Applications

Of Data Science

Recurrent Neural Networks

Applications of Data Science - Class 18

Giora Simchoni

gsimchoni@gmail.com and add #dsapps in subject

Stat. and OR Department, TAU

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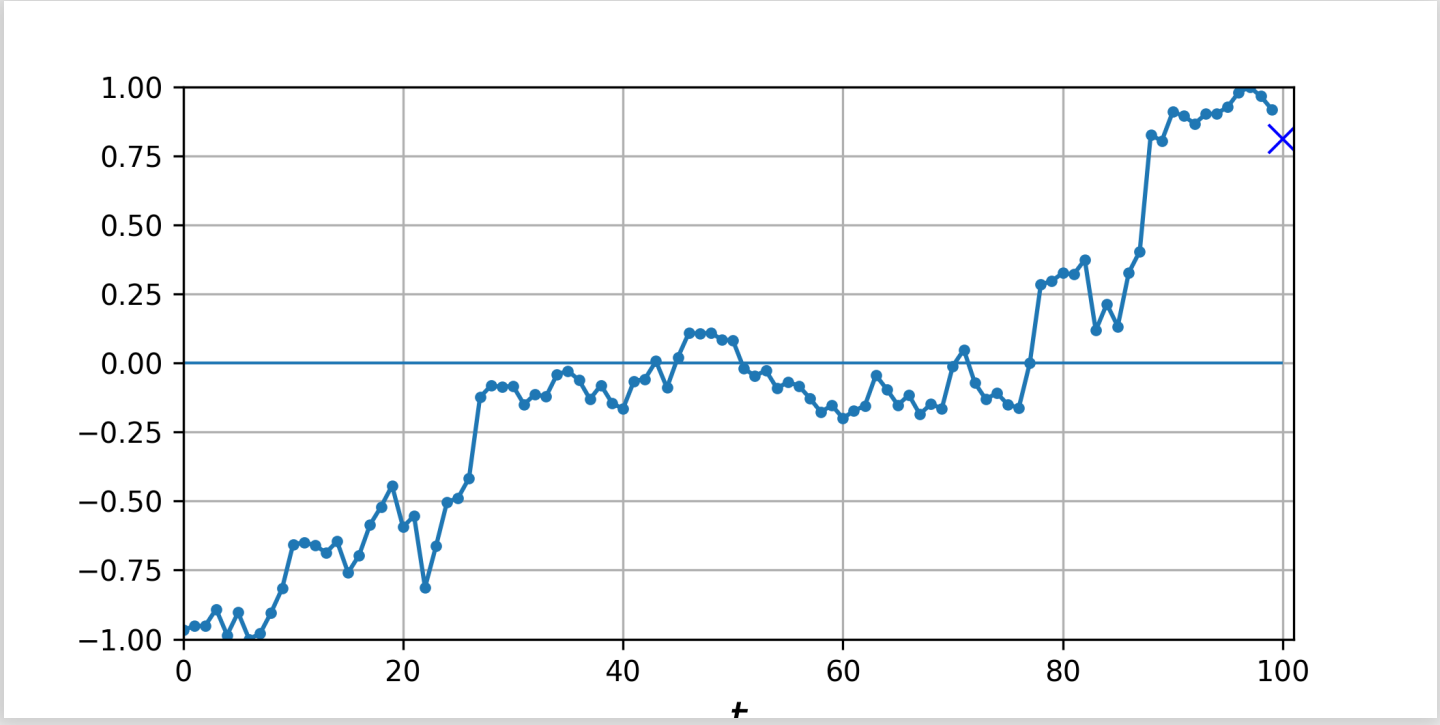
Time keeps moving on

(Janis Joplin)

What would Simone do next?

What would be the price of GOOG tomorrow?

```
df = pd.read_csv("../data/fortune500_100_days.csv")
google = df[df['Fortune500'] == 'GOOG'].values[0][1:]
plot_series(google[:-1], 100, google[-1], y_label='')
plt.show()
```



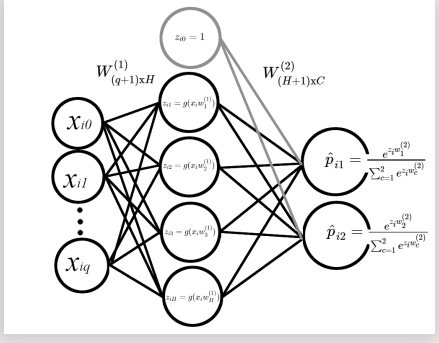
What is he going to say next?

Simple RNN

The Setting

Suppose we have a univariate time series $(x_{i1}, x_{i2}, \ldots, x_{iT})$ of T time steps, where $i = 1, \ldots, N$ (e.g. Fortune $N = 500$ stock price, the last $T = 100$ days), and we want to predict y_i, which could be:

- The next day price (regression setting)
- Positive or negative outcome (classification setting)
- Simone Biles next move (???)

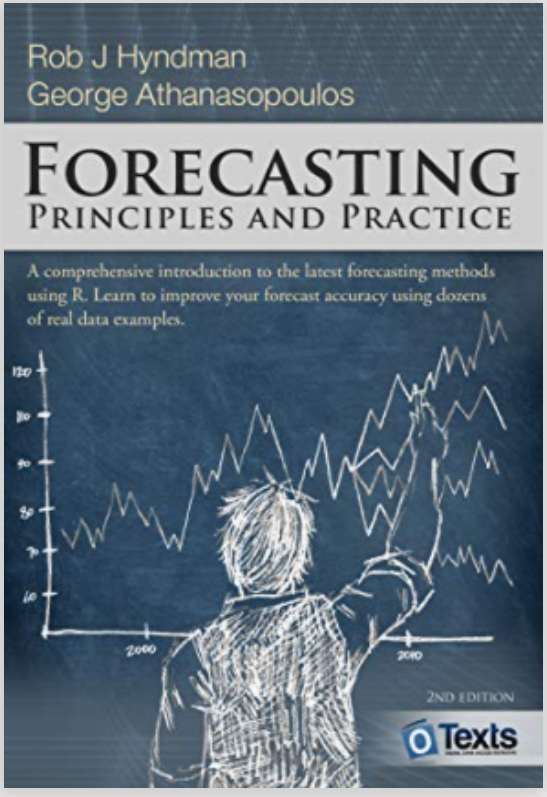


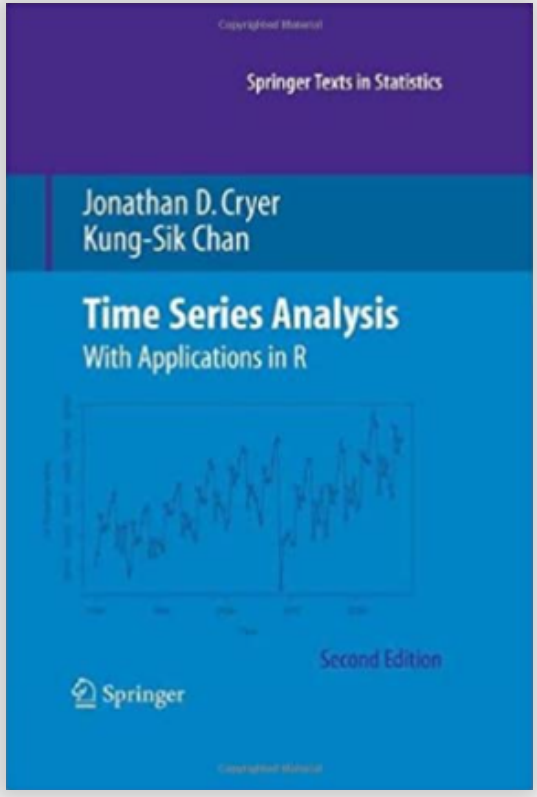
What are the disadvantages of a regular network in this setting?

Detour: Time Series Analysis

Don't invent the wheel!

Time Series Analysis is a big deal in Statistics.



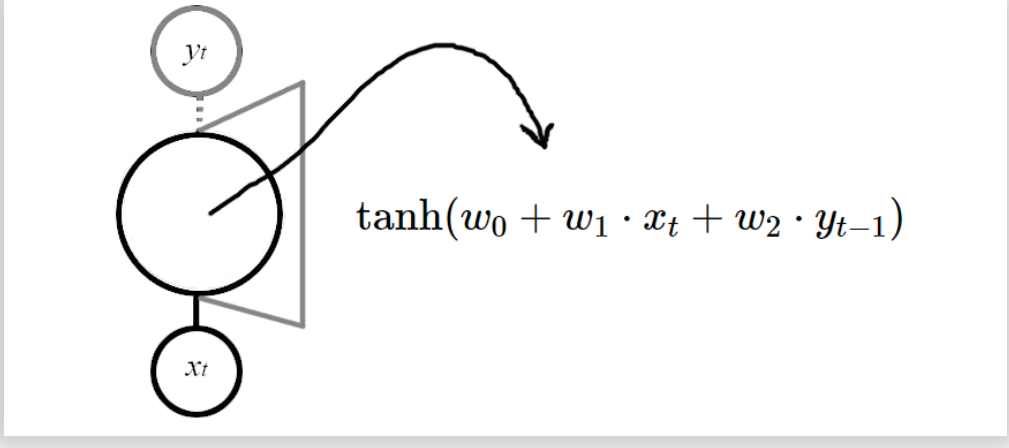


End of Detour

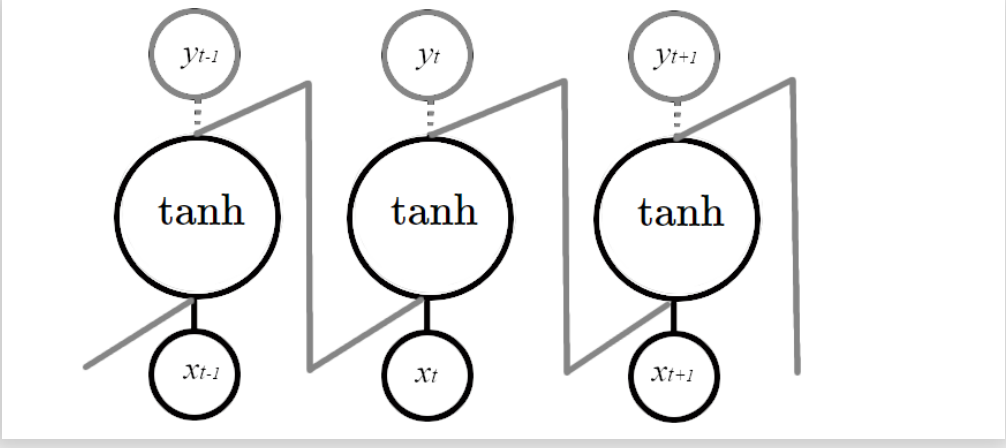
A Single Neuron RNN

The most basic Single-Neuron RNN would:

- take x_t, learn from it and output $\hat{y}_t$
- then take both the next input x_{t+1} and previous output $\hat{y}_t$, learn from them
- by learning we mean forward and backward propagating at each stage with some loss L (e.g. MSE)



Unrolling a Neuron



💡 But how many parameters are we actually learning?

What important NN principle is demonstrated here?

If you build it, they will come.

Remember we built a Logistic Regression NN? Guess what!

At high level nothing changes!

```
def single_rnn(X, y, epochs, alpha):
  w = np.array([1, 1, 1])
  ls = np.zeros(epochs)
  for i in range(epochs):
    l, w = optimize(X, y, alpha, w)
    ls[i] = l
  return ls, w

def optimize(X, y, alpha, w):
  y_pred_arr, l = forward(X, y, w)
  grad = backward(X, y, y_pred_arr, w)
  w = gradient_descent(alpha, w, grad)
  return l, w

def gradient_descent(alpha, w, grad):
  return w - alpha * grad
```

Forward Propagation

$$\hat{y}_1 = \tanh(w_0 + w_1 \cdot x_1 + w2 \cdot y_0)$$

$$\vdots$$

$$\hat{y}_T = tanh(w_0 + w_1 \cdot x_T + w2 \cdot \hat{y}_{T-1})$$

$$L = MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_{iT})^2$$

```
def forward(X, y, w):
  N, T = X.shape
  y_pred_arr = np.zeros((N, T + 1))
  y_pred = np.zeros(N)
  y_pred_arr[:, 0] = y_pred
  for t in range(T):
    y_pred = np.tanh(w[0] + X[:, t] * w[1] + y_pred * w[2])
    y_pred_arr[:, t + 1] = y_pred
  l = np.mean((y - y_pred)**2)
  return y_pred_arr, l
```

Backward Propagation

$$\frac{\partial \hat{y}_{i1}}{\partial w_0} = \frac{\partial \tanh(o_{i1})}{\partial o_{i1}} \frac{\partial o_{i1}}{\partial w_0} = [1 - \tanh^2(o_{i1})] \cdot 1 = 1 - \hat{y}_{i1}^2$$

$$\frac{\partial \hat{y}_{i2}}{\partial w_0} = \frac{\partial \tanh(o_{i2})}{\partial o_{i2}} \frac{\partial o_{i2}}{\partial w_0} = (1 - \hat{y}_{i2}^2)(1 + w_2 \frac{\partial \hat{y}_{i1}}{\partial w_0})$$

$$\vdots$$

$$\frac{\partial L}{\partial w_0} = \sum_{i=1}^{N} \frac{\partial L}{\partial \hat{y}_{iT}} \frac{\partial \hat{y}_{iT}}{\partial w_0} = \sum_{i=1}^{N} -\frac{2}{N}(y_i - \hat{y}_{iT}) \frac{\partial \tanh(o_{iT})}{\partial o_{iT}} \frac{\partial o_{iT}}{\partial w_0} =$$

$$= \sum_{i=1}^{N} -\frac{2}{N}(y_i - \hat{y}_{iT})(1 - \hat{y}_{iT}^2)[1 + w_2 \frac{\partial \hat{y}_{iT-1}}{\partial w_0}]$$

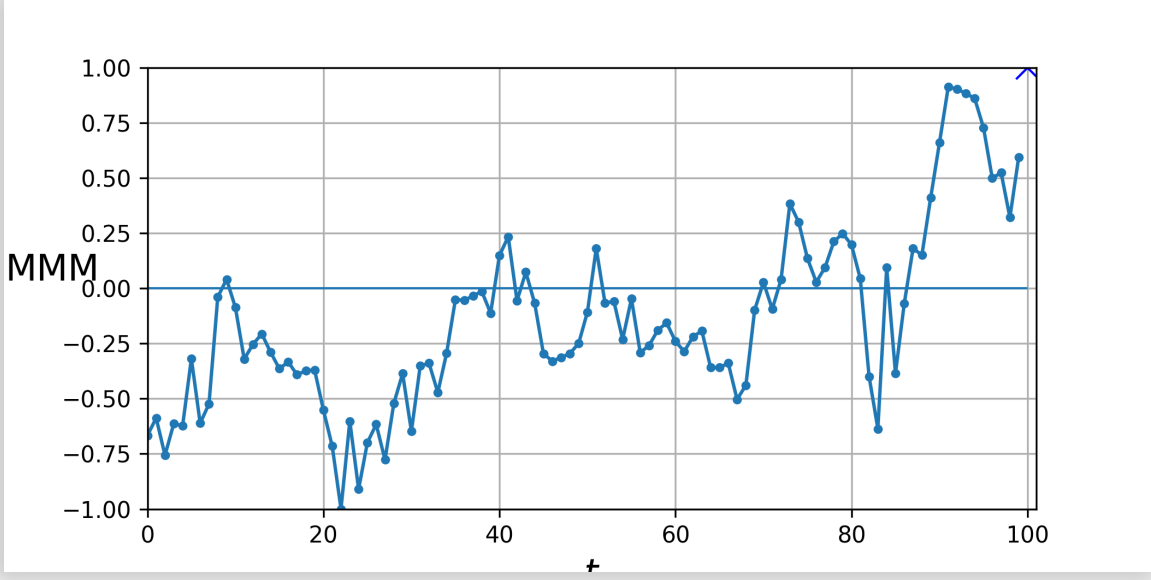
And you are cordially invited to do the same for $\frac{\partial L}{\partial w_1}$ and $\frac{\partial L}{\partial w_2}$.

Hope you have as much fun as I did.

```
def backward_t(X, y_pred_arr, w, grads, t, N):
  y_t = y_pred_arr[:, t]
  if t == 0:
    grads_w0 = np.ones((N, ))
    grads_w1 = X[:, t]
    grads_w2 = y_t
  else:
    dot_dyprev = w[2]
    dyprev_doprev = 1 - y_t ** 2
    grads_w0 = np.ones(N) + dot_dyprev * dyprev_doprev * grads[:,
    grads_w1 = X[:, t] + dot_dyprev * dyprev_doprev * grads[:, 1]
    grads_w2 = y_t + dot_dyprev * dyprev_doprev * grads[:, 2]
  return np.stack([grads_w0, grads_w1, grads_w2], axis=1)

def backward(X, y, y_pred_arr, w):
  N, T = X.shape
  y_pred = y_pred_arr[:, -1]
  dl_dypred = -2 * (y - y_pred) / N
  dypred_doT = 1 - y_pred ** 2
  grads =  np.zeros((N, 3))
  for t in range(T):
    grads = backward_t(X, y_pred_arr, w, grads, t, N)
  for j in range(3):
    grads[:, j] *= dl_dypred * dypred_doT
  final_grads = grads.sum(axis=0)
  return final_grads
```

The Fortune500 Stocks

```
df = pd.read_csv("../data/fortune500_100_days.csv")
X = df.iloc[:, 1:].values
y = X[:, -1]
X = X[:, :-1]

plt.clf()
plot_series(X[1, :], 100, y[1], y_label="MMM")
plt.show()
```



What would be a good MSE?

Predicting with the mean of y (the 101st day mean stock price)

```
np.mean((y - y.mean())**2)
```

```
## 0.3516210190443937
```

Predicting with the last column of X (the 100th day stock price)

```
np.mean((y - X[:, -1])**2)
```

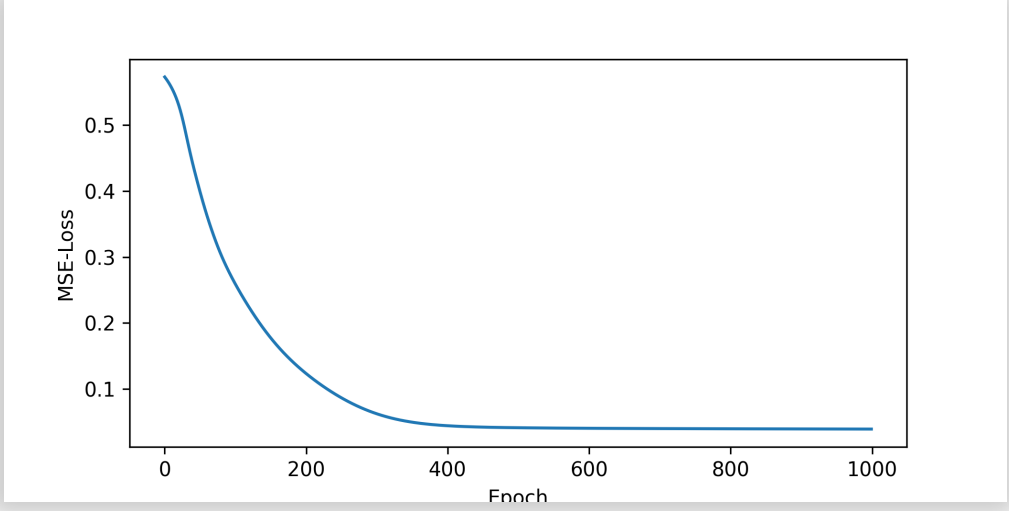
```
## 0.033289150367058463
```

Training with our neuron

```
mses, w = single_rnn(X, y, epochs=1000, alpha=0.01)
print(w)
```

```
## [-0.07161043  1.15476269  0.25800392]
```

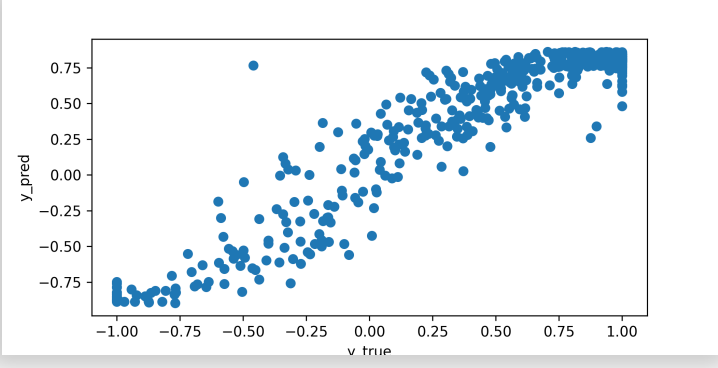
```
plt.plot(mses)
plt.ylabel('MSE-Loss'); plt.xlabel('Epoch')
plt.show()
```



```
y_pred_arr, mse = forward(X, y, w)
y_pred = y_pred_arr[:, -1]
print(mse)
```

```
## 0.03900926352398098
```

```
plt.scatter(y, y_pred)
plt.ylabel('y_pred'); plt.xlabel('y_true')
plt.show()
```



Are you surprised? How could we easily improve?

What would be a better aproach for this simple dataset?

Finally, Keras

```
from tensorflow.keras import Sequential
from tensorflow.keras.layers import SimpleRNN
from tensorflow.keras.optimizers import Adam

model = Sequential([
  SimpleRNN(1, input_shape=(None, 1))
])
model.compile(optimizer=Adam(lr=0.01), loss='mse')

X = X[:, :, np.newaxis]
y = y[:, np.newaxis]

print(X.shape)
```

```
## (502, 100, 1)
```

```
print(y.shape)
```

```
## (502, 1)
```

```
history = model.fit(X, y, epochs=50, verbose=0)
```

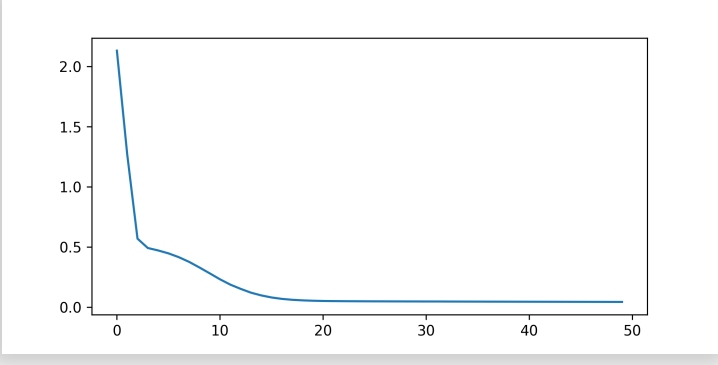
```
print(model.get_weights()[2], model.get_weights()[0], model.get_we
```

```
## [-0.05025313] [[0.8963843]] [[0.44938323]]
```

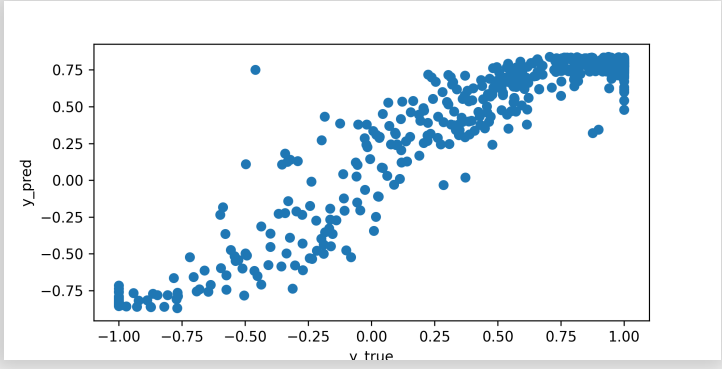
```
y_pred = model.predict(X, verbose=0)
print(np.mean((y - y_pred) **2))
```

```
## 0.04377151881286946
```

```
plt.plot(history.history['loss'])
plt.show()
```



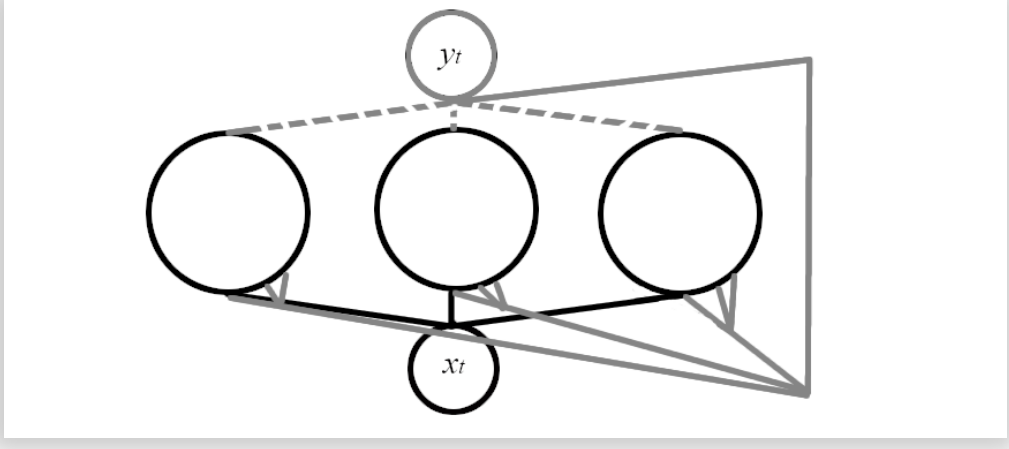
```
plt.scatter(y, y_pred)
plt.ylabel('y_pred'); plt.xlabel('y_true')
plt.show()
```



Add inputs, Add neurons

$$\hat{Y}_t = \tanh(W_0 + X_t \cdot W_1 + \hat{Y}_{t-1} \cdot W_2)$$

- X_t is n batch size X m inputs
- W_1 is m inputs X p neurons
- $\hat{Y}_t$ is n batch size X p neurons
- W_2 is p neurons X p neurons
- W_0 is p X 1 bias vector



Add layers

```
model = Sequential([
  SimpleRNN(10, return_sequences=True, input_shape=[None, 1]),
  SimpleRNN(5, return_sequences=True),
  SimpleRNN(1)
])

model.compile(optimizer=Adam(lr=0.01), loss='mse')
```

```
model.summary()
```

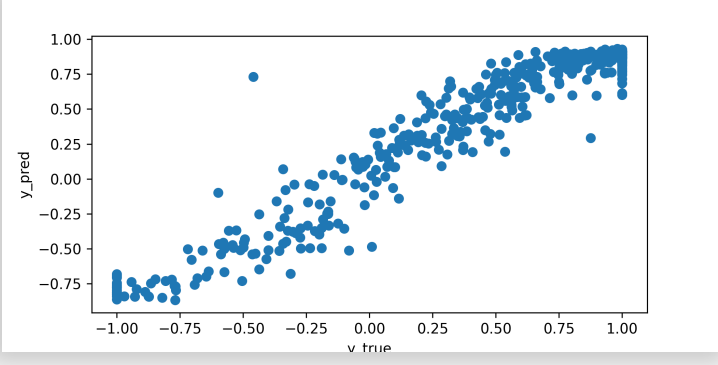
```
## Model: "sequential_1"
## _________________________________________________________________
## Layer (type)                 Output Shape              Param #
## =================================================================
## simple_rnn_1 (SimpleRNN)     (None, None, 10)          120
## _________________________________________________________________
## simple_rnn_2 (SimpleRNN)     (None, None, 5)           80
## _________________________________________________________________
## simple_rnn_3 (SimpleRNN)     (None, 1)                 7
## =================================================================
## Total params: 207
## Trainable params: 207
## Non-trainable params: 0
## _________________________________________________________________
```

- 10 neurons each having: 1 inputs, 1 bias, all other 10 outputs in layer: 10 * (1 + 1 + 10)
- 5 neurons each having: 10 inputs, 1 bias, all other 5 outputs in layer: 5 * (10 + 1 + 5)
- 1 neurons each having: 5 inputs, 1 bias, all other 1 outputs in layer: 1 * (5 + 1 + 1)

```
history = model.fit(X, y, epochs=30, verbose=0)

y_pred = model.predict(X, verbose=0)
print(np.mean((y - y_pred) **2))
```

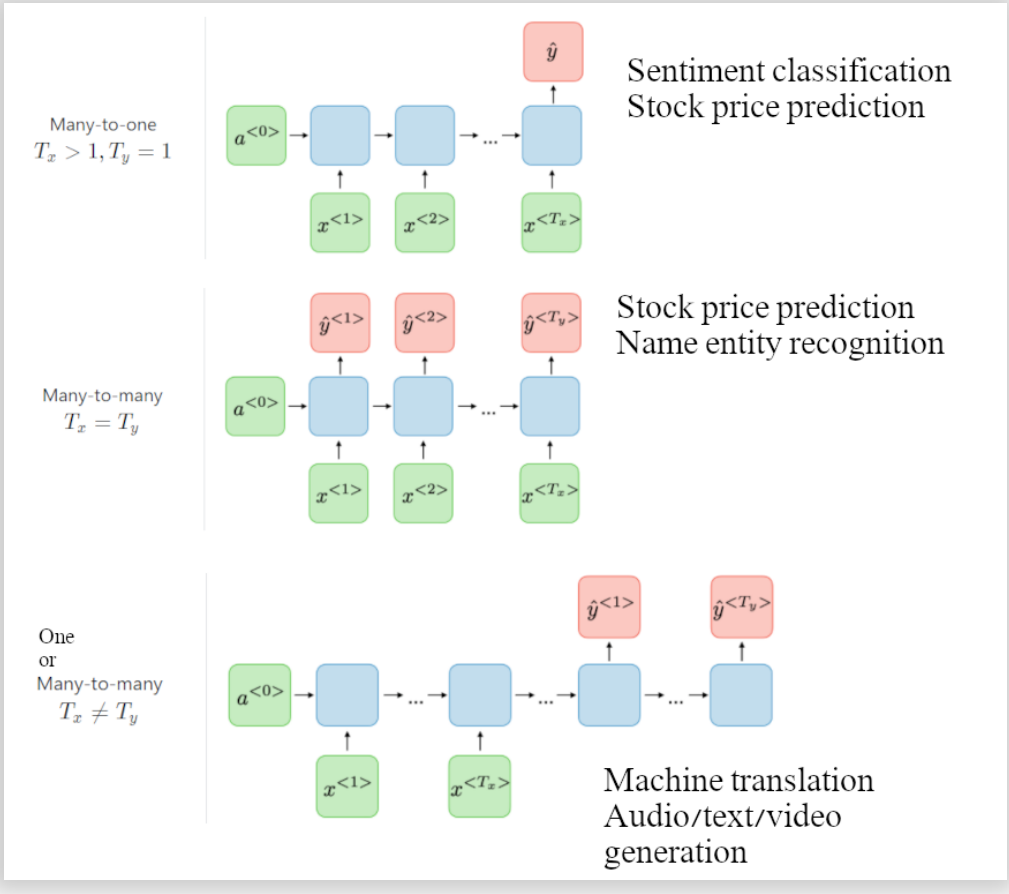
```
## 0.026084491948608103
```

```
plt.scatter(y, y_pred)
plt.ylabel('y_pred'); plt.xlabel('y_true')
plt.show()
```



💡 Though ~200 params for predicting 500 numbers... sounds a bit much.

Possibilities are endless



Source: CS230

Detour: Text is a Time Series!

But we first have to tokenize it

```
from tensorflow.keras.preprocessing import text, sequence

sentences = [
  'I love Stats so much',
  'I love ML too',
  'I love DS',
  'I love NN'
]

tokenizer = text.Tokenizer(num_words = 10)
tokenizer.fit_on_texts(sentences)

print(tokenizer.word_counts)
```

```
## OrderedDict([('i', 4), ('love', 4), ('stats', 1), ('so', 1), ('much', 1)
```

```
print(tokenizer.word_index)
```

```
## {'i': 1, 'love': 2, 'stats': 3, 'so': 4, 'much': 5, 'ml': 6, 'too': 7, '
```

```
print(tokenizer.index_word)
```

```
## {1: 'i', 2: 'love', 3: 'stats', 4: 'so', 5: 'much', 6: 'ml', 7: 'too', 8
```

Then make it a sequence

```
text_sequences = tokenizer.texts_to_sequences(sentences)

print(text_sequences)
```

```
## [[1, 2, 3, 4, 5], [1, 2, 6, 7], [1, 2, 8], [1, 2, 9]]
```

```
X = sequence.pad_sequences(text_sequences,
  padding='post', truncating='post', maxlen=4)

print(X)
```

```
## [[1 2 3 4]
##  [1 2 6 7]
##  [1 2 8 0]
##  [1 2 9 0]]
```

Now we can embed it

```
from tensorflow.keras.layers import Embedding

embed_layer = Embedding(input_dim= (10 + 1), output_dim=3)

print(embed_layer(np.array([1])))
```

```
## tf.Tensor([[ 0.00612465  0.00696361 -0.04569301]], shape=(1, 3), dtype=f
```

```
X_embedded = embed_layer(X)

print(X_embedded.shape)
```

```
## (4, 4, 3)
```

```
print(X_embedded)
```

```
## tf.Tensor(
## [[[ 0.00612465  0.00696361 -0.04569301]
##   [-0.00974723 -0.00407351  0.03557405]
##   [-0.03233683  0.00490437  0.04315286]
##   [-0.03733008  0.03002742 -0.02753231]]
##
##  [[ 0.00612465  0.00696361 -0.04569301]
```

End of Detour

Yelp!

~600K (!) text reviews of shops and restaurants, polarized to negative (1-2 stars) and positive (3-4 stars), 560K in training set.

```
(ds_train, ds_test), ds_info = tfds.load('yelp_polarity_reviews',
  split=['train', 'test'], with_info=True)

df_train = tfds.as_dataframe(ds_train, ds_info)
df_test = tfds.as_dataframe(ds_test, ds_info)
df_test['text'] = df_test['text'].str.decode('utf-8')
df_train['text'] = df_train['text'].str.decode('utf-8')

print(df_train.shape)
print(df_test.shape)
print(df_test.head(3))
```

```
## (560000, 2)

## (38000, 2)

##    label                                               text
## 0      0            Was not impressed, and will not return.
## 1      0  I went in to purchase overalls and was treated...
## 2      0  This place really is horrible... Every time I ...
```

Yelp! But with sequences

```
from sklearn.model_selection import train_test_split

max_features = 10000
seq_len = 100

tokenizer = text.Tokenizer(num_words=max_features)
tokenizer.fit_on_texts(df_train['text'])
text_sequences = tokenizer.texts_to_sequences(df_train['text'])
X = sequence.pad_sequences(text_sequences, padding='post',
  truncating='post', maxlen=seq_len)

X_train, X_test, y_train, y_test = train_test_split(X,
  df_train['label'], test_size = 0.2)

print(X_train.shape)
print(X_test.shape)
```

```
## (448000, 100)

## (112000, 100)
```

In case you're wondering, yes, there are smarter text generators, but even this 0.5M rows `X` matrix is only ~220MB.

Yelp with MLP

Remember there's nothing preventing you from using a simple NN, for (almost) everything:

```
from tensorflow.keras.layers import Dense
from tensorflow.keras.callbacks import EarlyStopping

n_cells = 10
epochs = 100
batch_size = 30
words_embed_dim = 50
callbacks = EarlyStopping(monitor='val_loss', patience=5)

mlp = Sequential([
  Embedding(max_features + 1, words_embed_dim),
  Dense(n_cells, activation='relu'),
  Dense(1, activation='sigmoid')
])

mlp.compile(loss = 'binary_crossentropy',
  optimizer='adam', metrics='accuracy')
```

```
mlp.summary()
```

```
## Model: "sequential_2"
## _________________________________________________________________
## Layer (type)                 Output Shape              Param #
## =================================================================
## embedding_1 (Embedding)      (None, None, 50)          500050
## _________________________________________________________________
## dense (Dense)                (None, None, 10)          510
## _________________________________________________________________
## dense_1 (Dense)              (None, None, 1)           11
## =================================================================
## Total params: 500,571
## Trainable params: 500,571
## Non-trainable params: 0
## _________________________________________________________________
```

```
history = mlp.fit(X_train, y_train, validation_split=0.1, callbac
  batch_size=batch_size, epochs=epochs)

mlp.evaluate(X_test, y_test)
```

```
## [0.6664084792137146, 0.5871875286102295]
```

Yelp with RNN

```
rnn = Sequential([
  Embedding(max_features + 1, words_embed_dim),
  SimpleRNN(n_cells, return_sequences=True),
  SimpleRNN(1, activation='sigmoid')
])

rnn.compile(loss = 'binary_crossentropy',
  optimizer='adam', metrics='accuracy')

rnn.summary()
```

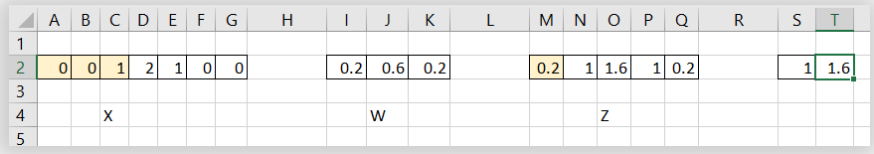
```
## Model: "sequential_3"
## _________________________________________________________________
## Layer (type)                 Output Shape              Param #
## =================================================================
## embedding_2 (Embedding)      (None, None, 50)          500050
## _________________________________________________________________
## simple_rnn_4 (SimpleRNN)     (None, None, 10)          610
## _________________________________________________________________
## simple_rnn_5 (SimpleRNN)     (None, 1)                 12
## =================================================================
## Total params: 500,672
## Trainable params: 500,672
## Non-trainable params: 0
## _________________________________________________________________
```

```
history = rnn.fit(X_train, y_train, validation_split=0.1, callbac
  batch_size=batch_size, epochs=epochs)

rnn.evaluate(X_test, y_test)
```

```
## [0.44967198371887207, 0.8164107203483582]
```

1D Convolution Layers

If you got it in 2D...



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
1																				
2	0	0	1	2	1	0	0		0.2	0.6	0.2		0.2	1	1.6	1	0.2		1	1.6
3																				
4			X							W					Z					
5																				

Or, in a formula: $Z_i = b + \sum_{v=0}^{f_w-1} X_{i-\frac{f_w-1}{2}+v} \cdot W_v$

Or, in Numpy:

```
np.convolve([0,1,2,1,0], [0.2,0.6,0.2][::-1], 'same')
```

```
## array([0.2, 1. , 1.6, 1. , 0.2])
```

> 💡 Why would we want this?

```
from tensorflow.keras.layers import Conv1D

rnn_conv1d = Sequential([
  Embedding(max_features + 1, words_embed_dim),
  Conv1D(filters=5, kernel_size=2, strides=1),
  SimpleRNN(n_cells, return_sequences=True),
  SimpleRNN(1, activation='sigmoid')
])

rnn_conv1d.compile(loss = 'binary_crossentropy',
  optimizer='adam', metrics='accuracy')

rnn_conv1d.summary()
```

```
## Model: "sequential_4"
## _________________________________________________________________
## Layer (type)                 Output Shape              Param #
## =================================================================
## embedding_3 (Embedding)      (None, None, 50)          500050
## _________________________________________________________________
## conv1d (Conv1D)              (None, None, 5)           505
## _________________________________________________________________
## simple_rnn_6 (SimpleRNN)     (None, None, 10)          160
## _________________________________________________________________
## simple_rnn_7 (SimpleRNN)     (None, 1)                 12
## =================================================================
## Total params: 500,727
## Trainable params: 500,727
## Non-trainable params: 0
```

```
history = rnn_conv1d.fit(X_train, y_train, validation_split=0.1, c
  batch_size=batch_size, epochs=epochs)

rnn_conv1d.evaluate(X_test, y_test)
```

```
## [0.4487762749195099, 0.825705349445343]
```

LSTM

RNN Cell has Short Memory

> I hated this bar, though the bartender was so handsome and the drink he made me was absolutely delicious.

The RNN sees `[I, hated, this, bar, ..., so, handsome, ... absolutely, delicious]`.

What do you think it would predict?

Enter Long Short-Term Memory cells (LSTM).

LSTM keeps track of its memory, of its state C_t, by constantly updating how much it needs to:

- forget from previous state: $f_t \cdot C_{t-1}$
- remember from current "candidate" state: $i_t \cdot \tilde{C}_t$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

Where i_t and f_t are "gates" between 0 and 1.

Finally, the state goes through $\tanh()$ activation and another 0-1 gate o_t, and the output is:

$$\hat{Y}_t = o_t \cdot tanh(C_t)$$

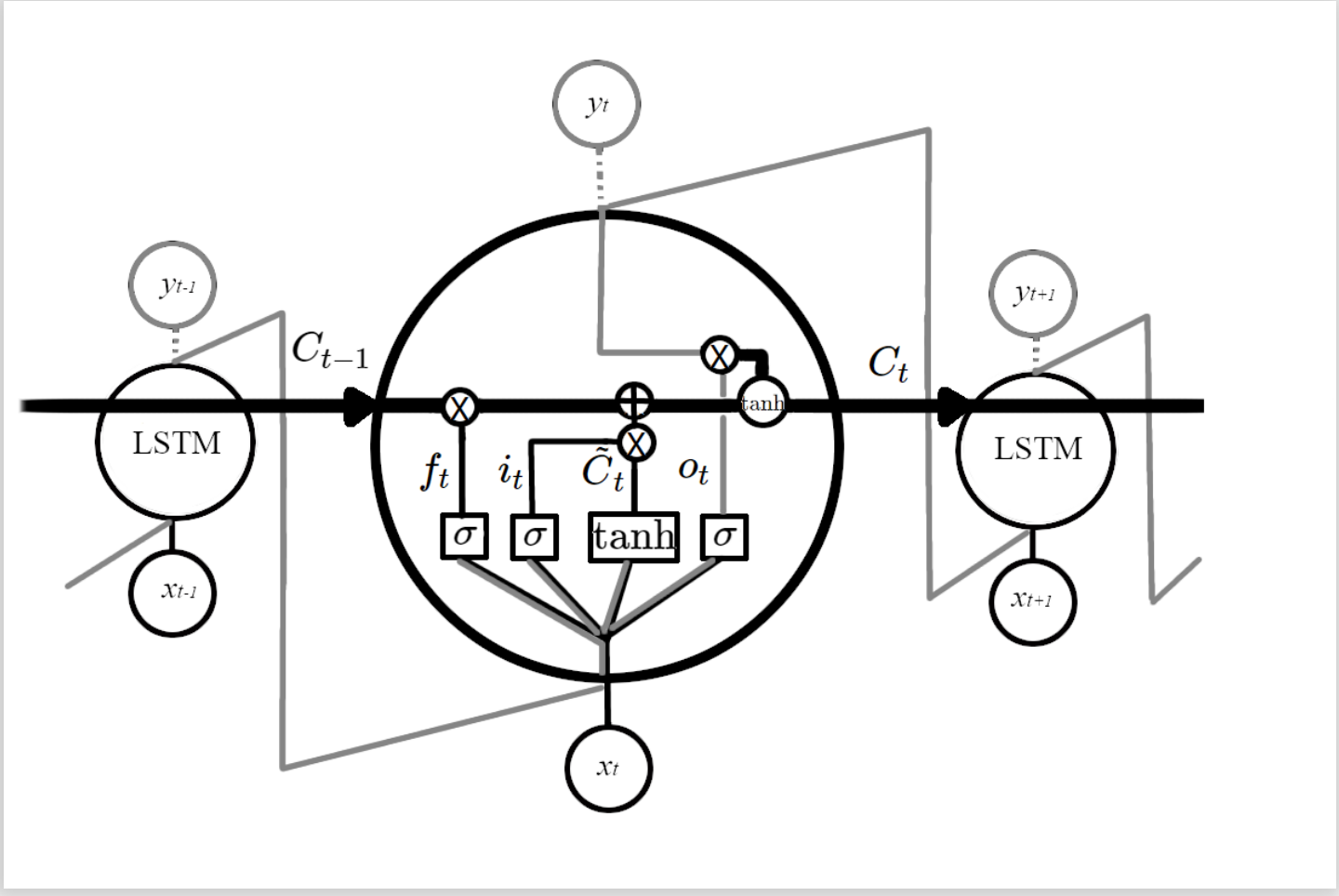
So how do we learn the gates and get $\tilde{C}_t$? Don't panic:

$$f_t = \sigma(W_{0f} + X_t \cdot W_{1f} + \hat{Y}_{t-1} \cdot W_{2f})$$
$$i_t = \sigma(W_{0i} + X_t \cdot W_{1i} + \hat{Y}_{t-1} \cdot W_{2i})$$
$$o_t = \sigma(W_{0o} + X_t \cdot W_{1o} + \hat{Y}_{t-1} \cdot W_{2o})$$

$$\tilde{C}_t = \tanh(W_{0c} + X_t \cdot W_{1c} + \hat{Y}_{t-1} \cdot W_{2c})$$

Where σ is the sigmoid function, shrinking any input to be between 0 and 1.

Or if you prefer a diagram



Yelp with LSTM

```
from tensorflow.keras.layers import LSTM

lstm = Sequential([
  Embedding(max_features + 1, words_embed_dim),
  LSTM(n_cells, return_sequences=True),
  LSTM(1, activation='sigmoid')
])
```

```
## WARNING:tensorflow:Layer lstm_1 will not use cuDNN kernel since it doesn
```

```
lstm.compile(loss = 'binary_crossentropy',
  optimizer='adam', metrics='accuracy')
```

So if RNN layer would have l parameters, LSTM would have...?

```
lstm.summary()
```

```
## Model: "sequential_5"
## _________________________________________________________________
## Layer (type)                 Output Shape              Param #
## =================================================================
## embedding_4 (Embedding)      (None, None, 50)          500050
## _________________________________________________________________
## lstm (LSTM)                  (None, None, 10)          2440
## _________________________________________________________________
## lstm_1 (LSTM)                (None, 1)                 48
## =================================================================
## Total params: 502,538
## Trainable params: 502,538
## Non-trainable params: 0
## _________________________________________________________________
```

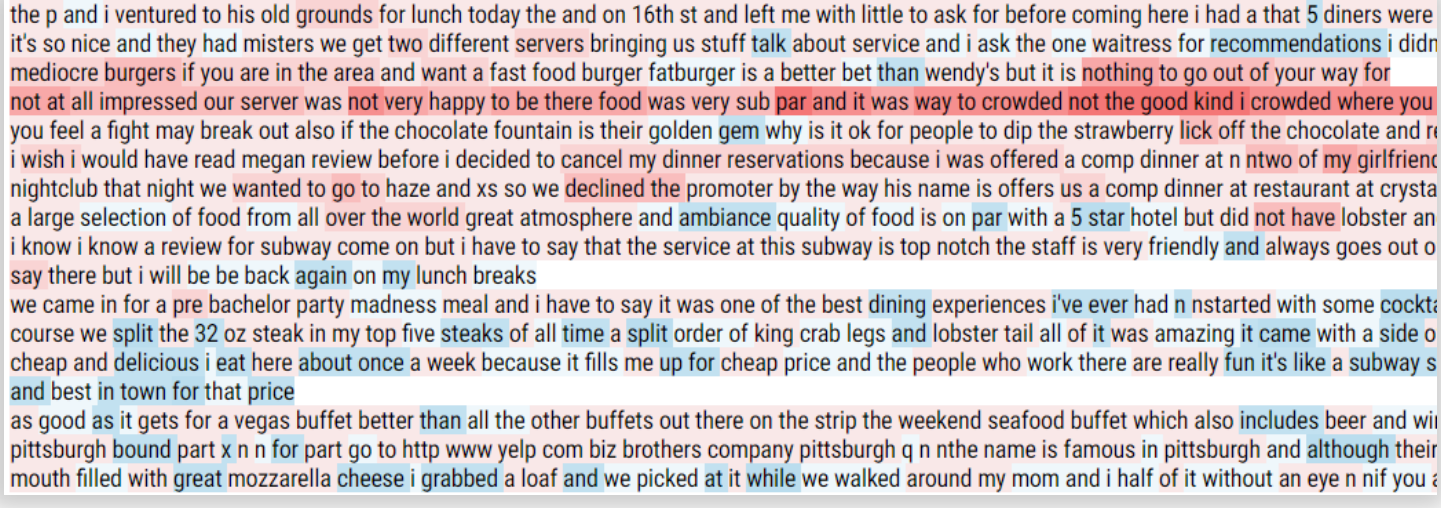
```
history = lstm.fit(X_train, y_train, validation_split=0.1, callbac
  batch_size=batch_size, epochs=epochs)

lstm.evaluate(X_test, y_test)
```

```
## [0.22240985929965973, 0.9227678775787354]
```

Beyond the black box

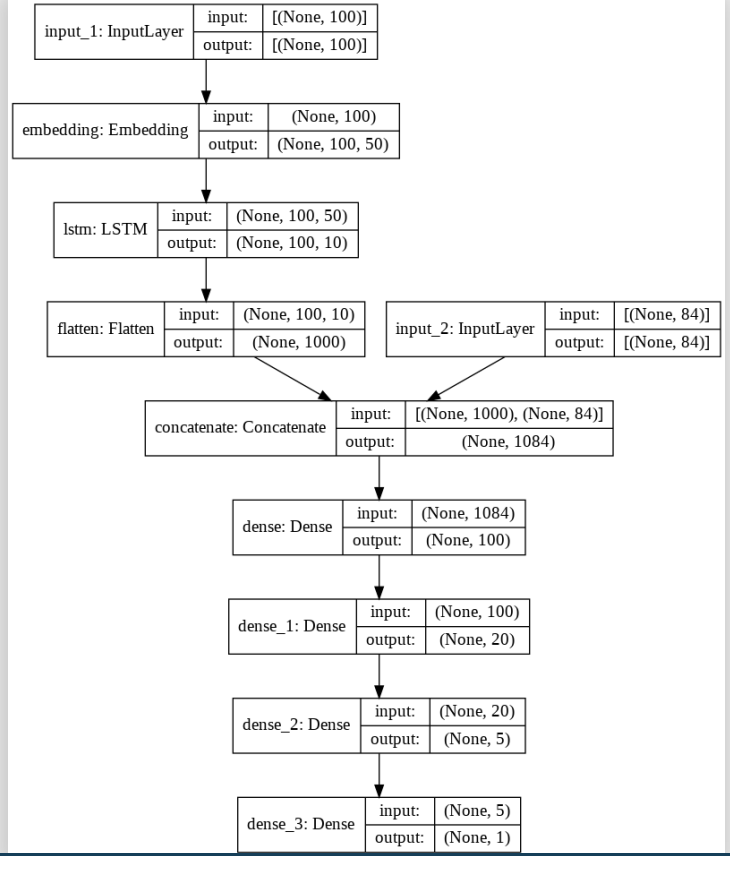
Sending "probes" can help us get what the LSTM is doing. By standardizing an LSTM neuron output to 0-1 and translating this to a cold-hot palette as was done here we can see what turns it on/off.

Here I checked the first neuron for a few test reviews (see full notebook in Colab):



Play with it!

For example, combining LSTM with the old MLP to predict women's shoes price:



Quora!

The Quora Question Pairs dataset has over 400K pairs of questions labeled for whether they're duplicate or not:

```
quora_df = pd.read_csv('../data/quora_small.csv')

quora_df[['question1', 'question2', 'is_duplicate']].head()
```

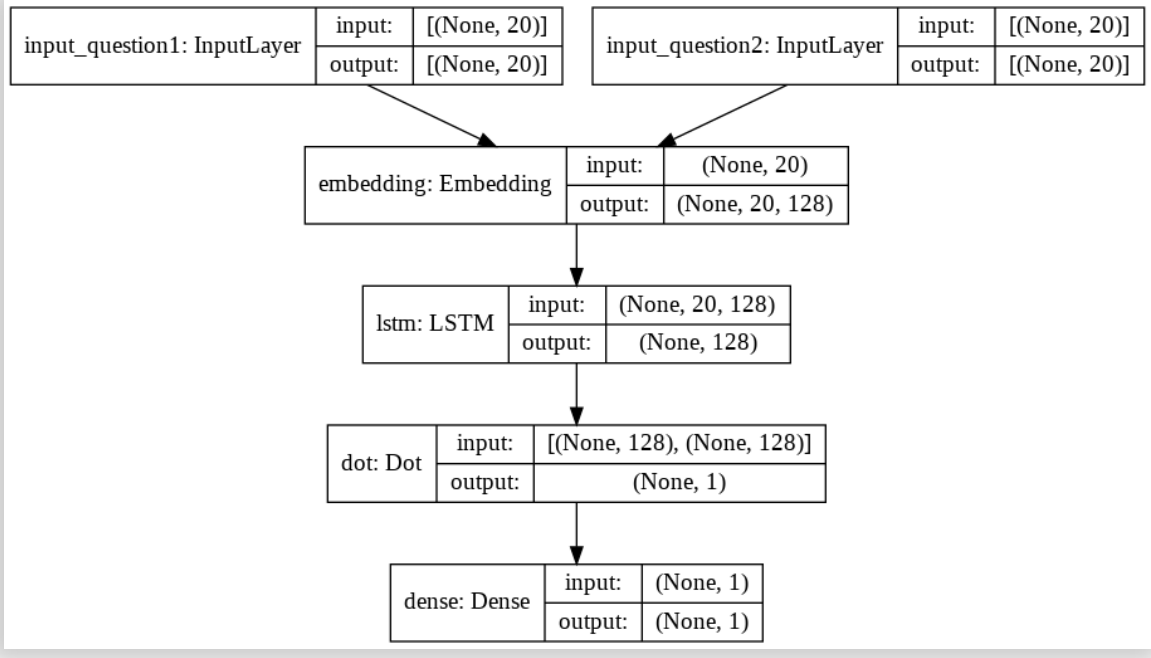
```
##                                                 question1  ... is_duplicate
## 0  What is the step by step guide to invest in sh...  ...             0
## 1  What is the story of Kohinoor (Koh-i-Noor) Dia...  ...             0
## 2  How can I increase the speed of my internet co...  ...             0
## 3  Why am I mentally very lonely? How can I solve...  ...             0
## 4  Which one dissolve in water quikly sugar, salt...  ...             0
##
## [5 rows x 3 columns]
```

```
quora_df['is_duplicate'].mean()
```

```
## 0.38
```

Siamese Recurrent Architecture

Deciding whether two "things" are the same or not is a challenge to any ML system. NN are a great framework for this kind of task through a Siamese architecture, and LSTMs are great for text. We're following RStudio's AI Blog.



```
from tensorflow.keras import Model
from tensorflow.keras.layers import Dot, Input
from tensorflow.keras.regularizers import l2

max_features = 50000
tokenizer = text.Tokenizer(num_words=max_features)
tokenizer.fit_on_texts(quora_df['question1'].append(quora_df['ques

question1 = tokenizer.texts_to_sequences(quora_df['question1'])
question2 = tokenizer.texts_to_sequences(quora_df['question2'])

seq_len = 20
question1_padded = sequence.pad_sequences(question1, maxlen=seq_le
question2_padded = sequence.pad_sequences(question2, maxlen=seq_le

input1 = Input(shape = (seq_len,), name = "input_question1")
input2 = Input(shape = (seq_len, ), name = "input_question2")

word_embedder = Embedding(
  input_dim = max_features + 2, output_dim = 128,
  input_length = seq_len,
  embeddings_regularizer = l2(0.0001)
)

seq_embedder = LSTM(units = 128,
  kernel_regularizer = l2(0.0001)
)
```

```
vector1 = seq_embedder(word_embedder(input1))
vector2 = seq_embedder(word_embedder(input2))

cosine_similarity = Dot(axes=1)([vector1, vector2])

output = Dense(1, activation = 'sigmoid')(cosine_similarity)

model = Model(inputs = [input1, input2], outputs = output)
model.compile(optimizer = 'adam', loss = 'binary_crossentropy', me
```

```
# messy print, see notebook in Colab
model.summary()
```

```
train_sample, val_sample = train_test_split(quora_df.index, test_s

train_question1_padded = question1_padded[train_sample,]
train_question2_padded = question2_padded[train_sample,]
train_is_duplicate = quora_df['is_duplicate'][train_sample]

val_question1_padded = question1_padded[val_sample,]
val_question2_padded = question2_padded[val_sample,]
val_is_duplicate = quora_df['is_duplicate'][val_sample]

history = model.fit(
  [train_question1_padded, train_question2_padded],
  train_is_duplicate,
  batch_size = 64,
  epochs = 100,
  callbacks = [EarlyStopping(monitor='val_loss', patience=5, resto
  validation_data = ([val_question1_padded, val_question2_padded],
)

model.evaluate(([val_question1_padded, val_question2_padded], val_
```

```
## [0.43971124291419983, 0.8325954079627991]
```

Save the model, put this function in the most basic Shiny/Dash app, and...

```
def predict_question_pairs(model, tokenizer, q1, q2):
    q1 = tokenizer.texts_to_sequences([q1])
    q2 = tokenizer.texts_to_sequences([q2])

    q1 = sequence.pad_sequences(q1, maxlen=seq_len, value = max_fe
    q2 = sequence.pad_sequences(q2, maxlen=seq_len, value = max_fe

    return model.predict([q1, q2])[0][0]

predict_question_pairs(
  model,
  tokenizer,
  "What does a LSTM do?",
  "How does a LSTM work?"
)
```

```
## 0.5638776
```