House Prices - Advanced Regression Techniques

Background &Objectives

Ask a home buyer to describe their dream house, and they probably won't begin with the height of the basement ceiling or the proximity to an east-west railroad. The dataset proves that much more influences price negotiations than the number of bedrooms or a white-picket fence.

Objective: With 79 explanatory variables describing (almost) every aspect of residential homes in Ames, Iowa, the project predict the final price of each home.

In [1]:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from scipy.stats import norm
from sklearn.preprocessing import StandardScaler
from scipy import stats
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import ElasticNet, Lasso,  BayesianRidge, LassoLarsIC
from sklearn.ensemble import RandomForestRegressor,  GradientBoostingRegressor
from sklearn.kernel_ridge import KernelRidge
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import RobustScaler
from sklearn.base import BaseEstimator, TransformerMixin, RegressorMixin, clone
from sklearn.model_selection import KFold, cross_val_score, train_test_split
from sklearn.metrics import mean_squared_error
import xgboost as xgb
import lightgbm as lgb
```

Data Import & Description

In [2]:

```
train_csv = pd.read_csv('train.csv')
test_csv = pd.read_csv('test.csv')
```

In [3]:

```
train_csv['dataset']='1'
test_csv['dataset']='0'
hp_csv=pd.concat([train_csv,test_csv],axis=0)
```

In [ ]:

```
train_csv.
```

In [4]:

```
train_csv.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 82 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             1460 non-null   int64
 1   MSSubClass     1460 non-null   int64
 2   MSZoning       1460 non-null   object
 3   LotFrontage    1201 non-null   float64
 4   LotArea        1460 non-null   int64
 5   Street         1460 non-null   object
 6   Alley          91 non-null     object
 7   LotShape       1460 non-null   object
 8   LandContour    1460 non-null   object
 9   Utilities      1460 non-null   object
 10  LotConfig      1460 non-null   object
 11  LandSlope      1460 non-null   object
 12  Neighborhood   1460 non-null   object
 13  Condition1     1460 non-null   object
```

In [5]:

```
test_csv.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1459 entries, 0 to 1458
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Id             1459 non-null   int64  
 1   MSSubClass     1459 non-null   int64  
 2   MSZoning       1455 non-null   object 
 3   LotFrontage    1232 non-null   float64
 4   LotArea        1459 non-null   int64  
 5   Street         1459 non-null   object 
 6   Alley          107 non-null    object 
 7   LotShape       1459 non-null   object 
 8   LandContour    1459 non-null   object 
 9   Utilities      1457 non-null   object 
 10  LotConfig      1459 non-null   object 
 11  LandSlope      1459 non-null   object 
 12  Neighborhood   1459 non-null   object 
 13  Condition1     1459 non-null   object 
 14  Condition2     1459 non-null   object 
 15  BldgType       1459 non-null   object 
 16  HouseStyle     1459 non-null   object 
 17  OverallQual    1459 non-null   int64  
 18  OverallCond    1459 non-null   int64  
 19  YearBuilt      1459 non-null   int64  
 20  YearRemodAdd   1459 non-null   int64  
 21  RoofStyle      1459 non-null   object 
 22  RoofMatl       1459 non-null   object 
 23  Exterior1st    1458 non-null   object 
 24  Exterior2nd    1458 non-null   object 
 25  MasVnrType     1443 non-null   object 
 26  MasVnrArea     1444 non-null   float64
 27  ExterQual      1459 non-null   object 
 28  ExterCond      1459 non-null   object 
 29  Foundation     1459 non-null   object 
 30  BsmtQual       1415 non-null   object 
 31  BsmtCond       1414 non-null   object 
 32  BsmtExposure   1415 non-null   object 
 33  BsmtFinType1   1417 non-null   object 
 34  BsmtFinSF1     1458 non-null   float64
 35  BsmtFinType2   1417 non-null   object 
 36  BsmtFinSF2     1458 non-null   float64
 37  BsmtUnfSF      1458 non-null   float64
 38  TotalBsmtSF    1458 non-null   float64
 39  Heating        1459 non-null   object 
 40  HeatingQC      1459 non-null   object 
 41  CentralAir     1459 non-null   object 
 42  Electrical     1459 non-null   object 
 43  1stFlrSF       1459 non-null   int64  
 44  2ndFlrSF       1459 non-null   int64  
 45  LowQualFinSF   1459 non-null   int64  
 46  GrLivArea      1459 non-null   int64  
 47  BsmtFullBath   1457 non-null   float64
 48  BsmtHalfBath   1457 non-null   float64
 49  FullBath       1459 non-null   int64  
 50  HalfBath       1459 non-null   int64  
 51  BedroomAbvGr   1459 non-null   int64  
```

```
 52  KitchenAbvGr   1459 non-null   int64
 53  KitchenQual    1458 non-null   object
 54  TotRmsAbvGrd   1459 non-null   int64
 55  Functional     1457 non-null   object
 56  Fireplaces     1459 non-null   int64
 57  FireplaceQu    729 non-null    object
 58  GarageType     1383 non-null   object
 59  GarageYrBlt    1381 non-null   float64
 60  GarageFinish   1381 non-null   object
 61  GarageCars     1458 non-null   float64
 62  GarageArea     1458 non-null   float64
 63  GarageQual     1381 non-null   object
 64  GarageCond     1381 non-null   object
 65  PavedDrive     1459 non-null   object
 66  WoodDeckSF     1459 non-null   int64
 67  OpenPorchSF    1459 non-null   int64
 68  EnclosedPorch  1459 non-null   int64
 69  3SsnPorch      1459 non-null   int64
 70  ScreenPorch    1459 non-null   int64
 71  PoolArea       1459 non-null   int64
 72  PoolQC         3 non-null      object
 73  Fence          290 non-null    object
 74  MiscFeature    51 non-null     object
 75  MiscVal        1459 non-null   int64
 76  MoSold         1459 non-null   int64
 77  YrSold         1459 non-null   int64
 78  SaleType       1458 non-null   object
 79  SaleCondition  1459 non-null   object
 80  dataset        1459 non-null   object
dtypes: float64(11), int64(26), object(44)
memory usage: 923.4+ KB
```

In [6]:

```
hp_csv.head()
```

Out[6]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Ut
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	A
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	A
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	A
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	A
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	A

5 rows × 82 columns

In [7]:

```
y=hp_csv['SalePrice'][hp_csv['dataset']=='1']
y.describe()
```

Out[7]:

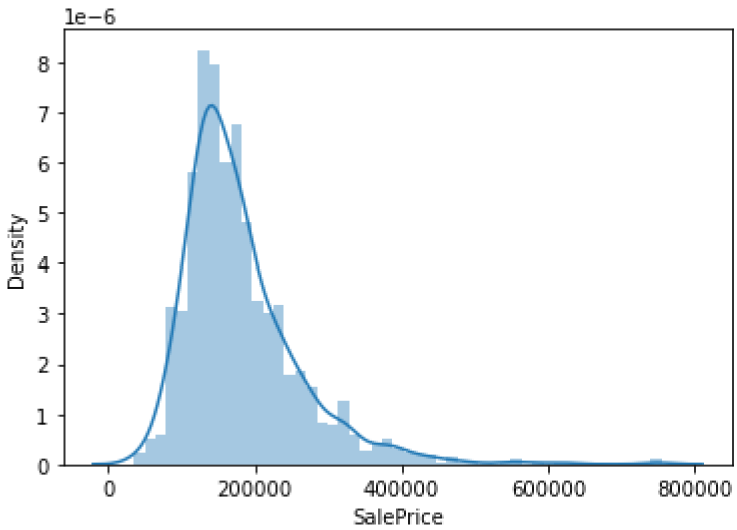
```
count      1460.000000
mean     180921.195890
std       79442.502883
min       34900.000000
25%      129975.000000
50%      163000.000000
75%      214000.000000
max      755000.000000
Name: SalePrice, dtype: float64
```

In [8]:

```
sns.distplot(y)
```

Out[8]:

```
<AxesSubplot:xlabel='SalePrice', ylabel='Density'>
```



Data processing

missing data

In [9]:

```
total=hp_csv.isnull().sum().sort_values(ascending=False)
percent=(hp_csv.isnull().sum()/hp_csv.isnull().count()).sort_values(ascending=True)
missingdata=pd.concat([total,percent],axis=1,keys=['total','percent'])
missingdata=missingdata[missingdata['total']>0]
```

In [10]:

```
print(missingdata)
```

```
               total   percent
PoolQC          2909  0.996574
MiscFeature     2814  0.964029
Alley           2721  0.932169
Fence           2348  0.804385
SalePrice       1459  0.499829
FireplaceQu     1420  0.486468
LotFrontage      486  0.166495
GarageYrBlt      159  0.054471
GarageQual       159  0.054471
GarageFinish     159  0.054471
GarageCond       159  0.054471
GarageType       157  0.053786
BsmtCond          82  0.028092
BsmtExposure      82  0.028092
BsmtQual          81  0.027749
BsmtFinType2      80  0.027407
BsmtFinType1      79  0.027064
MasVnrType        24  0.008222
```

In [11]:

```
missd_name=list(missingdata.index)
object_list=[]
non_object_list=[]
for i in missd_name:
    if hp_csv[i].dtype==object:
        object_list.append(i)
    else:
        non_object_list.append(i)
print("object_list:",object_list)
print("non_object_list:",non_object_list)
```

```
object_list: ['PoolQC', 'MiscFeature', 'Alley', 'Fence', 'FireplaceQ
u', 'GarageQual', 'GarageFinish', 'GarageCond', 'GarageType', 'BsmtCon
d', 'BsmtExposure', 'BsmtQual', 'BsmtFinType2', 'BsmtFinType1', 'MasVn
rType', 'MSZoning', 'Functional', 'Utilities', 'Electrical', 'Exterior
2nd', 'Exterior1st', 'SaleType', 'KitchenQual']
non_object_list: ['SalePrice', 'LotFrontage', 'GarageYrBlt', 'MasVnrAr
ea', 'BsmtFullBath', 'BsmtHalfBath', 'BsmtFinSF1', 'GarageCars', 'Gara
geArea', 'TotalBsmtSF', 'BsmtUnfSF', 'BsmtFinSF2']
```

In [12]:

```
for i in object_list:
    hp_csv[i].fillna('None',inplace=True)
```

In [13]:

```
for i in non_object_list[2:]:
    hp_csv[i].fillna(0,inplace=True)
```

For those over 40% missing values,it means that it can be deleted. Therefore, 'PoolQC','MiscFeature','Alley','Fence', and 'FireplaceQu' should be deleted.

In [14]:

```
hp_new=hp_csv.drop(['PoolQC','MiscFeature','Alley','Fence','FireplaceQu'],axis=1)
```

In [15]:

```
hp_csv['LotFrontage']=hp_csv.groupby(['Neighborhood']).transform(lambda x: x.fillna(
```

In [16]:

```
hp_csv['LotFrontage']=hp_csv['LotFrontage'].astype(int)
```

Variable processing and encoding

In [17]:

```
full_name=list(hp_csv.columns)
object_full_list=[]
nonobject_full_list=[]
for i in full_name:
    if hp_csv[i].dtype==object:
        object_full_list.append(i)
    else:
        nonobject_full_list.append(i)
print("object_list:",object_full_list)
print("nonobject_list:",nonobject_full_list)
```

```
object_list: ['MSZoning', 'Street', 'Alley', 'LotShape', 'LandContou
r', 'Utilities', 'LotConfig', 'LandSlope', 'Neighborhood', 'Condition
1', 'Condition2', 'BldgType', 'HouseStyle', 'RoofStyle', 'RoofMatl',
'Exterior1st', 'Exterior2nd', 'MasVnrType', 'ExterQual', 'ExterCond',
'Foundation', 'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1',
'BsmtFinType2', 'Heating', 'HeatingQC', 'CentralAir', 'Electrical', 'K
itchenQual', 'Functional', 'FireplaceQu', 'GarageType', 'GarageFinis
h', 'GarageQual', 'GarageCond', 'PavedDrive', 'PoolQC', 'Fence', 'Misc
Feature', 'SaleType', 'SaleCondition', 'dataset']
nonobject_list: ['Id', 'MSSubClass', 'LotFrontage', 'LotArea', 'Overal
lQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'Bsm
tFinSF1', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF', '2ndFl
rSF', 'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'Fu
llBath', 'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd',
'Fireplaces', 'GarageYrBlt', 'GarageCars', 'GarageArea', 'WoodDeckSF',
'OpenPorchSF', 'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolAre
a', 'MiscVal', 'MoSold', 'YrSold', 'SalePrice']
```

In [18]:

```
for i in object_full_list+non_object_list:
    lbl=LabelEncoder()
    lbl.fit(list(hp_csv[i].values))
    hp_csv[i]=lbl.transform(list(hp_csv[i].values))
```

In [19]:

```
hp_csv.head()
```

Out[19]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Ut
0	1	60	4	0	8450	1	1	3	3	
1	2	20	4	1	9600	1	1	3	3	
2	3	60	4	2	11250	1	1	0	3	
3	4	70	4	3	9550	1	1	0	3	
4	5	60	4	4	14260	1	1	0	3	

5 rows × 82 columns

In [20]:

```
from sklearn.preprocessing import MinMaxScaler
hp_new2=hp_csv.drop(['Id','SalePrice'],axis=1)
col_name=list(hp_new2.columns)
scaler=MinMaxScaler().fit(hp_new2[col_name])
hp_new2[col_name]=scaler.transform(hp_new2[col_name])
hp_new2
```

Out[20]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Ut
0	0.235294	0.8	0.000000	0.033420	1.0	0.5	1.0	1.0	
1	0.000000	0.8	0.000343	0.038795	1.0	0.5	1.0	1.0	
2	0.235294	0.8	0.000685	0.046507	1.0	0.5	0.0	1.0	
3	0.294118	0.8	0.001028	0.038561	1.0	0.5	0.0	1.0	
4	0.235294	0.8	0.001371	0.060576	1.0	0.5	0.0	1.0	
...	...	...	...	...	...	...	...	...	
1454	0.823529	1.0	0.998629	0.002973	1.0	0.5	1.0	1.0	
1455	0.823529	1.0	0.998972	0.002776	1.0	0.5	1.0	1.0	
1456	0.000000	0.8	0.999315	0.087406	1.0	0.5	1.0	1.0	
1457	0.382353	0.8	0.999657	0.042726	1.0	0.5	1.0	1.0	
1458	0.235294	0.8	1.000000	0.038921	1.0	0.5	1.0	1.0	

2919 rows × 80 columns

In [21]:

```
full_col=list(hp_new2.columns)
train_cc=hp_new2[full_col]
skew_cc=train_cc.skew(axis=0)
skew=skew_cc[abs(skew_cc)>0.75]
skew=skew.to_frame(name='skewness')
print(skew)
print(skew.index)
```

```
                skewness
MSSubClass      1.376165
MSZoning       -2.575195
LotArea        12.829025
Street        -15.508104
LandContour    -3.118295
Utilities      33.990952
LotConfig      -1.196901
LandSlope       4.977715
Condition1      2.984648
Condition2     12.066294
BldgType        2.193388
RoofStyle       1.554106
RoofMatl        8.712245
MasVnrArea      1.557110
ExterQual      -1.802335
ExterCond      -2.499003
BsmtCond       -2.864057
BsmtExposure   -1.115430
BsmtFinType2   -3.045893
BsmtFinSF2      3.478350
Heating        12.084999
CentralAir     -3.460801
Electrical     -3.049382
1stFlrSF        1.470360
2ndFlrSF        0.862118
LowQualFinSF   12.094977
GrLivArea       1.270010
BsmtHalfBath    3.933616
KitchenAbvGr    4.304467
TotRmsAbvGrd    0.758757
Functional     -3.820689
GarageQual     -3.075732
GarageCond     -3.597639
PavedDrive     -2.980616
WoodDeckSF      1.843380
OpenPorchSF     2.536417
EnclosedPorch   4.005950
3SsnPorch      11.381914
ScreenPorch     3.948723
PoolArea       16.907017
PoolQC        -20.734650
Fence          -1.994802
MiscFeature     5.066925
MiscVal        21.958480
SaleType       -3.325081
SaleCondition  -2.789472
Index(['MSSubClass', 'MSZoning', 'LotArea', 'Street', 'LandContour',
       'Utilities', 'LotConfig', 'LandSlope', 'Condition1', 'Condition
2',
       'BldgType', 'RoofStyle', 'RoofMatl', 'MasVnrArea', 'ExterQual',
```

```
       'ExterCond', 'BsmtCond', 'BsmtExposure', 'BsmtFinType2', 'BsmtF
inSF2',
       'Heating', 'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF',
       'LowQualFinSF', 'GrLivArea', 'BsmtHalfBath', 'KitchenAbvGr',
       'TotRmsAbvGrd', 'Functional', 'GarageQual', 'GarageCond', 'Pave
dDrive',
       'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch', '3SsnPorch',
       'ScreenPorch', 'PoolArea', 'PoolQC', 'Fence', 'MiscFeature', 'M
iscVal',
       'SaleType', 'SaleCondition'],
      dtype='object')
```

In [22]:

```
for i in list(skew.index):
    hp_csv[i]=np.log1p(hp_csv[i])
```

In [23]:

```
full_col=list(hp_csv.columns)
train_cc=hp_csv[full_col]
skew_cc=train_cc.skew(axis=0)
skew=skew_cc[abs(skew_cc)>0.75]
skew=skew.to_frame(name='skewness')
print(skew)
print(skew.index)
```

```
                skewness
MSZoning       -3.749173
Street        -15.508104
LandContour    -3.528663
Utilities      32.722387
LotConfig      -1.353095
LandSlope       4.486542
Condition1     -0.959142
Condition2     -4.781968
BldgType        1.971066
RoofStyle       1.294681
RoofMatl        8.254887
ExterQual      -3.049371
ExterCond      -3.182679
BsmtCond       -3.320867
BsmtExposure   -1.457024
BsmtFinType2   -3.951148
BsmtFinSF2      2.515870
Heating         9.592262
```

In [24]:

```
hp_new2.describe()
```

Out[24]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotSh
count	2919.000000	2919.000000	2919.000000	2919.000000	2919.000000	2919.000000	2919.000
mean	0.218457	0.793765	0.500000	0.041450	0.995889	0.492806	0.649
std	0.250104	0.171681	0.288824	0.036865	0.063996	0.130046	0.469
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
25%	0.000000	0.800000	0.250000	0.028877	1.000000	0.500000	0.000
50%	0.176471	0.800000	0.500000	0.038108	1.000000	0.500000	1.000
75%	0.294118	0.800000	0.750000	0.048003	1.000000	0.500000	1.000
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000

8 rows × 80 columns

In [89]:

```
train_new=hp_new2[hp_new2['dataset']==1]
test_new=hp_new2[hp_new2['dataset']==0]
```

feature selection and deduction

K-means

In [27]:

```
train_real=train_new.drop(['dataset'],axis=1)
```

In [90]:

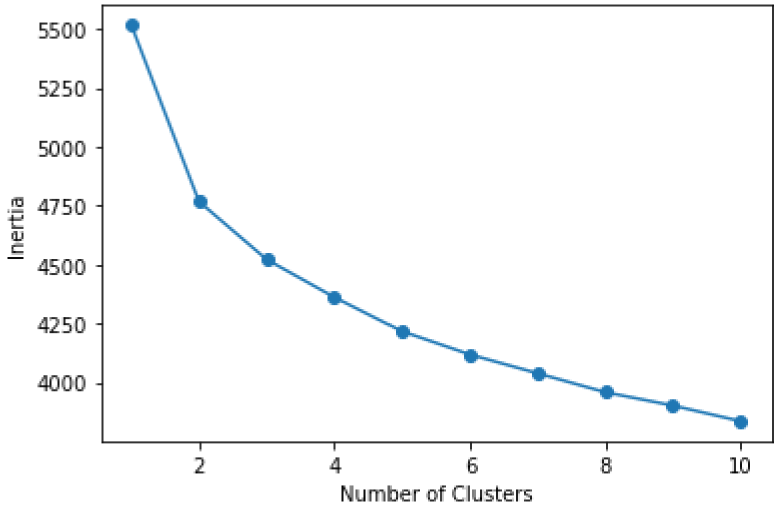
```
test_real = test_new.drop(['dataset'],axis=1)
```

In [30]:

```
from sklearn.cluster import KMeans
inertia=[]
list_num_clusters = list(range(1,11))
for num_clusters in list_num_clusters:
    km=KMeans(n_clusters=num_clusters)
    km.fit(train_real)
    inertia.append(km.inertia_)
```

In [31]:

```
plt.plot(list_num_clusters,inertia)
plt.scatter(list_num_clusters,inertia)
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia')
plt.show()
```



In [32]:

```
km2=KMeans(n_clusters=3).fit(train_real)
train_real['group']=km2.labels_
```

In [33]:

```
train_new2=pd.concat([train_new,train_real['group']],axis=1)
```

In [34]:

```
train_new2.head()
```

Out[34]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utiliti
0	0.235294	0.8	0.000000	0.033420	1.0	0.5	1.0	1.0	0
1	0.000000	0.8	0.000343	0.038795	1.0	0.5	1.0	1.0	0
2	0.235294	0.8	0.000685	0.046507	1.0	0.5	0.0	1.0	0
3	0.294118	0.8	0.001028	0.038561	1.0	0.5	0.0	1.0	0
4	0.235294	0.8	0.001371	0.060576	1.0	0.5	0.0	1.0	0

5 rows × 81 columns

In [43]:

```
from pandas import DataFrame
y_sale=DataFrame({'SalePrice':y})
```

In [44]:

```
y_sale
```

Out[44]:

	SalePrice
0	208500.0
1	181500.0
2	223500.0
3	140000.0
4	250000.0
...	...
1455	175000.0
1456	210000.0
1457	266500.0
1458	142125.0
1459	147500.0

1460 rows × 1 columns

In [46]:

```
train_new3=pd.concat([train_new2,y_sale],axis=1)
print(train_new3.head())
```

```
   MSSubClass  MSZoning  LotFrontage   LotArea  Street  Alley  LotShap
e  \
0    0.235294       0.8     0.000000  0.033420     1.0    0.5       1.
0
1    0.000000       0.8     0.000343  0.038795     1.0    0.5       1.
0
2    0.235294       0.8     0.000685  0.046507     1.0    0.5       0.
0
3    0.294118       0.8     0.001028  0.038561     1.0    0.5       0.
0
4    0.235294       0.8     0.001371  0.060576     1.0    0.5       0.
0

   LandContour  Utilities  LotConfig  ...  Fence  MiscFeature  MiscVal
\
0          1.0        0.0        1.0  ...    1.0         0.25      0.0
1          1.0        0.0        0.5  ...    1.0         0.25      0.0
2          1.0        0.0        1.0  ...    1.0         0.25      0.0
3          1.0        0.0        0.0  ...    1.0         0.25      0.0
4          1.0        0.0        0.5  ...    1.0         0.25      0.0

     MoSold  YrSold  SaleType  SaleCondition  dataset  group  SalePric
e
0  0.090909    0.50       1.0            0.8      1.0      1   208500.
0
1  0.363636    0.25       1.0            0.8      1.0      0   181500.
0
2  0.727273    0.50       1.0            0.8      1.0      1   223500.
0
3  0.090909    0.00       1.0            0.0      1.0      0   140000.
0
4  1.000000    0.50       1.0            0.8      1.0      1   250000.
0

[5 rows x 82 columns]
```

In [47]:

```
group_data=train_new3.groupby(['group']).mean()
group_data['SalePrice']
```

Out[47]:

```
group
0    152732.001890
1    240521.496610
2    121530.891496
Name: SalePrice, dtype: float64
```

Difference in sales is obivous so it may be a good clustering However, too much dimensions ends in 3 clusters might lose a lot of information. The target is to predict the housing price so the K-means method is not applicable for predicting housing prices. Next Steps: (1) Used PCA to decrease the dimensions (2) Used models(Regression, Bagging and boosting methods) to predict the housing prices

PCA

In [48]:

```
train_real2=train_real.drop('group',axis=1)
```

In [49]:

```
train_real2.shape
```

Out[49]:

```
(1460, 79)
```

In [91]:

```
test_real.shape
```

Out[91]:

```
(1459, 79)
```

In [51]:

```
from sklearn.decomposition import PCA
pca_list=list()
feature_weight_list=list()
for n in range(1,40):
    PCAmod=PCA(n_components=n)
    PCAmod.fit(train_real2)
    pca_list.append(pd.Series({'n':n,'model':PCAmod,
                               'var':PCAmod.explained_variance_ratio_.sum()}))
    abs_feature_values=np.abs(PCAmod.components_).sum(axis=0)
    feature_weight_list.append(pd.DataFrame({
                                'n':n,
                                'features':train_real2.columns,
                                'values':abs_feature_values/abs_feature_values.sum()
}))
pca_df=pd.concat(pca_list,axis=1).T.set_index('n')
pca_df
```

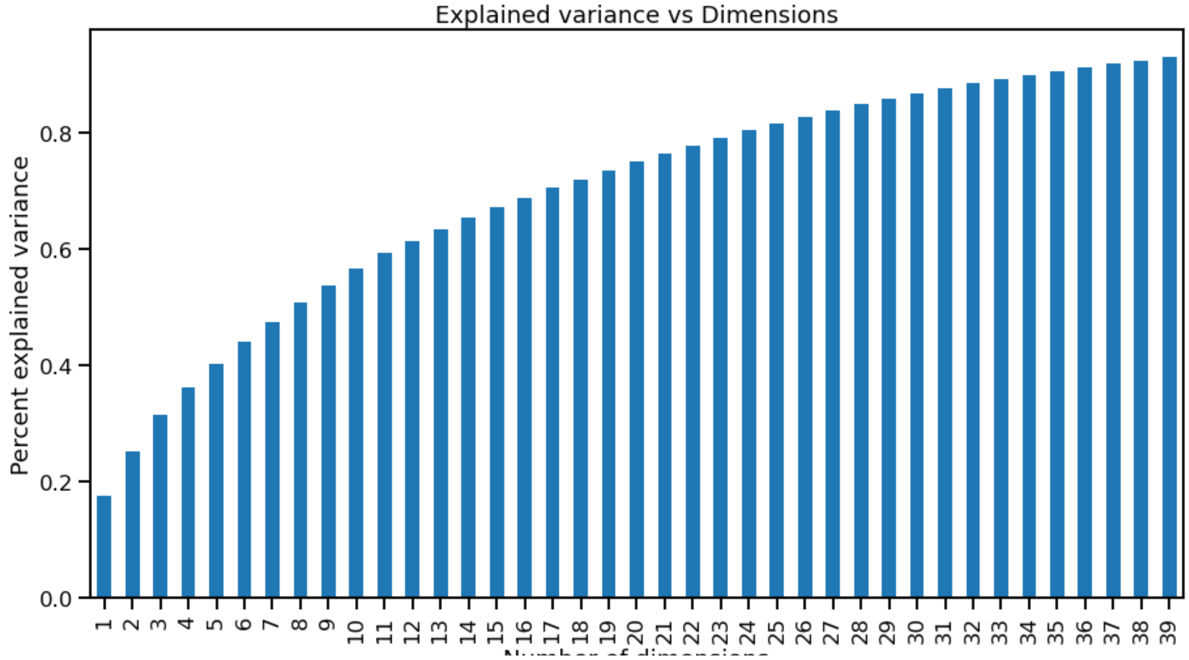
Out[51]:

n	model	var
1	PCA(n_components=1)	0.176047
2	PCA(n_components=2)	0.253102
3	PCA(n_components=3)	0.315185
4	PCA(n_components=4)	0.36202
5	PCA(n_components=5)	0.402422
6	PCA(n_components=6)	0.440148
7	PCA(n_components=7)	0.475287
8	PCA(n_components=8)	0.507335
9	PCA(n_components=9)	0.538172
10	PCA(n_components=10)	0.566593
11	PCA(n_components=11)	0.592579
12	PCA(n_components=12)	0.614398
13	PCA(n_components=13)	0.634967
14	PCA(n_components=14)	0.654127
15	PCA(n_components=15)	0.672641
16	PCA(n_components=16)	0.68879
17	PCA(n_components=17)	0.705023
18	PCA(n_components=18)	0.720251
19	PCA(n_components=19)	0.735925
20	PCA(n_components=20)	0.751022
21	PCA(n_components=21)	0.765266
22	PCA(n_components=22)	0.77862
23	PCA(n_components=23)	0.791751

n	model	var
24	PCA(n_components=24)	0.804461
25	PCA(n_components=25)	0.816113
26	PCA(n_components=26)	0.827413
27	PCA(n_components=27)	0.838586
28	PCA(n_components=28)	0.849058
29	PCA(n_components=29)	0.858548
30	PCA(n_components=30)	0.867633
31	PCA(n_components=31)	0.876647
32	PCA(n_components=32)	0.884759
33	PCA(n_components=33)	0.892515
34	PCA(n_components=34)	0.89962
35	PCA(n_components=35)	0.906323
36	PCA(n_components=36)	0.912802
37	PCA(n_components=37)	0.918935
38	PCA(n_components=38)	0.924703
39	PCA(n_components=39)	0.930199

In [52]:

```
sns.set_context('talk')
plt.figure(figsize=(15, 8))
ax = pca_df['var'].plot(kind='bar')
ax. set(xlabel='Number of dimensions',
       ylabel='Percent explained variance',
       title='Explained variance vs Dimensions');
```



79 dimensions could be deducted to 35 dimensions, with variances more than 90.6%

In [53]:

```
pca=PCA(n_components=35)
X_scaled=pca.fit_transform(train_real2)
print(X_scaled)
print(X_scaled.shape)
```

```
[[ 0.62139404 -0.09039312 -0.56881117 ... -0.04505445  0.08500836
  -0.13048469]
 [ 0.14268384  0.57654452 -0.32490471 ...  0.06578555 -0.05847321
  -0.14479061]
 [ 0.87281173  0.12776005  0.21598469 ... -0.0675353   0.00393354
  -0.0256786 ]
 ...
 [ 0.0727726  -0.30419109 -0.31129305 ...  0.10830725  0.38508199
   0.02175034]
 [-0.61378183  0.22254815 -0.40579911 ... -0.00675809  0.10073956
   0.26285867]
 [-0.24102832  0.61016369 -0.51363074 ... -0.00328618  0.12384418
   0.13034319]]
(1460, 35)
```

In [92]:

```
pca=PCA(n_components=35)
Test_scaled=pca.fit_transform(test_real)
print(Test_scaled.shape)
```

```
(1459, 35)
```

Modelling

We choose several models and use 5-folds cross-calidation to evaluate these models. Models include:

LinearRegression Ridge Lasso Random Forrest Gradient Boosting Tree Support Vector Regression Linear Support Vector Regression ExtraTreesRegressor XgBoost Adaboost GBDT

In [55]:

```
from sklearn.model_selection import cross_val_score, GridSearchCV, KFold
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor, Extra
from sklearn.svm import SVR, LinearSVR
from sklearn.linear_model import ElasticNet, SGDRegressor, BayesianRidge
from sklearn.kernel_ridge import KernelRidge
from xgboost import XGBRegressor
from sklearn.ensemble import AdaBoostRegressor
from sklearn.ensemble import GradientBoostingRegressor
```

In [62]:

```
y1=np.log1p(y)
```

In [58]:

```
X_scaled=pd.DataFrame(X_scaled)
```

In [59]:

```
X_scaled.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 35 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   0       1460 non-null   float64
 1   1       1460 non-null   float64
 2   2       1460 non-null   float64
 3   3       1460 non-null   float64
 4   4       1460 non-null   float64
 5   5       1460 non-null   float64
 6   6       1460 non-null   float64
 7   7       1460 non-null   float64
 8   8       1460 non-null   float64
 9   9       1460 non-null   float64
 10  10      1460 non-null   float64
 11  11      1460 non-null   float64
 12  12      1460 non-null   float64
 13  13      1460 non-null   float64
 14  14      1460 non-null   float64
```

In [60]:

```
models = {}
models['LR'] = LinearRegression()
models['Ridge'] = Ridge()
models['Lasso']=Lasso(alpha=0.01,max_iter=10000)
models['RF']=RandomForestRegressor()
models['SVR']= SVR()
models['LR']= LinearSVR()
models['Ela']= ElasticNet(alpha=0.001,max_iter=10000)
models['SGD'] = SGDRegressor(max_iter=1000,tol=1e-3)
models['Bay'] = BayesianRidge()
models['KR'] = KernelRidge(alpha=0.6, kernel='polynomial', degree=2, coef0=2.5)
models['Extra'] = ExtraTreesRegressor()
models['XGB'] = XGBRegressor()
models['Ada'] = AdaBoostRegressor()
models['GBDT'] = GradientBoostingRegressor()
```

In [63]:

```
kf = KFold(10)
for model in models:
    cv_result = cross_val_score(models[model], X_scaled, y1, cv=kf, scoring="neg_mea
    print('%s model scoring %s, std %s' % (model,
                                           round(np.sqrt(-cv_result.mean()),4),
                                           cv_result.std()))
```

```
LR model scoring 0.1535, std 0.006914052523403825
Ridge model scoring 0.153, std 0.007007363047927657
Lasso model scoring 0.1956, std 0.008428107648325018
RF model scoring 0.1791, std 0.006197784294547 58
SVR model scoring 0.1592, std 0.004861613521901746
Ela model scoring 0.1531, std 0.006963691626275504
SGD model scoring 0.1641, std 0.007061279691485609
Bay model scoring 0.153, std 0.006999910729121719
KR model scoring 0.1508, std 0.006837252265078653
Extra model scoring 0.1731, std 0.006562451583580815
XGB model scoring 0.1674, std 0.006237492230090017
Ada model scoring 0.2084, std 0.006634095025716003 6
GBDT model scoring 0.1699, std 0.006902300916498008
```

Narrow down to better perfermance models: Adaboost RF,Extra Lasso

Next we do some hyperparameters tuning. First define a gridsearch method.

Lasso

In [73]:

```
grid=GridSearchCV(estimator=Lasso(),
                  param_grid=
                  {'alpha':[0.0001,0.00015,0.0002,0.0005,0.01],
                   'max_iter':[10000],
                  'normalize':[True,False]},
                  cv=kf,
                  scoring='neg_mean_squared_error')
grid_result=grid.fit(X_scaled,y1)
print('Lasso best_estimatoris %s,scoring %s'
      %(grid_result.best_params_,
        round(np.sqrt(-1*grid_result.best_score_),4)
     ))
```

```
Lasso best_estimatoris {'alpha': 0.0002, 'max_iter': 10000, 'normaliz
e': False},scoring 0.1529
```

Bagging Models

In [74]:

```
bagging_models={'RandomForest':RandomForestRegressor(),
               'ExtraTree':ExtraTreesRegressor()}
bagging_params={'n_estimators':[10,50,100,200,500,800]}
```

In [75]:

```
kf=KFold(10)
for model in bagging_models:
    grid=GridSearchCV(estimator=bagging_models[model],
                      param_grid=bagging_params,
                      cv=kf,
                      scoring='neg_mean_squared_error')
    grid_result=grid.fit(X_scaled,y1)
    print('%s model best_estimatoris %s,scoring %s'
      %(model,
        grid_result.best_params_,
        round(np.sqrt(-1*grid_result.best_score_),4)))
```

```
RandomForest model best_estimatoris {'n_estimators': 100},scoring 0.17
73
ExtraTree model best_estimatoris {'n_estimators': 500},scoring 0.1731
```

Boosting models

In [78]:

```
boosting_models={'Adaboost':AdaBoostRegressor()}
boosting_params={'n_estimators':[10,50,100,200,500,800],
                 'learning_rate':[0.005,0.01,0.1,0.5,1]}
kf=KFold(10)
for model in boosting_models:
    grid=GridSearchCV(estimator=boosting_models[model],
                      param_grid=boosting_params,
                      cv=kf,
                      scoring='neg_mean_squared_error')
    grid_result=grid.fit(X_scaled,y1)
    print('%s model best_estimatoris %s,scoring %s'
      %(model,
        grid_result.best_params_,
        round(np.sqrt(-1*grid_result.best_score_),4)))
```

```
Adaboost model best_estimatoris {'learning_rate': 1, 'n_estimators': 1
00},scoring 0.2034
```

In [93]:

```
ad = AdaBoostRegressor(n_estimators = 100, learning_rate = 1)
ad .fit(X_scaled,y1)
y_predit=  ad.predict(Test_scaled)
```

In [95]:

```
y_predit
```

Out[95]:

```
array([11.69792134, 11.9451477 , 12.28589869, ..., 11.8111241 ,
       11.80571857, 12.40334841])
```

In [96]:

```
y_sale=np.expm1(y_predit)
```

In [97]:

```
y_sale.shape
```

Out[97]:

```
(1459,)
```

In [98]:

```
test_csv.shape
```

Out[98]:

```
(1459, 81)
```

Submission

In [99]:

```
submission=pd.DataFrame({
    'ID':test_csv['Id'],
    'SalePrice':y_sale
})
submission.to_csv('submission.csv',index=False)
```

In [100]:

```
ls= Lasso(alpha=0.01,max_iter=10000)
ls. fit (X_scaled,y1)
y_lasso=  ls.predict(Test_scaled)
y_lasso=np.expm1(y_lasso)
submission=pd.DataFrame({
    'ID':test_csv['Id'],
    'SalePrice':y_lasso
})
submission.to_csv('submission2.csv',index=False)
```

In [103]:

```
submission=pd.DataFrame({
    'ID':test_csv['Id'],
    'SalePrice':(y_sale+y_lasso*2)/3
})
submission.to_csv('submission3.csv',index=False)
```

Flaws and Next step

Conclusion: After cleaning the data, encoding and model fitting, the project had a 20% root mean squared error.

Flaws: (1) After The PCA deductions, the data retain 35 dimensions, which are still to much. (2) I did not use the features importance selections to choose from original variables. (3) I did not use the stack modelling to combine different models,which means the model might be overfitting.

Next step: (1) Use features importance methods to select models. (2) Explore other ways to deduct the dimensions (3) Use stack models to combine all models