CS 190I
Deep Learning
Recurrent Neural Network and Sequence Learning

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Acknowledgement: Slides borrowed from Bhiksha Raj’s 11485 and Mu Li & Alex Smola’s 157 courses on Deep Learning, with modification

Why are you learning this?

- ChatGPT shows amazing capability in conversation.
- Do you want to understand the principles behind ChatGPT?
- Do you want to develop your own ChatGPT?

Outline

- Recurrent Neural Network
- Sequence-to-sequence learning
- Transformer network (next lecture)
- Pretrained Language Models (next next)
  - BERT
  - GPT, ChatGPT

Language Modeling

- Given a sentence y, estimate the probability

$$P(y) = \prod_t P(y_{t+1} \mid y_1 \ldots y_t)$$

$$P(y_{t+1} \mid y_1 \ldots y_t) = f_\theta(y_1, \ldots, y_t)$$

The cat sits on a __

y_1 y_2 y_3 y_4 y_5 y_6

$p(y_6 \mid y_1, \ldots, y_5)$

mat	0.15
rug	0.13
chair	0.08
hat	0.05
dog	0.01

Vocabulary

- To model P(y|x)
- Consider a ten-word sentence, chosen from common English dictionary about 5k words
  - 5000^{10} possible sentences
  - need a table of $5000^{10} \cdot 5000^{10}$ entries, infeasible
- source and target sentences need to break into smaller units.
- Multiple ways to segment
- Language specific considerations

Tokenization

- Break sentences into tokens, basic elements of processing
- Word-level Tokenization
  - Break by space and punctuation.
  - English, French, German, Spanish

The most eager is Oregon which is enlisting 5,000 drivers in the country’s biggest experiment.

  - Special treatment: numbers replaced by special token [number]
  - How large is the Vocabulary? Cut-off by frequency, the rest replaced by [UNK]

Pros and Cons of Word-level Tokenization

- Easy to implement
- Cons:
  - Out-of-vocabulary (OOV) or unknown tokens, e.g. Covid
  - Tradeoff between parameters size and unknown chances.
    - Smaller vocab => fewer parameters to learn, easier to generate (deciding one word from smaller dictionary), more OOV
    - Larger vocab => more parameters to learn, harder to generate, less OOV
  - Hard for certain languages with continuous script: Japanese, Chinese, Korean, Khmer, etc. Need separate word segmentation tool (can be neural networks)

最热切的是俄勒冈州，该州正在招募 5,000 名司机参与该国最大的试验。

Character-level Tokenization

- Each letter and punctuation is a token

T	h	e	m	o	s	t	e	a	g	e	r	i	s	O	r	e	g	…

- Pros:
  – Very small vocabulary (except for some languages, e.g. Chinese)
  – No Out-of-Vocabulary token
- Cons:
  – A sentence can be longer sequence
  – Tokens do not representing semantic meaning

Subword-level Tokenization

- Goal:

The most eager is Oregon which is en listing 5,000 driver s in the country 's big g est experiment.

  - moderate size vocabulary
  - no OOV
- Idea:
  - represent rare words (OOV) by sequence of subwords
- Byte Pair Encoding (BPE)
  - not necessarily semantic meaningful
  - Originally for data compression

Philip Gage. A New Algorithm for Data Compression, 1994

Byte Pair Encoding

- Use smallest sequence of strings to represent original string. Group frequent pair of bytes together.
- Put all characters into symbol table
- For each loop, until table reach size limit
  - count frequencies of symbol pair
  - replace most frequent pair with a new symbol, add to symbol table

Byte Pair Encoding (BPE) for Text Tokenization

1. Initialize vocabulary with all characters as tokens (also add end-of-word symbol) and frequencies
2. Loop until vocabulary size reaches capacity
   1. Count successive pairs of tokens in corpus
   2. Rank and select the top frequent pair
   3. Combine the pair to form a new token, add to vocabulary
3. Output final vocabulary and tokenized corpus

Rico Sennrich et al. Neural Machine Translation of Rare Words with Subword Units. 2016

Example

l, o, w, e, r, n, s, t, i, d, </w>	‘l o w</w>’ : 5 ‘l o w e r</w>’ : 2 ’n e w e s t</w>’ : 6 ‘w i d e s t</w>’ : 3
l, o, w, e, r, n, s, t, i, d, </w>, es	‘l o w</w>’ : 5 ‘l o w e r</w>’ : 2 ’n e w es t</w>’ : 6 ‘w i d es t</w>’ : 3
l, o, w, e, r, n, s, t, i, d, </w>, es, est	‘l o w</w>’ : 5 ‘l o w e r</w>’ : 2 ’n e w est</w>’ : 6 ‘w i d est</w>’ : 3
l, o, w, e, r, n, s, t, i, d, </w>, es, est, est</w>	‘l o w</w>’ : 5 ‘l o w e r</w>’ : 2 ’n e w est</w>’ : 6 ‘w i d est</w>’ : 3
l, o, w, e, r, n, s, t, i, d, </w>, es, est, est</w>, lo,	‘lo w</w>’ : 5 ‘lo w e r</w>’ : 2 ’n e w est</w>’ : 6 ‘w i d est</w>’ : 3
l, o, w, e, r, n, s, t, i, d, </w>, es, est, est</w>, lo, low	‘low</w>’ : 5 ‘low e r</w>’ : 2 ’n e w est</w>’ : 6 ‘w i d est</w>’ : 3

Predict Next Token Probability

There are many methods to predict the next token:

- N-gram: assuming

$$p\left(x_t \middle| x_1, \ldots, x_{t-1}\right) = p\left(x_t \middle| x_{t-k}, \ldots, x_{t-1}\right)$$

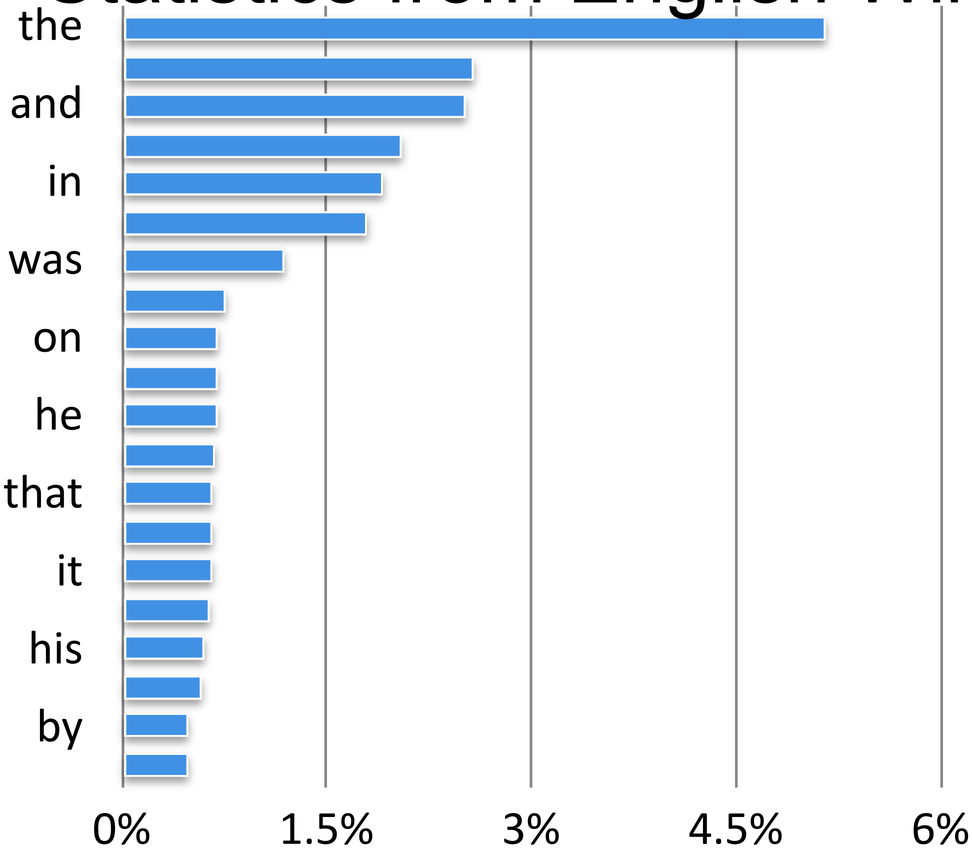
  , and estimate it directly
- Context MLP: use DNN to estimate

$$p\left(x_t \middle| x_{t-k}, \ldots, x_{t-1}\right)$$

- CNN-LM (previous lecture)
- RNN-LM, LSTM, GRU
- GPT

Word and Bigram

Statistics from English Wikipedia and books



cond. prob. $p(x_2|x_1)$

	first	united	the	a	be
the	0.014	0.006			
of			0.283	0.030	
would					0.191
with			0.187	0.122	

Challenge of n-gram LM

- Vocabulary: V
- n-gram needs a probability table of size V^n
- Common V size 30k ~ 100k
- Hard to estimate and hard to generalize
- Solution: Parameterization with generative model
  - $p(y_t \mid y_1, \cdots, y_{t-1}; \theta) = f_\theta(y_1, \cdots, y_{t-1})$
  - f can be a carefully designed and computationally tractable function, e.g. a neural network (later lectures).

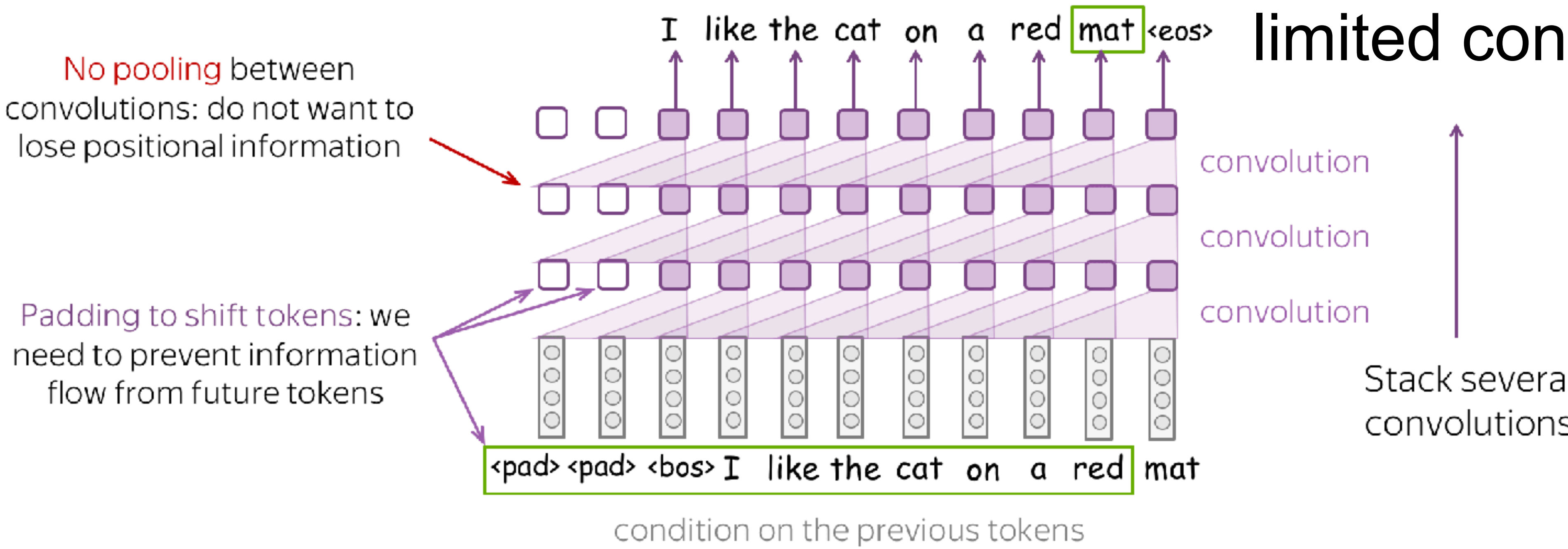
CNN Language Model

$$P(y_{t+1} \mid y_1, \ldots, y_t) \approx \mathrm{CNN}_\theta(y_{t-k}, \ldots, y_t)$$

predict the next token

But,

limited cont



https://lena-voita.github.io/nlp_course/models/convolutional.html

Limitation of CNN-LM

- CNN-LM only has a fixed-length receptive field
  - probability of next token only dependent on a fixed-size context
- But sentences are of variable length
- How to handle sentences with variable length?
- Idea:
  - adding memory to network
  - adaptive updating memory

Recurrent Memory

- Introduce memory representation
- RNN-LM: use RNN to estimate

$$p\left(x_t \middle| x_1, \ldots, x_{t-1}\right) = \text{softmax}(W \cdot h_t)$$

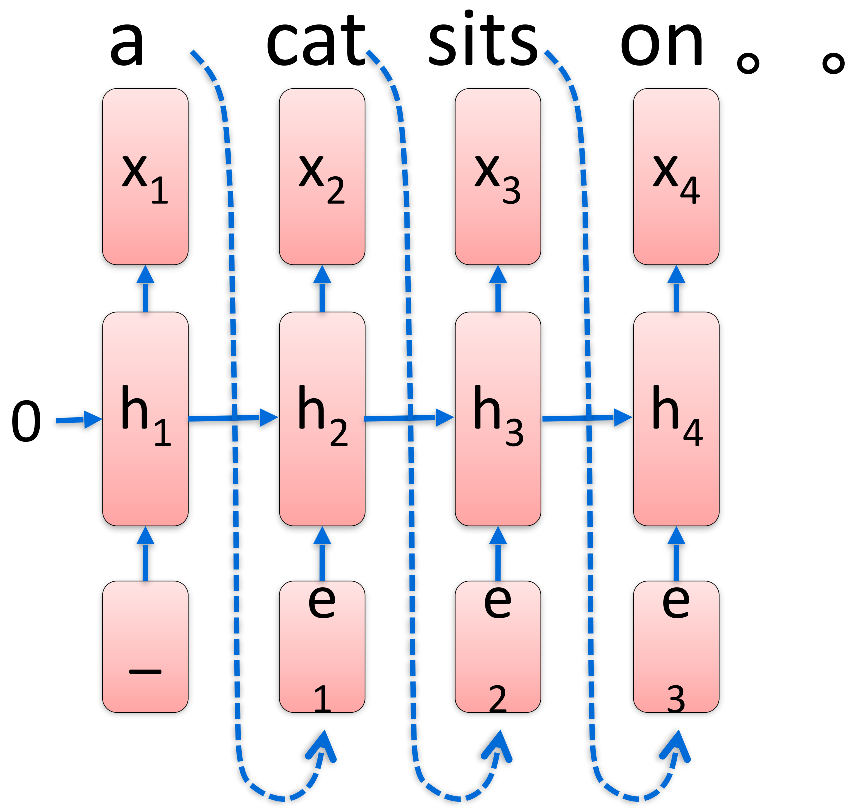
$$h_t = RNN(h_{t-1}, Emb(x_{t-1}))$$

- RNN cell can be
  - Simple feedforward neural network
  - Long-short term memory
  - Gated recurrent units

Recurrent Neural Network

$$p(x_t \mid x_1, \ldots, x_{t-1}) = \text{softmax}(U \cdot h_t)$$

$$h_t = \sigma\left(W \cdot \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix} + b \right)$$



Elman, Finding Structure in Time. Cog. Sci. 1990.

Mikolov et al, Recurrent neural network based language model. Interspeech 2010.

Training RNN-LM

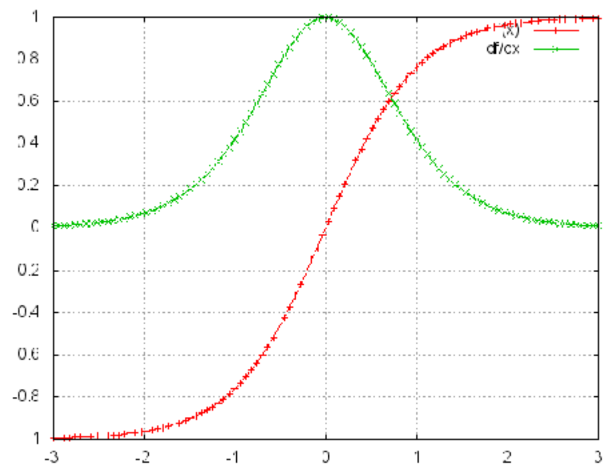
- Risk:
  - Loss: cross-entropy for every next-token given prefix context
  - CE(x_t+1, f(x_1, …, x_t))
- SGD
  - Calculate gradient: Back-propogation through time (BPTT)
  - ∇E_t

Back-propagation for RNN (python)

```
def bptt(self, x, y):
    T = len(y)
    # Perform forward propagation
    o, s = self.forward_propagation(x)
    # We accumulate the gradients in these variables
    dLdU = np.zeros(self.U.shape)
    dLdV = np.zeros(self.V.shape)
    dLdW = np.zeros(self.W.shape)
    delta_o = o
    delta_o[np.arange(len(y)), y] -= 1.
    # For each output backwards...
    for t in np.arange(T)[::-1]:
        dLdV += np.outer(delta_o[t], s[t].T)
        # Initial delta calculation: dL/dz
        delta_t = self.V.T.dot(delta_o[t]) * (1 - (s[t] ** 2))
        # Backpropagation through time (for at most self.bptt_truncate steps)
        for bptt_step in np.arange(max(0, t-self.bptt_truncate), t+1)[::-1]:
            # Add to gradients at each previous step
            dLdW += np.outer(delta_t, s[bptt_step-1])
            dLdU[:,x[bptt_step]] += delta_t
            # Update delta for next step dL/dz at t-1
            delta_t = self.W.T.dot(delta_t) * (1 - s[bptt_step-1] ** 2)
    return [dLdU, dLdV, dLdW]
```

Computational Issue: Gradient Vanishing

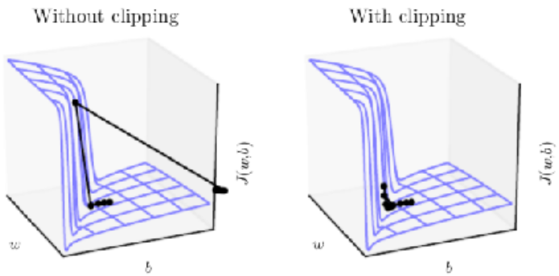
- tanh has derivative close to zero at both ends



Pascanu et al. On the difficulty of training recurrent neural networks. ICML 2013

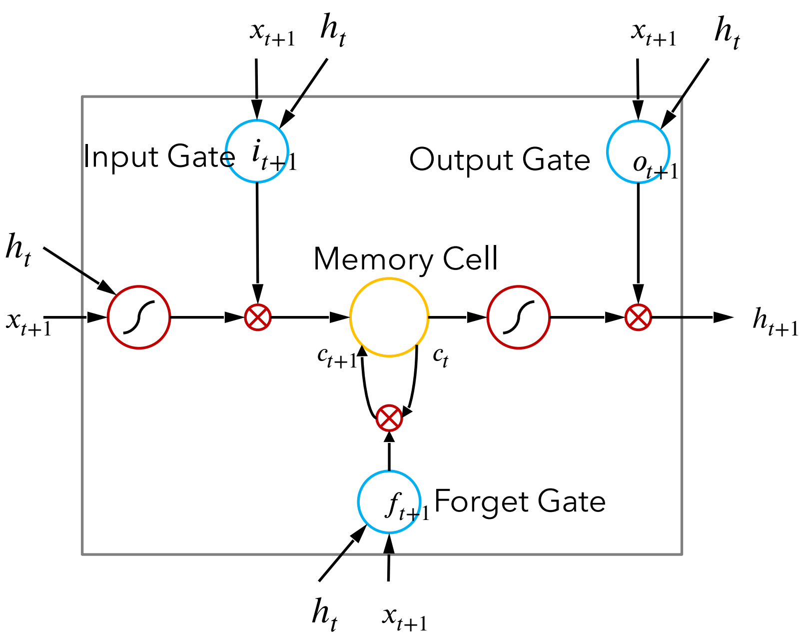
Gradient Exploding

- Use gradient clipping
- Two options: clip by absolute value or rescale norm
- if $|g| > \eta,\ \hat{g} \leftarrow \eta$
- if $|g| > \eta,\ \hat{g} \leftarrow \dfrac{\eta}{|g|} g$



Long-Short Term Memory (LSTM)

- Replace cell with more advanced one
- Adaptively memorize short and long term information



$$i_{t+1} = \sigma(M_{ix}x_{t+1} + M_{ih}h_t + b_i)$$
$$f_{t+1} = \sigma(M_{fx}x_{t+1} + M_{fh}h_t + b_f)$$
$$o_{t+1} = \sigma(M_{ox}x_{t+1} + M_{oh}h_t + b_o)$$

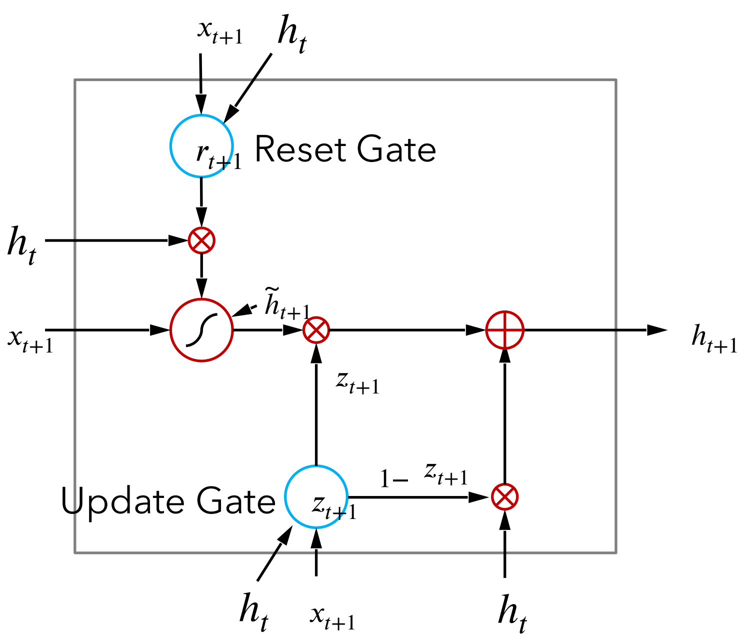
$$a_{t+1} = \tanh(M_{cx}x_{t+1} + M_{ch}h_t + b_a)$$

$$c_{t+1} = f_{t+1} \otimes c_t + i_{t+1} \otimes a_{t+1}$$
$$h_{t+1} = o_{t+1} \otimes \tanh(c_{t+1})$$

Hochreiter & Schmidhuber. Long Short-Term Memory, 1997
Gers et al. Learning to Forget: Continual Prediction with LSTM. 2000

Gated Recurrent Unit (GRU)

- Adaptively memorize short and long term information
- like LSTM, but fewer parameters



Input: x_t

Memory: h_t

$$r_{t+1} = \sigma(M_{rx}x_{t+1} + M_{rh}h_t + b_r)$$

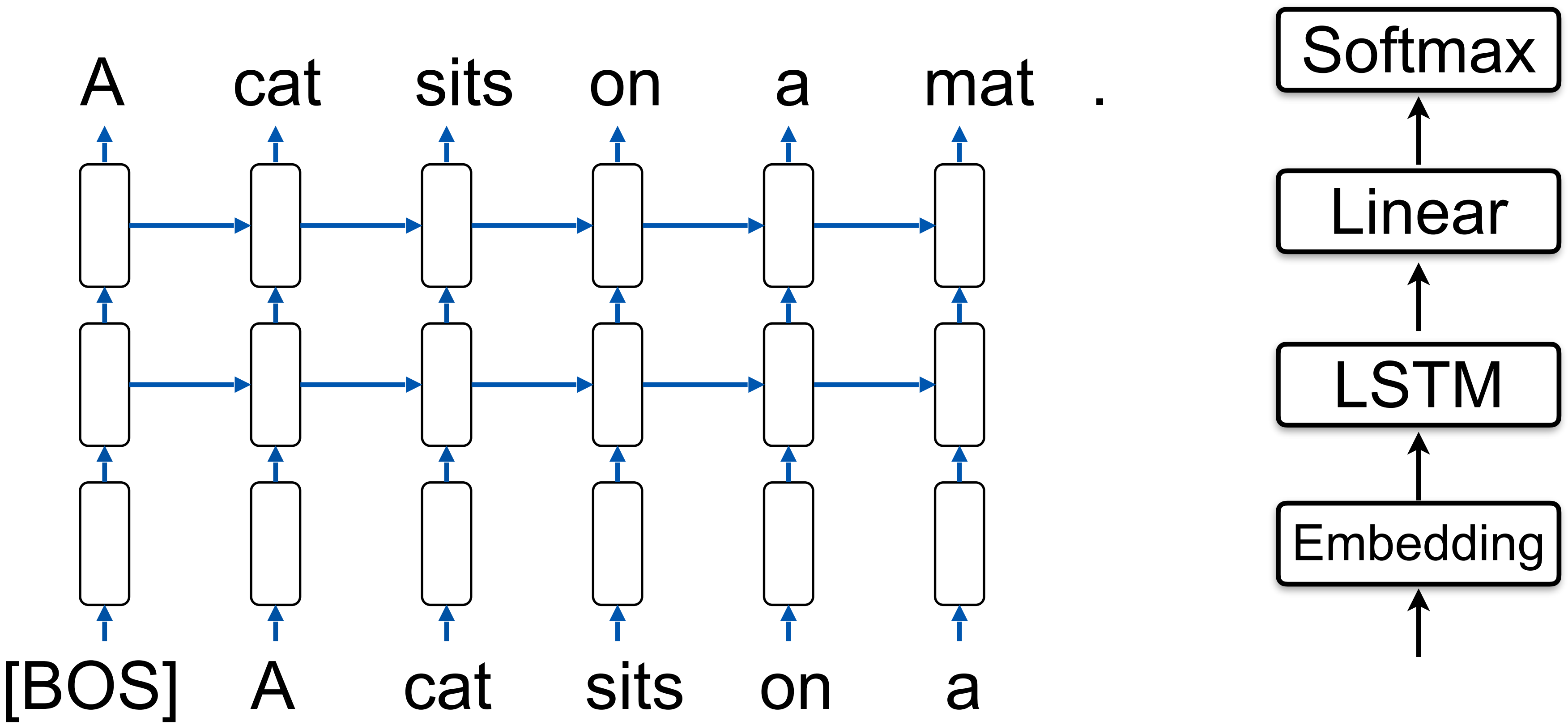
$$z_{t+1} = \sigma(M_{zx}x_{t+1} + M_{zh}h_t + b_z)$$

$$\tilde{h}_{t+1} = \tanh(M_{hx}x_{t+1} + M_{hh}(r_{t+1} \otimes h_t) + b_h)$$

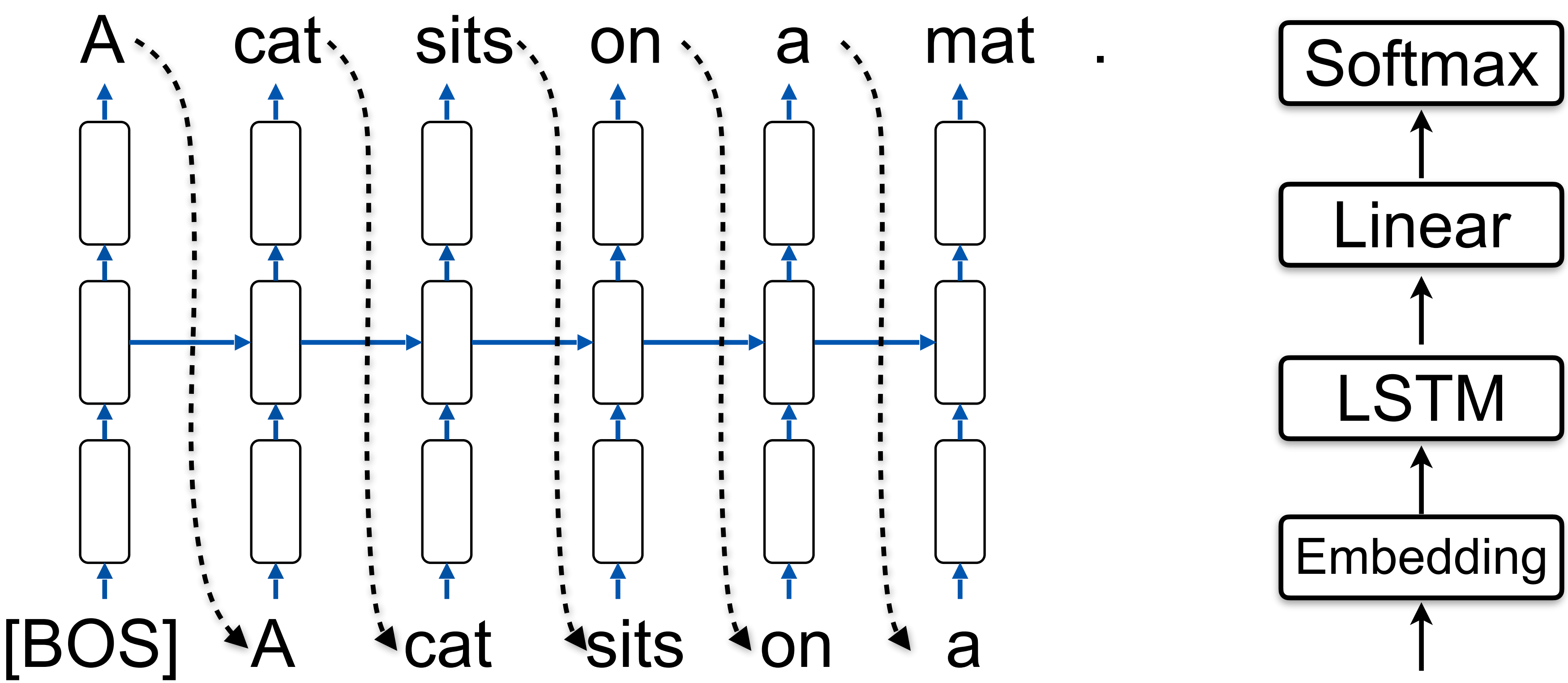
$$h_{t+1} = z_{t+1} \otimes \tilde{h}_{t+1} + (\mathbf{1} - \boldsymbol{z}_{t+1}) \otimes \boldsymbol{h}_t$$

Cho et al. Learning Phrase Representations using RNN Encoder–Decoder for Statistical Machine Translation. 2014

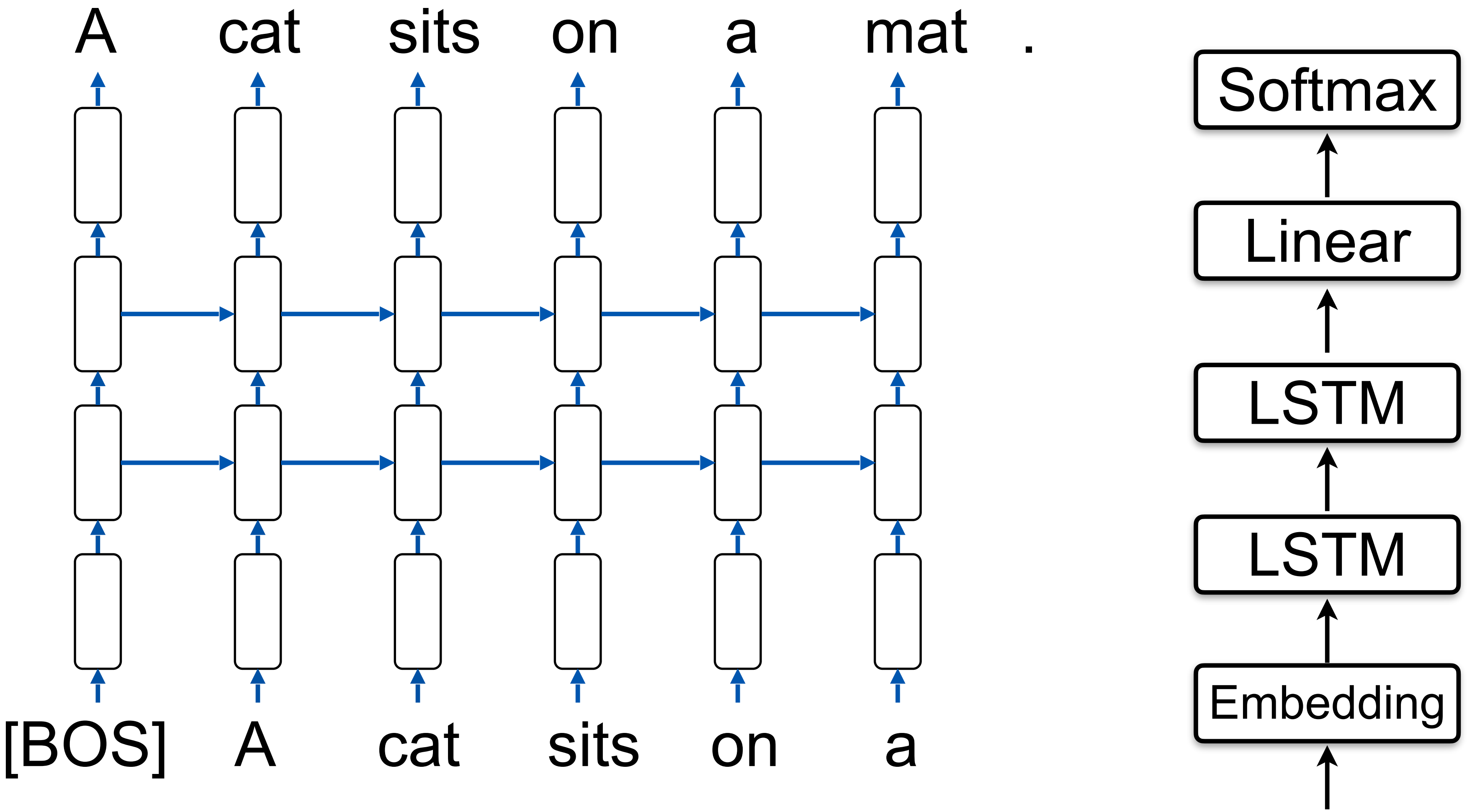
LSTM Language Modelling



LSTM Generation



LSTM: More layers



Expressive Power of RNN-LM

Perplexity:

$$PPL = P(x_1, \ldots, x_N)^{-\frac{1}{N}} = \exp(-\frac{1}{N}\sum_{n=1}^{N} \log P(x_n \mid x_1 \ldots x_{n-1}))$$

Model	Test Perplexity	Number of Params [billions]
Sigmoid-RNN-2048 (Ji et al., 2015a)	68.3	4.1
Interpolated KN 5-gram, 1.1B n-grams (Chelba et al., 2013)	67.6	1.76
Sparse Non-Negative Matrix LM (Shazeer et al., 2015)	52.9	33
RNN-1024 + MaxEnt 9-gram features (Chelba et al., 2013)	51.3	20
LSTM-512-512	54.1	0.82
LSTM-1024-512	48.2	0.82
LSTM-2048-512	43.7	0.83
LSTM-8192-2048 (No Dropout)	37.9	3.3
LSTM-8192-2048 (50% Dropout)	32.2	3.3
2-Layer LSTM-8192-1024 (BIG LSTM)	30.6	1.8
BIG LSTM+CNN Inputs	**30.0**	**1.04**
BIG LSTM+CNN Inputs + CNN Softmax	39.8	**0.29**
BIG LSTM+CNN Inputs + CNN Softmax + 128-dim correction	35.8	**0.39**
BIG LSTM+CNN Inputs + Char LSTM predictions	47.9	**0.23**

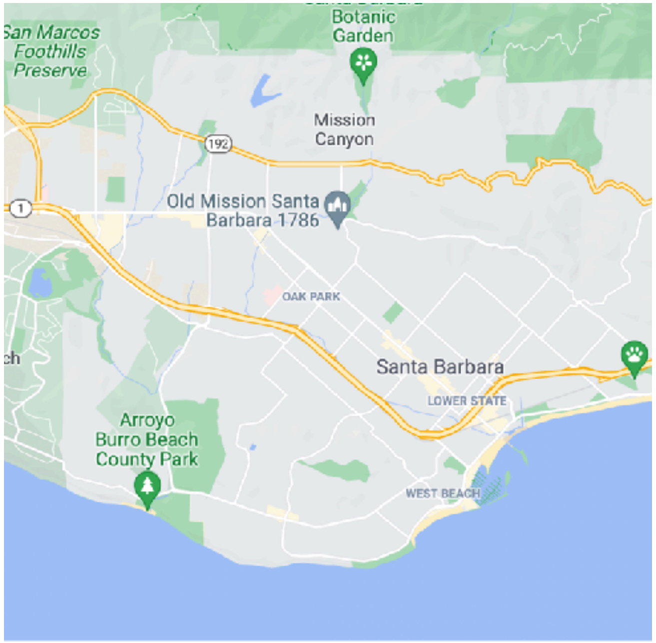
Jozefowicz et al. Exploring the limits of language modelling, 2016

Sequence Labelling

Understanding Query Intention

Noodle house near Santa Barbara
[Keyword] [Location]

How to go from Santa Barbara to Log Angeles ?
[Origin] [Destination]



Sequence Labelling

Named entity recognition

date   Location

In **April 1775** fighting broke out between **Massachusetts** militia units and **British** regulars at **Lexington** and **Concord** .

Geo-Political

Sequence Labelling

- Named entity recognition

  In **April 1775** fighting broke out between **Massachusetts** militia units and **British** regulars at **Lexington** and **Concord** .

- Semantic role labeling

The excess supply pushed gasoline prices down in that period .
subject verb object

- Question Answering: subject parsing

  Who created Harry Potter ?

Represent the Output Labels

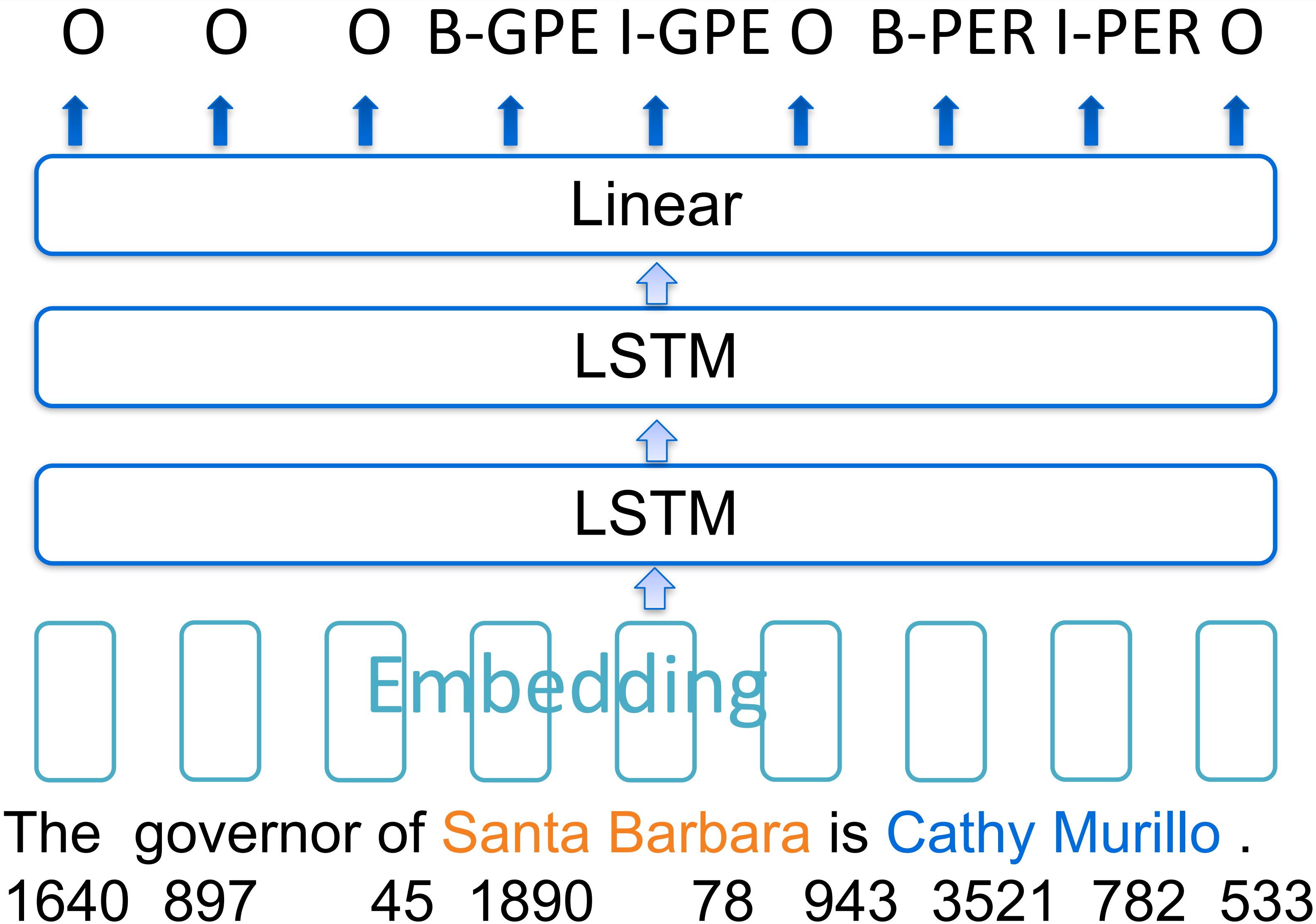
- BIO scheme

O O O B-GPE I-GPE O B-PER I-PER O

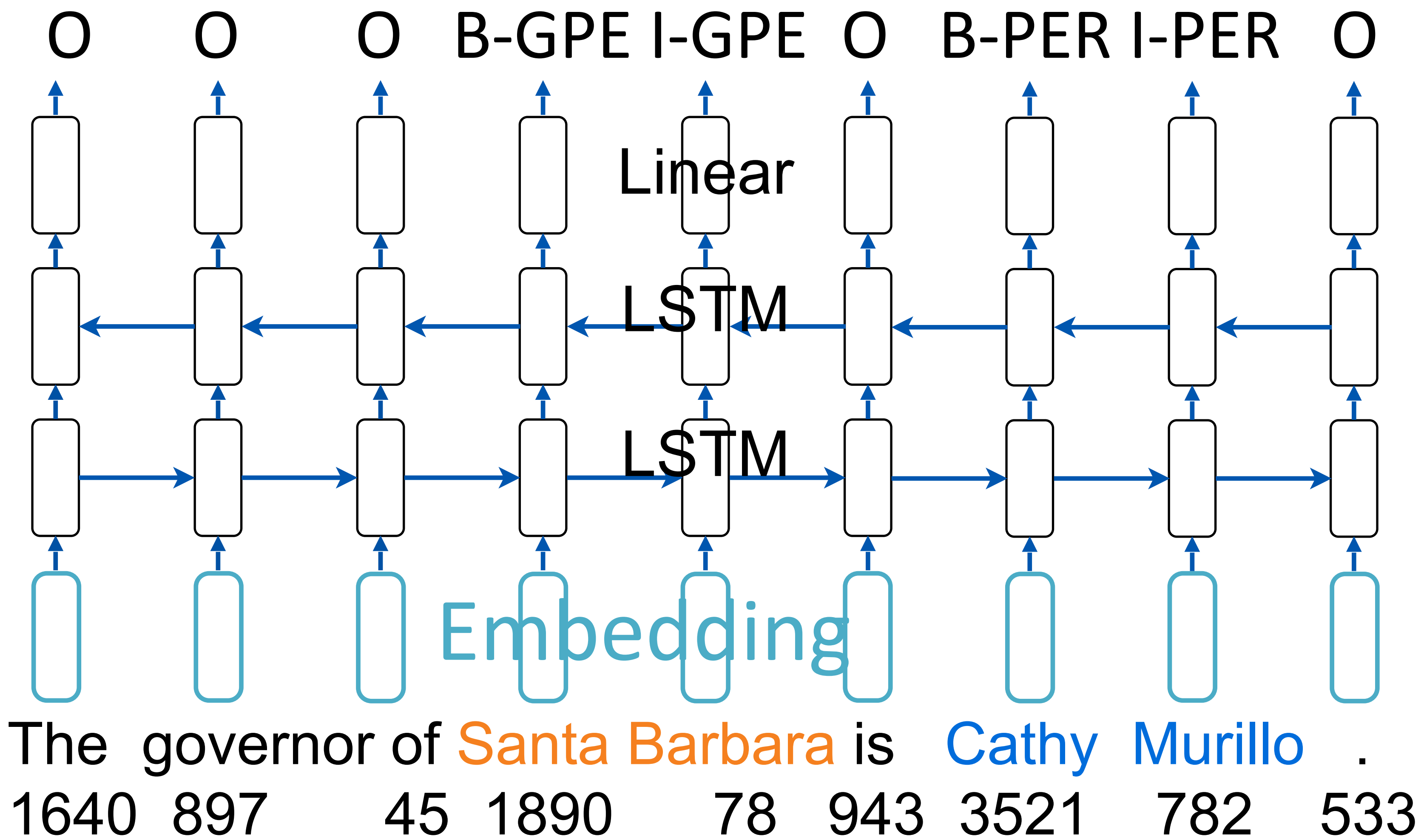
The governor of Santa Barbara is Cathy Murillo .

1640 897 45 1890 78 943 3521 782 533

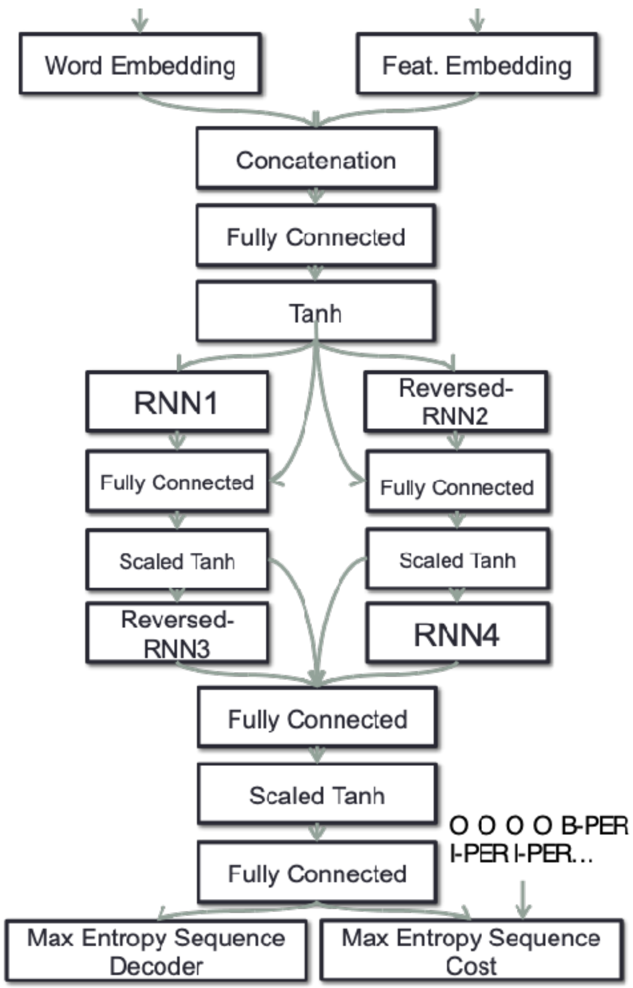
RNN/LSTM for Sequence Labelling



Bi-LSTM


O O O B-GPE I-GPE O B-PER I-PER O
Linear
LSTM
LSTM
Embedding
The governor of Santa Barbara is Cathy Murillo .
1640 897 45 1890 78 943 3521 782 533

Twisted NN for NER



Chinese NER

OntoNotes Data 4-class:

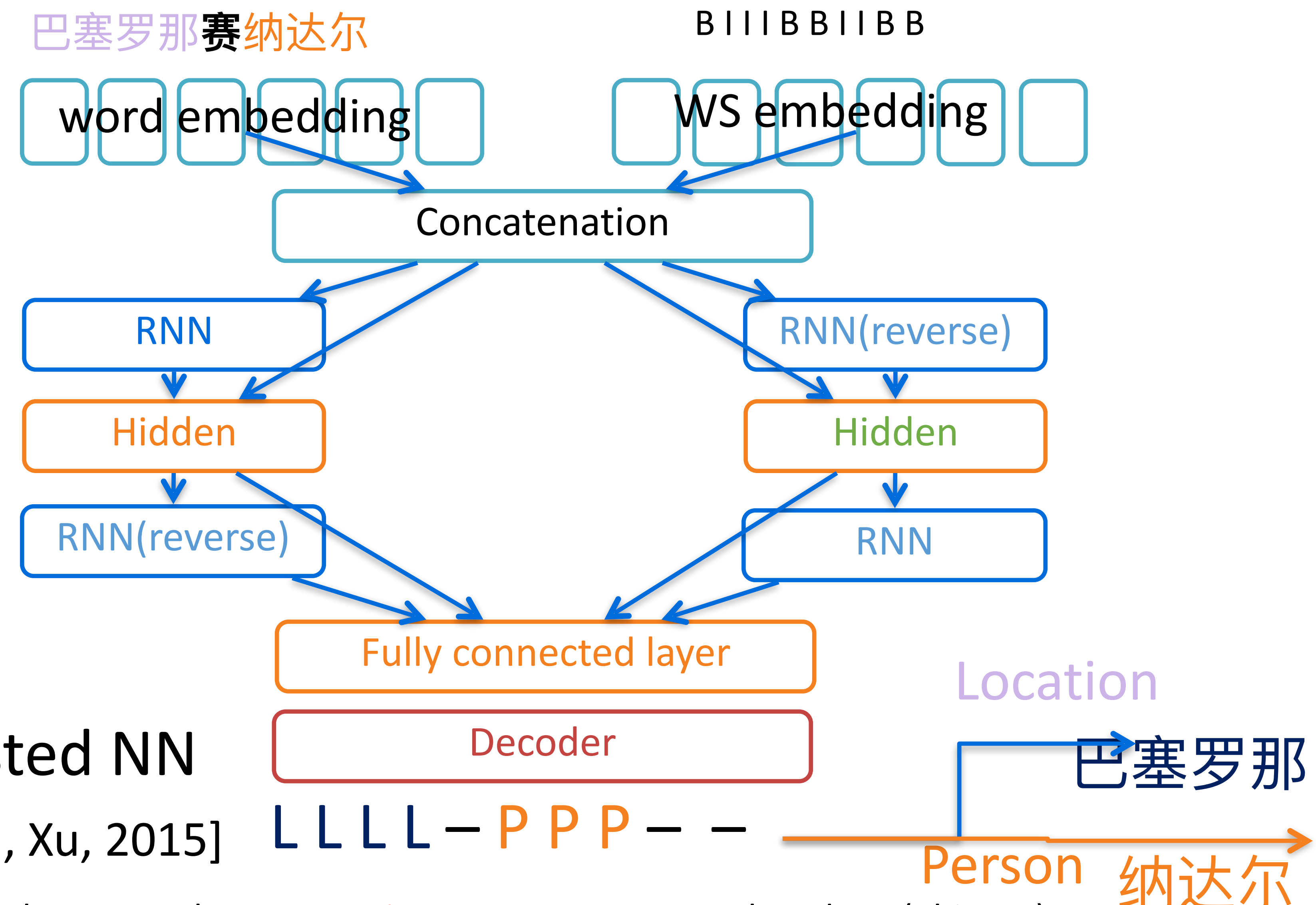
Model	P	R	F1
Bi-NER-WA* Wang et al.	84.42	76.34	80.18
RNN-2b with WS ours	84.75	77.85	81.15

* Wang et al used bilingual data

OntoNotes Data 18-class:

Model	P	R	F1
Sameer Pradhan et al.	78.20	66.45	71.85
RNN-2b with WS ours	78.69	70.54	74.39

Twisted NN [Zefu Lu, Lei Li, Wei Xu, 2015]



Twisted NN

[Lu, Li, Xu, 2015]

State-of-the-art result: F1 74.39% on ontonotes-5.0 18-class data. (Chinese)

Sequence Labelling using LSTM (Pytorch)

```
class LSTMTagger(nn.Module):

    def __init__(self, embedding_dim, hidden_dim, vocab_size, tagset_size):
        super(LSTMTagger, self).__init__()
        self.hidden_dim = hidden_dim

        self.word_embeddings = nn.Embedding(vocab_size, embedding_dim)

        # The LSTM takes word embeddings as inputs, and outputs hidden states
        # with dimensionality hidden_dim.
        self.lstm = nn.LSTM(embedding_dim, hidden_dim)

        # The linear layer that maps from hidden state space to tag space
        self.hidden2tag = nn.Linear(hidden_dim, tagset_size)

    def forward(self, sentence):
        embeds = self.word_embeddings(sentence)
        lstm_out, _ = self.lstm(embeds.view(len(sentence), 1, -1))
        tag_space = self.hidden2tag(lstm_out.view(len(sentence), -1))
        tag_scores = F.log_softmax(tag_space, dim=1)
        return tag_scores
```

Training in Pytorch

```
model = LSTMTagger(EMBEDDING_DIM, HIDDEN_DIM, len(word_to_ix), len(tag_to_ix))
loss_function = nn.NLLLoss()
optimizer = optim.SGD(model.parameters(), lr=0.1)

# See what the scores are before training
# Note that element i,j of the output is the score for tag j for word i.
# Here we don't need to train, so the code is wrapped in torch.no_grad()
with torch.no_grad():
    inputs = prepare_sequence(training_data[0][0], word_to_ix)
    tag_scores = model(inputs)
    print(tag_scores)

for epoch in range(300):  # again, normally you would NOT do 300 epochs, it is toy data
    for sentence, tags in training_data:
        # Step 1. Remember that Pytorch accumulates gradients.
        # We need to clear them out before each instance
        model.zero_grad()

        # Step 2. Get our inputs ready for the network, that is, turn them into
        # Tensors of word indices.
        sentence_in = prepare_sequence(sentence, word_to_ix)
        targets = prepare_sequence(tags, tag_to_ix)

        # Step 3. Run our forward pass.
        tag_scores = model(sentence_in)

        # Step 4. Compute the loss, gradients, and update the parameters by
        #  calling optimizer.step()
        loss = loss_function(tag_scores, targets)
        loss.backward()
        optimizer.step()
```

Testing in Pytorch

```
# See what the scores are after training
with torch.no_grad():
    inputs = prepare_sequence(training_data[0][0], word_to_ix)
    tag_scores = model(inputs)
```

Better Loss Function (advanced)

- Loss using Conditional Random Fields

$$
\begin{aligned}
-\log(P(\mathbf{y}\,|\,\mathbf{X})) &= -\log\left(\frac{\exp\left(\sum_{k=1}^{\ell} U(\mathbf{x}_k, y_k) + \sum_{k=1}^{\ell-1} T(y_k, y_{k+1})\right)}{Z(\mathbf{X})}\right) \\
&= \log\left(Z(\mathbf{X})\right) - \log\left(\exp\left(\sum_{k=1}^{\ell} U(\mathbf{x}_k, y_k) + \sum_{k=1}^{\ell-1} T(y_k, y_{k+1})\right)\right) \\
&= \log\left(Z(\mathbf{X})\right) - \left(\sum_{k=1}^{\ell} U(\mathbf{x}_k, y_k) + \sum_{k=1}^{\ell-1} T(y_k, y_{k+1})\right) \\
&= Z_{\log}(\mathbf{X}) - \left(\sum_{k=1}^{\ell} U(\mathbf{x}_k, y_k) + \sum_{k=1}^{\ell-1} T(y_k, y_{k+1})\right)
\end{aligned}
$$

Next

- Sequence to sequence learning
- Transformer network