Cognitive Components of Speech

-On Phonemes as Cognitive Components of Speech

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Outline

1. Cognitive component analysis
2. Pre-processing
3. Unsupervised vs. Supervised
4. Timescales and meaning
5. Conclusion

COCA - Definition

- **What is Cognitive Component Analysis (COCA)?**

  COCA is the process of unsupervised grouping of data such that the ensuing group structure is well-aligned with that resulting from human cognitive activity.

  - Unsupervised learning discovers statistical regularities;
  - Human cognition is a supervised on-going process.

- **Human Behavior**

  Cognition is hard to quantify – its direct consequence: human behavior is easy to access and model.

L.K. Hansen, P. Ahrendt, and J. Larsen, “Towards cognitive component analysis”. In *AKRR’05* –International and Interdisciplinary Conference on Adaptive Knowledge Representation and Reasoning. Jun 2005.

COCA - Definition

- **Key Point**

  To investigate the consistency of statistical regularities in a signaling ecology and human cognitive activity! ...

  We are interested in the performance of unsupervised learning $p(\mathbf{x} \mid \theta)$ **and supervised learning** $p(\mathbf{y} \mid \mathbf{x}, \theta)$ **under equivalent representations.**

- **Hypothesis: independence and sparseness**

  Independence reduces perception-to-action mapping;
  Optimal representation by sparse distributed codes.

-D. J. Field, “What is the goal of sensory coding?, ” Neural Computation, vol. 6, pp. 559–601, 1994.
-B. A. Olshausen and D. J. Field, "Sparse coding of sensory inputs,” Current Opinion in Neurobiology, vol. 14(4), pp.481-487, 2004

Independence Hypothesis

- Independence dramatically reduces perception-to-action mapping by using factorial codes.
- Low level cognition is based on independence in natural ensemble statistics, e.g. visual feature extraction, color imagery, natural sound coding, even video data, etc. in primary sensory systems.
- The activation of each visual cortical feature detector is supposed to be as statistically independent from the others as possible.
- The receptive field properties of auditory nerve cells invoke a strategy of ***sparse independent*** manner to represent natural sounds.

-A. J. Bell and T. J. Sejnowski, "The 'independent components' of natural scenes are edge filters," *Vision Research*, vol. 37, pp.3327–3338, 1997.

-P. Hoyer and A. Hyvrinen, "Independent component analysis applied to feature extraction from colour and stereo images," *Network: Comput. Neural Syst.*, vol. 11, pp. 191–210, 2000.

-M. S. Lewicki, "Efficient coding of natural sounds," *Nature Neuroscience*, vol. 5, pp. 356–363, 2002.

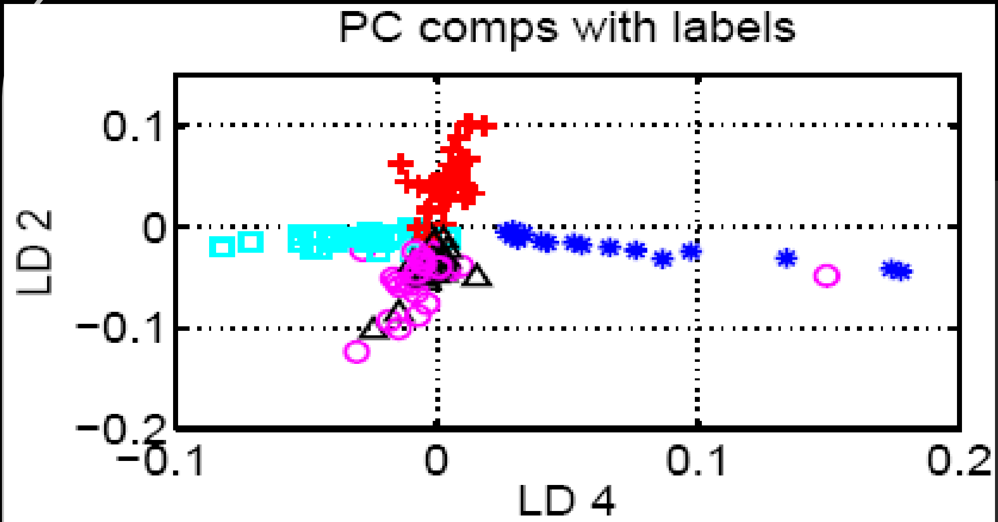
-E. Doi and T. Inui and T. W. Lee and T. Wachtler and T. J. Sejnowski , " Spatiochromatic Receptive Field Properties Derived from Information-Theoretic Analyses of Cone Mosaic Responses to Natural Scenes, " Neural Comput., vol. 15(2), pp. 397-417, 2003.

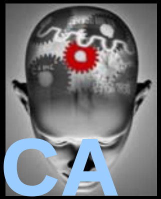
-J. H. van Hateren and D. L. Ruderman, "Independent Component Analysis of Natural Image Sequences Yields Spatio-Temporal Filters Similar to Simple Cells in Primary Visual Cortex," Proc. Biological Sciences, vol. 265(1412), pp. 2315-2320, 1998.

-B. A. Olshausen and K. N. O'Connor , "A new window on sound ," Nature Neuroscience, vol. 5, pp. 292-294, 2002.

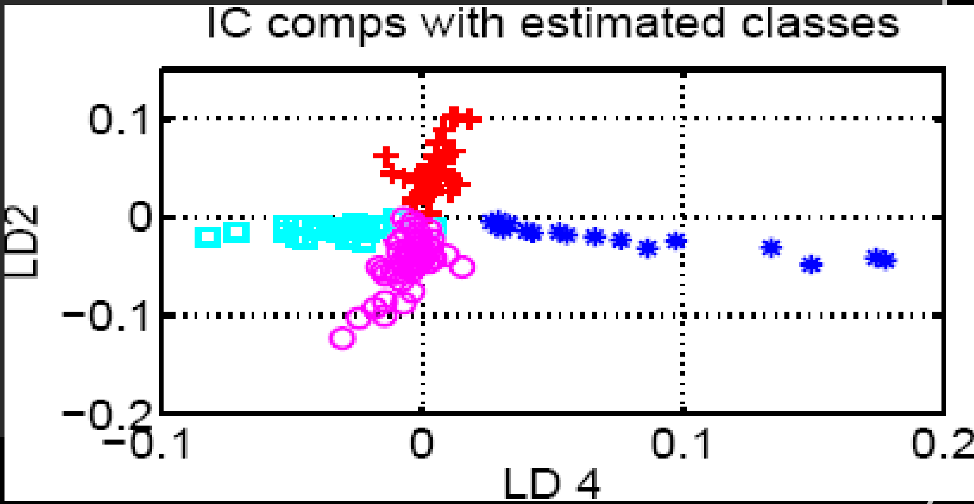
-H.B. Barlow, "Unsupervised learning," Neural Computation, vol. 1, pp. 295–311, 1989.

Example of ICA

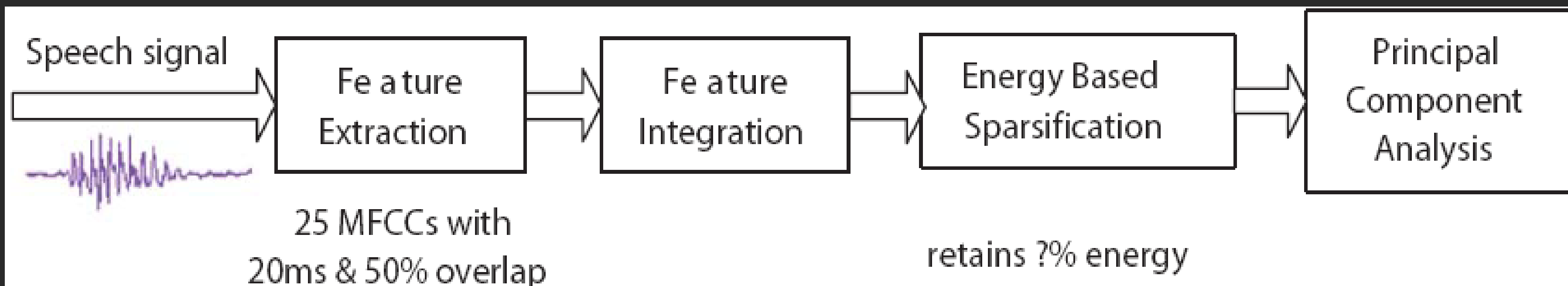




- Linear mixture of independent topics in text analysis
- Sparse ‘ray-structure’
- One-to-one correspondence
- Using the magnitude of the source signals as a classification scheme, we get more than 90% classification accuracy.



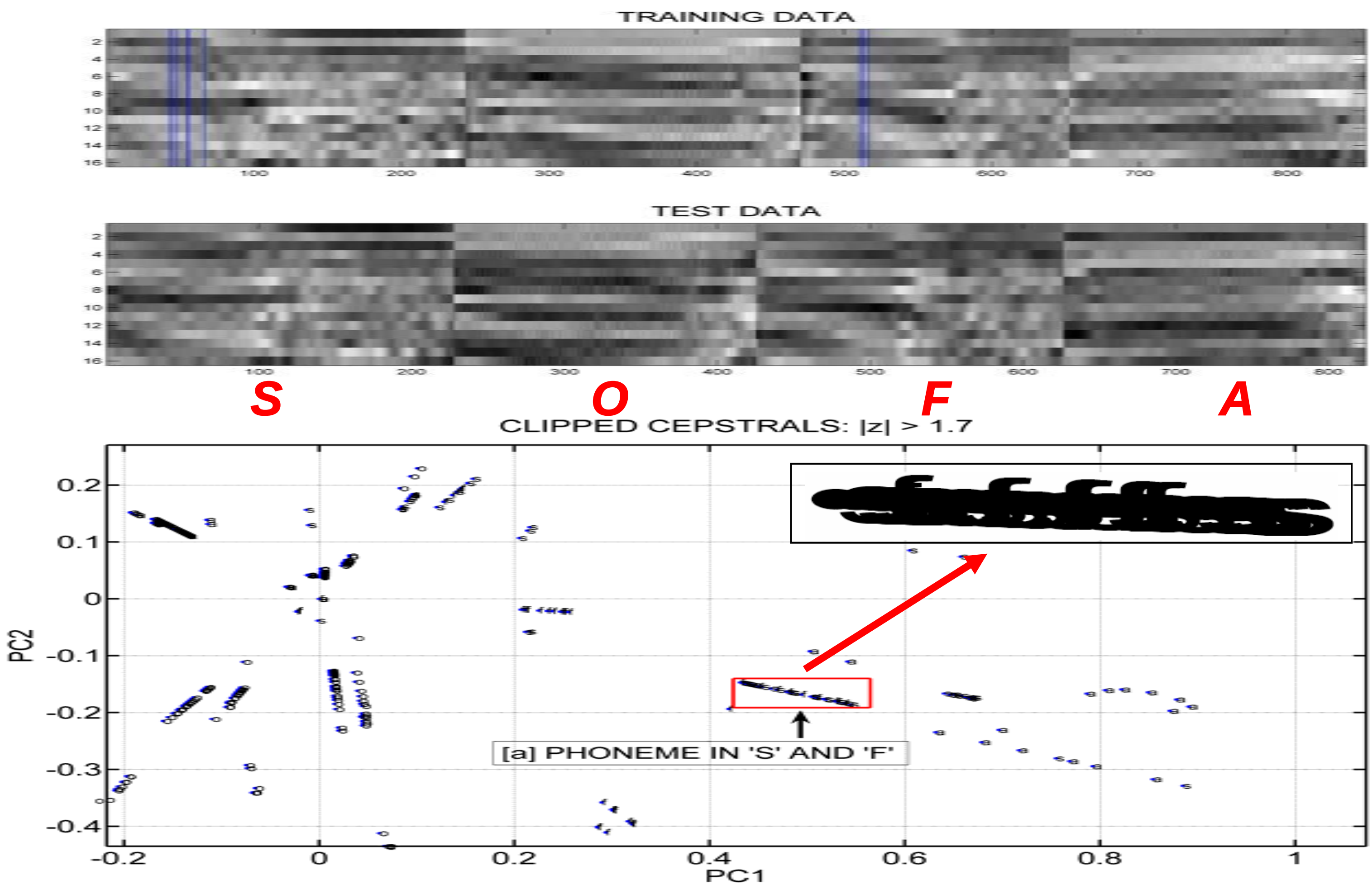
Preprocessing pipeline



- **MFCC**
  - *Does ear work as a Fourier analyzer?*
  - Non-linear frequency perception
  - Critical band
- **Stacking**
  - The simplest method for feature integration.
- **Energy Based Sparsification**
  - filter out the small (weak) signals
  - emulate the **detectability** and **sensory magnitude**
- **PCA (LSI)**
  - the basis of cognitive processes

W. Kintsch, “Predication,” *Cognitive Science*, vol. 25, pp.173–202, 2001.

Phonemes-LSI



Invariant Cue

The stable phoneme-relevant cognitive components (e.g. /e/ sound) are understood as ‘invariant cue’ characteristics of speech.

The perceived signals are derived as stable phonetic features despite of the different acoustic properties produced in *different trials* and *different speakers*.

Unsupervised vs. Supervised

We are interested in the performance of unsupervised learning and supervised learning under equivalent representations.

- ICA+Naive Bayes classifier vs. Mixture of Gaussian

Unsupervised learning: Unsupervised-then-supervised learning scheme to represent the 'ecological' grouping.

- ICA

$$\mathbf{x} = \mathbf{A}\mathbf{s}$$

- Naive Bayes

$$p(C_i \mid \mathbf{s}) = \frac{p(\mathbf{s} \mid C_i)\, p(C_i)}{\sum_i p(\mathbf{s} \mid C_i)\, p(C_i)}$$

$$p(\mathbf{s} \mid C_i) = \prod_{j=1}^{k} p(s_j \mid C_i)$$

Unsupervised -then- Supervised learning scheme

- Mixture of Gaussian

$$p(C_i \mid \mathbf{x}) = \frac{p(\mathbf{x} \mid C_i)\, p(C_i)}{\sum_i p(\mathbf{x} \mid C_i)\, p(C_i)}$$

$$p(\mathbf{x} \mid C_i) = \sum_j p(\mathbf{x} \mid j, C_i)\, p(j \mid C_i)$$

Time scales and meaning

- Music features are categorized into 3 time scales:

•short time scale (30ms): instant frequency, e.g. harmonics and pitch;

•medium time scale (~700ms): timbre, modulation;

•long time scale (~10s): perceptual information, e.g. beat and mood.

- In COCA experiments:

-at 10-40ms, there are generalizable `fingerprint' of *phonemes*;

-at 1 s, there are generalizable *speaker* specific sparse components.

-We are interested in what we can discover with different time scales: gender? Age? Height?...

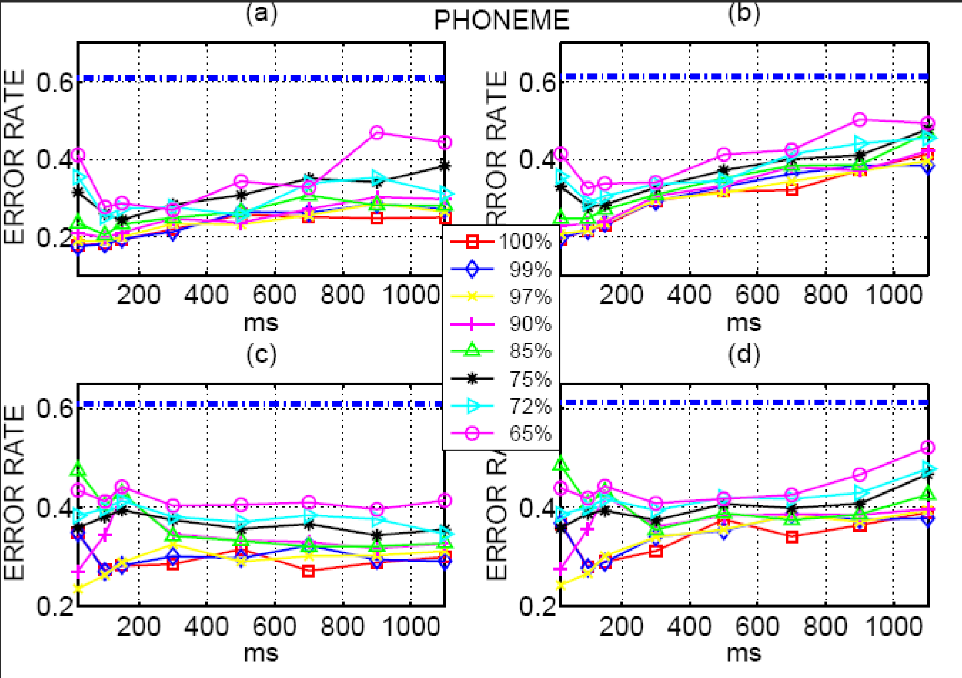
Meng, A., Ahrendt, P., & Larsen, J. (2005). Improving Music Genre Classification by Short-Time Feature Integration. *IEEE International Conference on Acoustics, Speech, and Signal Processing*, vol. 5, pp. 497-500.

Experiments-Phonemes

Data: TIMIT database

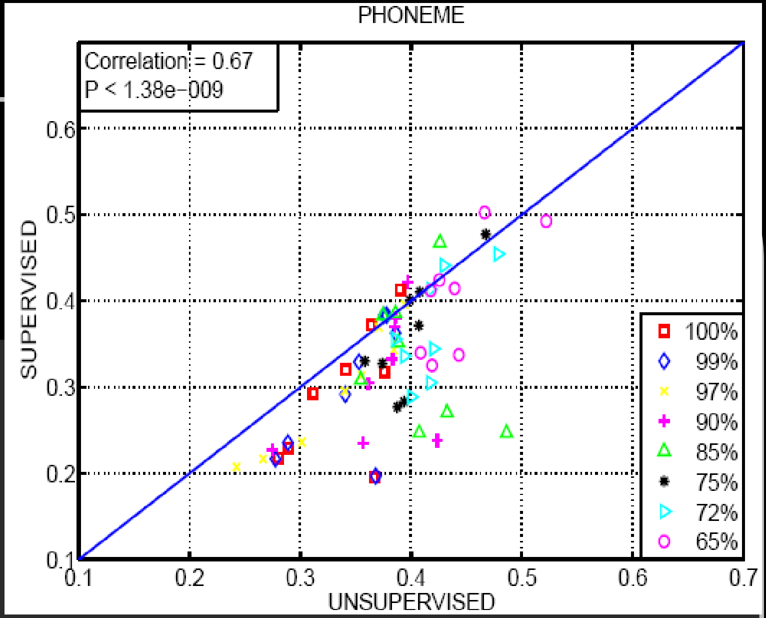
Data preparation:

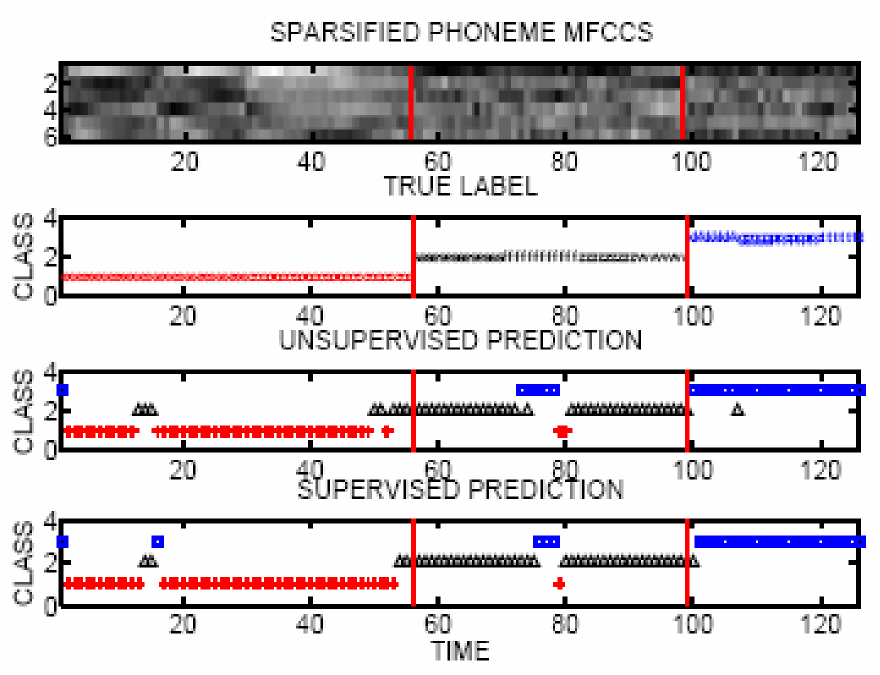
- Speech from 46 speakers (23 male, 23 female), reading 10 sentences
- Group phonemes into 3 classes: Vowels; Fricatives and Others;
- Stack features with a variety of time scales: from 20ms to 1100ms;
- Sparsify features with diverse thresholds z: to keep the retained energy from 100% to 65%.



Error rate comparison

For the given time scales and thresholds, data locate around $y = x$, and the correlation coefficient ρ=0.67, p<1.38e−09.



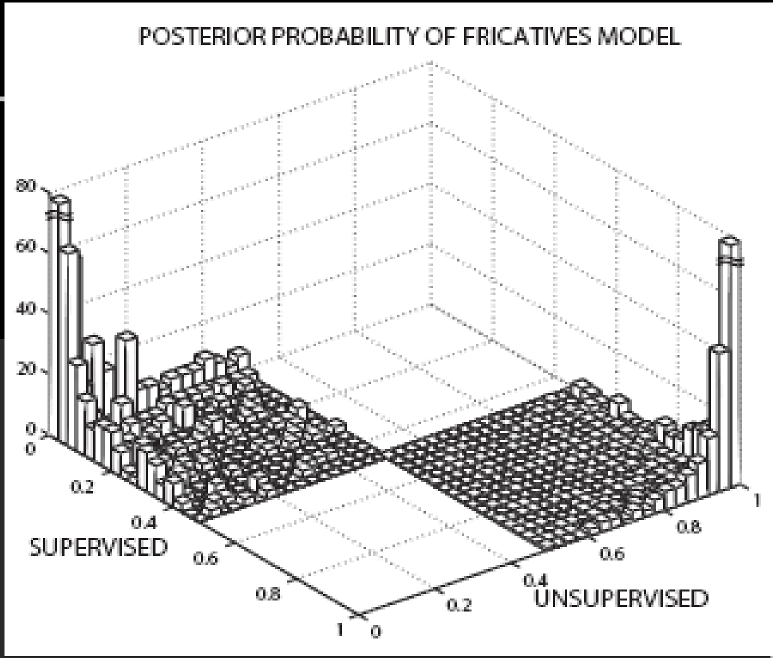


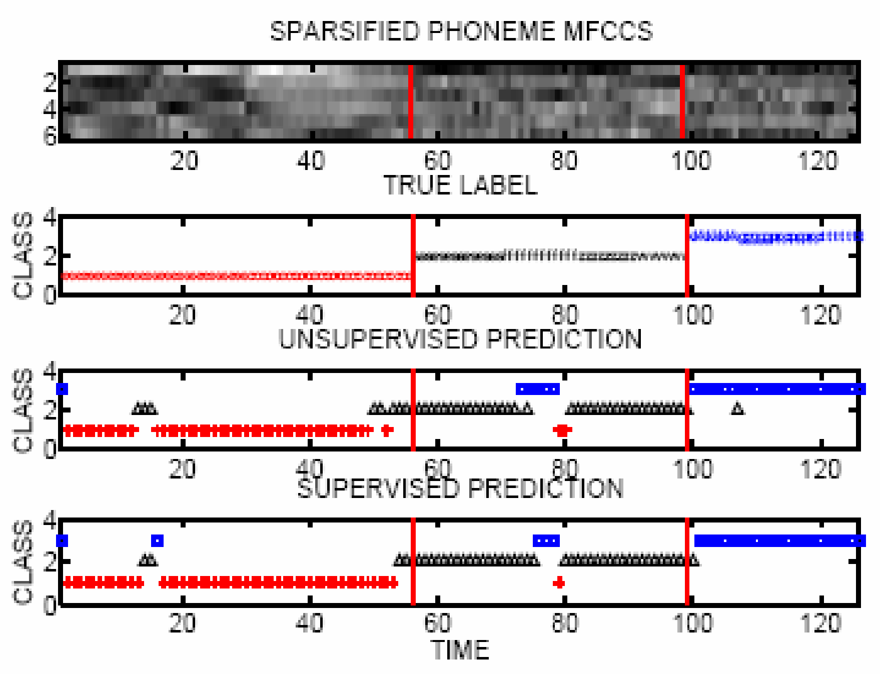
Sample-to-sample correlation

- 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%.

posterior probability comparison

- One experiment: 100*ms* with 97% remaining energy.
- If two models are the exact match, we should expect that the posterior probabilities locate along the diagonal of the histograms with high distribution at (1, 1) and (0, 0).
- The matching in this case is around 57%.





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Conclusion

- COCA is the process of unsupervised grouping of data such that the ensuing group structure is well-aligned with that resulting from human cognitive activity.
- Unsupervised vs. Supervised learning

  A devised protocol to test the consistency of statistical regularities (unsupervised learning) and human cognitive processes (supervised learning of human labels).
- The comparison has been carried out at different levels: error rate comparison; sample-to-sample correlation; posterior probability comparison.
- The protocol has successfully revealed the consistency of two classifications.