Amos House Price Predictions

ML workflow:

1. SetUp
2. Import Data
3. Explore(EDA)
4. Splitting
5. Modelling
6. Splitting

1. SetUp

We are going to import all the necesary libraries here.

In [1]:
```
import sys
import logging

import pickle
import pandas as pd
import numpy as np
import math

# creating path object
from pathlib import Path

# visualization
import matplotlib
import plotly
import matplotlib.pyplot as plt
import plotly.express as px
import seaborn as sns

# machine learning
import sklearn

from sklearn.linear_model import LinearRegression
```

```python
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor, plot_tree
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
# preprocessing
from sklearn.preprocessing import (
    OneHotEncoder,
    OrdinalEncoder,
    FunctionTransformer,
    PolynomialFeatures,
    StandardScaler
)
# imputing missing values
from sklearn.impute import SimpleImputer
# evaluation metrics
from sklearn.metrics import r2_score, mean_absolute_percentage_error
# compose
from sklearn.compose import ColumnTransformer
# making pipeline
from sklearn.pipeline import Pipeline
# feature selections
from sklearn.feature_selection import VarianceThreshold
# model selections eg.splitting
from sklearn.model_selection import train_test_split, learning_curve,GridSearchCV
# pca decompositon
from sklearn.decomposition import PCA
# evaluation metrics
from sklearn.metrics import mean_absolute_percentage_error, mean_absolute_error, r2_score
```

We have all the libraries in place. Let us print our library versions. This step ensures reproducability

In [2]:
```python
# Printing version of our libraries
print("Platform: ", sys.platform)
print("Python: ", sys.version)
print("---")
print("Matplotlib: ", matplotlib.__version__)
print("Pandas: ", pd.__version__)
print("Seaborn: ", sns.__version__)
print("Plotly Express: ", plotly.__version__)
print("Numpy: ", np.__version__)
print("Sklearn: ", sklearn.__version__)
```

```
Platform:  win32
Python:  3.13.2 (tags/v3.13.2:4f8bb39, Feb  4 2025, 15:23:48) [MSC v.1942 64 bit (AMD64)]
---
Matplotlib:  3.10.0
Pandas:  2.2.3
Seaborn:  0.13.2
Plotly Express:  6.0.0
Numpy:  2.2.2
Sklearn:  1.6.1
```

Define the logging configurations.

In [3]:
```python
# Configure
config_path = Path.cwd()/"Training"/"Configure"
config_path.mkdir(parents=True, exist_ok=True)
logging.basicConfig(
    level=logging.INFO,
    filename = config_path / "logging.log",
)
```

Let us not define matplotlib configurations.

In [4]:
```python
#Matplotlib configuration
plt.rc("font", size=12)
plt.rc("axes", labelsize=12, titlesize=14)
plt.rc("legend", fontsize=8)
plt.rc("xtick", labelsize=10)
plt.rc("ytick", labelsize=10)
%matplotlib inline
```

Making two functions that will help us saving images and the other saving a trained model.

In [5]:
```python
# save figure function
def save_plot(fname, filetype, fig=None, dpi=300, tight_layout=True, format="png"):
    """Saving the plot as an image
    Save a plot image within ``Train/Images`` folders. The fname will be the name of the image with the
    extension .(format).``Note`` the default format is png.
    The plot by default will be saved under 300 resolution as inches.

    Parameters:
    ----------
    fname: str
        ->String object for the name of the plot.
    filetype: str
        -> Plot type eg plt(matplotlib), or px(plotly.express)
    fig: px.Figure
```

```python
        -> figure object form plotly.express
    dpi: int
        -> Numerical variable for the pixel resolution.
    tight_layout: bool
        -> If true the plot will be save on a tight layout.
    format: str
        -> String object for the image extension. By default is 'png' but we can have: 'jpeg', 'jpg', etc..

    Returns:
    --------
        None
    """
    # Root path
    image_path = Path.cwd() / "Training" / "Images"
    # Making the folders
    logging.info("Creting image path")
    image_path.mkdir(parents=True, exist_ok=True)
    # Image name
    image_name = image_path /f"{fname}.{format}"
    # Layout format
    if filetype == "plt":
        if tight_layout:
            plt.tight_layout()
        # Saving the plot
        logging.info(f"Saving the plot as {fname}.{format}")
        plt.savefig(fname=image_name, dpi=dpi, format=format)
        # logging saving
        logging.info(f"Sucess! Saved the plot as {fname}.{format}")
    elif filetype == "px":
        logging.info(f"Saving the plot as {fname}.{format}")
        # writting the image
        fig.write_image(file= image_name, format= format)
        logging.info(f"Sucess! Saved the plot as {fname}.{format}")
```

In [6]:

```python
# Saving the model
def save_model(mname, model):
    """Saving the model.
    Get the model and save it using pickle. The model will have the name from mname.

    Parameters:
    ----------
    mname: str
        Name of the model as a string object
    model: sklearn.model
        The trained model
    Returns:
    --------
```

```
    None
    """
    # Root path
    model_path = Path.cwd() / "Training" / "Models"
    # Making the folders
    logging.info("Creating Model path")
    model_path.mkdir(parents=True, exist_ok=True)
    # Model name
    model_name = model_path / f"{mname}.pkl"
    logging.info(f"Saving the model as {mname}.pkl")
    # Creating the pickle file
    with open(model_name, "wb") as f:
        pickle.dump(model, f)
    # final log
    logging.info(f"Sucess! Saved the model as {mname}.pkl")
```

We have a solid setup sections, let us start data importation.

2. Import and EDA

I have cleated a Training module where I have all my classes. We are going to get the `wrangleRepository` class that does the following:

1. Get the data from the csv file
2. Do a basic cleaning
3. Feature selection
4. Feature engineering
5. Outlier removing

In [7]:
```
from Training import WrangleRepository

# instantiating the class
repo = WrangleRepository()
print(type(repo))
repo
```

```
<class 'Training.WrangleRepository'>
```

Out[7]:
```
WrangleRepository filepath=C:\Users\MY PC\Desktop\Projects\Regression\AmosHousePriceModelling\train.csv
```

Let us now us the function to lead the data in `Desktop/Projects/Regression/AmosHousePriceModelling/train.csv`

In [8]:
```
repo.wrangle()
df = repo.get_data("wrangled")
```

```python
print(df.shape)
df.head()
```

(1460, 80)

Out[8]:

Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	LotConfig	...	PoolArea	PoolQC	Fence
1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub	Inside	...	0	NaN	NaN
2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub	FR2	...	0	NaN	NaN
3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub	Inside	...	0	NaN	NaN
4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub	Corner	...	0	NaN	NaN
5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub	FR2	...	0	NaN	NaN

5 rows × 80 columns

We have our data successfully. We will start by doing basic data cleaning.

In [9]:
```python
df.describe().T
```

Out[9]:

	count	mean	std	min	25%	50%	75%	max
MSSubClass	1460.0	56.897260	42.300571	20.0	20.00	50.0	70.00	190.0
LotFrontage	1201.0	70.049958	24.284752	21.0	59.00	69.0	80.00	313.0
LotArea	1460.0	10516.828082	9981.264932	1300.0	7553.50	9478.5	11601.50	215245.0
OverallQual	1460.0	6.099315	1.382997	1.0	5.00	6.0	7.00	10.0
OverallCond	1460.0	5.575342	1.112799	1.0	5.00	5.0	6.00	9.0
YearBuilt	1460.0	1971.267808	30.202904	1872.0	1954.00	1973.0	2000.00	2010.0
YearRemodAdd	1460.0	1984.865753	20.645407	1950.0	1967.00	1994.0	2004.00	2010.0
MasVnrArea	1452.0	103.685262	181.066207	0.0	0.00	0.0	166.00	1600.0
BsmtFinSF1	1460.0	443.639726	456.098091	0.0	0.00	383.5	712.25	5644.0
BsmtFinSF2	1460.0	46.549315	161.319273	0.0	0.00	0.0	0.00	1474.0
BsmtUnfSF	1460.0	567.240411	441.866955	0.0	223.00	477.5	808.00	2336.0
TotalBsmtSF	1460.0	1057.429452	438.705324	0.0	795.75	991.5	1298.25	6110.0
1stFlrSF	1460.0	1162.626712	386.587738	334.0	882.00	1087.0	1391.25	4692.0
2ndFlrSF	1460.0	346.992466	436.528436	0.0	0.00	0.0	728.00	2065.0
LowQualFinSF	1460.0	5.844521	48.623081	0.0	0.00	0.0	0.00	572.0
GrLivArea	1460.0	1515.463699	525.480383	334.0	1129.50	1464.0	1776.75	5642.0
BsmtFullBath	1460.0	0.425342	0.518911	0.0	0.00	0.0	1.00	3.0
BsmtHalfBath	1460.0	0.057534	0.238753	0.0	0.00	0.0	0.00	2.0
FullBath	1460.0	1.565068	0.550916	0.0	1.00	2.0	2.00	3.0
HalfBath	1460.0	0.382877	0.502885	0.0	0.00	0.0	1.00	2.0
BedroomAbvGr	1460.0	2.866438	0.815778	0.0	2.00	3.0	3.00	8.0
KitchenAbvGr	1460.0	1.046575	0.220338	0.0	1.00	1.0	1.00	3.0
TotRmsAbvGrd	1460.0	6.517808	1.625393	2.0	5.00	6.0	7.00	14.0
Fireplaces	1460.0	0.613014	0.644666	0.0	0.00	1.0	1.00	3.0
GarageYrBlt	1379.0	1978.506164	24.689725	1900.0	1961.00	1980.0	2002.00	2010.0
GarageCars	1460.0	1.767123	0.747315	0.0	1.00	2.0	2.00	4.0

	count	mean	std	min	25%	50%	75%	max
GarageArea	1460.0	472.980137	213.804841	0.0	334.50	480.0	576.00	1418.0
WoodDeckSF	1460.0	94.244521	125.338794	0.0	0.00	0.0	168.00	857.0
OpenPorchSF	1460.0	46.660274	66.256028	0.0	0.00	25.0	68.00	547.0
EnclosedPorch	1460.0	21.954110	61.119149	0.0	0.00	0.0	0.00	552.0
3SsnPorch	1460.0	3.409589	29.317331	0.0	0.00	0.0	0.00	508.0
ScreenPorch	1460.0	15.060959	55.757415	0.0	0.00	0.0	0.00	480.0
PoolArea	1460.0	2.758904	40.177307	0.0	0.00	0.0	0.00	738.0
MiscVal	1460.0	43.489041	496.123024	0.0	0.00	0.0	0.00	15500.0
MoSold	1460.0	6.321918	2.703626	1.0	5.00	6.0	8.00	12.0
YrSold	1460.0	2007.815753	1.328095	2006.0	2007.00	2008.0	2009.00	2010.0
SalePrice	1460.0	180921.195890	79442.502883	34900.0	129975.00	163000.0	214000.00	755000.0

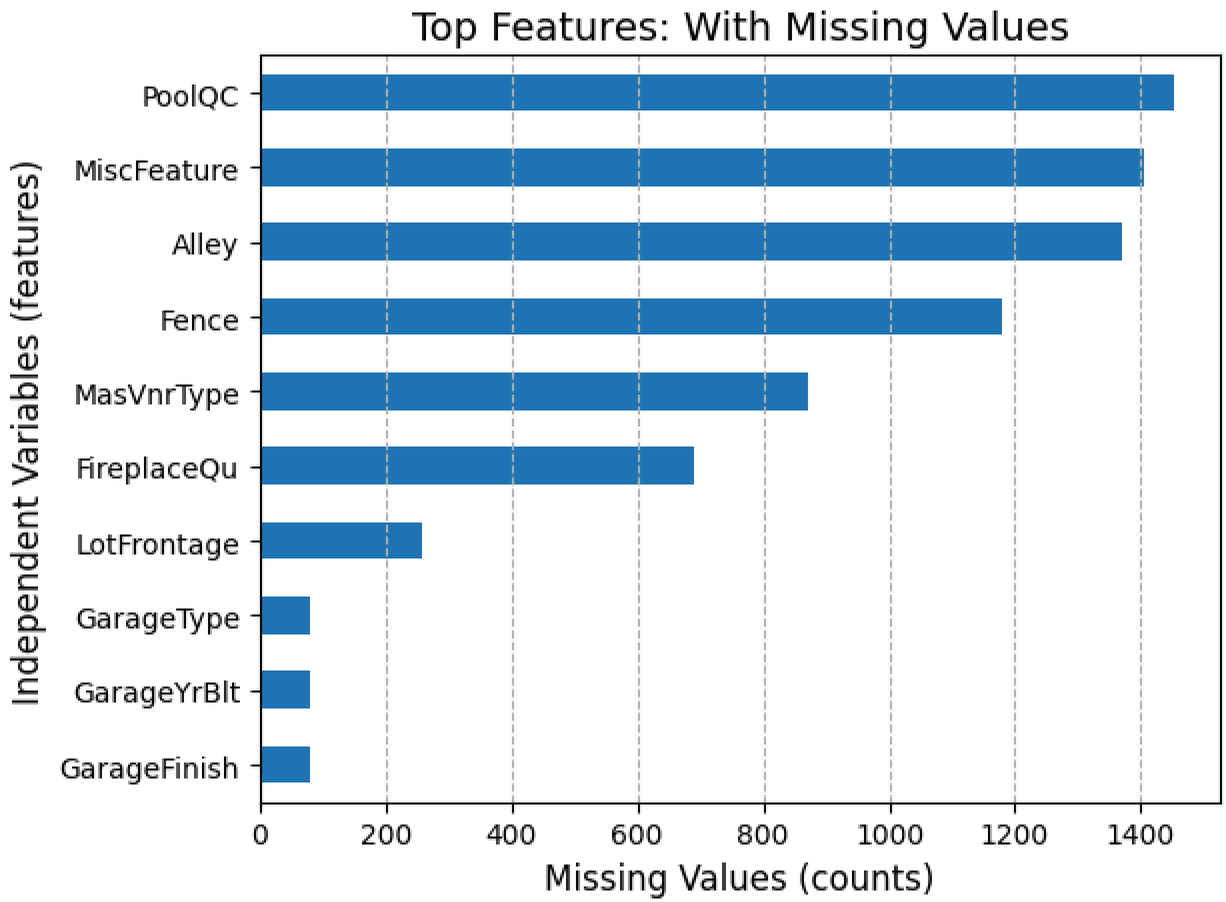
As seen, we have 1460 number of houses. Some of the features have missing values and we need to work on that. Also it is important to note that some features have outliers for example `lotArea`. This is determined from the sense that, we have a mean of approximately 10,500 and std of 9900 with the maximum value being at 255,000. Clearly we have outlier and most likely our data will be skewed.

In [10]:
```
# checking for missing values
missing_values = (df.isnull().sum()[df.isnull().sum() > 1]).sort_values()
print(f"Missing values in our Features: \n{missing_values}")
```

```
Missing values in our Features:
MasVnrArea         8
BsmtQual          37
BsmtCond          37
BsmtFinType1      37
BsmtFinType2      38
BsmtExposure      38
GarageCond        81
GarageQual        81
GarageFinish      81
GarageYrBlt       81
GarageType        81
LotFrontage      259
FireplaceQu      690
MasVnrType       872
Fence           1179
Alley           1369
MiscFeature     1406
PoolQC          1453
dtype: int64
```

In [11]:

```
# plotting the top 10 most missing values
missing_values.tail(10).plot(kind="barh")
plt.xlabel("Missing Values (counts)")
plt.ylabel("Independent Variables (features)")
plt.title("Top Features: With Missing Values")
plt.grid(linestyle="--", axis="x")
save_plot(fname="top10_missing_values", filetype="plt")
plt.show()
```



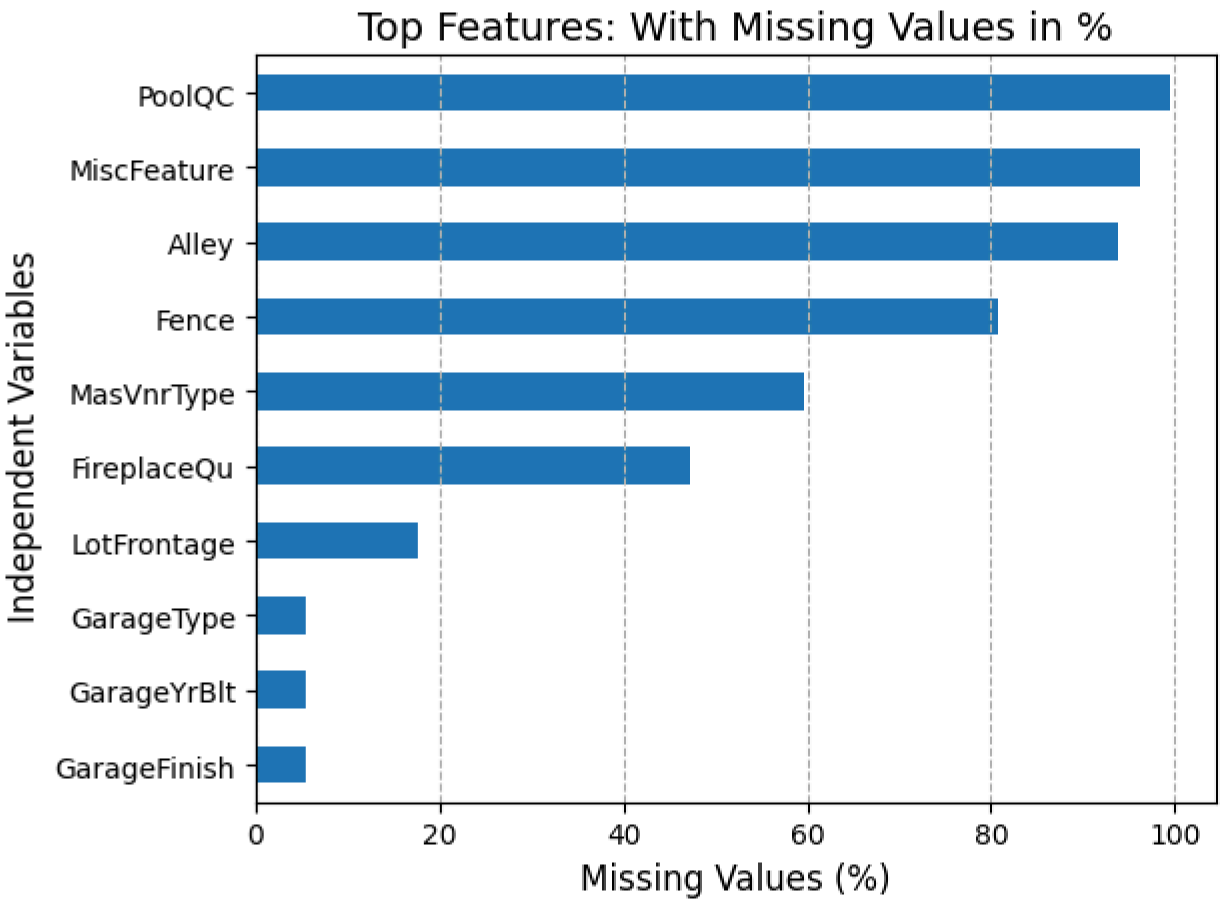
In [12]:
```
# percentage counts
missing_values_pct = pd.Series(((100 * missing_values.values / len(df))),
                               index=missing_values.index, name="missing_pct")
missing_values_pct
```

Out[12]:

```
MasVnrArea       0.547945
BsmtQual         2.534247
BsmtCond         2.534247
BsmtFinType1     2.534247
BsmtFinType2     2.602740
BsmtExposure     2.602740
GarageCond       5.547945
GarageQual       5.547945
GarageFinish     5.547945
GarageYrBlt      5.547945
GarageType       5.547945
LotFrontage     17.739726
FireplaceQu     47.260274
MasVnrType      59.726027
Fence           80.753425
Alley           93.767123
MiscFeature     96.301370
PoolQC          99.520548
Name: missing_pct, dtype: float64
```

In [13]:

```
# plotting the top 10 pct features with missing values
missing_values_pct.tail(10).plot(kind="barh")
plt.xlabel("Missing Values (%)")
plt.ylabel("Independent Variables ")
plt.title("Top Features: With Missing Values in %")
plt.grid(linestyle="--", axis="x")
save_plot(fname="top10_missing_values_pct", filetype="plt")
plt.show()
```



The above plot tells us that some features like pool are not present in many properties. We need to remove those features which have many missing values. To do that we will use VarianceThreshold object to compute those features which will be useless to our model.

Some advantes of removing low variance features are:

1. Reduce features dimensionality
2. Improve model performance by reducing overfitting
3. Reduce training time

But before we do Variance reduction we are going to drop those feature with over 50% missing values.

In [14]:

```
# getting columns with over 60% missing values
mask = missing_values_pct > 50
missing_cols = missing_values_pct[mask].index.to_list()
print(type(missing_cols))
print(missing_cols)
```

```
<class 'list'>
['MasVnrType', 'Fence', 'Alley', 'MiscFeature', 'PoolQC']
```

In [15]:
```python
repo.basic_cleaning(missing_values_pct=missing_values_pct)
df = repo.get_data("basic")
print(df.shape)
df.head()
```

```
(1460, 75)
```

Out[15]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	Utilities	LotConfig	LandSlope	...	EnclosedPorch	3SsnPo
Id													
1	60	RL	65.0	8450	Pave	Reg	Lvl	AllPub	Inside	Gtl	...	0	
2	20	RL	80.0	9600	Pave	Reg	Lvl	AllPub	FR2	Gtl	...	0	
3	60	RL	68.0	11250	Pave	IR1	Lvl	AllPub	Inside	Gtl	...	0	
4	70	RL	60.0	9550	Pave	IR1	Lvl	AllPub	Corner	Gtl	...	272	
5	60	RL	84.0	14260	Pave	IR1	Lvl	AllPub	FR2	Gtl	...	0	

5 rows × 75 columns

Done, we have dropped those features with so many missing values. Let us go ahead and check the variance for all the numerical features first.

In [16]:
```python
repo.feature_selection()
df = repo.get_data("selected")
print(df.shape)
df.head()
```

```
(1460, 67)
```

Out[16]:

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF2	...	Centra
Id												
1	60	65.0	8450	7	5	2003	2003	196.0	706	0	...	
2	20	80.0	9600	6	8	1976	1976	0.0	978	0	...	
3	60	68.0	11250	7	5	2001	2002	162.0	486	0	...	
4	70	60.0	9550	7	5	1915	1970	0.0	216	0	...	
5	60	84.0	14260	8	5	2000	2000	350.0	655	0	...	

5 rows × 67 columns

Let us check low and high cardinal features.

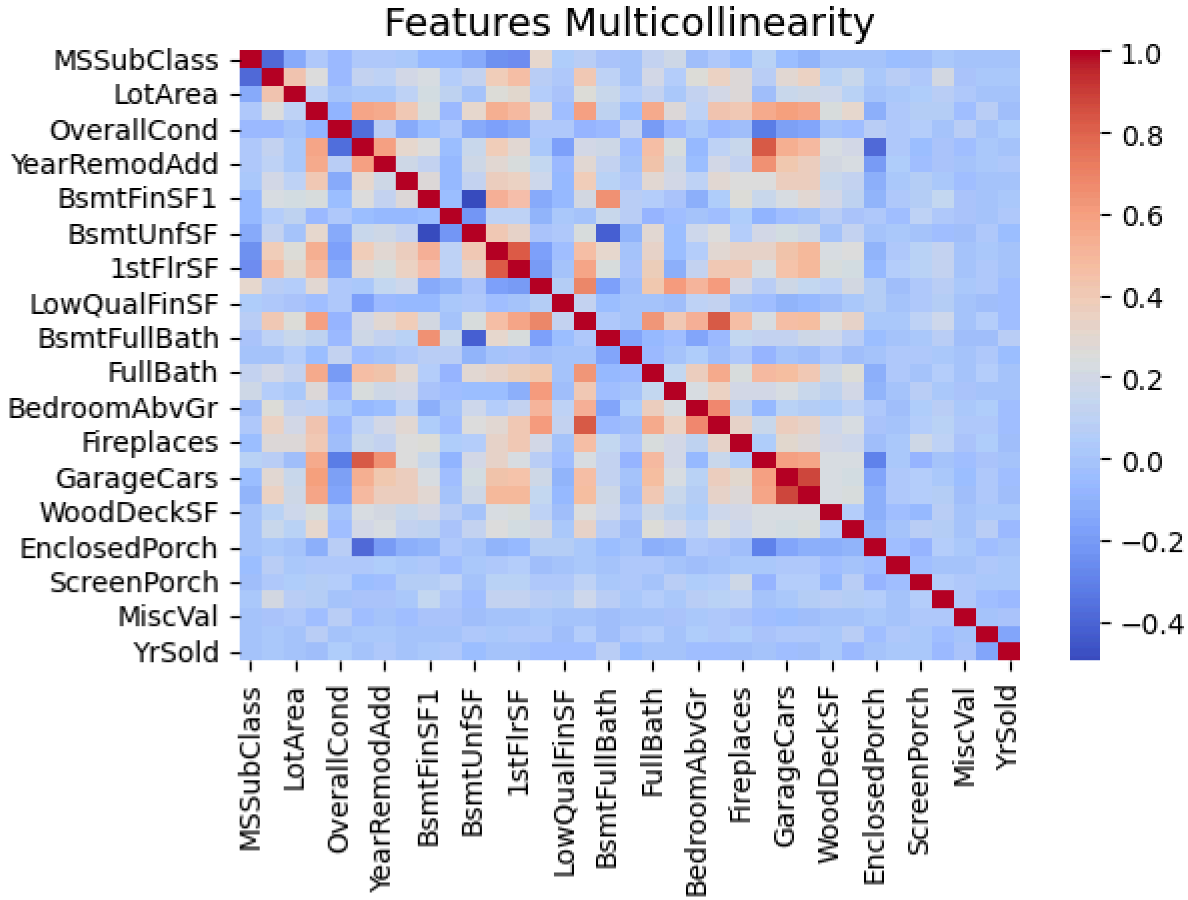
In [17]:

```
df.select_dtypes(include="object").nunique()
```

Out[17]:
```
MSZoning          5
LotShape          4
LandContour       4
LotConfig         5
LandSlope         3
Neighborhood     25
Condition1        9
BldgType          5
HouseStyle        8
RoofStyle         6
Exterior1st      15
Exterior2nd      16
ExterQual         4
ExterCond         5
Foundation        6
BsmtQual          4
BsmtCond          4
BsmtExposure      4
BsmtFinType1      6
BsmtFinType2      6
HeatingQC         5
CentralAir        2
Electrical        5
KitchenQual       4
Functional        7
FireplaceQu       5
GarageType        6
GarageFinish      3
PavedDrive        3
SaleType          9
SaleCondition     6
dtype: int64
```

I think there are no cardinal features.Let us check how our features are correlated with one another.

In [18]:
```
corr = df.select_dtypes(include="number").drop(columns="SalePrice").corr()
sns.heatmap(corr, cmap="coolwarm")
plt.title("Features Multicollinearity")
save_plot(fname="mulitcollinearity", filetype="plt")
```



In [19]:

```
# which features have a correlation above 90%
corr_matrix = abs(df.select_dtypes(include="number").drop(columns="SalePrice").corr())
upper_triangle = np.triu(np.ones(corr_matrix.shape), k=1).astype(bool)
upper_matrix = corr_matrix.where(upper_triangle)
upper_matrix
```

Out[19]:

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF
MSSubClass	NaN	0.386347	0.139781	0.032628	0.059316	0.027850	0.040581	0.022936	0.069836	0.06564
LotFrontage	NaN	NaN	0.426095	0.251646	0.059213	0.123349	0.088866	0.193458	0.233633	0.04990
LotArea	NaN	NaN	NaN	0.105806	0.005636	0.014228	0.013788	0.104160	0.214103	0.11117
OverallQual	NaN	NaN	NaN	NaN	0.091932	0.572323	0.550684	0.411876	0.239666	0.05911
OverallCond	NaN	NaN	NaN	NaN	NaN	0.375983	0.073741	0.128101	0.046231	0.04022
YearBuilt	NaN	NaN	NaN	NaN	NaN	NaN	0.592855	0.315707	0.249503	0.04910
YearRemodAdd	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0.179618	0.128451	0.06775
MasVnrArea	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0.264736	0.07231
BsmtFinSF1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0.05011
BsmtFinSF2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
BsmtUnfSF	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
TotalBsmtSF	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
1stFlrSF	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
2ndFlrSF	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
LowQualFinSF	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
GrLivArea	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
BsmtFullBath	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
BsmtHalfBath	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
FullBath	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
HalfBath	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
BedroomAbvGr	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
TotRmsAbvGrd	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
Fireplaces	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
GarageYrBlt	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
GarageCars	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
GarageArea	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF
WoodDeckSF	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
OpenPorchSF	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
EnclosedPorch	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
3SsnPorch	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
ScreenPorch	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
PoolArea	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
MiscVal	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
MoSold	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
YrSold	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na

35 rows × 35 columns

In [20]:

```
high_corr = [col for col in upper_matrix.columns
             if any(upper_matrix[col] > 0.9)
             ]
high_corr
```

Out[20]:

```
[]
```

So we do have highly correlated features. Let us go ahead now and do feature engineering.

In [21]:

```
sub_class = {
        20: "1-STORY 1946 & NEWER ALL STYLES",
        30: "1-STORY 1945 & OLDER",
        40:     "1-STORY W/FINISHED ATTIC ALL AGES",
        45:     "1-1/2 STORY - UNFINISHED ALL AGES",
        50:     "1-1/2 STORY FINISHED ALL AGES",
        60:     "2-STORY 1946 & NEWER",
        70:     "2-STORY 1945 & OLDER",
        75:     "2-1/2 STORY ALL AGES",
        80:     "SPLIT OR MULTI-LEVEL",
        85:     "SPLIT FOYER",
        90:     "DUPLEX - ALL STYLES AND AGES",
       120:     "1-STORY PUD (Planned Unit Development) - 1946 & NEWER",
       150:     "1-1/2 STORY PUD - ALL AGES",
       160:     "2-STORY PUD - 1946 & NEWER",
       180:     "PUD - MULTILEVEL - INCL SPLIT LEV/FOYER",
```

```
    190:     "2 FAMILY CONVERSION - ALL STYLES AND AGES"

}

print(type(sub_class))
print(sub_class)
```

```
<class 'dict'>
{20: '1-STORY 1946 & NEWER ALL STYLES', 30: '1-STORY 1945 & OLDER', 40: '1-STORY W/FINISHED ATTIC ALL AGES', 45: '1-1/2 STORY - UNF
INISHED ALL AGES', 50: '1-1/2 STORY FINISHED ALL AGES', 60: '2-STORY 1946 & NEWER', 70: '2-STORY 1945 & OLDER', 75: '2-1/2 STORY AL
L AGES', 80: 'SPLIT OR MULTI-LEVEL', 85: 'SPLIT FOYER', 90: 'DUPLEX - ALL STYLES AND AGES', 120: '1-STORY PUD (Planned Unit Develop
ment) - 1946 & NEWER', 150: '1-1/2 STORY PUD - ALL AGES', 160: '2-STORY PUD - 1946 & NEWER', 180: 'PUD - MULTILEVEL - INCL SPLIT LE
V/FOYER', 190: '2 FAMILY CONVERSION - ALL STYLES AND AGES'}
```

In [22]:

```
repo.feature_engineering(sub_class=sub_class)
df = repo.get_data("engineered")
print(df.shape)
df.head()
```

```
(1460, 73)
```

Out[22]:

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF2	...	Garage
Id												
1	2-STORY 1946 & NEWER	65.0	8450	7	5	2003	2003	196.0	706	0	...	
2	1-STORY 1946 & NEWER ALL STYLES	80.0	9600	6	8	1976	1976	0.0	978	0	...	
3	2-STORY 1946 & NEWER	68.0	11250	7	5	2001	2002	162.0	486	0	...	
4	2-STORY 1945 & OLDER	60.0	9550	7	5	1915	1970	0.0	216	0	...	
5	2-STORY 1946 & NEWER	84.0	14260	8	5	2000	2000	350.0	655	0	...	

5 rows × 73 columns

Note we still have missing values and outliers. In the case of missig value, we will impute them inside a pipeline.

Now let us first check the distributions of our features. We will do this step manually step by step.In We will be refrencing the describe objects for our dataframe.

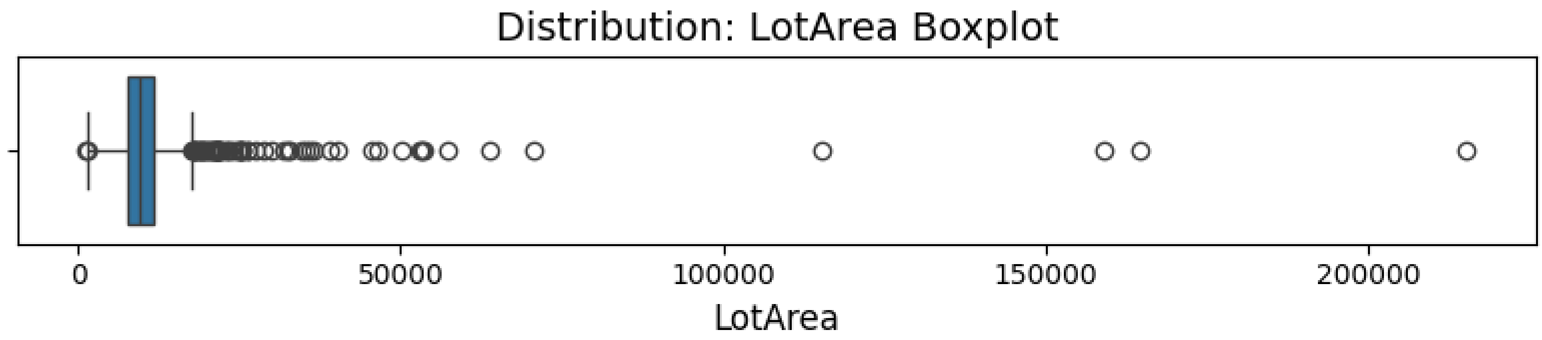
Features with most outliers:

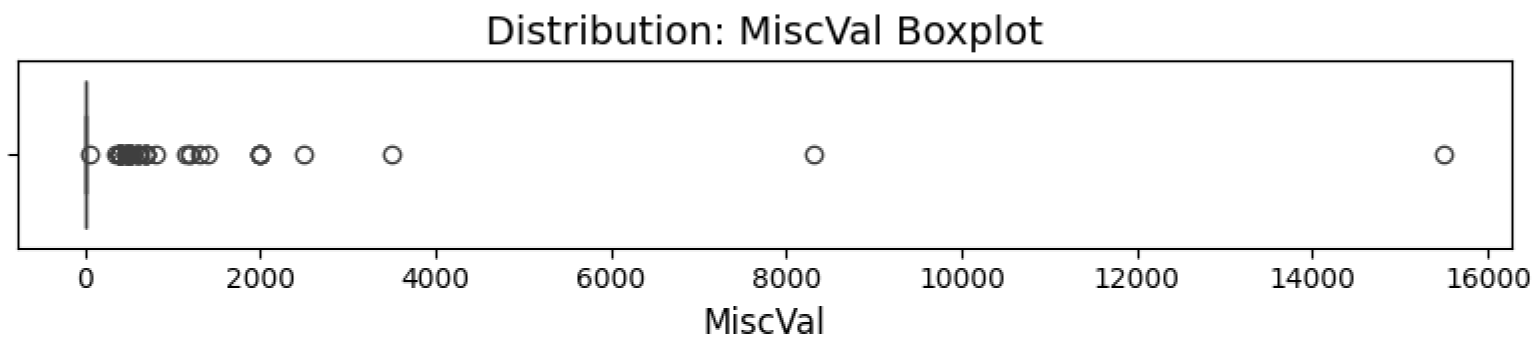
1. LotArea:
    - Mean: 10,500
    - std: 9980
    - max: 215,000
    - Loss: $\frac{215,000}{10,500} = 20.5$
2. LowQualFinSF:
    - Mean: 6
    - std: 48.6
    - max: 572
    - Loss: $\frac{572}{49} = 11.6$
3. MiscVal:
    - Mean: 43.5
    - std: 496
    - Max: 15,500
    - Loss: $\frac{15,500}{496} = 31.6$

We will look into those three features and see those outliears and remove them.

In [23]:

```python
# columns to check/huge outliers
cols = ["LotArea", "LowQualFinSF", "MiscVal"]
for col in cols:
    plt.figure(figsize=(8, 2))
    sns.boxplot(x=df[col])
    plt.title(f"Distribution: {col} Boxplot")
    save_plot(fname=f"Distribution_outlier_{col}", filetype="plt")
    plt.show()
```





Indeed we have outliers in our colums and we need to remove them. We will remove outlier in the upper quantile(90%)

In [24]:
```
# removed outlier
repo.remove_outliers()
df = repo.get_data()
print(df.shape)
df.head()
```

```
(1170, 73)
```

Out[24]:

Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF2	...	Garage
1	2-STORY 1946 & NEWER	65.0	8450	7	5	2003	2003	196.0	706	0	...	
2	1-STORY 1946 & NEWER ALL STYLES	80.0	9600	6	8	1976	1976	0.0	978	0	...	
3	2-STORY 1946 & NEWER	68.0	11250	7	5	2001	2002	162.0	486	0	...	
5	2-STORY 1946 & NEWER	84.0	14260	8	5	2000	2000	350.0	655	0	...	
6	1-1/2 STORY FINISHED ALL AGES	85.0	14115	5	5	1993	1995	0.0	732	0	...	

5 rows × 73 columns

4. Splitting

Now that we have our class well defined and we also have the most current data, the next thing we want to do is split our data into train and validation set.

In [25]:
```
# Vertical split
target = "SalePrice"
X = df.drop(columns=target)
y = df[target]
print(f"X shape: {X.shape}")
print(f"y shape: {y.shape}")
```

```
X shape: (1170, 72)
y shape: (1170,)
```

In [26]:
```
# Horizontal split
X_train, X_val, y_train, y_val = train_test_split(
```

```
    X, y, test_size=0.15
)
print(f"X_train shape: {X_train.shape}")
print(f"y_train shape: {y_train.shape}")
print(f"X_val shape: {X_val.shape}")
print(f"y_val shape: {y_val.shape}")
```

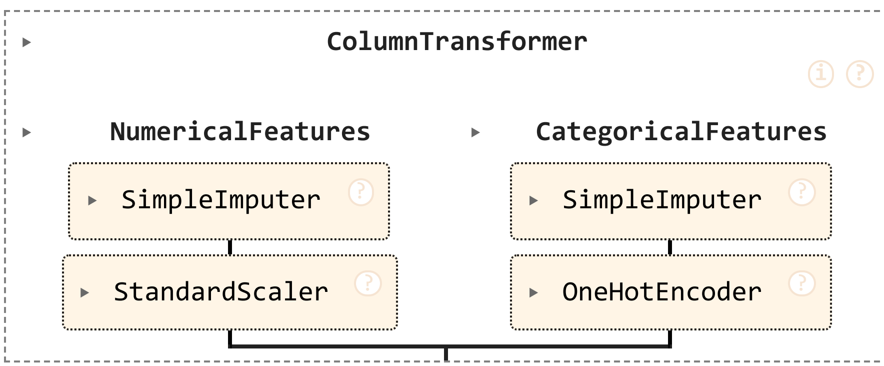
```
X_train shape: (994, 72)
y_train shape: (994,)
X_val shape: (176, 72)
y_val shape: (176,)
```

5. Pipeline

In [27]:

```
# numerical pipeline
num_pipeline = Pipeline([
    ("imputer", SimpleImputer(strategy="mean")),
    ("scaler", StandardScaler())
])
# categorical pipeline
cat_pipeline = Pipeline([
    ("imputer", SimpleImputer(strategy="most_frequent")),
    ("encoder", OneHotEncoder(handle_unknown="ignore"))
])
# column transformer
col_pipeline = ColumnTransformer([
    ("NumericalFeatures", num_pipeline, X_train.select_dtypes(include="number").columns),
    ("CategoricalFeatures", cat_pipeline, X_train.select_dtypes(include="object").columns)
])
col_pipeline
```

Out[27]:



6. PCA Decomposition

In order to visualize our feature matrix (independent variables) against dependent variable `SalePrice`, we need to reduce the number of dimensions of the feature matrix. In our case we want just one dimension.

We will continue to build the pipeline and created a pca_pipeline that we will then fit and transform into a single vector, of 1-dimension matrix.

In [28]:
```
# building the pipeline
pca_pipeline = Pipeline(
    [
        ("preprocess", col_pipeline),
        ("PCA Algorithm", PCA(n_components=1, random_state=42))
    ]
)
# fitting and transforming
X_t = pca_pipeline.fit_transform(X_train)
print("Type of X_t: ", type(X_t))
print("Total Number of items: ", len(X_t))
print("Number of dimensions: ", X_t.ndim)
print("Transformed X_train: \n", X_t[:4])
```

```
Type of X_t:  <class 'numpy.ndarray'>
Total Number of items:  994
Number of dimensions:  2
Transformed X_train:
 [[-1.86861579]
 [-3.87269582]
 [ 0.26245341]
 [ 2.75529971]]
```

Now that we have that, the next thing we want to do is making a function that will help us make the image instantly.

In [29]:
```
def scatter_plot(x, y, y_pred, label):
    """
    Make a scatter plot comparing actual vs. predicted values.

    Parameters:
        x: array-like
            Independent variable (e.g., PCA-transformed features)
        y: array-like
            Actual target values (e.g., true Sale Prices)
        y_pred: array-like
            Predicted target values
        label: str
            Label for the plot title
    """
    df = pd.DataFrame({
        "x": x.ravel(),
```

```python
        "y": y,
        "y_pred": y_pred
    })

    df_melt = pd.melt(
        frame=df,
        id_vars="x",
        value_vars=["y", "y_pred"],
        var_name="Set",
        value_name="Sale Price"
    )

    fig = px.scatter(
        data_frame=df_melt,
        x="x",
        y="Sale Price",
        color="Set",
        title=f"{label} Scatter Plot: Decomposed Features vs. Sale Price"
    )

    fig.update_layout(
        xaxis_title="Decomposed Feature(s)",
        yaxis_title="Sale Price ($)",
        legend_title="Plot Type",
        template = "plotly_white"
    )

    # return
    return fig
```

In [30]:
```python
fig = scatter_plot(X_t, y_train,y_pred=None, label="")
save_plot(fname="DecomposedScatter", filetype="plt")
fig.show()
```

<Figure size 640x480 with 0 Axes>

We have our beautiful scatter plot and it seems like our features follow a polynomial kind of a function. We should keep this in mind. But for now let us have our baseline model.

7. Baseline and Linear Regression Model

In [31]:
```
y_mean = y_train.mean()
baseline_model = len(y_train) * [y_mean]
print("Mean Sale Price: ", int(y_mean))
```

```
Mean Sale Price:  175846
```

We have our baseline model, let us evaluate it's performance using mean absolute error which is computed as

MAE = $\frac{1}{n}\sum_i^n (y_i - \hat y_i)^2$

MAPE = $\frac{100}{n}\sum_i^n \frac{(y_i - \hat y_i)^2}{y_i}$

And finally computing coefficient of determination r2 score as: $R^2 = 1 - \frac{\sum_i^n y_i - \hat y}{\sum_i^n y_i - \bar y}$

Note:

1. y_i - Actual dependent values
2. $\hat y_i$ - Predicted values
3. $\bar y_i$ - Mean
4. n - Number of samples|

In [32]:

```
mae = mean_absolute_error(y_train, baseline_model)
mape = mean_absolute_percentage_error(y_train, baseline_model)
cod = r2_score(y_train, baseline_model)
print(f"MAE: ${np.round(mae, 2)}")
print(f"MAPE: {100 * np.round(mape, 2)}%")
print(f"R2: {100 * np.round(cod, 2)}%")
```

```
MAE: $51164.6
MAPE: 33.0%
R2: 0.0%
```

In [33]:

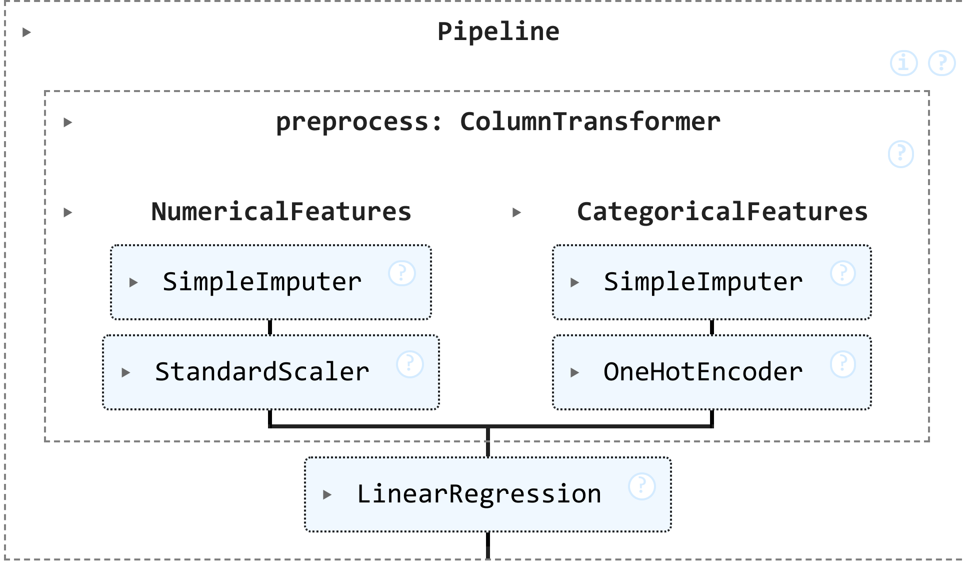
```
fig = scatter_plot(X_t, y_train,y_pred=baseline_model, label="Baseline Model")
save_plot(fname="BaselineModelScatter", filetype="plt")
fig.show()
```

<Figure size 640x480 with 0 Axes>

We are off by 36% from the actual values. This is a reasonable range but there is room for imporvement. We will train a linear regression model first.

In [34]:
```
# linear regression
linear_model = Pipeline(
    [
        ("preprocess", col_pipeline),
        ("linear_model", LinearRegression())
    ]
)
# Training the model
linear_model.fit(X_train, y_train)
```

Out[34]:



In [35]:

```
# model evaluation using mae, mape, coefficient of difference(cod, R2)
pred = linear_model.predict(X_train)
# With training data
mae = mean_absolute_error(y_train, pred)
mape = mean_absolute_percentage_error(y_train, pred)
cod = r2_score(y_train, pred)
print(f"Training MAE: ${np.round(mae, 2)}")
print(f"Training MAPE: {100 * np.round(mape, 2)}%")
print(f"Training R2: {100 * np.round(cod, 2)}%")
```

```
Training MAE: $11391.7
Training MAPE: 7.000000000000001%
Training R2: 94.0%
```

We are of by 7% with our true values. Next let us evaluate our model with the validation dataset. We will check if there is any form of overfitting that need to be addressed.

In [109…

```
# model evaluation using mae, mape, coefficient of difference(cod, R2)
pred = linear_model.predict(X_val)
# With training data
mae = mean_absolute_error(y_val, pred)
mape = mean_absolute_percentage_error(y_val, pred)
cod = r2_score(y_val, pred)
print(f"Validation MAE: ${np.round(mae, 2)}")
print(f"Validation MAPE: {100 * np.round(mape, 2)}%")
print(f"Validation R2: {100 * np.round(cod, 2)}%")
```

```
Validation MAE: $16265.29
Validation MAPE: 9.0%
Validation R2: 88.0%
```

In [37]:
```
from Training import LearningCurve


lc = LearningCurve(estimator=linear_model, X=X, y=y)
print(type(lc))
lc
```

```
<class 'Training.LearningCurve'>
```

Out[37]:
```
LearningCurve: <class 'sklearn.pipeline.Pipeline'>
```

In [38]:
```
# Getting learning curve list
lc.learning_curve()
data = lc.get_data("lc")
print(type(data))
data
```

```
[learning_curve] Training set sizes: [ 93 304 514 725 936]
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  25 out of  25 | elapsed:   10.5s finished
<class 'list'>
```

Out[38]:
```
[array([ 93, 304, 514, 725, 936]),
 array([1.        , 0.97686676, 0.95751753, 0.94935131, 0.9460286 ]),
 array([0.43860028, 0.71470291, 0.85816672, 0.87820229, 0.87343716])]
```

In [39]:
```
# Making the dataframe
lc.make_dataframe()
df_lc = lc.get_data("df_lc")
print(type(df_lc))
df_lc.head()
```

```
<class 'pandas.core.frame.DataFrame'>
```

Out[39]:

	Train Size	Train R2	Validation R2
0	93	1.000000	0.438600
1	304	0.976867	0.714703
2	514	0.957518	0.858167
3	725	0.949351	0.878202
4	936	0.946029	0.873437

In [40]:
```
# melt our datframe
lc.melt_dataframe()
df_melt = lc.get_data("melt_lc")
print(type(df_melt))
df_melt.head()
```

```
<class 'pandas.core.frame.DataFrame'>
```

Out[40]:

	Train Size	Set	R2
0	93	Train R2	1.000000
1	304	Train R2	0.976867
2	514	Train R2	0.957518
3	725	Train R2	0.949351
4	936	Train R2	0.946029

In [41]:
```
# plotting the figure
lc.plot_lc()
fig = lc.get_data()
fig.show()
```

With the above infomation we might want to build a class called LearningCurve that will have all that information.

That is good information. Next thing we want to do is plot the scatter plot and seen.

In [42]:
```
val_pred = linear_model.predict(X_val)
val_X_t = pca_pipeline.fit_transform(X_val)
```

In [43]:
```
fig = scatter_plot(x=val_X_t, y=y_val, y_pred=val_pred, label="Linear Model")
save_plot(fname="LinerModelScatter", filetype="plt")
fig.show()
```

<Figure size 640x480 with 0 Axes>

In [44]:
```
# let us save the model
save_model(mname="LinearRegressionModel", model=linear_model)
```

8. ID mapping

In [45]:
```
repo = WrangleRepository(file_name="test (1).csv")
repo
```

Out[45]:
```
WrangleRepository filepath=C:\Users\MY PC\Desktop\Projects\Regression\AmosHousePriceModelling\test (1).csv
```

In [46]:
```
# getting the data
repo.wrangle()
```

```
df = repo.get_data("wrangled")
print(df.shape)
df.head()
```

(1459, 79)

Out[46]:

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

5 rows × 79 columns

In [47]:

```
# basic cleaning (no)
repo.basic_cleaning(clean=False)
df = repo.get_data("basic")
print(df.shape)
df.head()
```

(1459, 79)

Out[47]:

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

5 rows × 79 columns

In [48]:

```
# feature selction (n0)
repo.feature_selection(variance_selector=False)
```

```
df = repo.get_data("selected")
print(df.shape)
df.head()
```

(1459, 79)

Out[48]:

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

5 rows × 79 columns

In [49]:

```
# feature engineering
repo.feature_engineering(sub_class=sub_class)
df = repo.get_data("engineered")
print(df.shape)
df.head()
```

(1459, 85)

Out[49]:

Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	LotConfig	...	MoSold	YrSold	SaleTy
1461	1-STORY 1946 & NEWER ALL STYLES	RH	80.0	11622	Pave	NaN	Reg	Lvl	AllPub	Inside	...	6	2010	W
1462	1-STORY 1946 & NEWER ALL STYLES	RL	81.0	14267	Pave	NaN	IR1	Lvl	AllPub	Corner	...	6	2010	W
1463	2-STORY 1946 & NEWER	RL	74.0	13830	Pave	NaN	IR1	Lvl	AllPub	Inside	...	3	2010	W
1464	2-STORY 1946 & NEWER	RL	78.0	9978	Pave	NaN	IR1	Lvl	AllPub	Inside	...	6	2010	W
1465	1-STORY PUD (Planned Unit Development) - 1946 ...	RL	43.0	5005	Pave	NaN	IR1	HLS	AllPub	Inside	...	1	2010	W

5 rows × 85 columns

In [50]:

```
# final mapping
df_test = df[X_train.columns]
print(df_test.shape)
df_test.head()
```

```
(1459, 72)
```

Out[50]:

Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF2	...	Ga
1461	1-STORY 1946 & NEWER ALL STYLES	80.0	11622	5	6	1961	1961	0.0	468.0	144.0	...	
1462	1-STORY 1946 & NEWER ALL STYLES	81.0	14267	6	6	1958	1958	108.0	923.0	0.0	...	
1463	2-STORY 1946 & NEWER	74.0	13830	5	5	1997	1998	0.0	791.0	0.0	...	
1464	2-STORY 1946 & NEWER	78.0	9978	6	6	1998	1998	20.0	602.0	0.0	...	
1465	1-STORY PUD (Planned Unit Development) - 1946 ...	43.0	5005	8	5	1992	1992	0.0	263.0	0.0	...	

5 rows × 72 columns

In [51]:

```
from Training import TestPredicter
# Get the predictions
tp = TestPredicter(test_data=df_test, model=linear_model)
print(type(tp))
tp
```

```
<class 'Training.TestPredicter'>
```

Out[51]:

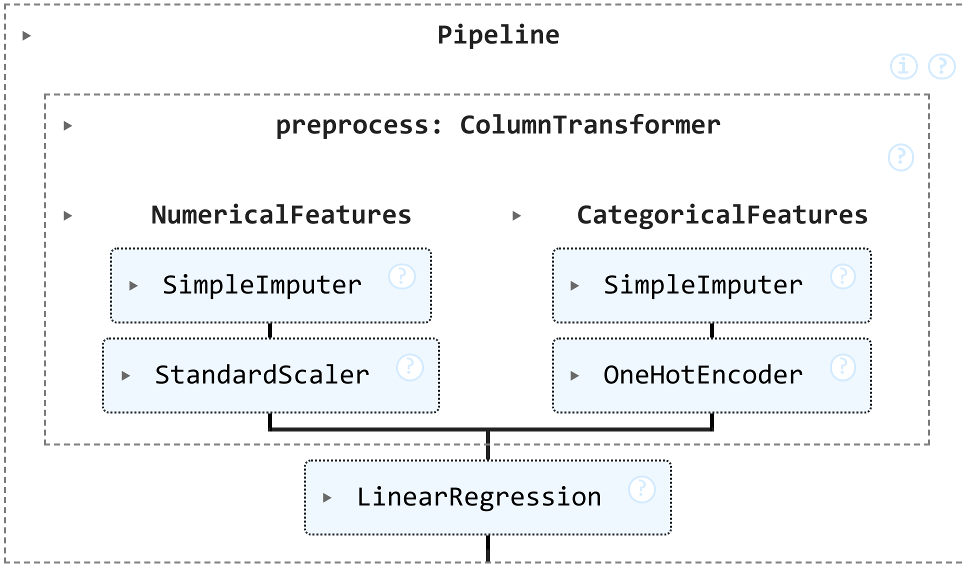
```
TestMapper on C:\Users\MY PC\Desktop\Projects\Regression\AmosHousePriceModelling
```

In [52]:

```
# linear regression
linear_model = Pipeline(
    [
        ("preprocess", col_pipeline),
        ("linear_model", LinearRegression())
    ]
)
```

```python
# Training the model
linear_model.fit(X_train, y_train)
```

Out[52]:



In [53]:

```python
tp.predict()
pred = tp.get_data("prediction")
print(type(pred))
pred[:4]
```

```
<class 'numpy.ndarray'>
```

Out[53]:

```
array([111934.25406071, 158050.42262291, 179127.82260186, 195072.54704813])
```

In [54]:

```python
tp.id_mapper(label="linear_regression")
sub = tp.get_data("mapped")
print(type(sub))
print(sub.shape)
sub.head()
```

```
<class 'pandas.core.frame.DataFrame'>
(1459, 1)
```

Out[54]:

Id	SalePrice
1461	111934.254061
1462	158050.422623
1463	179127.822602
1464	195072.547048
1465	185396.000891

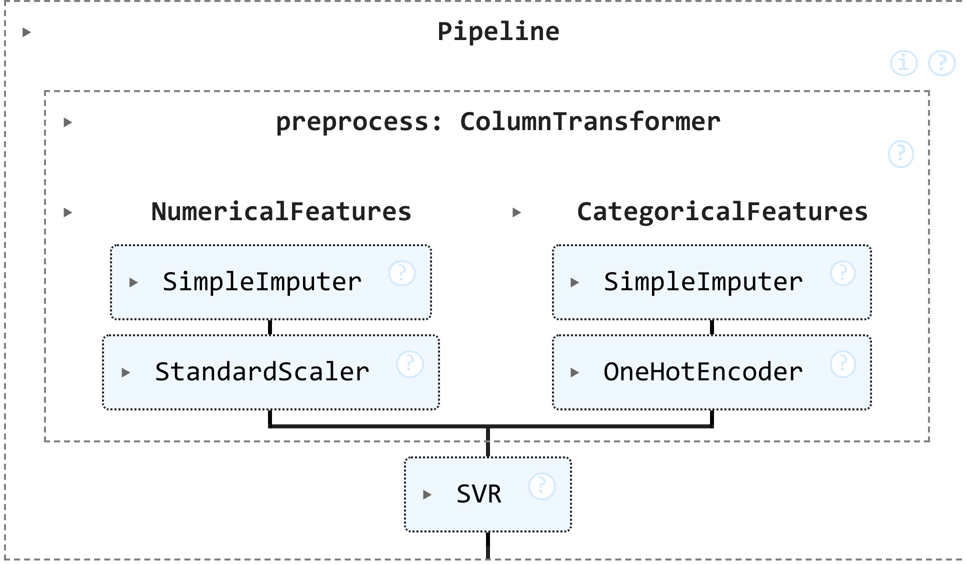
9. Polynomial Features (degree 2) and SVR

To improve our model performance we need to include a polynomial of degree 2 to our support vector regressor (SVR)

In [55]:

```
# building the pipeline
svr_pipeline = Pipeline(
    [
        ("preprocess", col_pipeline),
        ("svr_model", SVR(kernel="poly", degree=2))
    ]
)
# Training the model
svr_model = svr_pipeline.fit(X_train, y_train)
svr_model
```

Out[55]:

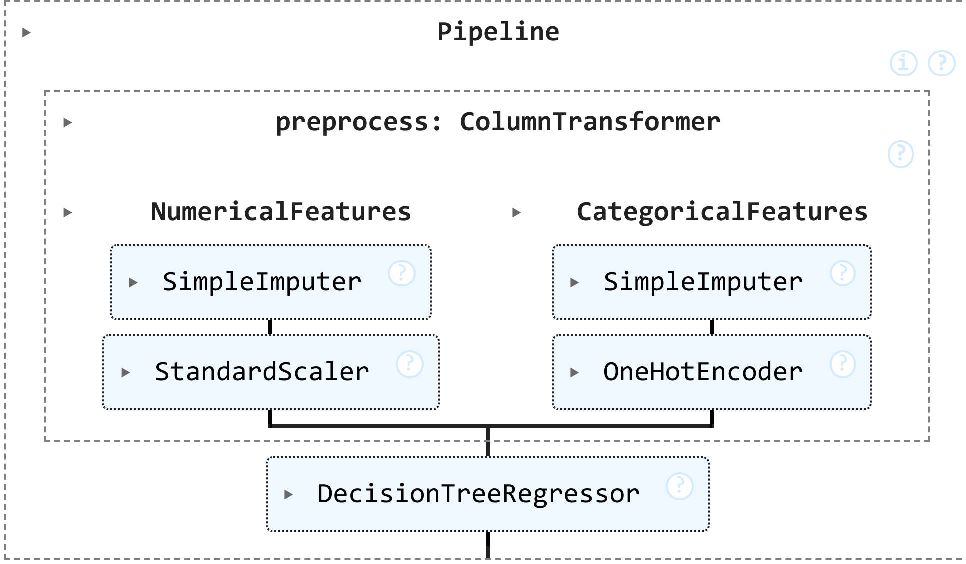


10. Decision Tree Regressor

In [56]:

```
# Building the pipeline with decision tree regressor
tree_pipeline = Pipeline(
    [
        ("preprocess", col_pipeline),
        ("tree_model", DecisionTreeRegressor(random_state=42))
    ]
)
# Training the model
tree_model = tree_pipeline.fit(X_train, y_train)
tree_model
```

Out[56]:



We have now trained a decision tree model, next up is to evaluate our model and continue to do hyperameter tuning.

In [57]:

```
# model evaluation using mae, mape, coefficient of difference(cod, R2)
pred = tree_model.predict(X_train)
# With training data
mae = mean_absolute_error(y_train, pred)
mape = mean_absolute_percentage_error(y_train, pred)
cod = r2_score(y_train, pred)
print(f"Training MAE: ${np.round(mae, 2)}")
print(f"Training MAPE: {100 * np.round(mape, 2)}%")
print(f"Training R2: {100 * np.round(cod, 2)}%")
```

```
Training MAE: $0.0
Training MAPE: 0.0%
Training R2: 100.0%
```

In [58]:

```
# Evaluation using validation set
# model evaluation using mae, mape, coefficient of difference(cod, R2)
pred = tree_model.predict(X_val)
# With training data
mae = mean_absolute_error(y_val, pred)
mape = mean_absolute_percentage_error(y_val, pred)
cod = r2_score(y_val, pred)
print(f"Training MAE: ${np.round(mae, 2)}")
print(f"Training MAPE: {100 * np.round(mape, 2)}%")
print(f"Training R2: {100 * np.round(cod, 2)}%")
```

```
Training MAE: $26578.59
Training MAPE: 14.000000000000002%
Training R2: 56.99999999999999%
```

Definately we have some element of overfitting, let's visualize this using a plot. We are going to use the LearningCurve class that has all the three modules.

In [59]:
```python
# get the learning curve class
lc = LearningCurve(estimator=tree_model, X=X, y=y)
print(type(lc))
lc
```

```
<class 'Training.LearningCurve'>
```

Out[59]:
```
LearningCurve: <class 'sklearn.pipeline.Pipeline'>
```

In [60]:
```python
# Het learning curve list data
lc.learning_curve()
tree_lc = lc.get_data("lc")
print(type(tree_lc))
tree_lc[:4]
```

```
[learning_curve] Training set sizes: [ 93 304 514 725 936]
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  25 out of  25 | elapsed:    3.0s finished
<class 'list'>
```

Out[60]:
```
[array([ 93, 304, 514, 725, 936]),
 array([1., 1., 1., 1., 1.]),
 array([0.11831156, 0.54036325, 0.72716731, 0.69733103, 0.75523564])]
```

In [61]:
```python
# make the learning curve dataframe
lc.make_dataframe()
tree_lc_df = lc.get_data("df_lc")
print(type(tree_lc_df))
print(tree_lc_df.shape)
tree_lc_df
```

```
<class 'pandas.core.frame.DataFrame'>
(5, 3)
```

Out[61]:

	Train Size	Train R2	Validation R2
0	93	1.0	0.118312
1	304	1.0	0.540363
2	514	1.0	0.727167
3	725	1.0	0.697331
4	936	1.0	0.755236

In [62]:

```
# Melting the dataframe
lc.melt_dataframe()
tree_lc_melt = lc.get_data("melt_lc")
print(type(tree_lc_melt))
print(tree_lc_melt.shape)
tree_lc_melt.head()
```

```
<class 'pandas.core.frame.DataFrame'>
(10, 3)
```

Out[62]:

	Train Size	Set	R2
0	93	Train R2	1.0
1	304	Train R2	1.0
2	514	Train R2	1.0
3	725	Train R2	1.0
4	936	Train R2	1.0

In [63]:

```
# making the plot
lc.plot_lc()
fig = lc.get_data()
print(type(fig))
save_plot(fname="decion_tree_model_learning_curve", filetype="plt", fig=fig)
fig.show()
```

```
<class 'plotly.graph_objs._figure.Figure'>
```

```
<Figure size 640x480 with 0 Axes>
```

As seen we are overfitting and we need to improve our model by doing the following:

1. Reduce model complexity- reducing the depth of the model
2. Do a cross validation (kfold)
3. hyperameter tuning

But before we do that, let us get the maxim depth of our model.

In [64]:
```
# trianing different trees
train_acc = []
val_acc = []
d_params = range(1, 10)
for d in d_params:
```

```python
    # training the model
    model = Pipeline(
        [
            ("preprocess", col_pipeline),
            ("model", DecisionTreeRegressor(max_depth=d, random_state=42))
        ]
    )
    model.fit(X_train, y_train)
    # R2
    train_acc.append(r2_score(y_train, model.predict(X_train)))
    val_acc.append(r2_score(y_val, model.predict(X_val)))
```

In [65]:

```python
# building a dataframe
df_result = pd.DataFrame(
    {
        "Depth": d_params,
        "Train Accuracy": train_acc,
        "Validation Accuracy": val_acc
    }
)
df_result
```

Out[65]:

	Depth	Train Accuracy	Validation Accuracy
0	1	0.453900	0.334842
1	2	0.629325	0.501178
2	3	0.762974	0.628356
3	4	0.830680	0.702260
4	5	0.886568	0.636079
5	6	0.924428	0.597267
6	7	0.951208	0.762117
7	8	0.971141	0.814099
8	9	0.982418	0.623959

In [66]:

```python
# meltiing the dataframe,
result_melt = pd.melt(
    frame=df_result,
    id_vars="Depth",
    value_vars=["Train Accuracy", "Validation Accuracy"],
    value_name="Accuracy",
```

```
    var_name="Set"
)
result_melt.head()
```

Out[66]:

	Depth	Set	Accuracy
0	1	Train Accuracy	0.453900
1	2	Train Accuracy	0.629325
2	3	Train Accuracy	0.762974
3	4	Train Accuracy	0.830680
4	5	Train Accuracy	0.886568

In [67]:

```
# plotting
fig = px.line(
    data_frame=result_melt,
    x = "Depth",
    y = "Accuracy",
    color = "Set",
    title="Decision Tree Model: Training and validataion accuracy curves"
)
fig.update_layout(
    xaxis_title="Depth of the Tree",
    yaxis_title="Accuracy",
    legend_title="Accuracy"
)
fig.show()
```

As seen in the plot above a depth of seven is having the highest validation accuracy. Let us train our final model using the depth of seven first and define other hyperameters that will help reduce overfitting.

In [68]:

```
params = {
    "tree_model__min_samples_split": [3,4,5,6],
    "tree_model__min_samples_leaf": [1,2,3,4]
}
params
```

Out[68]:

```
{'tree_model__min_samples_split': [3, 4, 5, 6],
 'tree_model__min_samples_leaf': [1, 2, 3, 4]}
```

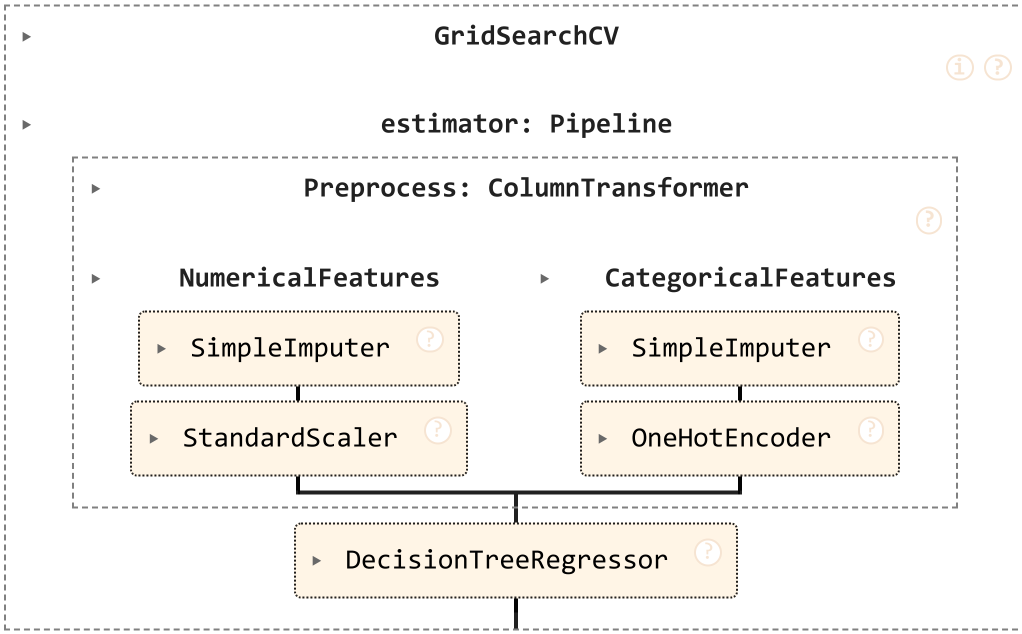
In [69]:

```
# model pipeline
tree_model_pipeline = Pipeline(
    [
```

```python
        ("Preprocess", col_pipeline),
        ("tree_model", DecisionTreeRegressor(max_depth=7, random_state=42))
    ]
)

# Grid search
tree_model_cv = GridSearchCV(
    estimator=tree_model_pipeline,
    param_grid=params,
    n_jobs=-1,
    cv=5,
    verbose=1
)
tree_model_cv
```

Out[69]:

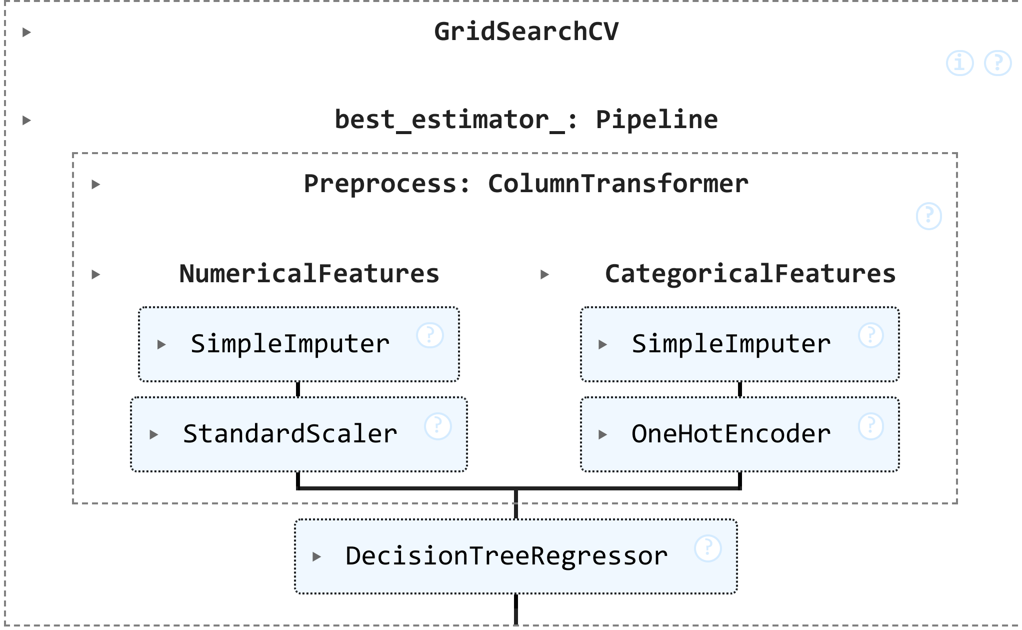


In [70]:

```python
# fitting the model
tree_model_cv.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 16 candidates, totalling 80 fits
```

Out[70]:



In [71]:

```
# getting the best paramers
tree_model_cv.best_params_
```

Out[71]:

```
{'tree_model__min_samples_leaf': 1, 'tree_model__min_samples_split': 4}
```

In [72]:

```
# Betting the model cv results into a dataframe
cv_result = pd.DataFrame.from_dict(tree_model_cv.cv_results_)
print(type(cv_result))
print(cv_result.shape)
cv_result.head()
```

```
<class 'pandas.core.frame.DataFrame'>
(16, 15)
```

Out[72]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_tree_model__min_samples_leaf	param_tree_model__min_samples_split	
0	0.209090	0.027543	0.058873	0.017155	1	3	{'tr
1	0.182238	0.010539	0.039121	0.003061	1	4	{'tr
2	0.174386	0.005411	0.045016	0.005904	1	5	{'tr
3	0.170947	0.010402	0.042823	0.006001	1	6	{'tr
4	0.226941	0.033243	0.060980	0.012052	2	3	{'tr

In [73]:

```
# making splits score dataframe
score_col = ["rank_test_score", "split0_test_score", "split1_test_score", "split2_test_score", "split3_test_score", "split4_test_s
split_score = cv_result[score_col]
# melting the dataframe
split_score = pd.melt(frame=split_score, var_name="Set", value_name="Score", id_vars="rank_test_score")
split_score.head()
```

Out[73]:

	rank_test_score	Set	Score
0	13	split0_test_score	0.772907
1	1	split0_test_score	0.776451
2	8	split0_test_score	0.759828
3	16	split0_test_score	0.762805
4	2	split0_test_score	0.750379

In [74]:

```
# plotting
fig = px.line(
    data_frame=split_score,
    x=split_score.index,
    y="Score",
    color="Set",
    title="Hyperameter Sets: Decision Tree Model"
)
fig.update_layout(
    xaxis_title="Training Index",
```

```
    yaxis_title="Accuracy (%)",
    legend_title="Split Type"
)
fig.show()
```

As seen some model had really high accuracies but now let us get the best model and parameters.

In [75]:
```
tree_model_cv.best_params_
```

Out[75]:
```
{'tree_model__min_samples_leaf': 1, 'tree_model__min_samples_split': 4}
```

Now that we have our best model, let us evaluate it.

In [76]:
```
# model evaluation using mae, mape, coefficient of difference(cod, R2)
pred = tree_model_cv.predict(X_train)
```

```
# With training data
mae = mean_absolute_error(y_train, pred)
mape = mean_absolute_percentage_error(y_train, pred)
cod = r2_score(y_train, pred)
print(f"Training MAE: ${np.round(mae, 2)}")
print(f"Training MAPE: {100 * np.round(mape, 2)}%")
print(f"Training R2: {100 * np.round(cod, 2)}%")
```

```
Training MAE: $11483.79
Training MAPE: 7.000000000000001%
Training R2: 95.0%
```

In [77]:
```
# model evaluation using mae, mape, coefficient of difference(cod, R2)
pred = tree_model_cv.predict(X_val)
# With training data
mae = mean_absolute_error(y_val, pred)
mape = mean_absolute_percentage_error(y_val, pred)
cod = r2_score(y_val, pred)
print(f"Training MAE: ${np.round(mae, 2)}")
print(f"Training MAPE: {100 * np.round(mape, 2)}%")
print(f"Training R2: {100 * np.round(cod, 2)}%")
```

```
Training MAE: $22159.47
Training MAPE: 12.0%
Training R2: 73.0%
```

We have tried to reduce overfitting but one more thing to be done is increaing the data. Since this is a kaggle competition, then we will not do that. we will investige this property using a learning curve.

In [78]:
```
lc = LearningCurve(estimator=tree_model_cv, X=X, y=y)
print(type(lc))
lc
```

```
<class 'Training.LearningCurve'>
```

Out[78]:
```
LearningCurve: <class 'sklearn.model_selection._search.GridSearchCV'>
```

In [79]:
```
# learning curve list
lc.learning_curve()
ls = lc.get_data("lc")
print(type(ls))
ls[:4]
```

```
[learning_curve] Training set sizes: [ 93 304 514 725 936]
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  25 out of  25 | elapsed:  1.4min finished
<class 'list'>
```

```
Out[79]: [array([ 93, 304, 514, 725, 936]),
          array([0.91356261, 0.94798811, 0.95389146, 0.94835213, 0.9373437 ]),
          array([0.27786857, 0.65022828, 0.72233115, 0.75555916, 0.77462749])]
```

```
In [80]: # getting the data
         lc.make_dataframe()
         ld = lc.get_data("df_lc")
         print(type(ld))
         print(ld.shape)
         ld.head()
```

```
<class 'pandas.core.frame.DataFrame'>
(5, 3)
```

Out[80]:

	Train Size	Train R2	Validation R2
0	93	0.913563	0.277869
1	304	0.947988	0.650228
2	514	0.953891	0.722331
3	725	0.948352	0.755559
4	936	0.937344	0.774627

```
In [81]: # getting the melted data
         lc.melt_dataframe()
         ld = lc.get_data("melt_lc")
         print(type(ld))
         print(ld.shape)
         ld.head()
```

```
<class 'pandas.core.frame.DataFrame'>
(10, 3)
```

Out[81]:

	Train Size	Set	R2
0	93	Train R2	0.913563
1	304	Train R2	0.947988
2	514	Train R2	0.953891
3	725	Train R2	0.948352
4	936	Train R2	0.937344

In [82]:
```python
# getting the data
lc.plot_lc()
fig = lc.get_data()
print(type(fig))
fig.show()
```

```
<class 'plotly.graph_objs._figure.Figure'>
```

Definately this plot confirms that we need more data which we don't have maybe we can improve our model using another method.One thing we have done successfully is that we have been able to reduce overfitting as seen. We will start doing bagging and boosting learning methods to try and see if our model performance will increase and we reduce overfitting.

In [83]:
```python
# saving the model
save_model(mname="decision_tree_model", model=tree_model_cv)
```

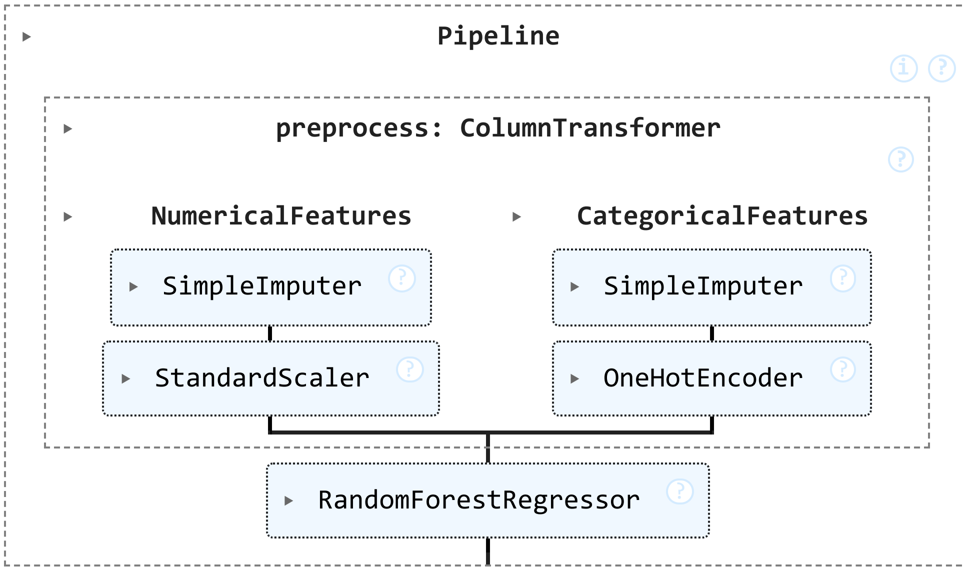
11. Bagging Model

Random forest model is one of the bagging models. We are going to train that and see the progress.

In [84]:

```
# Model pipeline
forest_model = Pipeline(
    [
        ("preprocess", col_pipeline),
        ("forest_model", RandomForestRegressor(max_depth=7))
    ]
)
# Training the model
forest_model.fit(X_train, y_train)
```

Out[84]:



In [85]:

```
# model evaluation using mae, mape, coefficient of difference(cod, R2)
pred = forest_model.predict(X_train)
# With training data
mae = mean_absolute_error(y_train, pred)
mape = mean_absolute_percentage_error(y_train, pred)
cod = r2_score(y_train, pred)
print(f"Training MAE: ${np.round(mae, 2)}")
print(f"Training MAPE: {100 * np.round(mape, 2)}%")
print(f"Training R2: {100 * np.round(cod, 2)}%")
```

```
Training MAE: $10335.71
Training MAPE: 6.0%
Training R2: 96.0%
```

In [86]:
```
# model evaluation using mae, mape, coefficient of difference(cod, R2)
pred = forest_model.predict(X_val)
# With training data
mae = mean_absolute_error(y_val, pred)
mape = mean_absolute_percentage_error(y_val, pred)
cod = r2_score(y_val, pred)
print(f"Validation MAE: ${np.round(mae, 2)}")
print(f"Validation MAPE: {100 * np.round(mape, 2)}%")
print(f"Validation R2: {100 * np.round(cod, 2)}%")
```

```
Validation MAE: $16426.49
Validation MAPE: 9.0%
Validation R2: 89.0%
```

Actually this model is perfoming better. We will first check for overfitting and them do a hyperameter tuning.

In [87]:
```
lcf = LearningCurve(estimator=forest_model, X=X, y=y)
print(type(lcf))
lcf
```

```
<class 'Training.LearningCurve'>
```

Out[87]:
```
LearningCurve: <class 'sklearn.pipeline.Pipeline'>
```

In [88]:
```
# Getting the learning curve list
lcf.learning_curve()
lcf_list = lcf.get_data("lc")
print(type(lcf_list))
lcf
```

```
[learning_curve] Training set sizes: [ 93 304 514 725 936]
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  25 out of  25 | elapsed:   32.1s finished
<class 'list'>
```

Out[88]:
```
LearningCurve: <class 'sklearn.pipeline.Pipeline'>
```

In [89]:
```
# getting the dataframe
lcf.make_dataframe()
lcf_df = lcf.get_data("df_lc")
print(type(lcf_df))
print(lcf_df.shape)
lcf_df
```

```
<class 'pandas.core.frame.DataFrame'>
(5, 3)
```

Out[89]:

	Train Size	Train R2	Validation R2
0	93	0.952477	0.798010
1	304	0.971097	0.831800
2	514	0.967815	0.850644
3	725	0.964742	0.855944
4	936	0.962920	0.872585

In [90]:

```
# melting the dataframe
lcf.melt_dataframe()
lcf_melt = lcf.get_data("melt_lc")
print(type(lcf_melt))
print(lcf_melt.shape)
lcf_melt.head()
```

```
<class 'pandas.core.frame.DataFrame'>
(10, 3)
```

Out[90]:

	Train Size	Set	R2
0	93	Train R2	0.952477
1	304	Train R2	0.971097
2	514	Train R2	0.967815
3	725	Train R2	0.964742
4	936	Train R2	0.962920

In [91]:

```
# plotting the learning curve
lcf.plot_lc()
fig = lcf.get_data()
print(type(fig))
fig.show()
```

```
<class 'plotly.graph_objs._figure.Figure'>
```

With more data we can actually get better results. Our model is not overfitting but we will try different hyperameter to see if we will get a better optimal parameters

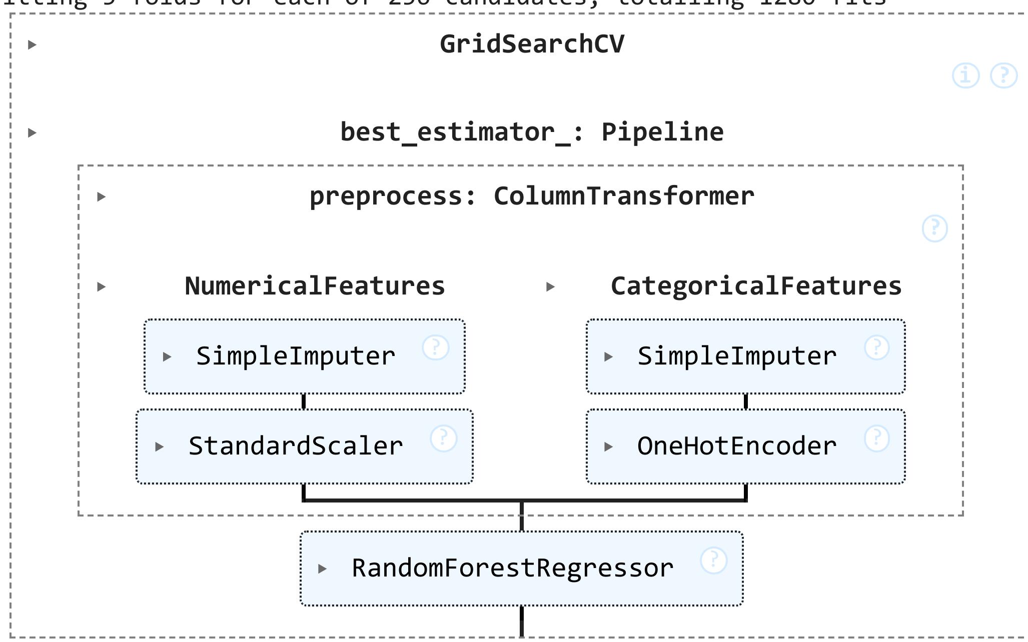
In [93]:
```
f_params = {
    "forest_model__n_estimators": range(20, 100, 20),
    "forest_model__max_depth": range(4,12,2),
    "forest_model__min_samples_split": [4,6,8,10],
    "forest_model__min_samples_leaf": [1,2,3,4]
}
f_params
```

```
Out[93]: {'forest_model__n_estimators': range(20, 100, 20),
          'forest_model__max_depth': range(4, 12, 2),
          'forest_model__min_samples_split': [4, 6, 8, 10],
          'forest_model__min_samples_leaf': [1, 2, 3, 4]}
```

```
In [94]: # model pipeline
forest_model_cv = Pipeline(
    [
        ("preprocess", col_pipeline),
        ("forest_model", RandomForestRegressor(random_state=42))
    ]
)
# Cross validation
forest_model_cv = GridSearchCV(
    estimator=forest_model_cv,
    param_grid=f_params,
    cv=5,
    n_jobs=-1,
    verbose=1
)
# Training the model
forest_model_cv.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 256 candidates, totalling 1280 fits
```

Out[94]:




```
In [99]: # Getting the model best parameters
forest_model_cv.best_params_
```

Out[99]:
```
{'forest_model__max_depth': 10,
 'forest_model__min_samples_leaf': 2,
 'forest_model__min_samples_split': 4,
 'forest_model__n_estimators': 60}
```

In [100…
```python
# Getting the cv results
# Betting the model cv results into a dataframe
cv_result = pd.DataFrame.from_dict(forest_model_cv.cv_results_)
print(type(cv_result))
print(cv_result.shape)
cv_result.head()
```

```
<class 'pandas.core.frame.DataFrame'>
(256, 17)
```

Out[100…

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_forest_model__max_depth	param_forest_model__min_samples_leaf	paran
0	0.639304	0.020015	0.053631	0.008212	4	1	
1	1.131988	0.033393	0.059633	0.011264	4	1	
2	1.886548	0.151949	0.072804	0.018020	4	1	
3	2.473378	0.201929	0.067602	0.002350	4	1	
4	0.597211	0.006840	0.046773	0.001308	4	1	

In [101…
```python
# making splits score dataframe
score_col = ["rank_test_score", "split0_test_score", "split1_test_score", "split2_test_score", "split3_test_score", "split4_test_s
split_score = cv_result[score_col]
# melting the dataframe
split_score = pd.melt(frame=split_score, var_name="Set", value_name="Score", id_vars="rank_test_score")
split_score.head()
```

Out[101…

	rank_test_score	Set	Score
0	249	split0_test_score	0.832552
1	234	split0_test_score	0.837057
2	221	split0_test_score	0.842257
3	211	split0_test_score	0.841496
4	250	split0_test_score	0.832640

In [102…

```
# plotting
fig = px.line(
    data_frame=split_score,
    x=split_score.index,
    y="Score",
    color="Set",
    title="Hyperameter Sets: Decision Tree Model"
)
fig.update_layout(
    xaxis_title="Training Index",
    yaxis_title="Accuracy (%)",
    legend_title="Split Type"
)
fig.show()
```

With that information let us evaluation our best model.

In [107…

```
# model evaluation using mae, mape, coefficient of difference(cod, R2)
pred = forest_model_cv.best_estimator_.predict(X_train)
# With training data
mae = mean_absolute_error(y_train, pred)
mape = mean_absolute_percentage_error(y_train, pred)
cod = r2_score(y_train, pred)
print(f"Training MAE: ${np.round(mae, 2)}")
print(f"Training MAPE: {100 * np.round(mape, 2)}%")
print(f"Training R2: {100 * np.round(cod, 2)}%")
```

```
Training MAE: $7489.56
Training MAPE: 5.0%
Training R2: 97.0%
```

In [108…
```
# model evaluation using mae, mape, coefficient of difference(cod, R2)
pred = forest_model_cv.best_estimator_.predict(X_val)
# With training data
mae = mean_absolute_error(y_val, pred)
mape = mean_absolute_percentage_error(y_val, pred)
cod = r2_score(y_val, pred)
print(f"Validation MAE: ${np.round(mae, 2)}")
print(f"Validation MAPE: {100 * np.round(mape, 2)}%")
print(f"Validation R2: {100 * np.round(cod, 2)}%")
```

```
Validation MAE: $16474.68
Validation MAPE: 9.0%
Validation R2: 88.0%
```

This model is perfoming pletty well.

Let us save map our ids for submission and finally save the model.

In [110…
```
# id mapping
tcf = TestPredicter(test_data=df_test, model=forest_model_cv)
print(type(tcf))
tcf
```

```
<class 'Training.TestPredicter'>
```

Out[110…
```
TestMapper on C:\Users\MY PC\Desktop\Projects\Regression\AmosHousePriceModelling
```

In [112…
```
# Getting the predictions
tcf.predict()
pred_f = tcf.get_data("prediction")
print(type(pred_f))
pred_f[:4]
```

```
<class 'numpy.ndarray'>
```

Out[112…
```
array([126023.64599443, 156174.380588  , 190244.77318438, 179339.0265955 ])
```

In [114…
```
# mapping the ids
tcf.id_mapper(label="forest")
sub_f = tcf.get_data("mapped")
print(type(df))
print(sub_f.shape)
sub_f.head()
```

```
<class 'pandas.core.frame.DataFrame'>
(1459, 1)
```

Out[114…

Id	SalePrice
1461	126023.645994
1462	156174.380588
1463	190244.773184
1464	179339.026595
1465	193461.518541

In [116…

```
val_pred_f = forest_model_cv.predict(X_val)
```

In [117…

```
# Scatter plot
fig = scatter_plot(x=val_X_t, y=y_val, y_pred=val_pred_f, label="Random Forest Model")
save_plot(fname="LinerModelScatter", filetype="plt")
fig.show()
```

```
<Figure size 640x480 with 0 Axes>
```

In [118…

```
# saving the model
save_model(mname="RandomFores_model", model=forest_model_cv)
```

12. Boosting Model

We will try a boosting model, gradient boostng model and see it's perfomance. If it is going to perform better than the rest of the models.

In [ ]:

```

```