Machine_Learning_Project (Jaeha Huh)

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Independent project : Supervised learning

Predicting the price of a house price

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[1]:
```
import numpy as np
import matplotlib.pyplot as plt  # A library for representing multiple data in␣
↪a two-dimensional coordinate system
import seaborn as sns    # statistical data visualization
color = sns.color_palette()
from scipy.stats import norm, skew # A library for standard continuous/
↪differential probability distribution and various statistical tests.
from scipy import stats
import warnings
warnings.filterwarnings(action = 'ignore') # turn off the warning
import pandas as pd
from sklearn.model_selection import train_test_split # for dividing the␣
↪training and test set
from sklearn.linear_model import RidgeCV
from sklearn.neural_network import MLPRegressor
from xgboost import XGBRegressor
from sklearn import metrics  # A library for result
from sklearn.preprocessing import MinMaxScaler   # normalization tool
pd.options.display.max_rows = 4000   # Set the setting value to 4,000 to see␣
↪the entire result

#Code that allows you to see the graph directly from the browser that ran␣
↪jupyter notebook.
%matplotlib inline
```

1. Project Goal

- **The goal of the project is to divide the dataset into a training set and a test set, and predict housing prices using a supervised machine learning models with given features.**

2. Data Set

- **The dataset has a total of 81 features and includes factors used to evaluate the** house, such as street, house size, building type, house condition, number of toilets, etc. The description of each column is written below.

[2]:
```
db = pd.read_csv('housing.csv')
db.head(15)
```

[2]:
```
    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
5    6          50       RL         85.0    14115   Pave   NaN      IR1
6    7          20       RL         75.0    10084   Pave   NaN      Reg
7    8          60       RL          NaN    10382   Pave   NaN      IR1
8    9          50       RM         51.0     6120   Pave   NaN      Reg
9   10         190       RL         50.0     7420   Pave   NaN      Reg
10  11          20       RL         70.0    11200   Pave   NaN      Reg
11  12          60       RL         85.0    11924   Pave   NaN      IR1
12  13          20       RL          NaN    12968   Pave   NaN      IR2
13  14          20       RL         91.0    10652   Pave   NaN      IR1
14  15          20       RL          NaN    10920   Pave   NaN      IR1

   LandContour Utilities  … PoolArea PoolQC  Fence MiscFeature MiscVal  \
0          Lvl    AllPub  …        0    NaN    NaN         NaN       0
1          Lvl    AllPub  …        0    NaN    NaN         NaN       0
2          Lvl    AllPub  …        0    NaN    NaN         NaN       0
3          Lvl    AllPub  …        0    NaN    NaN         NaN       0
4          Lvl    AllPub  …        0    NaN    NaN         NaN       0
5          Lvl    AllPub  …        0    NaN  MnPrv        Shed     700
6          Lvl    AllPub  …        0    NaN    NaN         NaN       0
7          Lvl    AllPub  …        0    NaN    NaN        Shed     350
8          Lvl    AllPub  …        0    NaN    NaN         NaN       0
9          Lvl    AllPub  …        0    NaN    NaN         NaN       0
10         Lvl    AllPub  …        0    NaN    NaN         NaN       0
11         Lvl    AllPub  …        0    NaN    NaN         NaN       0
12         Lvl    AllPub  …        0    NaN    NaN         NaN       0
13         Lvl    AllPub  …        0    NaN    NaN         NaN       0
14         Lvl    AllPub  …        0    NaN   GdWo         NaN       0

   MoSold YrSold  SaleType  SaleCondition  SalePrice
0       2   2008        WD         Normal     208500
1       5   2007        WD         Normal     181500
2       9   2008        WD         Normal     223500
3       2   2006        WD        Abnorml     140000
4      12   2008        WD         Normal     250000
5      10   2009        WD         Normal     143000
```

```
6       8   2007         WD         Normal     307000
7      11   2009         WD         Normal     200000
8       4   2008         WD        Abnorml     129900
9       1   2008         WD         Normal     118000
10      2   2008         WD         Normal     129500
11      7   2006        New        Partial     345000
12      9   2008         WD         Normal     144000
13      8   2007        New        Partial     279500
14      5   2008         WD         Normal     157000

[15 rows x 81 columns]
```

- Column information

SalePrice - the property's sale price in dollars. This is the target variable that you're trying to predict.

MSSubClass: The building class

MSZoning: The general zoning classification

LotFrontage: Linear feet of street connected to property

LotArea: Lot size in square feet

Street: Type of road access

Alley: Type of alley access

LotShape: General shape of property

LandContour: Flatness of the property

Utilities: Type of utilities available

LotConfig: Lot configuration

LandSlope: Slope of property

Neighborhood: Physical locations within Ames city limits

Condition1: Proximity to main road or railroad

Condition2: Proximity to main road or railroad (if a second is present)

BldgType: Type of dwelling

HouseStyle: Style of dwelling

OverallQual: Overall material and finish quality

OverallCond: Overall condition rating

YearBuilt: Original construction date

YearRemodAdd: Remodel date

RoofStyle: Type of roof

RoofMatl: Roof material

Exterior1st: Exterior covering on house

Exterior2nd: Exterior covering on house (if more than one material)

MasVnrType: Masonry veneer type

MasVnrArea: Masonry veneer area in square feet

ExterQual: Exterior material quality

ExterCond: Present condition of the material on the exterior

Foundation: Type of foundation

BsmtQual: Height of the basement

BsmtCond: General condition of the basement

BsmtExposure: Walkout or garden level basement walls

BsmtFinType1: Quality of basement finished area

BsmtFinSF1: Type 1 finished square feet

BsmtFinType2: Quality of second finished area (if present)

BsmtFinSF2: Type 2 finished square feet

BsmtUnfSF: Unfinished square feet of basement area

TotalBsmtSF: Total square feet of basement area

Heating: Type of heating

HeatingQC: Heating quality and condition

CentralAir: Central air conditioning

Electrical: Electrical system

1stFlrSF: First Floor square feet

2ndFlrSF: Second floor square feet

LowQualFinSF: Low quality finished square feet (all floors)

GrLivArea: Above grade (ground) living area square feet

BsmtFullBath: Basement full bathrooms

BsmtHalfBath: Basement half bathrooms

FullBath: Full bathrooms above grade

HalfBath: Half baths above grade

Bedroom: Number of bedrooms above basement level

Kitchen: Number of kitchens

KitchenQual: Kitchen quality

TotRmsAbvGrd: Total rooms above grade (does not include bathrooms)

Functional: Home functionality rating

Fireplaces: Number of fireplaces

FireplaceQu: Fireplace quality

GarageType: Garage location

GarageYrBlt: Year garage was built

GarageFinish: Interior finish of the garage

GarageCars: Size of garage in car capacity

GarageArea: Size of garage in square feet

GarageQual: Garage quality

GarageCond: Garage condition

PavedDrive: Paved driveway

WoodDeckSF: Wood deck area in square feet

OpenPorchSF: Open porch area in square feet

EnclosedPorch: Enclosed porch area in square feet

3SsnPorch: Three season porch area in square feet

ScreenPorch: Screen porch area in square feet

PoolArea: Pool area in square feet

PoolQC: Pool quality

Fence: Fence quality

MiscFeature: Miscellaneous feature not covered in other categories

MiscVal: $Value of miscellaneous feature

MoSold: Month Sold

YrSold: Year Sold

SaleType: Type of sale

SaleCondition: Condition of sale

3. Data Structure

- **Columns were divided into nominal_vars, ranking_vars, and continue_vars, respectively. In the case of ranking_vars, the values are strings, and each value is a column representing a ranking or step. In the case of continue_vars, the values are columns that are numeric columns. Columns that do not fall under these two were included in nominal_vars.**

[3]:
```
# nominal vars
nominal_vars = [
    'MSZoning', 'LandContour', 'Utilities',
    'LotConfig', 'Neighborhood', 'Condition1', 'Condition2', 'BldgType',
    'HouseStyle', 'RoofStyle', 'RoofMatl', 'Exterior1st',
    'Exterior2nd', 'MasVnrType', 'Foundation', 'Heating', 'Electrical',
    'GarageType', 'MiscFeature',
    'SaleType', 'SaleCondition'
]
```

[4]:
```
# ranking vars
ranking_vars = [
    'OverallCond', 'ExterQual', 'ExterCond', 'BsmtQual', 'BsmtCond',
    'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2', 'HeatingQC', 'KitchenQual',
    'FireplaceQu', 'GarageQual', 'GarageCond', 'PoolQC', 'Fence', 'Street',␣
↪'Alley',
    'LandSlope', 'Functional', 'GarageFinish', 'MoSold', 'YrSold', 'PavedDrive',
    'CentralAir', 'LotShape', 'MSSubClass',
]
```

[5]:
```
# continuous vars
continue_vars = [
    'LotFrontage', 'LotArea', 'MasVnrArea', 'BsmtFinSF1', 'BsmtFinSF2',␣
↪'BsmtUnfSF',
    'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF', 'GrLivArea',␣
↪'BsmtFullBath',
    'BsmtHalfBath', 'FullBath', 'HalfBath', 'TotRmsAbvGrd', 'BedroomAbvGr',␣
↪'KitchenAbvGr',
    'Fireplaces', 'GarageCars', 'GarageArea', 'WoodDeckSF', 'OpenPorchSF',␣
↪'EnclosedPorch',
    '3SsnPorch', 'ScreenPorch', 'PoolArea', 'MiscVal', 'GarageYrBlt',␣
↪'YearBuilt', 'YearRemodAdd',
    'OverallQual'
]
```

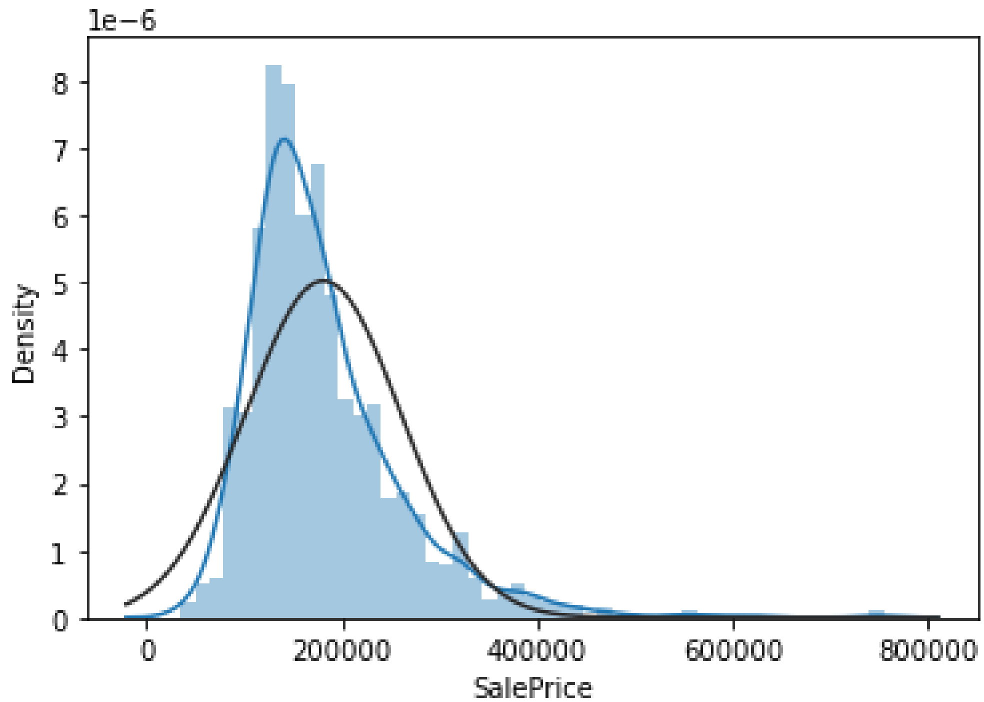
[6]:
```
# Example) As such, continue_vars contains data that are numeric columns.
db[continue_vars].describe()
```

[6]:
```
       LotFrontage       LotArea   MasVnrArea   BsmtFinSF1   BsmtFinSF2  \
count  1201.000000   1460.000000  1452.000000  1460.000000  1460.000000
mean     70.049958  10516.828082   103.685262   443.639726    46.549315
std      24.284752   9981.264932   181.066207   456.098091   161.319273
min      21.000000   1300.000000     0.000000     0.000000     0.000000
25%      59.000000   7553.500000     0.000000     0.000000     0.000000
50%      69.000000   9478.500000     0.000000   383.500000     0.000000
75%      80.000000  11601.500000   166.000000   712.250000     0.000000
```

```
max     313.000000  215245.000000  1600.000000  5644.000000  1474.000000

         BsmtUnfSF  TotalBsmtSF     1stFlrSF     2ndFlrSF  LowQualFinSF  …  \
count  1460.000000  1460.000000  1460.000000  1460.000000   1460.000000  …
mean    567.240411  1057.429452  1162.626712   346.992466      5.844521  …
std     441.866955   438.705324   386.587738   436.528436     48.623081  …
min       0.000000     0.000000   334.000000     0.000000      0.000000  …
25%     223.000000   795.750000   882.000000     0.000000      0.000000  …
50%     477.500000   991.500000  1087.000000     0.000000      0.000000  …
75%     808.000000  1298.250000  1391.250000   728.000000      0.000000  …
max    2336.000000  6110.000000  4692.000000  2065.000000    572.000000  …

       OpenPorchSF  EnclosedPorch    3SsnPorch  ScreenPorch     PoolArea  \
count  1460.000000    1460.000000  1460.000000  1460.000000  1460.000000
mean     46.660274      21.954110     3.409589    15.060959     2.758904
std      66.256028      61.119149    29.317331    55.757415    40.177307
min       0.000000       0.000000     0.000000     0.000000     0.000000
25%       0.000000       0.000000     0.000000     0.000000     0.000000
50%      25.000000       0.000000     0.000000     0.000000     0.000000
75%      68.000000       0.000000     0.000000     0.000000     0.000000
max     547.000000     552.000000   508.000000   480.000000   738.000000

            MiscVal  GarageYrBlt    YearBuilt  YearRemodAdd  OverallQual
count   1460.000000  1379.000000  1460.000000   1460.000000  1460.000000
mean      43.489041  1978.506164  1971.267808   1984.865753     6.099315
std      496.123024    24.689725    30.202904     20.645407     1.382997
min        0.000000  1900.000000  1872.000000   1950.000000     1.000000
25%        0.000000  1961.000000  1954.000000   1967.000000     5.000000
50%        0.000000  1980.000000  1973.000000   1994.000000     6.000000
75%        0.000000  2002.000000  2000.000000   2004.000000     7.000000
max    15500.000000  2010.000000  2010.000000   2010.000000    10.000000

[8 rows x 32 columns]
```

[7]:
```python
# The chart below shows the slope and distribution of house prices.
print(f'skew: {db.SalePrice.skew()}')
sns.distplot(db.SalePrice, fit = norm)
f = plt.figure()
plt.show()
```

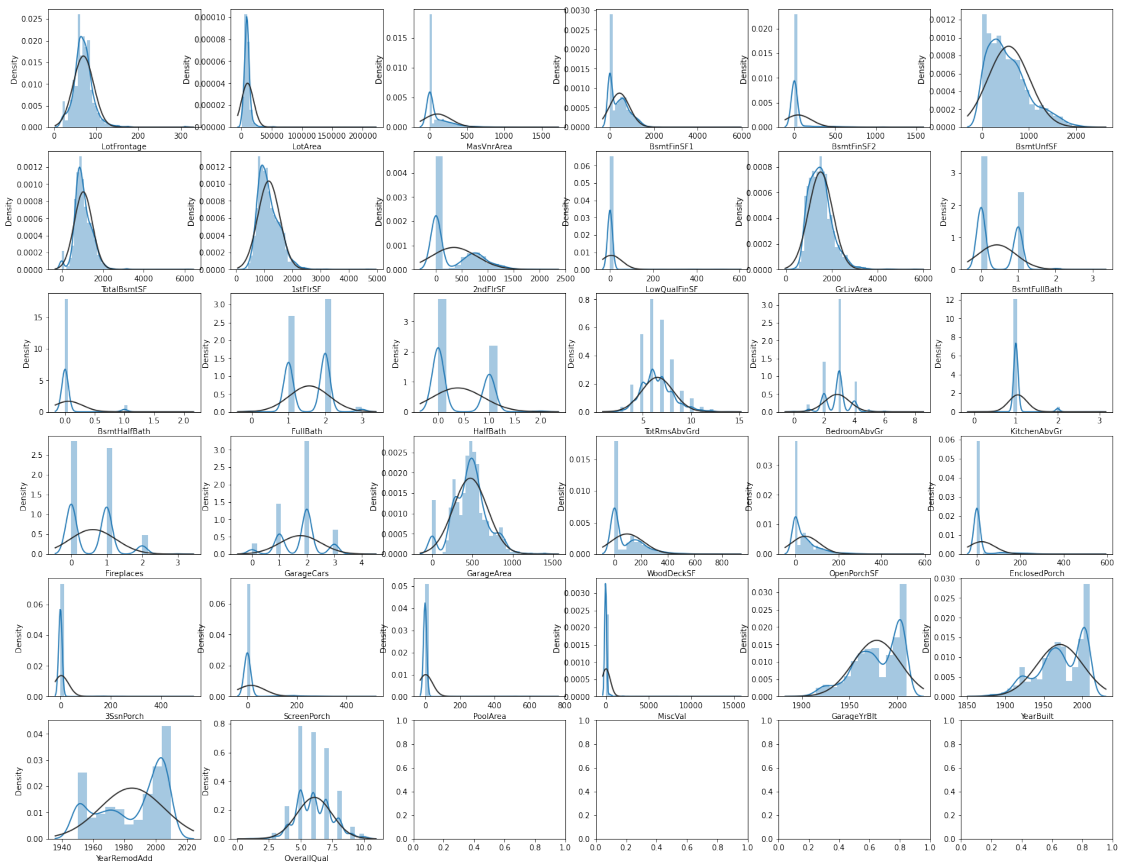
```
skew: 1.8828757597682129
```




```
<Figure size 432x288 with 0 Axes>
```

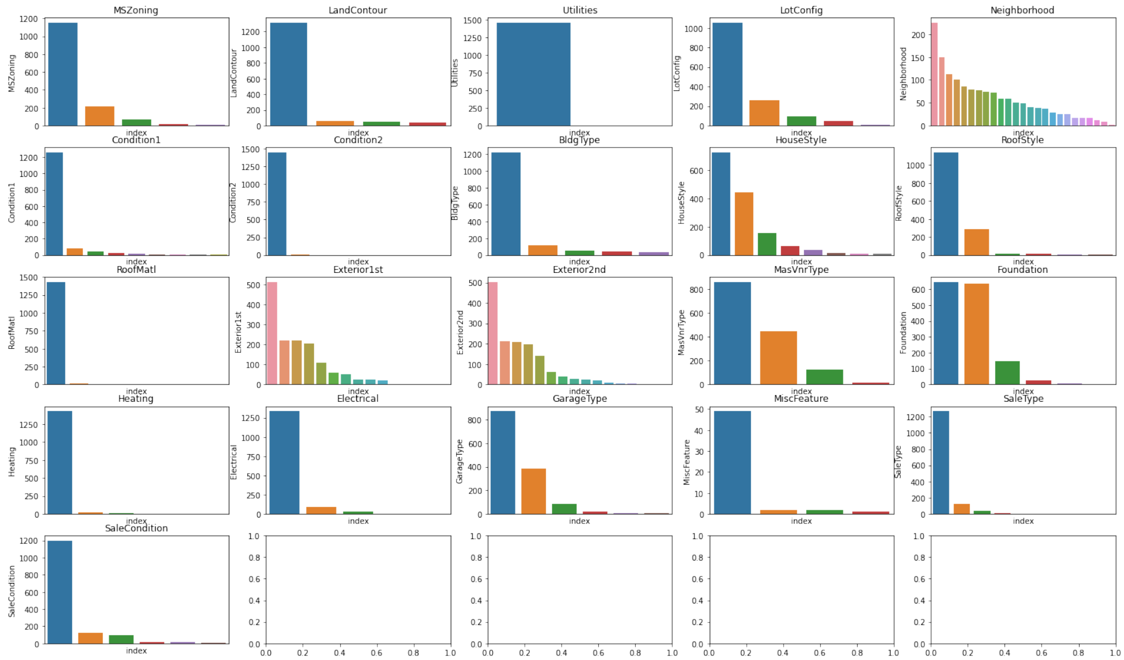
- **House prices are generally in the 200,000 dollars range, with outliers ranging from 34,900 dollars to 755,000 dollars.**

[8]:
```
f, ax = plt.subplots(6, 6, figsize = (25, 20))
for i, c in enumerate(continue_vars):
    sns.distplot(db[c], fit = stats.norm, ax = ax[i//6, i%6])
```



- **The above charts are charts showing the distribution of each column of continue_vars. Each chart shows a variety of distributions from dense to irregularly distributed columns.**

[9]:
```
f, ax = plt.subplots(5, 5, figsize = (25, 15))
for i, c in enumerate(nominal_vars):
    g = sns.barplot(data = pd.DataFrame(db[c].value_counts()).reset_index(),␣
 ↪x='index', y = c, ax = ax[i//5, i%5])
    g.set(xticks = [])
    g.set(title = c)
```

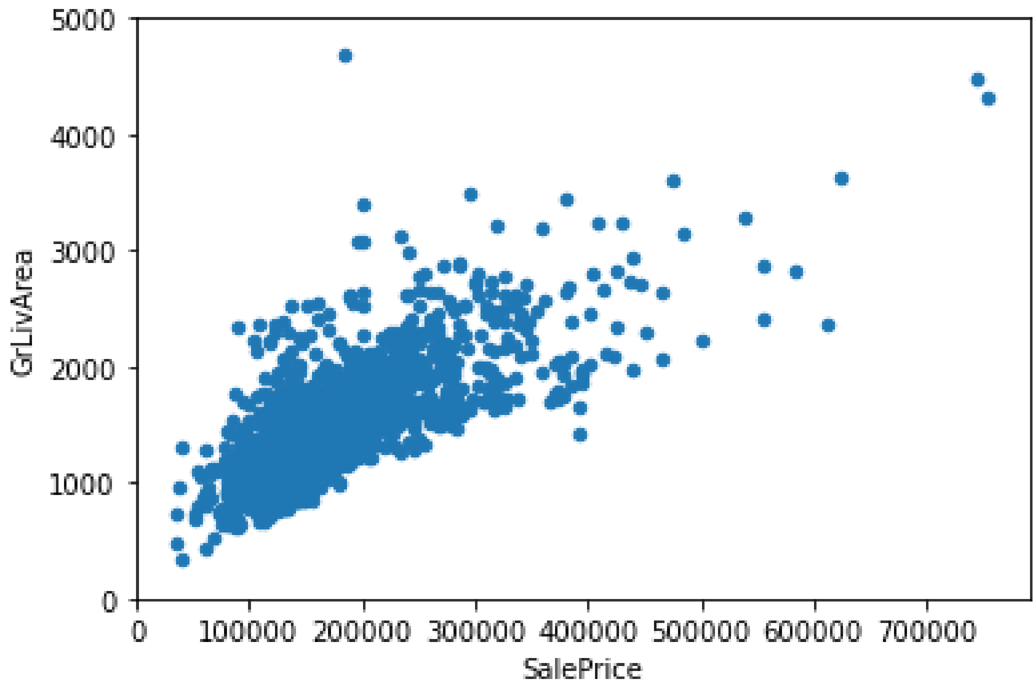


- **In the chart above, the charts of the columns belong to the normal_vars. In common, it shows a concentrated pattern in one value in each column.**

[10]:
```python
# Delete column "id" which is index.
db.drop(['Id'], axis = 1, inplace = True)
```

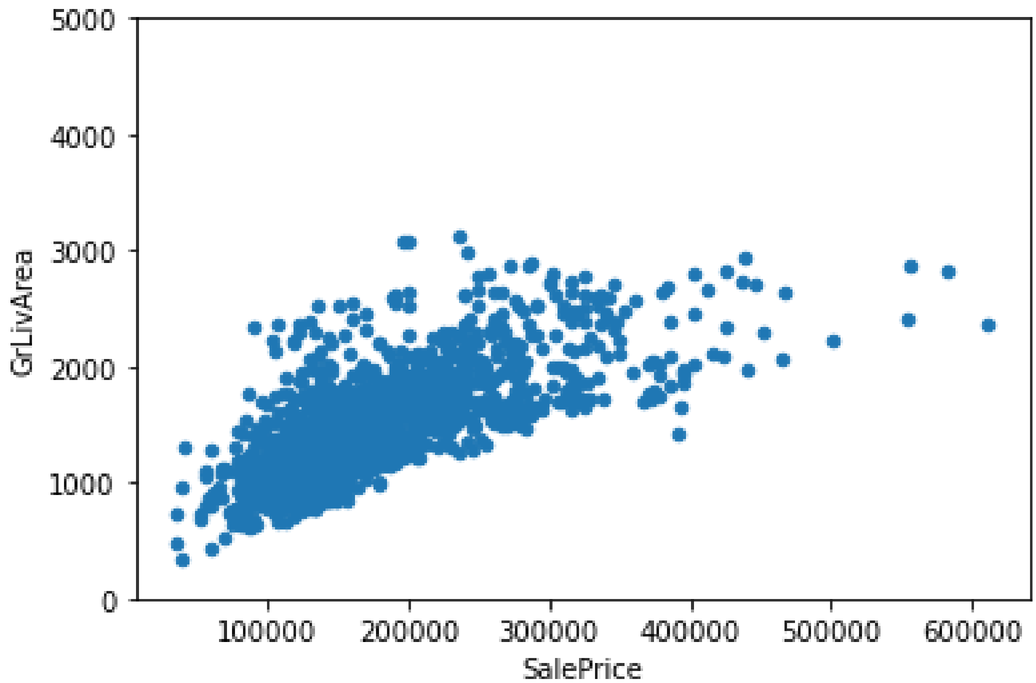
- **The chart below is the distribution chart of the GrLivArea according to the house price. GrivArea had a high distribution of data at the bottom and a small number of outliers. Thus, the results of the machine learning model did not have a significant impact, but the outliers in the GrLiv Area column were deleted.**

[11]:
```python
db[['SalePrice', 'GrLivArea']].plot.scatter(x = 'SalePrice', y = 'GrLivArea')
plt.ylim(0, 5000)
plt.show()
```



- **The chart with outliers removed is shown below. The 3,000 to 5,000 square feet values shown in the chart above have been removed.**

[12]:
```
db.drop(db.GrLivArea.sort_values(ascending = False)[:15].index, axis = 0,␣
 ↪inplace = True)
db[['SalePrice', 'GrLivArea']].plot.scatter(x = 'SalePrice', y = 'GrLivArea')
plt.ylim(0, 5000)
plt.show()
```



4. Missing Values

   - **There is a significant amount of missing values in this dataset. The method of deleting missing values is also one way, but in some columns, more than 90% of the data was found to be missing values, so the method of deleting them was not used. The data types in each column are also different, so I filled in the missing values using a replacement method suitable for each column.**

[13]:
```python
db.isnull().sum() # Number of missing values for each column.
```

[13]:
```
MSSubClass         0
MSZoning           0
LotFrontage      257
LotArea            0
Street             0
Alley           1355
LotShape           0
LandContour        0
Utilities          0
LotConfig          0
LandSlope          0
Neighborhood       0
Condition1         0
Condition2         0
BldgType           0
```

HouseStyle	0
OverallQual	0
OverallCond	0
YearBuilt	0
YearRemodAdd	0
RoofStyle	0
RoofMatl	0
Exterior1st	0
Exterior2nd	0
MasVnrType	8
MasVnrArea	8
ExterQual	0
ExterCond	0
Foundation	0
BsmtQual	37
BsmtCond	37
BsmtExposure	38
BsmtFinType1	37
BsmtFinSF1	0
BsmtFinType2	38
BsmtFinSF2	0
BsmtUnfSF	0
TotalBsmtSF	0
Heating	0
HeatingQC	0
CentralAir	0
Electrical	1
1stFlrSF	0
2ndFlrSF	0
LowQualFinSF	0
GrLivArea	0
BsmtFullBath	0
BsmtHalfBath	0
FullBath	0
HalfBath	0
BedroomAbvGr	0
KitchenAbvGr	0
KitchenQual	0
TotRmsAbvGrd	0
Functional	0
Fireplaces	0
FireplaceQu	689
GarageType	80
GarageYrBlt	80
GarageFinish	80
GarageCars	0
GarageArea	0

```
GarageQual          80
GarageCond          80
PavedDrive           0
WoodDeckSF           0
OpenPorchSF          0
EnclosedPorch        0
3SsnPorch            0
ScreenPorch          0
PoolArea             0
PoolQC            1440
Fence             1167
MiscFeature       1391
MiscVal              0
MoSold               0
YrSold               0
SaleType             0
SaleCondition        0
SalePrice            0
dtype: int64
```

- **As above, out of about 1,400 rows of data, more than 90% of the columns are missing values. The chart below shows the percentage of missing values in each column.**

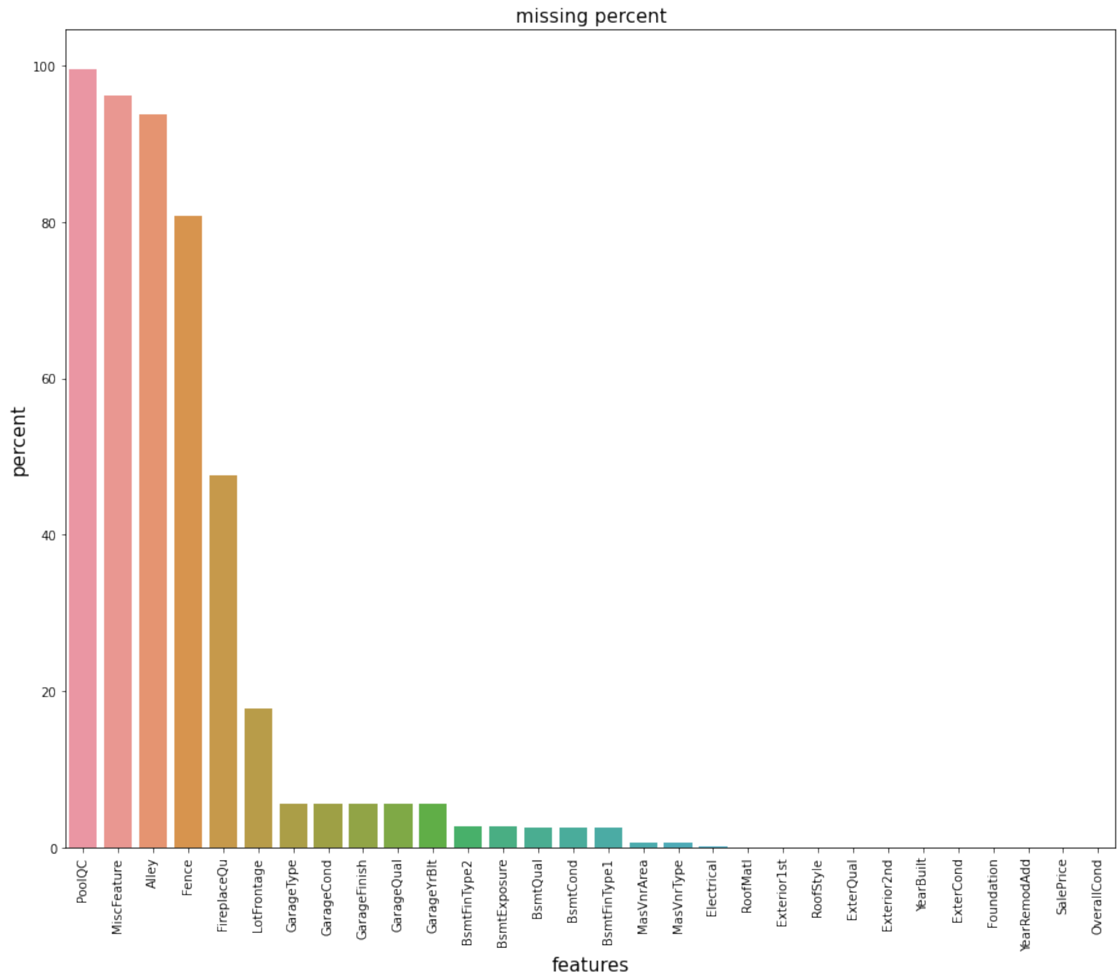
[14]:
```
count = db.isnull().sum()
percent = (count / db.isnull().count() * 100).sort_values(ascending = False)
missing_table = pd.DataFrame({'percent': percent})
missing_table.head(10)
```

[14]:

	percent
PoolQC	99.653979
MiscFeature	96.262976
Alley	93.771626
Fence	80.761246
FireplaceQu	47.681661
LotFrontage	17.785467
GarageType	5.536332
GarageCond	5.536332
GarageFinish	5.536332
GarageQual	5.536332

[15]:
```
f, ax = plt.subplots(figsize = (15, 12))
plt.xticks(rotation = '90')
sns.barplot(x = percent.index[:30], y = percent[:30])
plt.title('missing percent', fontsize = 15)
plt.xlabel('features', fontsize = 15)
plt.ylabel('percent', fontsize = 15)
```

```
plt.show()
```



- **According to the chart, PoolQC, MiscFeature, Alley, Fence columns show an overwhelmingly high rate of missing.**

[16]:
```
db["PoolQC"] = db["PoolQC"].fillna("None")
db["MiscFeature"] = db["MiscFeature"].fillna("None")
db["Alley"] = db["Alley"].fillna("None")
db["Fence"] = db["Fence"].fillna("None")
db["FireplaceQu"] = db["FireplaceQu"].fillna("None")

for col in ('GarageType', 'GarageFinish', 'GarageQual', 'GarageCond'):
    db[col] = db[col].fillna('None')

for col in ('GarageYrBlt', 'GarageArea', 'GarageCars'):
    db[col] = db[col].fillna(0)
```

```
for col in ('BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF','TotalBsmtSF',␣
↪'BsmtFullBath', 'BsmtHalfBath'):
    db[col] = db[col].fillna(0)

for col in ('BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1',␣
↪'BsmtFinType2'):
    db[col] = db[col].fillna('None')

db["MasVnrType"] = db["MasVnrType"].fillna("None")
db["MasVnrArea"] = db["MasVnrArea"].fillna(0)
db["Functional"] = db["Functional"].fillna("Typ")
db['MSSubClass'] = db['MSSubClass'].fillna("None")



# mean value replacements
db['MSZoning'] = db['MSZoning'].fillna(db['MSZoning'].mode()[0])
db['Electrical'] = db['Electrical'].fillna(db['Electrical'].mode()[0])
db['KitchenQual'] = db['KitchenQual'].fillna(db['KitchenQual'].mode()[0])
db['Exterior1st'] = db['Exterior1st'].fillna(db['Exterior1st'].mode()[0])
db['Exterior2nd'] = db['Exterior2nd'].fillna(db['Exterior2nd'].mode()[0])
db['SaleType'] = db['SaleType'].fillna(db['SaleType'].mode()[0])
db['LotFrontage'] = db['LotFrontage'].fillna(db['LotFrontage'].mode()[0])
```

- **For columns with string data, None is inserted for missing values, and 0 is inserted for columns with numeric data. In this case, mean value imputation was used for columns that significantly affect model training when replaced with 0 or None.**

[17]:
```
# The number of missing values in the dataset after data insertion is completed.
db.isnull().sum().sum()
```

[17]: 0

- **The string data is replaced with a numeric data using the get_dummies() method. In this case, the method used by get_dummies() is One-Hot Encording**

[18]:
```
db = pd.get_dummies(db)
print(db.shape)
```

```
(1445, 302)
```

5. Machine learning models

- **Models applied to supervised learning tested a total of three models: MLP Regressor, Ridge Regressor, and XGB Register. After testing normalized and unnormalized data, proceed with a model that can achieve better results.**
- **MLP Regression is short for multi-layer perceptron, which can be described as an upgraded version of logistic regression and artificial neural networks. MLP**

has the advantage of being able to better divide the division boundary in the form of adding a hidden layer between the input layer and output layer, which are logistic returns.

- **Ridge Regression is a model that uses a normalization method to increase the predictive power of a linear model. Using the basic linear model is very suitable for frequently occurring overfitting, i.e., data, resulting in extremely fluctuating graphs, and the coefficient value of linear regression representing it is large. To prevent this situation, ridge regression is a random small adjustment of the coefficient by adding an equation. Therefore, it is a technique that can expect good results by minimizing errors and penalizing functions.**
- **XGB Regression is an ensemble method based on a decision tree, and among them, it is a machine learning technique based on the boosting method. It is also introduced as a good technique to prevent overfitting and has the advantage of supporting cross validation.**

[19]:
```
# db is an existing data set, db_normalized is a normalized data set.
target = db['SalePrice']
db = db[db.columns.difference(['SalePrice'])]
scaler = MinMaxScaler(feature_range=(0, 100))
scaler.fit(db)
db_normalized = scaler.transform(db)
```

[20]:
```
# Divide the training set and test set through sklearn's train_test_split␣
↪function.
x_train, x_test, y_train, y_test = train_test_split(db, target, test_size=0.2,␣
↪shuffle=True,  random_state=34)
x_train_nor, x_test_nor, y_train_nor, y_test_nor =␣
↪train_test_split(db_normalized, target, test_size=0.2, shuffle=True, ␣
↪random_state=34)
```

MLP Regression

- **After testing the normalized and unnormalized datasets, I find a model with better results through parameter testing.**

[21]:
```
# Unnormalized dataset
regressorMLP = MLPRegressor()
regressorMLP.fit(x_train, y_train)
y_pred = regressorMLP.predict(x_test)
print("Training set score: {:.2f}".format(regressorMLP.score(x_train, y_train)))
print("Test set score: {:.2f}".format(regressorMLP.score(x_test, y_test)))
```

```
Training set score: 0.70
Test set score: 0.69
```

[22]:
```
# normalized dataset
regressorMLP = MLPRegressor()
```

```
regressorMLP.fit(x_train_nor, y_train_nor)
y_pred = regressorMLP.predict(x_test_nor)
print("Training set score: {:.2f}".format(regressorMLP.score(x_train_nor,␣
↪y_train_nor)))
print("Test set score: {:.2f}".format(regressorMLP.score(x_test_nor,␣
↪y_test_nor)))
```

```
Training set score: 0.60
Test set score: 0.58
```

- **The unnormalized data showed better results, so I proceeded to the unnormalized dataset. Then, I performed the activation parameter test.**

[23]:

```
#Activation function for the hidden layer
print('# activation = identity')
regressorMLP = MLPRegressor(activation = 'identity') #no-op activation, returns␣
↪f(x) = x
regressorMLP.fit(x_train, y_train)
print("Training set score: {:.2f}".format(regressorMLP.score(x_train, y_train)))
print("Test set score: {:.2f}".format(regressorMLP.score(x_test, y_test)))
print('\n')
print('# activation = logistic')
regressorMLP = MLPRegressor(activation = 'logistic') #the logistic sigmoid␣
↪function, returns f(x) = 1 / (1 + exp(-x))
regressorMLP.fit(x_train, y_train)
print("Training set score: {:.2f}".format(regressorMLP.score(x_train, y_train)))
print("Test set score: {:.2f}".format(regressorMLP.score(x_test, y_test)))
print('\n')
print('# activation = tanh')
regressorMLP = MLPRegressor(activation = 'tanh') #the hyperbolic tan function,␣
↪returns f(x) = tanh(x)
regressorMLP.fit(x_train, y_train)
print("Training set score: {:.2f}".format(regressorMLP.score(x_train, y_train)))
print("Test set score: {:.2f}".format(regressorMLP.score(x_test, y_test)))
print('\n')
print('# activation = relu')
regressorMLP = MLPRegressor(activation = 'relu') #the rectified linear unit␣
↪function, returns f(x) = max(0, x)
regressorMLP.fit(x_train, y_train)
print("Training set score: {:.2f}".format(regressorMLP.score(x_train, y_train)))
print("Test set score: {:.2f}".format(regressorMLP.score(x_test, y_test)))
print('\n')
```

```
# activation = identity
Training set score: 0.63
Test set score: 0.61
```

```
# activation = logistic
Training set score: -6.04
Test set score: -5.32


# activation = tanh
Training set score: -6.04
Test set score: -5.32


# activation = relu
Training set score: 0.69
Test set score: 0.68
```

- **Since relu showed the most accurate result, I set relu as the activation parameter and tested the solver.**

[24]:
```python
print('# solver= lbfgs') #  an optimizer in the family of quasi-Newton methods.
regressorMLP = MLPRegressor(activation = 'relu', solver = 'lbfgs')
regressorMLP.fit(x_train, y_train)
print("Training set score: {:.2f}".format(regressorMLP.score(x_train, y_train)))
print("Test set score: {:.2f}".format(regressorMLP.score(x_test, y_test)))
print('\n')
print('# solver= sgd') #stochastic gradient descent.
regressorMLP = MLPRegressor(activation = 'relu', solver = 'sgd')
regressorMLP.fit(x_train, y_train)
print("Training set score: {:.2f}".format(regressorMLP.score(x_train, y_train)))
print("Test set score: {:.2f}".format(regressorMLP.score(x_test, y_test)))
print('\n')
print('# solver= adam') #a stochastic gradient-based optimizer
regressorMLP = MLPRegressor(activation = 'relu', solver = 'adam')
regressorMLP.fit(x_train, y_train)
print("Training set score: {:.2f}".format(regressorMLP.score(x_train, y_train)))
print("Test set score: {:.2f}".format(regressorMLP.score(x_test, y_test)))
print('\n')
```

```
# solver= lbfgs
Training set score: 0.80
Test set score: 0.80


# solver= sgd
Training set score: -398246593408596574901647103141702983447571735191826427008415233462745601503522037653757939618600938535933608094200761493170792418636905852391026298366525717345172331345372637120991304494125133509833218080599769937967316
992.00
```

```
Test set score: -327462736949123958976558440279613001886379426634649138752485787
```

```
# solver= adam
Training set score: 0.69
Test set score: 0.69
```

- **lbfgs showed the best value, so I fixed it as the solver and tested the alpha value (L2 regularization parameter).**

[25]:
```
print('# alphas=0.01')
regressorMLP = MLPRegressor(activation = 'relu', solver = 'lbfgs', alpha = 0.01)
regressorMLP.fit(x_train, y_train)
print("Training set score: {:.2f}".format(regressorMLP.score(x_train, y_train)))
print("Test set score: {:.2f}".format(regressorMLP.score(x_test, y_test)))
print('\n')
print('# alphas=0.1')
regressorMLP = MLPRegressor(activation = 'relu', solver = 'lbfgs', alpha = 0.1)
regressorMLP.fit(x_train, y_train)
print("Training set score: {:.2f}".format(regressorMLP.score(x_train, y_train)))
print("Test set score: {:.2f}".format(regressorMLP.score(x_test, y_test)))
print('\n')
print('# alphas=1')
regressorMLP = MLPRegressor(activation = 'relu', solver = 'lbfgs',alpha = 1)
regressorMLP.fit(x_train, y_train)
print("Training set score: {:.2f}".format(regressorMLP.score(x_train, y_train)))
print("Test set score: {:.2f}".format(regressorMLP.score(x_test, y_test)))
print('\n')
print('# alphas=10')
regressorMLP = MLPRegressor(activation = 'relu', solver = 'lbfgs',alpha = 10)
regressorMLP.fit(x_train, y_train)
print("Training set score: {:.2f}".format(regressorMLP.score(x_train, y_train)))
print("Test set score: {:.2f}".format(regressorMLP.score(x_test, y_test)))
print('\n')
print('# alphas=100')
regressorMLP = MLPRegressor(activation = 'relu', solver = 'lbfgs',alpha = 100)
regressorMLP.fit(x_train, y_train)
print("Training set score: {:.2f}".format(regressorMLP.score(x_train, y_train)))
print("Test set score: {:.2f}".format(regressorMLP.score(x_test, y_test)))
print('\n')
print('# alphas=1000')
regressorMLP = MLPRegressor(activation = 'relu', solver = 'lbfgs',alpha = 1000)
regressorMLP.fit(x_train, y_train)
```

```
print("Training set score: {:.2f}".format(regressorMLP.score(x_train, y_train)))
print("Test set score: {:.2f}".format(regressorMLP.score(x_test, y_test)))
print('\n')
```

```
# alphas=0.01
Training set score: 0.80
Test set score: 0.80


# alphas=0.1
Training set score: 0.80
Test set score: 0.81


# alphas=1
Training set score: 0.80
Test set score: 0.80


# alphas=10
Training set score: 0.79
Test set score: 0.79


# alphas=100
Training set score: 0.80
Test set score: 0.79


# alphas=1000
Training set score: 0.80
Test set score: 0.80
```

- **After completing parameter testing, MLP Regression model was trained with the parameters that gave the best results.**

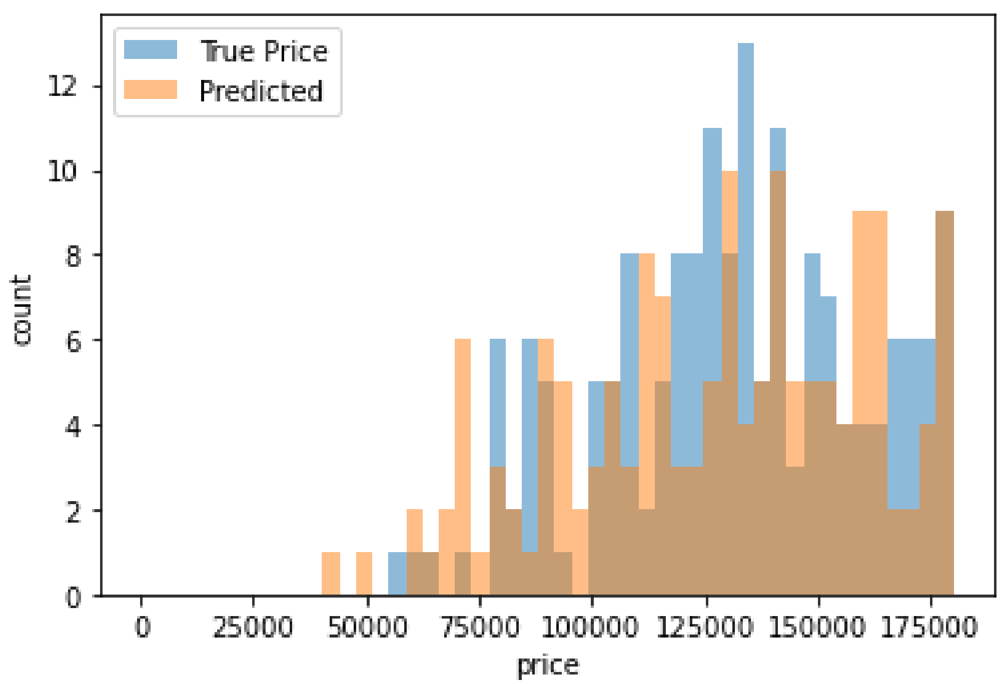
[26]:
```
# The model to which the parameters with the best results were applied
regressorMLP = MLPRegressor(activation = 'relu',solver = 'lbfgs', alpha = 100)
regressorMLP.fit(x_train, y_train)
y_pred = regressorMLP.predict(x_test)
```

[27]:
```
# Mean, MAE, MSE, RMSE, R2 score of the model
print('Mean of SalePrice', np.mean(target))
# MAE: the difference between the original and predicted values extracted by␣
 ↪averaged the absolute difference over the data set.
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
```

```
# MSE: the difference between the original and predicted values extracted by␣
↪squared the average difference over the data set.
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
# RMSE: the error rate by the square root of MSE.
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
↪y_pred)))
# R2: the coefficient of how well the values fit compared to the original␣
↪values. The value from 0 to 1 interpreted as percentages. The higher the␣
↪value is, the better the model is.
print('R2:', metrics.r2_score(y_test, y_pred))
```

```
Mean of SalePrice 178395.9141868512
Mean Absolute Error: 25676.825170743752
Mean Squared Error: 1339127823.8277714
Root Mean Squared Error: 36594.095477655566
R2: 0.7877078683056064
```

[28]:
```
bins = np.linspace(0, 180000)
plt.hist(y_test, bins, alpha = 0.5, label = 'True Price')
plt.hist(y_pred, bins, alpha = 0.5, label = 'Predicted')
plt.legend(loc = 'upper left')
plt.xlabel('price')
plt.ylabel('count')
plt.show()
```



- **The graph above is a graph that visually shows the difference between the actual house price and the predicted house price. A relatively large part of it intersects, but several parts do not intersect.**

Ridge Regression

[29]:
```
# Unnormalized dataset
alphas = [0.000001, 0.00001, 0.0001, 0.001, 0.01, 0.1,0.5, 1, 10, 15, 20, 30,␣
↪40, 100]
regressorR = RidgeCV(alphas = alphas)
regressorR.fit(x_train, y_train)
y_pred = regressorR.predict(x_test)
print("Training set score: {:.2f}".format(regressorR.score(x_train, y_train)))
print("Test set score: {:.2f}".format(regressorR.score(x_test, y_test)))
```

```
Training set score: 0.93
Test set score: 0.91
```

[30]:
```
# Normalized dataset
alphas = [0.000001, 0.00001, 0.0001, 0.001, 0.01, 0.1,0.5, 1, 10, 15, 20, 30,␣
↪40, 100]
regressorRR = RidgeCV(alphas = alphas)
regressorRR.fit(x_train_nor, y_train_nor)
y_pred = regressorRR.predict(x_test_nor)
print("Training set score: {:.2f}".format(regressorRR.score(x_train_nor,␣
↪y_train_nor)))
print("Test set score: {:.2f}".format(regressorRR.score(x_test_nor,␣
↪y_test_nor)))
```

```
Training set score: 0.94
Test set score: 0.90
```

- **The unnormalized data showed better results, so I proceeded to the unnormalized dataset.**

[31]:
```
print('# alphas=0.0001')
regressorR = RidgeCV(alphas = [0.0001])
regressorR.fit(x_train, y_train)
print("Training set score: {:.2f}".format(regressorR.score(x_train, y_train)))
print("Test set score: {:.2f}".format(regressorR.score(x_test, y_test)))
print('\n')
print('# alphas=0.001')
regressorR = RidgeCV(alphas = [0.001])
regressorR.fit(x_train, y_train)
print("Training set score: {:.2f}".format(regressorR.score(x_train, y_train)))
print("Test set score: {:.2f}".format(regressorR.score(x_test, y_test)))
print('\n')
print('# alphas=0.01')
regressorR = RidgeCV(alphas = [0.01])
```

```
regressorR.fit(x_train, y_train)
print("Training set score: {:.2f}".format(regressorR.score(x_train, y_train)))
print("Test set score: {:.2f}".format(regressorR.score(x_test, y_test)))
print('\n')
print('# alphas=0.1')
regressorR = RidgeCV(alphas = [0.1])
regressorR.fit(x_train, y_train)
print("Training set score: {:.2f}".format(regressorR.score(x_train, y_train)))
print("Test set score: {:.2f}".format(regressorR.score(x_test, y_test)))
print('\n')
print('# alphas=1')
regressorR = RidgeCV(alphas = [1])
regressorR.fit(x_train, y_train)
print("Training set score: {:.2f}".format(regressorR.score(x_train, y_train)))
print("Test set score: {:.2f}".format(regressorR.score(x_test, y_test)))
print('\n')
print('# alphas=10')
regressorR = RidgeCV(alphas = [10])
regressorR.fit(x_train, y_train)
print("Training set score: {:.2f}".format(regressorR.score(x_train, y_train)))
print("Test set score: {:.2f}".format(regressorR.score(x_test, y_test)))
print('\n')
print('# alphas=100')
regressorR = RidgeCV(alphas = [100])
regressorR.fit(x_train, y_train)
print("Training set score: {:.2f}".format(regressorR.score(x_train, y_train)))
print("Test set score: {:.2f}".format(regressorR.score(x_test, y_test)))
print('\n')
```

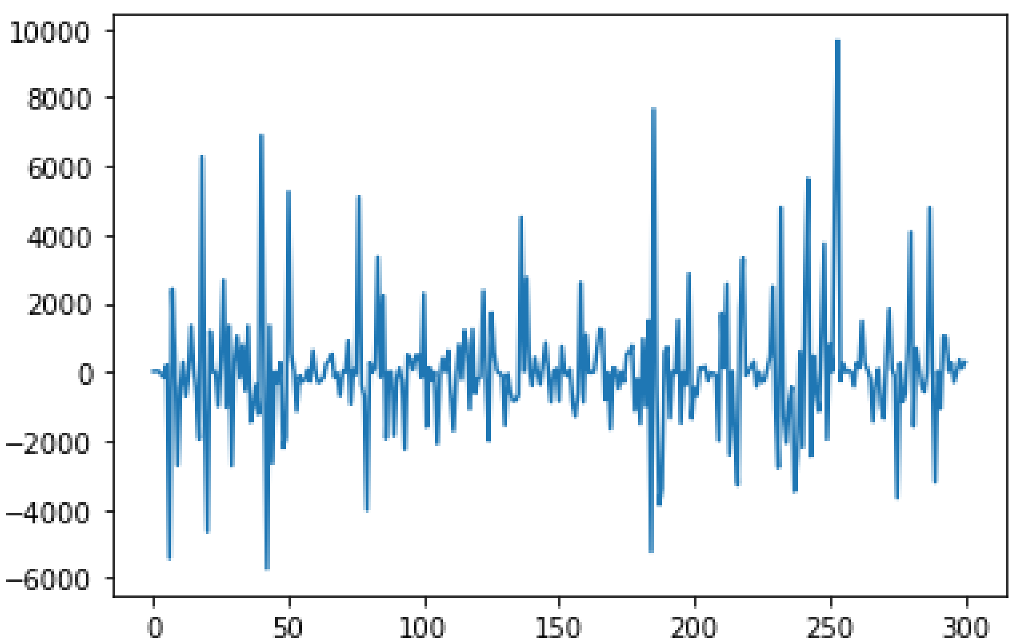
```
# alphas=0.0001
Training set score: 0.88
Test set score: 0.57


# alphas=0.001
Training set score: 0.94
Test set score: 0.90


# alphas=0.01
Training set score: 0.94
Test set score: 0.90


# alphas=0.1
Training set score: 0.94
Test set score: 0.90
```

```
# alphas=1
Training set score: 0.94
Test set score: 0.91


# alphas=10
Training set score: 0.93
Test set score: 0.91


# alphas=100
Training set score: 0.92
Test set score: 0.90
```

- **The alpha value from 0.0001 to 0.001 shows a relatively low result, while the alpha value from 0.001 to 0.9 shows that the range of change in the result is not large and stable.**
- **The two charts below are charts for comparing weight vectors.**

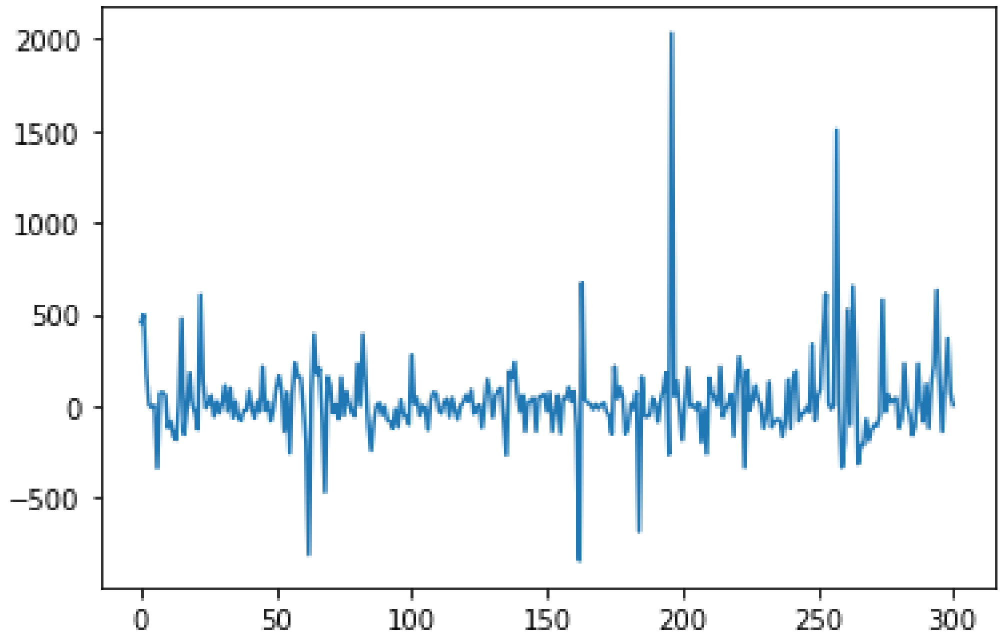
[32]:
```
#Unnormalized dataset chart
plt.plot(regressorR.coef_)
```

[32]:
```
[<matplotlib.lines.Line2D at 0x1be2166a550>]
```



[33]:
```
#Normalized dataset chart
plt.plot(regressorRR.coef_)
```

[33]: [<matplotlib.lines.Line2D at 0x1be2119f910>]

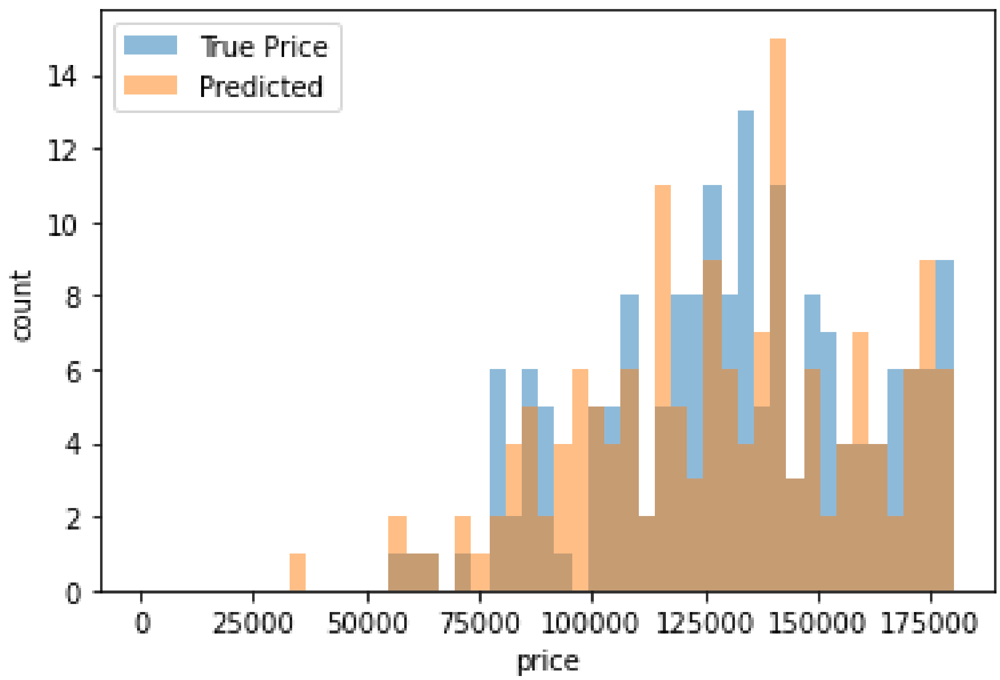


- **Like the charts above, it can be seen that the chart without normalization has large fluctuations, and the chart with normalization has small fluctuations.**

[34]:
```
# The model to which the parameters with the best results were applied␣
↪(unnormalized data and alpha value = 10)
regressorR = RidgeCV(alphas = [10])
regressorR.fit(x_train, y_train)
y_pred = regressorR.predict(x_test)
print('Mean of SalePrice', np.mean(target))
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
↪y_pred)))
print('R2:', metrics.r2_score(y_test, y_pred))
```

```
Mean of SalePrice 178395.9141868512
Mean Absolute Error: 16342.555776968436
Mean Squared Error: 539413182.0742222
Root Mean Squared Error: 23225.270333716726
R2: 0.914486748576945
```

[35]:
```
bins = np.linspace(0, 180000)
plt.hist(y_test, bins, alpha = 0.5, label = 'True Price')
plt.hist(y_pred, bins, alpha = 0.5, label = 'Predicted')
plt.legend(loc = 'upper left')
plt.xlabel('price')
plt.ylabel('count')
plt.show()
```



- **The Ridge Regressor graph has an additional cross section compared to the previous MLP regressor graph, and the R2 score shows a result value of 0.91. Mean Absolute Error(MAE) is also significantly reduced from about 25677 to 16343 compared to MLP, showing satisfactory results.**

XGB Regression

[36]:
```
#max_depth: Maximum tree depth for base learners (default: 3)
#learning_rate: Decide how much weight to use for each training step (default:␣
↪0.1)
#n_estimaters: Number of gradient boosted trees
#reg_alpha: L1 regularization term on weights
#reg_lambda: L2 regularization term on weights
#n_jobs: Number of parallel threads used to run xgboost. (default: -1 for use␣
↪all cores of the computer)
#min_child_weight: Minimum sum of weights for all observations needed in child .
```

```
XGB = XGBRegressor(max_depth = 3,learning_rate = 0.1,n_estimators =␣
↪1000,reg_alpha = 0.001,reg_lambda = 0.000001,n_jobs = -1,min_child_weight =␣
↪3)
XGB.fit(x_train,y_train)
y_pred = XGB.predict(x_test)
#Unnormalized dataset
print("Training set score: {:.2f}".format(XGB.score(x_train, y_train)))
print("Test set score: {:.2f}".format(XGB.score(x_test, y_test)))
```

```
Training set score: 1.00
Test set score: 0.92
```

[37]:
```
#Normalized dataset
print("Training set score: {:.2f}".format(XGB.score(x_train_nor, y_train_nor)))
print("Test set score: {:.2f}".format(XGB.score(x_test_nor, y_test_nor)))
```

```
Training set score: 0.19
Test set score: 0.19
```

- **In the case of XGB Regression, normalized data shows exceptionally low result values. Therefore, the test was conducted with a unnormalized data set.**

[38]:
```
print('# n_estimators=10')
XGB = XGBRegressor(max_depth = 3,learning_rate = 0.1,n_estimators =␣
↪10,reg_alpha = 0.001,reg_lambda = 0.000001,n_jobs = -1,min_child_weight = 3)
XGB.fit(x_train,y_train)
print("Training set score: {:.2f}".format(XGB.score(x_train, y_train)))
print("Test set score: {:.2f}".format(XGB.score(x_test, y_test)))
print('\n')
print('# n_estimators=50')
XGB = XGBRegressor(max_depth = 3,learning_rate = 0.1,n_estimators =␣
↪50,reg_alpha = 0.001,reg_lambda = 0.000001,n_jobs = -1,min_child_weight = 3)
XGB.fit(x_train,y_train)
print("Training set score: {:.2f}".format(XGB.score(x_train, y_train)))
print("Test set score: {:.2f}".format(XGB.score(x_test, y_test)))
print('\n')
print('# n_estimators=100')
XGB = XGBRegressor(max_depth = 3,learning_rate = 0.1,n_estimators =␣
↪100,reg_alpha = 0.001,reg_lambda = 0.000001,n_jobs = -1,min_child_weight = 3)
XGB.fit(x_train,y_train)
print("Training set score: {:.2f}".format(XGB.score(x_train, y_train)))
print("Test set score: {:.2f}".format(XGB.score(x_test, y_test)))
print('\n')
print('# n_estimators=300')
XGB = XGBRegressor(max_depth = 3,learning_rate = 0.1,n_estimators =␣
↪300,reg_alpha = 0.001,reg_lambda = 0.000001,n_jobs = -1,min_child_weight = 3)
XGB.fit(x_train,y_train)
print("Training set score: {:.2f}".format(XGB.score(x_train, y_train)))
```

```
print("Test set score: {:.2f}".format(XGB.score(x_test, y_test)))
print('\n')
print('# n_estimators=600')
XGB = XGBRegressor(max_depth = 3,learning_rate = 0.1,n_estimators =␣
↪600,reg_alpha = 0.001,reg_lambda = 0.000001,n_jobs = -1,min_child_weight = 3)
XGB.fit(x_train,y_train)
print("Training set score: {:.2f}".format(XGB.score(x_train, y_train)))
print("Test set score: {:.2f}".format(XGB.score(x_test, y_test)))
print('\n')
print('# n_estimators=900')
XGB = XGBRegressor(max_depth = 3,learning_rate = 0.1,n_estimators =␣
↪900,reg_alpha = 0.001,reg_lambda = 0.000001,n_jobs = -1,min_child_weight = 3)
XGB.fit(x_train,y_train)
print("Training set score: {:.2f}".format(XGB.score(x_train, y_train)))
print("Test set score: {:.2f}".format(XGB.score(x_test, y_test)))
print('\n')
print('# n_estimators=1000')
XGB = XGBRegressor(max_depth = 3,learning_rate = 0.1,n_estimators =␣
↪1000,reg_alpha = 0.001,reg_lambda = 0.000001,n_jobs = -1,min_child_weight =␣
↪3)
XGB.fit(x_train,y_train)
print("Training set score: {:.2f}".format(XGB.score(x_train, y_train)))
print("Test set score: {:.2f}".format(XGB.score(x_test, y_test)))
```

```
# n_estimators=10
Training set score: -0.02
Test set score: 0.05


# n_estimators=50
Training set score: 0.95
Test set score: 0.90


# n_estimators=100
Training set score: 0.97
Test set score: 0.91


# n_estimators=300
Training set score: 0.99
Test set score: 0.91


# n_estimators=600
Training set score: 1.00
Test set score: 0.92
```

```
# n_estimators=900
Training set score: 1.00
Test set score: 0.92


# n_estimators=1000
Training set score: 1.00
Test set score: 0.92
```

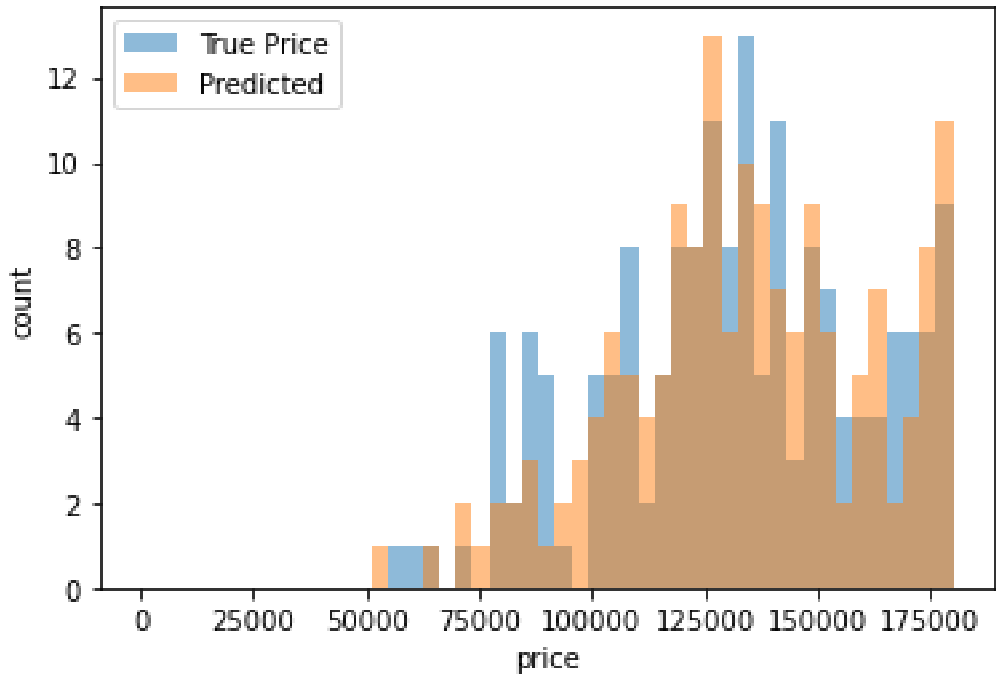
- **When n_estimator is 10, it goes down to an unpredictable level, and the score steadily rises to 100, and then stabilizes from 300. In the case of other parameters, only n_estimator was tested as they did not significantly affect the result value.** .

[39]:
```
XGB = XGBRegressor(max_depth = 3,learning_rate = 0.1,n_estimators =␣
 ↪1000,reg_alpha = 0.001,reg_lambda = 0.000001,n_jobs = -1,min_child_weight =␣
 ↪3)
XGB.fit(x_train,y_train)
y_pred = XGB.predict(x_test)
```

[40]:
```
print('Mean of SalePrice', np.mean(target))
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
 ↪y_pred)))
print('R2:', metrics.r2_score(y_test, y_pred))
```

```
Mean of SalePrice 178395.9141868512
Mean Absolute Error: 14712.978116890139
Mean Squared Error: 529691715.21889216
Root Mean Squared Error: 23015.032374926006
R2: 0.9160278941533361
```

[41]:
```
bins = np.linspace(0, 180000)
plt.hist(y_test, bins, alpha = 0.5, label = 'True Price')
plt.hist(y_pred, bins, alpha = 0.5, label = 'Predicted')
plt.legend(loc = 'upper left')
plt.xlabel('price')
plt.ylabel('count')
plt.show()
```



- **Although it is small in terms of R2 score, it shows better performance than the Ridge regression model. The difference is not large, so although the difference is not shown in the chart, you can check the Mean Absolute Error(MAE) value reduced from 16,000 to 14,000.**

6. Result

- **In the case of the MLP regression model, after normalization/unnormalization testing, parameter testing was performed to find a solver under activation, and then the alpha value was tested. It can be seen that the R2 score of the final model is 0.78 and Mean Absolute Error(MAE) is 25677, which is low considering the average house price is 178,395.**

- **In the case of the Ridge regression model, alpha parameter testing was performed, and weight comparison was performed through the chart. An R2 score of 0.91 and Mean Absolute Error(MAE) is 16343 showed improved results compared to the MLP model.**

- **In the XGB model, you can see that a lot of parameters are applied, but the difference in parameter values except for n_estimator does not have a big effect on the result, so only n_estimators were performed. R2 score of 0.91 showed the same results as Ridge, and Mean Absolute Error(MAE) showed better results than Ridge regression model.**

- **Among the three models, MLP regression model showed the lowest performance, and the XGB regression model showed the best score compared to Ridge regression model, although by a little. MLP regression model, Ridge regression model,**

and XGB regression model all showed better scores when data is not normalized. In particular, XGB regression model showed an abnormal increase from 0.19 to 0.92 when normalization was not performed.