# Sequence Tagging with LSTMs

CS 780/880 Natural Language Processing Lecture 16

Samuel Carton, University of New Hampshire

# Last lecture

RNNs

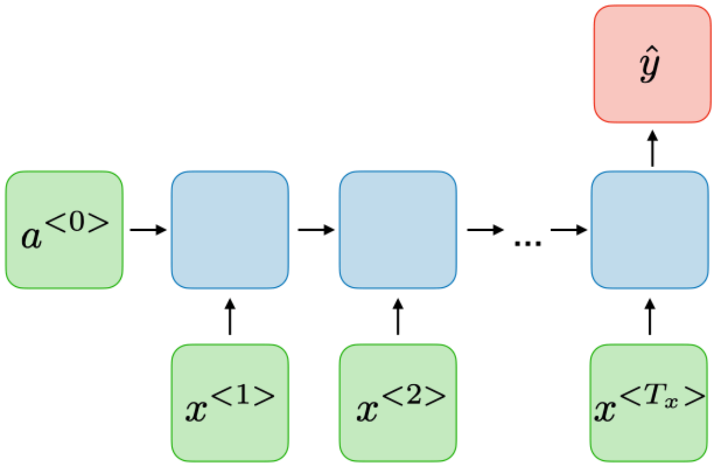
- One-to-one
- **Many-to-one**
- Many-to-many

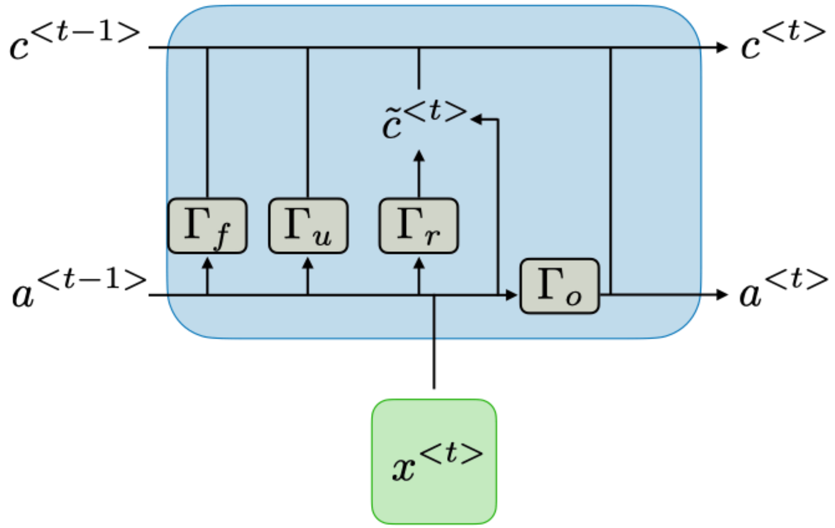
LSTMS

Increasing RNN capacity

- Depth
- Bidirectionality

Dropout

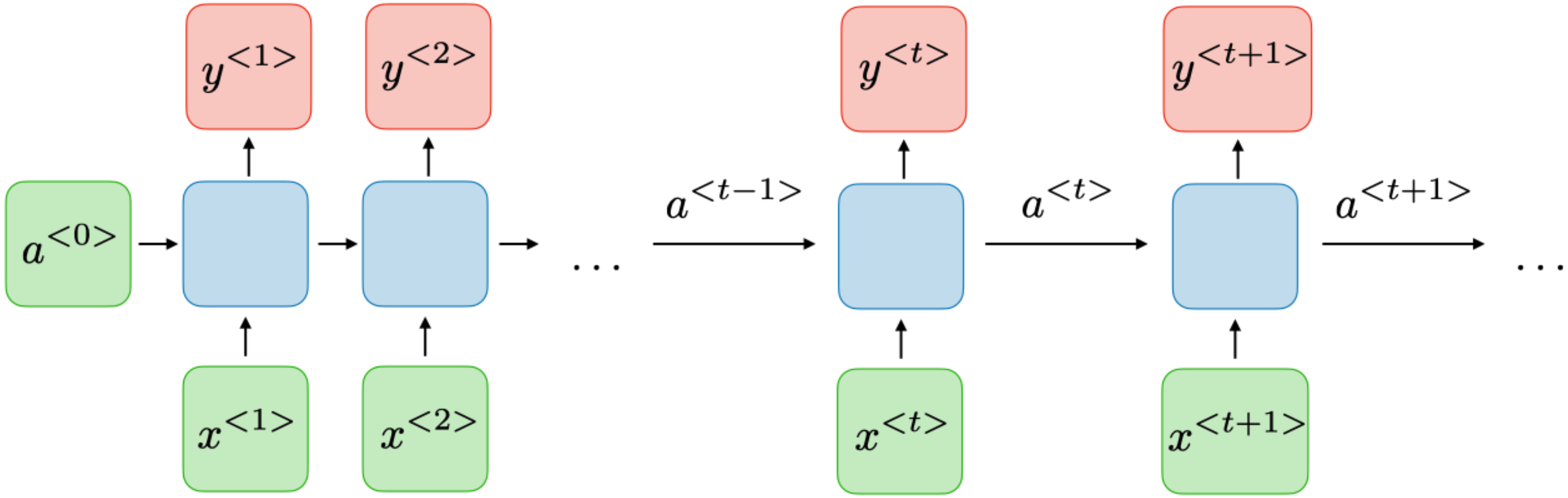


# LSTMs: NLP Swiss army knife

LSTMs are exciting for us because they are the Swiss army knife of NLP models.

- Sequence classification
- Sequence tagging
- Language modeling
- Text-to-text (e.g. translation)



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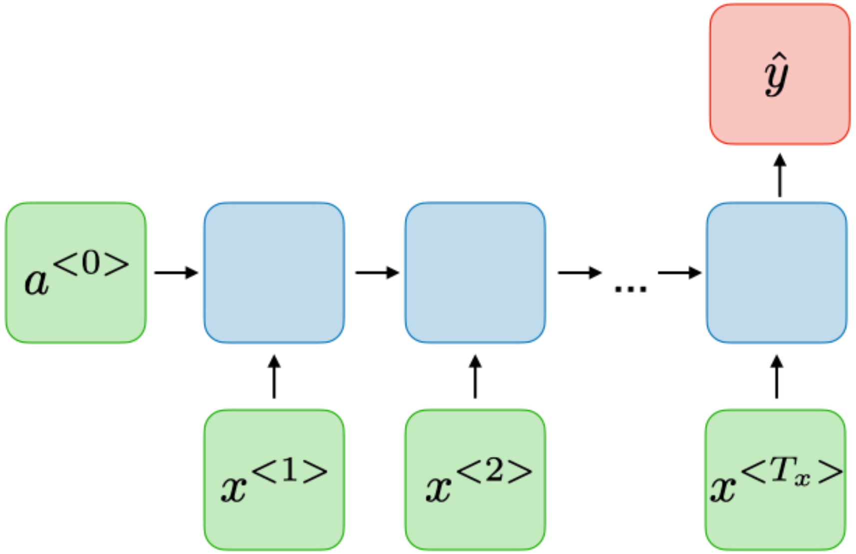

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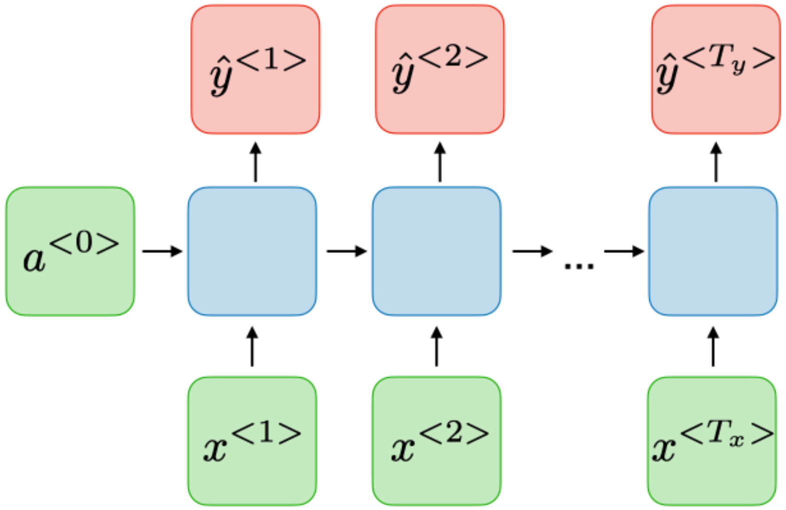

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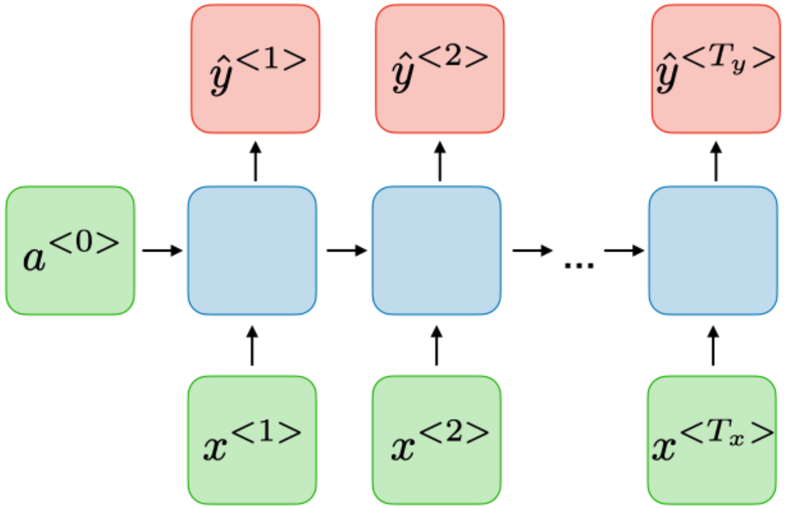
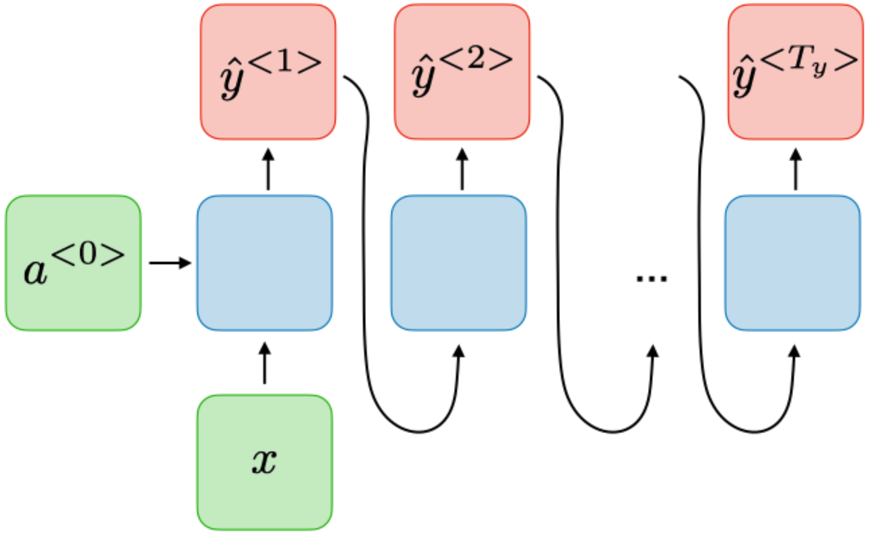



and



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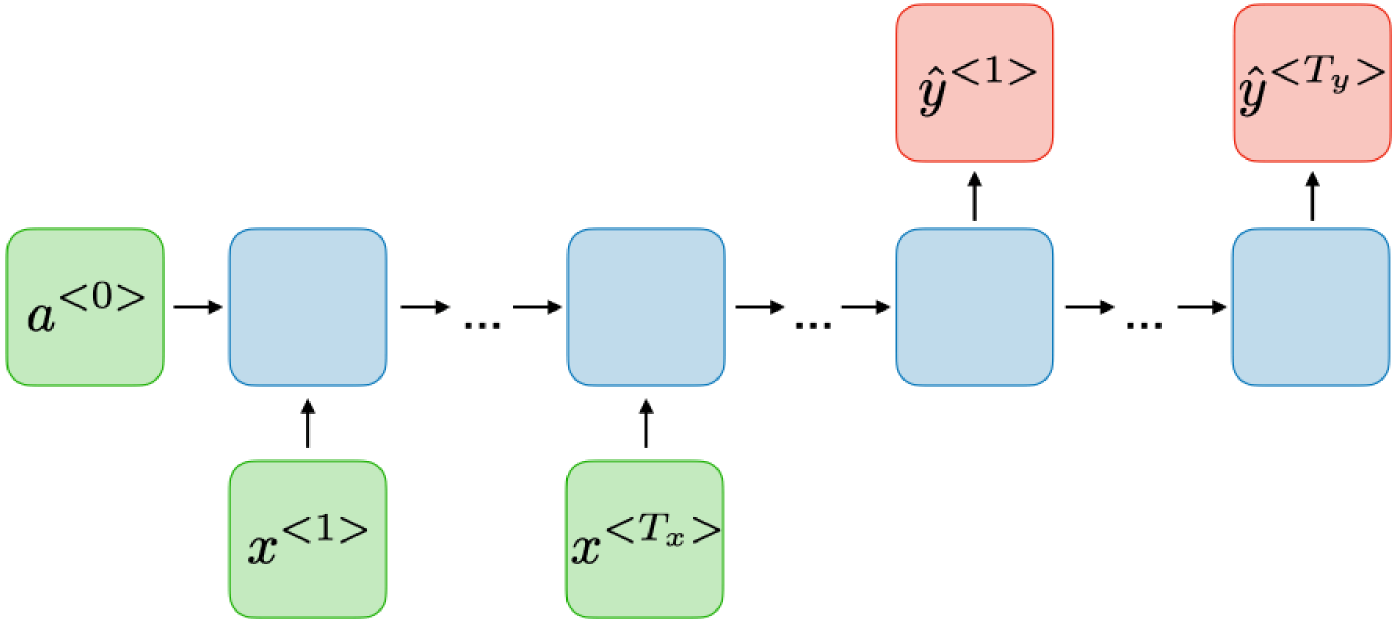
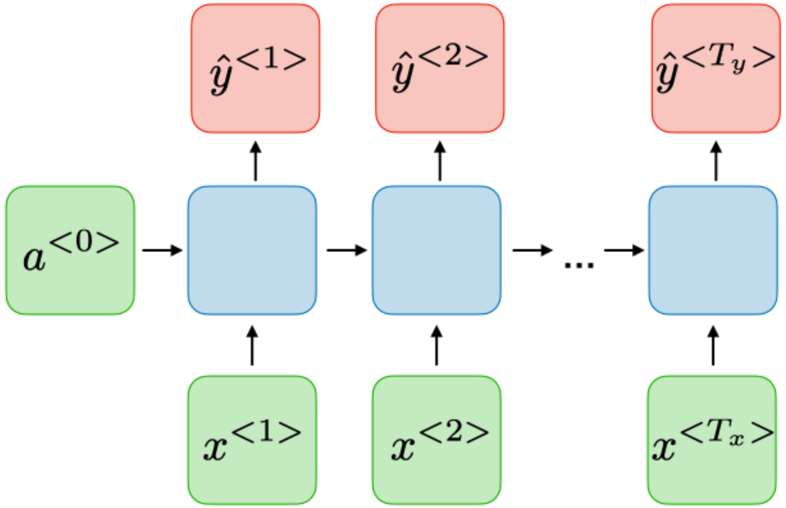
- Language modeling
- **Text-to-text (e.g. translation)**



# LSTMs: NLP Swiss army knife

LSTMs are exciting for us because they are the Swiss army knife of NLP models.

- Sequence classification
- **Sequence tagging**
- Language modeling
- Text-to-text (e.g. translation)



# Sequence tagging

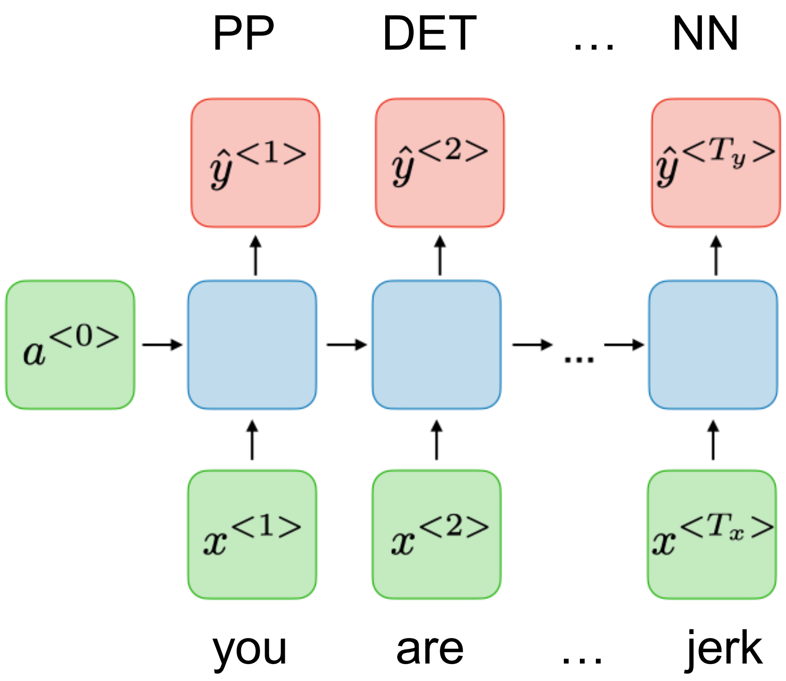
**Basic idea**: Given a corpus of text where each **word** has a label, learn to predict word labels for unseen texts

- Part-of-speech tagging
- Named entity recognition
  - "In his speech to the UN today, **George Bush** addressed the rising problems of…"
- Explanations
  - "You are a real **piece of garbage** human being." → Predicted toxic

# Sequence tagging

Context sensitive.

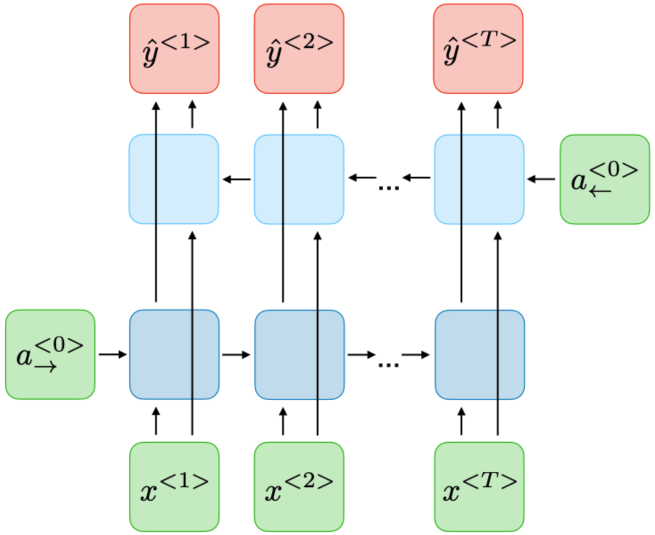
- “You are a real jerk!”
- “I am really craving some Jamaican jerk chicken right now.”

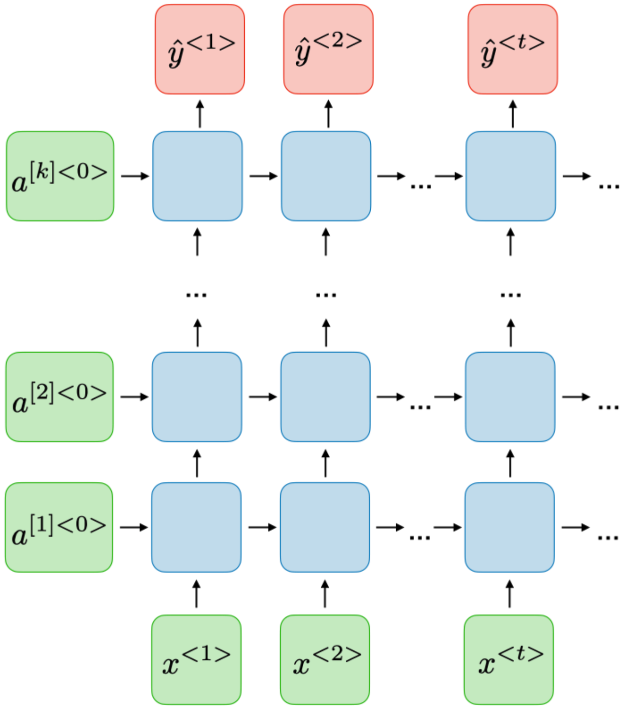


# Sequence tagging

Context sensitive.

- “You are a real jerk!”
- “I am really craving some Jamaican jerk chicken right now.”



# Loading GloVe vectors with Gensim

```
import gensim.downloader as api
```

```
# We're gonna be working with Twitter text today, so we'll use a Twitter-specific set of
# pretrained word embeddings
vector_model = api.load('glove-twitter-100')
```

```
[=================================================-] 99.9% 386.6/387.1MB downloaded
```

# Loading GloVe vectors with Gensim

```python
# We can see that this particular model has special embeddings for
# various kinds of things you'll find in tweets
vector_model.index_to_key[0:15]
```

```
['<user>',
 '.',
 ':',
 'rt',
 ',',
 '<repeat>',
 '<hashtag>',
 '<number>',
 '<url>',
 '!',
 'i',
 'a',
 '"',
 'the',
 '?']
```

```python
# It's also apparently got multilingual stuff in it
vector_model.index_to_key[-15:]
```

```
['ｇａｍｅ',
 'ｱﾑﾈｼｱ',
 'ｴｴ',
 'ｶﾞﾘｶﾞﾘ',
 'ｷｲ',
 'ｹﾞｼｯ',
 'ﾃﾍﾍﾟﾛｯ',
 'ﾃﾞﾓ',
 'ﾊﾞｲﾊﾞｰｲ',
 'ﾊﾞﾝﾁ',
 'ﾔﾒﾀﾏｴ',
 'ﾖｲｼｮｯ',
 'ﾞﾞｵﾔｽﾐｰ',
 '<unk>',
 '<pad>']
```

# Twitter POS tagging dataset

Named Entity Recognition in Tweets: An Experimental Study (Ritter et al., 2011)

https://raw.githubusercontent.com/aritter/twitter_nlp/master/data/annotated/pos.txt

```
@paulwalk USR
It PRP
's VBZ
the DT
view NN
from IN
where WRB
I PRP
'm VBP
living VBG
for IN
two CD
weeks NNS
. .
Empire NNP
State NNP
Building NNP
= SYM
ESB NNP
. .
Pretty RB
bad JJ
storm NN
here RB
last JJ
evening NN
. .
```

```
@MiSS_SOTO USR
I PRP
think VBP
that DT
's VBZ
when WRB
I PRP
'm VBP
gonna VBG
be VB
there RB

On IN
Thanksgiving NNP
after IN
you PRP
done VBN
eating VBG
its PRP
#TimeToGetOut HT
unless IN
you PRP
wanna VBP
help VB
with IN
the DT
dishes NNS
```

# Reading and preprocessing POS data

```
@paulwalk USR
It PRP
's VBZ
the DT
view NN
from IN
where WRB
I PRP
'm VBP
living VBG
for IN
two CD
weeks NNS
. .
Empire NNP
State NNP
Building NNP
= SYM
ESB NNP
. .
Pretty RB
bad JJ
storm NN
here RB
last JJ
evening NN
. .
```

```python
import pandas as pd
import csv
raw_pos_df = pd.read_csv(pos_url, sep=' ', quoting=csv.QUOTE_NONE, names=['token', 'tag'])
display(raw_pos_df)
```

| | token | tag |
|---|---|---|
| **0** | @paulwalk | USR |
| **1** | It | PRP |
| **2** | 's | VBZ |
| **3** | the | DT |
| **4** | view | NN |
| **...** | ... | ... |
| **15180** | wanna | VBP |
| **15181** | talk | VB |
| **15182** | to | TO |
| **15183** | u | PRP |
| **15184** | !!!!! | . |

15185 rows × 2 columns

# Reading and preprocessing POS data

```python
tagged_tweets = []
current_tweet = {'tokens':[], 'tags':[]}

for row_index, row in raw_pos_df.iterrows(): # this will yield each row as a pd.Series object
    if row['token'].startswith('@'): # if we hit a new tweet...
        if len(current_tweet['tokens']) > 0: # add the current tweet to the list if it isn't empty
            tagged_tweets.append(current_tweet)
        current_tweet = {'tokens':[], 'tags':[]} #then reset the current tweet

    current_tweet['tokens'].append(row['token']) # then begin accumulating into current tweet
    current_tweet['tags'].append(row['tag'])

if len(current_tweet['tokens']) > 0: # add the current tweet to the list if it isn't empty
    tagged_tweets.append(current_tweet)

#Pandas knows how to create a DataFrame from a list of dictionaries
pos_df = pd.DataFrame(tagged_tweets)
display(pos_df)
```

# Reading and preprocessing POS data

| | tokens | tags |
|---|---|---|
| **0** | [@paulwalk, It, 's, the, view, from, where, I,... | [USR, PRP, VBZ, DT, NN, IN, WRB, PRP, VBP, VBG... |
| **1** | [@MiSS_SOTO, I, think, that, 's, when, I, 'm, ... | [USR, PRP, VBP, DT, VBZ, WRB, PRP, VBP, VBG, V... |
| **2** | [@robmoysey, Eyeopener, vs, ., Ryerson, Quiddi... | [USR, NNP, CC, ., NNP, NN, NN, DT, NNP, IN, CD... |
| **3** | [@RUQuidditch, #Rams, RT] | [USR, HT, RT] |
| **4** | [@ZodiacFacts, :, #ZodiacFacts, As, an, #Aries... | [USR, :, HT, IN, DT, HT, NN, VBZ, RB, IN, WP, ... |
| **...** | ... | ... |
| **467** | [@DailyCaller, tomorrow, !, http://is.gd/fKm4j... | [USR, NN, ., URL, PRP, VBP, RB, VBN, TO, NNP, ... |
| **468** | [@DORSEY33, lol, aw, ., i, thought, u, was, ta... | [USR, UH, UH, ., PRP, VBD, PRP, VBD, VBG, IN, ... |
| **469** | [@Bibhu2109, No, ., He, 's, gonna, run, out, o... | [USR, UH, ., PRP, VBZ, VBG, VB, IN, IN, NN, DT... |
| **470** | [@SincerelyKRenee, but, u, can, just, get, her... | [USR, CC, PRP, MD, RB, VB, PRP, NN, NN, CC, VB... |
| **471** | [@MyssLidia, :, If, u, call, someone, 5x, 's, ... | [USR, :, IN, PRP, VBP, NN, NN, VBZ, DT, NN, CC... |

472 rows × 2 columns

# Reading and preprocessing POS data

49 possible POS tags in this particular dataset

```
# And we can also get a canonical list of all possible tags
tags = raw_pos_df['tag'].unique()
tags
```

```
array(['USR', 'PRP', 'VBZ', 'DT', 'NN', 'IN', 'WRB', 'VBP', 'VBG', 'CD',
       'NNS', '.', 'NNP', 'SYM', 'RB', 'JJ', ':', 'URL', 'HT', 'VB',
       'VBN', 'RT', 'CC', 'TO', 'WP', ',', 'UH', 'RP', 'JJS', 'PRP$',
       'VBD', "''", 'POS', 'JJR', 'MD', 'NNPS', '(', 'WDT', 'VPP', 'EX',
       ')', 'PDT', 'RBR', 'LS', 'TD', 'FW', 'RBS', 'NONE', 'O'],
      dtype=object)
```

# Reading and preprocessing POS data

```python
def token_to_ID(token):
    token = token.lower()
    if token.startswith('@'):
        return vector_model.key_to_index['<user>']
    elif token.startswith('#'):
        return vector_model.key_to_index['<hashtag>']
    elif token.startswith('http'):
        return vector_model.key_to_index['<url>']
    elif token in vector_model.key_to_index:
        return vector_model.key_to_index[token]
    else:
        return vector_model.key_to_index['<unk>']

pos_df['input_ids'] = pos_df['tokens'].apply(lambda tokens:[token_to_ID(token) for token in tokens])
```

```python
# We also need to map tags to tag IDs
tag2id = {tag:id for id, tag in enumerate(tags)}
pos_df['tag_ids'] = pos_df['tags'].apply(lambda tags:[tag2id[tag] for tag in tags])
```

# Reading and preprocessing POS data

| | tokens | tags | input_ids | tag_ids |
|---|---|---|---|---|
| **0** | [@paulwalk, It, 's, the, view, from, where, I,... | [USR, PRP, VBZ, DT, NN, IN, WRB, PRP, VBP, VBG... | [0, 33, 41, 13, 3056, 133, 329, 10, 57, 1704, ... | [0, 1, 2, 3, 4, 5, 6, 1, 7, 8, 5, 9, 10, 11, 1... |
| **1** | [@MiSS_SOTO, I, think, that, 's, when, I, 'm, ... | [USR, PRP, VBP, DT, VBZ, WRB, PRP, VBP, VBG, V... | [0, 10, 186, 45, 41, 92, 10, 57, 316, 56, 175,... | [0, 1, 7, 3, 2, 6, 1, 7, 8, 19, 14, 5, 12, 5, ... |
| **2** | [@robmoysey, Eyeopener, vs, ., Ryerson, Quiddi... | [USR, NNP, CC, ., NNP, NN, NN, DT, NNP, IN, CD... | [0, 519575, 917, 1, 215106, 85242, 302, 53, 12... | [0, 12, 22, 11, 12, 4, 4, 3, 12, 5, 9, 4, 4, 1... |
| **3** | [@RUQuidditch, #Rams, RT] | [USR, HT, RT] | [0, 6, 5] | [0, 18, 21] |
| **4** | [@ZodiacFacts, :, #ZodiacFacts, As, an, #Aries... | [USR, :, HT, IN, DT, HT, NN, VBZ, RB, IN, WP, ... | [0, 2, 6, 124, 172, 6, 6315, 32, 44, 121, 86, ... | [0, 16, 18, 5, 3, 18, 4, 2, 14, 5, 24, 1, 7, 5... |
| **...** | ... | ... | ... | ... |
| **467** | [@DailyCaller, tomorrow, !, http://is.gd/fKm4j... | [USR, NN, ., URL, PRP, VBP, RB, VBN, TO, NNP, ... | [0, 328, 9, 8, 10, 57, 55, 4968, 16, 218, 110,... | [0, 4, 11, 17, 1, 7, 14, 20, 23, 12, 14, 5, 1,... |
| **468** | [@DORSEY33, lol, aw, ., i, thought, u, was, ta... | [USR, UH, UH, ., PRP, VBD, PRP, VBD, VBG, IN, ... | [0, 88, 751, 1, 10, 621, 51, 93, 3427, 734, 59... | [0, 26, 26, 11, 1, 30, 1, 30, 8, 5, 3, 4, 11, ... |
| **469** | [@Bibhu2109, No, ., He, 's, gonna, run, out, o... | [USR, UH, ., PRP, VBZ, VBG, VB, IN, IN, NN, DT... | [0, 30, 1, 107, 41, 316, 899, 99, 39, 580, 191... | [0, 26, 11, 1, 2, 8, 19, 5, 5, 4, 3, 4, 26] |
| **470** | [@SincerelyKRenee, but, u, can, just, get, her... | [USR, CC, PRP, MD, RB, VB, PRP, NN, NN, CC, VB... | [0, 79, 51, 102, 59, 87, 168, 185, 148, 36, 43... | [0, 22, 1, 34, 14, 19, 1, 4, 4, 22, 7, 14, 19,... |
| **471** | [@MyssLidia, :, If, u, call, someone, 5x, 's, ... | [USR, :, IN, PRP, VBP, NN, NN, VBZ, DT, NN, CC... | [0, 2, 74, 51, 462, 238, 1193514, 41, 11, 125,... | [0, 16, 5, 1, 7, 4, 4, 2, 3, 4, 22, 1, 7, 14, ... |

472 rows × 4 columns

# Training a LSTM POS tagger—Dataset

```python
class POSTaggingDataset(Dataset):
  def __init__(self,
               tag_ids=None,
               input_ids=None):

    self.tag_ids = tag_ids
    self.input_ids = input_ids

  def __len__(self):
    return len(self.tag_ids)

  def __getitem__(self, idx):
    rdict = {
      'tag_ids': torch.tensor(self.tag_ids[idx], dtype=torch.int64),
      'input_ids': torch.tensor(self.input_ids[idx], dtype=torch.int64)
    }
    return rdict
```

```python
train_dataset = POSTaggingDataset(train_df['tag_ids'], train_df['input_ids'])
dev_dataset = POSTaggingDataset(dev_df['tag_ids'], dev_df['input_ids'])
```

# Training a LSTM POS tagger—Dataset

```
from pprint import pprint
pprint(train_dataset[0])
print(train_dataset[0]['input_ids'].shape)
```

```
{'input_ids': tensor([      0,       2,     525,     291,      99,      28,      80,     140,
          10510,      46,    3761,      53,     435,       9,     183,     538,
             16,   12446,      55,    1898,    1417,      15,      68,     291,
              8,      59,     121,     231,     320,       9,     211,      16,
         960077,     389, 1193514,    1352,       1,    2431,      80,     143,
           6404,      41,    3645,      35,      13,    4948,     148,       1]),
 'tag_ids': tensor([ 0, 16, 19,  1, 27, 16,  1,  7, 20,  5, 12,  3,  4, 11, 19, 15, 23, 19,
          5, 12,  2,  1,  7,  1, 17, 14, 14, 14,  4, 11,  8, 23, 12, 14, 26, 26,
         11, 14,  1, 30, 12, 32,  4,  5,  3,  4,  4, 11])}
torch.Size([48])
```

# Training a LSTM POS tagger—DataLoader

```
from torch.utils.data import DataLoader
from typing import List, Dict

# And now we will need to do padding for both the tag IDs and token IDs

def POS_collate(batch:List[Dict[str, torch.Tensor]]):
    tag_id_vectors = [example['tag_ids'] for example in batch]
    tag_id_vector_matrix = torch.nn.utils.rnn.pad_sequence(tag_id_vectors, batch_first=True, padding_value=0)

    input_id_vectors = [example['input_ids'] for example in batch]
    input_id_vector_matrix = torch.nn.utils.rnn.pad_sequence(input_id_vectors, batch_first=True,
                                                             padding_value=vector_model.key_to_index['<pad>'])

    return {
        'tag_ids':tag_id_vector_matrix,
        'input_ids':input_id_vector_matrix
    }
```

```
batch_size = 10
train_dataloader = DataLoader(train_dataset, batch_size=batch_size, collate_fn = POS_collate, shuffle=True)
dev_dataloader = DataLoader(dev_dataset, batch_size=batch_size, collate_fn = POS_collate, shuffle=False)
```

# Training a LSTM POS tagger—DataLoader

```
first_train_batch = next(iter(train_dataloader))
print('First training batch:')
pprint(first_train_batch)

print('First training batch sizes:')
pprint({key:value.shape for key, value in first_train_batch.items()})
```

```
First training batch:
{'input_ids': tensor([[      0,      10,     247,  ..., 1193515, 1193515, 1193515],
        [      0,      10,      64,  ..., 1193514,       8,       5],
        [      0,     277,       6,  ..., 1193515, 1193515, 1193515],
        ...,
        [      0,     122,     524,  ..., 1193515, 1193515, 1193515],
        [      0,     265,      21,  ..., 1193515, 1193515, 1193515],
        [      0,       2,       6,  ..., 1193515, 1193515, 1193515]]),
 'tag_ids': tensor([[ 0,  1,  7,  ...,  0,  0,  0],
        [ 0,  1,  7,  ..., 16, 17, 21],
        [ 0, 29, 18,  ...,  0,  0,  0],
        ...,
        [ 0, 15,  4,  ...,  0,  0,  0],
        [ 0, 19,  1,  ...,  0,  0,  0],
        [ 0, 16, 18,  ...,  0,  0,  0]])}
First training batch sizes:
{'input_ids': torch.Size([10, 66]), 'tag_ids': torch.Size([10, 66])}
```

# Training a LSTM POS tagger—Model

```
! pip install --quiet "pytorch-lightning==1.9.4"

# PyTorch Lightning recently released v2.0 (March 15 2023), but it changes some syntax,
# so I am teaching the last 1.9.x version for now.
# https://github.com/Lightning-AI/lightning/releases
```

```
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 827.8/827.8 KB 39.2 MB/s eta 0:00:00
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━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 158.8/158.8 KB 18.6 MB/s eta 0:00:00
```

# Training a LSTM POS tagger—Model

```python
class LSTMPOSTagger(pl.LightningModule):
  def __init__(self,
               word_vectors:np.ndarray,
               num_classes:int,
               learning_rate:float,
               padding_id:int,
               lstm_hidden_size:int=100, # how big the inner vectors of the LSTM will be,
               lstm_layers:int =2, # how many layers the LSTM will have
               dropout_prob:float=0.1,
               **kwargs):
    super().__init__( **kwargs)

    # The __init__ function will be identical to the classifier version
    self.word_embeddings = torch.nn.Embedding.from_pretrained(embeddings=torch.tensor(word_vectors),
                                                              freeze=True)
    self.lstm = torch.nn.LSTM(input_size = word_vectors.shape[1], # The LSTM will be taking in word vectors
                              hidden_size = lstm_hidden_size,
                              num_layers=lstm_layers,
                              bidirectional=True,
                              dropout=dropout_prob,
                              batch_first=True # This is important. Set to False by default for some reason.
                              )

    # Output layer input size has to be doubled because the LSTM is bidirectional
    self.output_layer  = torch.nn.Linear(2*lstm_hidden_size, num_classes)
    self.lstm_layers = lstm_layers
    self.learning_rate = learning_rate
    self.padding_id = padding_id # we'll need this later
    self.train_accuracy = Accuracy(task='multiclass', num_classes=num_classes)
    self.val_accuracy = Accuracy(task='multiclass', num_classes=num_classes)
```

SAME!

# Training a LSTM POS tagger—Model

```
def forward(self, tag_ids:torch.Tensor, input_ids:torch.Tensor, verbose=False):

    #The first part of the forward() function is the same too
    inputs_embeds = self.word_embeddings(input_ids) #(batch size x sequence length x embedding size)
    padding_mask = (input_ids != self.padding_id).int()
    input_lengths = padding_mask.sum(dim=1).detach().cpu()
    packed_embeddings = pack_padded_sequence(inputs_embeds, input_lengths, batch_first=True, enforce_sorted=False)
    packed_output, (final_hidden, final_state) = self.lstm.forward(packed_embeddings)

    # But now we need to look at all the LSTM output, not just the final hidden state
    # So first we unpack the packed output
    output, _ = pad_packed_sequence(packed_output, batch_first=True, padding_value=0.0, total_length=input_ids.shape[1])

    # output is actually nicely shaped for us: (batch size x sequence length x 2*lstm hidden size)
    py_logits = self.output_layer(output) #(batch size x sequence length x num_classes)
    py = torch.argmax(py_logits, dim=2)

    # We end up with one loss value per token
    # Annoyingly, this function wants the class to be the second dimension
    losses = torch.nn.functional.cross_entropy(py_logits.transpose(1,2), tag_ids, reduction='none')

    # Then the final thing we need to do is zero out the losses for padding
    padded_losses = losses * padding_mask
    loss = padded_losses.mean()

    return {'py':py,
            'loss':loss}
```

# Training a LSTM POS tagger—Model

```python
# And then everything else is the same!
def configure_optimizers(self):
  return [torch.optim.Adam(self.parameters(), lr=self.learning_rate)]

def training_step(self, batch, batch_idx):
  result = self.forward(**batch)
  loss = result['loss']
  self.log('train_loss', result['loss'])
  self.train_accuracy.update(result['py'], batch['tag_ids'])
  return loss

def training_epoch_end(self, outs):
  print(f'Epoch {self.current_epoch} training accuracy:', self.train_accuracy.compute())
  self.train_accuracy.reset()

def validation_step(self, batch, batch_idx):
  result = self.forward(**batch)
  self.val_accuracy.update(result['py'], batch['tag_ids'])
  return result['loss']

def validation_epoch_end(self, outs):
  print(f'Epoch {self.current_epoch} validation accuracy:', self.val_accuracy.compute())
  self.val_accuracy.reset()
```

# Training a LSTM POS tagger—Model

```
tagger_model = LSTMPOSTagger(word_vectors=vector_model.vectors,
                             num_classes = len(tags),
                             learning_rate = 0.001, #I'll typically start with something like 1e-3 for LSTMs
                             padding_id = vector_model.key_to_index['<pad>'],
                             lstm_hidden_size=100,
                             lstm_layers=2,
                             dropout_prob=0.1)
print('Model:')
print(tagger_model)
```

```
Model:
LSTMPOSTagger(
  (word_embeddings): Embedding(1193516, 100)
  (lstm): LSTM(100, 100, num_layers=2, batch_first=True, dropout=0.1, bidirectional=True)
  (output_layer): Linear(in_features=200, out_features=49, bias=True)
  (train_accuracy): MulticlassAccuracy()
  (val_accuracy): MulticlassAccuracy()
)
```

# Training a LSTM POS tagger—Model

```
from pprint import pprint
with torch.no_grad():
    first_train_output = tagger_model(**first_train_batch, verbose=True)

print('First training output:')
pprint(first_train_output)

print('Output item shapes:')
pprint({key:value.shape for key, value in first_train_output.items()})
```

```
First training output:
{'loss': tensor(0.2590),
 'py': tensor([[ 0,  1,  7,  ..., 12, 12, 12],
        [ 0,  1,  7,  ..., 16, 17, 21],
        [ 0, 29, 18,  ..., 12, 12, 12],
        ...,
        [ 0, 12,  4,  ..., 12, 12, 12],
        [ 0, 19,  1,  ..., 12, 12, 12],
        [ 0, 16, 18,  ..., 12, 12, 12]])}
Output item shapes:
{'loss': torch.Size([]), 'py': torch.Size([10, 66])}
```

# Training a LSTM POS tagger—Trainer

```python
from pytorch_lightning import Trainer
from pytorch_lightning.callbacks.progress import TQDMProgressBar

pos_trainer = Trainer(
    accelerator="auto",
    devices=1 if torch.cuda.is_available() else None,
    max_epochs=10,
    callbacks=[TQDMProgressBar(refresh_rate=20)],
    val_check_interval = 0.5,
    )
```

```
INFO:pytorch_lightning.utilities.rank_zero:GPU available: True (cuda), used: True
INFO:pytorch_lightning.utilities.rank_zero:TPU available: False, using: 0 TPU cores
INFO:pytorch_lightning.utilities.rank_zero:IPU available: False, using: 0 IPUs
INFO:pytorch_lightning.utilities.rank_zero:HPU available: False, using: 0 HPUs
```

# Training a LSTM POS tagger—Trainer

```
pos_trainer.fit(model=tagger_model,
                train_dataloaders=train_dataloader,
                val_dataloaders=dev_dataloader)
```

```
Epoch 0 validation accuracy: tensor(0.0449, device='cuda:0')
Epoch 0 validation accuracy: tensor(0.0723, device='cuda:0')
Epoch 0 training accuracy: tensor(0.0509, device='cuda:0')
Epoch 1 validation accuracy: tensor(0.1089, device='cuda:0')
Epoch 1 validation accuracy: tensor(0.1472, device='cuda:0')
Epoch 1 training accuracy: tensor(0.1122, device='cuda:0')
Epoch 2 validation accuracy: tensor(0.1831, device='cuda:0')
Epoch 2 validation accuracy: tensor(0.2083, device='cuda:0')
Epoch 2 training accuracy: tensor(0.1895, device='cuda:0')
Epoch 3 validation accuracy: tensor(0.2194, device='cuda:0')
Epoch 3 validation accuracy: tensor(0.2348, device='cuda:0')
Epoch 3 training accuracy: tensor(0.2285, device='cuda:0')
Epoch 4 validation accuracy: tensor(0.2426, device='cuda:0')
Epoch 4 validation accuracy: tensor(0.2483, device='cuda:0')
Epoch 4 training accuracy: tensor(0.2610, device='cuda:0')
Epoch 5 validation accuracy: tensor(0.2530, device='cuda:0')
Epoch 5 validation accuracy: tensor(0.2626, device='cuda:0')
Epoch 5 training accuracy: tensor(0.2768, device='cuda:0')
Epoch 6 validation accuracy: tensor(0.2643, device='cuda:0')
Epoch 6 validation accuracy: tensor(0.2719, device='cuda:0')
Epoch 6 training accuracy: tensor(0.2812, device='cuda:0')
Epoch 7 validation accuracy: tensor(0.2737, device='cuda:0')
Epoch 7 validation accuracy: tensor(0.2753, device='cuda:0')
Epoch 7 training accuracy: tensor(0.3019, device='cuda:0')
Epoch 8 validation accuracy: tensor(0.2769, device='cuda:0')
Epoch 8 validation accuracy: tensor(0.2758, device='cuda:0')
Epoch 8 training accuracy: tensor(0.3055, device='cuda:0')
Epoch 9 validation accuracy: tensor(0.2744, device='cuda:0')
Epoch 9 validation accuracy: tensor(0.2781, device='cuda:0')
INFO:pytorch_lightning.utilities.rank_zero:`Trainer.fit` stopped: `max_epochs=10` reached.
Epoch 9 training accuracy: tensor(0.3073, device='cuda:0')
```

# Concluding thoughts

Sequence tagging

- POS tagging

LSTMs as a NLP Swiss army knife

Domain-specific word embeddings

Masked loss