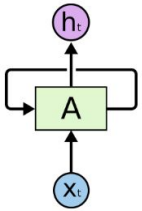

RNN

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Agenda

- Basics
- Bag of applications
- LSTM & GRU
- Bag of tricks
- Other architecture considerations (attention, memory etc.)

Picture credits: http://colah.github.io/

DeepDrumpf
@DeepDrumpf

I'm a Neural Network trained on Trump's transcripts. Priming text in [ ]s. Donate (gofundme.com/deepdrumpf) to interact! Created by @hayesbh.

deepdrumpf2016.com
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Following

[Hillary Clinton] was all talk. I was screaming -- jobs and extremists, not policy. But I won. @ChadHGriffin @HillaryClinton #debates2016

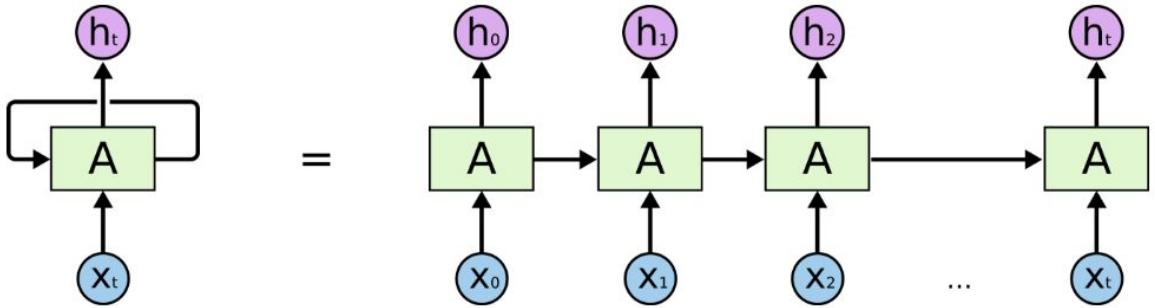
RETWEETS 68 LIKES 139

7:56 PM - 26 Sep 2016

2 68 139

Recurrent Neural Networks (RNN)

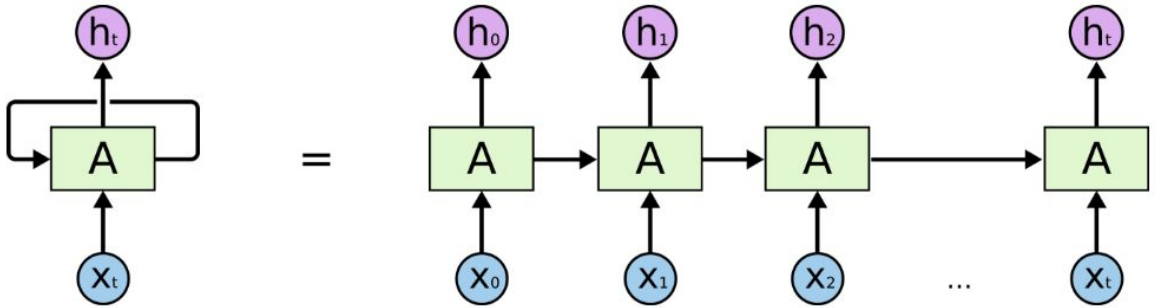
- A neural network with a closed loop -> Wire the output back to the input.
- Lots of sequential data around us: text, music, speech, video, etc.
- We can feed sequential data into RNN frame by frame: speech recognition, video classification, etc.
- We can also expect RNN to emit sequential output: Language modeling, machine translation, speech generation, video generation.



Recurrent Neural Networks (RNN)

$$\boldsymbol{a}^{(t)} = \boldsymbol{b} + \boldsymbol{W}\boldsymbol{h}^{(t-1)} + \boldsymbol{U}\boldsymbol{x}^{(t)}$$

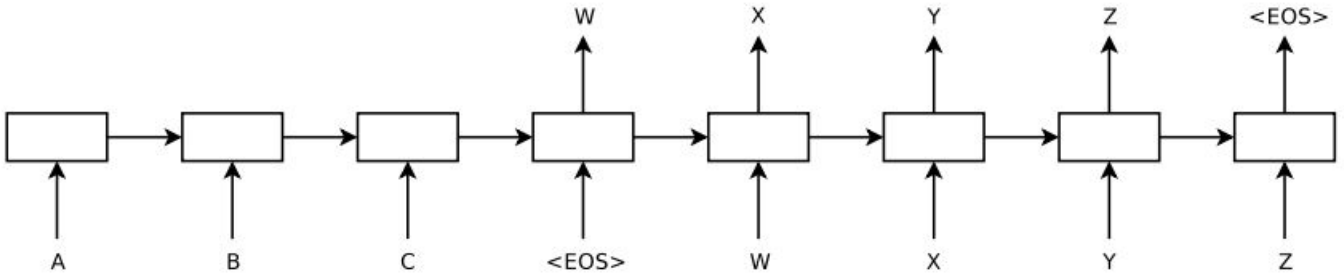
$$\begin{aligned} \boldsymbol{h}^{(t)} &= \tanh(\boldsymbol{a}^{(t)}) \\ \boldsymbol{o}^{(t)} &= \boldsymbol{c} + \boldsymbol{V}\boldsymbol{h}^{(t)} \\ \hat{\boldsymbol{y}}^{(t)} &= \text{softmax}(\boldsymbol{o}^{(t)}) \end{aligned}$$



Machine Translation

- Encoder-Decoder RNN model. Encodes the sentence using an RNN, and decode the hidden state into another language.
- Since 2015, RNNs started to beat traditional phrase-based systems.

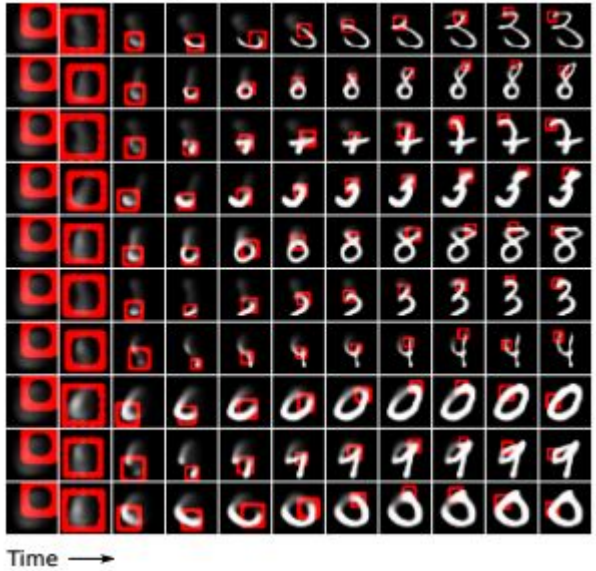
(Sutskever et al., 2015)

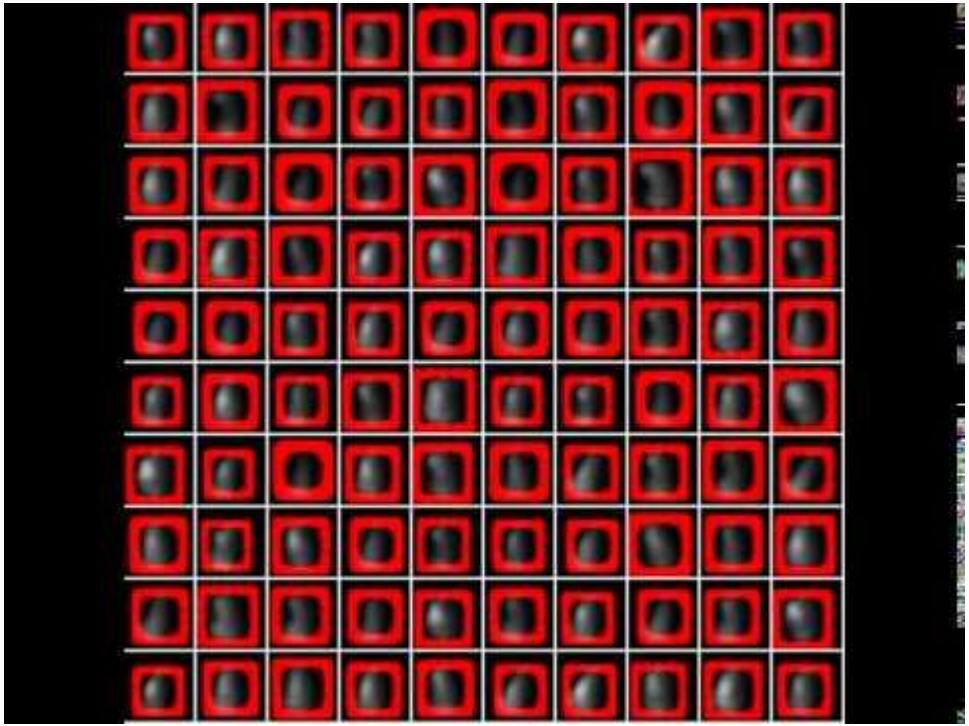


DRAW

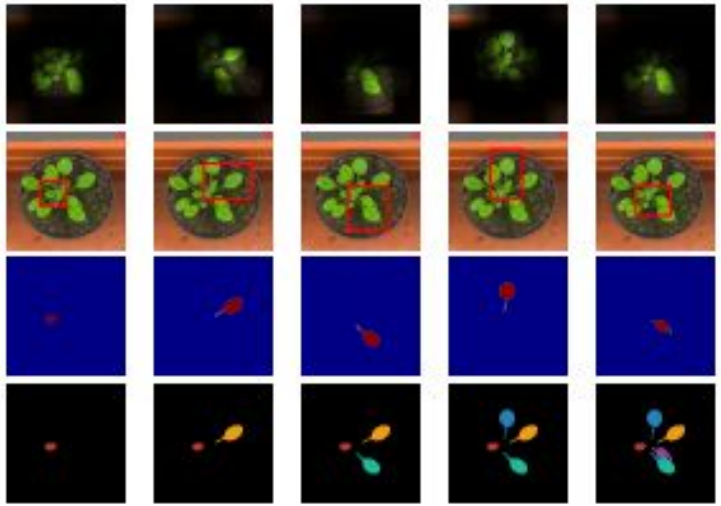
(Gregor et al., 2015)

https://youtu.be/Zt-7MI9eKEo





Instance Segmentation



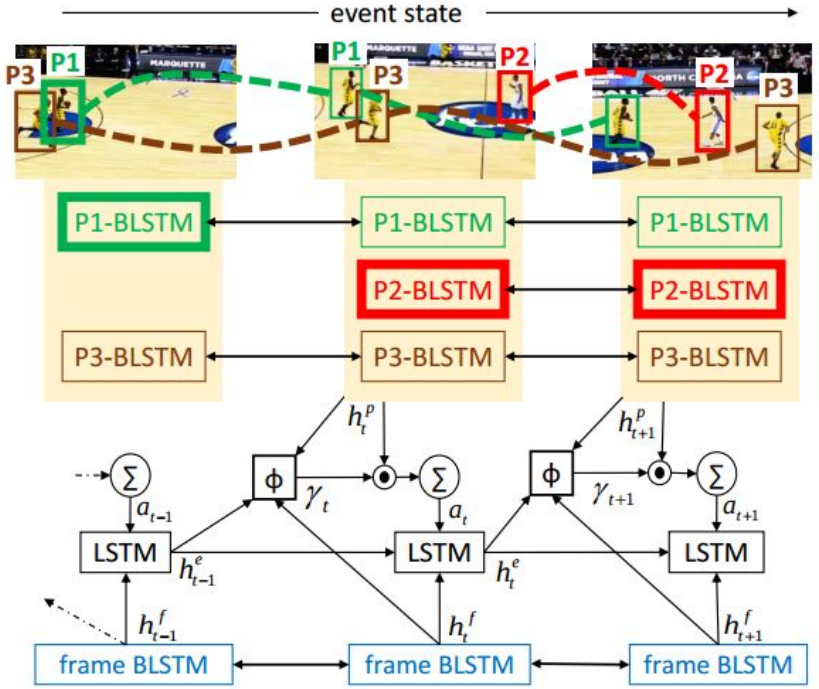
(Ren et al., 2016)

https://youtu.be/wJWydIqtFMM

Detecting Events and Key Actors

- Use bidirectional RNN to model features of a moving player.

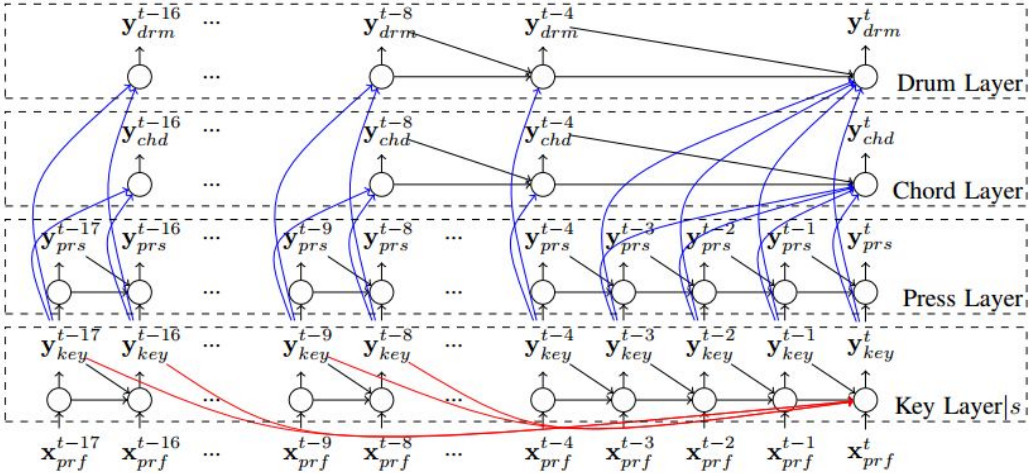
(Vignesh Ramanathan et al., 2016)



Music Generation

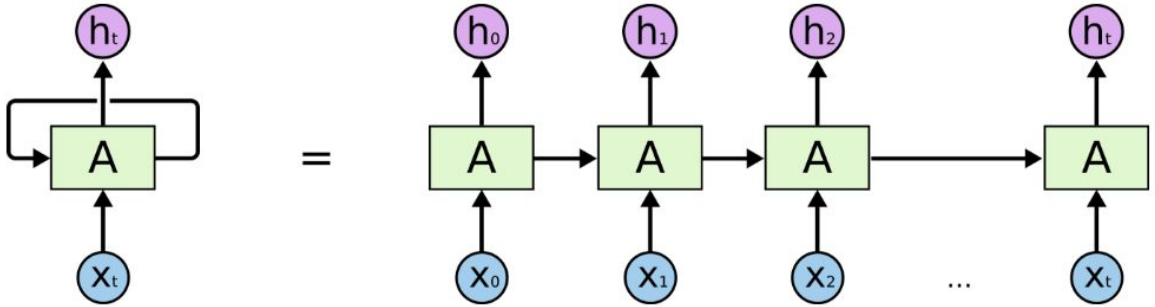
https://vimeo.com/192711856

(Chu et al., 2016)



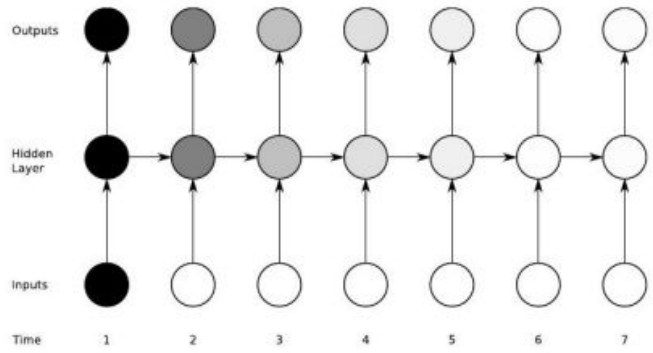
Training RNN with BPTT

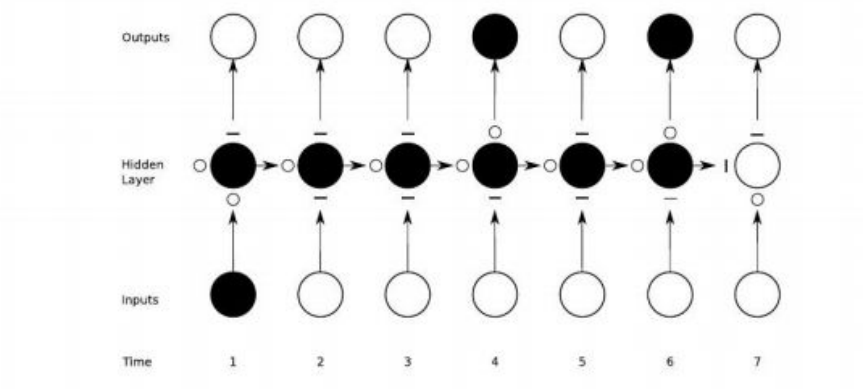
- BPTT = Backpropagation through time
- Unroll the RNN as if they are sharing weights every layer.
- Each time step generates a gradient vector towards the weights.
- Average all the gradients collected at each time step.



RNN vanishing gradients

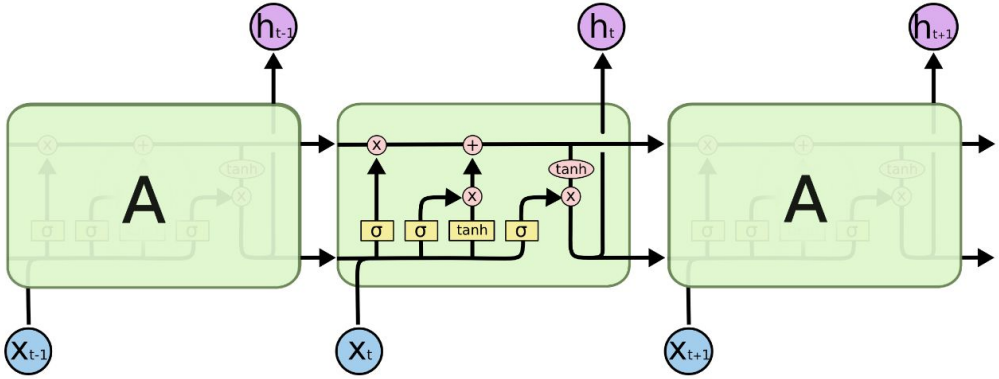
- Vanilla RNNs suffers at vanishing gradients problems.
- The derivative the activation nonlinearities, sigmoid or tanh, is smaller than 1.
- Therefore, the hidden transfer function should be a linear function.

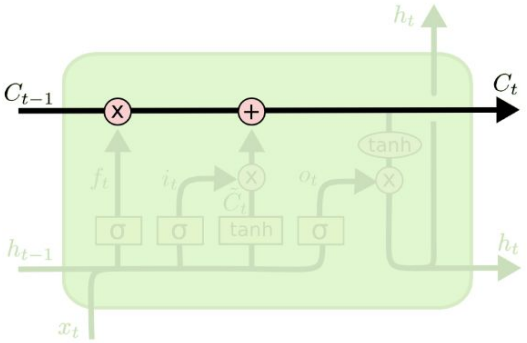




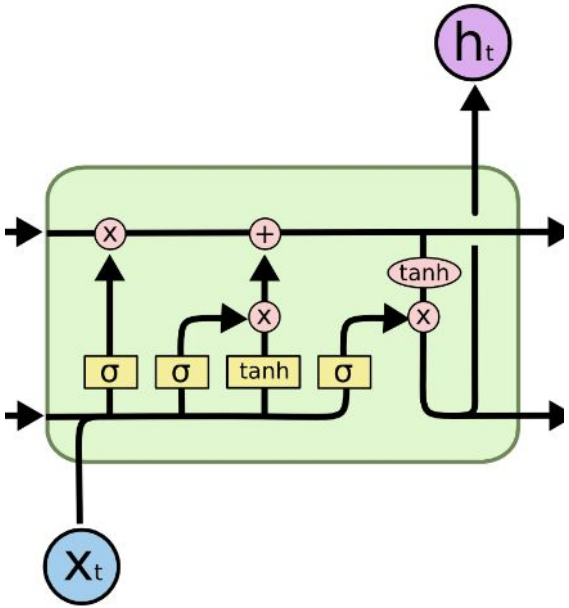
LSTM

- Stands for Long Short-Term Memory (Hochreiter and Schmidhuber, 1997)
- A linear pathway for the gradient to flow effortlessly.
- Gated units: multiplicative gates controls input, forget, and output.





LSTM



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

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

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

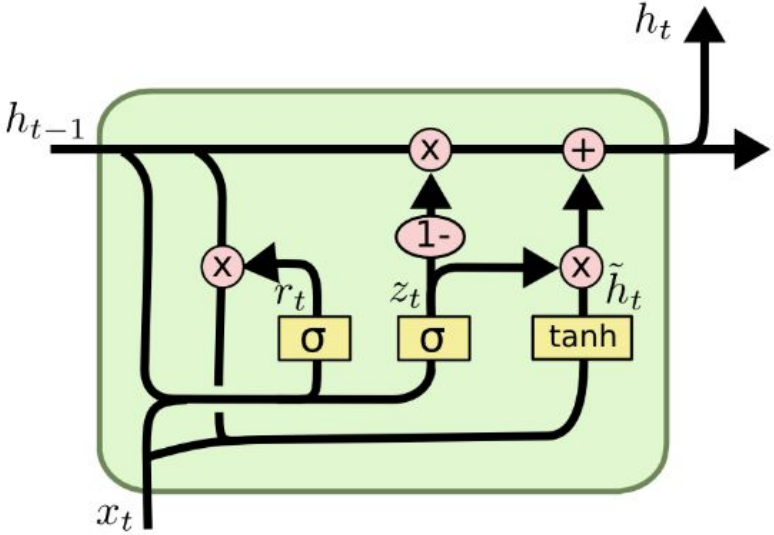
$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

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

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

GRU

- Stands for Gated Recurrent Unit (Chung et al., 2015)



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

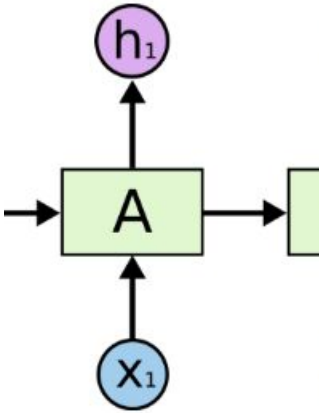
$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Examples (Python for-loop)

```
dim = 256  # Hidden dimension of LSTM
batch_size = 32  # Batch size
cell = tf.nn.rnn_cell.BasicLSTMCell(dim)
state = tf.zeros([batch_size, dim * 2])
inputs = ... # List of input tensors
outputs = []
for t in range(20):
  output, state = cell(inputs[t], state)
  outputs.append(output)
  tf.get_variable_scope().reuse_variables()
loss = f(outputs, targets)
```

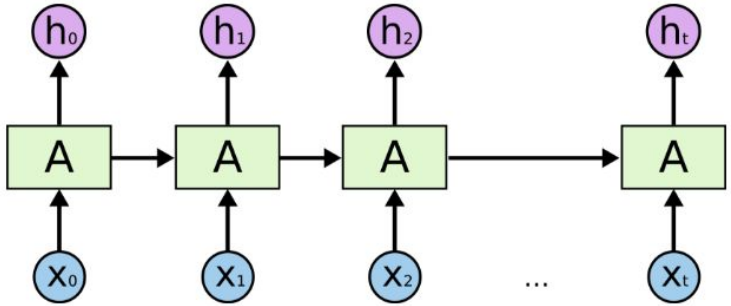
RNN Cell Object

- In TensorFlow, RNNs are usually implemented in a cell object.
- Cell is callable, which will unroll the RNN for one more iteration.
- Input: x_t, state_{t-1}
- Output: h_t, state_{t}



Padding

- For faster computation and better gradient estimates, typically make the input into mini-batches.
- However, not all sequences have the same length.
- We need to pad the shorter sequences with zeros.
- We can also select the hidden states at specific length by the end of computation.



Example (Dynamic RNN)

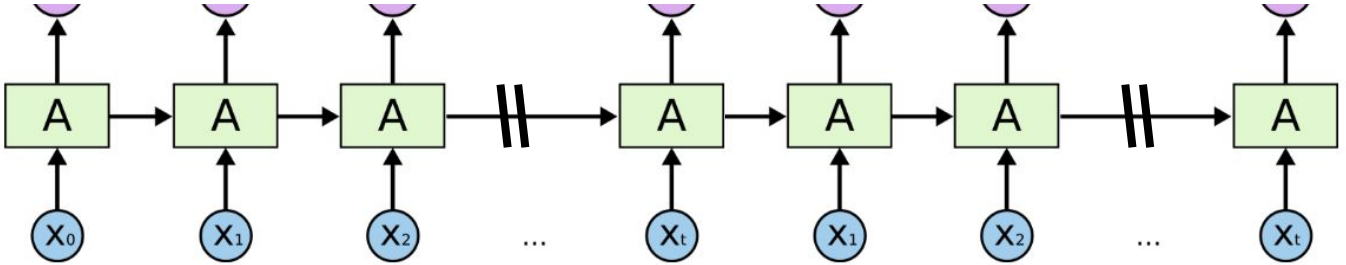
```
cell = tf.nn.rnn_cell.BasicLSTMCell(dim)
# Sequence length of each example.
seq_len = tf.constant(np.array([1, 2, 3, 4]))
outputs, last_states = tf.nn.dynamic_rnn(
    cell=cell, dtype=tf.float32, sequence_length=seq_len,
inputs=x)
```

Use of DynamicRNN Function

- Handles different sequence length per batch.
- Faster graph building time, by using **tf.while_loop** internally.
- Syntax is stricter, have to wrap everything in the for loop inside the cell object.

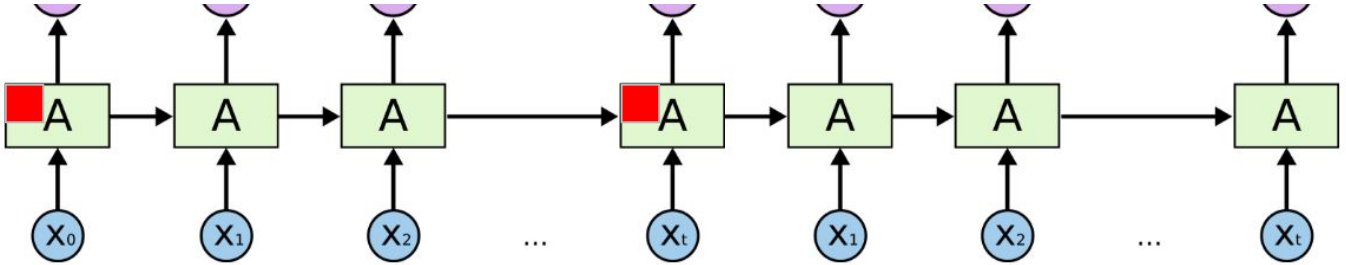
Truncated BPTT

- Many RNN training is bounded by the GPU memory.
- All the activations need to be stored at every timestep.
- For very long sequence length (>1000 steps), this is not realistic.
- We can fix the unrolling at K timesteps, upper bound memory usage by K.
- Sacrificing the quality of the gradient, or in other word, the long-range dependency error signal.



Checkpointing

- We can sacrifice the computation time in exchange for memory space.
- Only store forward pass activation every K steps.
- Need to recompute activations during backward pass
- Takes 2 forward passes + 1 backward pass, but max(K, T/K) timesteps memory usage.



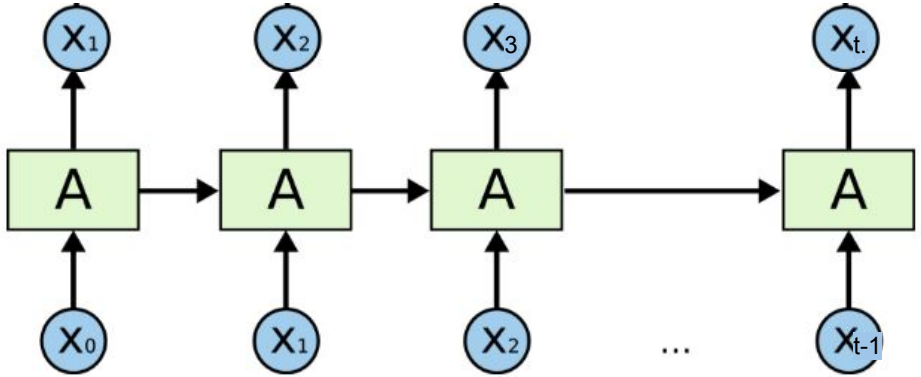
Gradient Clipping

- Even with LSTMs, sometimes the gradient can still explode.
- When that happens, you will get a NaN after hours of training.
- Always good to add gradient clipping in your code of training RNN.

```
tvars = tf.trainable_variables()
grads, _ = tf.clip_by_global_norm(
        tf.gradients(_opt_cost, tvars), 5.0)
optimizer.apply_gradients(zip(grads, tvars))
```

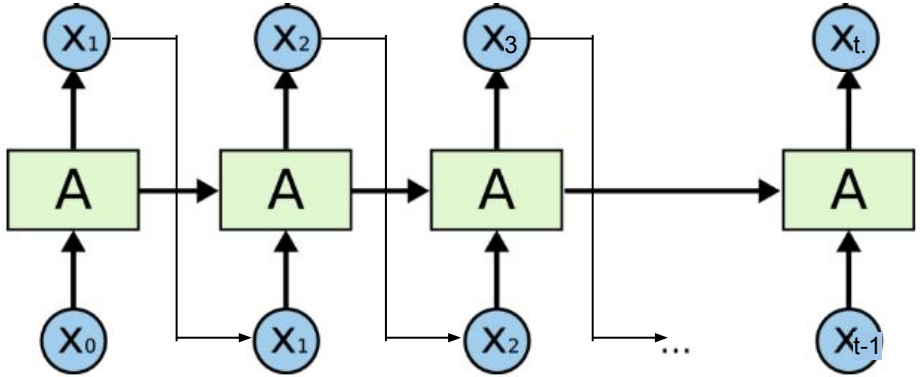
Training Generative RNN Model

- Common way of training generative RNN is to maximize the log probability of the training sequence.
- Apply the chain rule: sum_t (log $p(x_{t+1} \mid x_{1:t})$)
- Common way is to always use the groundtruth sequence $x_{1:t}$ to warm up.



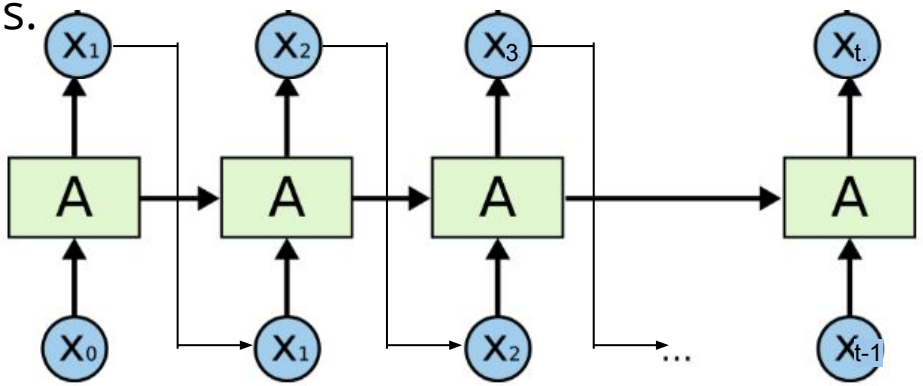
Training Generative RNN Model

- At test time, to generate new sequences, we take the output of the RNN, and feed it back into the input.
- May not be optimal, never trained to plan for more than 1 step.



Beam Search

- While optimal decoding is combinatorial, we can allow keeping a candidate list of size B (beam size).
- Keep top N most probable sequences, and expand each of them with the next output choice, and take N top candidates.
- Similar to sequential Monte Carlo.
- End up running B forward passes.



Scheduled Sampling

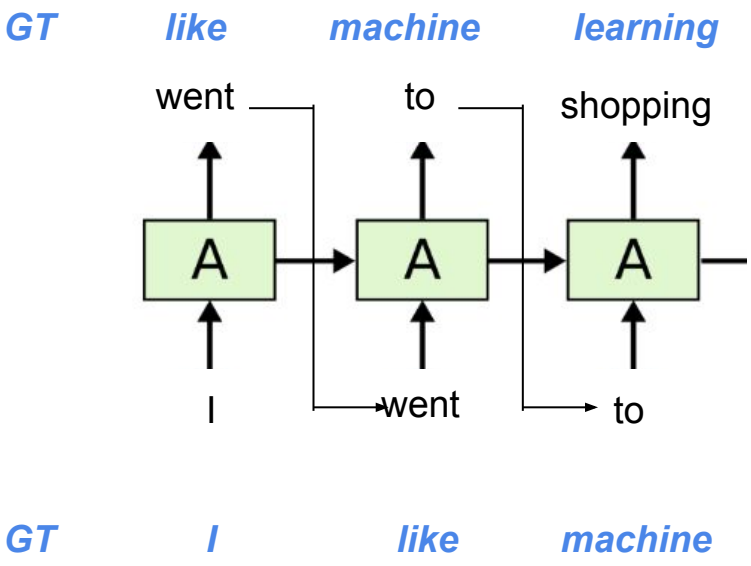
- At training stage, the network has never seen any fake sentences as input.
- At test stage, once the network generates something unlike a real sentence, it will have less experience keep generating.
- Remedy #1: At training, at each timestep, we do a coinflip:
  - Either feed in the groundtruth input
  - Or use the network's current output as input

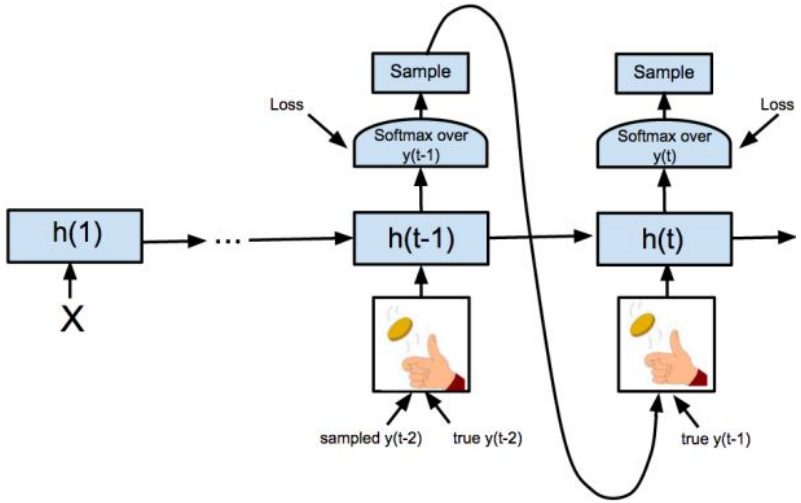
  But we still train the output against the groundtruth, even if the input is already sampled from the network.

- Annealing, and eventually always using network's output as input.
- Used in Google's Image Captioning algorithm (Bengio et al., 2015).

Scheduled Sampling

- An inconsistent learning objective (Huszar, 2015)

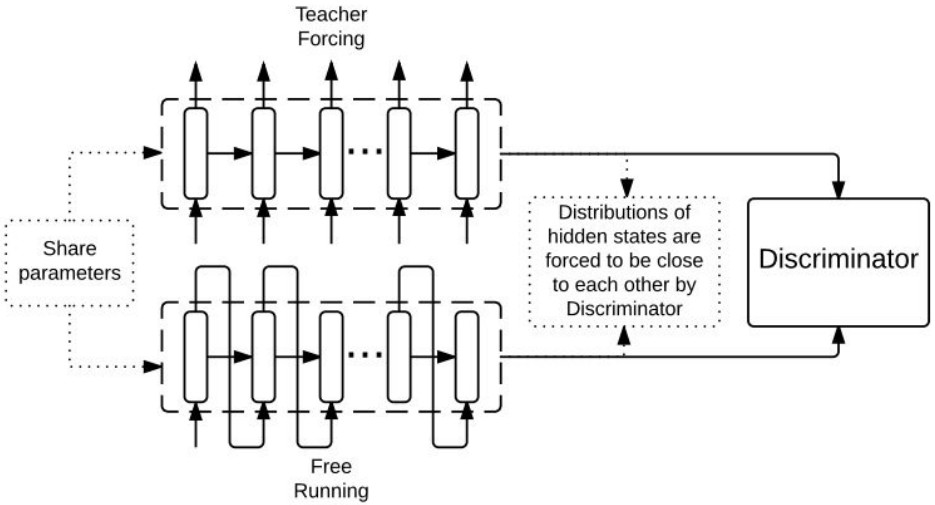




Professor-Forcing

- Use a Generative Adversarial Network idea (Goodfellow et al. 2015).
- Train RNN as usual [1], but also sample free-runs [2]
- Send the hidden states of both [1] and [2] to a discriminator (also an RNN).

(Lamb et al., 2016)



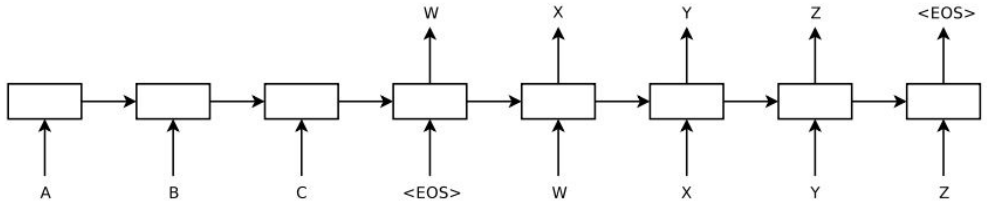
Reward-Augmented ML

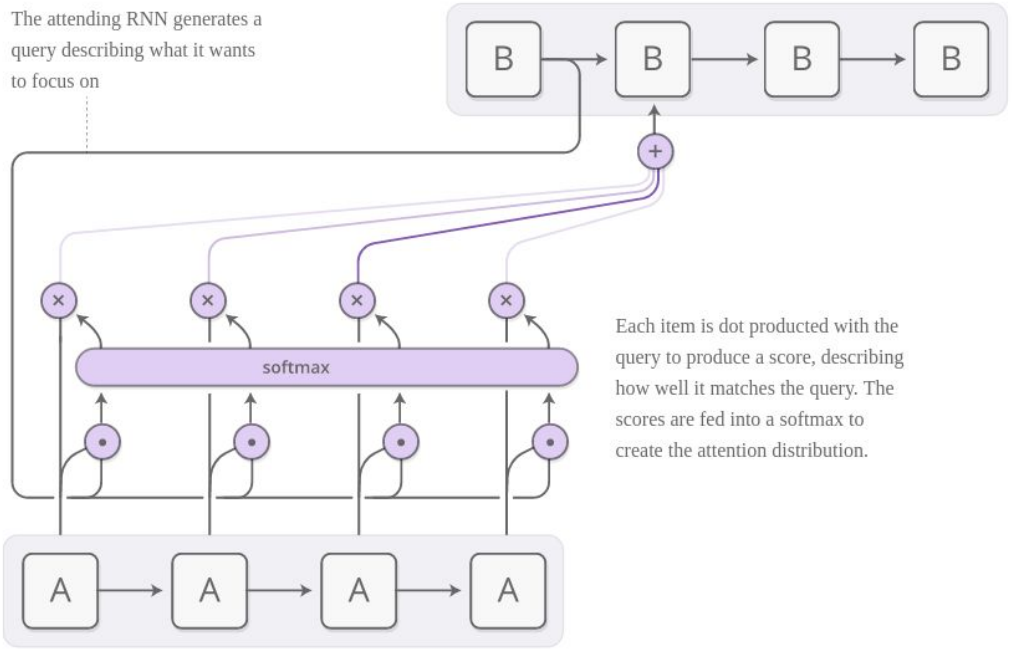
- Maximum likelihood may not be the best objective, certainly not when we evaluate those generative models.
- In MT, BLEU scores and variants are widely used (non-differentiable).
- Tempting to use BLEU as the reward function and just apply RL, except it's very difficult to kick off training.
- Idea is that we can treat reward as unnormalized energy of true distribution, and minimize the KL between model distribution, and data distribution soften by the reward(y, y*).
- Returns to log likelihood, if reward(y, y*) is the delta function.

(Norouzi et al., 2016)

Recurrent Attention

- In MT, RNN can be forgetful in long sequences.
- Want to have a look back mechanism while decoding.
- Attention in the form of a weighted sum of a bag of items (Bahdanau et al., 2014).





Recurrent Attention

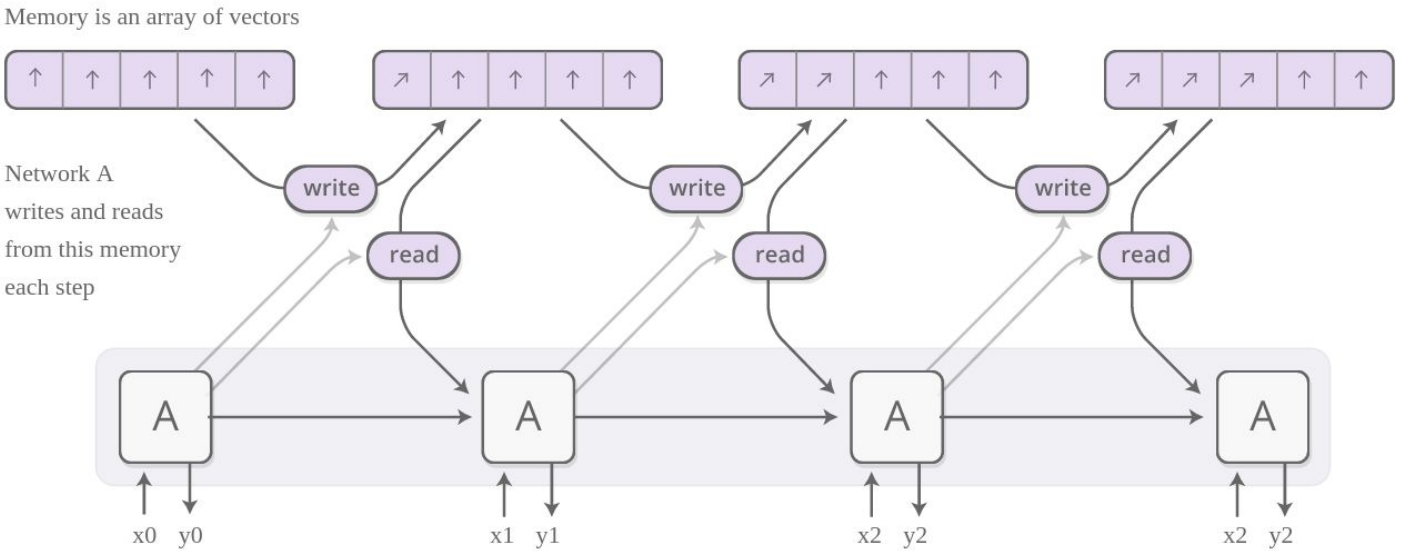
- Can also attend on spatial level in vision tasks.
- Initialize at uniform.
- Use the previous hidden state to control the attention of the next.

(Xu et al., 2015)

(b) A woman is throwing a frisbee in a park.

Neural Turing Machine

- Proposed an external memory which supports soft-read and soft-write using attention mechanism (Graves et al., 2014).



Phased LSTM

(Neil et al., 2016)