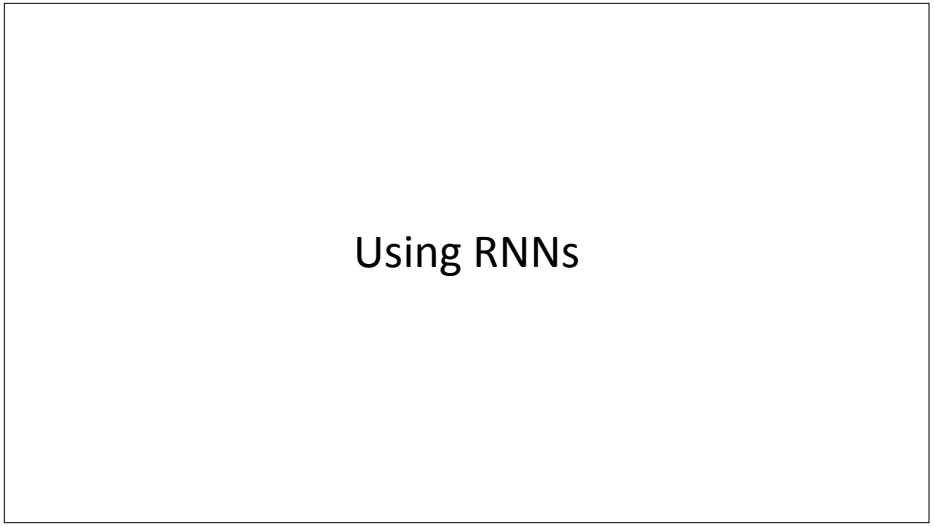
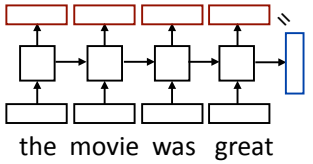
# Using RNNs



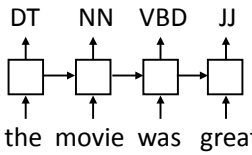
## What do RNNs produce?




- 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

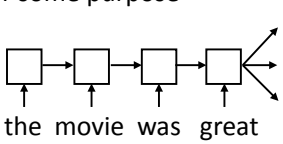
## RNN Uses

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



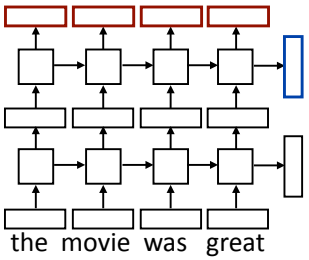

output **y** = score for each tag, then softmax

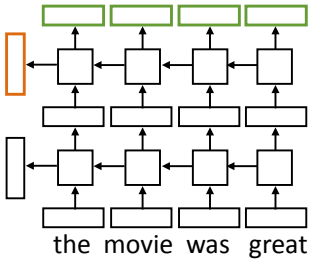
- Acceptor/encoder: encode a sequence into a fixed-sized vector and use that for some purpose




predict sentiment (matmul + softmax)
translate
paraphrase/compress

## Multilayer Bidirectional RNN

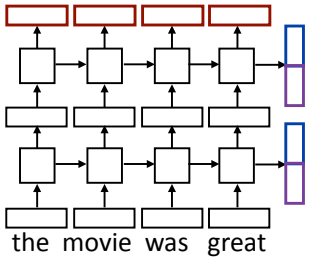



- Sentence classification based on concatenation of both final outputs

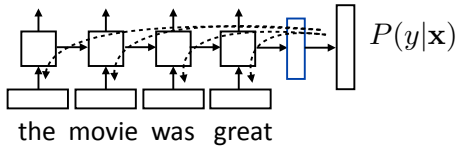
- Token classification based on concatenation of both directions' token representations

## What do LSTMs return in PyTorch?



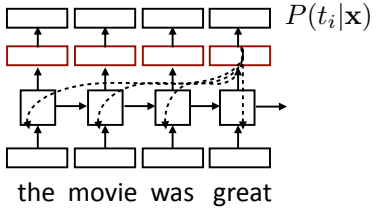

- Hidden/cell states are a 2-tuple, tensors of size [num_layers * num_directions, batch size, dimensionality]
  - 2x1xdim here
- Outputs are a single tensor of size [seq_len, batch size, num_directions * hidden_size]
  - 4x1xdim here

## 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

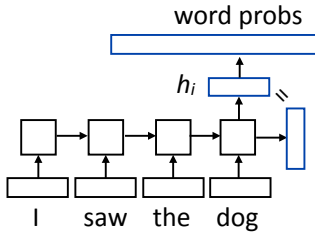
## Training RNNs




- 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



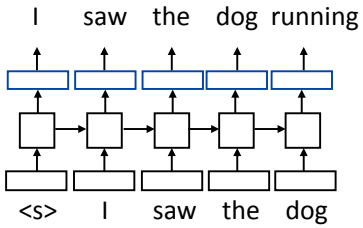

$$P(w|\text{context}) = \frac{\exp(\mathbf{w} \cdot \mathbf{h_i})}{\sum_{w'} \exp(\mathbf{w}' \cdot \mathbf{h_i})}$$

equivalent to

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

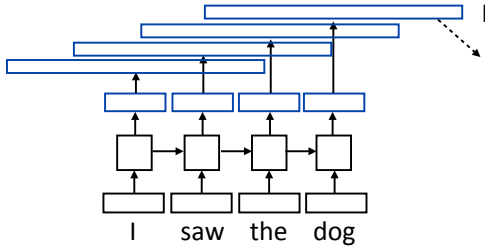
- *W* is a (vocab size) x (hidden size) matrix; linear layer in PyTorch (rows are word embeddings)

# Training RNNLMs



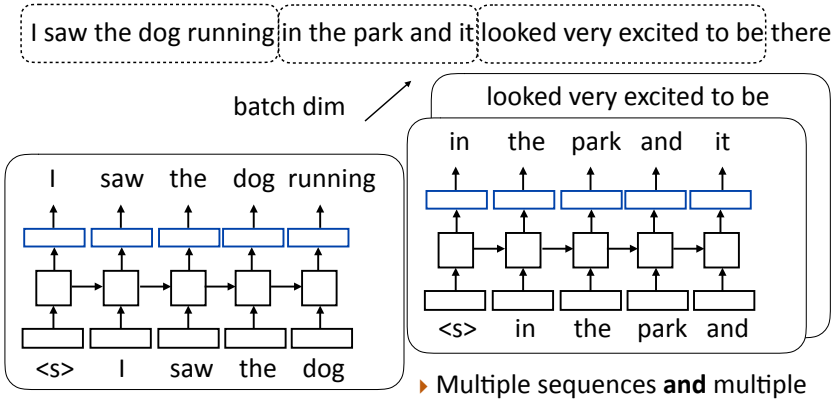

- Input is a sequence of words, output is those words shifted by one,
- Allows us to train on predictions across several timesteps simultaneously (similar to batching but this is NOT what we refer to as batching)

# Training RNNLMs




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

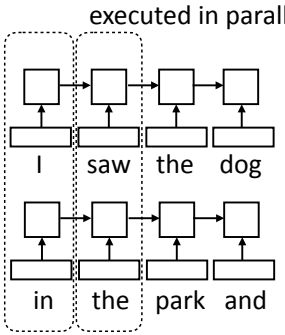
# Batched LM Training




- 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, or in [batch, seq len, word dim] if you set batch_first = True




- 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)

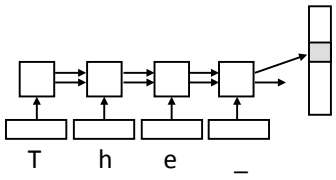
$$\frac{1}{n}\sum_{i=1}^{n}\log P(w_i|w_1,\ldots,w_{i-1})$$

- 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

```
The sole importance of the crossing of the Berezina lies in the fact
that it plainly and indubitably proved the fallacy of all the plans for
cutting off the enemy's retreat and the soundness of the only possible
line of action--the one Kutuzov and the general mass of the army
demanded--namely, simply to follow the enemy up. The French crowd fled
at a continually increasing speed and all its energy was directed to
reaching its goal. It fled like a wounded animal and it was impossible
to block its path. This was shown not so much by the arrangements it
made for crossing as by what took place at the bridges. When the bridges
broke down, unarmed soldiers, people from Moscow and women with children
who were with the French transport, all--carried on by vis inertiae--
pressed forward into boats and into the ice-covered water and did not,
surrender.
```

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

```
"You mean to imply that I have nothing to eat out of.... On the
contrary, I can supply you with everything even if you want to give
dinner parties," warmly replied Chichagov, who tried by every word he
spoke to prove his own rectitude and therefore imagined Kutuzov to be
animated by the same desire.

Kutuzov, shrugging his shoulders, replied with his subtle penetrating
smile: "I meant merely to say what I said."
```

Karpathy et al. (2015)

# Visualizing LSTMs

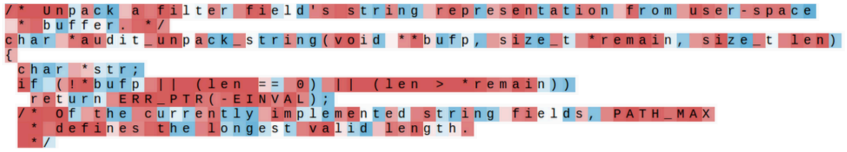
- Train *character* LSTM language model (predict next character based on history) over two datasets: War and Peace and Linux kernel source code
- Visualize activations of specific cells to see what they track
- Stack: activation based on indentation

```
#ifdef CONFIG_AUDITSYSCALL
static inline int audit_match_class_bits(int class, u32 *mask)
{
  int i;
  if (classes[class]) {
    for (i = 0; i < AUDIT_BITMASK_SIZE; i++)
      if (mask[i] & classes[class][i])
        return 0;
  }
  return 1;
}
```

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)