From features to neural networks

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Advanced Natural Language Processing
http://people.cs.umass.edu/~brenocon/anlp2017/

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MaxEnt / Log-Linear models

- **x**: input (all previous words)
- **y**: output (next word)
- **f(x,y)** => R^d feature function [[domain knowledge here!]]
- **v**: R^d parameter vector (weights)

$$p(y|x;v) = \frac{\exp\left(v \cdot f(x,y)\right)}{\sum_{y' \in \mathcal{Y}} \exp\left(v \cdot f(x,y')\right)}$$

Application to history-based LM:

$$P(w_1..w_T) = \prod_t P(w_t \mid w_1..w_{t-1})$$
$$= \prod_t \frac{\exp(v \cdot f(w_1..w_{t-1}, w_t))}{\sum_{w \in \mathcal{V}} \exp(v \cdot f(w_1..w_{t-1}, w))}$$

Too many features

- Millions to billions of features: performance often keeps improving!
- Engineering issue: feature name=>number mapping
- Feature selection ... mixed results
  - Count cutoffs: great computational benefits; typically not for performance
  - Features seen only once at training time typically help (!), or even features not seen at training time
  - Predictive value: mutual info. / info. gain / chi-square
  - L1 regularization: encourages θ sparsity, but not always better than L2
    - [structured sparsity more interesting: Yogatama, Martins tutorial]
  - Personal opinion: feature-based models just want a high diversity of weak signals

Feature hashing

- Feature hashing: make e.g. N(u,v,w) mapping random with collisions (!) *(Weinberger et al. 2009)*
  - Accuracy loss low since collisions are rare (since features are sparse). Works well, great for large-scale data (memory usage constant!)
  - Practically: use a fast string hashing function (e.g. murmurhash or Python's internal one)
- This is a type of *randomized projection* Ax. Typically not better than the original representation.
  - Instead of randomized embeddings, better generalization from learning them

Dense representations

- Feature hashing as dense representation

$$x \xrightarrow{\text{A (fixed)}} z \xrightarrow{\text{B (learned)}} y$$

$$P(w_{next} \mid w_{prev}) \propto \exp(A_{w_{prev}} \cdot B_{w_{next}})$$

- Saul and Pereira 1997 as dense representation

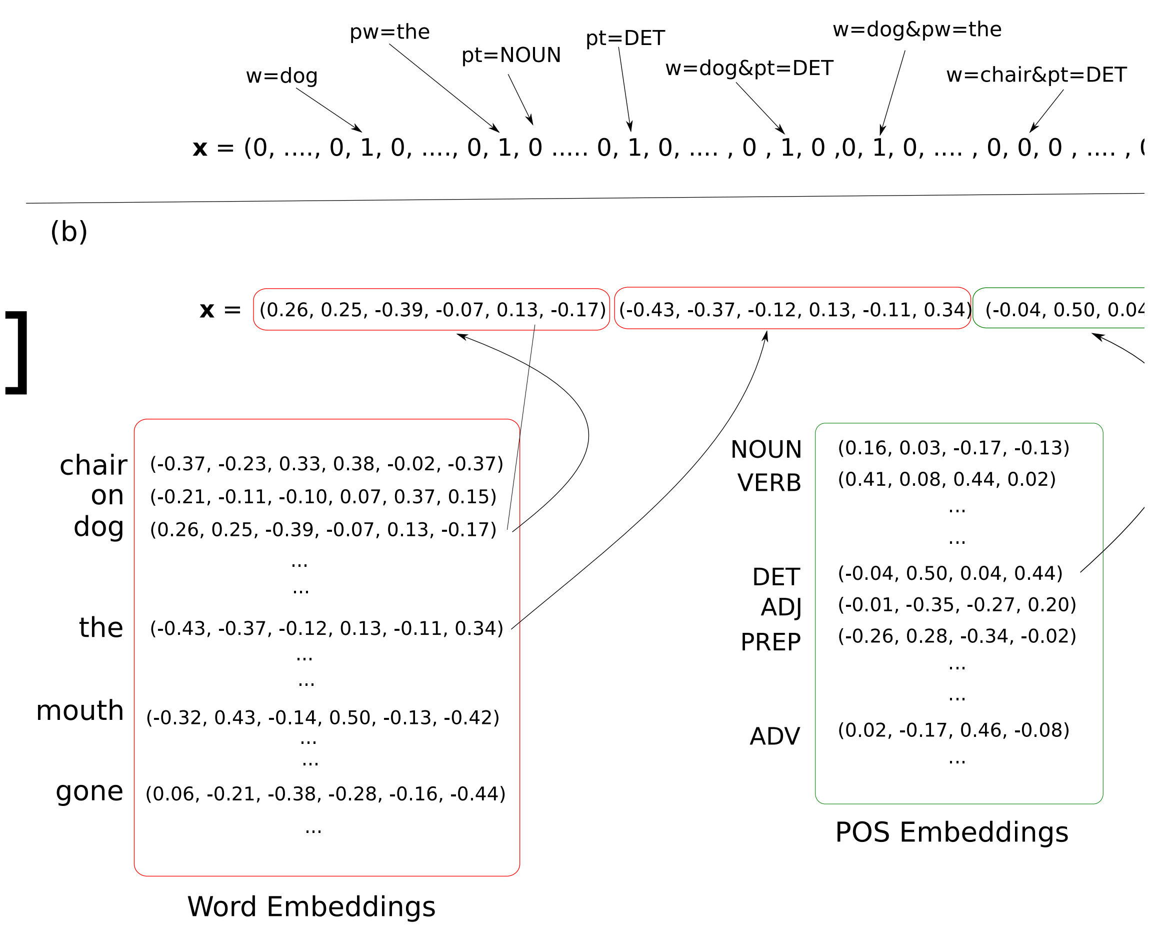
$$x \xrightarrow{\text{A (learned)}} z \xrightarrow{\text{B (learned)}} y$$

$$P(w_{next} \mid w_{prev}) = A_{w_{prev}} \cdot B_{w_{next}}$$

- Mnih and Hinton 2007: log-bilinear model [similar: "word2vec" Mikolov et al.]

$$P(w_{next} \mid w_{prev}) \propto \exp(A_{w_{prev}} \cdot B_{w_{next}})$$

  - Learn with gradient descent
  - (this is simplified from their version)



Neural networks

- Idea: learn distributed representations of concepts
    - Nonlinear functions seem to help
- Multilayer perceptron: http://playground.tensorflow.org/

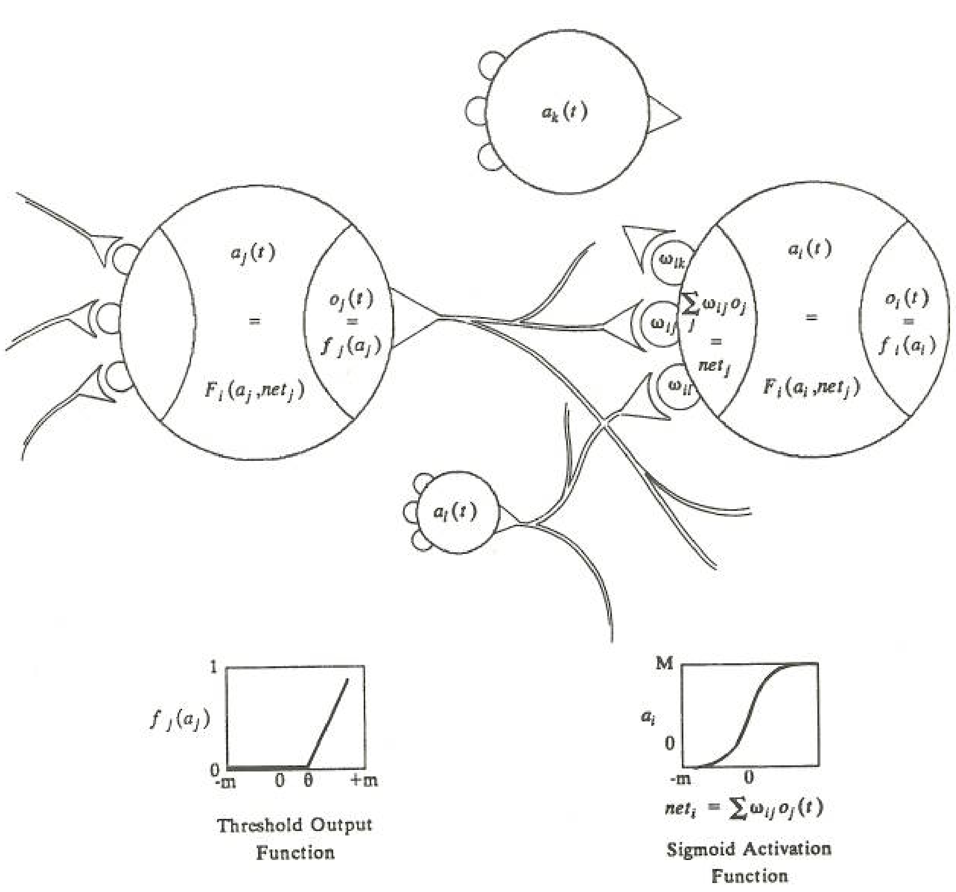
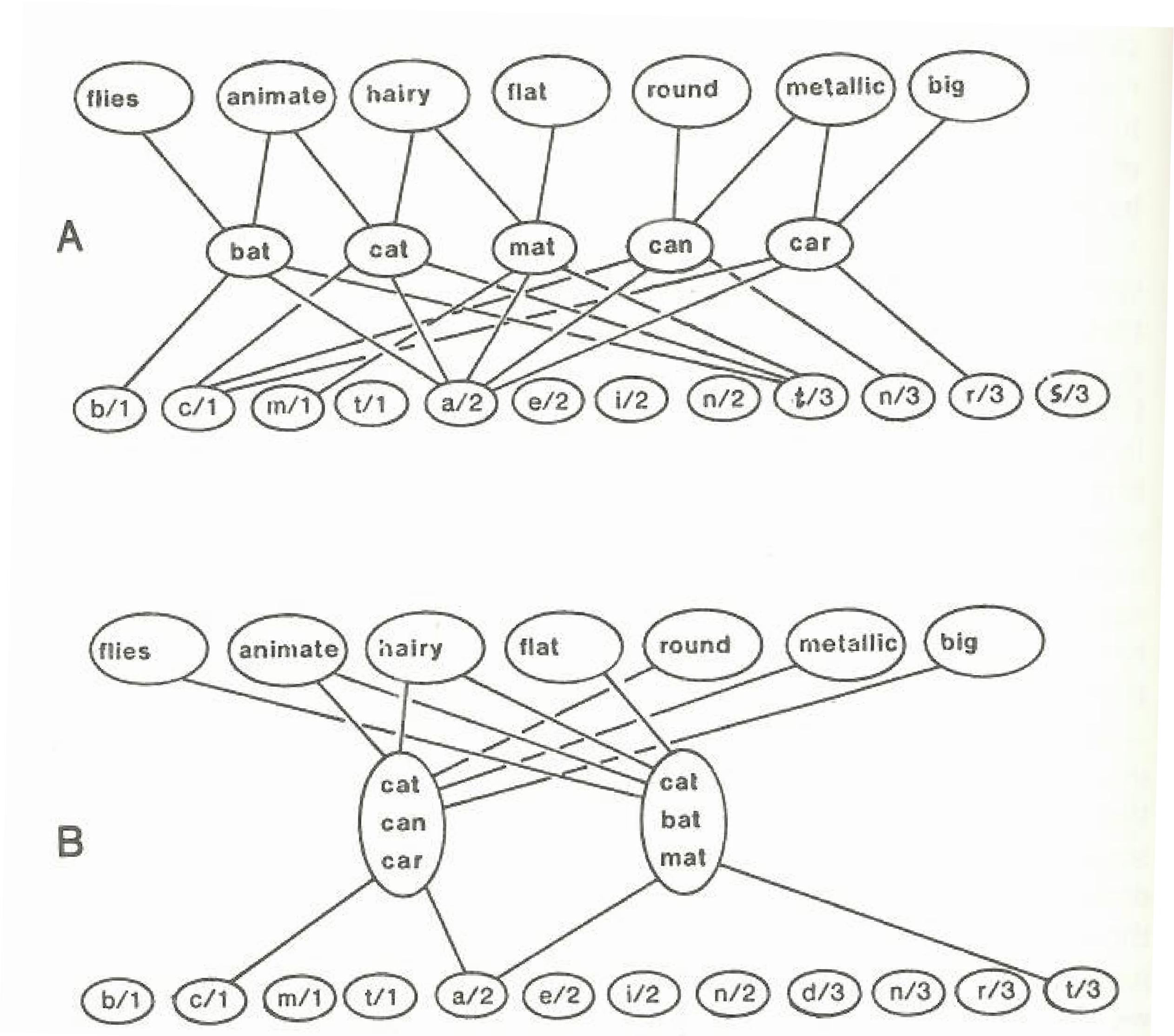


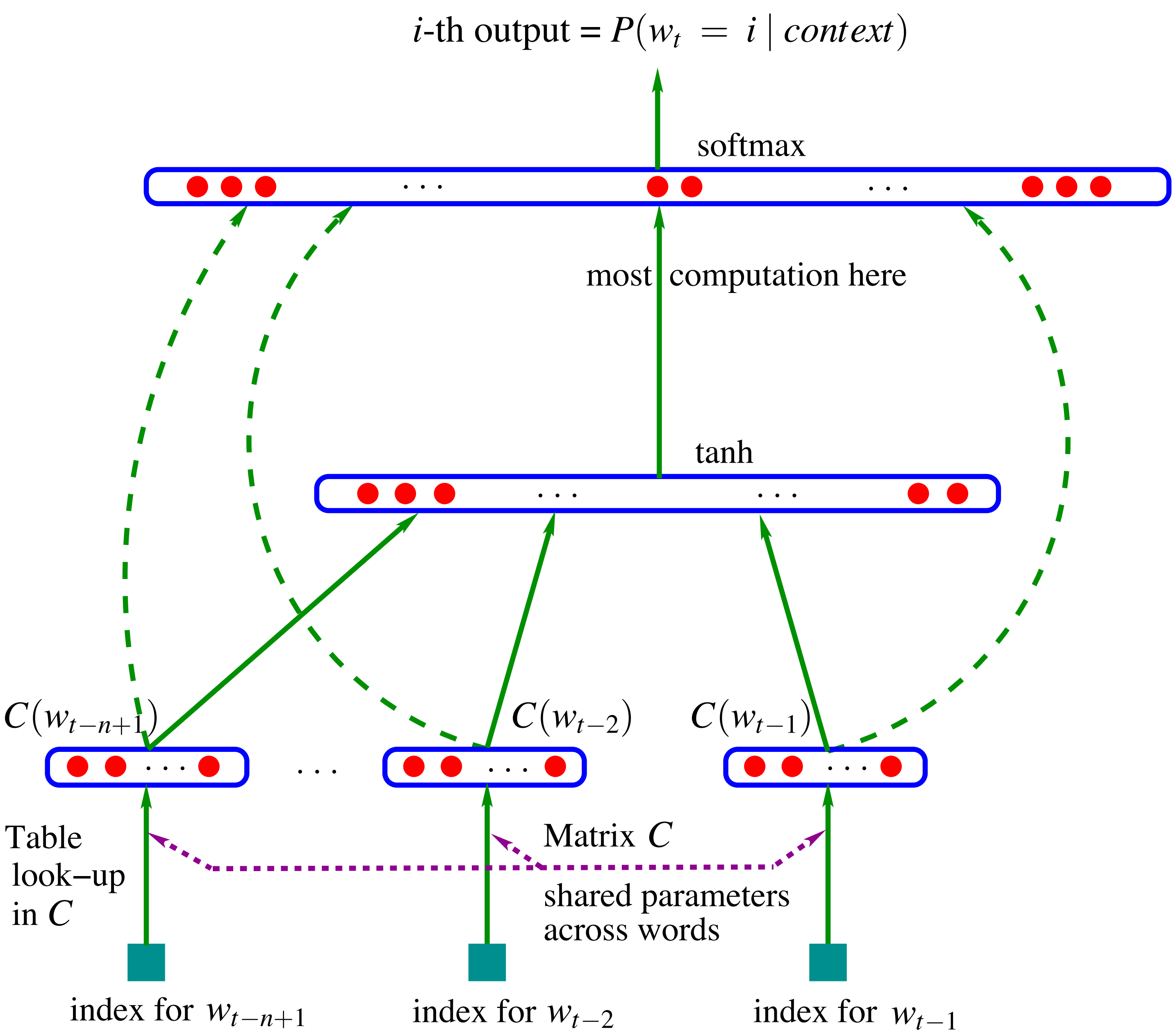
FIGURE 1. The basic components of a parallel distributed processing system.



[Diagrams from: Rumelhart and McClelland (ed.) 1986, *Parallel Distributed Processing*]

Bengio et al. 2003: N-gram multilayer perceptron

$$f(w_t, \cdots, w_{t-n+1}) = \hat{P}(w_t | w_1^{t-1})$$



Learn: C, W, U, H, d (chain rule)

$$C(i) \in \mathbb{R}^m$$ Word embedding parameters

$$x = (C(w_{t-1}), C(w_{t-2}), \cdots, C(w_{t-n+1}))$$

Lookup layer with concatenation: (kinda) hidden layer size *(n-1)m*

another hidden layer, size *h*

$$y = b + Wx + U \tanh(\underbrace{d + Hx}_{})$$

Vocab output: log-probs size *V*

$$\hat{P}(w_t | w_{t-1}, \cdots w_{t-n+1}) = \frac{e^{y_{w_t}}}{\sum_i e^{y_i}}.$$

Output layer (softmax / log-linear)

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Word/feature embeddings

- "Lookup layer": from discrete input features (words, ngrams, etc.) to continuous vectors
  - Anything that was directly used in log-linear models, move to using vectors
- As model parameters: learn them like everything else
- As external information: use pretrained embeddings
  - Common in practice: use a faster-to-train model on very large, perhaps different, dataset
    [e.g. *word2vec*, *glove* pretrained word vectors]
- Shared representations for
  domain adaptation and multitask learning