Predict monthly milk production

February 13, 2022

[1]:
```python
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.deterministic import CalendarFourier, DeterministicProcess
from statsmodels.graphics.tsaplots import plot_pacf
from statsmodels.tsa.stattools import adfuller
from scipy.signal import periodogram
from scipy.stats.mstats import normaltest
from sklearn.model_selection import train_test_split, RandomizedSearchCV
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.multioutput import MultiOutputRegressor
from xgboost import XGBRegressor
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.pipeline import Pipeline
import tensorflow as tf
import keras
from warnings import simplefilter
simplefilter("ignore")
# Set Matplotlib defaults
plt.style.use("seaborn-whitegrid")
plt.rc("figure", autolayout=True, figsize=(11, 5))
plt.rc("axes", labelweight="bold", labelsize="large", titleweight="bold",␣
 ↪titlesize=16, titlepad=10)
plot_params = dict(color="0.75", style=".-", markeredgecolor="0.25",␣
 ↪markerfacecolor="0.25", legend=False)
%config InlineBackend.figure_format = 'retina'
```

[2]:
```python
def seasonal_plot(X, y, period, freq, ax=None):
    if ax is None:
        _, ax = plt.subplots()
    palette = sns.color_palette("husl", n_colors=X[period].nunique(),)
```

```
    ax = sns.lineplot(x=freq, y=y, hue=period, data=X, ci=False, ax=ax, palette=palette, legend=False)
    ax.set_title(f"Seasonal Plot ({period}/{freq})")
    for line, name in zip(ax.lines, X[period].unique()):
        y_ = line.get_ydata()[-1]
        ax.annotate(name, xy=(1, y_), xytext=(6, 0), color=line.get_color(), xycoords=ax.get_yaxis_transform(),
                    textcoords="offset points", size=14, va="center")
    return ax


def plot_periodogram(ts, detrend='linear', ax=None):
    from scipy.signal import periodogram
    fs = pd.Timedelta("1Y") / pd.Timedelta("1D")
    freqencies, spectrum = periodogram(ts, fs=fs, detrend=detrend, window="boxcar", scaling='spectrum')
    if ax is None:
        _, ax = plt.subplots()
    ax.step(freqencies, spectrum, color="purple")
    ax.set_xscale("log")
    ax.set_xticks([1, 2, 4, 6, 12, 26, 52, 104])
    ax.set_xticklabels(["Annual (1)", "Semiannual (2)", "Quarterly (4)", "Bimonthly (6)", "Monthly (12)",
                        "Biweekly (26)", "Weekly (52)", "Semiweekly (104)"], rotation=30)
    ax.ticklabel_format(axis="y", style="sci", scilimits=(0, 0))
    ax.set_ylabel("Variance")
    ax.set_title("Periodogram")
    return ax

def lagplot(x, y=None, lag=1, standardize=False, ax=None, **kwargs):
    from matplotlib.offsetbox import AnchoredText
    x_ = x.shift(lag)
    if standardize:
        x_ = (x_ - x_.mean()) / x_.std()
    if y is not None:
        y_ = (y - y.mean()) / y.std() if standardize else y
    else:
        y_ = x
    corr = y_.corr(x_)
    if ax is None:
        fig, ax = plt.subplots()
    scatter_kws = dict(alpha=0.75, s=3)
    line_kws = dict(color='C3', )
    ax = sns.regplot(x=x_, y=y_, scatter_kws=scatter_kws, line_kws=line_kws, lowess=True, ax=ax, **kwargs)
```

```
    at = AnchoredText(f"{corr:.2f}", prop=dict(size="large"), frameon=True,␣
↪loc="upper left")
    at.patch.set_boxstyle("square, pad=0.0")
    ax.add_artist(at)
    ax.set(title=f"Lag {lag}", xlabel=x_.name, ylabel=y_.name)
    return ax


def plot_lags(x, y=None, lags=6, nrows=1, lagplot_kwargs={}, **kwargs):
    import math
    kwargs.setdefault('nrows', nrows)
    kwargs.setdefault('ncols', math.ceil(lags / nrows))
    kwargs.setdefault('figsize', (kwargs['ncols'] * 2, nrows * 2 + 0.5))
    fig, axs = plt.subplots(sharex=True, sharey=True, squeeze=False, **kwargs)
    for ax, k in zip(fig.get_axes(), range(kwargs['nrows'] * kwargs['ncols'])):
        if k + 1 <= lags:
            ax = lagplot(x, y, lag=k + 1, ax=ax, **lagplot_kwargs)
            ax.set_title(f"Lag {k + 1}", fontdict=dict(fontsize=14))
            ax.set(xlabel="", ylabel="")
        else:
            ax.axis('off')
    plt.setp(axs[-1, :], xlabel=x.name)
    plt.setp(axs[:, 0], ylabel=y.name if y is not None else x.name)
    fig.tight_layout(w_pad=0.1, h_pad=0.1)
    return fig

# define train test split function
def train_test_datasets(df, x_len=12, y_len=1, test_loops=12):
    D = df.values
    rows, periods = D.shape

    # Training set creation
    loops = periods + 1 - x_len - y_len
    train = []
    for col in range(loops):
        train.append(D[:, col:col+x_len+y_len])
    train = np.vstack(train)
    X_train, y_train = np.split(train, [-y_len], axis=1)

    # Test set creation
    if test_loops > 0:
        X_train, X_test = np.split(X_train, [-rows*test_loops], axis=0)
        y_train, y_test = np.split(y_train, [-rows*test_loops], axis=0)
    else: # No test set: X_test is used to generate the future forecast
        X_test = D[:, -x_len:]
        y_test = np.full((X_test.shape[0], y_len), np.nan) #Dummy value
```

```
    # Formatting required for scikit-learn
    if y_len == 1:
        y_train = y_train.ravel()
        y_test = y_test.ravel()

    return X_train, y_train, X_test, y_test

# define score metric function
def kpi(y_train, y_train_pred, y_test, y_test_pred, name=''):
    df = pd.DataFrame(columns = ['MAE','RMSE', 'Bias', 'MAE_pct', 'RMSE_pct',␣
↪'r2_score'], index=['Train','Test'])
    df.index.name = name
    df.loc['Train','MAE_pct'] = 100*np.mean(abs(y_train - y_train_pred))/np.
↪mean(y_train)
    df.loc['Train','RMSE_pct'] = 100*np.sqrt(np.mean((y_train -␣
↪y_train_pred)**2))/np.mean(y_train)
    df.loc['Train','Bias'] = 100*np.mean((y_train - y_train_pred))/np.
↪mean(y_train)
    df.loc['Train','r2_score'] =  r2_score(y_train, y_train_pred)
    df.loc['Train','MAE'] = mean_absolute_error(y_train, y_train_pred)
    df.loc['Train','RMSE'] = mean_squared_error(y_train, y_train_pred,␣
↪squared=False)
    df.loc['Test','MAE_pct'] = 100*np.mean(abs(y_test - y_test_pred))/np.
↪mean(y_test)
    df.loc['Test','RMSE_pct'] = 100*np.sqrt(np.mean((y_test - y_test_pred)**2))/
↪np.mean(y_test)
    df.loc['Test','Bias'] = 100*np.mean((y_test - y_test_pred))/np.mean(y_test)
    df.loc['Test','r2_score'] =  r2_score(y_test, y_test_pred)
    df.loc['Test','MAE'] = mean_absolute_error(y_test, y_test_pred)
    df.loc['Test','RMSE'] = mean_squared_error(y_test, y_test_pred,␣
↪squared=False)
    df = df.astype(float).round(2) #Round number for display
    print(df)
```

[3]:
```
df = pd.read_csv(r'C:
↪\Users\MUHAMMAD-SHALABY\Downloads\3\Time-Series-Forecasting-LSTM-main\monthly_milk_producti
↪csv')
df.tail()
```

[3]:

	Date	Production
163	1975-08	858
164	1975-09	817
165	1975-10	827
166	1975-11	797
167	1975-12	843

[4]:
```python
df.Date = pd.to_datetime(df.Date)
```

[5]:
```python
index = pd.date_range(start=df.Date.min(), end='1976-01', freq='M')
index
```

[5]:
```
DatetimeIndex(['1962-01-31', '1962-02-28', '1962-03-31', '1962-04-30',
               '1962-05-31', '1962-06-30', '1962-07-31', '1962-08-31',
               '1962-09-30', '1962-10-31',
               …
               '1975-03-31', '1975-04-30', '1975-05-31', '1975-06-30',
               '1975-07-31', '1975-08-31', '1975-09-30', '1975-10-31',
               '1975-11-30', '1975-12-31'],
              dtype='datetime64[ns]', length=168, freq='M')
```

[6]:
```python
df.shape
```

[6]:
```
(168, 2)
```

[7]:
```python
df.set_index(index, inplace=True)
```

[8]:
```python
df.head()
```

[8]:

	Date	Production
1962-01-31	1962-01-01	589
1962-02-28	1962-02-01	561
1962-03-31	1962-03-01	640
1962-04-30	1962-04-01	656
1962-05-31	1962-05-01	727

[9]:
```python
df.drop('Date', axis=1, inplace=True)
df.head()
```

[9]:

	Production
1962-01-31	589
1962-02-28	561
1962-03-31	640
1962-04-30	656
1962-05-31	727

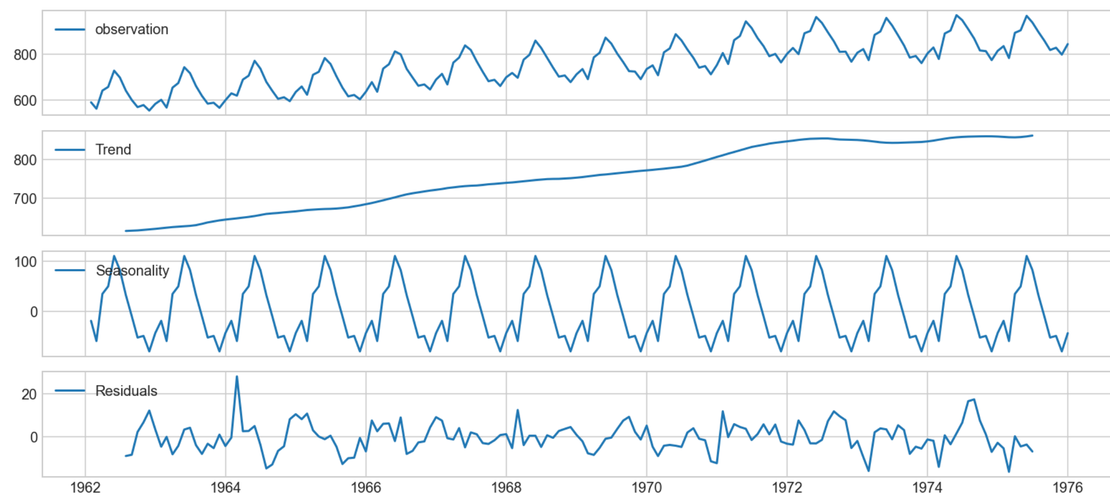
[10]:
```python
df.isnull().sum() # check if there is missing values in data
```

[10]:
```
Production    0
dtype: int64
```

[11]:
```python
#df.fillna(0, inplace=True) # fiiling missing values by 0, maybe there is no␣
↪production in these months
```

[12]:
```
ss_decomposition = seasonal_decompose(df)
estimated_obs = ss_decomposition.observed # additive series
estimated_trend = ss_decomposition.trend # upword trend
estimated_seasonal = ss_decomposition.seasonal # annual seaonality
estimated_residual = ss_decomposition.resid
```

[13]:
```
fig, axes = plt.subplots(4, 1, sharex=True, sharey=False)

axes[0].plot(estimated_obs, label='observation')
axes[0].legend(loc='upper left');

axes[1].plot(estimated_trend, label='Trend')
axes[1].legend(loc='upper left');

axes[2].plot(estimated_seasonal, label='Seasonality')
axes[2].legend(loc='upper left');

axes[3].plot(estimated_residual, label='Residuals')
axes[3].legend(loc='upper left');
```



[14]:
```
check = normaltest(df) # nonstationary
check
```

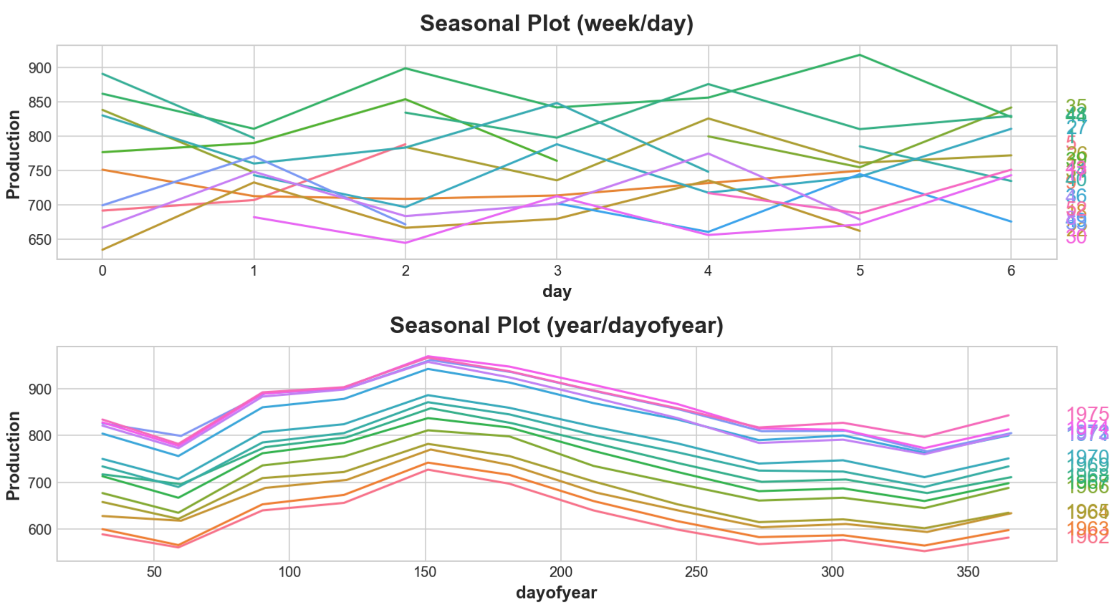
[14]:
```
NormaltestResult(statistic=masked_array(data=[10.28850715539463],
             mask=[False],
       fill_value=1e+20), pvalue=array([0.00583283]))
```

[15]:
```
adf, pvalue, usedlag, nobs, critical_values, icbest = adfuller(df)

print("ADF: ", adf)
```

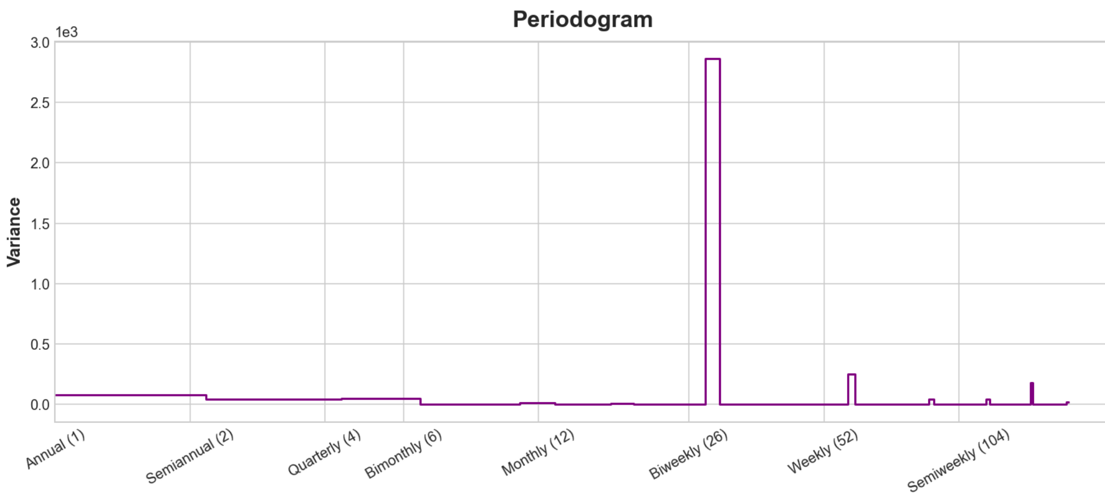
```
print("p-value:", pvalue) # nonstationary
```

```
ADF:  -1.3038115874221246
p-value: 0.627426708603034
```

[16]:
```
X = df.copy()

# days within a week
X["day"] = X.index.dayofweek  # the x-axis (freq)
X["week"] = X.index.week  # the seasonal period (period)

# days within a year
X["dayofyear"] = X.index.dayofyear
X["year"] = X.index.year
fig, (ax0, ax1) = plt.subplots(2, 1, figsize=(11, 6))
seasonal_plot(X, y="Production", period="week", freq="day", ax=ax0)
seasonal_plot(X, y="Production", period="year", freq="dayofyear", ax=ax1);
```



[17]:
```
plot_periodogram(df['Production']); # strong biwekely seasonality
```

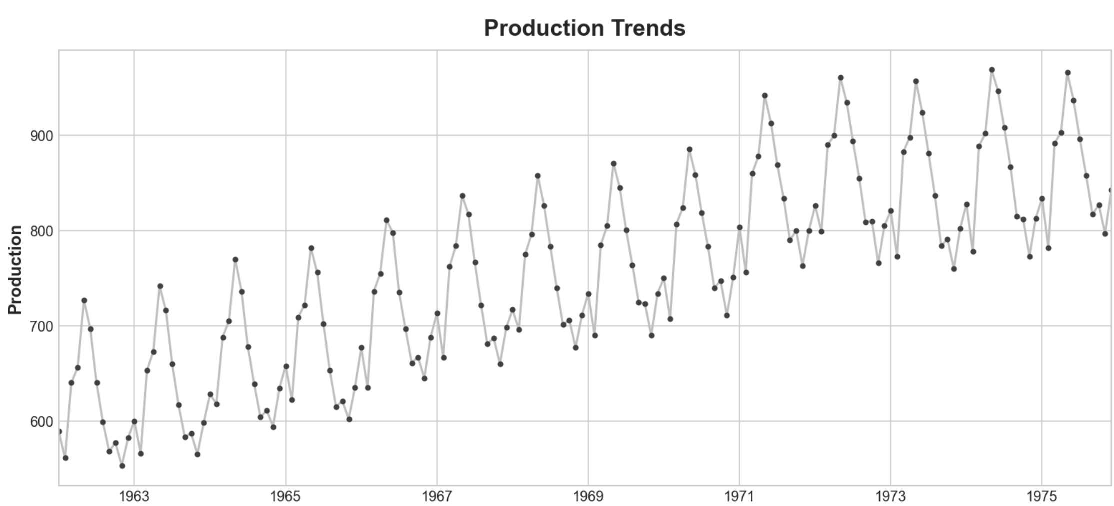


[18]:
```python
df.set_index(pd.PeriodIndex(df.index, freq="M"), inplace=True)

df.head()
```

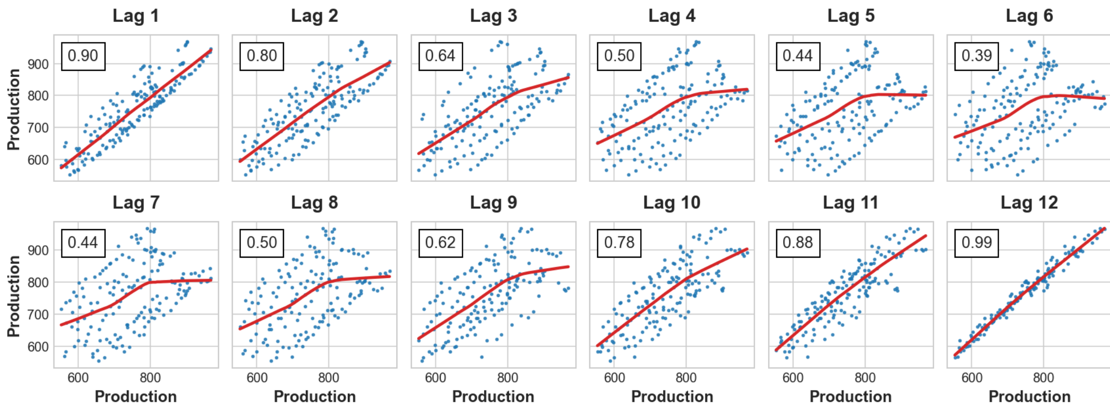
[18]:

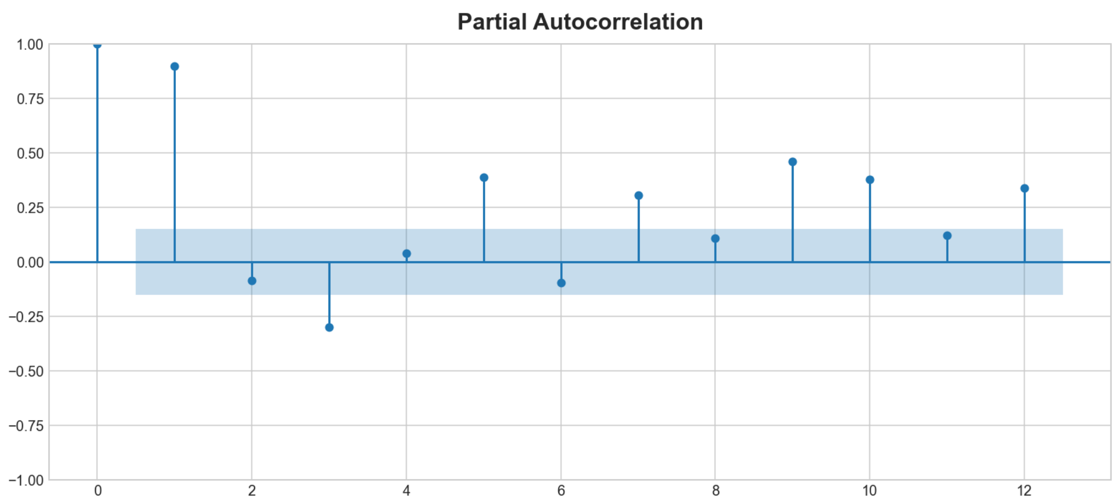
	Production
1962-01	589
1962-02	561
1962-03	640
1962-04	656
1962-05	727

[19]:
```python
ax = df.Production.plot(title='Production Trends', **plot_params)
_ = ax.set(ylabel="Production")
```



[20]:
```python
_ = plot_lags(df.Production, lags=12, nrows=2)
_ = plot_pacf(df.Production, lags=12) # strong lag 12
```





[21]:
```python
df = df.T # data transpose to prepare data split
df.head()
```

[21]:
```
                1962-01  1962-02  1962-03  1962-04  1962-05  1962-06  1962-07  \
Production          589      561      640      656      727      697      640

                1962-08  1962-09  1962-10  …  1975-03  1975-04  1975-05  \
Production          599      568      577  …      892      903      966

                1975-06  1975-07  1975-08  1975-09  1975-10  1975-11  1975-12
Production          937      896      858      817      827      797      843
```

```
[1 rows x 168 columns]
```

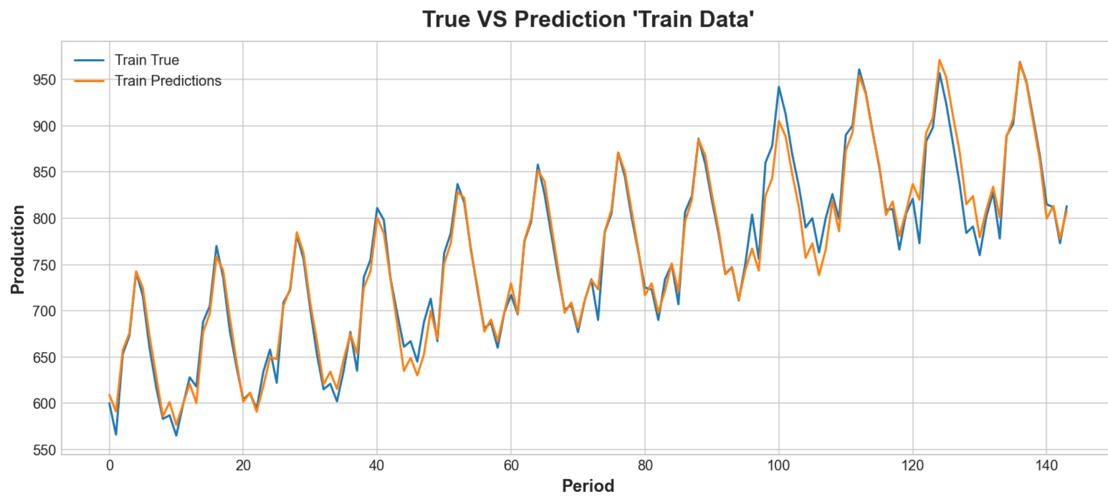
[22]:

```python
# Linear Regression as first model to compare

X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=12, y_len=1,␣
 ↪test_loops=12)

#scaler = MinMaxScaler()
#scaler.fit(X_train)
#X_train = scaler.transform(X_train)
#X_test = scaler.transform(X_test)

reg = Pipeline([('scaler', MinMaxScaler()), ('LinearRegression',␣
 ↪LinearRegression())])

#reg = LinearRegression() # Create a linear regression object
reg = reg.fit(X_train, y_train) # Fit it to the training data
# Create two predictions for the training and test sets
y_train_pred = reg.predict(X_train)
y_test_pred = reg.predict(X_test)
kpi(y_train, y_train_pred, y_test, y_test_pred, name='Regression')
```

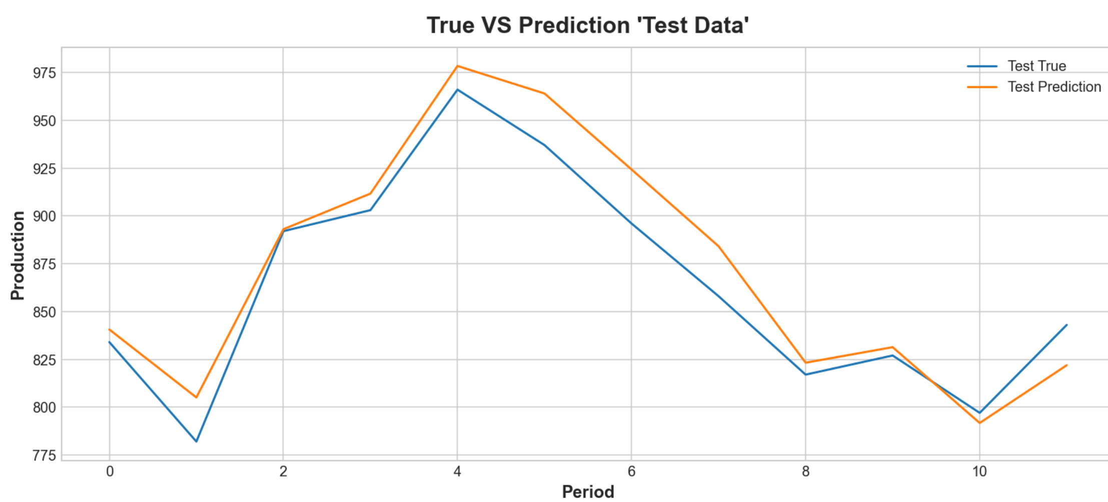
```
              MAE   RMSE  Bias  MAE_pct  RMSE_pct  r2_score
Regression
Train       10.91  14.83 -0.00     1.44      1.96      0.98
Test        14.17  17.18 -1.13     1.64      1.99      0.90
```

[23]:

```python
plt.plot(y_train, label='Train True')
plt.plot(y_train_pred, label='Train Predictions')
plt.title("True VS Prediction 'Train Data'")
plt.xlabel("Period")
plt.ylabel("Production")
plt.legend();
```



[24]:
```
plt.plot(y_test, label='Test True')
plt.plot(y_test_pred, label='Test Prediction')
plt.title("True VS Prediction 'Test Data'")
plt.xlabel("Period")
plt.ylabel("Production")
plt.legend();
```



[25]:
```
# prediction

X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=12, y_len=1,␣
↪test_loops=0)

#scaler = MinMaxScaler()
```

```
#scaler.fit(X_train)
#X_train = scaler.transform(X_train)
#X_test = scaler.transform(X_test)

reg = Pipeline([('scaler', MinMaxScaler()), ('LinearRegression',␣
 ↪LinearRegression())])

#reg = LinearRegression() # Create a linear regression object
reg = reg.fit(X_train,y_train) # Fit it to the training data
reg_forecast = pd.DataFrame(data=reg.predict(X_test), index=df.index,␣
 ↪columns=['Next_Month'])
reg_forecast
```

[25]:

	Next_Month
Production	848.5295

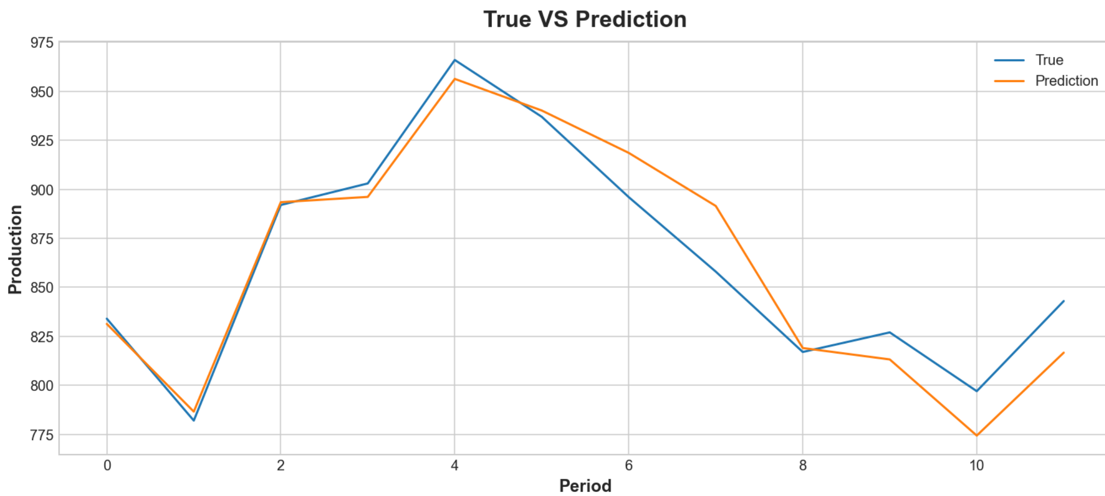
[26]:

```
# use Random Forest with default parameters

X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=12, y_len=1,␣
 ↪test_loops=12)

scaler = MinMaxScaler()
scaler.fit(X_train)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)

forest = RandomForestRegressor()
forest.fit(X_train, y_train)

y_train_pred = forest.predict(X_train)
y_test_pred = forest.predict(X_test)
kpi(y_train, y_train_pred, y_test, y_test_pred, name='Forest')
```

	MAE	RMSE	Bias	MAE_pct	RMSE_pct	r2_score
Forest						
Train	4.88	6.49	-0.00	0.64	0.86	1.00
Test	12.44	16.36	0.14	1.44	1.90	0.91

[27]:

```
plt.plot(y_test, label='True')
plt.plot(y_test_pred, label='Prediction')
plt.title("True VS Prediction")
plt.xlabel("Period")
plt.ylabel("Production")
plt.legend();
```



[28]:

```
# prediction

X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=12, y_len=1,␣
↪test_loops=0)

scaler = MinMaxScaler()
scaler.fit(X_train)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)

forest.fit(X_train, y_train) # Fit it to the training data
forecast = pd.DataFrame(data=forest.predict(X_test), index=df.index)
forecast
```

[28]:

	0
Production	840.0

[29]:

```
X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=12, y_len=1,␣
↪test_loops=12)

scaler = MinMaxScaler()
scaler.fit(X_train)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)

max_depth = list(range(1,11)) + [None]
min_samples_split = range(2,20)
min_samples_leaf = range(1,15)
max_features = range(2,11)
bootstrap = [True] #We force bootstrap
```

```
max_samples = [.7,.8,.9,.95,1]

param_dist = {'max_depth': max_depth,
              'min_samples_split': min_samples_split,
              'min_samples_leaf': min_samples_leaf,
              'max_features': max_features,
              'bootstrap': bootstrap,
              'max_samples': max_samples}

forest1 = RandomForestRegressor(n_jobs=1)
forest_cv = RandomizedSearchCV(forest1, param_dist, cv=6, n_jobs=-1, verbose=1,␣
↪n_iter=400, scoring='neg_mean_absolute_error')
forest_cv.fit(X_train, y_train)

print('Tuned Forest Parameters:', forest_cv.best_params_)
```

```
Fitting 6 folds for each of 400 candidates, totalling 2400 fits
Tuned Forest Parameters: {'min_samples_split': 3, 'min_samples_leaf': 1,
'max_samples': 0.9, 'max_features': 10, 'max_depth': 10, 'bootstrap': True}
```

[30]:
```
X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=12, y_len=1,␣
↪test_loops=12)

scaler = MinMaxScaler()
scaler.fit(X_train)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)

max_depth = list(range(6, 11)) + [None]
min_samples_split = range(2, 11)
min_samples_leaf = range(1, 6)
max_features = range(7, 13)
bootstrap = [True] #We force bootstrap
max_samples = [0.5, 0.6, 0.7, 0.8, 0.9]

param_dist_f = {'max_depth': max_depth,
              'min_samples_split': min_samples_split,
              'min_samples_leaf': min_samples_leaf,
              'max_features': max_features,
              'bootstrap': bootstrap,
              'max_samples': max_samples}

forest_f = RandomForestRegressor(n_jobs=1)
forest_cv_f = RandomizedSearchCV(forest_f, param_dist_f, cv=6, n_jobs=-1,␣
↪verbose=1, n_iter=400, scoring='neg_mean_absolute_error')
forest_cv_f.fit(X_train, y_train)
```

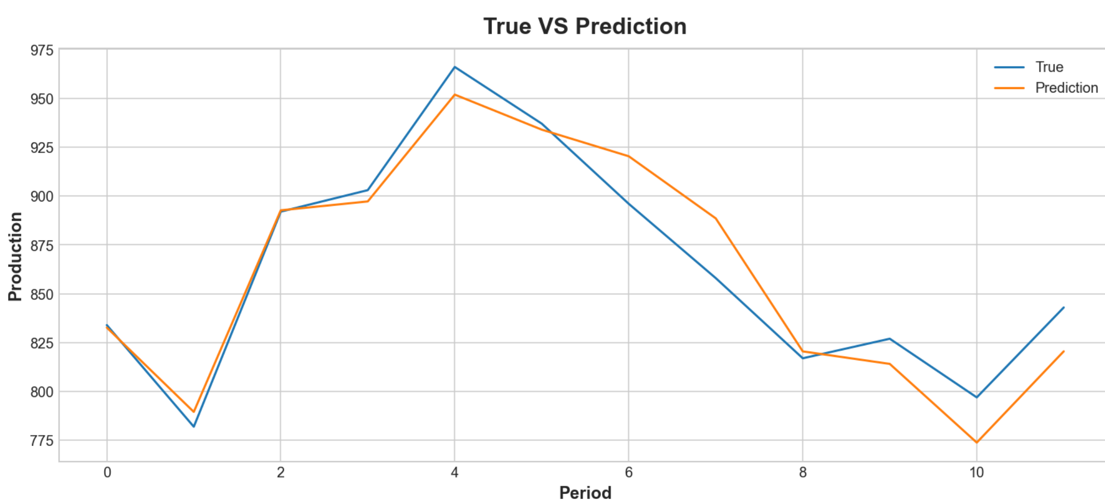
```
print('Tuned Forest Parameters:', forest_cv_f.best_params_)
```

```
Fitting 6 folds for each of 400 candidates, totalling 2400 fits
Tuned Forest Parameters: {'min_samples_split': 4, 'min_samples_leaf': 1,
'max_samples': 0.9, 'max_features': 11, 'max_depth': None, 'bootstrap': True}
```

[190]:
```
X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=12, y_len=1,␣
↪test_loops=12)

forest_final = RandomForestRegressor(min_samples_split=3, min_samples_leaf=1,
                                     max_samples=0.8, max_features=10,␣
↪max_depth=9, bootstrap=True)
forest_final.fit(X_train, y_train)

y_train_pred = forest_final.predict(X_train)
y_test_pred = forest_final.predict(X_test)
kpi(y_train, y_train_pred, y_test, y_test_pred, name='forest_final')
```

	MAE	RMSE	Bias	MAE_pct	RMSE_pct	r2_score
forest_final						
Train	6.03	8.04	0.03	0.80	1.06	0.99
Test	12.44	15.92	0.15	1.44	1.85	0.91

[191]:
```
plt.plot(y_test, label='True')
plt.plot(y_test_pred, label='Prediction')
plt.title("True VS Prediction")
plt.xlabel("Period")
plt.ylabel("Production")
plt.legend();
```



[192]:
```python
# prediction

X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=12, y_len=1,␣
 ↪test_loops=0)

scaler = MinMaxScaler()
scaler.fit(X_train)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)

forest_final.fit(X_train, y_train) # Fit it to the training data
forecast = pd.DataFrame(data=forest_final.predict(X_test), index=df.index)
forecast
```

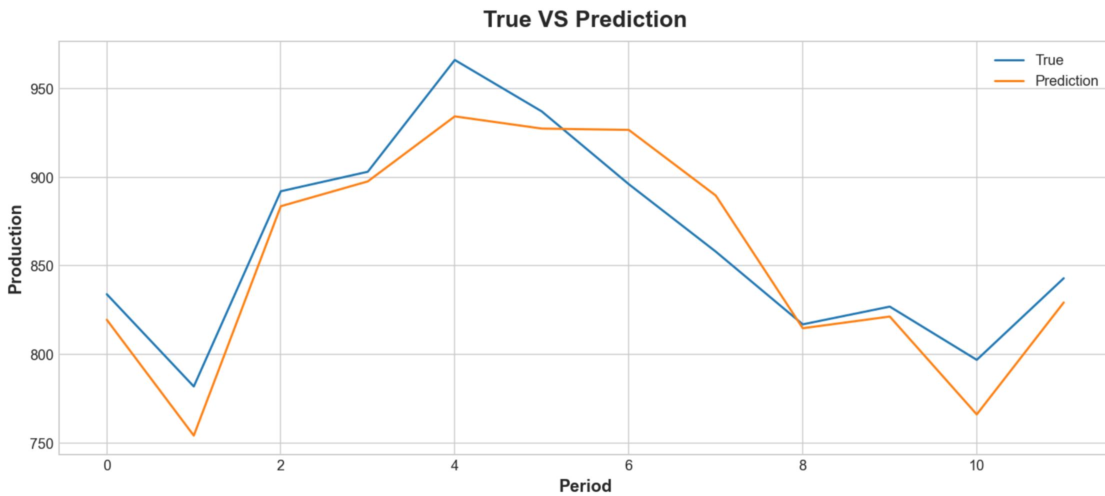
[192]:

	0
Production	841.632167

[34]:
```python
# XGB model to predict one period

X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=12, y_len=1,␣
 ↪test_loops=12)

scaler = MinMaxScaler()
scaler.fit(X_train)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)

xgb = XGBRegressor() # predict 1 period

xgb.fit(X_train, y_train)

y_train_pred = xgb.predict(X_train)
y_test_pred = xgb.predict(X_test)
kpi(y_train, y_train_pred, y_test, y_test_pred, name='xgb')
```

	MAE	RMSE	Bias	MAE_pct	RMSE_pct	r2_score
xgb						
Train	0.00	0.01	0.00	0.00	0.00	1.00
Test	17.65	20.98	0.84	2.05	2.43	0.85

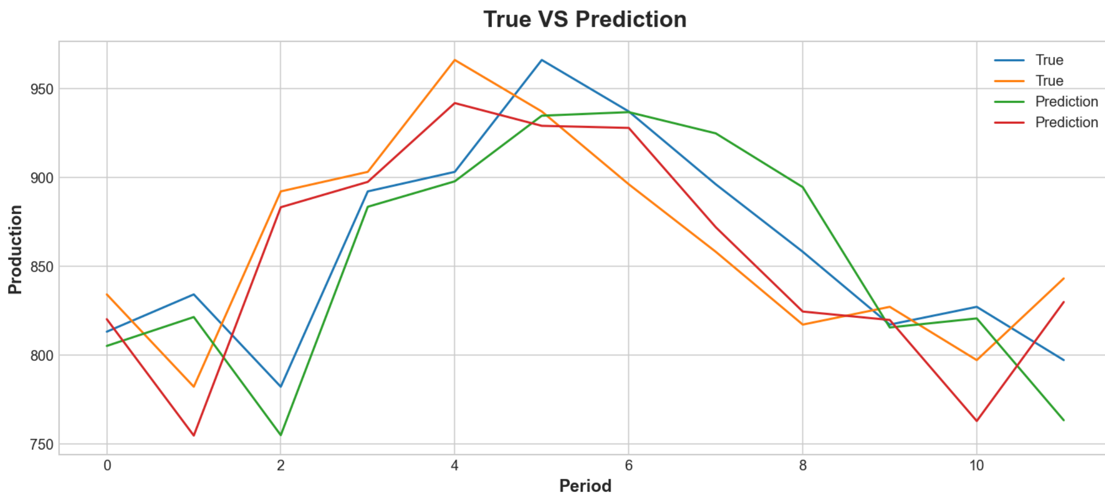
[35]:
```python
plt.plot(y_test, label='True')
plt.plot(y_test_pred, label='Prediction')
plt.title("True VS Prediction")
plt.xlabel("Period")
plt.ylabel("Production")
plt.legend();
```



[36]:
```
# MultiRegressor using XGB model to predict more than one period

X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=12, y_len=2,␣
↪test_loops=12)

scaler = MinMaxScaler()
scaler.fit(X_train)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)

xgb = XGBRegressor() # predict 1 period
mul = MultiOutputRegressor(xgb, n_jobs=-1) # if predict more than 1 period

mul.fit(X_train, y_train)

y_train_pred = mul.predict(X_train)
y_test_pred = mul.predict(X_test)
kpi(y_train, y_train_pred, y_test, y_test_pred, name='Multi')
```

	MAE	RMSE	Bias	MAE_pct	RMSE_pct	r2_score
Multi						
Train	0.00	0.00	-0.00	0.00	0.00	1.00
Test	16.55	20.15	0.78	1.92	2.34	0.87

[37]:
```
plt.plot(y_test, label='True')
plt.plot(y_test_pred, label='Prediction')
plt.title("True VS Prediction")
plt.xlabel("Period")
plt.ylabel("Production")
plt.legend();
```



[38]:
```
# prediction

X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=12, y_len=2,␣
↪test_loops=0)

scaler = MinMaxScaler()
scaler.fit(X_train)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)

mul.fit(X_train, y_train) # Fit it to the training data
forecast = pd.DataFrame(data=mul.predict(X_test), index=df.index)
forecast
```

[38]:

	0	1
Production	832.989014	783.293884

0.1 Deep Learning (LSTM) model

[44]:
```
def split_sequence(sequence, n_steps):
    X, y = list(), list()
    for i in range(len(sequence)):
        # find the end of this pattern
        end_ix = i + n_steps
        # check if we are beyond the sequence
        if end_ix > len(sequence)-1:
            break
        # gather input and output parts of the pattern
        seq_x, seq_y = sequence[i:end_ix], sequence[end_ix]
        X.append(seq_x)
```

```
        y.append(seq_y)
    return np.array(X), np.array(y)
```

[45]:
```
df = pd.read_csv(r'C:
↪\Users\MUHAMMAD-SHALABY\Downloads\3\Time-Series-Forecasting-LSTM-main\monthly_milk_producti
↪csv')
df.Date = pd.to_datetime(df.Date)
df.set_index('Date', inplace=True)
df.tail()
```

[45]:
```
            Production
Date
1975-08-01         858
1975-09-01         817
1975-10-01         827
1975-11-01         797
1975-12-01         843
```

[46]:
```
scaler = MinMaxScaler()
data = scaler.fit_transform(df)

# Split
cut = int(len(data) *0.9)

train, test = data[:cut,:], data[cut:,:]
```

[47]:
```
n_steps = 3
n_features = 1

X_train, y_train = split_sequence(train, n_steps)
X_test, y_test = split_sequence(test, n_steps)
```

[48]:
```
X_train.shape, X_test.shape
```

[48]:
```
((148, 3, 1), (14, 3, 1))
```

[49]:
```
# reshape from [samples, timesteps] into [samples, timesteps, features]

X_train = X_train.reshape((X_train.shape[0], X_train.shape[1], n_features))
X_test = X_test.reshape((X_test.shape[0], X_test.shape[1], n_features))
```

[50]:
```
X_train.shape, X_test.shape
```

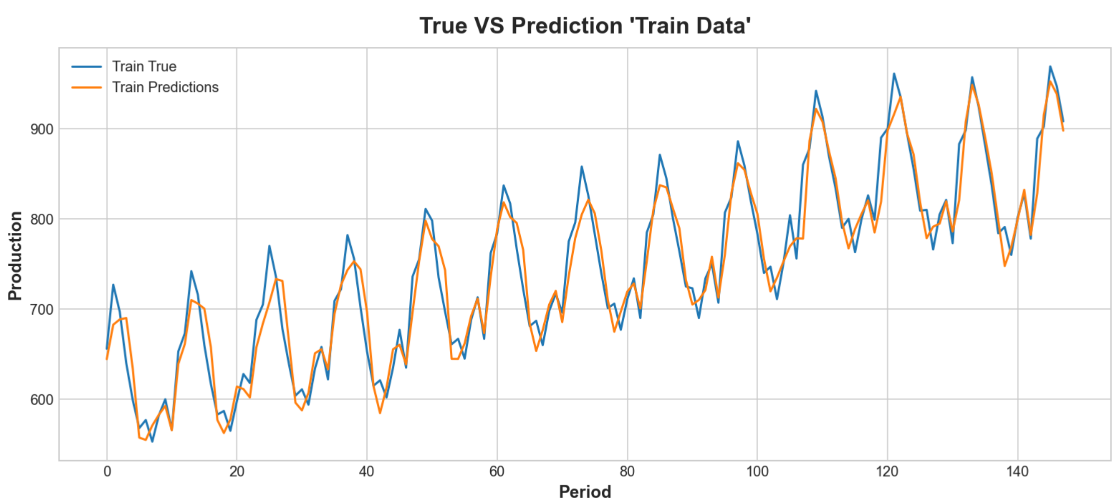
[50]:
```
((148, 3, 1), (14, 3, 1))
```

[51]:
```
tf.keras.backend.clear_session()
tf.random.set_seed(42)
```

```
np.random.seed(42)


model = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=60, kernel_size=5,
                      strides=1, padding="causal",
                      activation="relu",
                      input_shape=(n_steps, n_features)),
  tf.keras.layers.LSTM(60, return_sequences=True),
  tf.keras.layers.LSTM(60),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 400)
])


model.compile(loss='mean_squared_error',optimizer='adam')

history = model.fit(X_train, y_train, validation_data=(X_test, y_test),␣
 ↪epochs=300 ,batch_size=4, verbose=0)
```

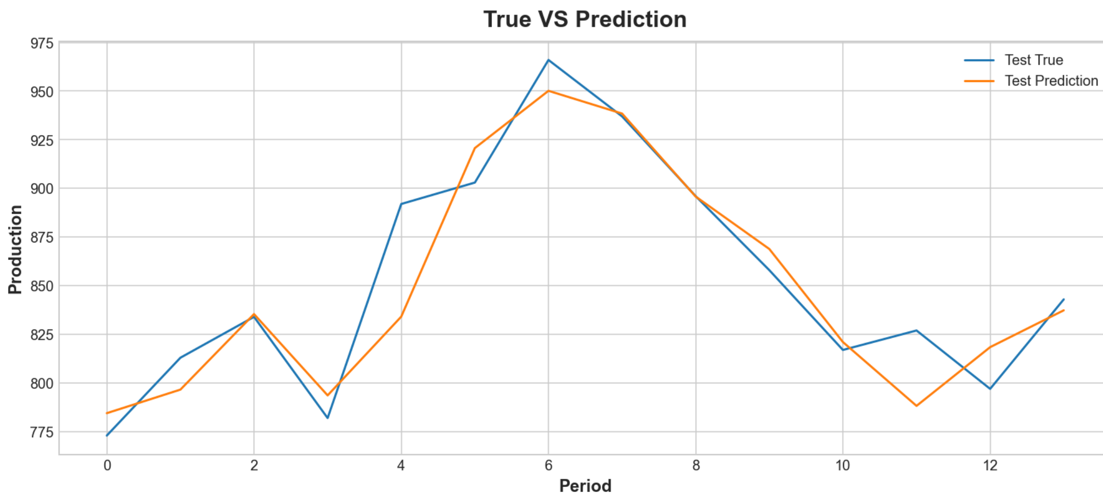
[52]:
```
y_train = scaler.inverse_transform(y_train)
y_train_pred = scaler.inverse_transform(model.predict(X_train))
```

[53]:
```
plt.plot(y_train, label='Train True')
plt.plot(y_train_pred, label='Train Predictions')
plt.title("True VS Prediction 'Train Data'")
plt.xlabel("Period")
plt.ylabel("Production")
plt.legend();
```



[54]:
```
y_test = scaler.inverse_transform(y_test)
y_test_pred = scaler.inverse_transform(model.predict(X_test))
```

[55]:
```
plt.plot(y_test, label='Test True')
plt.plot(y_test_pred, label='Test Prediction')
plt.title("True VS Prediction")
plt.xlabel("Period")
plt.ylabel("Production")
plt.legend();
```



[56]:
```
kpi(y_train, y_train_pred, y_test, y_test_pred, name='LSTM')
```

	MAE	RMSE	Bias	MAE_pct	RMSE_pct	r2_score
LSTM						
Train	18.92	24.73	0.44	2.53	3.31	0.94
Test	15.34	21.68	0.46	1.80	2.54	0.85

[57]:
```
# demonstrate prediction
future_pred = data[-n_steps:]
x_input = future_pred
x_input = x_input.reshape((1, n_steps, n_features))
yhat = model.predict(x_input, verbose=0)
yhat = scaler.inverse_transform(yhat)
print('Prediction of Next Month Production is: ', round(float(yhat), 2))
```

```
Prediction of Next Month Production is:  870.25
```

[58]:
```
forecast = pd.DataFrame(data=yhat, columns=['Next_Production'])
forecast
```

[58]:
```
   Next_Production
0       870.246826
```

0.2 Forecast more than one period LSTM

[2]:
```
# split a univariate sequence into samples
def split_sequence(sequence, n_steps_in, n_steps_out):
    X, y = list(), list()
    for i in range(len(sequence)):
        # find the end of this pattern
        end_ix = i + n_steps_in
        out_end_ix = end_ix + n_steps_out
        # check if we are beyond the sequence
        if out_end_ix > len(sequence):
            break
        # gather input and output parts of the pattern
        seq_x, seq_y = sequence[i:end_ix], sequence[end_ix:out_end_ix]
        X.append(seq_x)
        y.append(seq_y)
    return np.array(X), np.array(y)
```

[3]:
```
df = pd.read_csv(r'C:
↪\Users\MUHAMMAD-SHALABY\Downloads\3\Time-Series-Forecasting-LSTM-main\monthly_milk_producti
↪csv')
df.Date = pd.to_datetime(df.Date)
df.set_index('Date', inplace=True)
df.tail()
```

[3]:
```
            Production
Date
1975-08-01         858
1975-09-01         817
1975-10-01         827
1975-11-01         797
1975-12-01         843
```

[4]:
```
data = np.array(df['Production'])

# Split
cut = int(len(data) *0.9)

train, test = data[:cut], data[cut:]
```

[6]:
```
n_steps_in, n_steps_out = 3, 2
n_features = 1

X_train, y_train = split_sequence(train, n_steps_in, n_steps_out)
```

```
X_test, y_test = split_sequence(test, n_steps_in, n_steps_out)

X_train.shape, X_test.shape
```

[6]: ((147, 3), (13, 3))

[7]:
```
# reshape from [samples, timesteps] into [samples, timesteps, features]

X_train = X_train.reshape((X_train.shape[0], X_train.shape[1], n_features))
X_test = X_test.reshape((X_test.shape[0], X_test.shape[1], n_features))

X_train.shape, X_test.shape
```

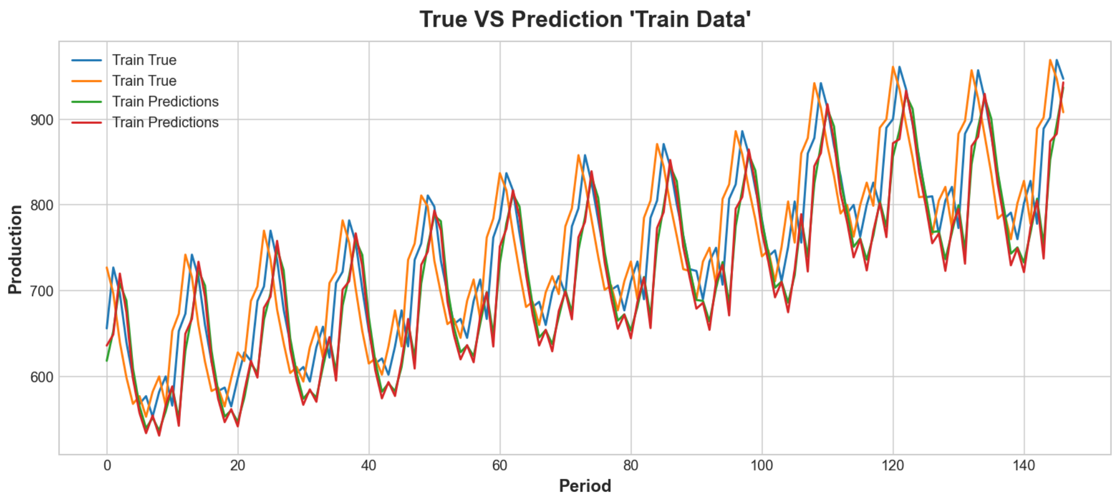
[7]: ((147, 3, 1), (13, 3, 1))

[11]:
```
tf.keras.backend.clear_session()
tf.random.set_seed(42)
np.random.seed(42)

# define model
model1 = tf.keras.models.Sequential(
  tf.keras.layers.Conv1D(filters=60, kernel_size=5,
                      strides=1, padding="causal",
                      activation="relu",
                      input_shape=(n_steps_in, n_features)))
model1.add(tf.keras.layers.LSTM(100, activation='relu', return_sequences=True,␣
 ↪input_shape=(n_steps_in, n_features)))
model1.add(tf.keras.layers.LSTM(100, activation='relu'))
model1.add(tf.keras.layers.Dense(n_steps_out))
model1.compile(optimizer='adam', loss='mse')
# fit model
model1.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=300␣
 ↪,batch_size=4, verbose=0)
```

[11]: <keras.callbacks.History at 0x1ecd0bab6a0>

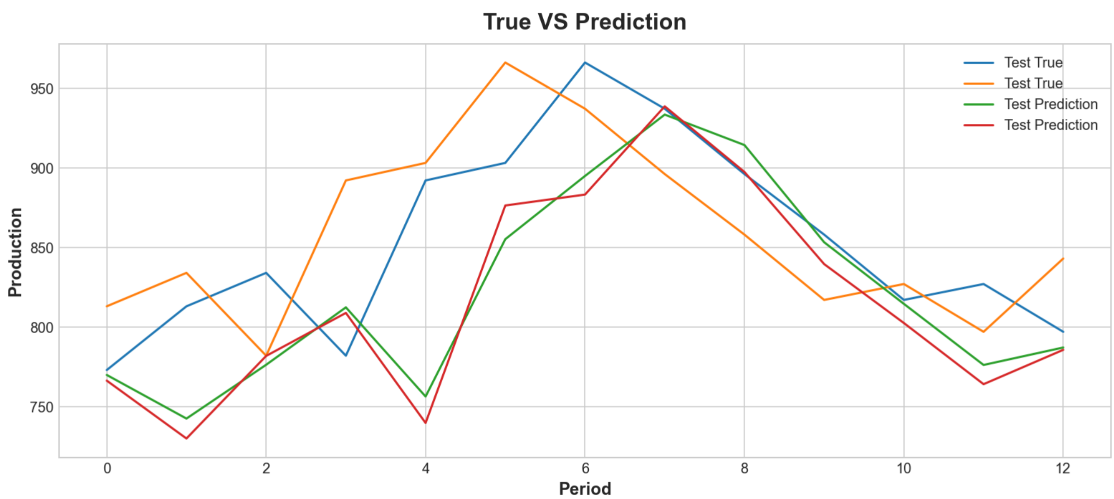
[12]:
```
y_train_pred = model1.predict(X_train)
```

[13]:
```
plt.plot(y_train, label='Train True')
plt.plot(y_train_pred, label='Train Predictions')
plt.title("True VS Prediction 'Train Data'")
plt.xlabel("Period")
plt.ylabel("Production")
plt.legend();
```



[14]:
```
y_test_pred = model1.predict(X_test)
```

[15]:
```
plt.plot(y_test, label='Test True')
plt.plot(y_test_pred, label='Test Prediction')
plt.title("True VS Prediction")
plt.xlabel("Period")
plt.ylabel("Production")
plt.legend();
```



[16]:
```
mean_absolute_error(y_test, y_test_pred)
```

[16]: 48.67992225060097

[19]:
```
# demonstrate prediction
future_pred = data[-n_steps_in:]
x_input = future_pred
x_input = x_input.reshape((1, n_steps_in, n_features))
yhat = model1.predict(x_input, verbose=0)
print('Prediction of Next two Months Production is: ', yhat)
```

```
Prediction of Next two Months Production is:  [[806.9777 813.0213]]
```

1 under testing

[ ]:
```
df = pd.read_csv(r'C:
↪\Users\MUHAMMAD-SHALABY\Downloads\3\Time-Series-Forecasting-LSTM-main\monthly_milk_producti
↪csv')
df.Date = pd.to_datetime(df.Date)
df.set_index('Date', inplace=True)
df.tail()
```

[ ]:
```
sc = MinMaxScaler()
data = sc.fit_transform(df)

# Split
cut = int(len(data) *0.8)

train, test = data[:cut,:], data[cut:,:]
```

[ ]:
```
n_steps = 12
n_features = 1

X_train, y_train = split_sequence(train, n_steps)
X_test, y_test = split_sequence(test, n_steps)
```

[ ]:
```
# reshape from [samples, timesteps] into [samples, timesteps, features]
n_features = 1
X_train = X_train.reshape((X_train.shape[0], X_train.shape[1]))
X_test = X_test.reshape((X_test.shape[0], X_test.shape[1]))

X_train.shape, X_test.shape
```

[ ]:
```
forest_final = RandomForestRegressor(min_samples_split=3, min_samples_leaf=1,
                                     max_samples=0.8, max_features=10,␣
↪max_depth=9, bootstrap=True)
forest_final.fit(X_train, y_train)

y_train_pred = forest_final.predict(X_train)
y_test_pred = forest_final.predict(X_test)
```

```
kpi(y_train, y_train_pred, y_test, y_test_pred, name='forest_final')
```

[ ]:
```
l = data[-n_steps:]
l = l.reshape(n_features, n_steps)
l.shape
```

[ ]:
```
z = forest_final.predict(l)
z
```

[ ]:
```
z = sc.inverse_transform(z.reshape(1, -1))
z
```