
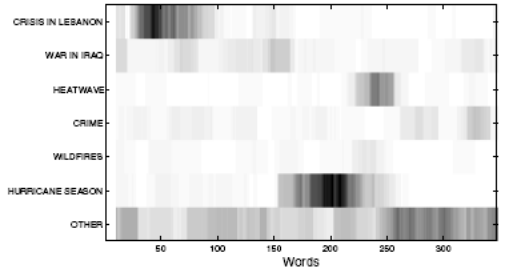


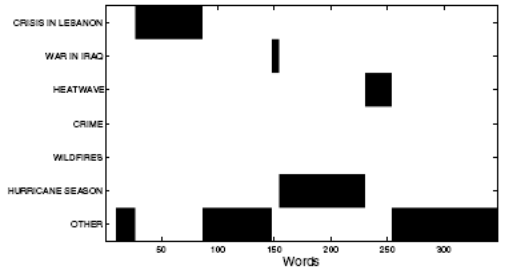
Fig. 1. The system setup. The audio stream is first processed using audio segmentation. Segments are then using an automatic speech recognition (ASR) system to produce text segments. The text is then processed using a vector representation of text and apply non-negative matrix factorization (NMF) to find a topic space.



(a) Manual segmentation.



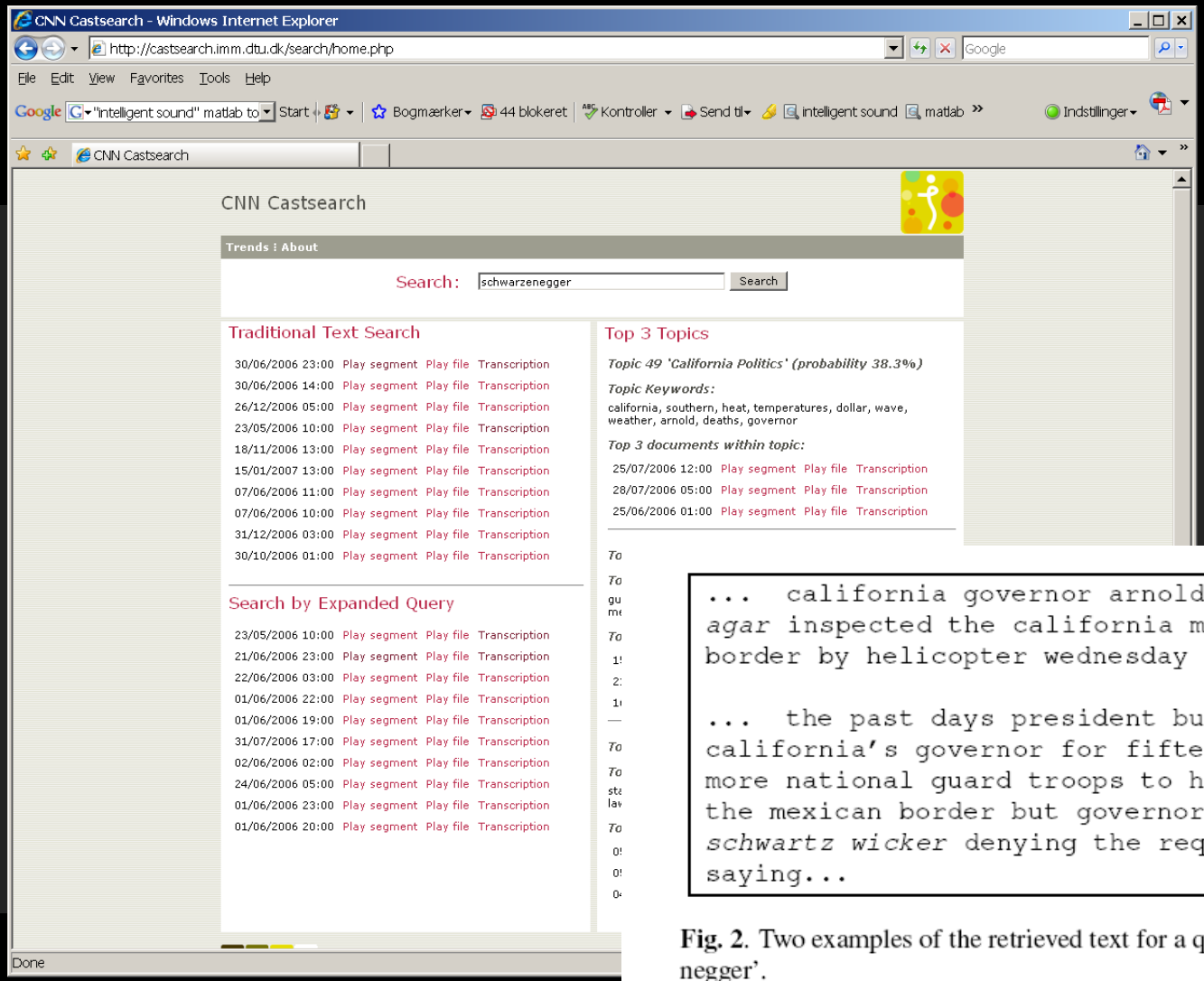
(b) $p(k|d^*)$ for each context. Black means high probability.



(c) The segmentation based on $p(k|d^*)$.

Fig. 3. Figure 3(a) shows the manual segmentation of the news show into 7 classes. Figure 3(b) shows the distribution $p(k|d^*)$ used to do the actual segmentation shown in figure 3(c). The NMF-segmentation is in general consistent with the manual segmentation. Though, the segment that is manually segmented as 'crime' is labeled 'other' by the NMF-segmentation

Mølgaard et al. 2007



... california governor arnold's *fortson agar* inspected the california mexico border by helicopter wednesday to see ...

... the past days president bush asking california's governor for fifteen hundred more national guard troops to help patrol the mexican border but governor orville *schwartz wicker* denying the request saying...

Fig. 2. Two examples of the retrieved text for a query on 'schwarzenegger'.

castsearch.imm.dtu.dk

MiRocket

- Time frequency analysis pipeline: MFCC's @ 30 ms windows
- Temporal integration and genre classification at 1000ms
- Music recommendation in 12-D genre space

A. Meng, P. Ahrendt, J. Larsen, L.K. Hansen: *Temporal Feature Integration for Music Genre Classification. IEEE* Transactions on Audio and Speech and Language Processing 15(5): 1654-1664 (2007)

T. Lehn-Schiøler, J. Arenas-García, K.B. Petersen and L.K. Hansen: *A Genre Classification Plug-in for Data Collection. Proc. 7th Intl. Conf. on Music Information Retrieval, ISMIR 2006, pp. 320-321, Victoria, Canada, Oct.* (2006).

L.K. Hansen, T. Lehn-Schiøler, K.B. Petersen, J. Arenas-Garcia, J. Larsen, and S.H. Jensen: *Learning and clean-up in a large music database. EUSIPCO 2007, European Conference on Signal Processing, Poznan (2007).*

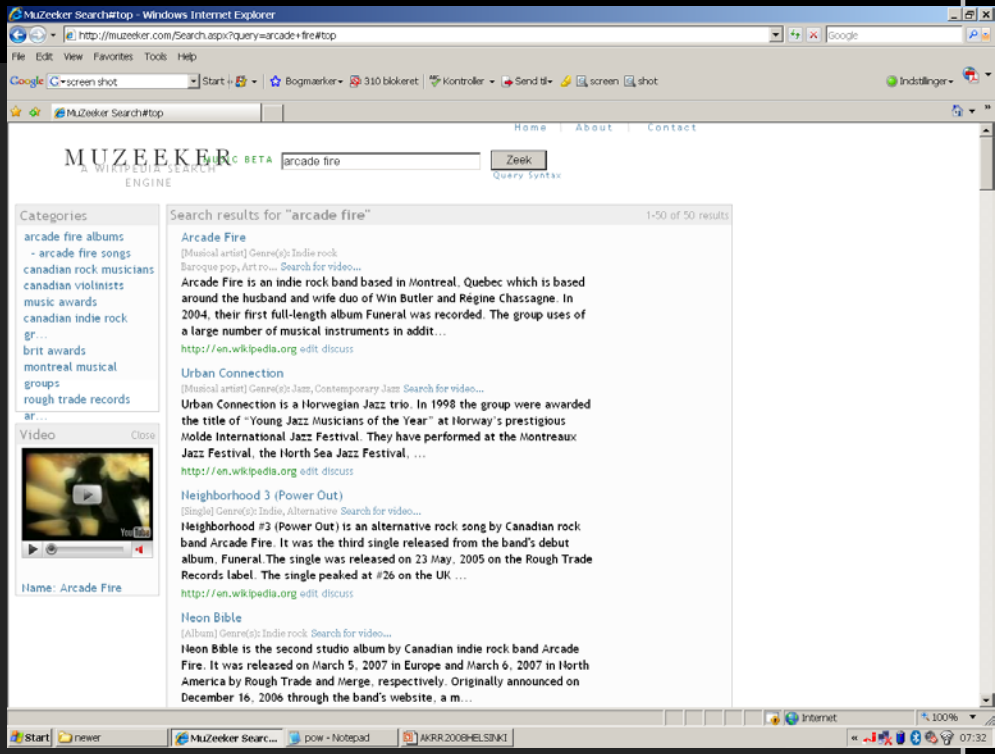
muzeeker

Wikipedia based common sense

Wikipedia used as a proxy for the music users mental model

Implementation: Filter retrieval using Wikipedia's article/ categories

muzeeker.com



S. Halling, M.K. Sigurdsson, J.E. Larsen, S. Knudsen, L.K. Hansen: *MuZeeker: A domain SpecificWikipedia-based Search Engine. In Proc. First International Workshop on Mobile Multimedia Processing. Tampa, USA (2008).*

J.E. Larsen, S. Halling, M. Sigurdsson and L.K. Hansen: *MuZeeker - Adapting a music search engine for mobile phones. To appear in Springer Lecture Notes in Computer Science 'Mobile Multimedia Processing: Fundamentals,* Methods, and Applications', Selected papers from First International Workshop on Mobile Multimedia Processing, Tampa, USA. (2010).

So representations are optimal, what about attention?

Top down vs bottom up attention

Bottom up

Attention determined by feature of the input

Audio

Cocktail party effect (Pollack+ Pickett, 57)

Visual

Classical spatial novelty saliency (Itti+Koch, 04)

Top down

Attention determined by state of the observer

Audio

Cocktail party problem (Cherry, 64)

Visual

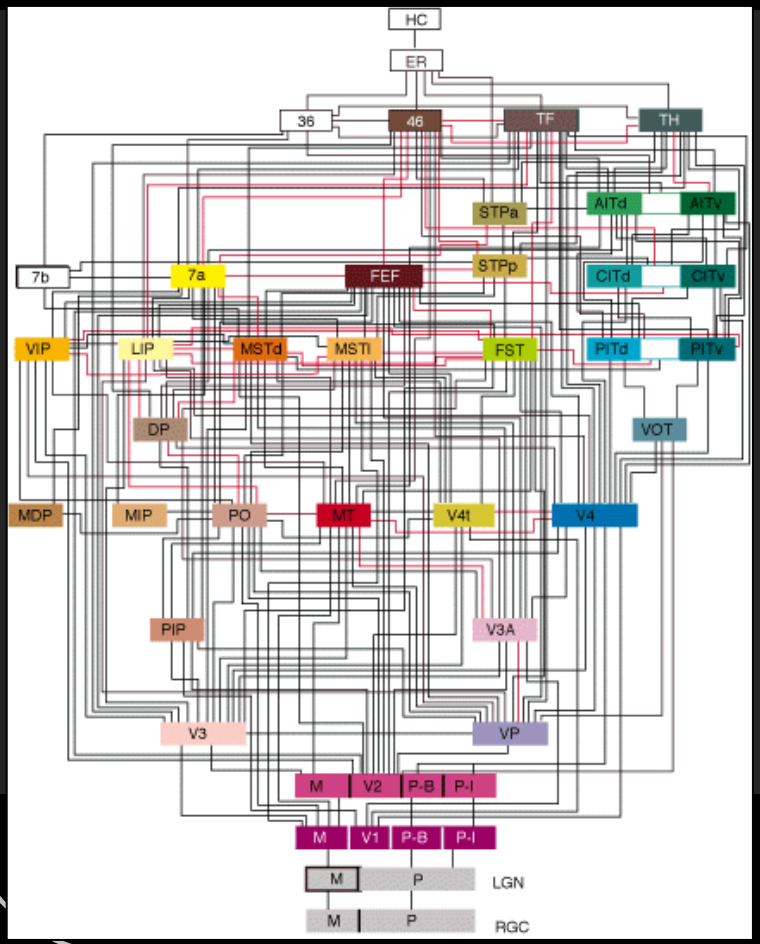
ambiguous pictures

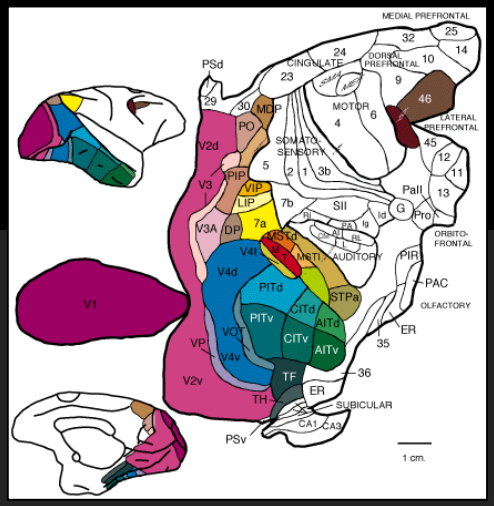
eye tracking

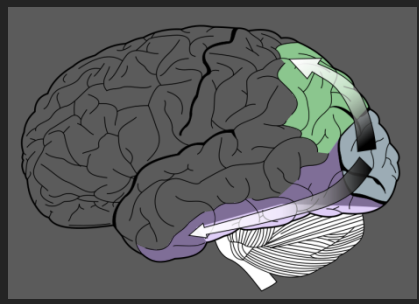
See e.g. J.M. Wolfe et al. "How fast can you change your mind? The speed of top-down guidance in visual search" Vision Research 44 (2004) 1411–1426

DTU

Visual system hierarchy







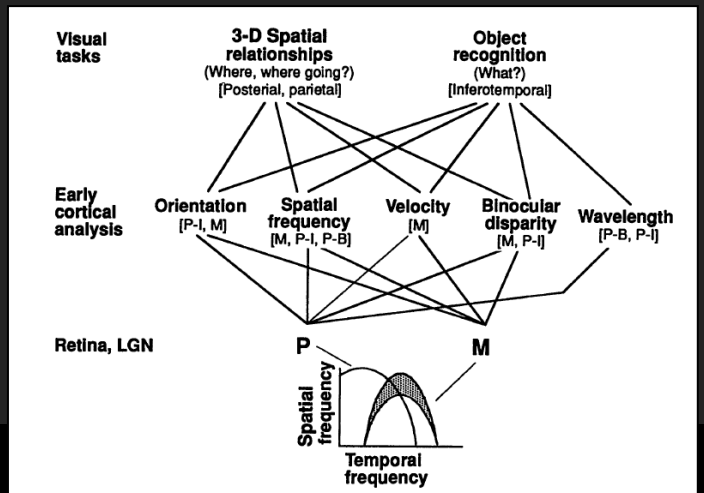
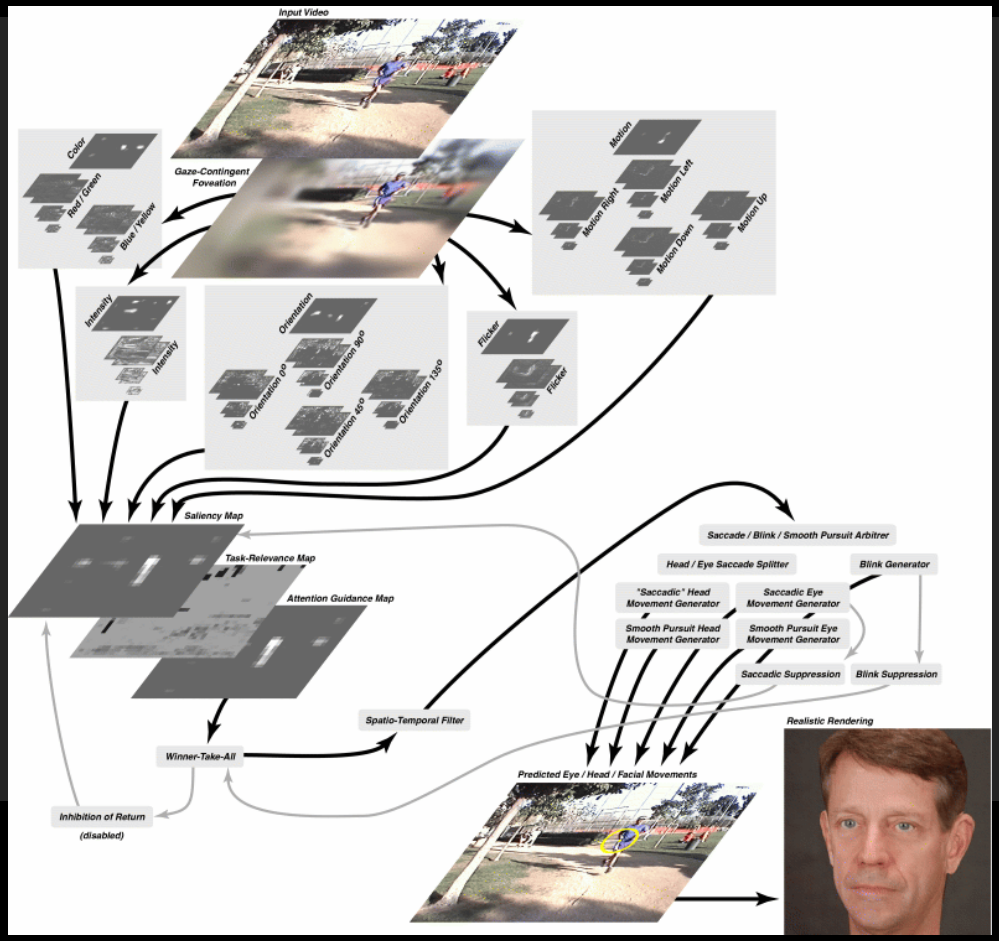


Fig. 3. Convergence and divergence in visual processing. Arrows represent major lines of information flow from subcortical P and M streams (bottom) to the selectivities represented among neurons at early stages of cortical analysis (middle) and from there to two general tasks of vision (top level). The hatched portion of the M cell curve represents their nonlinear component of processing. The processing streams associated with each property in the middle row are assigned on the basis of a high incidence of selectivity recorded physiologically (*6, 7*).

DJ Felleman,DC. Van Essen. "Distributed hierarchical processing in the primate cerebral cortex." *Cerebral cortex* 1, no. 1 (1991): 1-47.

Realistic Avatar Eye and Head Animation Using a Neurobiological Model of Visual Attention

L. Itti,[1] N. Dhavale[1] and F. Pighin[2]



Itti, Dhavale & Pighin, Proc. SPIE, 2003

ML model of ”optimal” top down attention

1. The task is implemented as decision problem

2. Attention is represented as the choice over set of detailed features

Standard probabilistic classifier

Model of posterior probability

$$p(c|x,z)$$

Two sets of features

i) Features setting the context **’the gist’ (x)**

(Friedman,79; Torralba et al., 04)

ii) **Potential features (z)** considered by the attention mechanism

A. Friedman: Framing pictures: the role of knowledge in automatized encoding and memory of gist. Journal of Experimental Psychology: General 1979;108:316–355.

DTU

Mathematical model

The GIST

We are interested in a partial observation **x** under a decision task: Choose among "C" actions

$$
\begin{aligned}
p(c|\boldsymbol{x}) &= \int p(c, \boldsymbol{z}|\boldsymbol{x}) d\boldsymbol{z} \\
&= \frac{\int p(c, \boldsymbol{x}, \boldsymbol{z}) d\boldsymbol{z}}{\sum_{c=1}^{C} \int p(c, \boldsymbol{x}, \boldsymbol{z}) d\boldsymbol{z}}
\end{aligned}
$$

Focus

versus getting additional information though z_j

$$
\begin{aligned}
p(c|\boldsymbol{x}, z_j) &= \sum_{c=1}^{C} \int p(c, \boldsymbol{z}|\boldsymbol{x}) \prod_{i \neq j} dz_i \\
&= \frac{\int p(c, \boldsymbol{x}, \boldsymbol{z}) \prod_{i \neq j} dz_i}{\sum_{c=1}^{C} \int p(c, \boldsymbol{x}, \boldsymbol{z}) \prod_{i \neq j} dz_i}
\end{aligned}
$$

DTU

Measure the information gain

First used by Lindley (1956) for experimental design..

ON A MEASURE OF THE INFORMATION PROVIDED BY AN EXPERIMENT[1, 2]

By D. V. Lindley

University of Cambridge and University of Chicago

1. Summary. A measure is introduced of the information provided by an experiment. The measure is derived from the work of Shannon [10] and involves the knowledge prior to performing the experiment, expressed through a prior probability distribution over the parameter space. The measure is used to compare some pairs of experiments without reference to prior distributions; this method of comparison is contrasted with the methods discussed by Black-[illegible]. Finally, the measure is applied to provide a solution to some problems of experimental design, where the object of experimentation is not to reach decisions but rather to gain knowledge about the world.

D. V. Lindley, "On a measure of the information provided by an experiment," Annals Mathematical Statistics, vol. 4, pp. 986–1005, 1956.

Information theoretical model

$$\Delta S_j(\boldsymbol{x}, z_j) = -\sum_{c=1}^{C} \int \log p(c, \boldsymbol{z}|\boldsymbol{x}) p(c, \boldsymbol{z}|\boldsymbol{x}) d\boldsymbol{z} + \sum_{c=1}^{C} \log p(c|\boldsymbol{x}, z_j) p(c|\boldsymbol{x}, z_j)$$

$$G_j(\boldsymbol{x}) \equiv \int \Delta S_j(\boldsymbol{x}, z_j) p(z_j|\boldsymbol{x}) dz_j$$

$$= \sum_{c=1}^{C} \int \log p(c|\boldsymbol{x}, z_j) p(c, z_j|\boldsymbol{x}) dz_j - \sum_{c=1}^{C} \int \log p(c, \boldsymbol{z}|\boldsymbol{x}) p(c, \boldsymbol{z}|\boldsymbol{x}) d\boldsymbol{z}.$$

Gaussian-Discrete distribution

$$p(c, \boldsymbol{x}, \boldsymbol{z}) = \sum_{k=1}^{K} p(k)p(c|k)p(\boldsymbol{x}, \boldsymbol{z}|k)$$

Component probabilities

Class emission probabilities

Joints Gaussian component density of "gist" and features

Information gain by requesting the j'th feature

$$G_j(\boldsymbol{x}) = \sum_{c=1}^{C}\sum_{k=1}^{K} p(c|k)p(k|\boldsymbol{x}) \times \int \log\left[p(c,\boldsymbol{x},z_j)\right] p(z_j|\boldsymbol{x},k)dz_j$$
$$- \sum_{k=1}^{K} p(k|\boldsymbol{x}) \int \log\left[p(\boldsymbol{x},z_j)\right] p(z_j|\boldsymbol{x},k)dz_j$$
$$+ \text{const.}$$

1D integrals over normal distribution pdf

Visual attention: Binary decision based on GIST / FOCUS

27 image features in total

1-9: GIST....whole image NMF factors

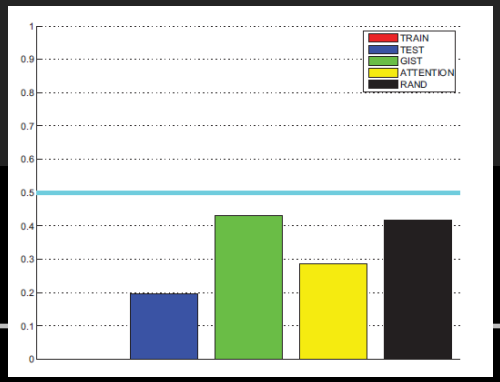
10-27: Foci: 10x10 patch NMF factors

N_{train} = 2000

N_{test} = 600

Attention = 28%

Random = 41% (p<0.01)



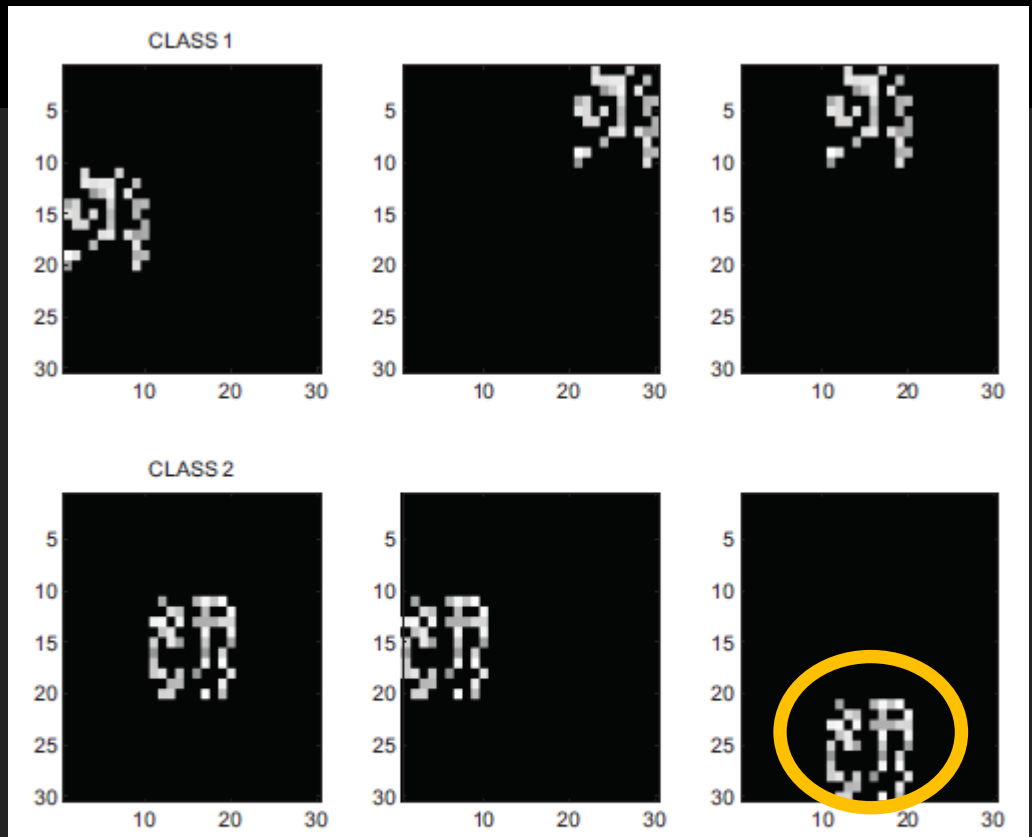


Fig. 2. Visual domain example. The visual data (30×30 pixels) is designed as a 3×3 array of locations in which one of two binary sparse patterns can be located (two signal classes $C = 2$). The gist consists of 9 NMF features computed from a large training set of images, while the low-level features are 18 additional NMF features trained on local 10×10 patches.

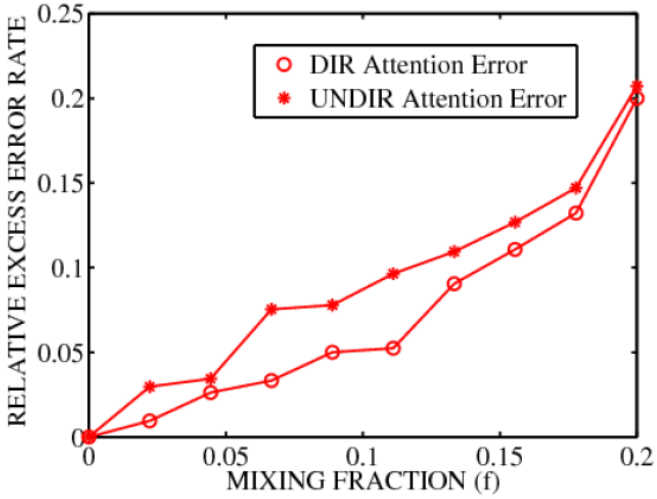
The Role of Top-Down Attention in the Cocktail Party: Revisiting Cherry's Experiment after Sixty Years

Letizia Marchegiani*†, Seliz G. Karadoğan*, Tobias Andersen*, Jan Larsen* and Lars Kai Hansen*‡

Weak and Strong Top-Down Attention

$$p(y|k) \rightarrow p(y|k,\beta) = \frac{p(y|k)^{\beta}}{\sum_c p(y|k)^{\beta}}$$

$$P(j) = \frac{\exp(\gamma G_j)}{\sum_{j'} \exp(\gamma G_{j'})}$$



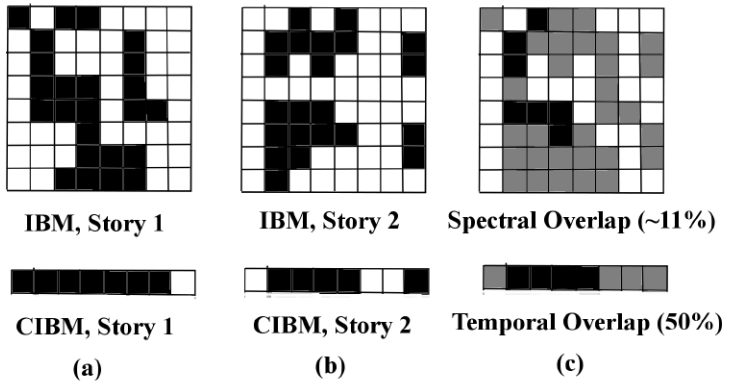


Figure 7.3: The illustrations of temporal and spectral overlap definitions, the bins represent time-frequency regions of an IBM (frequency bins are not equally spaced, gammatone filtering is used). Only black regions represent overlapped parts on (c).

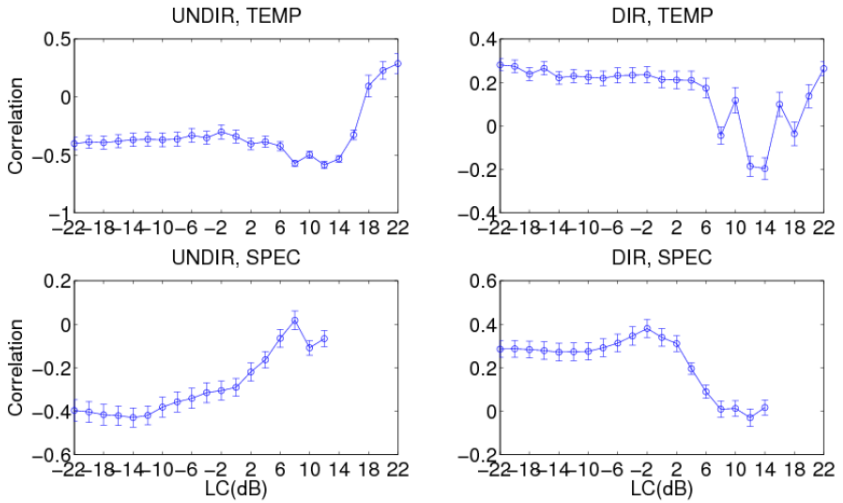
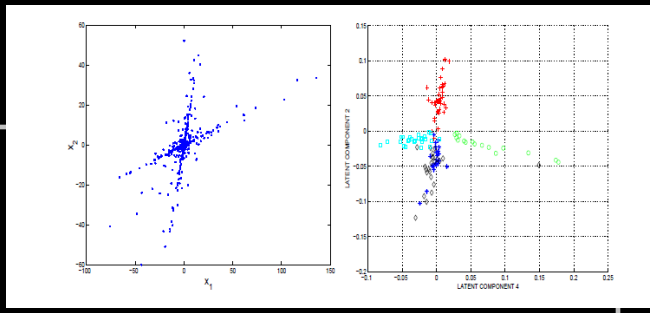


Figure 7.6: Correlation for different LC values, WinLength = 20ms and NumChan=32. Left to right: Undirected and Directed. Top to bottom: Temporal and Spectral.



Summary

Evidence that cognitive components are the ”chunks” of attention

Optimality: Representations are quite uniquely determined by statistical and physical properties of the environment

Attention a function of sensory representations and the mental state/goal/task of the beholder

Optimality: A simple information optimizing mechanism can use task information to determine what to do next and thereby improve decision making

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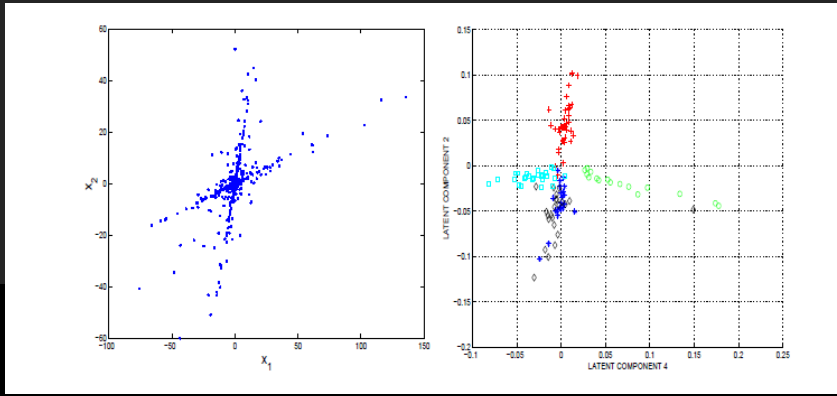
Conclusions & outlook

Evidence that phonemes, gender, identity are independent components ’objects’ in the (time stacked) MFCC representation

Evidence that human categorization is based on sparse independent components in social networks, text, digital media

Conjecture: Objects in digital media can be identified as independent components: The brain uses old tricks from perception to solve complex ”modern” problems.



Acknowledgments

- Danish Re
- EU Com
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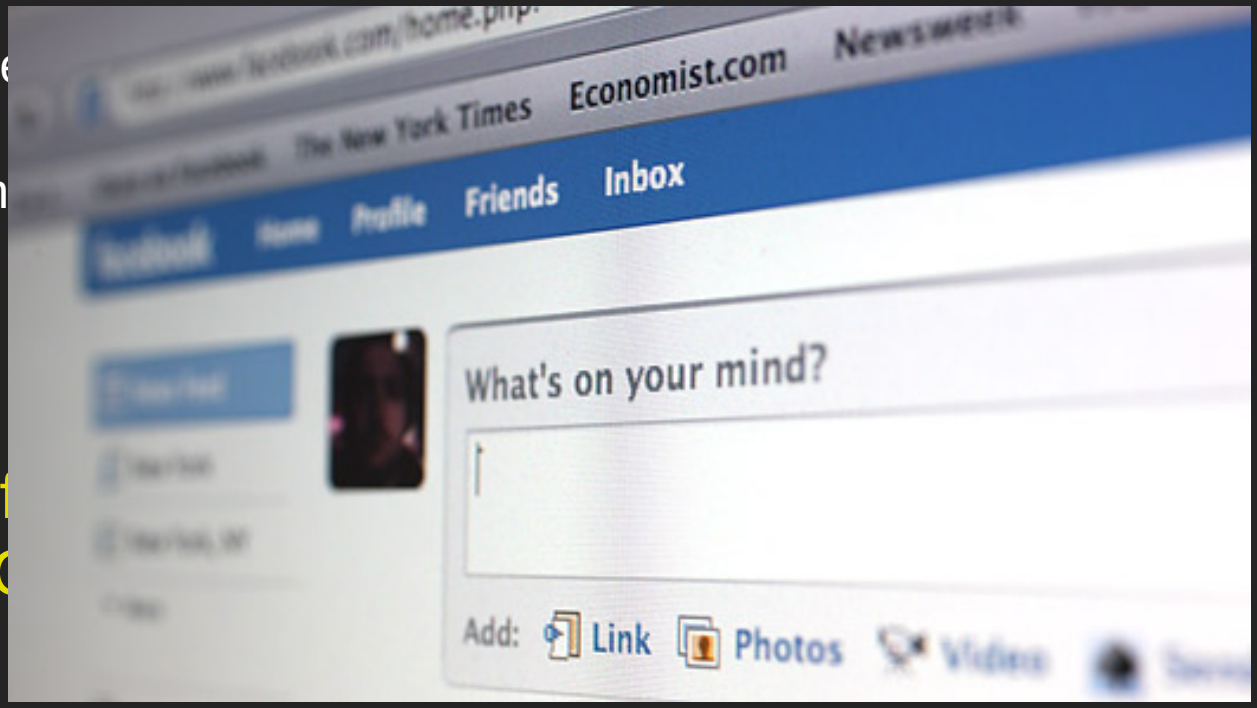

DTU:Toolbox