Distributed Representation

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Topics in Representation Learning

1. Greedy Layer-Wise Unsupervised Pretraining
2. Transfer Learning and Domain Adaptation
3. Semi-supervised Disentangling of Causal Factors
4. Distributed Representation
5. Exponential Gains from depth
6. Providing Clues to Discover Underlying Causes

Distributed Representation of Concepts

- Representation composed of many elements that can be set separately from each other
- They are one of the most important tools for representation learning
- They are powerful because they can use n features with k values to describe k^n different concepts

Neural nets use distributed rep.

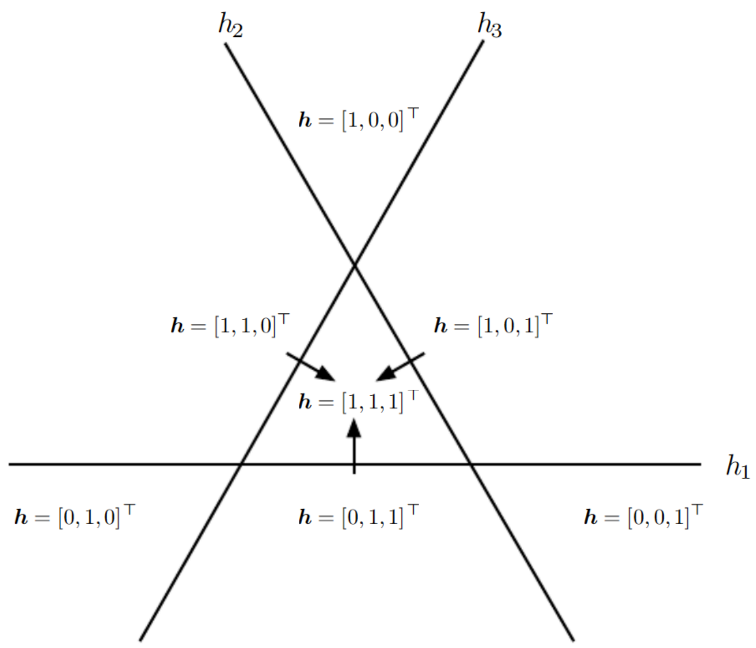
- Neural networks with multiple hidden units and probabilistic models with multiple latent variables both make use of the strategy of distributed representation
- Many deep models are motivated by hidden units can learn to represent causal factors that explain the data
  - Each direction in representation space can correspond to the value of a different underlying configuration variable

Ex: distributed representation

- A vector of n binary features that can take 2^n configurations
- Each potentially corresponding to a different region of input space
- Can be compared to a symbolic representation where the input is associated with a single symbol or category

Distributed representation

- Input space is broken into regions

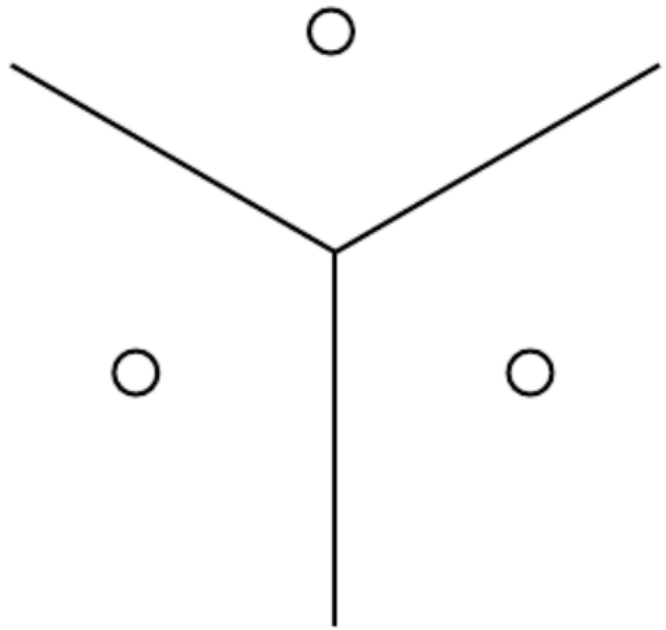


Non-distributed Representations

- Following learning algorithms are based on non-distributed representations
  - K-means
  - K nearest neighbor
  - Decision trees
  - GMMs
  - Kernel machines
  - NLP based on n-grams

Nearest Neighbor input space

- Nearest neighbor is non-distributed



Distributed vs Symbolic Rep.

- Important concept that distinguishes a distributed representation from a symbolic one:
  - Generalization arises due to shared attributes between different concepts
  - As pure symbols cat and dog are as far from each other as any two symbols
  - If one associates them with meaningful distributed representation then many things that can be said about cats can generalize to cats
    - Distributed representation may contain entries "$\mathrm{has\_fur}$" or "$\mathrm{no\_of\_legs}$" that have the same value

- Learning about each of them without having to see all the configurations of all others
- Generative model can learn a representation of images of faces with separate directions in representation space capturing different underlying factors of variation

Disentangling gender and glasses

- One direction in representation space is gender, another is whether wearing glasses