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 $W = w_1, w_2, w_3, \ldots, w_n$
- Question: what is $p(W)$?
- Sparse data: Many good English sentences will not have been seen before

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

$$
p(w_1, w_2, w_3, \ldots, w_n) = \prod_{i=2}^{n} p(w_i | w_1, \ldots, w_{i-1})
$$

(not much gained yet, $p(w_n | w_1, w_2, \ldots, w_{n-1})$ 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)
  - $k$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

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

\[
x_{t-1} \quad h_{t-1} \quad W \quad y_{t-1} \quad h_t \quad W \quad y_t \quad h_{t+1} \quad W \quad y_{t+1}
\]

\[
x_{t-1} \quad x_t \quad x_{t+1}
\]
RNN parameters

\[ h_t = f(W^{(hh)}h_{t-1} + W^{(hx)}x_t) \]  
\[ \hat{y}_t = \text{softmax}(W^{(S)}h_t) \]  
\[ P(x_{t+1} = v_j \mid x_t, \ldots x_1) = \hat{y}_{t,j} \]

- 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

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

\[
\hat{g} \leftarrow \frac{\partial \mathcal{L}}{\partial \theta}
\]

if \( \| g \| \geq \text{threshold} \) then

\[
\hat{g} \leftarrow \frac{\text{threshold}}{\| g \|} \hat{g}
\]

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?