

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib as mpl
from mpl_toolkits.mplot3d import Axes3D
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import StandardScaler,QuantileTransformer
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
```

```
%matplotlib inline
```

Working on Train dataframe

```
from google.colab import files
uploaded = files.upload()
```

Choose Files

house price...iction - 1.zip

- house prices prediction - 1.zip(application/x-zip-compressed) - 96191 bytes, last modified: 12/7/2024 - 100% done

Saving house prices prediction - 1.zip to house prices prediction - 1.zip

```
import os
os.listdir('/content/')
```

```
[ '.config',
  'drive',
  'house prices prediction (1).zip',
  'house prices prediction.zip',
  'house prices prediction - 1.zip',
  'sample_data']
```

```
traindf = pd.read_csv('/content/house prices prediction - 1.zip')
traindf.head()
```

5 rows × 81 columns

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	PoolArea	PoolQC	Fence	Mis
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN	
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN	
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	

```
traindf.columns
```

```
Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street',
      'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig',
      'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgType',
      'HouseStyle', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd',
      'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType',
      'MasVnrArea', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual',
      'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1',
      'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating',
      'HeatingQC', 'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF',
      'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath',
      'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
      'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType',
      'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual',
      'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF',
      'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'PoolQC',
      'Fence', 'MiscFeature', 'MiscVal', 'MoSold', 'YrSold', 'SaleType',
      'SaleCondition', 'SalePrice'],
      dtype='object')
```

```
numeric_df = traindf.select_dtypes(include='number')
correlation_matrix = numeric_df.corr()
correlation_matrix['SalePrice'].sort_values(ascending = False)
```

```
SalePrice      1.000000
OverallQual    0.790982
```

GrLivArea	0.708624
GarageCars	0.640409
GarageArea	0.623431
TotalBsmtSF	0.613581
1stFlrSF	0.605852
FullBath	0.560664
TotRmsAbvGrd	0.533723
YearBuilt	0.522897
YearRemodAdd	0.507101
GarageYrBlt	0.486362
MasVnrArea	0.477493
Fireplaces	0.466929
BsmtFinSF1	0.386420
LotFrontage	0.351799
WoodDeckSF	0.324413
2ndFlrSF	0.319334
OpenPorchSF	0.315856
HalfBath	0.284108
LotArea	0.263843
BsmtFullBath	0.227122
BsmtUnfSF	0.214479
BedroomAbvGr	0.168213
ScreenPorch	0.111447
PoolArea	0.092404
MoSold	0.046432
3SsnPorch	0.044584
BsmtFinSF2	-0.011378
BsmtHalfBath	-0.016844
MiscVal	-0.021190
Id	-0.021917
LowQualFinSF	-0.025606
YrSold	-0.028923
OverallCond	-0.077856
MSSubClass	-0.084284
EnclosedPorch	-0.128578
KitchenAbvGr	-0.135907
Name: SalePrice, dtype: float64	

```
req_tr = ["GarageArea", "OverallQual", "TotalBsmtSF", "1stFlrSF", "2ndFlrSF", "LowQualFinSF", "GrLivArea", "BsmtFullBath", "BsmtHalfBath", "FullBath"]
selected_tr = traindf[req_tr]
```

```
selected_tr.loc[:, 'TotalBath'] = (selected_tr['BsmtFullBath'].fillna(0) +
                                   selected_tr['BsmtHalfBath'].fillna(0) +
                                   selected_tr['FullBath'].fillna(0) +
                                   selected_tr['HalfBath'].fillna(0))
```

```
selected_tr.loc[:, 'TotalSF'] = (selected_tr['TotalBsmtSF'].fillna(0) +
                                 selected_tr['1stFlrSF'].fillna(0) +
                                 selected_tr['2ndFlrSF'].fillna(0) +
                                 selected_tr['LowQualFinSF'].fillna(0) +
                                 selected_tr['GrLivArea'].fillna(0))
```



<ipython-input-32-530500eb8649>:1: SettingWithCopyWarning:  
A value is trying to be set on a copy of a slice from a DataFrame.  
Try using .loc[row\_indexer,col\_indexer] = value instead

See the caveats in the documentation: [https://pandas.pydata.org/pandas-docs/stable/user\\_guide/indexing.html#returning-a-view-versus-a-copy](https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)  
selected\_tr.loc[:, 'TotalBath'] = (selected\_tr['BsmtFullBath'].fillna(0) +  
<ipython-input-32-530500eb8649>:6: SettingWithCopyWarning:  
A value is trying to be set on a copy of a slice from a DataFrame.  
Try using .loc[row\_indexer,col\_indexer] = value instead

See the caveats in the documentation: [https://pandas.pydata.org/pandas-docs/stable/user\\_guide/indexing.html#returning-a-view-versus-a-copy](https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)  
selected\_tr.loc[:, 'TotalSF'] = (selected\_tr['TotalBsmtSF'].fillna(0) +

selected\_tr

	GarageArea	OverallQual	TotalBsmtSF	1stFlrSF	2ndFlrSF	LowQualFinSF	GrLivArea	BsmtFullBath	BsmtHalfBath	FullBath	HalfB
0	548	7	856	856	854	0	1710	1	0	2	
1	460	6	1262	1262	0	0	1262	0	1	2	
2	608	7	920	920	866	0	1786	1	0	2	
3	642	7	756	961	756	0	1717	1	0	1	
4	836	8	1145	1145	1053	0	2198	1	0	2	
...	...	...	...	...	...	...	...	...	...	...	...
1455	460	6	953	953	694	0	1647	0	0	2	
1456	500	6	1542	2073	0	0	2073	1	0	2	
1457	252	7	1152	1188	1152	0	2340	0	0	2	
1458	240	5	1078	1078	0	0	1078	1	0	1	
1459	276	5	1256	1256	0	0	1256	1	0	1	

1460 rows × 15 columns

Next steps: [Generate code with selected\\_tr](#) [View recommended plots](#)

## Keeping only the necessary columns

```
train_df = selected_tr[['TotRmsAbvGrd', 'TotalBath', 'GarageArea', 'TotalSF', 'OverallQual', 'SalePrice']]
```

train\_df

	TotRmsAbvGrd	TotalBath	GarageArea	TotalSF	OverallQual	SalePrice
0	8	4	548	4276	7	208500
1	6	3	460	3786	6	181500
2	6	4	608	4492	7	223500
3	7	2	642	4190	7	140000
4	9	4	836	5541	8	250000
...	...	...	...	...	...	...
1455	7	3	460	4247	6	175000
1456	7	3	500	5688	6	210000
1457	9	2	252	5832	7	266500
1458	5	2	240	3234	5	142125
1459	6	3	276	3768	5	147500

1460 rows × 6 columns

Next steps: [Generate code with train\\_df](#) [View recommended plots](#)

## Splitting the dataset and Creating Pipeline

```
from sklearn.model_selection import train_test_split
train_set, test_set = train_test_split(train_df, test_size = 0.2, random_state = 42)
print(f"Rows in train set: {len(train_set)}\nRows in test set: {len(test_set)}\n")
```

Rows in train set: 1168  
Rows in test set: 292

```
housing = train_set.drop("SalePrice", axis=1)
housing_labels = train_set["SalePrice"].copy()
```

```

from sklearn.impute import SimpleImputer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
my_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy="median")),
    ('std_scaler', StandardScaler())
])

X_train = my_pipeline.fit_transform(housing)

X_train

```

```

array([[ -0.96456591, -0.48377079, -0.86383727, -0.13352109, -0.82044456],
       [ 0.27075534,  0.61127627, -0.45626397, -0.13428593, -0.08893368],
       [-1.58222654, -1.57881784, -2.25716927, -1.32207838, -0.82044456],
       ...,
       [-0.96456591, -0.48377079,  0.45366713, -1.16605156, -0.82044456],
       [ 0.27075534, -0.48377079, -1.23349678, -0.26966215,  0.64257719],
       [ 0.27075534, -0.48377079,  0.87071888,  0.28025593,  0.64257719]])

```

```
Y_train = housing_labels
```

```
Y_train
```

```

254    145000
1066    178000
 638     85000
 799    175000
 380    127000
   ...
1095    176432
1130    135000
1294    115000
 860    189950
1126    174000
Name: SalePrice, Length: 1168, dtype: int64

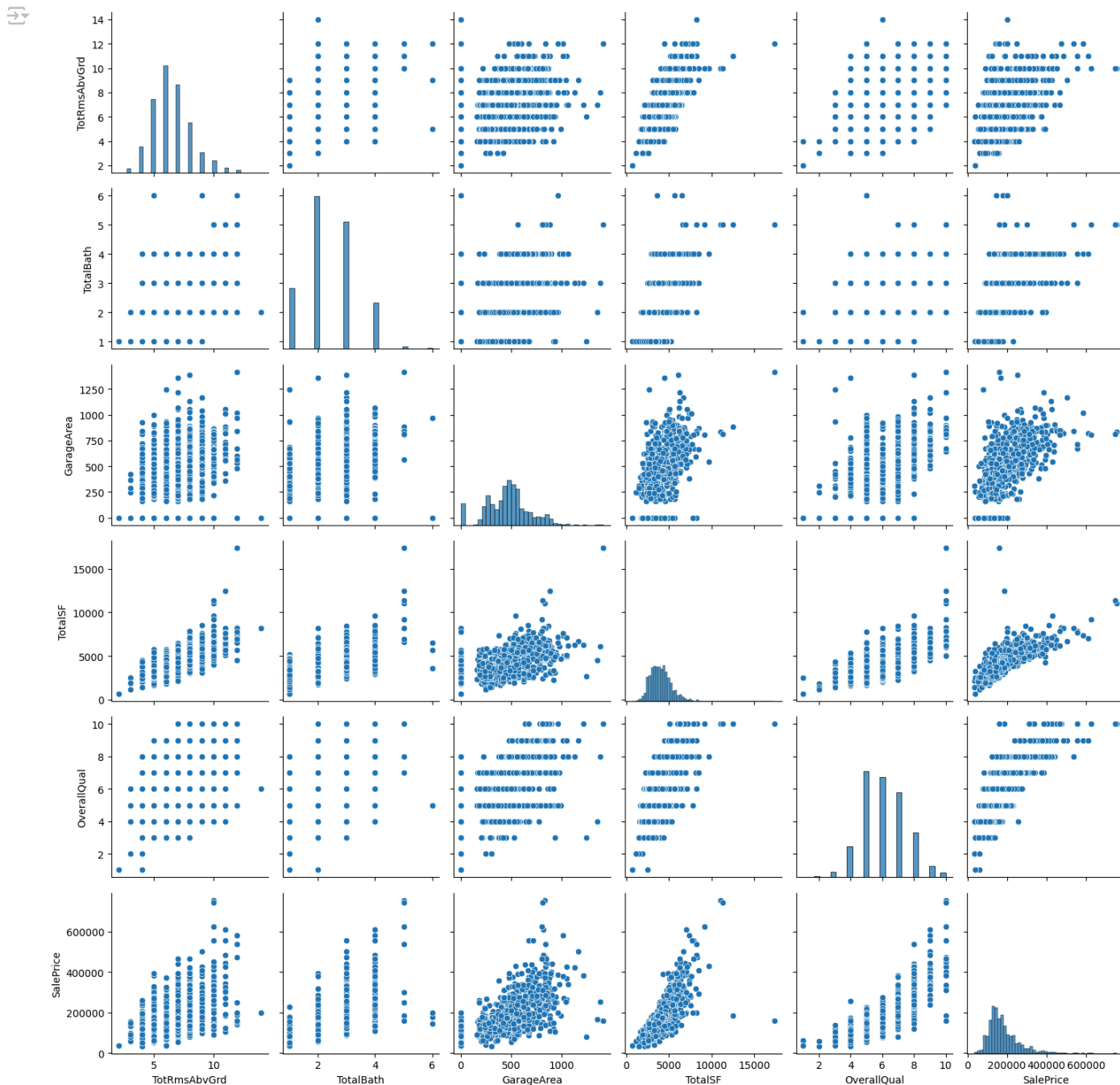
```

## ✖ Correlations

```

import warnings
warnings.filterwarnings("ignore", category=UserWarning)
%matplotlib inline
sns.pairplot(train_df)
plt.tight_layout()
plt.show()

```



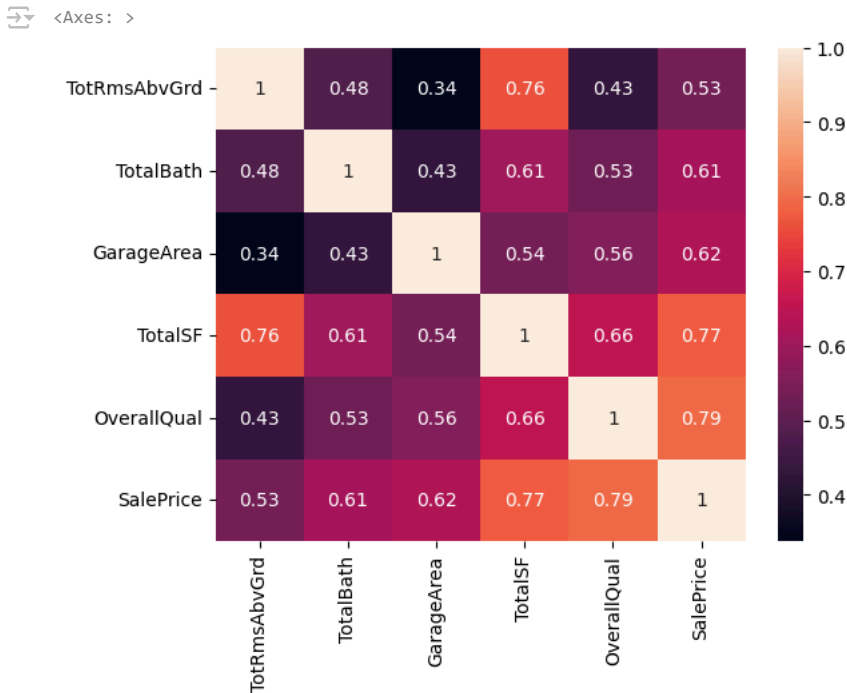
```
corr_matrix = train_df.corr()
corr_matrix['SalePrice'].sort_values(ascending = False)
```

```

SalePrice      1.000000
OverallQual    0.790982
TotalSF        0.773909
GarageArea     0.623431
```

```
TotalBath      0.613005
TotRmsAbvGrd   0.533723
Name: SalePrice, dtype: float64

sns.heatmap(train_df.corr(),annot = True)
```



Working with Test Dataframe

```
from google.colab import files
uploaded = files.upload()

Choose Files house price...iction - 2.zip
• house prices prediction - 2.zip(application/x-zip-compressed) - 87192 bytes, last modified: 12/7/2024 - 100% done
Saving house prices prediction - 2.zip to house prices prediction - 2.zip
```

```
import os
os.listdir('/content/')

['.config',
'drive',
'house prices prediction (1).zip',
'house prices prediction.zip',
'house prices prediction - 2.zip',
'house prices prediction - 1.zip',
'sample_data']

testdf = pd.read_csv('/content/house prices prediction - 2.zip')
```

```
testdf.head()
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	ScreenPorch	PoolArea	Poo
0	1461	20	RH	80.0	11622	Pave	NaN	Reg	Lvl	AllPub	...	120	0	I
1	1462	20	RL	81.0	14267	Pave	NaN	IR1	Lvl	AllPub	...	0	0	I
2	1463	60	RL	74.0	13830	Pave	NaN	IR1	Lvl	AllPub	...	0	0	I
3	1464	60	RL	78.0	9978	Pave	NaN	IR1	Lvl	AllPub	...	0	0	I
4	1465	120	RL	43.0	5005	Pave	NaN	IR1	HLS	AllPub	...	144	0	I

5 rows × 80 columns

```
req_tst = ["GarageArea","OverallQual","TotalBsmSF","1stFlrSF","2ndFlrSF","LowQualFinSF","GrLivArea","BsmFullBath","BsmHalfBath","FullBath"]

selected_tst = testdf[req_tst]
```

```
selected_tst.loc[:, 'TotalBath'] = (selected_tst['BsmtFullBath'].fillna(0) +
                                   selected_tst['BsmtHalfBath'].fillna(0) +
                                   selected_tst['FullBath'].fillna(0) +
                                   selected_tst['HalfBath'].fillna(0))

selected_tst.loc[:, 'TotalSF'] = (selected_tst['TotalBsmtSF'].fillna(0) +
                                  selected_tst['1stFlrSF'].fillna(0) +
                                  selected_tst['2ndFlrSF'].fillna(0) +
                                  selected_tst['LowQualFinSF'].fillna(0) +
                                  selected_tst['GrLivArea'].fillna(0))
```

<ipython-input-51-88b69dcf1189>:1: SettingWithCopyWarning:  
A value is trying to be set on a copy of a slice from a DataFrame.  
Try using .loc[row\_indexer,col\_indexer] = value instead

See the caveats in the documentation: [https://pandas.pydata.org/pandas-docs/stable/user\\_guide/indexing.html#returning-a-view-versus-a-copy](https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)

selected\_tst.loc[:, 'TotalBath'] = (selected\_tst['BsmtFullBath'].fillna(0) +  
<ipython-input-51-88b69dcf1189>:6: SettingWithCopyWarning:  
A value is trying to be set on a copy of a slice from a DataFrame.  
Try using .loc[row\_indexer,col\_indexer] = value instead

See the caveats in the documentation: [https://pandas.pydata.org/pandas-docs/stable/user\\_guide/indexing.html#returning-a-view-versus-a-copy](https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)

selected\_tst.loc[:, 'TotalSF'] = (selected\_tst['TotalBsmtSF'].fillna(0) +

selected\_tst

	GarageArea	OverallQual	TotalBsmtSF	1stFlrSF	2ndFlrSF	LowQualFinSF	GrLivArea	BsmtFullBath	BsmtHalfBath	FullBath	HalfB
0	730.0	5	882.0	896	0	0	896	0.0	0.0	1	
1	312.0	6	1329.0	1329	0	0	1329	0.0	0.0	1	
2	482.0	5	928.0	928	701	0	1629	0.0	0.0	2	
3	470.0	6	926.0	926	678	0	1604	0.0	0.0	2	
4	506.0	8	1280.0	1280	0	0	1280	0.0	0.0	2	
...	...	...	...	...	...	...	...	...	...	...	...
1454	0.0	4	546.0	546	546	0	1092	0.0	0.0	1	
1455	286.0	4	546.0	546	546	0	1092	0.0	0.0	1	
1456	576.0	5	1224.0	1224	0	0	1224	1.0	0.0	1	
1457	0.0	5	912.0	970	0	0	970	0.0	1.0	1	
1458	650.0	7	996.0	996	1004	0	2000	0.0	0.0	2	

1459 rows x 14 columns

Next steps:

Generate code with selected\_tst

View recommended plots

```
test_df_unproc = selected_tst[['TotRmsAbvGrd', 'TotalBath', 'GarageArea', 'TotalSF', 'OverallQual']]
```

test\_df\_unproc

	TotRmsAbvGrd	TotalBath	GarageArea	TotalSF	OverallQual
0	5	1.0	730.0	2674.0	5
1	6	2.0	312.0	3987.0	6
2	6	3.0	482.0	4186.0	5
3	7	3.0	470.0	4134.0	6
4	5	2.0	506.0	3840.0	8
...	...	...	...	...	...
1454	5	2.0	0.0	2730.0	4
1455	6	2.0	286.0	2730.0	4
1456	7	2.0	576.0	3672.0	5
1457	6	2.0	0.0	2852.0	5
1458	9	3.0	650.0	4996.0	7

1459 rows x 5 columns

Next steps:

Generate code with test\_df\_unproc

View recommended plots

```
test_df = test_df_unproc.fillna(test_df_unproc.mean())
```

```
x_test = my_pipeline.transform(test_df[['TotRmsAbvGrd', 'TotalBath', 'GarageArea', 'TotalSF', 'OverallQual']].values)
```

```
x_test
```

```
array([[ -0.96456591, -1.57881784,  1.2024646 , -1.10333489, -0.82044456],
       [ -0.34690528, -0.48377079, -0.77853123, -0.09910341, -0.08893368],
       [ -0.34690528,  0.61127627,  0.02713693,  0.05309923, -0.82044456],
       ...,
       [  0.27075534, -0.48377079,  0.47262403, -0.34002719, -0.82044456],
       [ -0.34690528, -0.48377079, -2.25716927, -0.96719384, -0.82044456],
       [  1.50607659,  0.61127627,  0.82332664,  0.67261751,  0.64257719]])
```

## ▼ Model Selection

```
model = LinearRegression()
#model = DecisionTreeRegressor()
#model = RandomForestRegressor()
model.fit(X_train,Y_train)
```

```
▼ LinearRegression
LinearRegression()
```

```
y_train_pred = model.predict(X_train)
```

```
y_train_pred[:5]
```

```
array([137667.57956441, 175034.19941421,  79632.65207176, 149652.98819495,
       146674.06395314])
```

```
some_data = housing.iloc[:5]
some_labels = housing_labels.iloc[:5]
```

```
proc_data = my_pipeline.transform(some_data)
```

```
model.predict(proc_data)
```

```
array([137667.57956441, 175034.19941421,  79632.65207176, 149652.98819495,
       146674.06395314])
```

```
list(some_labels)
```

```
[145000, 178000, 85000, 175000, 127000]
```

```
train_mse = mean_squared_error(Y_train,y_train_pred)
```

```
train_rmse = np.sqrt(train_mse)
```

```
print(f"Training MSE: {train_mse:.2f}, Training RMSE: {train_rmse:.2f}")
```

```
Training MSE: 1460715662.52, Training RMSE: 38219.31
```

## ▼ Cross - Validation

```
from sklearn.model_selection import cross_val_score
scores = cross_val_score(model,X_train,Y_train,scoring="neg_mean_squared_error",cv = 200)
rmse_scores = np.sqrt(-scores)
```

```
rmse_scores
```

```
array([ 16599.40639047, 18325.22018653, 29307.41492256, 30900.62181786,
        42713.28158503, 13517.92728875, 28466.43684333, 26159.1789478 ,
        16694.35747291, 44185.04242239, 14432.4514348 , 29621.4888739 ,
        15288.08646946, 20343.83312791, 26928.48898473, 30286.90600734,
        27591.27659228, 49704.26333128, 48966.56719948, 24506.05029869,
        51513.14668133, 16136.46039114, 18384.50681523, 28433.24926957,
        55483.42476232, 13885.14122222, 40018.30732342, 22655.21809999,
        122894.24572375, 36980.15773466, 16527.48051189, 26495.91857289,
        40892.94110057, 26980.63750536, 67733.44140093, 13173.00917782,
        17673.54848644, 28785.9566716 , 34551.83798472, 37734.44853911,
        23765.3506236 , 19538.738731 , 29343.3959128 , 32180.98454967,
        35319.05373078, 38228.16511844, 26372.59349178, 28064.67081093,
        ...])
```



```

36009.27109903, 26029.75222025, 22669.10866239, 37583.20518266,
27672.46756544, 26860.18618909, 25473.16521999, 21242.95056337,
20053.45561874, 30889.23473073, 52117.08856944, 36544.31900032,
133524.62025163, 42636.85773552, 33816.59478726, 44585.1371374 ,
42323.63535859, 21634.77565968, 41502.66165963, 30636.54557842,
26746.16642826, 15309.84320432, 54226.73045149, 33988.79845478,
47823.05327476, 25585.65094945, 45620.12007825, 49937.324193 ,
52677.22772022, 17932.7405338 , 39969.26806934, 31599.91071606,
17807.77621148, 35954.46526772, 222456.2247121 , 29094.22010999,
41529.46627467, 27720.37789678, 19879.42245214, 19675.41805076,
27383.1292489 , 121547.27719409, 26427.98421929, 26079.76589143,
24510.70593577, 26086.37349027, 21568.58923443, 20429.16535944,
18474.26446438, 21666.68595951, 94822.5377186 , 32141.09120185,
8609.78735922, 41595.17941681, 33000.48070685, 58430.66413254,
24607.56247791, 19281.14045192, 48953.28952053, 21346.29508891,
33273.25058659, 21946.70716609, 23678.86240679, 20746.75417475,
21033.03402566, 23193.73512545, 45194.85383363, 36114.70313285,
63940.04213846, 24185.33375536, 49971.70176585, 23553.19770034,
28356.19941834, 31601.84917239, 19743.02818178, 17925.67263047,
34345.32569996, 38262.53910803, 23418.1606015 , 64217.99081748,
41955.49432203, 13247.58126398, 18706.70154528, 14929.35502952,
22986.02338424, 26476.05190717, 29223.71986739, 36860.45324045,
53228.19467845, 26809.73400444, 17945.13852327, 13424.19020028,
38847.92761809, 18784.0050538 , 23201.64372092, 26436.65261068,
34499.10132104, 22410.38113845, 44522.02672058, 35721.51276097,
23316.23467097, 19451.35764774, 16880.77324834, 26453.2948389 ,
19300.88970697, 52027.66249345, 39417.73705746, 25123.5414658 ,
27711.68996535, 23370.47417554, 23421.00277133, 19624.96789495,
53322.45020398, 21718.09001705, 32640.1271753 , 19244.51215297,
46049.03252092, 16703.9195712 , 19728.41459881, 66589.43304565,
23503.5915548 , 40376.68920578, 21942.97964157, 26392.09561029,
15193.36709344, 19879.70112264, 18899.08624785, 15821.45950323,
23143.73085732, 16814.75337692, 45032.51530946, 9162.69902713,
34188.77514645, 18846.8667917 , 9098.06239376, 15607.68522491,
25658.10246257, 50905.34291163, 28106.85449056, 10840.69989811,
19224.05599128, 29592.35328826, 23886.98660851, 41962.2412104 ,
23032.83632699, 17362.50355856, 10380.08339328, 25285.63428966,
99149.81938064, 16461.75020861, 33451.89182822, 23785.07005972]])

```

```

def print_scores(scores):
    print("Scores:", scores)
    print("Mean:", scores.mean())
    print("Standard Deviation", scores.std())

```

```
print_scores(rmse_scores)
```

```

Scores: [ 16599.40639047 18325.22018653 29307.41492256 30900.62181786
 42713.28158503 13517.92728875 28466.43684333 26159.1789478
16694.35747291 44185.04242239 14432.4514348 29621.4888739
15288.08646946 20343.83312791 26928.48898473 30286.90600734
27591.27659228 49704.26333128 48966.56719948 24506.05029869
51513.14668133 16136.46039114 18384.50681523 28433.24926957
55483.42476232 13885.14122222 40018.30732342 22655.21809999
122894.24572375 36980.15773466 16527.48051189 26495.91857289
40892.94110057 26980.63750536 67733.44140093 13173.00917782
17673.54848644 28785.9566716 34551.83798472 37734.44853911
23765.3506236 19538.738731 29343.3959128 32180.98454967
35319.05373078 38228.16511844 26372.59349178 28064.67081093
36009.27109903 26029.75222025 22669.10866239 37583.20518266
27672.46756544 26860.18618909 25473.16521999 21242.95056337
20053.45561874 30889.23473073 52117.08856944 36544.31900032
133524.62025163 42636.85773552 33816.59478726 44585.1371374
42323.63535859 21634.77565968 41502.66165963 30636.54557842
26746.16642826 15309.84320432 54226.73045149 33988.79845478
47823.05327476 25585.65094945 45620.12007825 49937.324193
52677.22772022 17932.7405338 39969.26806934 31599.91071606
17807.77621148 35954.46526772 222456.2247121 29094.22010999
41529.46627467 27720.37789678 19879.42245214 19675.41805076
27383.1292489 121547.27719409 26427.98421929 26079.76589143
24510.70593577 26086.37349027 21568.58923443 20429.16535944
18474.26446438 21666.68595951 94822.5377186 32141.09120185
8609.78735922 41595.17941681 33000.48070685 58430.66413254
24607.56247791 19281.14045192 48953.28952053 21346.29508891
33273.25058659 21946.70716609 23678.86240679 20746.75417475
21033.03402566 23193.73512545 45194.85383363 36114.70313285
63940.04213846 24185.33375536 49971.70176585 23553.19770034
28356.19941834 31601.84917239 19743.02818178 17925.67263047
34345.32569996 38262.53910803 23418.1606015 64217.99081748
41955.49432203 13247.58126398 18706.70154528 14929.35502952
22986.02338424 26476.05190717 29223.71986739 36860.45324045
53228.19467845 26809.73400444 17945.13852327 13424.19020028
38847.92761809 18784.0050538 23201.64372092 26436.65261068
34499.10132104 22410.38113845 44522.02672058 35721.51276097
23316.23467097 19451.35764774 16880.77324834 26453.2948389
19300.88970697 52027.66249345 39417.73705746 25123.5414658
27711.68996535 23370.47417554 23421.00277133 19624.96789495
53322.45020398 21718.09001705 32640.1271753 19244.51215297
46049.03252092 16703.9195712 19728.41459881 66589.43304565]

```