Convolutional Neural Networks (for NLP)

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Few word about me

- I am an Applied Research scientist at VK.com

- Part-time Research Scientist at iPavlov
- Worked at Yandex
- Graduated from Moscow Institute of Physics and Technology
- Recently defended a PhD thesis
  "Noise Robustness in Various NLP Tasks"

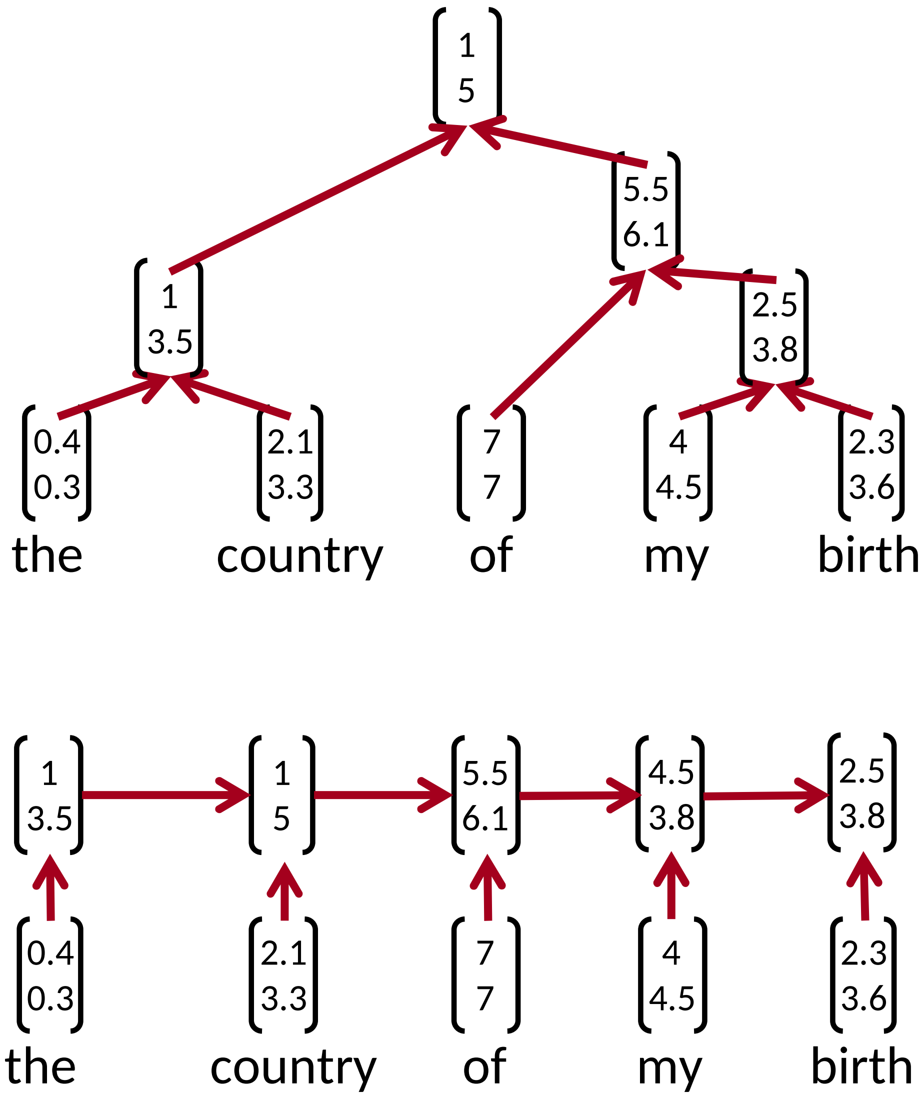
Overview of today

- From RNNs to CNNs

- CNN Variant 1: Simple single layer
- Application: Sentence classification
- More details and tricks
- Evaluation
- Comparison between sentence models

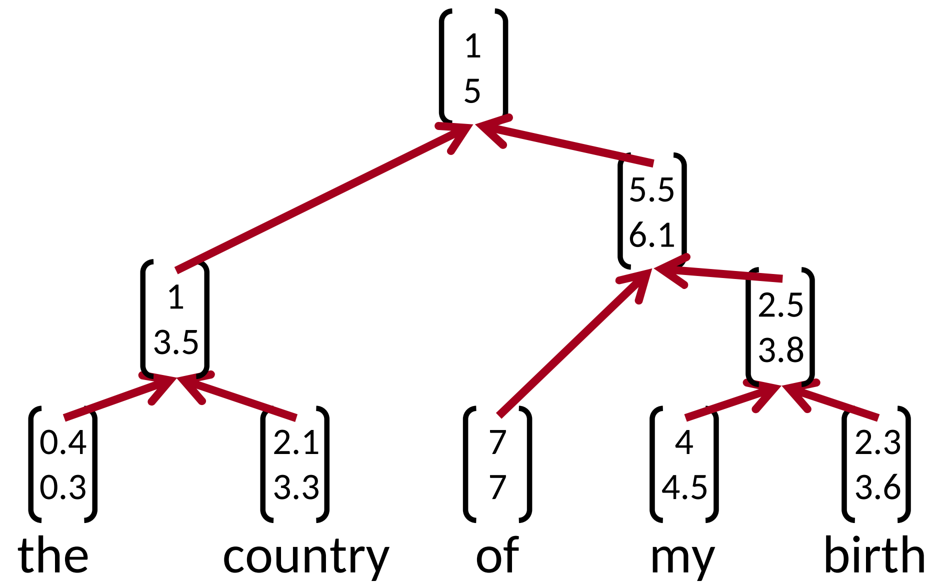
- CNN Variant 2: Complex multi layer

From RNNs to CNNs

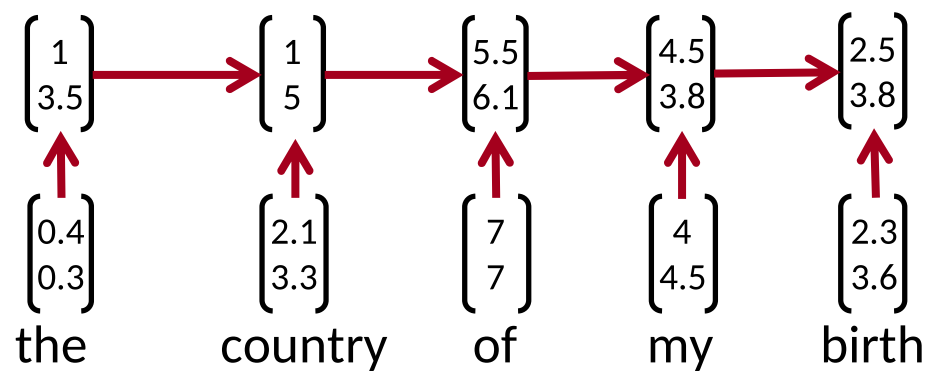


From RNNs to CNNs

- 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

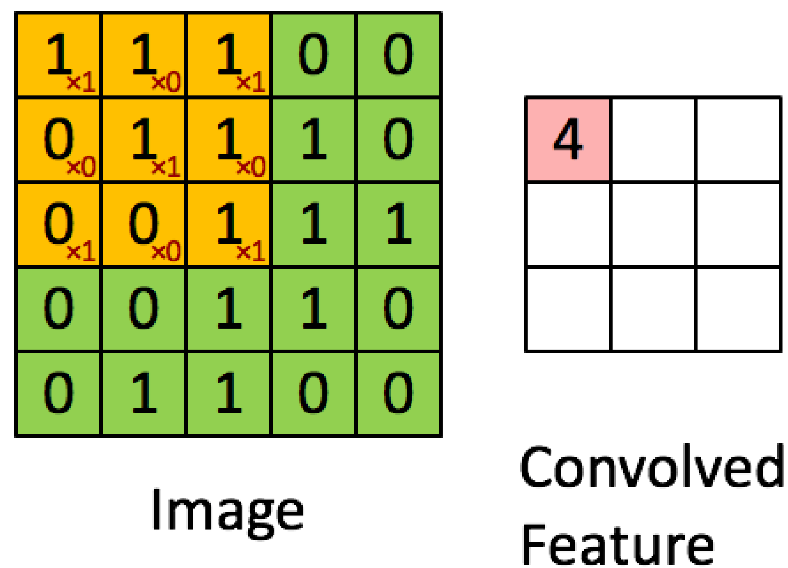
What is convolution anyway?

- 1d discrete convolution generally:

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

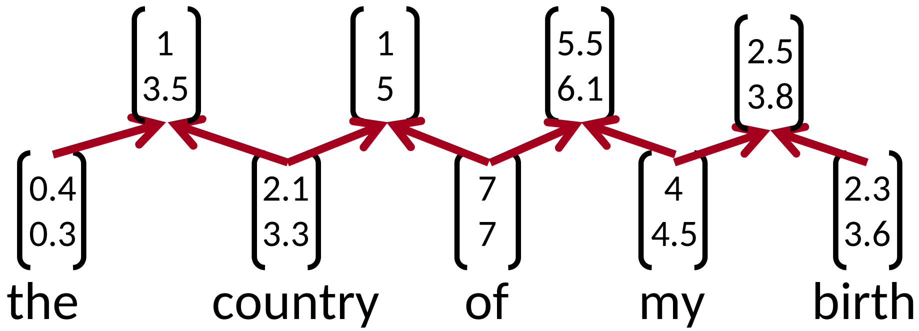
- Convolution is great to extract features from images

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



From RNNs to CNNs

- First layer: compute all bigram vectors



- Same computation as in RNN but for every pair

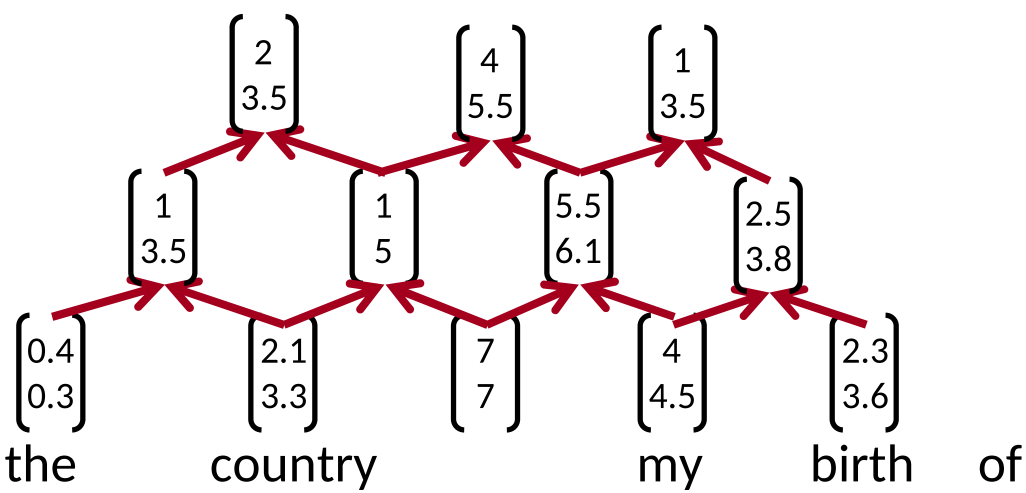
$$p = \tanh\left(W \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + b \right)$$

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

From RNNs to CNNs

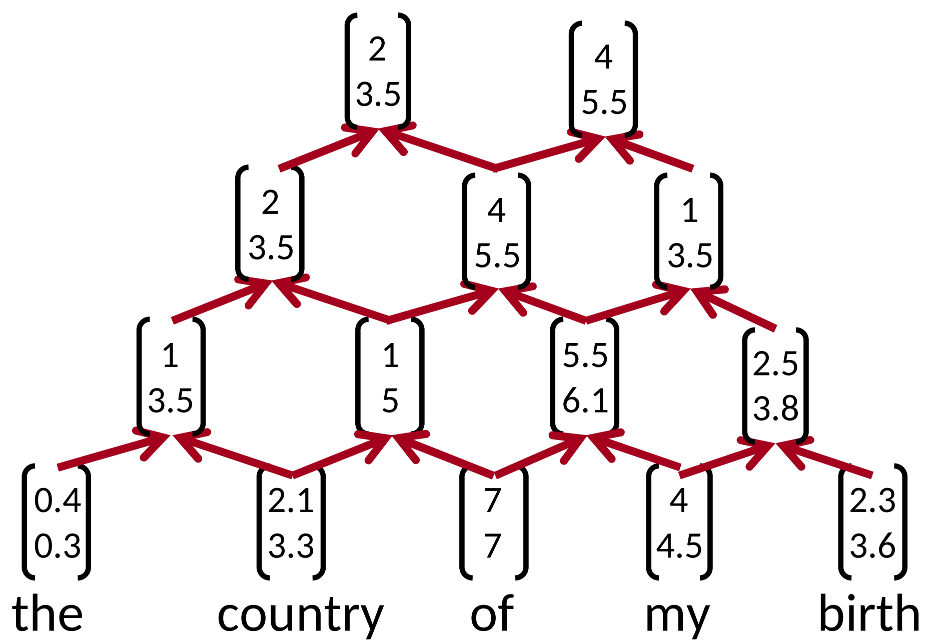
- Now multiple options to compute higher layers.
- First option (simple to understand but not necessarily best)
- Just repeat with different weights:

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



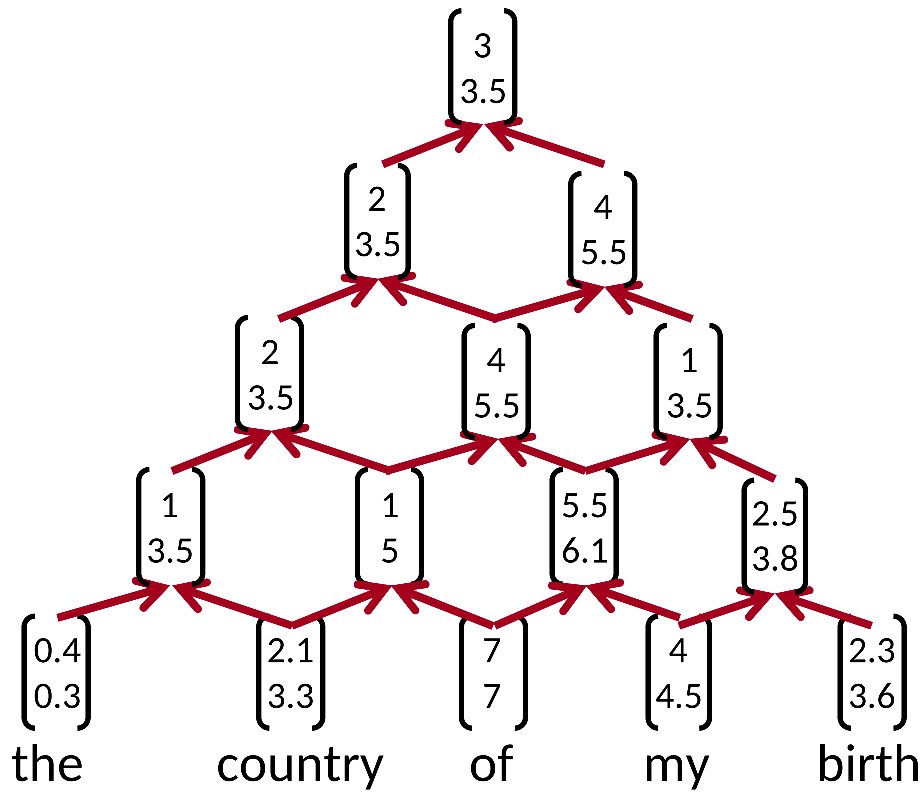
From RNNs to CNNs

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



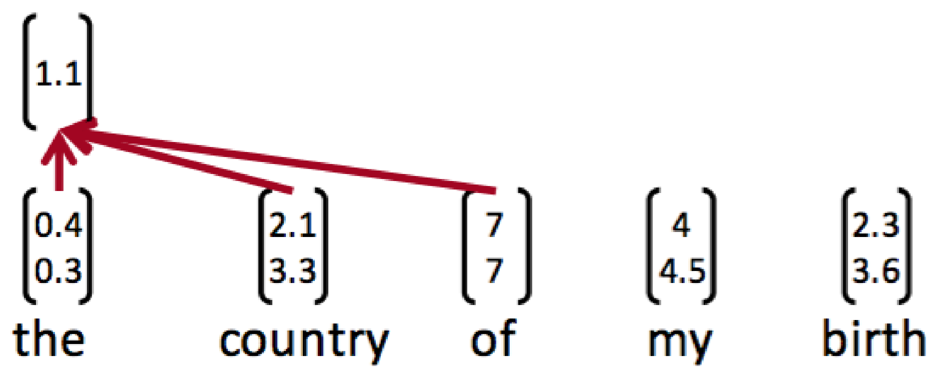
From RNNs to CNNs

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



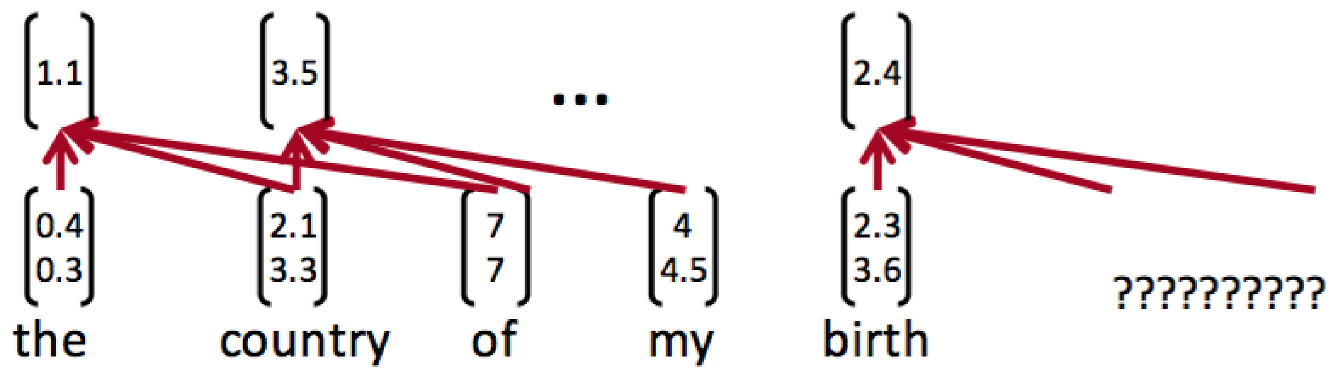
Single Layer CNN

- 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

- 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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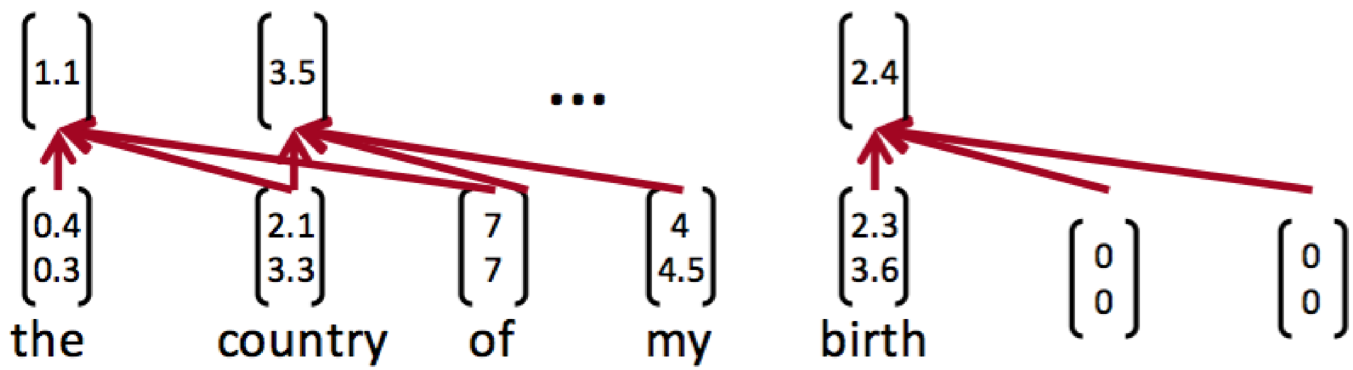


Single layer CNN: Pooling layer

- 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)

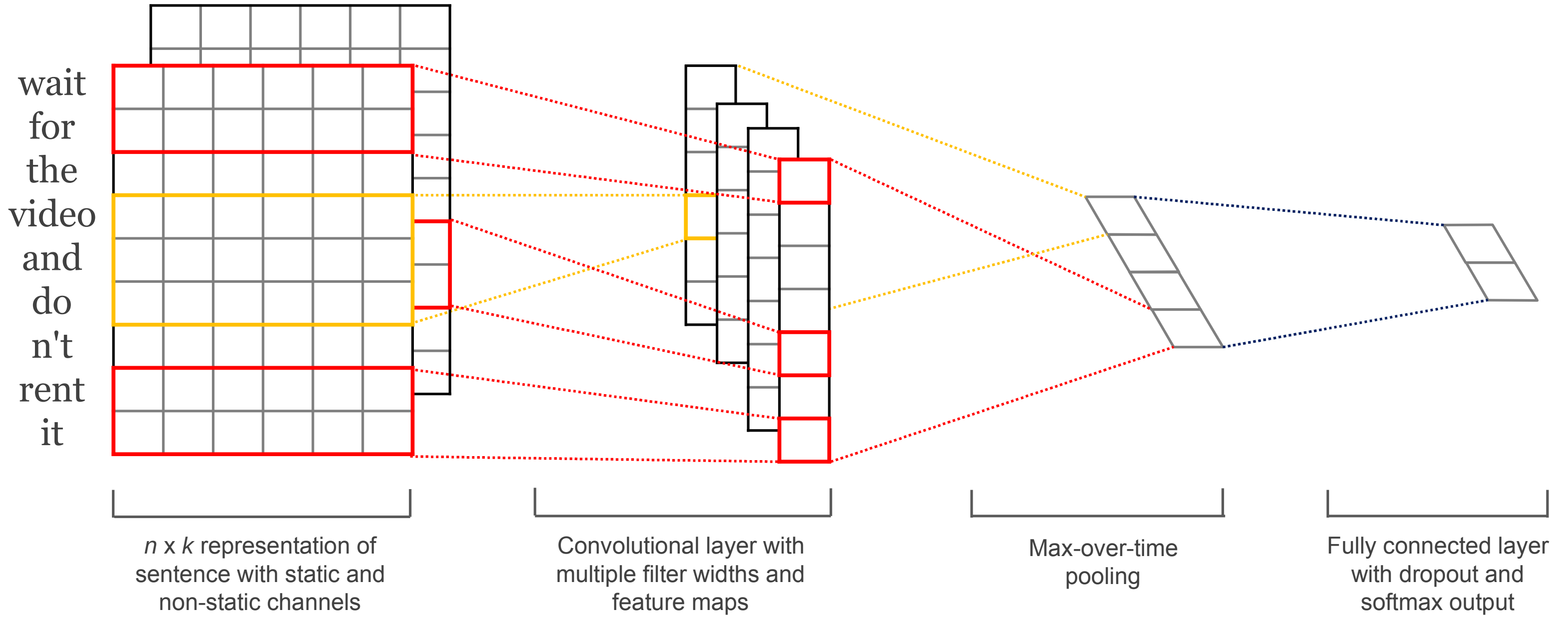


Figure 1: Model architecture with two channels for an example sentence.

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 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 is 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 hyper-parameter)

- 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 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

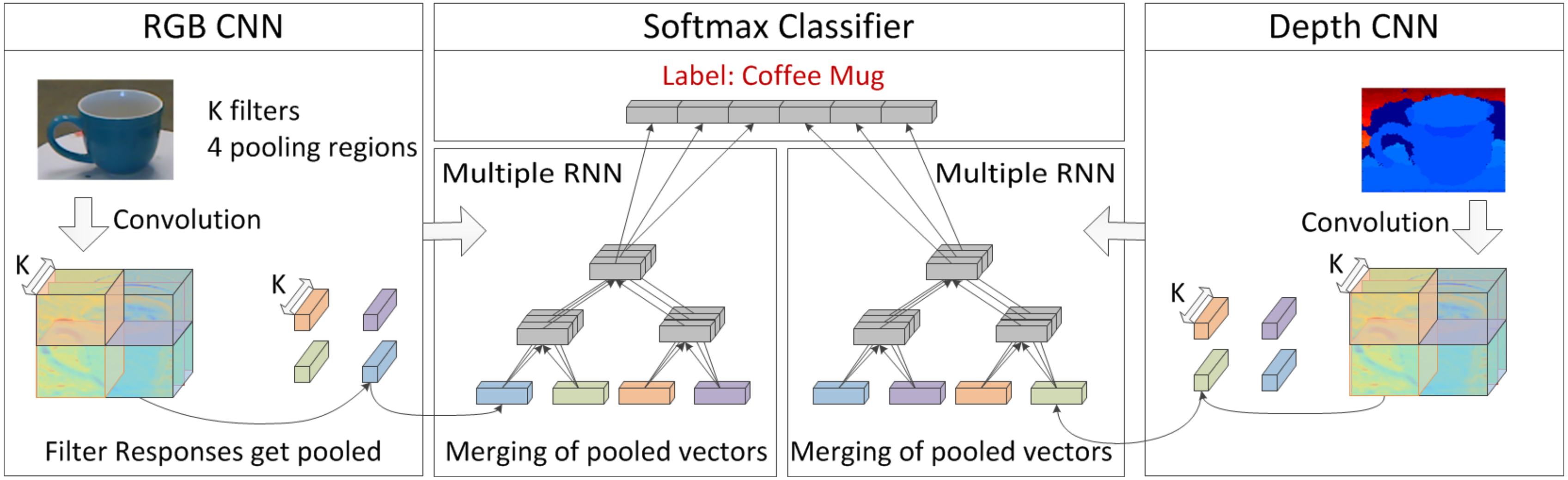
Problem with comparison?

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

- Still remarkable results and simple architecture!

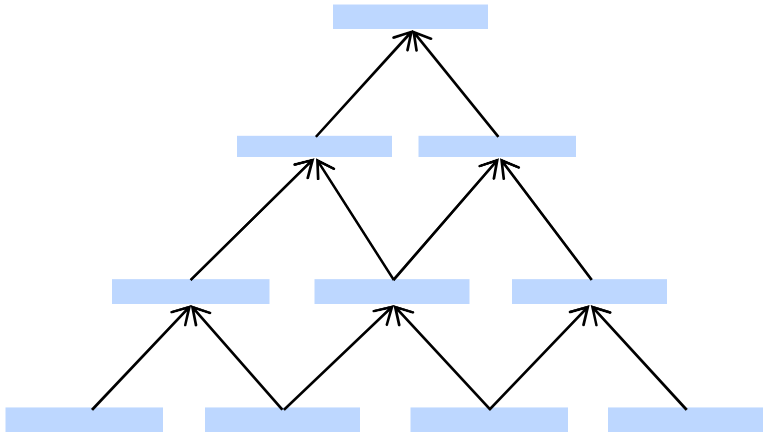
- Difference to window and RNN architectures we described in previous lectures: pooling, many filters and dropout
- Ideas can be used in RNNs too
- Tree-LSTMs obtain better performance on sentence datasets

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

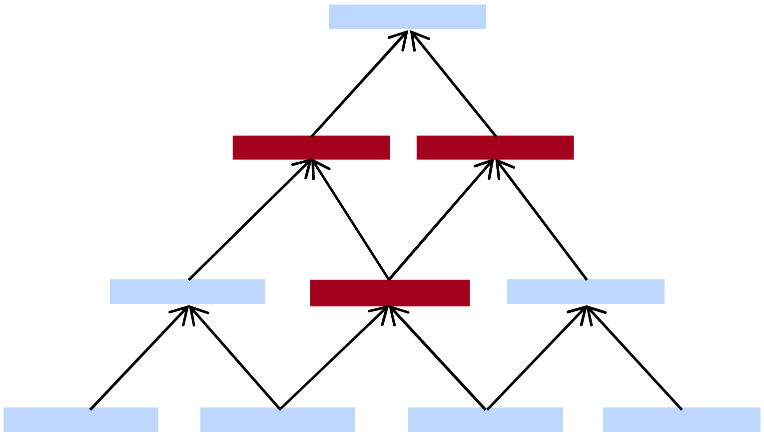


Relationship between RNNs and CNNs

- CNN



RNN



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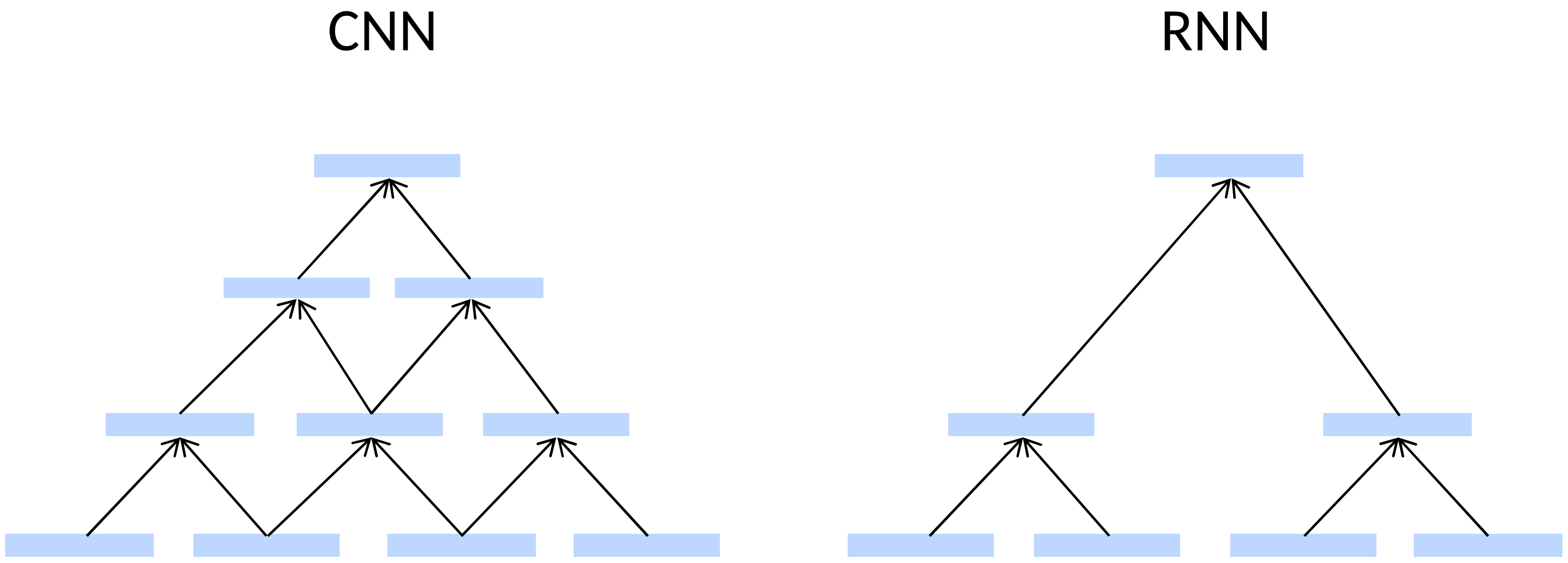
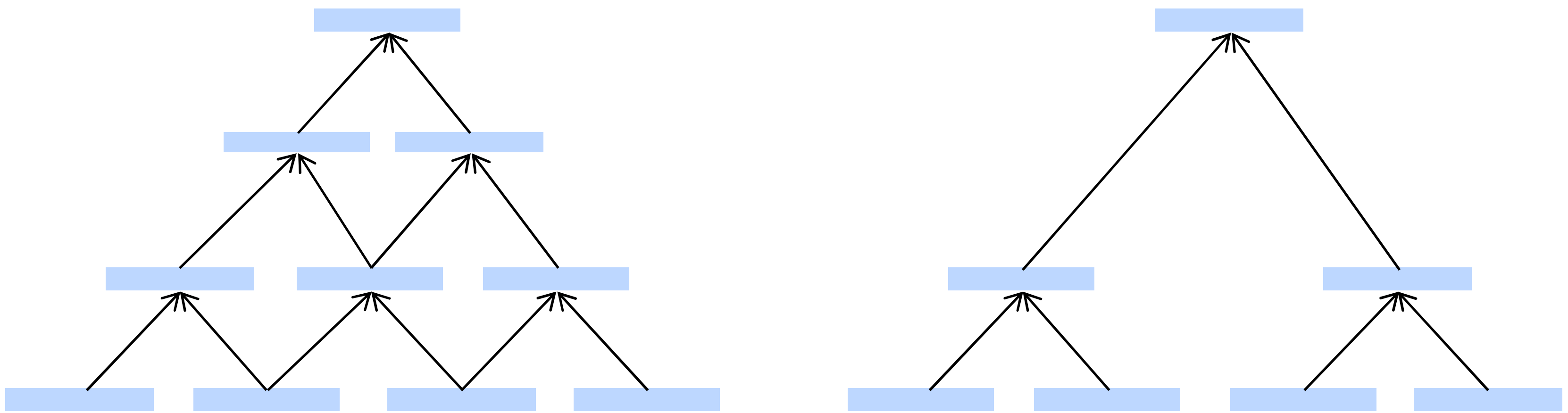
- 

Relationship between RNNs and CNNs

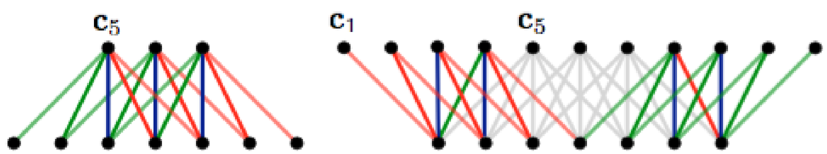
- CNN RNN



- **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

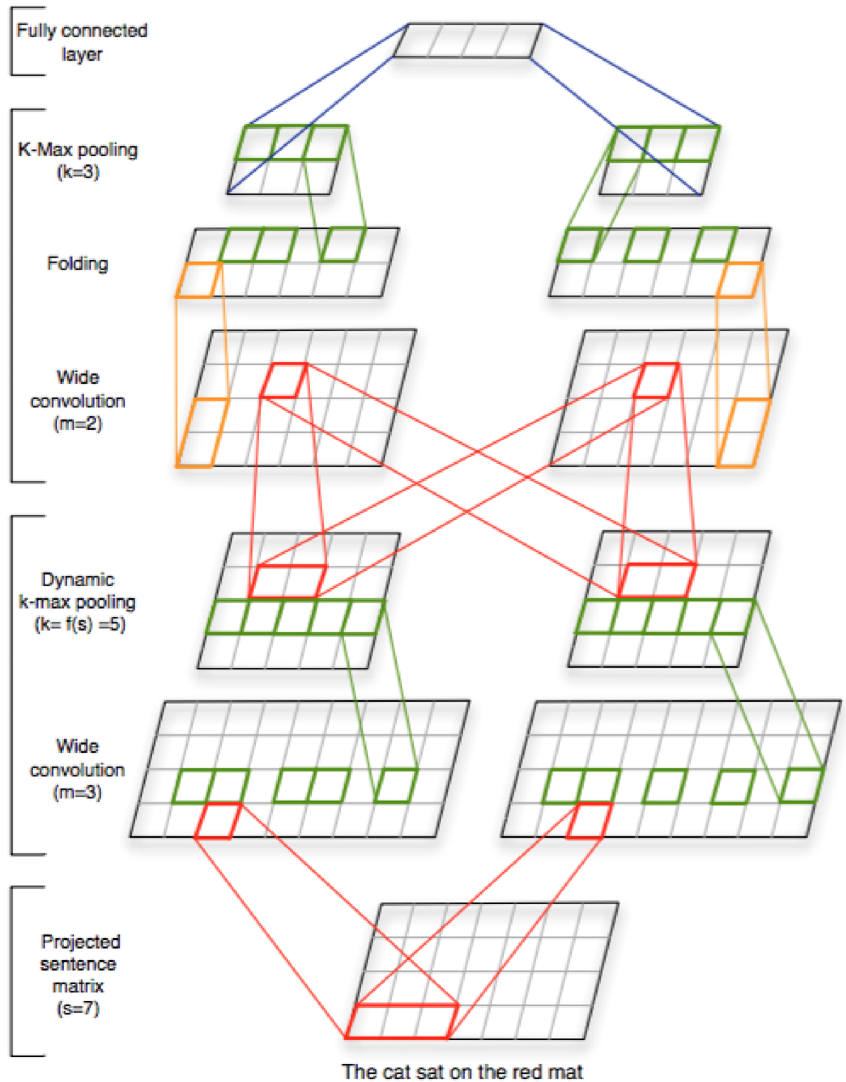
CNN alternatives

- Narrow vs wide convolution



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

- Kalchbrenner et al. (2014)



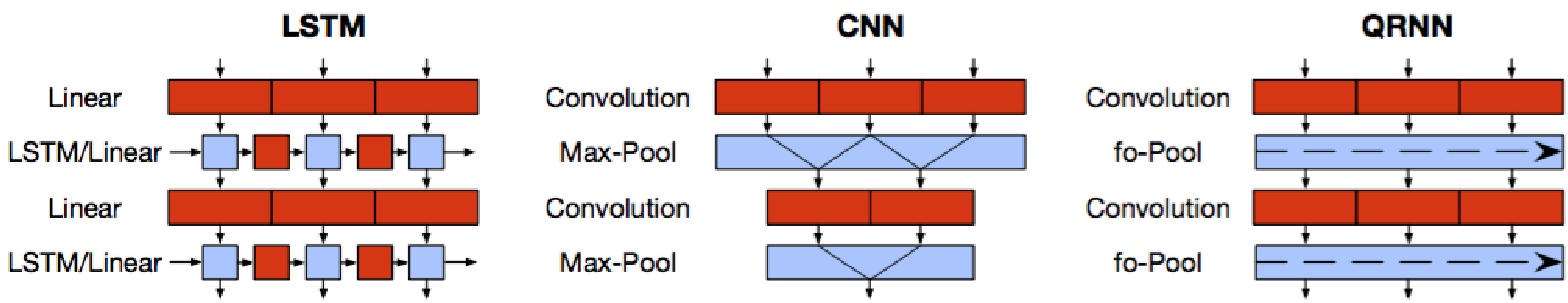
Model comparison

- **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:

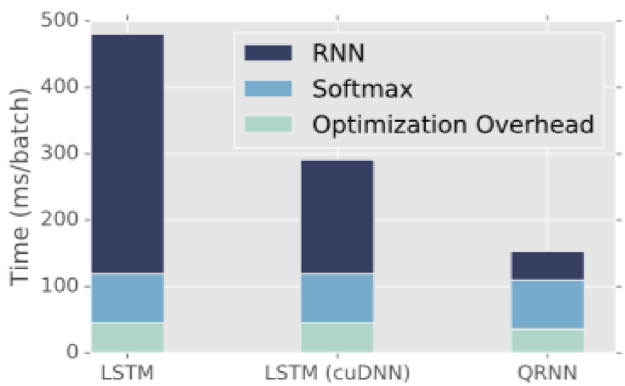
$$\mathbf{h}_t = \mathbf{f}_t \odot \mathbf{h}_{t-1} + (1 - \mathbf{f}_t) \odot \mathbf{z}_t,$$

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



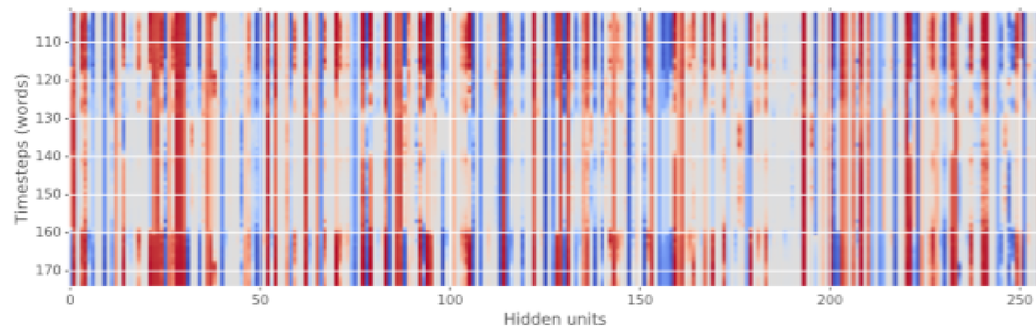
		Sequence length				
		32	64	128	256	512
Batch size	8	**5.5x**	**8.8x**	**11.0x**	**12.4x**	**16.9x**
	16	**5.5x**	**6.7x**	**7.8x**	**8.3x**	**10.8x**
	32	**4.2x**	**4.5x**	**4.9x**	**4.9x**	**6.4x**
	64	**3.0x**	**3.0x**	**3.0x**	**3.0x**	**3.7x**
	128	**2.1x**	**1.9x**	**2.0x**	**2.0x**	**2.4x**
	256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

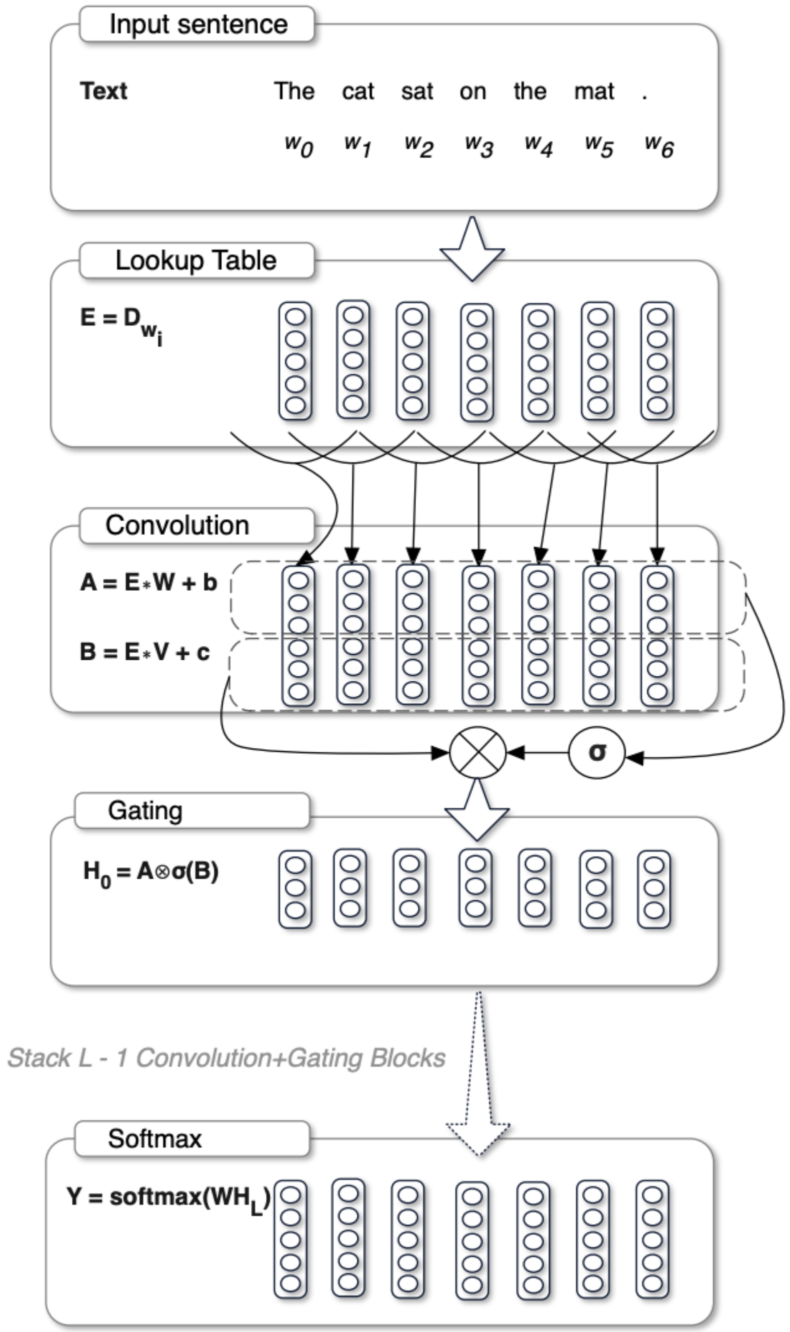


- Example:
- Initial positive review
- *Review starts out positive*
  At 117: "not exactly a bad story"
  At 158: "I recommend this movie to everyone, even if you've never played the game"

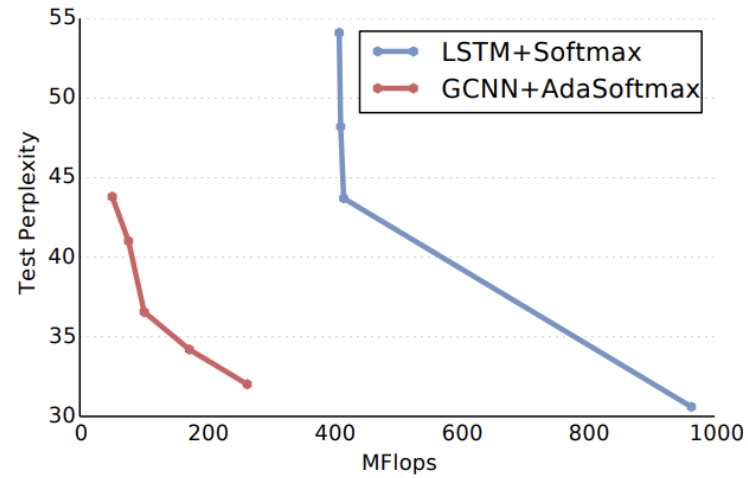
Gated Convolutions

Gated Linear Unit:

$$h_l(\mathbf{X}) = (\mathbf{X} * \mathbf{W} + \mathbf{b}) \otimes \sigma(\mathbf{X} * \mathbf{V} + \mathbf{c})$$



Gated Convolutions



Model	Test PPL	Hardware
Sigmoid-RNN-2048 (Ji et al., 2015)	68.3	1 CPU
Interpolated KN 5-Gram (Chelba et al., 2013)	67.6	100 CPUs
Sparse Non-Negative Matrix LM (Shazeer et al., 2014)	52.9	-
RNN-1024 + MaxEnt 9 Gram Features (Chelba et al., 2013)	51.3	24 GPUs
LSTM-2048-512 (Jozefowicz et al., 2016)	43.7	32 GPUs
2-layer LSTM-8192-1024 (Jozefowicz et al., 2016)	30.6	32 GPUs
BIG GLSTM-G4 (Kuchaiev & Ginsburg, 2017)	23.3*	8 GPUs
LSTM-2048 (Grave et al., 2016a)	43.9	1 GPU
2-layer LSTM-2048 (Grave et al., 2016a)	39.8	1 GPU
GCNN-13	38.1	1 GPU
GCNN-14 Bottleneck	31.9	8 GPUs

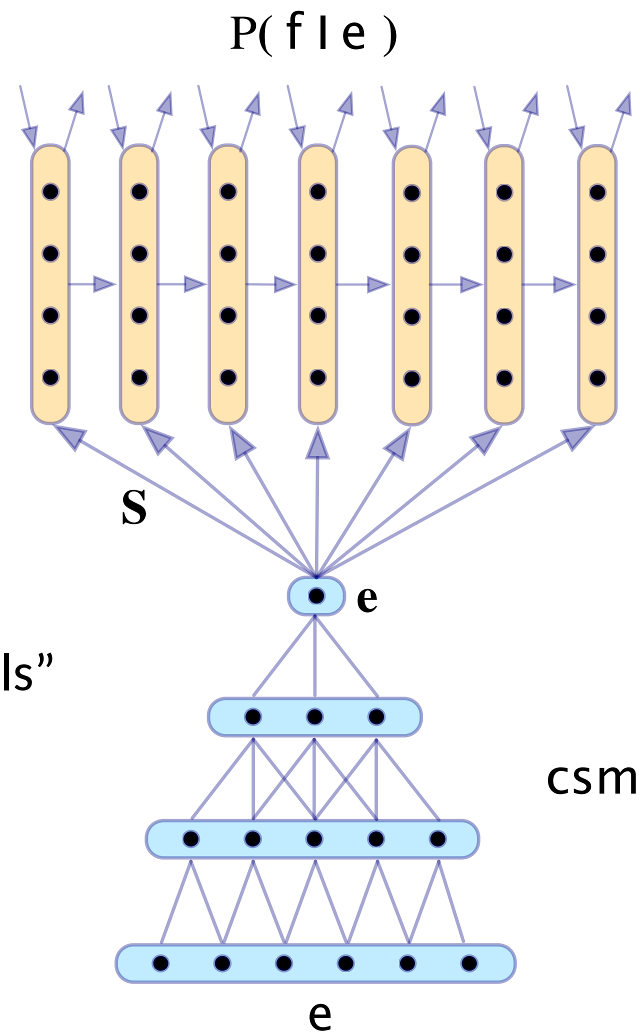
Table 2. Results on the Google Billion Word test set. The GCNN outperforms the LSTMs with the same output approximation.

CNN application: Translation

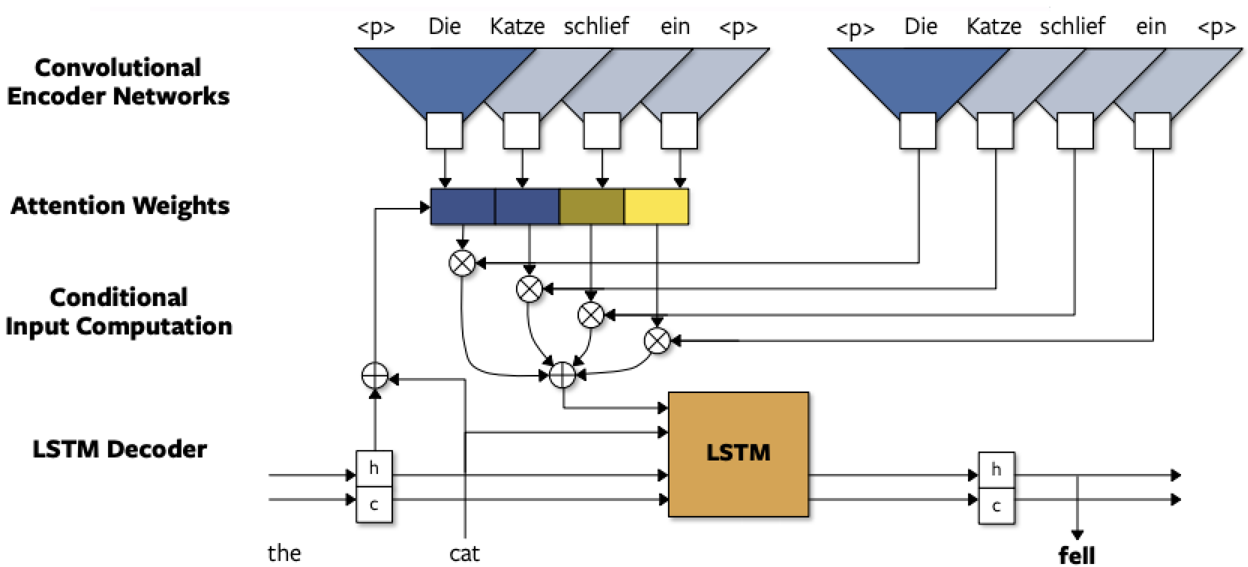
- One of the first successful neural machine translation efforts

- Uses CNN for encoding and RNN for decoding

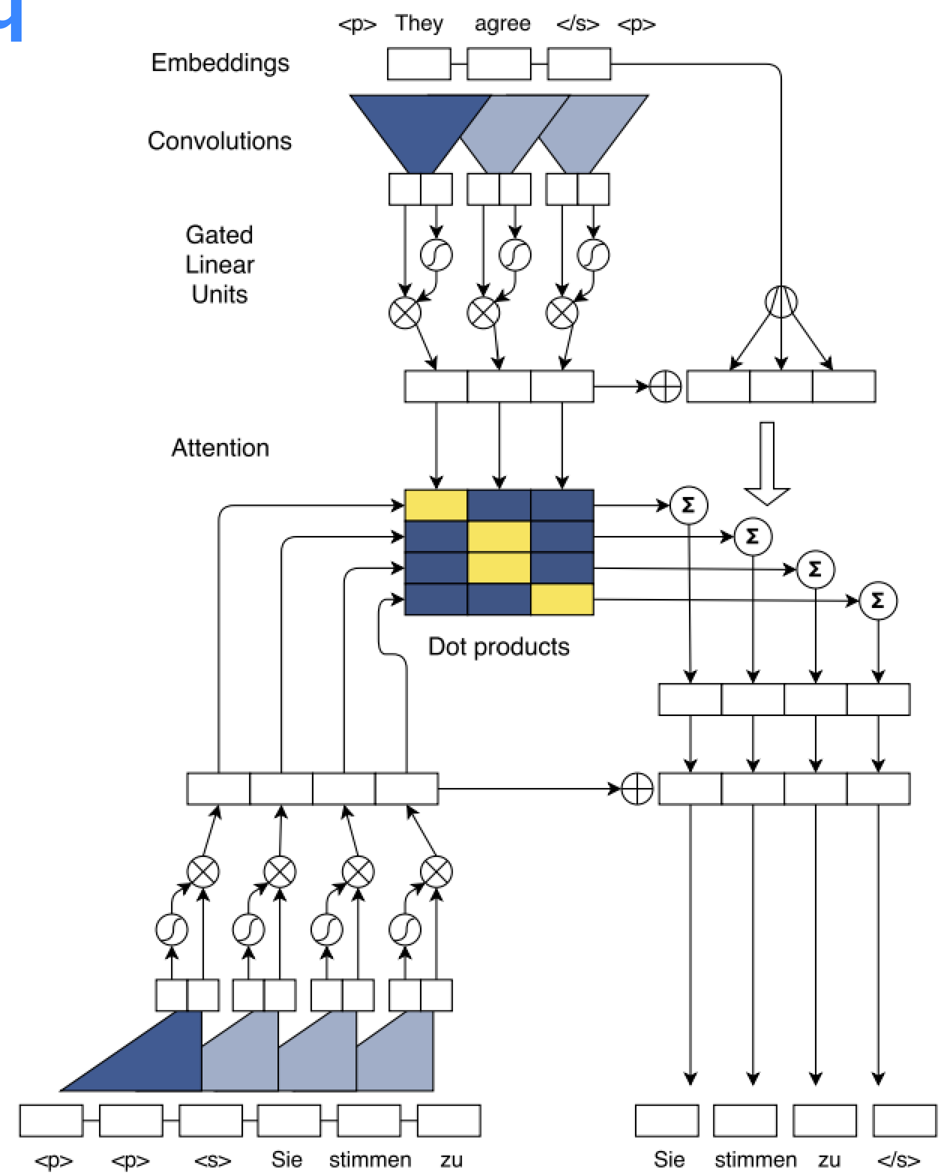
- Kalchbrenner and Blunsom (2013)
  "Recurrent Continuous Translation Models"



Convolutional Encoder



Convolutional Seq2Seq



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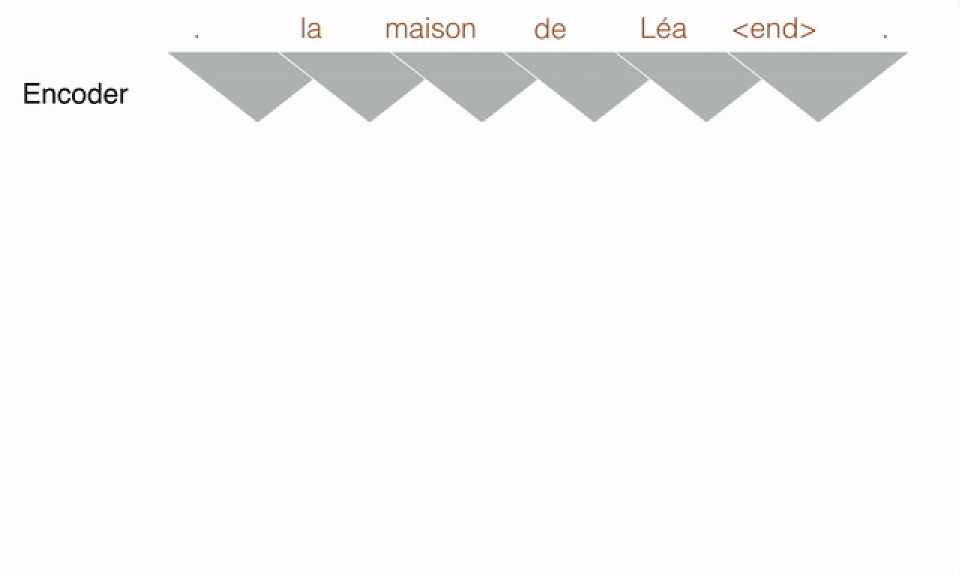

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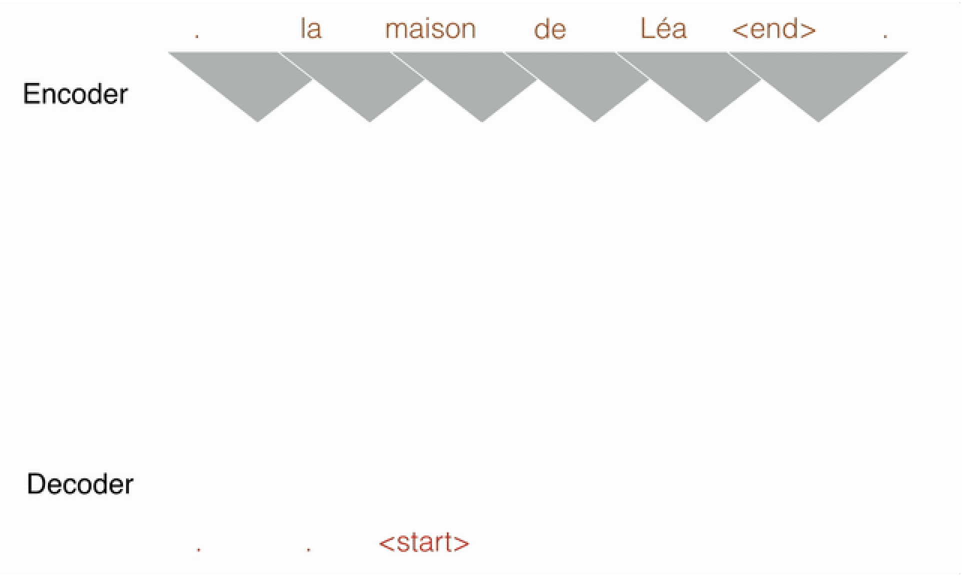

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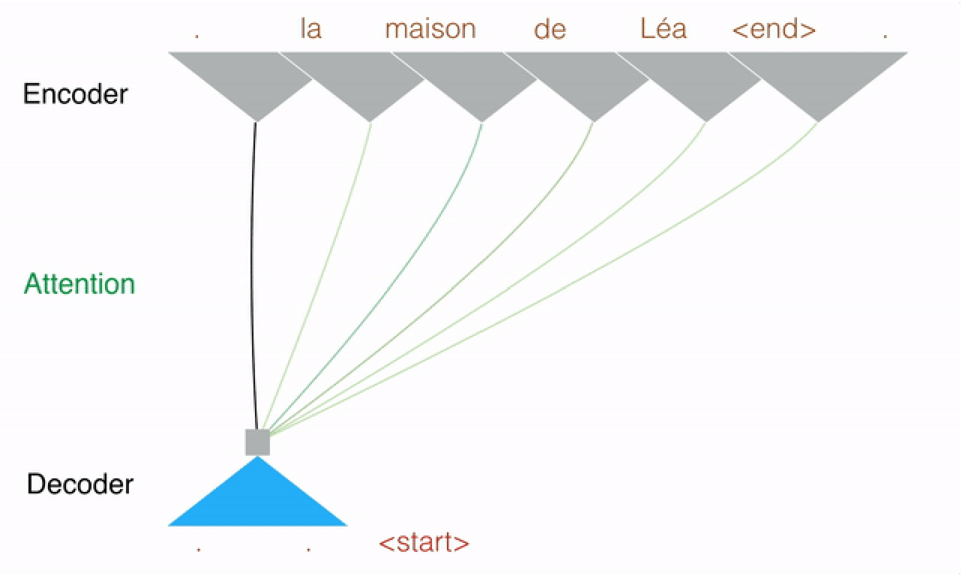

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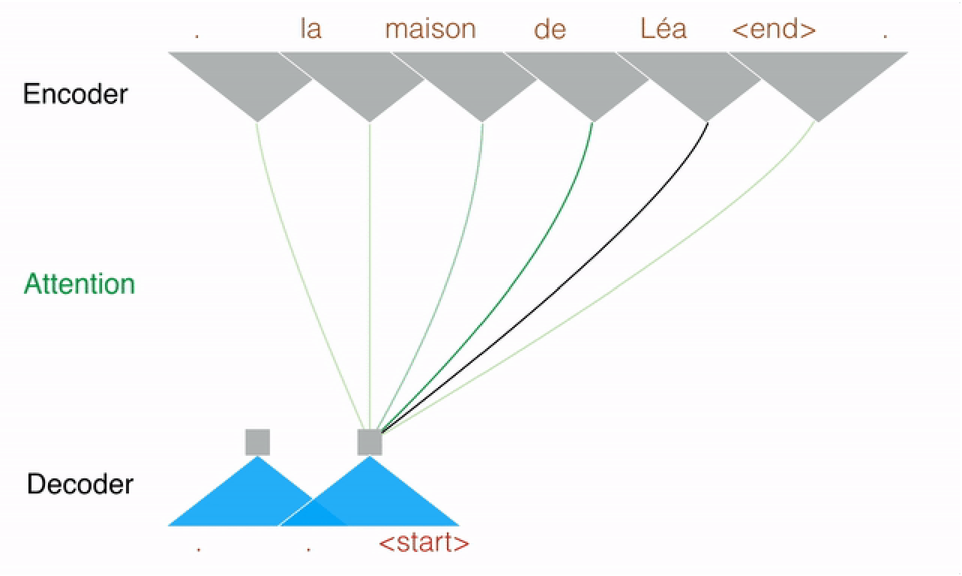

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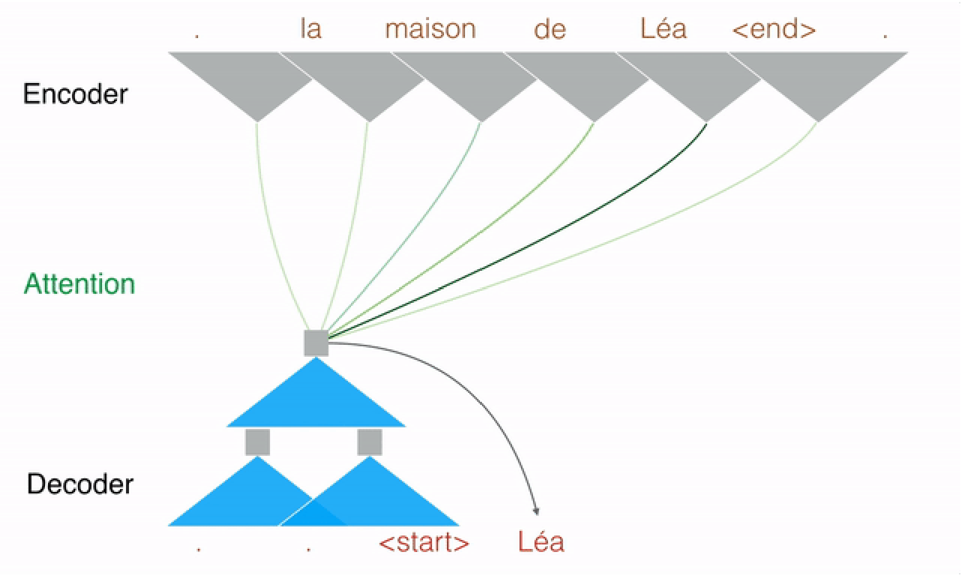

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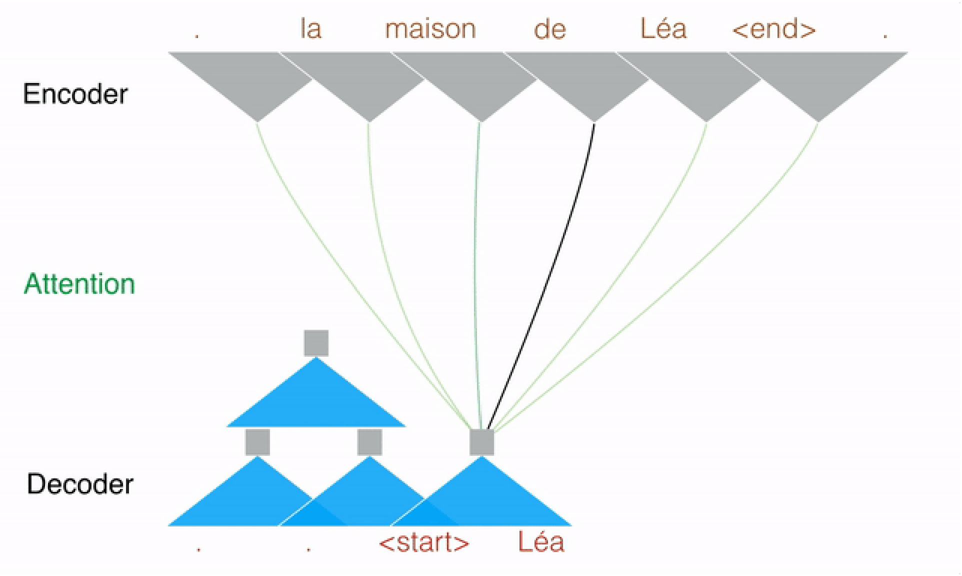

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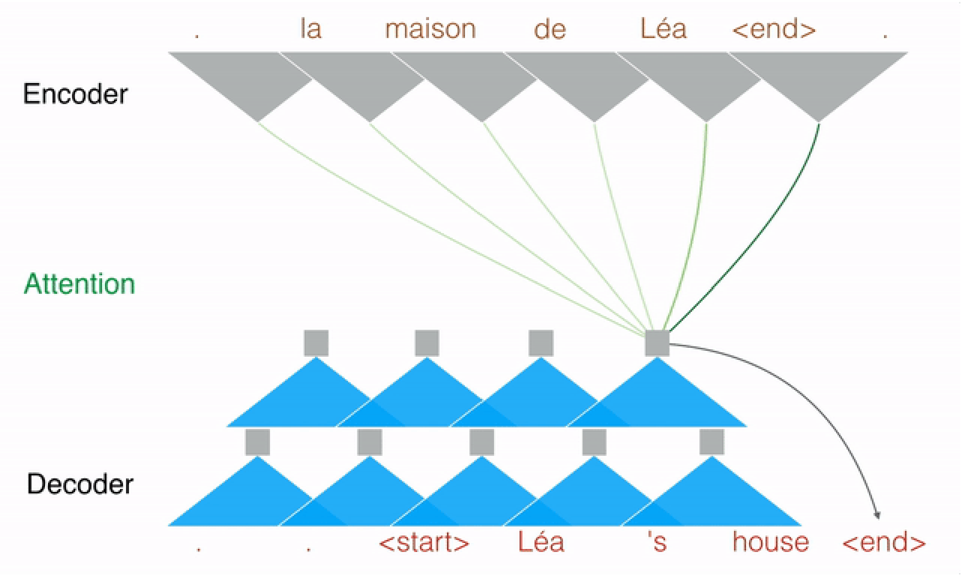


Lightweight and Dynamic Convolutions

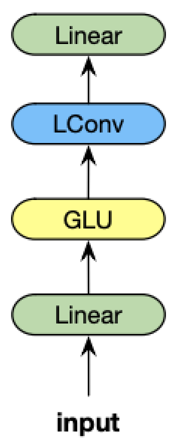
$$\mathrm{DepthwiseConv}(X, W_{c,:}, i, c) = \sum_{j=1}^{k} W_{c,j} \cdot X_{(i+j-\lceil \frac{k+1}{2} \rceil),c}$$

$$\mathrm{LightConv}(X, W_{\lceil \frac{cH}{d} \rceil,:}, i, c) = \mathrm{DepthwiseConv}(X, \mathrm{softmax}(W_{\lceil \frac{cH}{d} \rceil,:}), i, c)$$

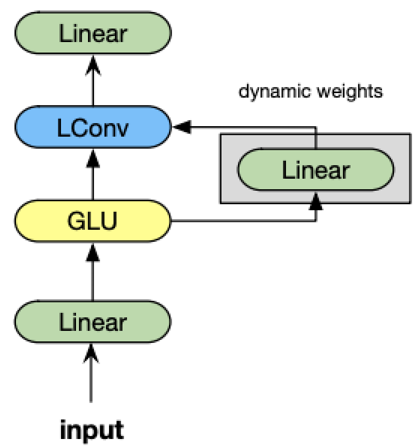
$$\mathrm{DynamicConv}(X, i, c) = \mathrm{LightConv}(X, f(X_i)_{h,:}, i, c)$$

we model f with a simple linear module with learned weights $W^Q \in \mathbb{R}^{H \times k \times d}$, i.e., $f(X_i) = \sum_{c=1}^{d} W^Q_{h,j,c} X_{i,c}$.

Lightweight and Dynamic Convolutions



(b) Lightweight convolution



(c) Dynamic convolution

Lightweight and Dynamic Convolutions

Model	Param (En-De)	WMT En-De	WMT En-Fr
Gehring et al. (2017)	216M	25.2	40.5
Vaswani et al. (2017)	213M	28.4	41.0
Ahmed et al. (2017)	213M	28.9	41.4
Chen et al. (2018)	379M	28.5	41.0
Shaw et al. (2018)	-	29.2	41.5
Ott et al. (2018)	210M	29.3	**43.2**
LightConv	202M	28.9	43.1
DynamicConv	213M	**29.7**	**43.2**

Table 1: Machine translation accuracy in terms of BLEU for WMT En-De and WMT En-Fr on newstest2014.

Model	Param (Zh-En)	IWSLT	WMT Zh-En
Deng et al. (2018)	-	33.1	-
Hassan et al. (2018)	-	-	24.2
Self-attention baseline	292M	34.4	23.8
LightConv	285M	34.8	24.3
DynamicConv	296M	**35.2**	**24.4**

Table 2: Machine translation accuracy in terms of BLEU on IWSLT and WMT Zh-En.

Thank you for your attention!

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