In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
train_data='C:/Users/swetha/Desktop/train.csv'
train_data=pd.read_csv(train_data)
train_data.describe()
test_data='C:/Users/swetha/Desktop/test.csv'
test_data=pd.read_csv(test_data)
test_data.describe()
```

Out[1]:

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	Bs
count	1459.000000	1459.000000	1232.000000	1459.000000	1459.000000	1459.000000	1459.000000	1459.000000	1444.000000	14
mean	2190.000000	57.378341	68.580357	9819.161069	6.078821	5.553804	1971.357779	1983.662783	100.709141	4
std	421.321334	42.746880	22.376841	4955.517327	1.436812	1.113740	30.390071	21.130467	177.625900	4
min	1461.000000	20.000000	21.000000	1470.000000	1.000000	1.000000	1879.000000	1950.000000	0.000000	
25%	1825.500000	20.000000	58.000000	7391.000000	5.000000	5.000000	1953.000000	1963.000000	0.000000	
50%	2190.000000	50.000000	67.000000	9399.000000	6.000000	5.000000	1973.000000	1992.000000	0.000000	3
75%	2554.500000	70.000000	80.000000	11517.500000	7.000000	6.000000	2001.000000	2004.000000	164.000000	7
max	2919.000000	190.000000	200.000000	56600.000000	10.000000	9.000000	2010.000000	2010.000000	1290.000000	40

8 rows × 37 columns

In [8]:

```
print("train_data shape:", train_data.shape)
print("test_data shape:", test_data.shape)
```

```
train_data shape: (1460, 81)
test_data shape: (1459, 80)
```

In [10]:

```
print(train_data.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  \
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

  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 rows x 81 columns]
```

In [11]:

```
plt.style.use(style='ggplot')
```

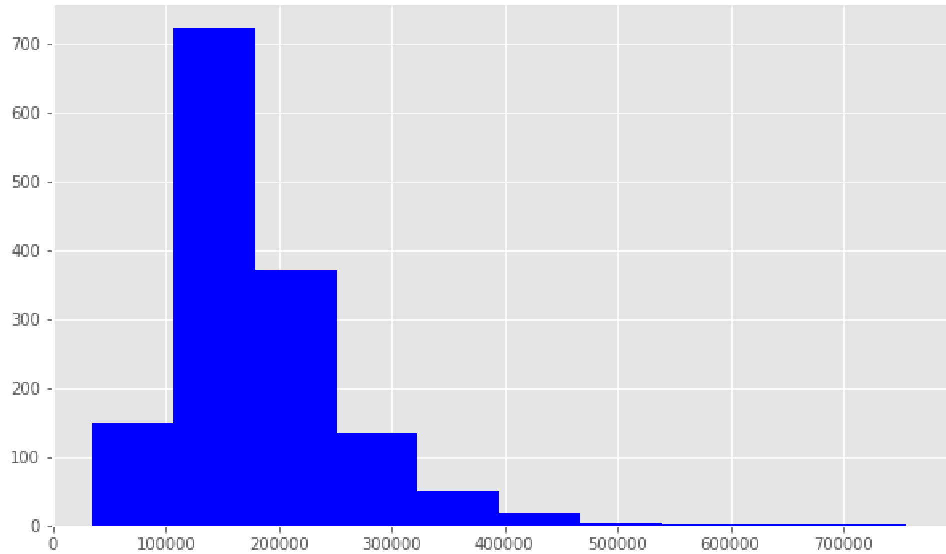
```
plt.rcParams['figure.figsize'] = (10, 6)
print (train_data.SalePrice.describe())
```

```
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 [12]:

```
print ("Skew is:", train_data.SalePrice.skew())
plt.hist(train_data.SalePrice, color='blue')
plt.show()
```

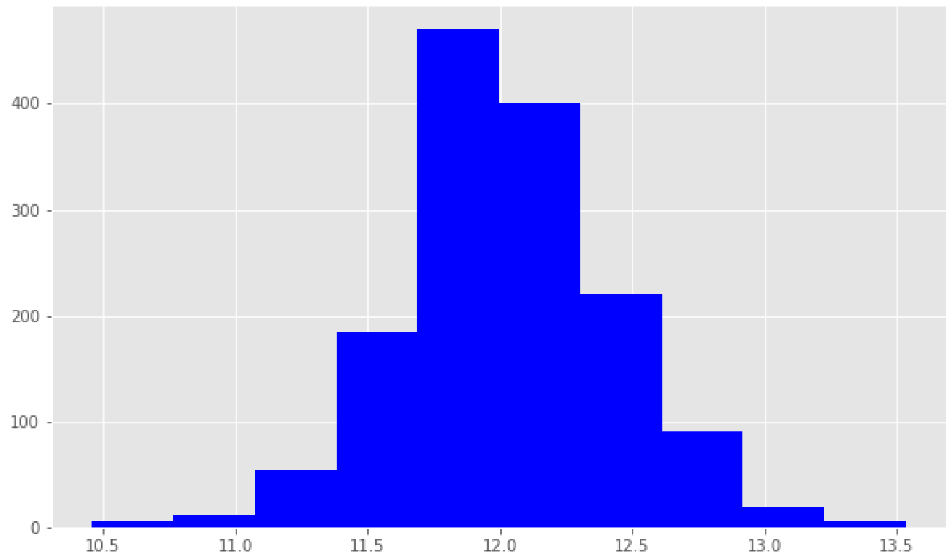
```
Skew is: 1.8828757597682129
```



In [13]:

```
target = np.log(train_data.SalePrice)
print ("\n Skew is:", target.skew())
plt.hist(target, color='blue')
plt.show()
```

```
 Skew is: 0.12133506220520406
```



In [14]:

```
numeric_features = train_data.select_dtypes(include=[np.number])
corr = numeric_features.corr()
print (corr['SalePrice'].sort_values(ascending=False)[:5], '\n')
print (corr['SalePrice'].sort_values(ascending=False)[-5:])
```

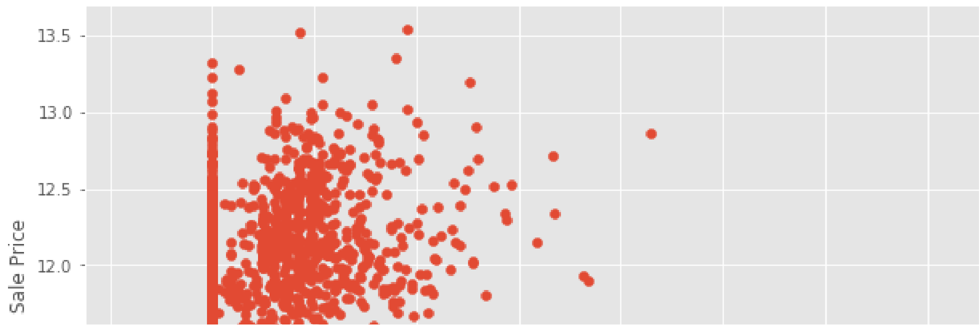
```
SalePrice      1.000000
OverallQual    0.790982
GrLivArea      0.708624
GarageCars     0.640409
GarageArea     0.623431
Name: SalePrice, dtype: float64

YrSold          -0.028923
OverallCond     -0.077856
MSSubClass      -0.084284
EnclosedPorch   -0.128578
KitchenAbvGr    -0.135907
Name: SalePrice, dtype: float64
```

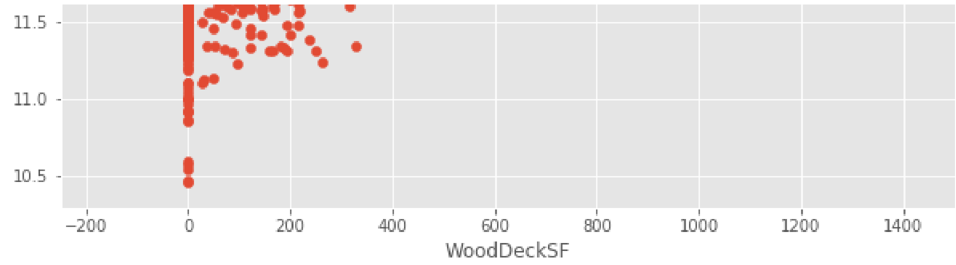
In [15]:

```
plt.scatter(x=train_data['WoodDeckSF'],y=target)
plt.ylabel('sale price')
plt.xlabel('WoodDeckSF')
plt.show()
```

In [16]:

```
train_data=train_data[train_data['WoodDeckSF']< 1200]
plt.scatter(x=train_data['WoodDeckSF'],y=np.log(train_data.SalePrice))
plt.xlim(-250,1500)
plt.ylabel('Sale Price')
plt.xlabel('WoodDeckSF')
plt.show()
```





In [17]:

```
nulls = pd.DataFrame(train_data.isnull().sum().sort_values(ascending=False)[:25])
nulls.columns = ['Null Count']
nulls.index.name = 'Feature'
print(nulls)
```

```
              Null Count
Feature
PoolQC              1453
MiscFeature         1406
Alley               1369
Fence               1179
FireplaceQu          690
LotFrontage          259
GarageCond            81
GarageType            81
GarageYrBlt           81
GarageFinish          81
GarageQual            81
BsmtExposure          38
BsmtFinType2          38
BsmtFinType1          37
BsmtCond              37
BsmtQual              37
MasVnrArea             8
MasVnrType             8
Electrical             1
Utilities              0
YearRemodAdd           0
MSSubClass             0
Foundation             0
ExterCond              0
ExterQual              0
```

In [18]:

```
categoricals = train_data.select_dtypes(exclude=[np.number])
print(categoricals.describe())
```

```
       MSZoning Street Alley LotShape LandContour Utilities LotConfig  \
count      1460   1460    91     1460        1460      1460      1460
unique        5      2     2        4           4         2         5
top          RL   Pave  Grvl      Reg         Lvl    AllPub    Inside
freq       1151   1454    50      925        1311      1459      1052

       LandSlope Neighborhood Condition1     ...      GarageType  \
count       1460         1460       1460     ...            1379
unique         3           25          9     ...               6
top          Gtl        NAmes       Norm     ...          Attchd
freq        1382          225       1260     ...             870

       GarageFinish GarageQual GarageCond PavedDrive PoolQC  Fence  \
count          1379       1379       1379       1460      7    281
unique            3          5          5          3      3      4
top             Unf         TA         TA          Y     Gd  MnPrv
freq            605       1311       1326       1340      3    157

       MiscFeature SaleType SaleCondition
count           54     1460          1460
unique           4        9             6
top           Shed       WD        Normal
freq            49     1267          1198
```

```
[4 rows x 43 columns]
```

In [19]:

```
print ("Original: \n")
print (train_data.Street.value_counts(), "\n")
```

```
Original:

Pave    1454
Grvl       6
Name: Street, dtype: int64
```

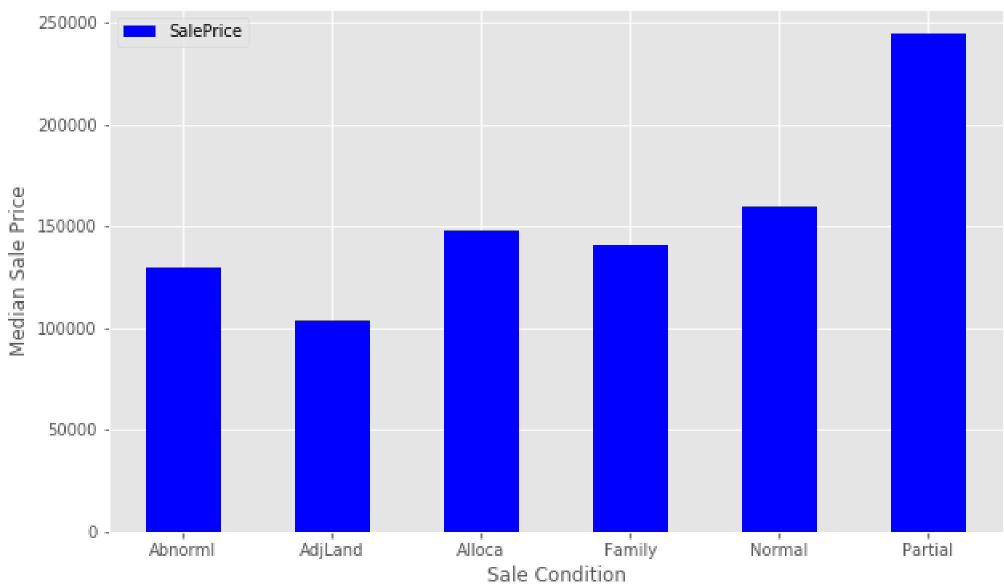
In [21]:

```
train_data['enc_street'] = pd.get_dummies(train_data.Street, drop_first=True)
test_data['enc_street'] = pd.get_dummies(test_data.Street, drop_first=True)
print ('Encoded: \n')
print (train_data.enc_street.value_counts())
```

```
Encoded:

1    1454
0       6
Name: enc_street, dtype: int64
```

In [22]:

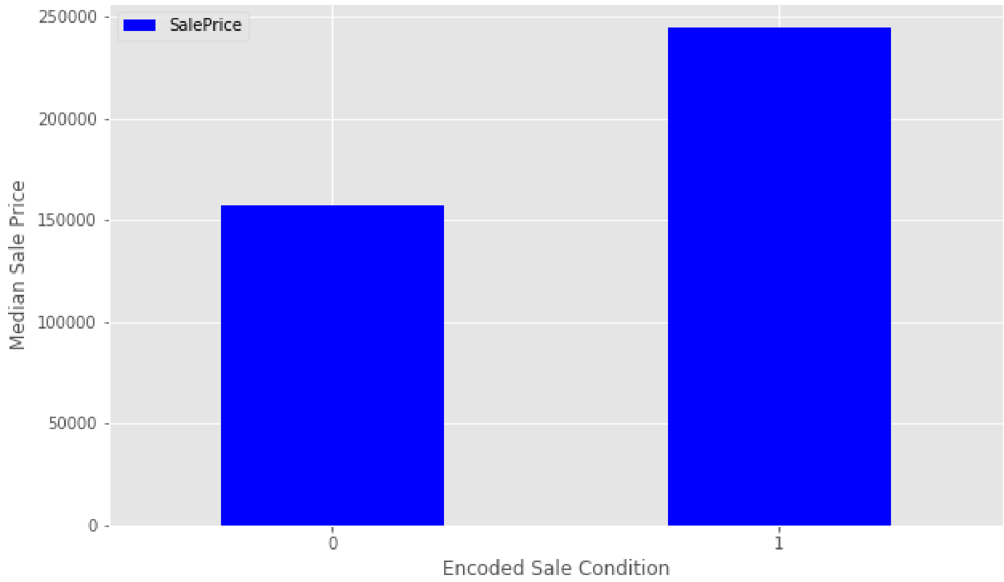
```
condition_pivot = train_data.pivot_table(index='SaleCondition', values='SalePrice', aggfunc=np.medi
an)
condition_pivot.plot(kind='bar', color='blue')
plt.xlabel('Sale Condition')
plt.ylabel('Median Sale Price')
plt.xticks(rotation=0)
plt.show()
```



In [23]:

```
def encode(x) : return 1 if x== 'Partial' else 0
train_data['enc_condition'] = train_data.SaleCondition.apply(encode)
test_data['enc_condition'] = test_data.SaleCondition.apply(encode)
condition_pivot = train_data.pivot_table(index='enc_condition', values='SalePrice', aggfunc=np.medi
an)
condition_pivot.plot(kind='bar', color='blue')
plt.xlabel('Encoded Sale Condition')
plt.ylabel('Median Sale Price')
plt.xticks(rotation=0)
plt.show()
```

```
plt.show()
```



In [26]:

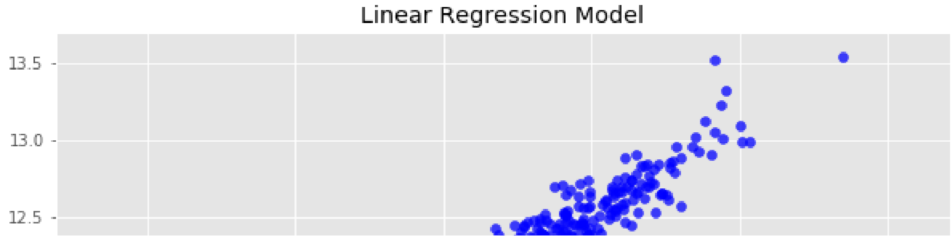
```
data = train_data.select_dtypes(include=[np.number]).interpolate().dropna()

print(sum(data.isnull().sum() != 0))

y = np.log(train_data.SalePrice)
X = data.drop(['SalePrice', 'Id'], axis=1)

from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn import linear_model

X_train_data, X_test_data, y_train_data, y_test_data = train_test_split(X, y, random_state=42, test
_size=.50)

lr = linear_model.LinearRegression()

model = lr.fit(X_train_data, y_train_data)
print("R^2 is: \n", model.score(X_test_data, y_test_data))
```

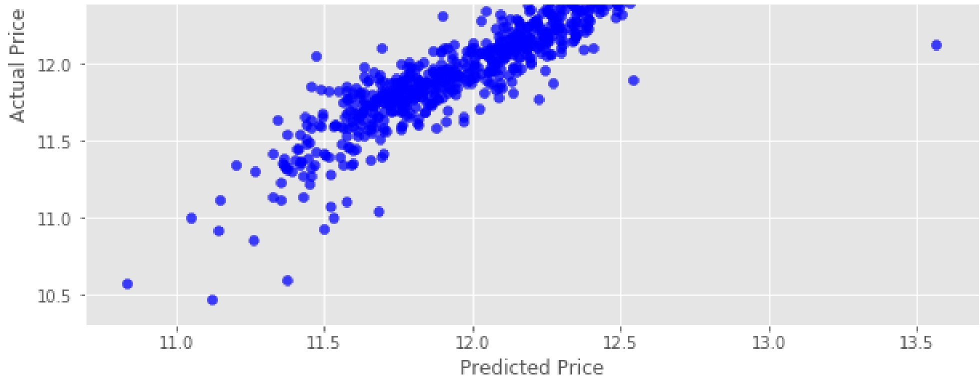
```
0
R^2 is:
 0.8564064602783424
```

In [27]:

```
predictions = model.predict(X_test_data)
print('RMSE is: \n', mean_squared_error(y_test_data, predictions))
actual_values = y_test_data
plt.scatter(predictions, actual_values, alpha=.75,
            color='b')
plt.xlabel('Predicted Price')
plt.ylabel('Actual Price')
plt.title('Linear Regression Model')
plt.show()
```

```
RMSE is:
 0.02394509463942047
```





In [29]:

```
submission = pd.DataFrame()
submission['Id']= test_data.Id
feats = test_data.select_dtypes(
include=[np.number]).drop(['Id'], axis=1).interpolate()
predictions = model.predict(feats)
final_predictions = np.exp(predictions)
print("Original predictions are: \n", predictions[:40], "\n")
print("Final predictions are: \n", final_predictions[:40])
```

```
Original predictions are:
 [11.64895308 11.94044415 12.02718676 12.16293269 12.09403452 12.07047626
 12.1687319  12.04426022 12.17618814 11.67184269 12.16642843 11.61225858
 11.52634696 11.95546319 11.71022329 12.72590215 12.42180477 12.51715624
 12.4580164  12.93300047 12.59926236 12.1888906  12.0113667  11.98331652
 12.21426629 12.22087499 12.65961758 12.40790143 12.13720351 12.2588244
 12.16809354 11.46426006 12.34979425 12.61164918 12.55310659 12.22537645
 12.0431446  11.95569907 12.02735878 11.95820936]

Final predictions are:
 [114571.35343198 153344.78374893 167240.26268141 191555.46600358
 178802.03377128 174638.99980394 192669.56384032 170120.14884681
 194111.52398311 117224.09162669 192226.26594999 110443.41456896
 101351.19674025 155665.25627003 121810.67644177 336348.17931076
 248153.99179247 272980.66261582 257304.73463441 413743.07486959
 296339.89113047 196592.94557298 164615.32964291 160061.99951776
 201645.46075501 202982.48872687 314776.32245404 244727.69658731
 186689.76603865 210833.58478991 192546.6112499   95249.97766235
 230912.52675172 300033.42918215 282972.94895208 203898.26512872
 169930.46461656 155701.97973291 167269.03412926 156093.32693999]
```

In [32]:

```
submission['SalePrice'] = final_predictions
```

In [33]:

```
submission
```

Out[33]:

	Id	SalePrice
0	1461	114571.353432
1	1462	153344.783749
2	1463	167240.262681
3	1464	191555.466004
4	1465	178802.033771
5	1466	174638.999804
6	1467	192669.563840
7	1468	170120.148847
8	1469	194111.523983
9	1470	117224.091627

	Id	SalePrice
9	1470	[illegible]
10	1471	192226.265950
11	1472	110443.414569
12	1473	101351.196740
13	1474	155665.256270
14	1475	121810.676442
15	1476	336348.179311
16	1477	248153.991792
17	1478	272980.662616
18	1479	257304.734634
19	1480	413743.074870
20	1481	296339.891130
21	1482	196592.945573
22	1483	164615.329643
23	1484	160061.999518
24	1485	201645.460755
25	1486	202982.488727
26	1487	314776.322454
27	1488	244727.696587
28	1489	186689.766039
29	1490	210833.584790
...	...	...
1429	2890	86907.103282
1430	2891	129737.004413
1431	2892	75257.706921
1432	2893	94986.358081
1433	2894	59612.255071
1434	2895	295909.261968
1435	2896	254236.338752
1436	2897	199398.834811
1437	2898	154965.623789
1438	2899	208737.231563
1439	2900	148531.119637
1440	2901	196225.569718
1441	2902	178987.320737
1442	2903	343731.862124
1443	2904	344602.616175
1444	2905	88128.048886
1445	2906	232363.630129
1446	2907	121566.202475
1447	2908	131786.316016
1448	2909	153124.097829
1449	2910	83789.225334
1450	2911	91184.451395
1451	2912	144493.976251
1452	2913	95963.610525
1453	2914	86090.649570
1454	2915	94429.122479
1455	2916	95093.464891
1456	2917	160328.550453
1457	2918	109073.351547

	Id	SalePrice
1458	2919	239689.987069

1459 rows × 2 columns

In [ ]:

In [ ]: