Sequence Models

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Slides adapted from Richard Socher

Language models

- **Language models** answer the question: How likely is a string of English words good English?
- Autocomplete on phones and websearch
- Creating English-looking documents
- Very common in machine translation systems
  - Help with reordering / style

$$p_{\text{lm}}(\text{the house is small}) > p_{\text{lm}}(\text{small the is house})$$

  - Help with word choice

$$p_{\text{lm}}(\text{I am going home}) > p_{\text{lm}}(\text{I am going house})$$

N-Gram Language Models

- Given: a string of English words $W = w_1, w_2, w_3, ..., w_n$
- Question: what is $p(W)$?
- Sparse data: Many good English sentences will not have been seen before

$\longrightarrow$ Decomposing $p(W)$ using the chain rule:

$$p(w_1, w_2, w_3, ..., w_n) = \\ p(w_1)\, p(w_2|w_1)\, p(w_3|w_1, w_2) \dots p(w_n|w_1, w_2, ... w_{n-1})$$

(not much gained yet, $p(w_n|w_1, w_2, ... w_{n-1})$ is equally sparse)

Markov Chain

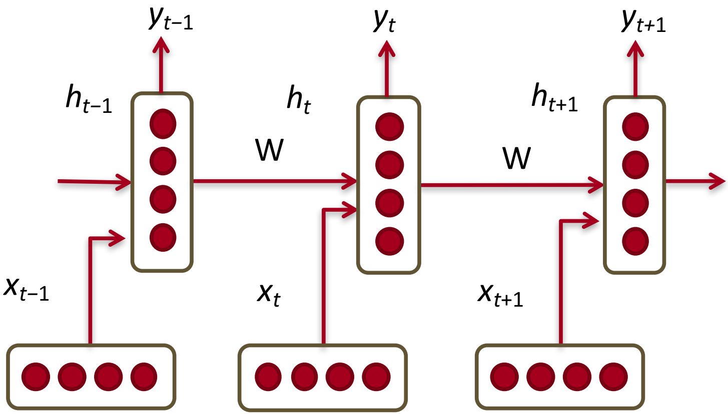
- **Markov independence assumption**:
  - only previous history matters
  - limited memory: only last k words are included in history (older words less relevant)

  $\longrightarrow$ k**th order Markov model**
- For instance 2-gram language model:

$$p(w_1, w_2, w_3, ..., w_n) \simeq p(w_1)\, p(w_2|w_1)\, p(w_3|w_2)...p(w_n|w_{n-1})$$

- What is conditioned on, here w_{i-1} is called the **history**. Estimated from counts.

Recurrent Neural Networks



- Condition on all previous words
- Hidden state at each time step

RNN parameters

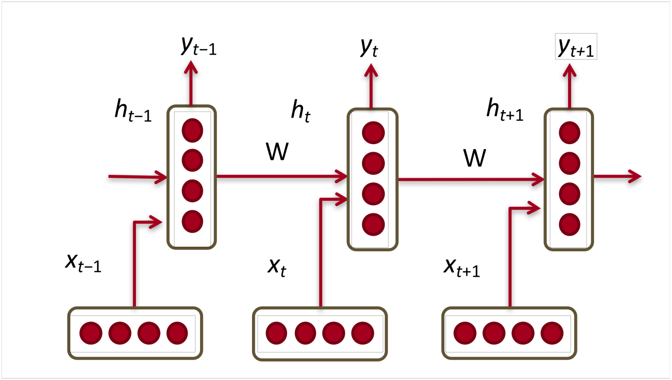
$$h_t = f(W^{(hh)} h_{t-1} + W^{(hx)} x_t) \quad (1)$$

$$\hat{y}_t = \text{softmax}(W^{(S)} h_t) \quad (2)$$

$$P(x_{t+1} = v_j \mid x_t, \ldots x_1) = \hat{y}_{t,j} \quad (3)$$

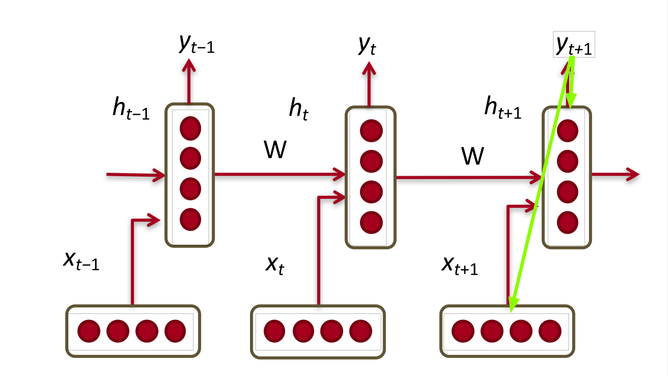
- Learn parameter h_0 to initialize hidden layer
- x_t is representation of input (e.g., word embedding)
- $\hat{y}$ is probability distribution over vocabulary

Training Woes



Multiplying same matrix over and over

Training Woes



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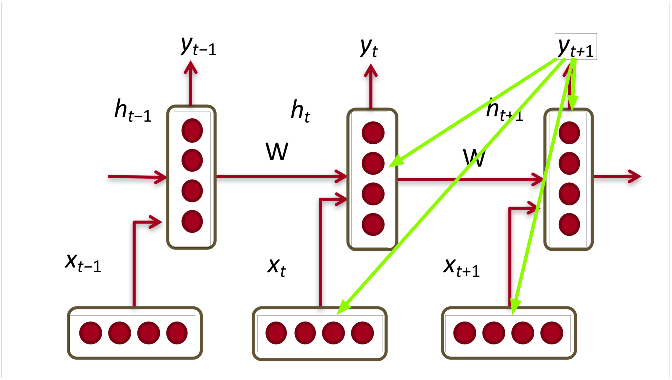
Training Woes



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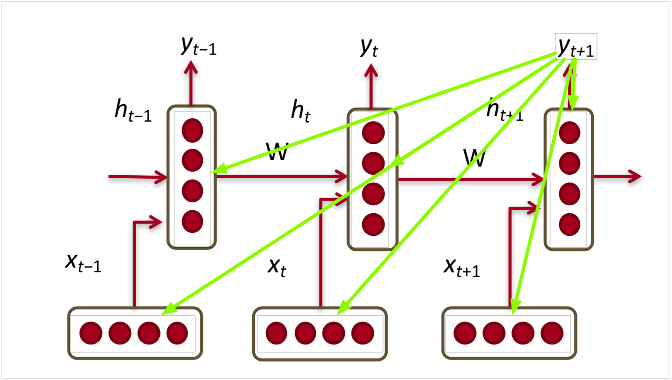
Training Woes



Multiplying same matrix over and over

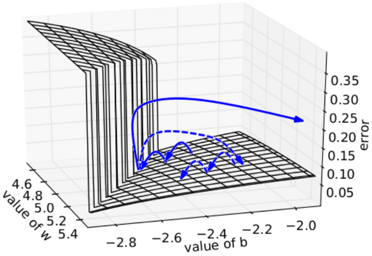
Vanishing / Exploding Gradient

- Work out the math:
  - Define β_W / β_h as upper bound of norms of W, h
  - Bengio et al 1994: Partial derivative is $(\beta_W \beta_h)^{t-k}$
  - This can be very small or very big
- If it's big, SGD jumps too far
- If it's small, we don't learn what we need: "Jane walked into the room. John walked in too. It was late in the day. Jane said hi to ____"

Gradient Clipping

Algorithm 1 Pseudo-code for norm clipping the gradients whenever they explode

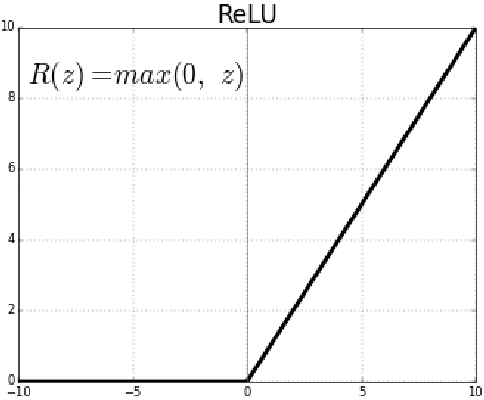
$\hat{\mathbf{g}} \leftarrow \frac{\partial \mathcal{E}}{\partial \theta}$
if $\|\hat{\mathbf{g}}\| \geq threshold$ **then**
  $\hat{\mathbf{g}} \leftarrow \frac{threshold}{\|\hat{\mathbf{g}}\|} \hat{\mathbf{g}}$
end if



From Pascanu et al. 2013

- If they get too big, stop at boundary
- Prevents (dashed) values from jumping around (solid)

Fixing Vanishing Gradients



- ReLU activation
- Initialize W to identity matrix

RNN Recap

- Simple model
- Complicated training (but good toolkits available)
- Do we need to remember everything?