Machine Learning Model for Predicting a Ship's Crew Size

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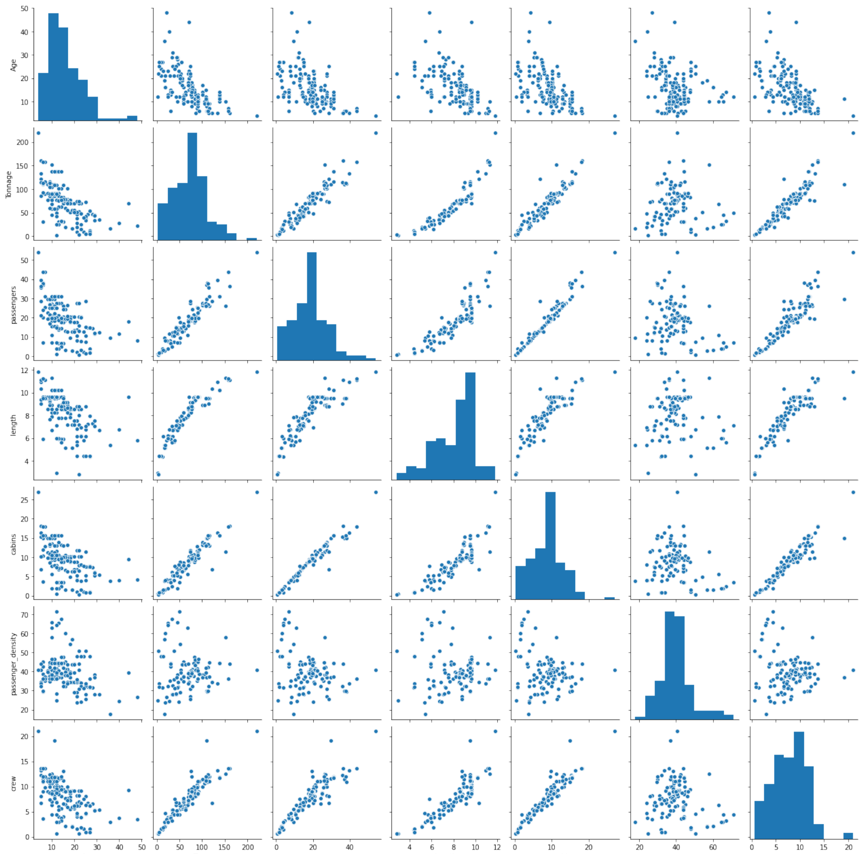
1 Basic statistics

```
df=pd.read_csv("cruise_ship_info.csv")
df.describe()
```

	Age	Tonnage	passengers	length	cabins	passenger_density	crew
count	158	158	158	158	158	158	158
mean	15.6899	71.2847	18.4574	8.13063	8.83	39.9009	7.79418
std	7.61569	37.2295	9.67709	1.79347	4.47142	8.63922	3.50349
min	4	2.329	0.66	2.79	0.33	17.7	0.59
25%	10	46.013	12.535	7.1	6.1325	34.57	5.48
50%	14	71.899	19.5	8.555	9.57	39.085	8.15
75%	20	90.7725	24.845	9.51	10.885	44.185	9.99
max	48	220	54	11.82	27	71.43	21

```
cols = ['Age', 'Tonnage', 'passengers', 'length',
   'cabins','passenger_density','crew']
_ = sns.pairplot(df[cols])
```



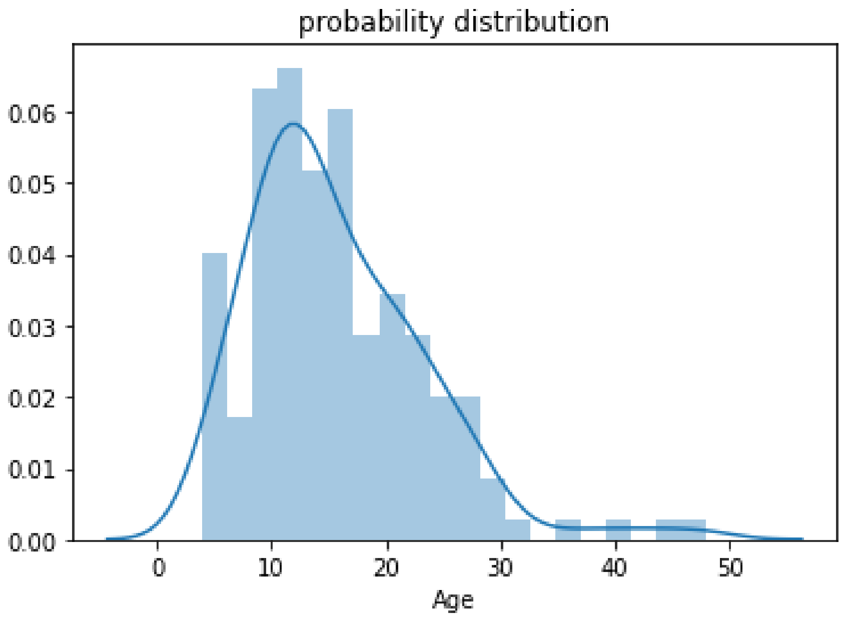
2 Observations

1. We observe that variables are on different scales, for sample the Age variable ranges from about 16 years to 48 years, while the Tonnage variable ranges from 2 to 220, see probability density plots below. It is therefore important that when a regression model is built using these variables, variables be brought to same scale either by standardizing or normalizing the data.

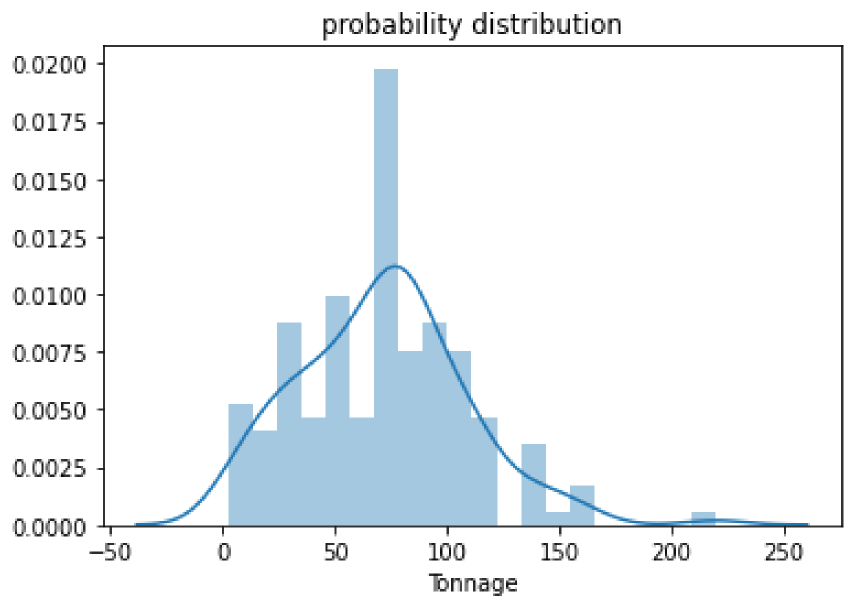
2. We also observe that the target variable 'crew' correlates well with 4 predictor variables, namely, 'Tonnage', 'passengers', 'length', and 'cabins'.

```
sns.distplot(df['Age'],bins=20)
```

```
plt.title('probability distribution')
plt.show()
```




```
sns.distplot(df['Tonnage'],bins=20)
plt.title('probability distribution')
plt.show()
```



3 Variable selection for predicting "crew" size

3.1 Calculation of covariance matrix

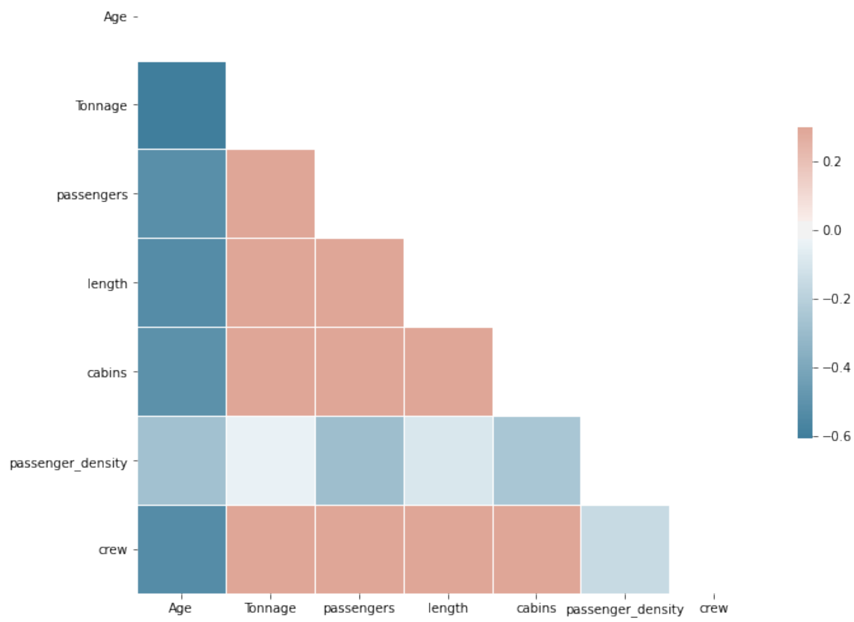
```
corr = df.corr()

# Generate a mask for the upper triangle
mask = np.triu(np.ones_like(corr, dtype=bool))

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(11, 9))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(230, 20, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
_ = sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
```



3.2 Selecting important variables

From the covariance matrix plot above, we see that the "crew" variable correlates strongly with 4 predictor variables: "Tonnage", "passengers", "length, and "cabins".

```
cols_selected = ['Tonnage', 'passengers', 'length',
   'cabins','crew']
df[cols_selected].head()
```

	Tonnage	passengers	length	cabins	crew
0	30.277	6.94	5.94	3.55	3.55
1	30.277	6.94	5.94	3.55	3.55
2	47.262	14.86	7.22	7.43	6.7
3	110	29.74	9.53	14.88	19.1
4	101.353	26.42	8.92	13.21	10

```
X = df[cols_selected].iloc[:,0:4].values     #
   features matrix
y = df[cols_selected]['crew'].values         # target
   variable
```

4 Data partitioning into training and testing sets

In order to build a simplified regression model, we shall focus only on ordinal features. The categorical features "Ship_name" and "Cruise_line" will not be used. A simple model built using only the 4 ordinal features "Tonnage", "passengers", "length, and "cabins" will be simple to interpret.

```
from sklearn.model_selection import train_test_split
X = df[cols_selected].iloc[:,0:4].to_numpy()
y = df[cols_selected]['crew'].to_numpy()
X_train, X_test, y_train, y_test = train_test_split(
    X,
                                                                        y,
                                                                        test_size=0.4,
                                                                           random_state=0)
```

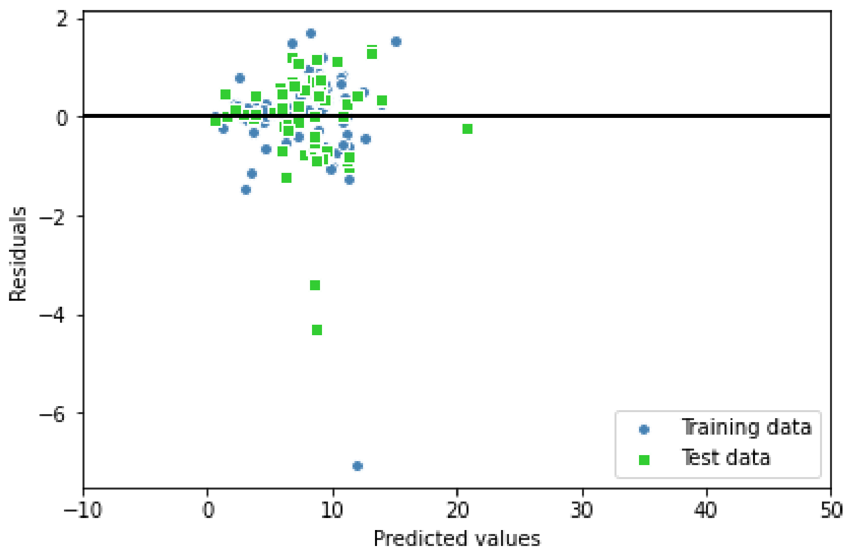
5 Building a linear regression model

```
from sklearn.linear_model import LinearRegression
slr = LinearRegression()

slr.fit(X_train, y_train)
y_train_pred = slr.predict(X_train)
y_test_pred = slr.predict(X_test)
```

```
plt.scatter(y_train_pred,  y_train_pred - y_train,
            c='steelblue', marker='o',
               edgecolor='white',
            label='Training data')
plt.scatter(y_test_pred,  y_test_pred - y_test,
            c='limegreen', marker='s',
               edgecolor='white',
            label='Test data')
plt.xlabel('Predicted values')
plt.ylabel('Residuals')
plt.legend(loc='upper left')
plt.hlines(y=0, xmin=-10, xmax=50, color='black',
   lw=2)
plt.xlim([-10, 50])
```

```
plt.tight_layout()
plt.legend(loc='lower right')
plt.show()
```



6 Evaluation of regression model

```
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error

print('MSE train: %.3f, test: %.3f' % (
        mean_squared_error(y_train, y_train_pred),
        mean_squared_error(y_test, y_test_pred)))
print('R^2 train: %.3f, test: %.3f' % (
        r2_score(y_train, y_train_pred),
        r2_score(y_test, y_test_pred)))
```

```
MSE train: 0.955, test: 0.889
R^2 train: 0.920, test: 0.928
```

7 Regression coefficients

```
slr.fit(X_train, y_train).intercept_
```

```
-0.7525074496158393
```

```
slr.fit(X_train, y_train).coef_
```

```
array([ 0.01902703, -0.15001099,  0.37876395,  0.77613801])
```

8 Feature Standardization, Cross Validation, and Hyper-parameter Tuning

```
from sklearn.metrics import r2_score
from sklearn.model_selection import train_test_split
X = df[cols_selected].iloc[:,0:4].to_numpy()
y = df[cols_selected]['crew'].to_numpy()
from sklearn.preprocessing import StandardScaler
sc_y = StandardScaler()
sc_x = StandardScaler()
y_std = sc_y.fit_transform(y_train.reshape(-1, 1))
```

```
train_score = []
test_score = []

for i in range(10):
    X_train, X_test, y_train, y_test =
       train_test_split( X, y, test_size=0.4,
       random_state=i)
    y_train_std =
       sc_y.fit_transform(y_train.reshape(-1,
       1)).flatten()
    from sklearn.preprocessing import StandardScaler
    from sklearn.decomposition import PCA
    from sklearn.linear_model import LinearRegression
    from sklearn.pipeline import Pipeline
    pipe_lr = Pipeline([('scl',
       StandardScaler()),('pca',
       PCA(n_components=4)),('slr',
       LinearRegression())])
```

```
    pipe_lr.fit(X_train, y_train_std)
    y_train_pred_std=pipe_lr.predict(X_train)
    y_test_pred_std=pipe_lr.predict(X_test)
    y_train_pred=sc_y.inverse_transform(y_train_pred_std)
    y_test_pred=sc_y.inverse_transform(y_test_pred_std)
    train_score = np.append(train_score,
       r2_score(y_train, y_train_pred))
    test_score = np.append(test_score,
       r2_score(y_test, y_test_pred))
```

```
train_score
```

```
array([0.92028261, 0.91733937, 0.94839385, 0.93899476, 0.90621451,
       0.91156903, 0.92726066, 0.94000795, 0.93922948, 0.93629554])
```

```
test_score
```

```
array([0.92827978, 0.93807946, 0.8741834 , 0.89901199, 0.94781315,
       0.91880183, 0.91437408, 0.89660876, 0.90427477, 0.90139208])
```

```
print('R2 train: %.3f +/- %.3f' %
   (np.mean(train_score),np.std(train_score)))
```

```
R2 train: 0.929 +/- 0.013
```

```
print('R2 test: %.3f +/- %.3f' %
   (np.mean(test_score),np.std(test_score)))
```

```
R2 test: 0.912 +/- 0.021
```

9 Techniques of Dimensionality Reduction

9.1 Principal Component Analysis (PCA)

```
train_score = []
test_score = []
cum_variance = []

for i in range(1,5):
    X_train, X_test, y_train, y_test =
       train_test_split( X, y, test_size=0.4,
       random_state=0)
    y_train_std =
       sc_y.fit_transform(y_train.reshape(-1,
       1)).flatten()
    from sklearn.preprocessing import StandardScaler
    from sklearn.decomposition import PCA
    from sklearn.linear_model import LinearRegression
    from sklearn.pipeline import Pipeline
    pipe_lr = Pipeline([('scl',
       StandardScaler()),('pca',
       PCA(n_components=i)),('slr',
       LinearRegression())])
    pipe_lr.fit(X_train, y_train_std)
    y_train_pred_std=pipe_lr.predict(X_train)
    y_test_pred_std=pipe_lr.predict(X_test)
    y_train_pred=sc_y.inverse_transform(y_train_pred_std)
    y_test_pred=sc_y.inverse_transform(y_test_pred_std)
    train_score = np.append(train_score,
       r2_score(y_train, y_train_pred))
    test_score = np.append(test_score,
       r2_score(y_test, y_test_pred))
    cum_variance = np.append(cum_variance,
       np.sum(pipe_lr.fit(X_train,
       y_train).named_steps['pca'].explained_variance_ratio_))
```

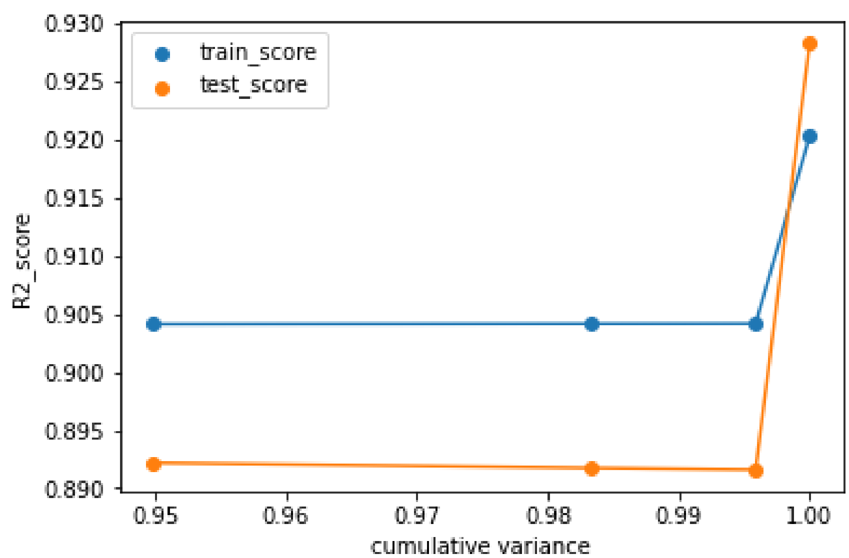
```
train_score
```

```
array([0.90411898, 0.9041488 , 0.90416405, 0.92028261])
```

```
test_score
```

```
array([0.89217843, 0.89174896, 0.89159266, 0.92827978])
```

```
plt.scatter(cum_variance,train_score, label =
    'train_score')
plt.plot(cum_variance, train_score)
plt.scatter(cum_variance,test_score, label =
    'test_score')
plt.plot(cum_variance, test_score)
plt.xlabel('cumulative variance')
plt.ylabel('R2_score')
plt.legend()
plt.show()
```



Observations (PCA)

We observe that by increasing the number of principal components from 1 to 4, the train and test scores improve. This is because with less components, there is high bias error in the model, since model is overly simplified. As we increase the number of principal components, the bias error will reduce, but complexity in the model increases.

9.2 Regularized Regression: Lasso

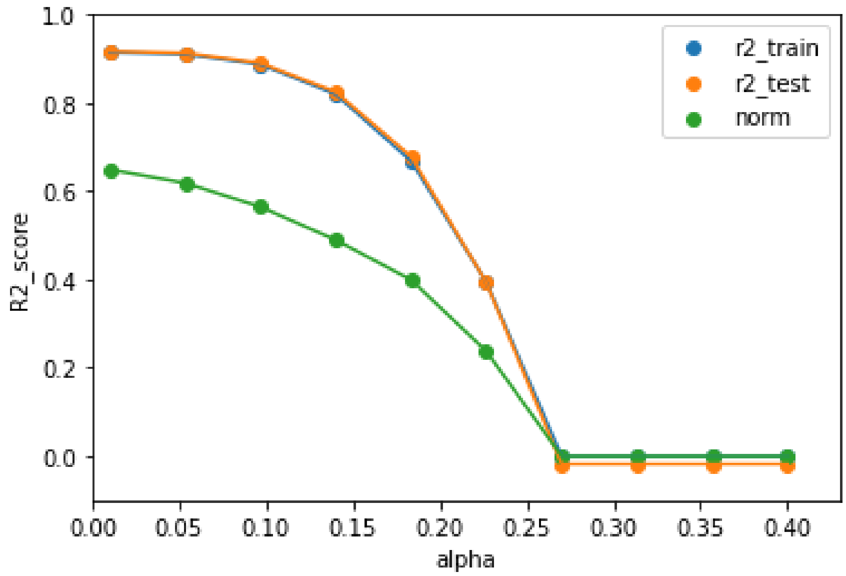
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.4, random_state=0)
y_train_std = sc_y.fit_transform(y_train.reshape(-1,
    1)).flatten()
X_train_std = sc_x.fit_transform(X_train)
X_test_std = sc_x.transform(X_test)
```

```
alpha = np.linspace(0.01,0.4,10)
```

```
from sklearn.linear_model import Lasso
lasso = Lasso(alpha=0.7)

r2_train=[]
r2_test=[]
norm = []
for i in range(10):
    lasso = Lasso(alpha=alpha[i])
    lasso.fit(X_train_std,y_train_std)
    y_train_std=lasso.predict(X_train_std)
    y_test_std=lasso.predict(X_test_std)
    r2_train=np.append(r2_train,r2_score(y_train,sc_y.inverse_transform(
    r2_test=np.append(r2_test,r2_score(y_test,sc_y.inverse_transform(y_t
    norm= np.append(norm,np.linalg.norm(lasso.coef_))
```

```
plt.scatter(alpha,r2_train,label='r2_train')
plt.plot(alpha,r2_train)
plt.scatter(alpha,r2_test,label='r2_test')
plt.plot(alpha,r2_test)
plt.scatter(alpha,norm,label = 'norm')
plt.plot(alpha,norm)
plt.ylim(-0.1,1)
plt.xlim(0,.43)
plt.xlabel('alpha')
plt.ylabel('R2_score')
plt.legend()
plt.show()
```



Observations (Lasso)

We observe that as the regularization parameter α increases, the norm of the regression coefficients become smaller and smaller. This means more regression coefficients are forced to zero, which intend increases bias error (over simplification). The best value to balance bias-variance tradeoff is when α is kept low, say $\alpha = 0.1$ or less.