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
    \[ p_{lm}(\text{the house is small}) > p_{lm}(\text{small the is house}) \]
  - Help with word choice
    \[ p_{lm}(\text{I am going home}) > p_{lm}(\text{I am going house}) \]
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

→ Decomposing \( p(W) \) using the chain rule:

\[
p(w_1, w_2, w_3, ..., w_n) = \prod_{i=1}^{n} p(w_i | w_1, w_2, ..., w_{i-1})
\]

(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)

  $\rightarrow$  $k$th order Markov model

- For instance 2-gram language model:

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

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

- RNNs tie the weights at each time step
- Condition on all previous words
- Hidden state at each time step
- RAM requirement only scales with number of words

\[ h_{t-1} \xrightarrow{W} y_{t-1} \]
\[ h_t \xrightarrow{W} y_t \]
\[ h_{t+1} \xrightarrow{W} y_{t+1} \]
RNN parameters

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

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

\[ P(x_{t+1} = v_j | x_t, \ldots, x_1) = \hat{y}_{t,j} \]  
(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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Multiplying same matrix over and over
Vanishing / Exploding Gradient

- Work out the math:
  - Define $\beta_W / \beta_h$ 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

\[
\hat{g} \leftarrow \frac{\partial \mathcal{L}}{\partial \theta} \\
\text{if } \|\hat{g}\| \geq \text{threshold} \text{ then} \\
\quad \hat{g} \leftarrow \frac{\text{threshold}}{\|\hat{g}\|} \hat{g} \\
\text{end if}
\]

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

$$R(z) = \max(0, z)$$
RNN Recap

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