The main agenda is not to build the best model for this data but to learn about how to use regularization and apply the theory concepts I learn about ridge and lasso.

In [1]:
```
import warnings
warnings.filterwarnings('ignore')
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import Normalizer
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
sns.set(style="darkgrid")
```

In [2]:
```
df = pd.read_csv('auto-mpg.csv')
```

In [3]:
```
print(df.shape)
df.head()
```

```
(398, 9)
```

Out[3]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin	car name
0	18.0	8	307.0	130	3504	12.0	70	1	chevrolet chevelle malibu
1	15.0	8	350.0	165	3693	11.5	70	1	buick skylark 320
2	18.0	8	318.0	150	3436	11.0	70	1	plymouth satellite
3	16.0	8	304.0	150	3433	12.0	70	1	amc rebel sst
4	17.0	8	302.0	140	3449	10.5	70	1	ford torino

Basic idea about data

In [4]:
```
# checking for any null value present in the dataset
# we are good to go as no null value we have.
df.isna().sum()
```

Out[4]:
```
mpg             0
cylinders       0
displacement    0
horsepower      0
weight          0
acceleration    0
model year      0
origin          0
car name        0
dtype: int64
```

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 398 entries, 0 to 397
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   mpg           398 non-null    float64
 1   cylinders     398 non-null    int64  
 2   displacement  398 non-null    float64
 3   horsepower    398 non-null    object 
 4   weight        398 non-null    int64  
 5   acceleration  398 non-null    float64
 6   model year    398 non-null    int64  
 7   origin        398 non-null    int64  
 8   car name      398 non-null    object 
dtypes: float64(3), int64(4), object(2)
memory usage: 28.1+ KB
```

- 'horsepower' column is object type so let's convert it into float.

  `There is non numeric value ('?') present in 6 rows so because of less dirty row we can drop those rows.`
- Also df.describe() indicate that feature scalling is required and attribute ranges differently for regression analysis.

In [6]:
```
# Basic information about data
df.describe()
```

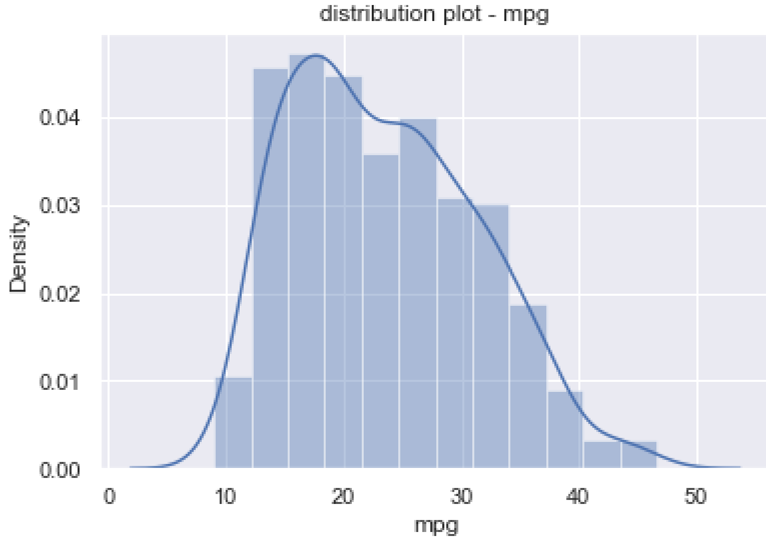
Out[6]:

	mpg	cylinders	displacement	weight	acceleration	model year	origin
count	398.000000	398.000000	398.000000	398.000000	398.000000	398.000000	398.000000
mean	23.514573	5.454774	193.425879	2970.424623	15.568090	76.010050	1.572864
std	7.815984	1.701004	104.269838	846.841774	2.757689	3.697627	0.802055
min	9.000000	3.000000	68.000000	1613.000000	8.000000	70.000000	1.000000
25%	17.500000	4.000000	104.250000	2223.750000	13.825000	73.000000	1.000000
50%	23.000000	4.000000	148.500000	2803.500000	15.500000	76.000000	1.000000
75%	29.000000	8.000000	262.000000	3608.000000	17.175000	79.000000	2.000000
max	46.600000	8.000000	455.000000	5140.000000	24.800000	82.000000	3.000000

In [7]:
```
# data preprocessing
df = df[df.horsepower!='?']
df.drop(columns='car name', axis=1, inplace=True )
df.horsepower = df.horsepower.astype(float)
```

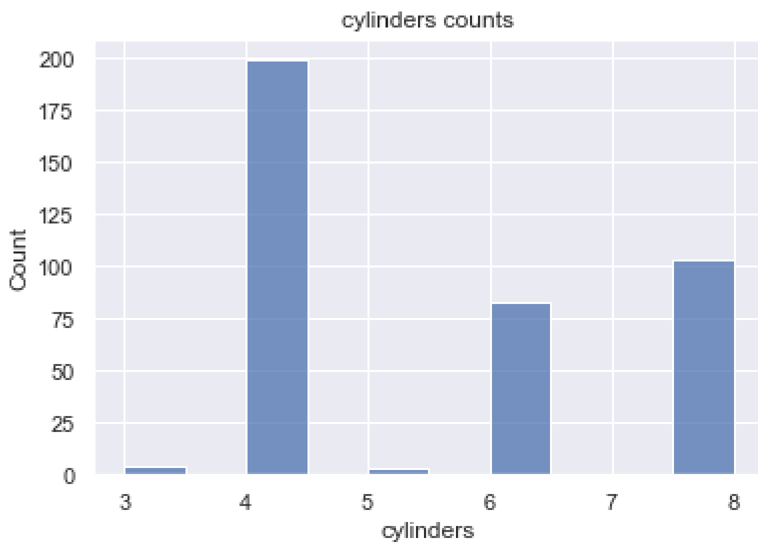
In [8]:
```
print(sns.distplot(df.mpg).set_title('distribution plot - mpg'))
# slightly right skewed distribution
```

```
Text(0.5, 1.0, 'distribution plot - mpg')
```



In [9]:
```
print(sns.histplot(df.cylinders).set_title('cylinders counts'))
# mejorly 4 cylinders in the data
```

```
Text(0.5, 1.0, 'cylinders counts')
```



In [10]:
```
# distribution and skewness of data for further analysis
fig, axs = plt.subplots(3, 2, figsize=(14, 14))

sns.histplot(data=df, x="mpg", color="skyblue", kde=True, ax=axs[0, 0])
sns.histplot(data=df, x="acceleration", color="red", kde=True, ax=axs[0, 1])
sns.histplot(data=df, x="displacement", color="olive", kde=True, ax=axs[1, 0])
sns.histplot(data=df, x="horsepower", color="gold", kde=True, ax=axs[1, 1])
sns.histplot(data=df, x="weight", color="teal", kde=True, ax=axs[2, 0])
plt.show()
```

In [ ]:

In [11]:
```
# target and feature seperation
y = df.iloc[:,0:1]
X = df.iloc[:,1:]
```

In [12]:
```
# scalling using L2 norm
norm_scaler = Normalizer().fit(X)
X.loc[:,:] = norm_scaler.transform(X)
X.head(3)
```

Out[12]:

	cylinders	displacement	horsepower	weight	acceleration	model year	origin
0	0.002272	0.087202	0.036926	0.995299	0.003409	0.019883	0.000284
1	0.002154	0.094240	0.044428	0.994372	0.003096	0.018848	0.000269
2	0.002316	0.092049	0.043419	0.994593	0.003184	0.020262	0.000289

In [13]:
```
# splitting data into 2/3 training set and 1/3 testing set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.33, random_sta
```

In [14]:
```
# model fitting
model_linear = LinearRegression()
model_linear.fit(X_train, y_train)
```

Out[14]:
```
▾ LinearRegression
LinearRegression()
```

In [15]:
```
# prediction
y_pred_linear = model_linear.predict(X_test)
```

In [16]:
```
mean_squared_error(y_test, y_pred_linear)
```

Out[16]:
```
7.509541105366527
```

In [17]:
```
# checking weights/theta of each feature
model_linear.coef_
```

Out[17]:
```
array([[-2921.95396213,   -59.97523525,  -392.17357538, -1627.07954354,
        -1067.47680963,  1132.17455966,   509.93710123]])
```

In [ ]:

Let's implement liner regression with regularization.

In [18]:
```
from sklearn.linear_model import RidgeCV, LassoCV
#from sklearn.model_selection import cross_val_score
```

In [19]:
```
alphas = [10**-6, 10**-5, 10**-4, 10**-3, 10**-2, 10**-1, 0.5]
model_RidgeCV = RidgeCV(alphas=alphas, cv=10).fit(X_train, y_train)
y_pred_RidgeCV = model_RidgeCV.predict(X_test)
```

In [20]:
```
mean_squared_error(y_test, y_pred_RidgeCV)
```

Out[20]:
```
7.54016330504988
```

In [ ]:

In [21]:
```
model_LassoCV = LassoCV(alphas=alphas, cv=10).fit(X_train, y_train)
y_pred_LassoCV = model_LassoCV.predict(X_test)
```

In [22]:
```
mean_squared_error(y_test, y_pred_LassoCV)
```

Out[22]:
```
7.5140637978676965
```

In [23]:
```
# best alpha for each model
model_LassoCV.alpha_, model_RidgeCV.alpha_
```

Out[23]:
```
(1e-05, 1e-05)
```

In [24]:
```
# Comparison of regression models
compare = pd.DataFrame(data = [model_RidgeCV.coef_.tolist()[0], model_LassoCV.coef_.tc
             columns=X_test.columns,
             index=['RidgeCV', 'LassoCV', 'OLR'])
compare['best_alpha'] = [model_RidgeCV.alpha_, model_LassoCV.alpha_, None]
compare['mean_squared_error'] = [mean_squared_error(y_test, y_pred_RidgeCV), mean_squa
compare
```

Out[24]:

	cylinders	displacement	horsepower	weight	acceleration	model year	origi
RidgeCV	-1328.106284	-44.785126	-345.248721	-1041.002511	-991.355322	1101.180946	207.97598
LassoCV	-2591.741749	-53.626718	-376.485111	-1453.931703	-1036.970086	1128.985007	334.90813
OLR	-2921.953962	-59.975235	-392.173575	-1627.079544	-1067.476810	1132.174560	509.93710

In [ ]:

Observation:

- As we can see that LassoCV reduce the overfitting far batter than RidgeCV.
- Also, LassoCV helped to reduce coefficient of attritube to zero, eventually in helps in feature selections process to improve the model over other.
- for example 'weight' attribute is not that important in prediction as it's coefficient is zero in LassoCV shown in above table. Similarly for 'cylinders' and 'origin' column.
- Similarly, if we carefully obeserv the above then get to know that as per the LassoCV 'displacement' attribute is directly dependent on mpg wheres in RidgeCV its inversly proportional to target variable.

Note that L1 regularization or Lasso create sparcity in the data. weights of corresponding features became zero.

In [ ]:

Most of the columns can treat as categorical, like cylinders, model year, origin, horsepower (with feature engineering), and use other algorithms to get better accuracy.

In [ ]: