Lecture 9: Intro to NLP, NLP ConvNets, word embeddings

Natural language processing: syntax level

- POS-tagging

POS tagging

VBZ

DT/ The JJ/ quick JJ/ brown NN/ fox ~~NNS~~/ jumps IN/ over DT/ the JJ/ lazy NN/ dog

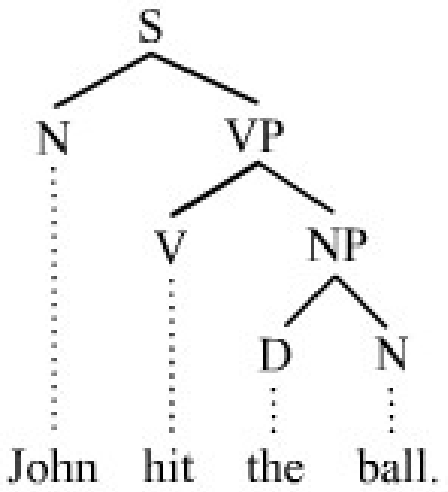
- -RRB- - Right bracket
- CD - Cardinal number
- EX - Existential there
- IN - Preposition
- JJR - Comparative adjective
- LS - List Item Marker
- NN - Singular noun
- NNP - Proper singular noun
- PDT - Predeterminer
- PRP - Personal pronoun
- RB - Adverb
- RBS - Superlative Adverb
- SYM - Symbol
- UH - Interjection
- VBD - Verb, past tense
- VBN - Verb, past participle
- VBZ - Verb, 3rd ps. sing. present
- WP - wh-pronoun
- WRB - wh-adverb
- CC - Coordinating conjunction
- DT - Determiner
- FW - Foreign word
- JJ - Adjective
- JJS - Superlative adjective
- MD - Modal
- NNS - Plural noun
- NNPS - Proper plural noun
- POS - Possesive ending
- PP$ - Possesive pronoun
- RBR - Comparative adverb
- RP - Particle
- TO - to
- VB - Verb, base form
- VBG - Verb, gerund/present participle
- VBP - Verb, non 3rd ps. sing. present
- WDT - wh-determiner
- WP$ - Possesive wh-pronoun

http://cogcomp.cs.illinois.edu/demo/pos/

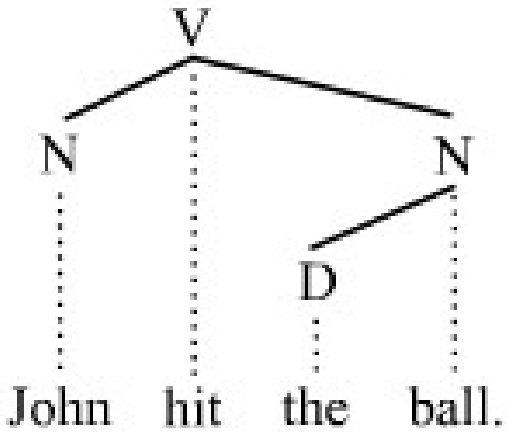
Natural language processing: syntax level

- POS-tagging
- Sentence syntax parsing

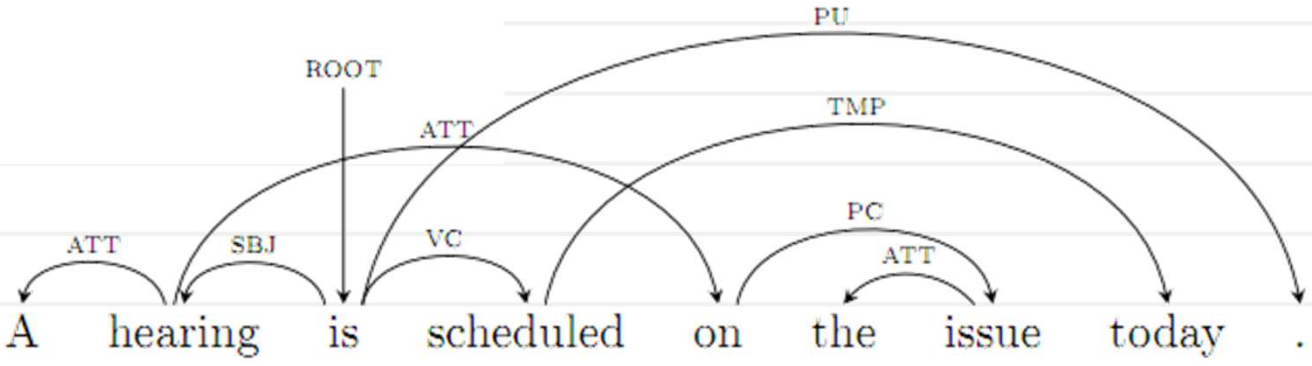
Sentence parsing



Constituency-based parse tree



Dependency-based parse tree



Natural language processing: syntax level

- POS-tagging
- Sentence syntax parsing
- Named entity recognition

Named entity recognition

Who?
Where?

Mrs. Green spoke today in New York.
Green chairs the finance committee…

[example from Koller and Friedman textbook]

Natural language processing: syntax level

- POS-tagging
- Sentence syntax parsing
- Named entity recognition
- Coreference resolution
- Semantic role labeling (SRL)

Semantic role labeling

He would n't ***accept*** *anything of value from those he was writing about*

V: verb

A0: acceptor

A1: thing accepted

A2: accepted-from

AM-MOD: modal

AM-NEG: negation

Source: CoNLL-2004

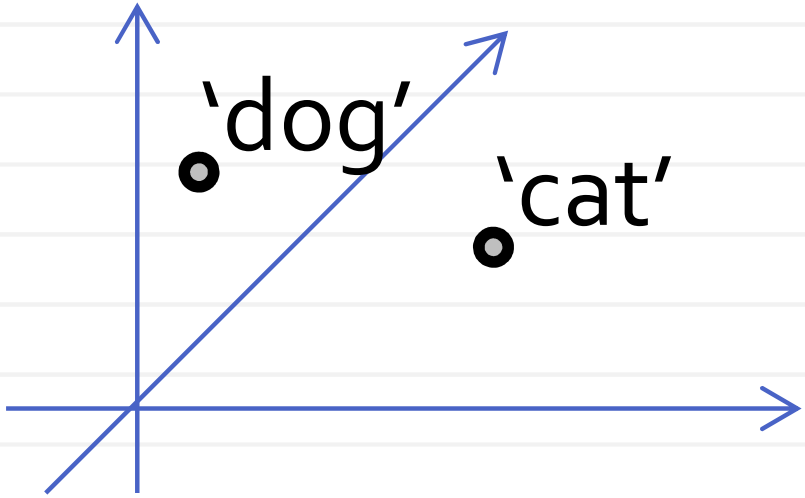
Natural language processing: semantic level

- Synonyms/paraphrases
- Question answering
- Chatbots/dialog system
- Machine translation
- Text summarization
- ….

Word-based NLP

Baseline approach:

- Enumerate words ("lexicon","vocabulary")
- Use *one-hot* encoding



x_{cat}: [0 0 0 0 1 0 0 0 0]

x_{kitten}: [0 0 0 0 0 0 0 1 0 0]

x_{teapot}: [0 1 0 0 0 0 0 0 0 0]

Problem: $||x_{cat} - x_{kitten}|| = ||x_{cat} - x_{teapot}||$

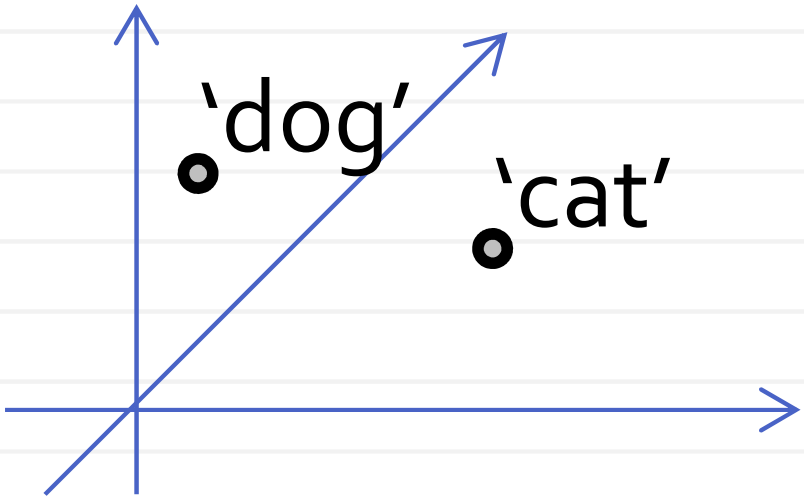
Solution: intermediate representations

Word-based NLP

x_{cat}: [0 0 0 0 1 0 0 0 0]

x_{kitten}: [0 0 0 0 0 0 1 0 0]

x_{teapot}: [0 1 0 0 0 0 0 0 0]



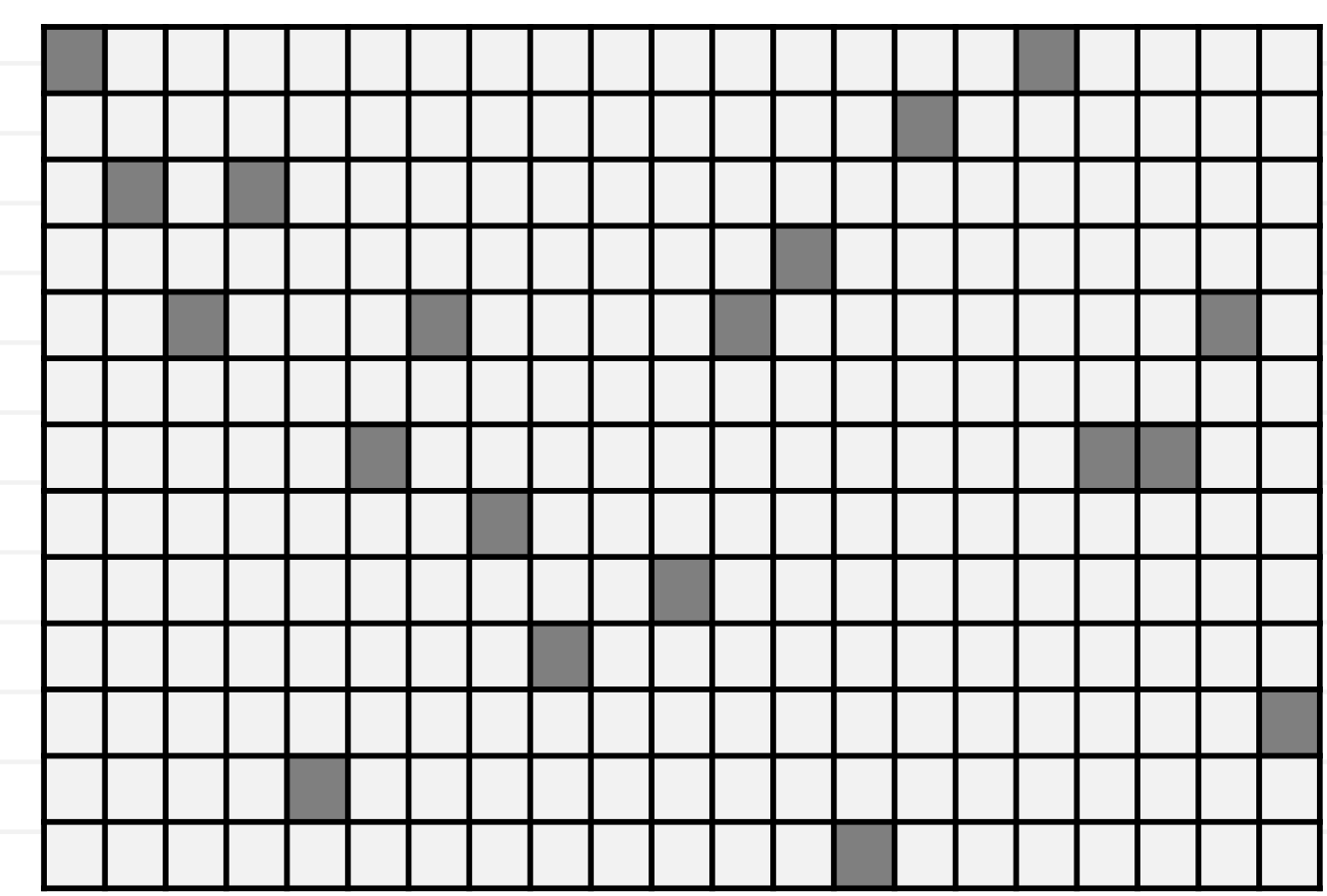
Problem: very high dimensionality

Partial remedy 1: lemmatize ("*Dogs* -> *dog*", "*I'm*" ->"I be")
Side-effect 1: lemmatization looses information

Partial remedy 2: replace infrequent words with "OOV"
Side-effect 2: infrequent words are often very informative

Character-level NLP

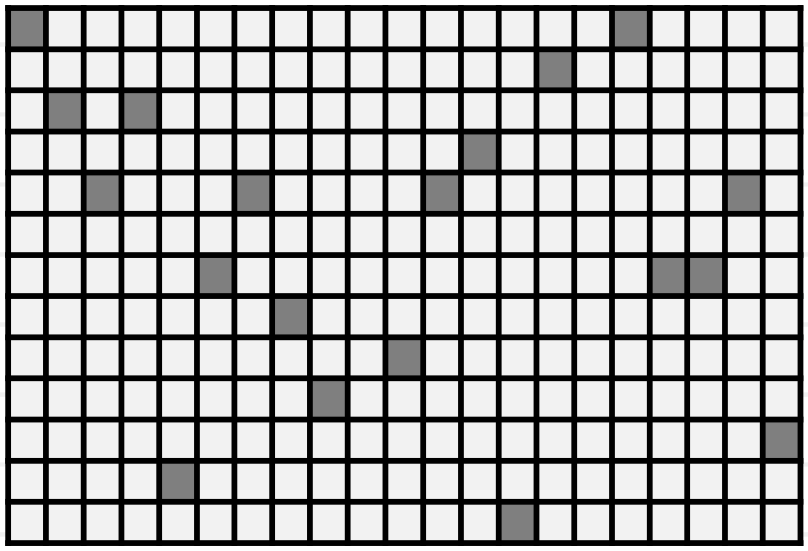
A cat sat on the mat.



70 rows (alphabetic, digits, main punctuation symbols)

symbols

Character-level NLP: advantages



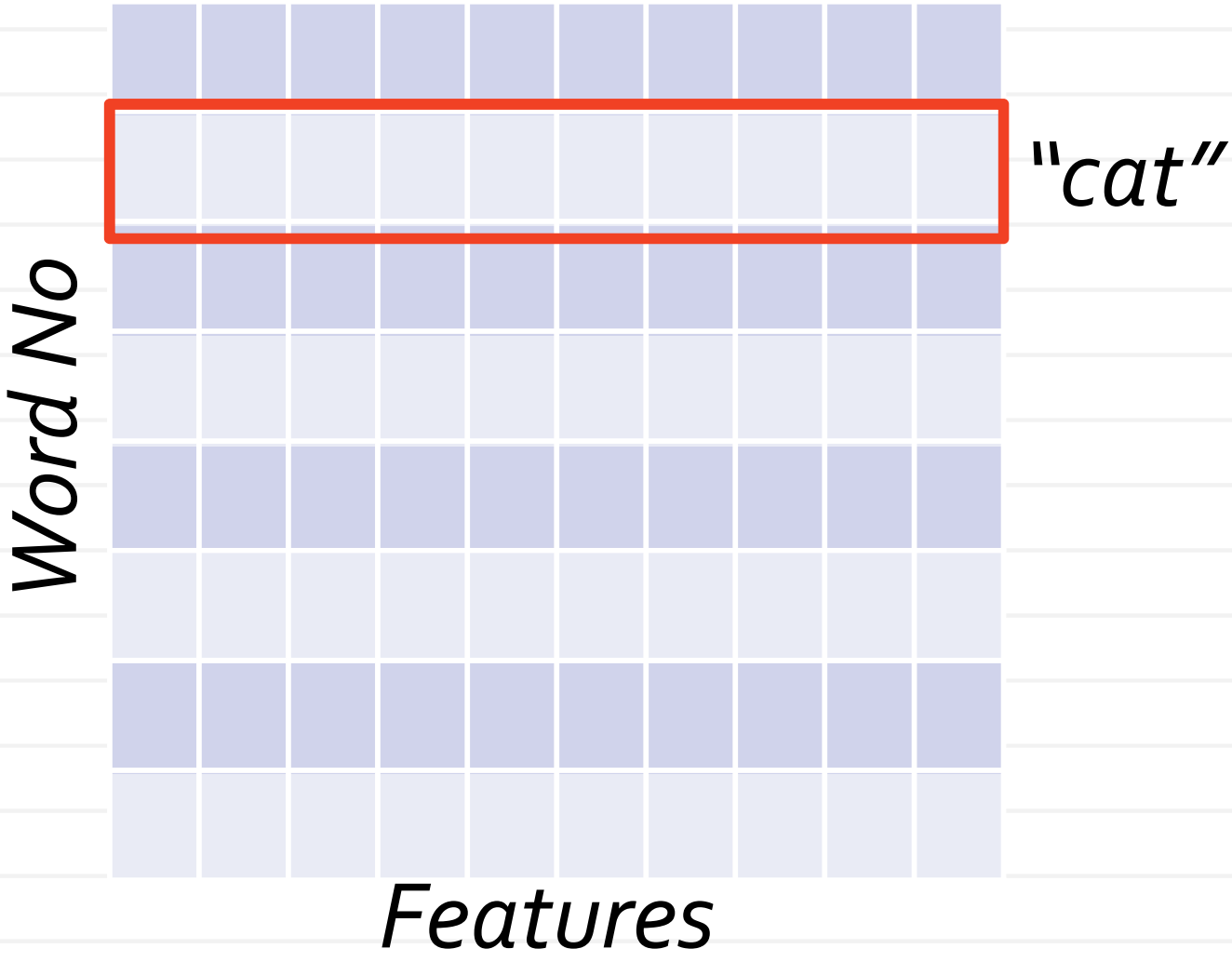
Character-level NLP is good because:

- *school* ≈ *School*
- *colour* ≈ *color*
- *2006* ≈ *2007*
- ||*Vyatka - Satka*|| < || *Vyatka - San-Francisco*||

Vision vs Natural Language Processing

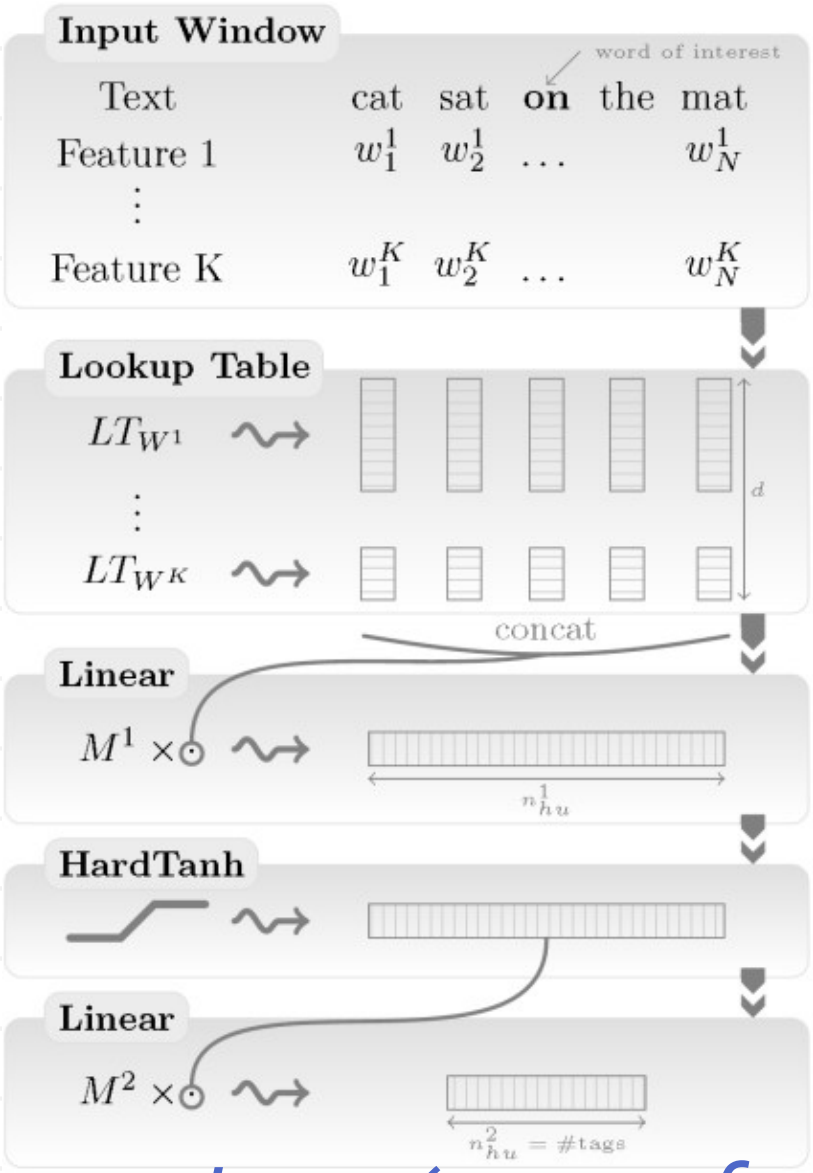
- **Vision based on pixels:** low-level (5D vectors), noisy, unary and pairwise statistics already informative
- **NLP based on words:** unary statistics very informative (much higher-level units), very different nature (large discrete codebooks)
- **NLP based on letters:** low-level, need to consider long combinations to catch meaning (pairwise not enough)

Embedding layer: main layer for word-level

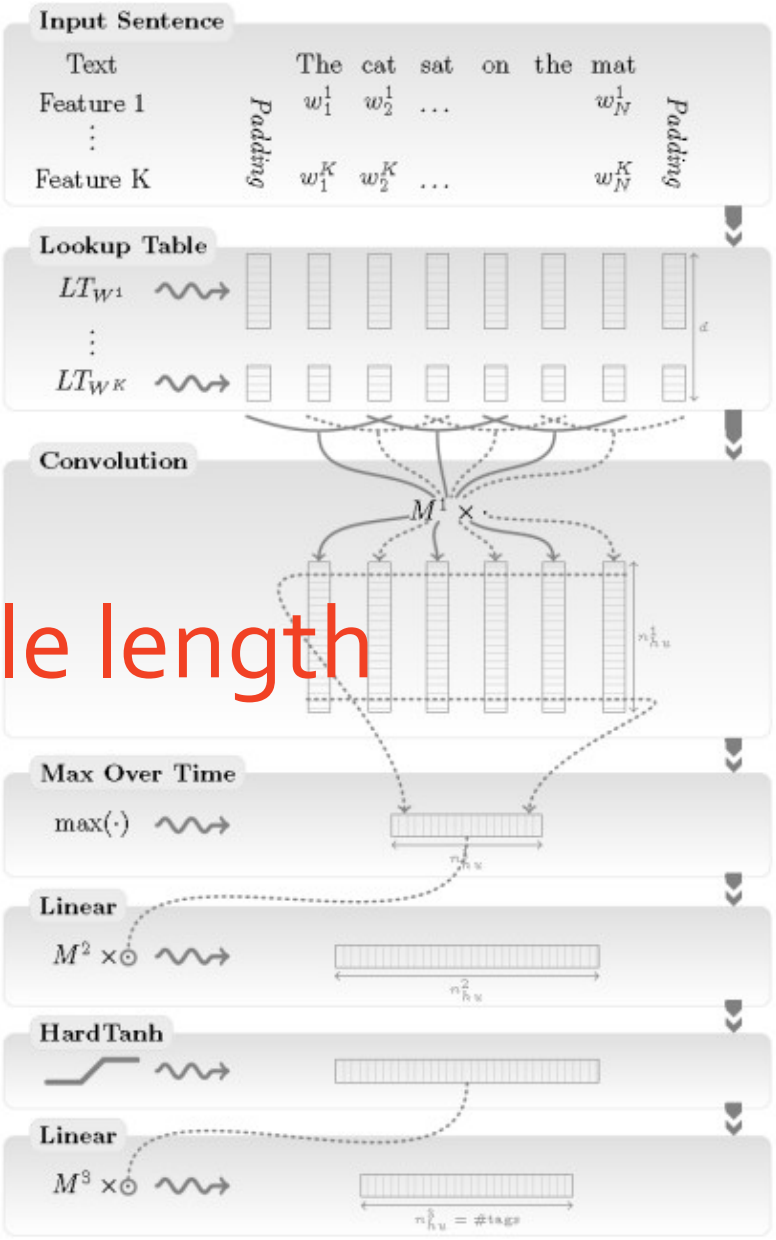


- Maps integer numbers to vectors
- Can be seen as a multiplicative layer that takes one-hot embeddings as inputs

Supervised deep-learning for NLP



word No, root No, capitalization, etc.



Variable length

Loss (e.g. softmax)

[Collobert et al. 11]

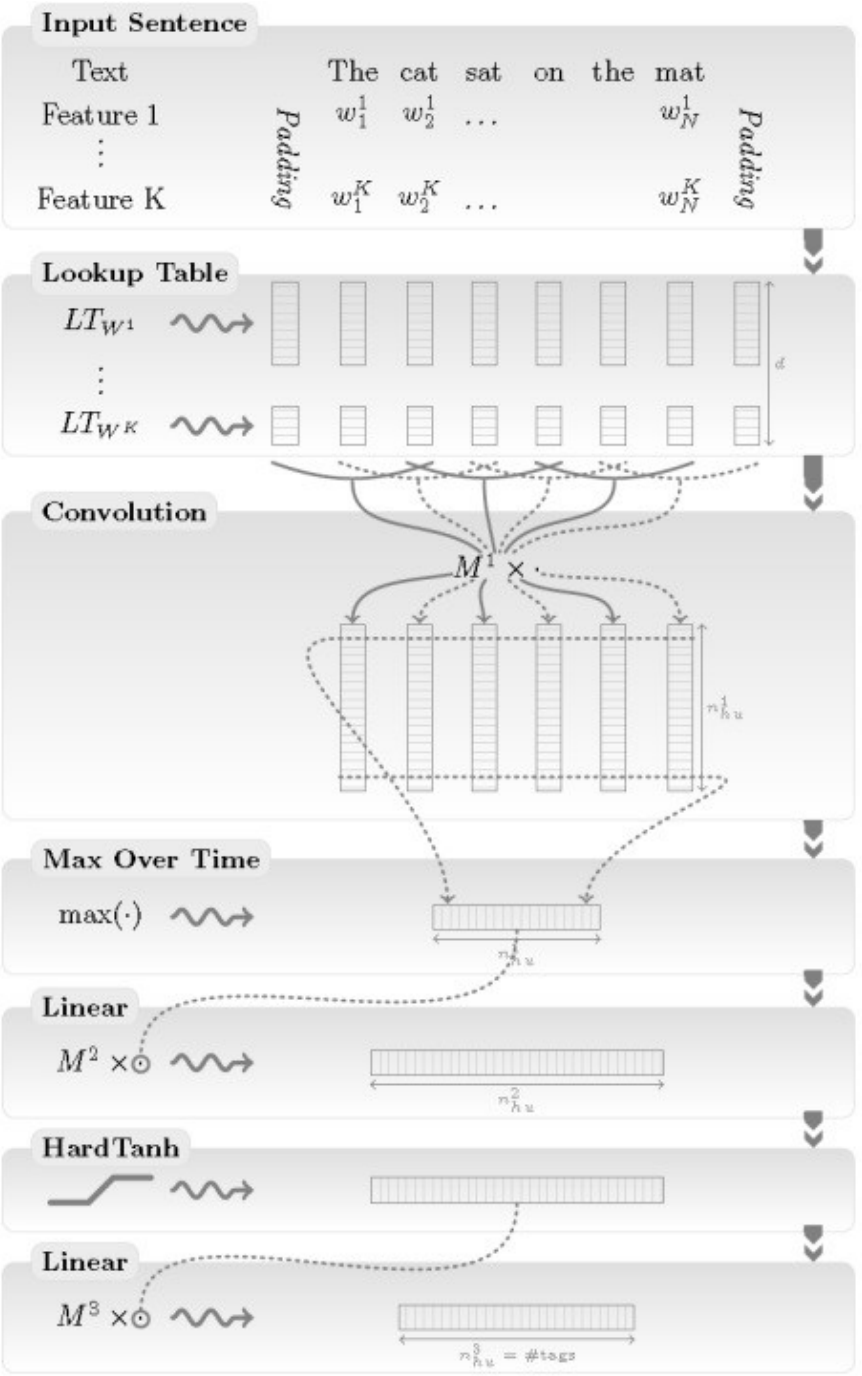
Loss (e.g. softmax)

NLP (almost) from scratch: sentence-based

Remark:

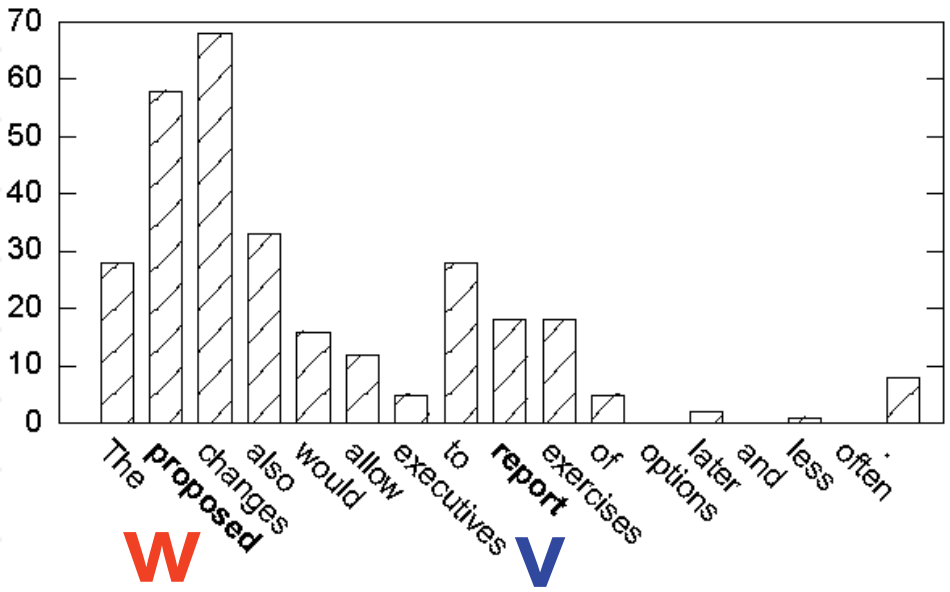
- ConvNet type architecture (weight-sharing)
- For SRL, encode which verb and which word we consider using *i-pos*$_v$ and *i-pos*$_w$ features

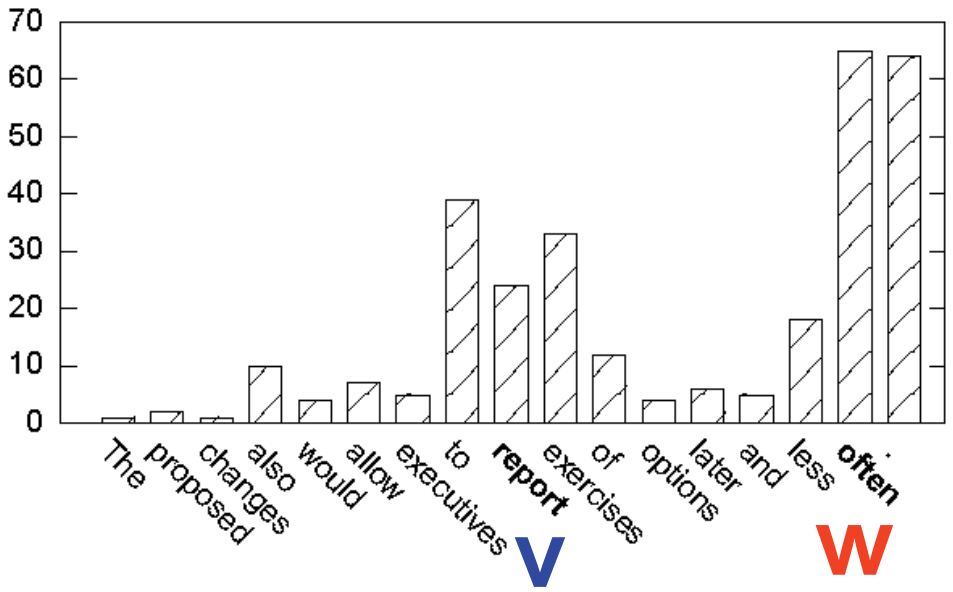
[Collobert et al. 11]



Max-activations

- Max-layer produces 300 dim feature
- Max-layer is independent across dimensions
- How many times a certain word is selected:





(another) ConvNet for language

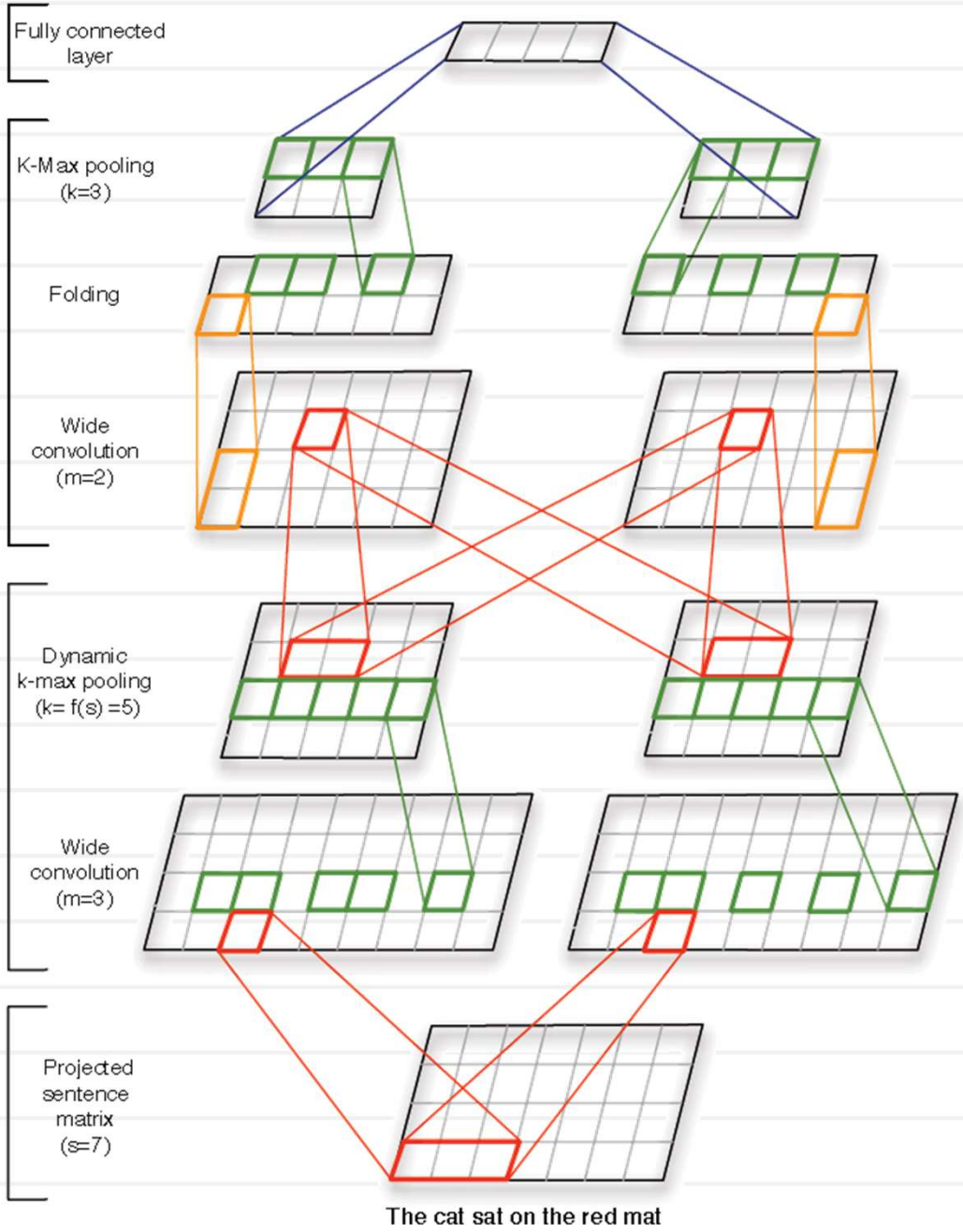
Each word encoded with a vector (e.g. "one-hot")

Filters act along temporal dimension

"Folding" = sum pooling along embedding direction

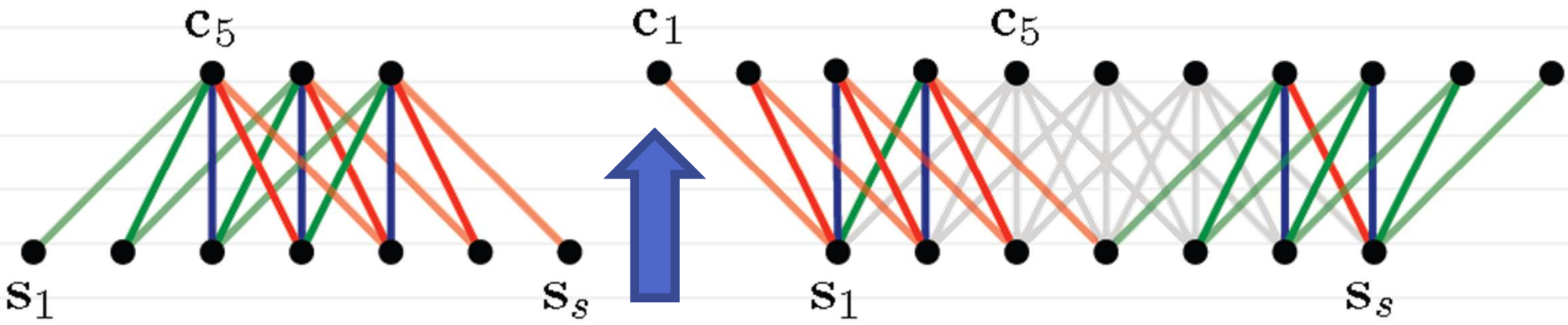
New idea: k-max pooling

[Kalchbrenner *et al.*, ACL14]



(another) ConvNet for language

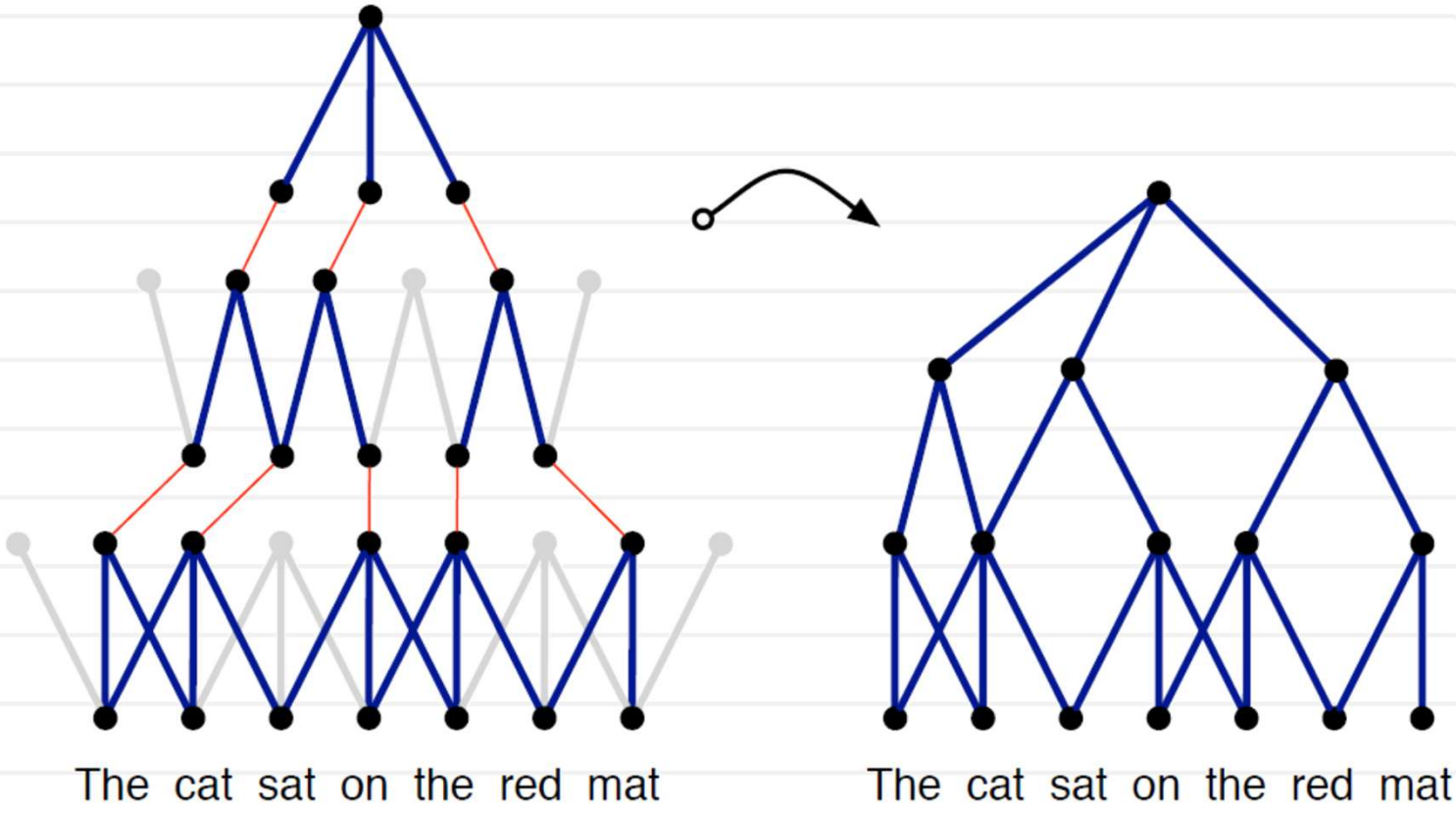
Each word encoded with "one-hot" embedding



"Valid" convolution "Wide" convolution

[Kalchbrenner *et al.*,. ACL14]

k-max pooling and dynamic k-max pooling



- K-max pooling picks k largest elements in each channel
- Ordering is kept
- Dynamic k-max pooling allocates k to each layer using

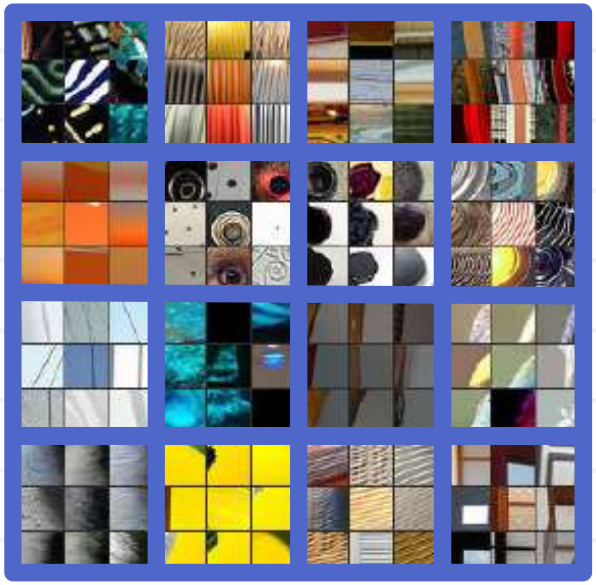
$$k_l = \max(\, k_{top},\, \lceil \frac{L-l}{L} s \rceil \,)$$

[Kalchbrenner *et al.*,. ACL14]

Visualizing filters

Layer 1

[Zeiler Fergus 14]



Layer 2

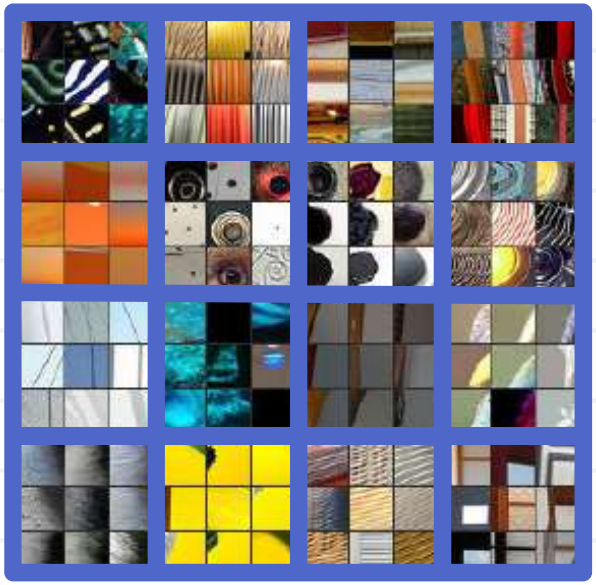
			POSITIVE			
lovely	comedic	moments	and	several	fine	performances
good	script	,	good	dialogue	,	funny
sustains	throughout	is	daring	,	inventive	and
well	written	,	nicely	acted	and	beautifully
remarkably	solid	and	subtly	satirical	tour	de
			NEGATIVE			
,	nonexistent	plot	and	pretentious	visual	style
it	fails	the	most	basic	test	as
so	stupid	,	so	ill	conceived	,
,	too	dull	and	pretentious	to	be
hood	rats	butt	their	ugly	heads	in

[Kalchbrenner *et al.*,ACL14]

Visualizing filters

Layer 1

[Zeiler Fergus 14]

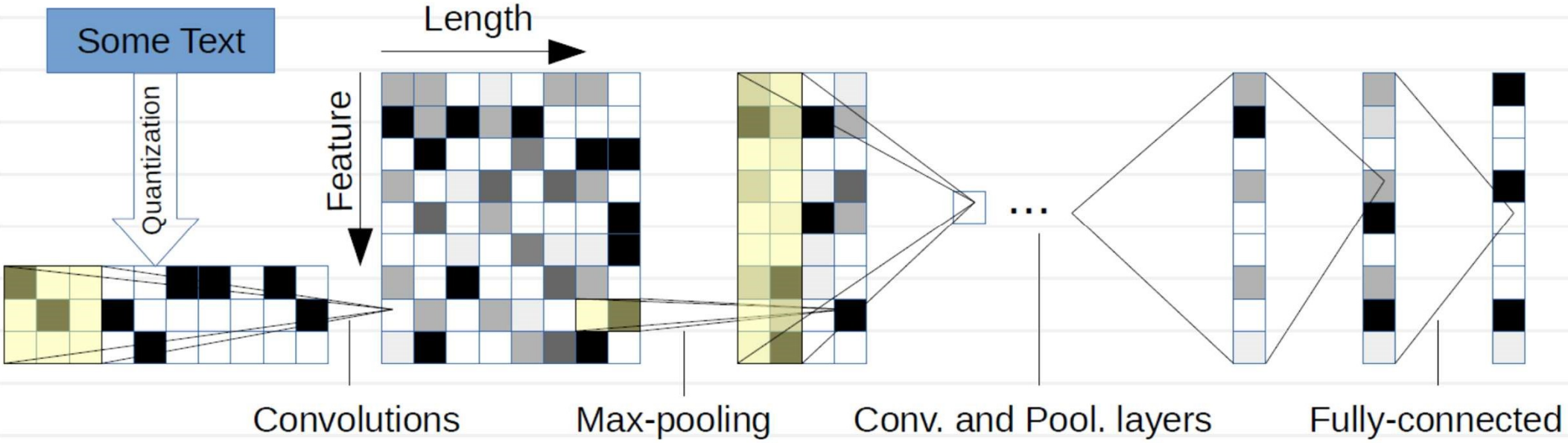


Layer 2

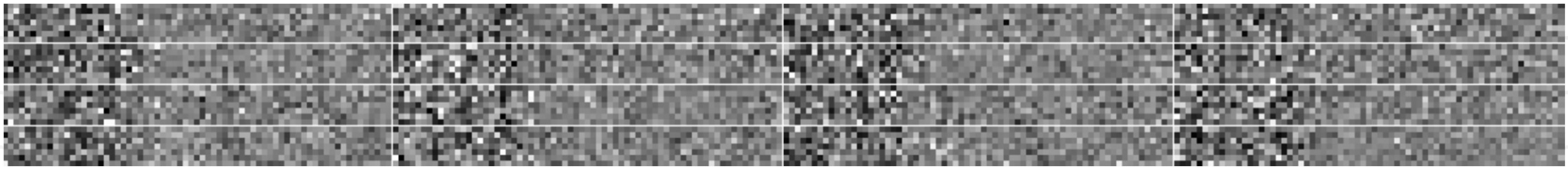
			'NOT'			
n't	have	any	huge	laughs	in	its
no	movement	,	no	,	not	much
n't	stop	me	from	enjoying	much	of
not	that	kung	pow	is	n't	funny
not	a	moment	that	is	not	false
			'TOO'			
,	too	dull	and	pretentious	to	be
either	too	serious	or	too	lighthearted	,
too	slow	,	too	long	and	too
feels	too	formulaic	and	too	familiar	to
is	too	predictable	and	too	self	conscious

[Kalchbrenner *et al.*,ACL14]

Character-level ConvNet



- Trained for classification end-to-end
- All reviews are clipped to 1014 characters



Learned weights at the 1st layer

[Zhang et al.15]

Character-level ConvNet: evaluation

Dataset	Classes	Train Samples	Test Samples	Epoch Size
AG's News	4	120,000	7,600	5,000
Sogou News	5	450,000	60,000	5,000
DBPedia	14	560,000	70,000	5,000
Yelp Review Polarity	2	560,000	38,000	5,000
Yelp Review Full	5	650,000	50,000	5,000
Yahoo! Answers	10	1,400,000	60,000	10,000
Amazon Review Full	5	3,000,000	650,000	30,000
Amazon Review Polarity	2	3,600,000	400,000	30,000

- Sentiment prediction and topic prediction
- Data augmentation using synonyms thesaurus

[Zhang et al.15]

Character-level ConvNet: evaluation

Larger →

Model	AG	Sogou	DBP.	Yelp P.	Yelp F.	Yah. A.	Amz. F.	Amz. I
BoW	11.19	7.15	3.39	7.76	42.01	31.11	45.36	9.60
BoW TFIDF	10.36	6.55	2.63	6.34	40.14	28.96	44.74	9.00
ngrams	7.96	2.92	1.37	**4.36**	43.74	31.53	45.73	7.98
ngrams TFIDF	**7.64**	**2.81**	**1.31**	4.56	45.20	31.49	47.56	8.46
Bag-of-means	**16.91**	**10.79**	**9.55**	**12.67**	**47.46**	**39.45**	**55.87**	**18.39**
LSTM	13.94	4.82	1.45	5.26	41.83	29.16	40.57	6.10
Lg. w2v Conv.	9.92	4.39	1.42	4.60	40.16	31.97	44.40	5.88
Sm. w2v Conv.	11.35	4.54	1.71	5.56	42.13	31.50	42.59	6.00
Lg. w2v Conv. Th.	9.91	-	1.37	4.63	39.58	31.23	43.75	5.80
Sm. w2v Conv. Th.	10.88	-	1.53	5.36	41.09	29.86	42.50	5.63
Lg. Lk. Conv.	8.55	4.95	1.72	4.89	40.52	29.06	45.95	5.84
Sm. Lk. Conv.	10.87	4.93	1.85	5.54	41.41	30.02	43.66	5.85
Lg. Lk. Conv. Th.	8.93	-	1.58	5.03	40.52	28.84	42.39	5.52
Sm. Lk. Conv. Th.	9.12	-	1.77	5.37	41.17	28.92	43.19	5.51
Lg. Full Conv.	9.85	8.80	1.66	5.25	38.40	29.90	40.89	5.78
Sm. Full Conv.	11.59	8.95	1.89	5.67	38.82	30.01	40.88	5.78
Lg. Full Conv. Th.	9.51	-	1.55	4.88	38.04	29.58	40.54	5.51
Sm. Full Conv. Th.	10.89	-	1.69	5.42	**37.95**	29.90	40.53	5.66
Lg. Conv.	12.82	4.88	1.73	5.89	39.62	29.55	41.31	5.51
Sm. Conv.	15.65	8.65	1.98	6.53	40.84	29.84	40.53	5.50
Lg. Conv. Th.	13.39	-	1.60	5.82	39.30	**28.80**	40.45	**4.93**
Sm. Conv. Th.	14.80	-	1.85	6.49	40.16	29.84	**40.43**	5.67

Word-level CNN

Char-level CNN

[Zhang et al.15]

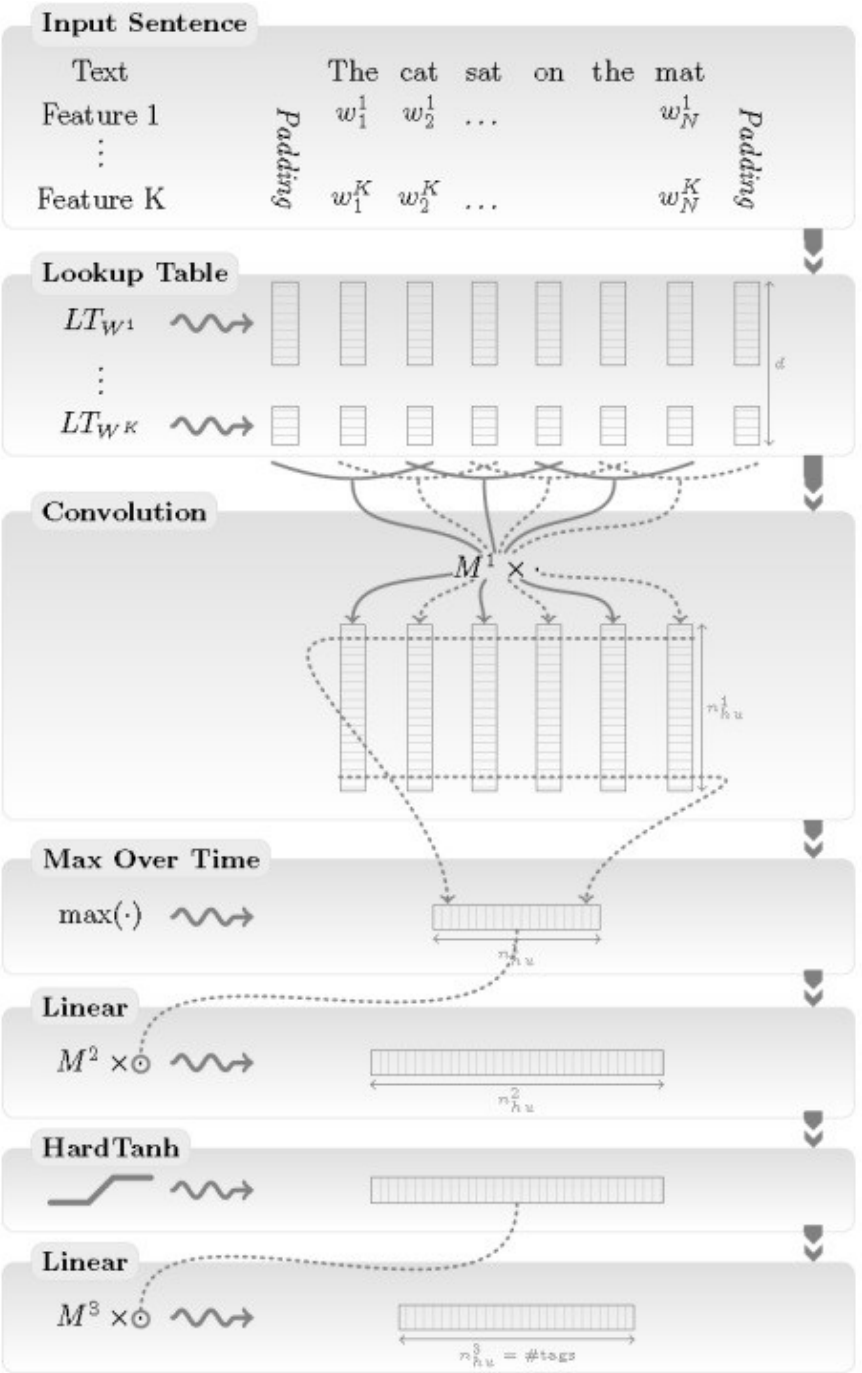
Problem with supervised word embeddings

Weak-spot!

Mapping from one-hot vectors to general vectors (aka "embedding layer")

- O(10 mln – 100 mln parameters)
- We now have most parameters at the deepest level (bad!)

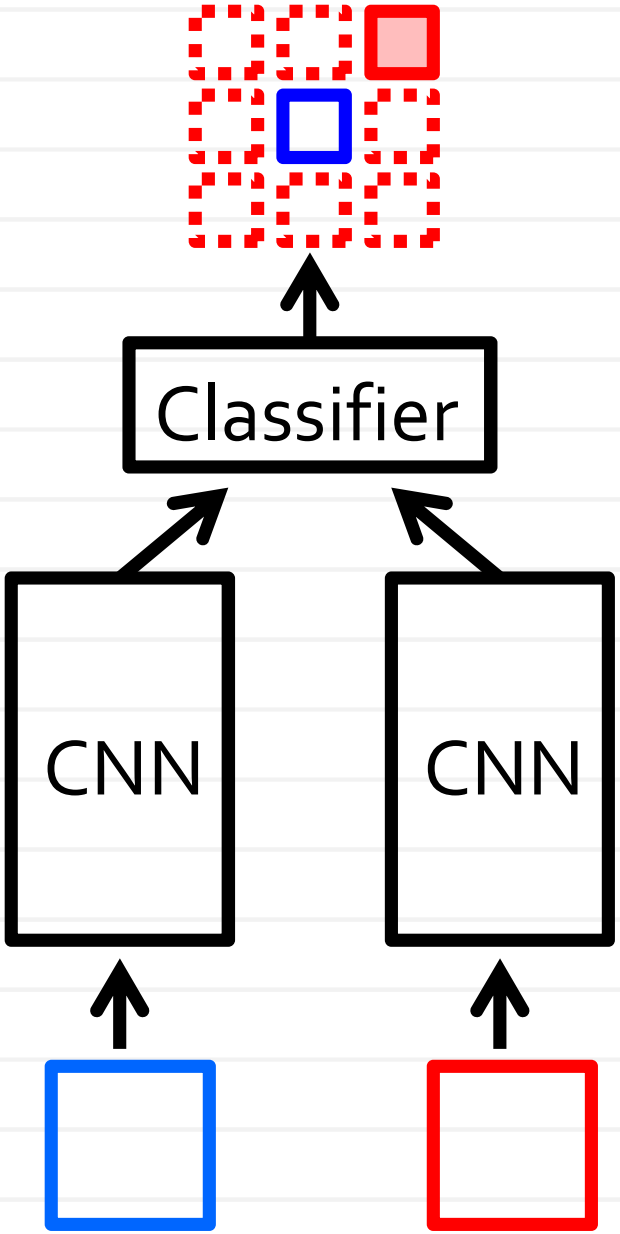
[Collobert et al. 11]

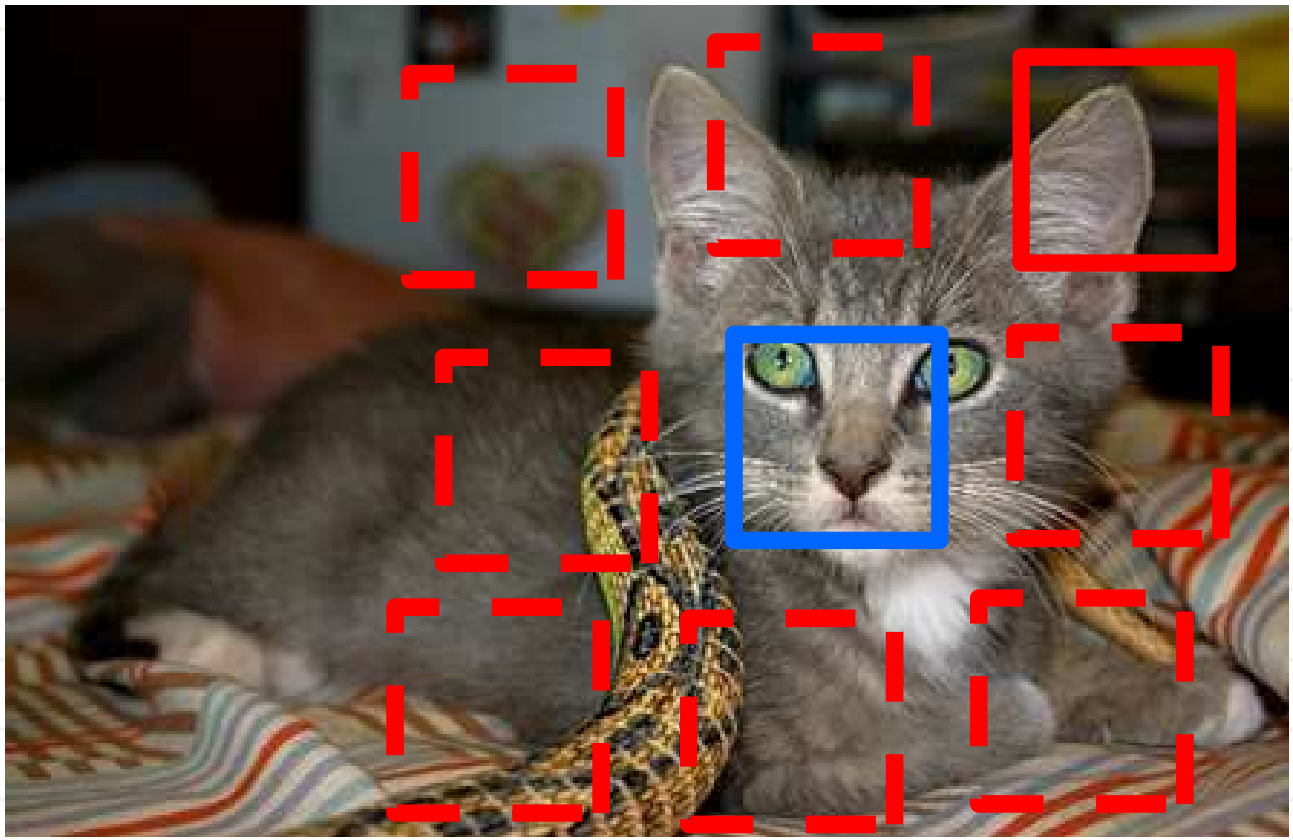


Predictive learning

- Given an element predict *nearby* elements (e.g. next, previous, adjacent, etc.)
- Does not require annotated data ("self-supervised")
- Usually considered as unsupervised, but often works much better than "plain" unsupervised
- Particularly prominent in NLP, but now gaining popularity in many fields

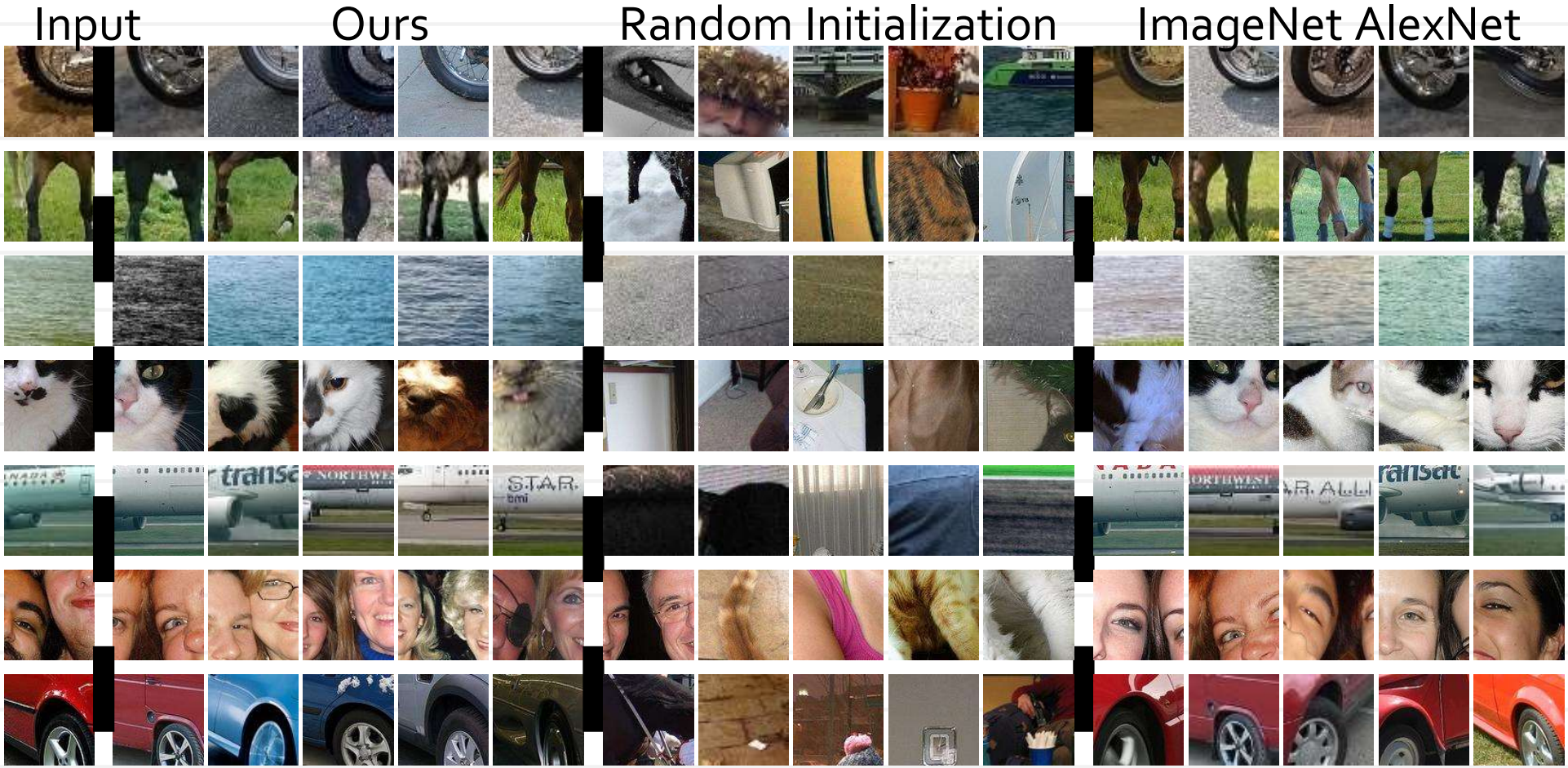
Predictive learning for still images





[Doersch et al. ICCV15]

Predictive learning for still images

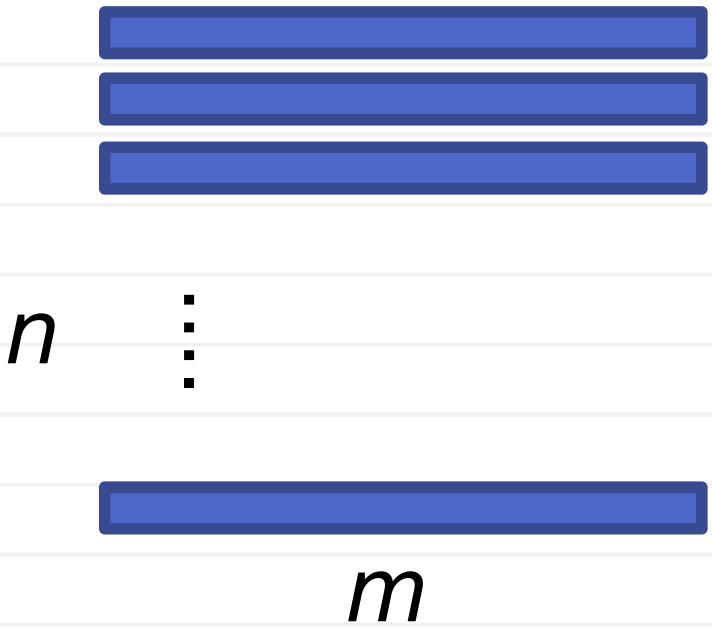


[Doersch et al. ICCV15]

Factorization-based word embeddings

the *distributional hypothesis* : similar context = similar meaning

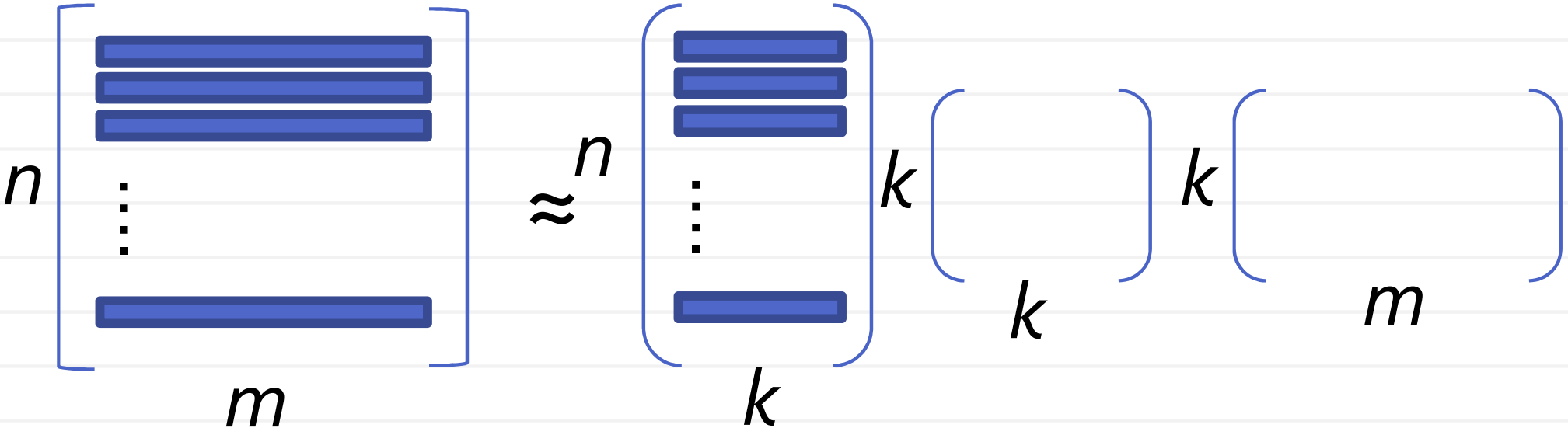
co-occurrence matrix



- Co-occurences within certain range (*window*)
- Might want to distinguish left and right co-occurences ($m = 2n$ in this case)
- We can remove too "rare" dimensions

Factorization-based word embeddings

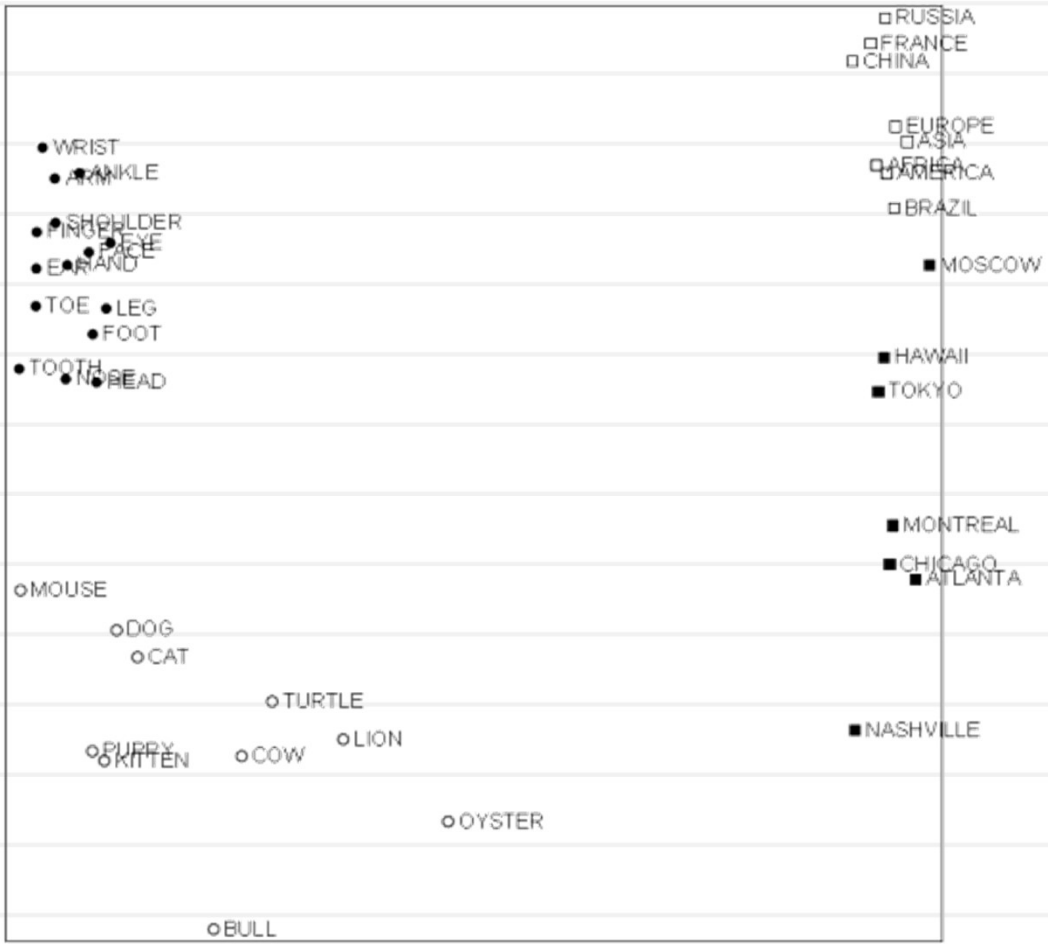
One can reduce dimension of the representation:

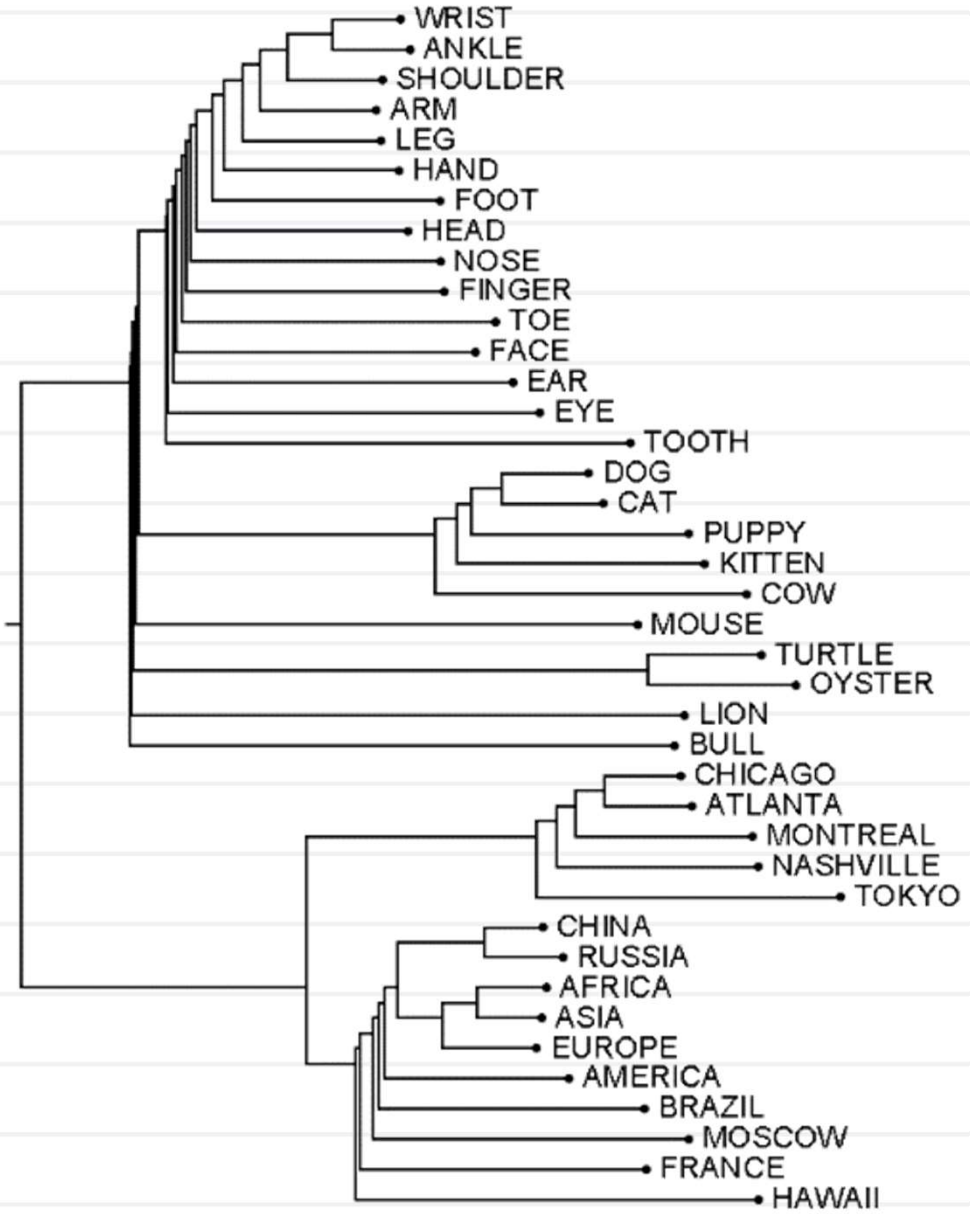


- SVD allows to get word vectors of e.g. 100 dimensions
- Removing negatives, renormalizing and square-rooting helps

Visualizing word space

MDS visualization:





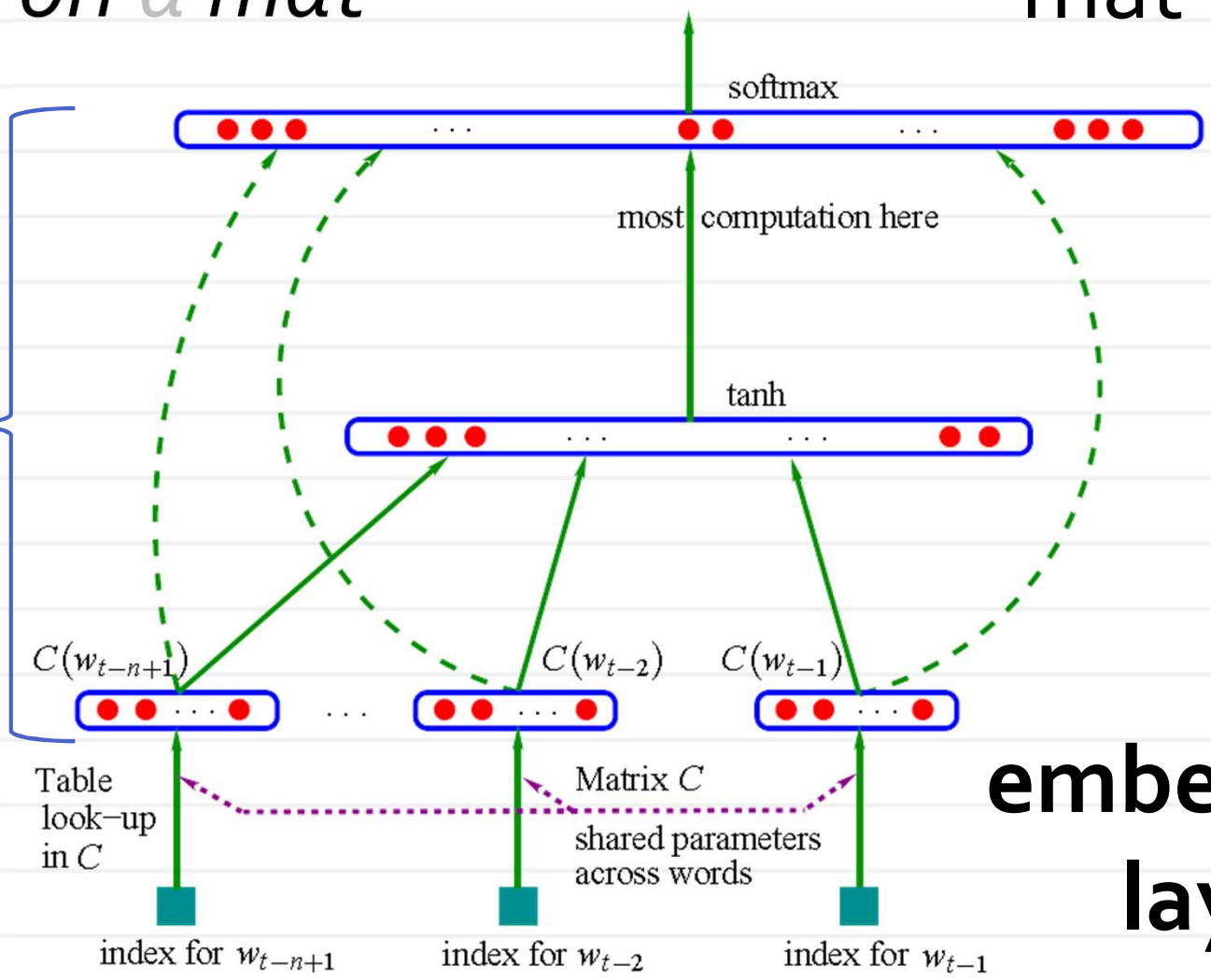
[Ronde et al. 2006]

DL for word embeddings

A cat sat on a mat

"mat"

Neural network

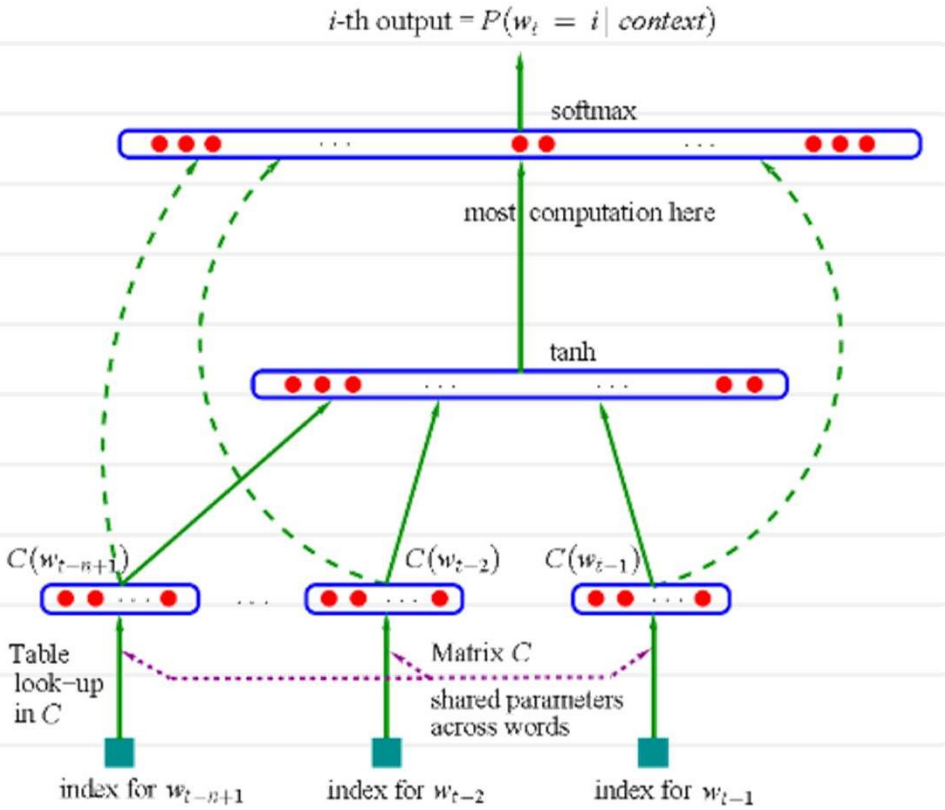


embedding layer

"cat" "sat" "on"

[Bengio et al. JMLR03]

DL for word embeddings



[Bengio et al. JMLR03]

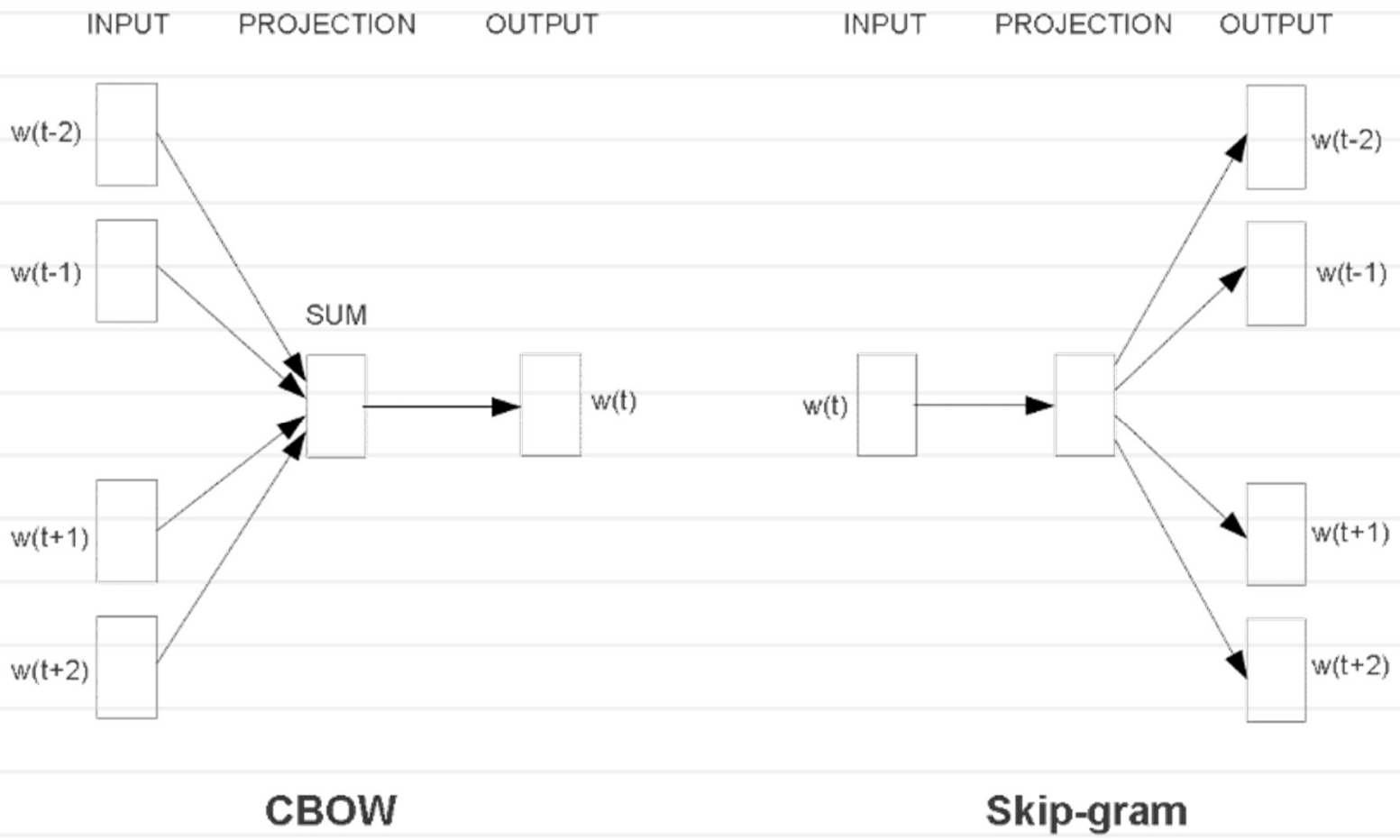
$$x = [C(w_{t-1}, C(w_{t-2}, \ldots, C(w_{t-n+1})]$$

$$y = b + Wx + U\tanh(d + Hx)$$

$$P(w_t|w_{t-1}, \ldots, w_{t-n+1}) = \frac{\exp(y_{w_t})}{\sum_i \exp(y_i)}$$

New architectures for word embedding

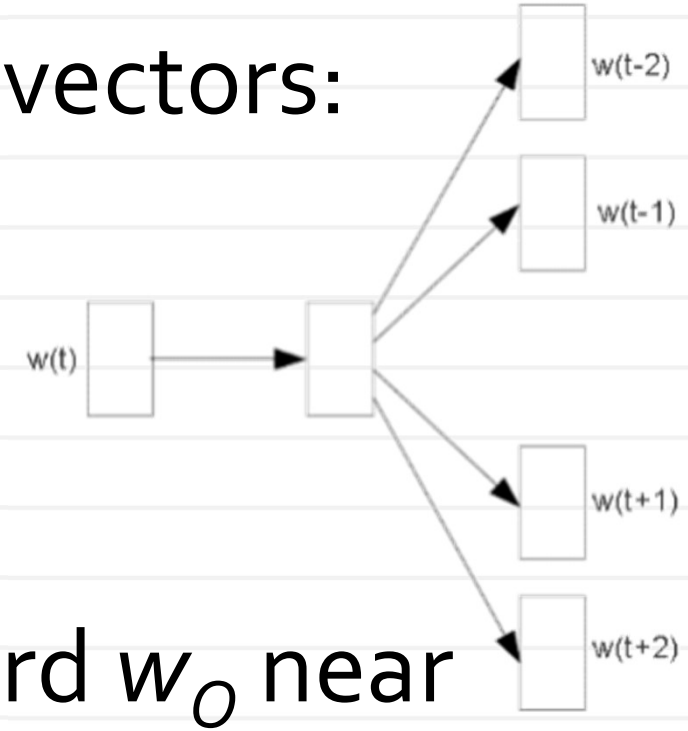
Both architectures learn an embedding of words into vector space (no hidden layer)



[Mikolov et al. 2013]

Skip-gram model

Each word w is assigned **two** vectors: v_w and v'_w



The probability to see the word w_O near the word w_I is then:

$$p(w_O|w_I) = \frac{\exp({v'_{w_O}}^T v_{w_I})}{\sum_{w=1}^{W} \exp({v'_w}^T v_{w_I})}$$

Skip-gram model

Computing the probability:

$$p(w_O|w_I) = \frac{\exp({v'_{w_O}}^T v_{w_I})}{\sum_{w=1}^{W} \exp({v'_w}^T v_{w_I})}$$

Overall objective (given a center word, predict surrounding ones):

$$J(v, v') = \frac{1}{T} \sum_{t=1}^{T} \sum_{\substack{j=-c \\ j \notin 0}}^{c} \log p(w_{t+j}|w_t; v, v')$$

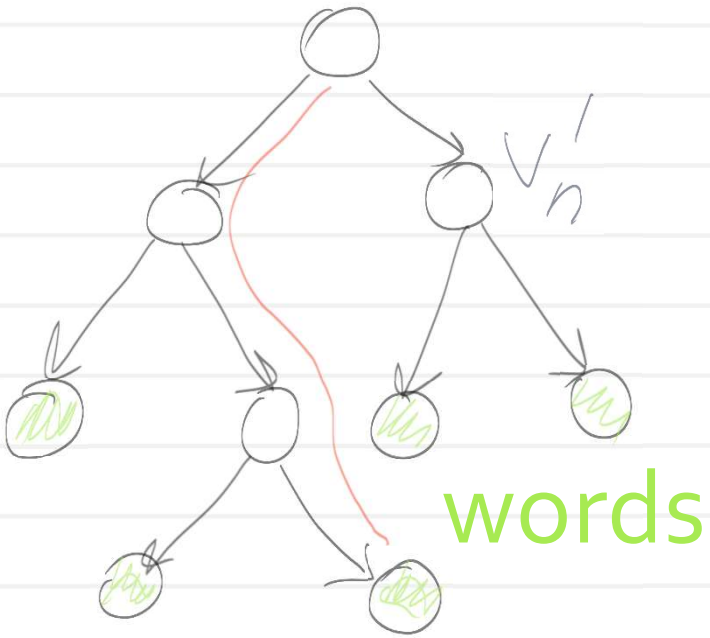
We can now learn embedding on a large corpus

Evaluating the denominator

$$p(w_O|w_I) = \frac{\exp({v'_{w_O}}^T v_{w_I})}{\sum_{w=1}^{W} \exp({v'_w}^T v_{w_I})}$$

Impractical!

Idea 1: *Hiearchical softmax*

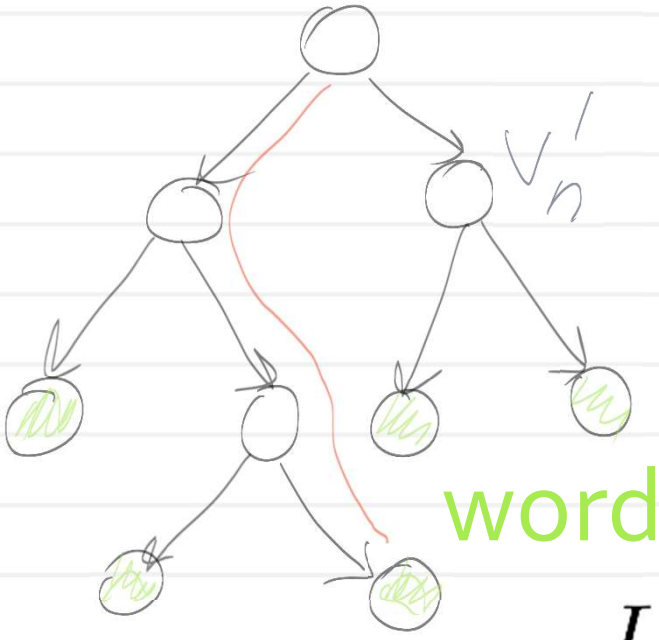


Probability of a word = probability of a path

[Mnih & Hinton 2009]

Hierarchical softmax

[Mnih & Hinton 2009]



Probability of a word = probability of a path

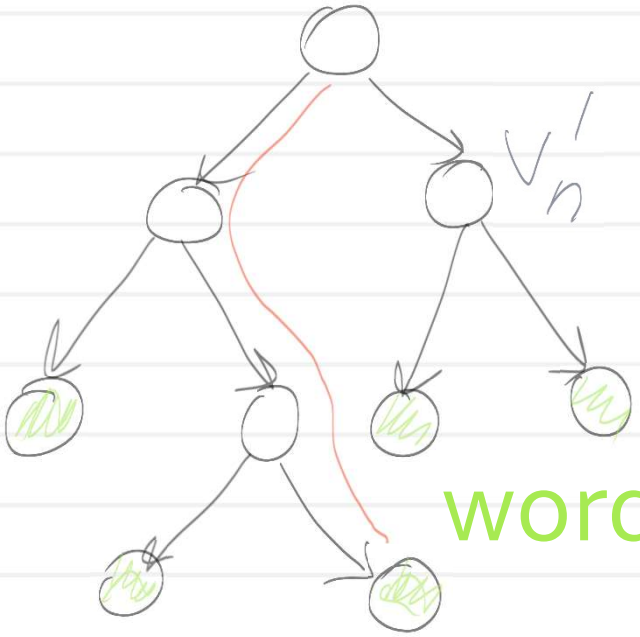
+1 for right turn,
-1 for left turn

$$P(w|w_I) = \prod_{j=1}^{L(w)-1} \sigma(\pm {v'_{n(w,j)}}^T v_{w_I})$$

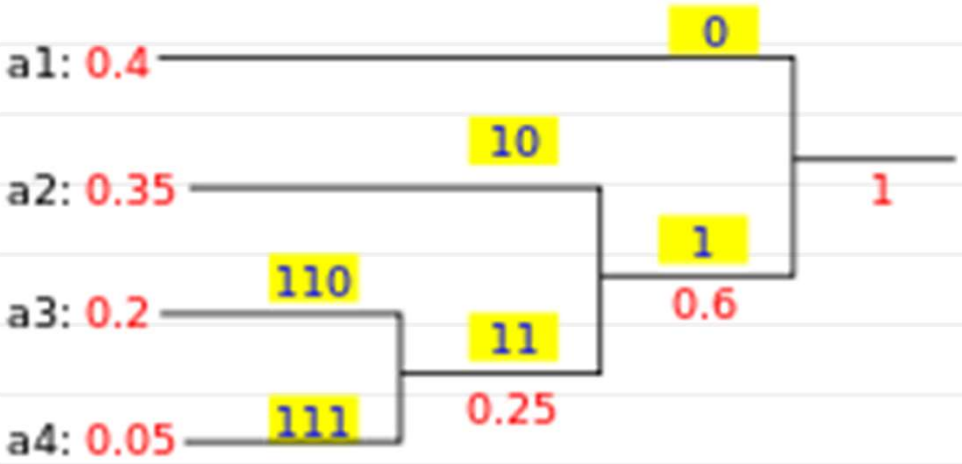
Resulting conditional distribution is normalized!

Proof idea: $\sigma(x) + \sigma(-x) = 1$

Hierarchical softmax



Probability of a word = probability of a path



- Tree choice affects quality and speed
- Mikolov et al. use *Huffman tree* (maximizing speed): frequent words have short paths

Negative sampling

Idea 2: *Negative sampling*

Maximizing:

$$J(v, v') = \sum_{w_I} \left(\frac{1}{T} \sum_{w \in C^+(w_I)} \log \sigma({v'_w}^T v_{w_I}) + \right.$$

$$\left. + \mathbb{E}_{w \sim P(w)} [\log \sigma(-{v'_w}^T v_{w_I})] \right)$$

approximating by a few samples (2 – 20)

$$\frac{1}{Z} P^{3/4}_{\text{empirical}}(w)$$

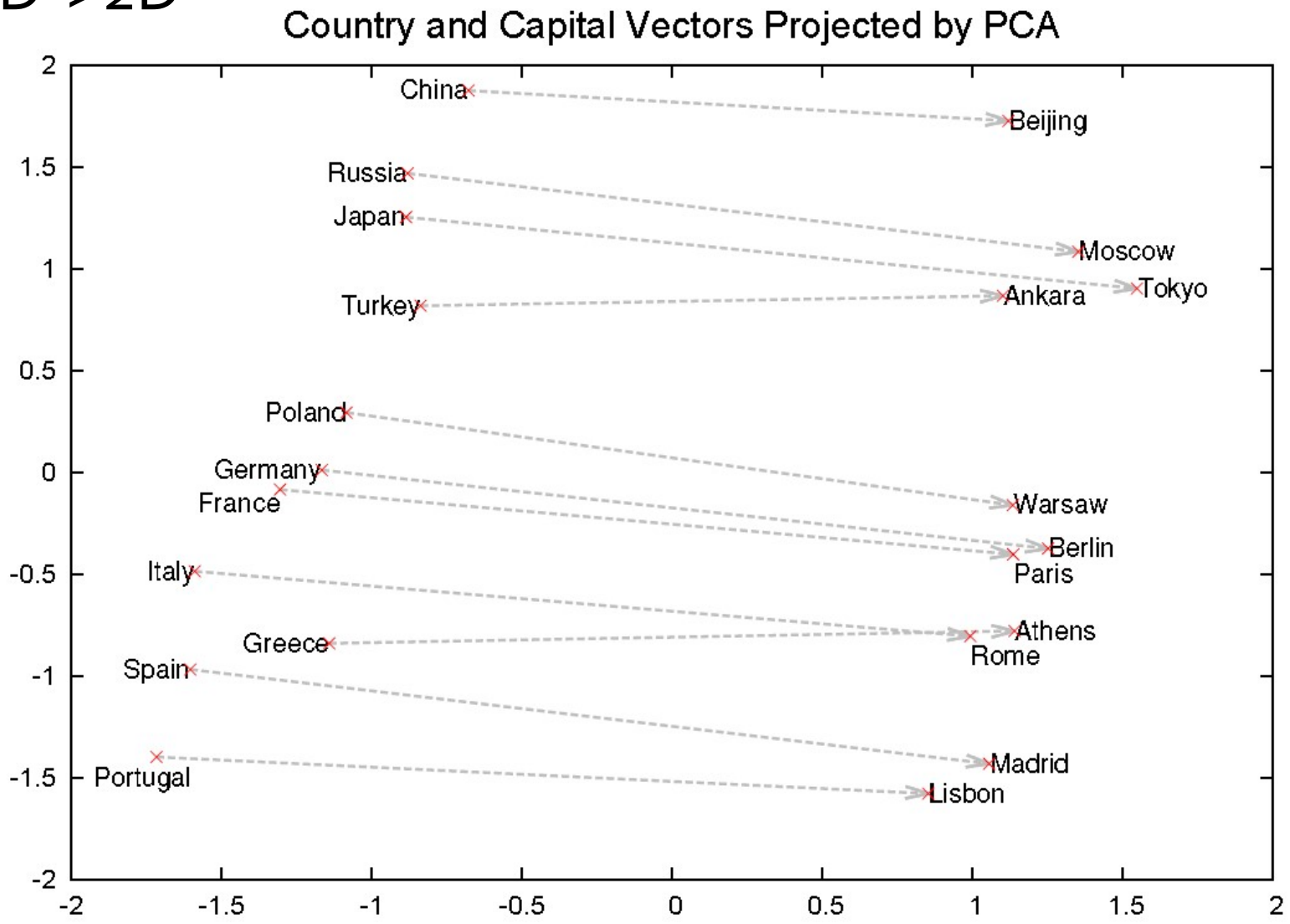
Evaluating using analogies

	Type of relationship	Word Pair 1		Word Pair 2	
semantic	Common capital city	Athens	Greece	Oslo	Norway
	All capital cities	Astana	Kazakhstan	Harare	Zimbabwe
	Currency	Angola	kwanza	Iran	rial
	City-in-state	Chicago	Illinois	Stockton	California
	Man-Woman	brother	sister	grandson	granddaughter
syntactic	Adjective to adverb	apparent	apparently	rapid	rapidly
	Opposite	possibly	impossibly	ethical	unethical
	Comparative	great	greater	tough	tougher
	Superlative	easy	easiest	lucky	luckiest
	Present Participle	think	thinking	read	reading
	Nationality adjective	Switzerland	Swiss	Cambodia	Cambodian
	Past tense	walking	walked	swimming	swam
	Plural nouns	mouse	mice	dollar	dollars
	Plural verbs	work	works	speak	speaks

$$q = v(\text{'Greece'}) - v(\text{'Athens'}) + v(\text{'Oslo'})$$

Word2vec analogies

PCA: 1000D->2D



[Mikolov et al. 2013]

Ground truth analogies

Type of relationship	Word Pair 1		Word Pair 2	
Common capital city	Athens	Greece	Oslo	Norway
All capital cities	Astana	Kazakhstan	Harare	Zimbabwe
Currency	Angola	kwanza	Iran	rial
City-in-state	Chicago	Illinois	Stockton	California
Man-Woman	brother	sister	grandson	granddaughter
Adjective to adverb	apparent	apparently	rapid	rapidly
Opposite	possibly	impossibly	ethical	unethical
Comparative	great	greater	tough	tougher
Superlative	easy	easiest	lucky	luckiest
Present Participle	think	thinking	read	reading
Nationality adjective	Switzerland	Swiss	Cambodia	Cambodian
Past tense	walking	walked	swimming	swam
Plural nouns	mouse	mice	dollar	dollars
Plural verbs	work	works	speak	speaks

[Mikolov et al. 2013]

Evaluating using analogies

Model	Vector Dimensionality	Training words	Accuracy [%]			Training time [days]
			Semantic	Syntactic	Total	
3 epoch CBOW	300	783M	15.5	53.1	36.1	1
3 epoch Skip-gram	300	783M	50.0	55.9	53.3	3
1 epoch CBOW	300	783M	13.8	49.9	33.6	0.3
1 epoch CBOW	300	1.6B	16.1	52.6	36.1	0.6
1 epoch CBOW	600	783M	15.4	53.3	36.2	0.7
1 epoch Skip-gram	300	783M	45.6	52.2	49.2	1
1 epoch Skip-gram	300	1.6B	52.2	55.1	53.8	2
1 epoch Skip-gram	600	783M	56.7	54.5	55.5	2.5

[Mikolov et al. 2013]

Evaluating using analogies

Model	Vector Dimensionality	Training words	Accuracy [%]		
			Semantic	Syntactic	Total
Collobert-Weston NNLM	50	660M	9.3	12.3	11.0
Turian NNLM	50	37M	1.4	2.6	2.1
Turian NNLM	200	37M	1.4	2.2	1.8
Mnih NNLM	50	37M	1.8	9.1	5.8
Mnih NNLM	100	37M	3.3	13.2	8.8
Mikolov RNNLM	80	320M	4.9	18.4	12.7
Mikolov RNNLM	640	320M	8.6	36.5	24.6
Huang NNLM	50	990M	13.3	11.6	12.3
Our NNLM	20	6B	12.9	26.4	20.3
Our NNLM	50	6B	27.9	55.8	43.2
Our NNLM	100	6B	34.2	**64.5**	50.8
CBOW	300	783M	15.5	53.1	36.1
Skip-gram	300	783M	**50.0**	55.9	**53.3**

[Mikolov et al. 2013]

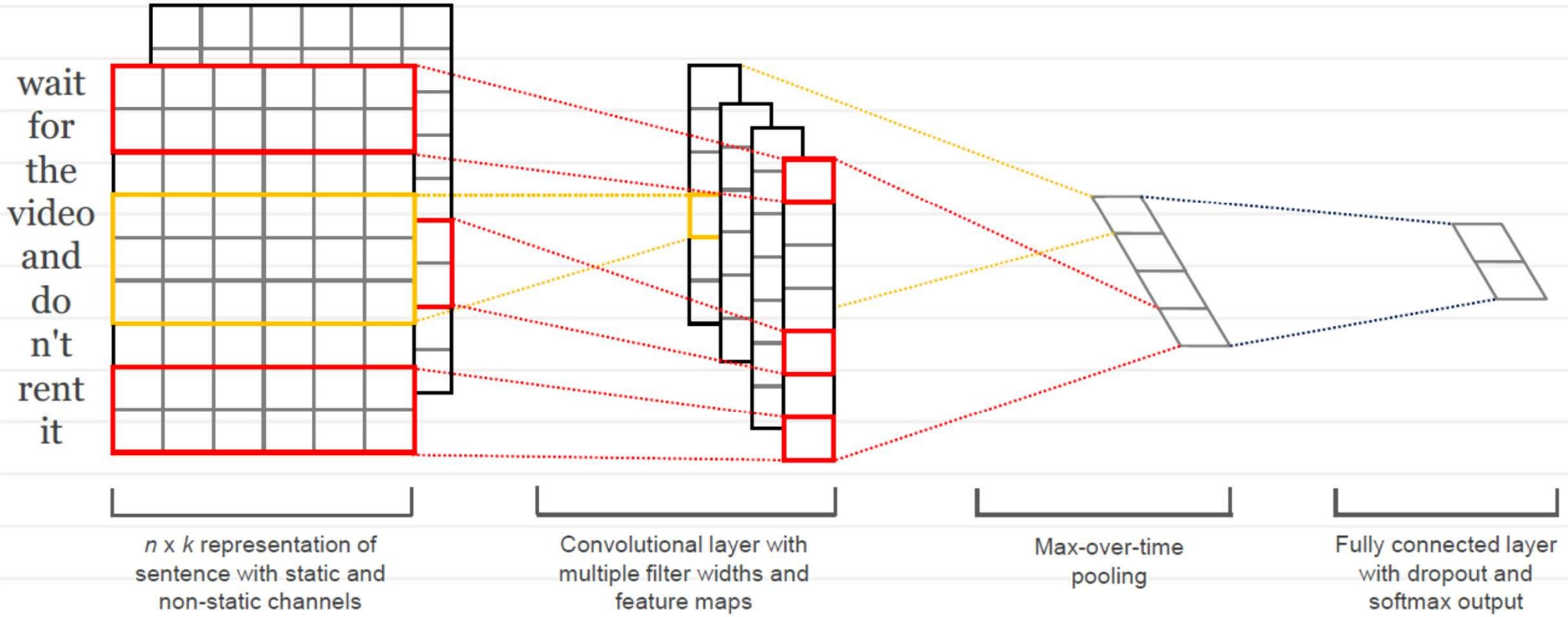
Evaluating using analogies

Trained on 783M words, 300 dim

Relationship	Example 1	Example 2	Example 3
France - Paris	Italy: Rome	Japan: Tokyo	Florida: Tallahassee
big - bigger	small: larger	cold: colder	quick: quicker
Miami - Florida	Baltimore: Maryland	Dallas: Texas	Kona: Hawaii
Einstein - scientist	Messi: midfielder	Mozart: violinist	Picasso: painter
Sarkozy - France	Berlusconi: Italy	Merkel: Germany	Koizumi: Japan
copper - Cu	zinc: Zn	gold: Au	uranium: plutonium
Berlusconi - Silvio	Sarkozy: Nicolas	Putin: Medvedev	Obama: Barack
Microsoft - Windows	Google: Android	IBM: Linux	Apple: iPhone
Microsoft - Ballmer	Google: Yahoo	IBM: McNealy	Apple: Jobs
Japan - sushi	Germany: bratwurst	France: tapas	USA: pizza

[Mikolov et al. 2013]

Word2vec reuse



- Simple ConvNet initialized with word2vec

[Kim EMNLP14]

Word2vec reuse

Model	MR	SST-1	SST-2	Subj	TREC	CR	MPQA
CNN-rand	76.1	45.0	82.7	89.6	91.2	79.8	83.4
CNN-static	81.0	45.5	86.8	93.0	92.8	84.7	**89.6**
CNN-non-static	**81.5**	48.0	87.2	93.4	93.6	84.3	89.5
CNN-multichannel	81.1	47.4	**88.1**	93.2	92.2	**85.0**	89.4
RAE (Socher et al., 2011)	77.7	43.2	82.4	–	–	–	86.4
MV-RNN (Socher et al., 2012)	79.0	44.4	82.9	–	–	–	–
RNTN (Socher et al., 2013)	–	45.7	85.4	–	–	–	–
DCNN (Kalchbrenner et al., 2014)	–	48.5	86.8	–	93.0	–	–
Paragraph-Vec (Le and Mikolov, 2014)	–	**48.7**	87.8	–	–	–	–
CCAE (Hermann and Blunsom, 2013)	77.8	–	–	–	–	–	87.2
Sent-Parser (Dong et al., 2014)	79.5	–	–	–	–	–	86.3
NBSVM (Wang and Manning, 2012)	79.4	–	–	93.2	–	81.8	86.3
MNB (Wang and Manning, 2012)	79.0	–	–	**93.6**	–	80.0	86.3
G-Dropout (Wang and Manning, 2013)	79.0	–	–	93.4	–	82.1	86.1
F-Dropout (Wang and Manning, 2013)	79.1	–	–	**93.6**	–	81.9	86.3
Tree-CRF (Nakagawa et al., 2010)	77.3	–	–	–	–	81.4	86.1
CRF-PR (Yang and Cardie, 2014)	–	–	–	–	–	82.7	–
SVM_S (Silva et al., 2011)	–	–	–	–	**95.0**	–	–

[Kim EMNLP14]

FastText: going towards character-level

||*Vyatka* - *Satka*|| < || *Vyatka* - *San-Francisco*||

skoltech = <sko, skol, kolt, olte, ltec, tech, ech>,<skoltech>

$$v_w = \sum_{u \in B(w)} z_u$$

FastText vector

bag of n-grams + the word itself

Learning with negative sampling:

$$J(v, v') = \sum_{w_I} \Big(\frac{1}{T} \sum_{w \in C^+(w_I)} \log \sigma({v'_w}^T v_{w_I}) + \\ + \mathbb{E}_{w \sim P(w)} [\log \sigma(-{v'_w}^T v_{w_I})] \Big)$$

[Bojanowski et al. ACL2017]

FastText: going towards character-level

$$v_w = \sum_{u \in B(w)} z_u$$

FastText vector

bag of n-grams + the word itself

Learning with negative sampling:

$$J(v, v') = \sum_{w_I} \Big(\frac{1}{T} \sum_{w \in C^+(w_I)} \log \sigma({v'_w}^T v_{w_I}) + \mathbb{E}_{w \sim P(w)} [\log \sigma(-{v'_w}^T v_{w_I})] \Big)$$

- In practice, using a range of n for n-grams, e.g. n = 2,3,4,5,6
- Using hashing to hash all n-grams into K-entries learning K n-gram vectors

[Bojanowski et al. ACL2017]

FastText: results

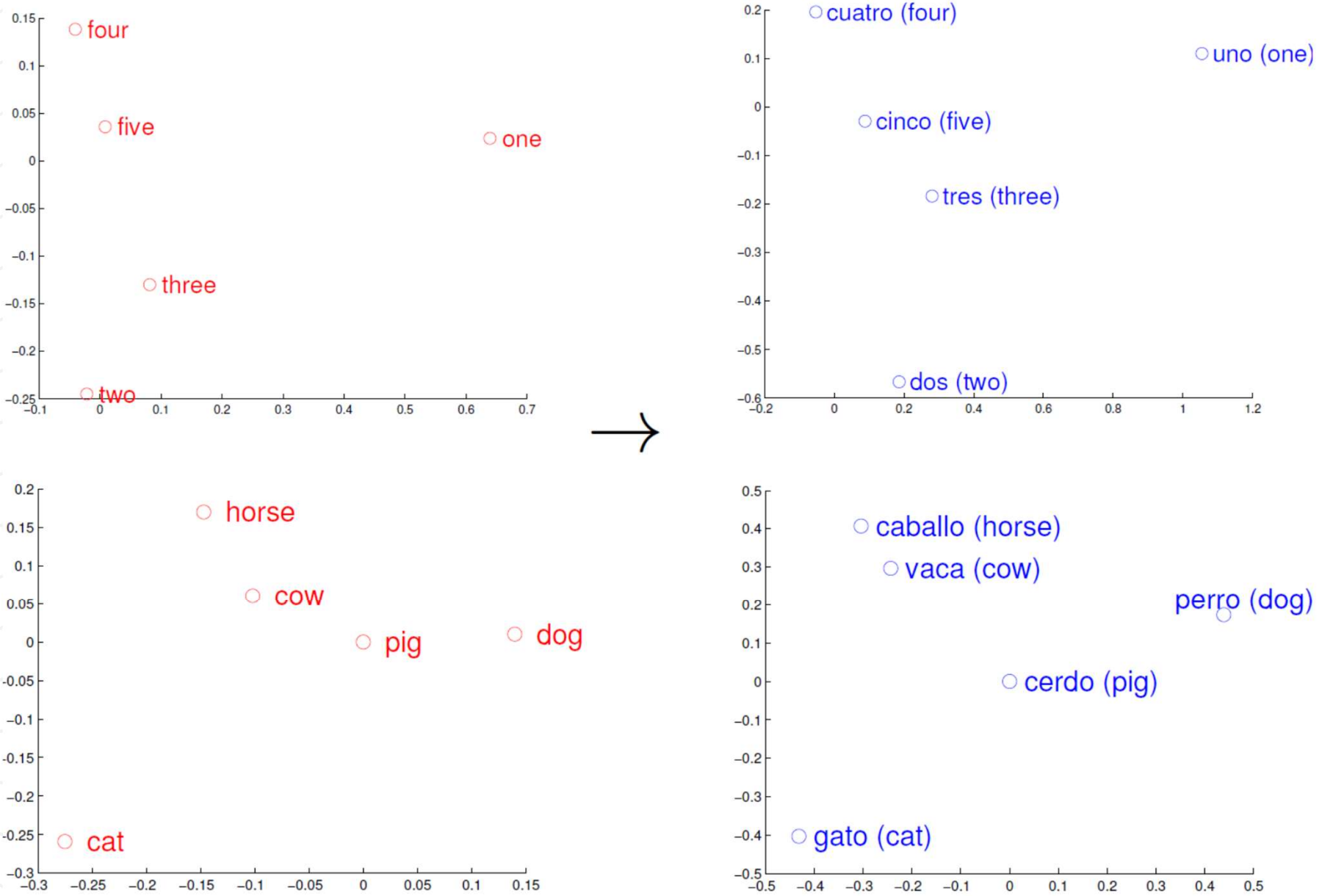
		sg	cbow	sisg-	sisg
AR	WS353	51	52	54	**55**
DE	GUR350	61	62	64	**70**
	GUR65	78	78	**81**	**81**
	ZG222	35	38	41	**44**
EN	RW	43	43	46	**47**
	WS353	72	**73**	71	71
ES	WS353	57	58	58	**59**
FR	RG65	70	69	**75**	**75**
RO	WS353	48	52	51	**54**
RU	HJ	59	60	60	**66**

Correlation with human judgement of word similarity: big boost for languages with rich morphology (e.g. Ru)

		sg	cbow	sisg
CS	Semantic	25.7	27.6	27.5
	Syntactic	52.8	55.0	77.8
DE	Semantic	66.5	66.8	62.3
	Syntactic	44.5	45.0	56.4
EN	Semantic	78.5	78.2	77.8
	Syntactic	70.1	69.9	74.9
IT	Semantic	52.3	54.7	52.3
	Syntactic	51.5	51.8	62.7

Word analogy: huge boost in syntactic, mild degradation in semantic

Going cross-lingual

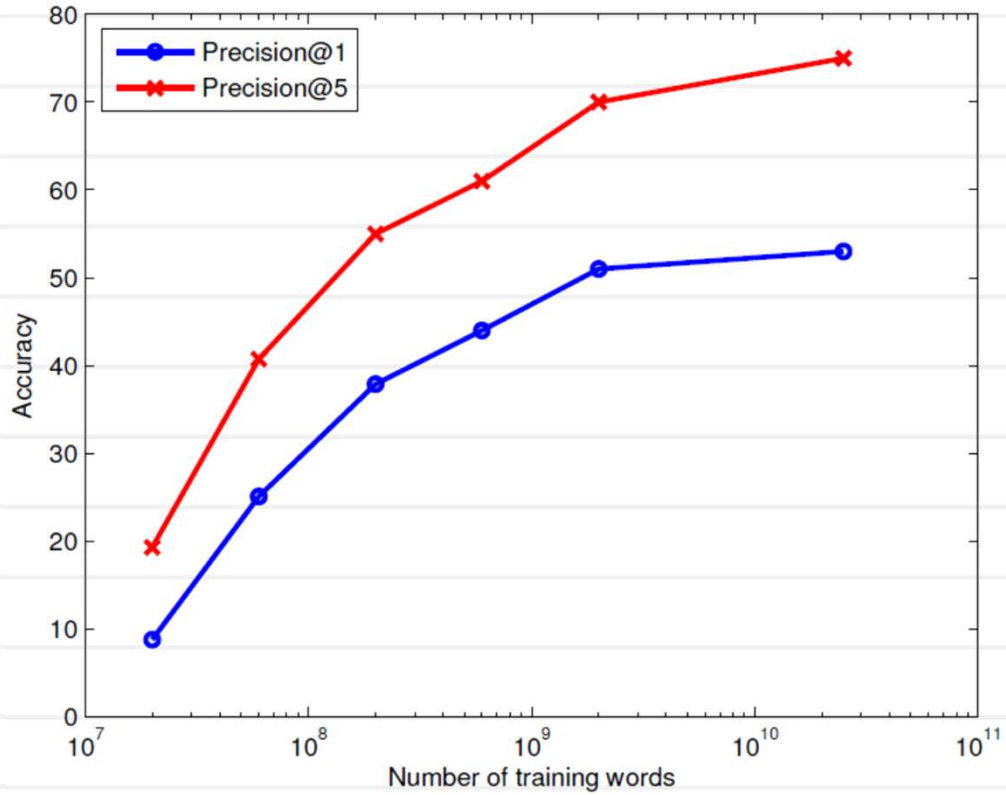


[Mikolov et al. 2013]

Going cross-lingual

$$\min_W \sum_{i=1}^{n} \|Wx_i - z_i\|^2$$

Train on 5K most frequent



Influence of word2vec training set

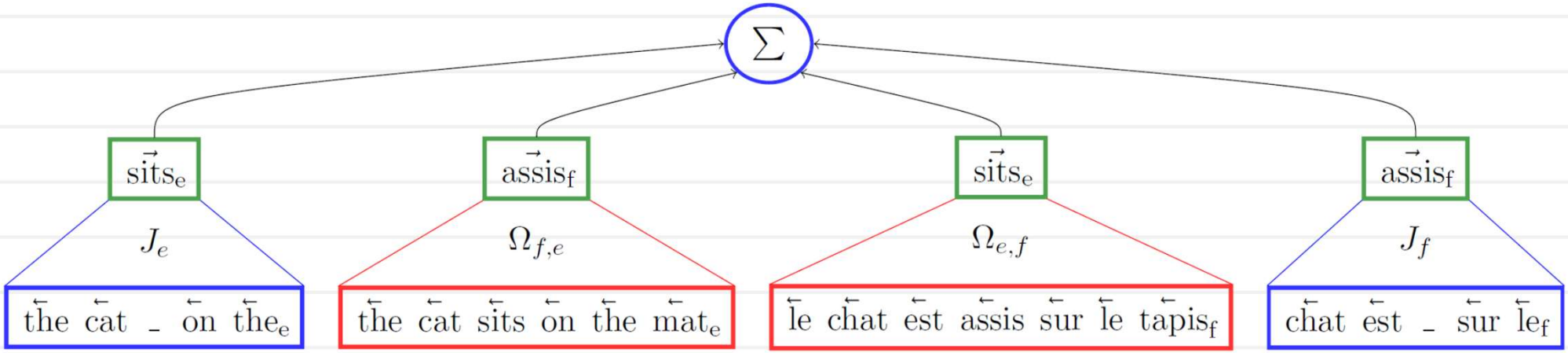
Spanish word	Computed English Translations	Dictionary Entry
emociones	emotions emotion feelings	emotions
protegida	wetland undevelopable protected	protected
imperio	dictatorship imperialism tyranny	empire
determinante	crucial key important	determinant
preparada	prepared ready prepare	prepared
millas	kilometers kilometres miles	miles
hablamos	talking talked talk	talk
destacaron	highlighted emphasized emphasised	highlighted

[Mikolov et al. 2013]

Trans-gram model

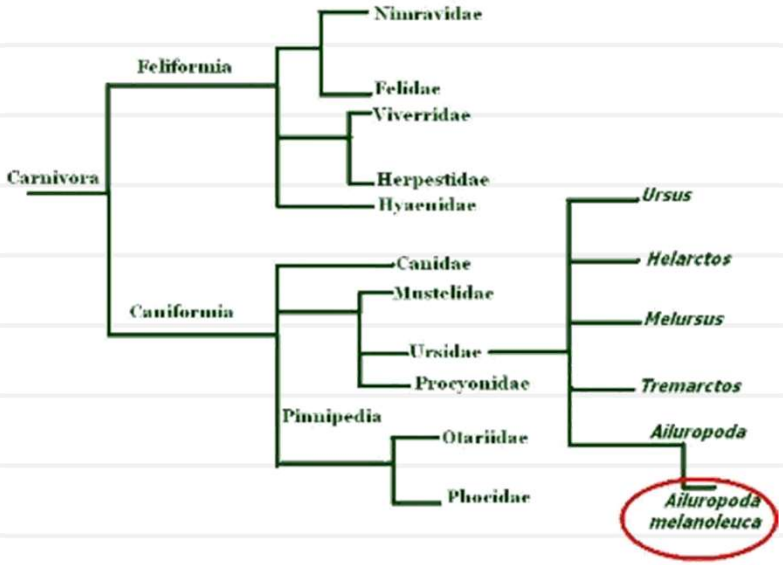
Trains from:

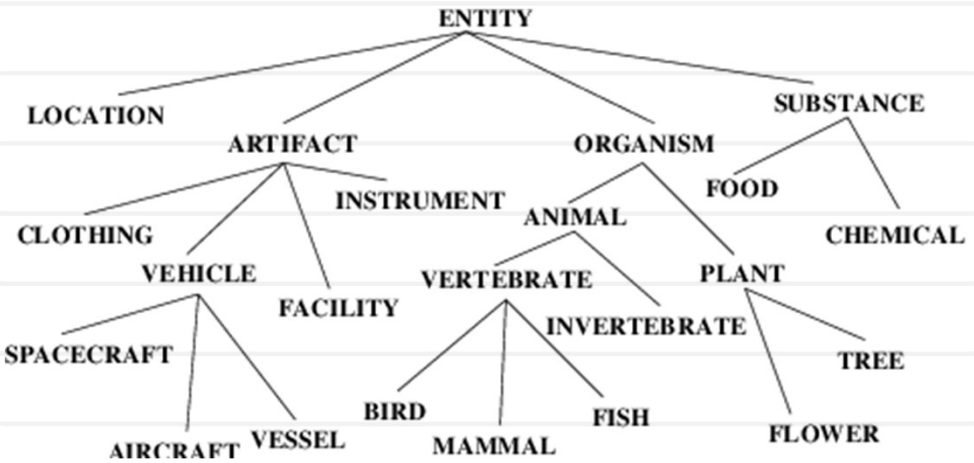
- Mono-lingual French corpus
- Mono-lingual English corpus
- Sentence-level aligned parallel corpus



[Coulmance et al. EMNLP15]

Hyperbolic embeddings: motivation



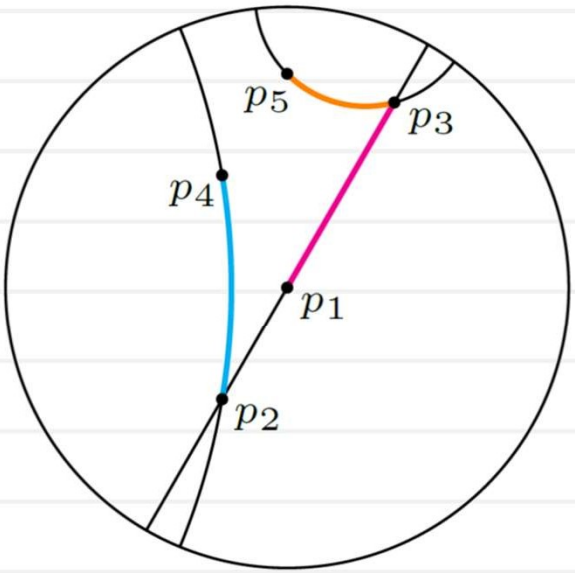


We often seek embeddings that embed tree-like graphs with low distortion:

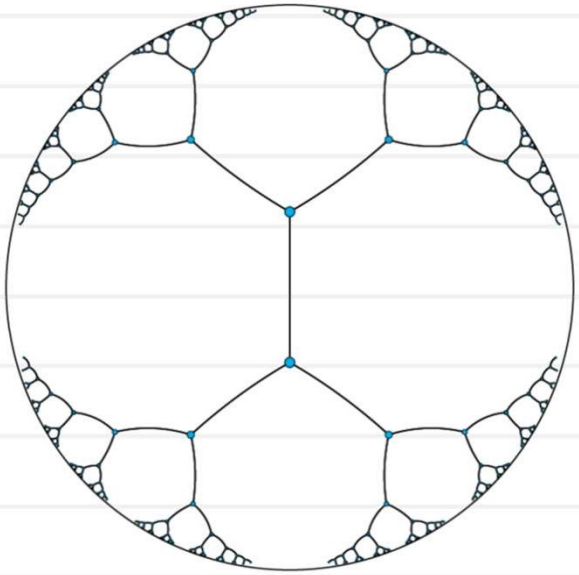
- The graph may be given to us
- The graph structure can be implicit (latent) in our data

Euclidean spaces are not good for embedding tree-like graphs with low distortion

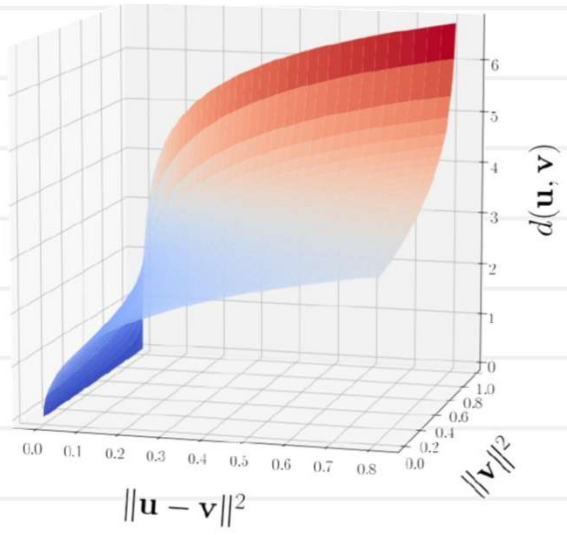
Poincare embeddings



(a) Geodesics of the Poincaré disk



(b) Embedding of a tree in $\mathcal{B}^2$



(c) Growth of Poincaré distance

Metric tensor:

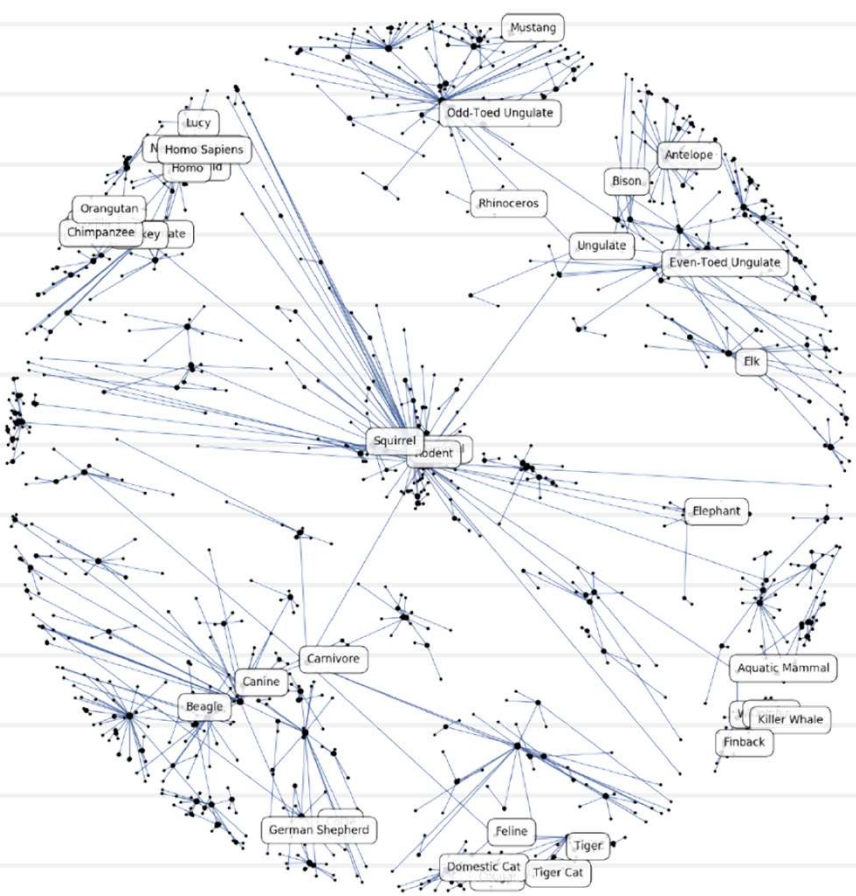
$$g_{\boldsymbol{x}} = \left(\frac{2}{1 - \|\boldsymbol{x}\|^2}\right)^2 g^E$$

Distance:

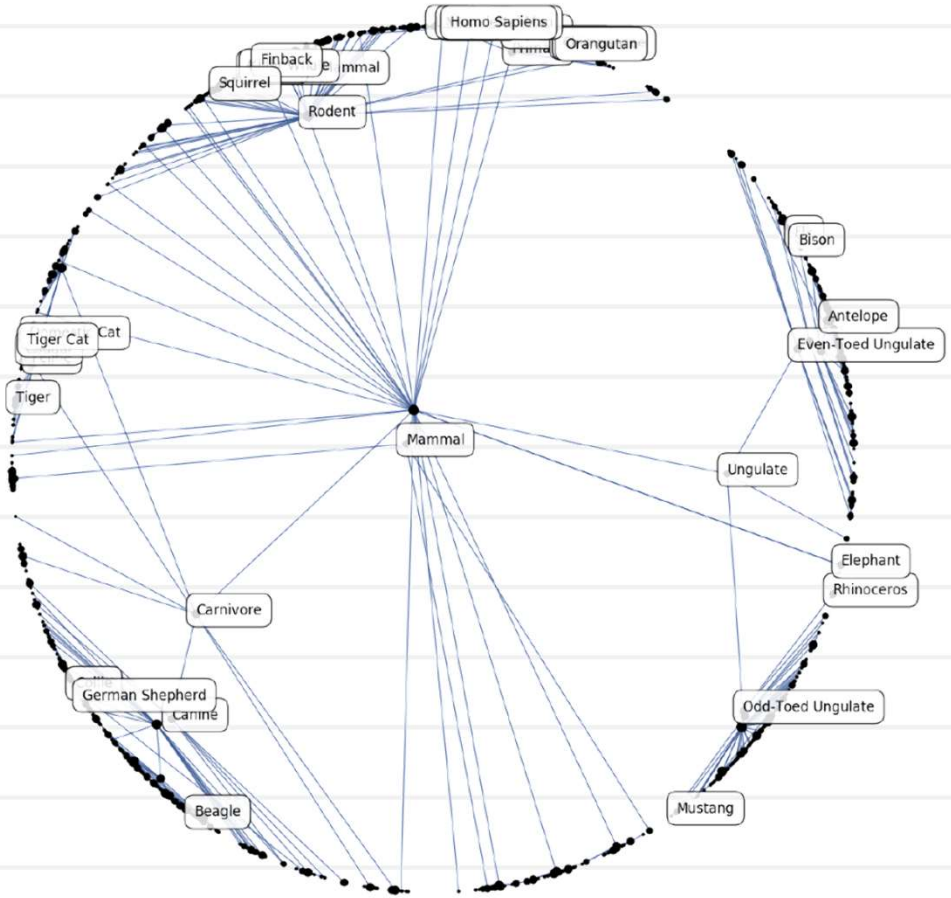
$$d(\boldsymbol{u}, \boldsymbol{v}) = \operatorname{arcosh}\left(1 + 2\frac{\|\boldsymbol{u} - \boldsymbol{v}\|^2}{(1 - \|\boldsymbol{u}\|^2)(1 - \|\boldsymbol{v}\|^2)}\right)$$

[Nickel Kiela NIPS17]

Poincare embeddings: WordNet mammals



(a) Intermediate embedding after 20 epochs



(b) Embedding after convergence

$$\mathcal{L}(\Theta) = \sum_{(u,v)\in\mathcal{D}} \log \frac{e^{-d(\boldsymbol{u},\boldsymbol{v})}}{\sum_{\boldsymbol{v}'\in\mathcal{N}(u)} e^{-d(\boldsymbol{u},\boldsymbol{v}')}}$$

[Nickel Kiela NIPS17]

Poincare embeddings: citation graph

Co-authorship probability:

$$P((u,v)=1 \mid \Theta) = \frac{1}{e^{(d(\boldsymbol{u},\boldsymbol{v})-r)/t}+1}$$

Maximum likelihood learning

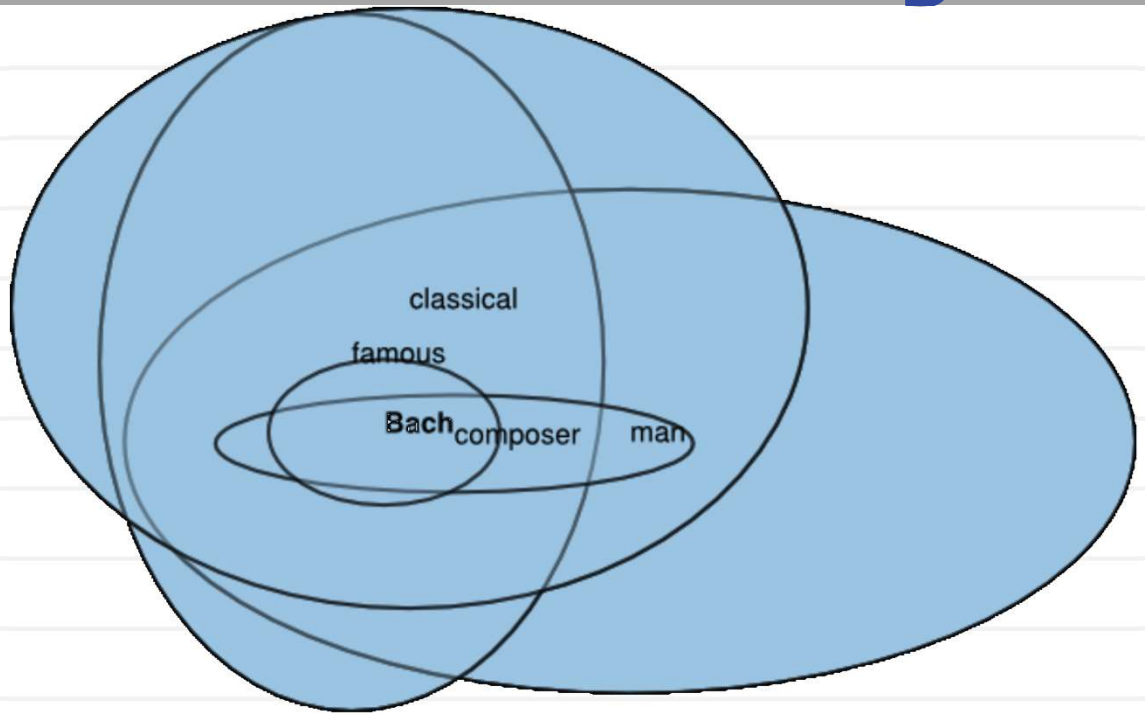
In prediction task, info for some pairs withdrawn (*r* and *t* tuned on the validation set)

Table 2: Mean average precision for Reconstruction and Link Prediction on network data.

		Dimensionality							
		Reconstruction				Link Prediction			
		10	20	50	100	10	20	50	100
AstroPh	**Euclidean**	0.376	0.788	0.969	0.989	0.508	0.815	0.946	0.960
N=18,772; E=198,110	**Poincaré**	0.703	0.897	0.982	0.990	0.671	0.860	0.977	0.988
CondMat	**Euclidean**	0.356	0.860	0.991	0.998	0.308	0.617	0.725	0.736
N=23,133; E=93,497	**Poincaré**	0.799	0.963	0.996	0.998	0.539	0.718	0.756	0.758
GrQc	**Euclidean**	0.522	0.931	0.994	0.998	0.438	0.584	0.673	0.683
N=5,242; E=14,496	**Poincaré**	0.990	0.999	0.999	0.999	0.660	0.691	0.695	0.697
HepPh	**Euclidean**	0.434	0.742	0.937	0.966	0.642	0.749	0.779	0.783
N=12,008; E=118,521	**Poincaré**	0.811	0.960	0.994	0.997	0.683	0.743	0.770	0.774

[Nickel Kiela NIPS17]

Gaussian embeddings



- Words embedded as Gaussians with diagonal covariances
- NB: Gaussians with KL divergence form hyperbolic geometry

$$-E(P_i, P_j) = D_{KL}(\mathcal{N}_j||\mathcal{N}_i) = \int_{x\in\mathbb{R}^n} \mathcal{N}(x;\mu_i,\Sigma_i)\log\frac{\mathcal{N}(x;\mu_j,\Sigma_j)}{\mathcal{N}(x;\mu_i,\Sigma_i)}dx$$

$$= \frac{1}{2}(\mathrm{tr}(\Sigma_i^{-1}\Sigma_j) + (\mu_i-\mu_j)^\top\Sigma_i^{-1}(\mu_i-\mu_j) - d - \log\frac{\det(\Sigma_j)}{\det(\Sigma_i)})$$

[Vilnis & McCallum ICLR15]

Gaussian embeddings

- Words embedded as Gaussians with diagonal covariances
- NB: Gaussians with KL divergence form hyperbolic geometry

Query Word	Nearby Words, Descending Variance
rock	mix sound blue folk jazz rap avant hardcore chillout shoegaze powerpop electroclash
food	drink meal meat diet spice juice bacon soya gluten stevia
feeling	sense mind mood perception compassion sadness coldness sincerity perplexity diffidence joviality
algebra	theory graph equivalence finite predicate congruence topology quaternion symplectic homomorphism

Figure 2: Elements of the top 100 nearest neighbor sets for chosen query words, sorted by descending variance (as measured by determinant of covariance matrix). Note that less specific and more ambiguous words have greater variance.

[Vilnis & McCallum ICLR15]

Recap

- NLP tasks are amenable to deep learning methods
- Char-level NLP is promising
- *Peculiarity 1:* mapping words to vectors (embedding layers)
- *Peculiarity 2:* variable sentence length (more next time)
- Lots of success with predictive learning
- Today's lecture: primer (word-level predictive learning), next lectures going to sentences and beyond

Bibliography

Douglas L. T. Rohde, Laura M. Gonnerman, and David C. Plaut. 2006. An improved model of semantic similarity based on lexical co-occurence. Communications of the ACM, 8:627–633.

Yoshua Bengio, Réjean Ducharme, Pascal Vincent, Christian Janvin: A Neural Probabilistic Language Model. Journal of Machine Learning Research 3: 1137-1155 (2003)

Karlin, Nurit. The Fat Cat Sat on the Mat. New York: HarperCollins, 1996

Tomas Mikolov, Ilya Sutskever, Kai Chen, Gregory S. Corrado, Jeffrey Dean:
Distributed Representations of Words and Phrases and their Compositionality. NIPS 2013: 3111-3119

Carl Doersch, Abhinav Gupta, Alexei A. Efros:
Unsupervised Visual Representation Learning by Context Prediction. ICCV 2015: 1422-1430

Bibliography

Tomas Mikolov, Kai Chen, Greg Corrado, Jeffrey Dean:
Efficient Estimation of Word Representations in Vector Space. CoRR abs/1301.3781 (2013)

Mnih, A. and Hinton, G.~E. A Scalable Hierarchical Distributed Language Model. NIPS 2009

Ronan Collobert, Jason Weston, Léon Bottou, Michael Karlen, Koray Kavukcuoglu, Pavel P. Kuksa:
Natural Language Processing (Almost) from Scratch. Journal of Machine Learning Research 12: 2493-2537 (2011)

Nal Kalchbrenner, Edward Grefenstette, Phil Blunsom:
A Convolutional Neural Network for Modelling Sentences. ACL (1) 2014: 655-665

Jocelyn Coulmance, Jean-Marc Marty, Guillaume Wenzek, Amine Benhalloum:Trans-gram, Fast Cross-lingual Word-embeddings. EMNLP 2015: 1109-1113

Bibliography

Vilnis, L., & McCallum, A. Word Representations via Gaussian Embedding. ICLR 2015

Piotr Bojanowski, Edouard Grave, Armand Joulin, Tomas Mikolov: Enriching Word Vectors with Subword Information. ACL 5: 135-146 (2017)

Maximilian Nickel, Douwe Kiela: Poincaré Embeddings for Learning Hierarchical Representations. NIPS 2017: 6341-6350