# Time Series Analysis Lecture — 1

## Train-Test Split for Time Series:

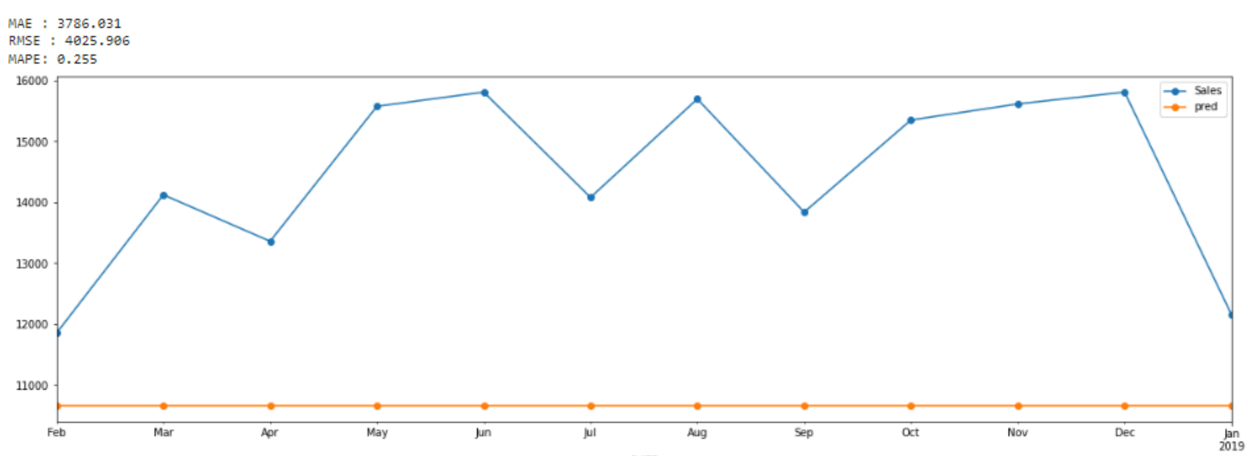
- **Method:** Time-based splitting, not random shuffling.
- **Rationale:** Predict future values based on past data.
- **Approach:** Reserve most recent data as test set.
- **Seasonality Consideration:** Include at least two full seasons in test data for seasonal series.

## Measures of Forecast Accuracy:

- **MAE (Mean Absolute Error):** Average absolute difference between original and predicted values.
- **MSE (Mean Squared Error):** Average squared difference between original and predicted values.
- **RMSE (Root Mean Squared Error):** Square root of MSE, indicating error rate.
- **MAPE (Mean Absolute Percentage Error):** Average of absolute percentage errors between actual and forecasted values.

## Simple Forecast Methods: (not-so-intelligent approaches)

1. Mean Forecast:

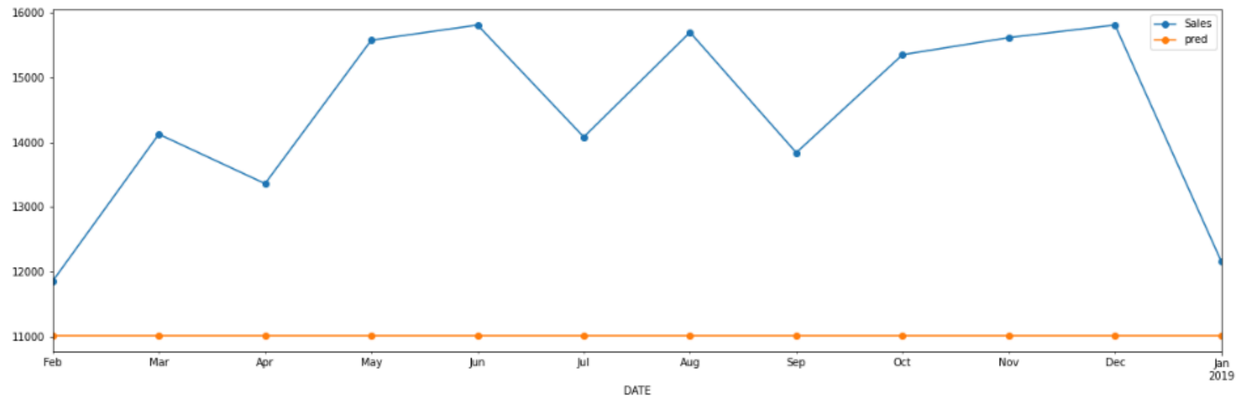



- Average of all past k values.

- MAPE: 25.5% error, indicating poor model performance.

2. Naive Approach:

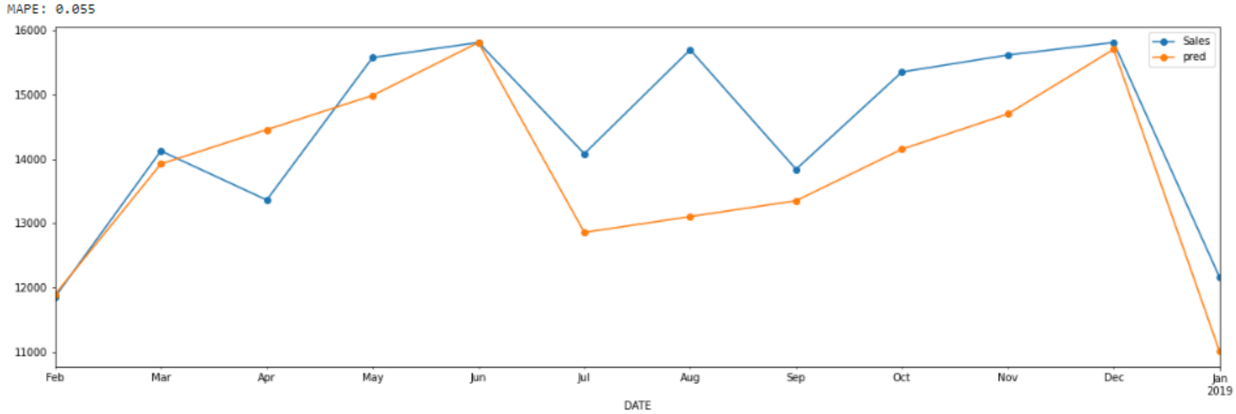
```
MAE : 3434.233
RMSE : 3697.005
MAPE: 0.23
```




- Uses value at time t=k for future forecasts.
- Slightly better performance (23% error) but still unreliable.

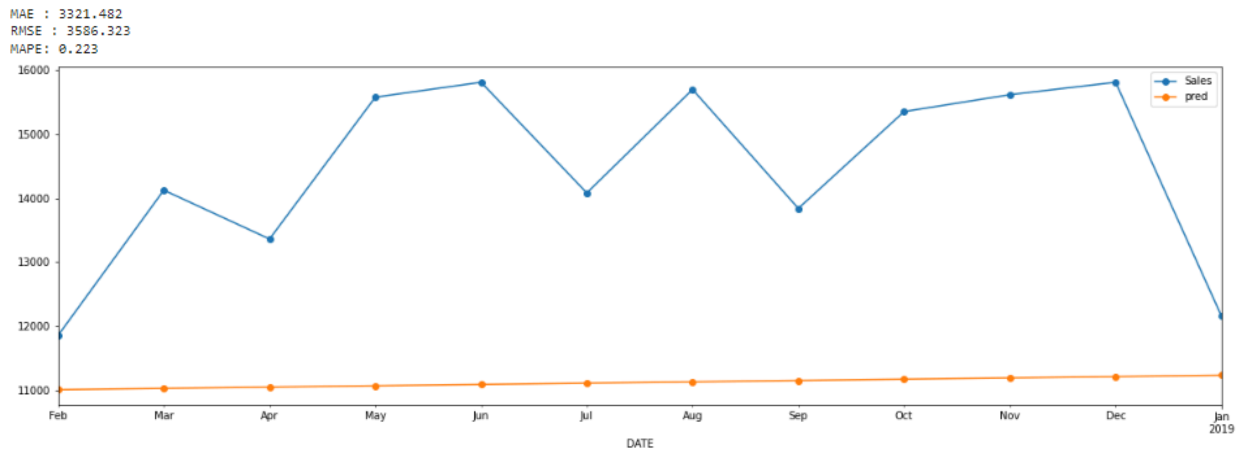
3. Seasonal Naive Forecast:

```
MAE : 800.867
RMSE : 1067.837
MAPE: 0.055
```



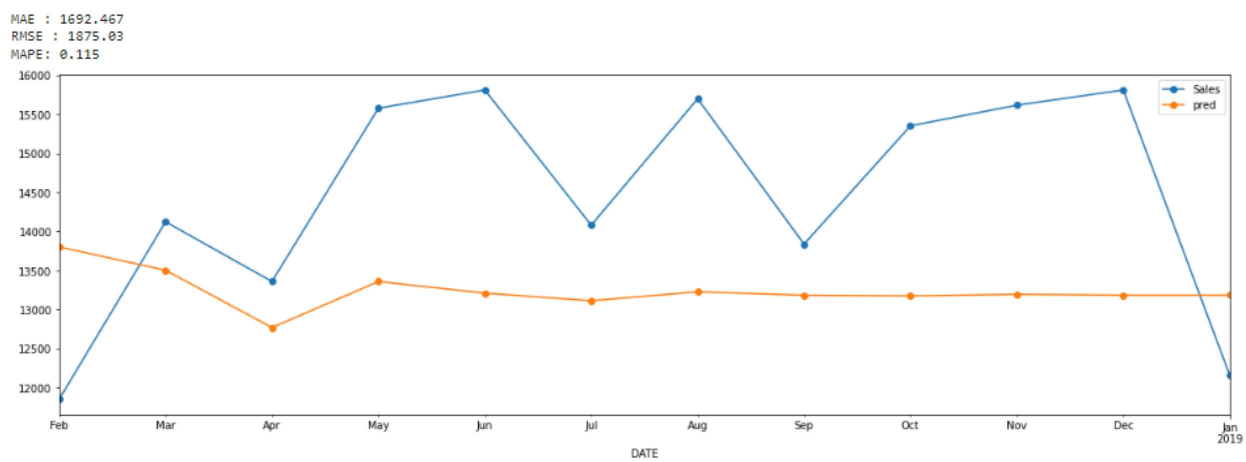

- Forecasts equal to last observed value from same season.
- Leverages seasonal patterns for predictions.

4. Drift Method:




- Allows forecasts to increase/decrease over time based on historical data change (drift).
- Highly sensitive to last value, using linear extrapolation.

5. Moving Average:



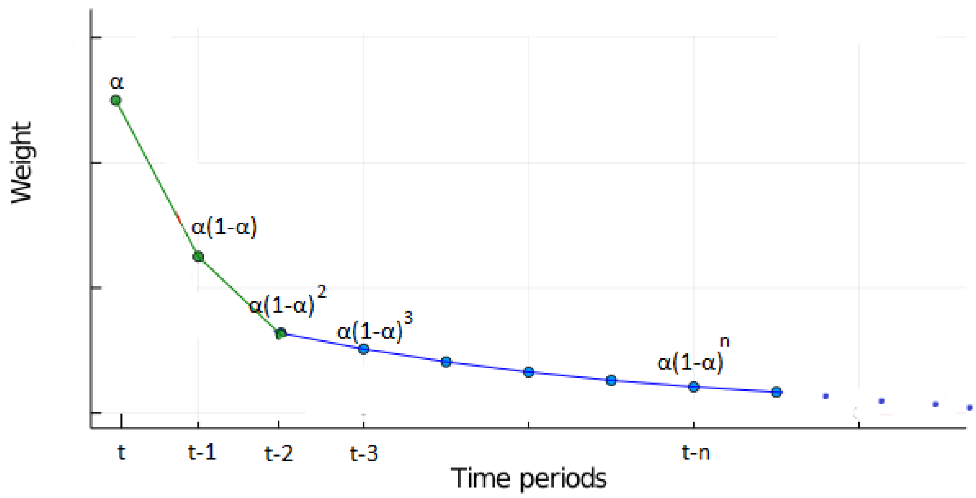

- Average of last k data points used for next point forecast.
- 11.5% error, better than other simple methods but can be misleading with seasonality.

**Note:** These methods, while straightforward, may not provide highly accurate forecasts, especially in the presence of complex patterns or seasonality.

## Exponential Smoothing Methods:

**Overview:** Weighted moving average with exponential weight decline for older data.

Simple Exponential Smoothing (SES):




- **Purpose:** Effective when no trend or seasonality in data.
- **Key:** Recent data weighted more heavily.
- **Smoothing Parameter (α):** Controls weight decay, range [0,1].
- **Forecasting Formula:** Let's consider the weight we assign to the recent most value be α.
  α is called the **smoothing parameter**.
  So, our forecast at time *t* for the time t+1 is:

$$\hat{y}_{t+1} = \alpha y_t + (1-\alpha)\hat{y}_t$$

- **Advantages:** Proper initialization, no beginning/end offset, correct forecast level.
- **Performance:** Straight-line forecast, 10% error, better than moving average.
- **Sensitivity:** Higher α makes forecast sensitive to recent observations.
- **Limitations:** Lacks trend and seasonality modeling.
- **Parameter Impact:**
  - Higher α: More weight to recent data, forecasts react more to recent changes.
  - Lower α: Less sensitivity to recent changes, smoother forecast.
  - The recommended starting value of α is: $\frac{1}{2 * seasonality}$
- **Application:** SES model applied to sales data showed a straight-line forecast due to reliance on the most recent value for all future values, with a notable improvement in error rate compared to moving average.