Sparse Attentive Backtracking: Temporal credit assignment through reminding

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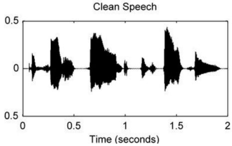
Overview

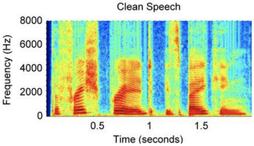
- Recurrent neural networks
  - sequence modeling
- Training RNNs
  - backpropagation through time (BPTT)
- Attention mechanism
- Sparse attentive backtracking

Sequence modeling

Variable length input and (or) output.

- Speech recognition
    - variable length input, variable length output





- Image captioning
    - Fixed size input, variable length output

A woman is throwing a frisbee in a park.

A stop sign is on a road with a mountain in the background.

A group of people sitting on a boat in the water.

A giraffe standing in a forest with trees in the background.

Show, Attend & Tell – arXiv preprint arXiv:1502.03044

Sequence modeling

More examples

- Text
  - Language modeling
  - Language understanding
  - Sentiment analysis
- Videos
  - Video generation.
  - Video understanding.
- Biological data
  - Medical imaging

Recurrent neural networks (RNNs)

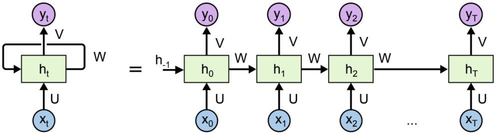
Handling variable length data

- Variable length input or output
- Variableorder
  - "In 2014, I visited Paris."
  - "I visited Paris in 2014."
- Use shared parameters across time

Recurrent neural networks (RNNs)

Vanilla recurrent neural networks

- Parameters of the network
  - U, W, V
  - unrolled across time



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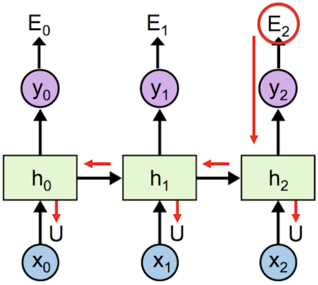
Training RNNs

Backpropagation through time (BPTT)

$$\frac{dE_2}{dU} = \frac{dE_2}{dh_2}(x_2^T + \frac{dh_2}{dh_1}(x_1^T + \frac{dh_1}{dh_0}x_0^T))$$



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Challenges with RNN training

Parameters are shared across time

- Number of parameters do not change with sequence length.
- Consequences
  - Optimization issue
  - Exploding or vanishing gradients
  - Assumption that same parameters can be used for different time steps.

Challenges with RNN training

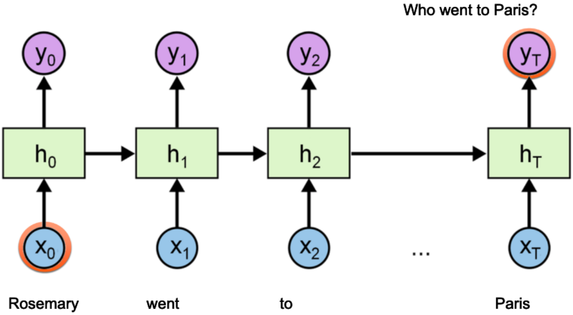
Train to predict the future from the past

- h_t is a lossy summary of $x_0, ..., x_t$
- Depending on criteria, h_t decides what information to keep
- **Long term dependency**: if y_t depends on distant past, then h_t has to keep information from many timesteps ago.

Long term dependency

Example of long term dependency

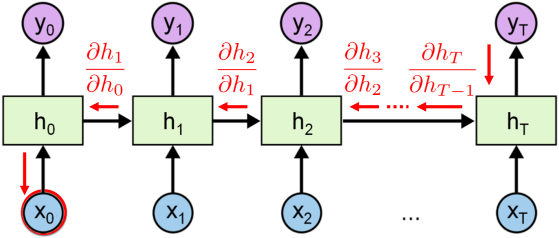
- Question answering task.
- Answer is the first word.



Exploding and vanishing gradient

Challenges in learn long term dependencies

- Exploding and vanishing gradient



Long short term memory (LSTM)

Gated recurrent neural networks that helps with long term dependency.

- Self-loop for gradients to flow for many steps
- Gates for learning what to remember or forget
- Long-short term memory (LSTM)

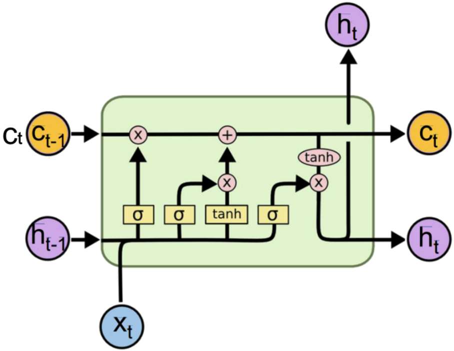
  Hochreiter, Sepp, and Jürgen Schmidhuber. "Long short-term memory." *Neural computation* 9.8 (1997): 1735-1780.
- Gated recurrent neural networks (GRU)

  Cho, Kyunghyun, et al. "Learning phrase representations using RNN encoder-decoder for statistical machine translation." arXiv preprint arXiv:1406.1078 (2014).

Long short term memory (LSTM)

Recurrent neural network with gates that dynamically decides what to put into, forget about and read from memory.

- Memory cell c_t
- Internal states h_t
- Gates for writing into, forgetting and reading from memory



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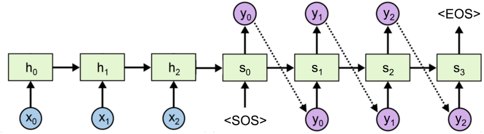
Encoder decoder model

Summarizes the input into a single h_t and decoder generates outputs conditioned on h_t.

- Encoder summarizes entire input sequence into a single vector h_t.
- Decoder generates outputs conditioned on h_t.
- Applications: machine translation, question answering tasks.
- Limitations: h_t in encoder is bottleneck.



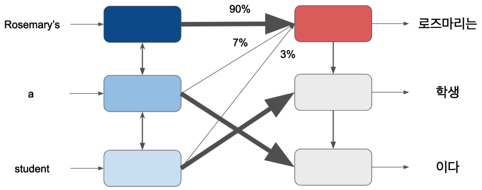
Attention mechanism

Removes the bottleneck in encoder decoder architecture using an **attention mechanism**.

- At each output step, learns an attention weight for each $h_0, ..., h_t$ in the encoder.

$$a_j = \frac{e^{A(z_j, h_j)}}{\sum_{j'} e^{A(z_j, h_{j'})}}$$

- Dynamically encodes into into context vector at each time step.
- Decoder generates outputs at each step conditioned on context vector cx_t.



Limitations of BPTT

The most popular RNN training method is backpropagation through time (BPTT).

- Sequential in nature.
- Exploding and vanishing gradient
- Not biologically plausible
  - Detailed replay of all past events.

Credit assignment

- Credit assignment: The correct division and attribution of blame to one's past actions in leading to a final outcome.
- Credit assignment in recurrent neural networks uses backpropgation through time (BPTT).
    - Detailed memory of all past events
    - Assigns soft credit to almost all past events
    - Diffusion of credit? difficulty of learning long-term dependencies

Credit assignment through time and memory

- Humans selectively recall memories that are relevant to the current behavior.
- Automatic reminding:
  - Triggered by contextual features.
  - Can serve a useful computational role in ongoing cognition.
  - Can be used for credit assignment to past events?
- Assign credit through only a few states, instead of all states:
  - Sparse, local credit assignment.
  - How to pick the states to assign credit to?

Credit assignment through time

Example: Driving on the highway, hear a loud popping sound. Didn't think too much about it, 20 minutes later stopped by side of the road. Realized one of the tire has popped.

- What we tend to do?
  - Memory replay of event in context: Immediately brings back the memory of the loud popping sound 20min ago.
- what BPTT does?
  - BPTT will replay all events within the past 20min.

Maybe something more biologically inspired?

- What we tend to do?
  - Memory replay of event in context: Immediately brings back the memory of the loud popping sound 20min ago.
- what BPTT does?
  - BPTT will replay all events within the past 20min.

Credit assignment through a few states?

- Can we assign credit only through a few states?
- How to pick which states to assign credit to?
- RNN models does not support such operations in the past. Needs to make **architecture changes**.
    - Can change both forward and backward.
    - Or just change backward pass.
- Change both forward and backward pass
    - Forward dense, backward sparse
    - Forward sparse, backward sparse

Sparse replay

Humans are trivially capable of assigning credit or blame to events even a **long time** after the fact, and do not need to replay all events from the present to the credited event sequentially and in reverse to do so.

- **Avoids competition** for the limited information-carrying capacity of the sequential path
- A simple form of **credit assignment**
- Imposes a trade-off that is absent in previous, dense self-attentive mechanisms: opening a connection to an interesting or useful timestep must be made at the price of excluding others.

Sparse attentive backtracking

- Use attention mechanism to select previous timestep to do backprop
    - Local backprop: truncated BPTT
    - Select previous hidden states - **sparsely**.
    - Skip-connections: natural for long-term dependency.

Algorithm

Algorithm 1 SAB-augmented LSTM

procedure SABCELL ($\boldsymbol{h}^{(t-1)}, \boldsymbol{c}^{(t-1)}, \boldsymbol{x}^{(t)}$)

Require: $k_{top} > 0$, $k_{att} > 0$, $k_{trunc} > 0$

Require: Memories $\boldsymbol{m}^{(i)} \in \mathcal{M}$

Require: Previous hidden state $\boldsymbol{h}^{(t-1)}$

Require: Previous cell state $\boldsymbol{c}^{(t-1)}$

Require: Input $\boldsymbol{x}^{(t)}$

$\hat{\boldsymbol{h}}^{(t)}, \boldsymbol{c}^{(t)} \leftarrow \texttt{LSTMCell}(\boldsymbol{h}^{(t-1)}, \boldsymbol{c}^{(t-1)}, \boldsymbol{x}^{(t)})$

for all $i \in 1 \dots |\mathcal{M}|$ **do**

$\quad \boldsymbol{d}_i^{(t)} \leftarrow \boldsymbol{W}_1 \boldsymbol{m}^{(i)} + \boldsymbol{W}_2 \hat{\boldsymbol{h}}^{(t)}$

$\quad a_i^{(t)} \leftarrow \boldsymbol{W}_3 \tanh(\boldsymbol{d}_i^{(t)})$

$a_{\text{ktop}}^{(t)} \leftarrow \texttt{sorted}(\boldsymbol{a}^{(t)})\texttt{[}k_{top}\texttt{+1]}$

$\tilde{\boldsymbol{a}}^{(t)} \leftarrow \text{ReLU}\left(\boldsymbol{a}^{(t)} - a_{\text{ktop}}^{(t)}\right)$

$\boldsymbol{s}^{(t)} \leftarrow \sum_{\boldsymbol{m}^{(i)} \in \mathcal{M}} \tilde{a}_i^{(t)} \boldsymbol{m}^{(i)} / \sum_i \tilde{a}_i^{(t)}$

$\boldsymbol{h}^{(t)} \leftarrow \hat{\boldsymbol{h}}^{(t)} + \boldsymbol{s}^{(t)}$

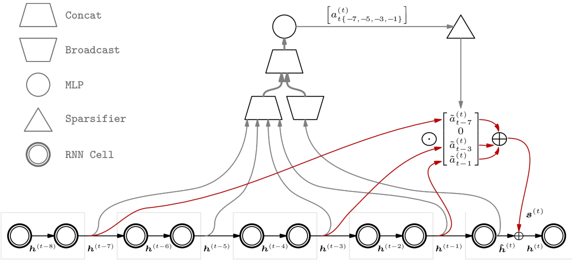
$\boldsymbol{y}^{(t)} \leftarrow \boldsymbol{V}_1 \boldsymbol{h}^{(t)} + \boldsymbol{V}_2 \boldsymbol{s}^{(t)} + \boldsymbol{b}$

if $t \equiv 0 \pmod{k_{att}}$ **then**

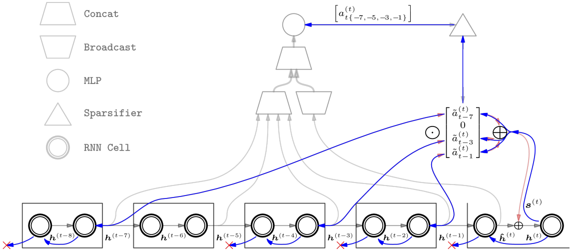
$\quad \mathcal{M}\texttt{.append(}\boldsymbol{h}^{(t)}\texttt{)}$

return $\boldsymbol{h}^{(t)}, \boldsymbol{c}^{(t)}, \boldsymbol{y}^{(t)}$

Forward pass



Backward pass



Long term dependency tasks

Copy task

	k_{trunc}	k_{top}	Copying (T=100) acc.	Copying (T=100) CE_{10}	Copying (T=100) CE	Copying (T=200) acc.	Copying (T=200) CE_{10}	Copying (T=200) CE	Copying (T=300) acc.	Copying (T=300) CE_{10}	Copying (T=300) CE
LSTM	*full BPTT*		99.8	0.030	0.002	56.0	1.07	0.046	35.9	0.197	0.047
	full self-attn.		100.0	0.0008	0.0000	100.0	0.001	0.000	100.0	0.002	7.5e-5
	1	-	20.6	1.984	0.165				14.0	2.077	0.065
	5	-	31.0	1.737	0.145	17.1	2.03	0.092			
	10	-	29.6	1.772	0.148	20.2	1.98	0.090			
	20	-	30.5	1.714	0.143	35.8	1.61	0.073	25.7	1.848	0.197
	150	-	-	-	-	35.0	1.596	0.073	24.4	1.857	0.058
SAB	1	1	57.9	1.041	0.087	39.9	1.516	0.069	43.1	0.231	0.045
	1	5	**100.0**	**0.001**	**0.000**				89.1	0.383	0.012
	5	5	**100.0**	**0.000**	**0.000**	**100.0**	**0.000**	**0.000**	**99.9**	**0.007**	**0.001**
	10	10	**100.0**	**0.000**	**0.001**	**100.0**	**0.000**	**0.000**			

Table 2: Test accuracy and cross-entropy (CE) loss performance on the copying task with sequence lengths of T=100, 200, and 300. Accuracies are given in percent for the last 10 characters. CE_{10} corresponds to the CE loss on the last 10 characters. These results are with mental updates; Compare with Table 4 for without.

Comparison to Transformers

Image class.				pMNIST	CIFAR10
	k_{trunc}	k_{top}	k_{att}	acc.	acc.
LSTM	*full BPTT*			90.3	58.3
LSTM	300	-	-		51.3
SAB	20	5	20	89.8	
SAB	20	10	20	90.9	
SAB	50	10	50	**94.2**	
SAB	16	10	16		**64.5**
Transformer (Vasvani'17)				**97.9**	62.2

Table 4: Test accuracy for the permutated MNIST and CIFAR10 classification tasks.

Language modeling tasks

Language	k_{trunc}	k_{top}	k_{att}	PTB BPC	Text8 BPC
LSTM	*full BPTT*			1.36	1.42
LSTM	1	-	-	1.47	1.56
LSTM	5	-	-	1.44	
LSTM	20	-	-	1.40	
SAB	10	5	10	1.42	1.47
SAB	10	10	10	1.40	1.45
SAB	20	5	20	1.39	1.45
SAB	20	10	20	1.37	1.44

Are mental updates important?

How important is backproping **through the local** updates (not just attention weights)?

Ablation	k_{trunc}	k_{top}	**Copying**, T=100 acc.	$\text{CE}_{\text{last } 10}$	CE	**Adding**, T=200 CE
no MU	1	1	49.0	1.252	0.104	
	5	5	98.3	0.042	0.0036	
	10	10	99.6	0.022	0.0018	2.171e-6
	5	all	40.5	1.529	0.127	

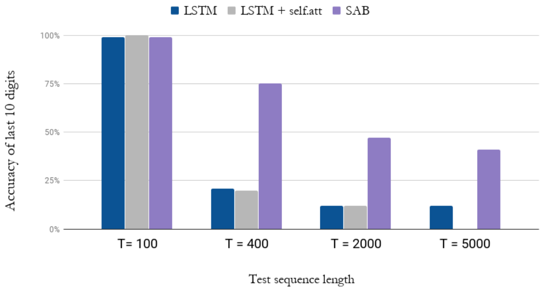
Generalization

- Generalization on longer sequences

Transfer Learning Results

Copy len. (T)	LSTM	LSTM +self-a.	SAB
100	99%	100%	99%
200	34%	52%	**95%**
300	25%	28%	**83%**
400	21%	20%	**75%**
2000	12%	12%	**47%**
5000	12%	OOM	**41%**

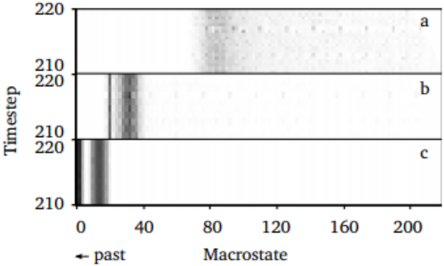
Generalization test for models trained on copy task with T=100



Attention heat map

- Learned attention over different timesteps during training

Copy Task with T = 200



Future work

- **Content-based rule for writing to memory**
  - Reduces memory storage
  - How to decide what to write to memory?
  - Humans show a systematic dependence on many content: salient, extreme, unusual, and unexpected experiences are more likely to be stored and subsequently remembered
- **Credit assignment through more abstract states/ memory?**
- **Model-based reinforcement learning**

Open-Source Release

- The source code is now open-source, at https://github.com/nke001/sparse_attentive_backtracking_release