# Time Series Prediction With Neural Networks

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#### Konture Technology Services

Predictive Autoscaling Platform for AWS (Deprecated)

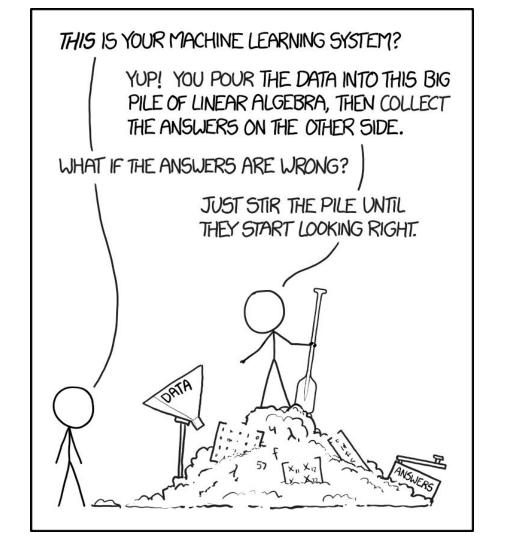
#### **Technology Services**

- Cloud Solutions Architecture
- Kubernetes
- DevOps
- Machine Learning
- Application Development



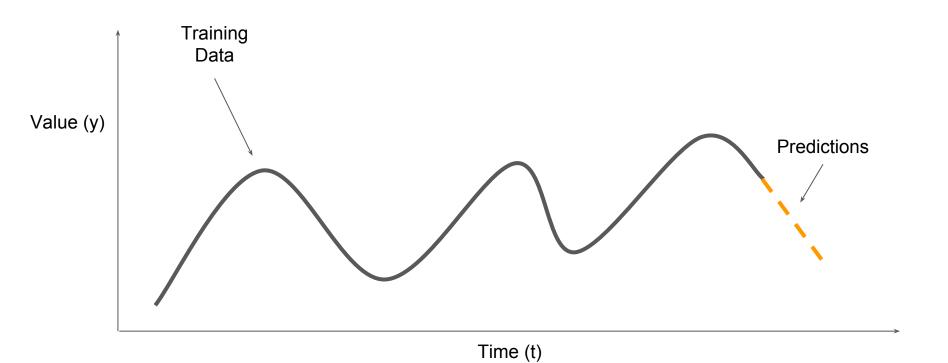
Section 1

Machine Learning Review



Credit: XKCD.com

#### Time Series Prediction



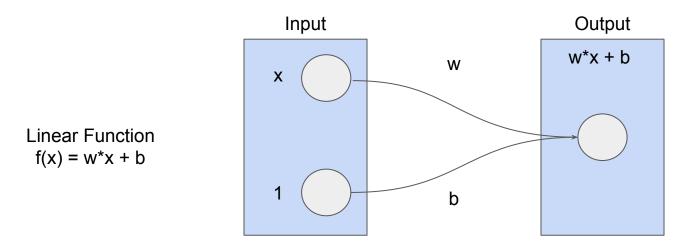
#### Some Application Areas

- Business Intelligence
  - o Predict Revenue, Costs, Profit, etc
- Energy (Smart Grid)
  - Predict usage spikes, allocate energy efficiently
- High-Frequency Trading
  - Predict stock prices
- Resource Optimization
  - Predict resource requirements, such as server capacity

#### **Artificial Neural Networks**

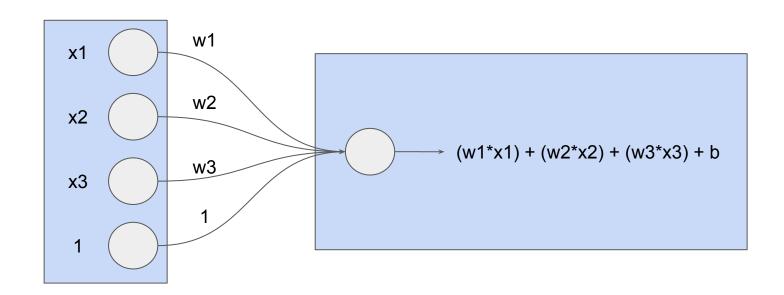
Mimic the way neurons in the brain work

Outputs and weights (parameters) from one neuron form the inputs of another - forming a directed weighted graph



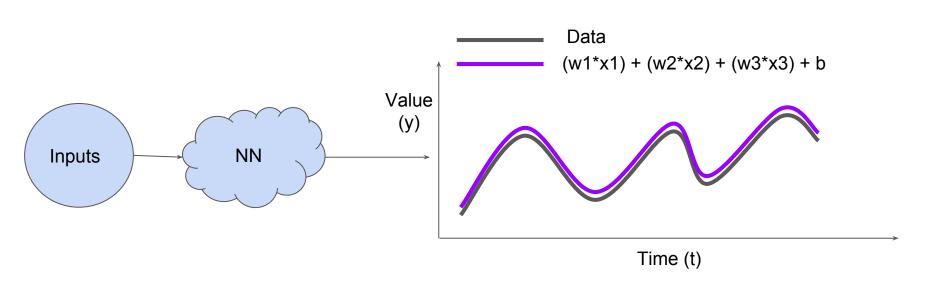
Source: Nishant Shukla (2017), Machine Learning With Tensorflow. Manning Publications

#### More Complex Inputs



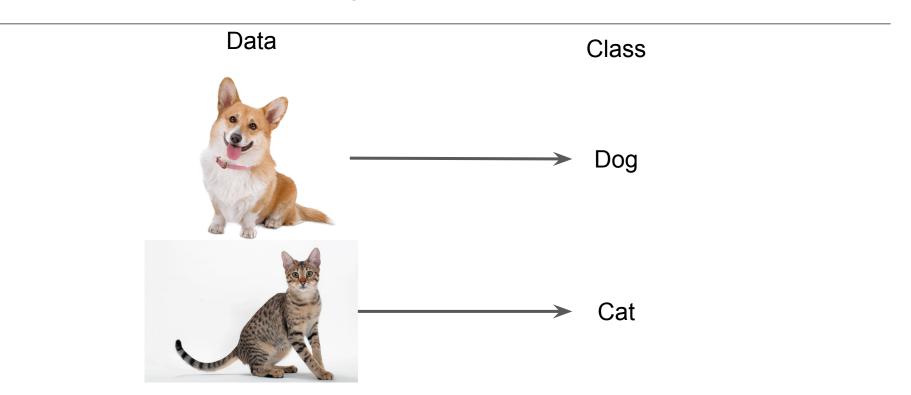
Source: Nishant Shukla (2017), Machine Learning With Tensorflow. Manning Publications

#### How Neural Networks Learn Time Series



#### Supervised Learning

We tell the algorithm what our classes are



### Time Series as Supervised Learning

	Raw		Supervised
X	Υ	X	Y
1	60	?	60
2	70	60	70
3	80	70	80
4	90	80	90
5	100	90	100
		100	?

## Univariate, Single Step Prediction

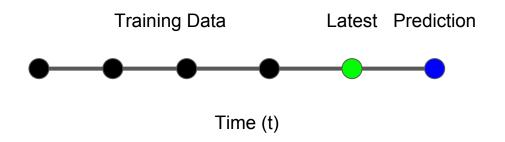
#### **Definition**

#### **Univariate, Single Step Prediction**

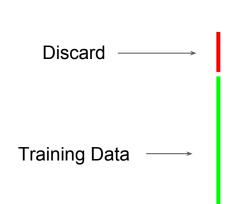
Predict a single, future value based on the previously observed value

#### Example

Given value of 100, what will the next value be?



## **Training Concept**



Supervised Dataset		
X	Υ	
?	60	
60	70	
70	80	
80	90	
90	100	

#### Training Pseudocode

Input training data as supervised set into neural network

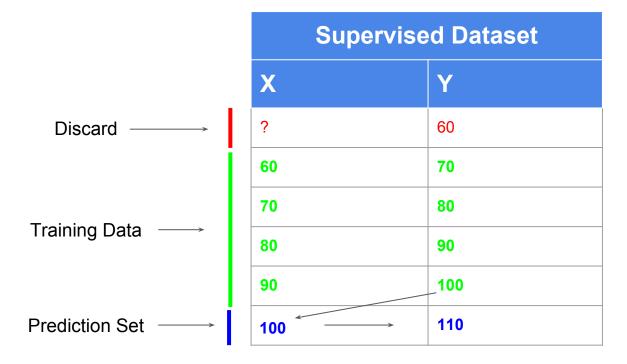
X is 3D array of (samples, timesteps, features)

Y is 2D array of(samples, class)

#### **Keras Pseudocode:**

model.fit(X, Y)

#### **Prediction Concept**



#### Prediction Pseudocode

```
def univariate_single_step_prediction():
    X = [100]
    Y = model.predict(X)
    return Y
```

Univariate, Multi-Step Prediction

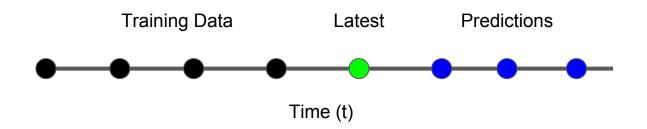
#### Definition

Given a previous value, what will the next *n* values be?

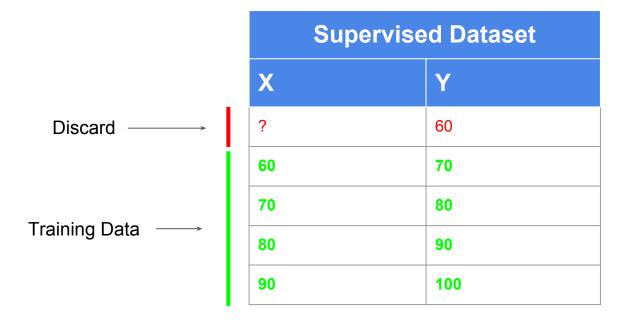
For each forward timestep:

Make a prediction

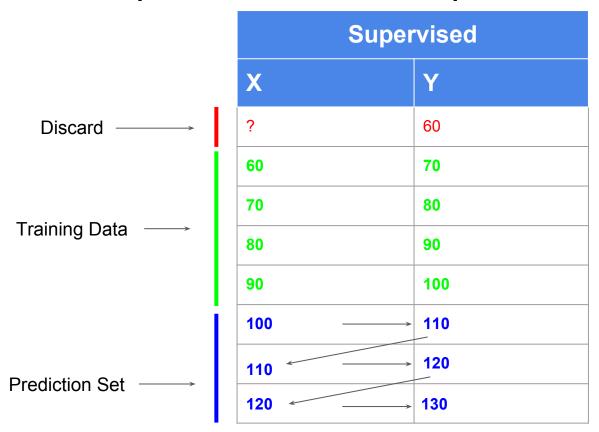
Take that prediction and feed back into model to emit the next prediction etc.



## Training Concept (Same as Single Step)



#### Multi-Step Prediction Concept



### Multi-Step Prediction Pseudocode

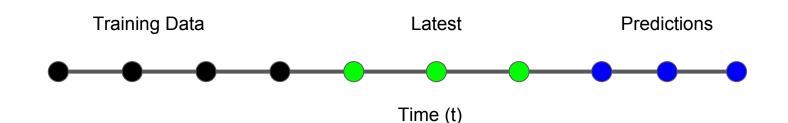
```
def multistep_prediction(timesteps=5):
  i = 0
  X = [100]
  Y = []
  while i < timesteps:</pre>
    Y[i] = model.predict(X[i])
    X[i+1] = Y[i]
    i+=1
  return Y
```

Multivariate, Multi-Step Time Series

#### **Multivariate Time Series**

Predict a sequence of future values based on *n* previously observed values

Given we observed [60,70,80,90,100], what will the next *m* values be in the sequence?



## Multivariate Training Concept

×	Y
[ 60, 70, 80, 90, 100 ]	[ 110 ]
[ 70, 80, 90, 100, 110 ]	[ 120 ]
[ 80, 90, 100, 110, 120]	[ 130 ]
[ 90, 100, 110, 120, 130]	[140]
[ 100, 110, 120, 130, 140 ]	[?]

#### **Training**

```
raw = [60, 70, 80, 90, 100, 110, 120, 130, 140]
X = [[60, 70, 80, 90, 100],
        [ 70, 80, 90, 100, 110],
        [ 80, 90, 100, 110, 120 ],
        [ 90, 100, 110, 120, 130 ]]
Y = [ [110],
      [120],
      [130],
      [140]]
```

## Multivariate, Multi-Step Prediction Concept

```
p1 = model.predict([60, 70, 80, 90, 100])
                p2 = model.predict([70, 80, 90, 100, p1])
                p3 = model.predict([80, 90, 100. p1, p2])
                P4 = model.predict([90, 100, p1, p2, p3])
```

### Multi-Step, Multivariate Pseudocode

```
def multistep_multivariate_prediction(timesteps=5):
  i = 0
 X = [60, 70, 80, 90, 100]
 Y = []
  while i < timesteps:</pre>
    Y[i] = model.predict(X[i:i+timesteps])
    X[i+1] = Y[i]
    i+=1
  return Y
```

**Multivariate Time Series Prediction** 

Part 2

#### Let's Do Something With Our Timestamps!

Up until now, we've discarded our timestamps from the raw data. But there's a lot of information encoded in the day, month, year, minute, etc of our observations. We shouldn't let it go to waste!

#### Decomposing Timestamps into Multiple Attributes

#### Timestamp = 1543289298

Year: 2018

Month: 11

Day of the Week: 1

Hour: 22Minute: 28

Year Month Day (one-hot) Hour Minute Prev. Value

X = [[2018], [11], [1,0,0,0,0,0,0], [22], [28], [60]]

Y = [[70]]

**Grand Finale** 

## Multivariate Time Series Prediction with Decomposed Timestamp Attributes

```
X = [
       [[2018], [11], [1,0,0,0,0,0], [22], [28], [60]],
       [[2018], [11], [1,0,0,0,0,0], [23], [32], [70]],
       [[2018], [11], [1,0,0,0,0,0], [24], [28], [80]],
      ]]
Y = [[90]]
```

#### Resources

Machinelearningmastery.com

Nishant Shukla (2017), Machine Learning With Tensorflow. Manning Publications

#### Thank You!

#### **Scott Crespo**

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