



# Sparse Attentive Backtracking: Temporal credit assignment through reminding

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# Credit assignment

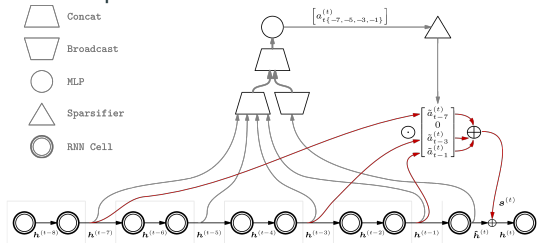
- **Credit assignment:** The correct division and attribution of blame to one's past actions in leading to a final outcome.
- Credit assignment in **recurrent neural networks** uses backpropagation through time (BPTT).
  - Detailed memory of all past events
  - Assign soft credit to almost all past events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

# Credit assignment through time and memory

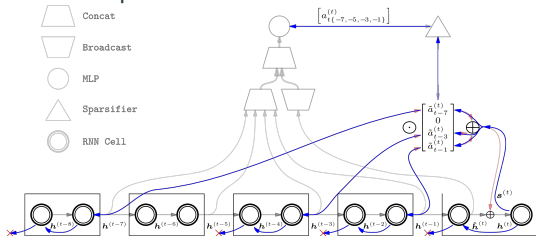
- Humans selectively recall memories that are relevant to the current behavior.
- Automatic reminding:
  - Triggered by contextual features.
  - Can serve a useful computation role in ongoing cognition.
  - Can be used for credit assignment to past events?
- Assign credit through only **a few states**,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

# Sparse Attentive Backtracking

## Forward pass



## Backward pass



# Some results

		Copying (T=100)			Copying (T=200)			Copying (T=300)			
$k_{\text{runc}}$	$k_{\text{top}}$	acc.	CE <sub>10</sub>	CE	acc.	CE <sub>10</sub>	CE	acc.	CE <sub>10</sub>	CE	
LSTM	<i>full BPTT</i>	99.8	0.030	0.002	56.0	1.07	0.046	35.9	0.197	0.047	
	<i>full self-attn.</i>	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	<b>100.0</b>	<b>0.001</b>	<b>0.000</b>				89.1	0.383	0.012
	5	5	<b>100.0</b>	<b>0.000</b>	<b>0.000</b>	<b>100.0</b>	<b>0.000</b>	<b>0.000</b>	<b>99.9</b>	<b>0.007</b>	<b>0.001</b>
	10	10	<b>100.0</b>	<b>0.000</b>	<b>0.001</b>	<b>100.0</b>	<b>0.000</b>	<b>0.000</b>			

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<sub>10</sub> corresponds to the CE loss on the last 10 characters. These results are with mental updates; Compare with Table 4 for without.

Image class.				pMNIST	CIFAR10
$k_{\text{runc}}$	$k_{\text{top}}$	$k_{\text{att}}$		acc.	acc.
LSTM	<i>full BPTT</i>			90.3	58.3
	300	-	-		51.3
SAB	20	5	20	89.8	
	20	10	20	90.9	
	50	10	50	<b>94.2</b>	
	16	10	16		<b>64.5</b>
Transformer (Vasvani'17)				<b>97.9</b>	62.2

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

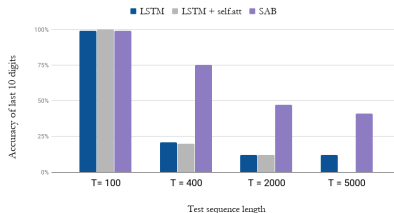
# Generalization and attention map

- Generalization on longer sequences

Transfer Learning Results

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

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



- Learned attention over different timesteps during training  
Copy Task with T = 200

