Deep Learning Course

Lecture 8:
Convolutional Neural Networks (for NLP)

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Based on Stanford CS224d

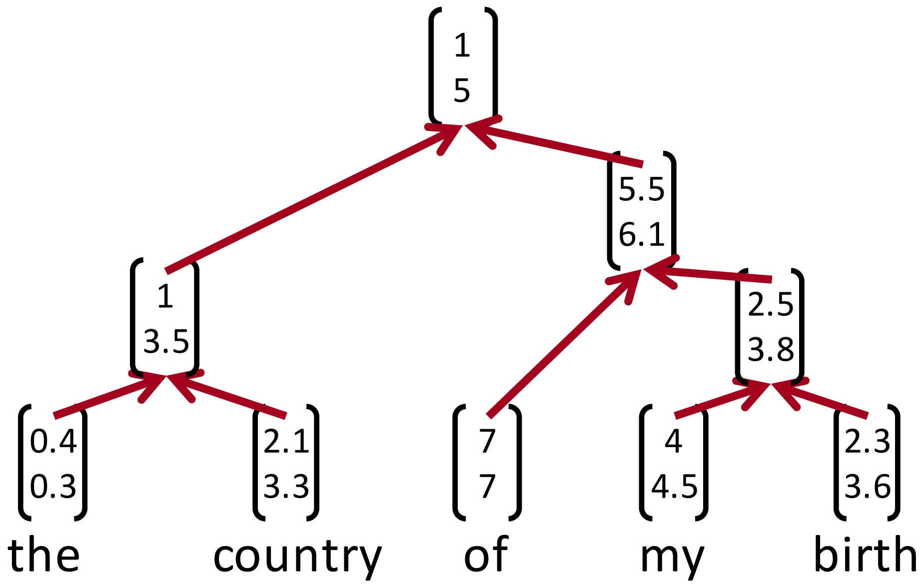
Overview of today

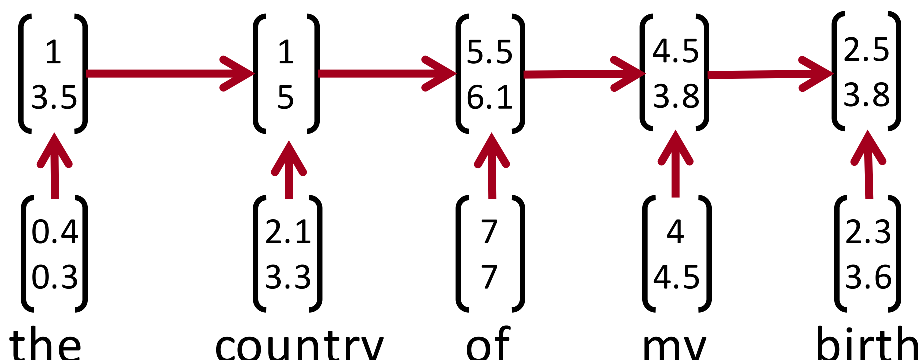
- From RNNs to CNNs

- CNN Variant 1: Simple single layer
- Application: Sentence classification
- More details and tricks
- Evaluation
- Comparison between sentence models: BoV, RNNs^2, CNNs

- CNN Variant 2: Complex multi layer

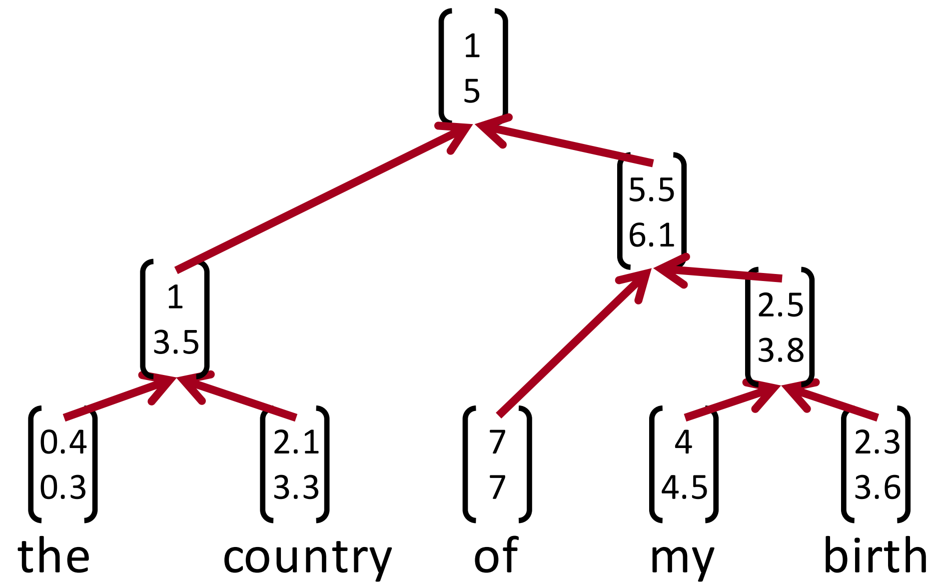
From RNNs to CNNs



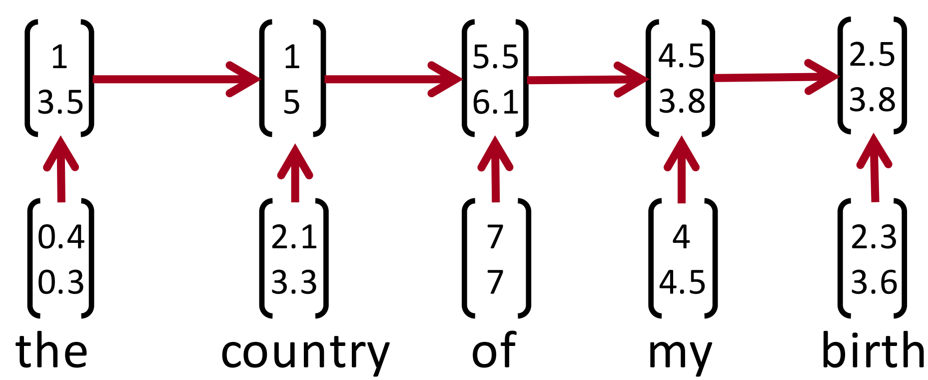


From RNNs to CNNs

- 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

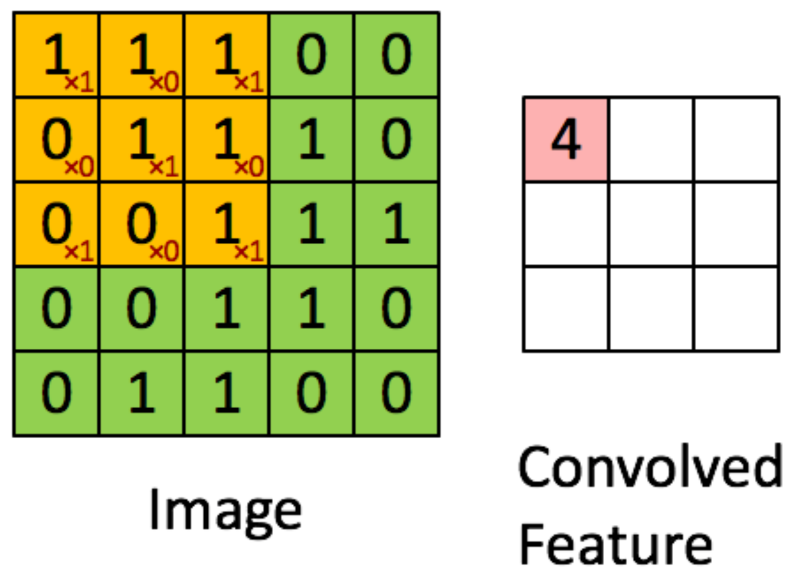
- RNN: Get compositional vectors for grammatical phrases only

- 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?

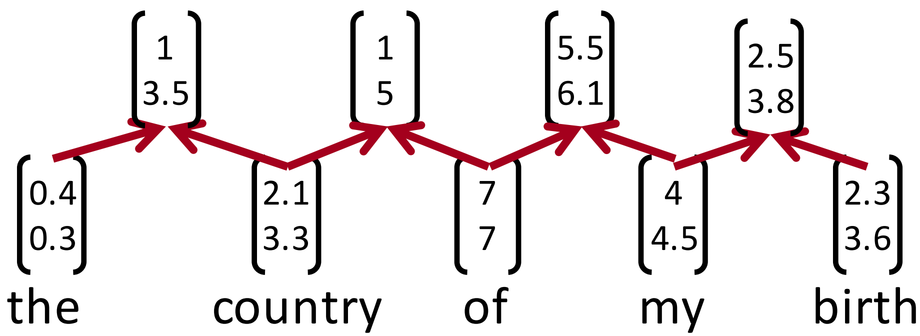
- 1d discrete convolution generally: $(f * g)[n] = \sum_{m=-M}^{M} f[n-m]g[m].$
- Convolution is great to extract features from images
- 2d example →
- Yellow shows filter weights
- Green shows input



Stanford UFLDL wiki

From RNNs to CNNs

- First layer: compute all bigram vectors



- Same computation as in RNN but for every pair

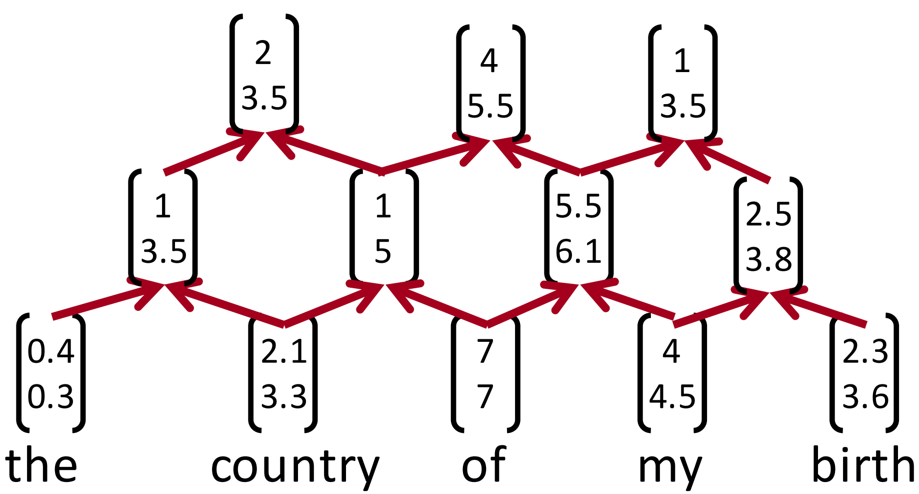
$$\boxed{p = \tanh\left(W\begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + b\right)}$$

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

From RNNs to CNNs

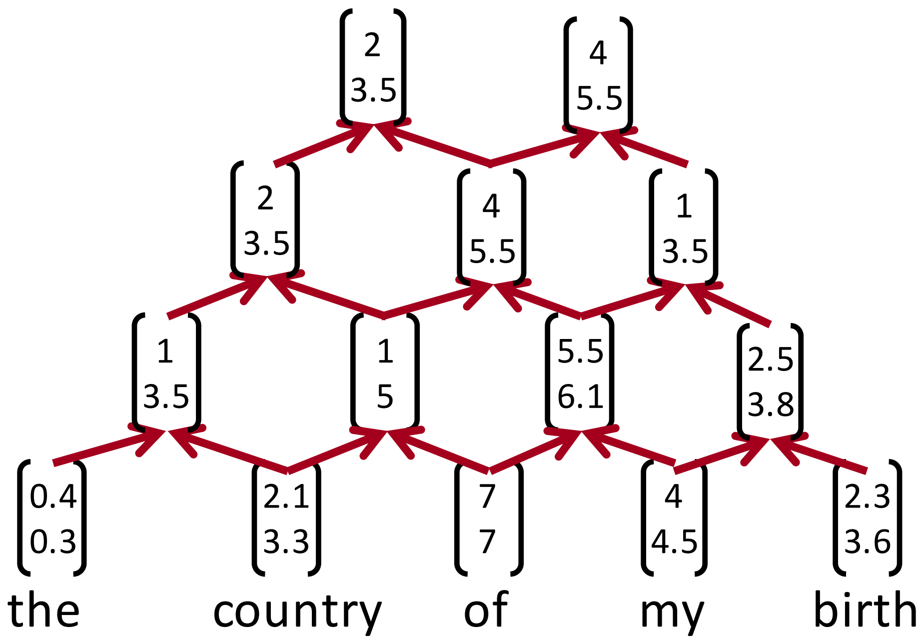
- Now multiple options to compute higher layers.
- First option (simple to understand but not necessarily best)
- Just repeat with different weights:

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



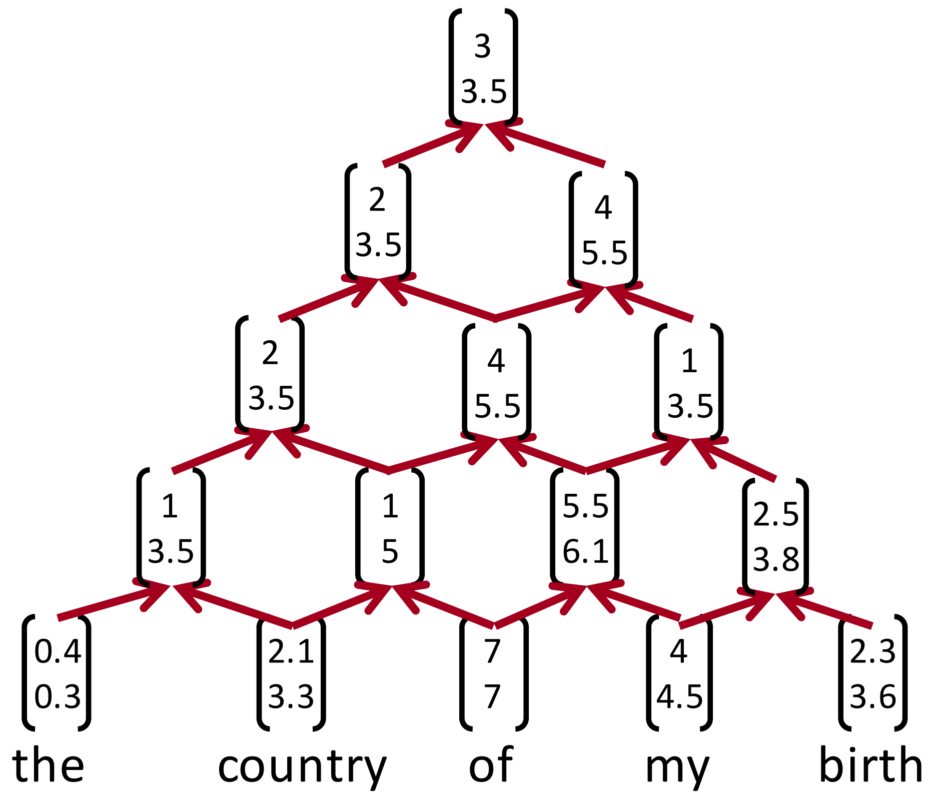
From RNNs to CNNs

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



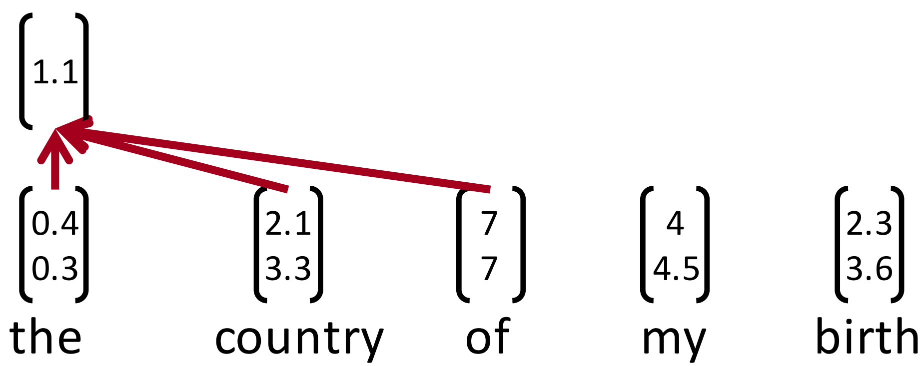
From RNNs to CNNs

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



Single Layer CNN

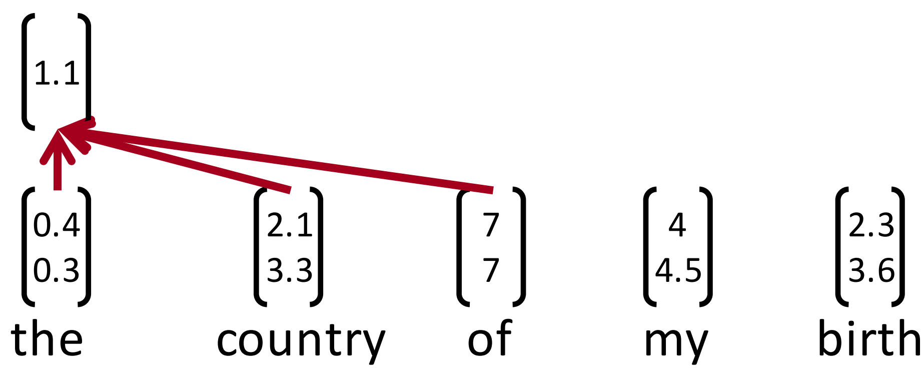
- A simple variant using one convolutional layer and **pooling**
- Based on Collobert and Weston (2011) and Kim (2014) "Convolutional Neural Networks for Sentence Classification"
- Word vectors: $\mathbf{x}_i \in \mathbb{R}^k$
- Sentence: $\mathbf{x}_{1:n} = \mathbf{x}_1 \oplus \mathbf{x}_2 \oplus \ldots \oplus \mathbf{x}_n$ (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

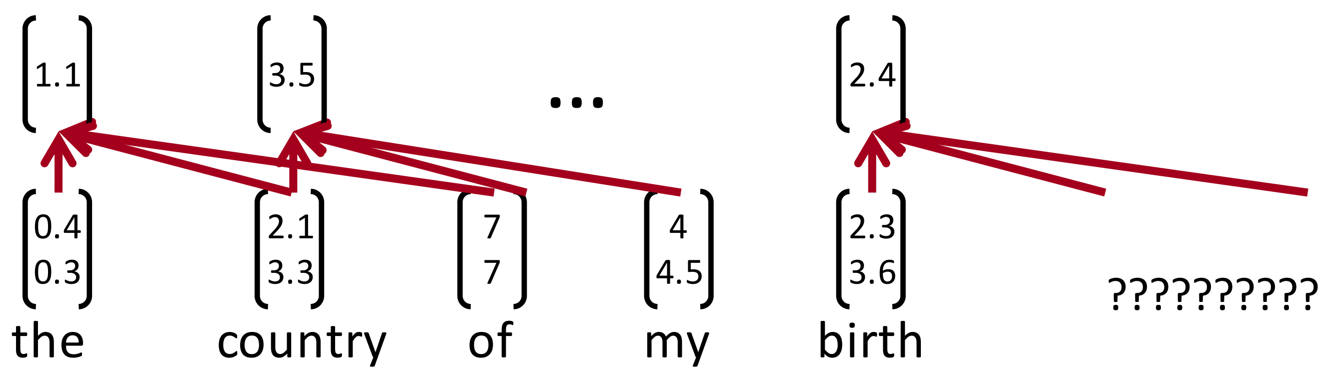
- Convolutional filter: $\mathbf{w} \in \mathbb{R}^{hk}$ (goes over window of h words)
- Note, filter is vector!
- Window size h could be 2 (as before) or higher, e.g. 3:
- To compute feature for CNN layer:

$$c_i = f(\mathbf{w}^T \mathbf{x}_{i:i+h-1} + b)$$



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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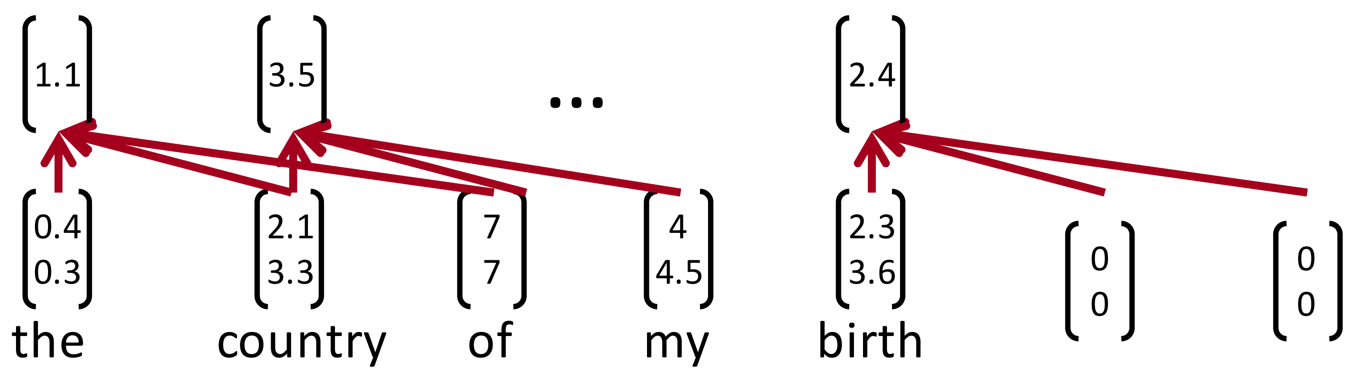


Single layer CNN: Pooling layer

- 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 (word2vec or Glove)
- Start with two copies
- Backprop into only one set, keep other "static"
- Both channels are added to c_i before max-pooling

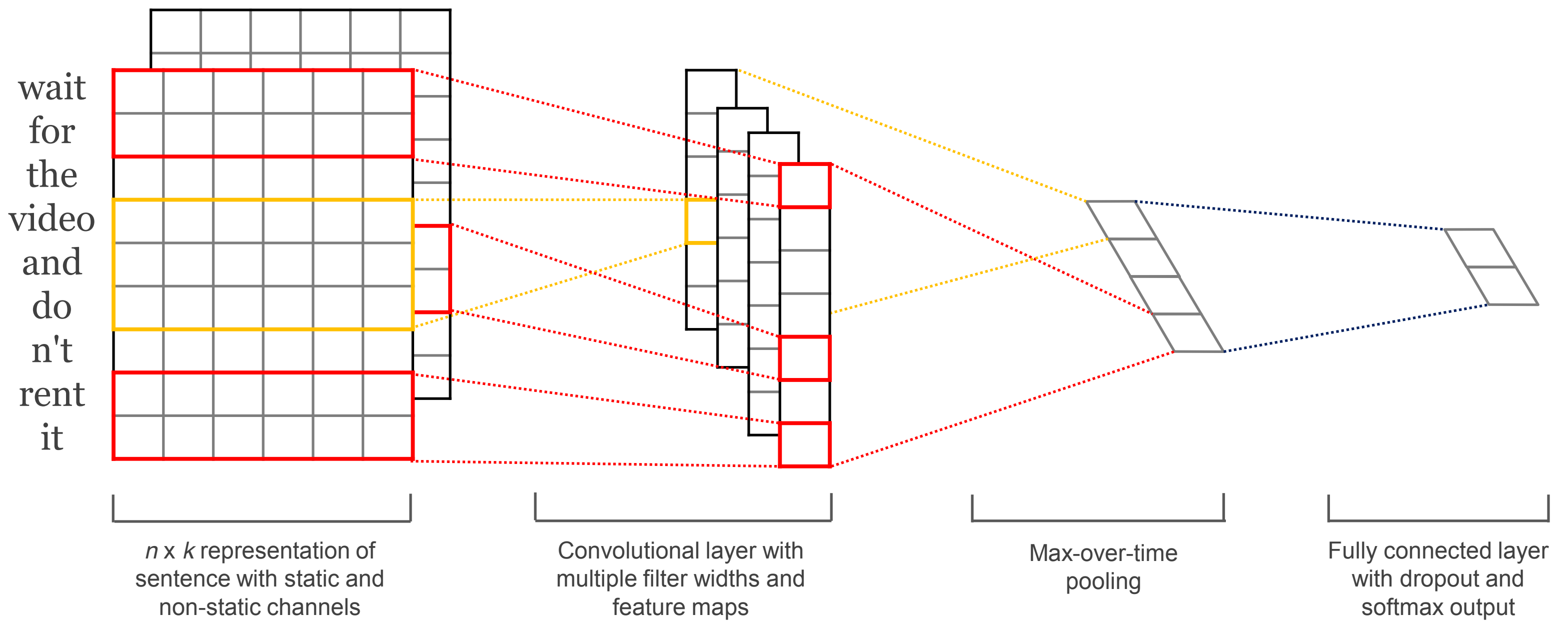
Classification after one CNN layer

- 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)



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 with 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)

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 $r_i = 1$

- At test time, there is no dropout, so feature vectors z are larger.
- 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 that: $\|W_{c\cdot}^{(S)}\| = s$

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 feature maps
- 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 highest accuracy 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	–
SVM_S (Silva et al., 2011)	–	–	–	–	**95.0**	–	–

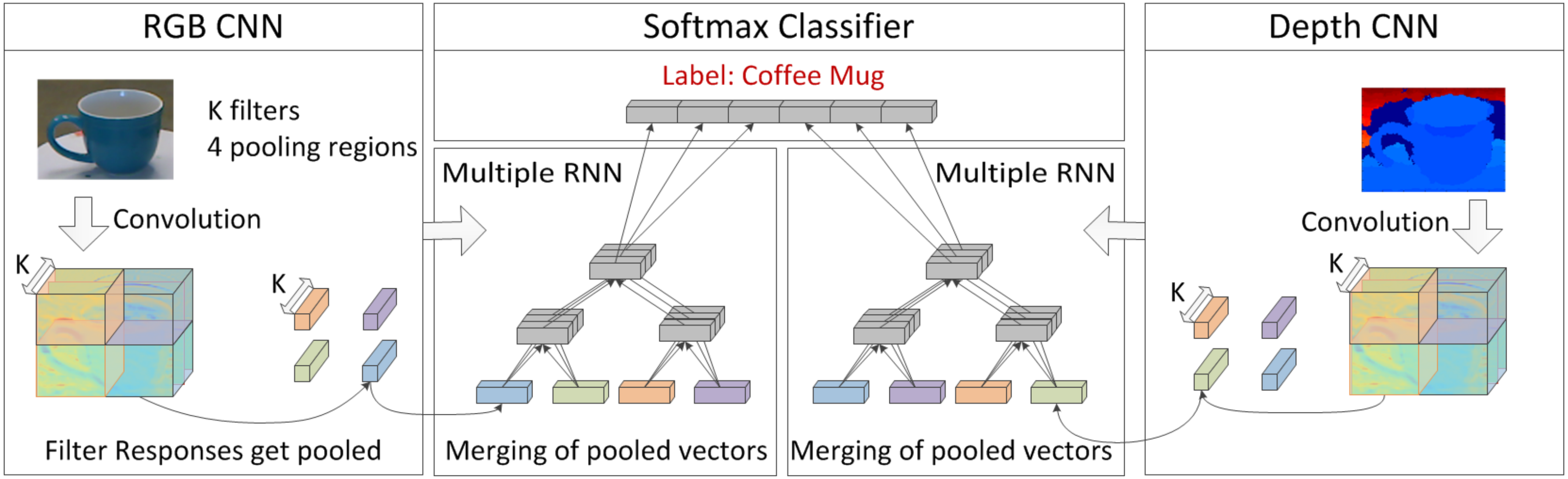
Problem with comparison?

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

- Still remarkable results and simple architecture!

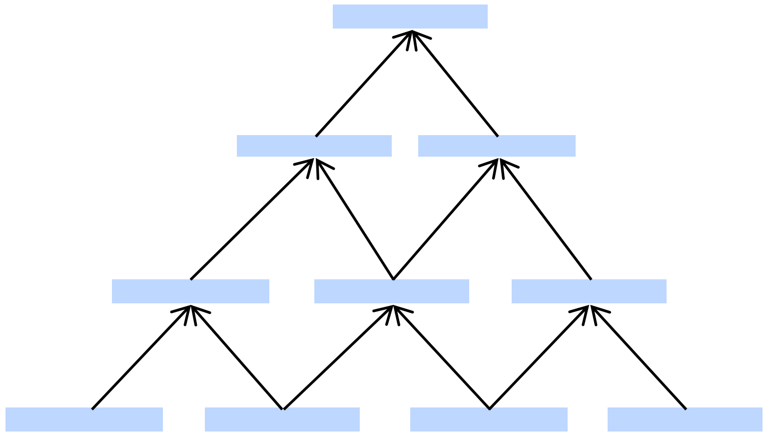
- Difference to window and RNN architectures we described in previous lectures: pooling, many filters and dropout
- Ideas can be used in RNN^2s too
- Tree-LSTMs obtain better performance on sentence datasets

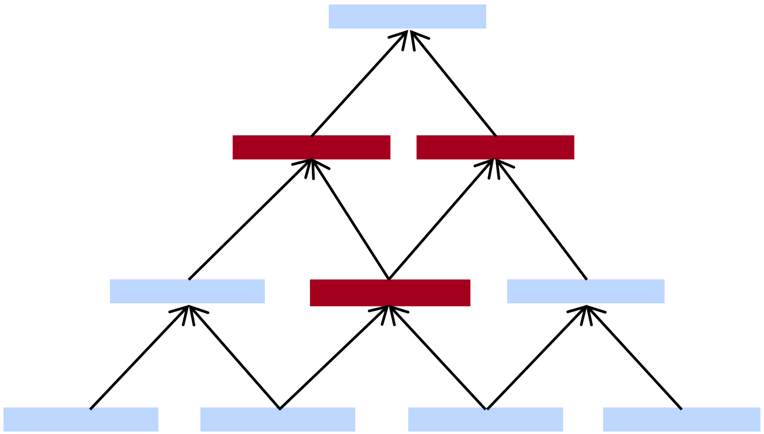
- Fixed tree RNNs explored in computer vision:
  Socher et al (2012): "Convolutional-Recursive Deep Learning for 3D Object Classification"



Relationship between RNNs and CNNs

- CNN RNN





Relationship between RNNs and CNNs

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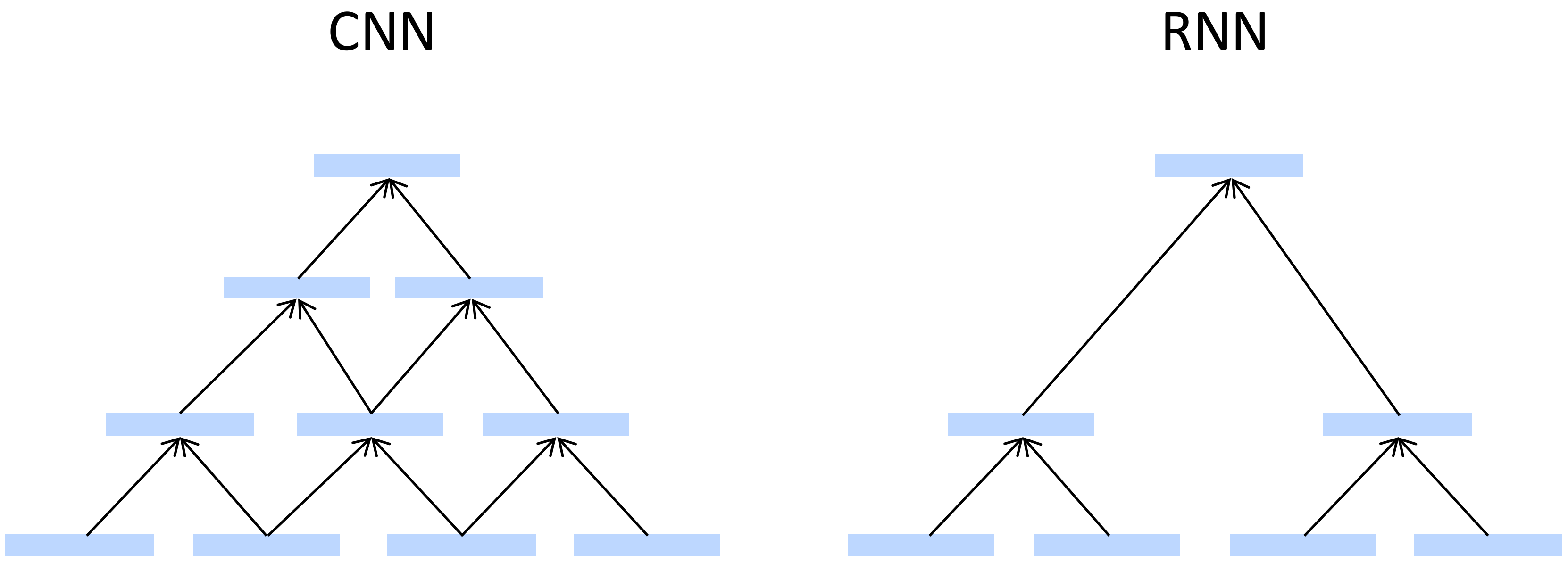
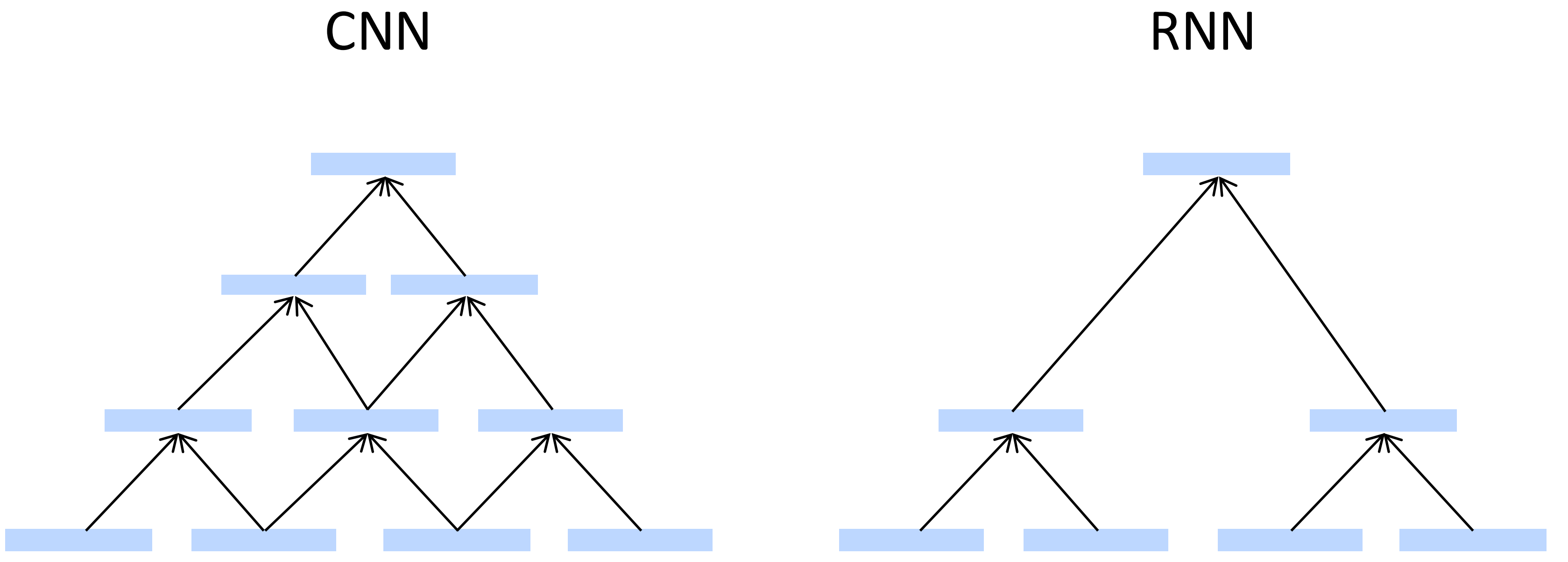


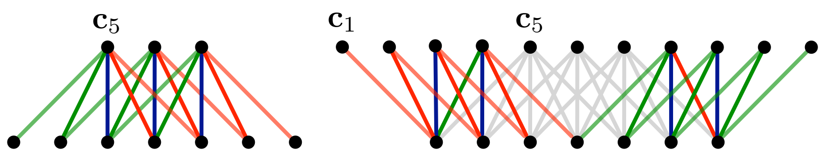
Relationship between RNNs and CNNs

- 

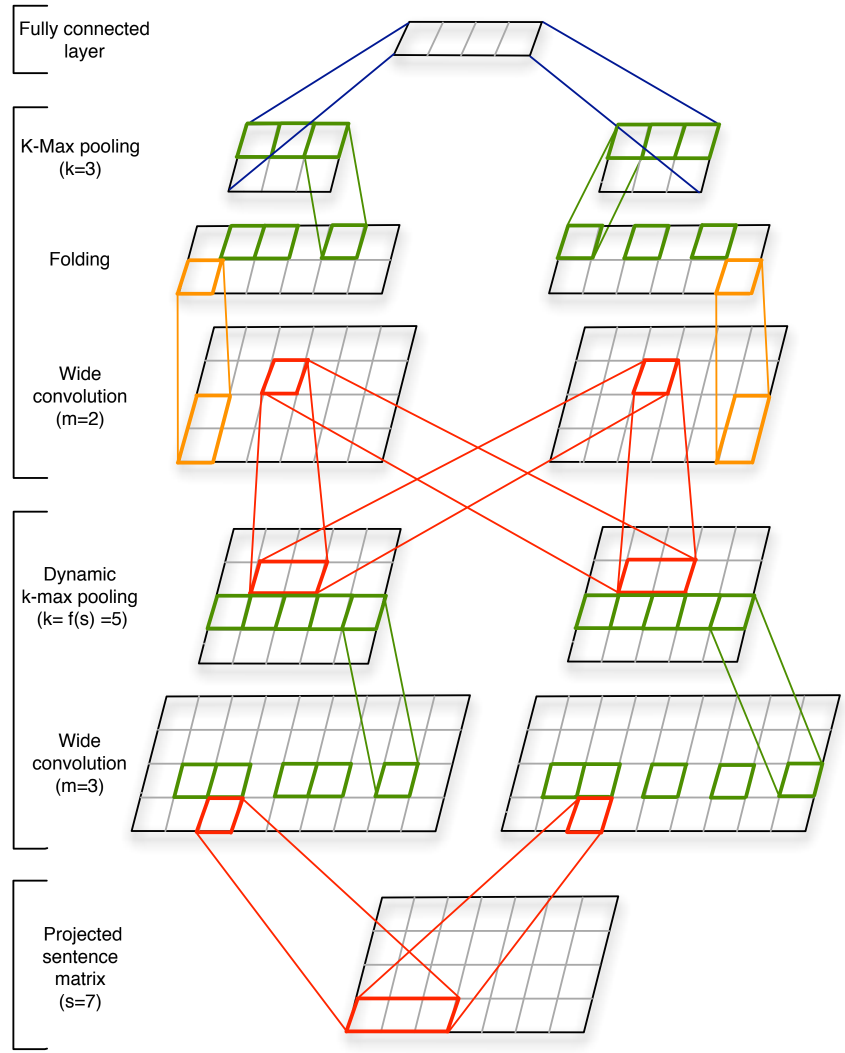
- **Stride size** flexible in CNNs, RNNs "weighted average pool"
- Tying (sharing) weights of filters inside vs across different layers
- CNN: multiple filters, additional layer type: max-pooling
- Balanced input independent structure vs input specific tree

CNN alternatives

- Narrow vs wide convolution



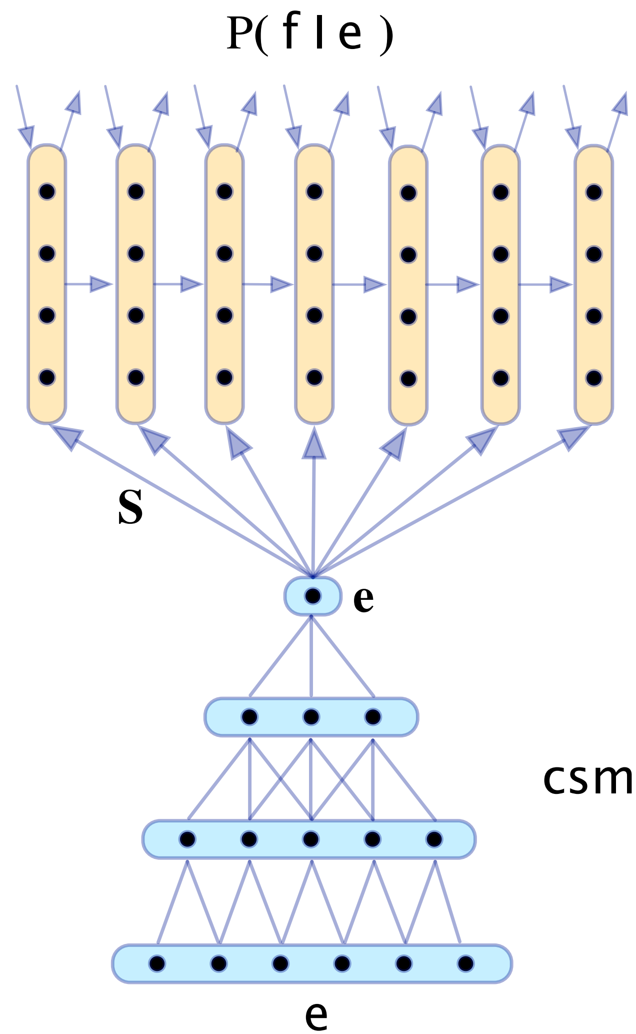
- Complex pooling schemes (over sequences) and deeper convolutional layers



- 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