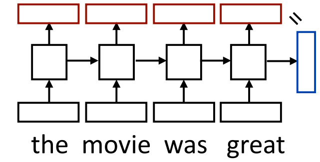
Using RNNs

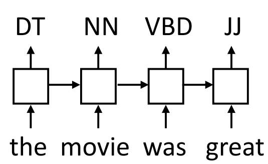
What do RNNs produce?



- Encoding of the sentence (final h_i/c_i) — can pass this a decoder or make a classification decision about the sentence
- Encoding of each word (each h_i) — can pass this to another layer to make a prediction (can also pool these to get a different sentence encoding)
- RNN can be viewed as a transformation of a sequence of vectors into a sequence of context-dependent vectors

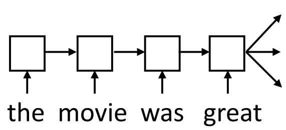
RNN Uses

- Transducer: make some prediction for each element in a sequence



output **y** = score for each tag, then softmax

- Acceptor/encoder: encode a sequence into a fixed-sized vector and use that for some purpose

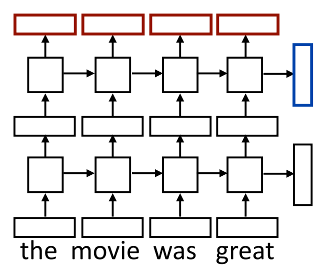


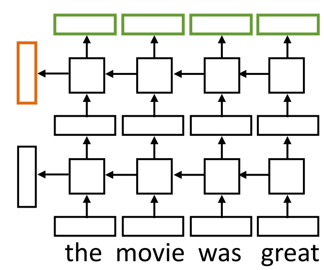
predict sentiment (matmul + softmax)

translate

paraphrase/compress

Multilayer Bidirectional RNN

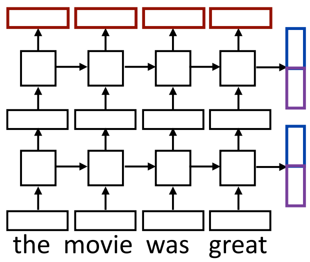




- Sentence classification based on concatenation of both final outputs

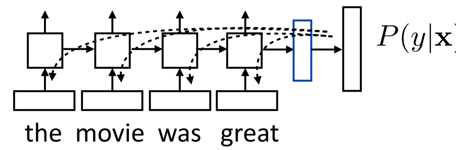
- Token classification based on concatenation of both directions' token representations

What do LSTMs return in PyTorch?



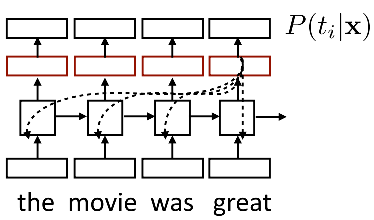
- Hidden/cell states are a 2-tuple, tensors of size [num_layers * num_directions, batch size, dimensionality]
  - 2x1xdim here
- Outputs are a single tensor of size [seq_len, batch size, num_directions * hidden_size]
  - 4x1xdim here

Training RNNs



- Loss = negative log likelihood of probability of gold label (or use SVM or other loss)
- Backpropagate through entire network, RNN parameters get a gradient update from each timestep
- Example: sentiment analysis

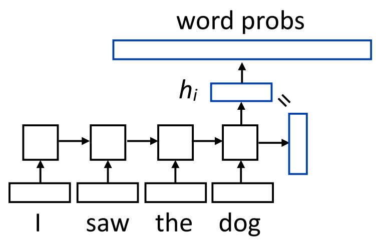
Training RNNs



- Loss = negative log likelihood of probability of gold predictions, summed over the tags
- Loss terms filter back through network
- Example: language modeling (predict next word given context)

RNN Language Modeling

RNN Language Modeling



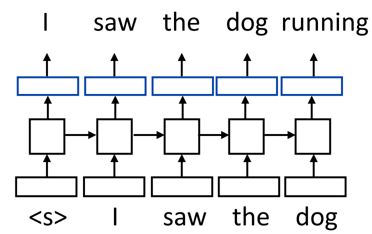
$$P(w|\text{context}) = \frac{\exp(\mathbf{w}\cdot\mathbf{h_i})}{\sum_{w'}\exp(\mathbf{w'}\cdot\mathbf{h_i})}$$

equivalent to

$$P(w|\text{context}) = \text{softmax}(W\mathbf{h}_i)$$

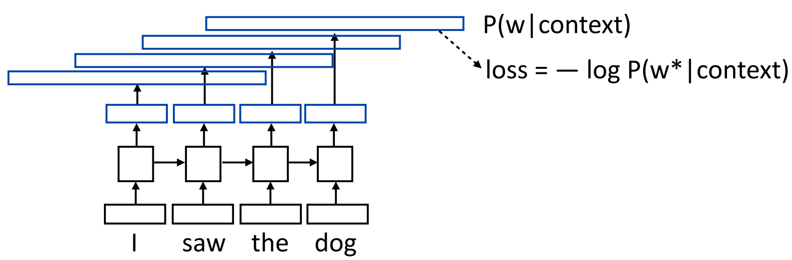
- *W* is a (vocab size) x (hidden size) matrix; linear layer in PyTorch (rows are word embeddings)

Training RNNLMs



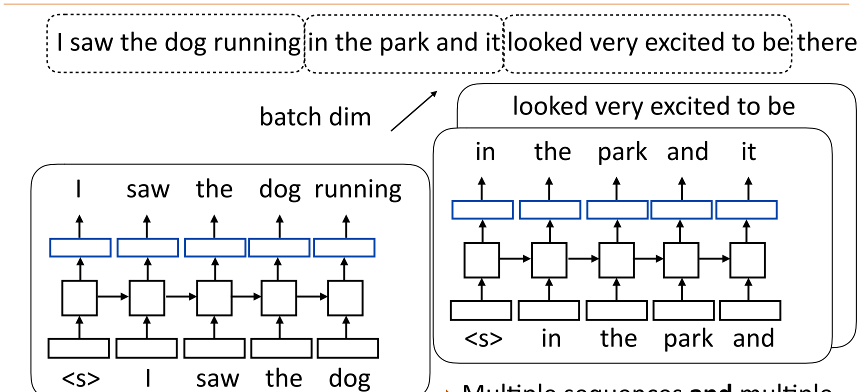
- Input is a sequence of words, output is those words shifted by one,
- Allows us to train on predictions across several timesteps simultaneously (similar to batching but this is NOT what we refer to as batching)

Training RNNLMs



- Total loss = sum of negative log likelihoods at each position
- In PyTorch: simply add the losses together and call .backward()

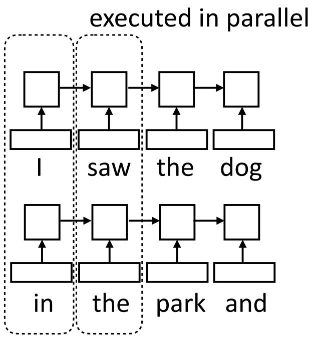
Batched LM Training



- Multiple sequences **and** multiple timesteps per sequence

Batched LM Training

- torch.nn.LSTM / torch.nn.GRU: expect input in [seq len, batch, word dim] format



- Input: [4, 2, dim]
- Cannot parallelize across timesteps of RNN since output depends on previous timesteps, so using larger batches gives better parallelism

Other Implementation Details

- torch.nn.Embedding: maps sequence of word indices to vectors
  - [126, 285] -> [[0.1, -0.07, 1.2],
    [-2.3, 0.2, 1.4]]
  - Moves from [sequence length] vector of indices -> [seq len, dim] tensor or [batch, sequence length] matrix -> [batch, seq len, dim tensor]

LM Evaluation

- Accuracy doesn't make sense — predicting the next word is generally impossible so accuracy values would be very low
- Evaluate LMs on the likelihood of held-out data (averaged to normalize for length)

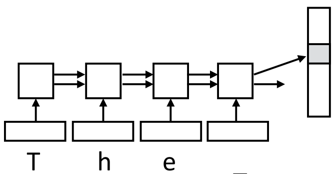
$$\frac{1}{n}\sum_{i=1}^{n}\log P(w_i|w_1,\ldots,w_{i-1})$$

- Perplexity: exp(average negative log likelihood). Lower is better
  - Suppose we have probs 1/4, 1/3, 1/4, 1/3 for 4 predictions
  - Avg NLL (base e) = 1.242 Perplexity = 3.464 <== geometric mean of denominators

Visualizing LSTM LMs

Visualizing LSTMs

- Train character LSTM language model (predict next character based on history) over two datasets: War and Peace and Linux kernel source code
- Visualize activations of specific cells (components of **c**) to understand them

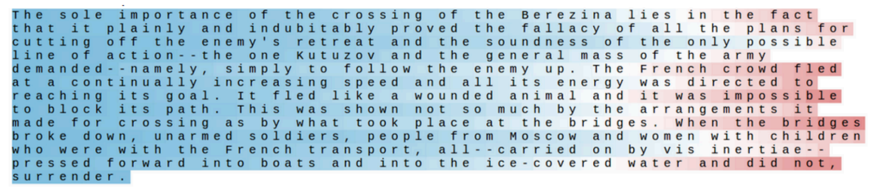


Plot this value over timesteps, blue is smaller, red is larger

Karpathy et al. (2015)

Visualizing LSTMs

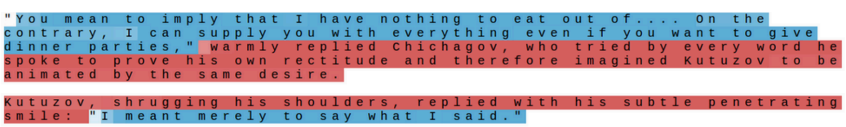
- Train character LSTM language model (predict next character based on history) over two datasets: War and Peace and Linux kernel source code
- Visualize activations of specific cells (components of **c**) to understand them
- Counter: know when to generate \n



Karpathy et al. (2015)

Visualizing LSTMs

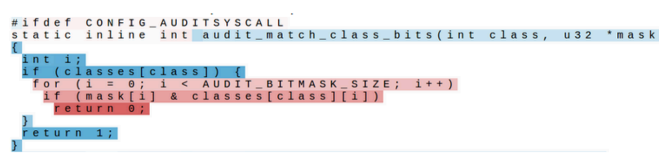
- Train *character* LSTM language model (predict next character based on history) over two datasets: War and Peace and Linux kernel source code
- Visualize activations of specific cells to see what they track
- Binary switch: tells us if we're in a quote or not



Karpathy et al. (2015)

Visualizing LSTMs

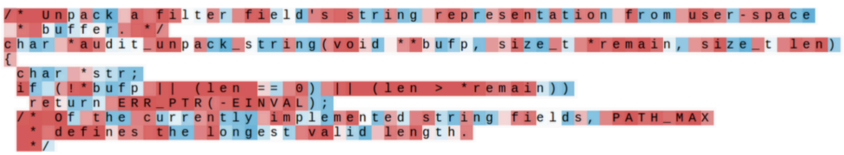
- Train *character* LSTM language model (predict next character based on history) over two datasets: War and Peace and Linux kernel source code
- Visualize activations of specific cells to see what they track
- Stack: activation based on indentation



Karpathy et al. (2015)

Visualizing LSTMs

- Train *character* LSTM language model (predict next character based on history) over two datasets: War and Peace and Linux kernel source code
- Visualize activations of specific cells to see what they track
- Uninterpretable: probably doing double-duty, or only makes sense in the context of another activation



Karpathy et al. (2015)

State-of-the-art LMs

- Good LSTM LMs have ~27M params, 4-5 layers
- Kneser-Ney 5-gram model with cache: PPL = 125.7
- LSTM: PPL ~ 60-80 (depending on how much you optimize it)
- LSTM character-level: PPL ~1.5 (205 character vocab)
- Better language models using transformers (will discuss after MT)

Melis et al. (2017)

Assessing the Ability of LSTMs to Learn Syntax-Sensitive Dependencies

Predicting Subject-Verb Agreement

- Predict whether a verb should be singular or plural

The roses **are** red The chair **is** red

- Challenging because there can be preposition phrases, relative clauses, etc. in between (*attractors*) that confuse the model:

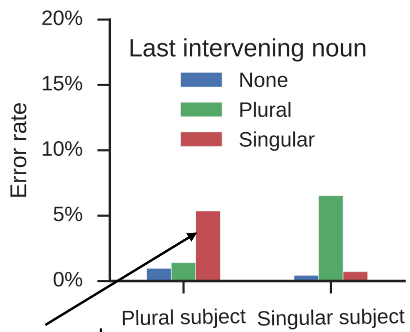
The roses in the *vase* by the *door* **are** red

door **is** red? bigram model would get confused by *attractors*

Linzen et al. (2016)

Predicting Subject-Verb Agreement

- Attractors don't fool an LSTM too much! Only wrong 5-6% of the time even in these tricky cases



The roses in the *vase* by the *door* **are** red

Linzen et al. (2016)

Predicting Subject-Verb Agreement

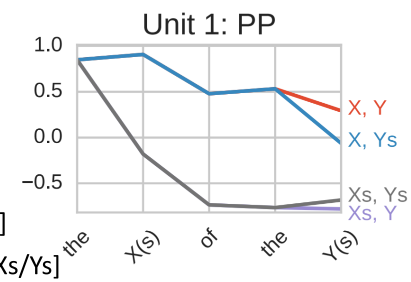
- Averaged activations over 40 sentences of the form "the Xs of the Ys" [is/are]

  The crown of the *king* is… [X/Y]

  The crowns of the *king* are… [Xs/Y]

  The fable of the *peasants* is… [X/Ys]

  The houses of the *peasants* are… [Xs/Ys]



- This neuron appears to have different values for Xs than for singular X

Linzen et al. (2016)

Recap and Next time

- LSTM forget gates help control sensitivity to old/new information
- LSTMs are a neural network module that can be used in both classification and sequence labeling. Can also be viewed as transforming a sequence of word embeddings into a sequence of new embeddings, now aware of context
- LSTMs are able to learn regular patterns in language: when text is quoted, subject-verb agreement
- Next time: machine translation