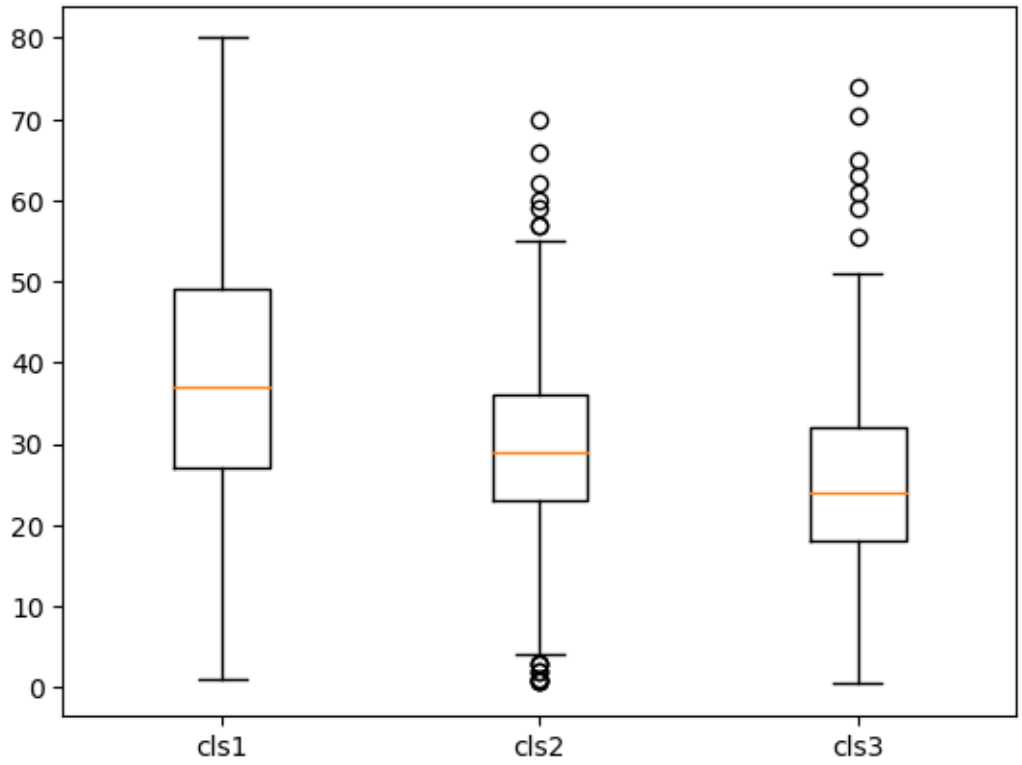
day-4-623

February 15, 2024

[1]:
```
# Drwaing boxplot based on pclass
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
df_titanic=pd.read_csv("titanic_train.csv")
cls1 = df_titanic[df_titanic['Pclass']==1]['Age'].dropna()
cls2 = df_titanic[df_titanic['Pclass']==2]['Age'].dropna()
cls3 = df_titanic[df_titanic['Pclass']==3]['Age'].dropna()
```

[2]:
```
l1 = [cls1,cls2,cls3]
plt.boxplot(l1, labels=["cls1","cls2","cls3"])
```

[2]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x1c8fda55710>,
  <matplotlib.lines.Line2D at 0x1c8fdf6e5d0>,
  <matplotlib.lines.Line2D at 0x1c8fdf7a910>,
  <matplotlib.lines.Line2D at 0x1c8fdf7b490>,
  <matplotlib.lines.Line2D at 0x1c8fdf87ad0>,
  <matplotlib.lines.Line2D at 0x1c8fdf90690>],
 'caps': [<matplotlib.lines.Line2D at 0x1c8fdf4a310>,
  <matplotlib.lines.Line2D at 0x1c8fdf6fd10>,
  <matplotlib.lines.Line2D at 0x1c8fdf84090>,
  <matplotlib.lines.Line2D at 0x1c8fdf84c50>,
  <matplotlib.lines.Line2D at 0x1c8fdf91250>,
  <matplotlib.lines.Line2D at 0x1c8fdf91d90>],
 'boxes': [<matplotlib.lines.Line2D at 0x1c8fdefc7d0>,
  <matplotlib.lines.Line2D at 0x1c8fdf79dd0>,
  <matplotlib.lines.Line2D at 0x1c8fdf86f50>],
 'medians': [<matplotlib.lines.Line2D at 0x1c8fdf78810>,
  <matplotlib.lines.Line2D at 0x1c8fdf857d0>,
  <matplotlib.lines.Line2D at 0x1c8fdf92810>],
 'fliers': [<matplotlib.lines.Line2D at 0x1c8fdf792d0>,
  <matplotlib.lines.Line2D at 0x1c8fdf86310>,
  <matplotlib.lines.Line2D at 0x1c8fdf932d0>],
 'means': []}
```



[3]:
```
# Permanently renaming sex field to "gender"
df_titanic.rename(columns={"Sex":"Gender"}, inplace=True)
df_titanic.head()
```

[3]:

	PassengerId	Survived	Pclass	Name	Gender	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th…	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1					
4	5	0	3	Allen, Mr. William Henry	male	35.0	0					

```
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
```

[4]:
```
# Converting male to 0 and female to 1
df_titanic['Gender'] = df_titanic['Gender'].map({'male':0, 'female':1})
df_titanic
# or
# df_titanic['Gender'] = df_titanic['Gender'].replace({'male':0, 'female':1})
# df_titanic
```

[4]:
```
     PassengerId  Survived  Pclass  \
0              1         0       3
1              2         1       1
2              3         1       3
3              4         1       1
4              5         0       3
..           …       …     …
886          887         0       2
887          888         1       1
888          889         0       3
889          890         1       1
890          891         0       3

                                                  Name  Gender   Age  SibSp  \
0                              Braund, Mr. Owen Harris       0  22.0      1
1    Cumings, Mrs. John Bradley (Florence Briggs Th…       1  38.0      1
2                               Heikkinen, Miss. Laina       1  26.0      0
3         Futrelle, Mrs. Jacques Heath (Lily May Peel)       1  35.0      1
4                             Allen, Mr. William Henry       0  35.0      0
..                                                 …     …   …    …
886                             Montvila, Rev. Juozas       0  27.0      0
887                      Graham, Miss. Margaret Edith       1  19.0      0
888          Johnston, Miss. Catherine Helen "Carrie"       1   NaN      1
889                             Behr, Mr. Karl Howell       0  26.0      0
890                               Dooley, Mr. Patrick       0  32.0      0

     Parch            Ticket     Fare Cabin Embarked
0        0         A/5 21171   7.2500   NaN        S
1        0          PC 17599  71.2833   C85        C
2        0  STON/O2. 3101282   7.9250   NaN        S
3        0            113803  53.1000  C123        S
4        0            373450   8.0500   NaN        S
..     …              …      …   …      …
886      0            211536  13.0000   NaN        S
887      0            112053  30.0000   B42        S
888      2        W./C. 6607  23.4500   NaN        S
889      0            111369  30.0000  C148        C
```

```
890      0            370376   7.7500   NaN        Q

[891 rows x 12 columns]
```

[5]:
```
# Selecting data age < 25 and gender 1
((df_titanic['Age']<25) & (df_titanic['Gender']==1)).sum()
```

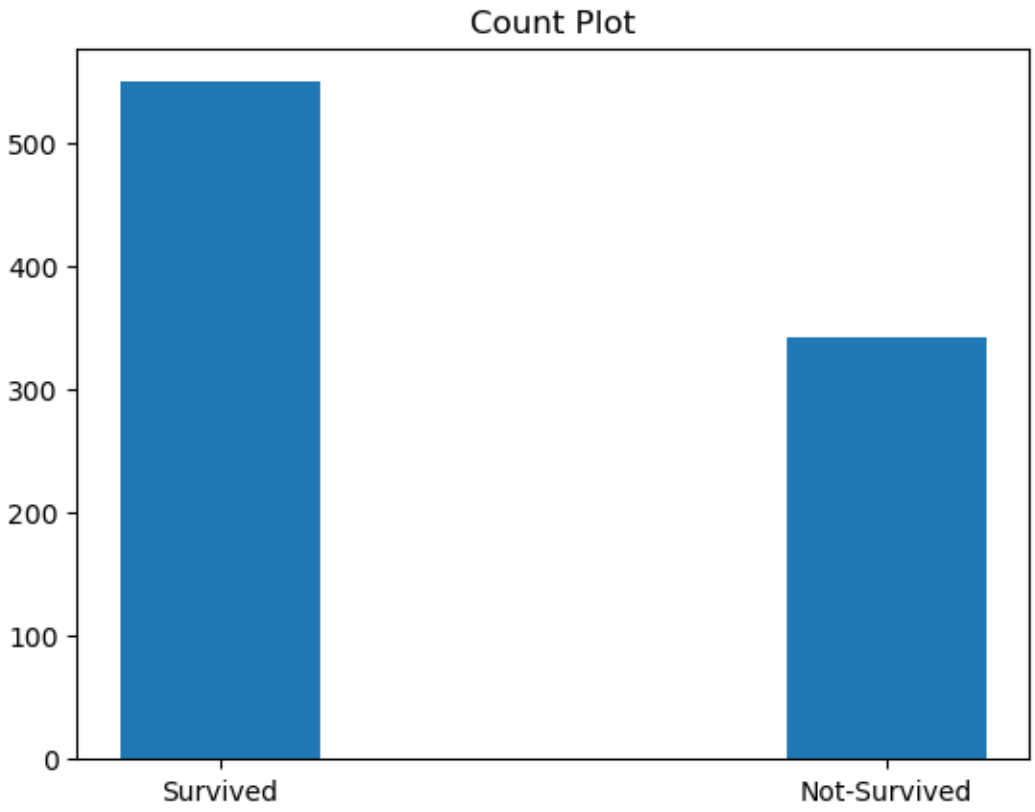
[5]:
```
117
```

[6]:
```
# Selecting how many male and female survived
gender = ['Male','Female']
male = ((df_titanic['Gender']==0) & (df_titanic['Survived'])).sum()
female = ((df_titanic['Gender']==1) & (df_titanic['Survived'])).sum()
print(male)
print(female)
```

```
109
233
```

[7]:
```
# Showing count of survivors and non-survivors
gender = ["Survived","Not-Survived"]
survived =  (df_titanic['Survived']==0).sum()
not_survived =(df_titanic['Survived']==1).sum()
count=[survived,not_survived]
plt.bar(gender,count, width=0.3)
plt.title("Count Plot")
```

[7]:
```
Text(0.5, 1.0, 'Count Plot')
```



[8]:
```
import seaborn as sns
tips = sns.load_dataset("tips")
tips.head()
```

[8]:

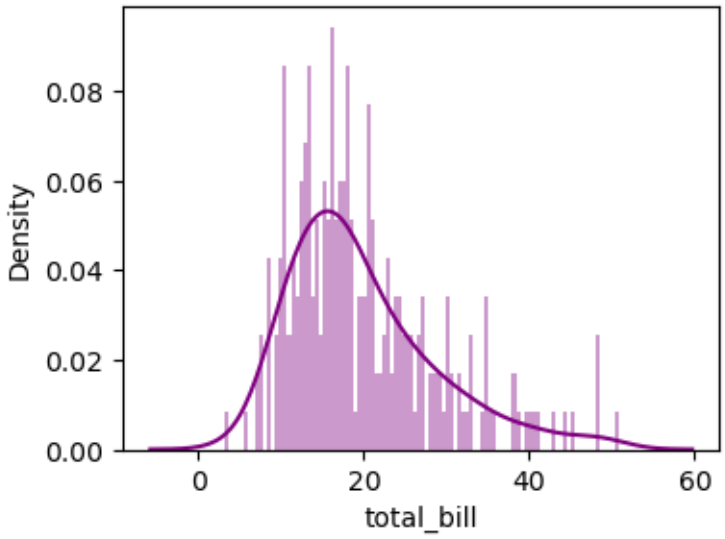
	total_bill	tip	sex	smoker	day	time	size
0	16.99	1.01	Female	No	Sun	Dinner	2
1	10.34	1.66	Male	No	Sun	Dinner	3
2	21.01	3.50	Male	No	Sun	Dinner	3
3	23.68	3.31	Male	No	Sun	Dinner	2
4	24.59	3.61	Female	No	Sun	Dinner	4

[9]:
```
# distplot
# It will take only one column

plt.figure(figsize=(4,3))
sns.distplot(tips['total_bill'], bins=100, kde=True, hist=True, color="purple")
```

```
C:\Users\tanut\AppData\Local\Temp\ipykernel_19500\3279888165.py:5: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.
```

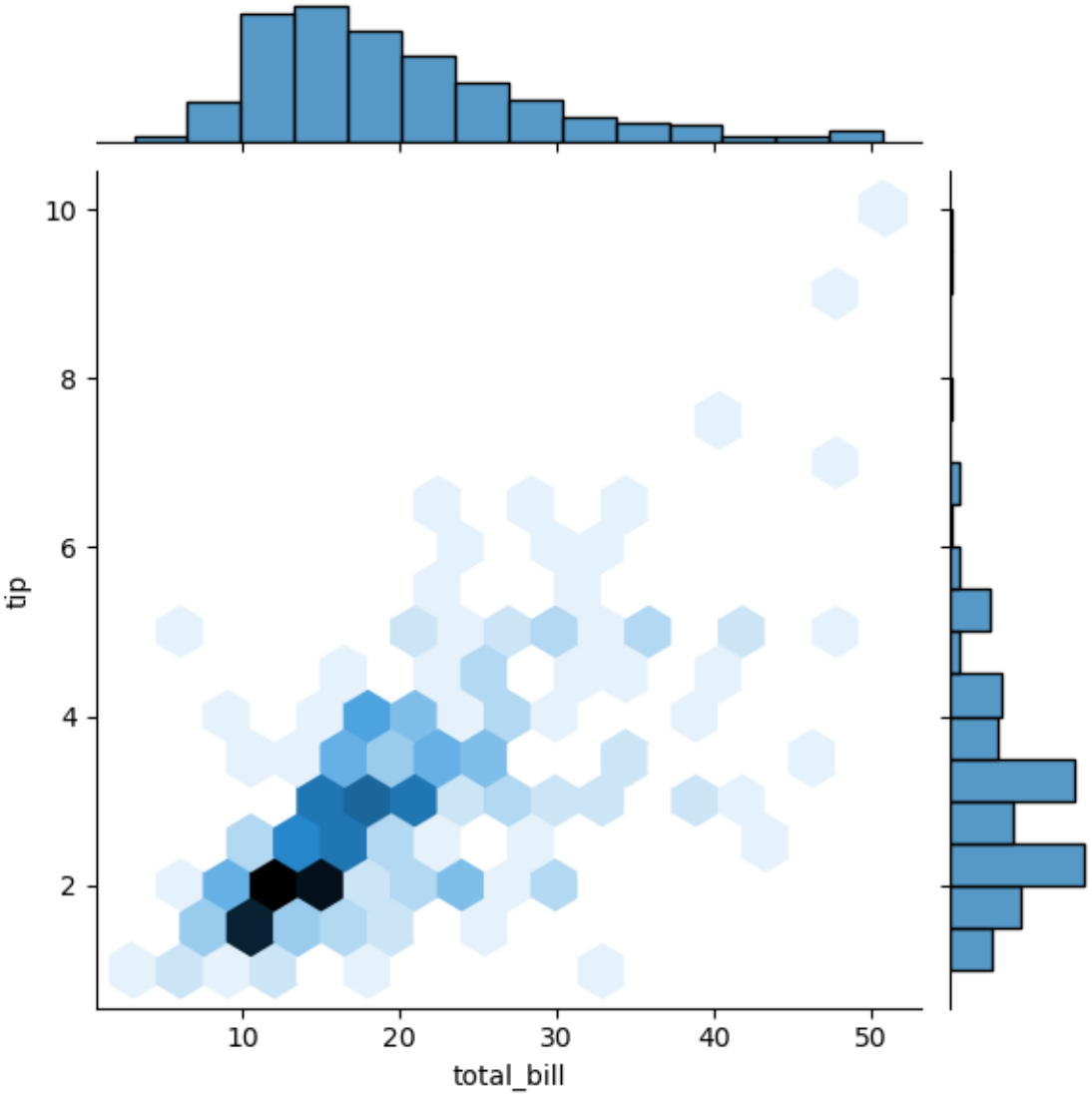
```
Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(tips['total_bill'], bins=100, kde=True, hist=True,
color="purple")
```

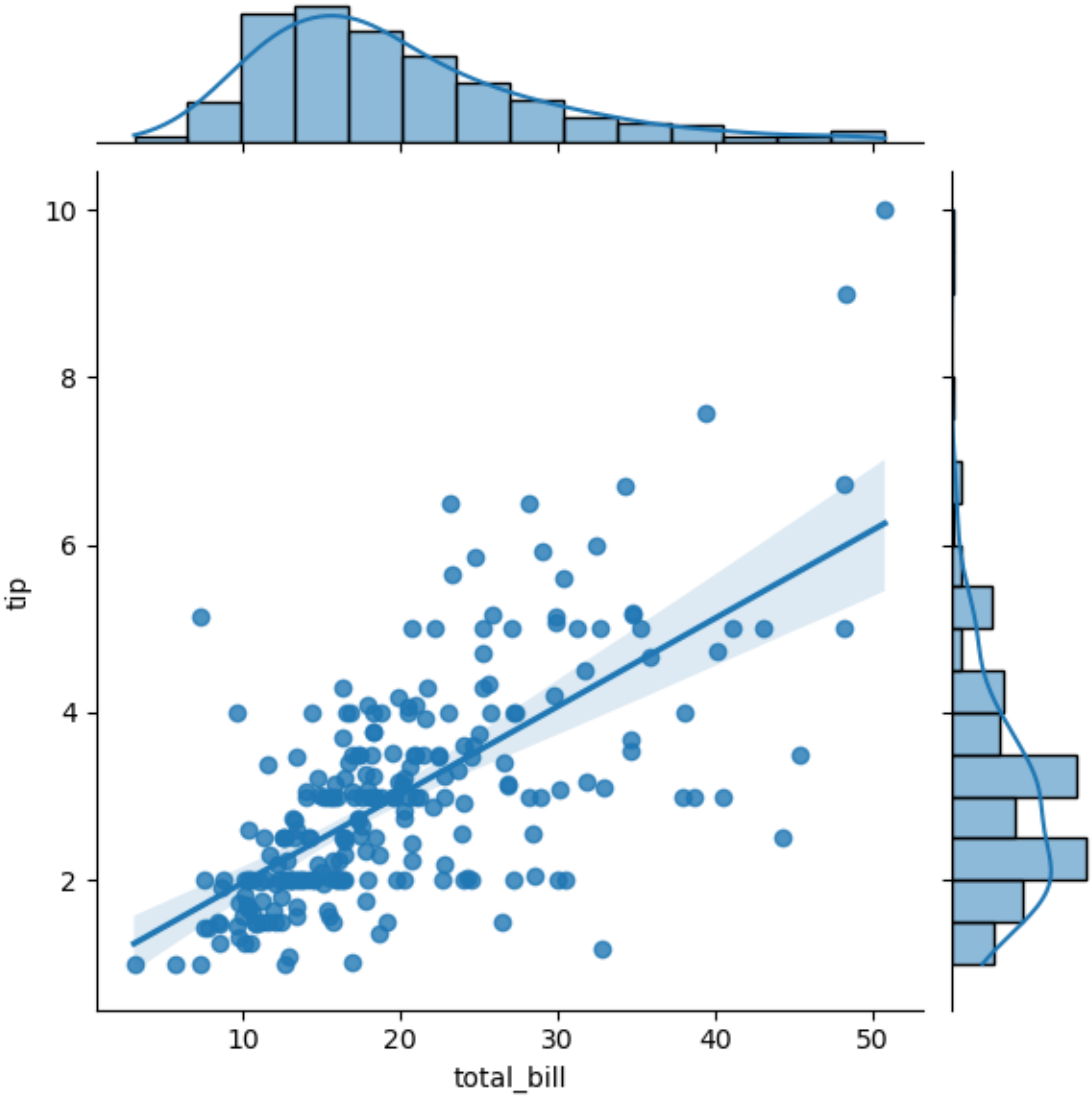
[9]:
```
<Axes: xlabel='total_bill', ylabel='Density'>
```

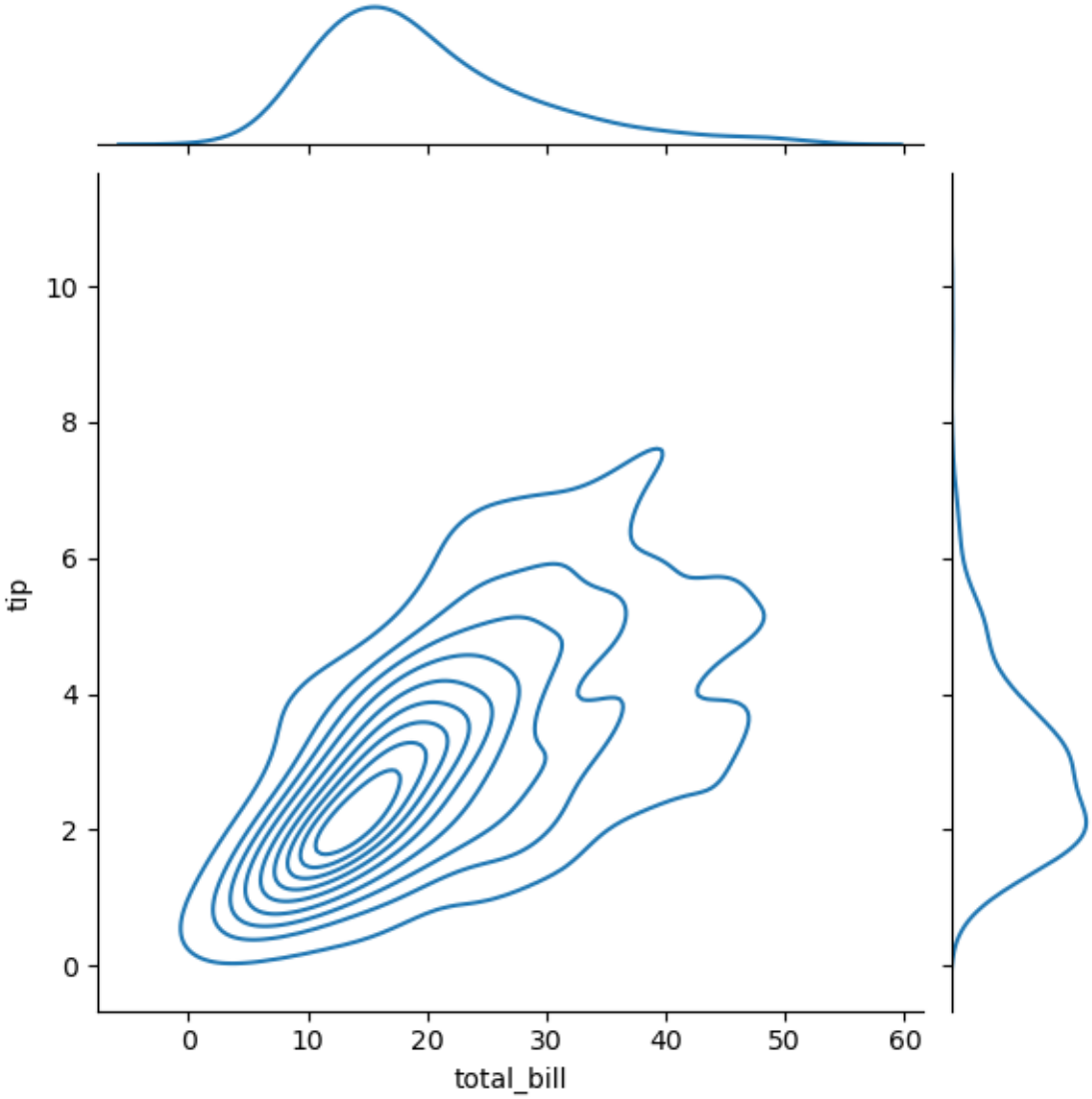


[10]:
```
# jointplot
sns.jointplot(x='total_bill',y='tip',data=tips, kind='hex')
sns.jointplot(x='total_bill',y='tip',data=tips, kind='reg')
sns.jointplot(x='total_bill',y='tip',data=tips, kind='kde')
```

[10]:
```
<seaborn.axisgrid.JointGrid at 0x1c88327bf50>
```


10
8
6
4
2
tip
10
20
30
40
50
total_bill

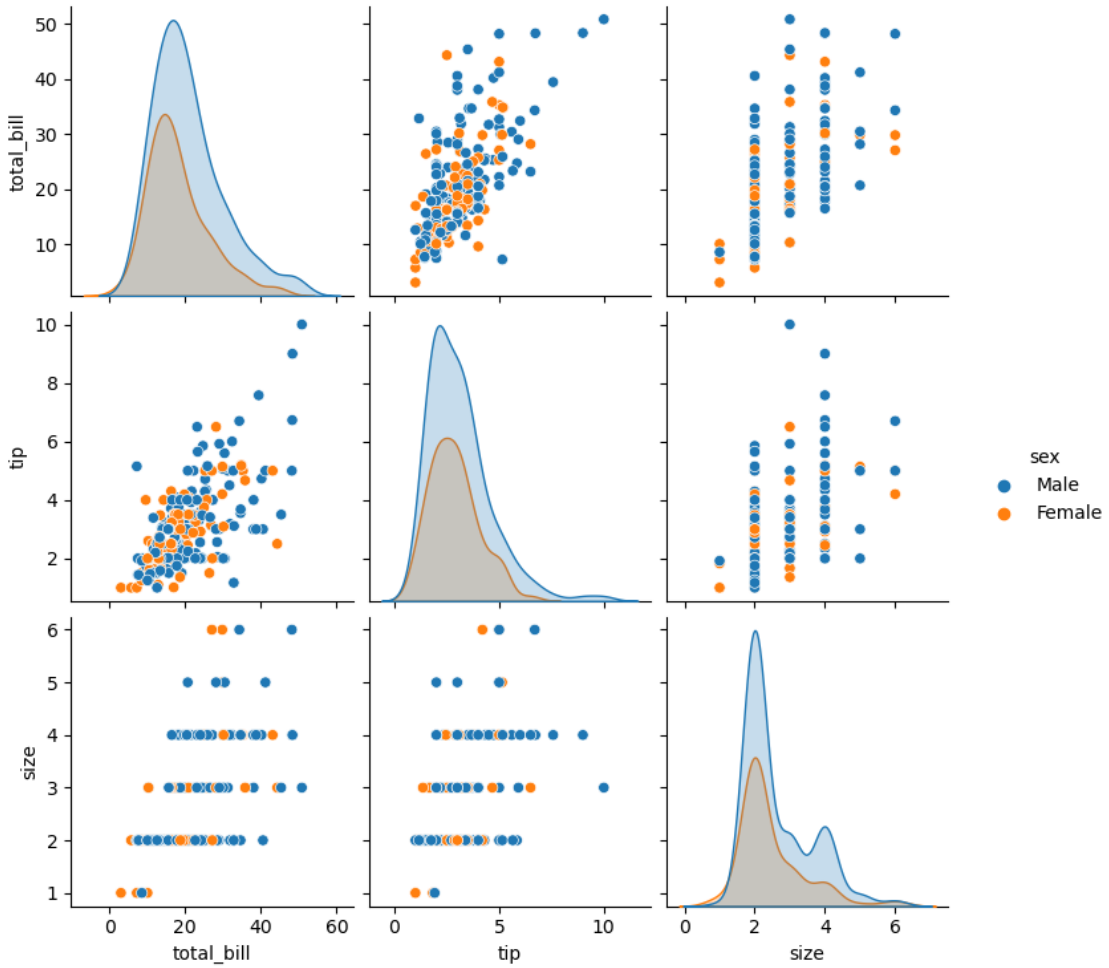

10
8
6
4
2
tip
10
20
30
40
50
total_bill



[11]:
```
# Pairplot
sns.pairplot(tips, hue="sex")
```

```
C:\ProgramData\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning:
The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

[11]: <seaborn.axisgrid.PairGrid at 0x1c8836bbf50>



[12]:
```
# ML Algorithms
# logistical regression is the statistical method used to model the␣
 ↪relationship between a binary dependent variable
# and one or more independent variables

# In logistic regression, the dependent variable is binary, meaning it can take␣
 ↪only two values 0 or 1

import numpy as np
from sklearn .metrics import accuracy_score, precision_score, recall_score,␣
 ↪f1_score, confusion_matrix
```

[13]:
```
y_pred = np.array([0.9,0.9,0.8,0.9,0.9,0.9,0.9,0.7,0.5,0.6])
y_true = np.array([0,1,1,0,0,1,0,1,0,1])
```

[14]:
```
#Accuracy measures the percentage of correctly classified instances and out of␣
 ↪all instances
accuracy = accuracy_score(y_true, np.round(y_pred))
accuracy
```

[14]: 0.6

[15]:
```
# Precision

# Precision measured the proportion of true positive prediction out of all␣
 ↪positive predictions
# Precision = true positive/all positive
precision = precision_score(y_true, np.round(y_pred))
precision
```

[15]: 0.5555555555555556

[16]:
```
# Recall

# Recall = true positive/actual positive
# Recall measures the proportion of true positive prediction out of all actual␣
 ↪positive cases
recall = recall_score(y_true, np.round(y_pred))
recall
```

[16]: 1.0

[17]:
```
# F1 score
# It is the mean of precision and recall
f1_score = f1_score(y_true, np.round(y_pred))
f1_score
```

[17]: 0.7142857142857143

[18]:
```
# Confusion matrix
# It is a table that gives the performance of a classification model.
# It shows true positive, true negative, false positive, false negative
matrix = confusion_matrix(y_true, np.round(y_pred))
matrix
```

[18]:
```
array([[1, 4],
       [0, 5]], dtype=int64)
```

[19]:
```
# Eg-1
# Logistic Regression
from sklearn.datasets import load_iris
from sklearn.linear_model import LogisticRegression
```

```
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
```

[20]:
```
iris = load_iris()
iris_df = pd.DataFrame(data=iris.data, columns=iris.feature_names)
iris_df['target'] = iris.target
iris_df['target_names'] = iris.target_names[iris.target]
iris_df
```

[20]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	\
0	5.1	3.5	1.4	0.2	
1	4.9	3.0	1.4	0.2	
2	4.7	3.2	1.3	0.2	
3	4.6	3.1	1.5	0.2	
4	5.0	3.6	1.4	0.2	
..	…	…	…	…	
145	6.7	3.0	5.2	2.3	
146	6.3	2.5	5.0	1.9	
147	6.5	3.0	5.2	2.0	
148	6.2	3.4	5.4	2.3	
149	5.9	3.0	5.1	1.8	

	target	target_names
0	0	setosa
1	0	setosa
2	0	setosa
3	0	setosa
4	0	setosa
..	…	…
145	2	virginica
146	2	virginica
147	2	virginica
148	2	virginica
149	2	virginica

[150 rows x 6 columns]

[21]:
```
# seperate dependent variable and independent variable
x = iris.data
x
```

[21]:
```
array([[5.1, 3.5, 1.4, 0.2],
       [4.9, 3. , 1.4, 0.2],
       [4.7, 3.2, 1.3, 0.2],
       [4.6, 3.1, 1.5, 0.2],
       [5. , 3.6, 1.4, 0.2],
       [5.4, 3.9, 1.7, 0.4],
```

```
[4.6, 3.4, 1.4, 0.3],
[5. , 3.4, 1.5, 0.2],
[4.4, 2.9, 1.4, 0.2],
[4.9, 3.1, 1.5, 0.1],
[5.4, 3.7, 1.5, 0.2],
[4.8, 3.4, 1.6, 0.2],
[4.8, 3. , 1.4, 0.1],
[4.3, 3. , 1.1, 0.1],
[5.8, 4. , 1.2, 0.2],
[5.7, 4.4, 1.5, 0.4],
[5.4, 3.9, 1.3, 0.4],
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[5.7, 3.8, 1.7, 0.3],
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[5.4, 3.4, 1.7, 0.2],
[5.1, 3.7, 1.5, 0.4],
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[5.1, 3.3, 1.7, 0.5],
[4.8, 3.4, 1.9, 0.2],
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[5. , 3.4, 1.6, 0.4],
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[4.7, 3.2, 1.6, 0.2],
[4.8, 3.1, 1.6, 0.2],
[5.4, 3.4, 1.5, 0.4],
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[5.5, 4.2, 1.4, 0.2],
[4.9, 3.1, 1.5, 0.2],
[5. , 3.2, 1.2, 0.2],
[5.5, 3.5, 1.3, 0.2],
[4.9, 3.6, 1.4, 0.1],
[4.4, 3. , 1.3, 0.2],
[5.1, 3.4, 1.5, 0.2],
[5. , 3.5, 1.3, 0.3],
[4.5, 2.3, 1.3, 0.3],
[4.4, 3.2, 1.3, 0.2],
[5. , 3.5, 1.6, 0.6],
[5.1, 3.8, 1.9, 0.4],
[4.8, 3. , 1.4, 0.3],
[5.1, 3.8, 1.6, 0.2],
[4.6, 3.2, 1.4, 0.2],
[5.3, 3.7, 1.5, 0.2],
[5. , 3.3, 1.4, 0.2],
[7. , 3.2, 4.7, 1.4],
[6.4, 3.2, 4.5, 1.5],
[6.9, 3.1, 4.9, 1.5],
```

```
[5.5, 2.3, 4. , 1.3],
[6.5, 2.8, 4.6, 1.5],
[5.7, 2.8, 4.5, 1.3],
[6.3, 3.3, 4.7, 1.6],
[4.9, 2.4, 3.3, 1. ],
[6.6, 2.9, 4.6, 1.3],
[5.2, 2.7, 3.9, 1.4],
[5. , 2. , 3.5, 1. ],
[5.9, 3. , 4.2, 1.5],
[6. , 2.2, 4. , 1. ],
[6.1, 2.9, 4.7, 1.4],
[5.6, 2.9, 3.6, 1.3],
[6.7, 3.1, 4.4, 1.4],
[5.6, 3. , 4.5, 1.5],
[5.8, 2.7, 4.1, 1. ],
[6.2, 2.2, 4.5, 1.5],
[5.6, 2.5, 3.9, 1.1],
[5.9, 3.2, 4.8, 1.8],
[6.1, 2.8, 4. , 1.3],
[6.3, 2.5, 4.9, 1.5],
[6.1, 2.8, 4.7, 1.2],
[6.4, 2.9, 4.3, 1.3],
[6.6, 3. , 4.4, 1.4],
[6.8, 2.8, 4.8, 1.4],
[6.7, 3. , 5. , 1.7],
[6. , 2.9, 4.5, 1.5],
[5.7, 2.6, 3.5, 1. ],
[5.5, 2.4, 3.8, 1.1],
[5.5, 2.4, 3.7, 1. ],
[5.8, 2.7, 3.9, 1.2],
[6. , 2.7, 5.1, 1.6],
[5.4, 3. , 4.5, 1.5],
[6. , 3.4, 4.5, 1.6],
[6.7, 3.1, 4.7, 1.5],
[6.3, 2.3, 4.4, 1.3],
[5.6, 3. , 4.1, 1.3],
[5.5, 2.5, 4. , 1.3],
[5.5, 2.6, 4.4, 1.2],
[6.1, 3. , 4.6, 1.4],
[5.8, 2.6, 4. , 1.2],
[5. , 2.3, 3.3, 1. ],
[5.6, 2.7, 4.2, 1.3],
[5.7, 3. , 4.2, 1.2],
[5.7, 2.9, 4.2, 1.3],
[6.2, 2.9, 4.3, 1.3],
[5.1, 2.5, 3. , 1.1],
[5.7, 2.8, 4.1, 1.3],
```

```
[6.3, 3.3, 6. , 2.5],
[5.8, 2.7, 5.1, 1.9],
[7.1, 3. , 5.9, 2.1],
[6.3, 2.9, 5.6, 1.8],
[6.5, 3. , 5.8, 2.2],
[7.6, 3. , 6.6, 2.1],
[4.9, 2.5, 4.5, 1.7],
[7.3, 2.9, 6.3, 1.8],
[6.7, 2.5, 5.8, 1.8],
[7.2, 3.6, 6.1, 2.5],
[6.5, 3.2, 5.1, 2. ],
[6.4, 2.7, 5.3, 1.9],
[6.8, 3. , 5.5, 2.1],
[5.7, 2.5, 5. , 2. ],
[5.8, 2.8, 5.1, 2.4],
[6.4, 3.2, 5.3, 2.3],
[6.5, 3. , 5.5, 1.8],
[7.7, 3.8, 6.7, 2.2],
[7.7, 2.6, 6.9, 2.3],
[6. , 2.2, 5. , 1.5],
[6.9, 3.2, 5.7, 2.3],
[5.6, 2.8, 4.9, 2. ],
[7.7, 2.8, 6.7, 2. ],
[6.3, 2.7, 4.9, 1.8],
[6.7, 3.3, 5.7, 2.1],
[7.2, 3.2, 6. , 1.8],
[6.2, 2.8, 4.8, 1.8],
[6.1, 3. , 4.9, 1.8],
[6.4, 2.8, 5.6, 2.1],
[7.2, 3. , 5.8, 1.6],
[7.4, 2.8, 6.1, 1.9],
[7.9, 3.8, 6.4, 2. ],
[6.4, 2.8, 5.6, 2.2],
[6.3, 2.8, 5.1, 1.5],
[6.1, 2.6, 5.6, 1.4],
[7.7, 3. , 6.1, 2.3],
[6.3, 3.4, 5.6, 2.4],
[6.4, 3.1, 5.5, 1.8],
[6. , 3. , 4.8, 1.8],
[6.9, 3.1, 5.4, 2.1],
[6.7, 3.1, 5.6, 2.4],
[6.9, 3.1, 5.1, 2.3],
[5.8, 2.7, 5.1, 1.9],
[6.8, 3.2, 5.9, 2.3],
[6.7, 3.3, 5.7, 2.5],
[6.7, 3. , 5.2, 2.3],
[6.3, 2.5, 5. , 1.9],
```

```
       [6.5, 3. , 5.2, 2. ],
       [6.2, 3.4, 5.4, 2.3],
       [5.9, 3. , 5.1, 1.8]])
```

[22]:
```
y = iris.target
y
```

[22]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

[23]:
```
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size=0.2,␣
↪random_state=101)
x_train.shape
x_test.shape
```

[23]:
```
(30, 4)
```

[24]:
```
clf = LogisticRegression()
```

[25]:
```
# To train the algorithm
clf.fit(x_train, y_train)
```

[25]:
```
LogisticRegression()
```

[26]:
```
y_pred = clf.predict(x_test)
y_pred
```

[26]:
```
array([0, 0, 0, 2, 1, 2, 1, 1, 2, 0, 2, 0, 0, 2, 2, 1, 1, 1, 0, 2, 1, 0,
       1, 1, 1, 1, 1, 2, 0, 0])
```

[27]:
```
d = pd.read_csv("bmi.csv")
d
```

[27]:

	Gender	Height	Weight	Index
0	Male	174	96	4
1	Male	189	87	2
2	Female	185	110	4
3	Female	195	104	3
4	Male	149	61	3
..	…	…	…	…
495	Female	150	153	5
496	Female	184	121	4

```
497  Female     141     136      5
498    Male     150      95      5
499    Male     173     131      5

[500 rows x 4 columns]
```

[28]:
```
g1 = (d['Gender']=='Female').sum()
g2 = (d['Gender']=='Male').sum()
g = [g1,g2]
g
```

[28]:
```
[255, 245]
```

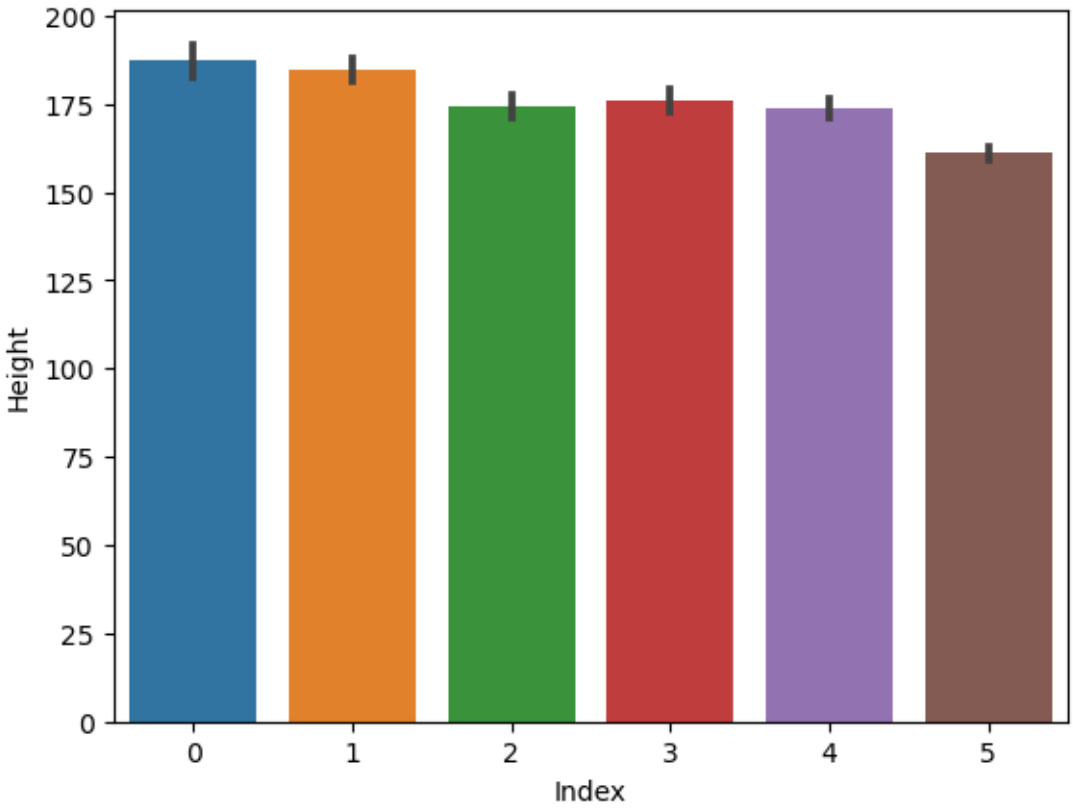
[29]:
```
# Converting male to 0 and female to 1
d['Gender'] = d['Gender'].map({'Male':0, 'Female':1})
d
```

[29]:
```
      Gender  Height  Weight  Index
0          0     174      96      4
1          0     189      87      2
2          1     185     110      4
3          1     195     104      3
4          0     149      61      3
..       …     …     …     …
495        1     150     153      5
496        1     184     121      4
497        1     141     136      5
498        0     150      95      5
499        0     173     131      5

[500 rows x 4 columns]
```

[30]:
```
import seaborn as sns
sns.barplot(y="Height",x="Index",data=d)
```

[30]:
```
<Axes: xlabel='Index', ylabel='Height'>
```


200
175
150
125
100
75
50
25
0
Height
0
1
2
3
4
5
Index