Machine Learning Course - CS-433

Unsupervised Learning

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Unsupervised learning

How can systems learn when there are no labels available? How to learn a meaningful internal representation for data examples? I.e., to represent them in a way that reflects the semantic structure of the overall collection of input patterns? This question is the central focus of unsupervised learning.

In unsupervised learning, our data consists only of features (or inputs) $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N$, vectors in $\mathbb{R}^D$, and there are **no outputs** y_n available.

Unsupervised learning seems to play an important role in how living beings learn. Variants of it seem to be more common in the brain than supervised learning.

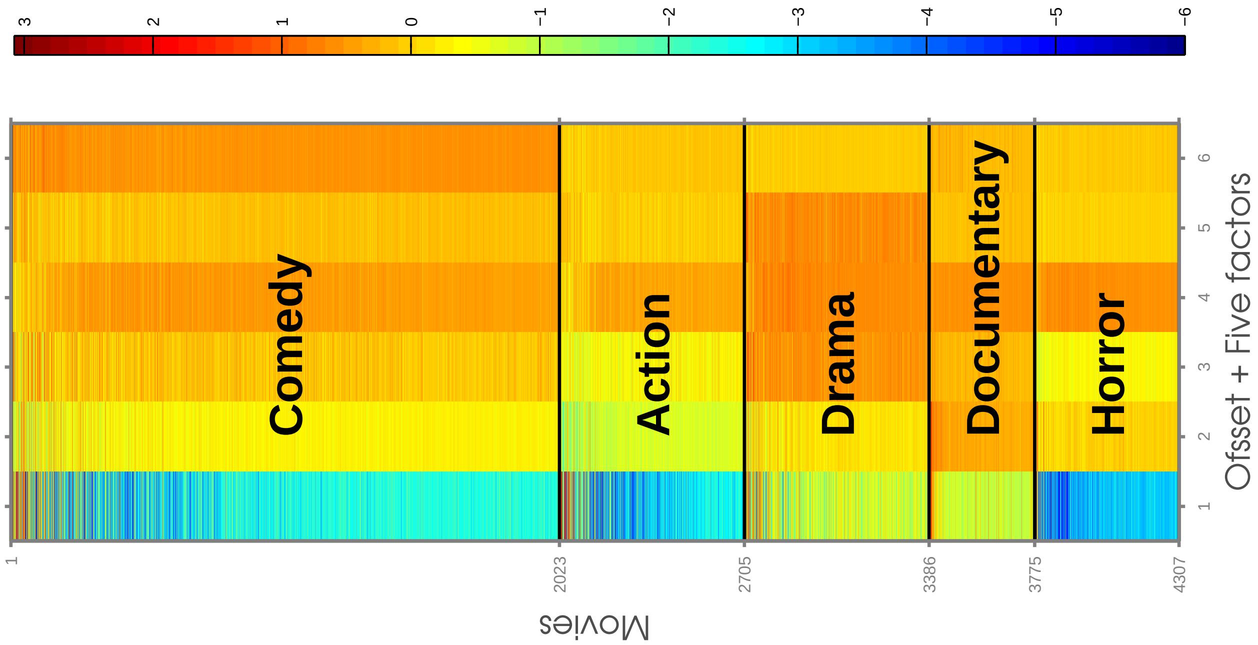
Two main directions in unsupervised learning are

- representation learning and
- density estimation & generative models

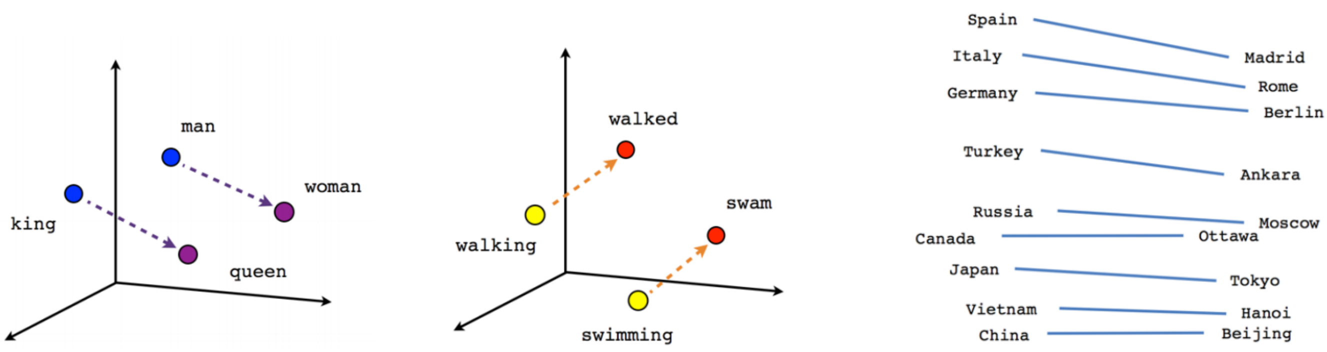
Examples *I need to study better what is matrix factorization!

Examples for Representation Learning

Given ratings of movies and viewers, we use matrix factorization to extract useful features (see e.g. Netflix Prize).



Learning word-representations using matrix-factorizations, `word2vec` (Mikolov et al. 2013).



Male-Female Verb tense Country-Capital

Given voting patterns of regions across Switzerland, we use PCA to extract useful features (Etter et al. 2014).

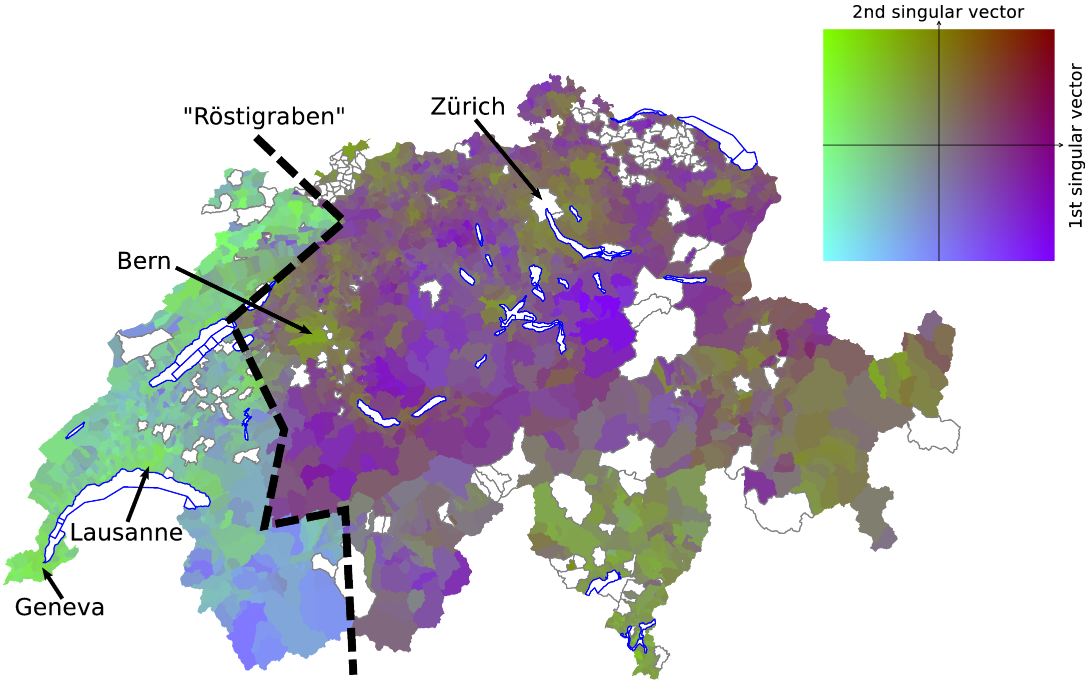
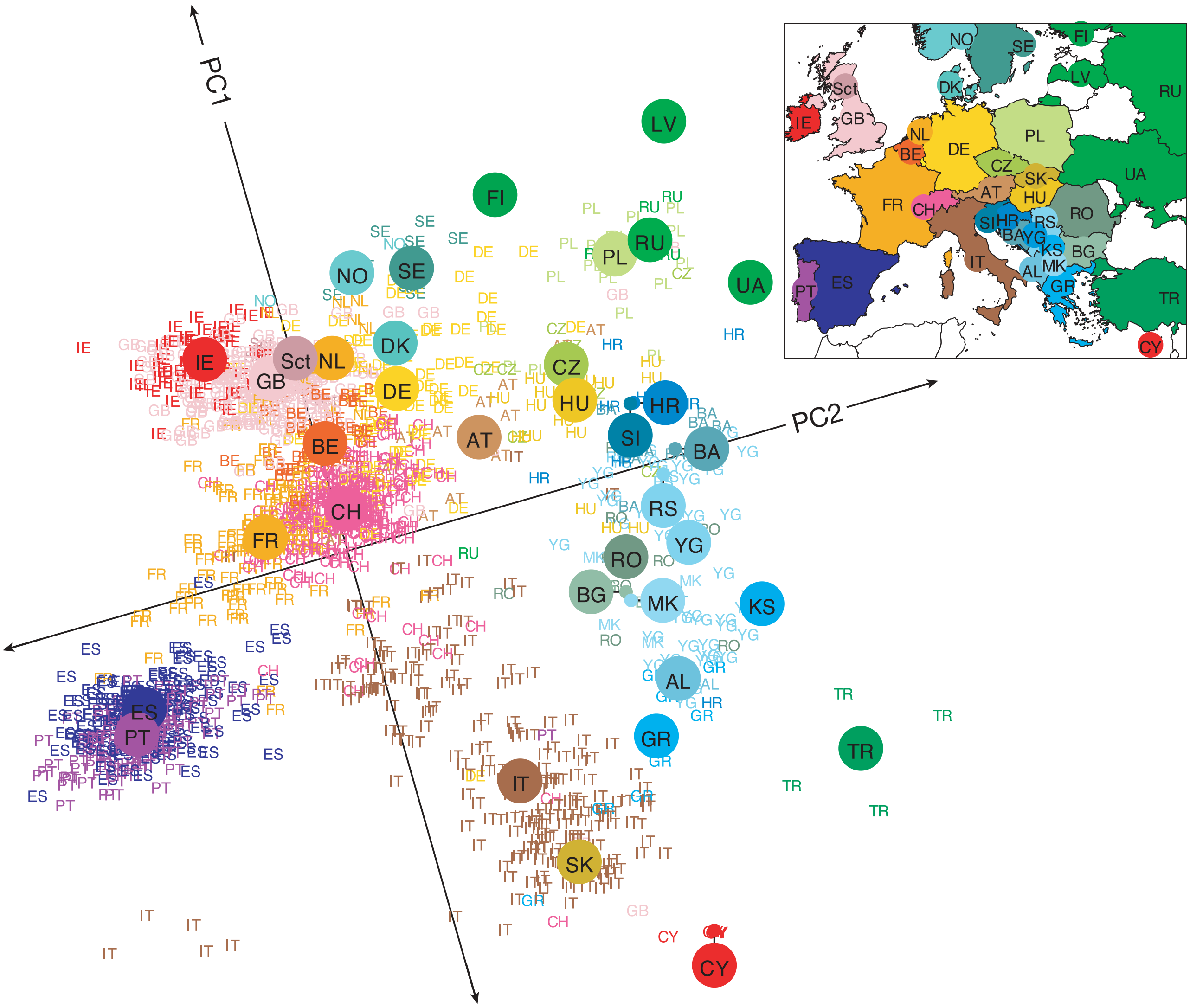


Figure 9: Voting patterns of Swiss municipalities. The color of a municipality is assigned using its location in Figure 8 and the color gradient shown in the upper right corner. Two municipalities with similar colors have similar voting patterns. The *Röstigraben*, corresponding to the cultural difference between French-speaking municipalities and German-speaking ones, is clearly visible from the difference in voting patterns. Regions shown in white are lakes or municipalities for which some vote results are missing (due to a merging of municipalities, for example). A more detailed map can be found online [2].

PCA Example 2: Genes mirror geography



Nature 2008, http://dx.doi.org/10.1038/nature07331

Examples for Clustering

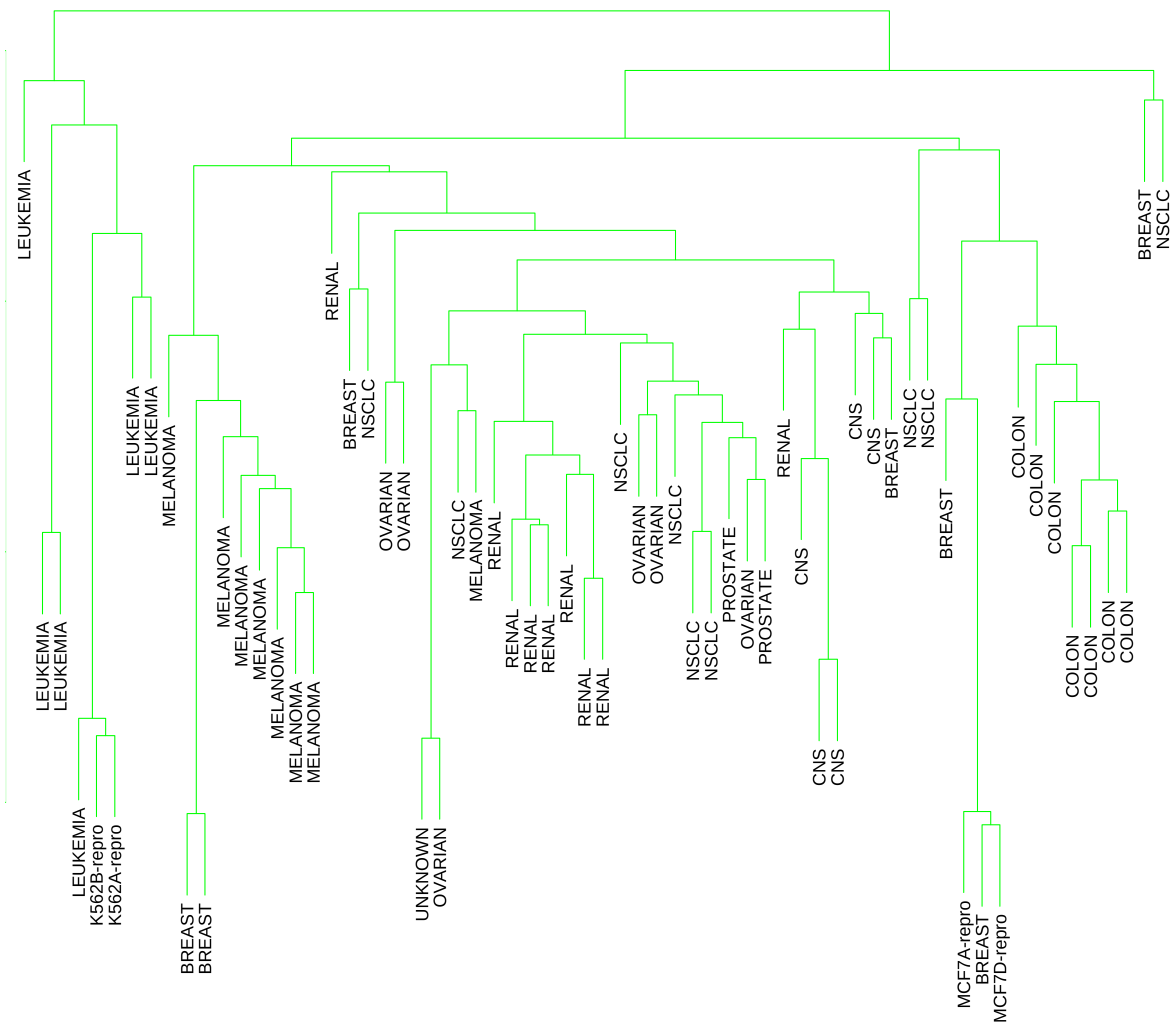
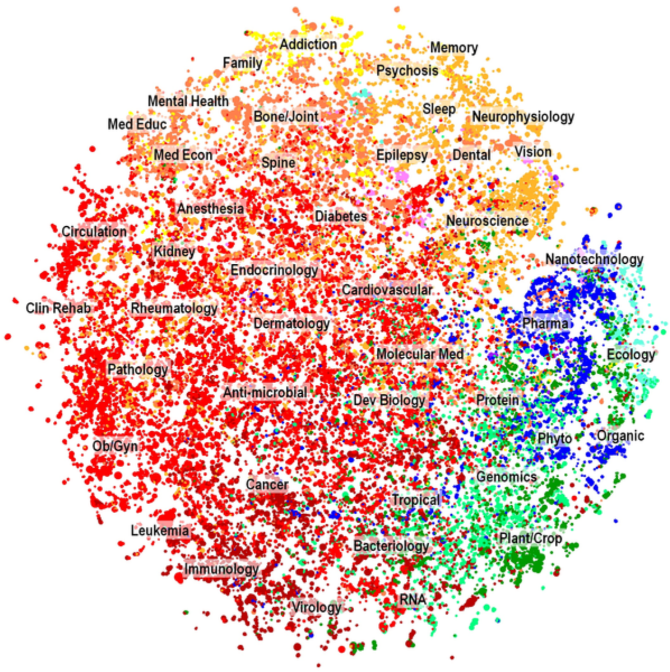


FIGURE 14.12. *Dendrogram from agglomerative hierarchical clustering with average linkage to the human tumor microarray data.*

Clustering more than two million biomedical publications (Kevin Boyack et.al. 2011)



Clustering articles published in Science (Blei & Lafferty 2007)

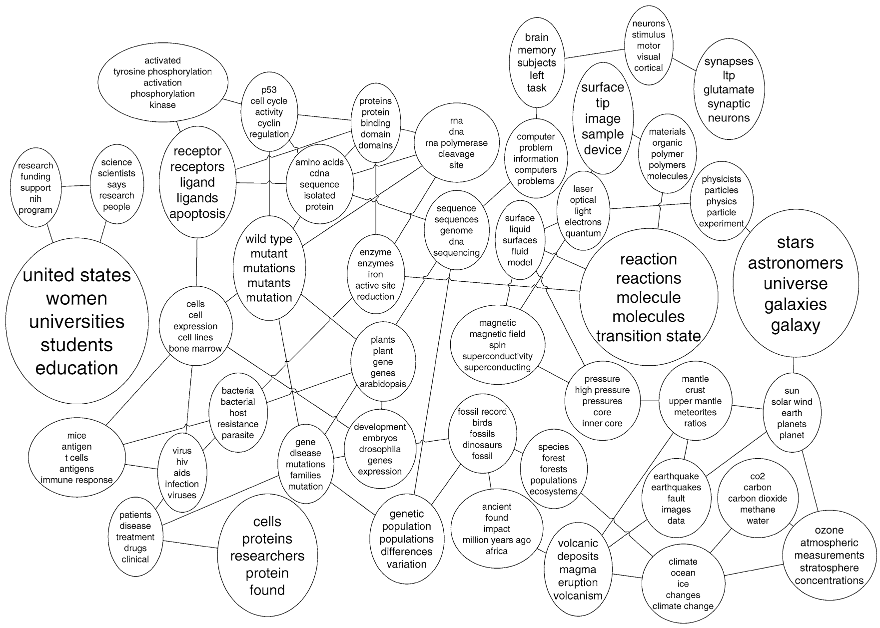


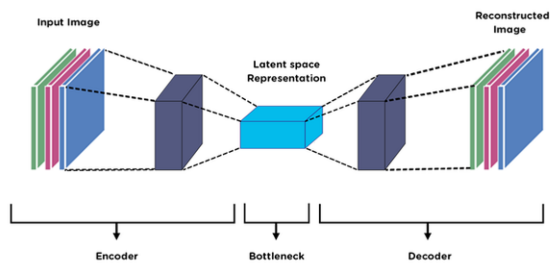
FIG. 2. *A portion of the topic graph learned from* 16,351 *OCR articles from Science* (1990–1999). *Each topic node is labeled with its five most probable phrases and has font proportional to its popularity in the corpus.* (*Phrases are found by permutation test.*) *The full model can be found in* *http://www.cs.cmu.edu/~lemur/science/* *and on STATLIB.*

Unsupervised Representation Learning & Generation

How does it work?

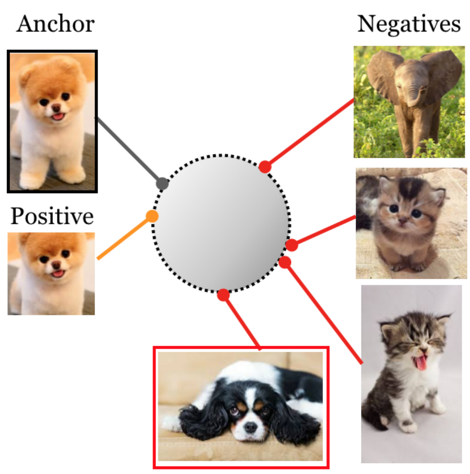
Define a unsupervised or self-supervised loss function, for

- Compression & Reconstruction
  (e.g. Auto-Encoder)



. image: Deepak Birla

- Consistency & Contrastive Learning
  (e.g. Noise-contrastive estimation)



. image: arxiv.org/pdf/2004.11362

- Generation
  (e.g. Auto-Encoder, Gaussian Mixture Model)

Examples:

(G = can be used as a generative model)

- Auto-Encoders (G)
  Invertible networks, learned compression, normalizing flows

- Representation Learning
  e.g. images, text, time-series, video. Combining unsupervised representation learning (pre-training) with supervised learning

- Language Models & Sequence Models (G)
  text generation, or sequence continuation, BERT
  video, audio & timeseries (auto-regressive, contrastive, ...)

- Generative Adversarial Networks (GAN) (G)
  see also *predictability minimization*

"A Style-Based Generator Architecture for Generative Adversarial Networks", CVPR 2019, https://arxiv.org/abs/1812.04948

- Contrastive image-language pretraining (CLIP)
  learns a joint representation space for images and text using contrastive learning

- Diffusion models (G)
  new state-of-the-art in image generation; these models can be adapted to generate images from text prompts (e.g., DALL-E 2, Stable Diffusion, Midjourney)

Source: Stable Diffusion model
https://stability.ai/blog/stable-diffusion-public-release