# Focus for this lecture

Acquire Raw Data → Prepare / Clean Data, Visualization → Feature Engineering → Pick Model and Hyper-params for Task → Model Training / Optimization → Evaluate Model Performance → Deploy Model

- Learning, Data and Time
- Glancing through AR and MA
- How does NN model this?

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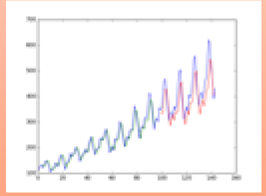
- Learning, Data and Time

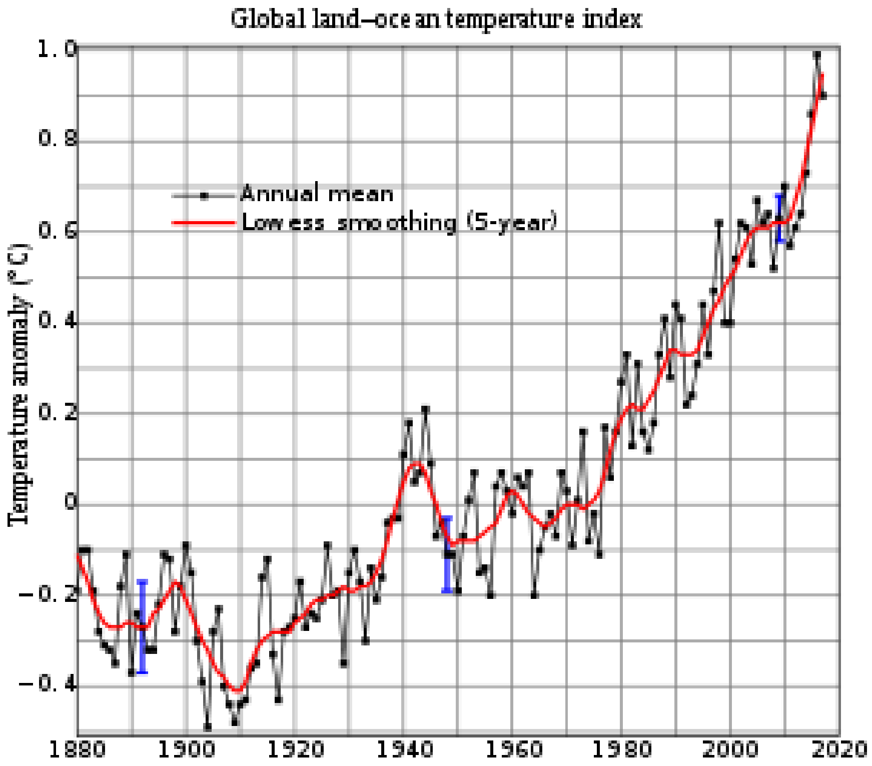


# Learning, Data and Time

# Examples

## BSE SENSEX


## Global Land Ocean temperature



# Examples

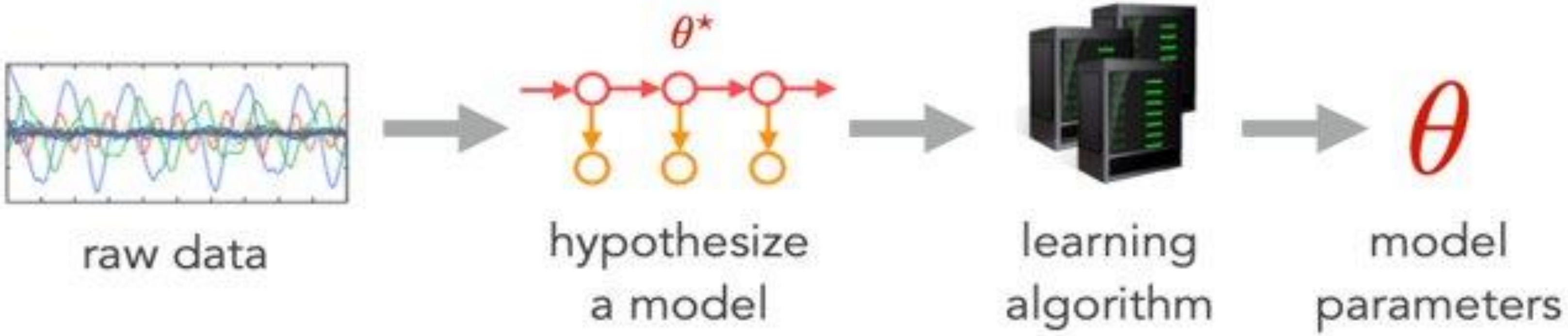
| Day | No. of Packets of Milk sold |
|---|---|
| Monday | 90 |
| Tuesday | 88 |
| Wednesday | 85 |
| Thursday | 75 |
| Friday | 72 |
| Saturday | 90 |
| Sunday | 102 |

| Year | Population(in Million) |
|---|---|
| 1921 | 251 |
| 1931 | 279 |
| 1941 | 319 |
| 1951 | 361 |
| 1961 | 439 |
| 1971 | 548 |
| 1981 | 685 |

# Time Series

- Time series is a sequence of observations often ordered in time.
- Popular Problem: Given a sequence, predict future samples.
- Applications:
  - Meteorology,
  - Finance,
  - Marketing etc.

# ML View Point




Using the model + learned parameters $\theta$:

- Track
- Predict
- Simulate
- Plan
- …

**Learning Problem**: find parameters $\theta$ s.t. $\theta \approx \theta^\star$

From: B. Boots

# Notation and Problem

- Notation: x[0], x[1], x[2], …, x[N].
- X[t], Where t is the time or index in the sequence.
- Assumption: Measurement at time t depends on three previous ones.
  - i.e., t-1, t-2 and t-3
- Why 3? We can have a different number.

# Data

| Raw Data | |
|---|---|
| Time | Sample |
| 1 | $X_1$ |
| 2 | $X_2$ |
| 3 | $X_3$ |
| 4 | $X_4$ |
| 5 | $X_5$ |
| 6 | $X_6$ |
| 7 | $X_7$ |

| Rearranged Data | | | |
|---|---|---|---|
| Feature-1 | Feature-2 | Feature-3 | $Y_i$ |
| $X_1$ | $X_2$ | $X_3$ | $X_4$ |
| $X_2$ | $X_3$ | $X_4$ | $X_5$ |
| $X_3$ | $X_4$ | $X_5$ | $X_6$ |
| $X_4$ | $X_5$ | $X_6$ | $X_7$ |

| Feature Vector | |
|---|---|
| Feature | $Y_i$ |
| $V_1$ | $X_4$ |
| $V_2$ | $X_5$ |
| $V_3$ | $X_6$ |
| $V_4$ | $X_7$ |

# A Simple Model

- $X[t] = w1\, X[t-1] + w2\, X[t-2] + w3\, X[t-3] + n$
  - Where n is noise.

- Problem:
  - Given the sequence X[0], X[1], …… X[N]
  - Find coefficients w1, w2, w3

- Find the coefficients w1,w2,w3 such that prediction error is minimal.

# Performance Metrics For Time Series Data

- We need a way to compare different time series techniques for a given dataset.
- Four common techniques are:
  - – mean absolute deviation,
  - – mean absolute percent error,
  - – the mean square error,
  - – root mean square error.

$\mathrm{X}_i : ACTUAL$

$\hat{\mathrm{X}}_i : PREDICTED$

$$\mathrm{MAD} = \sum_{i=1}^{n} \frac{\left|\mathrm{X}_i - \hat{\mathrm{X}}_i\right|}{n}$$

$$\mathrm{MAPE} = \frac{100}{n} \sum_{i=1}^{n} \frac{\left|\mathrm{X}_i - \hat{\mathrm{X}}_i\right|}{\hat{\mathrm{X}}_i}$$

$$\mathrm{MSE} = \sum_{i=1}^{n} \frac{\left(\mathrm{X}_i - \hat{\mathrm{X}}_i\right)^2}{n}$$

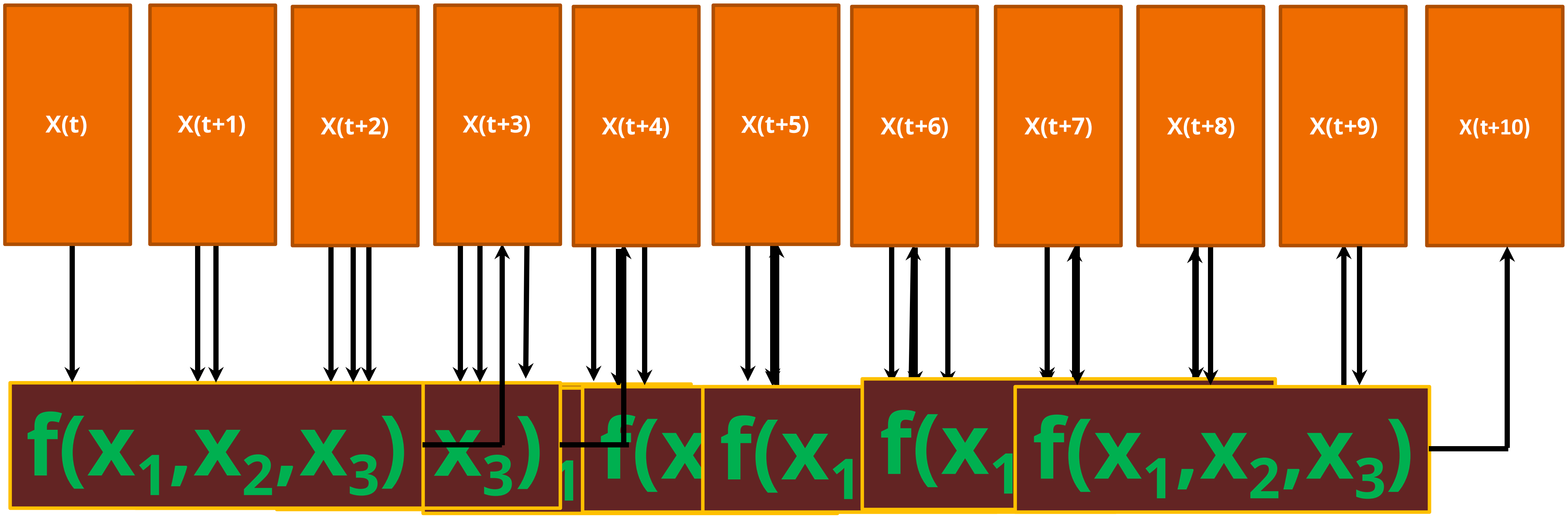
$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}}$$

# More Powerful Model

- $X_t = f(W, X_{t-1}, X_{t-2}, X_{t-3}) + n$
- Problem:
  - Given the sequence $X_0, X_1, \ldots\ldots X_N$
  - Find coefficients W
- Data may be modeled as in the above linear case.
- f() may be seen as a MLP

$$\min W \sum_{t=3}^{N} (X_t - f(W, X_{t\text{-}1}, X_{t\text{-}2}, X_{t\text{-}3}))^2$$

# Time series prediction



# Data (Revisit)

| Raw Data | |
|---|---|
| Time | Sample |
| 1 | $X_1$ |
| 2 | $X_2$ |
| 3 | $X_3$ |
| 4 | $X_4$ |
| 5 | $X_5$ |
| 6 | $X_6$ |
| 7 | $X_7$ |

| Rearranged Data | | | |
|---|---|---|---|
| Feature-1 | Feature-2 | Feature-3 | $Y_i$ |
| $X_1$ | $X_2$ | $X_3$ | $X_4$ |
| $X_2$ | $X_3$ | $X_4$ | $X_5$ |
| $X_3$ | $X_4$ | $X_5$ | $X_6$ |
| $X_4$ | $X_5$ | $X_6$ | $X_7$ |

| Feature Vector | |
|---|---|
| Feature | $Y_i$ |
| $V_1$ | $X_4$ |
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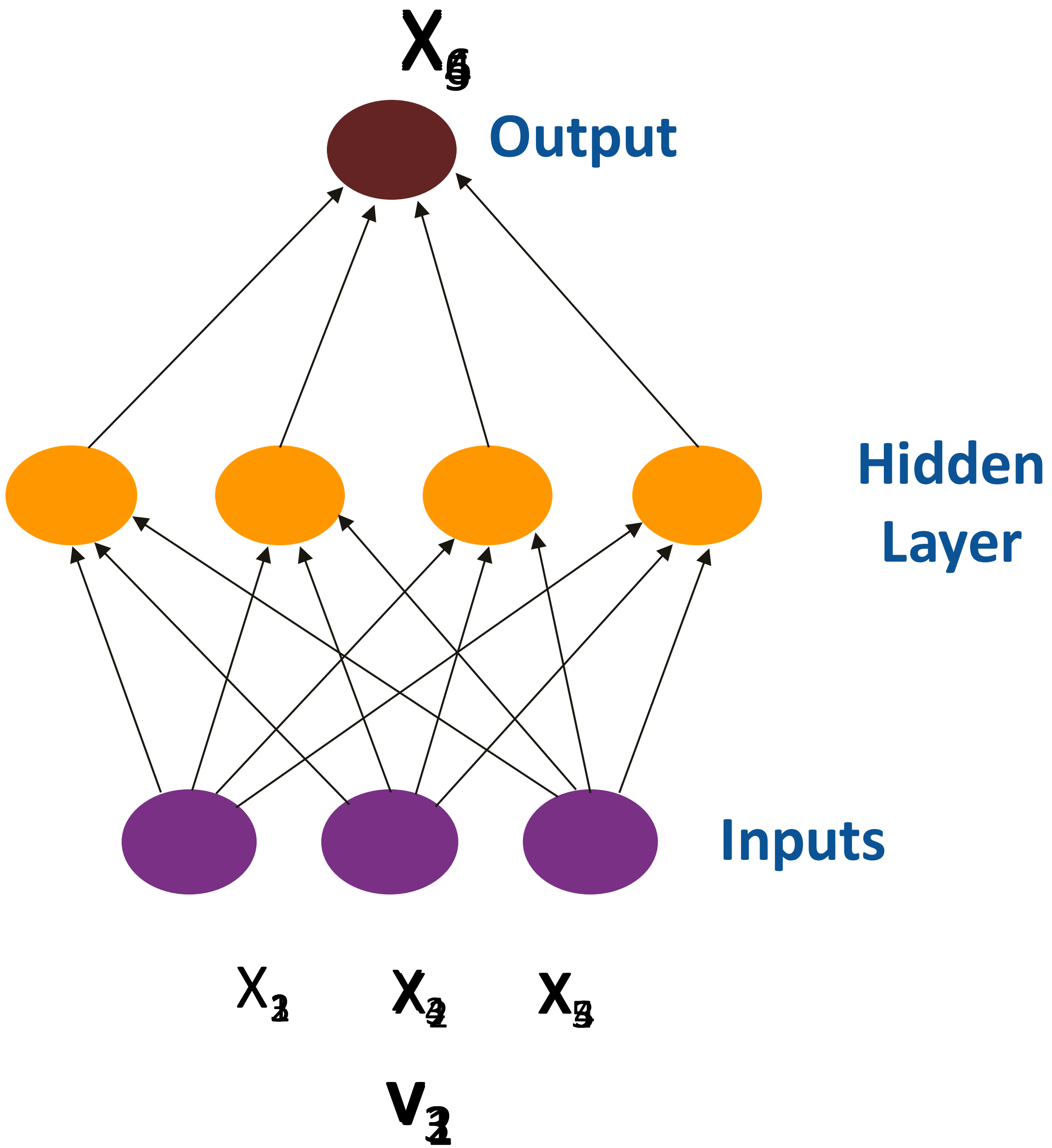
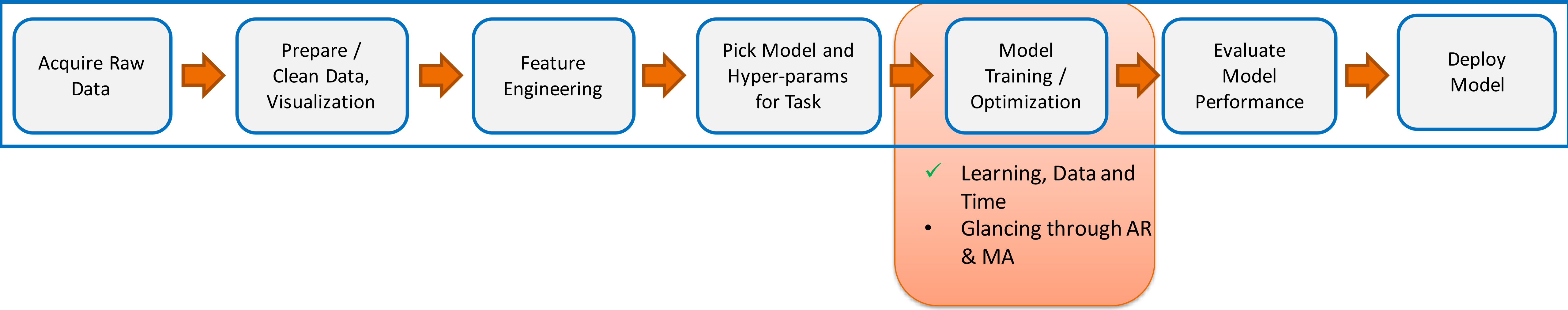
# Neural Networks for Time Series Forecasting



# Summary

- Predicting future samples is a new problem
- However, the solution is similar to what we know.
  - Cast as regression.
- Model can be linear
  - Linear regression
- Or nonlinear
  - MLP
- On how many past samples, the future sample will depend?
  - Order/model to be guessed?

# Questions




# Comments and Remarks

## Glancing through AR & MA

# Classical Models (AR and MA)

- Auto Regressive (**AR**) Model assumes $X_t = \alpha X_{t-1} + \epsilon_t$ ($\epsilon_t$ is random uncorrelated)
- **AR**: A model of order p is $X_t = \sum_{i=1}^{p} \alpha_i X_{t-i} + \epsilon_t$
- Moving Average (**MA**) model assumes $X_t = \epsilon_t + \beta \epsilon_{t-1}$
- **MA**: a model of order q is $X_t = \epsilon_t + \sum_{j=1}^{q} \beta_j \epsilon_{t-j}$

# Classical Models (ARMA & ARIMA)

- **ARMA (p,q):**

$$X_t = \sum_{i=1}^{p} \alpha_i X_{t-i} + \sum_{j=0}^{q} \beta_j X_{t-j}$$

  With $\beta_0 = 1$

- **ARIMA (p, d, q):**
  - A process is ARIMA (p, q, d) if $\nabla^d X$ is ARMA (p,q).
  - Where $\nabla X_t = X_t - X_{t-1}$ and $\nabla^2 X_t = \nabla(\nabla X_t)$

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# How does NN model this?

# Classical Methods to Machine Learning

- Use of data to discover the model and validate the model.
- Makes lesser assumptions.
- Power of nonlinearity
- Role of “test data” guaranteed future performance.

# Casestudy

MLP vs various methods

# Many Comparisons

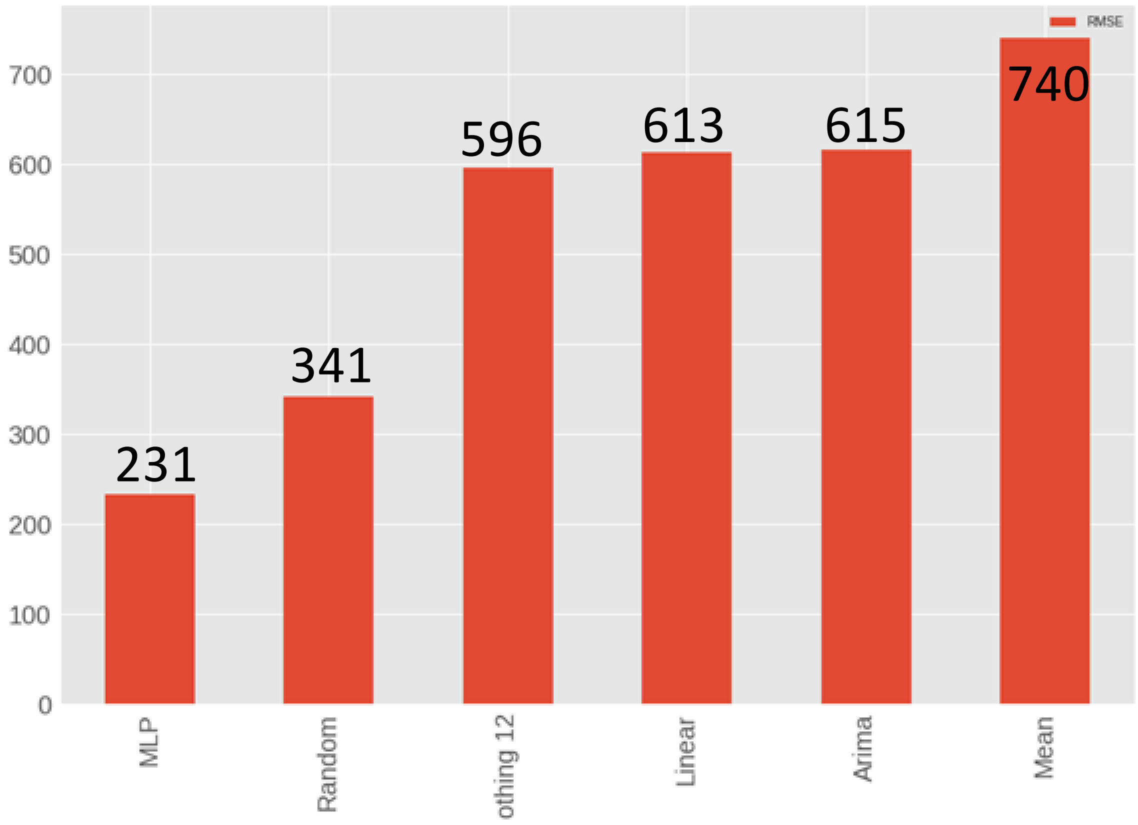
- MLP vs ARMA/ARIMA:
  - “Forecasting with artificial neural networks: The state of the art ” – 1998
    - Shows that ANNs are at par or better.
  - “Time series forecasting using a hybrid ARIMA and neural network model” G.P. Zhang (2003)
    - Shows how to get advantages of “both” worlds
- In 2018, we know more NN than what we did in 1998 or 2003!!

# Problem: Predict the prices of Onion

Code Available

# Comparisons

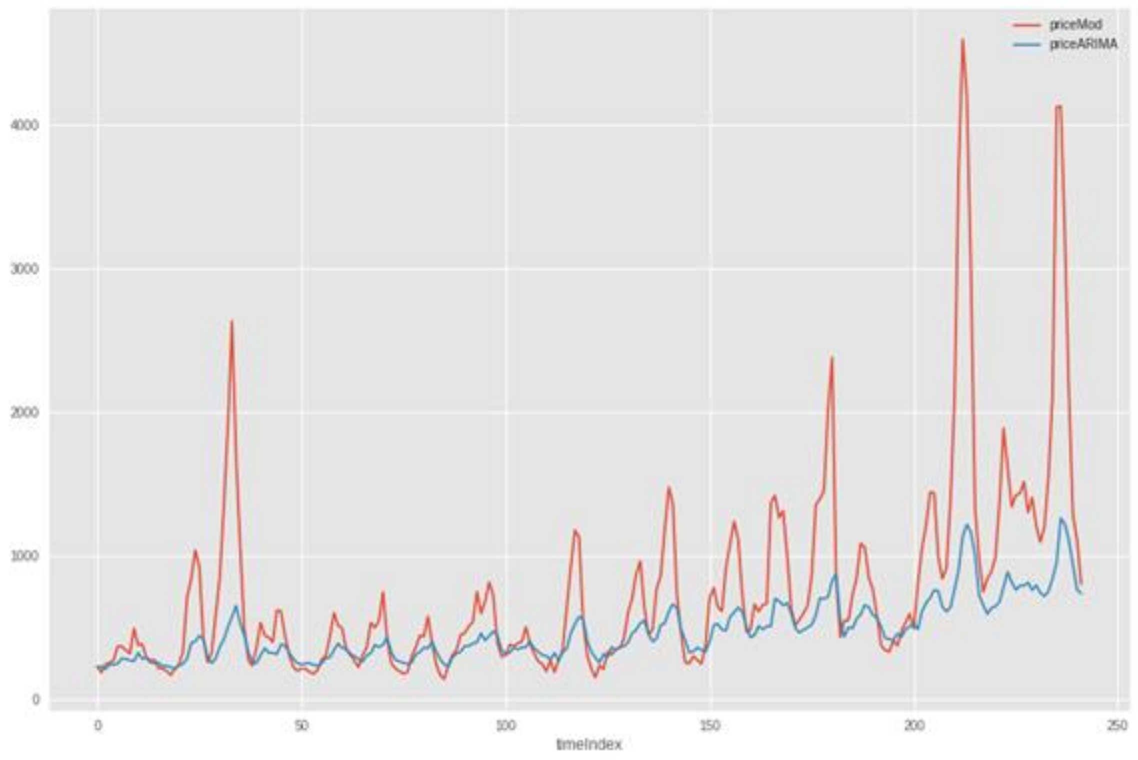
- RMSE of Time series using ARIMA, MLP, Random Walk, Linear, Mean



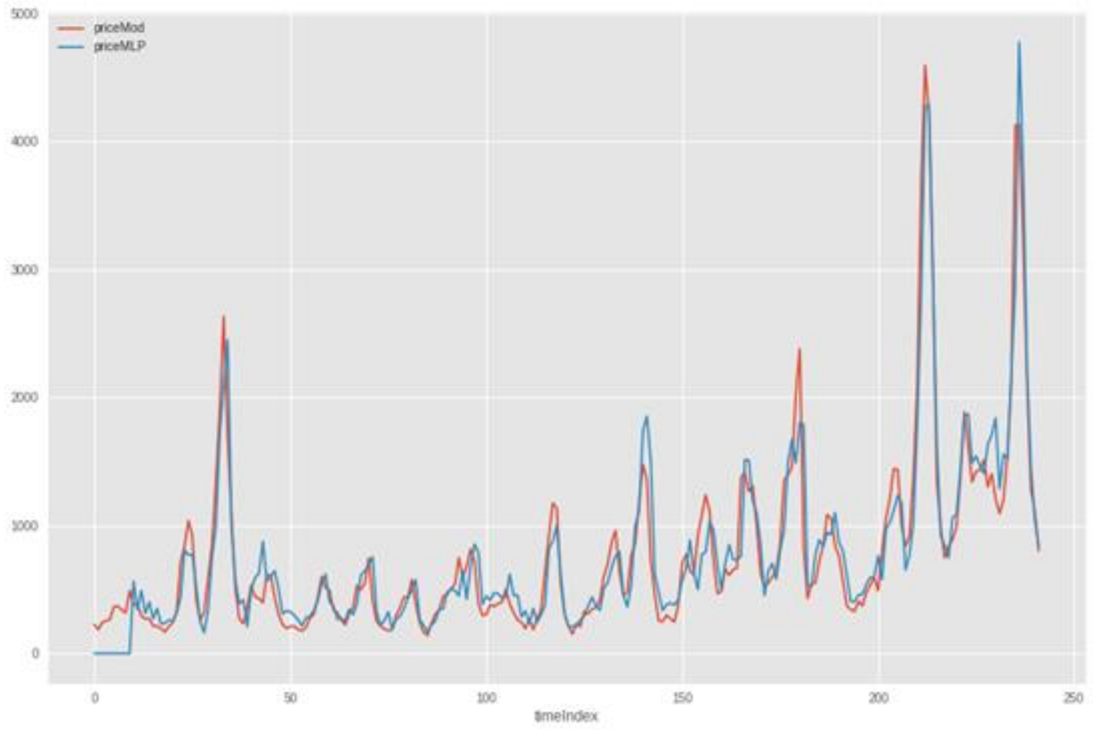
Code Available

# Prediction using ARIMA and MLP

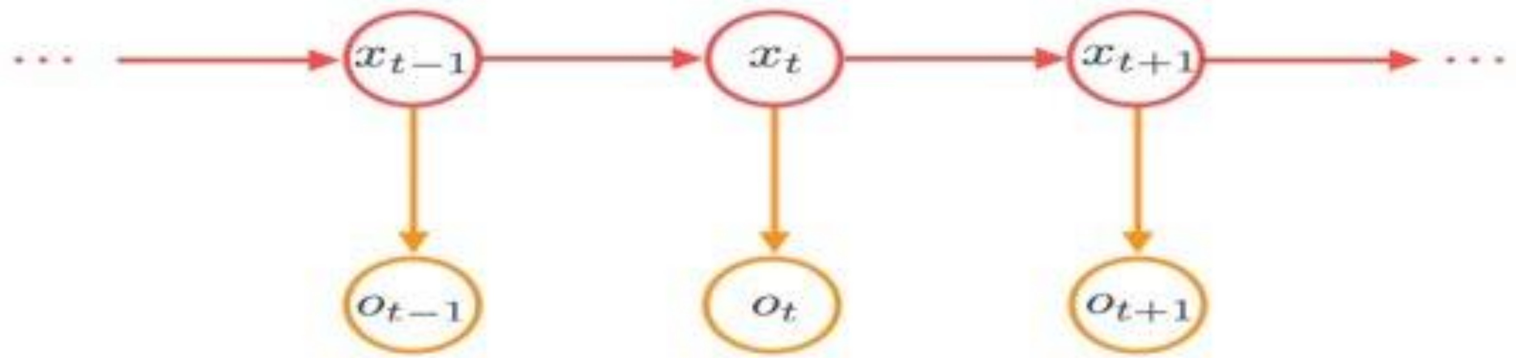
## ARIMA




## MLP



# Dynamic Systems




$$x_{t+1} = Ax_t + \epsilon \qquad \epsilon \sim N(0, Q)$$
$$o_t = Cx_t + \upsilon \qquad \upsilon \sim N(0, R)$$

$$\theta^{\star} = \{A, C, Q, R, x_1\}$$

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# Thanks!!!

## Questions?