Quasi-Recurrent Neural Networks

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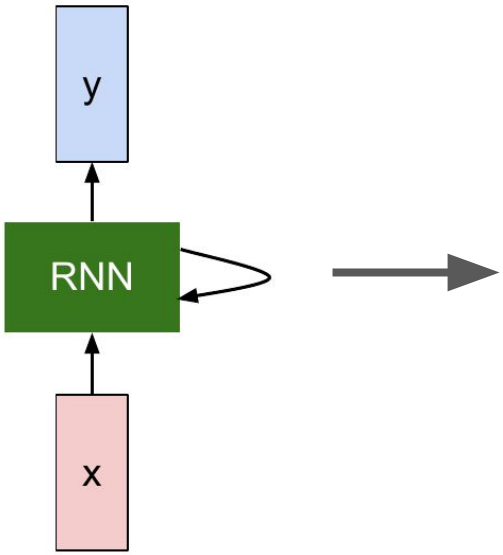
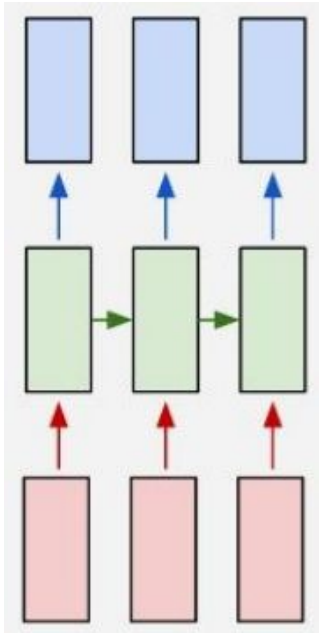
Introduction

- Recurrent Neural Networks limitations:
  - Sequential dependencies to previous computations limits parallelism
  - Difficult to train for longer sequences due to exploding/vanishing gradient
- Motivation: Combining the powers of convolutional networks with recurrent networks.

$$h_t = f_W(h_{t-1}, x_t)$$

$$y = W_h * h_t$$





Related work: Strongly-typed RNNs

- Introduces a “type system” to improve representational power of mainstream RNNs
  - Inspiration from unit type preservation principles in physics and functional programming disciplines
- Motivated from **PCA** analogy when performed on an unrolled RNN points out to a flaw in the traditional RNN update steps:

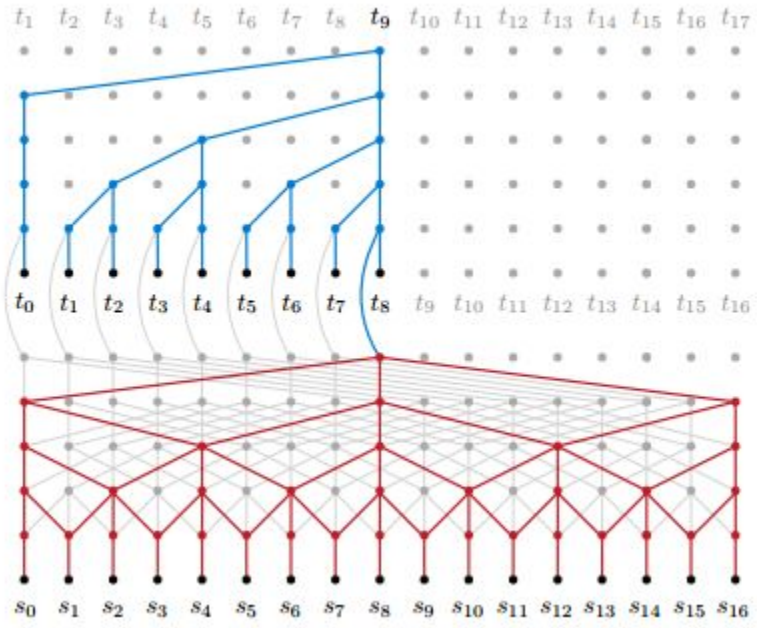
$$\mathbf{h}_t = \sum_{s=1}^{t} \mathbf{V}^{t-s} \cdot \mathbf{z}_s.$$

$$h_t = z_1 * V + z_2 * V^2 + .. \; z_t * V^t$$

- Summation of different units makes the result hard to reason about.

Related work: ByteNet

- Uses CNN to perform sequential tasks
- A binary tree as the network architecture, encoder-decoder units
- Improved parallelism and the gradient distribution against RNNs



Related work: PixelCNN

- Uses *masked convolutions* for sequence prediction
  - Shifting input signal to change so that convolution output corresponds to the next pixel
  - Essentially allows using existing implementations of the convolutional units
- Proposes generative model using CNN and RNNs

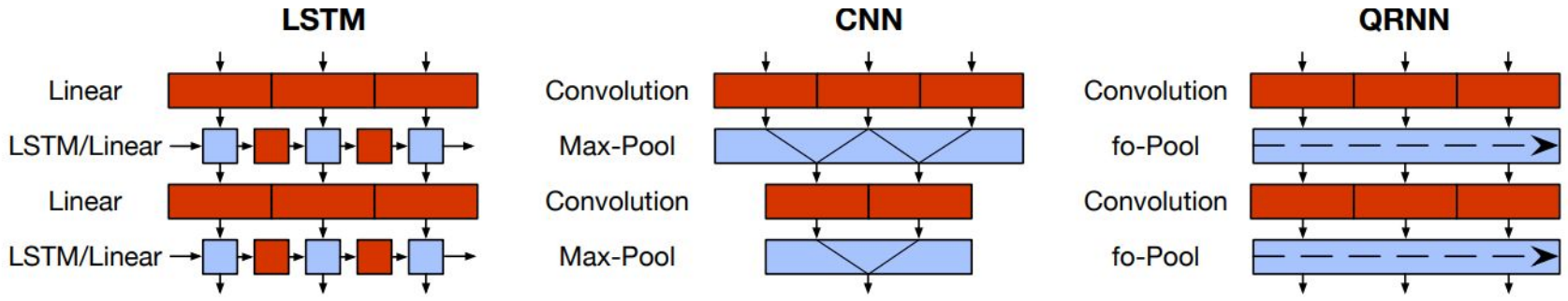
Contributions

- Learn parameters to a recurrent neural network using convolutional filters
  - Three options *f-pooling, fo-pooling, ifo pooling*
- Propose a generalization to the T-RNN approach
  - No hyperparameters in the recurrent step
- Applying recently techniques:
  - Zoneout regularization []
  - Dense Convolutional Networks []
  - Encoder-Decoder Models

Architecture: Main Idea

- Learn weights to be used in the recurrent step using convolutional filters
- Using convolutions to compute *n-gram* features

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



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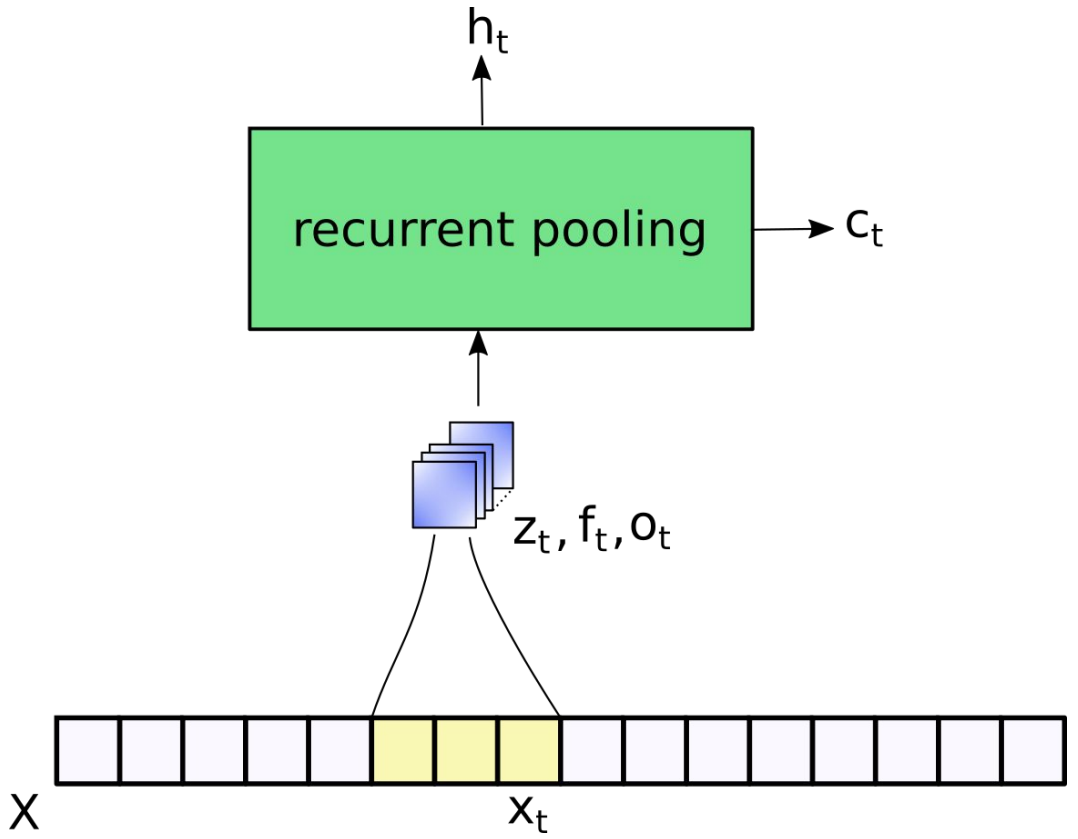


Architecture: Recurrent Pooling Step

- Convolutional features are multiplied *element-wise*
- Basic model *f*-pooling (*averaging the input*):

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

- fo-pooling (output gate):

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

- ifo-pooling (independent input and forget gate):

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \mathbf{z}_t$$
$$\mathbf{h}_t = \mathbf{o}_t \odot \mathbf{c}_t.$$

Architecture: Comparison to an LSTM cell

- Although the structure looks similar not exactly same as the LSTM:
  - Hidden states are not used when computing the gate signals
  - Hence the name *quasi-recurrent*

QRNN

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

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

LSTM

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \text{sigm} \\ \text{sigm} \\ \text{sigm} \\ \tanh \end{pmatrix} W^l \begin{pmatrix} h^{l-1}_t \\ h^l_{t-1} \end{pmatrix}$$

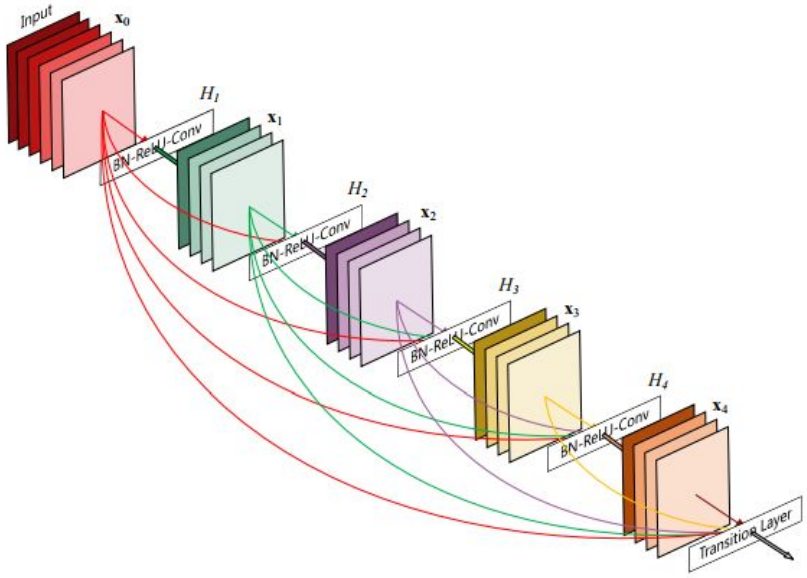
$$c^l_t = f \odot c^l_{t-1} + i \odot g$$
$$h^l_t = o \odot \tanh(c^l_t)$$

Variations: Regularization and Network Architectures

- Adopting Zoneout regularization from []:
  - Apply dropout to *f* gate such that:

$$\mathbf{F} = 1 - \text{dropout}(1 - \sigma(\mathbf{W}_f * \mathbf{X}))$$

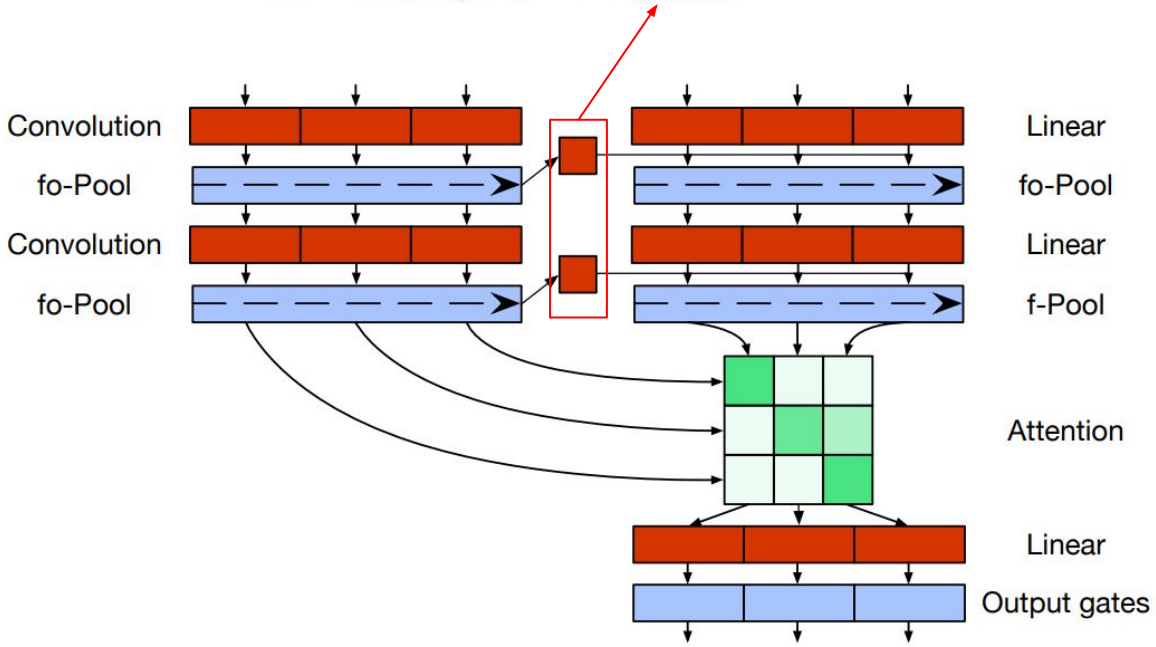
- Densely Connected Networks
  - An extensions to Residual Network
  - Connecting outputs of **every two** layers instead of just one at a time
  - **Concatenate** previous inputs instead of **adding**



Variations: Encoder-Decoder Models

- Encoder-decoder variant uses hidden states of the last encoder layer in the decoder

$$\mathbf{Z}^\ell = \tanh(\mathbf{W}_z^\ell * \mathbf{X}^\ell + \mathbf{V}_z^\ell \tilde{\mathbf{h}}_T^\ell)$$
$$\mathbf{F}^\ell = \sigma(\mathbf{W}_f^\ell * \mathbf{X}^\ell + \mathbf{V}_f^\ell \tilde{\mathbf{h}}_T^\ell)$$
$$\mathbf{O}^\ell = \sigma(\mathbf{W}_o^\ell * \mathbf{X}^\ell + \mathbf{V}_o^\ell \tilde{\mathbf{h}}_T^\ell),$$



Evaluation and Results

- Performance is measured in three tasks
  - Sentiment Analysis
  - Language Modelling
  - Neural Machine Translation
- Overall performs more accurately and trains faster than LSTM with same number of parameters

Experiments: Sentiment Classification

- Sentiment analysis on IMDb movie review dataset
- Better results than equal sized LSTM in shorter time
- L2 and Zoneout regularizations, dense connections

Model	Time / Epoch (s)	Test Acc (%)
NBSVM-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		
Densely-connected 4-layer LSTM (cuDNN optimized)	480	90.9
Densely-connected 4-layer QRNN	150	91.4
Densely-connected 4-layer QRNN with $k = 4$	160	91.1

Experiments: Sentiment Classification

- Sentiment analysis on IMDb movie review dataset
  - L2 and Zoneout regularizations, dense connections
  - 256 untis per layer
  - RMSprop
- Better results than equal sized LSTM in shorter time

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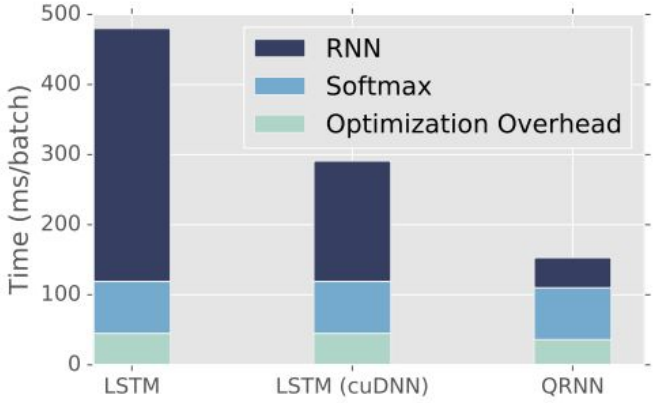
Experiments: Sentiment Classification

Timing Comparison to standard LSTM model

- Up to 16x speedup



		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**

Experiments: Machine Translation

- Encoder-Decoder model is used for German-English translations
  - ~100 characters per sentence
  - 320 units per layer
  - Filter size: 6 chars in the first encoder layer, 2 chars in the next layers
  - Adam optimizer

Model	**Train Time**	**BLEU (TED.tst2014)**
Word-level LSTM w/attn (Ranzato et al., 2016)	–	20.2
Word-level CNN w/attn, input feeding (Wiseman & Rush, 2016)	–	24.0
Our models		
Char-level 4-layer LSTM	4.2 hrs/epoch	16.53
Char-level 4-layer QRNN with $k = 6$	1.0 hrs/epoch	19.41

Conclusions

Pros:

- Proposes a faster and accurate network for sequential learning
- Reduces number of sequentially dependent variables
- Proves the generality by using recent regularization and network design techniques

Cons:

- Seemingly, does not work well without dense connections
- Performs worse than the state-of-the art for neural machine translation

References

- From lecture slides “14 - RNNs”
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