```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('darkgrid')
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

Read the data in the file 'housing.csv' into a data frame and look at the first few lines .

```
housingDf = pd.read_csv("housing.csv")
housingDf.head()
```

```
   Longitude  Latitude  HouseAge  AveRooms  AveBedrms  Population  AveOccu
0    -122.23     37.88        41       880      129.0         322       12
1    -122.22     37.86        21      7099     1106.0        2401      113
2    -122.24     37.85        52      1467      190.0         496       17
3    -122.25     37.85        52      1274      235.0         558       21
4    -122.25     37.85        52      1627      280.0         565       25

   MedInc  SalePrice
0  8.3252     452600
1  8.3014     358500
2  7.2574     352100
3  5.6431     341300
4  3.8462     342200
```

	Longitude	Latitude	HouseAge	AveRooms	AveBedrms	Population	AveOccup	MedInc	SalePrice
0	-122.23	37.88	41	880	129.0	322	126	8.3252	452600
1	-122.22	37.86	21	7099	1106.0	2401	1138	8.3014	358500
2	-122.24	37.85	52	1467	190.0	496	177	7.2574	352100
3	-122.25	37.85	52	1274	235.0	558	219	5.6431	341300
4	-122.25	37.85	52	1627	280.0	565	259	3.8462	342200

You can find documentation for this dataset in the California Housing dataset textfile. Open the file and try to understand what the variables represent. When you have finished you can get info from the data frame and continue your work.

```
housingDf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 9 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   Longitude   20640 non-null  float64
 1   Latitude    20640 non-null  float64
 2   HouseAge    20640 non-null  int64  
 3   AveRooms    20640 non-null  int64  
 4   AveBedrms   20433 non-null  float64
 5   Population  20640 non-null  int64  
 6   AveOccup    20640 non-null  int64  
 7   MedInc      20640 non-null  float64
 8   SalePrice   20640 non-null  int64  
dtypes: float64(4), int64(5)
memory usage: 1.4 MB
```

Are there any missing entries? Where?

we can see that we are missing the SalePrice column

Since all the variables are numeric calculate descriptive statistics for all the columns.

```
housingDf.describe()
```

```
          Longitude      Latitude      HouseAge      AveRooms     AveBedrm
count  20640.000000  20640.000000  20640.000000  20640.000000  20433.00000
mean    -119.569704     35.631861     28.639486   2635.763081    537.87055
std        2.003532      2.135952     12.585558   2181.615252    421.38507
min     -124.350000     32.540000      1.000000      2.000000      1.00000
25%     -121.800000     33.930000     18.000000   1447.750000    296.00000
50%     -118.490000     34.260000     29.000000   2127.000000    435.00000
75%     -118.010000     37.710000     37.000000   3148.000000    647.00000
max     -114.310000     41.950000     52.000000  39320.000000   6445.00000

          Population      AveOccup        MedInc      SalePrice
count  20640.000000  20640.000000  20640.000000   20640.000000
mean    1425.476744    499.539680      3.870671  206855.816909
std     1132.462122    382.329753      1.899822  115395.615874
min        3.000000      1.000000      0.499900   14999.000000
25%      787.000000    280.000000      2.563400  119600.000000
50%     1166.000000    409.000000      3.534800  179700.000000
75%     1725.000000    605.000000      4.743250  264725.000000
max    35682.000000   6082.000000     15.000100  500001.000000
```

	Longitude	Latitude	HouseAge	AveRooms	AveBedrms	Population
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.0000
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.47674
std	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.46212
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.000000
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	787.000000
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.00000
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.00000
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.0000

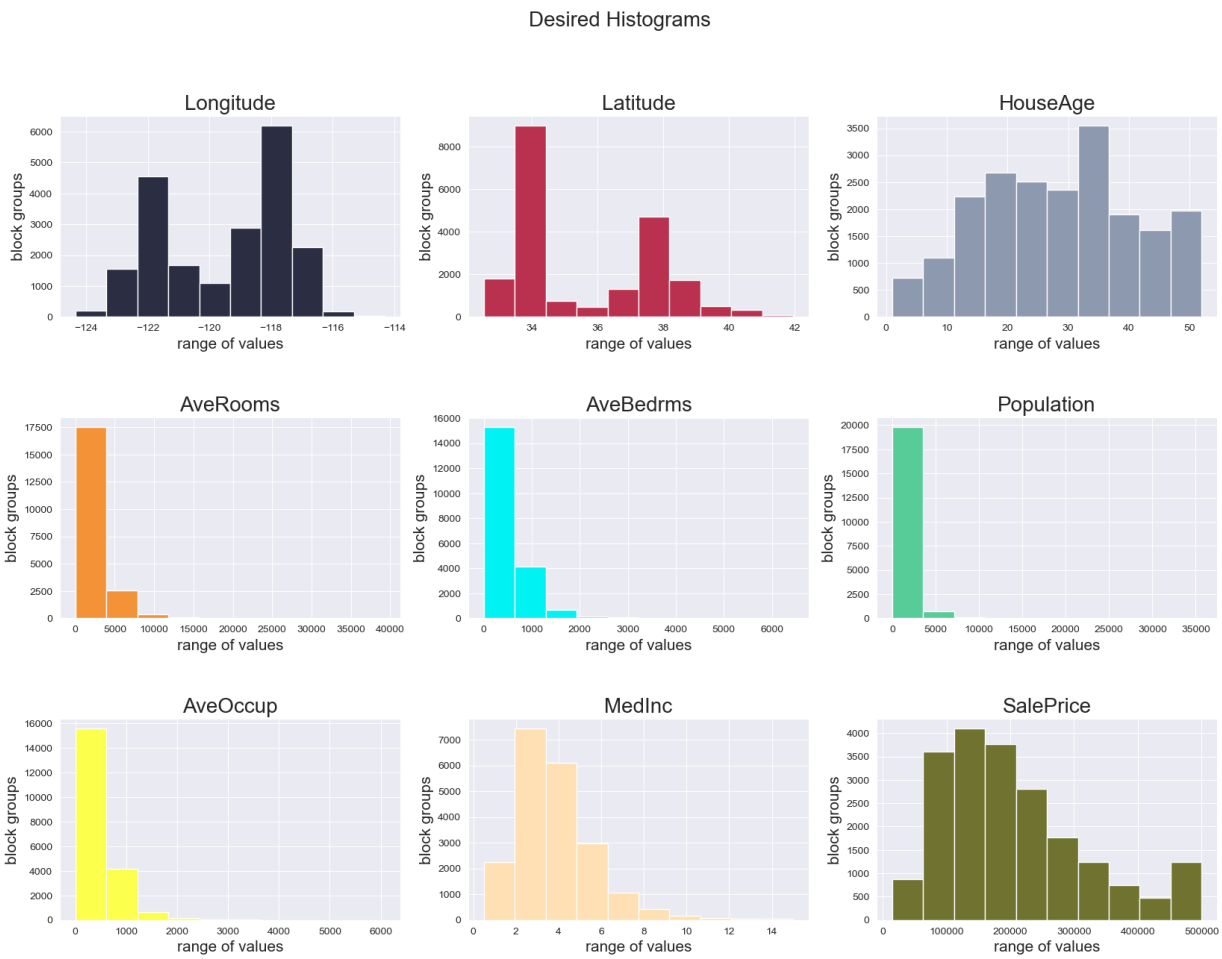
Exploratory Data Analysis

Make histograms for each column of the dataset. (Pandas can do it easily in one line, just make it big enough to see).

```
fig, axes = plt.subplots(nrows = 3, ncols =3, figsize = (20, 14))
fig.subplots_adjust(hspace = 0.5)
colors = ["#2B2D42", "#B9314F", "#8D99AE", "#F39237","#00F2F2","#57CC99","#F
for index, column in enumerate(housingDf.columns):
    ax = axes.flatten()[index]
    ax.hist(housingDf[column],color = colors[index], label = column)
    ax.set_title(column, size = 20)
    ax.set_xlabel("range of values", size = 15)
    ax.set_ylabel("block groups", size = 15)

plt.suptitle("Desired Histograms", size = 20)
```

```
Text(0.5, 0.98, 'Desired Histograms')

<Figure size 2000x1400 with 9 Axes>
```

Download

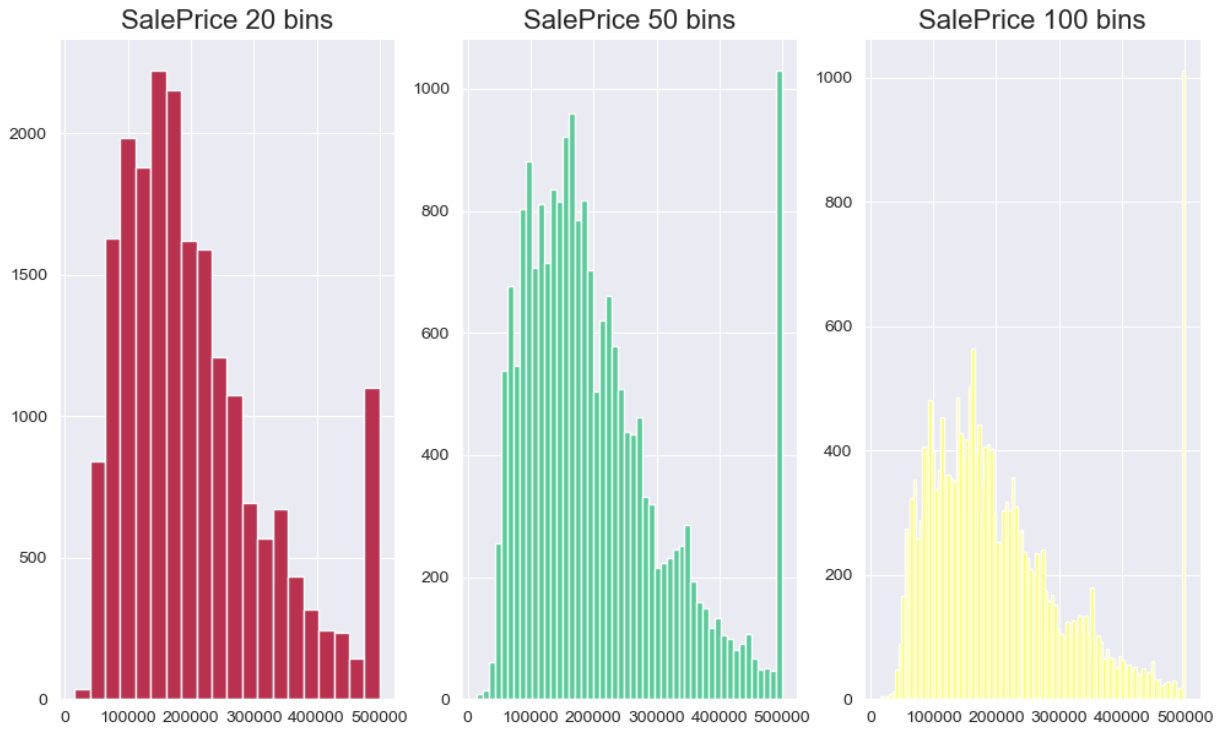


Take a closer look at the histogram of SalePrice. Redo it with 20, 50 and then 100 bins (3 histograms side by side).

```
fig, (ax1, ax2, ax3) = plt.subplots(1,3, figsize = (15,5))
housingDf['SalePrice'].hist(bins=20,figsize=(12,7), color= colors[1], ax = a
ax1.set_title("SalePrice 20 bins", fontsize=16)

housingDf['SalePrice'].hist(bins=50,figsize=(12,7), color= colors[5],ax = ax
ax2.set_title("SalePrice 50 bins", fontsize=16)

housingDf['SalePrice'].hist(bins=100,figsize=(12,7), color= colors[6],ax = a
ax3.set_title("SalePrice 100 bins", fontsize=16)
```

```
Text(0.5, 1.0, 'SalePrice 100 bins')

<Figure size 1200x700 with 3 Axes>
```

Download



Do you think there are really about 1000 houses with SalePrice exactly equal to 500001?

no there are more than 1000 they just optimized for the data set and made a limited set the the max prcie can be 500001

What do you think the original data looked like?

the original data looked more spread over a larger range and the limit of the hosing price is much higher

What has been done to the highest prices before recording them in the file?

each one of the higher prices has been reduced to be maximum value of 500001

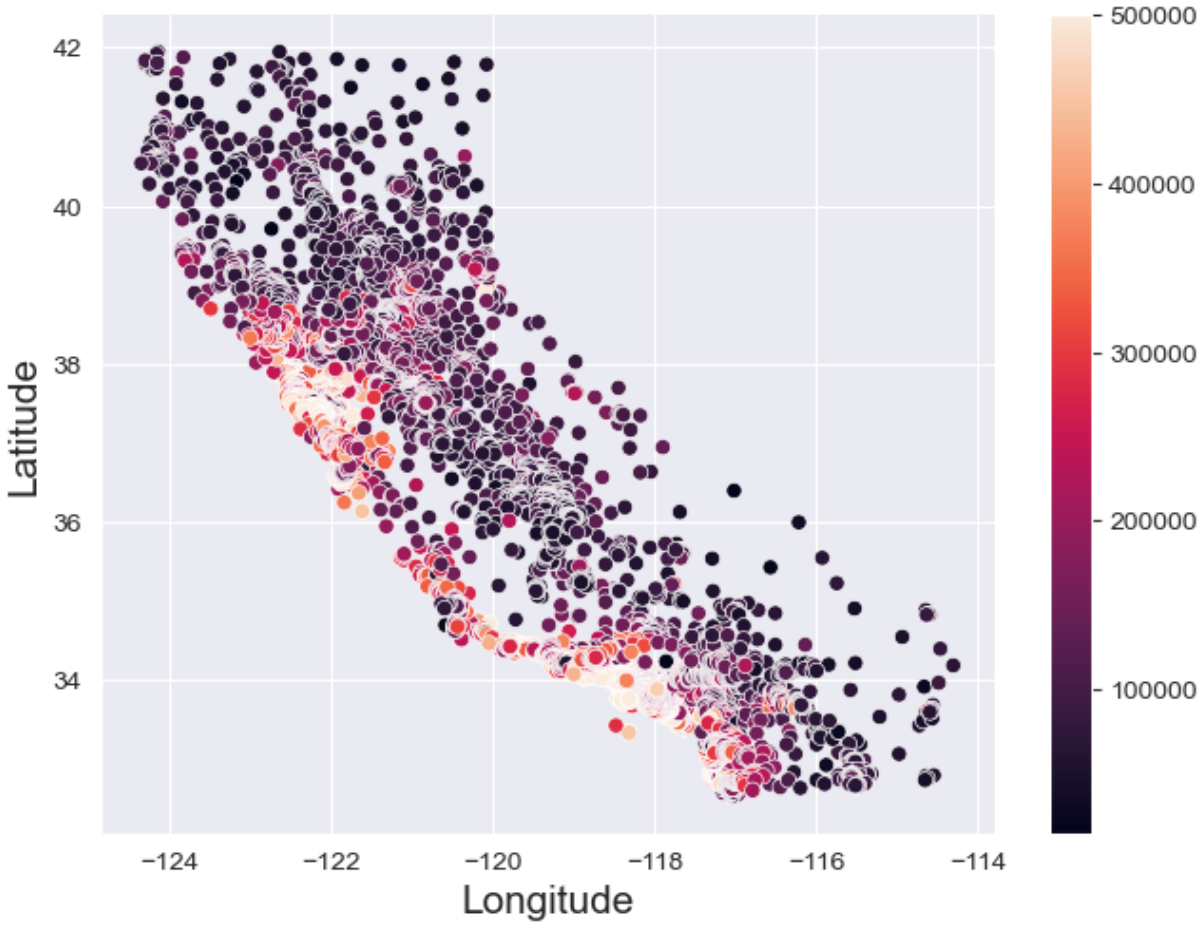
Now lets explore the relationships between pairs of variables.

First make a scatter plot with Longitude on the x axis and Latitude on the y axis. Colour the dots (hue) according to SalePrice. Choose a palette that shows the difference between the colours clearly.

```
ax = sns.relplot(data=housingDf, x=housingDf["Longitude"], y=housingDf["Lati
            hue='SalePrice',aspect=1,palette="rocket",legend=False)
norm = plt.Normalize(housingDf['SalePrice'].min(), housingDf['SalePrice'].ma
sm = plt.cm.ScalarMappable(cmap="rocket", norm=norm)
sm.set_array([])
ax.figure.colorbar(sm)
ax.figure.set_size_inches(7,5)
plt.xlabel('Longitude', size=15)
plt.ylabel('Latitude', size=15)
```

```
Text(13.319444444444445, 0.5, 'Latitude')

<Figure size 700x500 with 2 Axes>
```

Download



Now something cool - run the next cell...

```
from IPython.display import HTML
HTML('<iframe src="https://www.google.com/maps/embed?pb=!1m18!1m12!1m3!1d650
```

```
<IPython.core.display.HTML object>
```

Where are the prices generally higher?

the prices are higher in Los Angeles and San Francisco areas

Make a heatmap showing the correlations between the rest of the variables

```
corr = housingDf.corr()
f, ax = plt.subplots(figsize=(11, 9))
cmap = sns.diverging_palette(220, 10, as_cmap=True)
sns.heatmap(corr, cmap='coolwarm',vmin=-1, vmax=1, center=0,
            square=True, linewidths=-1, cbar_kws={"shrink": .5},annot=True)
```

```
<AxesSubplot: >

<Figure size 1100x900 with 2 Axes>
```

Download

Which variables will we want to use to predict Sale Price? Are there any you can drop?

we have 3 variables and to improve our model we can remove 2 of them, we can choose between: AveOccup, Population, AveBedrms

Split the Data and Scaling

Use train_test_split with proportion 70:30 between train and test sets. Use random_state = 10

```
housingDf = housingDf.dropna()
X= housingDf[['AveBedrms','Longitude','Latitude','HouseAge','AveRooms','MedI
y = housingDf['SalePrice'].values
```

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,rand
```

Linear Regression

Fit the model and print the coefficients and intercept

```
from sklearn.linear_model import LinearRegression
lreg = LinearRegression()
lreg.fit(X,y)
lreg.fit(X_train, y_train)
a,b =(lreg.coef_[0],lreg.intercept_)
print ("intercept :" , str(lreg.intercept_))
print('coefficients :' ,lreg.coef_)
```

```
intercept : -3493579.0128046256
coefficients : [ 1.01846689e+02 -4.09635147e+04 -3.95926414e+04  1.2393422
 -1.56383824e+01  4.24559077e+04]
```

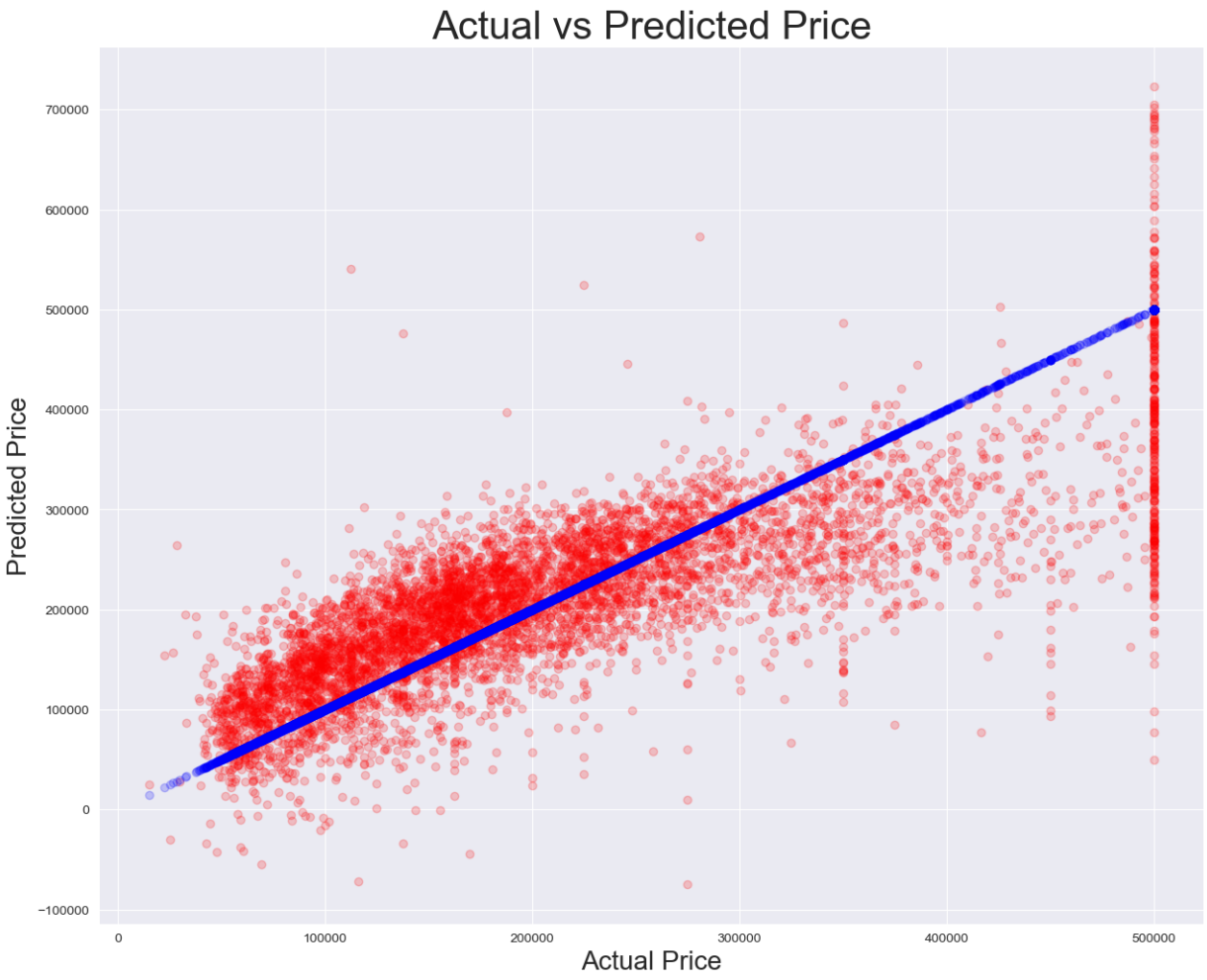
Predictions

Predict the SalePrice on the test set. Make a scatter plot with actual prices on the x axis and predicted values on the y axis

```
y_train_pred = lreg.predict(X_train)
test_pred = lreg.predict(X_test)
heu = [y_train_pred, test_pred]
plt.figure(figsize=(15,12))
plt.scatter(y_test, test_pred, color='red', alpha=0.2, label='Predicted')
plt.scatter(y_test, y_test, color='blue', alpha=0.2, label='Actual')

plt.xlabel('Actual Price', size = 20)
plt.ylabel('Predicted Price', size= 20)
plt.title('Actual vs Predicted Price', size =30)
```

```
Text(0.5, 1.0, 'Actual vs Predicted Price')

<Figure size 1500x1200 with 1 Axes>
```

Download



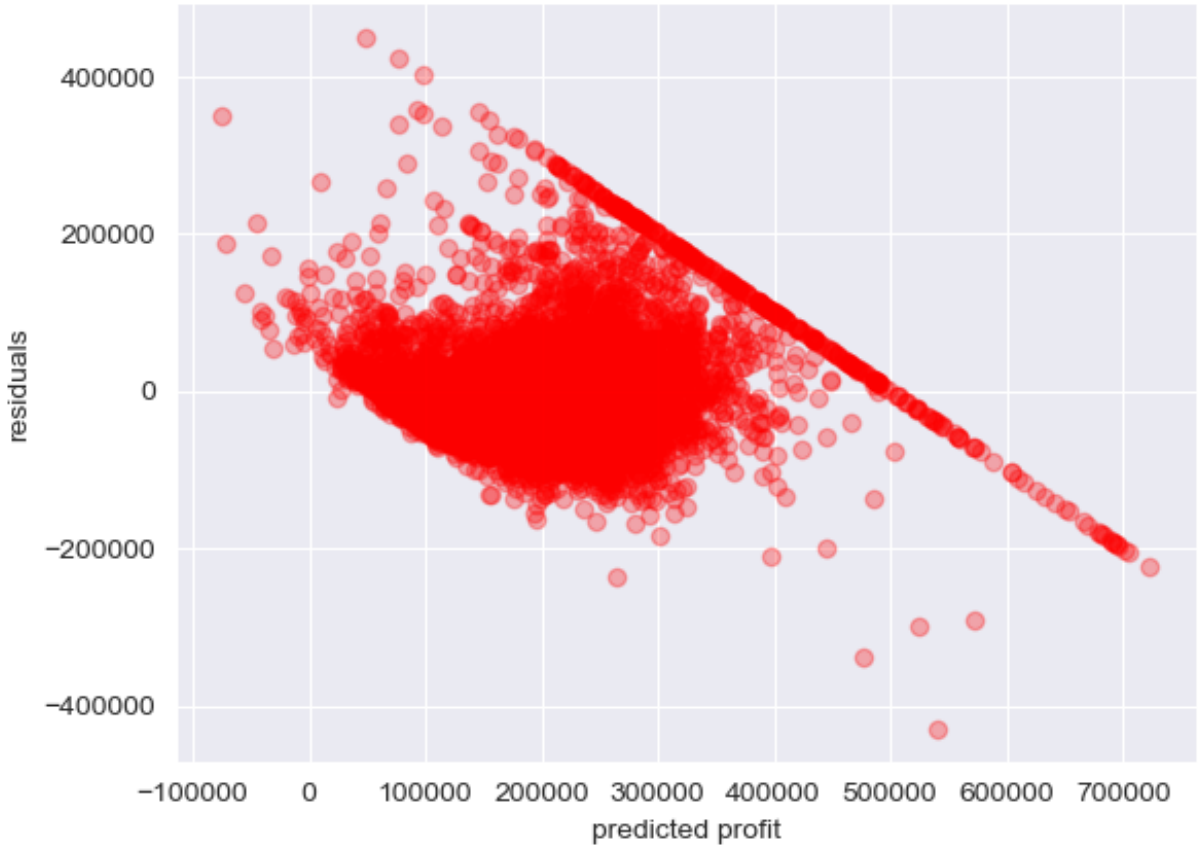
Residuals

Show the distribution plot of the residuals (histogram with density)

```
y_test_pred = lreg.predict(X_test)
resid = y_test-y_test_pred
plt.scatter(y_test_pred,resid, color = 'r',alpha = 0.3)
plt.hlines(y=0, xmin=2,xmax=15)
plt.xlabel('predicted profit')
plt.ylabel('residuals')
```

```
Text(0, 0.5, 'residuals')

<Figure size 640x480 with 1 Axes>
```

Download

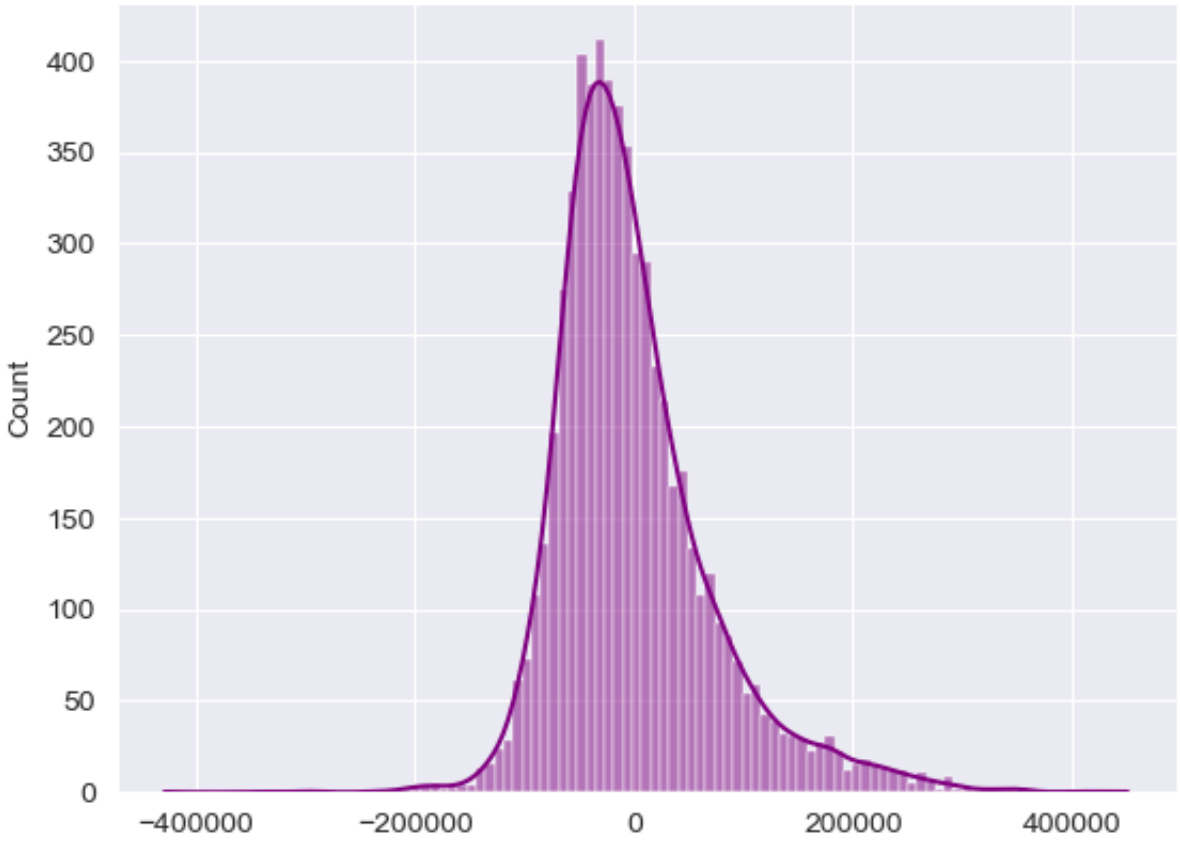


```
sns.histplot(resid, kde=True, color = 'purple')
```

```
<AxesSubplot: ylabel='Count'>
```

```
<Figure size 640x480 with 1 Axes>
```

Download



Evaluation

Calculate MAE, MSE, RMSE and R squared

```
#by Population
from sklearn.metrics import mean_squared_error,mean_absolute_error, r2_score
mse = mean_squared_error(y_test, y_test_pred)
rmse = mse**0.5
mae = mean_absolute_error(y_test, y_test_pred)
r2 = r2_score(y_test, y_test_pred)
print("MSE: ", mse," RMSE: ", rmse," MEA: ",mae," R**2", r2)
```

```
MSE:  5240641241.023194  RMSE:  72392.27335167196  MEA:  53102.79442755571
```

Conclusion

What can we learn about the model from the residual distribution?

we can learn that the AveBedrms column have a lot of affect on the prediction of the SalePrice of the household