Project Group 29

The final report will be a written report that clearly communicates the information below, in a manner suitable for the general audience who might or might not have taken a time series class. • A description of the methods you have chosen for this project. A textual and/or visual justification of why you chose these methods is required (i.e. what type of model did you choose, why, and how did you choose it). • A textual and/or visual report on your findings. • A graphical and tabular forecasting results that must include the RMSE of the forecasting of the Jan-Dec 2016. In addition to the report, you must submit a Jupyter notebook containing all your codes. Each group will submit one report and notebook.

In [433]:
```
#upload the libraries
import numpy as np
import pandas as pd
import statsmodels.api as sm
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.graphics.tsaplots import plot_pacf
from statsmodels.tsa.stattools import adfuller
import warnings
warnings.filterwarnings("ignore")
import datetime
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt
```

In [440]:
```
#upload the data
series = pd.read_csv('zillow-carlifornia.csv',header=0, index_col="Date"
, parse_dates=True,
squeeze=True)
series.head()
```

Out[440]:

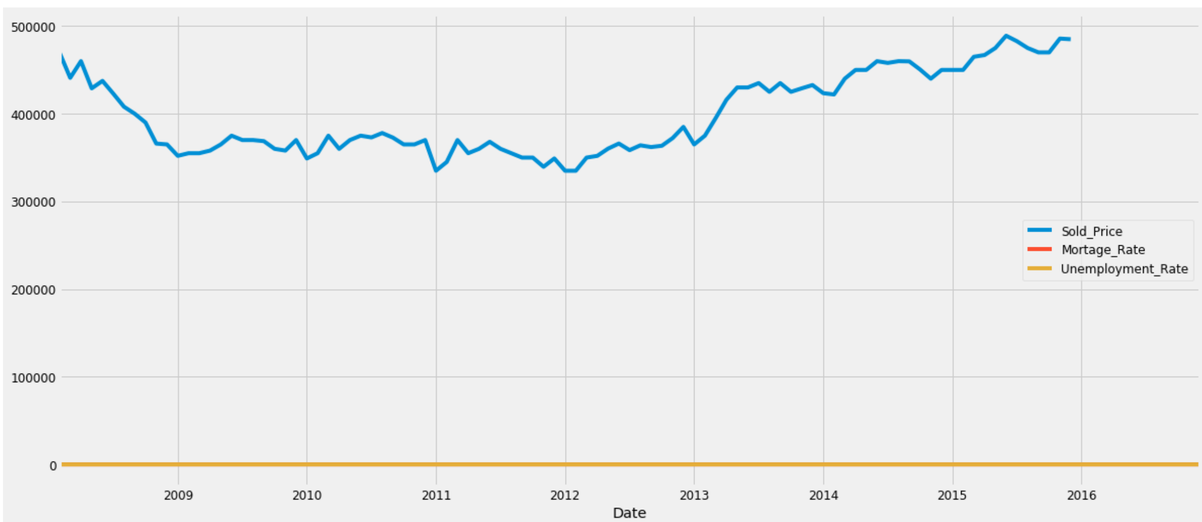
Date	MedianSoldPrice_AllHomes.California	MedianMortageRate	UnemploymentRate
2008-02-29	470000.0	5.29	6.3
2008-03-31	441000.0	5.44	6.2
2008-04-30	460000.0	5.42	6.4
2008-05-31	429000.0	5.47	6.3
2008-06-30	437500.0	5.60	6.2

In [441]:
```
#Change the column names
series=series.rename(columns={"Date": "ds","MedianSoldPrice_AllHomes.California":"Sold_Price", "MedianMortageRate":"Mortage_Rate", "UnemploymentRate":"Unemployment_Rate"})
series.head()
```

Out[441]:

	Sold_Price	Mortage_Rate	Unemployment_Rate
Date			
2008-02-29	470000.0	5.29	6.3
2008-03-31	441000.0	5.44	6.2
2008-04-30	460000.0	5.42	6.4
2008-05-31	429000.0	5.47	6.3
2008-06-30	437500.0	5.60	6.2

In [442]:
```
#Plot the original TS
series.plot()
plt.show()
```



In [443]:
```
series.isnull().sum()
```

Out[443]:
```
Sold_Price           12
Mortage_Rate          0
Unemployment_Rate     0
dtype: int64
```

In [445]:
```
series=series.dropna()
```

In [446]:
```
series.tail()
```

Out[446]:

Date	Sold_Price	Mortage_Rate	Unemployment_Rate
2015-08-31	475000.0	3.95	5.2
2015-09-30	470000.0	3.87	5.1
2015-10-31	470000.0	3.80	5.0
2015-11-30	485750.0	3.69	5.0
2015-12-31	485000.0	3.89	5.1

In [447]:
```
#Correlation between price and unemployment rate and mortage rate
#Correlation between price and mortage rate -> - 0.00839711. Not a signi
ficant negative correlation: if mortage rate goes down, the price goes u
p.
r1 = np.corrcoef(series.Sold_Price,series.Mortage_Rate)
r1
```

Out[447]:
```
array([[ 1.        , -0.00839711],
       [-0.00839711,  1.        ]])
```

In [448]:
```
#Correlation between price and unemployment rate
r2 = np.corrcoef(series.Sold_Price,series.Unemployment_Rate)
r2
```

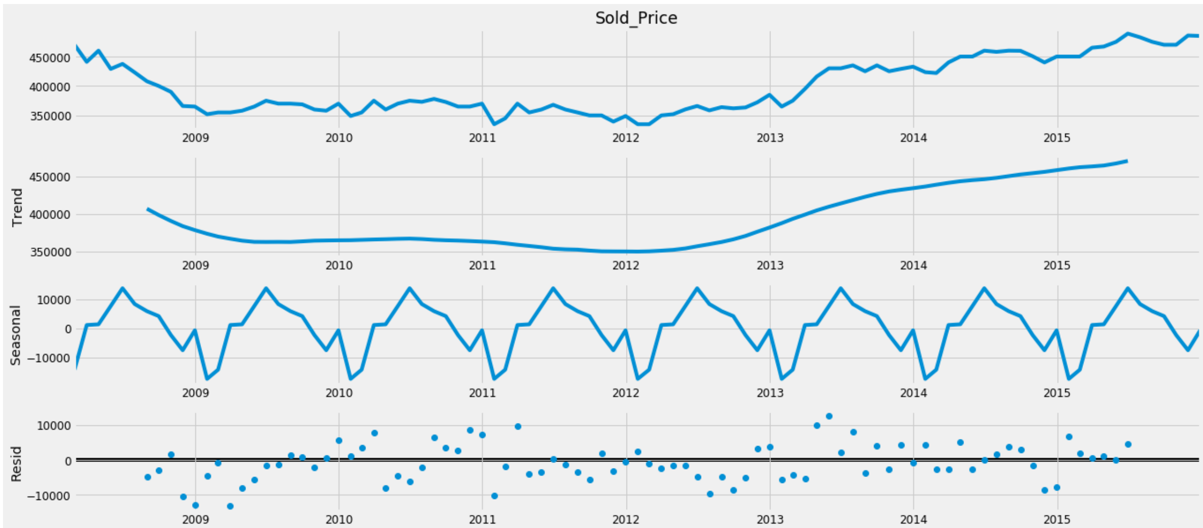
Out[448]:
```
array([[ 1.        , -0.64630235],
       [-0.64630235,  1.        ]])
```

In [449]:
```
#One-variable analysis
y = series['Sold_Price']
```

In [450]:
```
y.plot(figsize=(15, 6))
plt.show()
```

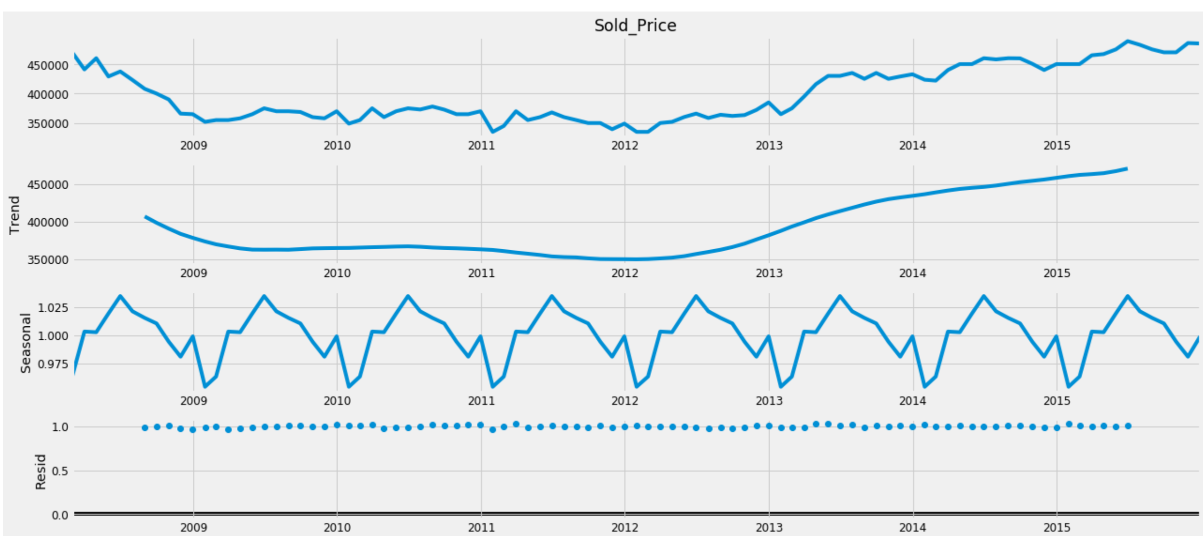
We can also visualize our data using a method called time-series decomposition that allows us to decompose our time series into three distinct components: trend, seasonality, and noise.

In [451]:
```
#Additive
from pylab import rcParams
rcParams['figure.figsize'] = 18, 8
decomposition = sm.tsa.seasonal_decompose(y, model='additive')
fig = decomposition.plot()
plt.show()
```



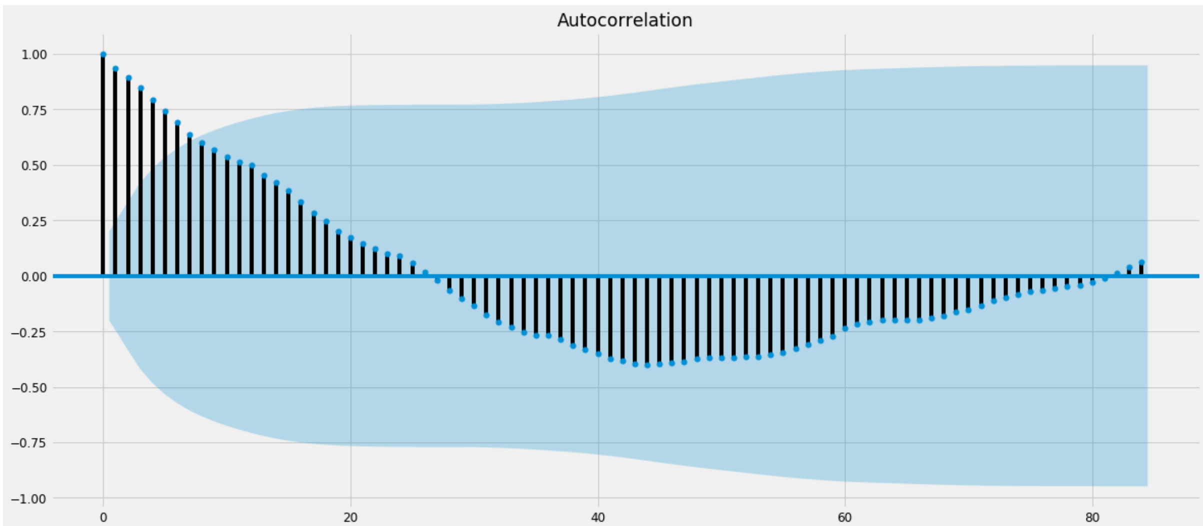
We have seasonality and trend here.

In [452]:
```
#Multiplictive
rcParams['figure.figsize'] = 18, 8
decomposition = sm.tsa.seasonal_decompose(y, model='multiplicative')
fig = decomposition.plot()
plt.show()
```

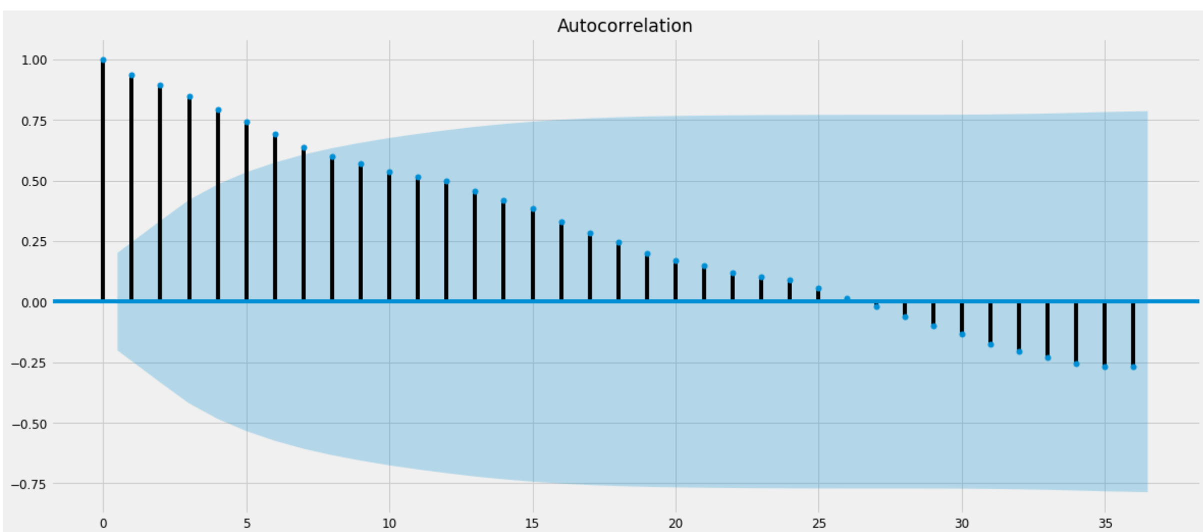


Autocorrelation helps us study how each time series observation is related to its recent (or not so recent) past. It is easy to get that tomorrow's house price is very likely to be related to today's house price. ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) are two powerful tools. ACF represents autocorrelation of a time series as a function of the time lag. PACF seeks to remove the indirect correlations that exist in the autocorrelation for an observation and an observation at a prior time step.m

In [392]:
```
#ACF plot
plot_acf(y, lags=84)
plt.show()
```

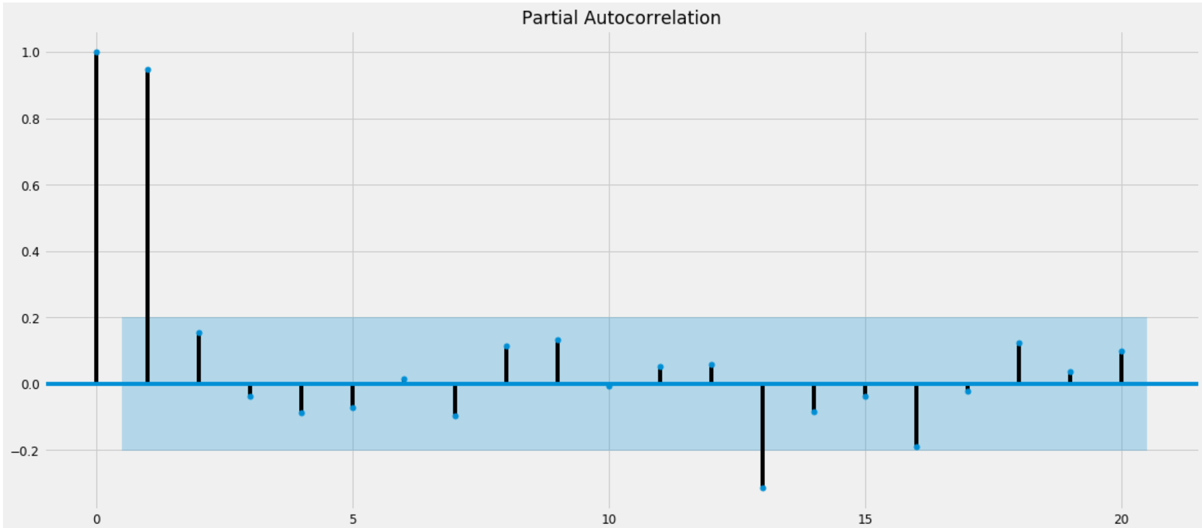


In [393]:
```
#3 years ACF
plot_acf(y, lags=36)
plt.show()
```



In [278]:

```
#PACF plot
plot_pacf(y,lags=20)
plt.show()
```



Dickey-Fuller test can be used to test if a time series is stationary or not.

In [394]:

```
plt.plot(y)
```

Out[394]:

```
[<matplotlib.lines.Line2D at 0x7fa55f0f73d0>]
```

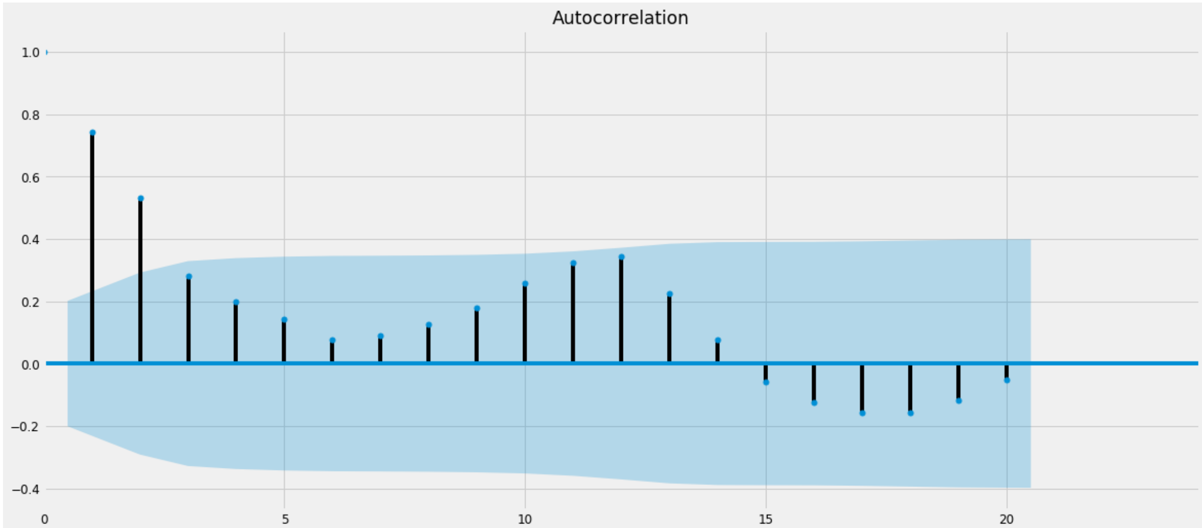
In [453]:

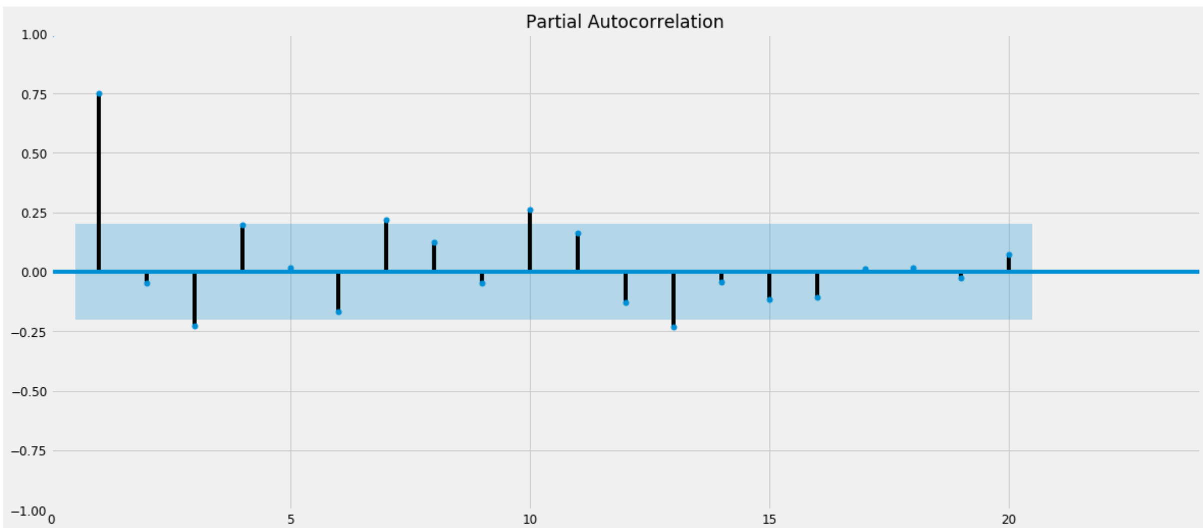
```python
from statsmodels.tsa.stattools import adfuller

X = y.values
result = adfuller(X)
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
print('Critical Values:')
for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))
```

```
ADF Statistic: -0.058792
p-value: 0.953391
Critical Values:
	1%: -3.513
	5%: -2.897
	10%: -2.586
```

Conclusion from the test: We can see that ADF statistics is larger than the critical values, meaning that we can fail to reject the null hypothesis and in turn that the time series is non-stationary.

In [396]:
```
plot_acf(y.diff(periods=3).bfill()); plt.xlim(0,24); plt.show()
plot_pacf(y.diff(periods=3).bfill()); plt.xlim(0,24); plt.ylim(-1,1);plt
.show()
```





Price Prediction using Prophet

Why Prophet: one of the most flexible models, works great with monthly data with seasonality and trend. Also, capture the historic pattern of the data and reproduce it in the prediction. Has a decent prediction power.

In [241]:
```
# evaluate prophet time series forecasting model on hold out dataset
from pandas import read_csv
from pandas import to_datetime
from pandas import DataFrame
from fbprophet import Prophet
from sklearn.metrics import mean_absolute_error
from matplotlib import pyplot
```

In [242]:

```
#upload the data
history = pd.read_csv('zillow-carlifornia.csv')
dt=history[['Date','MedianSoldPrice_AllHomes.California']]
dt=dt.rename(columns={"Date": "ds","MedianSoldPrice_AllHomes.California"
:"y"})
```

In [244]:

```
dt.head()
```

Out[244]:

	ds	y
0	2008-02-29	470000.0
1	2008-03-31	441000.0
2	2008-04-30	460000.0
3	2008-05-31	429000.0
4	2008-06-30	437500.0

In [245]:

```
dt=dt.dropna()
```

In [246]:

```
dt.dtypes
```

Out[246]:

```
ds      object
y      float64
dtype: object
```

In [247]:

```
dt.tail()
```

Out[247]:

	ds	y
90	2015-08-31	475000.0
91	2015-09-30	470000.0
92	2015-10-31	470000.0
93	2015-11-30	485750.0
94	2015-12-31	485000.0

In [337]:

```
#Train the model
m = Prophet(seasonality_mode='multiplicative', interval_width=0.95)
m.fit(dt)

#Make some predictions
future = m.make_future_dataframe(periods=12, freq = "m", include_history
= False)
forecast = m.predict(future)
forecast.head()
```

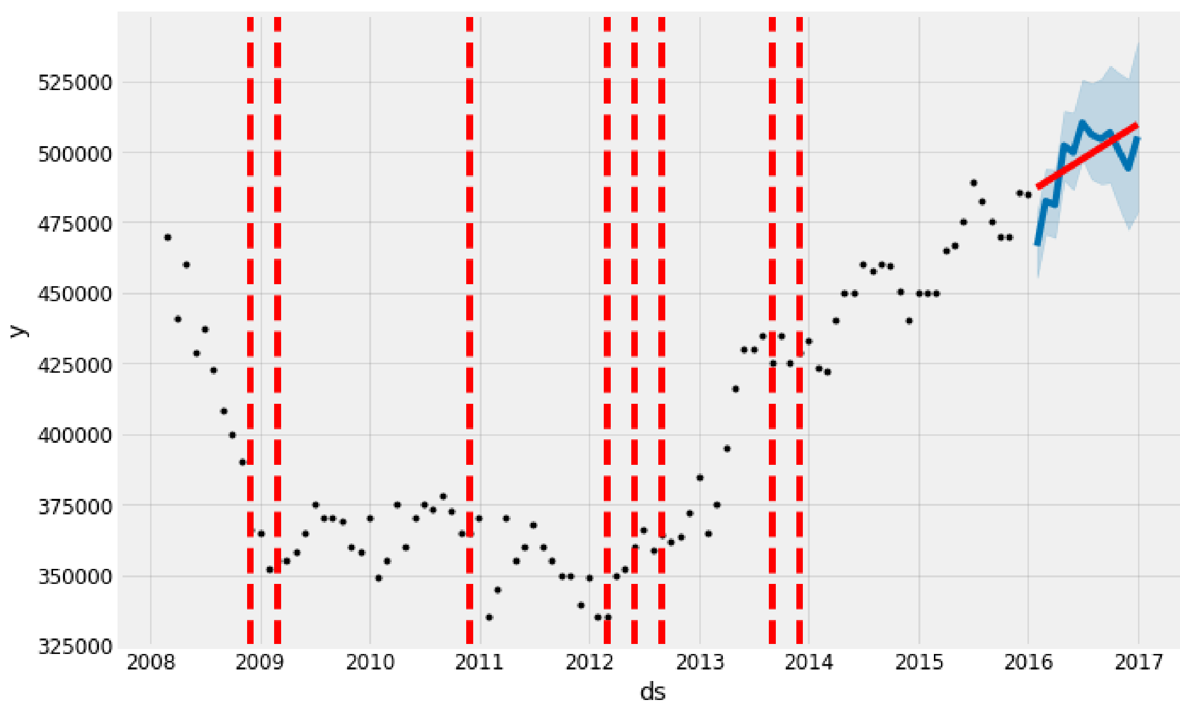
```
INFO:fbprophet:Disabling weekly seasonality. Run prophet with weekly_se
asonality=True to override this.
INFO:fbprophet:Disabling daily seasonality. Run prophet with daily_seas
onality=True to override this.
```

Out[337]:

	ds	trend	yhat_lower	yhat_upper	trend_lower	trend_upper	multiplicat
0	2016-01-31	487203.494579	455448.132733	478454.448993	486677.661066	487999.154072	
1	2016-02-29	489142.751534	470779.828637	494022.667016	487378.544912	491591.214568	
2	2016-03-31	491215.750348	469491.222905	493643.736778	488184.195155	495751.080909	
3	2016-04-30	493221.878233	489784.738182	514460.900088	488669.337892	499667.634435	
4	2016-05-31	495294.877047	486484.221276	513769.196250	489022.502373	504661.479661	

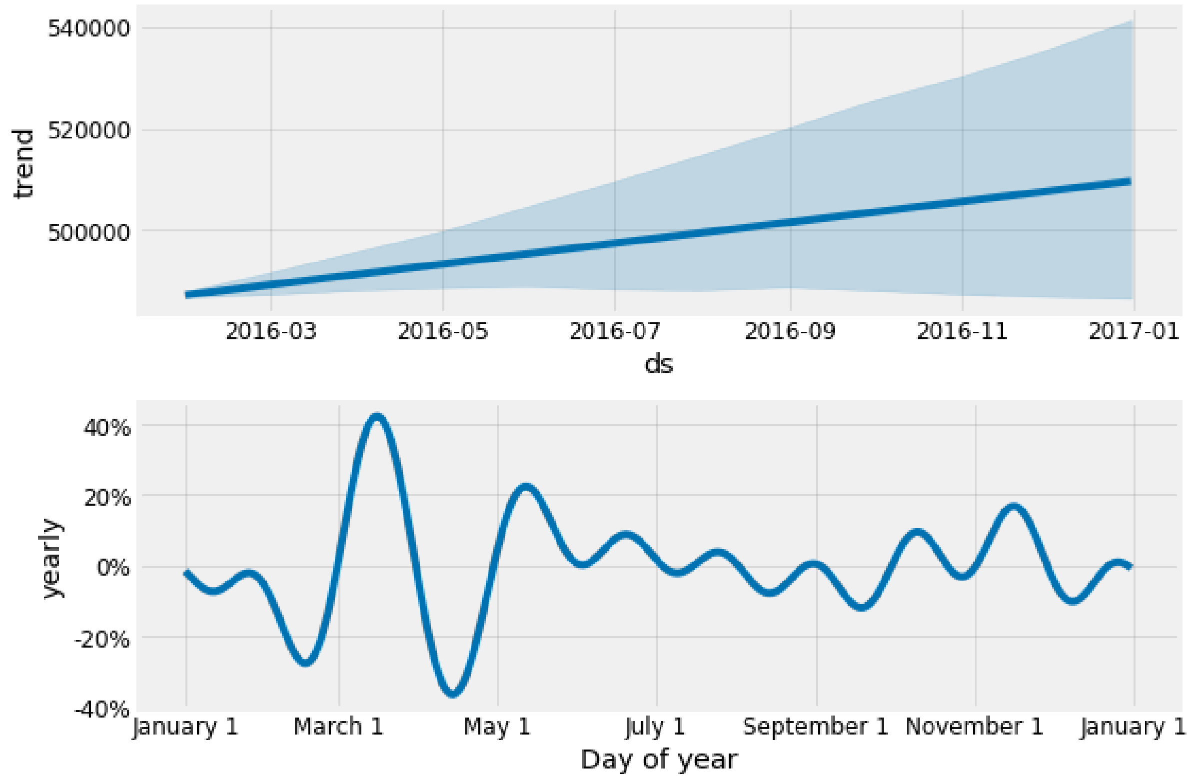
In [338]:

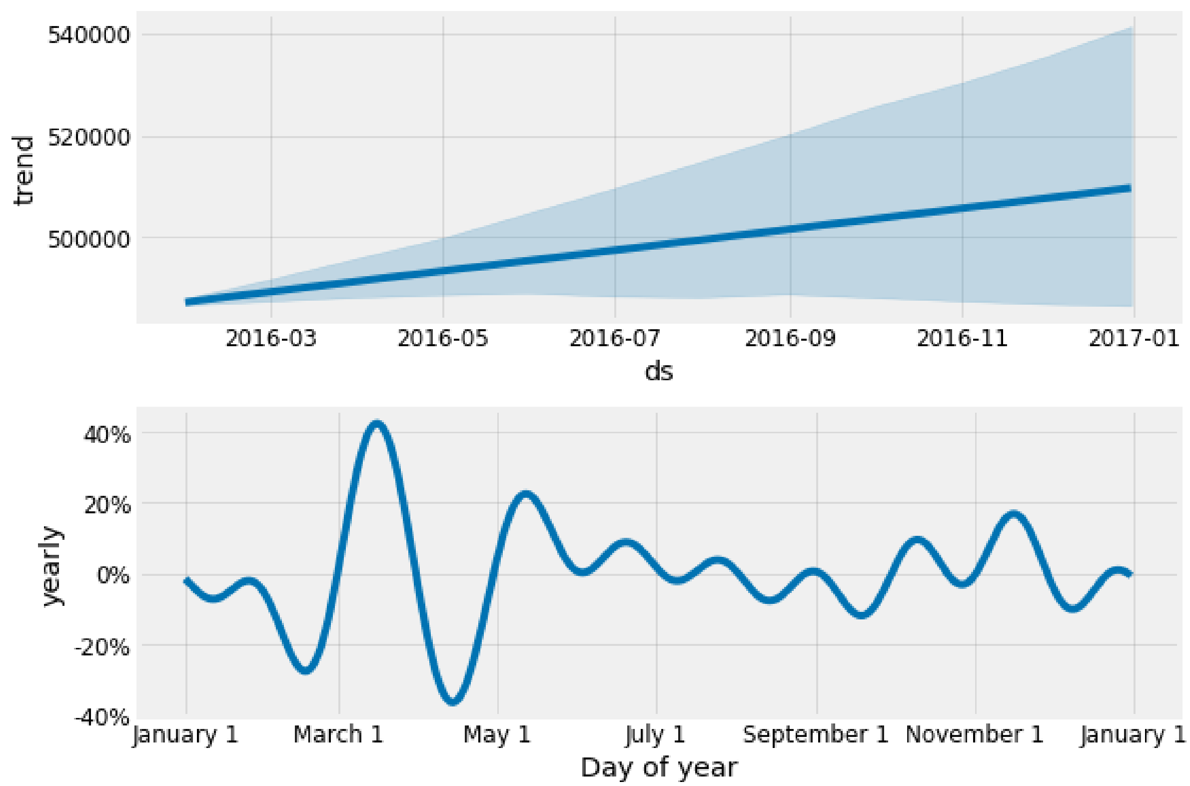
```
from fbprophet.plot import add_changepoints_to_plot
fig = m.plot(forecast)
a = add_changepoints_to_plot(fig.gca(), m, forecast)
```



In [339]:
```
m.plot_components(forecast)
```

Out[339]:




540000
520000
500000
trend
2016-03
2016-05
2016-07
2016-09
2016-11
2017-01
ds
40%
20%
0%
-20%
-40%
yearly
January 1
March 1
May 1
July 1
September 1
November 1
January 1
Day of year

In [340]:
```
prediction = forecast[["ds","yhat"]]
actual = pd.read_csv("test.csv")
```

In [341]:
```
actual.dtypes
```

Out[341]:
```
Month                    object
Median House Price        int64
dtype: object
```

In [342]:
```
y_true = actual["Median House Price"]
y_pred = prediction["yhat"]
```

In [355]:
```
#MSE
MSE = mean_squared_error(y_true, y_pred)
print(MSE)
```

```
95682341.39106478
```

In [359]:
```
#RMSE
RMSE = sqrt(MSE)
print(RMSE)
```

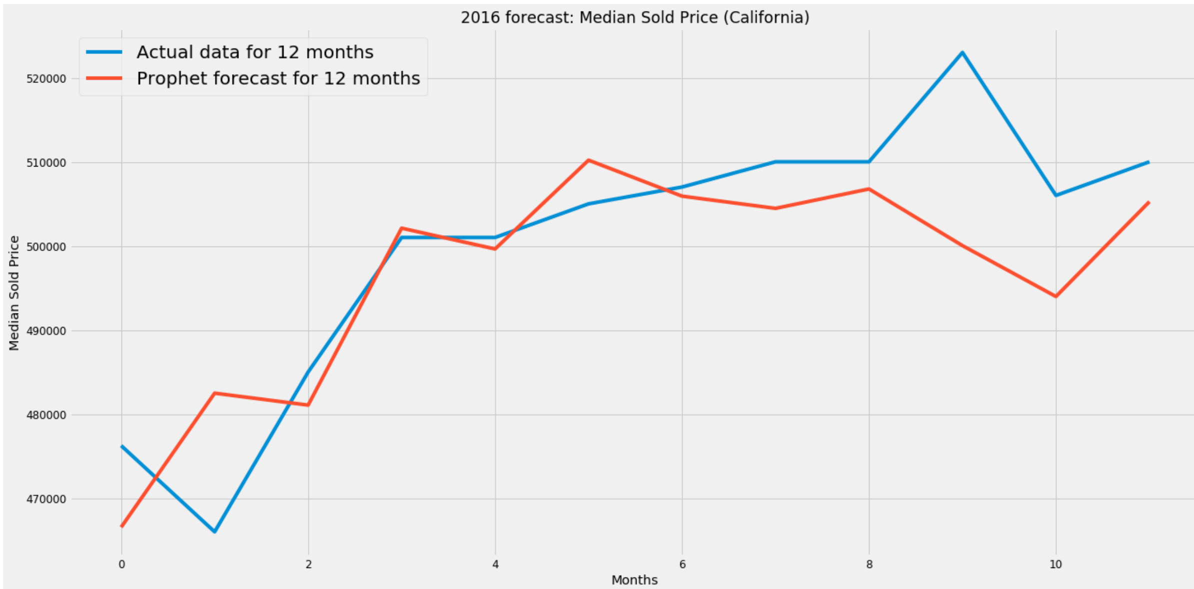
```
9781.73509102883
```

In [358]:
```
#coefficient of determination
from sklearn.metrics import r2_score
r2_score(y_true, y_pred)

#shows how model fits the observed data. Not a brilliant result, unfortu
natly.
```

Out[358]:
```
0.6021603243954623
```

The forecasted values tend to be 9782 orders different on average compared to what the real values would be.

In [352]:
```
#Plot the prediction vs actual
plt.figure(figsize=(20, 10))
plt.plot(y_true, label='Actual data for 12 months')
plt.plot(y_pred, label='Prophet forecast for 12 months')
plt.legend(loc='upper left', fontsize=20)
plt.xlabel('Months')
plt.ylabel('Median Sold Price')
plt.title('2016 forecast: Median Sold Price (California)')
plt.show()
```



In [351]:
```
#MAPE
def mean_absolute_percentage_error(y_true, y_pred):
    y_true, y_pred = np.array(y_true), np.array(y_pred)
    return np.mean(np.abs((y_true - y_pred) / y_true)) * 100

mean_absolute_percentage_error(y_true, y_pred)
```

Out[351]: 1.4614616981679576

In [ ]:
```
MSE: 95682341.39106478
RMSE: 9781.73509102883
MAPE: 1.4614616981679576
```