

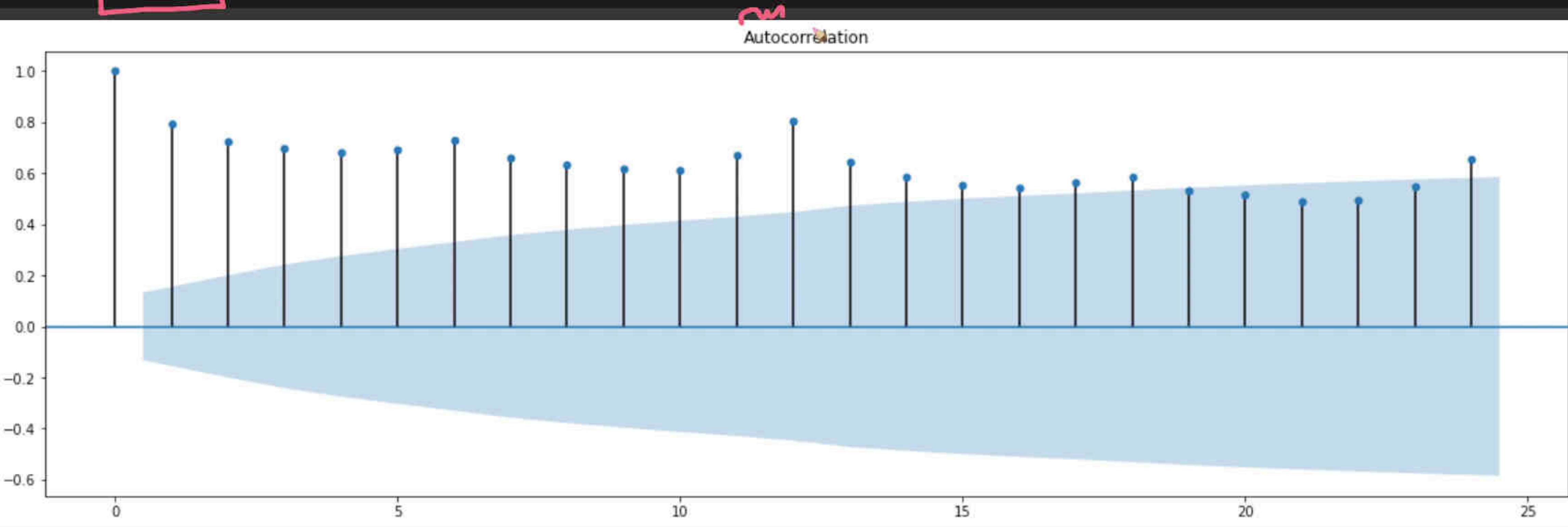
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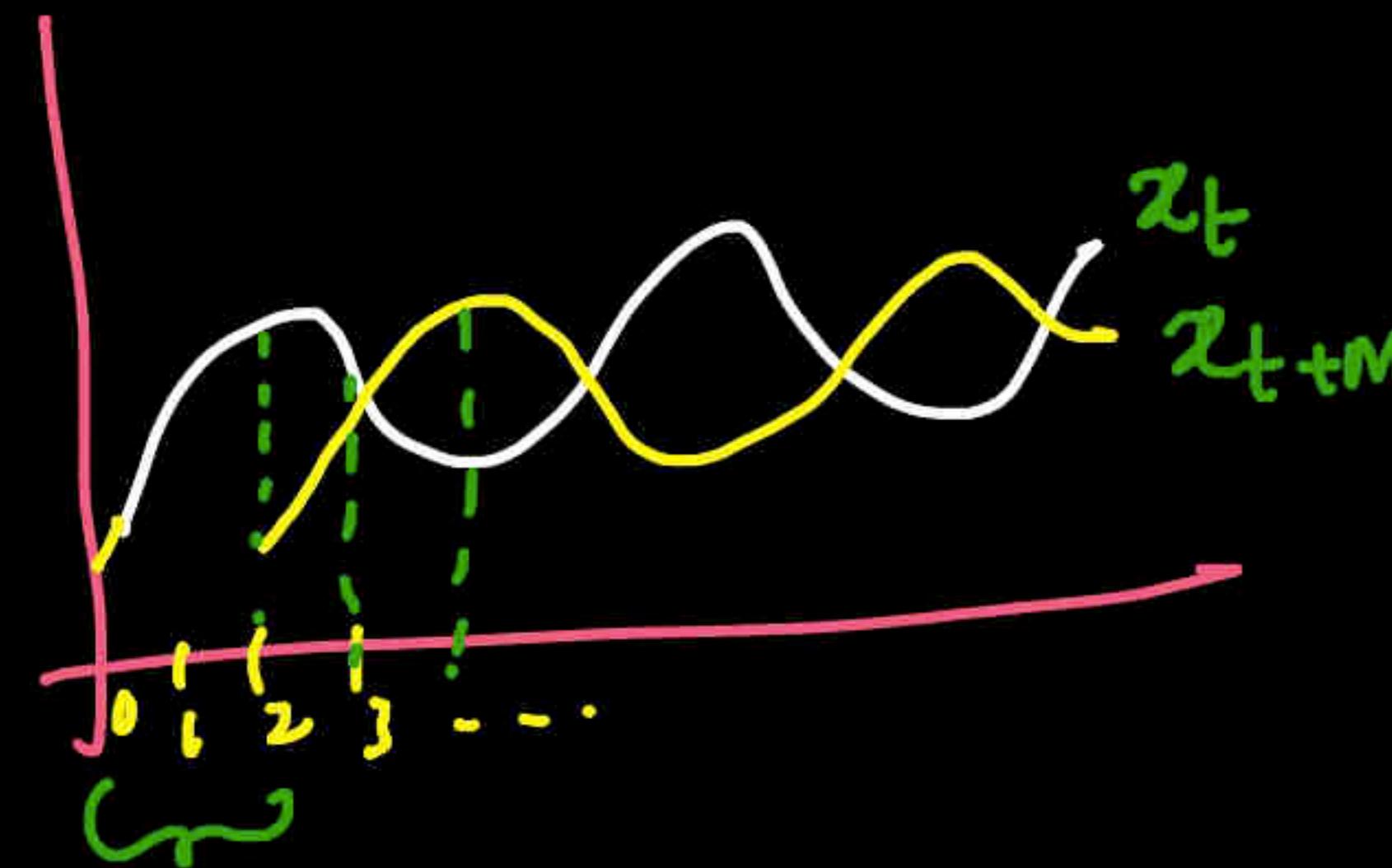
```
[ ] /usr/local/lib/python3.7/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning: pandas.util.testing is deprecated. Use the function  
import pandas.util.testing as tm
```

```
{x} [ ] from statsmodels.graphics.tsaplots import plot_acf, plot_pacf  
plot_acf(mobile_sales.Sales);
```



```
[ ] # for detrended time-series  
plot_acf(mobile_sales.Sales.diff().dropna());
```

ACF



$\text{corr}(x_t, x_{t+M})$

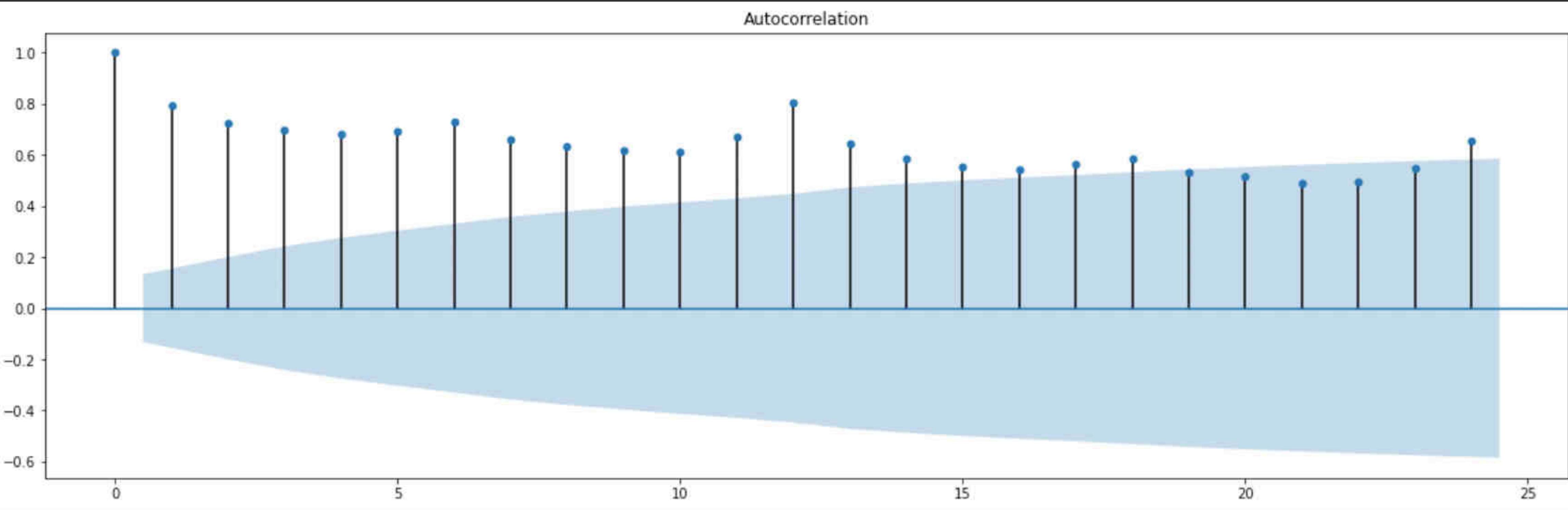
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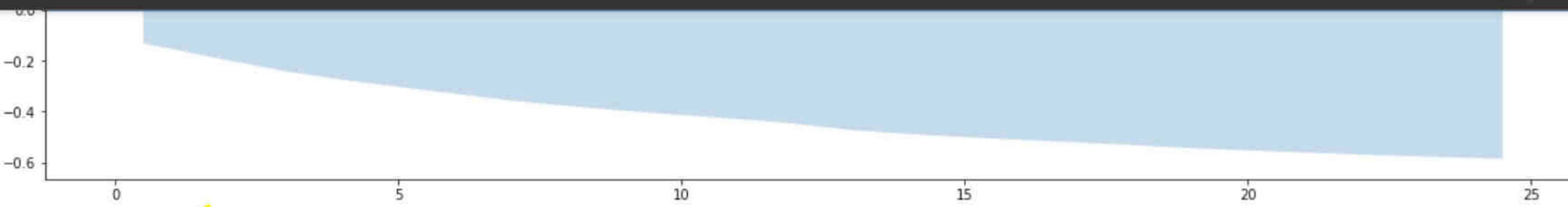
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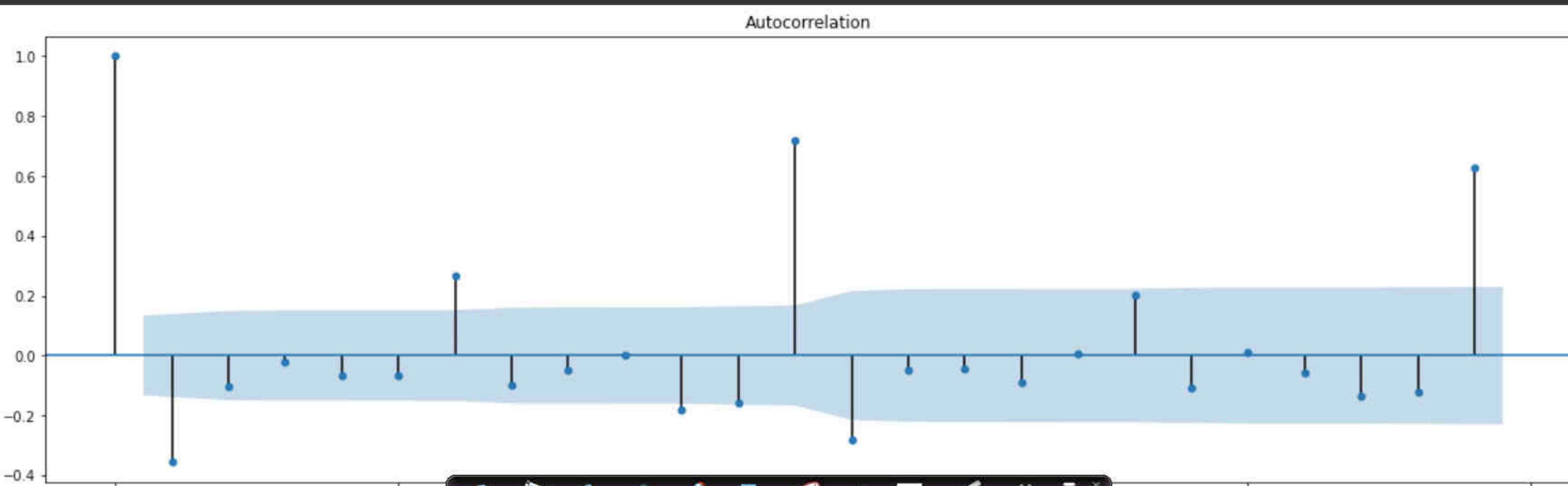


```
[ ] # for detrended time-series  
plot_acf(mobile_sales.Sales.diff().dropna());
```

+ Code + Text



▶ # for detrended time-series
plot_acf(mobile_sales.Sales.diff().dropna());



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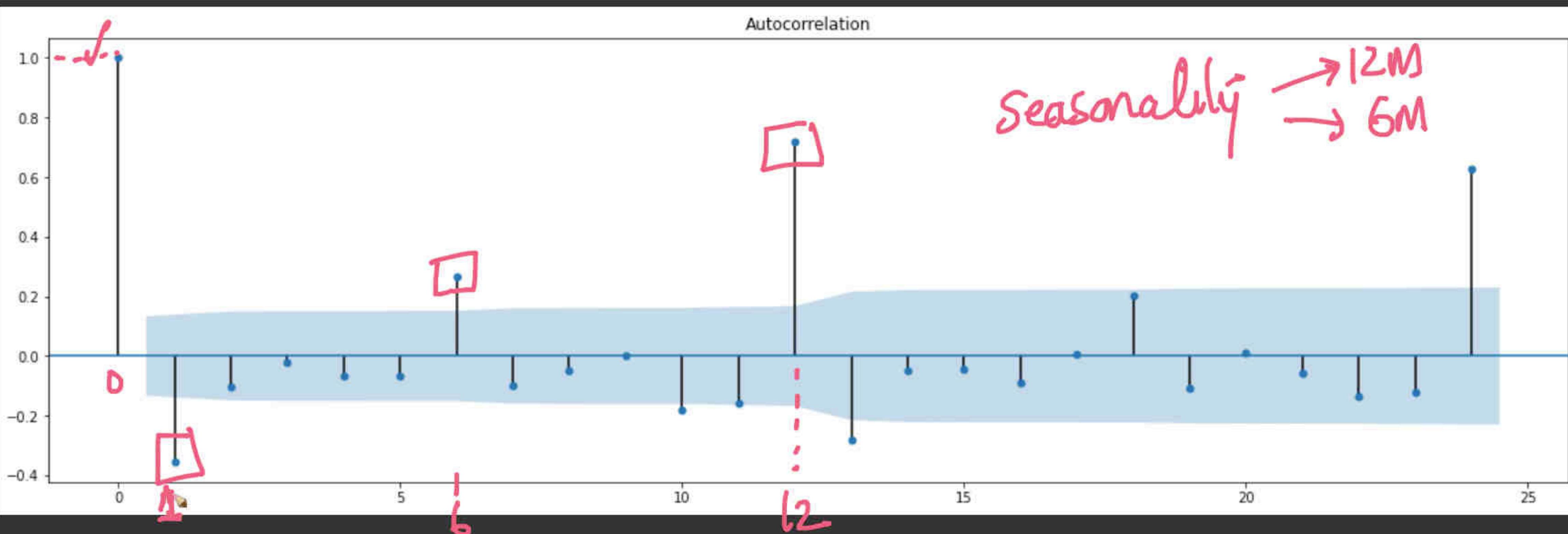
colab.research.google.com/drive/tvLADuayVVAWtY-fo3XXbi608UUnVQPdB#scrollTo=KBjlucs4QAP8

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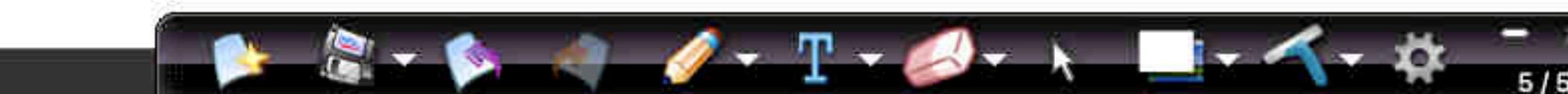
Reconnect

```
[ ] # for detrended time-series  
plot_acf(mobile_sales.Sales.diff().dropna());
```



```
▶ # PACF  
plot_pacf(mobile_sales.Sales);
```

Partial Autocorrelation



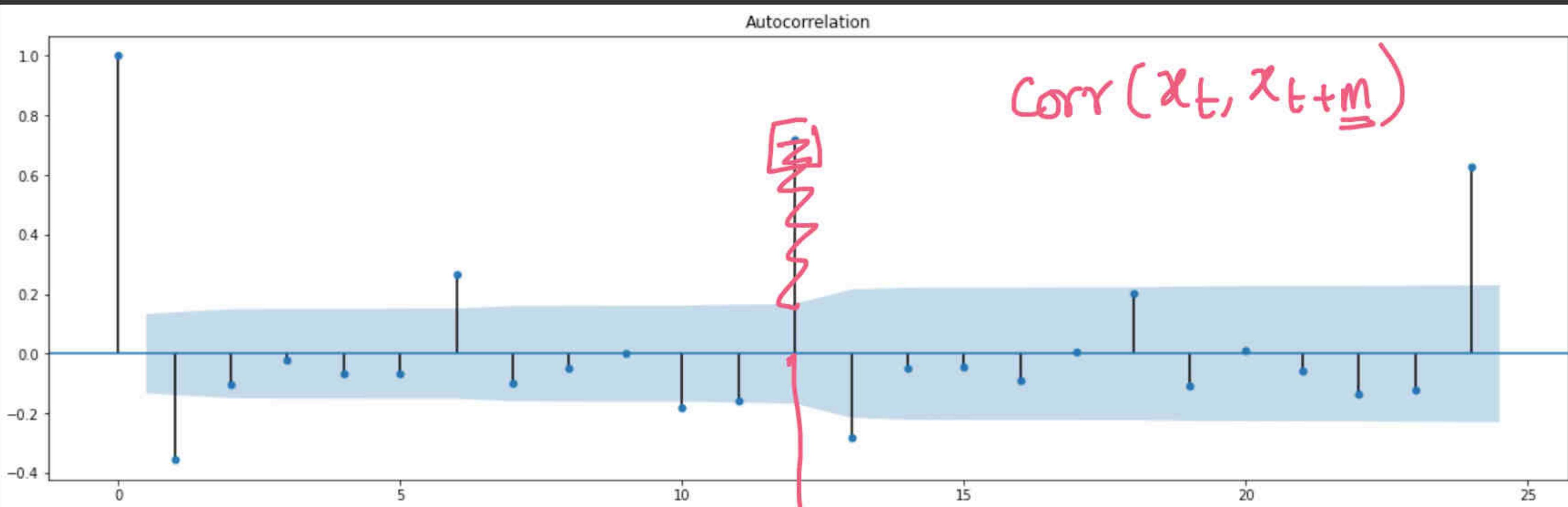
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Reconnect

```
[ ] # for detrended time-series  
plot_acf(mobile_sales.Sales.diff().dropna());
```



PACF
plot_pacf(mobile_sales.Sales);

Partial Autocorrelation

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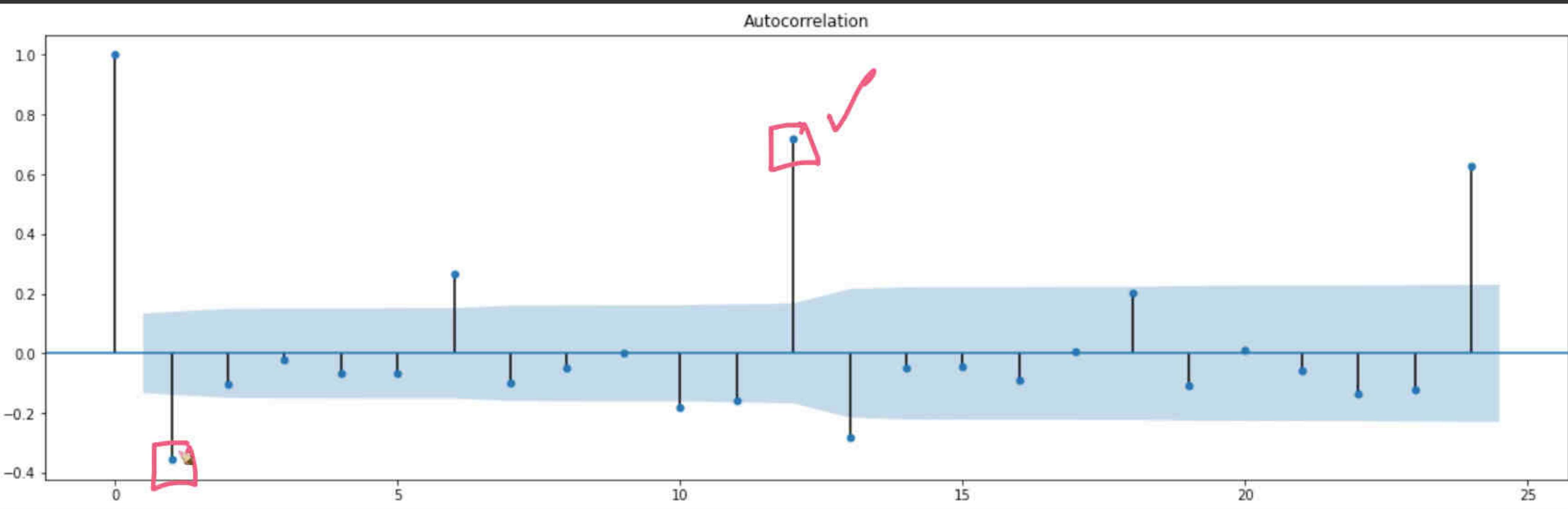
colab.research.google.com/drive/tvLADuayVVAWtY-fo3XXbi608UUnVQPdB#scrollTo=KBjlucs4QAP8



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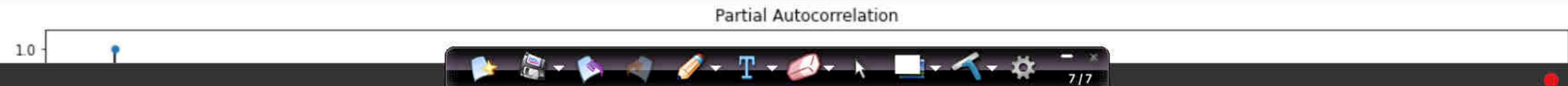
Reconnect |

```
[ ] # for detrended time-series  
plot_acf(mobile_sales.Sales.diff().dropna());
```



▶ # PACF
plot_pacf(mobile_sales.Sales);

Partial Autocorrelation

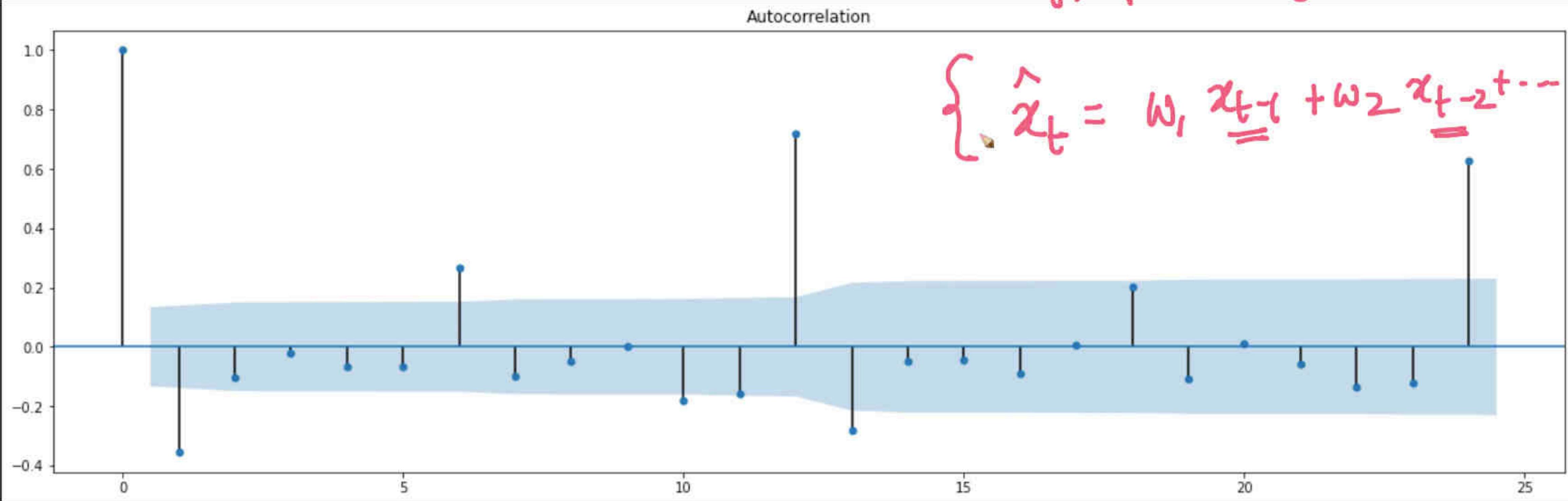


+ Code + Text

```
[ ] # for detrended time-series  
plot_acf(mobile_sales.Sales.diff().dropna());
```

VIF

$f_1 f_2 \dots f_d$



$$\hat{x}_t = w_1 \underline{x_{t-1}} + w_2 \underline{x_{t-2}} + \dots$$

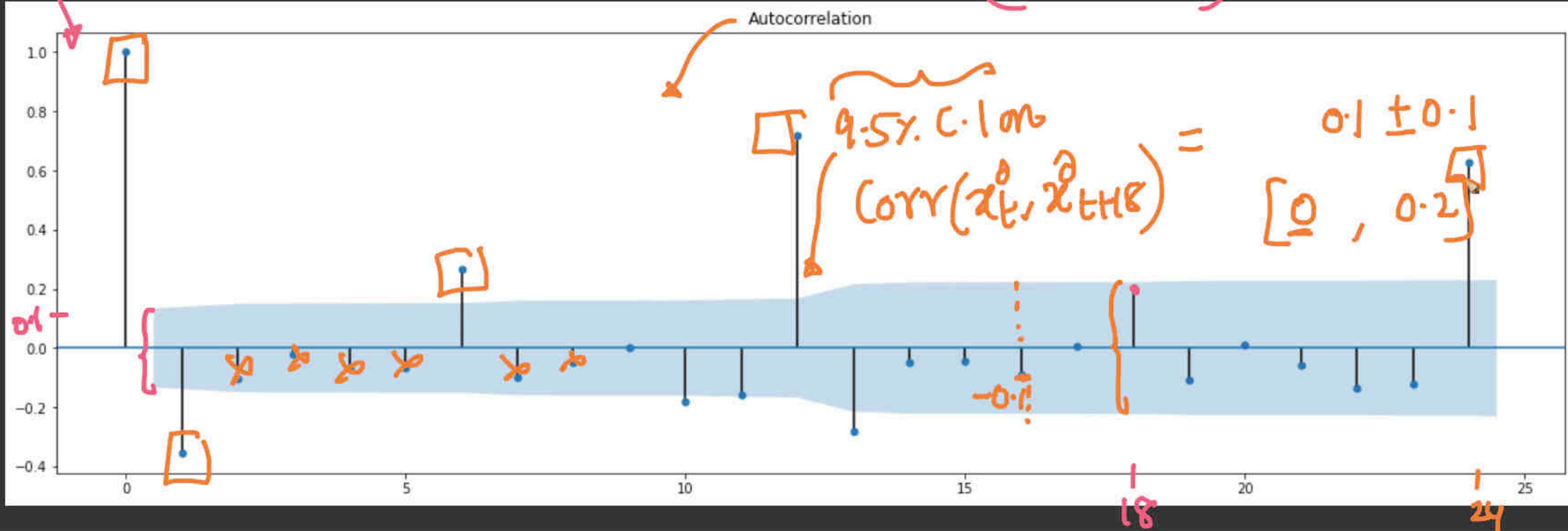
▶ # PACF
plot_pacf(mobile_sales.Sales);

Partial Autocorrelation

+ Code + Text

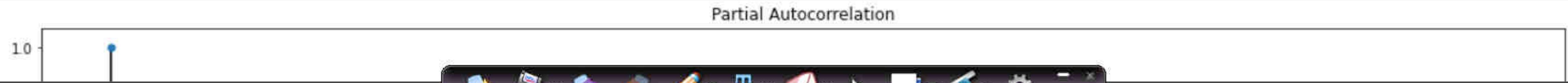
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[ ] # for detrended time-series
plot_acf(mobile_sales.Sales.diff().dropna());
```

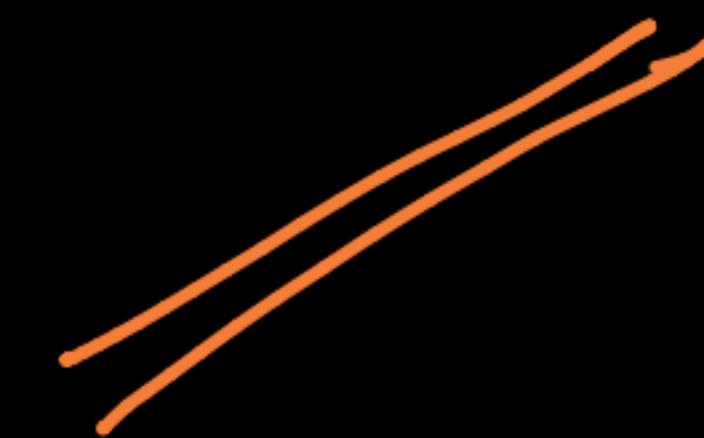
$$\text{Corr}(\hat{\alpha}_t^d, \hat{x}_{t+18}^d) = 0.1$$



```
[ ] # PACF
plot_pacf(mobile_sales.Sales);
```

Partial Autocorrelation





ACF

VS

PACF



$$\text{Corr}(x_t, x_{t+m})$$

{

correlation b/w
 x_t & $x_{t+m}^{(12)}$ after
all intermediate correlations
have been removed

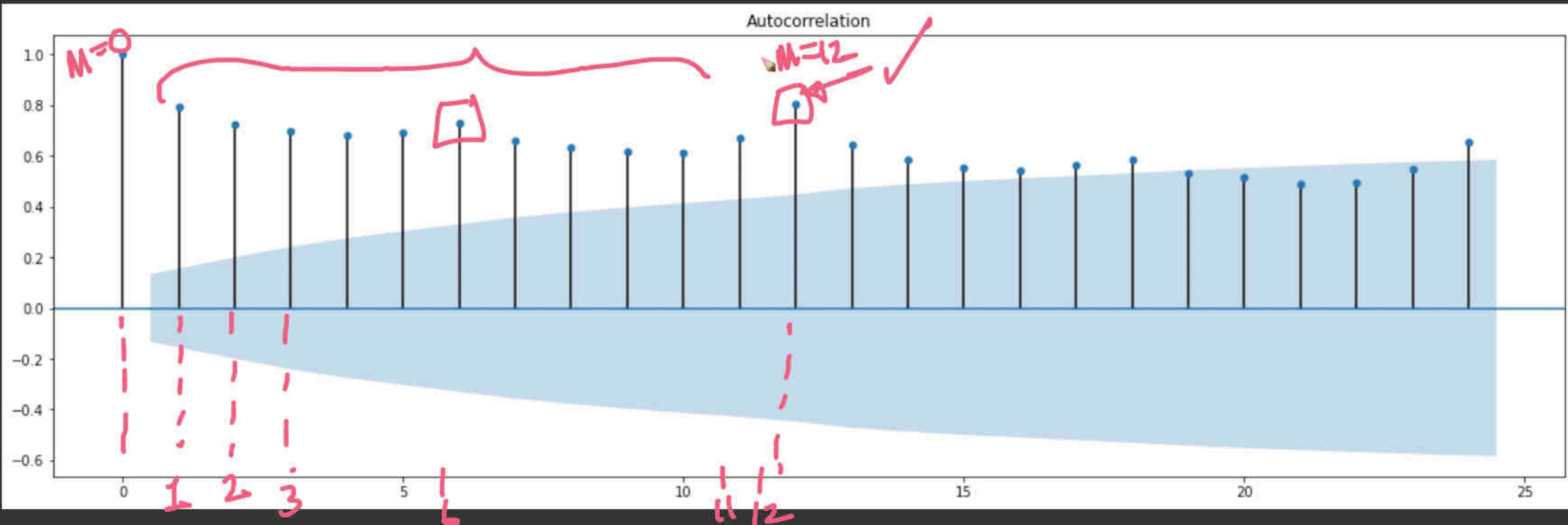
$$m=1, 2, 3, \dots, 11$$

+ Code + Text

```
[ ] from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
```

/usr/local/lib/python3.7/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning: pandas.util.testing is deprecated. Use the function
import pandas.util.testing as tm

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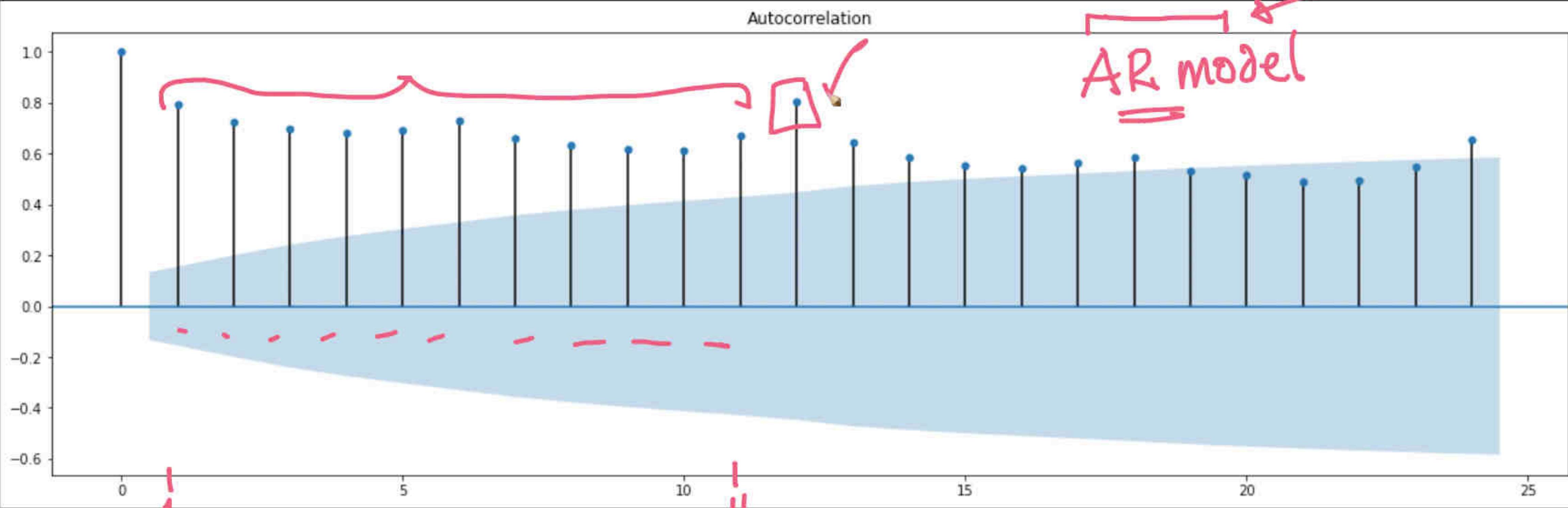
```
[ ] # for detrended time-series
```

+ Code + Text

```
[ ] from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
```

/usr/local/lib/python3.7/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning: pandas.util.testing is deprecated. Use the function
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```
[ ] from statsmodels.graphics.tsaplots import plot_acf, plot_pacf  
plot_acf(mobile_sales.Sales);
```



```
[ ] # for detrended time-series
```

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0

5

10

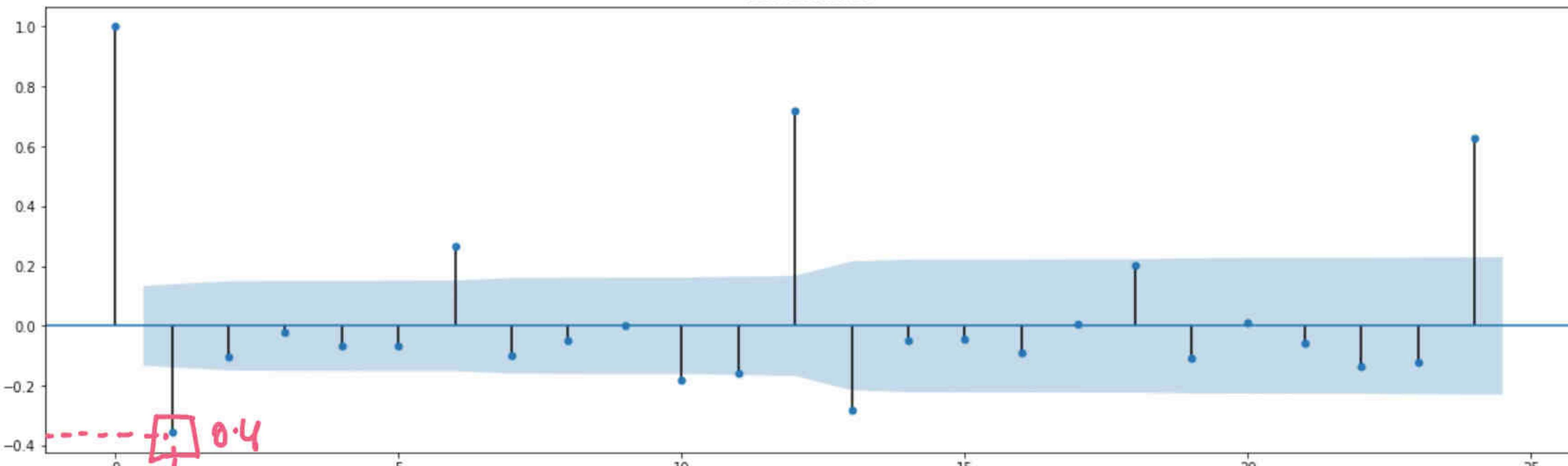
15

20

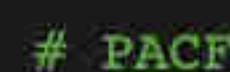
25

```
[ ] # for detrended time-series  
plot_acf(mobile_sales.Sales.diff().dropna());
```

Autocorrelation



1

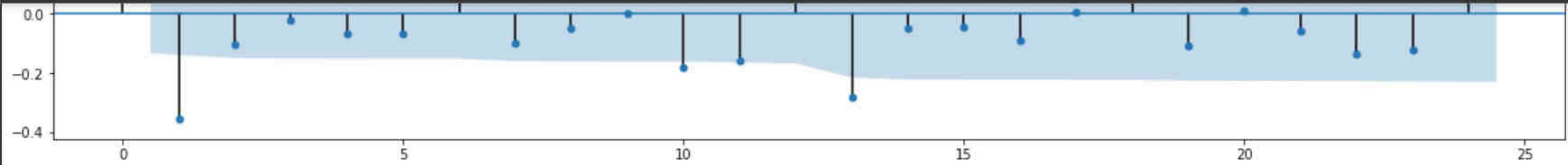


```
# PACF  
plot_pacf(mobile_sales.Sales);
```



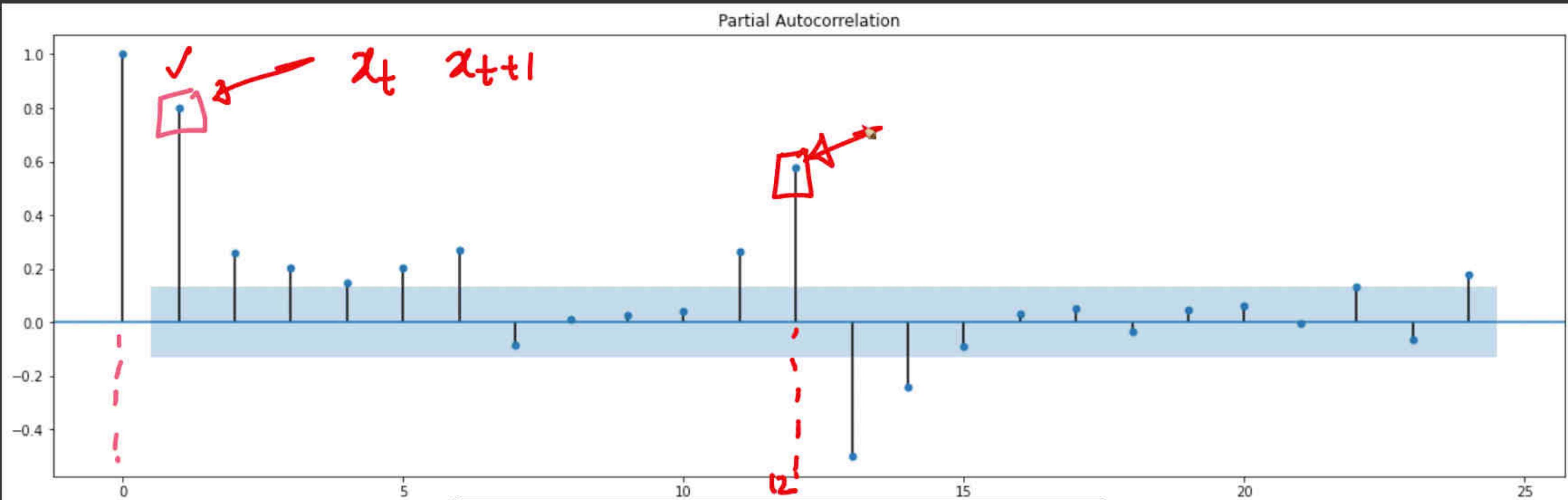
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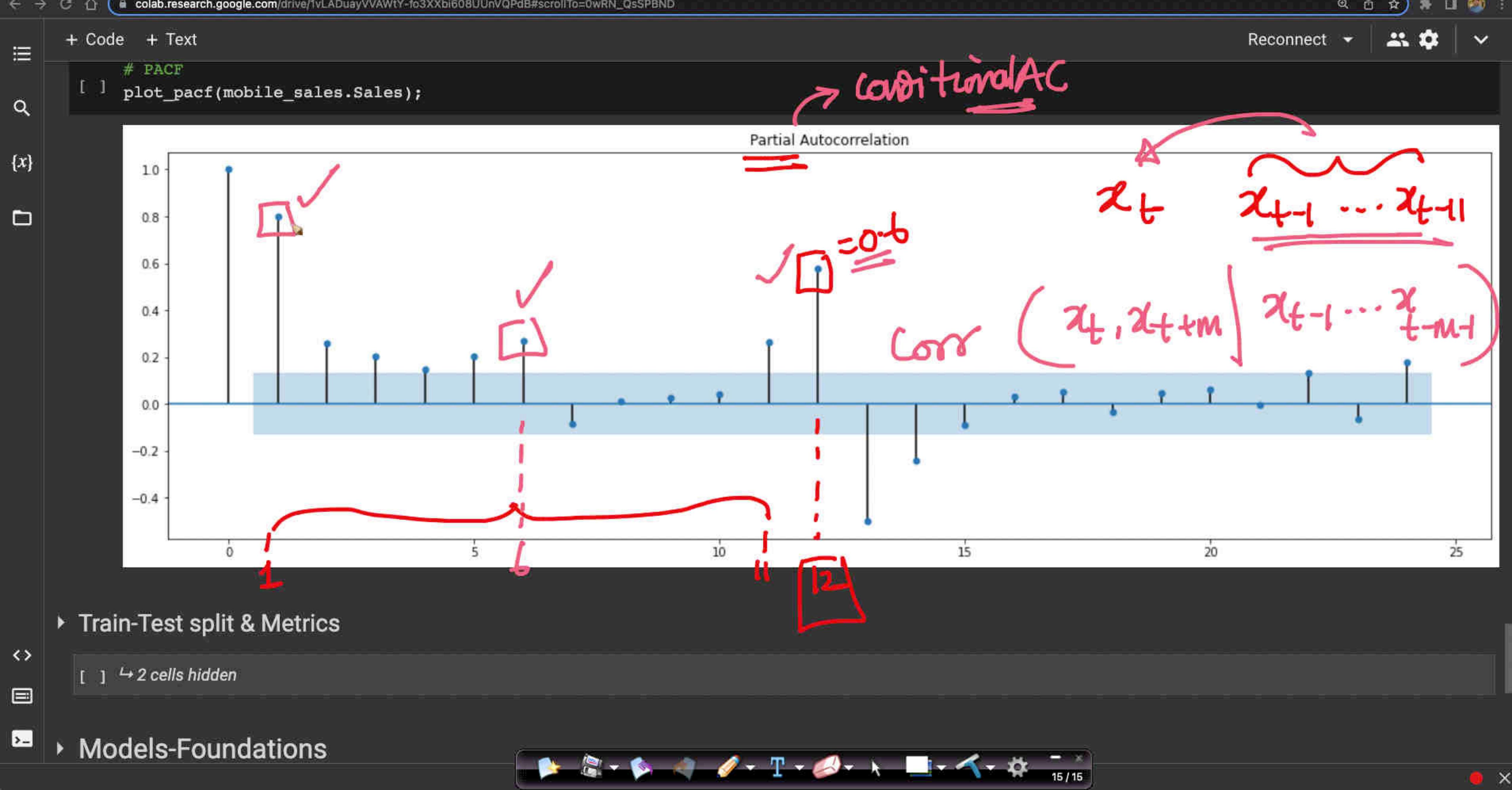
+ Text



[] # PACF → not detrended

```
# PACF
plot_pacf(mobile_sales.Sales);
```





PACF

$$\hat{x}_t = \overbrace{\text{Model}}^{\text{PACF}}(x_{t-1}, \dots, \overbrace{x_{t-11}}^{\text{Lag 11}})$$

$$x_t - \hat{x}_t = e_t$$

L $\rightarrow x_{t-12}$

$\text{corr}(e_t, x_{t-12}) = \text{corr. b/w actual TS}$
 & lagged TS - L2
 after account for
 $\text{all intermediate corr}$

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Train-Test split & Metrics

```
#last 12 months as test
train_max_date = mobile_sales.index[-12]
train_x = mobile_sales.loc[mobile_sales.index < mobile_sales.index[-12]].copy()
test_x = mobile_sales.loc[mobile_sales.index >= mobile_sales.index[-12]].copy()

test_x
```

Sales DATE

DATE	Sales
2018-02-01	11852.0
2018-03-01	14123.0
2018-04-01	13360.0
2018-05-01	15576.0
2018-06-01	15809.4
2018-07-01	14080.0
2018-08-01	15697.0
2018-09-01	13838.0
2018-10-01	15351.0

TIME Series

TBS

Train Test

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```
[ ] from sklearn.metrics import (
    mean_squared_error as mse,
    mean_absolute_error as mae,
    mean_absolute_percentage_error as mape
)

# Creating a function to print values of all these metrics.
def performance(actual, predicted):
    print('MAE :', round(mae(actual, predicted), 3))
    print('RMSE :', round(mse(actual, predicted)**0.5, 3))
    print('MAPE:', round(mape(actual, predicted), 3))
```

500-700

$\rightarrow 20\%$ $\rightarrow 20\%$

(Q) Why MAPE ?

$\frac{a - \hat{y}}{|a|} \times 100\%$

robust to outliers relative measure

100% → ideal

$$\frac{|x_t - \hat{x}_t|}{x_t}$$

Models-Foundations

26 cells hidden

ARIMA & SARIMA Models

11 cells hidden

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+ Code + Text

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[ ] from sklearn.metrics import (
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```

► Models-Foundations

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► ARIMA & SARIMA Models

[] ↳ 11 cells hidden

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MODELS-FOUNDATIONS

Mean model → MAPE

```
#train mean as test predicted  
test_x['pred'] = train_x['Sales'].mean()  
  
test_x.plot(style='-o')  
  
performance(test_x['Sales'], test_x['pred'])
```

MAE : 3786.031
RMSE : 4025.906
MAPE: 0.255

Step	Sales	Pred
1	11900	14000
2	14100	14000
3	13300	14000
4	15500	14000
5	15700	14000
6	14100	14000
7	15500	14000
8	13900	14000
9	15700	14000
10	15900	14000
11	15700	14000
12	13900	14000
13	15500	14000
14	15700	14000
15	15900	14000
16	15700	14000
17	15900	14000
18	15700	14000
19	15900	14000
20	15700	14000
21	15900	14000
22	12000	14000

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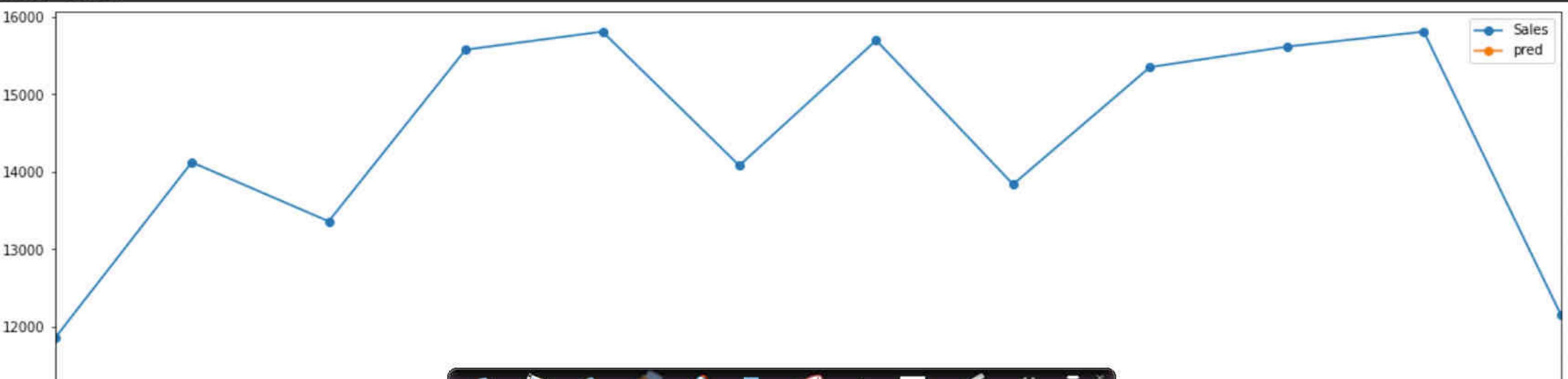
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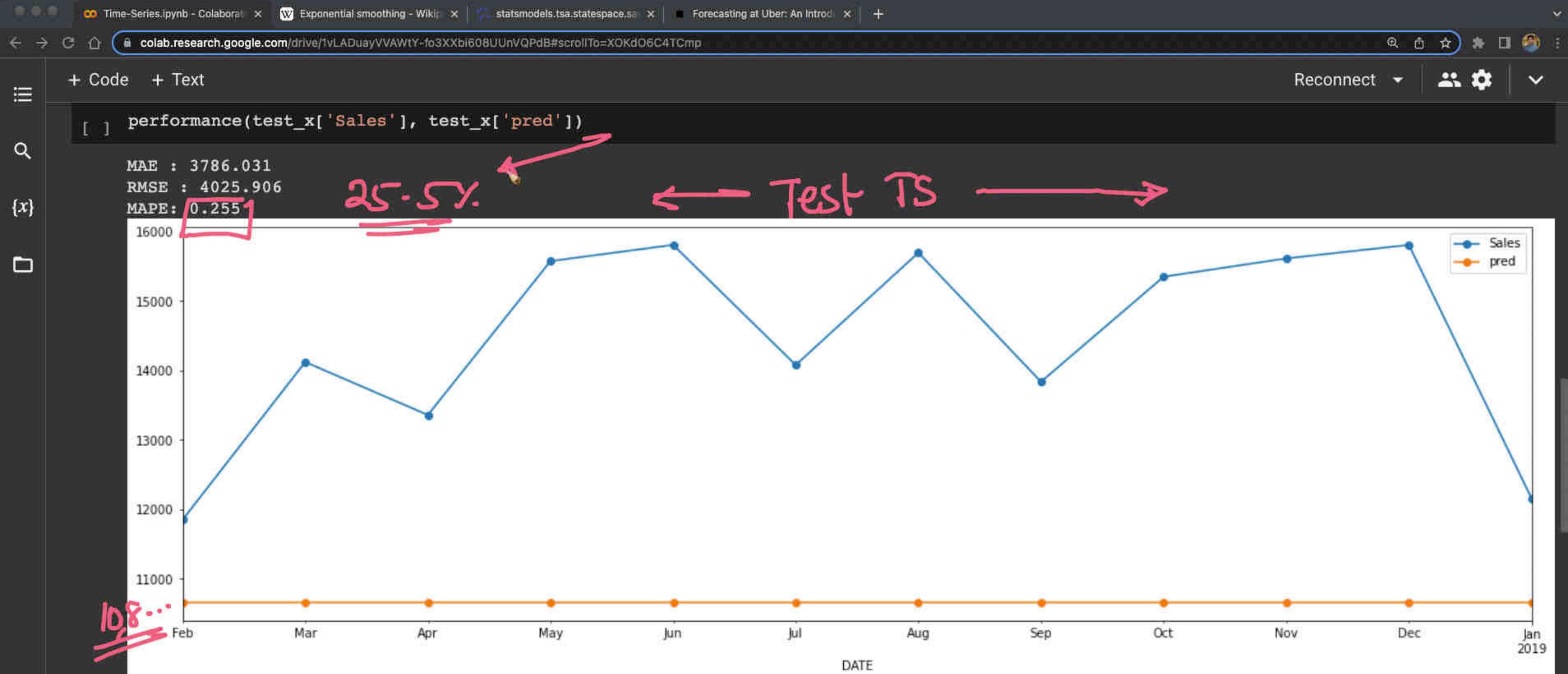
Models Foundations

Mean model

```
#train mean as test predicted ✓  
test_x['pred'] = train_x['Sales'].mean()  
  
test_x.plot(style='-o')  
  
performance(test_x['Sales'], test_x['pred'])
```

MAE : 3786.031
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▶ Naive forecasts

[] ↳ 2 cells hidden

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{x} Naive forecasts

Last value as the value at all future values: high variance model
test_x['pred'] = train_x['Sales'][-1]
test_x.plot(style='-o')
~~performance(test_x['Sales'], test_x['pred'])~~

MAE : 3434.233
RMSE : 3697.005
MAPE: 0.23

Index	Sales	pred
0	12000	12000
1	14100	14100
2	13300	13300
3	15400	15400
4	15700	15700
5	14100	14100
6	15500	15500
7	13800	13800
8	15600	15600
9	15300	15300
10	15800	15800
11	12100	12100

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Seasonal Naive

Seasonality
↳ 12 month (PACF)



$$\hat{y}_t = \underline{y_{t-12}}$$

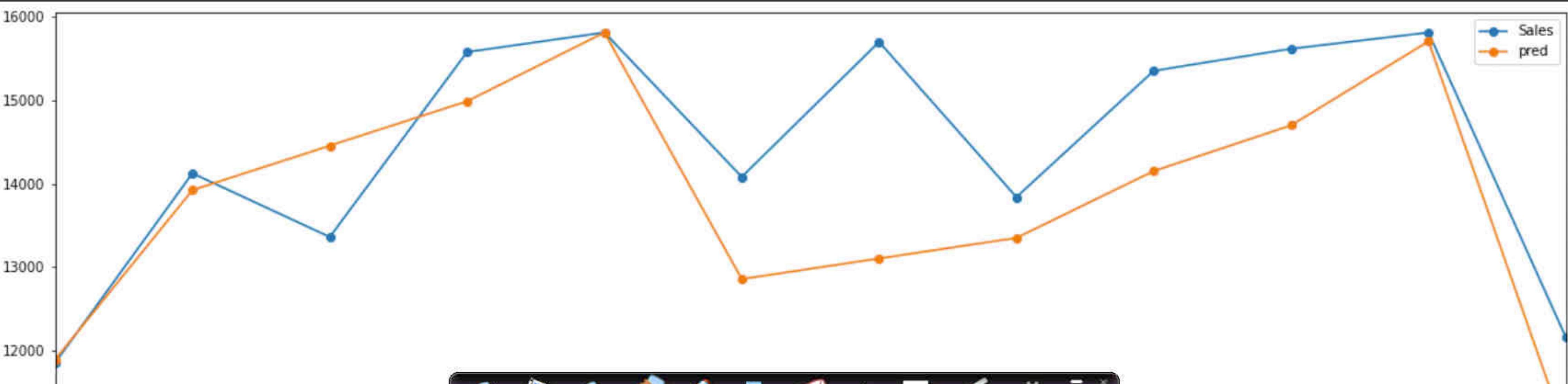
Forecast

(using y_t instead of x_t for convenience)



```
[ ] ## Seasonal Naive forecast: 1 year based on ACF and PACF plots
[ ] for i in test_x.index:
[ ]     test_x.loc[i]['pred'] = train_x.loc[i - pd.DateOffset(years=1)]['Sales']
[ ] 
[ ] test_x.plot(style='-o')
[ ] 
[ ] performance(test_x['Sales'], test_x['pred'])
```

MAE : 800.867
RMSE : 1067.837
MAPE: 0.055



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+ Code + Text

```
[ ] ## Seasonal Naive forecast: 1 year based on ACF and PACF plots
for i in test_x.index:
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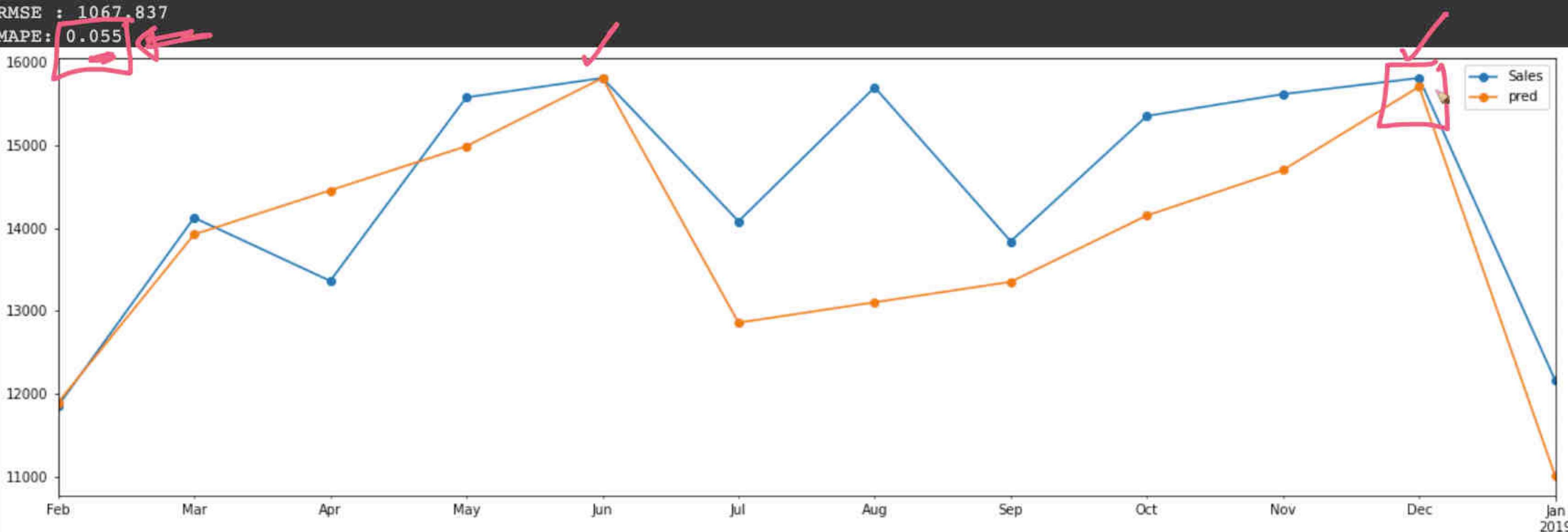
{x}
test_x.plot(style='-o')

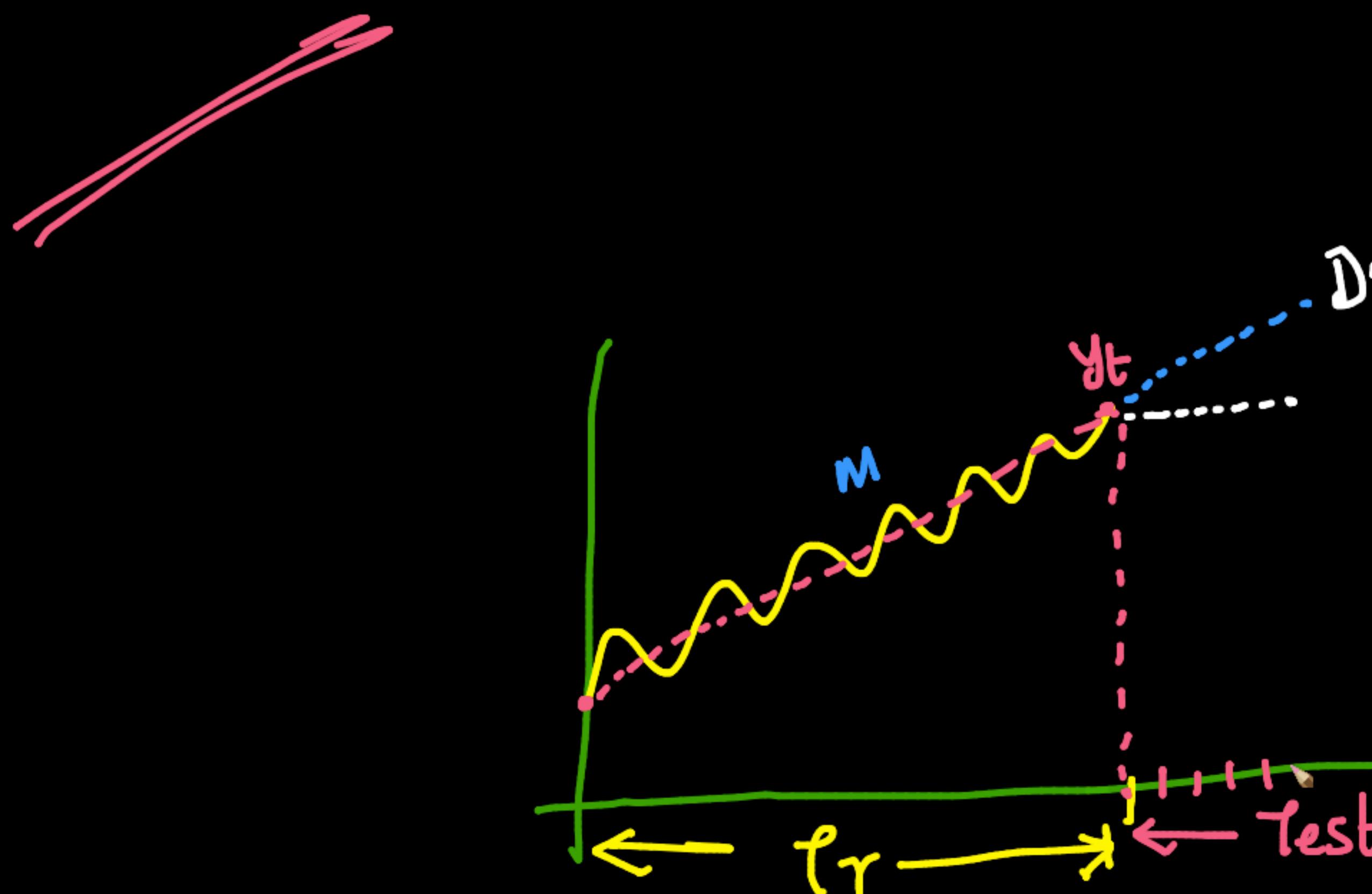
performance(test_x['Sales'], test_x['pred'])
```

MAE : 800.867

RMSE : 1067.837

MAPE: 0.055





Drift-Model
(Simple)

Trend-model

but NOT
Seasonality

+ Code + Text

Reconnect ▾

1 → 2 cells hidden

Simple Drift Model

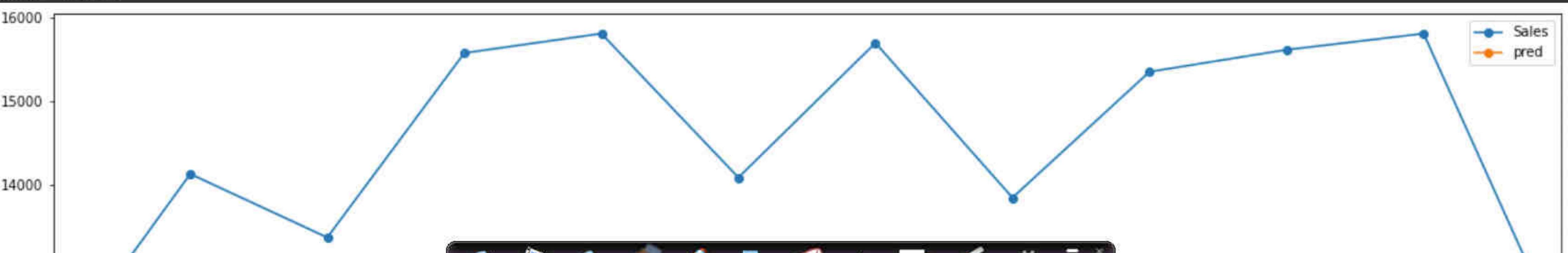
```
# Get the slope
y_t = train_x[ 'Sales' ][-1]
m = (y_t - train_x[ 'Sales' ][0]) / len(train_x)
h = np.linspace(0,len(test_x)-1, len(test_x))

test_x[ 'pred' ] = y_t + m * h
test_x.plot(style='-o')

performance(test_x[ 'Sales' ], test_x[ 'pred' ])
```

1, 2, 3, -

→ MAE : 3321.482
RMSE : 3586.323
MAPE: 0.223



+ Code + Text

Reconnect ▾

[1] ↳ 2 cells hidden

{x} ▾ Simple Drift Model

```
[ ] # Get the slope
y_t = train_x[ 'Sales' ][-1]
m = (y_t - train_x[ 'Sales' ][0]) / len(train_x)
h = np.linspace(0,len(test_x)-1, len(test_x))

test_x[ 'pred' ] = y_t + m * h

test_x.plot(style=' -o')

performance(test_x[ 'Sales' ], test_x[ 'pred' ])
```

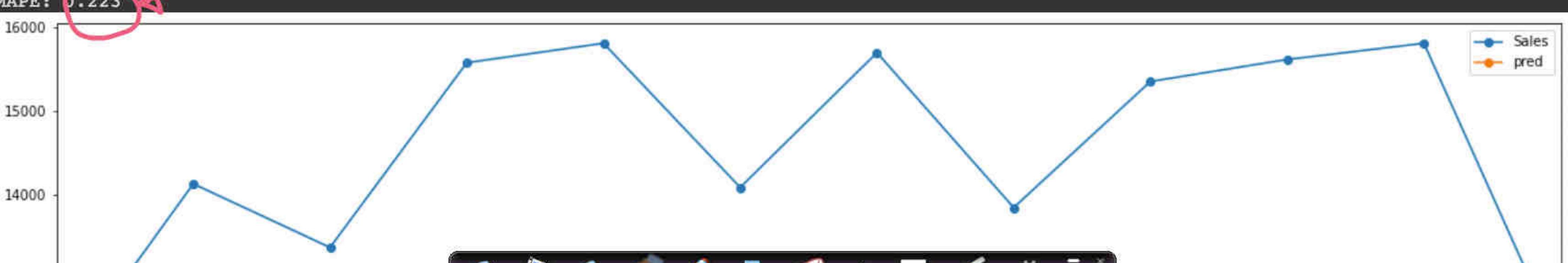
Lesson

- ① Trend is less important than Seasonality

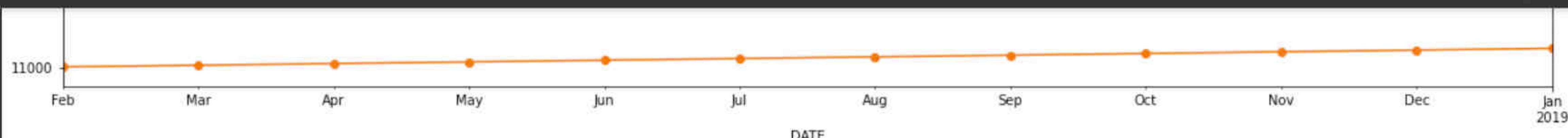
MAE : 3321.482

RMSE : 3586.323

MAPE: 0.223



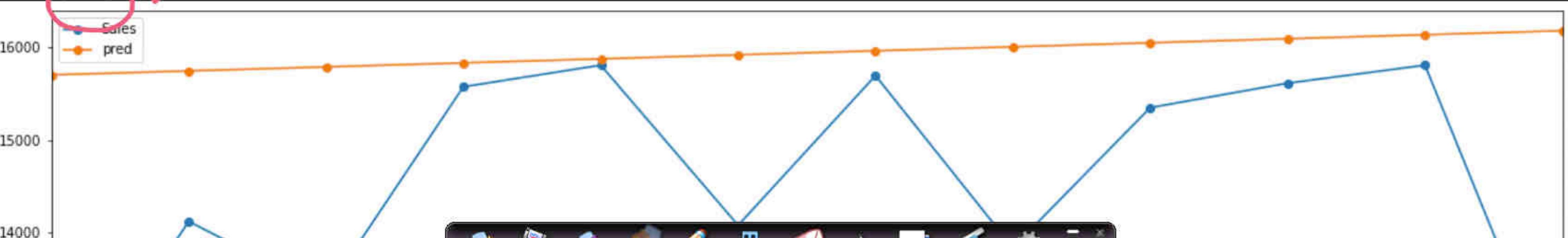
+ Code + Text



```
# sensitive to last value available  
# Get the slope  
y_t = train_x['Sales'][-2]  
m = (y_t - train_x['Sales'][0]) / len(train_x)  
h = np.linspace(0, len(test_x)-1, len(test_x))  
  
test_x['pred'] = y_t + m * h  
  
test_x.plot(style='-o')
```

```
performance(test_x['Sales'], test_x['pred'])
```

MAE : 1503.589
RMSE : 2013.071
MAPE: 0.115



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Moving average forecast

```
{x} df = train_x.copy()

df = df.append(pd.DataFrame(index = pd.date_range(start=df.index[-1], periods=12,freq='MS')[1:]))

pred = df.Sales.dropna().values

for i in range(12):
    pred = np.append(pred, pred[-3:].mean()) ##MA of window-length=3

test_x['pred'] = pred[-12:]
test_x.plot(style='-o')
performance(test_x['Sales'], test_x['pred'])
```

MAE : 1692.467
RMSE : 1875.03
MAPE: 0.115

The chart displays two series: 'Sales' (blue line with circular markers) and 'pred' (orange line with circular markers). The x-axis represents time, and the y-axis represents sales volume, ranging from 13,500 to 16,000. The 'Sales' series shows significant fluctuations, while the 'pred' series follows a smoother, downward-sloping trend.

Time Step	Sales	pred
1	13,800	13,800
2	14,100	13,700
3	13,300	13,600
4	15,100	13,500
5	15,600	13,400
6	15,800	13,300
7	14,100	13,200
8	15,700	13,100
9	13,900	13,000
10	15,400	12,900
11	15,700	12,800
12	15,900	12,700

$$\hat{x}_t = \frac{x_{t-1} + x_{t-2} + x_{t-3}}{3}$$

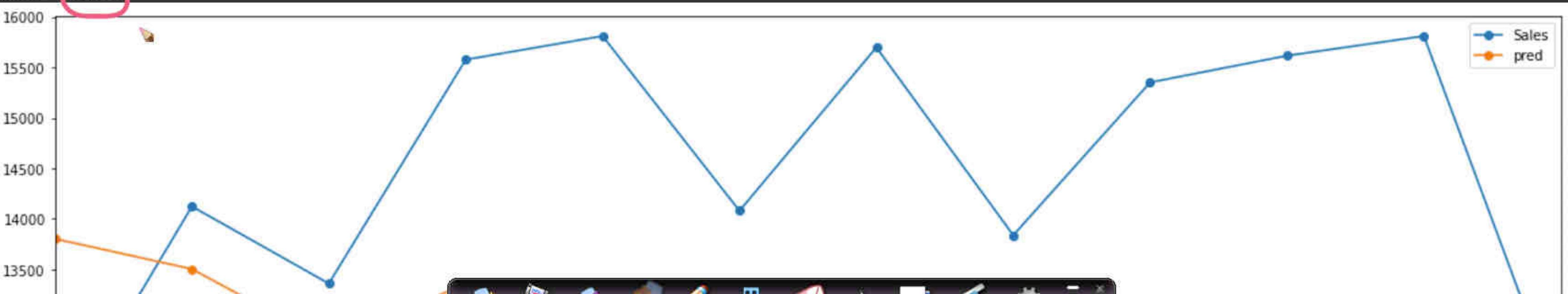
Moving average forecast

```
{x} df = train_x.copy()  
  
df = df.append(pd.DataFrame(index = pd.date_range(start=df.index[-1], periods=12,freq='MS')[1:]))  
  
pred = df.Sales.dropna().values  
  
for i in range(12):  
    pred = np.append(pred, pred[-3:].mean()) ##MA of window-length=3  
  
test_x['pred'] = pred[-12:]  
test_x.plot(style='^-o')  
performance(test_x['Sales'], test_x['pred'])
```

MAE : 1692.467

RMSE : 1875.03

MAPE: 0.115



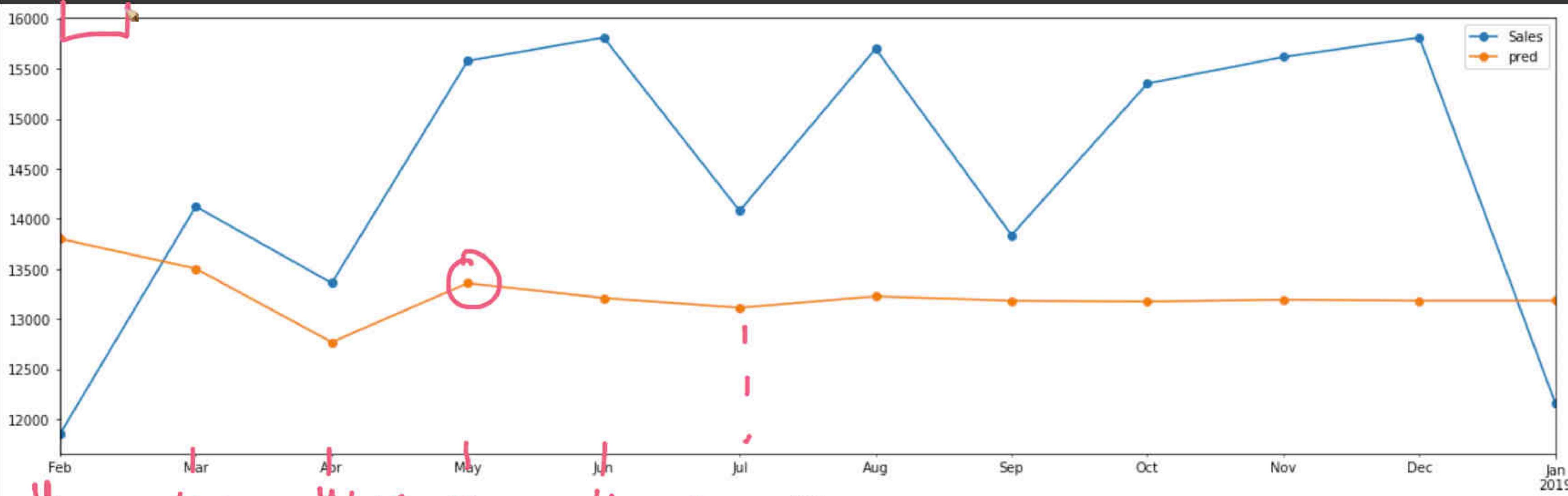
+ Code + Text

```
pred = np.append(pred, pred[-5:]).mean() #MAE OF WINDOW=10gains  
  
test_x['pred'] = pred[-12:]  
test_x.plot(style='.-o')  
performance(test_x['Sales'], test_x['pred'])
```

MAE : 1692.467

RMSE : 1875.03

MAPE: 0.115



y_{t+1} y_{t+2} y_{t+3} y_{t+4} y_{t+5}

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colab.research.google.com/drive/tvLADuayVVAWtY-fo3XXbi608UUnVQPdB#scrollTo=75hQpmq6VrV_

+ Code + Text Reconnect

Simple Drift Model

[] ↳ 2 cells hidden

Moving average forecast

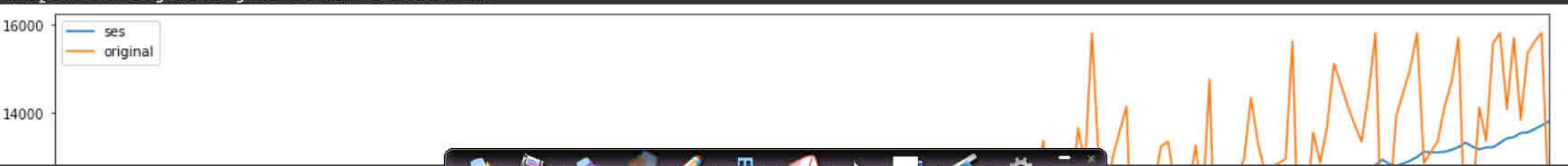
[] ↳ 1 cell hidden

Simple exponential smoothing

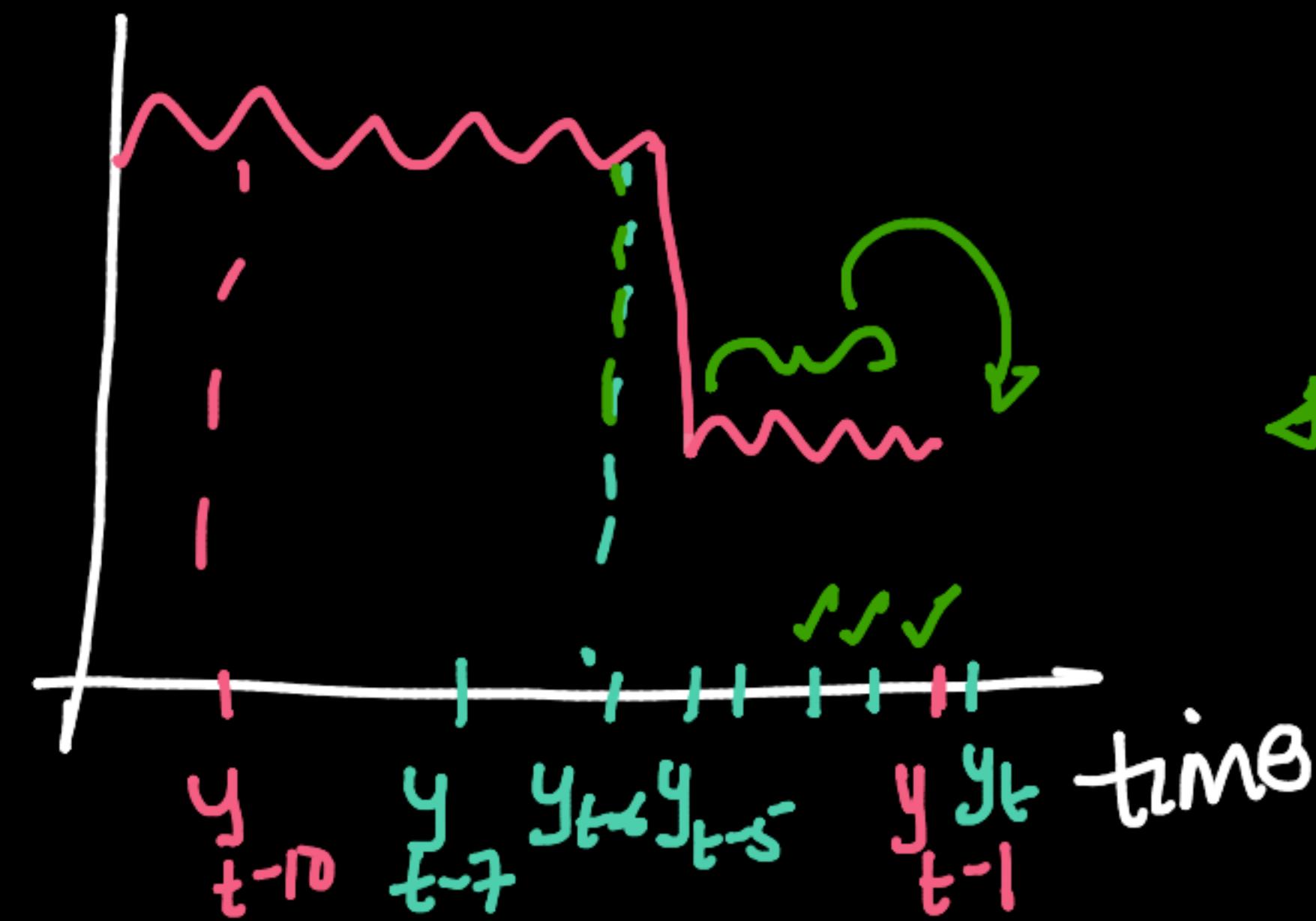
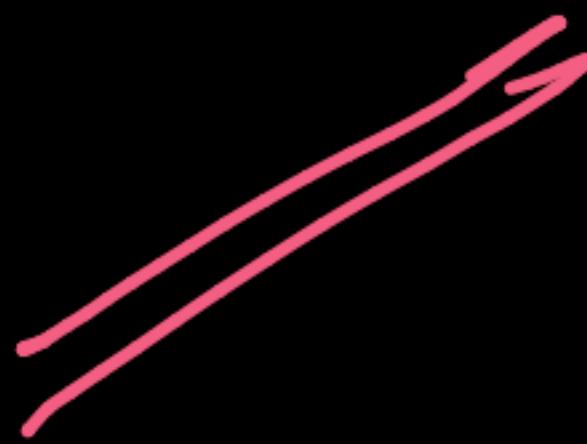
import statsmodels.api as sm
model = pd.Series(sm.tsa.SimpleExpSmoothing(mobile_sales.Sales).fit(smoothing_level=1/(2*12)).fittedvalues)

model.plot(label='ses')
mobile_sales.Sales.plot(label='original')
plt.legend()

/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_model.py:165: ValueWarning: No frequency information was provided, so inferring based on freq=
<matplotlib.legend.Legend at 0x7f2fc0bb4910>



36 / 36



$$\times y_t = \text{SMA}(\text{window}-1)$$

$$y_t = \text{WMA}$$

exponentially

Simple Expo.
Smoothing
(SES)

$$\begin{aligned}
 & y_0, y_1, \dots, y_t \\
 & \cdot \hat{y}_{t+1} \\
 & \left[\begin{array}{l} \hat{y}_{t+1} = \alpha \hat{y}_t + (1-\alpha) \hat{y}_t \\ \text{pred} \quad \text{actual} \end{array} \right] \xrightarrow{\text{recursive eqns}} \text{SES}
 \end{aligned}$$

$$\begin{aligned}
 & = \alpha \cdot y_t + (1-\alpha) [\alpha \cdot y_{t-1} + (1-\alpha) \hat{y}_{t-1}] \\
 & = \alpha \cdot y_t + \alpha (1-\alpha) y_{t-1} + (1-\alpha)^2 \hat{y}_{t-1}
 \end{aligned}$$

$$\alpha < \alpha_s < 1$$

= Code =

$$\left[\begin{array}{l} \hat{y}_{t-2} = \alpha \hat{y}_{t-1} + (1-\alpha) y_{t-2} \\ \vdots \end{array} \right]$$

→ time

y_0, y_1, \dots

y_t, \hat{y}_{t+1}

y_{t+1}, \hat{y}_{t+2}

\hat{y}_{t+2}

- - -

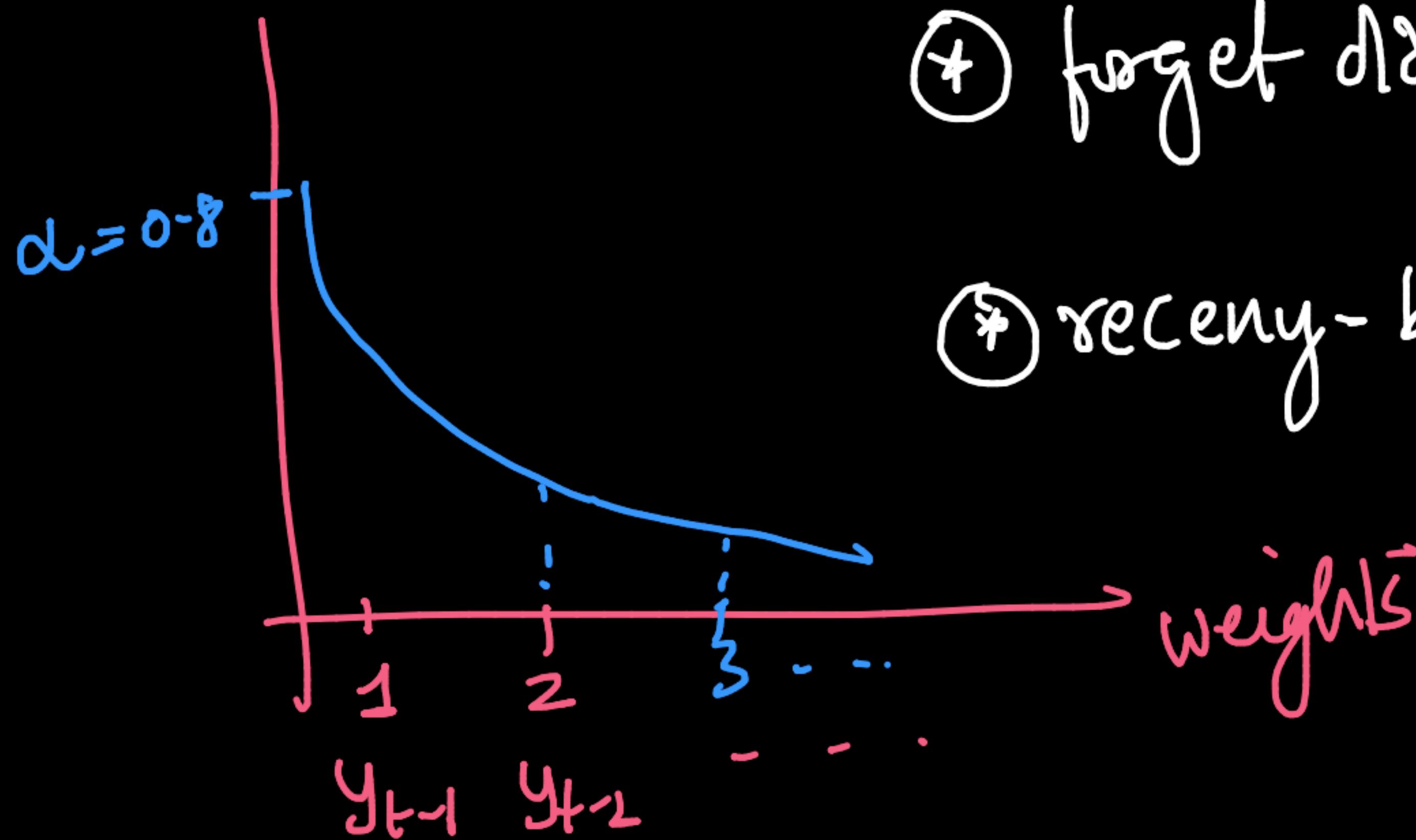
$$0 < \alpha < 1$$

Code

$$\hat{y}_{t+1} = \underbrace{\alpha y_t + \alpha(1-\alpha)y_{t-1} + \alpha(1-\alpha)^2 y_{t-2}}_{t \dots}$$

$$\hat{y}_{t+1} = \underbrace{0.8 y_t}_{\uparrow} + \underbrace{0.8(0.2) y_{t-1}}_{0.16} + \underbrace{0.8(0.2)^2 y_{t-2}}_{0.032} + 0.8(0.2)^3 y_{t-3} + \dots$$

$$\underbrace{0.0064}_{\dots}$$



- ④ forget older values exponentially fast...
- ④ recency-bias heavily :-)

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+ Code + Text Reconnect

Simple exponential smoothing

suggested < 2x Seasonality

```
import statsmodels.api as sm
model = pd.Series(sm.tsa.SimpleExpSmoothing(mobile_sales.Sales).fit(smoothing_level=1/(2*12)).fittedvalues)

model.plot(label='ses')
mobile_sales.Sales.plot(label='original')
plt.legend()
```

/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_model.py:165: ValueWarning: No frequency information was provided, so inferring % freq, ValueWarning)
<matplotlib.legend.Legend at 0x7f2fc0bb4910>

The figure is a line plot showing two time series over time. The y-axis ranges from 8,000 to 16,000. The 'original' series (orange line) exhibits high-frequency seasonal oscillations. The 'ses' series (blue line) is a smoother line representing the simple exponential smoothing fit. A legend in the top-left corner identifies the lines. Handwritten yellow annotations include a question mark above the plot, a circled 'suggested' with a bracket below it, and a circled '2x Seasonality'.

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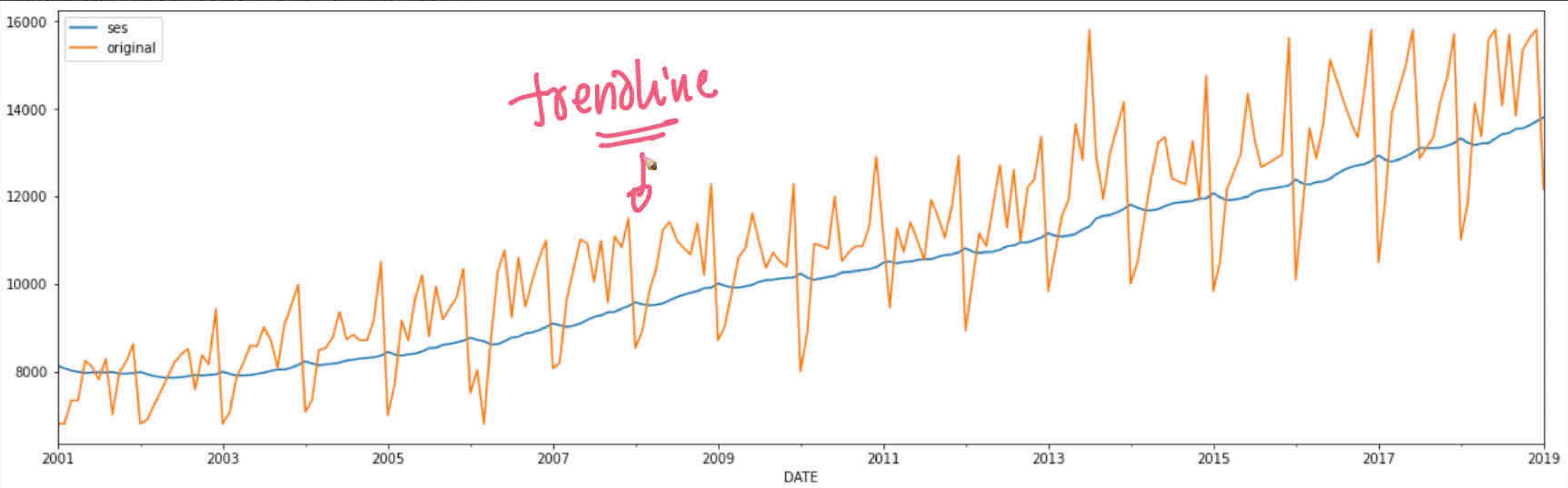


+ Code + Text

Reconnect

```
model.plot(label='ses')
mobile_sales.Sales.plot(label='original')
plt.legend()
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_model.py:165: ValueWarning: No frequency information was provided, so inferring % freq. ValueWarning)
<matplotlib.legend.Legend at 0x7f2fc0bb4910>
```



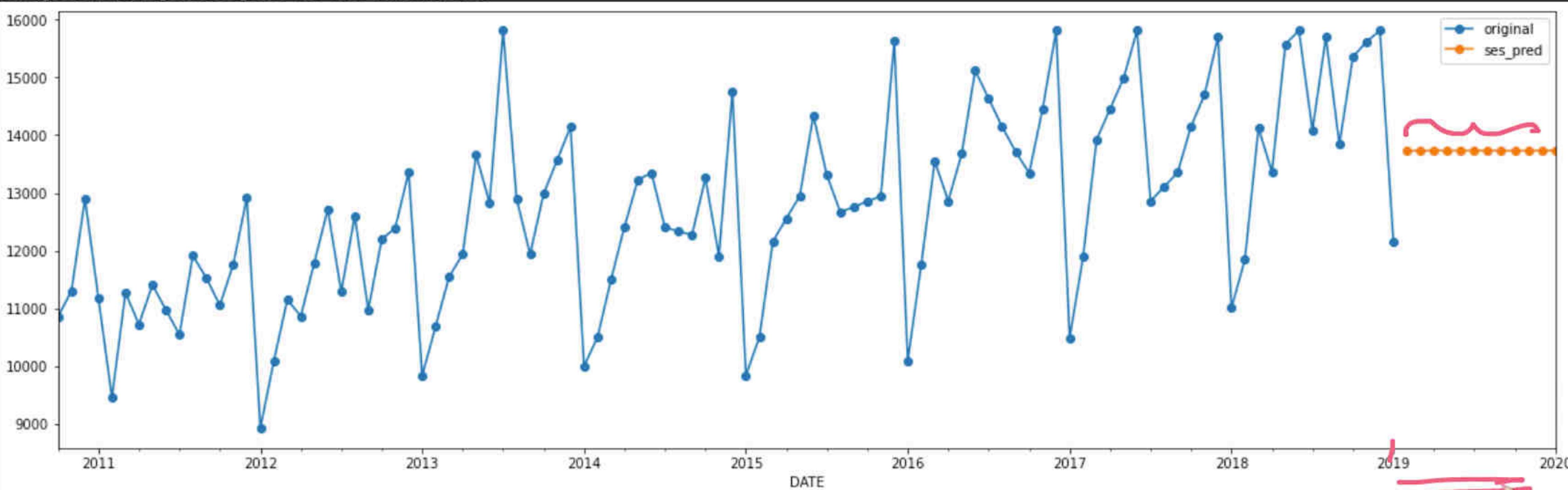
```
model = sm.tsa.SimpleExpSmoothing(mobile_sales.Sales).fit(smoothing_level=1/(2*12))
pred = model.forecast(steps = 12)
```



+ Code + Text

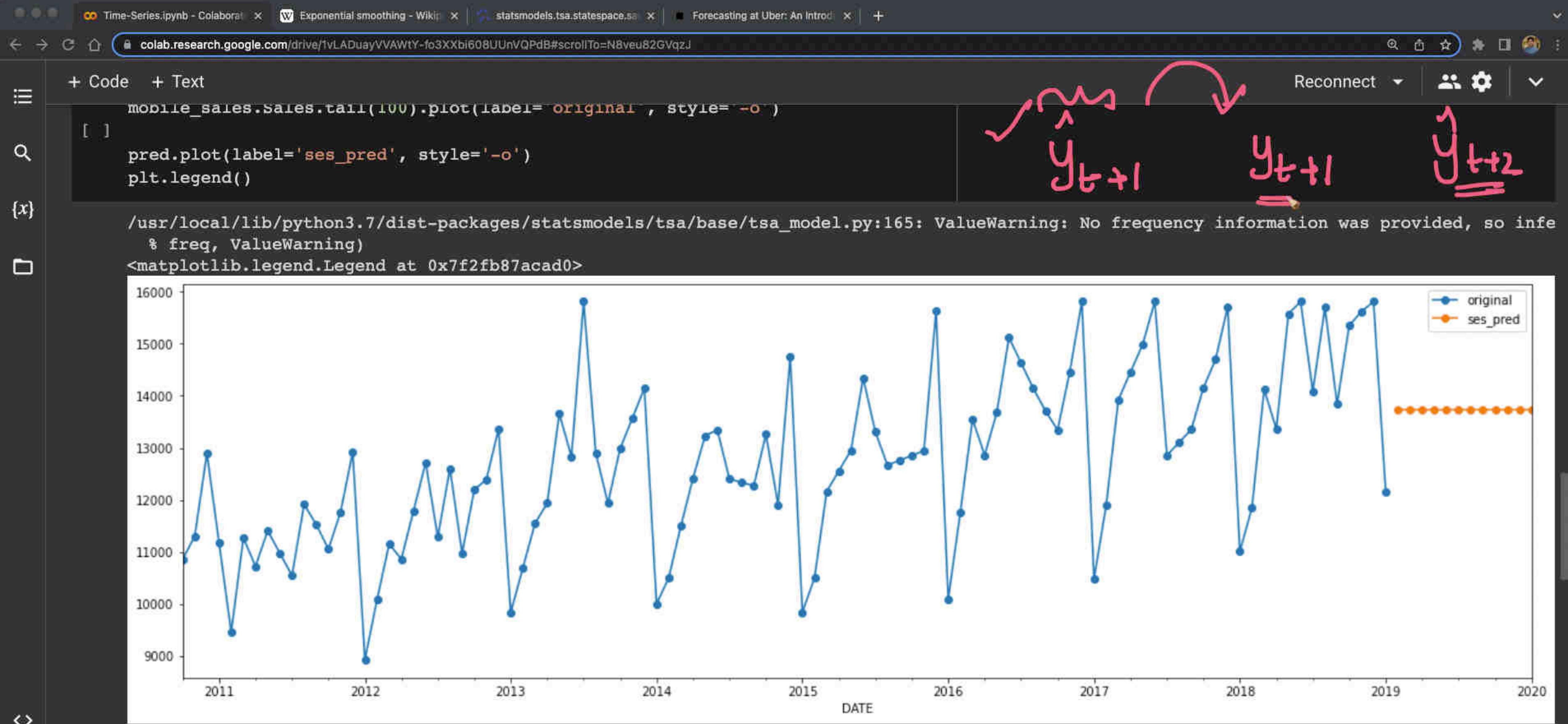
```
[ ] mobile_sales.Sales.tail(100).plot(label='original', style='.-o')  
pred.plot(label='ses_pred', style='.-o')  
plt.legend()
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_model.py:165: ValueWarning: No frequency information was provided, so inferring % freq. ValueWarning)  
<matplotlib.legend.Legend at 0x7f2fb87acad0>
```

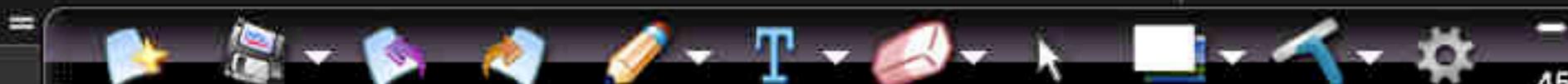


```
[ ] model = sm.tsa.SimpleExpSmoothing(train)
```





```
[ ] model = sm.tsa.SimpleExpSmoothing(train_x.Sales).fit(smoothing_level=1/(2*12))  
test_x['pred'] = model.forecast(steps =
```



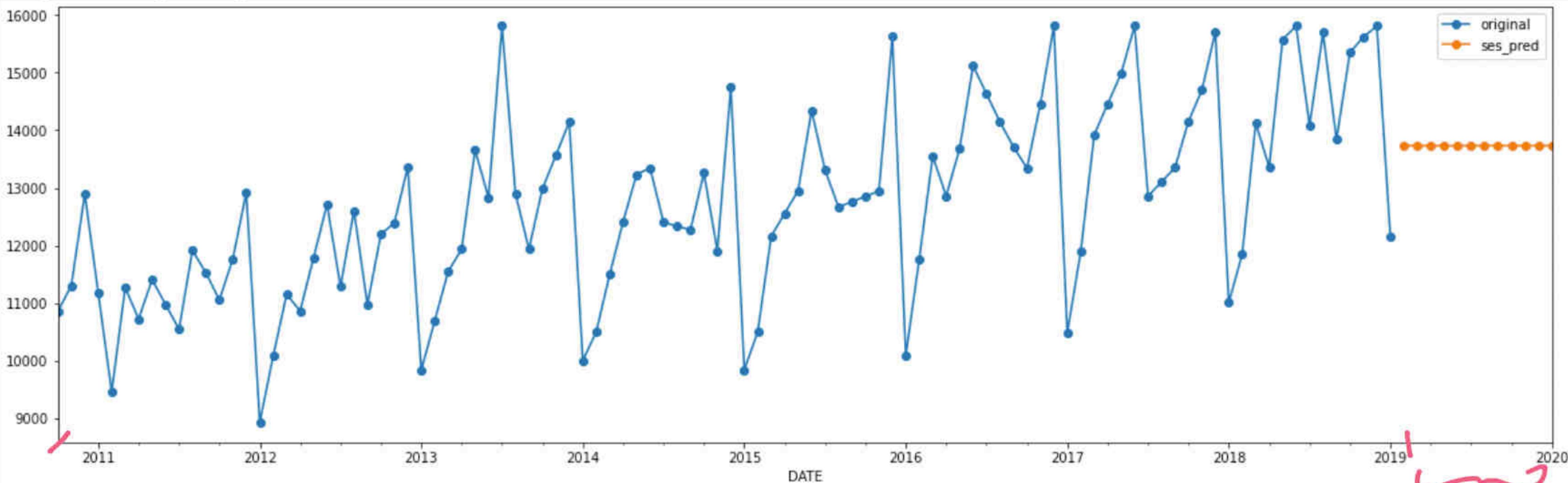
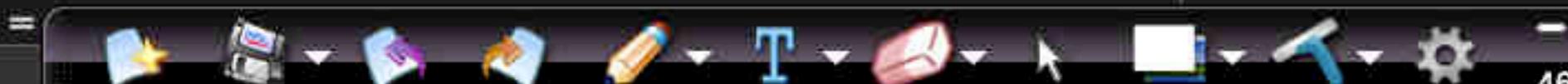
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Reconnect

+ Code + Text

mobile_sales.Sales.tail(100).plot(label='original', style='.-o')

 y_{t+1} ← ~~obs~~ y_t y_{t+1} $\sim \sim \sim$ pred.plot(label='ses_pred', style='.-o')
plt.legend()/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_model.py:165: ValueWarning: No frequency information was provided, so inferring % freq. ValueWarning)
<matplotlib.legend.Legend at 0x7f2fb87acad0>model = sm.tsa.SimpleExpSmoothing(train_x.Sales).fit(smoothing_level=1/(2*12))
test_x['pred'] = model.forecast(steps =

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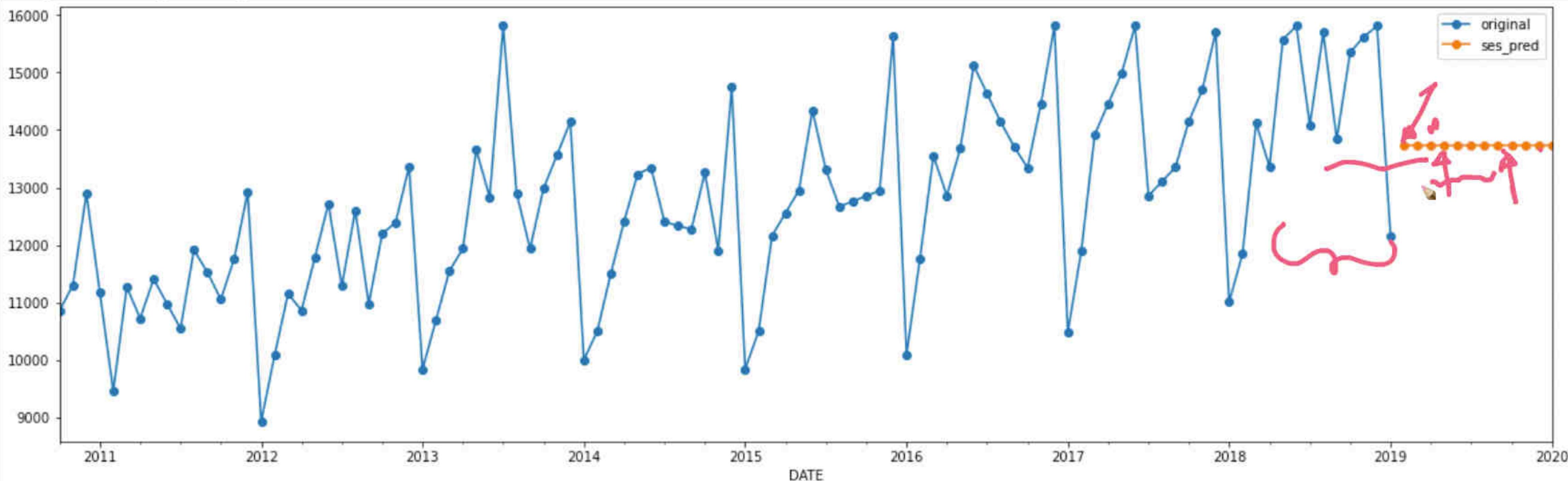
Reconnect

+ Code + Text

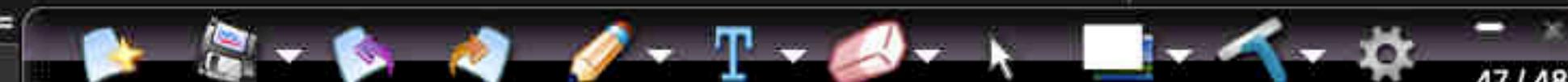
```
mobile_sales.Sales.tail(100).plot(label= 'original' , style= '-o')
```

```
[ ] pred.plot(label= 'ses_pred' , style= '-o')  
plt.legend()
```

```
{x} /usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_model.py:165: ValueWarning: No frequency information was provided, so inferring % freq. ValueWarning)  
<matplotlib.legend.Legend at 0x7f2fb87acad0>
```



```
[ ] model = sm.tsa.SimpleExpSmoothing(train_x.Sales).fit(smoothing_level=1/(2*12))  
test_x['pred'] = model.forecast(steps =
```



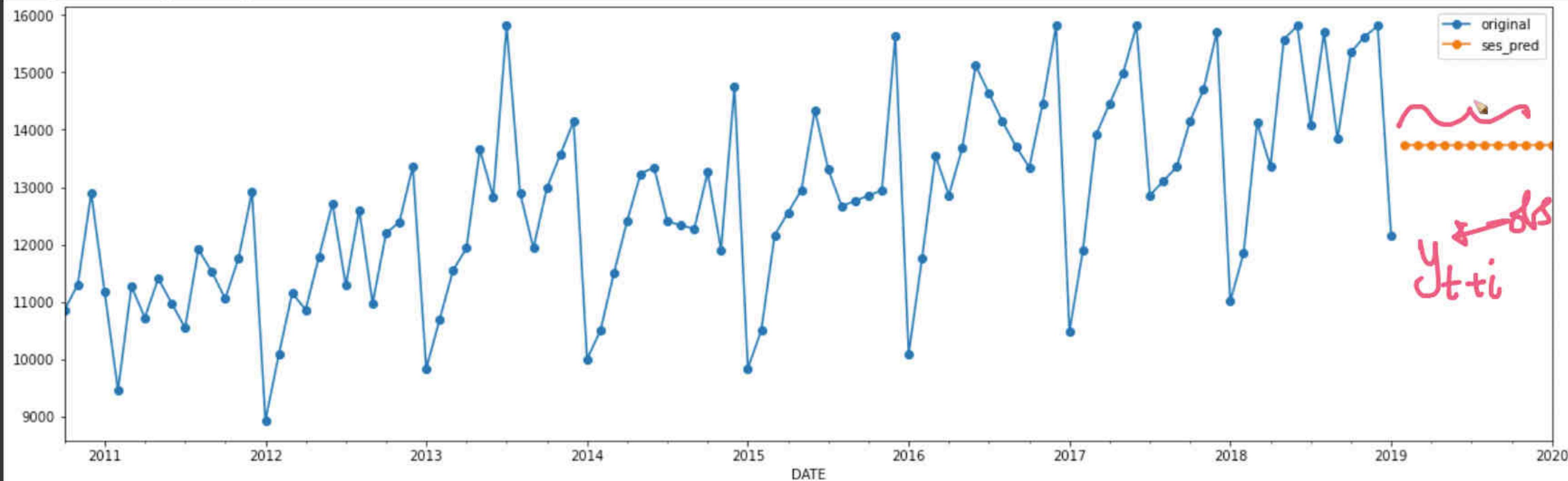
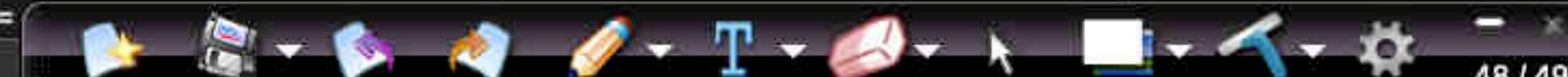
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Reconnect

+ Code + Text

mobile_sales.Sales.tail(100).plot(label='original', style='.-o')

[] pred.plot(label='ses_pred', style='.-o')
plt.legend(){x} /usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_model.py:165: ValueWarning: No frequency information was provided, so inferring % freq, ValueWarning)
<matplotlib.legend.Legend at 0x7f2fb87acad0>[] model = sm.tsa.SimpleExpSmoothing(train_x.Sales).fit(smoothing_level=1/(2*12))
test_x['pred'] = model.forecast(steps =

Two-way

SES
can detect
trend

 \hat{y}_{t+1} \hat{y}_{t+1} \hat{y}_{t+2} \hat{y}_{t+2} \hat{y}_{t+3} \hat{y}_{t+3}

Simpler

Our problem

SES
may not detect
trend

$y_0 \dots y_t$

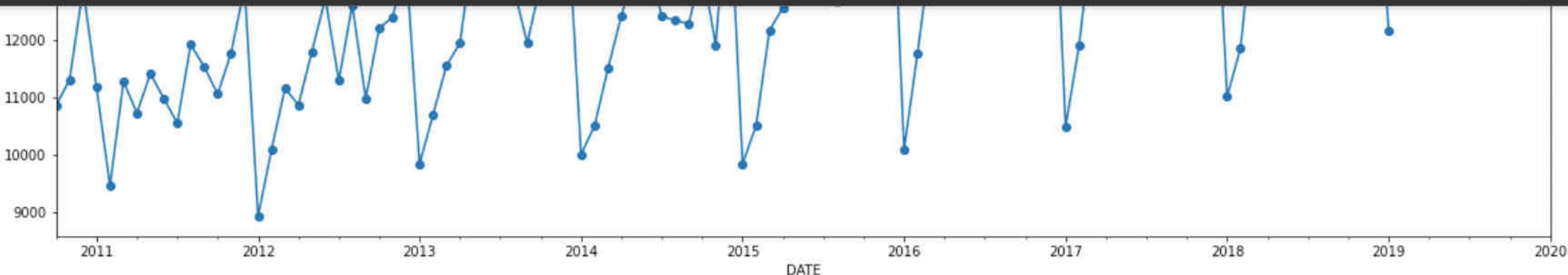
$\hat{y}_{t+1} \dots \hat{y}_{t+10}$

harder



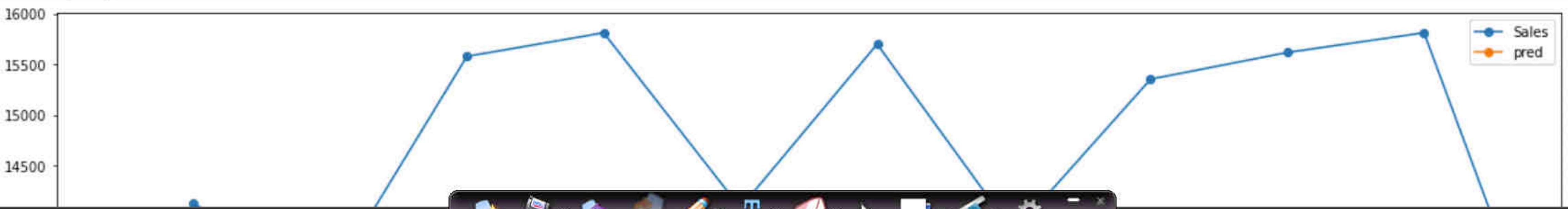
+ Code

+ Text



```
model = sm.tsa.SimpleExpSmoothing(train_x.Sales).fit(smoothing_level=1/(2*12))
test_x['pred'] = model.forecast(steps = 12)
test_x.plot(style='^-o')
performance(test_x['Sales'], test_x['pred'])
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_model.py:165: ValueWarning: No frequency information was provided, so inferring freq= freq, ValueWarning)
MAE : 1621.347
RMSE : 1830.599
MAPE: 0.109
```



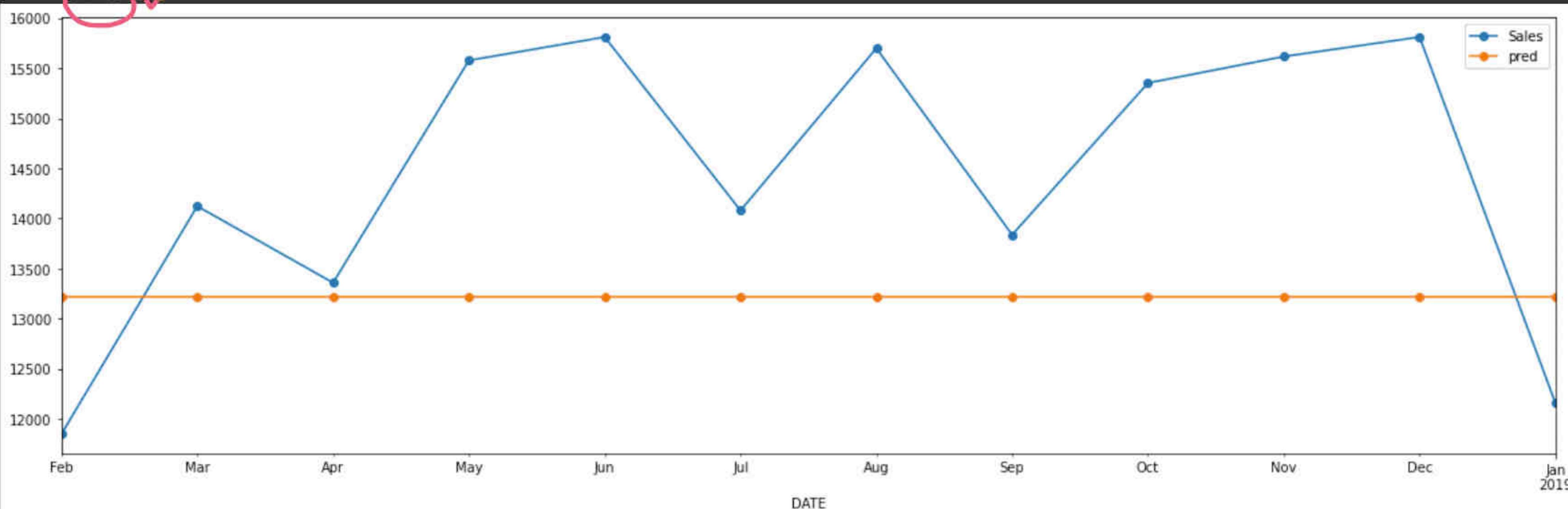
+ Code + Text

```
model = sm.tsa.SimpleExpSmoothing(train_x.Sales).fit(smoothing_level=1/(2*12))
test_x['pred'] = model.forecast(steps = 12)
test_x.plot(style='-o')
performance(test_x['Sales'], test_x['pred'])
```

/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_model.py:165: ValueWarning: No frequency information was provided, so inference uses freq='Q'.
MAE : 1621.347

RMSE : 1830.599

MAPE: 0.109



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+ Code + Text

Reconnect

Simple Drift Model

[] ↳ 2 cells hidden

Moving average forecast

▶ ↳ 1 cell hidden

Simple exponential smoothing

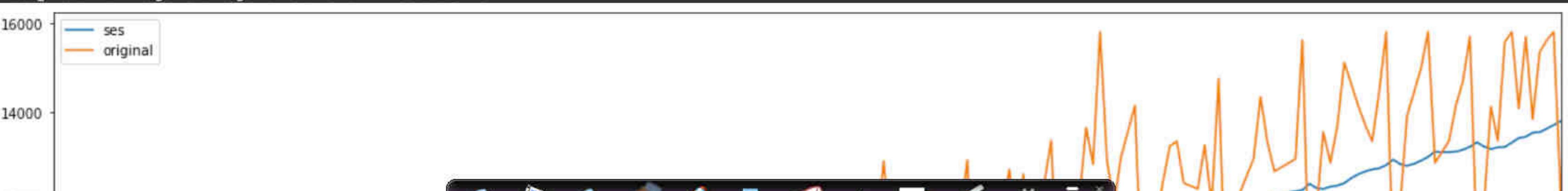
Missing trend & seasonality

~
10.5% MAPE

```
▶ import statsmodels.api as sm
model = pd.Series(sm.tsa.SimpleExpSmoothing(mobile_sales.Sales).fit(smoothing_level=1/(2*12)).fittedvalues)

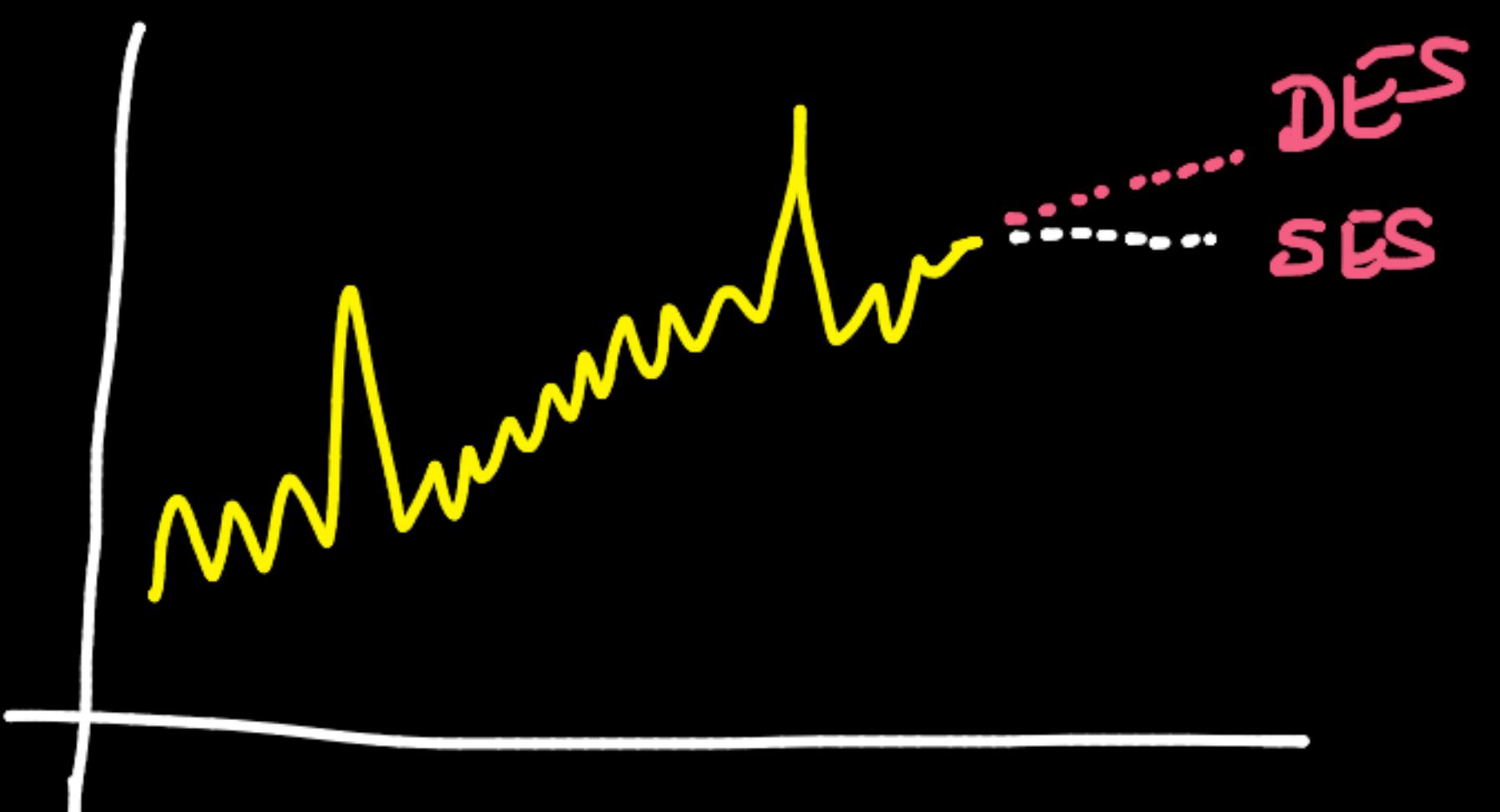
model.plot(label='ses')
mobile_sales.Sales.plot(label='original')
plt.legend()
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_model.py:165: ValueWarning: No frequency information was provided, so inferring freq, ValueWarning)
<matplotlib.legend.Legend at 0x7f2fc0bb4910>
```



(Intuition)

$$DES = SES + \text{Trend}$$



Double Exponential Smoothing (DES)

[Holt's Linear Model]

Single Exponential Smoothing

SES math:

$$0 < \alpha < 1$$



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

\cong expo-weighting

$$\hat{y}_{t+1} = \alpha y_t + (1-\alpha) \alpha \cdot y_{t-1} + \alpha (1-\alpha)^2 y_{t-2} + \dots$$

was trend
missing seasonality

DES - math:

$$\hat{y}_{t+1} = l_t + b_t \quad \xrightarrow{\text{simultaneous}} \sim 10-5\% MAPE$$

$0 < \alpha < 1$

$0 < \beta < 1$

level term
lag terms \dots

$l_t = \alpha \underline{y_t} + (1-\alpha) [l_{t-1} + b_{t-1}]$

$b_t = \beta \cdot (\underline{l_t} - \underline{l_{t-1}}) + (1-\beta) \underline{b_{t-1}}$

Trend term

previous slope

recursive expand

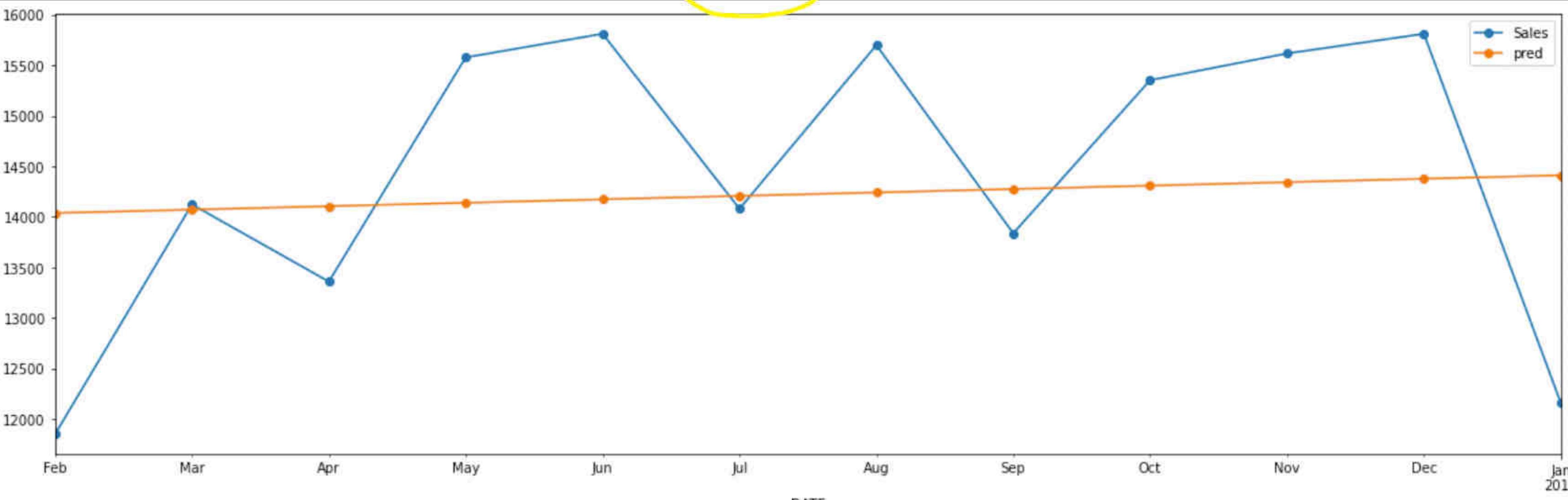
[+ Code](#) [+ Text](#)

Reconnect

```
# trend="add" or "multiplicative"
model = sm.tsa.ExponentialSmoothing(train_x.Sales, trend='add').fit(smoothing_level=1/(2*12))
test_x['pred'] = model.forecast(steps = 12)
test_x.plot(style='^-o')
performance(test_x['Sales'], test_x['pred'])
```

/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_model.py:165: ValueWarning: No frequency information was provided, so inferring based on % freq, ValueWarning)
MAE : 1172.756
RMSE : 1360.928
MAPE: 0.083

DES

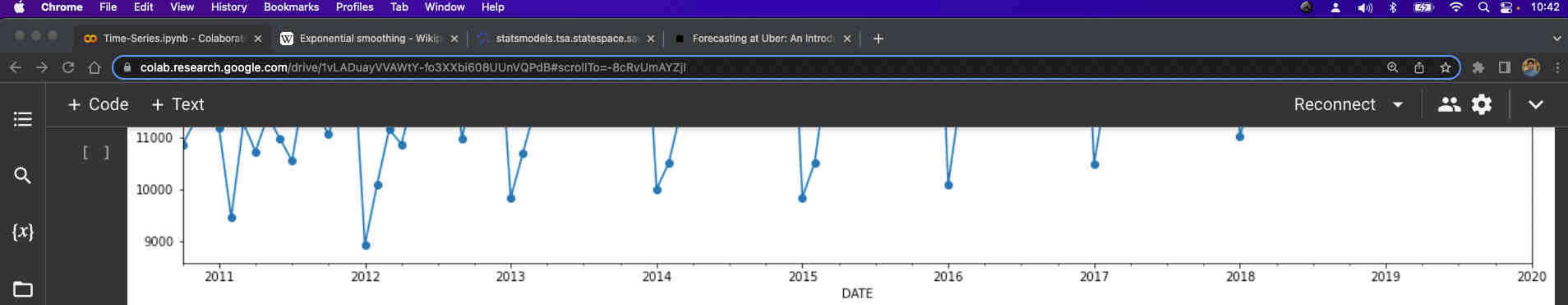


SES: ~10.5% MAPE

DES : ~8.3% MAPE

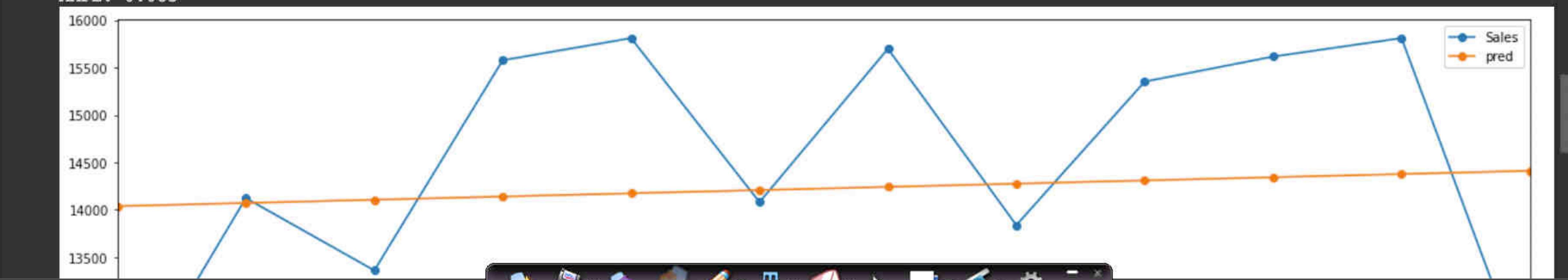
(trend)

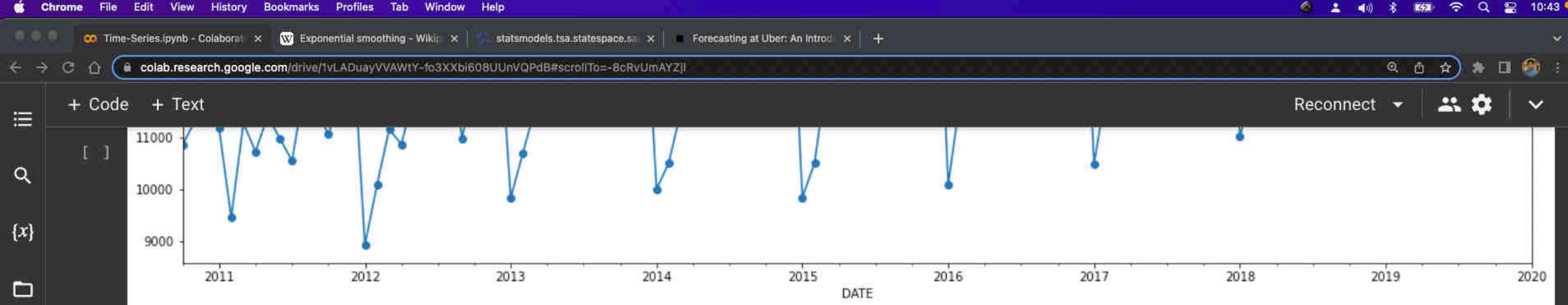
TES
(Trend & Seasonality)



trend="add" or "multiplicative"
model = sm.tsa.ExponentialSmoothing(train_x.Sales, trend='add').fit(smoothing_level=1/(2*12))
test_x['pred'] = model.forecast(steps = 12)
test_x.plot(style='^-o')
performance(test_x['Sales'], test_x['pred'])

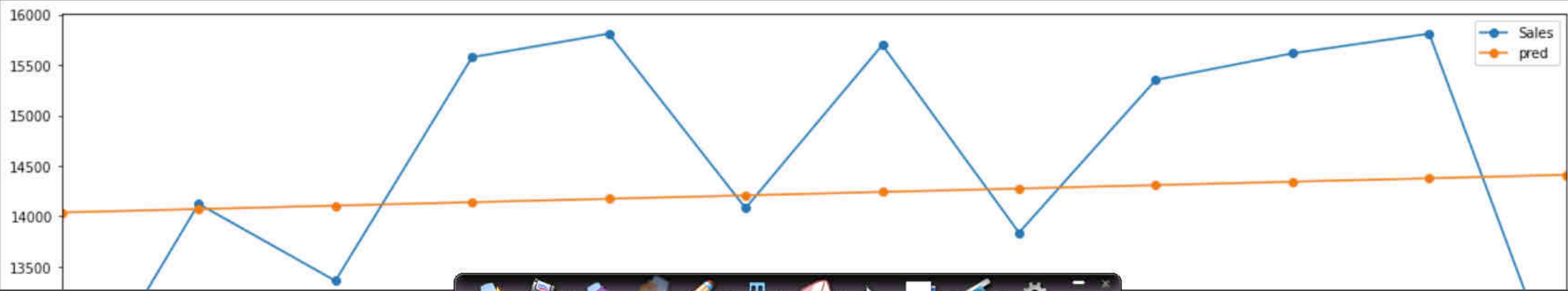
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_model.py:165: ValueWarning: No frequency information was provided, so inferring based on freq, ValueWarning)
MAE : 1172.756
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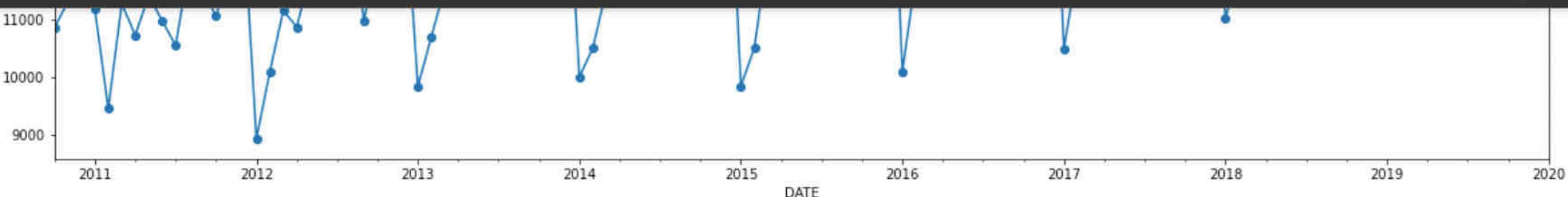
```
# trend="add" or "multiplicative"
model = sm.tsa.ExponentialSmoothing(train_x.Sales, trend='add').fit(smoothing_level=1/(2*12))
test_x['pred'] = model.forecast(steps = 12)
test_x.plot(style='^-o')
performance(test_x['Sales'], test_x['pred'])
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_model.py:165: ValueWarning: No frequency information was provided, so inferring freq, ValueWarning)
MAE : 1172.756
RMSE : 1360.928
MAPE: 0.083
```





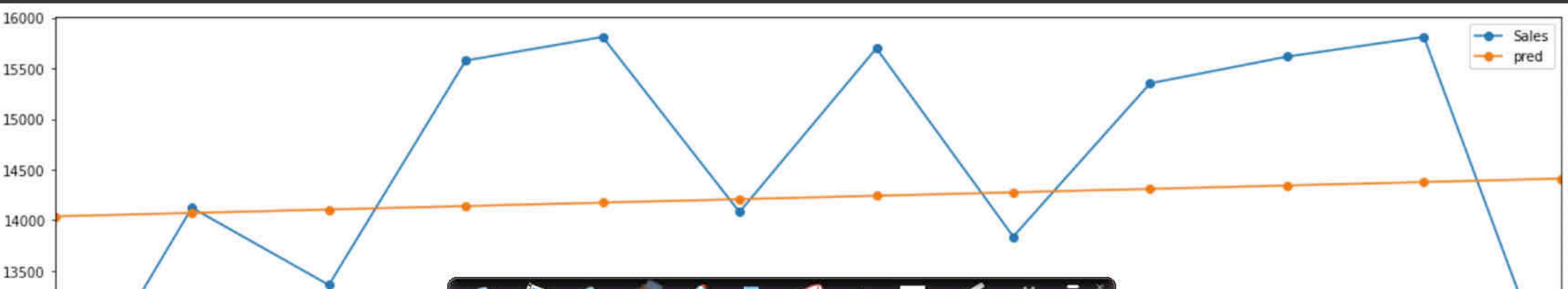
+ Code + Text

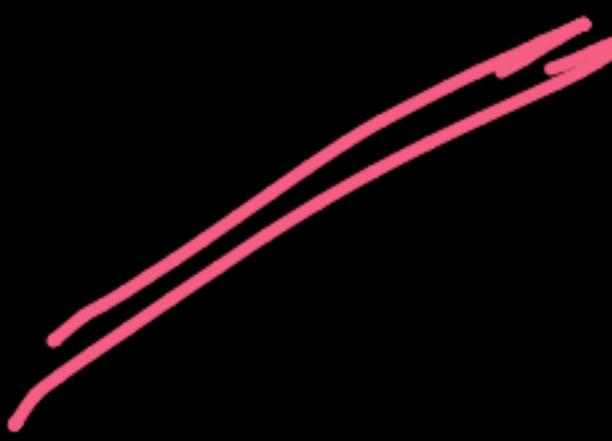


```
# trend="add" or "multiplicative"
model = sm.tsa.ExponentialSmoothing(train_x.Sales, trend='add').fit(smoothing_level=1/(2*12))
test_x['pred'] = model.forecast(steps = 12)
test_x.plot(style='.-o')
performance(test_x['Sales'], test_x['pred'])
```

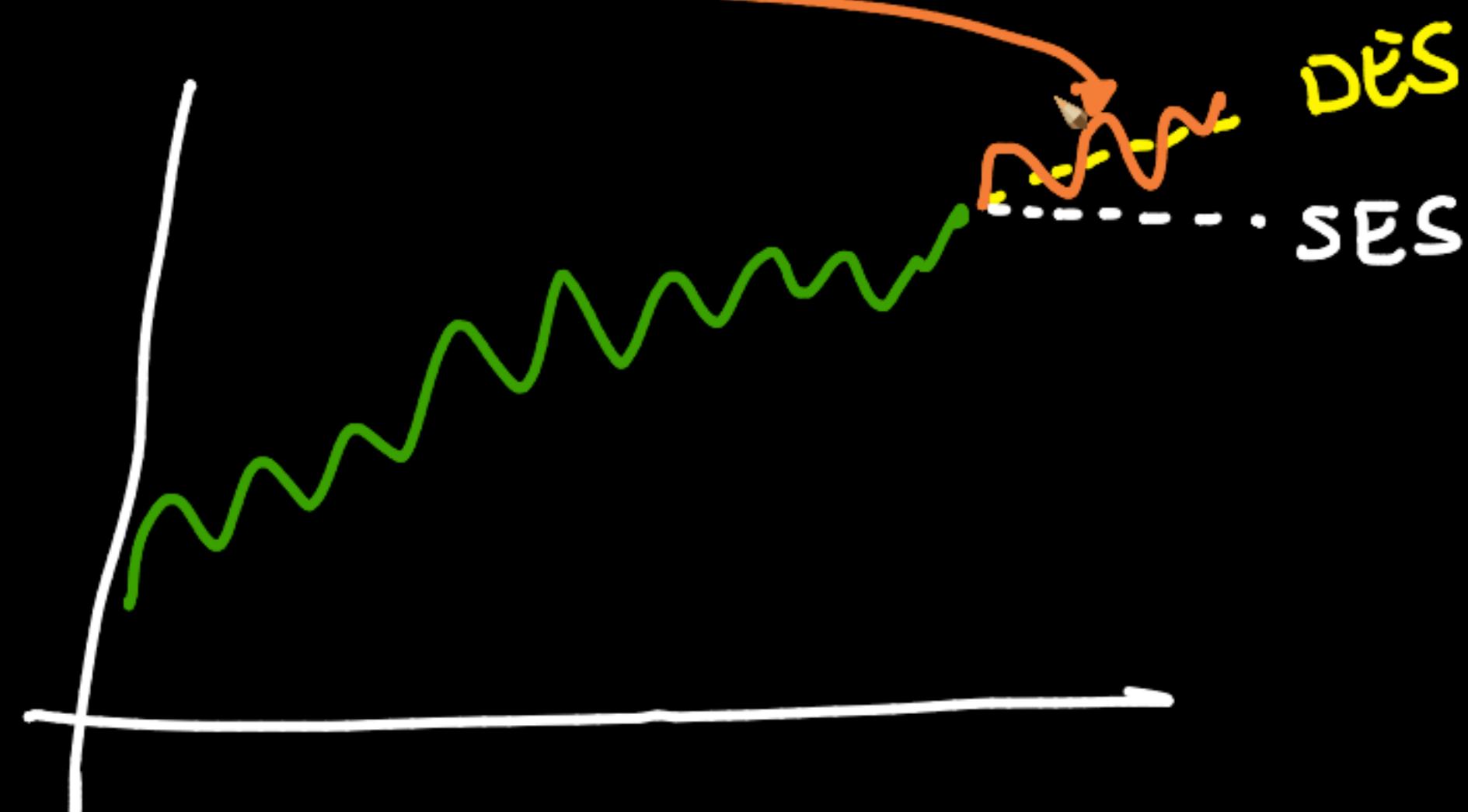
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_model.py:165: ValueWarning: No frequency information was provided, so inferring freq, ValueWarning)
MAE : 1172.756
RMSE : 1360.928
MAPE: 0.083

d, β : hyper parameters





TES = DES + Seasonality



TES
(Holt-Winters
model)



lag-terms (SES)
+ trend (DES)
+ Seasonality

$\{ \text{(data)} \downarrow$
 $m = 12 \text{ months}$

TES:

$(\alpha < 0, \beta > 1)$

$$\hat{y}_{t+1} = l_t + b_t + S_{t+1-M}$$

lag terms

trend

$$l_t = \alpha \underbrace{\left[\hat{y}_t - S_{t-M} \right]}_{\text{Subtract the Seasonality effect}} + (1-\alpha) \underbrace{\left[l_{t-1} + b_{t-1} \right]}_{\text{Previous values}}$$

$\hat{y}_t - S_{t-M}$

Subtract the
Seasonality effect

$$b_t = \beta (l_{t-1} - b_{t-1}) + (1-\beta) b_{t-1} \rightarrow \text{Same as earlier}$$

$$\underline{s}_t = \gamma \left[y_t - \overbrace{l_{t-1}}^{\text{Current Seasonality}} - \overbrace{b_{t-1}}^{\text{level term}} \right] + (1-\gamma) \left[\underline{s}_{t-m} \right]$$

↓
Current Seasonality

after removing level term
& trend term

↓
past Seasonality

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Reconnect

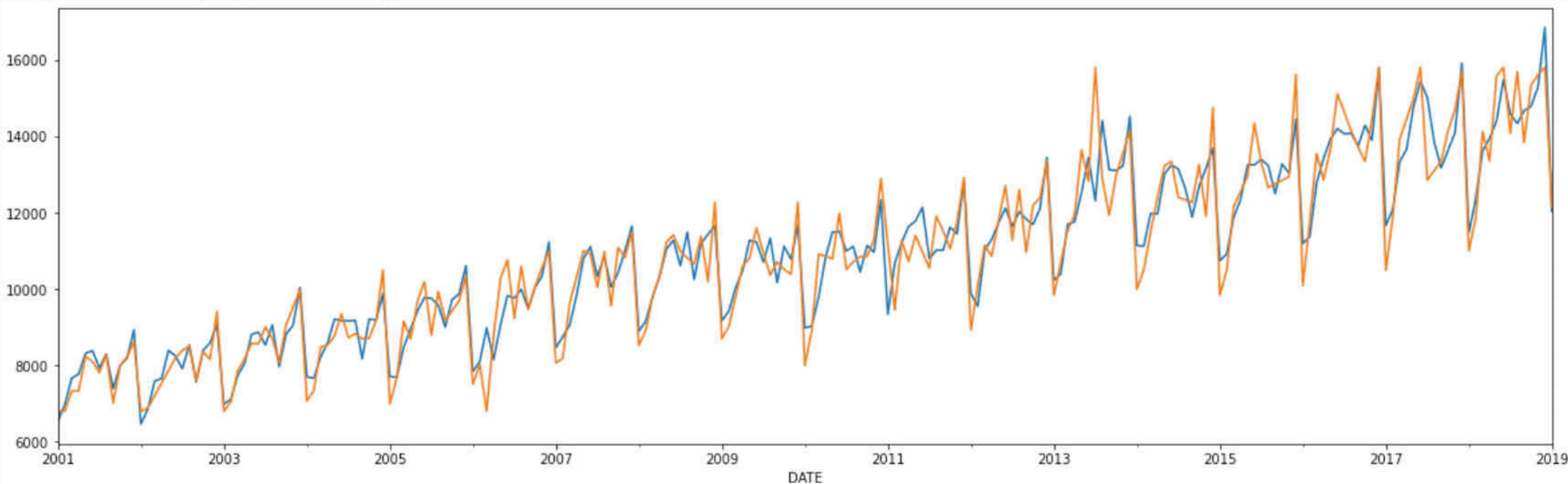
+ Code + Text

Reconnect

```
## seasonality="add" or "multiplicative"
model = sm.tsa.ExponentialSmoothing(mobile_sales.Sales, trend='add', seasonal='add').fit(smoothing_level=0.4)
model.fittedvalues.plot()
mobile_sales.Sales.plot()
```

$$\frac{1}{24/2} = M$$

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_model.py:165: ValueWarning: No frequency information was provided, so inferring freq, ValueWarning)
<matplotlib.axes._subplots.AxesSubplot at 0x7f2fb85e0d90>
```

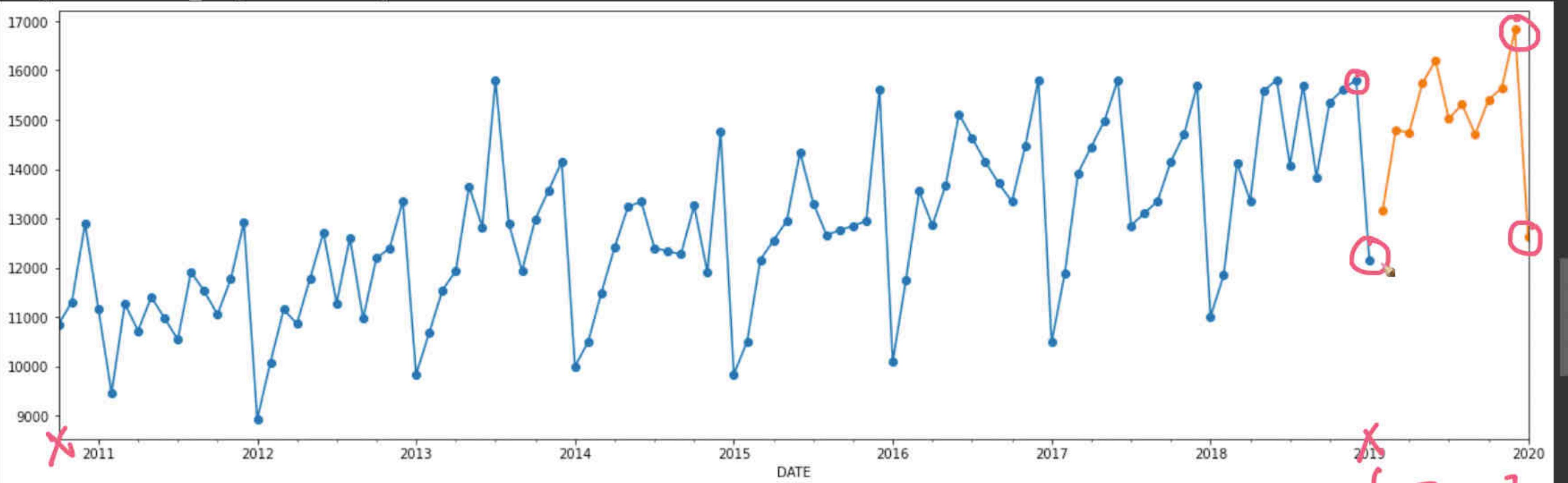


+ Code + Text



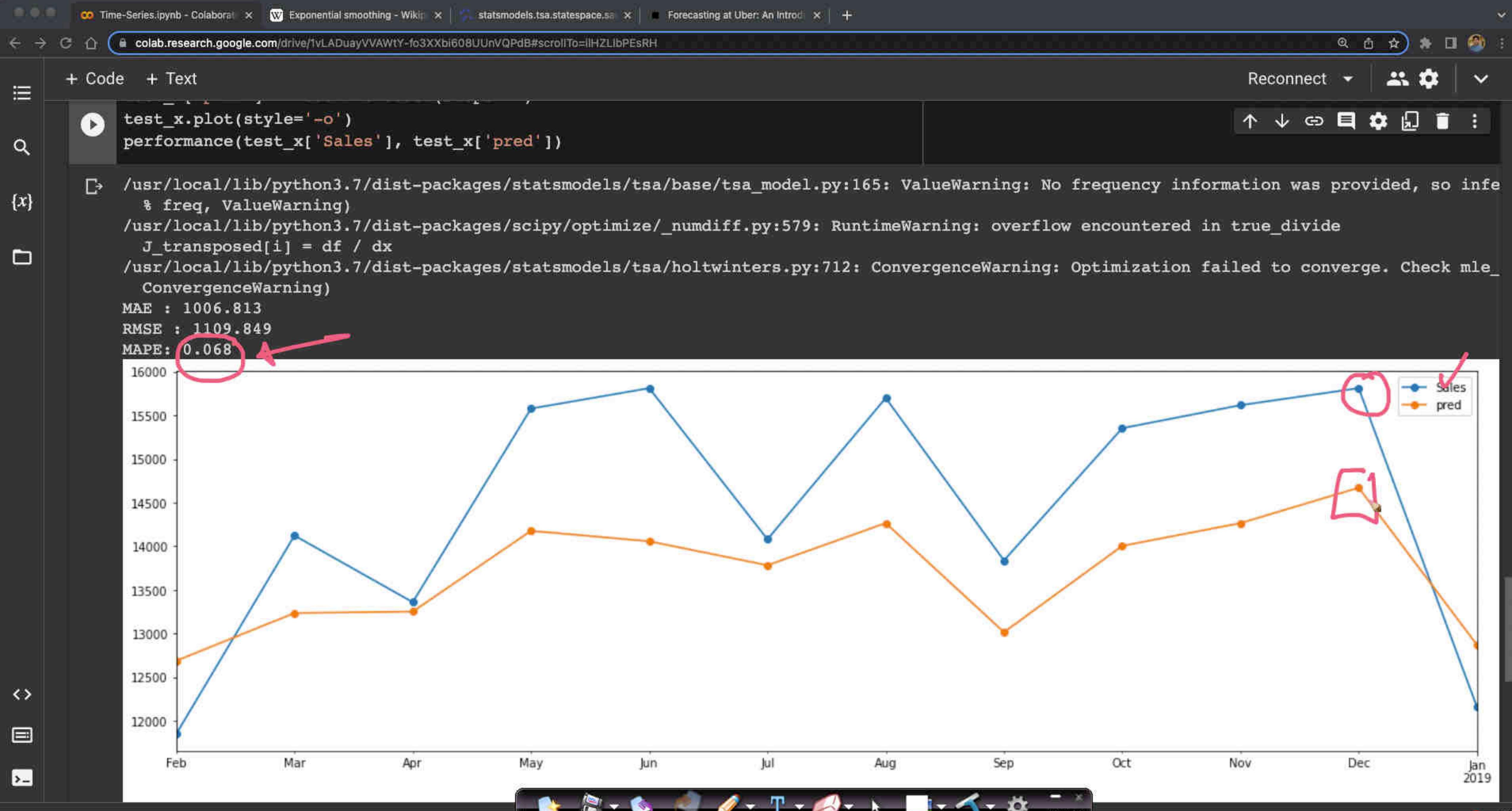
```
[ ] pred = model.forecast(steps = 12)
mobile_sales.Sales.tail(100).plot(style='.-o')
pred.plot(style='.-o')
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f2fb876df0>



```
[ ]
model = sm.tsa.ExponentialSmoothing(train_x.Sales, trend='add', seasonal='add').fit(smoothing_level=1/(2*12))
test_x['pred'] = model.forecast(steps=12)
test_x.plot(style='.-o')
```





[+ Code](#) [+ Text](#)

Reconnect

[] ↳ 3 cells hidden

x Exp: Mixture of Additive and Multiplicative models

```
model = sm.tsa.ExponentialSmoothing(train_x.Sales, trend='add', seasonal='mul').fit(smoothing_level=1/(2*12))
test_x.plot(style='-o')
performance(test_x['Sales'], test_x['pred'])
```

level terms

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_model.py:165: ValueWarning: No frequency information was provided, so inferring freq= freq, ValueWarning)
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/holtwinters.py:712: ConvergenceWarning: Optimization failed to converge. Check mle_
ConvergenceWarning)
MAE : 1006.813
RMSE : 1109.849
MAPE: 0.068
```



[+ Code](#) [+ Text](#)

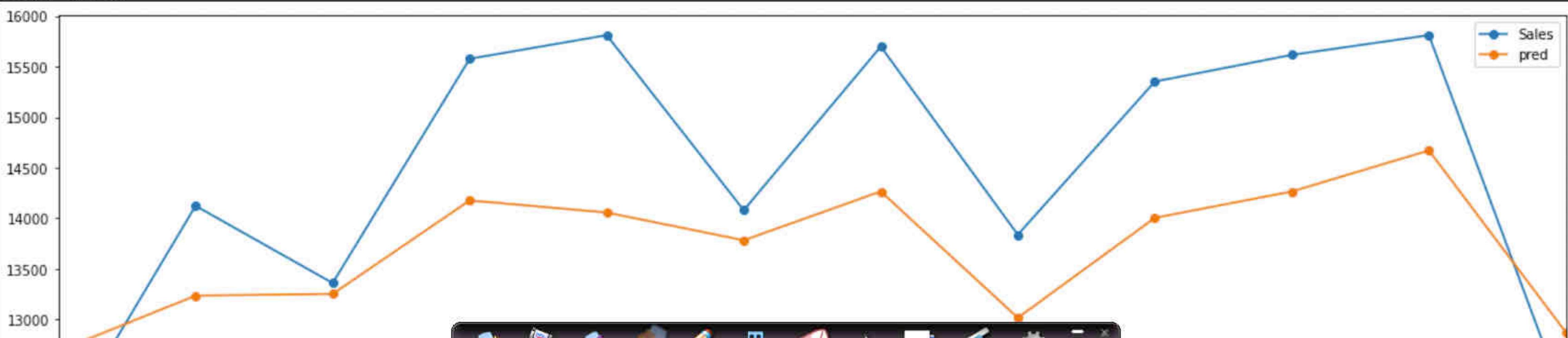
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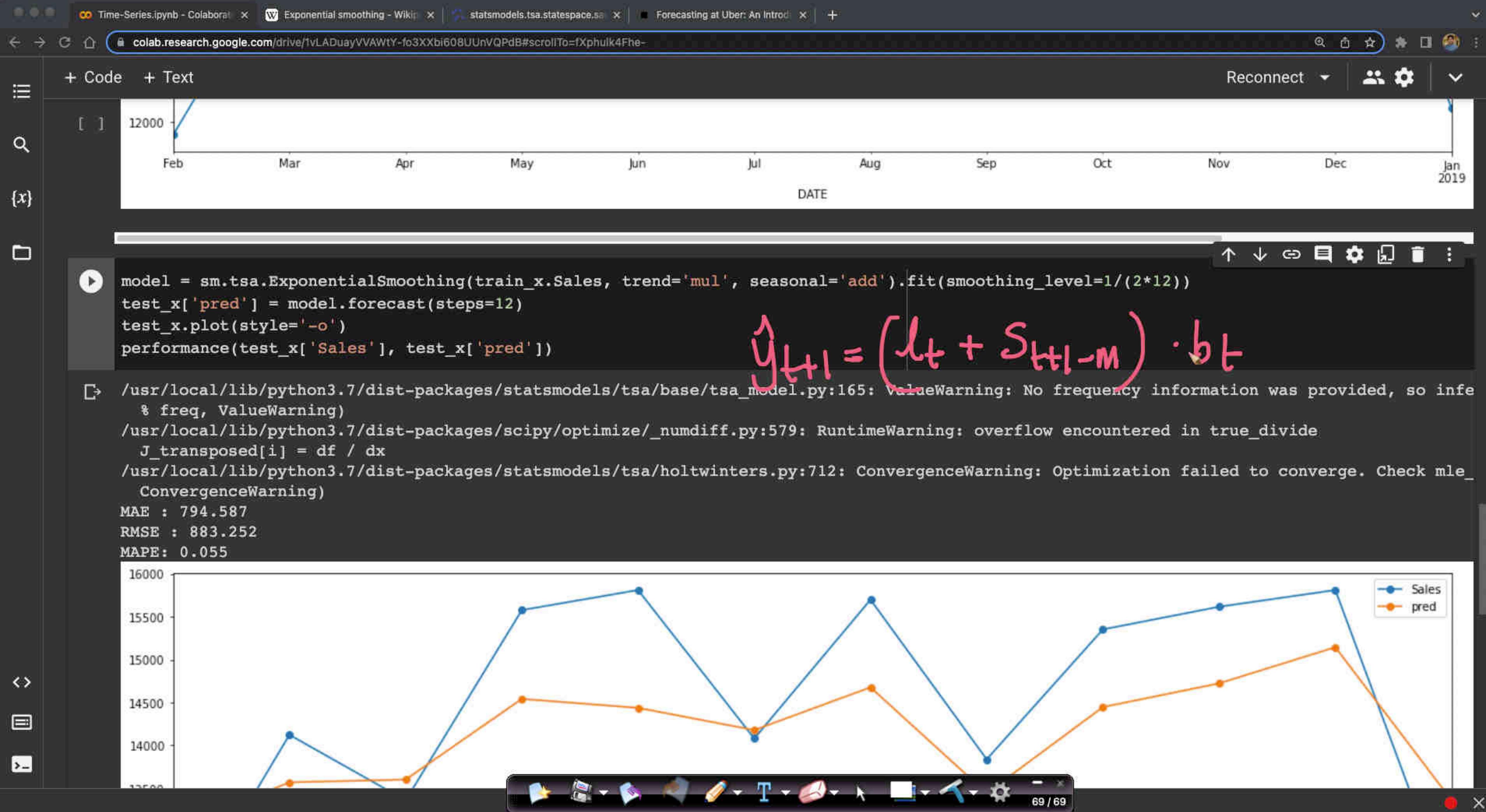
$$\hat{y}_{t+1} = (l_t + b_t) s_t$$

Exp: Mixture of Additive and Multiplicative models

```
model = sm.tsa.ExponentialSmoothing(train_x.Sales, trend='add', seasonal='mul').fit(smoothing_level=1/(2*12))
test_x.plot(style='-o')
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_model.py:165: ValueWarning: No frequency information was provided, so inferring freq= freq, ValueWarning)
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+ Code + Text

Reconnect

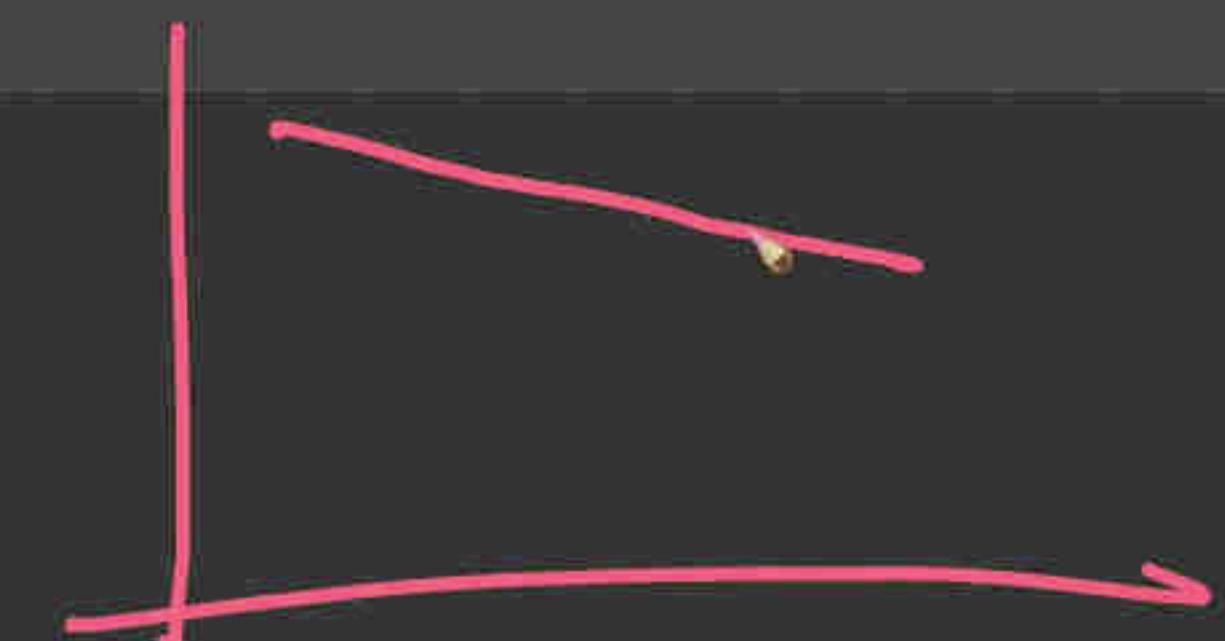
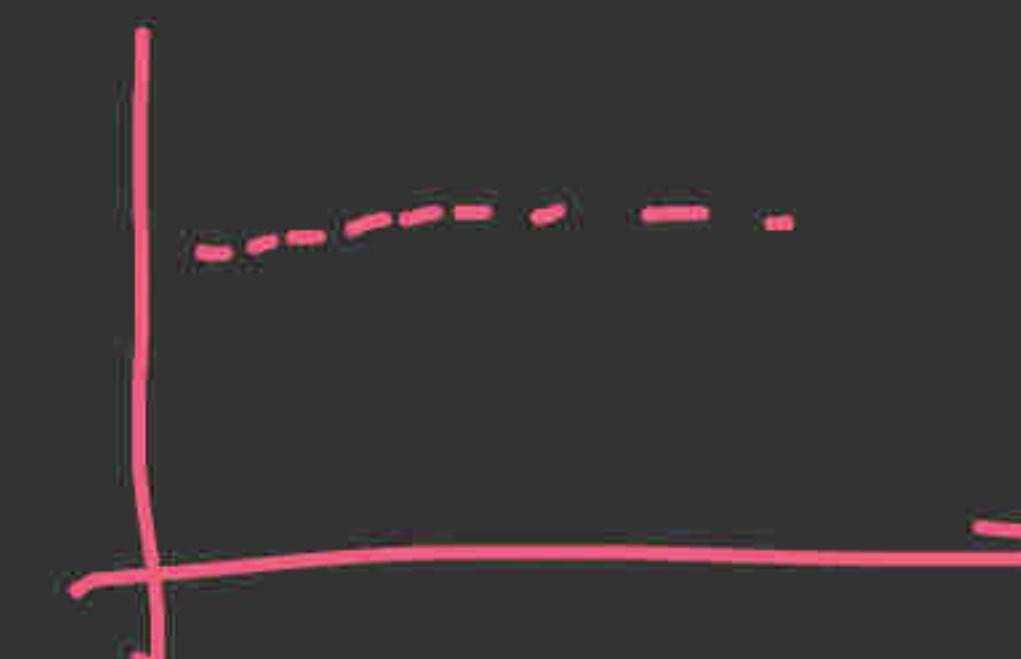
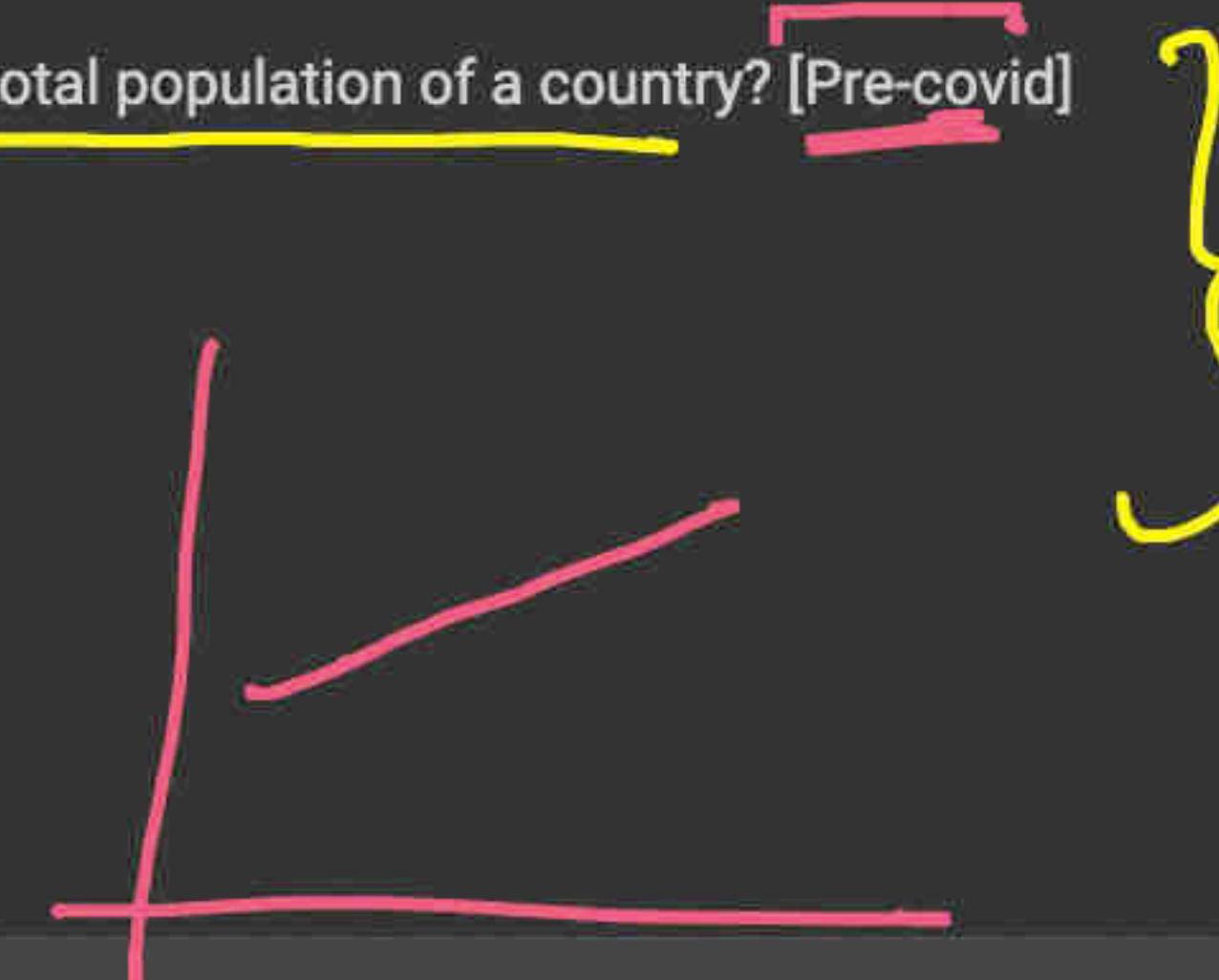
QUIZ: What is the best model to predict monthly total population of a country? [Pre-covid]

- ✓ 1. SES
- ✓ 2. DES
- ✗ 3. TES
- 4. Moving Average

level ✓
Trend ✓
Seasonality ←

► ARIMA & SARIMA Models

[] ↲ 11 cells hidden



Recap:

TS: Data Analysis \rightarrow ACF/PACF

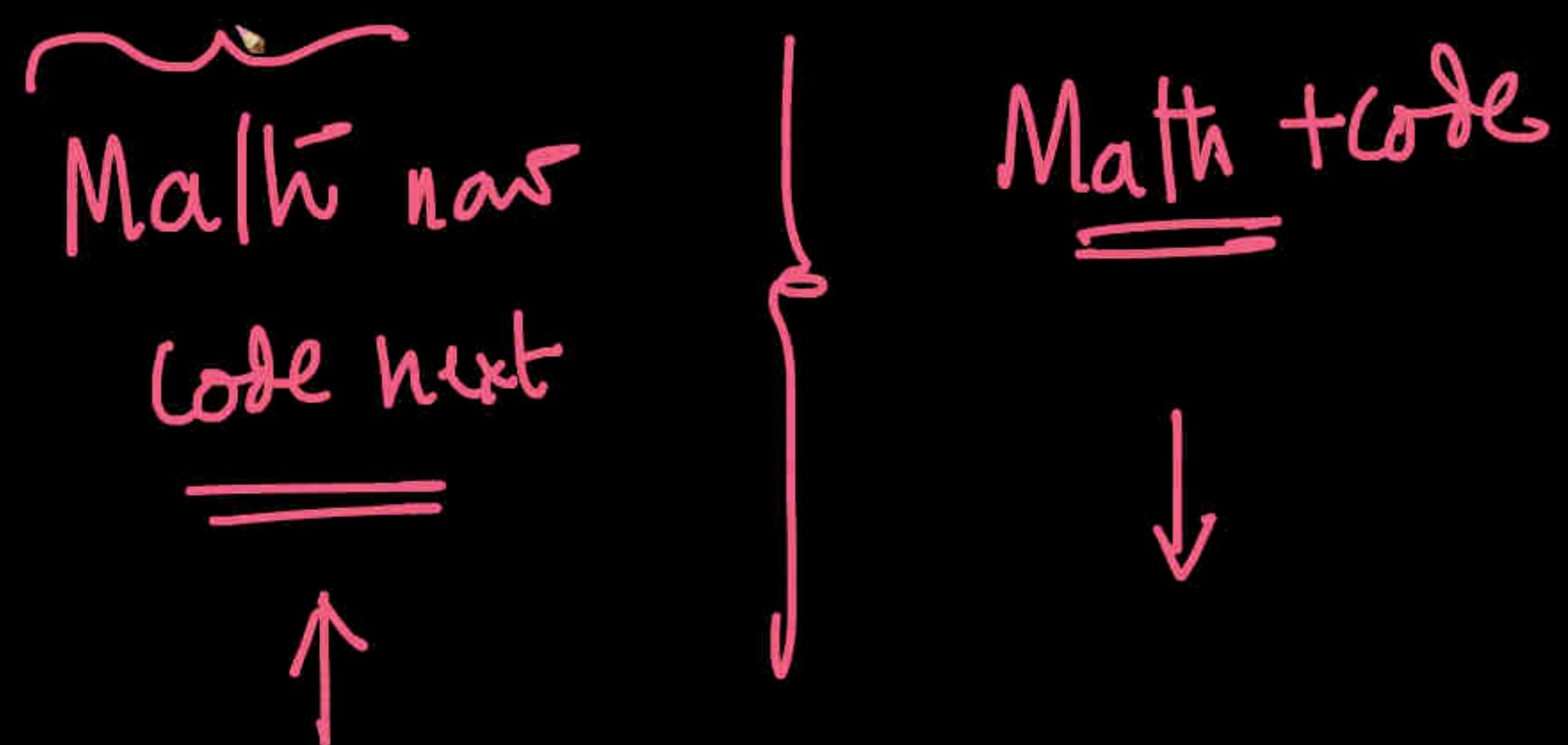
\hookrightarrow Outlier
 \hookrightarrow Imputation

• TSF: \rightarrow Naive Models

\rightarrow SES, DES, TES

modified
version of
lrg

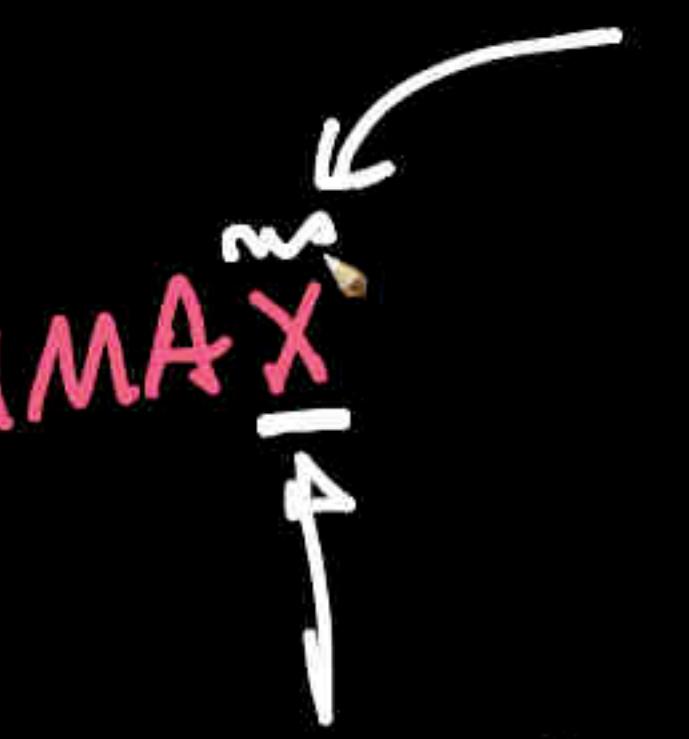
AR , MA, ARIMA, SARIMA



ARIMA
(models)

SARIMA

SARIMAX



exogenous
Variables

Notation:

$y_0, y_1, y_2, \dots, y_t, y_{t+1}, \dots$

← observations

$\hat{y}_{t-1}, \hat{y}_t, \hat{y}_{t+1}, \dots$

← Predictions

$\epsilon_{t-1}, \epsilon_t, \dots$

← Error terms

$$\epsilon_t = y_t - \hat{y}_t$$

μ

← Mean value of all y 's

AR(p): Auto regressive model

Ideally

$$y_t = \mu + \underbrace{\alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \dots + \alpha_p y_{t-p}}_{\text{weights}} + \epsilon_t$$

\hat{y}_t

The diagram illustrates the AR(p) model equation. It shows the components of the equation: the intercept (μ), the weights ($\alpha_1, \alpha_2, \dots, \alpha_p$), and the error term (ϵ_t). The weights are represented as a sum of products of past values ($y_{t-1}, y_{t-2}, \dots, y_{t-p}$) and their corresponding coefficients ($\alpha_1, \alpha_2, \dots, \alpha_p$). The predicted value (\hat{y}_t) is shown as a curved arrow pointing to the right side of the equation.

Params: $[\alpha_1, \dots, \alpha_p, \mu]$

hyper-param: p



SES

weighted-avg

↳ exponential

α : hyper-param

vs

AR(p)

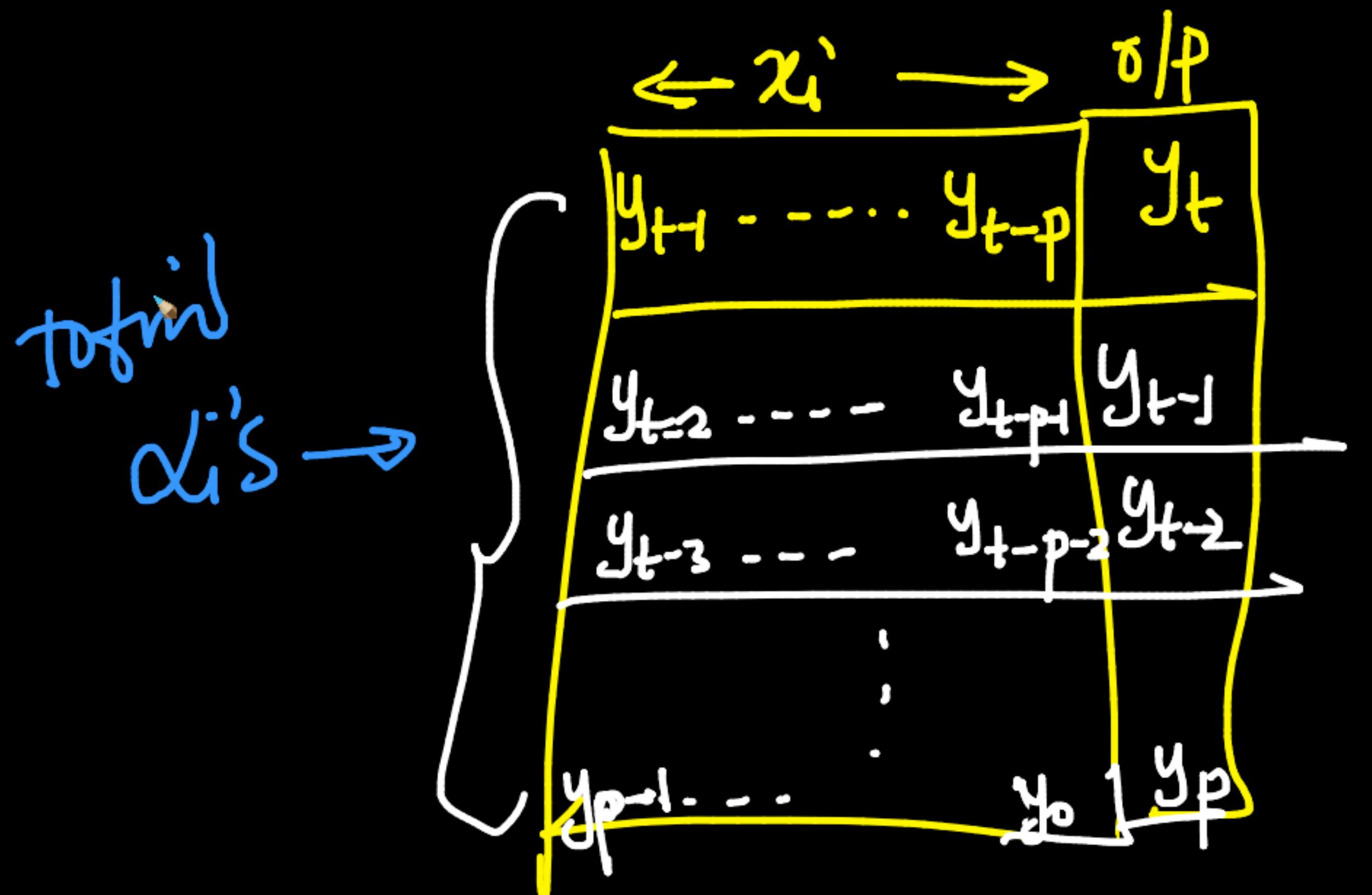
weighted-avg

↳ learnt \rightarrow dis

p: hyperparam

D_{train} fr \hat{y}_{reg}

$y_0 \dots y_t$



$\tilde{t-p}$ rows
10
1000

MA(q)
Moving average

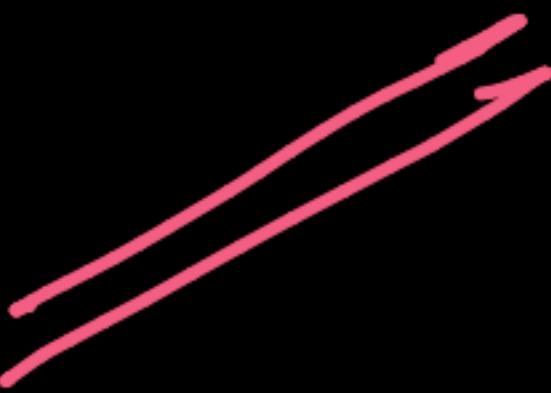
avg of all y_i 's in train - \bar{T}^S

$$y_t = \epsilon_t + \mu + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \dots + \theta_q \epsilon_{t-q}$$

$$y_{t-1} - \hat{y}_{t-1}$$

$$y_{t-2} - \hat{y}_{t-2}$$

{ Linear segr model
m last q-errors



ARMA(P,q)

$$y_t = \epsilon_t + \mu + \left(\sum_{i=1}^p \alpha_i \tilde{y}_{t-i} \right) + \left(\sum_{j=1}^q \theta_j \tilde{\epsilon}_{t-j} \right)$$

\hat{y}_t

A yellow bracket is drawn under the terms ϵ_t , μ , and $\sum_{i=1}^p \alpha_i \tilde{y}_{t-i}$. Another yellow bracket is drawn under the terms $\sum_{j=1}^q \theta_j \tilde{\epsilon}_{t-j}$.

~~Big Picture~~

AR(P)
MA(q)

ARMA(p,q)

ARIMA(p,q,d)

SARIMA(p,q,d,s,P,Q,D)
↳ Seasonality

SARIMAX

↳ exogenous/
external
variables

differenciation → removed
(trend)

Integration ← get back
trend

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Time-Series.ipynb

File Edit View Insert Runtime Tools Help All changes saved

+ Code + Text Reconnect Editing

ARIMA & SARIMA Models

- AR(p)
 - 2 cells hidden
- MA(q) models
 - 1 cell hidden
- ARIMA(p,d,q)
 - 2 cells hidden
- SARIMA (p,d,q,P,D,Q,s)
 - 1 cell hidden

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Reconnect Editing

8s completed at 18:41

Time_Series (1).ipynb Show all