Predict monthly Car Sales

February 14, 2022

[217]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.model_selection import train_test_split, RandomizedSearchCV,␣
↪GridSearchCV
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
from sklearn.neural_network import MLPRegressor
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'
np.random.seed(42)
```

[45]:
```
# 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 = []
```

```python
    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)
```

[442]:
```
data = pd.read_csv('norway_new_car_sales_by_make.csv')
data.tail()
```

[442]:

	Year	Month	Make	Quantity	Pct
3947	2016	1	Smart	6	0.1
3948	2016	1	Fiat	5	0.0
3949	2016	1	Jeep	4	0.0
3950	2016	1	Dacia	1	0.0
3951	2016	1	Maserati	1	0.0

[443]:
```
data['Period'] = data.Year.astype(str) + '-' + data.Month.astype(str).str.
↪zfill(2)
```

[444]:
```
data.head()
```

[444]:

	Year	Month	Make	Quantity	Pct	Period
0	2007	1	Toyota	2884	22.7	2007-01
1	2007	1	Volkswagen	2521	19.9	2007-01
2	2007	1	Peugeot	1029	8.1	2007-01
3	2007	1	Ford	870	6.9	2007-01
4	2007	1	Volvo	693	5.5	2007-01

[445]:
```
data.isnull().sum()
```

[445]:
```
Year         0
Month        0
Make        10
Quantity     0
Pct          0
Period       0
dtype: int64
```

[446]:
```
data[data.Make.isnull()] # There is months with out cars sales we will fill 0
```

[446]:

	Year	Month	Make	Quantity	Pct	Period
37	2007	1	NaN	1	0.0	2007-01
112	2007	3	NaN	1	0.0	2007-03
265	2007	7	NaN	1	0.0	2007-07
419	2007	11	NaN	1	0.0	2007-11
1256	2009	9	NaN	4	0.0	2009-09
1294	2009	10	NaN	4	0.0	2009-10
2399	2012	4	NaN	1	0.0	2012-04
2478	2012	6	NaN	1	0.0	2012-06
2517	2012	7	NaN	1	0.0	2012-07
3013	2013	9	NaN	1	0.0	2013-09

[447]:
```python
df = pd.pivot_table(data=data, values='Quantity', index='Make',␣
↪columns='Period', aggfunc='sum', fill_value=0)
df.head()
```

[447]:
```
Period        2007-01  2007-02  2007-03  2007-04  2007-05  2007-06  2007-07  \
Make
Alfa Romeo         16        9       21       20       17       21       14
Aston Martin        0        0        1        0        4        3        3
Audi              599      498      682      556      630      498      562
BMW               352      335      365      360      431      477      403
Bentley             0        0        0        0        0        1        0

Period        2007-08  2007-09  2007-10  …  2015-04  2015-05  2015-06  \
Make                                     …
Alfa Romeo         12       15       10  …        3        3        3
Aston Martin        0        0        0  …        2        2        0
Audi              590      393      554  …      665      585      640
BMW               348      271      562  …      733      693      849
Bentley             0        0        0  …        0        0        0

Period        2015-07  2015-08  2015-09  2015-10  2015-11  2015-12  2016-01
Make
Alfa Romeo          9        4        5        0        3        3        0
Aston Martin        0        0        0        0        0        0        0
Audi              754      541      494      549      592      496      559
BMW               617      860      777     1010      934     1024     1089
Bentley             0        0        0        0        0        0        0

[5 rows x 109 columns]
```

[448]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 65 entries, Alfa Romeo to Westfield
Columns: 109 entries, 2007-01 to 2016-01
dtypes: int64(109)
memory usage: 55.9+ KB
```

[449]:
```python
df.shape
```

[449]: (65, 109)

0.1 Linear Regression

[450]:
```
# 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)

reg = Pipeline([('scaler', MinMaxScaler()), ('LinearRegression',␣
↪LinearRegression())]) # Create a linear regression object

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           29.50  73.02  -0.0    17.91     44.32      0.95
Test            33.56  80.90   0.9    17.32     41.75      0.95
```

0.2 Random Forest

[209]:
```
# 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)

forest = Pipeline([('scaler', MinMaxScaler()), ('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   11.23  28.60 -0.14     6.67     16.99      0.99
Test    35.00  89.76  1.97    17.43     44.69      0.95
```

[215]:
```
X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=12, y_len=1,␣
↪test_loops=12)
```

```
pipe_grid = Pipeline([('scaler', MinMaxScaler()), ('Forestb',␣
↪RandomForestRegressor(n_jobs=1))])

param_dist = {'Forestb__n_estimators': list(range(100, 500, 100)),
              'Forestb__max_depth': list(range(1, 20)) + [None],
              'Forestb__min_samples_split': range(2, 20),
              'Forestb__min_samples_leaf': range(1, 20),
              'Forestb__max_features': [.1, .2, .3, .4, .5, .6, .7, .8, .9, 1]␣
↪+ ['auto'],
              'Forestb__bootstrap': [True],
              'Forestb__max_samples': [.1, .2, .3, .4, .5, .6, .7, .8, .9, 1]}

forest_cv = RandomizedSearchCV(pipe_grid, param_dist, cv=6, n_jobs=-1,␣
↪verbose=1, n_iter=400)

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: {'Forestb__n_estimators': 100,
'Forestb__min_samples_split': 7, 'Forestb__min_samples_leaf': 6,
'Forestb__max_samples': 0.5, 'Forestb__max_features': 0.4, 'Forestb__max_depth':
19, 'Forestb__bootstrap': True}
```

[216]:
```
X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=12, y_len=1,␣
↪test_loops=12)

pipe_grid_f = Pipeline([('scaler', MinMaxScaler()), ('Forestf',␣
↪RandomForestRegressor(n_jobs=1))])

param_dist_f = {'Forestf__n_estimators': [100],
                'Forestf__max_depth': list(range(17, 22)) + [None],
                'Forestf__min_samples_split': range(5, 10),
                'Forestf__min_samples_leaf': range(4, 9),
                'Forestf__max_features': [.35, .4, .45],
                'Forestf__bootstrap': [True],
                'Forestf__max_samples': [.45, .5, .55]}

forest_cv_f = GridSearchCV(pipe_grid_f, param_dist_f, n_jobs=-1, verbose=1)

forest_cv_f.fit(X_train, y_train)

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

```
Fitting 5 folds for each of 1350 candidates, totalling 6750 fits
```

```
Tuned Forest Parameters: {'Forestf__bootstrap': True, 'Forestf__max_depth': 19,
'Forestf__max_features': 0.4, 'Forestf__max_samples': 0.5,
'Forestf__min_samples_leaf': 5, 'Forestf__min_samples_split': 5,
'Forestf__n_estimators': 100}
```

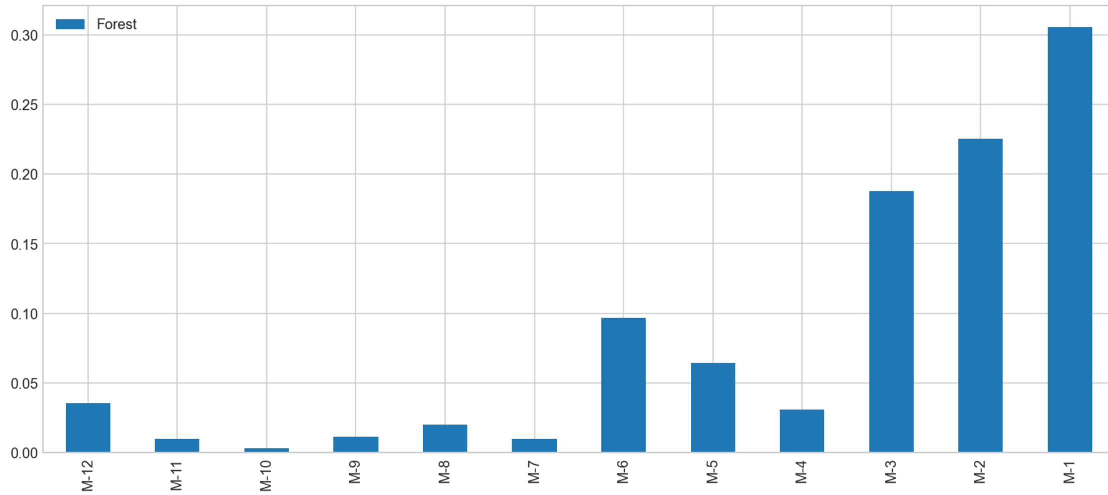
[457]:

```
X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=12, y_len=1,␣
 ↪test_loops=20)

forest_final = Pipeline([('scaler', MinMaxScaler()), ('ForestFinal',␣
 ↪RandomForestRegressor(n_estimators=100,
                                                                           ␣
 ↪           min_samples_split=5,
                                                                           ␣
 ↪           min_samples_leaf=5,
                                                                           ␣
 ↪           max_samples=0.5,
                                                                           ␣
 ↪           max_features=0.4,
                                                                           ␣
 ↪           max_depth=19,
                                                                           ␣
 ↪           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         23.53  60.29 -0.07    14.42     36.96      0.97
Test          34.27  94.47  1.89    18.19     50.14      0.94
```

[452]:

```
cols = X_train.shape[1]
features = [f'M-{cols-col}' for col in range(cols)]
data = forest_final.steps[1][1].feature_importances_.reshape(-1,1)
imp = pd.DataFrame(data=data, index=features, columns=['Forest'])
imp.plot(kind='bar'); # the most important months is the first previous three␣
 ↪months
```



[456]:
```
# prediction

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

forest_final = Pipeline([('scaler', MinMaxScaler()), ('ForestFinal',␣
↪RandomForestRegressor(n_estimators=100,
                                                                              ␣
↪           min_samples_split=5,
                                                                              ␣
↪           min_samples_leaf=5,
                                                                              ␣
↪           max_samples=0.5,
                                                                              ␣
↪           max_features=0.4,
                                                                              ␣
↪           max_depth=19,
                                                                              ␣
↪           bootstrap=True))])

forest_final.fit(X_train, y_train)

forecast = pd.DataFrame(data=forest_final.predict(X_test), index=df.index,␣
↪columns=['Next_Sales'])
forecast.tail(10)
```

[456]:

	Next_Sales
Make	
Subaru	273.765626

```
Suzuki         246.159222
Tata             0.035983
Tazzari          0.035983
Tesla          238.629376
Think            0.035983
Toyota        1279.202421
Volkswagen    1980.871566
Volvo          754.306872
Westfield        0.035983
```

0.3 sklearn neural network

[239]:
```
X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=12, y_len=1,␣
 ↪test_loops=12)

param_fixed = {'NN__activation': 'relu',
               'NN__solver': 'adam',
               'NN__early_stopping': True,
               'NN__n_iter_no_change': 50,
               'NN__validation_fraction': .1,
               'NN__tol': .0001}

NN_b = Pipeline([('scaler', MinMaxScaler()),
                 ('NN', MLPRegressor(hidden_layer_sizes=(20, 20),␣
 ↪**param_fixed, verbose=True))])

NN_b.fit(X_train, y_train)

y_train_pred = NN_b.predict(X_train)
y_test_pred = NN_b.predict(X_test)

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

```
Iteration 1, loss = 16971.36834111
Validation score: 0.920519
Iteration 2, loss = 5110.23720794
Validation score: 0.931789
Iteration 3, loss = 4565.24989091
Validation score: 0.939719
Iteration 4, loss = 3852.89505267
Validation score: 0.947731
Iteration 5, loss = 3449.10170482
Validation score: 0.952096
Iteration 6, loss = 3265.13428419
Validation score: 0.953008
Iteration 7, loss = 3209.02490989
Validation score: 0.954035
```

```
Iteration 8, loss = 3085.55584211
Validation score: 0.951573
Iteration 9, loss = 3064.69334411
Validation score: 0.954850
Iteration 10, loss = 3008.82441924
Validation score: 0.953426
Iteration 11, loss = 2999.89364823
Validation score: 0.954806
Iteration 12, loss = 2935.42363800
Validation score: 0.950930
Iteration 13, loss = 2945.29979431
Validation score: 0.952048
Iteration 14, loss = 2892.57673994
Validation score: 0.954456
Iteration 15, loss = 2898.20545926
Validation score: 0.953670
Iteration 16, loss = 2840.81105990
Validation score: 0.956535
Iteration 17, loss = 2853.17051733
Validation score: 0.955087
Iteration 18, loss = 2811.50052428
Validation score: 0.954550
Iteration 19, loss = 2859.53208914
Validation score: 0.957451
Iteration 20, loss = 2801.37358361
Validation score: 0.956494
Iteration 21, loss = 2826.67468237
Validation score: 0.953650
Iteration 22, loss = 2800.97152429
Validation score: 0.957574
Iteration 23, loss = 2774.53435708
Validation score: 0.957465
Iteration 24, loss = 2786.25617047
Validation score: 0.957286
Iteration 25, loss = 2759.36054757
Validation score: 0.957647
Iteration 26, loss = 2768.49175650
Validation score: 0.956920
Iteration 27, loss = 2775.32711925
Validation score: 0.957906
Iteration 28, loss = 2737.64666304
Validation score: 0.957604
Iteration 29, loss = 2740.10605118
Validation score: 0.958141
Iteration 30, loss = 2723.86415606
Validation score: 0.957617
Iteration 31, loss = 2734.11520275
Validation score: 0.956248
```

```
Iteration 32, loss = 2718.93903727
Validation score: 0.957583
Iteration 33, loss = 2708.15187273
Validation score: 0.957827
Iteration 34, loss = 2794.12130042
Validation score: 0.956448
Iteration 35, loss = 2717.14258181
Validation score: 0.958125
Iteration 36, loss = 2729.33100488
Validation score: 0.956359
Iteration 37, loss = 2807.90123038
Validation score: 0.954742
Iteration 38, loss = 2680.45248503
Validation score: 0.954734
Iteration 39, loss = 2678.08721670
Validation score: 0.956289
Iteration 40, loss = 2696.67853147
Validation score: 0.958213
Iteration 41, loss = 2660.16777892
Validation score: 0.958391
Iteration 42, loss = 2699.44483095
Validation score: 0.957891
Iteration 43, loss = 2671.49539269
Validation score: 0.955042
Iteration 44, loss = 2694.94566715
Validation score: 0.958042
Iteration 45, loss = 2657.01530109
Validation score: 0.958134
Iteration 46, loss = 2648.74621629
Validation score: 0.957668
Iteration 47, loss = 2637.09705193
Validation score: 0.958059
Iteration 48, loss = 2641.89330288
Validation score: 0.958081
Iteration 49, loss = 2639.54967327
Validation score: 0.957831
Iteration 50, loss = 2627.73160091
Validation score: 0.953220
Iteration 51, loss = 2623.89712487
Validation score: 0.957034
Iteration 52, loss = 2595.33693212
Validation score: 0.957714
Iteration 53, loss = 2590.92936057
Validation score: 0.957525
Iteration 54, loss = 2615.57414957
Validation score: 0.956998
Iteration 55, loss = 2628.97969433
Validation score: 0.957136
```

```
Iteration 56, loss = 2574.35117809
Validation score: 0.955533
Iteration 57, loss = 2598.76828229
Validation score: 0.957352
Iteration 58, loss = 2592.31860233
Validation score: 0.957899
Iteration 59, loss = 2629.03775109
Validation score: 0.957108
Iteration 60, loss = 2560.21381202
Validation score: 0.957306
Iteration 61, loss = 2572.66679465
Validation score: 0.956254
Iteration 62, loss = 2580.40615258
Validation score: 0.957401
Iteration 63, loss = 2561.93021908
Validation score: 0.953763
Iteration 64, loss = 2583.91167570
Validation score: 0.957855
Iteration 65, loss = 2577.15733048
Validation score: 0.954738
Iteration 66, loss = 2560.55920948
Validation score: 0.956368
Iteration 67, loss = 2582.89620406
Validation score: 0.953563
Iteration 68, loss = 2539.67821685
Validation score: 0.954502
Iteration 69, loss = 2586.50281436
Validation score: 0.958076
Iteration 70, loss = 2539.07454030
Validation score: 0.957650
Iteration 71, loss = 2539.17665727
Validation score: 0.957874
Iteration 72, loss = 2526.09039548
Validation score: 0.955149
Iteration 73, loss = 2578.01193607
Validation score: 0.958080
Iteration 74, loss = 2568.79862623
Validation score: 0.957712
Iteration 75, loss = 2552.06760454
Validation score: 0.956531
Iteration 76, loss = 2560.13477279
Validation score: 0.955206
Iteration 77, loss = 2482.22410817
Validation score: 0.957790
Iteration 78, loss = 2485.20904692
Validation score: 0.955304
Iteration 79, loss = 2482.92618286
Validation score: 0.957447
```

```
Iteration 80, loss = 2494.84606321
Validation score: 0.955910
Iteration 81, loss = 2508.87559548
Validation score: 0.957711
Iteration 82, loss = 2525.15199528
Validation score: 0.957607
Iteration 83, loss = 2485.24101376
Validation score: 0.958265
Iteration 84, loss = 2475.47789266
Validation score: 0.957764
Iteration 85, loss = 2464.08604742
Validation score: 0.957631
Iteration 86, loss = 2477.27369603
Validation score: 0.957531
Iteration 87, loss = 2472.67163458
Validation score: 0.957814
Iteration 88, loss = 2541.88006435
Validation score: 0.953028
Iteration 89, loss = 2455.09286815
Validation score: 0.956354
Iteration 90, loss = 2451.18673487
Validation score: 0.958016
Iteration 91, loss = 2473.74032244
Validation score: 0.955968
Iteration 92, loss = 2470.03417351
Validation score: 0.957904
Validation score did not improve more than tol=0.000100 for 50 consecutive
epochs. Stopping.
         MAE   RMSE  Bias  MAE_pct  RMSE_pct  r2_score
NN
Train  29.25  71.99 -0.83    17.37     42.77      0.95
Test   35.83  87.70  0.56    17.84     43.66      0.95
```

[240]:
```
X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=12, y_len=1,␣
↪test_loops=12)

NN = Pipeline([('scaler', MinMaxScaler()),
               ('NN', MLPRegressor(activation='relu',
                                   solver='adam',
                                   early_stopping=True,
                                   n_iter_no_change=50,
                                   validation_fraction=.1,
                                   tol=.0001))])

param_dist = {'NN__hidden_layer_sizes': [[neuron]*hidden_layer for neuron in␣
↪range(10,60,10) for hidden_layer in range(2,7)],
              'NN__alpha': [5, 1, .5, .1, .05, .01, .001],
```

```
              'NN__learning_rate_init': [.05, .01, .005, .001, .0005],
              'NN__beta_1': [.85, .875, .9, .95, .975, .99, .995],
              'NN__beta_2': [.99, .995, .999, .9995, .9999]}

NN_cv = RandomizedSearchCV(NN, param_dist, cv=10, verbose=2, n_jobs=-1,␣
 ↪n_iter=200, scoring='neg_mean_absolute_error')
NN_cv.fit(X_train, y_train)

print('Tuned NN Parameters:', NN_cv.best_params_)
```

```
Fitting 10 folds for each of 200 candidates, totalling 2000 fits
Tuned NN Parameters: {'learning_rate_init': 0.005, 'hidden_layer_sizes': [30,
30, 30, 30, 30], 'beta_2': 0.995, 'beta_1': 0.975, 'alpha': 0.001}

                MAE   RMSE  Bias  MAE_pct  RMSE_pct  r2_score
NN optimized
Train         28.55  69.02 -3.51    16.96     41.00      0.96
Test          34.66  86.15 -1.91    17.25     42.89      0.95
```

[469]:
```
X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=12, y_len=1,␣
 ↪test_loops=20)

NN_final = Pipeline([('scaler', MinMaxScaler()),
                     ('NN', MLPRegressor(activation='relu',
                                         solver='adam',
                                         early_stopping=True,
                                         n_iter_no_change=50,
                                         validation_fraction=.1,
                                         tol=.0001,
                                         hidden_layer_sizes=[30, 30, 30, 30,␣
 ↪30],
                                         alpha=.001,
                                         learning_rate_init=.005,
                                         beta_1=.97,
                                         beta_2=.995))])
NN_final.fit(X_train, y_train)

y_train_pred = NN_final.predict(X_train)
y_test_pred = NN_final.predict(X_test)

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

```
            MAE   RMSE  Bias  MAE_pct  RMSE_pct  r2_score
NN Final
Train     29.25  72.58 -1.45    17.93     44.49      0.95
Test      32.10  82.84 -1.93    17.04     43.97      0.95
```

[472]:
```
#Forecasting

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

NN_final = Pipeline([('scaler', MinMaxScaler()),
                     ('NN', MLPRegressor(activation='relu',
                                         solver='adam',
                                         early_stopping=True,
                                         n_iter_no_change=50,
                                         validation_fraction=.1,
                                         tol=.0001,
                                         hidden_layer_sizes=[30, 30, 30, 30,␣
↪30],
                                         alpha=.001,
                                         learning_rate_init=.005,
                                         beta_1=.97,
                                         beta_2=.995))])
NN_final.fit(X_train, y_train)

forecast = pd.DataFrame(data=NN_final.predict(X_test), index=df.index,␣
↪columns=['Next_Sales'])
forecast.tail(10)
```

[472]:

	Next_Sales
Make	
Subaru	237.845909
Suzuki	268.173489
Tata	0.988654
Tazzari	0.988654
Tesla	176.352180
Think	0.988654
Toyota	1151.028659
Volkswagen	1850.869401
Volvo	744.645220
Westfield	0.988654

0.3.1 LSTM

[511]:
```
X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=3, y_len=1,␣
↪test_loops=12)

sc = MinMaxScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

n_steps = 3 # =x_len
```

```
n_features = 1

# 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))
y_train = y_train.reshape(-1,1)
y_test = y_test.reshape(-1,1)

X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

[511]: ((5720, 3, 1), (1170, 3, 1), (5720, 1), (1170, 1))

[512]:
```
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=100 ,batch_size=16, verbose=0)
```

[514]:
```
y_train_pred = model.predict(X_train)
y_test_pred = model.predict(X_test)

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

```
        MAE    RMSE  Bias  MAE_pct  RMSE_pct  r2_score
LSTM
Train  30.29   77.26 -1.80    18.53     47.26      0.94
Test   38.94  106.53  2.26    20.54     56.19      0.92
```

[517]:
```
# Forecasting

X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=3, y_len=1,␣
↪test_loops=0)

sc = MinMaxScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

n_steps = 3 # =x_len
n_features = 1

# 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))
y_train = y_train.reshape(-1,1)
y_test = y_test.reshape(-1,1)
```

[501]:
```
tf.keras.backend.clear_session()
tf.random.set_seed(42)
np.random.seed(42)


model1 = 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)])


model1.compile(loss='mean_squared_error',optimizer='adam')

history = model1.fit(X_train, y_train, epochs=100 ,batch_size=16, verbose=0)
```

[518]:
```
forecast = pd.DataFrame(data=model1.predict(X_test), index=df.index,␣
↪columns=['Next_Sales'])
forecast.head()
```

[518]:

```
              Next_Sales
Make
Alfa Romeo      2.751791
Aston Martin    2.552545
Audi          507.842651
BMW           999.981812
Bentley         2.552545
```