



## Working with Sequences



# Advanced ML with TensorFlow on GCP

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End-to-End Lab on Structured Data ML

Production ML Systems

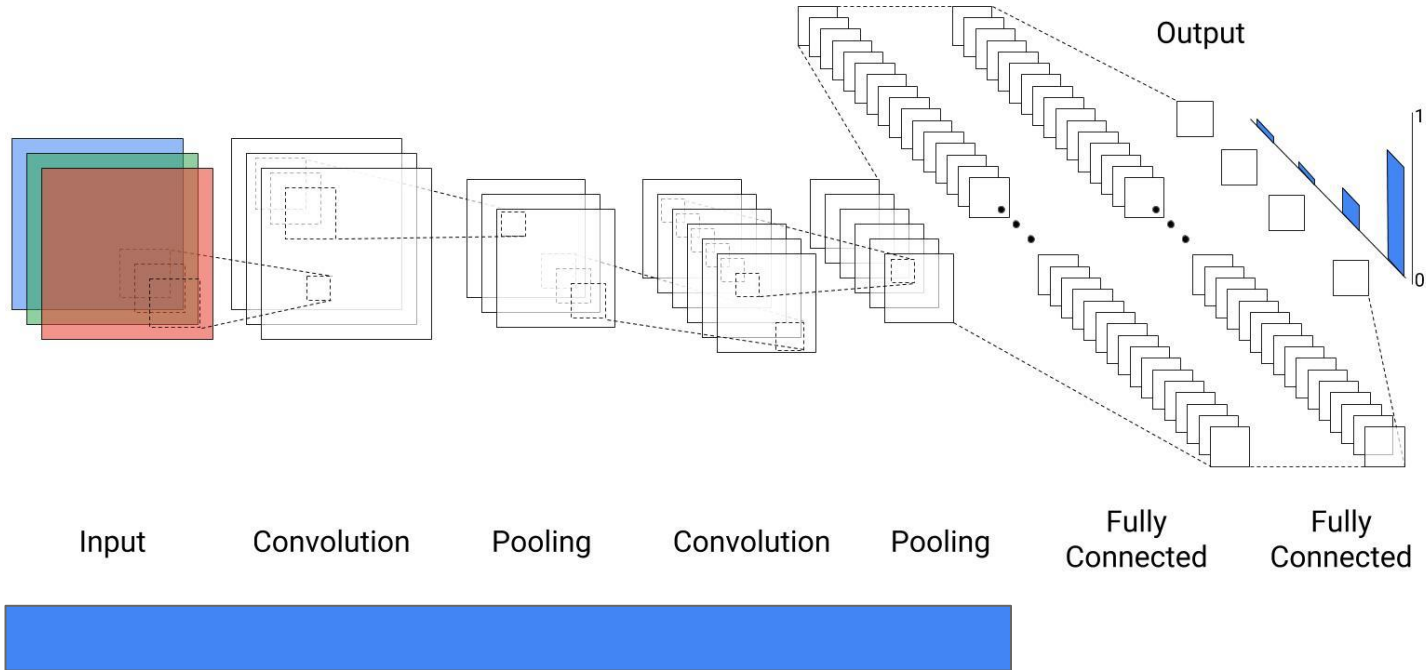
Image Classification Models

**Sequence Models**

Recommendation Systems



# Recall: CNNs as feature extractors

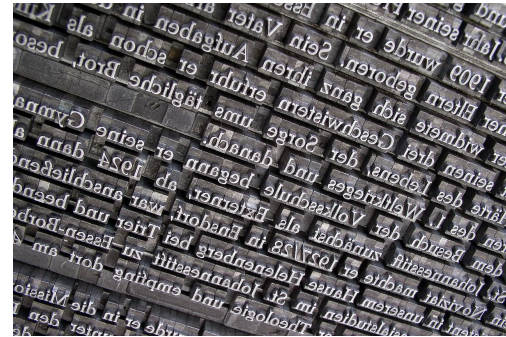
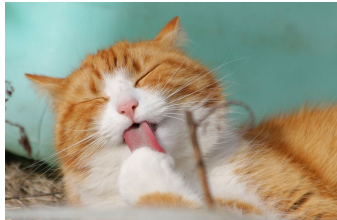


# Sequences are another common and important domain



The cat ate the mouse

Le chat a mangé la souris ∅



# Learn how to...

---

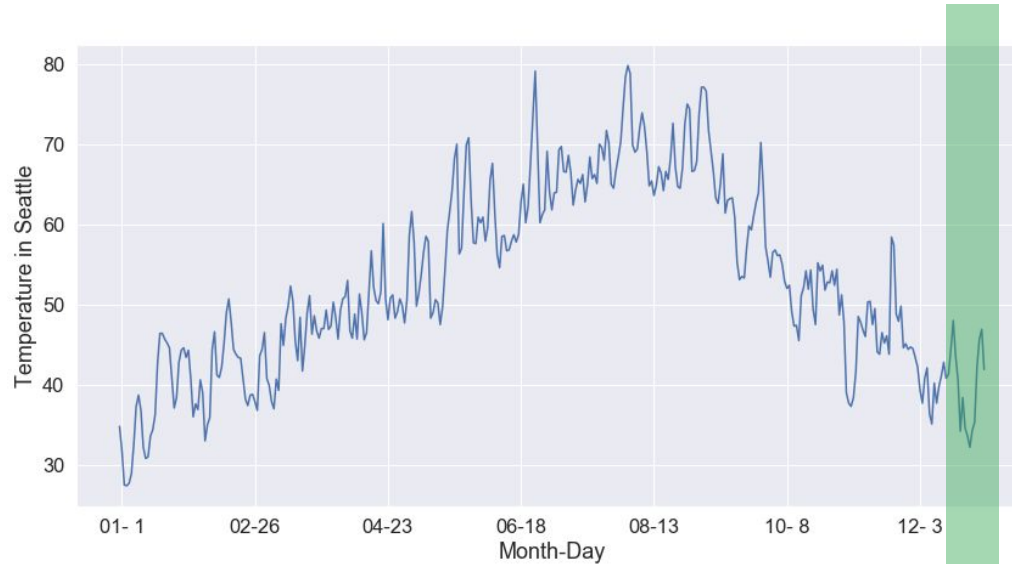
Define what sequence data is

Prepare sequence data for modeling

Apply classical approaches to sequence modeling



# What is a sequence?



Temperature (F)	...	Pressure (mBar)	Order
45	...	1105	1
62	...	976	2



# Predicting coin flips



Value	Time
heads	9:01:05am
tails	9:01:18am
heads	9:01:24am
...	...

Is this sequence data?

- A. Yes
- B. No



# Predicting coin flips



Value	Time
heads	9:01:05am
tails	9:01:18am
heads	9:01:24am
...	...

Is this sequence data?

A. Yes

B. No





# Coin flips



t1



t2



t3



t4

# What about natural language?

Is this sequence data?

A. Yes

B. No

Word	Order
The	1
language	2
spoken	3
in	4
France	5
is	6



# What about natural language?

Is this sequence data?

A. Yes

B. No

Word	Order
The	1
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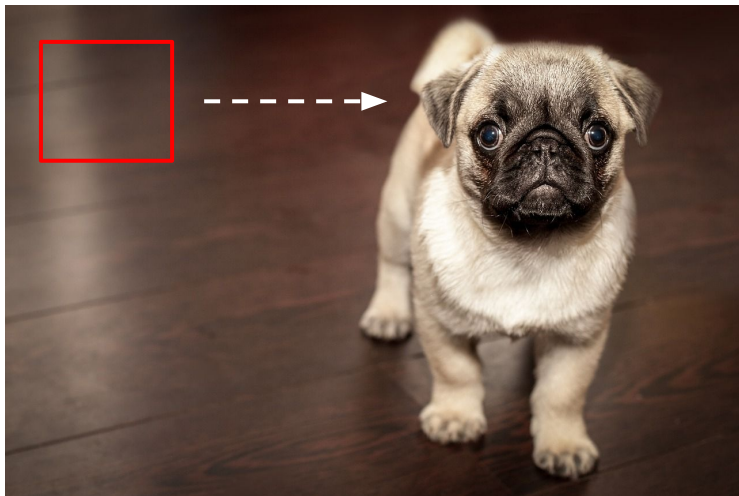
# Can we treat image data as a sequence?



Pixel RGB value	Pixel position
[255,255,0]	[0,0]
[255,0,255]	[0,1]
...	...



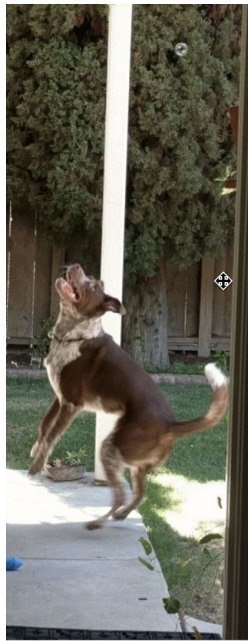
Images and traditional sequences are still similar in one respect



# Movies are sequences



t1



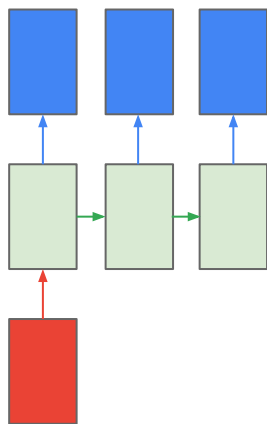
t2



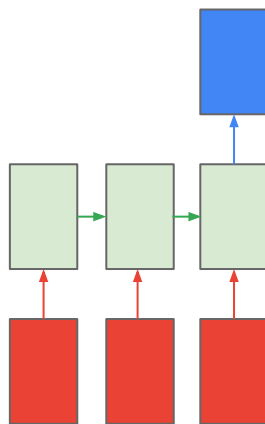
t3



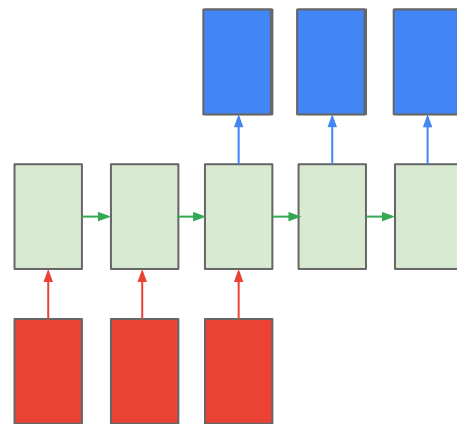
# Types of sequence models



One-to-sequence



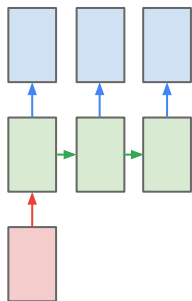
Sequence-to-one



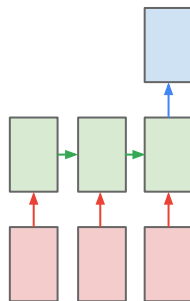
Sequence-to-sequence



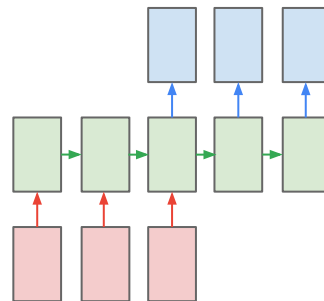
# What sort of problem is translation?



One-to-sequence



Sequence-to-one

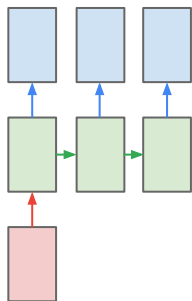


Sequence-to-sequence

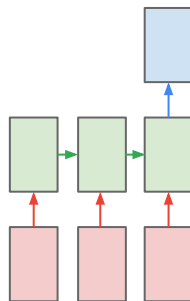




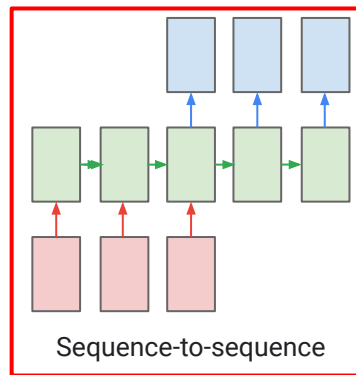
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Sequence-to-one

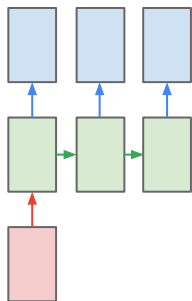


Sequence-to-sequence

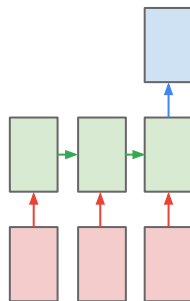
# What sort of problem is image captioning?



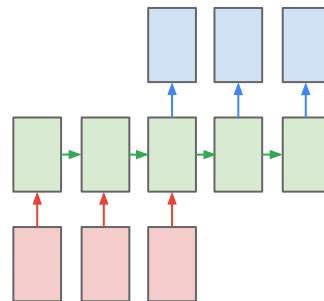
**Two hockey players are fighting over the puck.**



One-to-sequence



Sequence-to-one



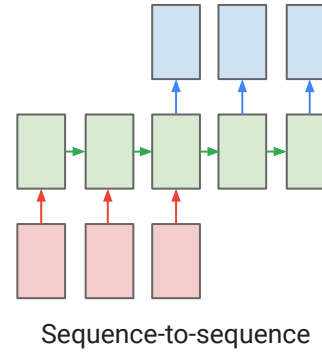
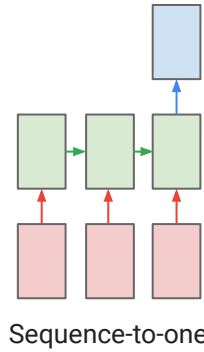
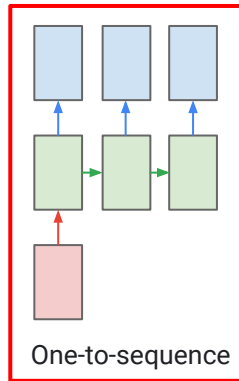
Sequence-to-sequence



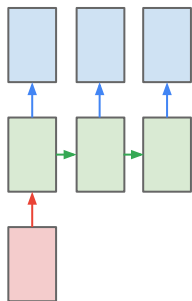
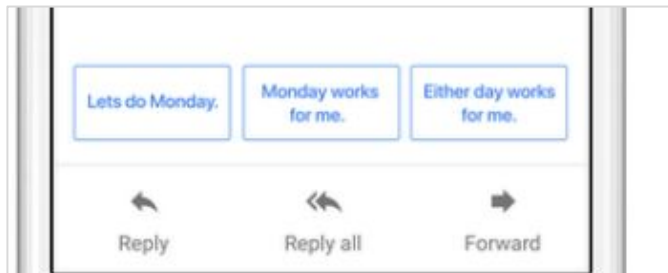
# What sort of problem is image captioning?



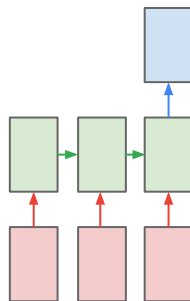
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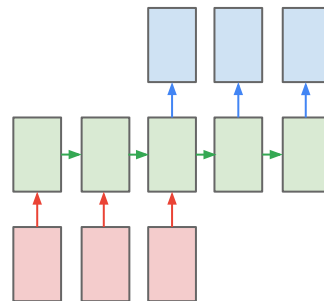
# What sort of problem is Smart Reply?



One-to-sequence

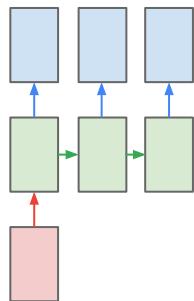
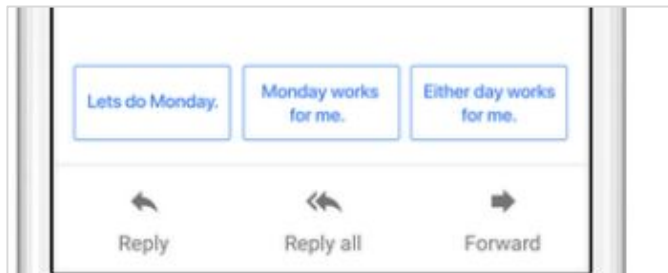


Sequence-to-one

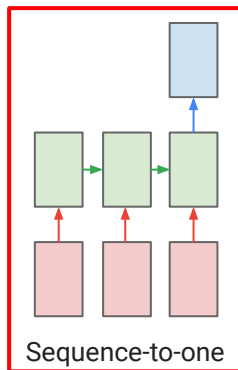


Sequence-to-sequence

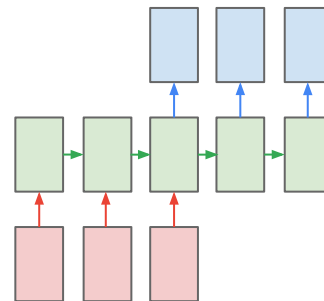
# What sort of problem is Smart Reply?



One-to-sequence



Sequence-to-one



Sequence-to-sequence

# What about “Predict the next X” models?

Recommended videos to watch:



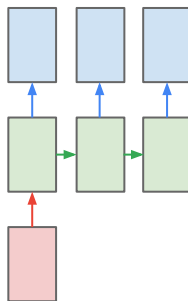
**Migrating your data warehouse to Google BigQuery: Lessons**

Google Cloud Platform  
5.6K views

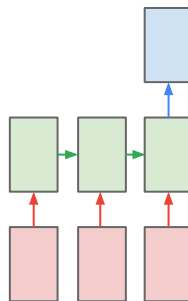


**Adding Machine Learning to your applications**

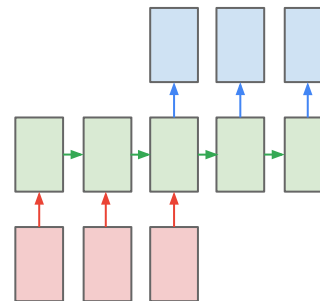
Google Cloud Platform  
21K views



One-to-sequence



Sequence-to-one



Sequence-to-sequence



# What about “Predict the next X” models?

Recommended videos to watch:



**Migrating your data warehouse to Google BigQuery: Lessons**

Google Cloud Platform  
5.6K views

1:01:52

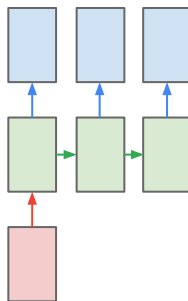


**Adding Machine Learning to your applications**

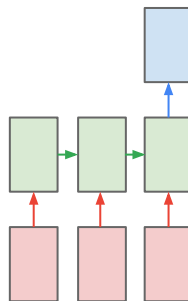
Google Cloud Platform  
21K views

39:01

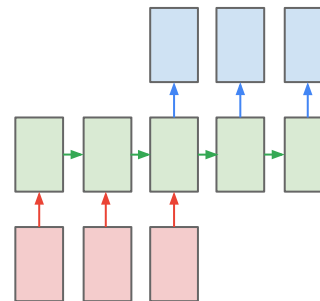
Many possible models!



One-to-sequence



Sequence-to-one



Sequence-to-sequence



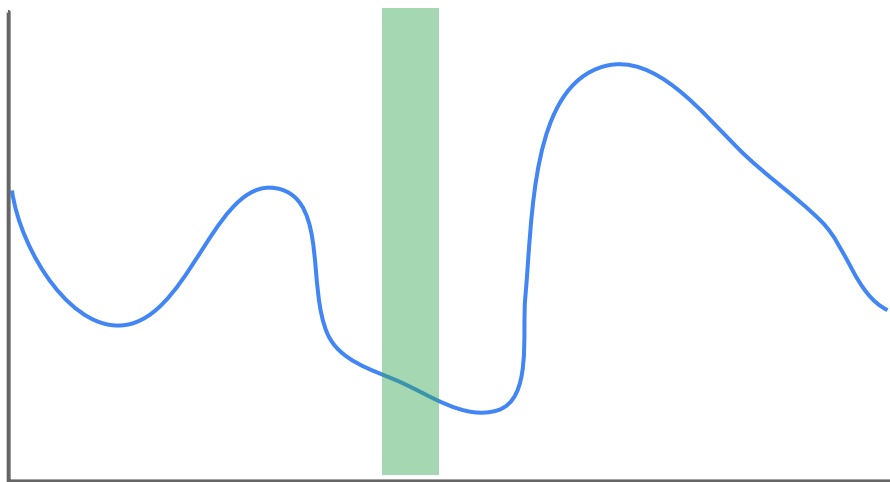
# Observing events as a sequence

Temperature (F)	...	Pressure (mBar)	Ordering Feature
45	...	1105	1
62	...	976	2

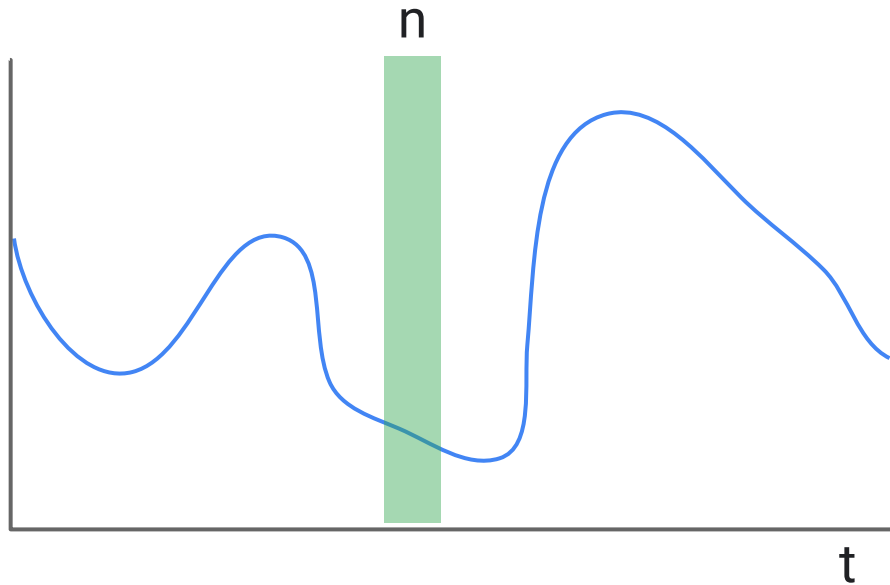




# Observing events as a sequence



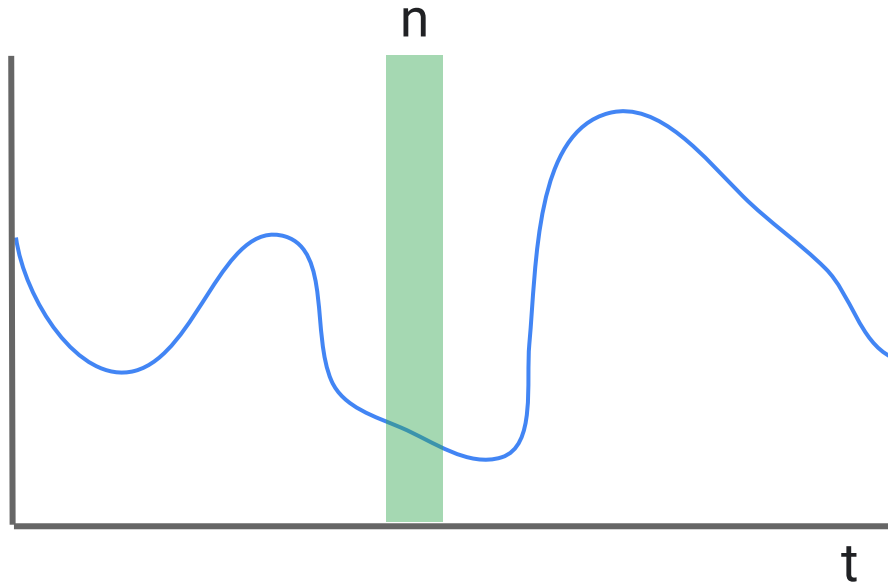
Quiz: How many rows will there be in our training set?



- A.  $t$
- B.  $\max(0, t - n + 1)$
- C.  $t - n$
- D.  $\max(0, t + n)$



Quiz: How many rows will there be in our training set?



A.  $t$

B.  $\max(0, t - n + 1)$

C.  $t - n$

D.  $\max(0, t + n)$

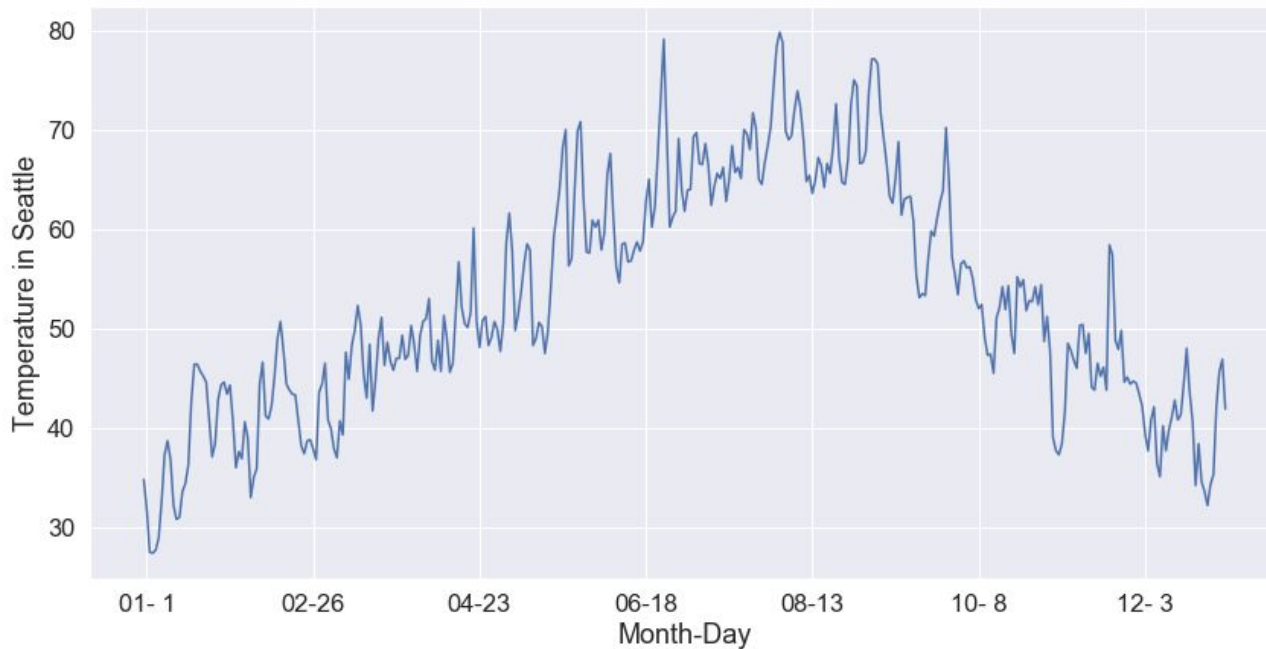


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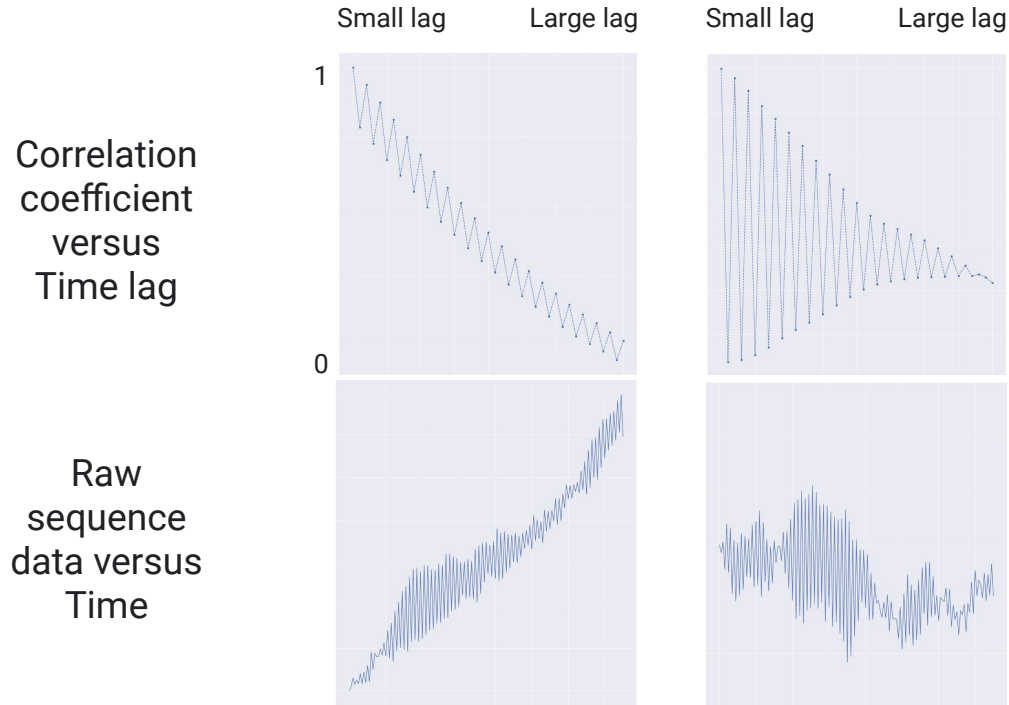
Price 10 minutes prior	...	Price 1 minute prior	Price
$t_0$	...	$t_9$	$t_{10}$
$t_1$	...	$t_{10}$	$t_{11}$
$t_2$	...	$t_{11}$	$t_{12}$
...	...	...	...
$t_{\text{seqlen}-10}$	...	$t_{\text{seqlen}-1}$	$t_{\text{seqlen}}$



# What's a good size for our sliding window?



# Autocorrelation graphs can reveal dependencies



# Quiz: Sometimes dependencies are known

## Assuming that:

1. You knew the data were periodic.
2. Rotation speed and water pressure were constant.
3. The sprinkler completed 1 rotation/minute.

What would be a good choice for sliding window length?



- A. 1 minute
- B. 30 seconds
- C. 2 minutes
- D. As long as possible



# Quiz: Sometimes dependencies are known

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First try a linear model

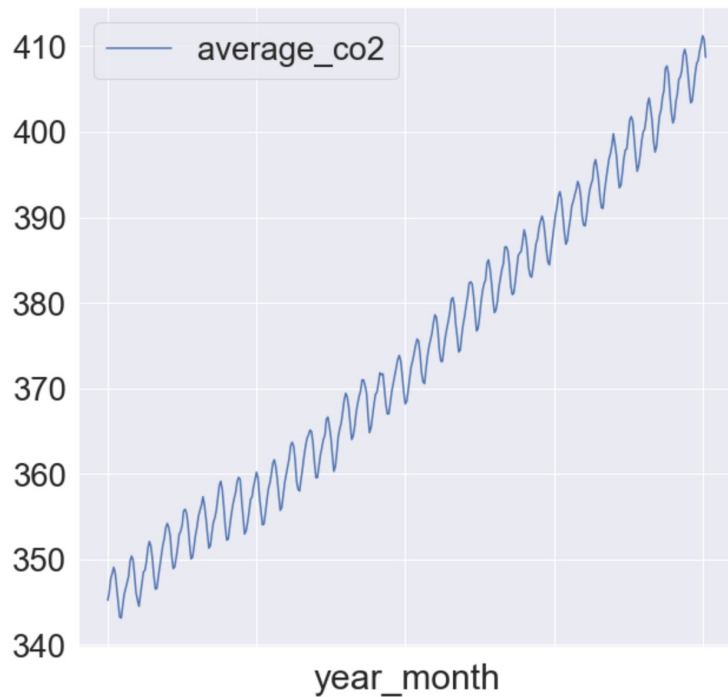


# Generating synthetic sequence data

```
def create_time_series():  
    freq = (np.random.random()*0.5) + 0.1 # 0.1 to 0.6  
    ampl = np.random.random() + 0.5 # 0.5 to 1.5  
    # -0.3 to +0.3 uniformly distributed  
    noise = [np.random.random()*0.3 for i in xrange(SEQ_LEN)]  
    x = np.sin(np.arange(0,SEQ_LEN) * freq) * ampl + noise  
    return x
```



# Real-world sequences are more complicated



# Each file consists of a comma-delimited string

```
def to_csv(filename, N):  
    with open(filename, 'w') as ofp:  
        for lineno in xrange(0, N):  
            seq = create_time_series()  
            line = ",".join(map(str, seq))  
            ofp.write(line + '\n')
```

```
train.csv  
0.13,0.52,0.76,0.71,0.63,0.29,0.15,-0.23,-0.34,-0.38  
0.27,0.32,0.63,0.63,0.8,0.75,0.63,0.23,0.18,-0.23  
0.3,0.49,0.87,1.08,1.17,1.25,1.46,1.52,1.65,1.46
```



# Creating an input function

```
def read_dataset(filename, mode, batch_size=512):
    def _input_fn():
        def decode_csv(row):
            # row is a string tensor containing the contents of one row
            features = tf.decode_csv(row, record_defaults=DEFAULTS)
            # string tensor -> list of 50 rank 0 float tensors
            label = features.pop() # remove last feature and use as label
            features = tf.stack(features) # list of rank 0 tensors -> single rank 1 tensor
            return {TIMESERIES_COL: features}, label

        # Create list of file names that match "glob" pattern (i.e. data_file_*.csv)
        dataset = tf.data.Dataset.list_files(filename)
        # Read in data from files
        dataset = dataset.flat_map(tf.data.TextLineDataset)
        # Parse text lines as comma-separated values (CSV)
        dataset = dataset.map(decode_csv)
        ...
    return _input_fn
```



# Compare model performance

```
eval_metric_ops = {  
    "RMSE": rmse,  
    "RMSE_same_as_last": same_as_last_benchmark(features, labels),  
}  
  
# RMSE when predicting same as last value  
def same_as_last_benchmark(features, labels):  
    predictions = features[TIMESERIES_COL][:,-1] # last value in input sequence  
    return tf.metrics.root_mean_squared_error(labels, predictions)
```



# Defining a linear model for time series prediction

```
def linear_model(features, mode, params):  
    X = features[TIMESERIES_COL]  
    predictions = tf.layers.dense(X, 1, activation=None)  
    return predictions
```



# Lab

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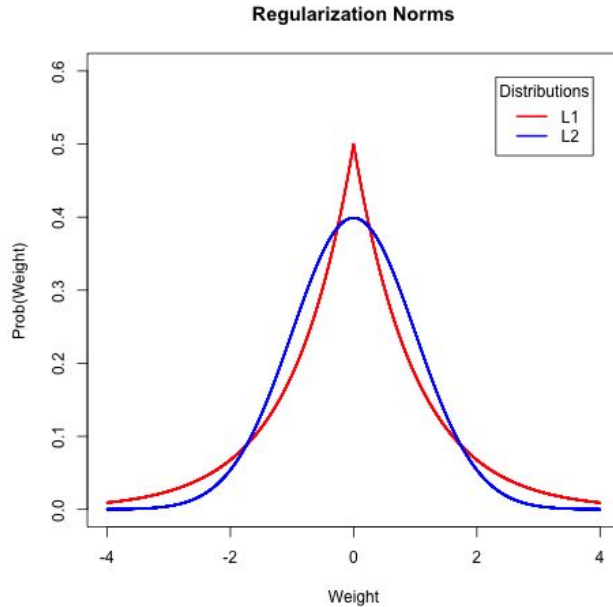
## Using linear models for sequences

In this lab you will be creating a linear model by completing the TODO steps in the `model.py` in your lab notebook.





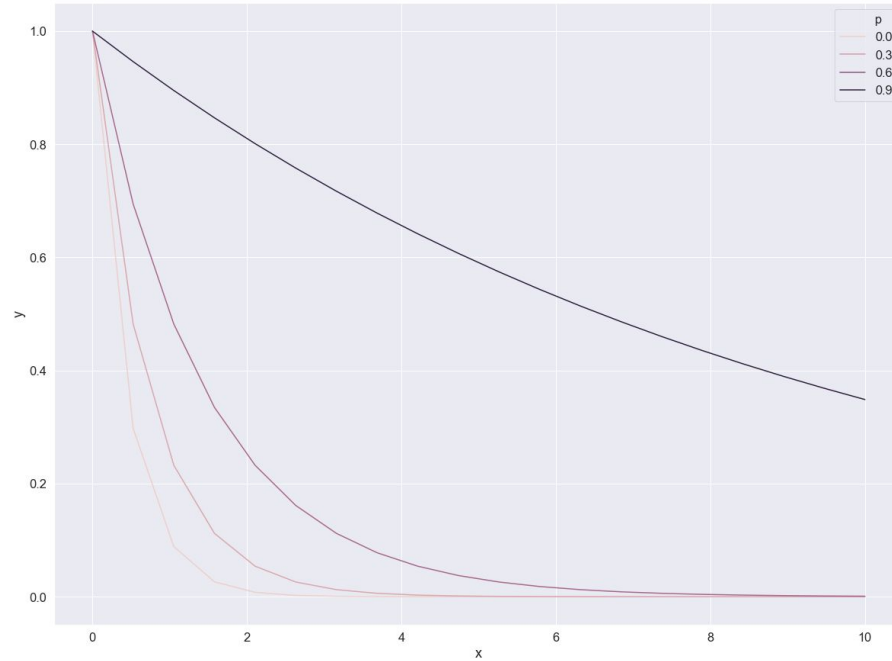
Sometimes, it's important that models capture aspects of the real world



Regularization can constrain for sparsity.



# Constrain the weights for better performance



Autoregressive ARMA models use moving averages

$$X_t = c + \sum_{i=1}^p \varphi_i X_{t-1} + \varepsilon_t$$



# Defining a DNN model for time series prediction

```
def dnn_model(features, mode, params):  
    X = features[TIMESERIES_COL]  
    h1 = tf.layers.dense(X, 10, activation=tf.nn.relu)  
    h2 = tf.layers.dense(h1, 3, activation=tf.nn.relu)  
    predictions = tf.layers.dense(h2, 1, activation=None)  
    return predictions
```



# Lab

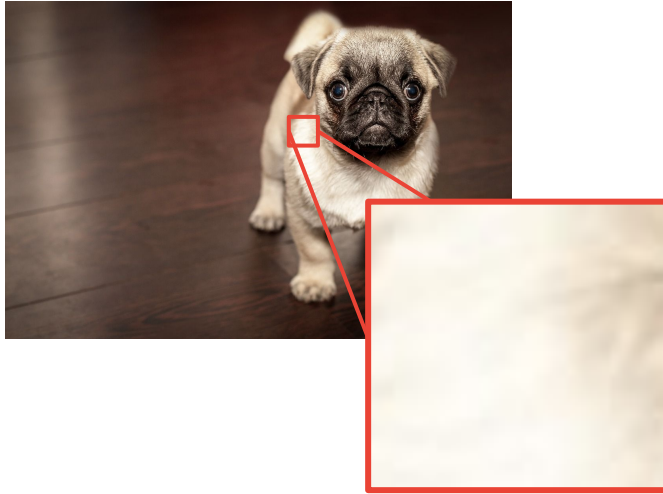
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## Using DNNs for sequences

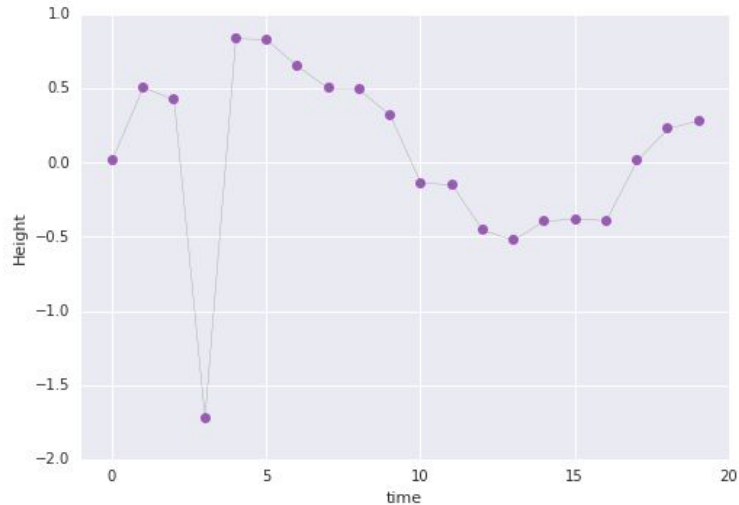
In this lab you will be using TensorFlow Hub to create re-usable embeddings.



# Locality is important for images and sequences



Quiz: Which convolution filters would be highly active at  $t = 4$ ?

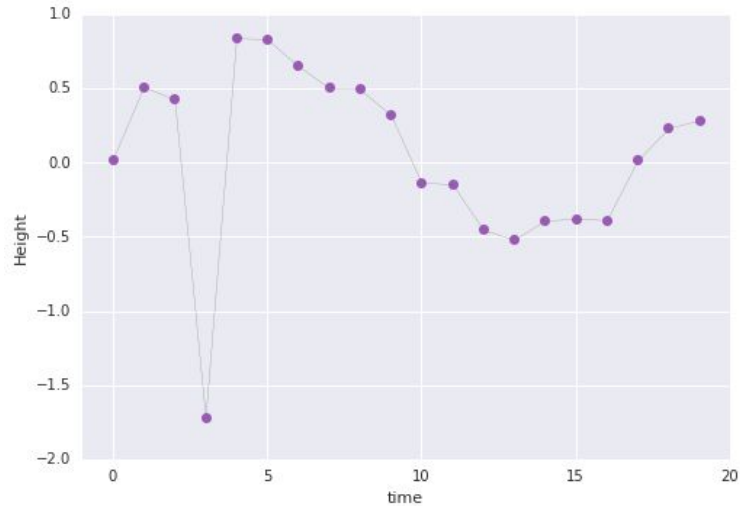


- A. [.5, .5, .5, .5]
- B. [.33, -.67, .33]
- C. [1.2, 1.0, .75, 1.0]
- D. [1.2, 1.0, -.75, 1.0]

Choose all that could apply.



Quiz: Which convolution filters would be highly active at  $t = 4$ ?



A.  $[.5, .5, .5, .5]$

B.  $[.33, -.67, .33]$

C.  $[1.2, 1.0, .75, 1.0]$

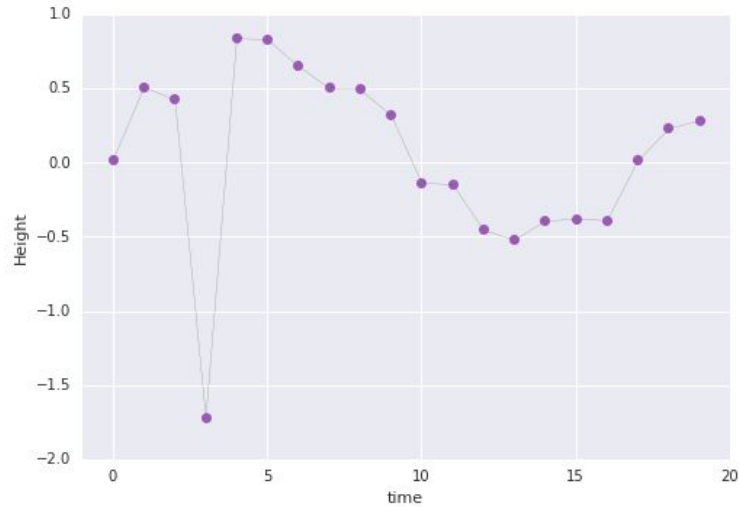
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Choose all that could apply.

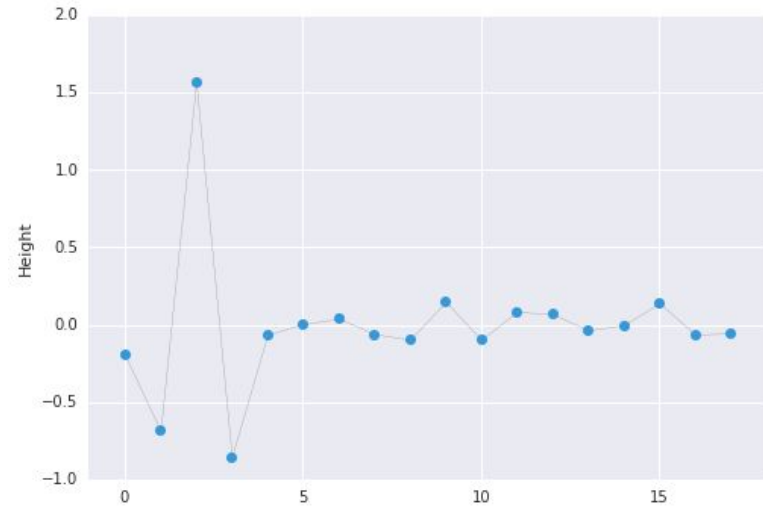




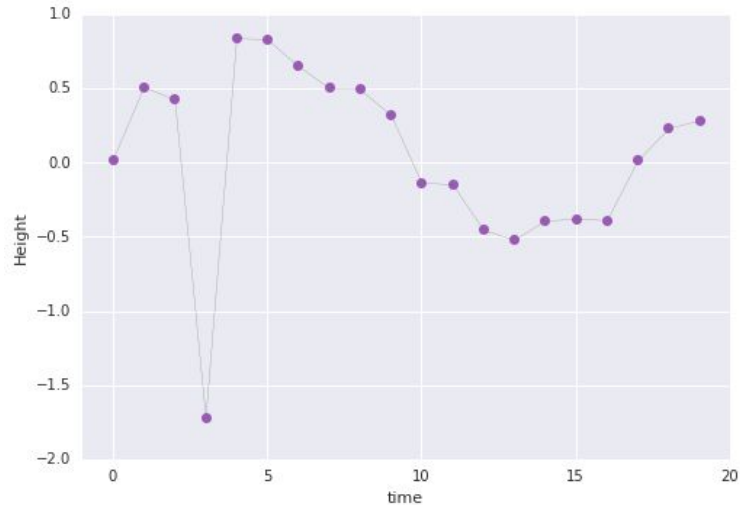
# Convolutional filters are pattern matchers



After convolving  $[.33, -.67, .33]$



Quiz: Of those that were active, which is more specific?



A. [.5, .5, .5, .5]

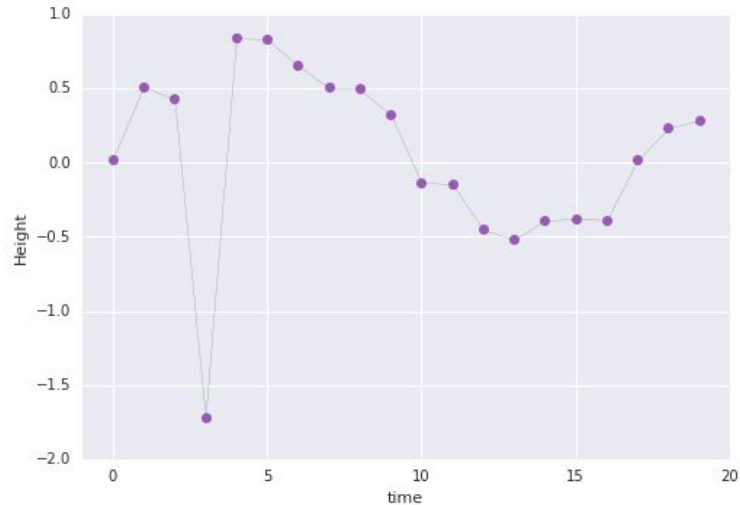
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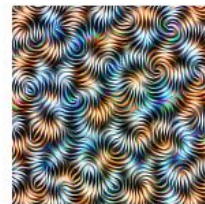
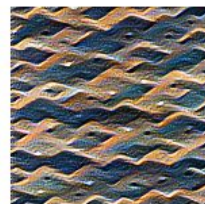
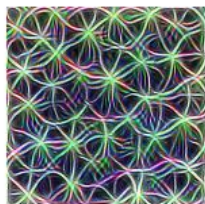
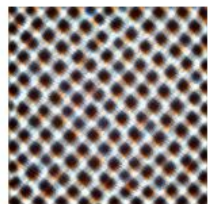
B. [.33, -.67, .33]

C. [1.2, 1.0, .75, 1.0]

D. [1.2, 1.0, -.75, 1.0]



# CNNs learn a hierarchy of features



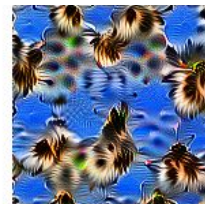
Bookshelves



Dog eyes



Text, rivets

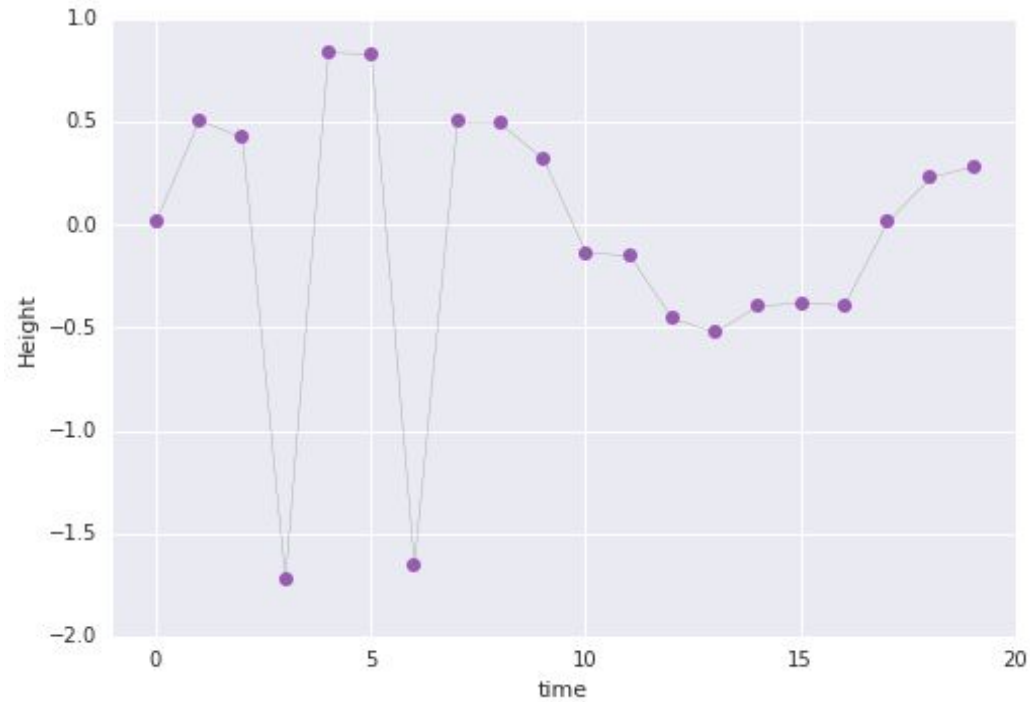


Birds

NETWORK DEPTH



# Detecting two quick drops



# Steps in applying a convolution

- 1 Flatten the input sequence.
- 2 Use `conv1d` to apply a number of filters to the sequence.
- 3 Use `max_pooling1d` to add some spatial invariance and downscaling.
- 4 Flatten the resulting output into a sequence.
- 5 Send it through a fully connected layer with the appropriate output node.



# Applying convolutions in TensorFlow

```
def cnn_model(features, mode, params):  
    X = tf.reshape(features[TIMESERIES_COL], [-1, N_INPUTS, 1]) # ?x10x1  
    c1 = tf.layers.max_pooling1d(  
        tf.layers.conv1d(X, filters=N_INPUTS//2,  
                        kernel_size=3, strides=1, # ?x10x5  
                        padding='same', activation=tf.nn.relu),  
        pool_size=2, strides=2  
    ) # ?x5x5  
    outlen = (N_INPUTS//2) * (N_INPUTS//2)  
    c1flat = tf.reshape(c1, [-1, outlen])  
    h1 = tf.layers.dense(c1flat, 3, activation=tf.nn.relu)  
    return tf.layers.dense(h1, 1, activation=None)
```



# Lab

---

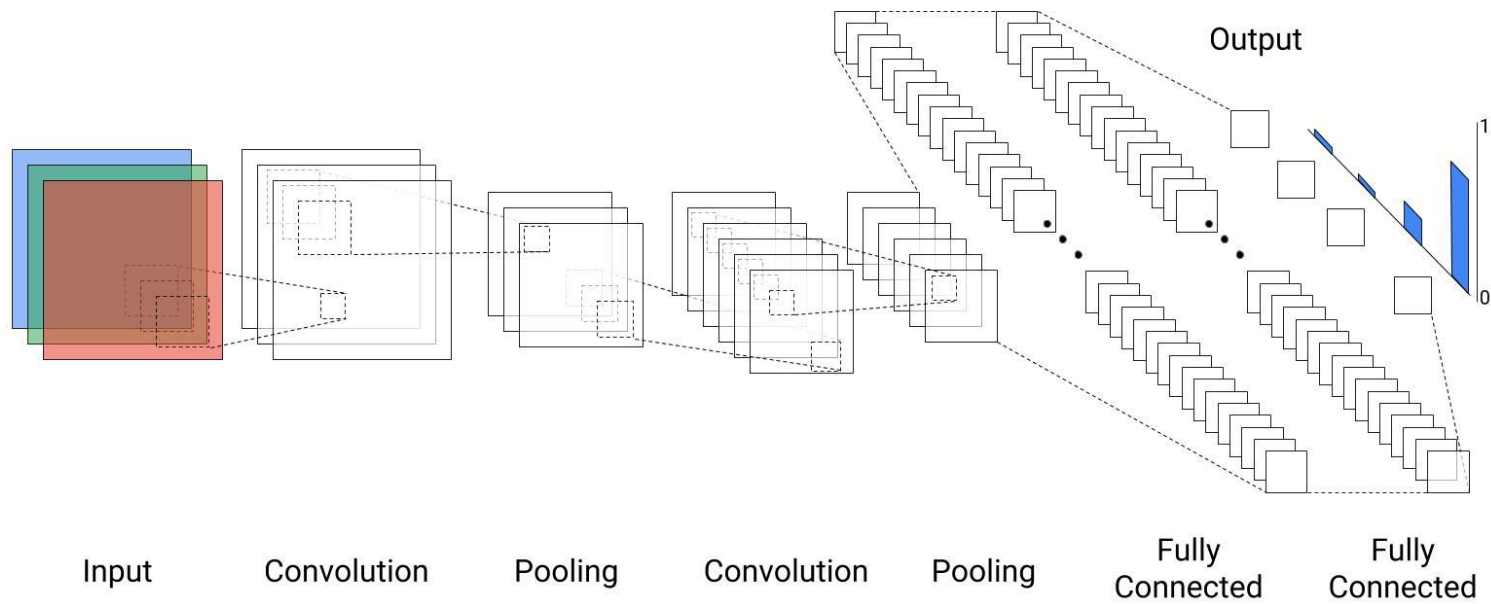
## Using CNNs for sequences

In this lab you will complete  
TODOs in `model.py` for a CNN  
model.

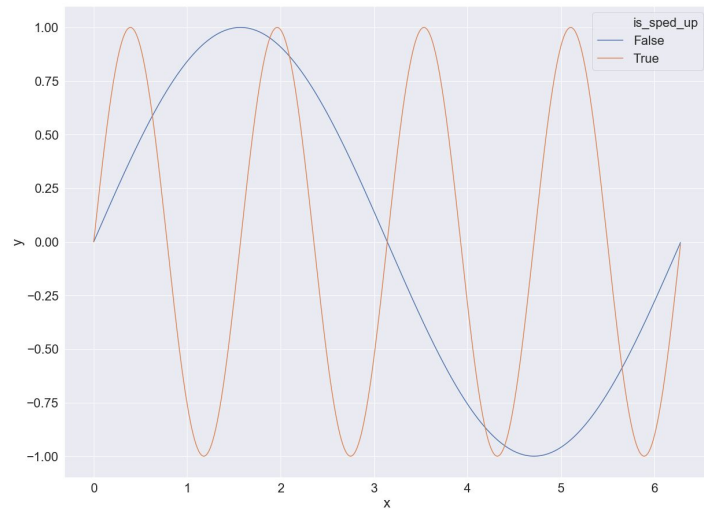




# Why didn't our CNN do much better than our DNN?



# The limitations of CNNs



# Handling variable length inputs and outputs

Customer 1



Customer 2



t1

t2

t3

t4

t5

t6



# Handling variable length inputs and outputs

1 Cutting and padding

2 Bagging



## Example: Predicting oil prices

Hour	Price
1	2
2	4
3	6
4	8
5	10
...	...

4 Hours Prior	3 Hours Prior	2 Hours Prior	1 Hour Prior	Label
2	4	6	8	10
...	...	...	...	...

$$w = \left[ \frac{1}{6}, \frac{1}{3}, \frac{1}{2}, \frac{2}{3} \right]$$



# How do we handle a shorter input?

4 Hours Prior	3 Hours Prior	2 Hours Prior	1 Hour Prior
3	6	9	12



# Padding

Pad	3 Hours Prior	2 Hours Prior	1 Hour Prior
0	6	9	12

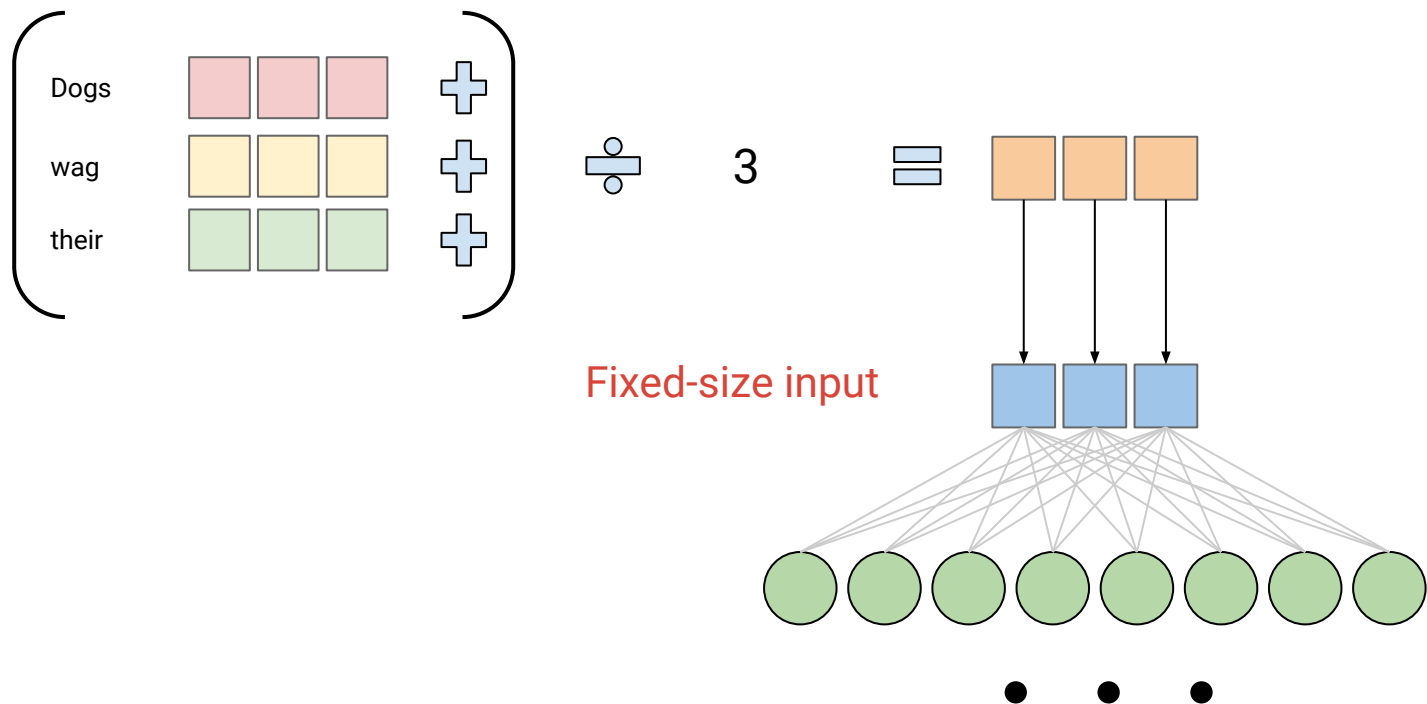
$$w = \begin{bmatrix} 1 & 1 & 1 & 2 \\ \cancel{6} & 3 & 2 & 3 \end{bmatrix}$$

3 Hours Prior	2 Hours Prior	1 Hour Prior	Pad
6	9	12	0

$$w = \begin{bmatrix} 1 & 1 & 1 & 2 \\ 6 & 3 & 2 & \cancel{3} \end{bmatrix}$$



# Bagging is an alternative to padding





# Order can be very important...

??

The		The
cat		<b>mat</b>
sat		sat
on	=	on
the		the
mat		<b>cat</b>



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