Copy_of_House_Price_Prediction

October 19, 2024

0.1 House Price Prediction dataset taken from **https://www.kaggle.com/competitions/house-prices-advanced-regression-techniques/da**

```
[ ]: # !unzip house-prices-advanced-regression-techniques.zip
```

```
Archive:  house-prices-advanced-regression-techniques.zip
replace data_description.txt? [y]es, [n]o, [A]ll, [N]one, [r]ename:
```

```
[ ]: import pandas as pd
```

```
[ ]: house_df = pd.read_csv('train.csv')
```

```
[ ]: house_df.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')
```

```
[ ]: house_df.isna().sum()
```

```
[ ]: Id                 0
     MSSubClass         0
     MSZoning           0
     LotFrontage      259
```

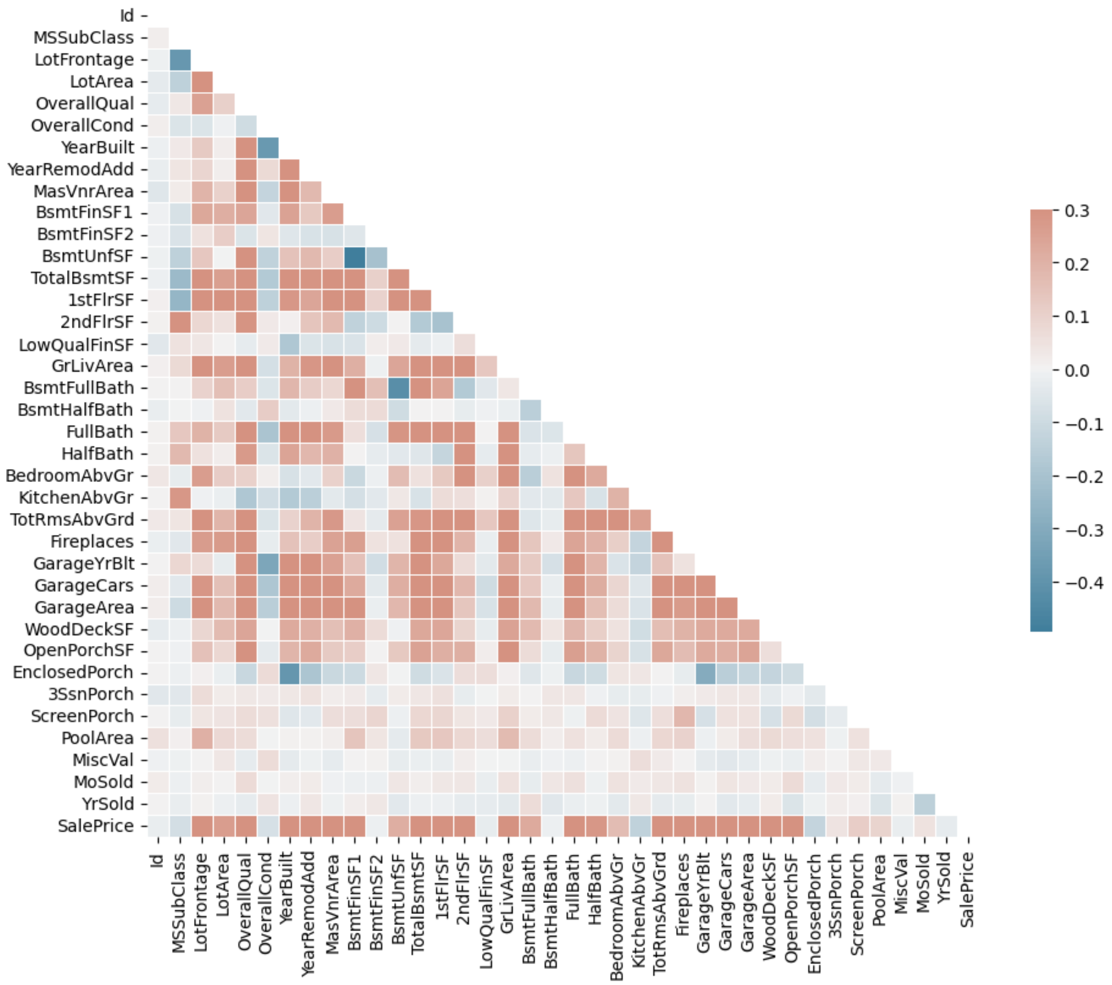
```
LotArea            0
                …
MoSold             0
YrSold             0
SaleType           0
SaleCondition      0
SalePrice          0
Length: 81, dtype: int64
```

[ ]:

```python
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
### I will just use the columns at random but in the lab work please see what
### relationship there is between target variable and other attribute
numeric_df = house_df.select_dtypes(['int64', 'float64'])

corr = numeric_df.corr()
mask = np.triu(np.ones_like(corr, dtype=bool))
f, ax = plt.subplots(figsize=(11, 9))
cmap = sns.diverging_palette(230, 20, as_cmap=True)
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
```

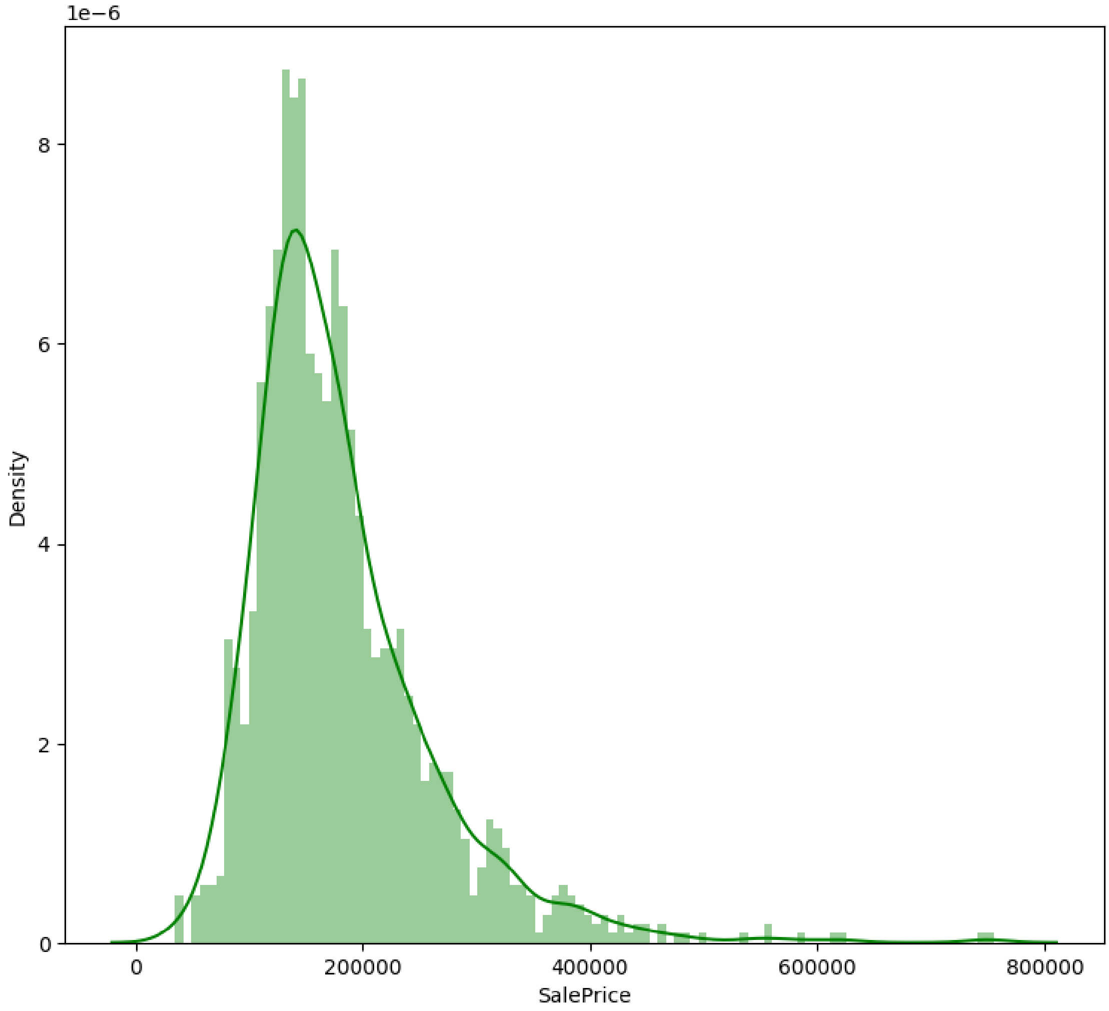
[ ]:

```
<Axes: >
```



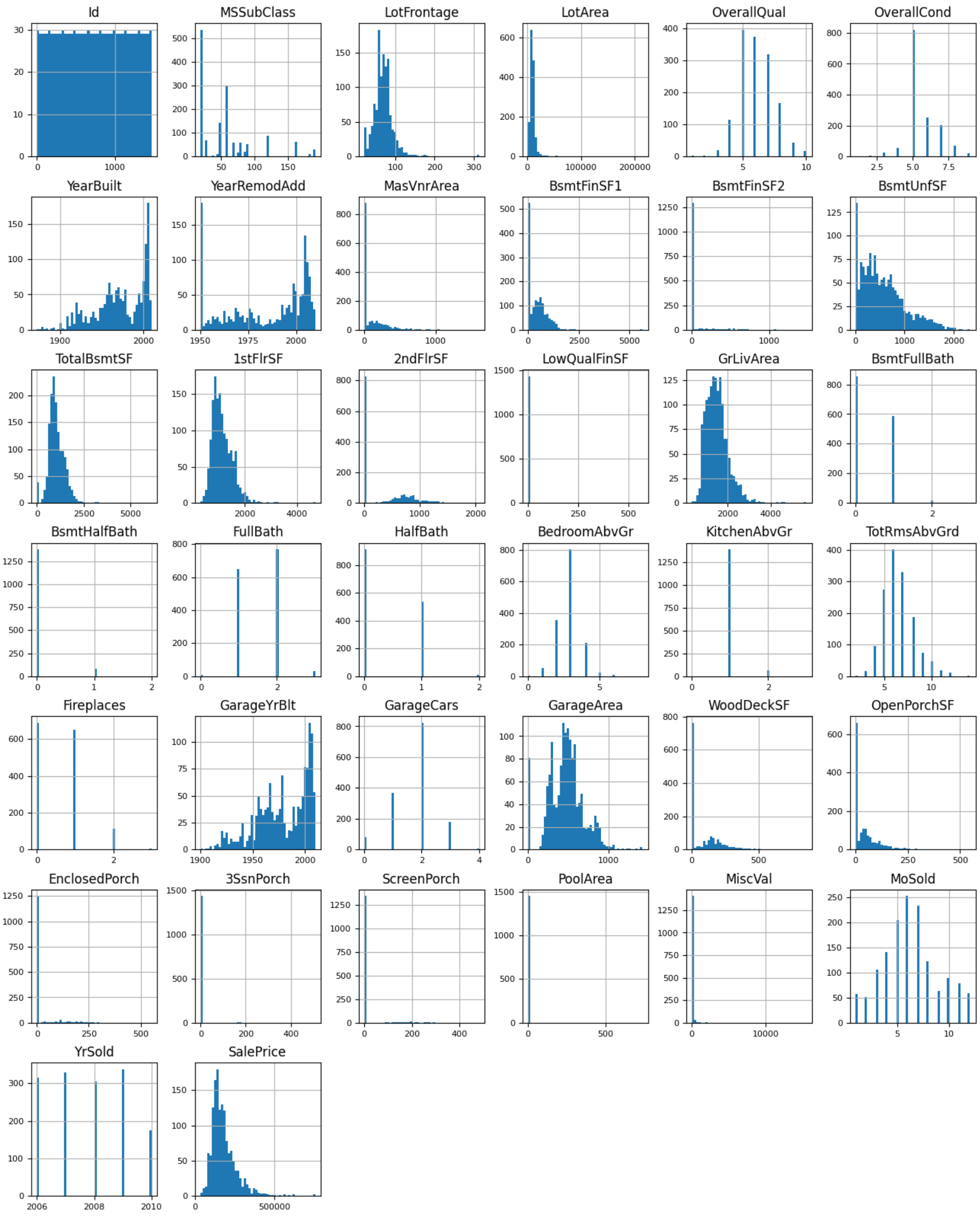
```
[ ]: plt.figure(figsize=(9, 8))
     sns.distplot(house_df['SalePrice'], color='g', bins=100, hist_kws={'alpha': 0.
      ↪4});
```

```
<ipython-input-73-f6ab0e3193d7>:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(house_df['SalePrice'], color='g', bins=100, hist_kws={'alpha':
0.4});
```



```
[ ]: numeric_df.hist(figsize=(16, 20), bins=50, xlabelsize=8, ylabelsize=8)
```

```
[ ]: array([[<Axes: title={'center': 'Id'}>,
             <Axes: title={'center': 'MSSubClass'}>,
             <Axes: title={'center': 'LotFrontage'}>,
             <Axes: title={'center': 'LotArea'}>,
             <Axes: title={'center': 'OverallQual'}>,
             <Axes: title={'center': 'OverallCond'}>],
            [<Axes: title={'center': 'YearBuilt'}>,
             <Axes: title={'center': 'YearRemodAdd'}>,
             <Axes: title={'center': 'MasVnrArea'}>,
             <Axes: title={'center': 'BsmtFinSF1'}>,
             <Axes: title={'center': 'BsmtFinSF2'}>,
             <Axes: title={'center': 'BsmtUnfSF'}>],
            [<Axes: title={'center': 'TotalBsmtSF'}>,
             <Axes: title={'center': '1stFlrSF'}>,
             <Axes: title={'center': '2ndFlrSF'}>,
             <Axes: title={'center': 'LowQualFinSF'}>,
             <Axes: title={'center': 'GrLivArea'}>,
             <Axes: title={'center': 'BsmtFullBath'}>],
            [<Axes: title={'center': 'BsmtHalfBath'}>,
             <Axes: title={'center': 'FullBath'}>,
             <Axes: title={'center': 'HalfBath'}>,
             <Axes: title={'center': 'BedroomAbvGr'}>,
             <Axes: title={'center': 'KitchenAbvGr'}>,
             <Axes: title={'center': 'TotRmsAbvGrd'}>],
            [<Axes: title={'center': 'Fireplaces'}>,
             <Axes: title={'center': 'GarageYrBlt'}>,
             <Axes: title={'center': 'GarageCars'}>,
             <Axes: title={'center': 'GarageArea'}>,
             <Axes: title={'center': 'WoodDeckSF'}>,
             <Axes: title={'center': 'OpenPorchSF'}>],
            [<Axes: title={'center': 'EnclosedPorch'}>,
             <Axes: title={'center': '3SsnPorch'}>,
             <Axes: title={'center': 'ScreenPorch'}>,
             <Axes: title={'center': 'PoolArea'}>,
             <Axes: title={'center': 'MiscVal'}>,
             <Axes: title={'center': 'MoSold'}>],
            [<Axes: title={'center': 'YrSold'}>,
             <Axes: title={'center': 'SalePrice'}>, <Axes: >, <Axes: >,
             <Axes: >, <Axes: >]], dtype=object)
```



```
[ ]: house_df.head()
```

```
[ ]:    Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
     0   1          60       RL         65.0     8450   Pave   NaN      Reg
     1   2          20       RL         80.0     9600   Pave   NaN      Reg
```

```
2   3          60        RL          68.0     11250   Pave    NaN       IR1
3   4          70        RL          60.0      9550   Pave    NaN       IR1
4   5          60        RL          84.0     14260   Pave    NaN       IR1

  LandContour Utilities  … PoolArea PoolQC Fence MiscFeature MiscVal MoSold  \
0         Lvl    AllPub  …        0    NaN   NaN         NaN       0      2
1         Lvl    AllPub  …        0    NaN   NaN         NaN       0      5
2         Lvl    AllPub  …        0    NaN   NaN         NaN       0      9
3         Lvl    AllPub  …        0    NaN   NaN         NaN       0      2
4         Lvl    AllPub  …        0    NaN   NaN         NaN       0     12

  YrSold  SaleType  SaleCondition  SalePrice
0   2008        WD         Normal     208500
1   2007        WD         Normal     181500
2   2008        WD         Normal     223500
3   2006        WD        Abnorml     140000
4   2008        WD         Normal     250000

[5 rows x 81 columns]
```

[ ]:
```
columns = ['MSSubClass', 'MSZoning', 'LotArea','LotFrontage', 'LotShape',␣
 ↪'Street','SaleCondition', 'OverallQual', 'YearBuilt', 'YearRemodAdd',␣
 ↪'MasVnrArea', 'BsmtFinSF1', 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF',␣
 ↪'GrLivArea', 'FullBath', 'HalfBath', 'GarageYrBlt', 'GarageCars',␣
 ↪'GarageArea', 'WoodDeckSF', 'OpenPorchSF', 'SalePrice']
```

[ ]:
```
house_df[columns].head()
```

[ ]:
```
   MSSubClass MSZoning  LotArea  LotFrontage LotShape Street SaleCondition  \
0          60       RL     8450         65.0      Reg   Pave        Normal
1          20       RL     9600         80.0      Reg   Pave        Normal
2          60       RL    11250         68.0      IR1   Pave        Normal
3          70       RL     9550         60.0      IR1   Pave       Abnorml
4          60       RL    14260         84.0      IR1   Pave        Normal

   OverallQual  YearBuilt  YearRemodAdd  …  2ndFlrSF  GrLivArea  FullBath  \
0            7       2003          2003  …       854       1710         2
1            6       1976          1976  …         0       1262         2
2            7       2001          2002  …       866       1786         2
3            7       1915          1970  …       756       1717         1
4            8       2000          2000  …      1053       2198         2

   HalfBath  GarageYrBlt  GarageCars  GarageArea  WoodDeckSF  OpenPorchSF  \
0         1       2003.0           2         548           0           61
1         0       1976.0           2         460         298            0
2         1       2001.0           2         608           0           42
3         0       1998.0           3         642           0           35
```

```
4         1       2000.0           3         836         192           84

   SalePrice
0     208500
1     181500
2     223500
3     140000
4     250000

[5 rows x 24 columns]
```

[ ]:

```
house_df[columns].isna().sum()
```

[ ]:

```
MSSubClass         0
MSZoning           0
LotArea            0
LotFrontage      259
LotShape           0
Street             0
SaleCondition      0
OverallQual        0
YearBuilt          0
YearRemodAdd       0
MasVnrArea         8
BsmtFinSF1         0
TotalBsmtSF        0
1stFlrSF           0
2ndFlrSF           0
GrLivArea          0
FullBath           0
HalfBath           0
GarageYrBlt       81
GarageCars         0
GarageArea         0
WoodDeckSF         0
OpenPorchSF        0
SalePrice          0
dtype: int64
```

[ ]:

```
null_cols = ['LotFrontage', 'GarageYrBlt', 'MasVnrArea']

for col in null_cols:
    house_df[col].fillna(house_df[col].mean(), inplace=True)
```

```
<ipython-input-79-caa3c8083d9b>:4: FutureWarning: A value is trying to be set on
a copy of a DataFrame or Series through chained assignment using an inplace
method.
The behavior will change in pandas 3.0. This inplace method will never work
```

```
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  house_df[col].fillna(house_df[col].mean(), inplace=True)
```

[ ]:
```
house_df[columns].isna().sum()
```

[ ]:
```
MSSubClass       0
MSZoning         0
LotArea          0
LotFrontage      0
LotShape         0
Street           0
SaleCondition    0
OverallQual      0
YearBuilt        0
YearRemodAdd     0
MasVnrArea       0
BsmtFinSF1       0
TotalBsmtSF      0
1stFlrSF         0
2ndFlrSF         0
GrLivArea        0
FullBath         0
HalfBath         0
GarageYrBlt      0
GarageCars       0
GarageArea       0
WoodDeckSF       0
OpenPorchSF      0
SalePrice        0
dtype: int64
```

[ ]:
```
X = house_df[['MSSubClass', 'MSZoning', 'LotArea','LotFrontage', 'LotShape',␣
 ↪'Street','SaleCondition', 'OverallQual', 'YearBuilt', 'YearRemodAdd',␣
 ↪'MasVnrArea', 'BsmtFinSF1', 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF',␣
 ↪'GrLivArea', 'FullBath', 'HalfBath', 'GarageYrBlt', 'GarageCars',␣
 ↪'GarageArea', 'WoodDeckSF', 'OpenPorchSF']]
Y = house_df['SalePrice']
```

[ ]:
```
X
```

```
[ ]:       MSSubClass MSZoning  LotArea  LotFrontage LotShape Street SaleCondition  \
     0             60       RL     8450         65.0      Reg   Pave        Normal
     1             20       RL     9600         80.0      Reg   Pave        Normal
     2             60       RL    11250         68.0      IR1   Pave        Normal
     3             70       RL     9550         60.0      IR1   Pave       Abnorml
     4             60       RL    14260         84.0      IR1   Pave        Normal
     …          …      …      …          …      …    …           …
     1455          60       RL     7917         62.0      Reg   Pave        Normal
     1456          20       RL    13175         85.0      Reg   Pave        Normal
     1457          70       RL     9042         66.0      Reg   Pave        Normal
     1458          20       RL     9717         68.0      Reg   Pave        Normal
     1459          20       RL     9937         75.0      Reg   Pave        Normal

           OverallQual  YearBuilt  YearRemodAdd  …  1stFlrSF  2ndFlrSF  \
     0               7       2003          2003  …       856       854
     1               6       1976          1976  …      1262         0
     2               7       2001          2002  …       920       866
     3               7       1915          1970  …       961       756
     4               8       2000          2000  …      1145      1053
     …           …        …           …  …       …       …
     1455            6       1999          2000  …       953       694
     1456            6       1978          1988  …      2073         0
     1457            7       1941          2006  …      1188      1152
     1458            5       1950          1996  …      1078         0
     1459            5       1965          1965  …      1256         0

           GrLivArea  FullBath  HalfBath  GarageYrBlt  GarageCars  GarageArea  \
     0          1710         2         1       2003.0           2         548
     1          1262         2         0       1976.0           2         460
     2          1786         2         1       2001.0           2         608
     3          1717         1         0       1998.0           3         642
     4          2198         2         1       2000.0           3         836
     …         …       …       …          …         …         …
     1455       1647         2         1       1999.0           2         460
     1456       2073         2         0       1978.0           2         500
     1457       2340         2         0       1941.0           1         252
     1458       1078         1         0       1950.0           1         240
     1459       1256         1         1       1965.0           1         276

           WoodDeckSF  OpenPorchSF
     0              0           61
     1            298            0
     2              0           42
     3              0           35
     4            192           84
     …          …          …
     1455           0           40
```

```
1456        349            0
1457          0           60
1458        366            0
1459        736           68

[1460 rows x 23 columns]
```

[ ]:

```
X.isna().sum()
```

[ ]:

```
MSSubClass       0
MSZoning         0
LotArea          0
LotFrontage      0
LotShape         0
Street           0
SaleCondition    0
OverallQual      0
YearBuilt        0
YearRemodAdd     0
MasVnrArea       0
BsmtFinSF1       0
TotalBsmtSF      0
1stFlrSF         0
2ndFlrSF         0
GrLivArea        0
FullBath         0
HalfBath         0
GarageYrBlt      0
GarageCars       0
GarageArea       0
WoodDeckSF       0
OpenPorchSF      0
dtype: int64
```

[ ]:

```
import matplotlib.pyplot as plt
```

[ ]:

```
import seaborn as sns
```

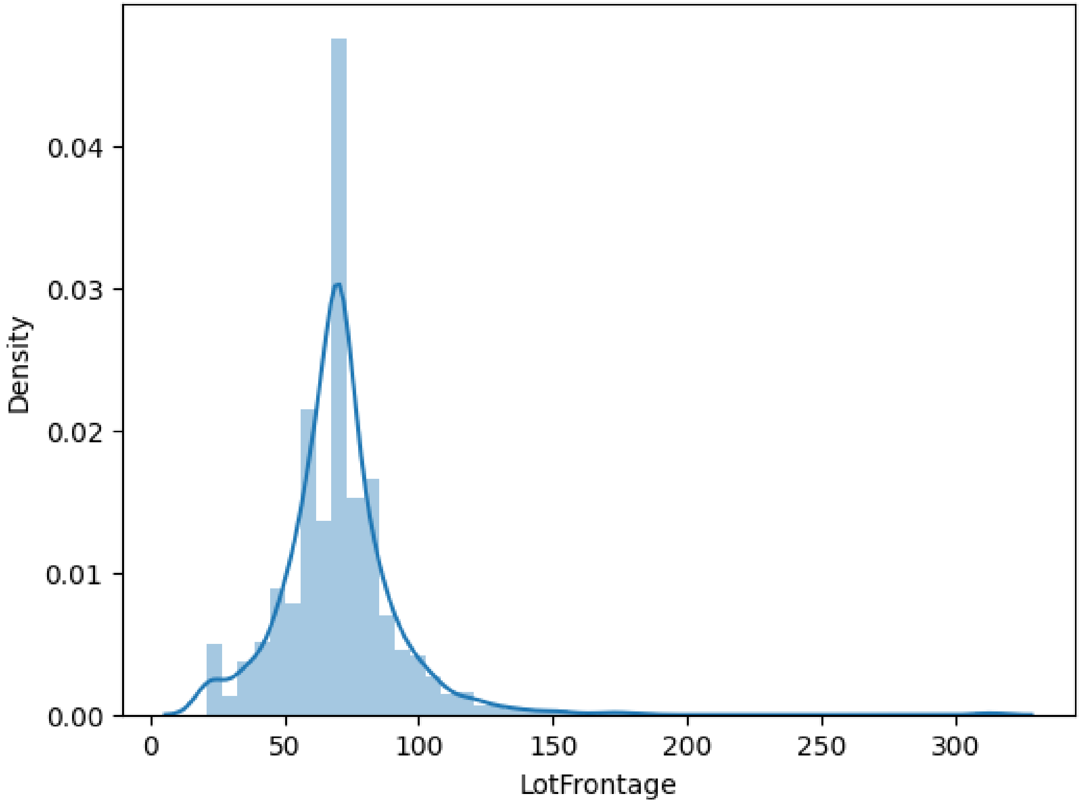
[ ]:

```
sns.distplot(X['LotFrontage']) #only works for old version of seaborn use␣
  ↪different method histplot/kdeplot
```

```
<ipython-input-86-e9dcc26ed7ac>:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).
```

```
For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(X['LotFrontage']) #only works for old version of seaborn use
different method histplot/kdeplot
```

[ ]:
```
<Axes: xlabel='LotFrontage', ylabel='Density'>
```



[ ]:
```
median_lotfrontage = X['LotFrontage'].median()
```

[ ]:
```
median_lotfrontage
```

[ ]:
```
70.04995836802665
```

[ ]:
```
X['LotFrontage'].fillna(median_lotfrontage,inplace=True)
```

```
<ipython-input-89-ca9726a0c5bd>:1: FutureWarning: A value is trying to be set on
a copy of a DataFrame or Series through chained assignment using an inplace
method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.
```

```
For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  X['LotFrontage'].fillna(median_lotfrontage,inplace=True)
<ipython-input-89-ca9726a0c5bd>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  X['LotFrontage'].fillna(median_lotfrontage,inplace=True)
```

```
[ ]: X.isna().sum()
```

```
[ ]: MSSubClass       0
     MSZoning         0
     LotArea          0
     LotFrontage      0
     LotShape         0
     Street           0
     SaleCondition    0
     OverallQual      0
     YearBuilt        0
     YearRemodAdd     0
     MasVnrArea       0
     BsmtFinSF1       0
     TotalBsmtSF      0
     1stFlrSF         0
     2ndFlrSF         0
     GrLivArea        0
     FullBath         0
     HalfBath         0
     GarageYrBlt      0
     GarageCars       0
     GarageArea       0
     WoodDeckSF       0
     OpenPorchSF      0
     dtype: int64
```

0.1.1 In categorical values that needs to be converted to numerical form and

0.1.2 In numerical values scale it down and split it

```
[ ]: from sklearn.model_selection import train_test_split
     from sklearn.preprocessing import StandardScaler
```

```
[ ]: X.dtypes
```

```
[ ]: MSSubClass         int64
     MSZoning          object
     LotArea            int64
     LotFrontage      float64
     LotShape          object
     Street            object
     SaleCondition     object
     OverallQual        int64
     YearBuilt          int64
     YearRemodAdd       int64
     MasVnrArea       float64
     BsmtFinSF1         int64
     TotalBsmtSF        int64
     1stFlrSF           int64
     2ndFlrSF           int64
     GrLivArea          int64
     FullBath           int64
     HalfBath           int64
     GarageYrBlt      float64
     GarageCars         int64
     GarageArea         int64
     WoodDeckSF         int64
     OpenPorchSF        int64
     dtype: object
```

```
[ ]: scaler = StandardScaler()
```

```
[ ]: numerical_columns = ['MSSubClass', 'LotArea','LotFrontage', 'OverallQual',␣
      ↪'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'BsmtFinSF1', 'TotalBsmtSF',␣
      ↪'1stFlrSF', '2ndFlrSF', 'GrLivArea', 'FullBath', 'HalfBath', 'GarageYrBlt',␣
      ↪'GarageCars', 'GarageArea', 'WoodDeckSF', 'OpenPorchSF']
     categorical_columns = ['MSZoning', 'LotShape', 'Street','SaleCondition']
```

```
[ ]: X[numerical_columns] = scaler.fit_transform(X[numerical_columns])
```

```
<ipython-input-95-cb7cdb47f1f9>: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
  X[numerical_columns] = scaler.fit_transform(X[numerical_columns])
```

```
[ ]: X['MSZoning'].unique()
```

```
[ ]: array(['RL', 'RM', 'C (all)', 'FV', 'RH'], dtype=object)
[ ]: X['LotShape'].unique()
```

```
[ ]: array(['Reg', 'IR1', 'IR2', 'IR3'], dtype=object)
```

```
[ ]: X['Street'].unique()
```

```
[ ]: array(['Pave', 'Grvl'], dtype=object)
```

```
[ ]: X['SaleCondition'].unique()
```

```
[ ]: array(['Normal', 'Abnorml', 'Partial', 'AdjLand', 'Alloca', 'Family'],
           dtype=object)
```

```
[ ]: encoded_value = pd.get_dummies(X[categorical_columns], sparse=False).
      ↪astype(int) #Alternative way to one hot encode categorical values
```

```
[ ]: X = pd.concat([X, encoded_value],axis=1)
```

```
[ ]: X.drop(columns=categorical_columns,inplace=True)
```

```
[ ]: X_train, X_test, y_train, y_test = train_test_split(X,Y,train_size=0.8)
```

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

```
[ ]: ((1168, 36), (292, 36), (1460, 36))
```

0.2 Define model for evaluation

```
[ ]: from sklearn.linear_model import LinearRegression
     from sklearn.ensemble import RandomForestRegressor
```

```
[ ]: linear = LinearRegression()
     random_forest = RandomForestRegressor()
```

```
[ ]: from sklearn.model_selection import KFold, cross_val_score
```

```
[ ]: algorithms = [linear, random_forest]
```

```
[ ]: algorithm_names = ['linear_regression', 'random forest']
```

```
[ ]: kfold = KFold(n_splits=5, shuffle=True)
```

```
[ ]: for i,model in enumerate(algorithms):
         scores = cross_val_score(model, X_train, y_train, cv=kfold,␣
      ↪scoring='neg_mean_squared_error')
         print(f"{algorithm_names[i]} - Score:{scores} - Mean Score{scores.mean()}")
```

```
linear_regression - Score:[-1.02688362e+09 -1.47332768e+09 -2.85422088e+09
-9.47078572e+08
```

```
 -1.50245785e+09] - Mean Score-1560793720.2089233
random forest - Score:[-6.34254723e+08 -1.49475153e+09 -5.53717701e+08
-1.25223134e+09
 -8.05098016e+08] - Mean Score-948010663.7559055
```

```
[ ]: from sklearn.model_selection import GridSearchCV
```

```
[ ]: param_grid = {
         'max_depth':[5,10,15],
         'n_estimators': [5, 6, 7, 8, 9, 10, 11, 12, 13, 15]
     }
```

```
[ ]: grid = GridSearchCV(estimator=random_forest, param_grid=param_grid, cv=kfold,␣
       ↪scoring='neg_mean_squared_error')
```

```
[ ]: grid.fit(X_train, y_train)
```

```
/usr/local/lib/python3.10/dist-packages/numpy/ma/core.py:2820: RuntimeWarning:
invalid value encountered in cast
  _data = np.array(data, dtype=dtype, copy=copy,
```

```
[ ]: GridSearchCV(cv=KFold(n_splits=5, random_state=None, shuffle=True),
                  estimator=RandomForestRegressor(),
                  param_grid={'max_depth': [5, 10, 15],
                              'n_estimators': [5, 6, 7, 8, 9, 10, 11, 12, 13, 15]},
                  scoring='neg_mean_squared_error')
```

```
[ ]: grid.best_params_
```

```
[ ]: {'max_depth': 10, 'n_estimators': 11}
```

```
[ ]: grid.best_score_
```

```
[ ]: -952854163.2083702
```

```
[ ]: yhat = grid.predict(X_test)
```

```
[ ]: from sklearn.metrics import mean_squared_error
```

```
[ ]: mean_squared_error(y_test, yhat)
```

```
[ ]: 674499445.7271372
```

```
[ ]: rf = grid.best_estimator_
```

```
[ ]: rf.feature_importances_
```

```
[ ]: array([2.23487517e-03, 1.63126416e-02, 7.86446822e-03, 5.65746555e-01,
            1.10634195e-02, 1.39303711e-02, 5.68856760e-03, 2.83416752e-02,
       3.84127177e-02, 2.46239340e-02, 5.42631552e-02, 1.09831676e-01,
       1.29365578e-03, 1.02920292e-03, 6.54701874e-03, 2.67570357e-02,
       5.95508356e-02, 8.16524694e-03, 8.34737969e-03, 4.72864434e-04,
       2.88807749e-04, 4.97098318e-05, 1.18677436e-03, 2.61996939e-03,
       3.86548875e-04, 1.61504808e-04, 7.48374244e-06, 1.08429694e-03,
       1.38070688e-05, 1.20365826e-06, 6.12056197e-04, 0.00000000e+00,
       2.26699342e-05, 1.12559084e-03, 1.17657771e-03, 7.85702989e-04])
```

[ ]:

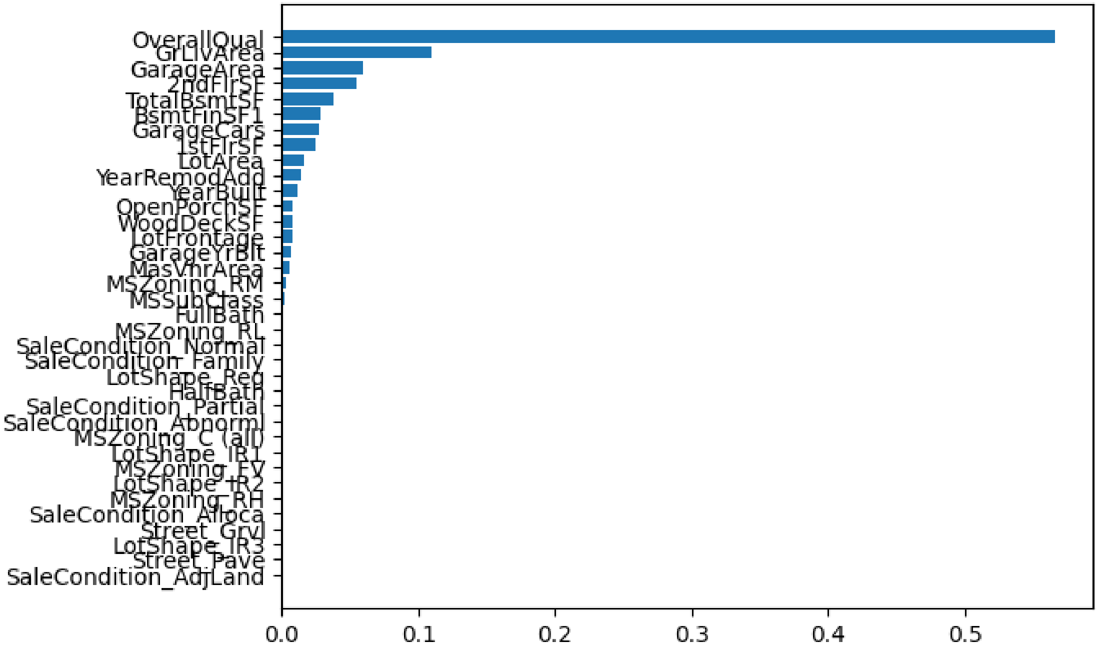
```python
sorted_idx = rf.feature_importances_.argsort()
```

[ ]:

```python
plt.barh(X.columns[sorted_idx], rf.feature_importances_[sorted_idx])
```

[ ]:

```
<BarContainer object of 36 artists>
```



1 Replicate this in LeaveOneOut

[ ]:

```python
# Code here
from sklearn.model_selection import LeaveOneOut

loo = LeaveOneOut()

random_forest = RandomForestRegressor()

param_grid = {
    'max_depth': [5, 10],
    'n_estimators': [5, 10, 15]
}

grid = GridSearchCV(estimator=random_forest, param_grid=param_grid, cv=loo,␣
 ↪scoring='neg_mean_squared_error')
```

```
[ ]: grid.fit(X_train, y_train)
```

```
[ ]: GridSearchCV(cv=LeaveOneOut(), estimator=RandomForestRegressor(),
                  param_grid={'max_depth': [5, 10], 'n_estimators': [5, 10, 15]},
                  scoring='neg_mean_squared_error')
```

```
[ ]: print(grid.best_params_)
     print(grid.best_score_)

     yhat = grid.predict(X_test)
     mean_squared_error(y_test, yhat)
```

```
{'max_depth': 10, 'n_estimators': 10}
-993319189.5942743
```

```
[ ]: 789141213.2074965
```

2 Analyze

Analyze here the difference between the two and possible reasons why they are different:

The K-Fold took a minute with gridsearchcv to find best model parameters, while LeaveOneOut was taking a lot of time, thats why I reduced the number of param_grid parameters

LOO is an extreme case of KFold where k equals the number of samples in the dataset. Each sample is used as the test set exactly once, while the rest of the dataset (all other samples) is used for training.

KFold often has a balance between bias and variance, especially with a reasonably chosen value for k (like 5 or 10), while LOO gives a very low-bias estimate (since the model is almost always trained on the entire dataset), can suffer from high variance, meaning that test errors can fluctuate significantly between iterations, especially on noisy data.

It is recommended to use LOO when the dataset is small, since leaving out one sample at a time doesn't lose too much information, and the higher variance can be tolerable.

Experiment with types of K-Fold cross-validations.

```
[ ]: #Code here
     from sklearn.model_selection import GridSearchCV, RepeatedKFold
     from sklearn.ensemble import RandomForestRegressor

     repeated_kfold = RepeatedKFold(n_splits=5, n_repeats=3, random_state=42)
```

```
param_grid = {
    'max_depth': [5, 10, 15],
    'n_estimators': [50, 100, 200]
}

model = RandomForestRegressor()

grid = GridSearchCV(estimator=model, param_grid=param_grid, cv=repeated_kfold,␣
 ↪scoring='neg_mean_squared_error')

grid.fit(X_train, y_train)

print("Best parameters:", grid.best_params_)

print("Best score:", grid.best_score_)
yhat = grid.predict(X_test)
mean_squared_error(y_test, yhat)
```

```
Best parameters: {'max_depth': 15, 'n_estimators': 200}
Best score: -1021803092.167171
```

```
[ ]: 650606371.9831071
```

```
[ ]: from sklearn.model_selection import GridSearchCV, TimeSeriesSplit
from sklearn.ensemble import RandomForestRegressor

tscv = TimeSeriesSplit(n_splits=5)

param_grid = {
    'max_depth': [5, 10, 15],
    'n_estimators': [50, 100, 200]
}

model = RandomForestRegressor()

grid = GridSearchCV(estimator=model, param_grid=param_grid, cv=tscv,␣
 ↪scoring='neg_mean_squared_error')

grid.fit(X_train, y_train)

print("Best parameters:", grid.best_params_)
print(grid.best_score_)

yhat = grid.predict(X_test)
mean_squared_error(y_test, yhat)
```

```
Best parameters: {'max_depth': 10, 'n_estimators': 100}
```

```
-1169338831.673592
```

[ ]:
```
665601982.8576424
```

2.1 Model this in Linear Regression (Conduct Grid Search for Ridge, Lasso)

[ ]:
```python
#Code here
from sklearn.linear_model import Ridge, Lasso
from sklearn.datasets import make_regression

ridge_param_grid = {
    'alpha': np.logspace(-3, 3, 7)  # Regularization strength
}

ridge_model = Ridge()

kfold = KFold(n_splits=5, shuffle=True, random_state=42)

ridge_grid = GridSearchCV(estimator=ridge_model, param_grid=ridge_param_grid,
                          cv=kfold, scoring='neg_mean_squared_error')

ridge_grid.fit(X_train, y_train)

print("Best parameters for Ridge:", ridge_grid.best_params_)
print("Best score for Ridge:", ridge_grid.best_score_)

print("SCORE: ", ridge_grid.score(X_test, y_test))
```

```
Best parameters for Ridge: {'alpha': 100.0}
Best score for Ridge: -1606732817.4639132
SCORE:  -938248170.5369987
```

[ ]:
```python
lasso_param_grid = {
    'alpha': np.logspace(-3, 3, 7)  # Regularization strength
}

lasso_model = Lasso()

lasso_grid = GridSearchCV(estimator=lasso_model, param_grid=lasso_param_grid,
                          cv=kfold, scoring='neg_mean_squared_error')

lasso_grid.fit(X_train, y_train)

print("Best parameters for Lasso:", lasso_grid.best_params_)
print("Best score for Lasso:", lasso_grid.best_score_)
print("SCORE: ", lasso_grid.score(X_test, y_test))
```

```
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
```

```
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 5.551e+11, tolerance: 5.429e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 5.065e+11, tolerance: 6.293e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 5.509e+11, tolerance: 5.749e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 5.798e+11, tolerance: 6.364e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 6.053e+11, tolerance: 6.045e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 5.177e+11, tolerance: 5.429e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 3.929e+11, tolerance: 6.293e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 3.626e+11, tolerance: 5.749e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
```

```
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 4.512e+11, tolerance: 6.364e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 5.741e+11, tolerance: 6.045e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.020e+11, tolerance: 5.429e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 4.292e+10, tolerance: 5.749e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 2.519e+09, tolerance: 6.364e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 2.269e+11, tolerance: 6.045e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 6.952e+08, tolerance: 5.749e+08
  model = cd_fast.enet_coordinate_descent(
```

```
Best parameters for Lasso: {'alpha': 1000.0}
Best score for Lasso: -1599765745.3049054
SCORE:  -966231868.7686061
```

Analyze and state the difference with the two (if any)

Analyze here: Ridge:

- Best suited for scenarios where all features are believed to contribute to the outcome, and there is multicollinearity among the features. For example, in cases like image processing or when dealing with polynomial regression.

Lasso:

- More effective in situations where feature selection is needed. It is beneficial when the model needs to be interpretable, or when you suspect that many features are irrelevant

Ridge and Lasso regression are valuable tools in the machine learning toolbox, each with its unique strengths. The choice between them often depends on the specific characteristics of the dataset and the goals of the analysis:

- Use Ridge when wee believe all features should contribute to the prediction, especially in the presence of multicollinearity.
- Use Lasso when we want to reduce the number of features by eliminating less important ones, leading to a simpler and more interpretable model.

2.2 Try Lasso/ Ridge with a polynomial Feature

[ ]:

```python
from sklearn.preprocessing import PolynomialFeatures

poly = PolynomialFeatures(degree=2)
X_train_poly = poly.fit_transform(X_train)
X_test_poly = poly.transform(X_test)

ridge_param_grid = {
    'alpha': np.logspace(-3, 3, 7)  # Regularization strength
}

ridge_model = Ridge()

kfold = KFold(n_splits=5, shuffle=True, random_state=42)

ridge_grid = GridSearchCV(estimator=ridge_model, param_grid=ridge_param_grid,
                          cv=kfold, scoring='neg_mean_squared_error')

ridge_grid.fit(X_train_poly, y_train)

print("Best parameters for Ridge:", ridge_grid.best_params_)
print("Best score for Ridge:", ridge_grid.best_score_)

print("SCORE: ", ridge_grid.score(X_test_poly, y_test))
```

```
Best parameters for Ridge: {'alpha': 1000.0}
Best score for Ridge: -1270653031.4742155
SCORE:  -640853884.7209431
```

[ ]:

```python
lasso_param_grid = {
    'alpha': np.logspace(-3, 3, 7)  # Regularization strength
}
```

```
lasso_model = Lasso()

lasso_grid = GridSearchCV(estimator=lasso_model, param_grid=lasso_param_grid,
                          cv=kfold, scoring='neg_mean_squared_error')

lasso_grid.fit(X_train_poly, y_train)

print("Best parameters for Lasso:", lasso_grid.best_params_)
print("Best score for Lasso:", lasso_grid.best_score_)
print("SCORE: ", lasso_grid.score(X_test_poly, y_test))
```

```
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.295e+11, tolerance: 5.429e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.364e+11, tolerance: 6.293e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.267e+11, tolerance: 5.749e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.142e+11, tolerance: 6.364e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.356e+11, tolerance: 6.045e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.295e+11, tolerance: 5.429e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.365e+11, tolerance: 6.293e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.267e+11, tolerance: 5.749e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.143e+11, tolerance: 6.364e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.356e+11, tolerance: 6.045e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.299e+11, tolerance: 5.429e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.368e+11, tolerance: 6.293e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.266e+11, tolerance: 5.749e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.149e+11, tolerance: 6.364e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.357e+11, tolerance: 6.045e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.311e+11, tolerance: 5.429e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.393e+11, tolerance: 6.293e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.287e+11, tolerance: 5.749e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.183e+11, tolerance: 6.364e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.369e+11, tolerance: 6.045e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 9.984e+10, tolerance: 5.429e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.456e+11, tolerance: 6.293e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.193e+11, tolerance: 5.749e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.289e+11, tolerance: 6.364e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.406e+11, tolerance: 6.045e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.052e+10, tolerance: 5.429e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.150e+10, tolerance: 6.293e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 2.884e+10, tolerance: 5.749e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.207e+10, tolerance: 6.364e+08
  model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 2.990e+10, tolerance: 6.045e+08
  model = cd_fast.enet_coordinate_descent(
Best parameters for Lasso: {'alpha': 1000.0}
Best score for Lasso: -1212745280.7858984
SCORE:  -648673265.3379784
```

Analyze and state the difference with the model with/out poolynomial feature

:Analyze here..

Incorporating polynomial features into regression models can significantly improve their ability to capture complex relationships within the data. However, it also introduces challenges related to overfitting, model complexity, and interpretability.

Choosing the Right Model: - The decision to use polynomial features should be based on a thorough understanding of the data, its relationships, and the specific goals of the modeling task. - Cross-validation and evaluation metrics should guide the decision, ensuring the selected model generalizes well to unseen data.