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Convolutional Neural Networks (for NLP)

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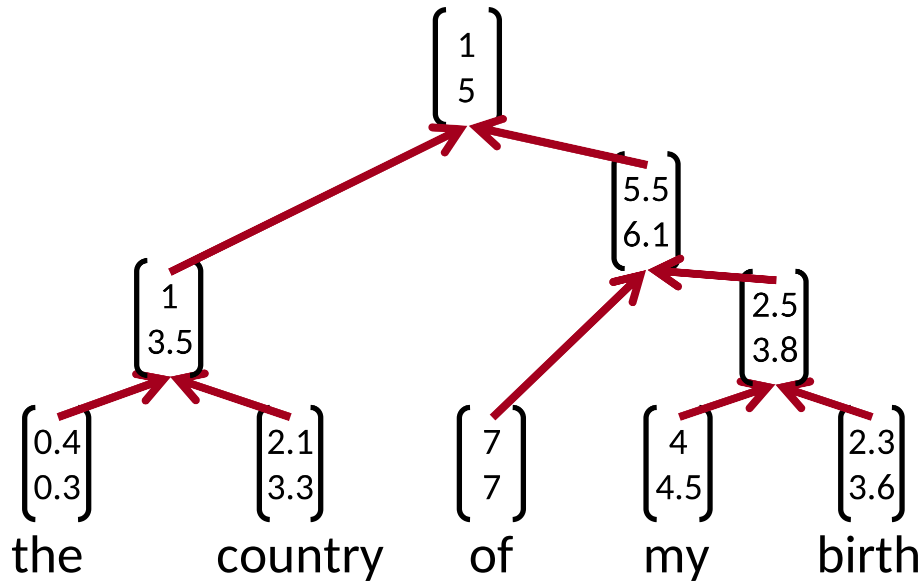
Overview of today

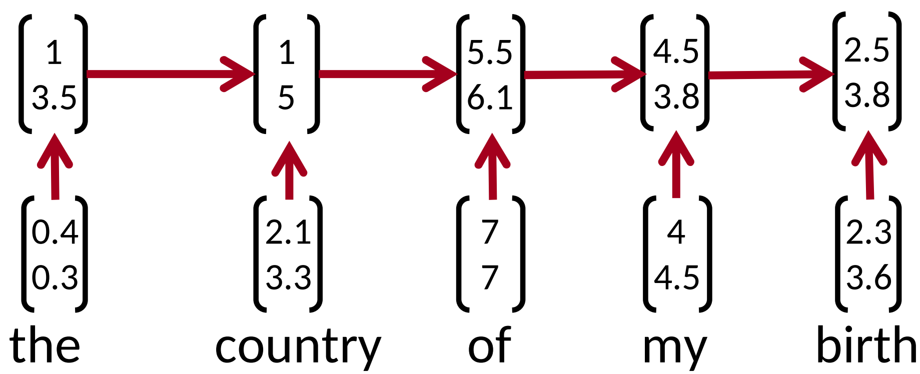
- From RNNs to CNNs

- CNN Variant1: Simple single layer
- Application: Sentence classification
- More details and tricks
- Evaluation
- Comparison between sentence models

- CNN Variant2: Complex multi layer

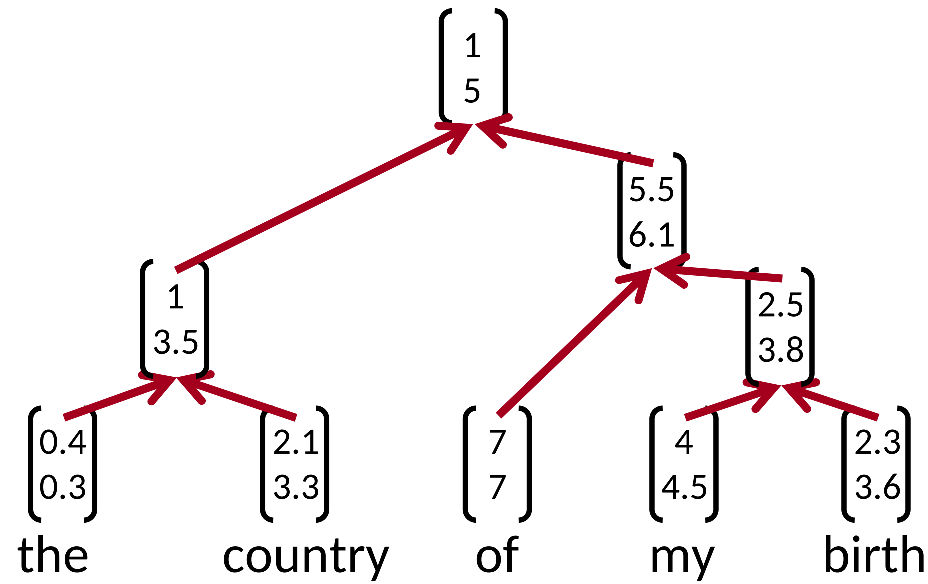
From RNNs to CNNs



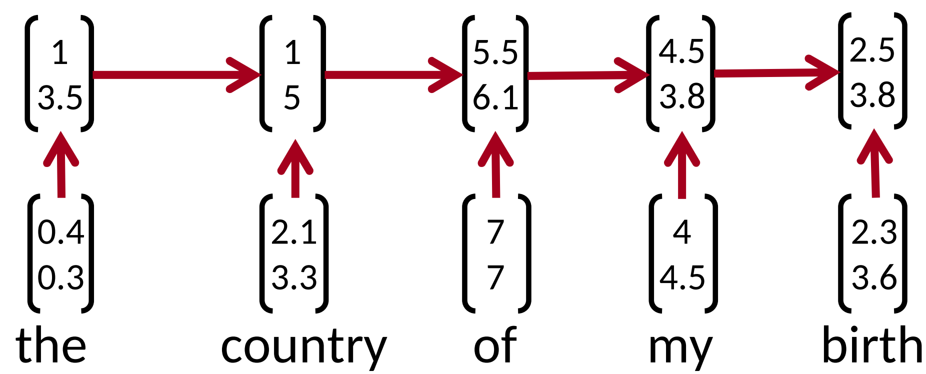


From RNNs to CNNs

- Recursive neural nets require a parser to get tree structure



- Recurrent neural nets cannot capture phrases without prefix context
And often capture too much of last words in final vector



From RNNs to CNNs

- RNN: Get compositional vectors for grammatical phrases only

- CNN: What if we compute vectors for every possible phrase?
- Example: “the country of my birth” computes vectors for:
  - the country, country of, of my, my birth, the country of, Country of my, of my birth, the country of my, country of my birth

- Regardless of whether it is grammatical
- Wouldn’t need parser
- Not very linguistically or cognitively plausible

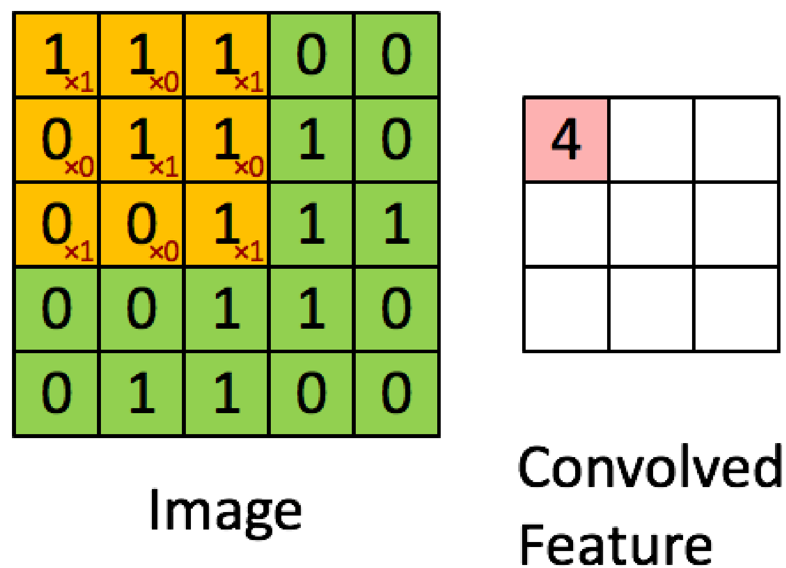
What is convolution anyway?

- 1d discrete convolution generally:

$$(f * g)[n] = \sum_{m=-M}^{M} f[n-m]g[m].$$

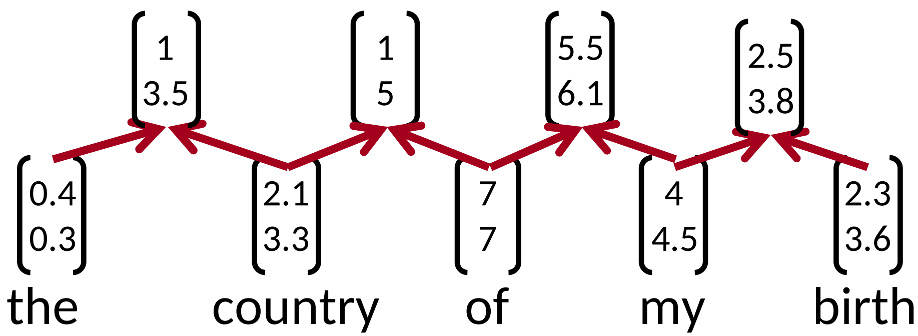
- Convolution is great to extract features from images

- 2d example
- Yellow shows filter weights
- Green shows input



From RNNs to CNNs

- First layer: compute all bigram vectors



- Same computation as in RNN but for every pair

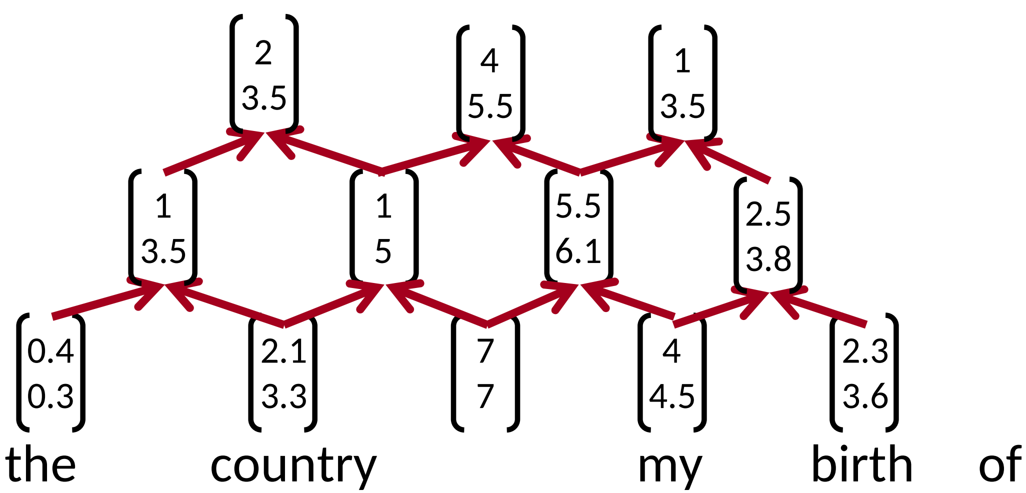
$$\boxed{p = \tanh\left(W\begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + b\right)}$$

- This can be interpreted as a convolution over the word vectors

From RNNs to CNNs

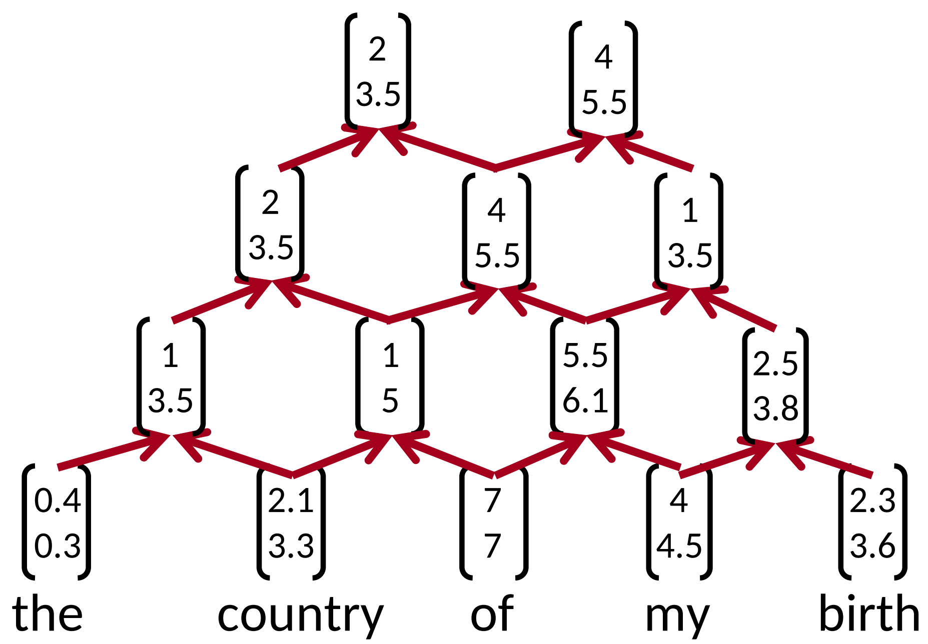
- Now multiple options to compute higher layers.
- First option (simple to understand but not necessarily best)
- Just repeat with different weights:

$$p = \tanh\left(W^{(2)}\begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + b\right)$$



From RNNs to CNNs

- First option (simple to understand but not necessarily best)



From RNNs to CNNs

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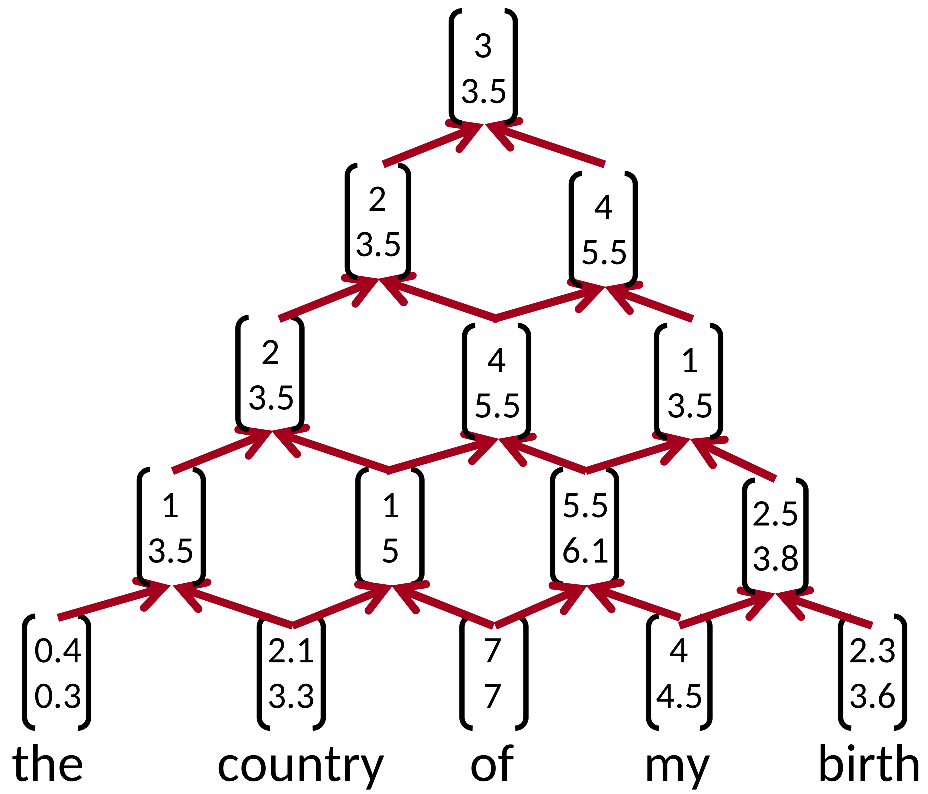
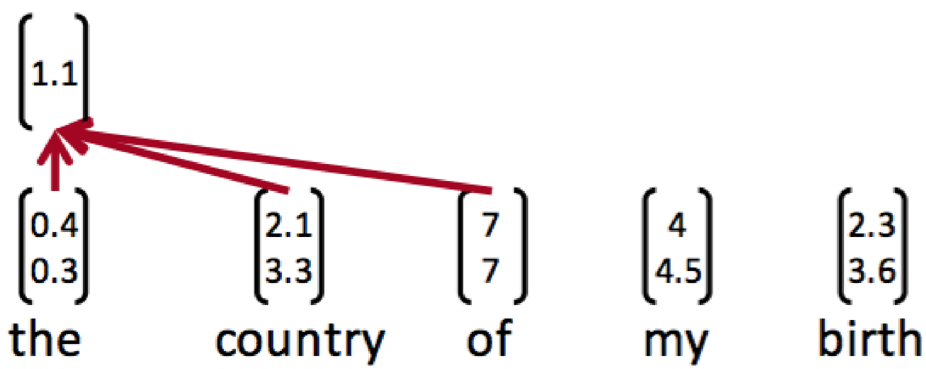


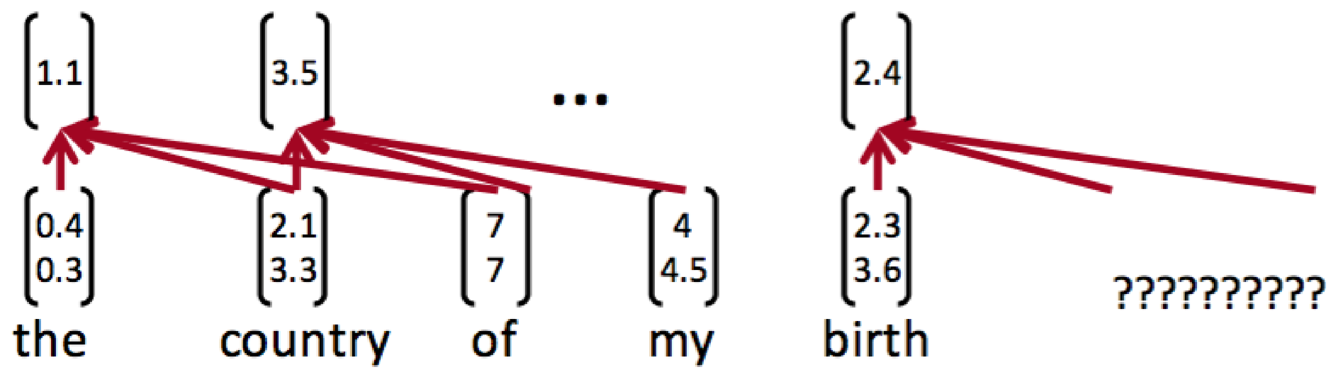
Single Layer CNN

- A simple variant using one convolutional layer and **pooling**
- Based on Collobert and Weston (2011) and Kim (2014) "Convolutional Neural Networks for Sentence Classification"
- Word vectors: $\mathbf{x}_i \in \mathbb{R}^k$
- Sentence: $\mathbf{x}_{1:n} = \mathbf{x}_1 \oplus \mathbf{x}_2 \oplus \ldots \oplus \mathbf{x}_n$ (vectors concatenated)
- Concatenation of words in range: $\mathbf{x}_{i:i+j}$
- Convolutional filter: $\mathbf{w} \in \mathbb{R}^{hk}$ (goes over window of h words)
- Could be 2 (as before) higher, e.g. 3:



Single layer CNN

- Filter w is applied to all possible windows (concatenated vectors)
- Sentence: $\mathbf{x}_{1:n} = \mathbf{x}_1 \oplus \mathbf{x}_2 \oplus \ldots \oplus \mathbf{x}_n$
- All possible windows of length h: $\{\mathbf{x}_{1:h}, \mathbf{x}_{2:h+1}, \ldots, \mathbf{x}_{n-h+1:n}\}$
- Result is a feature map: $\mathbf{c} = [c_1, c_2, \ldots, c_{n-h+1}] \in \mathbb{R}^{n-h+1}$



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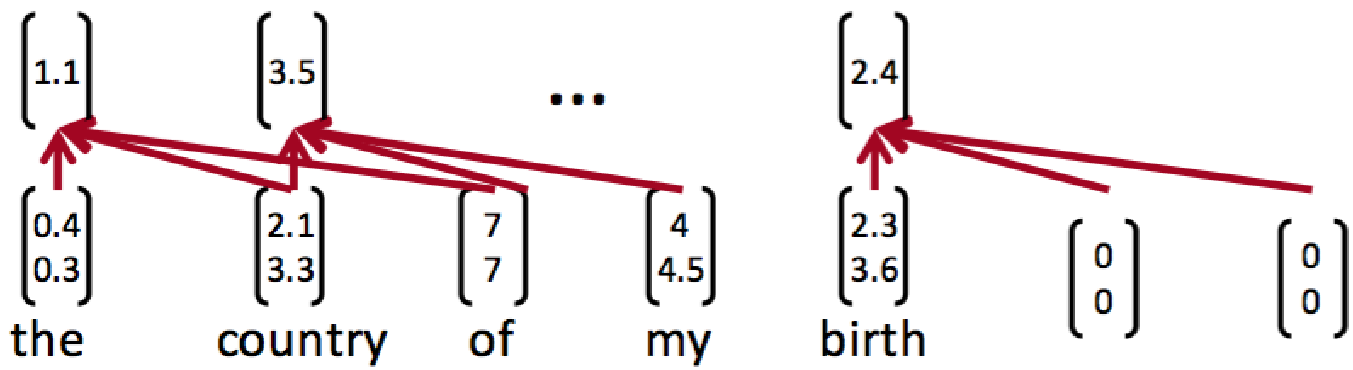

Single layer CNN: Pooling layer

- New building block: Pooling
- In particular: max-over-time pooling layer
- Idea: capture most important activation (maximum over time)

- From feature map $\mathbf{c} = [c_1, c_2, \ldots, c_{n-h+1}] \in \mathbb{R}^{n-h+1}$

- Pooled single number: $\hat{c} = \max\{\mathbf{c}\}$

- But we want more features!

Solution: Multiple filters

- Use multiple filter weights w
- Useful to have different window sizes h
- Because of max pooling $\hat{c} = \max\{\mathbf{c}\}$, length of **c** irrelevant

$$\mathbf{c} = [c_1, c_2, \ldots, c_{n-h+1}] \in \mathbb{R}^{n-h+1}$$

- So we can have some filters that look at unigrams, bigrams, tri-grams, 4-grams, etc.

Multi-channel idea

- Initialize with pre-trained word vectors (e.g. word2vec)
- Start with two copies
- Backprop into only one set, keep other "static"
- Both channels are added to c_i before max-pooling

Classification after one CNN layer

- First one convolution, followed by one max-pooling
- To obtain final feature vector: $\mathbf{z} = [\hat{c}_1, \ldots, \hat{c}_m]$
  (assuming m filters w)
- Simple final softmax layer $y = softmax\left(W^{(S)}z + b\right)$

Figure from Kim (2014)

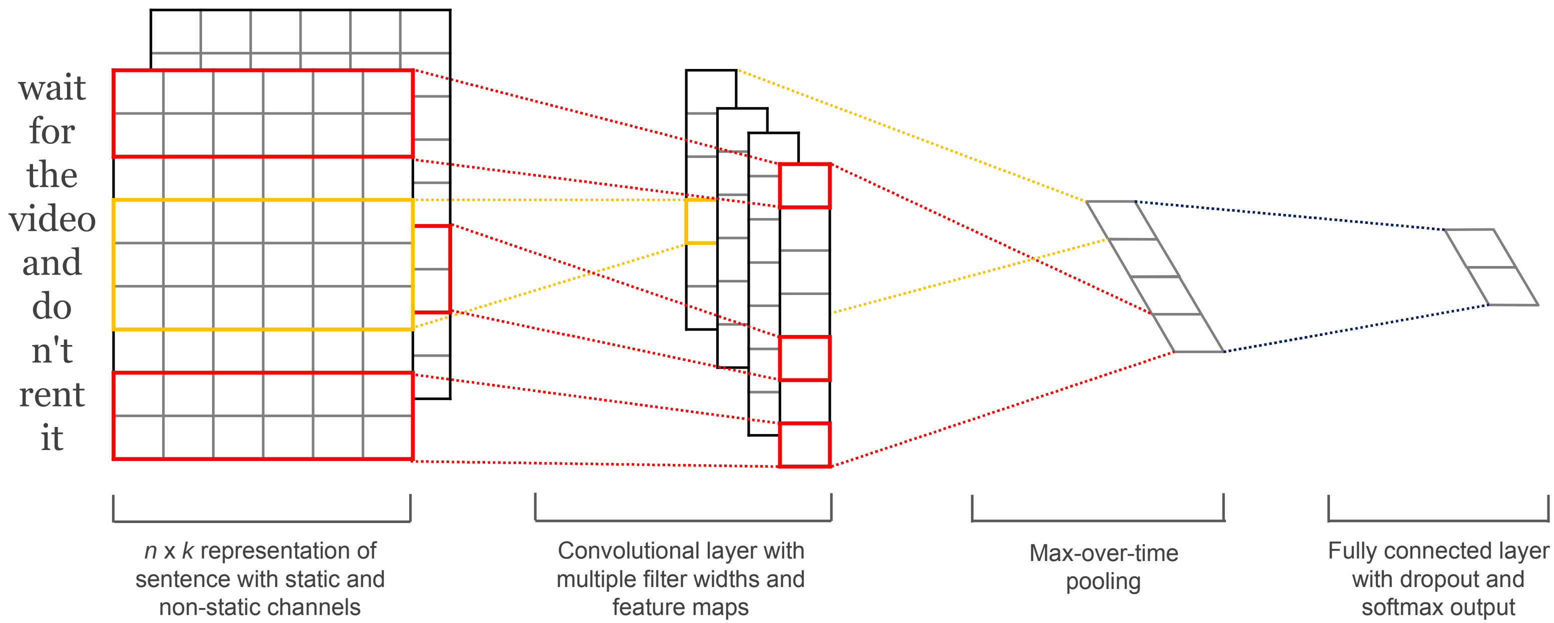

Figure 1: Model architecture with two channels for an example sentence.

n words (possibly zero padded) and each word vector has k dimensions

Tricks to make it work better: Dropout

- Idea: randomly mask/dropout/set to 0 some of the feature weights z
- Create masking vector r of Bernoulli random variables w probability p (a hyperparameter) of being 1

- Delete features during training:

$$y = softmax\left(W^{(S)}(r \circ z) + b\right)$$

- Reasoning: Prevents co-adaptation (overfitting to seeing specific feature constellations)

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Tricks to make it work better: Dropout

$$y = softmax\left(W^{(S)}(r \circ z) + b\right)$$

- At training time, gradients are backpropagated only through those elements of z vector for which r is 1

- At test time, there is no dropout, so feature vectors z ar
- Hence, we scale final vector by Bernoulli probability p

$$\hat{W}^{(S)} = pW^{(S)}$$

- Kim (2014) reports **2 – 4% improved accuracy** and ability to use very large networks without overfitting

Another regularization trick

- Somewhat less common
- Constrain l_2 norms of weight vectors of each class (row in softmax weight $W^{(S)}$) to fixed number s (also a hyperparameter)
- If $\|W_{c\cdot}^{(S)}\| > s$, then rescale it so $\|W_{c\cdot}^{(S)}\| = s$

All hyperparameters in Kim (2014)

- Find hyperparameters based on dev set
- Nonlinearity: reLu
- Window filter sizes h = 3,4,5
- Each filter size has 100 featuremaps
- Dropout p = 0.5
- L2 constraint s for rows of softmax s = 3
- Mini batch size for SGD training: 50
- Word vectors: pre-trained with word2vec, k = 300

- During training, keep checking performance on dev set and pick highestaccuracy weights for final evaluation

Experiments

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	
SVMs (Silva et al., 2011)					**95.0**		

Table 2: Results of our CNN models against other methods. **RAE**: Recursive Autoencoders with pre-trained word vectors from

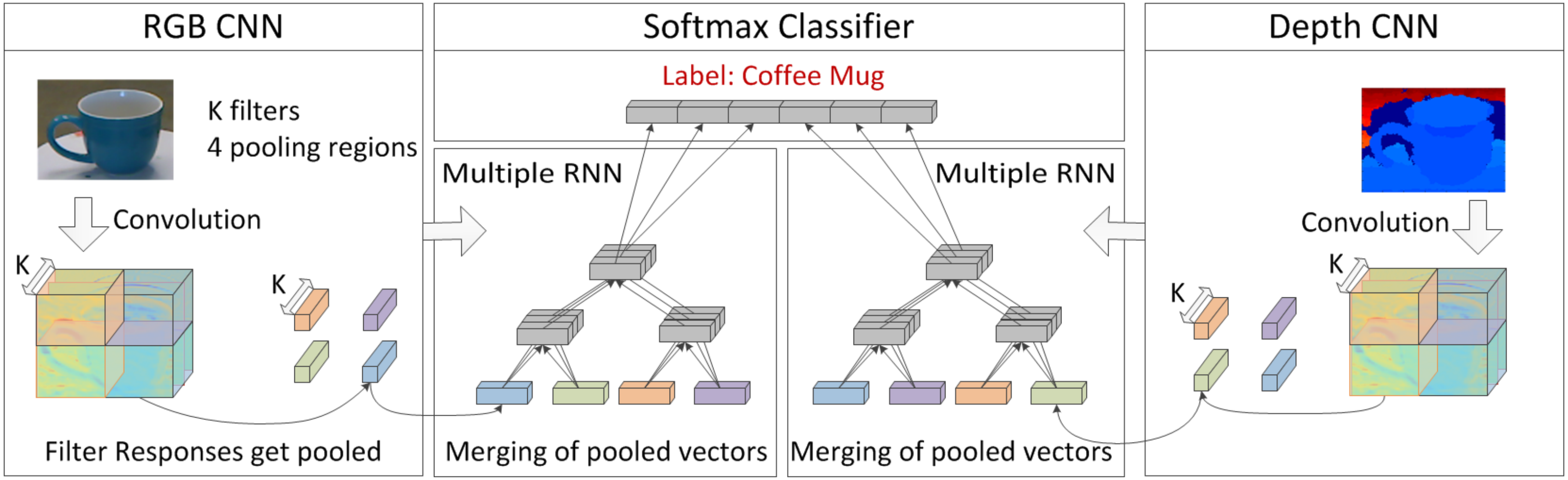
Problem with comparison?

- Dropout gives 2 – 4 % accuracy improvement
- Several baselines didn't use dropout

- Still remarkable results and simple architecture!

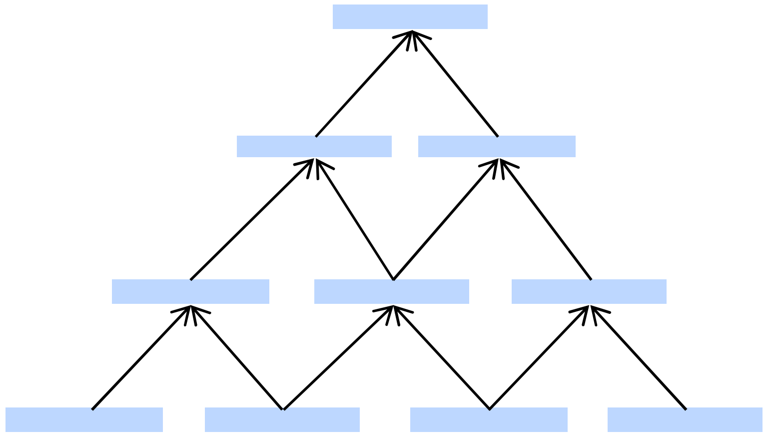
- Difference to window and RNN architectures we described in previous lectures: pooling, many filters and dropout
- Ideas can be used in RNNs too
- Tree-LSTMs obtain better performance on sentence datasets

- Fixed tree RNNs explored in computer vision: Socher et al (2012): "Convolutional-Recursive Deep Learning for 3D Object Classification"

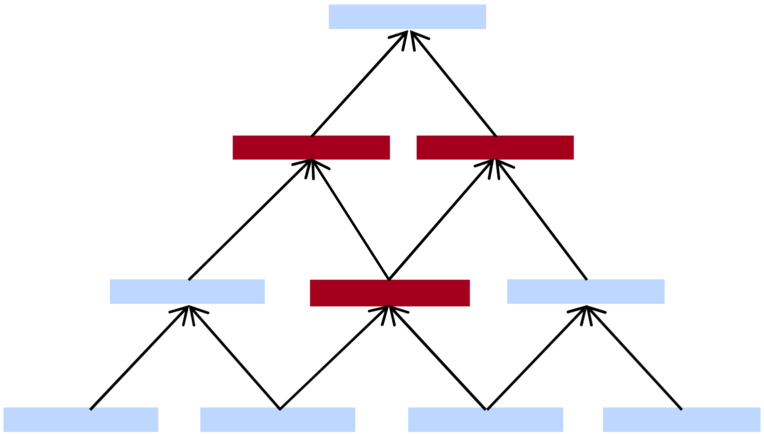


Relationship between RNNs and CNNs

- CNN

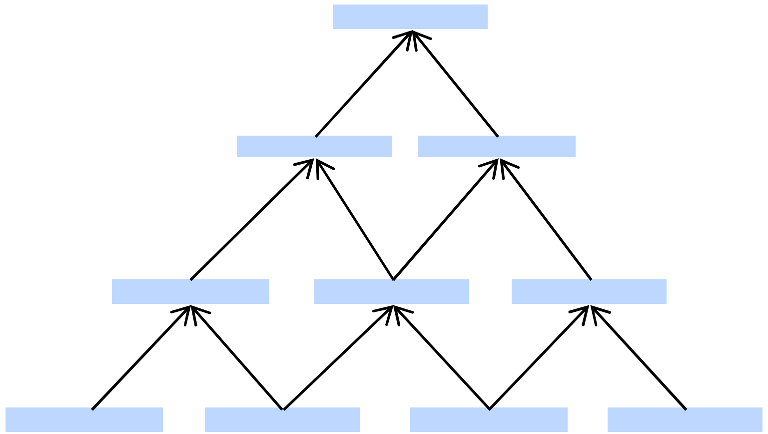


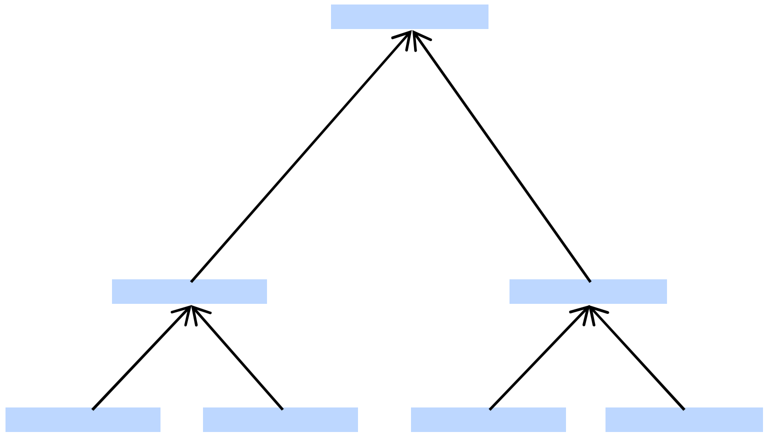
RNN



Relationship between RNNs and CNNs

- CNN RNN





Relationship between RNNs and CNNs

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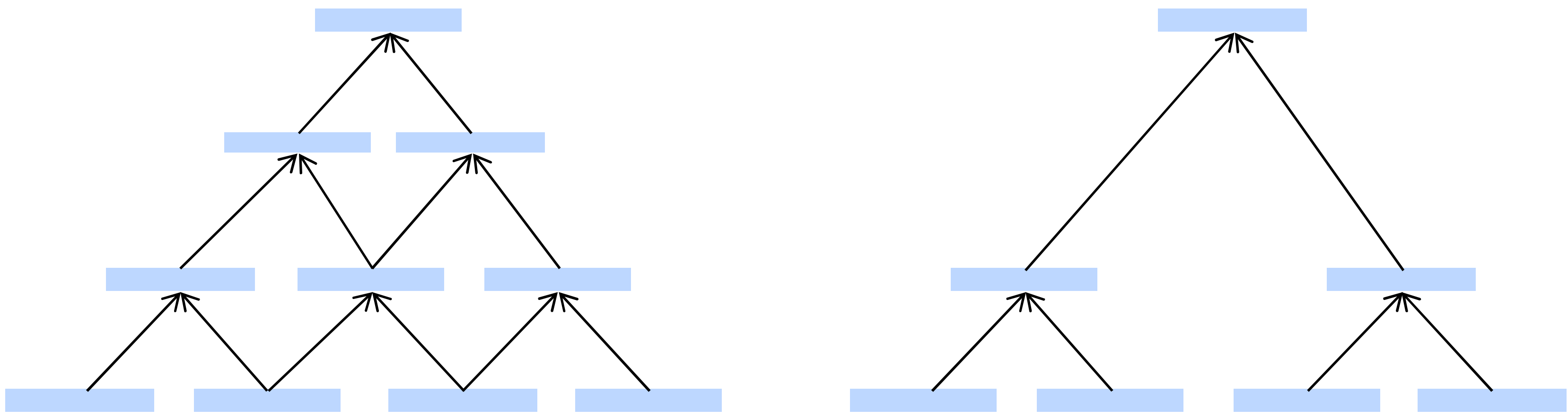
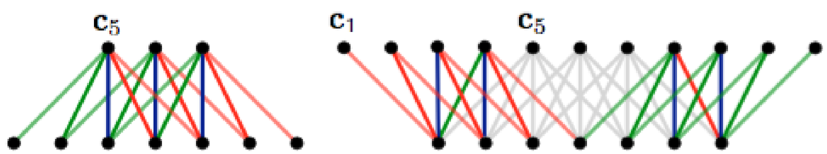


- **Stride size** flexible in CNNs, RNNs "weighted average pool"
- Tying (sharing) weights of filters inside vs across different layers
- CNN: multiple filters, additional layer type: max-pooling
- Balanced input independent structure vs input specific tree

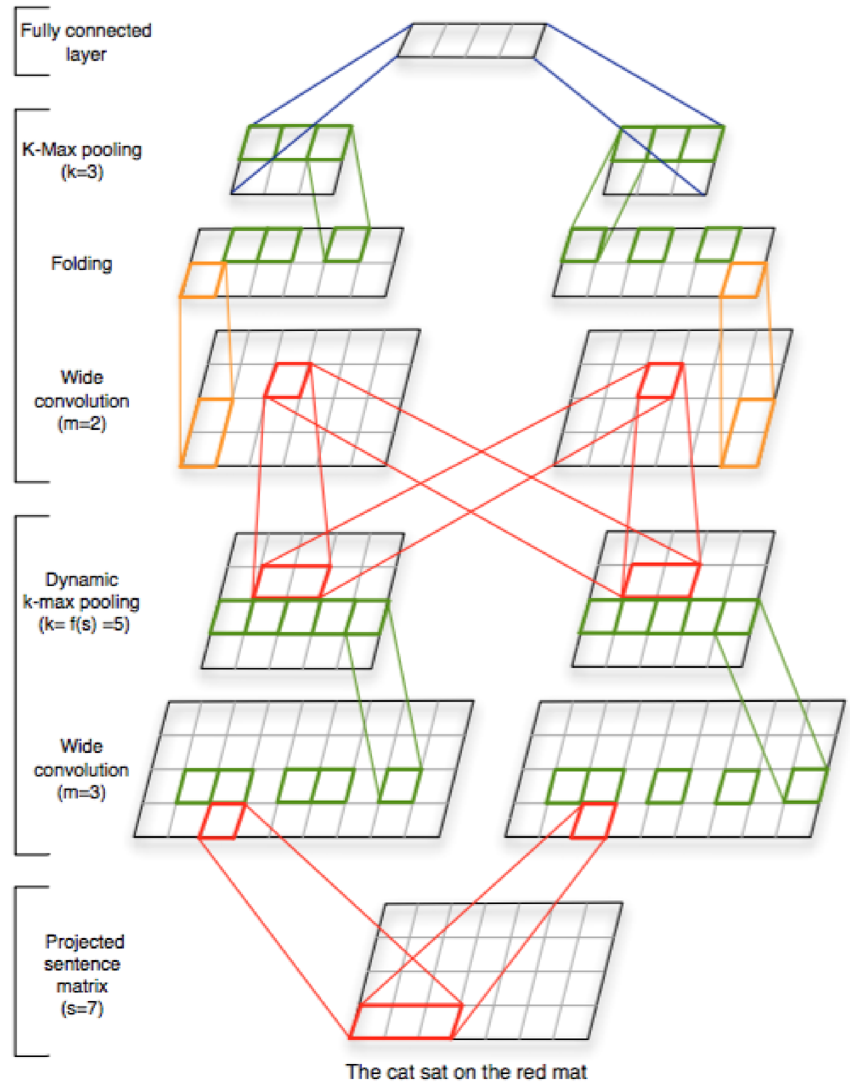
CNN alternatives

- Narrow vs wide convolution



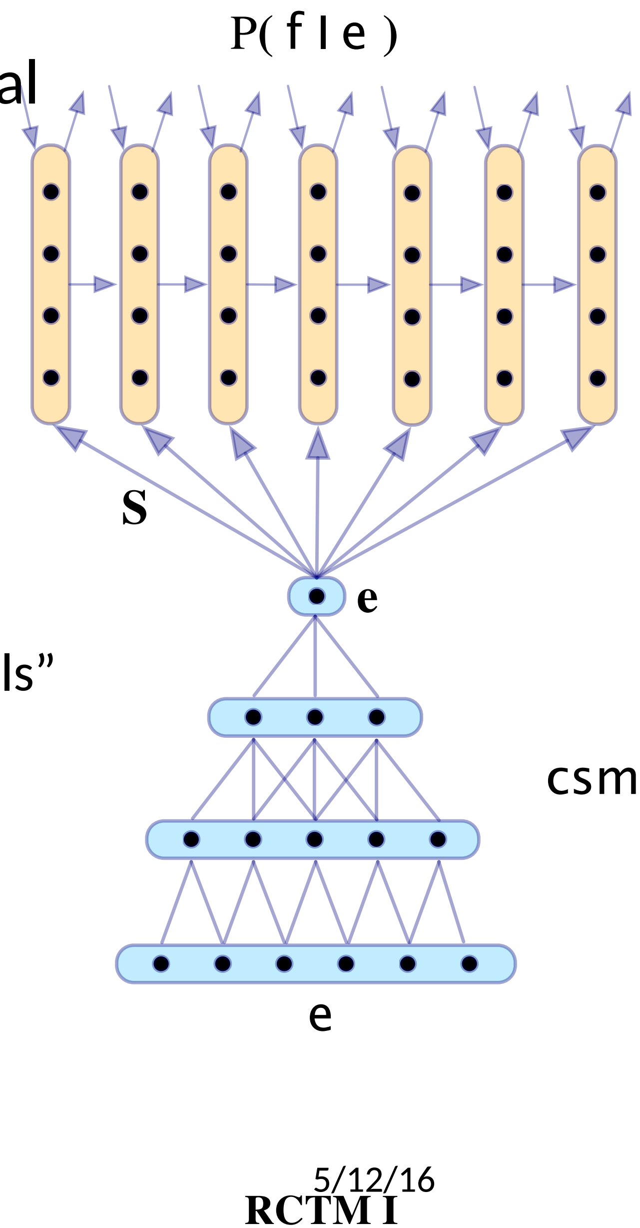
- Complex pooling schemes (over sequences) and deeper convolutional layers

- Kalchbrenner et al. (2014)



CNN application: Translation

- One of the first successful neural machine translation efforts
- Uses CNN for encoding and RNN for decoding
- Kalchbrenner and Blunsom (2013) "Recurrent Continuous Translation Models"



Model comparison

- **Bag of Vectors**: Surprisingly good baseline for simple classification problems. Especially if followed by a few layers!
- **Window Model**: Good for single word classification for problems that do not need wide context
- **CNNs:** good for classification, unclear how to incorporate phrase level annotation (can only take a single label), need zero padding for shorter phrases, hard to interpret, easy to parallelize on GPUs

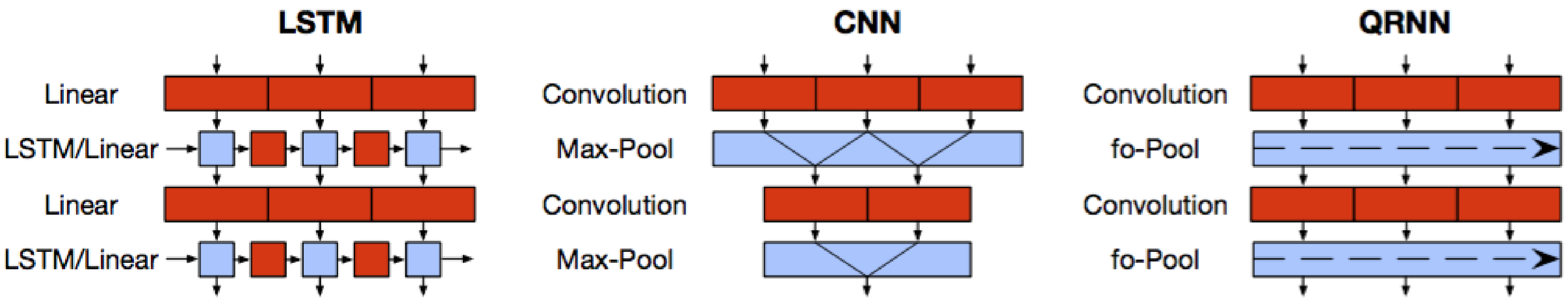
Model comparison

- **Recursive Neural Networks**: most linguistically plausible, interpretable, provide most important phrases (for visualization), need parse trees

- **Recurrent Neural Networks**: Most cognitively plausible (reading from left to right), not usually the highest classification performance but lots of improvements right now with gates (GRUs, LSTMs, etc).

- Best but also most complex models: Hierarchical recurrent neural networks with attention mechanisms and additional memory

Quasi-Recurrent Neural Network



- Parallelism computation across time:

$$\mathbf{z}_t = \tanh(\mathbf{W}_z^1\mathbf{x}_{t-1} + \mathbf{W}_z^2\mathbf{x}_t)$$
$$\mathbf{f}_t = \sigma(\mathbf{W}_f^1\mathbf{x}_{t-1} + \mathbf{W}_f^2\mathbf{x}_t)$$
$$\mathbf{o}_t = \sigma(\mathbf{W}_o^1\mathbf{x}_{t-1} + \mathbf{W}_o^2\mathbf{x}_t).$$

$$\mathbf{Z} = \tanh(\mathbf{W}_z * \mathbf{X})$$
$$\mathbf{F} = \sigma(\mathbf{W}_f * \mathbf{X})$$
$$\mathbf{O} = \sigma(\mathbf{W}_o * \mathbf{X}),$$

- Element-wise gated recurrence for parallelism across channels:

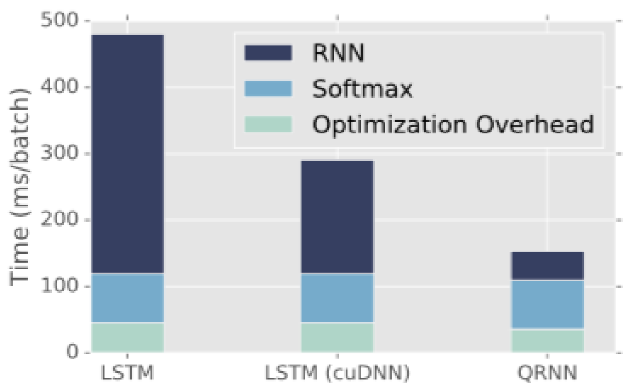
$$\mathbf{h}_t = \mathbf{f}_t \odot \mathbf{h}_{t-1} + (1 - \mathbf{f}_t) \odot \mathbf{z}_t,$$

Q-RNNs for Language Modeling

- Better

Model	Parameters	Validation	Test
LSTM (medium) (Zaremba et al., 2014)	20M	86.2	82.7
Variational LSTM (medium) (Gal & Ghahramani, 2016)	20M	81.9	79.7
LSTM with CharCNN embeddings (Kim et al., 2016)	19M	–	78.9
Zoneout + Variational LSTM (medium) (Merity et al., 2016)	20M	84.4	80.6
Our models			
LSTM (medium)	20M	85.7	82.0
QRNN (medium)	18M	82.9	79.9
QRNN + zoneout ($p = 0.1$) (medium)	18M	82.1	78.3

- Faster



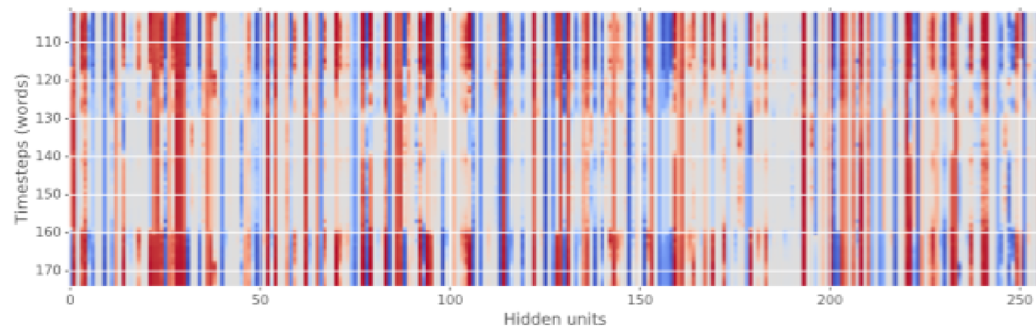
		Sequence length				
		32	64	128	256	512
Batch size	8	**5.5x**	**8.8x**	**11.0x**	**12.4x**	**16.9x**
	16	**5.5x**	**6.7x**	**7.8x**	**8.3x**	**10.8x**
	32	**4.2x**	**4.5x**	**4.9x**	**4.9x**	**6.4x**
	64	**3.0x**	**3.0x**	**3.0x**	**3.0x**	**3.7x**
	128	**2.1x**	**1.9x**	**2.0x**	**2.0x**	**2.4x**
	256	**1.4x**	**1.4x**	**1.3x**	**1.3x**	**1.3x**

Q-RNNs for Sentiment Analysis

- Often better and faster than LSTMs

Model	Time / Epoch (s)	Test Acc (%)
BSVM-bi (Wang & Manning, 2012)	–	91.2
2 layer sequential BoW CNN (Johnson & Zhang, 2014)	–	92.3
Ensemble of RNNs and NB-SVM (Mesnil et al., 2014)	–	92.6
2-layer LSTM (Longpre et al., 2016)	–	87.6
Residual 2-layer bi-LSTM (Longpre et al., 2016)	–	90.1
Our models		
Deeply connected 4-layer LSTM (cuDNN optimized)	480	90.9
Deeply connected 4-layer QRNN	150	91.4
D.C. 4-layer QRNN with $k = 4$	160	91.1

- More interpretable



- Example:
- Initial positive review
- *Review starts out positive*
  At 117: "*not exactly a bad story*"
  At 158: "*I recommend this movie to everyone, even if you've never played the game*"