Lasso and Ridge Regression

Linear Regression with regularization (L1 and L2). Regularizationis used to reduse overfitting.

```
import pandas as pd
import numpy  as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning: pandas.util.testing is deprecat
  import pandas.util.testing as tm
```

Reading file

```
df=pd.read_excel('Hitters.xlsx')
```

Seperating rows with Salary as null

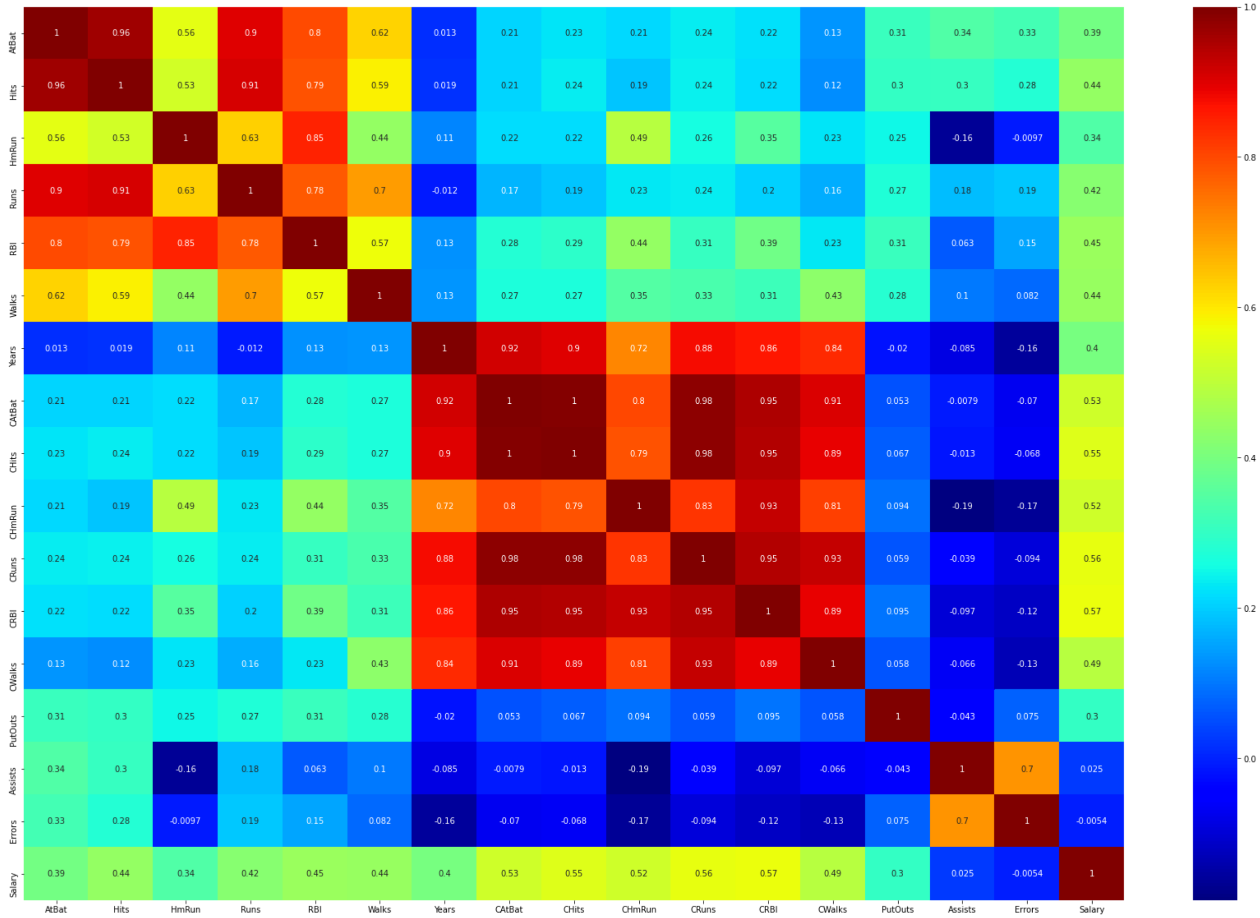
```
df=df.fillna(-1)
df1, df2 = [x for _, x in df.groupby(df['Salary'] ==-1)]
```

```
df2=df2.replace(-1,np.nan)
```

Heatmap of correlation marix

```
plt.figure(figsize=(30,20))
sns.heatmap(df1.corr(),annot = True,cmap="jet")
```

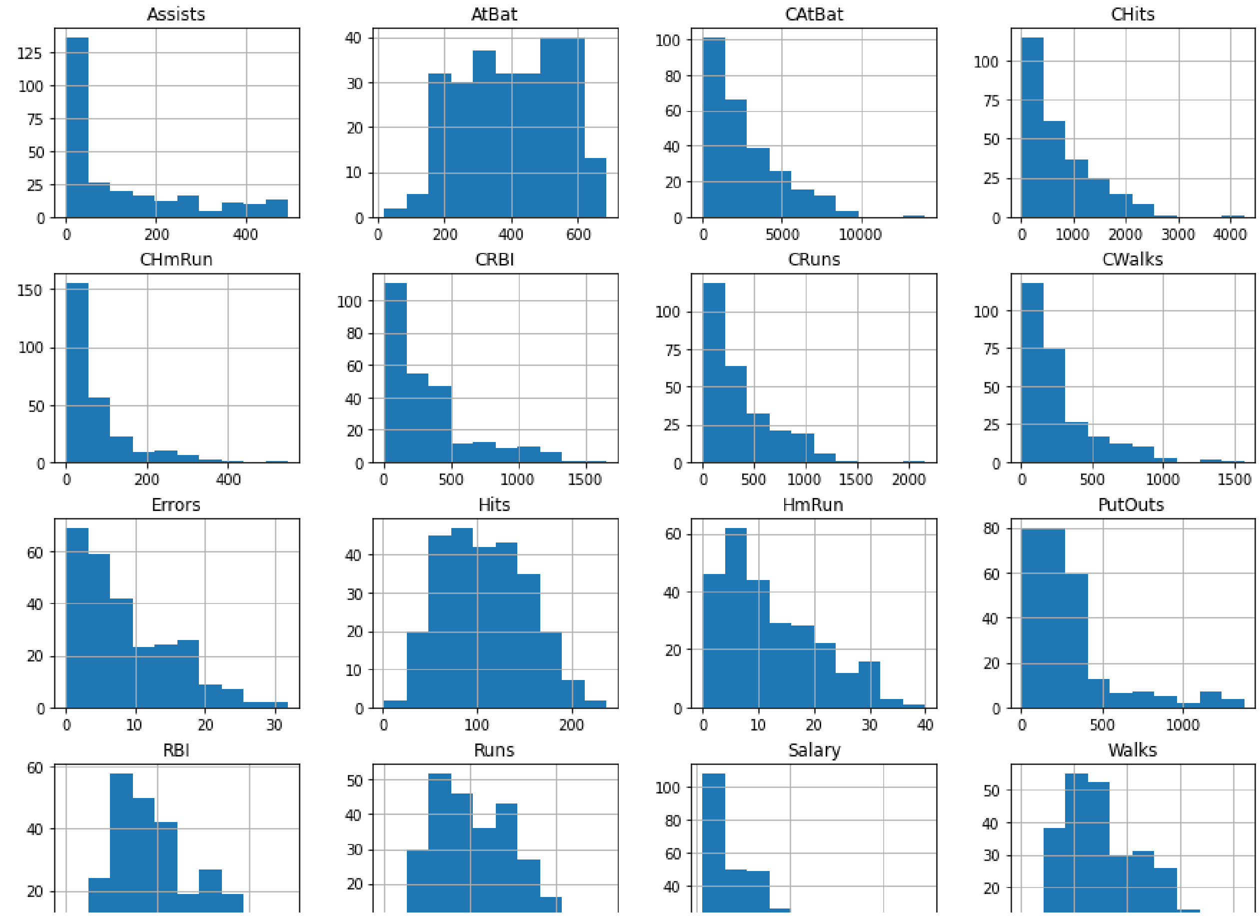
<matplotlib.axes._subplots.AxesSubplot at 0x7f7f66332198>



Disribution of diffent labels

```
plt.figure(figsize=(10,10))
df1.hist(figsize=(15,15))
plt.show()
```

<Figure size 720x720 with 0 Axes>



most of them are skewed so need to normalize

```
df1.corrwith(df1.Salary).sort_values(ascending=False)
```

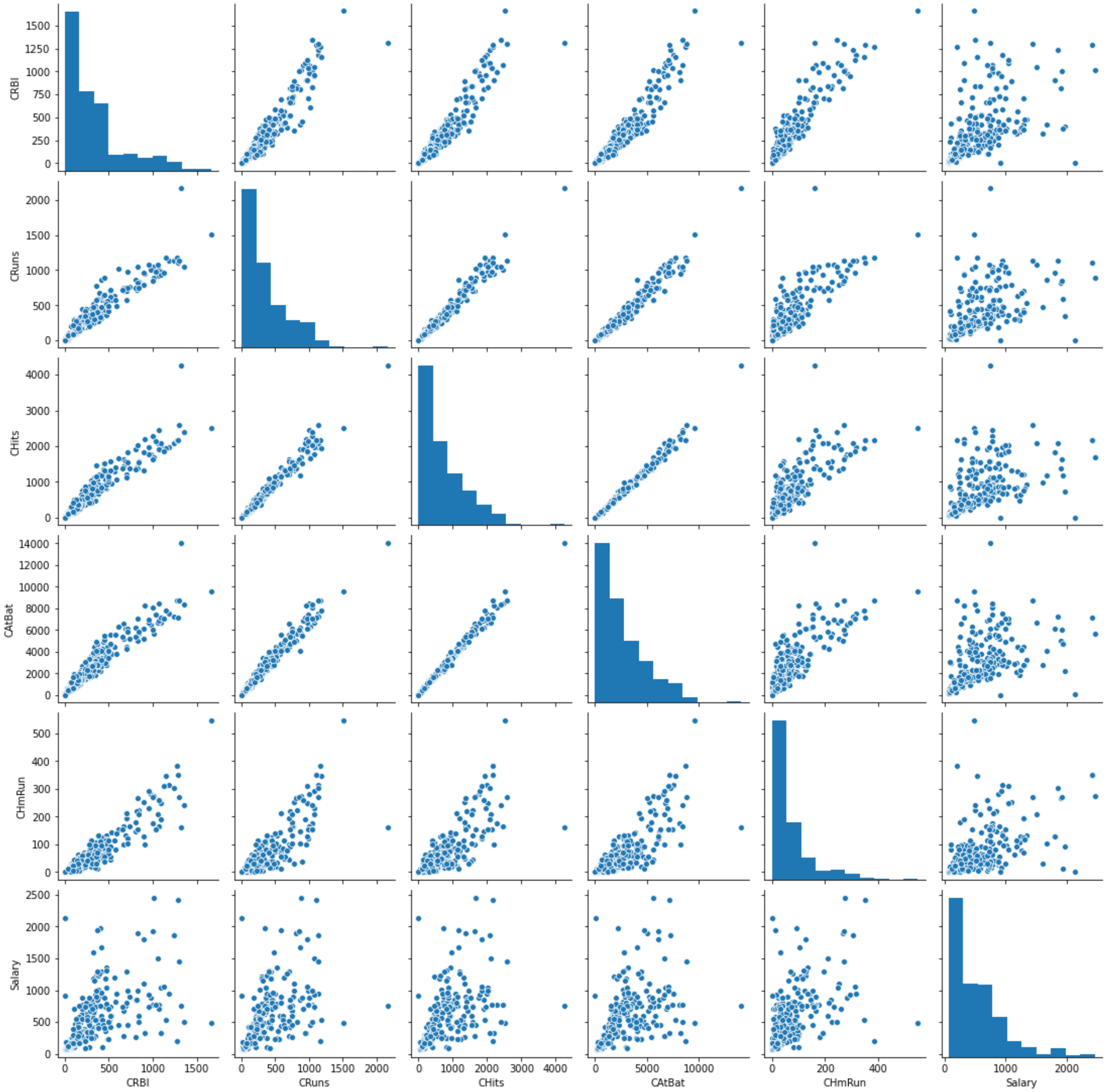
```
Salary     1.000000
CRBI       0.566966
CRuns      0.562678
CHits      0.548910
CAtBat     0.526135
CHmRun     0.524931
CWalks     0.489822
RBI        0.449457
Walks      0.443867
Hits       0.438675
```

Scatter plot of most correlated values

```
AtBat      0.394771
```

```
c=['CRBI','CRuns','CHits','CAtBat','CHmRun','Salary']
sns.pairplot(df1[c])
```

```
<seaborn.axisgrid.PairGrid at 0x7f7f600e4f28>
```



Most of the values have inter-correlation and the graph with salary is more diverse.

Handling object type data

```
df1.League=df1.League.replace('N',1)
df1.League=df1.League.replace('A',2)
df2.League=df2.League.replace('N',1)
df2.League=df2.League.replace('A',2)
```

```
df1.NewLeague=df1.NewLeague.replace('N',1)
df1.NewLeague=df1.NewLeague.replace('A',2)
df2.NewLeague=df2.NewLeague.replace('N',1)
df2.NewLeague=df2.NewLeague.replace('A',2)
```

```
df1.Division=df1.Division.replace('W',1)
df1.Division=df1.Division.replace('E',2)
df2.Division=df2.Division.replace('W',1)
df2.Division=df2.Division.replace('E',2)
```

```
cols = [col for col in df.columns if col not in ["Salary"]]
X = df1[cols]
```

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, df1['Salary'], test_size=0.25)
```

Ridge Regression uses L2 regularization and penalizes the weights

```
from sklearn.linear_model import Ridge
rid = Ridge(normalize=True)
rid.fit(X_train, y_train)
```

```
Ridge(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=None, normalize=True,
      random_state=None, solver='auto', tol=0.001)
```

```
rid.score(X_train,y_train)
```

```
0.43399537437145097
```

```
rid.score(X_test,y_test)
```

```
0.5263798697275235
```

```
rid.coef_
```

```
array([ 7.57376029e-02,  8.01521177e-01,  7.40717209e-01,  9.98604699e-01,
        1.07038172e+00,  1.90501378e+00,  2.09133885e+00,  9.41189137e-03,
        4.77396945e-02,  3.26372281e-01,  9.00073922e-02,  1.05706616e-01,
        5.29270520e-02, -2.48358984e+01,  7.65926274e+01,  1.47797880e-01,
       -2.88271454e-02, -1.14388675e+00, -1.27598350e+01])
```

The coef in ridge tend to zero for low correlated features

Lasso uses L1 regularization

```
from sklearn.linear_model import Lasso
las = Lasso(normalize=True)
las.fit(X_train, y_train)
```

```
Lasso(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=1000, normalize=True,
      positive=False, precompute=False, random_state=None, selection='cyclic',
      tol=0.0001, warm_start=False)
```

```
las.score(X_train,y_train)
```

```
0.4662700247509457
```

```
las.score(X_test,y_test)
```

```
0.53265415747286
```

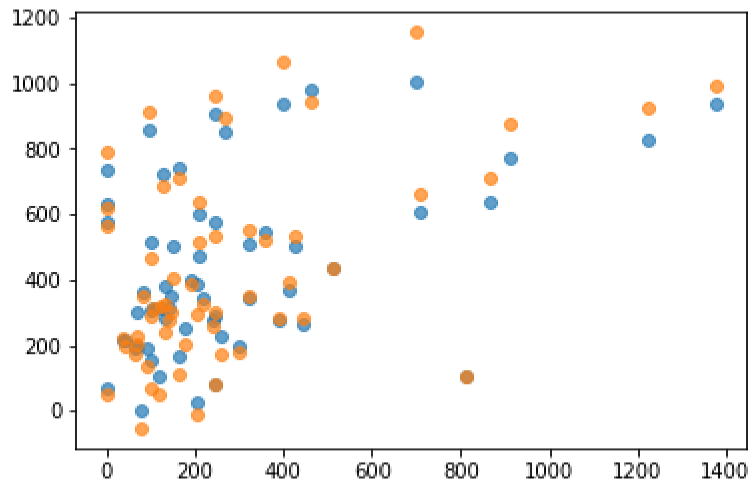
```
las.coef_
```

```
array([-0.00000000e+00,  1.69879583e+00,  0.00000000e+00,  0.00000000e+00,
        0.00000000e+00,  3.48642096e+00, -0.00000000e+00,  0.00000000e+00,
        4.84928277e-02,  0.00000000e+00,  0.00000000e+00,  4.54010805e-01,
       -0.00000000e+00, -1.76676732e+01,  1.22874139e+02,  2.28884054e-01,
       -0.00000000e+00, -1.56843386e+00, -0.00000000e+00])
```

Lasso will make the coef of least correlated features zero. Sometimes also used for feature selection.

```
plt.scatter(df2["PutOuts"],rid.predict(df2[cols]),alpha=0.7)
plt.scatter(df2["PutOuts"],las.predict(df2[cols]),alpha=0.7)
```

```
<matplotlib.collections.PathCollection at 0x7f7f5cbebd68>
```



Lasso and Ridge differ more for large values of Salary

Since the correlation of features with salary are considerably less the accuracies of models are less