RNN Architectures

EE807: Recent Advances in Deep Learning Lecture 6

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 Process a sequence of vectors by applying recurrence formula at every time step :



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Recap: Vanilla RNN

- Simple RNN
 - The state consists of a single "hidden" vector \mathbf{h}_t
 - Vanilla RNN (or sometimes called Elman RNN)

$$\mathbf{h}_{t} = f(\mathbf{h}_{t-1}, \mathbf{x}_{t}; \Theta)$$

$$\downarrow$$

$$\mathbf{h}_{t} = \tanh(\Theta_{hh}\mathbf{h}_{t-1} + \Theta_{xh}\mathbf{x}_{t})$$

$$\mathbf{y}_t = \Theta_{hy} \mathbf{h}_t$$



Why do we develop RNN architectures?

- For vanilla RNN, it is difficult to capture long-term dependency
- Vanishing gradient problem in vanilla RNN
 - The gradient vanishes over time
 - Which relates to optimization difficulties in CNN



- Many real-world temporal data is intrinsically long-term
 - Natural language
 - Speech
 - Video



• In order to solve much complicated **real-world problems** we need a better RNN architecture to capture **long-term dependency** in the data

1. RNN Architectures and Comparisons

- LSTM (Long Short-Term Memory) and their variants
 - GRU (Gated Recurrent Unit)
 - Stacked LSTM
 - Grid LSTM
 - Bi-directional LSTM

2. Breakthroughs of RNNs in Machine Translation

- Sequence to Sequence Learning with Neural Networks
- Neural Machine Translation with Attention
- Google's Neural Machine Translation (GNMT)

3. Overcoming the heavy computations of RNNs

- Convolutional Sequence to Sequence Learning
- Exploring Sparsity in Recurrent Neural Networks

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Long Short-Term Memory (LSTM)

- A special type of RNN unit
 - i.e., LSTM networks = RNN composed of LSTM units
- Originally proposed by [Hochreiter and Schmidhuber, 1997]
- Explicitly designed RNN to
 - Capture long-term dependency
 - More robust to vanishing gradient problem
- Composed of a cell, an input gate, an output gate, and a forget gate (will be covered in detail soon)



- A very old model, but why so popular?
 - Popularized by series of following works [Graves et al, 2013][Sutskever et al., 2014], ...
 - Work very well in variety of problems
 - Speech recognition
 - Machine translation
 - ...



Next, comparison with Vanilla RNN

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*source: https://en.wikipedia.org/wiki/Long_short-term_memory#/media/File:The_LSTM_cell.png 9

• Vanilla RNN (unrolled)



• Repeating modules in Vanilla RNN contains a single layer

$$\mathbf{h}_t = \tanh(\Theta_{hh}\mathbf{h}_{t-1} + \Theta_{xh}\mathbf{x}_t)$$





- The core idea behind LSTM
 - Able to control how much information to preserve from previous state
 - The horizontal line running through the top of the diagram (i.e., the **cell state** or **memory**)
 - Only linear interactions from the output of each "gates" (prevent vanishing gradient)
 - Control how much to remove or add information to the cell state



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*reference: http://colah.github.io/posts/2015-08-Understanding-LSTMs/ 13

RNN Architectures: LSTM

Step 1 : Decide what **information** we're going to **throw away** from the **cell state**

- A sigmoid layer called "Forget gate" f_t
- Looks at h_{t-1}, x_t and outputs a number between 0 and 1 for each cell state C_{t-1}
 - If 1: completely keep, if 0: completely remove
- e.g., language model trying to predict the next word based on all previous ones
 - The cell state might include the gender of the present subject
 - so that the correct pronouns can be used
 - When we see a new subject, we want to forget the gender of the old subject



$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

RNN Architectures: LSTM

Step 2 : Decide what **information** we're going to **store** in the cell state and **update**

- First, a sigmoid layer called the "Input gate" i_t decides which values to update
- Next, a tanh layer creates a vector of new candidate values C_t



$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

RNN Architectures: LSTM

Step 2 : Decide what **information** we're going to **store** in the cell state and **update**

- First, a sigmoid layer called the "Input gate" i_t decides which values to update
- Next, a tanh layer creates a vector of new candidate values C_t
- Then, update the old cell state C_{t-1} into the new cell state C_t
 - Multiply the old state by f_t
 - Add $i_t * ilde{C}_t$, new candidate values scaled by how much to update



Step 3 : Decide what we're going to **output**

- A sigmoid layer called "Output gate" o_t
- First go through o_t which decides what parts of the cell state to output
- Then, put the cell state C_t through tanh (push the values to be between -1 and 1) and multiply it by o_t



$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$
$$h_t = o_t * \tanh(C_t)$$

• Overall LSTM operations



$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t * \tanh(C_t)$$

Standard LSTM



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*reference: http://colah.github.io/posts/2015-08-Understanding-LSTMs/ 18

- Gated Recurrent Unit (GRU) [Cho et.al, 2014]
 - Combines the forget and input gates into a single "update gate" z_t
 - Controls the **ratio of information to keep** between previous state and new state
 - Reset gate r_t controls how much information to forget
 - Merges the cell state C_t and hidden state h_t
 - (+) Resulting in simpler model (less weights) than standard LSTM



$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t])$$
$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t])$$
$$\tilde{h}_t = \tanh(W \cdot [r_t * h_{t-1}, x_t])$$
$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Gated Recurrent Unit

Standard LSTM



$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t * \tanh(C_t)$$

- With simplified diagram
 - C : cell state (or memory)
 - h : hidden state (or output)
 - Dashed line indicates identity transformation



- Stacked LSTM [Graves et al, 2013]
 - Adds capacity by simply stacking LSTM layers on top of each other
 - Output of 1st layer LSTM goes into 2nd layer LSTM as an input
 - But no vertical interactions



- Grid LSTM [Kalchbrenner et al., 2016]
 - Extended version of stacked LSTM
 - LSTM units have memory connections along depth dimension as well as temporal dimension





	BPC	Parameters	Alphabet Size	Test data
Stacked LSTM (Graves, 2013)	1.67	27M	205	last 4MB
MRNN (Sutskever et al., 2011)	1.60	4.9M	86	last 10MB
GFRNN (Chung et al., 2015)	1.58	20M	205	last 5MB
Tied 2-LSTM	1.47	16.8M	205	last 5MB

Performance on wikipedia dataset (lower the better)

2D Grid LSTM

- What is the limitation of all previous models?
 - They learn representations only from **previous** time steps
 - Useful to learn **future** time steps in order to
 - Better understand the context
 - Eliminate ambiguity
- Example
 - "He said, Teddy bears are on sale"
 - "He said, Teddy Roosevelt was a great President"
 - In above two sentences, only seeing previous words is not enough to understand the sentence
- Solution
 - Also look ahead → Bidirectional RNNs

RNN Architectures: Bidirectional RNNs

- We can also extend RNNs into bi-directional models
 - The repeating blocks A could be **any types of RNNS** (Vanilla RNN, LSTM, or GRU)
 - The only difference is that there are additional paths from future time steps



Next, Comparison of Variants

- Which architecture is the best?
 - There is no clear winner; it **depends largely on the task**
 - More empirical exploration of RNNs can be found here [Jozefowicz et al., 2015]

Model	Advantages	Disadvantages	
LSTM	 Capable of modeling long-term sequential dependencies better than simple RNN More robust to vanishing gradients than simple RNN 	 Increases computational complexity Higher memory requirement than RNN due to multiple memory cells 	
Stacked LSTM	 Models long-term sequential dependencies due to deeper architecture 	 Higher memory requirement and computational complexity than LSTM due to stack of LSTM cells 	
Bidirectional LSTM	- Predicts both in the future and past context of the input sequence better than LSTM	- Increases computational complexity than LSTM	
GRU	 Capable of modeling long-term sequential dependencies Less memory requirements than LSTM 	- Higher computational complexity and memory requirements than RNN due to multiple hidden state vectors	
Grid LSTM	- Models multidimensional sequences with increased grid size	- Higher memory requirement and computational complexity than LSTM due to multiple recurrent connections	

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- What is machine translation?
 - Task of automatically **converting** source **text in one language to another** language
 - No single answer due to ambiguity/flexibility of human language (challenging)



- Classical machine translation methods
 - Rule-based machine translation (RBMT)
 - Statistical machine translation (SMT; use of statistical model)
- Neural Machine Translation (NMT)
 - Use of **neural network models to learn a statistical model** for machine translation

- Difficulties in Neural Machine Translation
 - Intrinsic difficulties of MT (ambiguity of language)
 - Variable length of input and output sequence (difficult to learn a single model)
- The core idea of sequence-to-sequence model [Sutskever et al., 2014]
 - Encoder-Decoder architecture (input → vector → output)
 - Use one RNN network (Encoder) to **read input sequence** at a time to obtain large **fixed-length vector representation**
 - Use another RNN (Decoder) to extract the output sequence from that vector



Input sequence "ABC" and output sequence "WXYZ"

- Encoder
 - Reads the input sentence, a sequence of vectors $\mathbf{x} = (x_1, \dots, x_T)$ into a vector c
 - Use RNNs such that $h_t = f(x_t, h_{t-1})$ and $c = q(\{h_1, \ldots, h_T\})$, where f and q are some non-linear functions
 - LSTMs as f and $q(\{h_1, \ldots, h_T\}) = h_T$ (in the original seq2seq model)
- Decoder
 - Trained to predict the next word $y_{t'}$ given the context vector c and the previously predicted words $\{y_1, \ldots, y_{t'-1}\}$
 - Defines a probability over the translation ${\bf y}$ by decomposing the joint probability into the ordered conditionals:

$$p(\mathbf{y}) = \prod_{t=1}^{T} p(y_t | \{y_1, \dots, y_{t'-1}\}, c),$$

where $y = (y_1, ..., y_T)$.

• The conditional probability is modeled as

$$p(y_t|\{y_1,\ldots,y_{t'-1}\},c) = g(y_{t-1},s_t,c),$$

where g is a nonlinear, potentially multi-layered function that outputs the probability of y_t and s_t is the hidden state of the RNN

- Example of the seq2seq model
 - For English \rightarrow French task
 - With 2-layer LSTM for encoder and encoder



Breakthroughs in NMT: Sequence-to-Sequence Learning

- Results on WMT'14 English to French dataset
 - Measure : BLEU(Bilingual Evaluation Understudy) score
 - Widely used quantitative measure for MT task
 - On par with the state-of-the-art SMT system (without any neural network)
 - Achieved better results than the previous baselines

Method	test BLEU score (ntst14)
Baseline System [29]	33.30
Cho et al. [5]	34.54
State of the art [9]	37.0
Rescoring the baseline 1000-best with a single forward LSTM	35.61
Rescoring the baseline 1000-best with a single reversed LSTM	35.85
Rescoring the baseline 1000-best with an ensemble of 5 reversed LSTMs	36.5
Oracle Rescoring of the Baseline 1000-best lists	~45

• Simple but very powerful in MT task



Breakthroughs in NMT: Joint Learning to Align and Translate

- NMT by Joint Learning to Align and Translate [Bahdanau et al., 2015]
- Problem of original encoder-decoder (or seq2seq) model
 - Need to compress all the necessary information of a source sentence into a fixed-length vector
 - Very **difficult to cope with long sentences**, especially when the test sequence is longer than the sentences in the training corpus
- Extension of encoder-decoder model + **attention** mechanism
 - Encode input sentence into a sequence of vectors
 - And chooses a subset of these vectors adaptively while decoding the translation
 - Frees the neural network model from having to squash all the information into a single fixed-length vector

• Define each conditional probability as:

$$p(y_i|\{y_1,\ldots,y_{i-1}\},\mathbf{x}) = g(y_{i-1},s_i,c_i),$$

where s_i is an RNN hidden state for time *i* computed by $s_i = f(s_{i-1}, y_{i-1}, c_i)$.

- Distinct context vector c_i for each target word y_i
- The context vector c_i is computed as weighted sum of h_i

$$c_i = \sum_{j=1}^T \alpha_{ij} h_j.$$

• The weight α_{ij} of each h_j is computed by

$$\alpha_{ij} = \frac{exp(e_{ij})}{\sum_{k=1}^{T} exp(e_{ik})},$$

where $e_{ij} = a(s_{i-1}, h_j)$ is an alignment model which scores **how well the inputs** around position*j* and the **output** position *i* **match**.



Illustration of the model

- Graphical illustration of seq2seq with attention
 - e.g., Chinese to English



Breakthroughs in NMT: Joint Learning to Align and Translate

- Results
 - RNNsearch (proposed) is better than RNNenc (vanilla seq2seq)
 - RNNsearch-50: model trained with sentences of length up to 50 words



Next, Google's NMT

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- Google's NMT [Wu et al., 2016]
 - Improves over previous NMT systems on accuracy and speed
 - 8-layer LSTMS for encoder/decoder with attention
 - Achieve model parallelism by assigning each LSTM layer into different GPUs
 - Add residual connections in standard LSTM
 - ... and lots of domain-specific details to apply it to production model



Google's Neural Machine Translation (GNMT)

- Adding residuals connections in stacked LSTM
 - In practice, LSTM has also problem of **vanishing gradient** when stacking more layers
 - Empirically, 4-layer works okay, 6-layer has problem, 8-layer does not work at all
 - Apply residual connections with 8-layer stacked LSTM worked best



Standard stacked LSTM



Stacked LSTM with residual connections

- Results
 - State-of-the-art results on various MT datasets
 - Also comparable with Human expert

	Model	BLEU	CPU decoding time
			per sentence (s)
	Word	23.12	0.2972
	Character (512 nodes)	22.62	0.8011
	WPM-8K	23.50	0.2079
	WPM-16K	24.36	0.1931
	WPM-32K	24.61	0.1882
	Mixed Word/Character	24.17	0.3268
1	PBMT [6]	20.7	
	RNNSearch [37]	16.5	
	RNNSearch-LV [37]	16.9	
	RNNSearch-LV [37]	16.9	
	Deep-Att $[45]$	20.6	

Table 5: Single model results on WMT En \rightarrow De (newstest2014)

Table 10: Mean of side-by-side scores on production data

	-			
	PBMT	GNMT	Human	Relative
				Improvement
$\mathrm{English} \to \mathrm{Spanish}$	4.885	5.428	5.504	87%
English \rightarrow French	4.932	5.295	5.496	64%
$\mathrm{English} \to \mathrm{Chinese}$	4.035	4.594	4.987	58%
$\text{Spanish} \to \text{English}$	4.872	5.187	5.372	63%
$\mathrm{French} \to \mathrm{English}$	5.046	5.343	5.404	83%
$\mathbf{Chinese} \to \mathbf{English}$	3.694	4.263	4.636	60%

GNMT with different configurations

Google's Multilingual Neural Machine Translation (Multilingual GNMT)

- Further improved in [Johnson et al., 2016]
- Extensions to make this model to be Multilingual NMT system by adding **artificial token** to indicate the required **target language**
 - e.g., the token "<2es>" indicates that the target sentence is in Spanish
 - Can do **multilingual NMT** using a **single model** w/o increasing the parameters



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Problem in RNNs

- The most fundamental problem of RNNs
 - Require heavy computations (slow)
 - Especially when we stack multiple layers
 - GNMT solved this by model parallelism

- How to alleviate this issue in terms of architectures?
 - CNN encoder
 - CNN encoder + decoder
 - Optimizing RNNs (pruning approach)

Solution 1-1. CNN encoder

- A convolutional encoder model for Neural Machine Translation [Gehring et al., 2016]
 - CNN encoder + RNN decoder
 - Replace the RNN encoder with stack of 1-D convolutions with nonlinearities
 - Two different CNNs for attention score computation and conditional input aggregation
 - More parallelizable than using RNN



Encoder	Words/s	BLEU
2-layer BiLSTM	109.9	23.6
Deep Conv. 8/4	231.1	23.7
Deep Conv. 15/5	203.3	24.0

- Convolutional sequence to sequence learning [Gehring et al., 2017]
 - CNNs for both encoder and encoder



WMT'14 English-French	BLEU
Wu et al. (2016) GNMT (Word 80K)	37.90
Wu et al. (2016) GNMT (Word pieces)	38.95
Wu et al. (2016) GNMT (Word pieces) + RL	39.92
ConvS2S (BPE 40K)	40.51

Performance

	BLEU	Time (s)
GNMT GPU (K80)	31.20	3,028
GNMT CPU 88 cores	31.20	1,322
GNMT TPU	31.21	384
ConvS2S GPU (K40) $b = 1$	33.45	327
ConvS2S GPU (M40) $b = 1$	33.45	221
ConvS2S GPU (GTX-1080ti) $b = 1$	33.45	142
ConvS2S CPU 48 cores $b = 1$	33.45	142
ConvS2S GPU (K40) $b = 5$	34.10	587
ConvS2S CPU 48 cores $b = 5$	34.10	482
ConvS2S GPU (M40) $b = 5$	34.10	406
ConvS2S GPU (GTX-1080ti) $b = 5$	34.10	256

Generation speed

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- Exploring Sparsity in Recurrent Neural Networks [Narang et al., 2017]
 - **Pruning RNNs** to improve **inference time** with marginal performance drop
 - Simple heuristics to calculate the threshold
 - And apply that threshold to every binary mask corresponds to each weight
 - Reduces the size of the model by 90%
 - Significant inference time speed-up using sparse matrix multiply around 2 imes to 7 imes

MODEL	# UNITS	CER	# PARAMS	RELATIVE PERF
RNN Dense Baseline	1760	10.67	67 million	0.0%
RNN Dense Small	704	14.50	11.6 million	-35.89%
RNN Dense Medium	2560	9.43	141 million	11.85%
RNN Sparse 1760	1760	12.88	8.3 million	-20.71%
RNN Sparse Medium	2560	10.59	11.1 million	0.75%
RNN Sparse Big	3072	10.25	16.7 million	3.95%
GRU Dense	2560	9.55	115 million	0.0%
GRU Sparse	2560	10.87	13 million	-13.82%
GRU Sparse Medium	3568	9.76	17.8 million	-2.20%

LAYER SIZE	SPARSITY	LAYER TYPE	TIME (μ sec)	SPEEDUP
1	0.9	51.11.I		
1760	0%	RNN	56	1
1760	95%	RNN	20	2.8
2560	95%	RNN	29	1.93
3072	95%	RNN	48	1.16
2560	0%	GRU	313	1
2560	95%	GRU	46	6.80
3568	95%	GRU	89	3.5

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GEMM (General Matrix-Matrix Multiply) times comparison

Summary

- RNN architectures have developed in a way that
 - Can better model long-term dependency
 - **Robust** to vanishing gradient problems
 - While having less memory or computational costs
- Breakthroughs in machine translation
 - Seq2seq model with attention
 - GNMT and extension to multilingual NMT
- Alleviating the problem of RNNs' heavy computations
 - Convolutional sequence to sequence learning
 - Pruning approach
- There are various applications combining RNNs with other networks
 - Image caption generation, visual question answering(VQA), etc.
 - Will be covered in later lectures

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