CSE 5243 INTRO. TO DATA MINING

Word Embedding

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How to let a computer understand meaning?

A cat sits on a mat.

#_$@^_&*^&_()_@_+@^=

Distributional semantics

- You can get a lot of value by representing a word by means of its neighbors (context)

“You shall know a word by the company it keeps”

(J. R. Firth 1957: 11)

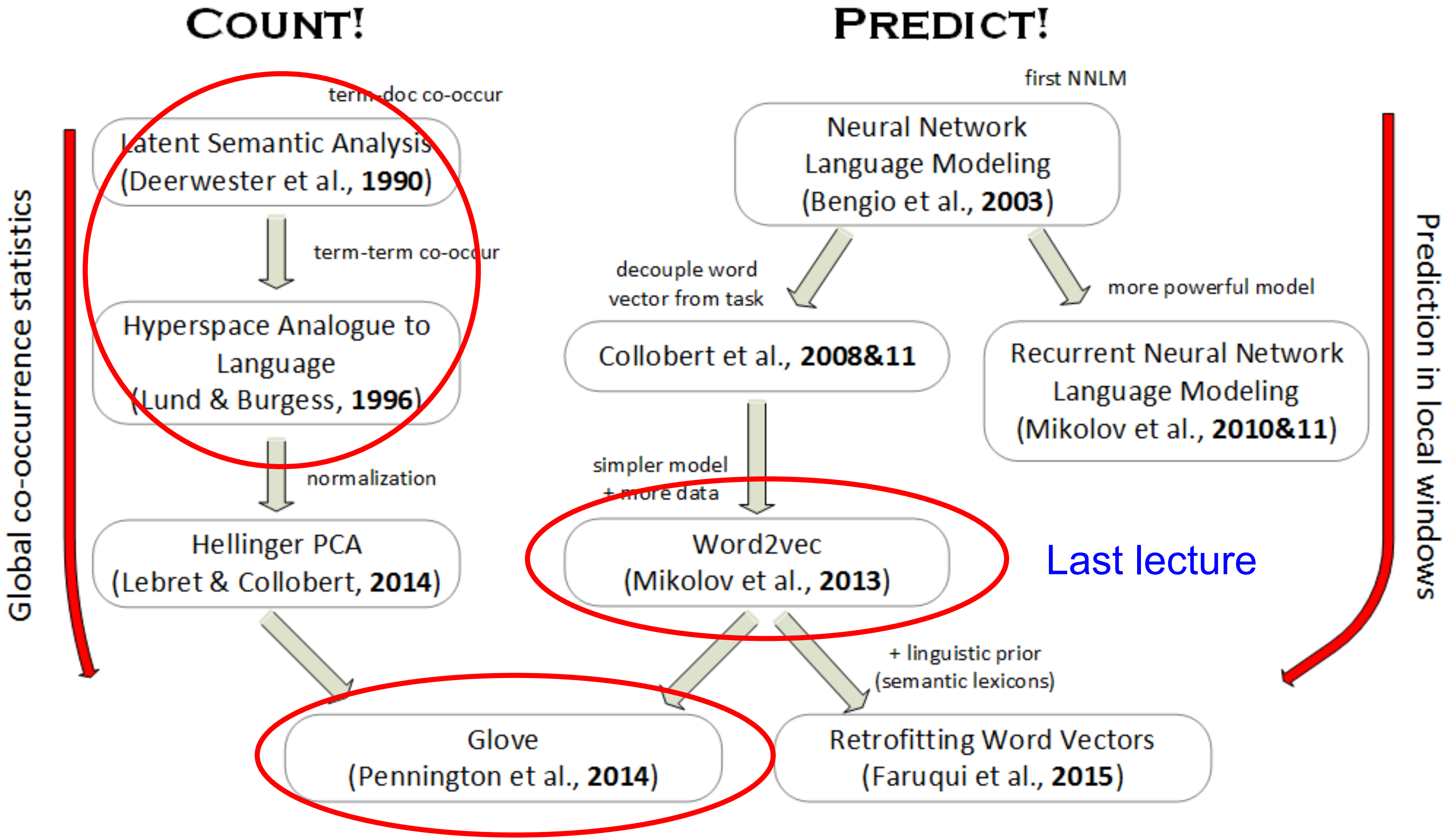
- One of the most successful ideas of modern statistical NLP

government debt problems turning into **banking** crises as has happened in

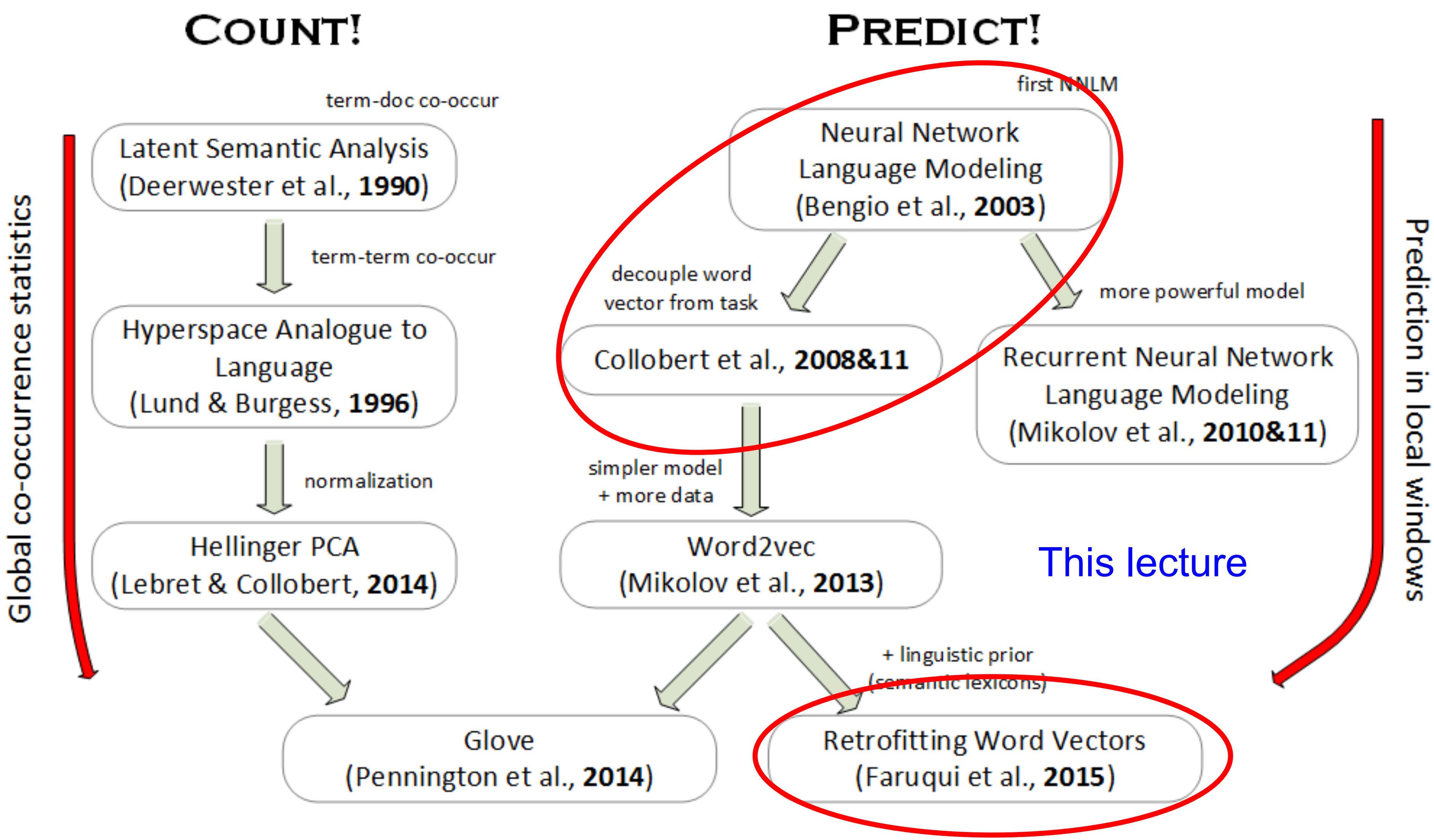
saying that Europe needs unified **banking** regulation to replace the hodgepodge

↖ These words will represent *banking* ↗

History of word embedding



History of word embedding



Different embeddings are based on different priors

Latent semantic analysis

"Words occur in same documents should be similar"

Word2vec

"Words occur in similar contexts should be similar"

Neural Network Language Modeling

"Word vectors should give plausible sentences high probability"

Collabert et al., 2008 & 2011

"Word vectors should facilitate downstream classification tasks"

Faruqui et al., 2015

"Words should follow linguistic constraints from semantic lexicons"

Latent semantic analysis: word-doc occurrence matrix

	Docs																			
Terms	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
data	1	1	0	0	2	0	0	0	0	0	1	2	1	1	1	0	1	0	0	0
examples	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
introduction	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
mining	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0
network	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1
package	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0

- Word-doc occurrence matrix will give general topics, e.g., all sports words will have similar entries
- Apply SVD for dimensionality reduction

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Word2vec: “Words occur in similar contexts should be similar”

I just played with my dog.
I just played with my cat.
My dog likes to sleep on my bed.
My cat likes to sleep on my bed.

- Word2vec will adjust the vector of a word to be similar to the vectors of its context words

- Words with similar contexts thus end up with similar vectors

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Probabilistic Language Modeling

- Goal: assign a probability to a sentence
  - Machine Translation:
    - Source sentence: 今晚大风
    - P(**large** winds tonight) < P(**strong** winds tonight)
  - Spell Correction
    - The office is about fifteen **minuets** from my house
      - P(about fifteen **minutes** from) > P(about fifteen **minuets** from)
  - Speech Recognition
    - P(I saw a van) >> P(eyes awe of an)
  - +Summarization, question answering, etc.

Probabilistic Language Modeling

- Goal: compute the probability of a sentence or a sequence of words:

$$P(w_1^m) = P(w_1, w_2, \ldots, w_m)$$

- How to compute the joint probability?

$$P(a, dog, is, running, in, a, room)$$

- Chain rule:

$$P(w_1, w_2, \ldots, w_m) = P(w_1)P(w_2 \mid w_1)P(w_3 \mid w_1, w_2) \ldots P(w_m \mid w_1, \ldots w_{m-1})$$

$$P(a, dog, is, running) =$$

$$P(a)P(dog \mid a)P(is \mid a, dog)P(running \mid a, dog, is)$$

Probabilistic Language Modeling

$$P(w_1, w_2, \ldots, w_m) = \prod_t^{m-1} P(w_t \mid w_1, \ldots w_{t-1})$$

- Key: $P(w_t \mid w_1, \ldots w_{t-1})$
- Just count? Exponential number of entries and sparsity.
- Markov assumption:

$$P(w_t \mid w_1, \ldots w_{t-1}) \approx P(w_t \mid w_{t-n+1}, \ldots w_{t-1})$$

Probabilistic Language Modeling

- N-gram (bigram)

$$P(running \mid a, dog, is) \approx P(running \mid is) = \frac{count(is, running)}{count(is)}$$

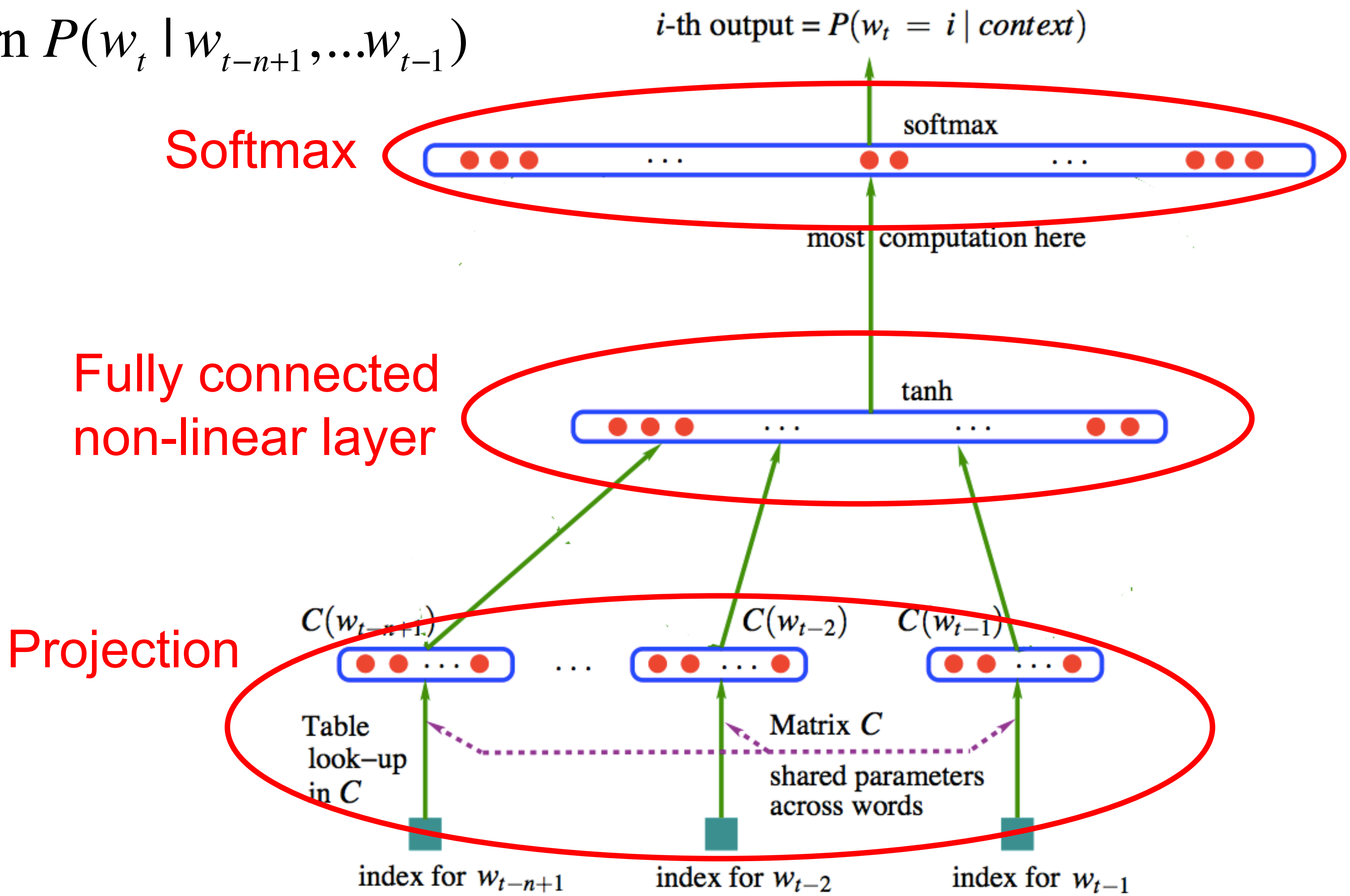
- What's the problem?
  - Small context window (typically bigram or trigram)
  - Not utilizing word similarity
    - Seeing "A dog is running in a room" should increase probability of
    - "The dog is walking in a room" and
    - "A cat is running in the room" and
    - "Some cats are running in the room"

- Solution: Neural Network Language Modeling!

A Neural Probabilistic Language Model.
Bengio et al. JMLR 2003.

Neural Network Language Model

Learn $P(w_t \mid w_{t-n+1},\ldots w_{t-1})$



The Lookup Table

- Each word in vocabulary maps to a vector in $\mathbb{R}^d$
- LookupTable: input of the i^th word is

$$x = (0,\ 0,\ \ldots,\ 1,\ 0,\ \ldots,\ 0) \quad 1 \text{ at position } i$$

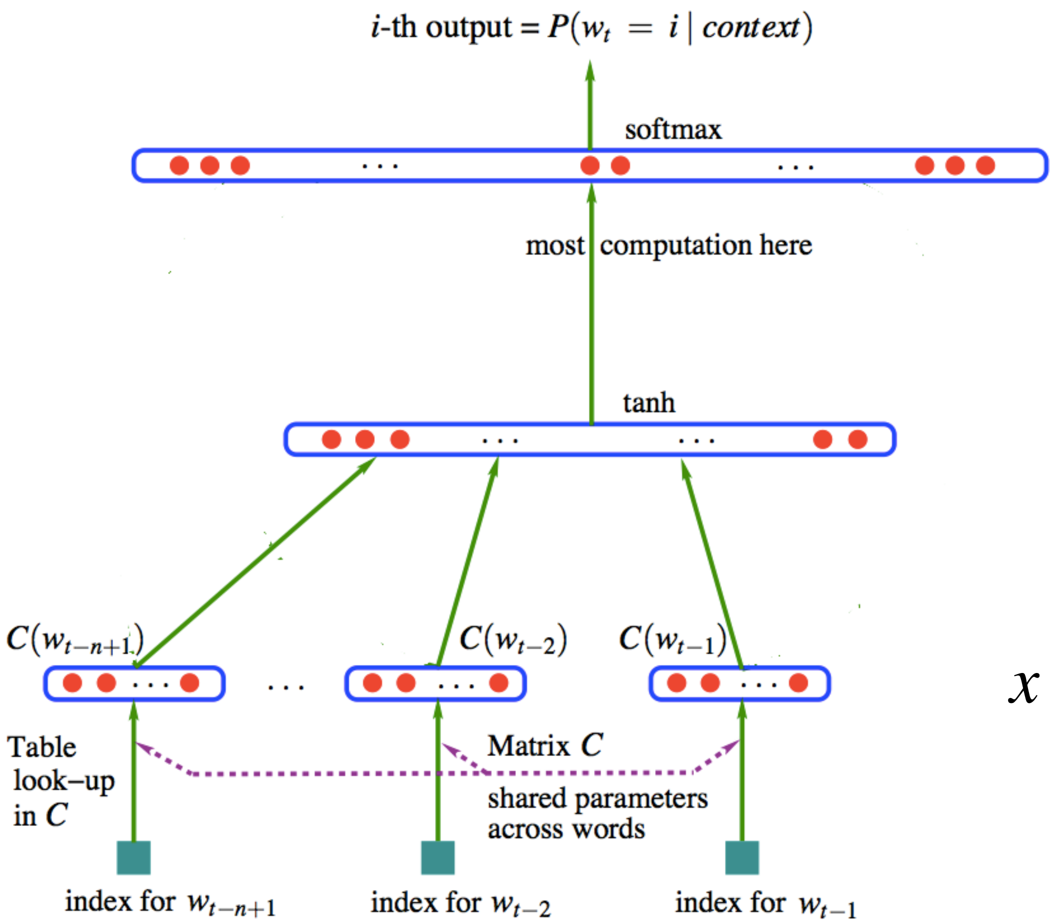
In the original space words are orthogonal.

cat = (0,0,0,0,0,0,0,0,0,1,0,0,0,0, …)
dog = (0,0,1,0,0,0,0,0,0,0,0,0,0,0, …)

To get the $\mathbb{R}^d$ embedding vector for the word we multiply *Cx* where *C* is a *d x D* matrix with *D* words in the vocabulary

C contains the word vectors!

Neural Network Language Model



$$P(w_t = i) = \frac{\exp(y_i)}{\sum_{j=1}^{D} \exp(y_j)}$$

softmax

$$y = Uz + b_2$$

output

$$z = \tanh(Hx + b_1)$$

non-linearity

$$x = (Cw_{t-n+1}, Cw_{t-n+2}, \ldots, Cw_{t-1})^T$$

projection

$$w_{t-n+1}, w_{t-n+2}, \ldots, w_{t-1}$$

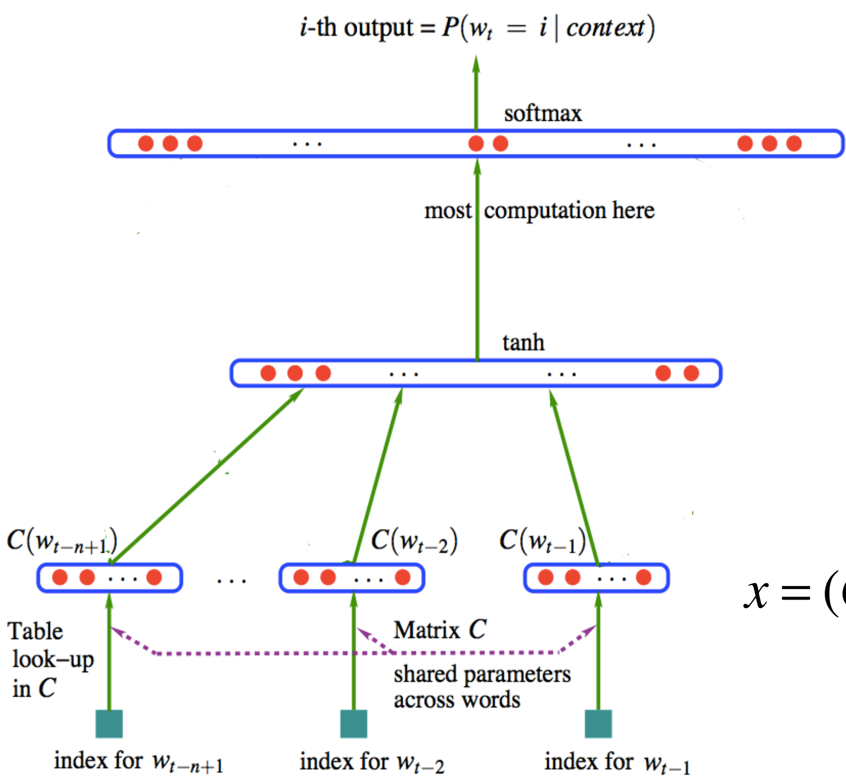
d : word vector dimensionality

n: window size

D: vocabulary size

h: # of hidden units

Dimensionality of each layer?



$$P(w_t = i) = \frac{\exp(y_i)}{\sum_{j=1}^{D} \exp(y_j)}$$

softmax

$$y = Uz + b_2 \qquad \boxed{D}$$

output

$$z = \tanh(Hx + b_1) \qquad \boxed{h}$$

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$$x = (Cw_{t-n+1}, Cw_{t-n+2}, \ldots, Cw_{t-1})^T \qquad \boxed{n * d}$$

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$$w_{t-n+1}, w_{t-n+2}, \ldots, w_{t-1}$$

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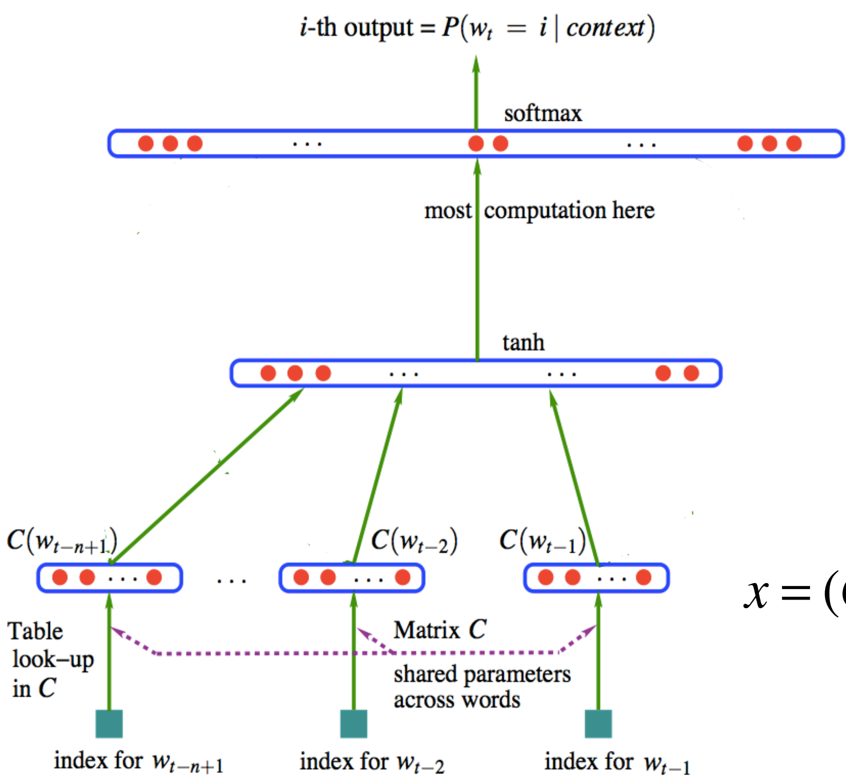
# of parameters in each layer?



$$P(w_t = i) = \frac{\exp(y_i)}{\sum_{j=1}^{D} \exp(y_j)}$$

softmax

$$y = Uz + b_2 \qquad \boxed{h * D + D}$$

output

$$z = \tanh(Hx + b_1) \qquad \boxed{n * d * h + h}$$

non-linearity

$$x = (Cw_{t-n+1}, Cw_{t-n+2}, \ldots, Cw_{t-1})^T \qquad \boxed{n * d}$$

projection

$$w_{t-n+1}, w_{t-n+2}, \ldots, w_{t-1}$$

Training

- All free parameters

$$\boldsymbol{\theta} = (C, H, U, b_1, b_2)$$

Costly!

- Backpropagation + Stochastic Gradient Ascent:

$$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \varepsilon \frac{\partial \log P(w_t \mid w_{t-n+1}, \ldots, w_{t-1})}{\partial \boldsymbol{\theta}}$$

Speed up training

- Most computations are at the output layer
  - In order to compute the normalization term of softmax, we have to compute the y_i for every word!
  - Cost (almost) linear to vocabulary size.
  - Same problem in Skip-gram

- Solutions: Approximate the normalized probability
  - Negative sampling
  - Noise contrastive estimation
  - Hierarchical softmax
  - …

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Refresher: Skip-gram

- Given the central word, predict surrounding words in a window of length c

- Objective function:

$$J(\theta) = \frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq j\leq c, j\neq 0} \log p(w_{t+j}|w_t)$$

- Softmax:

$$p(O|I) = \frac{\exp(v_O'^T v_I)}{\sum_{w\in V}\exp(v_w'^T v_I)}$$

$$\Rightarrow \frac{\partial \log p(O|I)}{\partial v_I} = v'_O - \sum_w p(w|I)v'_w$$

Negative sampling

- I: central word. O: a context word
- Original: Maximize $p(O \mid I, \theta)$
- We will derive an alternative which is less costly to compute
- Does pair (I,O) really come from the training data?

$$\theta = \arg\max_{\theta} p(D=1 \mid I, O, \theta)$$

$$\text{where } p(D=1 \mid I, O, \theta) = \sigma(v_I^T v_O^{'}) = \frac{1}{1+e^{-v_I^T v_O^{'}}}$$

- Trivial solution: same (long enough) vector for all words
- Contrast with negative words!

Negative sampling

- Solution: randomly sample k negative words w_i from a noise distribution, assume (I,w_i) are incorrect pairs
- I = "is", O = "running", w_1 = "walk", w_2 = "do", etc.

$$\text{maximize } \; p(D=1 \mid I, O, \theta) \bullet \prod_{i=1}^{k} p(D=0 \mid I, w_i, \theta)$$

$$\text{or } \; \log \sigma(v_I^T v_O^{'}) + \sum_{i=1}^{k} \mathbb{E}_{w_i \sim P_n(w)} [\log \sigma(-v_I^T v_{w_i}^{'})]$$

$$\text{where } \; P_n(w) = \frac{U(w)^{3/4}}{Z}, U(w) \text{ the unigram distribution}$$

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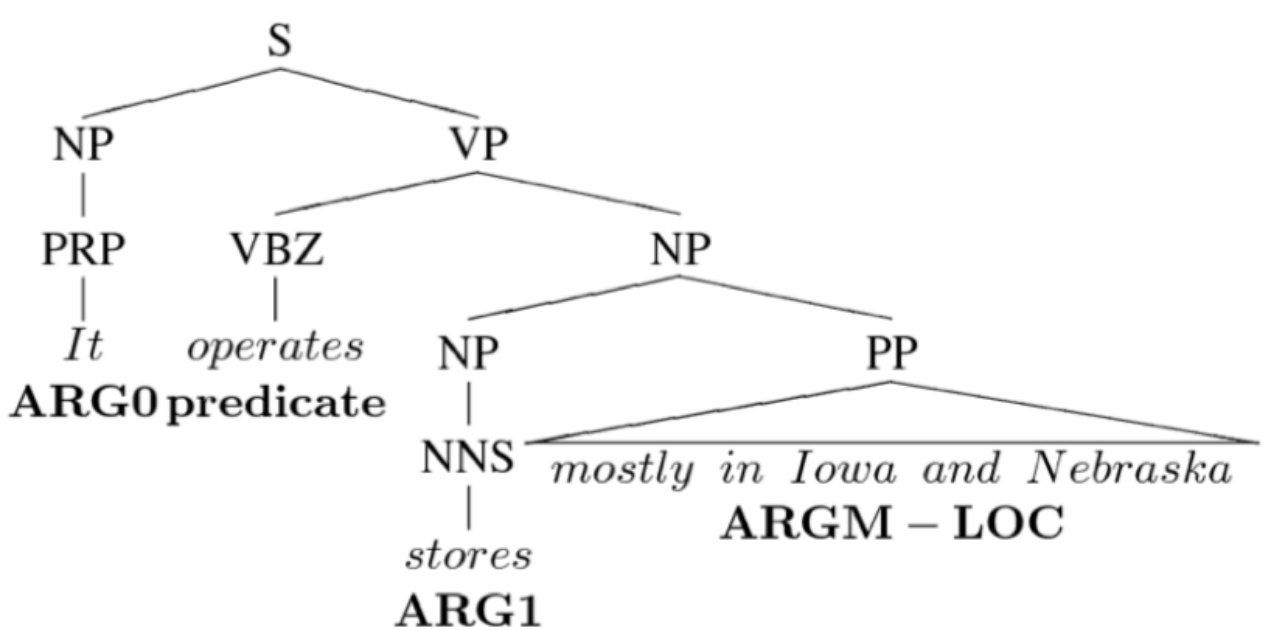
What to get from this work

- How to supervise the learning of word embedding using external classification tasks
- How to do semi-supervised learning of word embedding
- How to apply word vectors and neural networks in other traditional NLP tasks

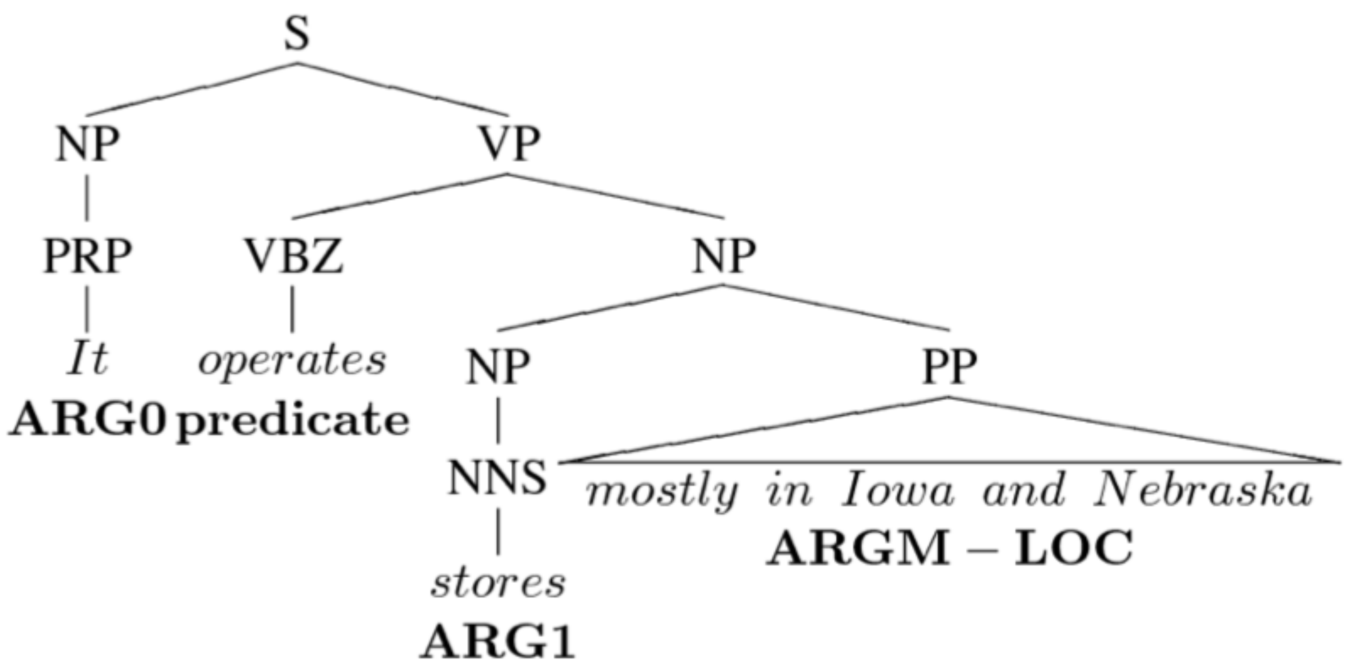
Embedding for other NLP tasks (Collobert et al., 2008&11)

- Part-Of-Speech Tagging (POS): syntactic roles (noun, adverb...)
- Chunking: syntactic constituents (noun phrase, verb phrase...)
- Name Entity Recognition (NER): person/company/location...
- Semantic Role Labeling (SRL):

  [John]$_{ARG0}$ [ate]$_{REL}$ [the apple]$_{ARG1}$ [in the garden]$_{ARGM-LOC}$

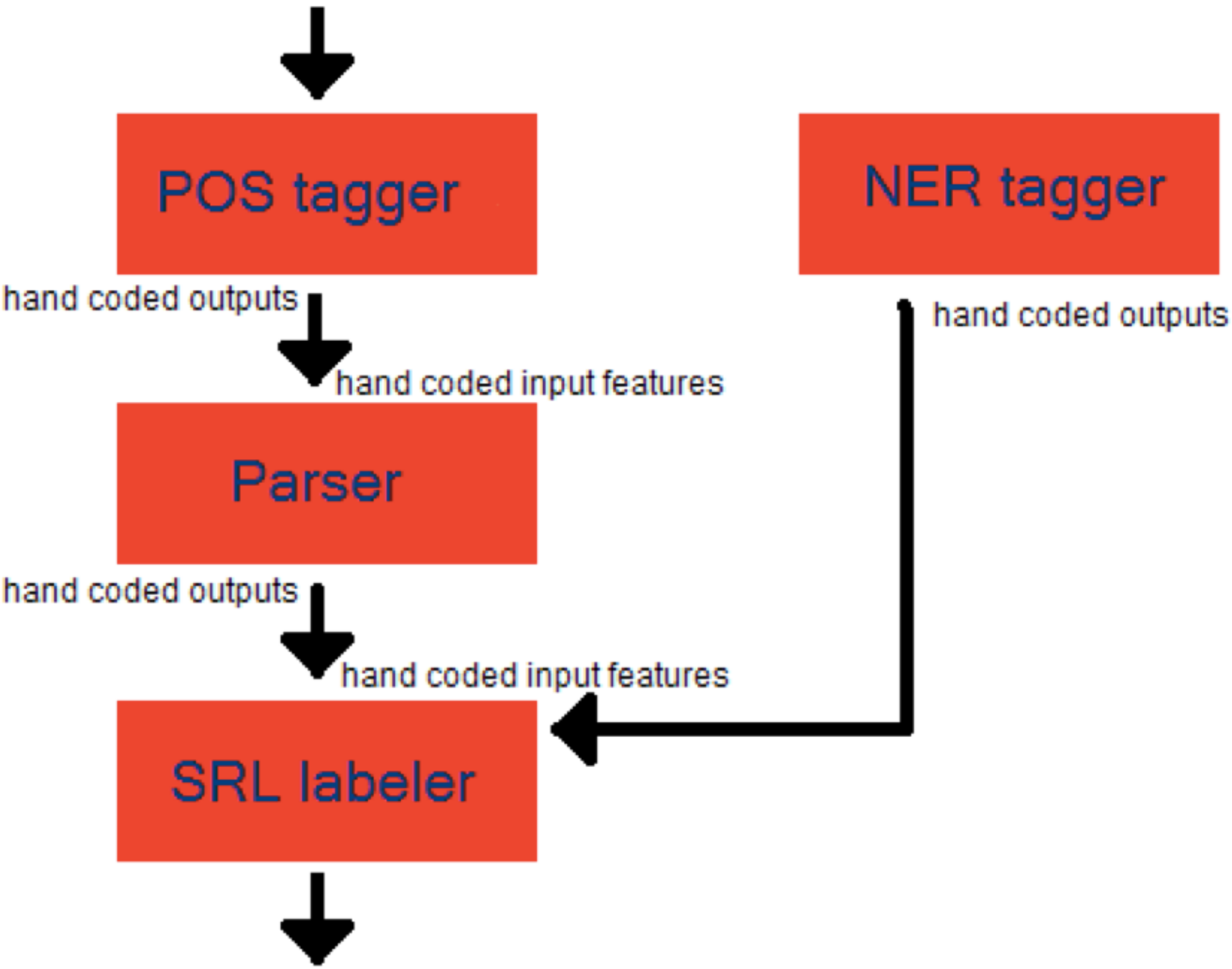


The Large-scale Feature Engineering Way



- Extract **hand-made features** e.g. from the parse tree
- Disjoint: all tasks trained separately, Cascade features
- Feed these features to a shallow classifier like SVM

The sub-optimal cascade



NLP: Large scale machine learning

Goals

- Task-specific engineering limits NLP scope
- Can we find unified hidden representations?
- Can we build unified NLP architecture?

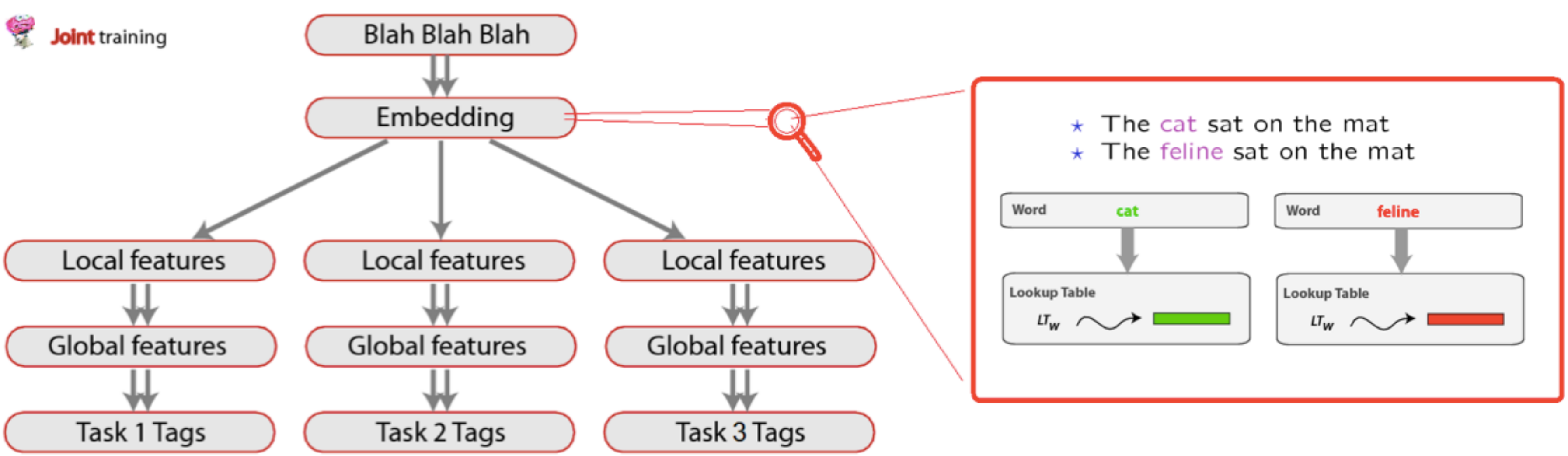
Means

- Start from scratch: forget (most of) NLP knowledge
- Compare against classical NLP benchmarks
- Our dogma: avoid task-specific engineering

The big picture

A unified architecture for all NLP (labeling) tasks:

Sentence:	*Felix*	*sat*	*on*	*the*	*mat*	.
POS:	NNP	VBD	IN	DT	NN	.
CHUNK:	NP	VP	PP	NP	NP-I	.
NER:	PER	-	-	-	-	-
SRL:	ARG1	REL	ARG2	ARG2-I	ARG2-I	-



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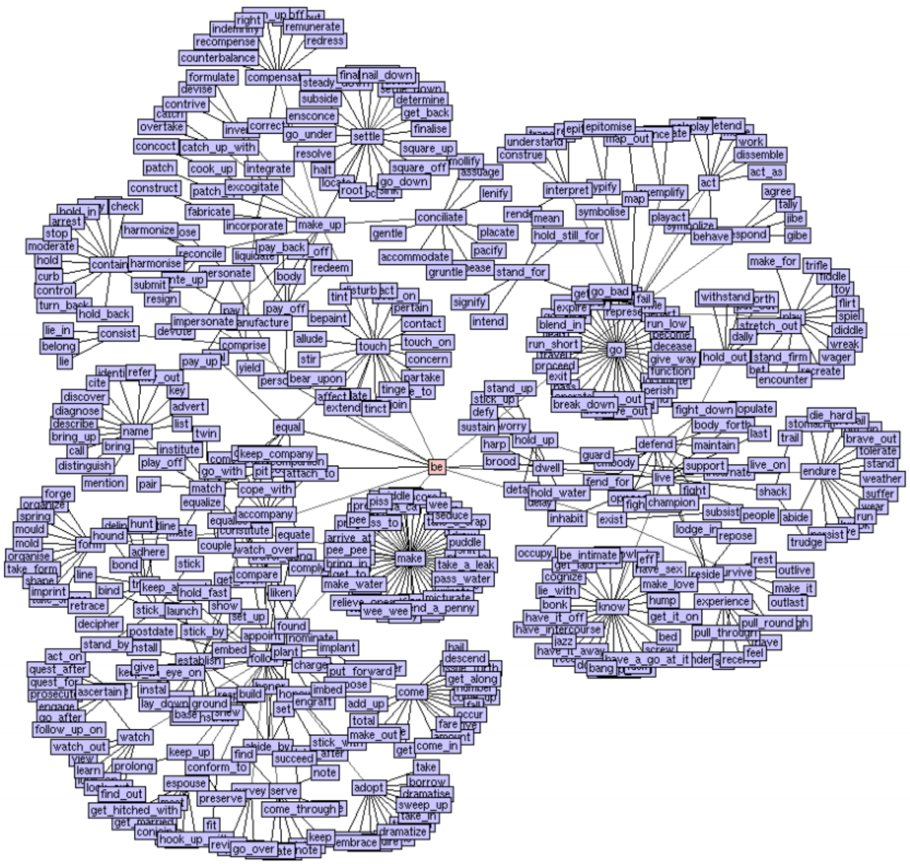
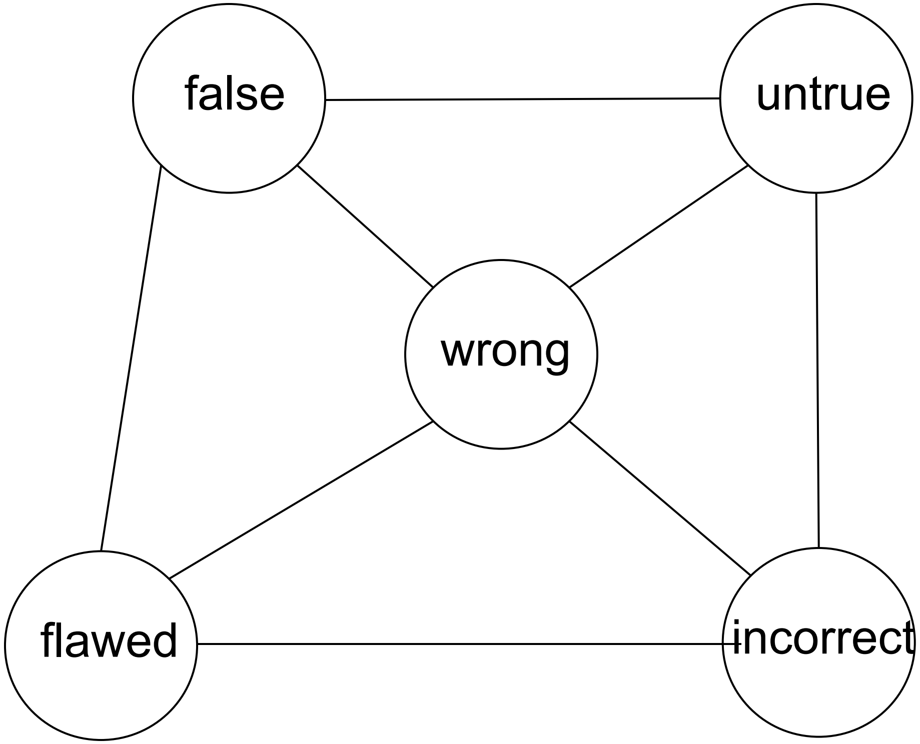
Semantic lexicon: WordNet

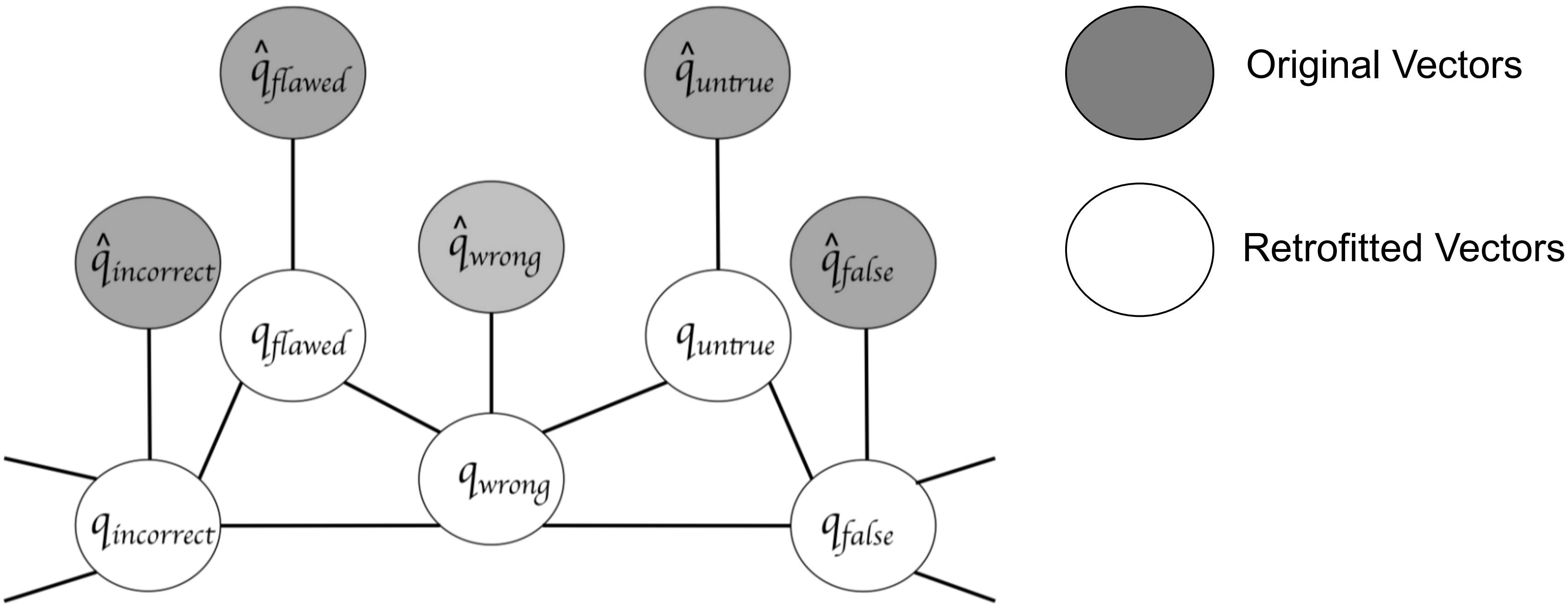




Retrofitting word vectors to semantic lexicons (NAACL'15)

- Incorporates information from lexicons in word vectors
- Post-processing approach
- Applicable to **any** word embedding method
- Applicable to **any** lexicon

Retrofitting



$$\Psi(Q) = \sum_{i=1}^{n} \left[\alpha_i \|q_i - \hat{q}_i\|^2 + \sum_{(i,j)\in E} \beta_{ij} \|q_i - q_j\|^2 \right]$$

Semantic lexicons used in this work

- PPDB: Lexical paraphrases obtained from parallel texts
- WordNet: synonyms, hypernyms and hyponyms
- FrameNet: Cause_change_of_position -> push=raise=growth

Lexicon	Words	Edges
PPDB	102,902	374,555
WordNet$_{syn}$	148,730	304,856
WordNet$_{all}$	148,730	934,705
FrameNet	10,822	417,456

Table 1. Approximate size of the graphs obtained from different lexicons

Experiment results

		Word Similarity		Synonym Selection	Syntactic Analysis	Sentiment Analysis
Lexicon	MEN-3k	RG-65	WS-353	TOEFL	SYN-REL	SA
Original Embedding: Glove	73.7	76.7	60.5	89.7	67.0	79.6
Semantic Lexicons: +PPDB	1.4	2.9	–1.2	**5.1**	–0.4	**1.6**
$+WN_{syn}$	0.0	2.7	0.5	**5.1**	–12.4	0.7
$+WN_{all}$	**2.2**	**7.5**	**0.7**	2.6	–8.4	0.5
+FN	–3.6	–1.0	–5.3	2.6	–7.0	0.0
SG	67.8	72.8	65.6	85.3	73.9	81.2
+PPDB	**5.4**	3.5	**4.4**	**10.7**	–2.3	**0.9**
$+WN_{syn}$	0.7	3.9	0.0	9.3	–13.6	0.7
$+WN_{all}$	2.5	**5.0**	1.9	9.3	–10.7	–0.3
+FN	–3.2	2.6	–4.9	1.3	–7.3	0.5

In this lecture…

- More types of supervision used in training word embedding
  - Language modeling
  - NLP labeling tasks
  - Semantic lexicons

- Ways to speed up
  - E.g., negative sampling
  - Necessary for training on huge text corpora
  - Scale up from hundreds of millions to hundreds of billions

- How word embeddings help other NLP tasks