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Natural Language Processing; Text Classification

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Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank

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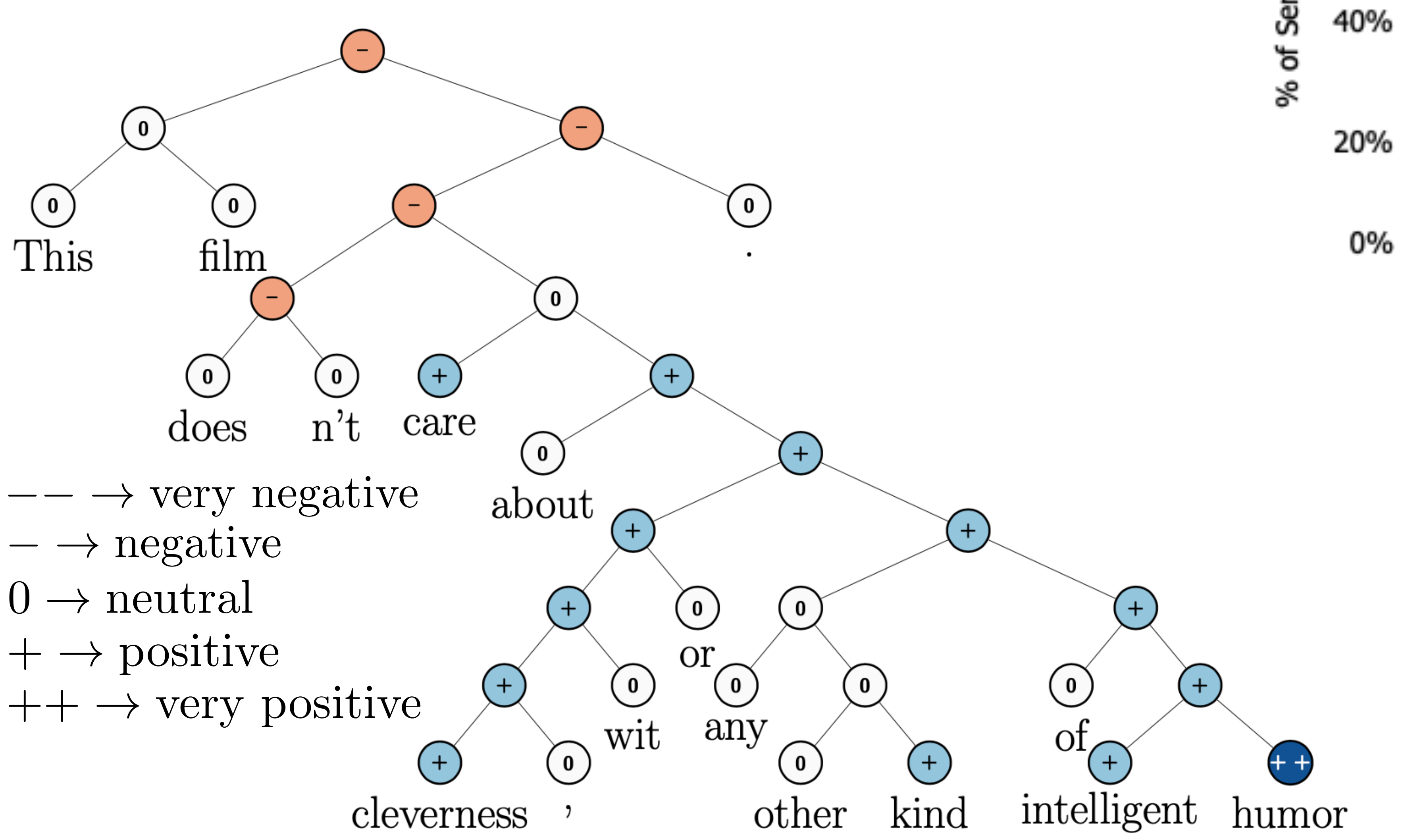
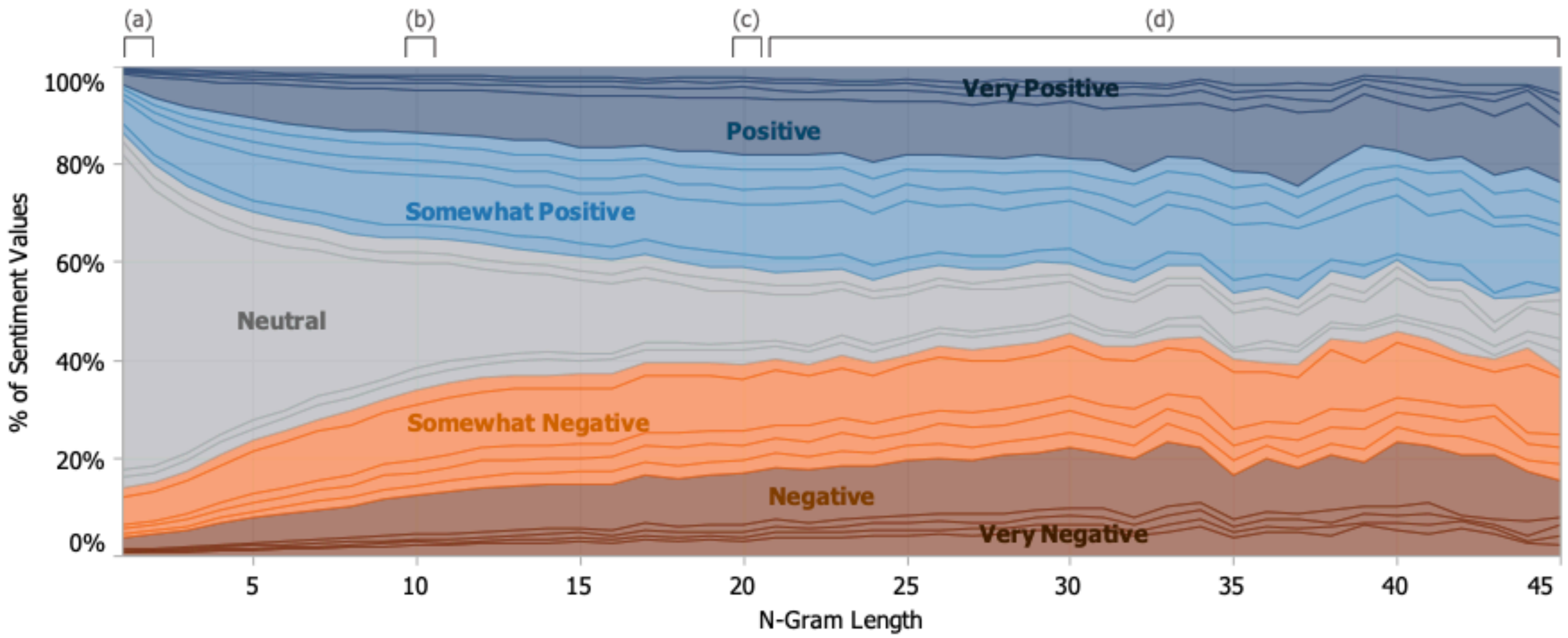
Stanford Sentiment Treebank

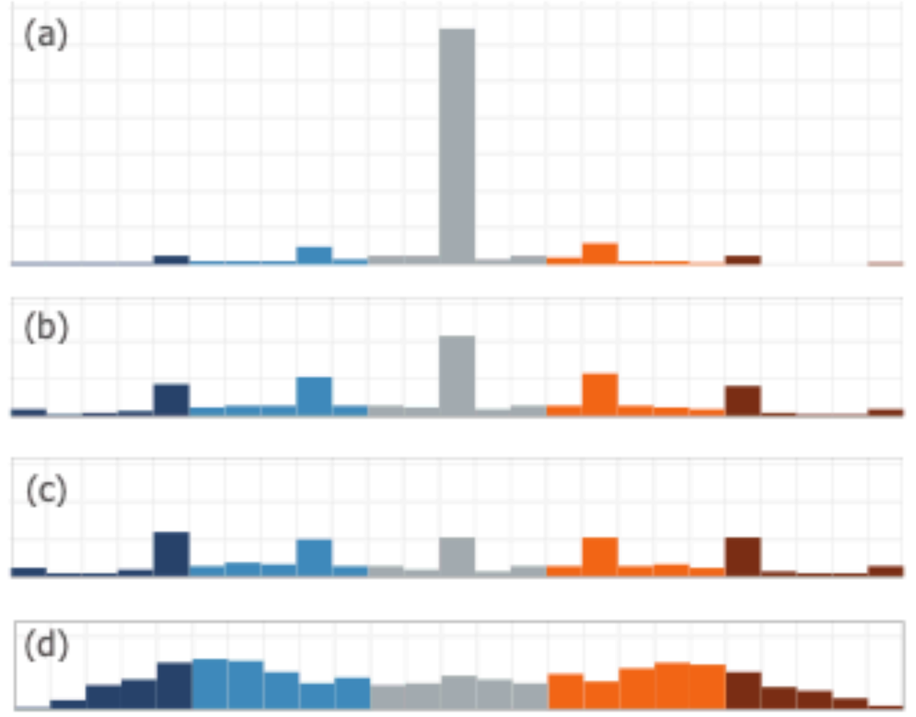
11,855 single sentences from movie reviews (https://www.rottentomatoes.com)

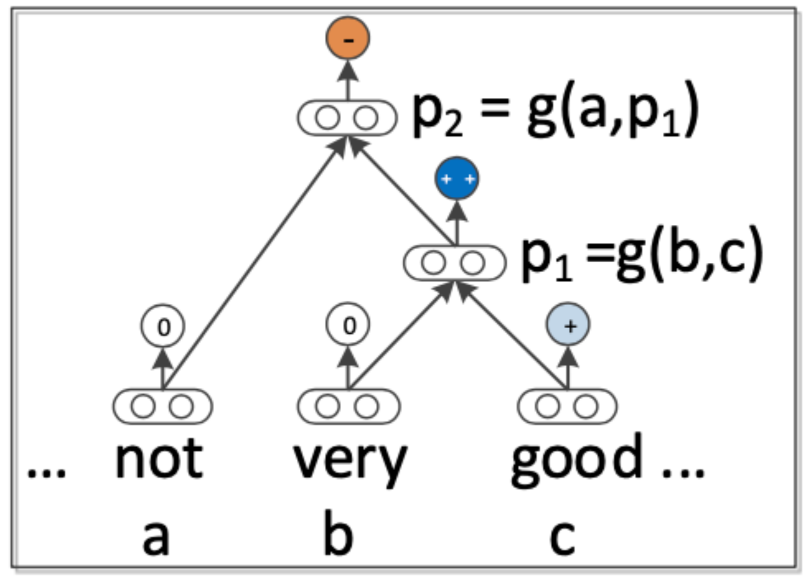
215,154 unique phrases from parse trees obtained from Stanford parser





Distributions of sentiment values for (a) unigrams, (b) 10-grams, (c) 20-grams, and (d) full sentences.





$L \in \mathbb{R}^{d \times |V|}$ vocabulary size

word embedding matrix

$y^a = \text{softmax}(W_s a)$

$W_s \in \mathbb{R}^{5 \times d}$

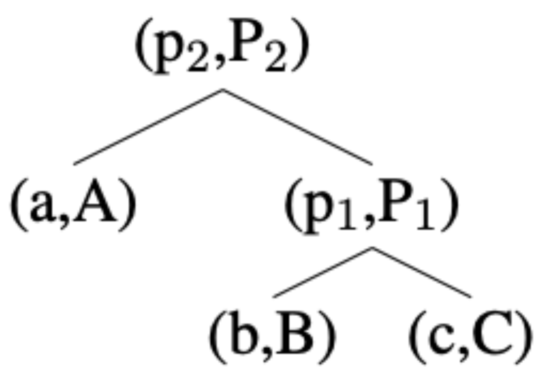
repeated for vectors b & c

Recursive Neural Netwok

$$p_1 = f\left(W \begin{bmatrix} b \\ c \end{bmatrix}\right), p_2 = f\left(W \begin{bmatrix} a \\ p_1 \end{bmatrix}\right)$$

$$f = \tanh, W \in \mathbb{R}^{d \times 2d}$$

Matrix-Vector Recursive NN



$$p_1 = f\left(W \begin{bmatrix} Cb \\ Bc \end{bmatrix}\right), P_1 = f\left(W_M \begin{bmatrix} B \\ C \end{bmatrix}\right)$$

word's matrix

Recursive Neural Tensor Network

$$h = \begin{bmatrix} b \\ c \end{bmatrix}^T V^{[1:d]}_{2d \times 2d \times d} \begin{bmatrix} b \\ c \end{bmatrix}; h_i = \begin{bmatrix} b \\ c \end{bmatrix}^T V^{[i]}_{2d \times 2d} \begin{bmatrix} b \\ c \end{bmatrix}$$

$$p_1 = f\left(\begin{bmatrix} b \\ c \end{bmatrix}^T V^{[1:d]} \begin{bmatrix} b \\ c \end{bmatrix} + W \begin{bmatrix} b \\ c \end{bmatrix}\right)$$

$$p_2 = f\left(\begin{bmatrix} a \\ p_1 \end{bmatrix}^T V^{[1:d]} \begin{bmatrix} a \\ p_1 \end{bmatrix} + W \begin{bmatrix} a \\ p_1 \end{bmatrix}\right)$$

$$E(\theta) = \sum_i \sum_j t_j^i \log y_j^i + \lambda \|\theta\|^2$$

$$\theta = (V, W, W_s, L)$$

$y^i \in \mathbb{R}^{C \times 1}$ → predicted distribution at node i

$t^i \in \mathbb{R}^{C \times 1}$ → target distribution at node i

Socher, Richard, et al. "Recursive deep models for semantic compositionality over a sentiment treebank." *Proceedings of the 2013 conference on empirical methods in natural language processing*. 2013.

Convolutional Neural Networks for Sentence Classification

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$x_i \in \mathbb{R}^k \rightarrow$ i-th word in the sentence

$x = (x_1, x_2, \dots, x_n) \rightarrow$ sentence of length n

$W = (W_1, W_2, \dots, W_h) \rightarrow$ filter

$W_j \in \mathbb{R}^{m \times k} \qquad b \in \mathbb{R}^m$

$$c_i = f\left(\sum_{j=1}^{h} W_j x_{i+j-1} + b\right)$$

$c_i \in \mathbb{R}^m$

$c = (c_1, c_2, \dots, c_{n-h+1})$

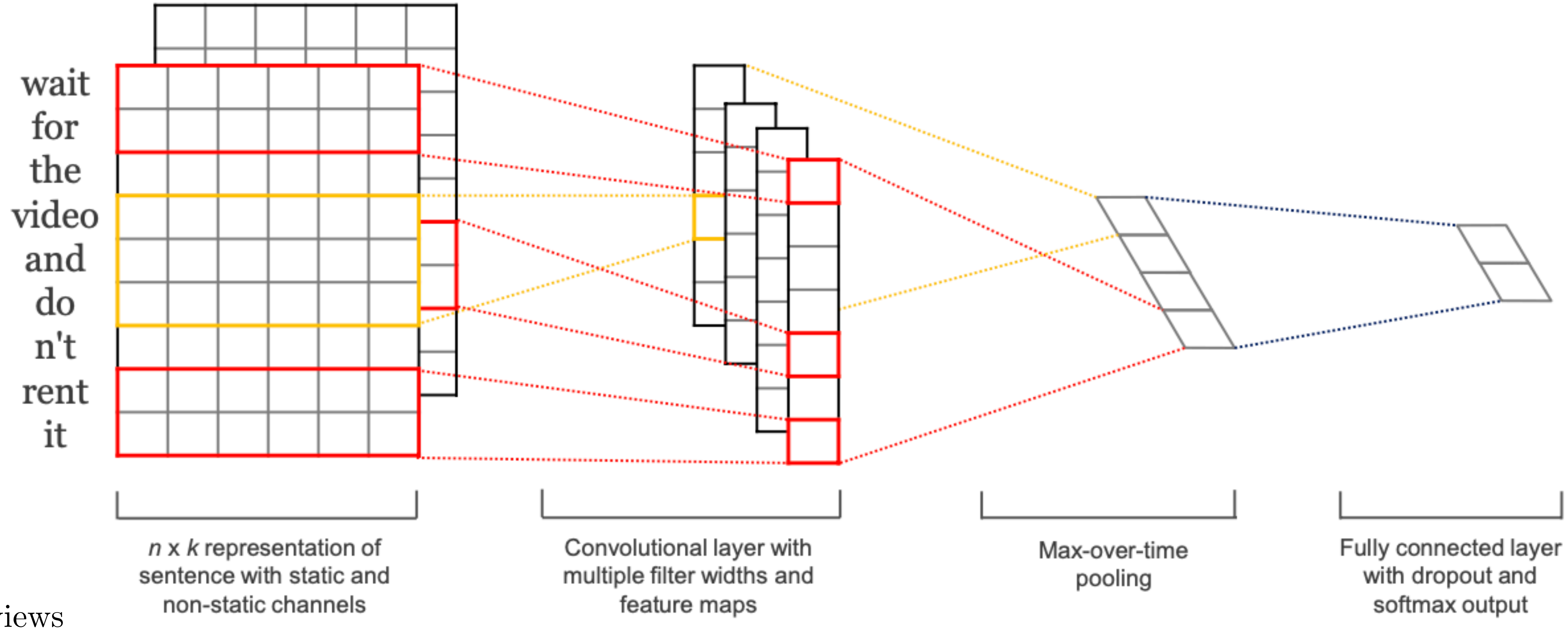
$z = \max_i c_i$

$y = W^y z + b^y$

$y = W^y (z \odot r) + b^y \rightarrow$ dropout

$\Pr(r = 1) = p = 1 - \Pr(r = 0)$

$\hat{W}^y = p W^y \rightarrow$ during testing



Movie Reviews

Stanford Sentiment Treebank

Subjectivity

Question

Customer reviews

Opinion polarity detection

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

c: Number of target classes, l: Average sentence length

Data	c	l	N	$\lvert V \rvert$	$\lvert V_{pre} \rvert$	***Test***
MR	2	20	10662	18765	16448	CV
SST-1	5	18	11855	17836	16262	2210
SST-2	2	19	9613	16185	14838	1821
Subj	2	23	10000	21323	17913	CV
TREC	6	10	5952	9592	9125	500
CR	2	19	3775	5340	5046	CV
MPQA	2	3	10606	6246	6083	CV

Kim, Yoon. "Convolutional neural networks for sentence classification." *arXiv preprint arXiv:1408.5882* (2014).

Distributed Representations of Sentences and Documents

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Bag-of-words weaknesses:

1) lose ordering of words
2) ignore semantics of words

"powerful" should be closer to "strong" than "Paris"

Vector Representation of Words

$W \rightarrow$ word matrix

$w_1, w_2, \ldots, w_T \rightarrow$ sequence of training words

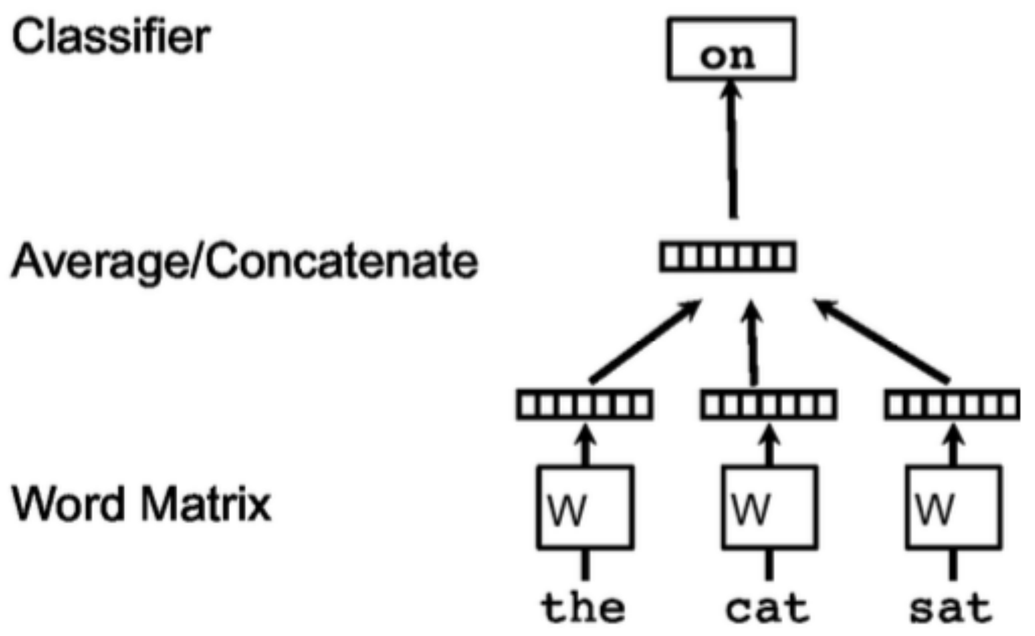
$$\frac{1}{T}\sum_{t=k}^{T-k} \log p(w_t | w_{t-k}, \ldots, w_{t+k})$$

$$p(w_t | w_{t-k}, \ldots, w_{t+k}) = \frac{e^{y_{w_t}}}{\sum_i e^{y_i}}$$

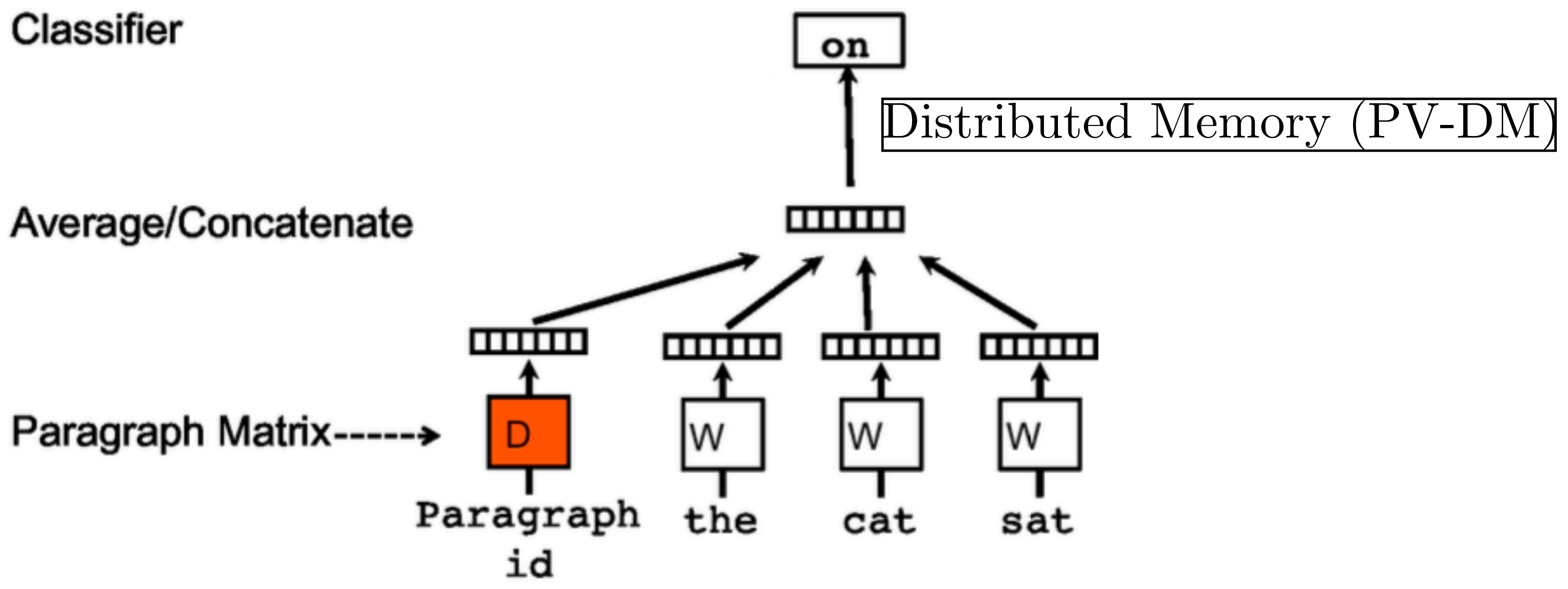
$$y = b + U\underbrace{h(w_{t-k}, \ldots, w_{t+k}; W)}$$

concatenation or average of word vectors extracted from W

hierarchical softmax & Huffman coding



Paragraph Vector



unsupervised training: optimize for D, W, U, b

inference: optimize for D_{test} given W, U, b

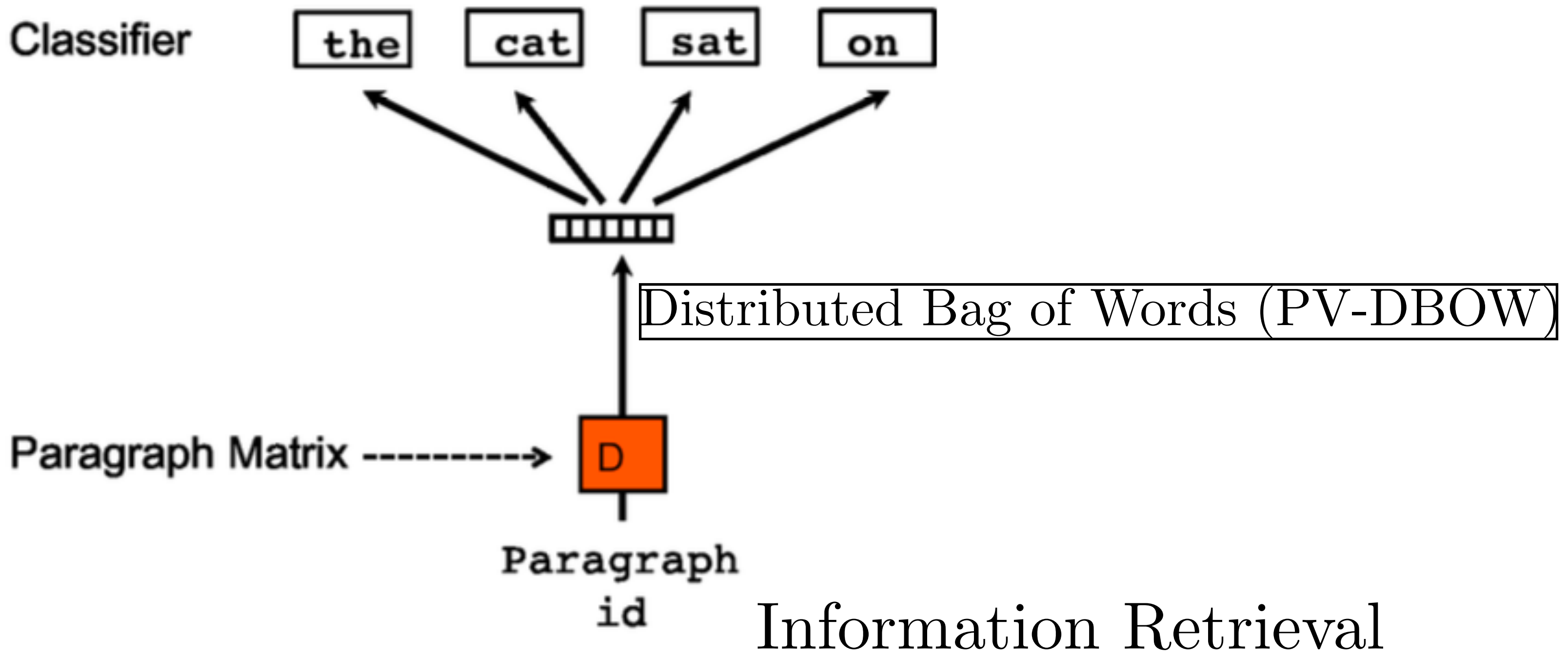
logistic classifier or support vector machines on D_{test}

IMDB dataset

Model	Error rate
BoW (bnc) (Maas et al., 2011)	12.20 %
BoW (bΔt'c) (Maas et al., 2011)	11.77%
LDA (Maas et al., 2011)	32.58%
Full+BoW (Maas et al., 2011)	11.67%
Full+Unlabeled+BoW (Maas et al., 2011)	11.11%
WRRBM (Dahl et al., 2012)	12.58%
WRRBM + BoW (bnc) (Dahl et al., 2012)	10.77%
MNB-uni (Wang & Manning, 2012)	16.45%
MNB-bi (Wang & Manning, 2012)	13.41%
SVM-uni (Wang & Manning, 2012)	13.05%
SVM-bi (Wang & Manning, 2012)	10.84%
NBSVM-uni (Wang & Manning, 2012)	11.71%
NBSVM-bi (Wang & Manning, 2012)	8.78%
Paragraph Vector	**7.42%**

Stanford Sentiment Treebank

Model	Error rate (Positive/ Negative)	Error rate (Fine-grained)
Naïve Bayes (Socher et al., 2013b)	18.2 %	59.0%
SVMs (Socher et al., 2013b)	20.6%	59.3%
Bigram Naïve Bayes (Socher et al., 2013b)	16.9%	58.1%
Word Vector Averaging (Socher et al., 2013b)	19.9%	67.3%
Recursive Neural Network (Socher et al., 2013b)	17.6%	56.8%
Matrix Vector-RNN (Socher et al., 2013b)	17.1%	55.6%
Recursive Neural Tensor Network (Socher et al., 2013b)	14.6%	54.3%
Paragraph Vector	**12.2%**	**51.3%**



Information Retrieval

Model	Error rate
Vector Averaging	10.25%
Bag-of-words	8.10 %
Bag-of-bigrams	7.28 %
Weighted Bag-of-bigrams	5.67%
Paragraph Vector	**3.82%**

Le, Quoc, and Tomas Mikolov. "Distributed representations of sentences and documents." *International conference on machine learning*. 2014.

Effective Use of Word Order for Text Categorization with Convolutional Neural Networks

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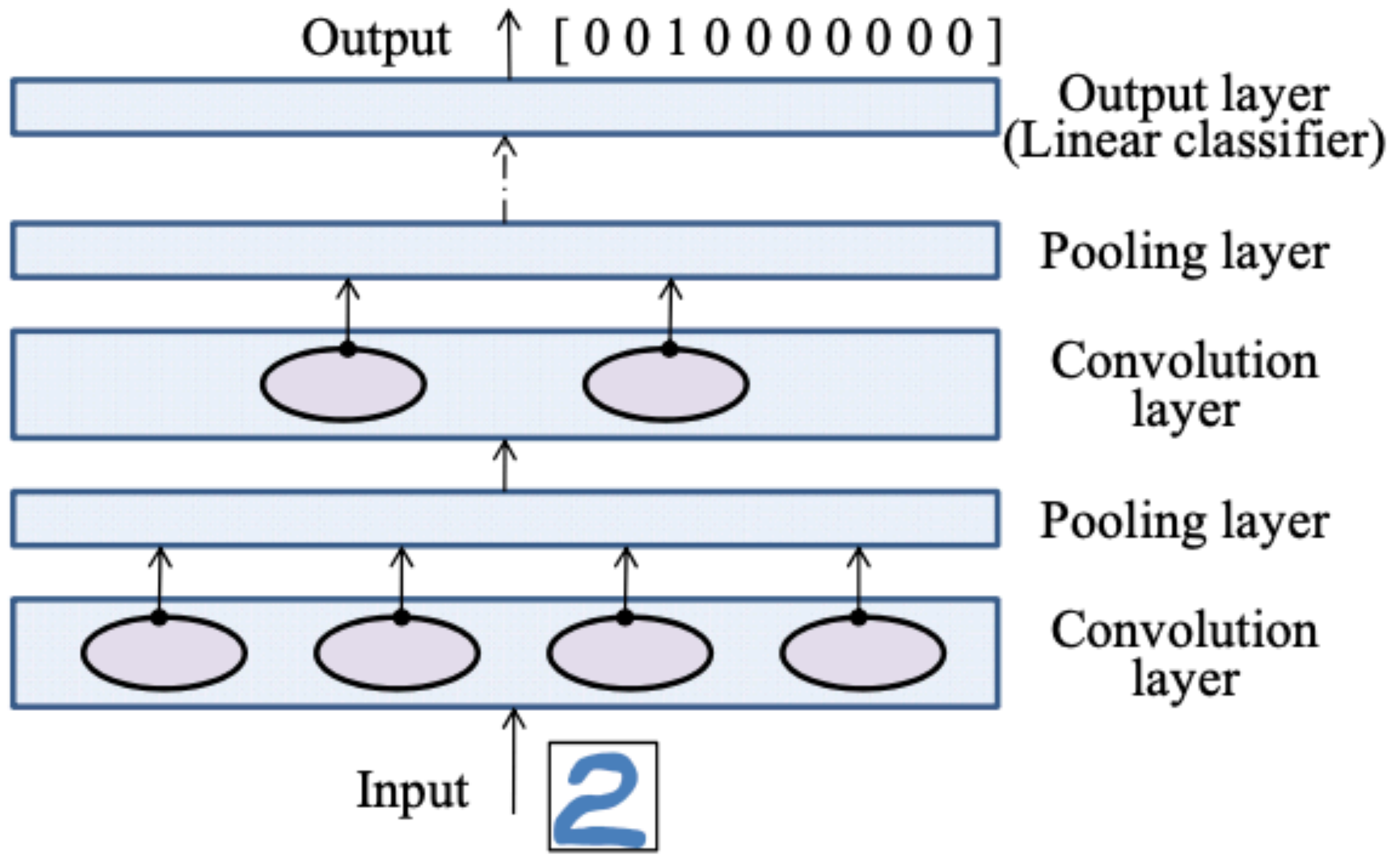

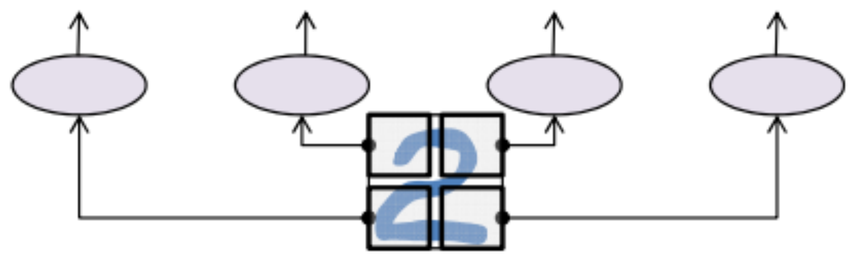

$$\boldsymbol{\sigma}(\mathbf{W}\cdot\mathbf{r}_\ell(\mathbf{x})+\mathbf{b})$$

CNN for text

$V = \{$ "don't", "hate", "I", "it", "love" $\}$ — vocabulary

D="I love it" — document

$$\mathbf{x} = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{matrix} \to \text{I} \\ \to \text{love} \\ \to \text{it} \end{matrix}$$

Seq-CNN

$$\mathbf{r}_0(\mathbf{x}) = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{matrix} \to \text{I} \\ \to \text{love} \end{matrix}$$

$$\mathbf{r}_1(\mathbf{x}) = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{matrix} \to \text{love} \\ \to \text{it} \end{matrix}$$

$$\mathbf{w}^k = \begin{bmatrix} w^k_{11} & w^k_{12} & w^k_{13} & w^k_{14} & w^k_{15} \\ w^k_{21} & w^k_{22} & w^k_{23} & w^k_{24} & w^k_{25} \end{bmatrix}$$

$$h^k_0 = \sigma(\mathbf{w}^k \cdot \mathbf{r}_0(\mathbf{x}) + b^k) = \sigma(w^k_{13} + w^k_{25} + b^k)$$

$$h^k_1 = \sigma(\mathbf{w}^k \cdot \mathbf{r}_1(\mathbf{x}) + b^k) = \sigma(w^k_{15} + w^k_{24} + b^k)$$

$$\mathbf{h}_0 = [h^1_0, \ldots, h^K_0]$$

$$\mathbf{h}_1 = [h^1_1, \ldots, h^K_1]$$

BOW-CNN

$$\mathbf{r}_0(\mathbf{x}) = [0, 0, 1, 0, 1]$$

$$\mathbf{r}_1(\mathbf{x}) = [0, 0, 0, 1, 1]$$

$$\mathbf{w}^k = [w^k_1, w^k_2, w^k_3, w^k_4, w^k_5]$$

$$h^k_0 = \sigma(\mathbf{w}^k \cdot \mathbf{r}_0(\mathbf{x}) + b^k) = \sigma(w^k_3 + w^k_5 + b^k)$$

$$h^k_1 = \sigma(\mathbf{w}^k \cdot \mathbf{r}_1(\mathbf{x}) + b^k) = \sigma(w^k_4 + w^k_5 + b^k)$$

Pooling for text

fix the number of pooling units and dynamically determine the pooling region size

methods	IMDB
bow-CNN	8.66
seq-CNN	8.39

predictive text regions (training set)

N1	completely useless ., return policy .
N2	it won't even, but doesn't work
N3	product is defective, very disappointing !
N4	is totally unacceptable, is so bad
N5	was very poor, it has failed
P1	works perfectly !, love this product
P2	very pleased !, super easy to, i am pleased
P3	'm so happy, it works perfect, is awesome !
P4	highly recommend it, highly recommended !
P5	am extremely satisfied, is super fast

predictive text regions (test set)

were unacceptably bad, is abysmally bad, were universally poor, was hugely disappointed, was enormously disappointed, is monumentally frustrating, are endlessly frustrating
best concept ever, best ideas ever, best hub ever, am wholly satisfied, am entirely satisfied, am incredicbly satisfied, 'm overall impressed, am awfully pleased, am exceptionally pleased, 'm entirely happy, are acoustically good, is blindingly fast,

Johnson, Rie, and Tong Zhang. "Effective use of word order for text categorization with convolutional neural networks." *arXiv preprint arXiv:1412.1058* (2014).

A Convolutional Neural Network for Modelling Sentences

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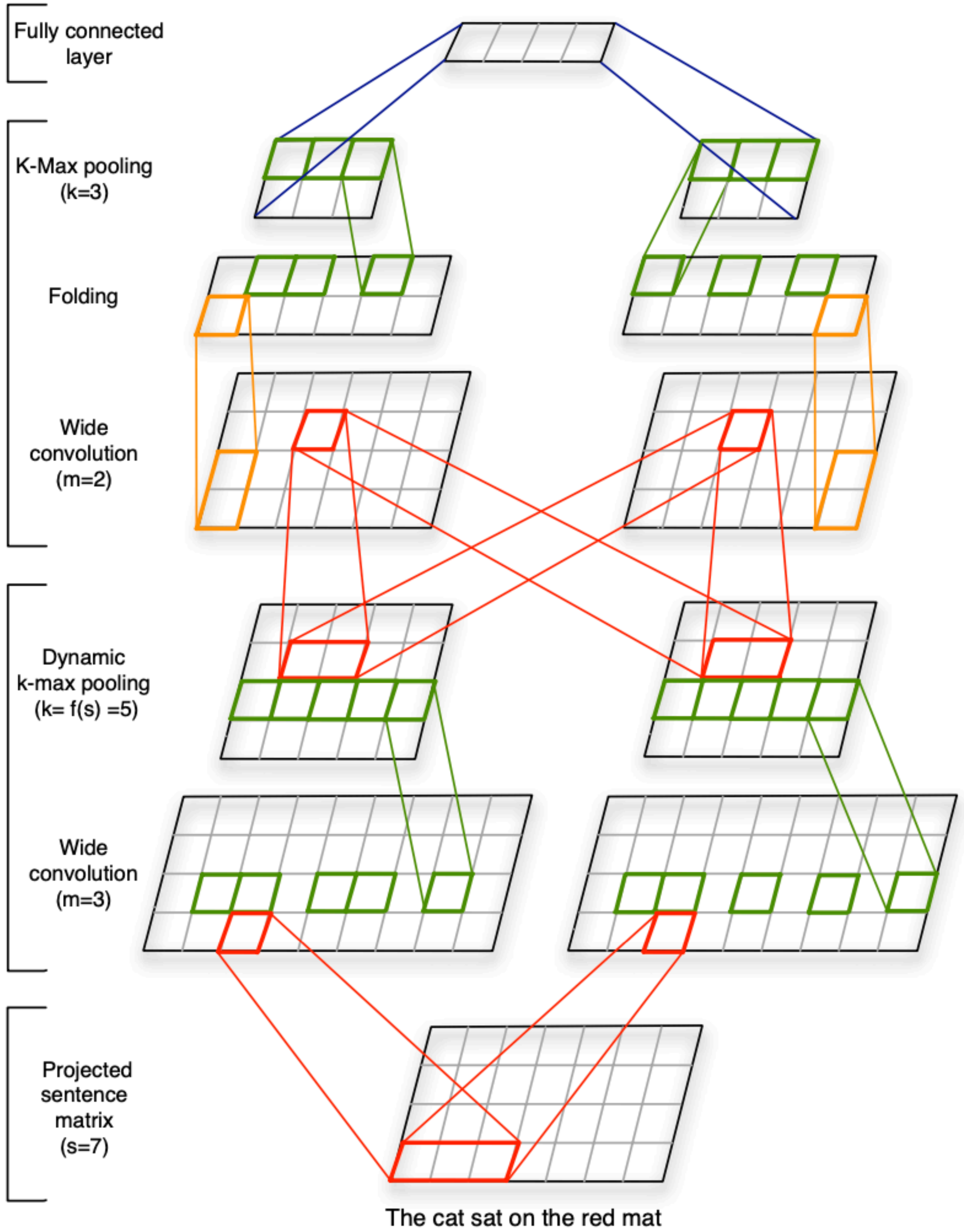
YouTube Video



Dynamic Convolutional Neural Network (DCNN)

$x \in \mathbb{R}^{d \times s} \rightarrow$ sentence matrix

$x = [x_1, x_2, \ldots, x_s], x_j \in \mathbb{R}^d \rightarrow$ embedding vector of word j in the sentence

$w \in \mathbb{R}^{d \times m} \rightarrow$ matrix of weights

$y_{ij} = w_{i,1:m}^T x_{i,j-m+1:j}, i = 1, \ldots, d, j = 1, \ldots, s+m-1 \rightarrow$ channel-wise convolution

$y \in \mathbb{R}^{d \times p}, p = s + m - 1$

Out-of-range input values $x_{i,j-m+1:j}$ for $j < m$ or $j > s$ are taken to be zero!

k-max pooling

$y_i \in \mathbb{R}^p \rightarrow$ row i of y

$y_i^{\max} \in \mathbb{R}^k \rightarrow k$ highest values of y_i

The order of values in $y_i^{\max}$ corresponds to the original order in y_i!

Dynamic k-max pooling

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

Folding

Sum

movie reviews dataset

Classifier	Fine-grained (%)	Binary (%)
NB	41.0	81.8
BiNB	41.9	83.1
SVM	40.7	79.4
RecNTN	45.7	85.4
Max-TDNN	37.4	77.1
NBoW	42.4	80.5
DCNN	**48.5**	**86.8**

TREC questions dataset.

Classifier	Features	Acc. (%)
Hier	unigram, POS, head chunks NE, semantic relations	91.0
MaxEnt	unigram, bigram, trigram POS, chunks, NE, supertags CCG parser, WordNet	92.6
MaxEnt	unigram, bigram, trigram POS, wh-word, head word word shape, parser hypernyms, WordNet	93.6
SVM	unigram, POS, wh-word head word, parser hypernyms, WordNet 60 hand-coded rules	95.0
Max-TDNN	unsupervised vectors	84.4
NBoW	unsupervised vectors	88.2
DCNN	unsupervised vectors	93.0

Kalchbrenner, Nal, Edward Grefenstette, and Phil Blunsom. "A convolutional neural network for modelling sentences." *arXiv preprint arXiv:1404.2188* (2014).

A Sensitivity Analysis Of (And Practitioners' Guide To) Convolutional Neural Networks For Sentence Classification

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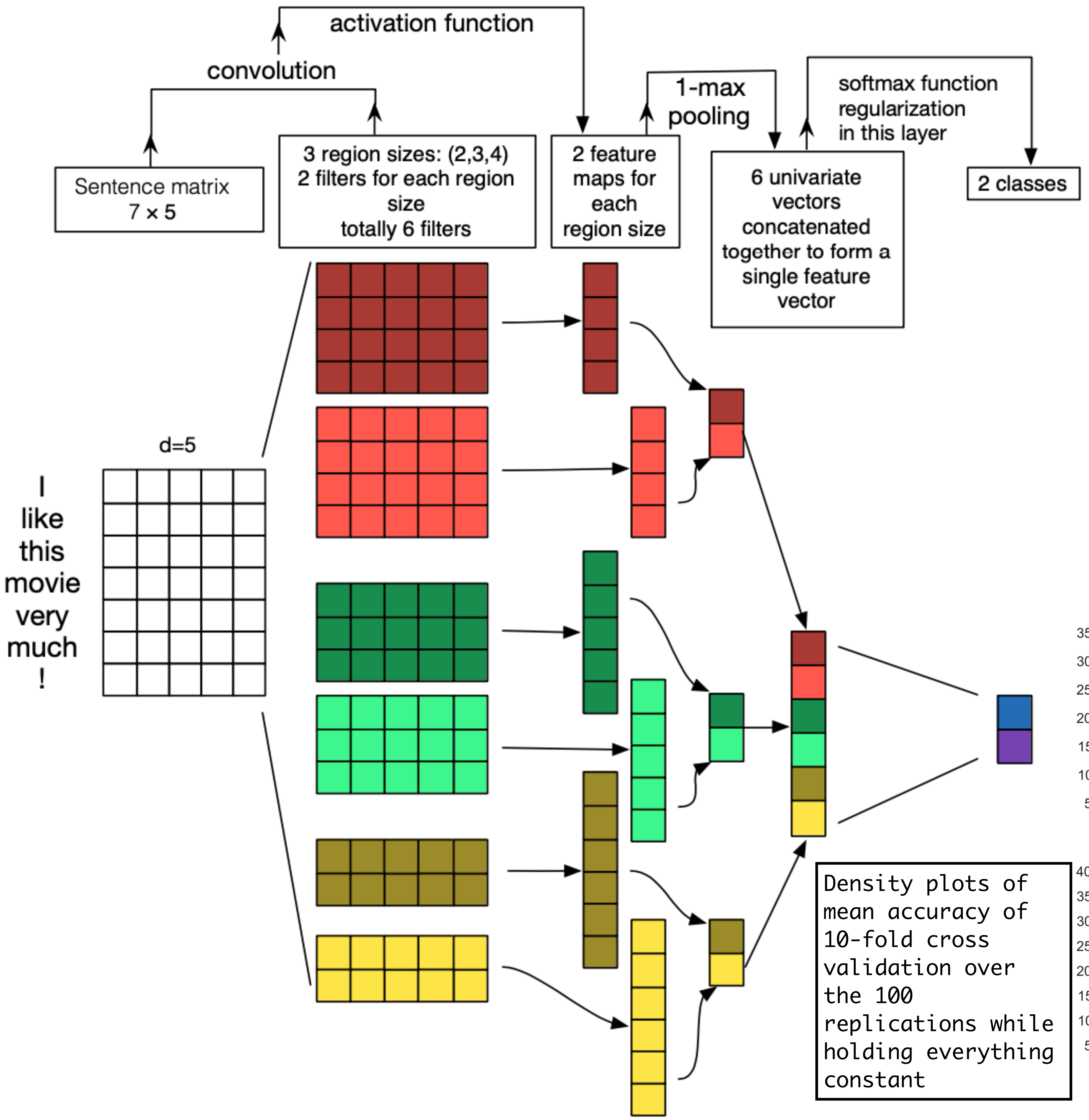
YouTube Video



$A \in \mathbb{R}^{s\times d} \rightarrow$ sentence matrix

$w \in \mathbb{R}^{h\times d} \rightarrow$ filter parameters

$o_i = w \cdot A[i:i+h-1,:]$

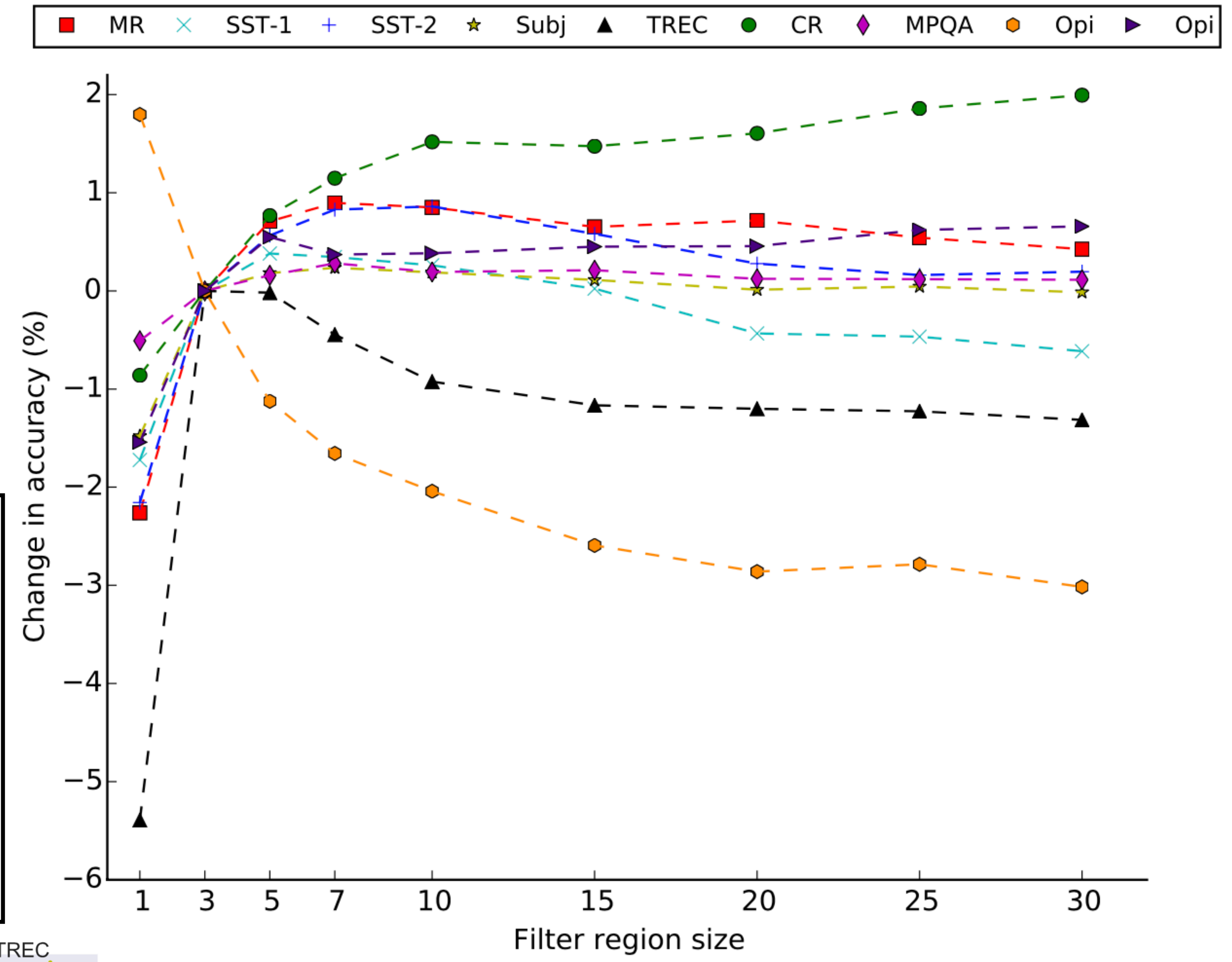
$o \in \mathbb{R}^{s-h+1} \rightarrow$ output vector

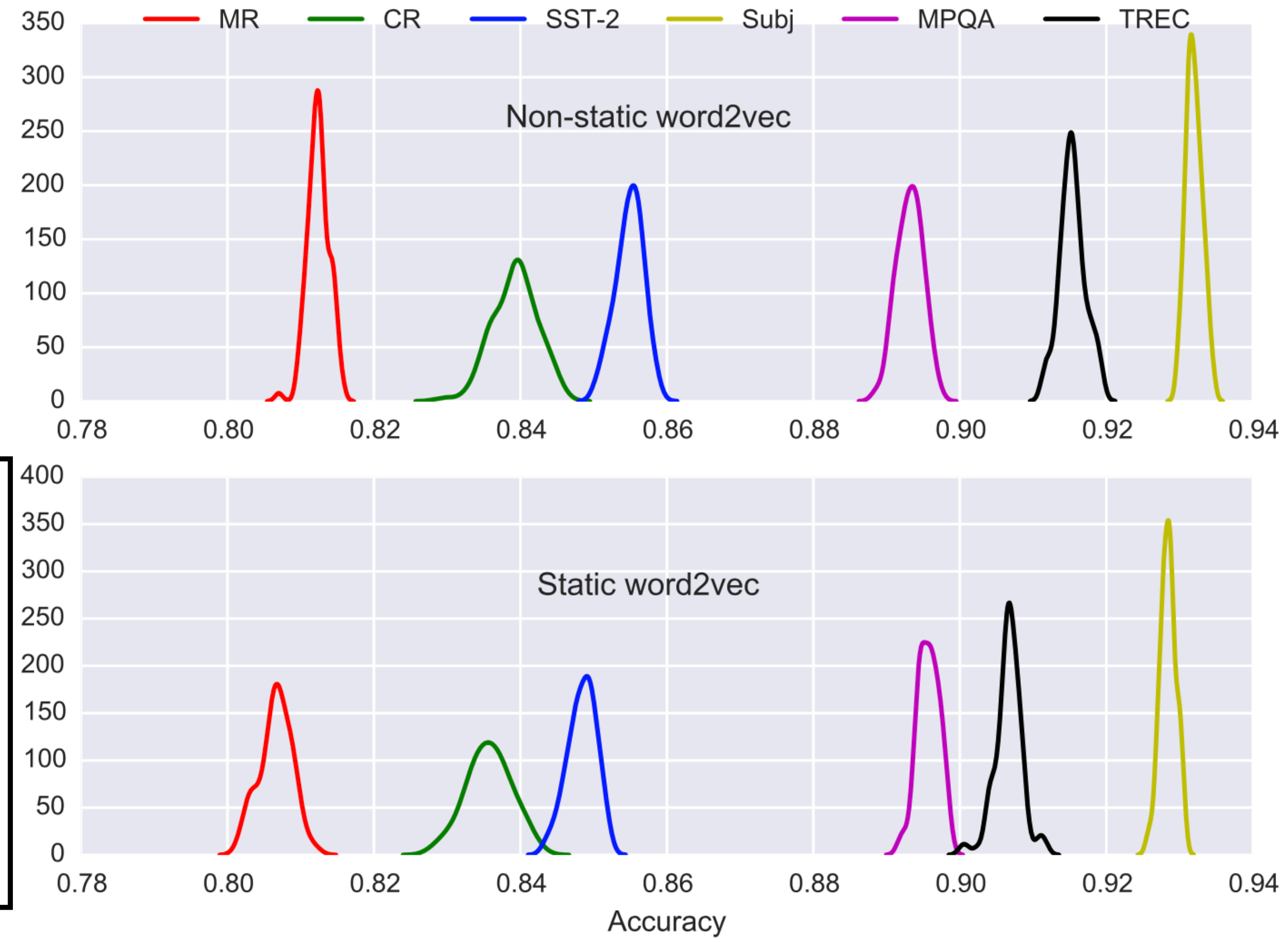
$c_i = f(o_i + b)$

$c \in \mathbb{R}^{s-h+1} \rightarrow$ feature map

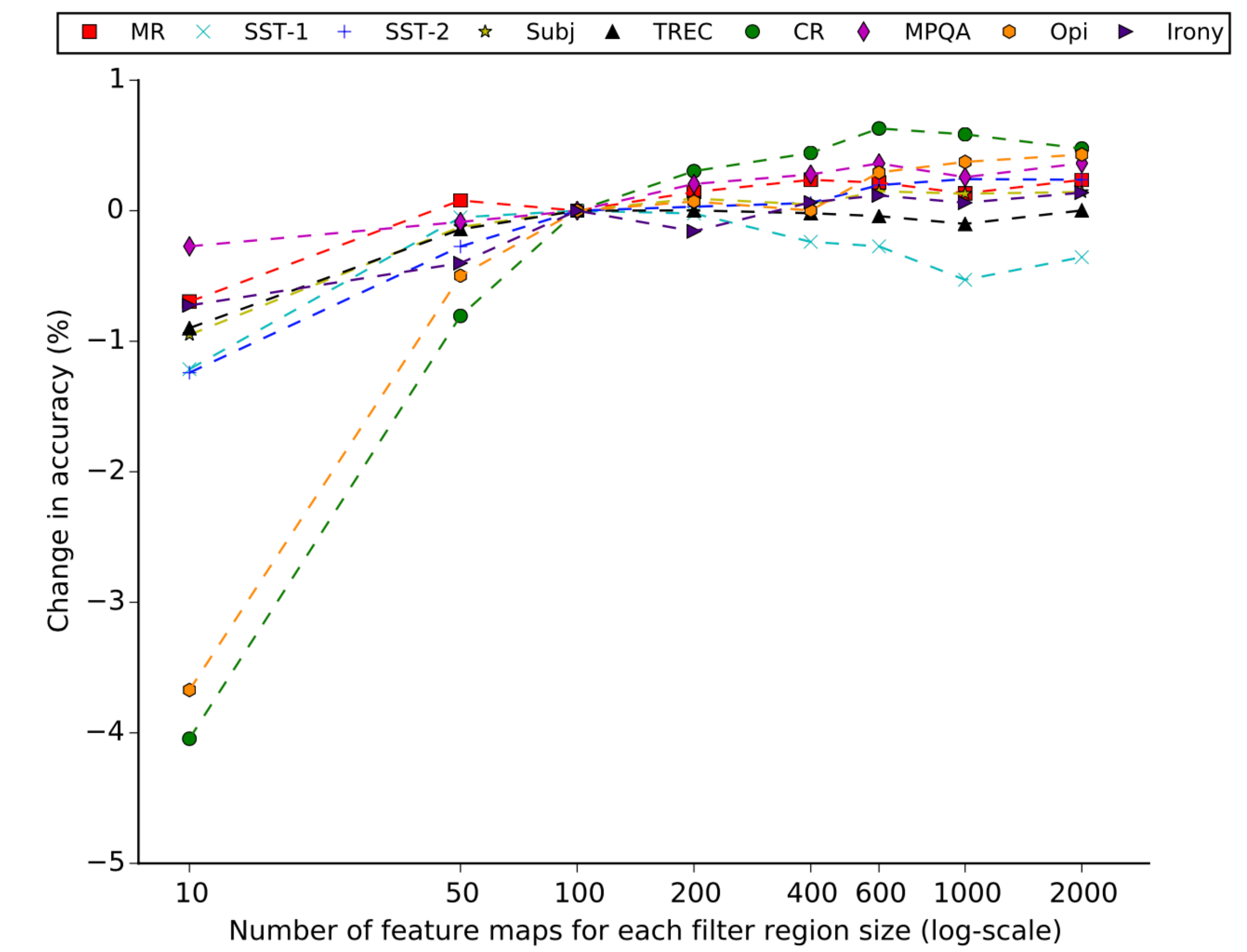
Baseline configuration

Description	Values
input word vectors	Google word2vec
filter region size	(3,4,5)
feature maps	100
activation function	ReLU
pooling	1-max pooling
dropout rate	0.5
$l2$ norm constraint	3





Density plots of mean accuracy of 10-fold cross validation over the 100 replications while holding everything constant



Zhang, Ye, and Byron Wallace. "A sensitivity analysis of (and practitioners' guide to) convolutional neural networks for sentence classification." *arXiv preprint arXiv:1510.03820* (2015).

Character-level Convolutional Networks for Text Classification

YouTube Video

Temporal Convolution Module

$g : \{1, 2, \ldots, l\} \to \mathbb{R}$

discrete input function

$f : \{1, 2, \ldots, k\} \to \mathbb{R}$

discrete kernel function

$h : \{1, 2, \ldots, \lfloor (l - k + 1)/d \rfloor\} \to \mathbb{R}$

convolution btw f & g with stride d

$$h(y) = \sum_{x=1}^{k} f(x) \cdot g(y \cdot d - x + c)$$

$c = k - d + 1$ is an offset constant.

$f_{ij}(x) \to$ many of such kernels/weights

$i = 1, \ldots, m \to$ input feature size

$j = 1, \ldots, n \to$ output feature size

$g_i(x) \to$ inputs

$h_j(x) \to$ outputs

$$h_j(y) = \sum_{i=1}^{m} \sum_{x=1}^{k} f_{ij}(x) \cdot g_i(y \cdot d - x + c)$$

Temporal Max-pooling Module

$$h(y) = \max_{x=1}^{k} g(y \cdot d - x + c)$$

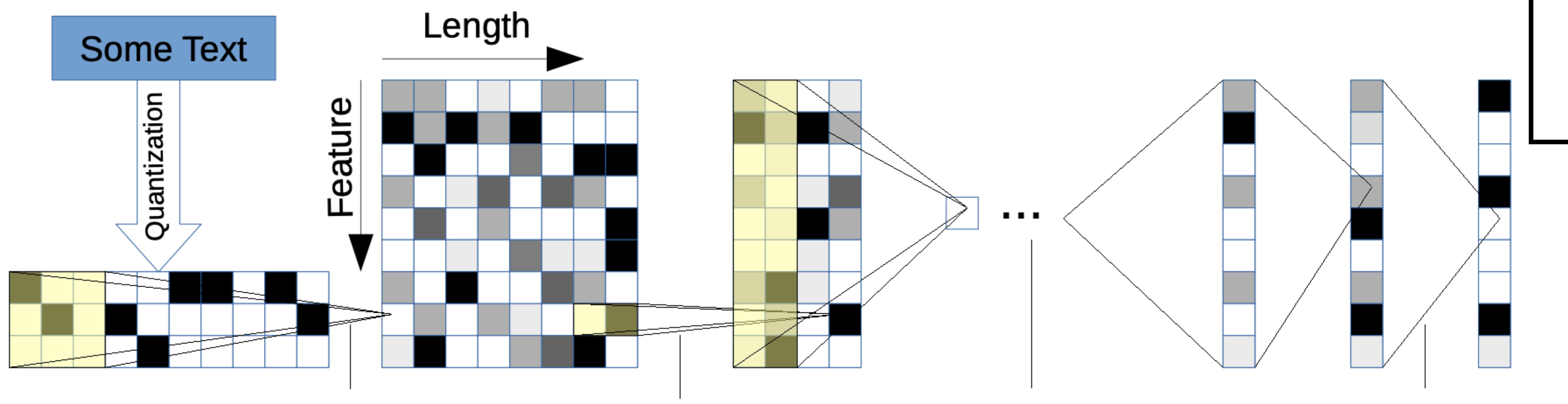
Character Quantization

abcdefghijklmnopqrstuvwxyz0123456789-,;.!?:'''/\|_@#$%^&*~`+-=<>()[]{}

1-of-70 (i.e., one-hot) encoding

$l_0 \to$ fixed-length sequences of 70 dimensional vectors

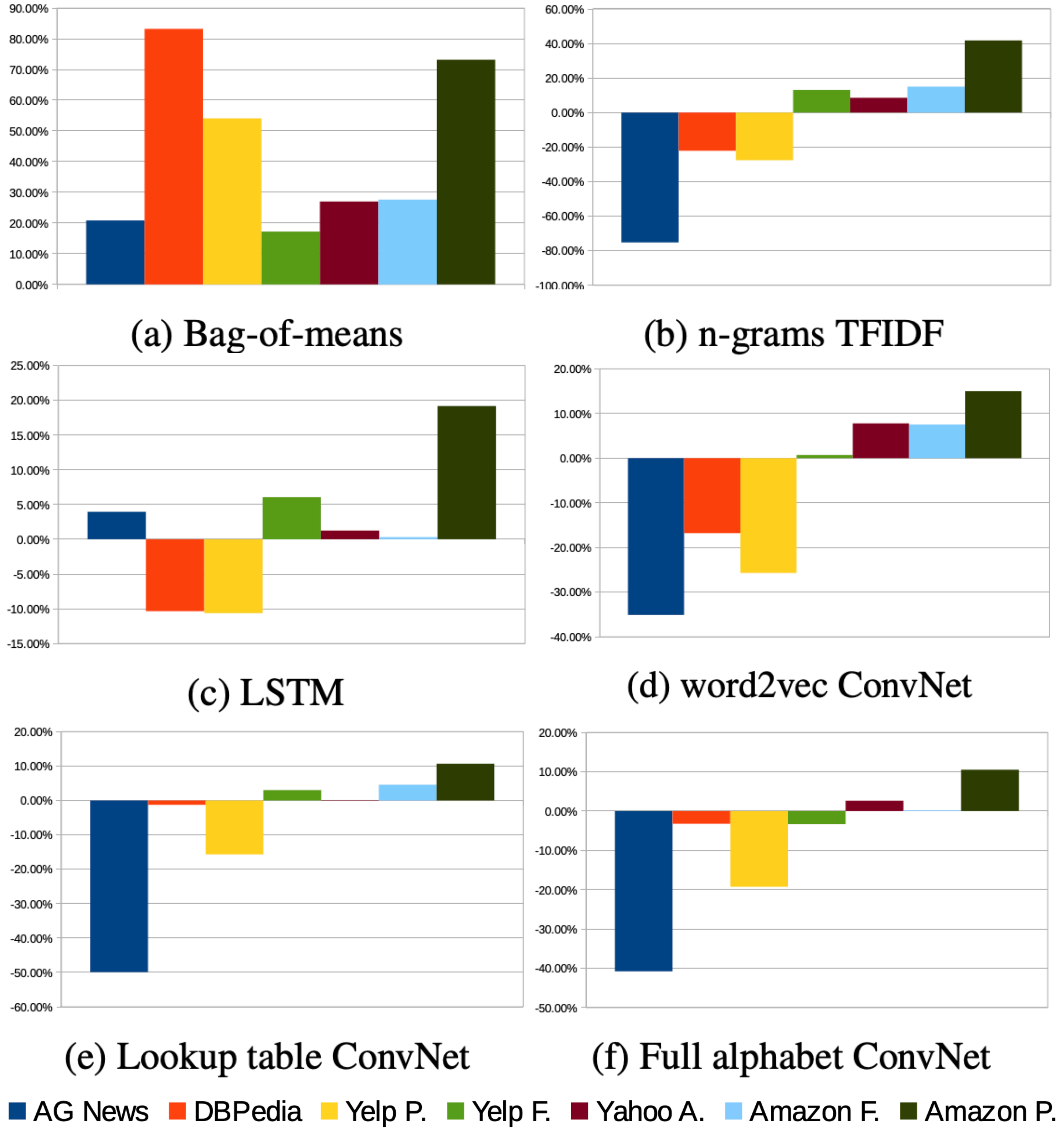
all-zero vector $\to$ any character not in the alphabet (including blank characters)



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

Model	AG	Sogou	DBP.	Yelp P.	Yelp F.	Yah. A.	Amz. F.	Amz. P.
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

Relative errors with comparison models



(a) Bag-of-means (b) n-grams TFIDF (c) LSTM (d) word2vec ConvNet (e) Lookup table ConvNet (f) Full alphabet ConvNet

Zhang, Xiang, Junbo Zhao, and Yann LeCun. "Character-level convolutional networks for text classification." *arXiv preprint arXiv:1509.01626* (2015).

Improved Semantic Representations From Tree-Structured Long Short-Term Memory Networks

Boulder

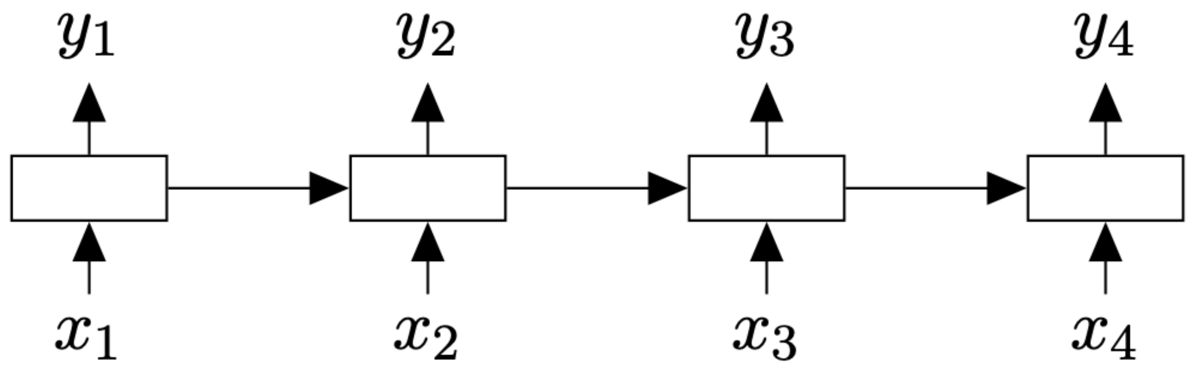
[YouTube Video]

Distributed representations of phrases and sentences:

– Bag-of-words models (independent of word order; "cats climb trees" v.s. "trees climb cats")

– sequence models

– tree-structured models



Recurrent Neural Networks (RNNs)

$h_t \in \mathbb{R}^n \rightarrow$ hidden state vector

$$h_t = \tanh\left(W x_t + U h_{t-1} + b\right)$$

Exploding or vanishing gradients!

Long Short-Term Memory (LSTM) networks

$$i_t = \sigma\left(W^{(i)} x_t + U^{(i)} h_{t-1} + b^{(i)}\right), \quad \rightarrow \text{input gate}$$

$$f_t = \sigma\left(W^{(f)} x_t + U^{(f)} h_{t-1} + b^{(f)}\right), \quad \rightarrow \text{forget gate}$$

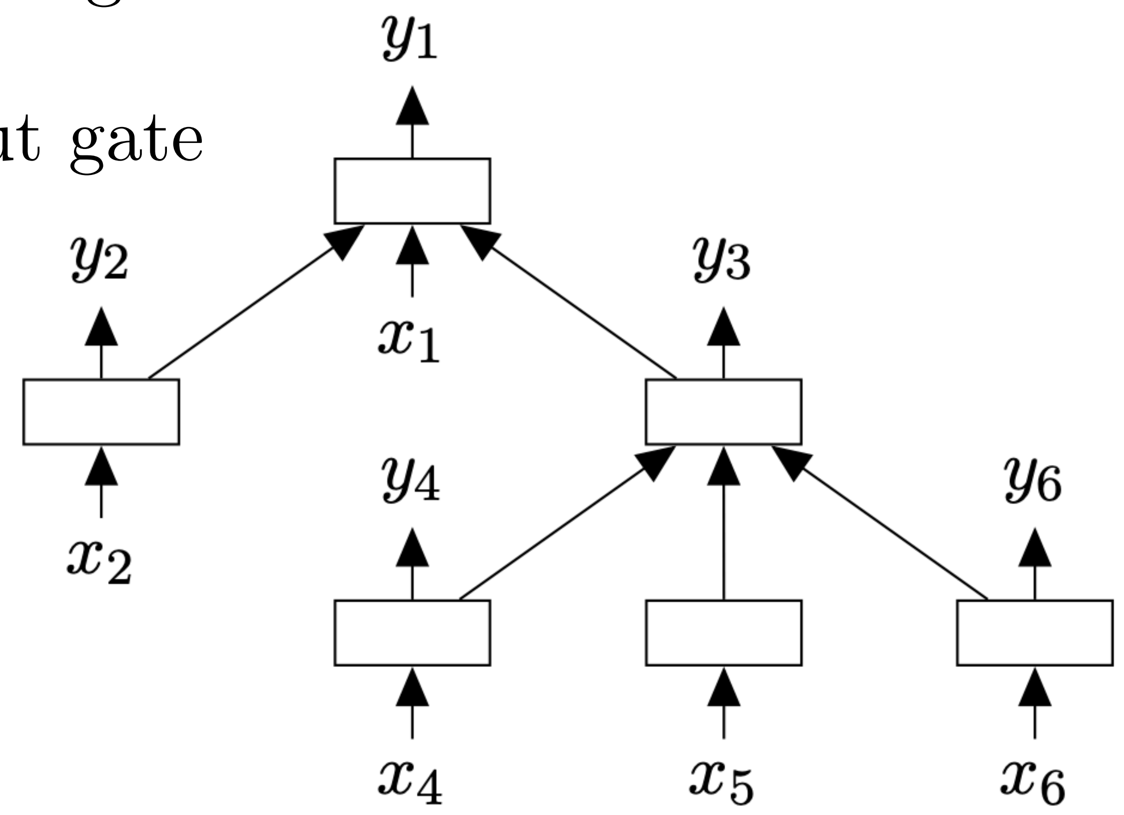
$$o_t = \sigma\left(W^{(o)} x_t + U^{(o)} h_{t-1} + b^{(o)}\right), \quad \rightarrow \text{output gate}$$

$$u_t = \tanh\left(W^{(u)} x_t + U^{(u)} h_{t-1} + b^{(u)}\right),$$

$$c_t = i_t \odot u_t + f_t \odot c_{t-1}, \quad \rightarrow \text{memory cell}$$

$$h_t = o_t \odot \tanh(c_t), \quad \rightarrow \text{hidden state}$$

Bidirectional & Multi-layer LSTMs



Tree-Structured LSTMS

– N-ary Tree-LSTM: Tree structures where the branching factor is at most N and where children are ordered (indexed from 1 to N)

– Child-Sum Tree-LSTM: High branching factor or unordered children

Child-Sum Tree-LSTM

Given a tree, let $C(j)$ denote the set of children of node j.

$$\tilde{h}_j = \sum_{k \in C(j)} h_k,$$

$$i_j = \sigma\left(W^{(i)} x_j + U^{(i)} \tilde{h}_j + b^{(i)}\right),$$

$$f_{jk} = \sigma\left(W^{(f)} x_j + U^{(f)} h_k + b^{(f)}\right), \quad k \in C(j)$$

$$o_j = \sigma\left(W^{(o)} x_j + U^{(o)} \tilde{h}_j + b^{(o)}\right),$$

$$u_j = \tanh\left(W^{(u)} x_j + U^{(u)} \tilde{h}_j + b^{(u)}\right),$$

$$c_j = i_j \odot u_j + \sum_{k \in C(j)} f_{jk} \odot c_k,$$

$$h_j = o_j \odot \tanh(c_j),$$

N-ary Tree-LSTM

$$i_j = \sigma\left(W^{(i)} x_j + \sum_{\ell=1}^{N} U_\ell^{(i)} h_{j\ell} + b^{(i)}\right),$$

$$f_{jk} = \sigma\left(W^{(f)} x_j + \sum_{\ell=1}^{N} U_{k\ell}^{(f)} h_{j\ell} + b^{(f)}\right),$$

$$o_j = \sigma\left(W^{(o)} x_j + \sum_{\ell=1}^{N} U_\ell^{(o)} h_{j\ell} + b^{(o)}\right),$$

$$u_j = \tanh\left(W^{(u)} x_j + \sum_{\ell=1}^{N} U_\ell^{(u)} h_{j\ell} + b^{(u)}\right)$$

$$c_j = i_j \odot u_j + \sum_{\ell=1}^{N} f_{j\ell} \odot c_{j\ell},$$

$$h_j = o_j \odot \tanh(c_j),$$

Tree-LSTM Classification

$$\hat{p}_\theta(y \mid \{x\}_j) = \text{softmax}\left(W^{(s)} h_j + b^{(s)}\right),$$

$$\hat{y}_j = \arg\max_y \hat{p}_\theta\left(y \mid \{x\}_j\right).$$

inputs observed at nodes in the subtree rooted at j

$$J(\theta) = -\frac{1}{m} \sum_{k=1}^{m} \log \hat{p}_\theta\left(y^{(k)} \,\middle|\, \{x\}^{(k)}\right) + \frac{\lambda}{2} \|\theta\|_2^2,$$

Semantic Relatedness of Sentence Pairs

Given a sentence pair, we wish to predict a real-valued similarity score in some range $[1, K]$, where $K > 1$ is an integer.

$$h_\times = h_L \odot h_R, \qquad h_s = \sigma\left(W^{(\times)} h_\times + W^{(+)} h_+ + b^{(h)}\right),$$

$$h_+ = |h_L - h_R|, \qquad r^T = [1\ 2\ \ldots\ K]$$

$$\hat{p}_\theta = \text{softmax}\left(W^{(p)} h_s + b^{(p)}\right),$$

$$\hat{y} = r^T \hat{p}_\theta,$$

Loss function (see the paper)!

Tai, Kai Sheng, Richard Socher, and Christopher D. Manning. "Improved semantic representations from tree-structured long short-term memory networks." *arXiv preprint arXiv:1503.00075* (2015).

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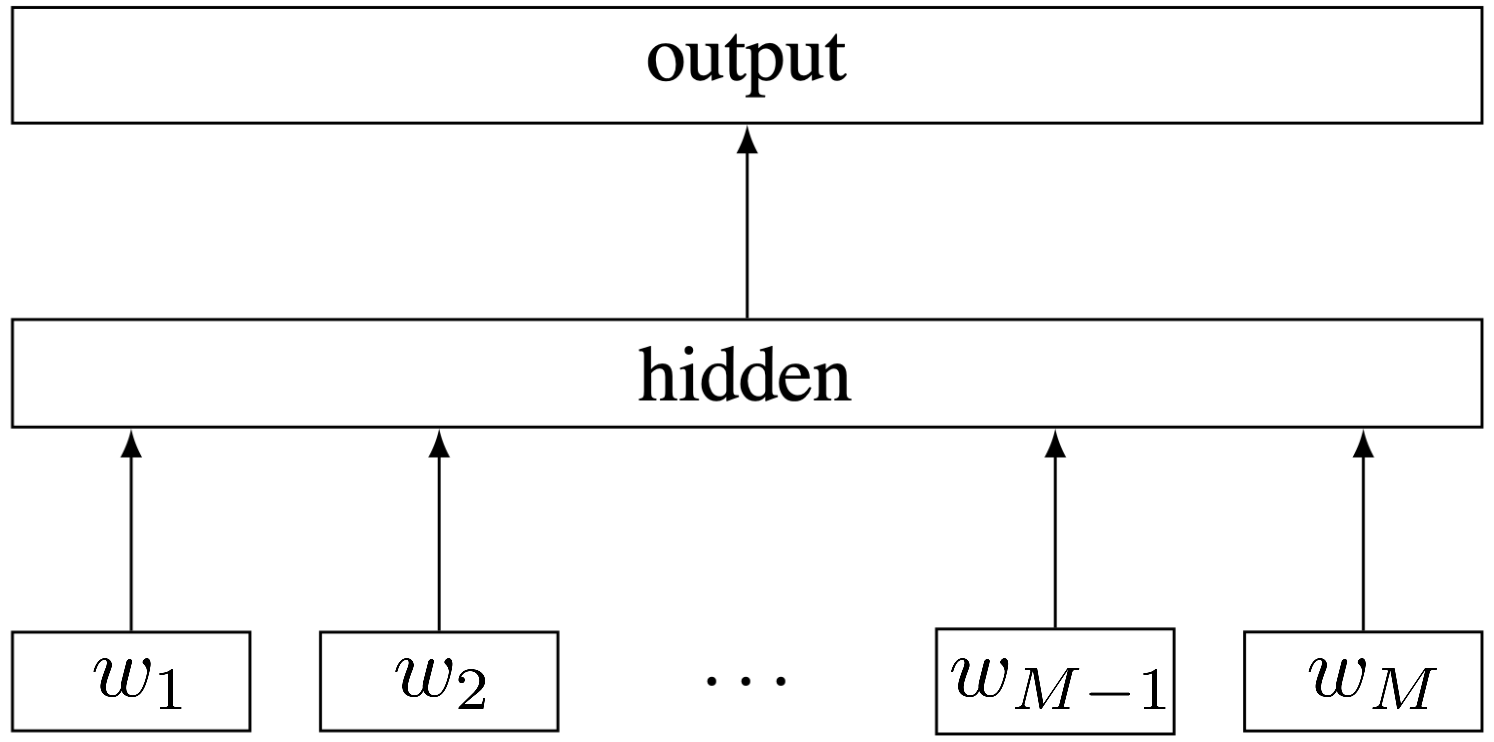
Bag Of Tricks For Efficient Text Classification

YouTube Playlist



Model architecture of `fastText` for a sentence with M ngram features $w_1, w_2, \ldots, w_M$. The features are embedded and averaged to form the hidden variable.

$$-\frac{1}{N}\sum_{n=1}^{N} y_n \log(f(BAx_n))$$

$N \rightarrow$ number of documents
$x_n \rightarrow$ normalized bag of features of document n
$y_n \rightarrow$ label
$A, B \rightarrow$ weight matrices
$A \rightarrow$ look-up table
$f \rightarrow$ softmax
Similar to the CBOW model!
$\mathcal{O}(kh) \rightarrow$ computational cost (softmax)
$k \rightarrow$ number of classes
$h \rightarrow$ dimension of text representation
$\mathcal{O}(h \log_2 k) \rightarrow$ hierarchical softmax

Test accuracy [%] on sentiment datasets.

Model	AG	Sogou	DBP	Yelp P.	Yelp F.	Yah. A.	Amz. F.	Amz. P.
BoW (Zhang et al., 2015)	88.8	92.9	96.6	92.2	58.0	68.9	54.6	90.4
ngrams (Zhang et al., 2015)	92.0	97.1	98.6	95.6	56.3	68.5	54.3	92.0
ngrams TFIDF (Zhang et al., 2015)	92.4	97.2	98.7	95.4	54.8	68.5	52.4	91.5
char-CNN (Zhang and LeCun, 2015)	87.2	95.1	98.3	94.7	62.0	71.2	59.5	94.5
char-CRNN (Xiao and Cho, 2016)	91.4	95.2	98.6	94.5	61.8	71.7	59.2	94.1
VDCNN (Conneau et al., 2016)	91.3	96.8	98.7	95.7	64.7	73.4	63.0	95.7
`fastText`, $h = 10$	91.5	93.9	98.1	93.8	60.4	72.0	55.8	91.2
`fastText`, $h = 10$, bigram	92.5	96.8	98.6	95.7	63.9	72.3	60.2	94.6

Training time for a single epoch on sentiment analysis datasets

	Zhang and LeCun (2015)		Conneau et al. (2016)			`fastText`
	small char-CNN	big char-CNN	depth=9	depth=17	depth=29	$h = 10$, bigram
AG	1h	3h	24m	37m	51m	1s
Sogou	-	-	25m	41m	56m	7s
DBpedia	2h	5h	27m	44m	1h	2s
Yelp P.	-	-	28m	43m	1h09	3s
Yelp F.	-	-	29m	45m	1h12	4s
Yah. A.	8h	1d	1h	1h33	2h	5s
Amz. F.	2d	5d	2h45	4h20	7h	9s
Amz. P.	2d	5d	2h45	4h25	7h	10s

Model	prec@1	Running time	
		Train	Test
Freq. baseline	2.2	-	-
Tagspace, $h = 50$	30.1	3h8	6h
Tagspace, $h = 200$	35.6	5h32	15h

Model	prec@1	Running time	
		Train	Test
`fastText`, $h = 50$	31.2	6m40	48s
`fastText`, $h = 50$, bigram	36.7	7m47	50s
`fastText`, $h = 200$	41.1	10m34	1m29
`fastText`, $h = 200$, bigram	46.1	13m38	1m37

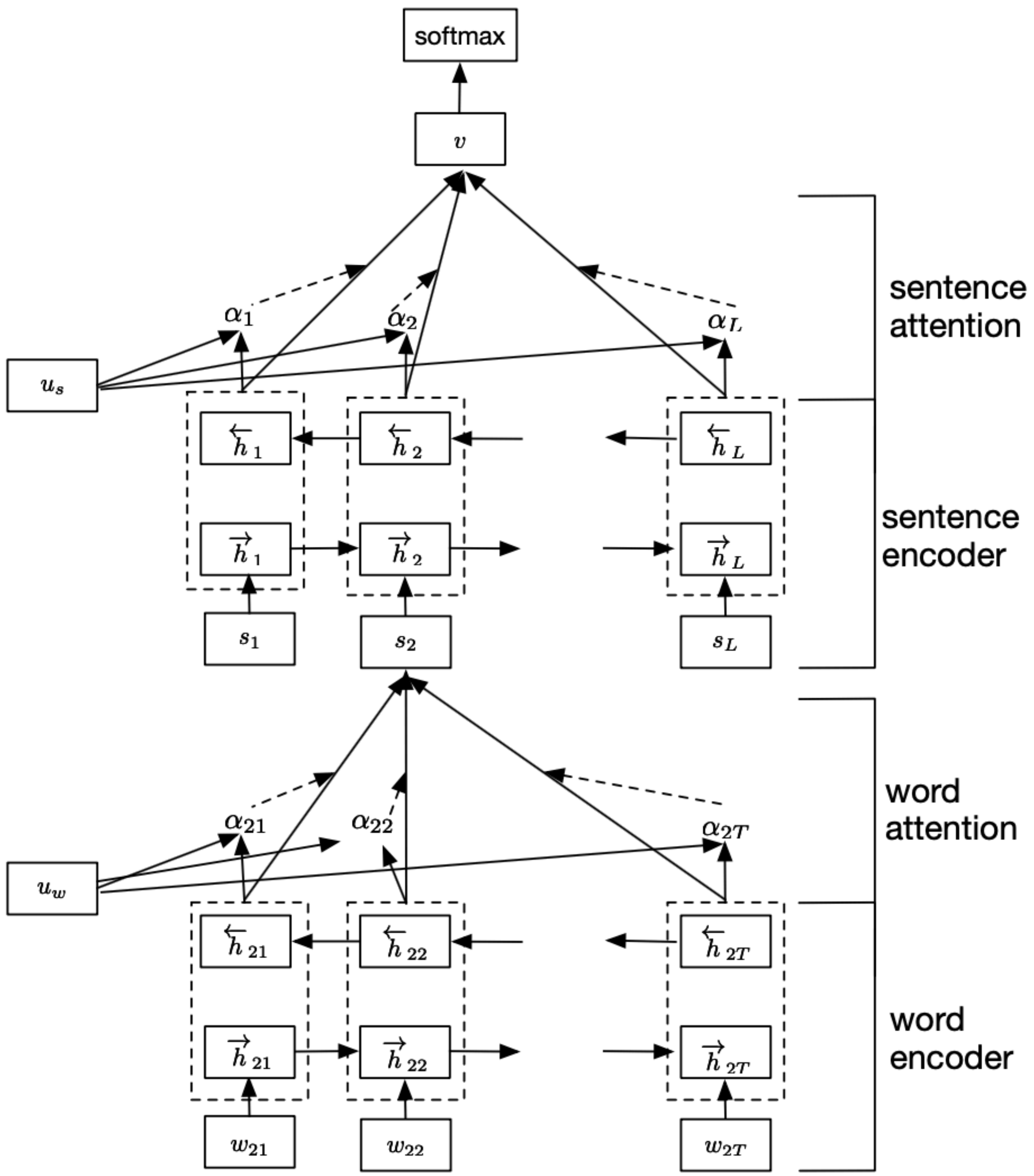
Tag prediction on YFCC100M (Large output space & large dataset)

Joulin, Armand, et al. "Bag of tricks for efficient text classification." *arXiv preprint arXiv:1607.01759* (2016).

Hierarchical Attention Networks for Document Classification

YouTube Playlist

words form sentences
sentences form a document



GRU-based sequence encoder

reset gate r_t

update gate z_t

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t$$
$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z)$$
$$\tilde{h}_t = \tanh(W_h x_t + r_t \odot (U_h h_{t-1}) + b_h)$$
$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r)$$

Word Encoder

$$x_{it} = W_e w_{it}, t \in [1, T],$$
$$\overrightarrow{h}_{it} = \overrightarrow{\text{GRU}}(x_{it}), t \in [1, T],$$
$$\overleftarrow{h}_{it} = \overleftarrow{\text{GRU}}(x_{it}), t \in [T, 1].$$
$$h_{it} = [\overrightarrow{h}_{it}, \overleftarrow{h}_{it}]$$

Word Attention

$$u_{it} = \tanh(W_w h_{it} + b_w)$$
$$\alpha_{it} = \frac{\exp(u_{it}^\top u_w)}{\sum_t \exp(u_{it}^\top u_w)}$$
$$s_i = \sum_t \alpha_{it} h_{it}.$$

$u_w \rightarrow$ word context

query "what is the informative word"

Sentence Encoder

$$\overrightarrow{h}_i = \overrightarrow{\text{GRU}}(s_i), i \in [1, L],$$
$$\overleftarrow{h}_i = \overleftarrow{\text{GRU}}(s_i), t \in [L, 1].$$
$$h_i = [\overrightarrow{h}_i, \overleftarrow{h}_i]$$

Sentence Attention

$$u_i = \tanh(W_s h_i + b_s),$$
$$\alpha_i = \frac{\exp(u_i^\top u_s)}{\sum_i \exp(u_i^\top u_s)},$$
$$v = \sum_i \alpha_i h_i,$$

Document Classification

$$p = \text{softmax}(W_c v + b_c)$$
$$L = -\sum_d \log p_{dj}$$

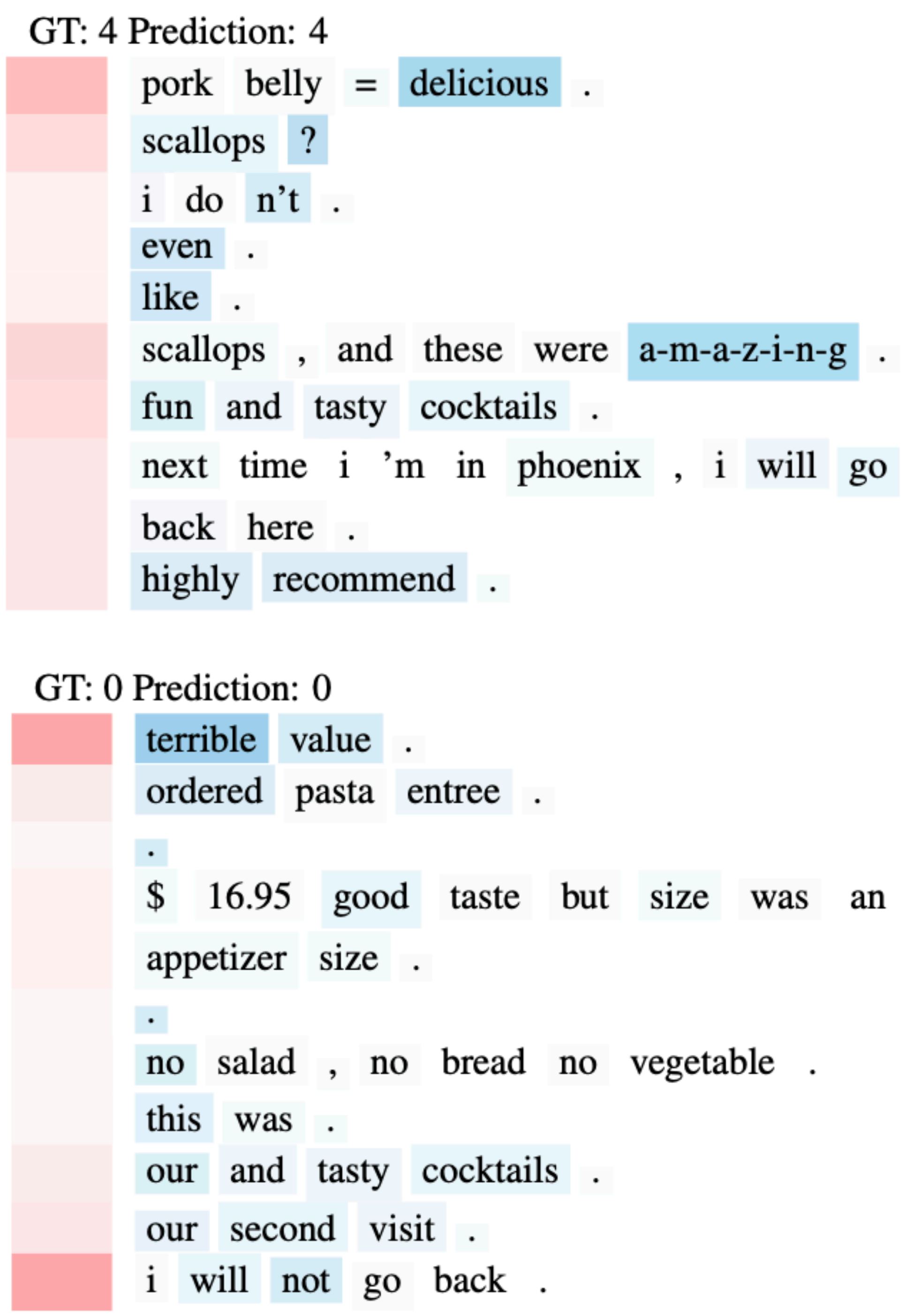
j is the label of document d.

sentiment estimation

topic classification

Data set	classes	documents
Yelp 2013	5	335,018
Yelp 2014	5	1,125,457
Yelp 2015	5	1,569,264
IMDB review	10	348,415
Yahoo Answer	10	1,450,000
Amazon review	5	3,650,000

Yelp 2013



Yang, Zichao, et al. "Hierarchical attention networks for document classification." Proceedings of the 2016 conference of the North American chapter of the association for computational linguistics: human language technologies. 2016.

Bidirectional LSTM-CRF Models for Sequence Tagging

Boulder

YouTube Video

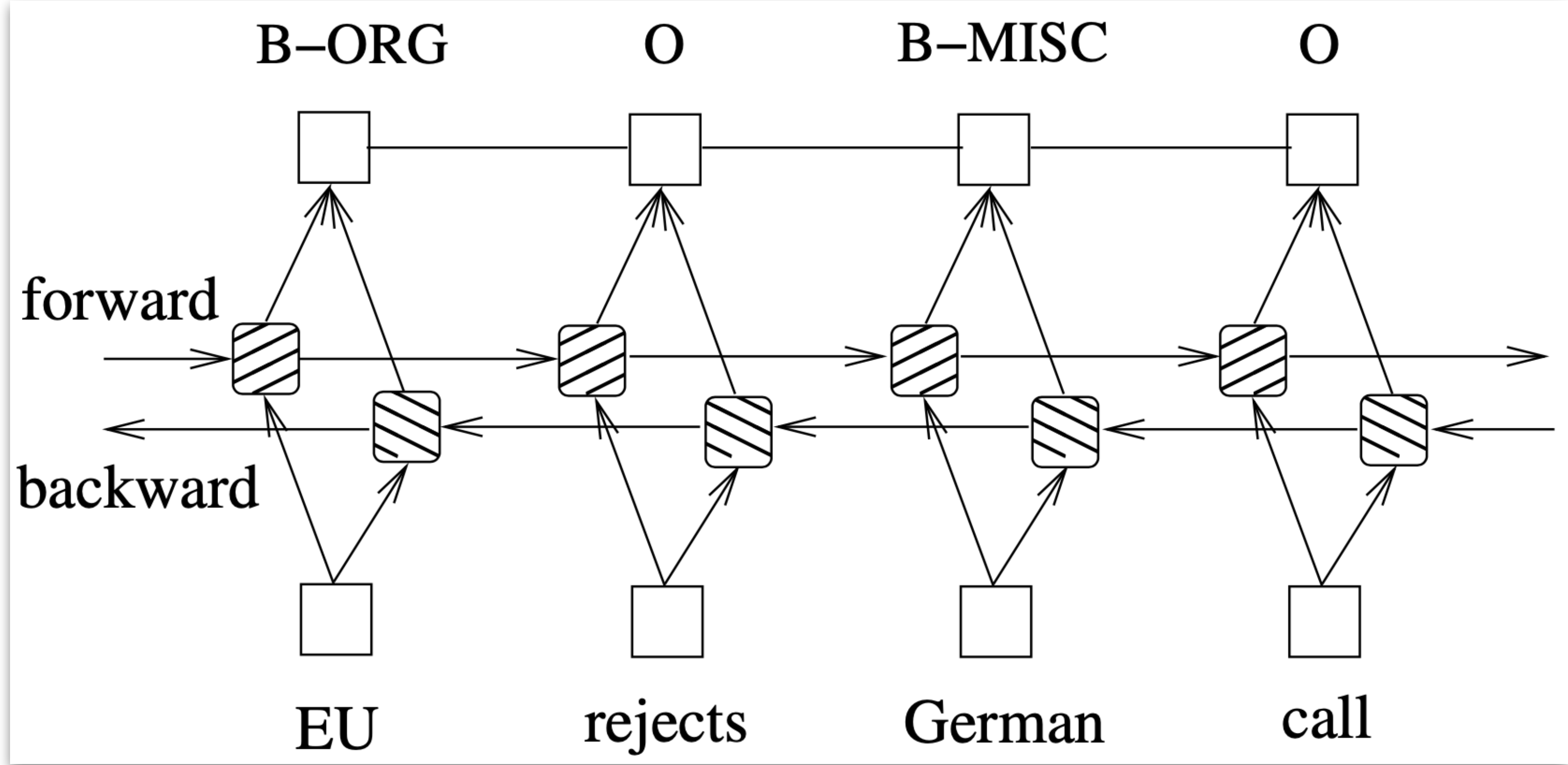
POS assigns each word with a unique tag that indicates its syntactic role. In chunking, each word is tagged with its phrase type. For example, tag B-NP indicates a word starting a noun phrase. In NER task, each word is tagged with other or one of four entity types: Person, Location, Organization, or Miscellaneous.

The output of taggers can be used for down streaming applications. For example, a named entity recognizer trained on user search queries can be utilized to identify which spans of text are products, thus triggering certain products ads. Another example is that such tag information can be used by a search engine to find relevant webpages.

- Penn TreeBank (PTB) POS tagging
- CoNLL 2000 chunking
- CoNLL 2003 named entity tagging

		POS	CoNLL2000	CoNLL2003
training	sentence #	39831	8936	14987
	token #	950011	211727	204567
validation	sentence #	1699	N/A	3466
	token #	40068	N/A	51578
test	sentences #	2415	2012	3684
	token #	56671	47377	46666
	label #	45	22	9

		POS	CoNLL2000	CoNLL2003
Random	Conv-CRF (Collobert et al., 2011)	96.37	90.33	81.47
	LSTM	97.10	92.88	79.82
	BI-LSTM	97.30	93.64	81.11
	CRF	97.30	93.69	83.02
	LSTM-CRF	**97.45**	93.80	84.10
	BI-LSTM-CRF	97.43	**94.13**	**84.26**
Senna	Conv-CRF (Collobert et al., 2011)	97.29	94.32	88.67 (89.59)
	LSTM	97.29	92.99	83.74
	BI-LSTM	97.40	93.92	85.17
	CRF	97.45	93.83	86.13
	LSTM-CRF	97.54	94.27	88.36
	BI-LSTM-CRF	**97.55**	**94.46**	**88.83 (90.10)**



A BI-LSTM-CRF model

LSTM memory cell

$$
\begin{aligned}
i_t &= \sigma(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i) \\
f_t &= \sigma(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f) \\
c_t &= f_t c_{t-1} + i_t tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \\
o_t &= \sigma(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o) \\
h_t &= o_t tanh(c_t)
\end{aligned}
$$

$f_\theta([x]_1^T) \rightarrow$ matrix of scores output by the network

drop for notation simplification

$[f_\theta]_{i,t} \rightarrow$ score for the i-th tag and the t-th word

$[A]_{i,j} \rightarrow$ transition score from i-th state to the j-th one for a pair of consecutive time steps

$$s([x]_1^T, [i]_1^T, \tilde{\theta}) = \sum_{t=1}^{T} ([A]_{[i]_{t-1},[i]_t} + [f_\theta]_{[i]_t,t})$$

a path of tags

$$\tilde{\theta} = \theta \cup \{[A]_{i,j} \forall i, j\}$$

Dynamic programming (training & inference)

Huang, Zhiheng, Wei Xu, and Kai Yu. "Bidirectional LSTM-CRF models for sequence tagging." *arXiv preprint arXiv:1508.01991* (2015).

Neural Architectures For Named Entity Recognition

Boulder

YouTube Playlist

Person: Adams and Person: Platt are both injured and will miss Location: England 's opening Miscellaneous: World Cup qualifier against Location: Moldova on Sunday .

Mark	Watney	visited	Mars
B-PER	I-PER	O	B-LOC

B-PER $\rightarrow$ beginning of a person name
I-PER $\rightarrow$ inside a person name
B-LOC $\rightarrow$ beginning of a location name
I-LOC $\rightarrow$ inside a location name
B-ORG $\rightarrow$ beginning of an organization name
I-ORG $\rightarrow$ inside an organization name
B-MISC $\rightarrow$ beginning of a miscellaneous entity name
I-MISC $\rightarrow$ inside a miscellaneous entity name
O $\rightarrow$ outside of a named entity

LSTM-CRF Model

$(\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n) \rightarrow$ input (sequence of vectors)

$(\mathbf{h}_1, \mathbf{h}_2, \ldots, \mathbf{h}_n) \rightarrow$ returned sequence from LSTM

$$\mathbf{i}_t = \sigma(\mathbf{W}_{xi}\mathbf{x}_t + \mathbf{W}_{hi}\mathbf{h}_{t-1} + \mathbf{W}_{ci}\mathbf{c}_{t-1} + \mathbf{b}_i)$$
$$\mathbf{c}_t = (1 - \mathbf{i}_t) \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tanh(\mathbf{W}_{xc}\mathbf{x}_t + \mathbf{W}_{hc}\mathbf{h}_{t-1} + \mathbf{b}_c)$$
$$\mathbf{o}_t = \sigma(\mathbf{W}_{xo}\mathbf{x}_t + \mathbf{W}_{ho}\mathbf{h}_{t-1} + \mathbf{W}_{co}\mathbf{c}_t + \mathbf{b}_o)$$
$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t),$$
$$\mathbf{h}_t = [\overrightarrow{\mathbf{h}}_t; \overleftarrow{\mathbf{h}}_t] \rightarrow \text{bidirectional LSTM}$$

Conditional Random Field (CRF)

$\mathbf{X} = (\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n)$

$\mathbf{y} = (y_1, y_2, \ldots, y_n) \rightarrow$ sequence of outputs

$P \in \mathbb{R}^{n \times k} \rightarrow$ matrix of scores

$k \rightarrow$ number of distinct tags

$P_{i,j} \rightarrow$ score of the j-th tag of the i-th word in a sentence

$$s(\mathbf{X}, \mathbf{y}) = \sum_{i=0}^{n} A_{y_i, y_{i+1}} + \sum_{i=1}^{n} P_{i, y_i} \rightarrow \text{score of } \mathbf{y}$$

$A \in \mathbb{R}^{(k+2)\times(k+2)} \rightarrow$ matrix of compatibility scores

$A_{i,j} \rightarrow$ score of a transition from tag i to j

$y_0, y_{n+1} \rightarrow$ start and end tags of a sequence

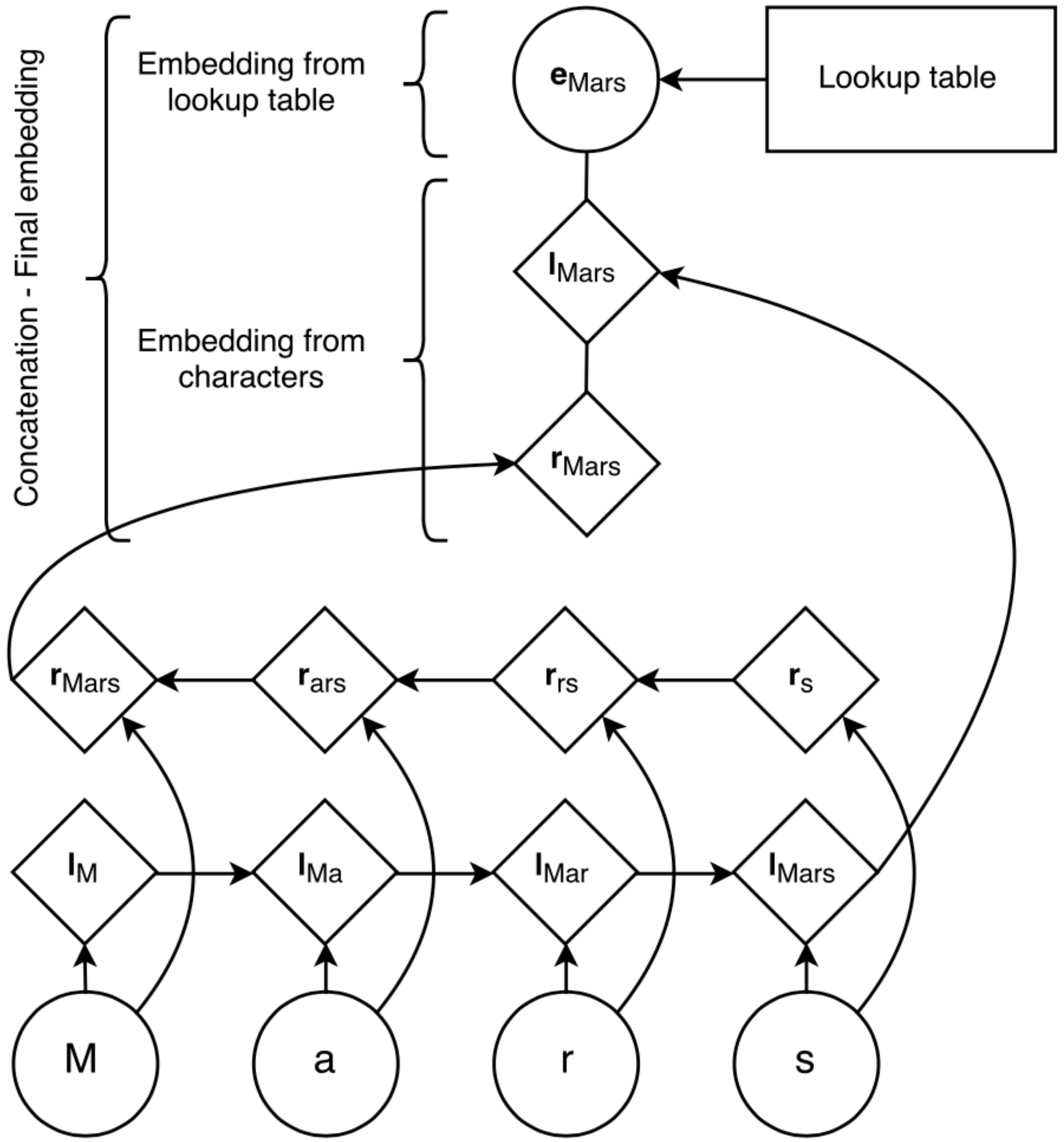
$$p(\mathbf{y}|\mathbf{X}) = \frac{e^{s(\mathbf{X},\mathbf{y})}}{\underbrace{\sum_{\tilde{\mathbf{y}} \in \mathbf{Y_X}}}_{\text{all possible tag sequences}} e^{s(\mathbf{X},\tilde{\mathbf{y}})}}$$

$$\log(p(\mathbf{y}|\mathbf{X})) = s(\mathbf{X}, \mathbf{y}) - \log\left(\sum_{\tilde{\mathbf{y}} \in \mathbf{Y_X}} e^{s(\mathbf{X},\tilde{\mathbf{y}})}\right)$$

$$\mathbf{y}^* = \underset{\tilde{\mathbf{y}} \in \mathbf{Y_X}}{\operatorname{argmax}}\, s(\mathbf{X}, \tilde{\mathbf{y}})$$ dynamic programming

Character-based models of words

Use dropout training to encourage the model to depend on both character-level and word-level representations



English NER results (CoNLL-2003 test set)

Model	F_1
LSTM-CRF (no char)	90.20
LSTM-CRF	**90.94**

Spanish NER (CoNLL-2002 test set)

LSTM-CRF – no char	83.44
LSTM-CRF	**85.75**

Lample, Guillaume, et al. "Neural architectures for named entity recognition." *arXiv preprint arXiv:1603.01360* (2016).

End-to-end Sequence Labeling via Bi-directional LSTM-CNNs-CRF

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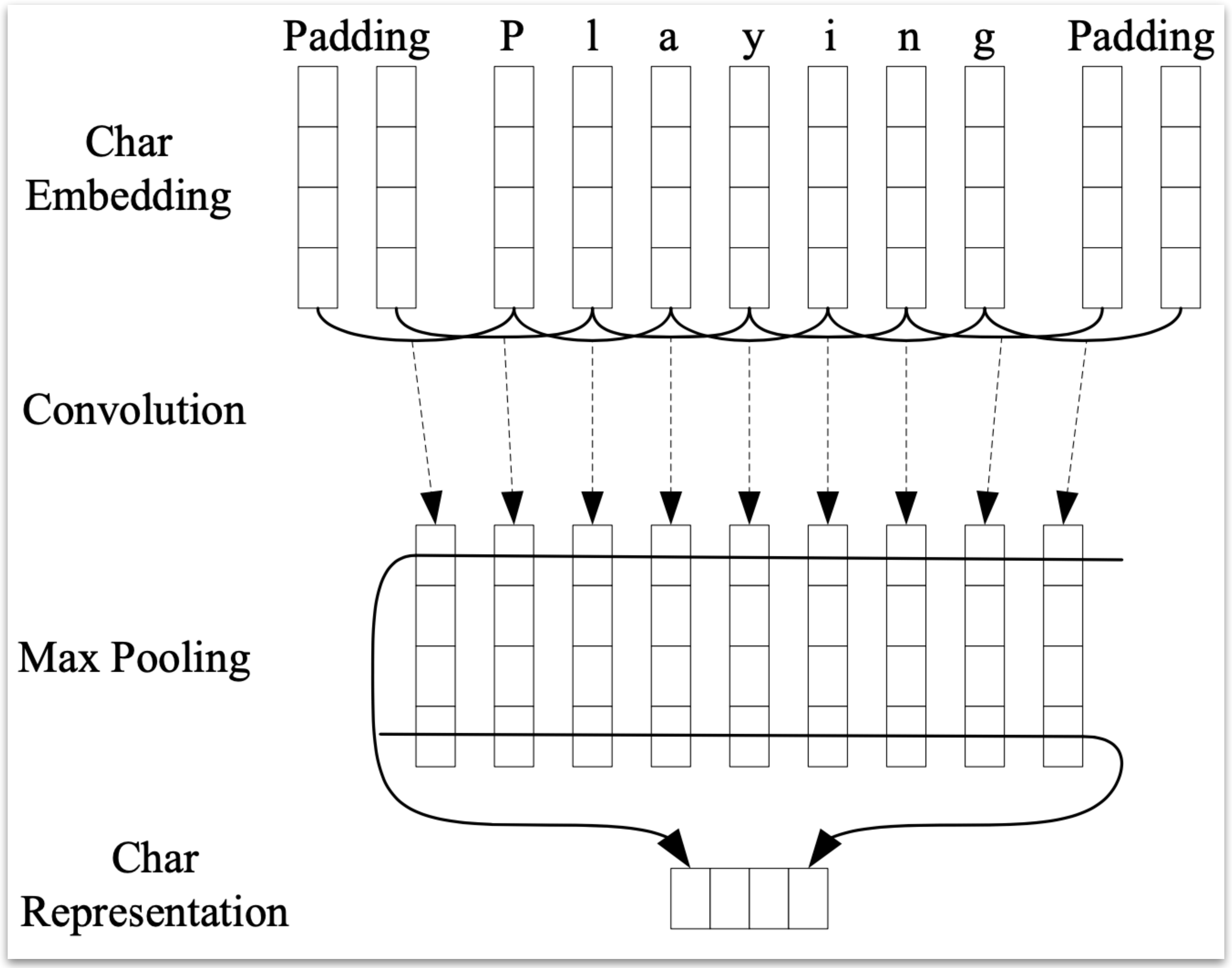
YouTube Video

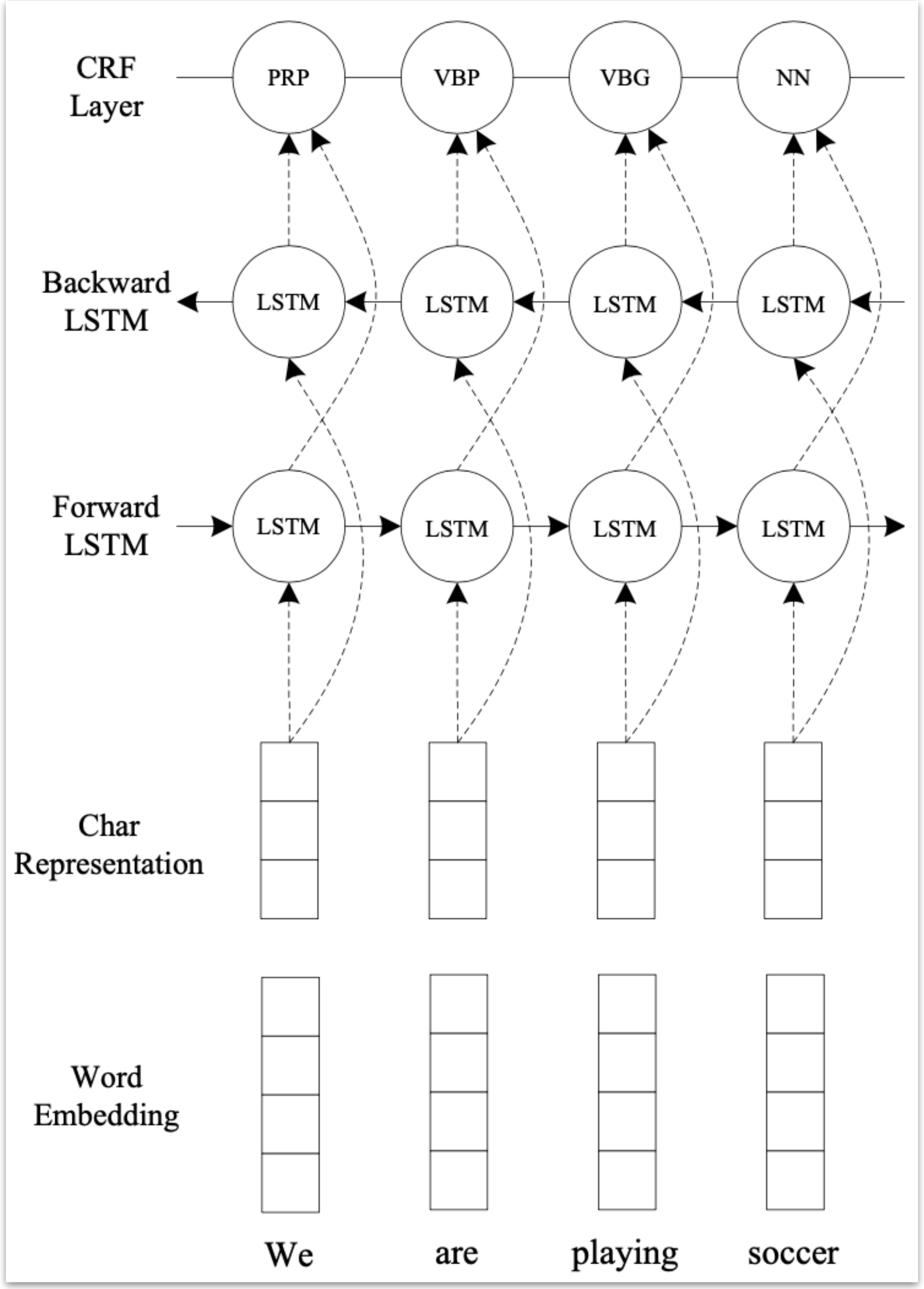
– Penn Treebank WSJ corpus for part-of-speech (POS) tagging
– CoNLL 2003 corpus for named entity recognition (NER)

CNN for Character-level Representation



LSTM Unit

$$
\begin{aligned}
\mathbf{i}_t &= \sigma(\boldsymbol{W}_i \mathbf{h}_{t-1} + \boldsymbol{U}_i \mathbf{x}_t + \boldsymbol{b}_i) \\
\mathbf{f}_t &= \sigma(\boldsymbol{W}_f \mathbf{h}_{t-1} + \boldsymbol{U}_f \mathbf{x}_t + \boldsymbol{b}_f) \\
\tilde{\mathbf{c}}_t &= \tanh(\boldsymbol{W}_c \mathbf{h}_{t-1} + \boldsymbol{U}_c \mathbf{x}_t + \boldsymbol{b}_c) \\
\mathbf{c}_t &= \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t \\
\mathbf{o}_t &= \sigma(\boldsymbol{W}_o \mathbf{h}_{t-1} + \boldsymbol{U}_o \mathbf{x}_t + \boldsymbol{b}_o) \\
\mathbf{h}_t &= \mathbf{o}_t \odot \tanh(\mathbf{c}_t)
\end{aligned}
$$



Conditional Random Fields (CRF)

In POS tagging, an adjective is more likely to be followed by a noun than a verb, and in NER, I-ORG cannot follow I-PER.

$\mathbf{z} = \{\mathbf{z}_1, \cdots, \mathbf{z}_n\} \rightarrow$ a generic input sequence

$\boldsymbol{y} = \{y_1, \cdots, y_n\} \rightarrow$ a generic sequence of labels

$$p(\boldsymbol{y}|\mathbf{z}; \mathbf{W}, \mathbf{b}) = \frac{\prod_{i=1}^{n} \psi_i(y_{i-1}, y_i, \mathbf{z})}{\sum_{y' \in \mathcal{Y}(\mathbf{z})} \prod_{i=1}^{n} \psi_i(y'_{i-1}, y'_i, \mathbf{z})}$$

$\mathcal{Y}(\mathbf{z}) \rightarrow$ set of possible label sequences

$\psi_i(\ell, \ell', \mathbf{z}) = \exp(\mathbf{W}^T_{\ell,\ell'} \mathbf{z}_i + \mathbf{b}_{\ell,\ell'})$ potential functions

$(\ell, \ell') \rightarrow$ label pair

$\log p(\boldsymbol{y}|\mathbf{z}; \mathbf{W}, \mathbf{b}) \rightarrow$ log-likelihood

$$\boldsymbol{y}^* = \underset{y \in \mathcal{Y}(\mathbf{z})}{\operatorname{argmax}}\, p(\boldsymbol{y}|\mathbf{z}; \mathbf{W}, \mathbf{b})$$

Viterbi algorithm!

POS tagging accuracy

Model	Acc.
Giménez and Màrquez (2004)	97.16
Toutanova et al. (2003)	97.27
Manning (2011)	97.28
Collobert et al. (2011)‡	97.29
Santos and Zadrozny (2014)‡	97.32
Shen et al. (2007)	97.33
Sun (2014)	97.36
Søgaard (2011)	97.50
This paper	**97.55**

NER F1 score

Model	F1
Chieu and Ng (2002)	88.31
Florian et al. (2003)	88.76
Ando and Zhang (2005)	89.31
Collobert et al. (2011)‡	89.59
Huang et al. (2015)‡	90.10
Chiu and Nichols (2015)‡	90.77
Ratinov and Roth (2009)	90.80
Lin and Wu (2009)	90.90
Passos et al. (2014)	90.90
Lample et al. (2016)‡	90.94
Luo et al. (2015)	91.20
This paper	**91.21**

Ma, Xuezhe, and Eduard Hovy. "End-to-end sequence labeling via bi-directional lstm-cnns-crf." *arXiv preprint arXiv:1603.01354* (2016).

Universal Language Model Fine-tuning for Text Classification

Boulder

YouTube Playlist

ULMFiT

Text Classification: 1. spam, fraud, and bot detection
2. emergency response
3. commercial document classification (legal discovery)

– discriminative fine-tuning
– slanted triangular learning rate
– gradual unfreezing

$\mathcal{T}_S \rightarrow$ source task

$\mathcal{T}_T \rightarrow$ target task with $\mathcal{T}_T \neq \mathcal{T}_S$

$\mathcal{H} \rightarrow$ hypothesis space

General-Domain LM pre-training

Wikitext-103

28,595 pre-processed Wikipedia articles

103 million words

Target task LM fine-tuning

– discriminative fine-tuning

$\theta_t = \theta_{t-1} - \eta \cdot \nabla_\theta J(\theta)$

$\theta = \{\theta^1, \ldots, \theta^L\}$

$\theta^\ell \rightarrow$ parameters of the model at the ℓ-th layer

$\eta^\ell \rightarrow$ learning rate of the ℓ-th layer

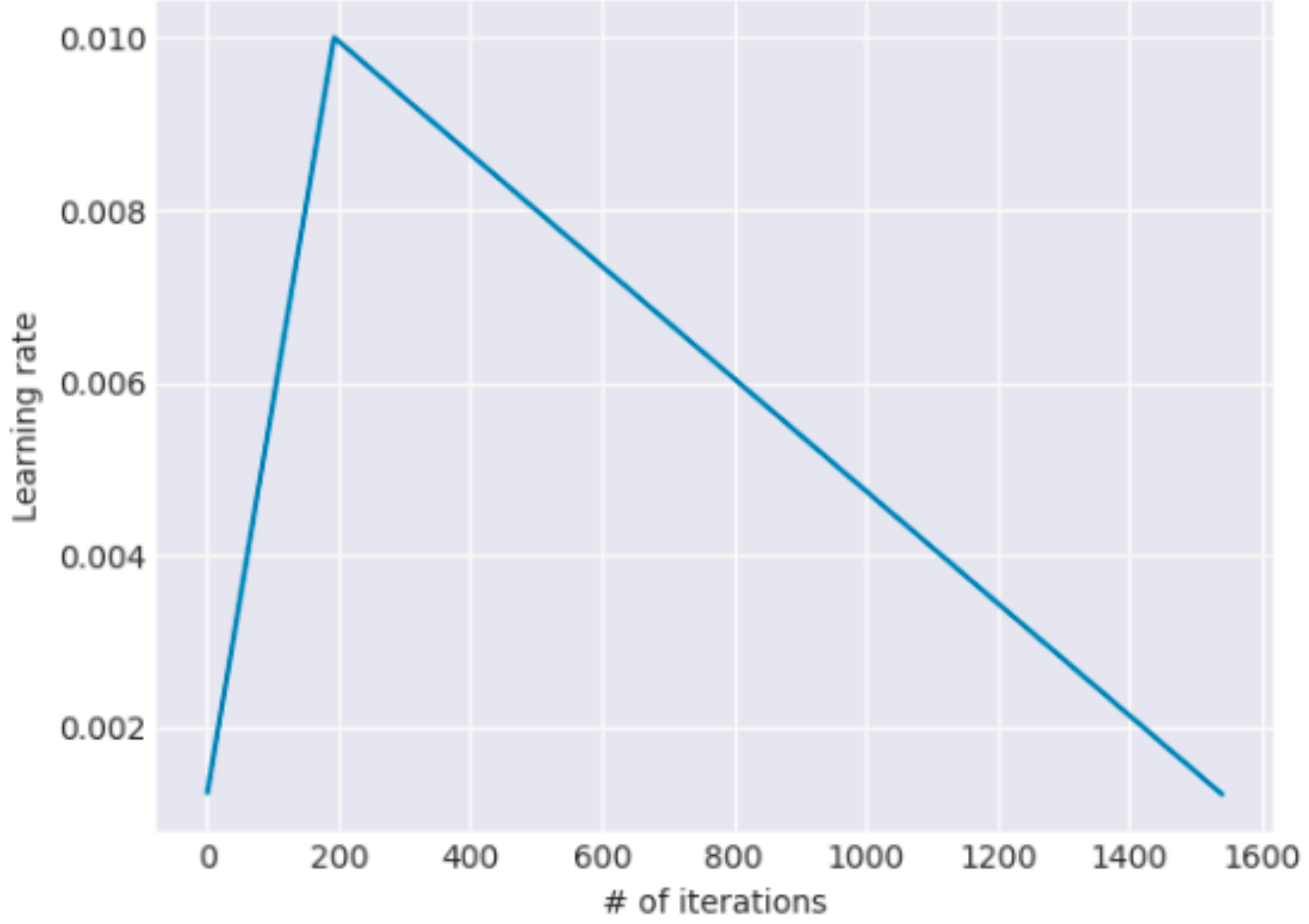
$\theta_t^l = \theta_{t-1}^l - \eta^l \cdot \nabla_{\theta^l} J(\theta)$ $\qquad \eta^{\ell-1} = \eta^\ell / 2.6$

– slanted triangular learning rate

$$cut = \lfloor T \cdot cut\_frac \rfloor$$

$$p = \begin{cases} t/cut, & \text{if } t < cut \\ 1 - \frac{t-cut}{cut \cdot (1/cut\_frac - 1)}, & \text{otherwise} \end{cases}$$

$$\eta_t = \eta_{max} \cdot \frac{1 + p \cdot (ratio - 1)}{ratio}$$



$T \rightarrow$ number of training iterations

$cut\_frac = 0.1$

$ratio = 32 \rightarrow$ how smaller the lowest LR is from the max LR

$\eta_{max} = 0.01$

Target task classifier fine-tuning

Two additional linear blocks

ReLU & softmax

$H = \{h_1, h_2, \ldots, h_T\}$

$h_c = [h_T, \text{maxpool}(H), \text{meanpool}(H)]$

– gradual unfreezing

back-propagation through time (BPTT)

BPTT for Text Classification (BPT3C)

Dataset	Type	# classes	# examples
TREC-6	Question	6	5.5k
IMDb	Sentiment	2	25k
Yelp-bi	Sentiment	2	560k
Yelp-full	Sentiment	5	650k
AG	Topic	4	120k
DBpedia	Topic	14	560k

	Model	Test		Model	Test
IMDb	CoVe (McCann et al., 2017)	8.2	TREC-6	CoVe (McCann et al., 2017)	4.2
	oh-LSTM (Johnson and Zhang, 2016)	5.9		TBCNN (Mou et al., 2015)	4.0
	Virtual (Miyato et al., 2016)	5.9		LSTM-CNN (Zhou et al., 2016)	3.9
	ULMFiT (ours)	**4.6**		ULMFiT (ours)	**3.6**

	AG	DBpedia	Yelp-bi	Yelp-full
Char-level CNN (Zhang et al., 2015)	9.51	1.55	4.88	37.95
CNN (Johnson and Zhang, 2016)	6.57	0.84	2.90	32.39
DPCNN (Johnson and Zhang, 2017)	6.87	0.88	2.64	30.58
ULMFiT (ours)	**5.01**	**0.80**	**2.16**	**29.98**

Howard, Jeremy, and Sebastian Ruder. "Universal language model fine-tuning for text classification." *arXiv preprint arXiv:1801.06146* (2018).

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Questions?

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