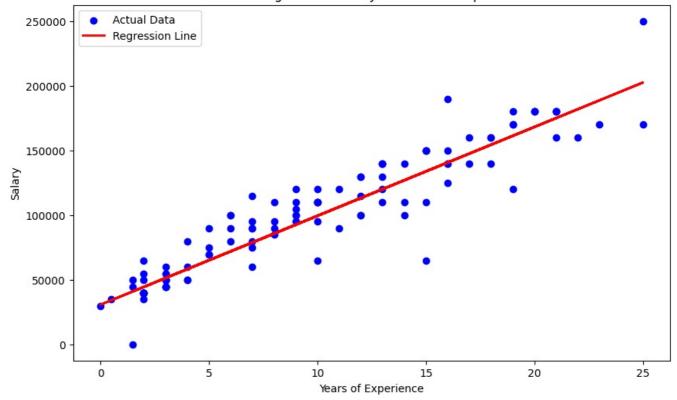
44. Salary Prediction according to Experience.

```
In [7]: import pandas as p
        import matplotlib.pyplot as m
        from sklearn.model selection import train test split
        from sklearn.linear model import LinearRegression
        from sklearn.metrics import mean squared error, r2 score
        da=p.read_csv("Salary_Experience.csv")
        da.info()
        da.dropna(axis=0,inplace=True)
        x=da['Years of Experience'].values.reshape(-1,1)
        y=da['Salary']
        x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3,
        random_state=42)
        model = LinearRegression()
        model.fit(x_train, y_train)
        y_pred = model.predict(x_test)
        m.figure(figsize=(10, 6))
        m.scatter(x_test, y_test, color='blue', label='Actual Data')
        m.plot(x_test, y_pred, color='red', linewidth=2, label='Regression Line')
        m.title('Linear Regression: Salary vs. Years of Experience')
        m.xlabel('Years of Experience');m.ylabel('Salary')
        m.legend();m.show()
        mse = mean_squared_error(y_test, y_pred)
        r2 = r2_score(y_test, y_pred)
        print("\nMean Squared Error:", mse)
        print("\nR-squared:", r2)
        Expe= [[3]] # Replace with the desired experience value
        Sal = model.predict(Expe)
        print(f"Predicted Salary for {Expe[0][0]} Year Experience : {Sal[0]}")
       <class 'pandas.core.frame.DataFrame'>
       RangeIndex: 375 entries, 0 to 374
       Data columns (total 2 columns):
           Column
                                 Non-Null Count Dtype
          Years of Experience 373 non-null
       0
                                                 float64
           Salary
                                 373 non-null
       dtypes: float64(2)
       memory usage: 6.0 KB
```

Linear Regression: Salary vs. Years of Experience



Mean Squared Error: 292476161.7847894

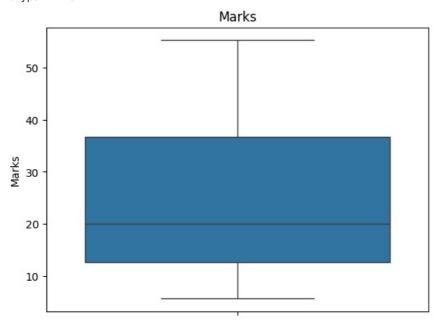
R-squared: 0.8705110527402834

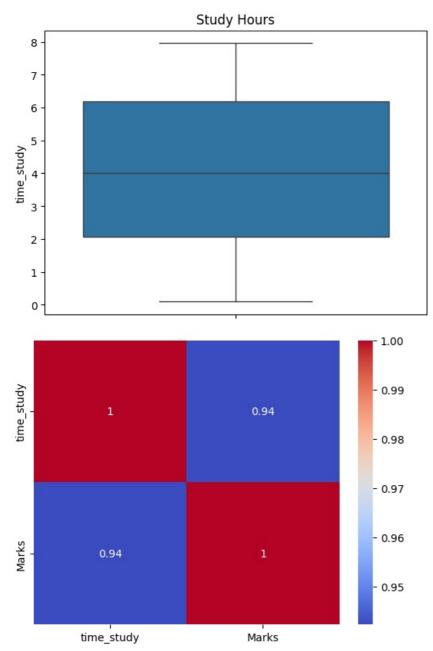
Predicted Salary for 3 Year Experience : 51539.68015642409

45. Marks Prediction according to Study Hours.

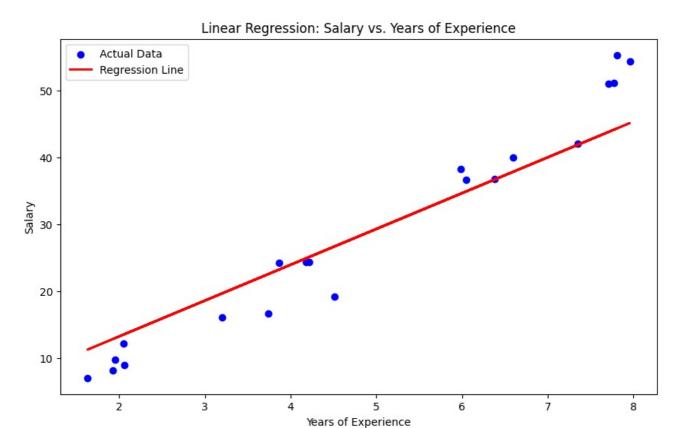
```
In [13]: import pandas as p
         \textbf{import} \ \texttt{matplotlib.pyplot} \ \textbf{as} \ \texttt{m}
         import seaborn as s
         from sklearn.model_selection import train_test_split
         from sklearn.linear_model import LinearRegression
         from sklearn.metrics import mean_squared_error, r2_score
         da=p.read csv("Student marks.csv")
         print(da.isna().sum())
         s.boxplot(da['Marks']);m.title('Marks')
         m.show()
         s.boxplot(da['time study']);m.title('Study Hours')
         m.show()
         s.heatmap(data=da.corr(), annot=True, cmap='coolwarm')
         m.show()
         X = da['time study'].values.reshape(-1,1)
         y = da['Marks']
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
         random_state=42)
         model = LinearRegression()
         model.fit(X_train, y_train)
         y_pred = model.predict(X_test)
         mse = mean_squared_error(y_test, y_pred)
         r2 = r2_score(y_test, y_pred)
         print("Mean Squared Error:", mse)
         print("R-squared:", r2)
         m.figure(figsize=(10, 6))
         m.scatter(X_test, y_test, color='blue', label='Actual Data')
         m.plot(X_test, y_pred, color='red', linewidth=2, label='Regression Line')
         m.title('Linear Regression: Salary vs. Years of Experience')
         m.xlabel('Years of Experience');m.ylabel('Salary')
         m.legend()
         m.show()
         Hours= [[20]]# Replace with the desired experience value
         predicted_marks = model.predict(Hours)
         print(f"Predicted Marks for {Hours[0][0]} Hours : {predicted_marks[0]}")
```

time_study 0
Marks 0
dtype: int64





Mean Squared Error: 25.23674562363223 R-squared: 0.9040228286990537



Predicted Marks for 20 Hours : 109.62199613197404

46. Boston housing price

a) Preprocessing & Exploration

```
In [17]: import pandas as p
         import seaborn as s
         import matplotlib.pyplot as m
         da=p.read_csv("boston.csv")
         da.info()
         print(da.describe())
         m.figure(figsize=(18,10))
         s.heatmap(data=da.corr(),annot=True,cmap='coolwarm')
         m.show()
         m.figure(figsize=(18,10))
         s.histplot(data=da, x='MEDV', bins=30, kde=True)
         m.title('Distribution of Pricing')
         m.show()
         m.figure(figsize=(18,10))
         s.scatterplot(data=da,x='RM',y='MEDV')
         m.title('Number of rooms to pricing')
         m.show()
         m.figure(figsize=(18,10))
         s.scatterplot(data=da,x='LSTAT',y='MEDV')
         m.title('Lower status Population and Pricing')
         m.show()
```

```
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):
 #
     Column
                Non-Null Count Dtype
 0
      CRTM
                506 non-null
                                   float64
 1
      ΖN
                506 non-null
                                   float64
      INDUS
                506 non-null
                                   float64
 2
 3
      CHAS
                506 non-null
                                   int64
 4
      NOX
                506 non-null
                                   float64
 5
                506 non-null
      RM
                                   float64
 6
      AGE
                506 non-null
                                   float64
 7
      DTS
                506 non-null
                                   float64
 8
      R\Delta D
                506 non-null
                                   int64
 9
      TAX
                506 non-null
                                   float64
 10
     PTRATTO
                506 non-null
                                   float64
                506 non-null
                                   float64
 11
     В
 12 LSTAT
                506 non-null
                                   float64
 13
     MEDV
                506 non-null
                                   float64
dtypes: float64(12), int64(2)
memory usage: 55.5 KB
               CRIM
                               7N
                                          INDUS
                                                         CHAS
                                                                        NOX
                                                                                       RM \
        506.000000
                      506.000000
                                    506.000000
                                                  506.000000
                                                                506.000000
                                                                              506.000000
count
          3.613524
                       11.363636
                                     11.136779
                                                    0.069170
                                                                  0.554695
                                                                                6.284634
mean
          8.601545
                       23.322453
                                      6.860353
                                                     0.253994
                                                                   0.115878
                                                                                0.702617
std
          0.006320
                        0.000000
                                      0.460000
                                                    0.000000
                                                                   0.385000
                                                                                3.561000
min
25%
          0.082045
                        0.000000
                                      5.190000
                                                    0.000000
                                                                   0.449000
                                                                                5.885500
                        0.000000
                                      9.690000
                                                    0.000000
                                                                  0.538000
                                                                                6.208500
50%
          0.256510
75%
          3.677083
                       12.500000
                                     18.100000
                                                    0.000000
                                                                   0.624000
                                                                                6.623500
                      100.000000
                                     27.740000
                                                    1.000000
                                                                                8.780000
max
         88.976200
                                                                  0.871000
                              DTS
                                            RAD
                                                          TAX
                                                                    PTRATIO
                                                                                        В
                AGF
count
        506.000000
                      506.000000
                                    506.000000
                                                  506.000000
                                                                506.000000
                                                                              506.000000
         68.574901
                        3.795043
                                      9.549407
                                                  408.237154
                                                                 18.455534
                                                                              356.674032
mean
std
         28.148861
                         2.105710
                                      8.707259
                                                  168.537116
                                                                  2.164946
                                                                               91.294864
          2.900000
                        1.129600
                                      1.000000
                                                  187.000000
                                                                 12.600000
                                                                                0.320000
min
25%
         45.025000
                        2.100175
                                      4.000000
                                                  279.000000
                                                                 17.400000
                                                                              375.377500
50%
         77.500000
                        3.207450
                                      5.000000
                                                  330.000000
                                                                 19.050000
                                                                              391.440000
75%
         94.075000
                        5.188425
                                     24.000000
                                                  666.000000
                                                                 20.200000
                                                                              396.225000
        100.000000
                       12.126500
                                     24.000000
                                                  711.000000
                                                                 22.000000
                                                                              396.900000
max
              LSTAT
                             MEDV
count
        506.000000
                      506.000000
         12.653063
                       22.532806
mean
std
          7.141062
                        9.197104
min
          1.730000
                        5.000000
25%
          6.950000
                       17.025000
50%
         11.360000
                       21.200000
         16.955000
75%
                       25.000000
         37.970000
                       50.000000
max
CRIM
             -0.2
                     0.41
                            -0.056
                                     0.42
                                             -0.22
                                                     0.35
                                                                             0.58
                                                                                     0.29
                                                                                                      0.46
     -0.2
                            -0.043
                                             0.31
                                                                     -0.31
                                                                             -0.31
                                                                                             0.18
                                                                                                             0.36
Z
INDUS
                            0.063
     0.41
                                                                                     0.38
CHAS
    -0.056
            -0.043
                    0.063
                                    0.091
                                             0.091
                                                     0.087
                                                             -0.099
                                                                    -0.0074
                                                                             -0.036
                                                                                     -0.12
                                                                                             0.049
                                                                                                     -0.054
                                                                                                             0.18
X
                                             -0.3
                            0.091
                                                                                     0.19
    0.42
                            0.091
                                     -0.3
                                                     -0.24
                                                             0.21
                                                                     -0.21
                                                                             -0.29
                                                                                             0.13
    -0.22
             0.31
M
AGE
    0.35
                            0.087
                                             -0.24
                                                                     0.46
                                                                             0.51
                                                                                     0.26
                                                                                             -0.27
                            -0.099
                                                                                     -0.23
                                                                                                             0.25
DIS
                                             0.21
                                                                                             0.29
RAD
             -0.31
                            -0.0074
                                             -0.21
                                                     0.46
                                                                                     0.46
                                                                                                      0.49
TAX
    0.58
             -0.31
                            -0.036
                                             -0 29
                                                     0.51
                                                                                     0.46
                                                                                                      0.54
     0.29
                     0.38
                             -0.12
                                     0.19
                                                     0.26
                                                             -0.23
                                                                     0.46
                                                                             0.46
                                                                                             -0.18
                                                                                                      0.37
             0.18
                            0.049
                                             0.13
                                                     -0.27
                                                             0.29
                                                                                     -0.18
                                                                                                              0.33
В
LSTAT
                            -0.054
    0.46
                                                                     0.49
                                                                             0.54
                                                                                     0.37
             0.36
                             0.18
                                                             0.25
                                                                                             0.33
    CRIM
                    INDUS
                                     NOX
                                                     AGE
                                                                     RAD
                                                                             TAX
                                                                                    PTRATIO
                                                                                               В
                                                                                                     LSTAT
                                                                                                             MEDV
```

1.0

0.8

0.6

- 0.4

- 0.2

- 0.0

- -0.2

-0.4

-0.6

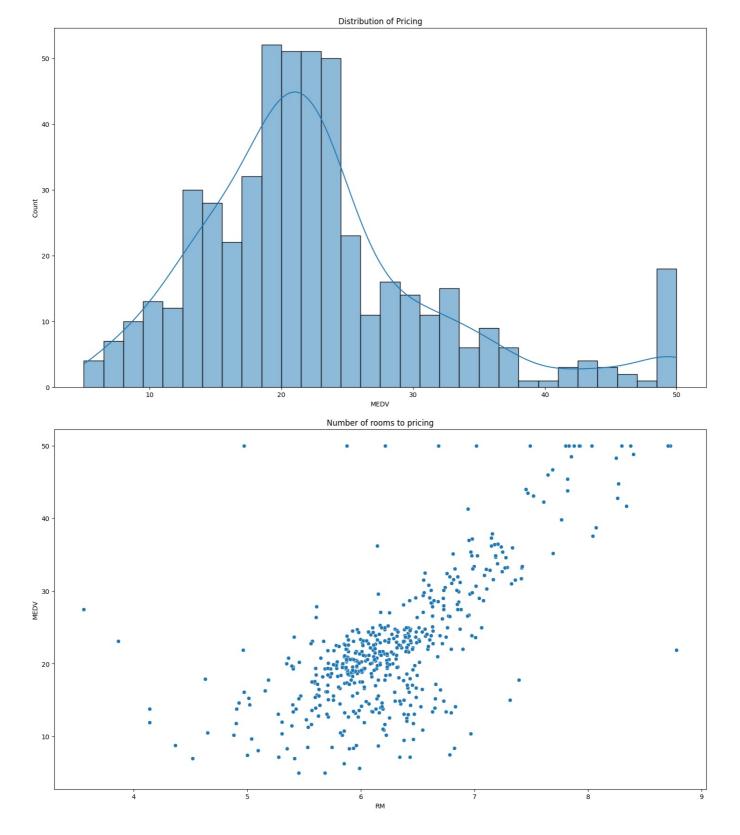
<class 'pandas.core.frame.DataFrame'>

ZN

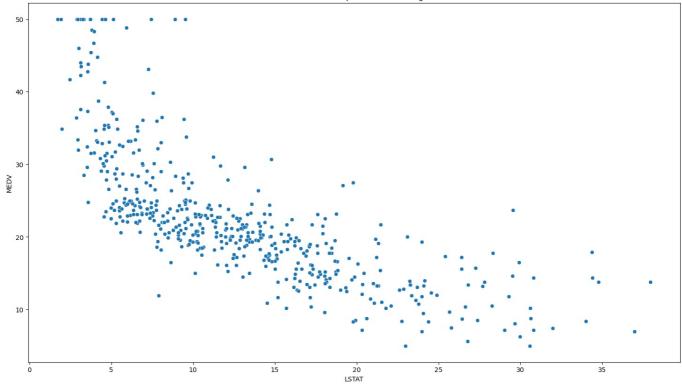
CHAS

RM

DIS







b. Splitting

```
In [20]: import numpy as n
          from sklearn.model_selection import train_test_split
          from sklearn.linear_model import LinearRegression
          from sklearn.metrics import mean_squared_error, r2_score
          X = da.drop('MEDV', axis=1)
          y = da['MEDV']
          X train, X test, y train, y test = train test split(X, y, test size=0.3, random state=42)
          print("Train set:", X_train.shape, y_train.shape)
print("Test set:", X_test.shape, y_test.shape)
          model = LinearRegression()
          model.fit(X_train, y_train)
          y_pred = model.predict(X_test)
          rmse = n.sqrt(mean_squared_error(y_test, y_pred))
          r2 = r2_score(y_test, y_pred)
          print("Root Mean Squared Error:", rmse)
          print("R-squared:", r2)
        Train set: (354, 13) (354,)
        Test set: (152, 13) (152,)
        Root Mean Squared Error: 4.638689926172827
        R-squared: 0.7112260057484925
```

47. Cricket match result

a. Data Preprocessing

```
import pandas as p
da=p.read_csv("matches.csv")
da.info()

#PRE_PROCESSING
miss=da.isna().sum()
print("\nMissing Values:\n",miss)
da.drop('umpire3', axis=1, inplace=True)
da.dropna(axis=0,inplace=True)
da.drop('date',axis=1,inplace=True)
print("\nMissing Values:\n",da.isna().sum())
```

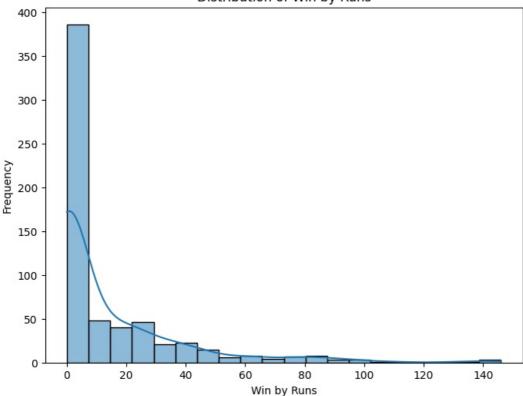
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 636 entries, 0 to 635
Data columns (total 18 columns):
#
    Column
                  Non-Null Count Dtype
                     -----
0
    id
                    636 non-null
                                     int64
                    636 non-null
629 non-null
1
    season
                                     int64
2
    city
                                     object
                    636 non-null
    date
                                     object
                    636 non-null
4
    team1
                                     object
    team2 636 non-null toss_winner 636 non-null
5
                                     object
6
                                     object
    toss decision 636 non-null
                                     object
                 636 non-null
8
    result
                                      object
9
    dl applied
                     636 non-null
                                      int64
10 winner
                     633 non-null
                                     object
                    636 non-null
11 win by runs
                                      int64
12 win_by_wickets 636 non-null
                                     int64
 13 player_of_match 633 non-null
                                     object
14 venue
                     636 non-null
                                     object
15 umpire1
                     635 non-null
                                      object
                     635 non-null
16 umpire2
                                      object
17 umpire3
                     0 non-null
                                      float64
dtypes: float64(1), int64(5), object(12)
memory usage: 89.6+ KB
Missing Values:
                     0
id
season
city
date
team1
team2
toss_winner
                    0
toss decision
result
dl applied
                    3
winner
win_by_runs
win_by_wickets
player_of_match
                    0
venue
umpire1
                    1
umpire2
                    1
umpire3
                  636
dtype: int64
Missing Values:
id
                   0
                  0
season
city
                  0
team1
team2
toss winner
toss decision
result
dl_applied
                  0
winner
                  0
win_by_runs
                  0
win by wickets
player_of_match
venue
umpire1
                  0
umpire2
dtype: int64
```

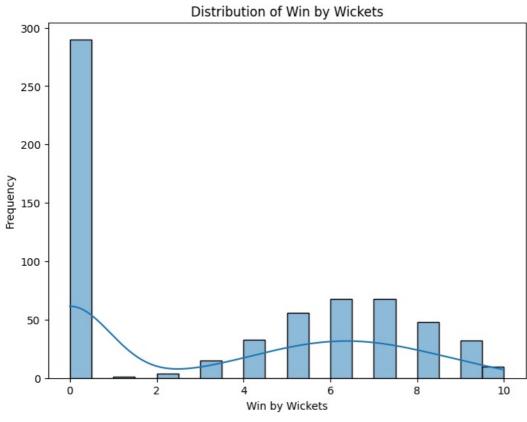
b. Data Exploration

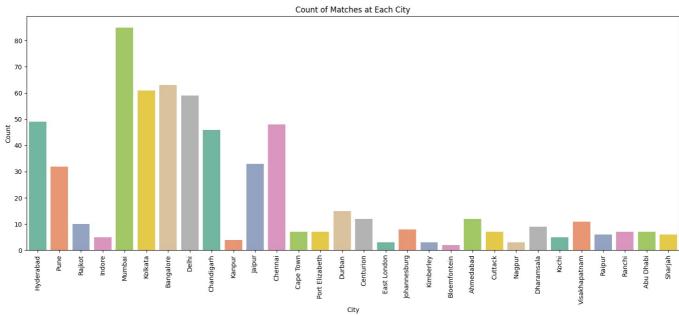
```
import matplotlib.pyplot as m
import seaborn as s
# Function to create a histogram
def hist(da, col, title, xlabel):
    m.figure(figsize=(8, 6))
    s.histplot(da[col], bins=20, kde=True)
    m.title(title)
    m.xlabel(xlabel)
    m.ylabel('Frequency')
    m.show()
# Function to create a count plot
def countplot(da, x, title, xlabel):
    m.figure(figsize=(15, 7))
```

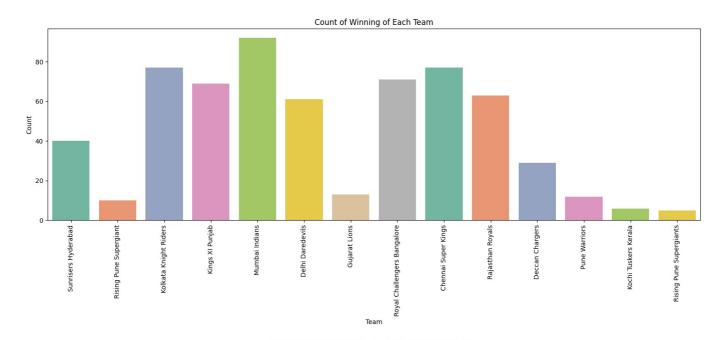
```
s.countplot(x=x, data=da, hue=x, palette='Set2', legend=False)
                m.title(title)
                m.xlabel(xlabel)
                m.ylabel('Count')
                m.xticks(rotation=90)
                m.tight_layout()
                m.show()
# Function to create a stacked bar chart
def sta_bar(da, x, y, title, xlabel, ylabel, legend_title=None):
                dp = da.groupby([x, y]).size().unstack()
                dp.plot(kind='bar', stacked=True, figsize=(10, 6))
                m.title(title)
                m.xlabel(xlabel)
                m.ylabel(ylabel)
                if legend title:
                                m.legend(title=legend title)
#DATA EXPLORATION
hist(da, 'win_by_runs', 'Distribution of Win by Runs', 'Win by Runs')
hist(da, 'win_by_wickets', 'Distribution of Win by Wickets', 'Win by Wickets')
countplot(da, 'city', 'Count of Matches at Each City', 'City')
countplot(da, 'winner', 'Count of Winning of Each Team', 'Team')
sta_bar(da, 'toss_decision', 'result', 'Toss Decision vs. Match Result', 'Toss Decision', 'Count', legend_title
sta_bar(da, 'season', 'toss_decision', 'Season-wise Toss Decision', 'Season', 'Count', legend_title='Toss Decision', 'Season', 'Count', legend_title='Toss Decision', 'Count', 'Count', legend_title='Toss Decision', 'Count', 'Coun
```

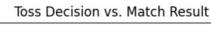
Distribution of Win by Runs

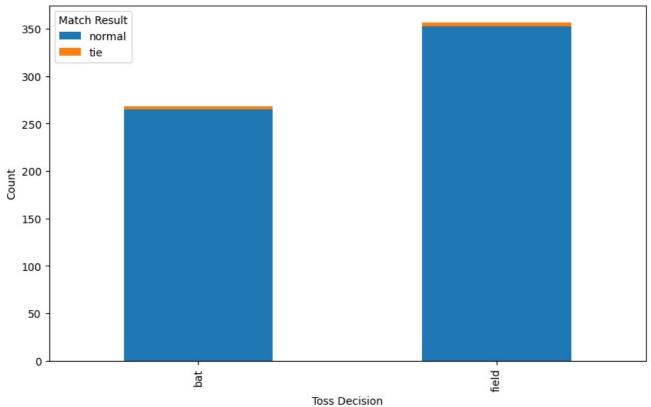


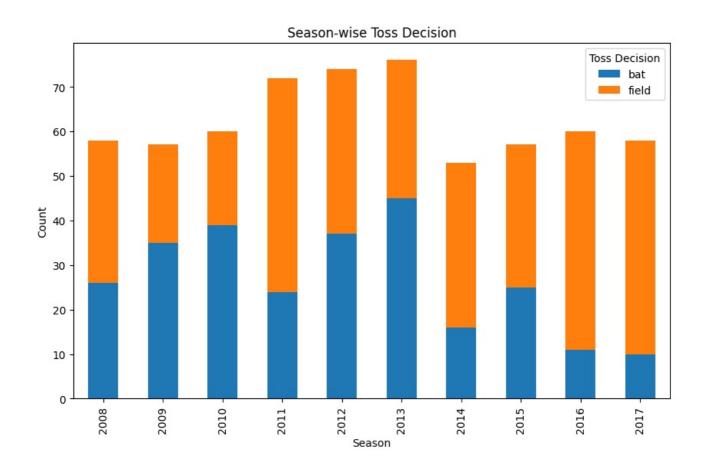












c. Splitting

```
In [13]: from sklearn.preprocessing import LabelEncoder
          from sklearn.model_selection import train_test_split
          import pandas as p
          da=p.read_csv("matches.csv")
          #Transformation
          categorical_columns = ['city', 'team1', 'team2', 'toss_winner',
          'toss_decision', 'result', 'player_of_match', 'venue', 'umpire1',
          'umpire2','winner','date']
          label encoders = {}
          for column in categorical_columns:
              label encoders[column] = LabelEncoder()
              da[column] = label_encoders[column].fit_transform(da[column])
          X = da.drop('winner', axis=1)
          y = da['winner']
          X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
          random_state=42)
          print("Train set:", X_train.shape, y_train.shape)
print("Test set:", X_test.shape, y_test.shape)
```

Train set: (445, 17) (445,) Test set: (191, 17) (191,)

48. Performance of a cricket player

a. Preprocessing

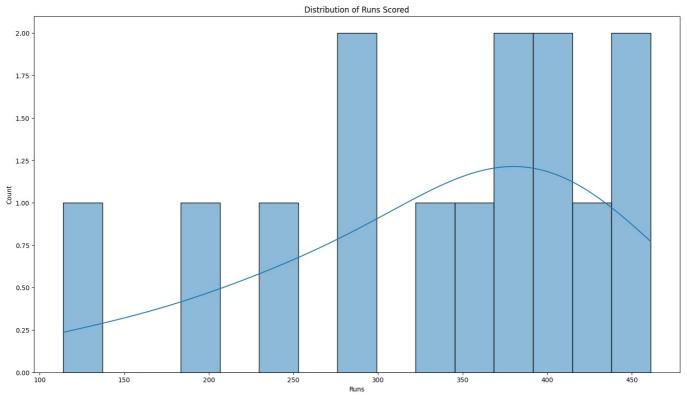
```
In [17]: import pandas as p
         da=p.read csv("Dhoni1.csv")
         da.info()
         #PRE PROCESSING
         miss=da.isna().sum()
         print("\nMissing Values:\n",miss)
         da.dropna(inplace=True)
         print("\nMissing Values:\n",da.isna().sum())
        <class 'pandas.core.frame.DataFrame'>
       RangeIndex: 15 entries, 0 to 14
        Data columns (total 14 columns):
                      Non-Null Count Dtype
        # Column
        0
            Year
                          15 non-null
                                           int64
                          14 non-null
        1
            Matches
                                           float64
                          14 non-null
            Innings
                                           float64
        3
            Ν.Ο.
                          14 non-null
                                           float64
            Runs
                           14 non-null
                                           float64
            Highest Score 14 non-null
                                           float64
            Average 14 non-null
                                           float64
            Strike Rate 14 non-null
                                           float64
                   14 non-null
14 non-null
        8
            100
                                           float64
        9
            50
                                           float64
        10 Fours
                         14 non-null
                                           float64
        11 Sixes
                          14 non-null
                                           float64
        12 Catches Taken 14 non-null
                                           float64
        13 Stumpings 14 non-null
                                           float64
        dtypes: float64(13), int64(1)
        memory usage: 1.8 KB
        Missing Values:
        Year
        Matches
                        1
        Innings
        N.O.
        Runs
        Highest Score
        Average
        Strike Rate
        100
        50
        Fours
        Sixes
        Catches Taken
       Stumpings
        dtype: int64
        Missing Values:
                         0
        Year
        Matches
        Innings
        Ν.Ο.
        Runs
                        0
        Highest Score
        Average
        Strike Rate
        100
        50
                        0
        Fours
        Sixes
                        0
       Catches Taken
                        0
        Stumpings
        dtype: int64
```

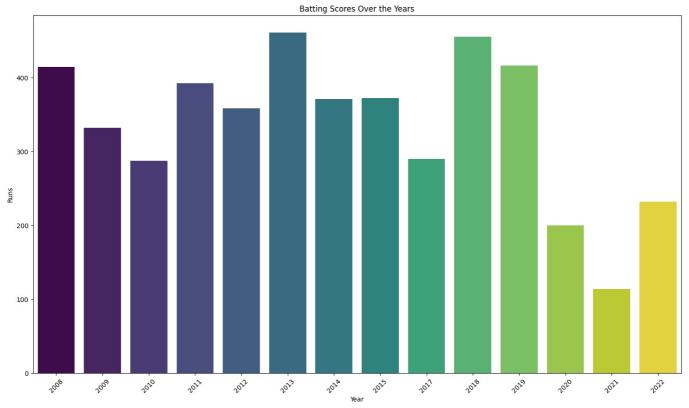
b. Exploration

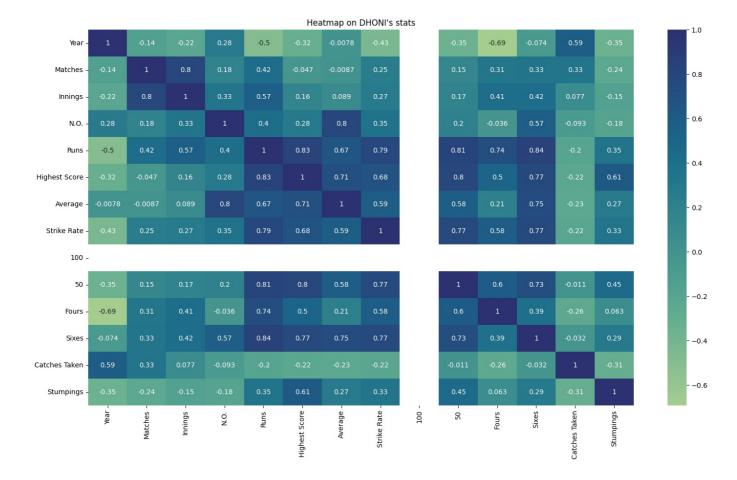
```
import matplotlib.pyplot as m
import seaborn as s

# First plot: Histogram
```

```
m.figure(figsize=(18,10))
s.histplot(da['Runs'], bins=15, kde=True)
m.title('Distribution of Runs Scored')
m.show()
# Second plot: Barplot
m.figure(figsize=(18,10))
s.barplot(data=da, x='Year', y='Runs', hue='Year', palette='viridis', legend=False)
m.title('Batting Scores Over the Years')
m.xlabel('Year')
m.ylabel('Runs')
m.xticks(rotation=45)
m.show()
# Third plot: Heatmap
m.figure(figsize=(18,10))
s.heatmap(data=da.corr(), annot=True, cmap='crest')
m.title("Heatmap on DHONI's stats")
m.show()
```







c. splitting

```
In [111... from sklearn.model_selection import train_test_split
X = da.drop('Average', axis=1)
y = da['Average']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
print("Train_set:", X_train.shape, y_train.shape)
print("Test_set:", X_test.shape, y_test.shape)
Train_set: (10, 13) (10,)
Test_set: (5, 13) (5,)
```

49. Crop yield

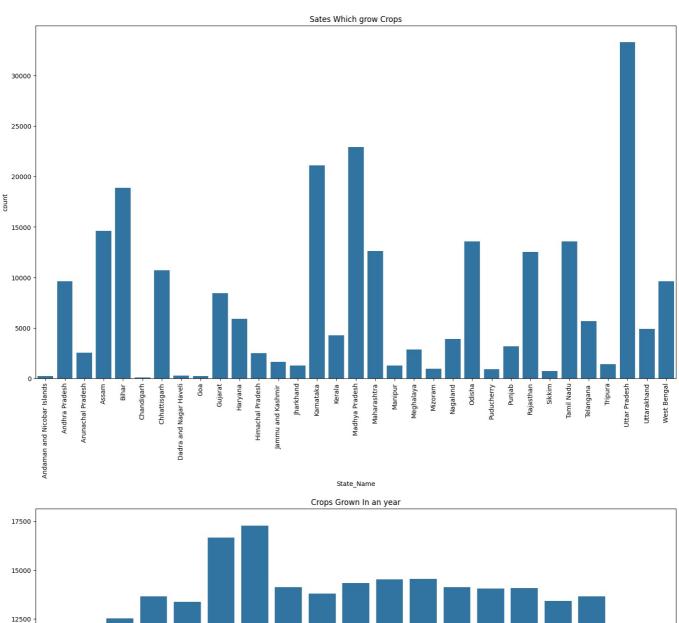
a. Preprocessing

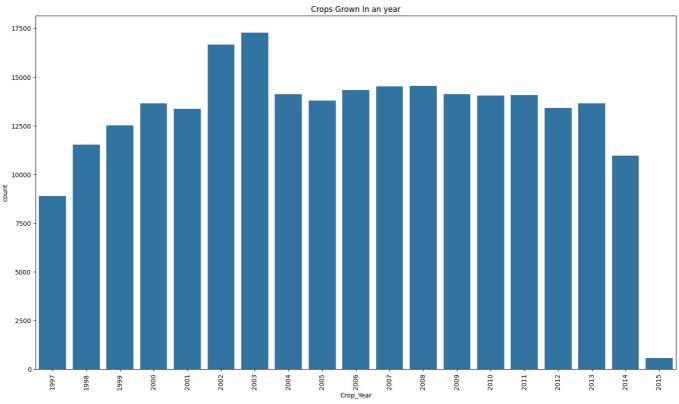
```
import pandas as p
da=p.read_csv("crop_pre.csv")
da.info()
#PRE_PROCESSING
miss=da.isna().sum()
print("\nMissing Values:\n",miss)
da.dropna(inplace=True)
print("\nMissing Values:\n",da.isna().sum())
```

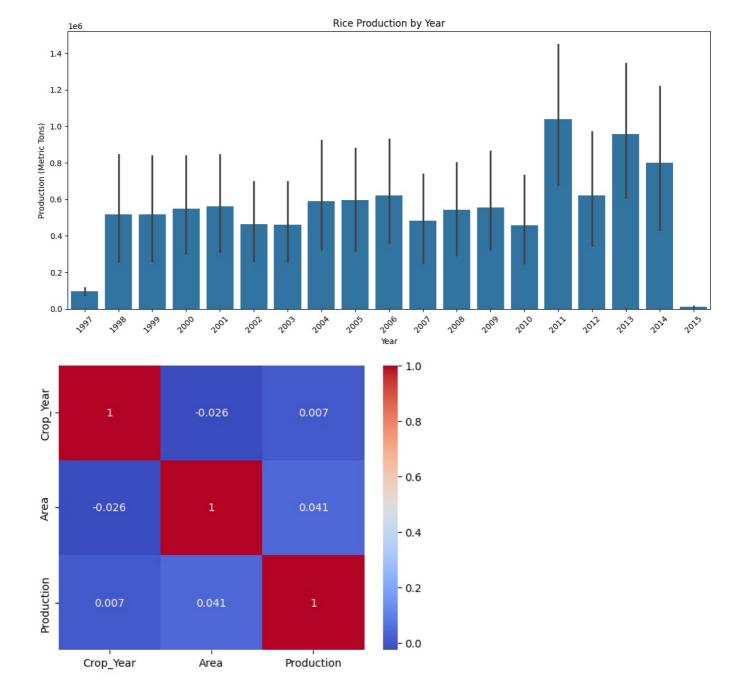
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 246091 entries, 0 to 246090
Data columns (total 7 columns):
               Non-Null Count Dtype
 # Column
                     -----
0 State_Name 246091 non-null object
    District_Name 246091 non-null object Crop_Year 246091 non-null int64 Season 246091 non-null object
    Season
4 Crop 246091 non-null object
5 Area 246091 non-null float64
6 Production 242361 non-null float64
dtypes: float64(2), int64(1), object(4)
memory usage: 13.1+ MB
Missing Values:
State Name
District Name
                      0
Crop Year
                      0
                      0
Season
Crop
                      0
                      0
Area
Production
                  3730
dtype: int64
Missing Values:
State Name
                    0
District Name
                  0
Crop Year
Season
                  0
Crop
                  0
Area
                  0
Production
                   0
dtype: int64
```

Data Exploration

```
In [35]: import matplotlib.pyplot as m
         import seaborn as s
         import pandas as p
         da=p.read csv("crop pre.csv")
         m.figure(figsize=(18,10))
         s.countplot(data=da, x='State_Name')
         m.title("Sates Which grow Crops")
         m.xticks(rotation=90)
         m.show()
         m.figure(figsize=(18,10))
         s.countplot(data=da,x='Crop_Year')
         m.title('Crops Grown In an year')
         m.xticks(rotation=90)
         m.show()
         m.figure(figsize=(12, 6))
         s.barplot(x=da['Crop_Year'], y=da['Production'],data=da)
         m.title('Rice Production by Year')
         m.xlabel('Year')
         m.ylabel('Production (Metric Tons)')
         m.xticks(rotation=45)
         m.tight layout()
         m.show()
         sn=da.select_dtypes(exclude=['object'])
         s.heatmap(data=sn.corr(),annot=True,cmap='coolwarm')
         m.show()
```







c. Splitting

Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js