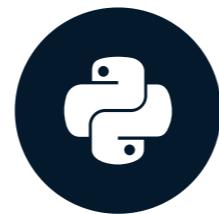


Considerations for categorical data

EXPLORATORY DATA ANALYSIS IN PYTHON



George Boorman

Curriculum Manager, DataCamp

Why perform EDA?

- Detecting patterns and relationships
- Generating questions, or **hypotheses**
- Preparing data for machine learning



¹ Image credit: <https://unsplash.com/@simonesecchi>

Representative data

- Sample represents the population

For example:

- Education versus income in USA
 - Can't use data from France

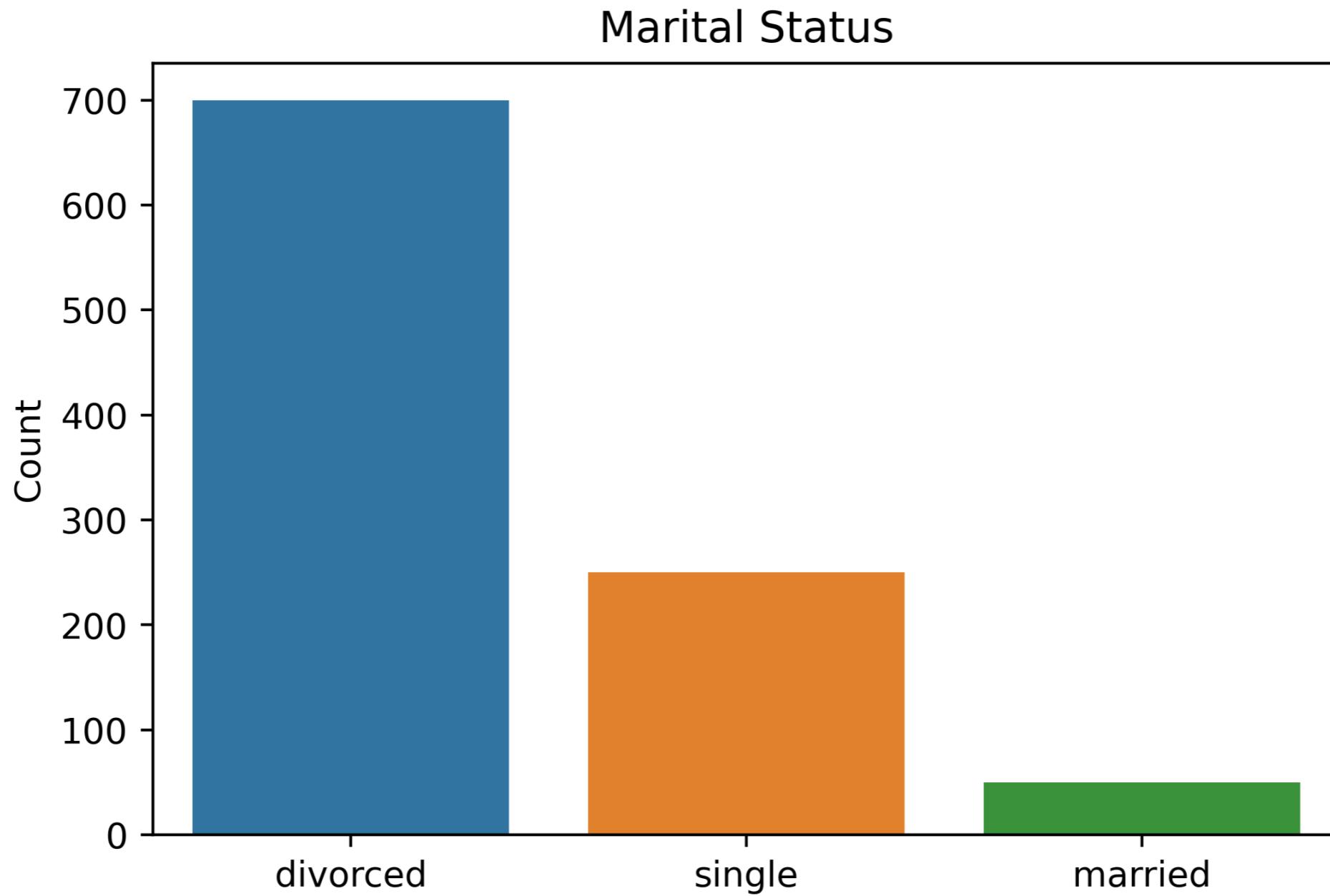


¹ Image credits: https://unsplash.com/@cristina_glebova; https://unsplash.com/@nimbus_vulpis

Categorical classes

- Classes = labels
- Survey people's attitudes towards marriage
 - Marital status
 - Single
 - Married
 - Divorced

Class imbalance



Class frequency

```
print(planes["Destination"].value_counts())
```

```
Cochin      4391  
Banglore    2773  
Delhi       1219  
New Delhi   888  
Hyderabad   673  
Kolkata     369
```

```
Name: Destination, dtype: int64
```

Relative class frequency

- 40% of internal Indian flights have a destination of Delhi

```
planes["Destination"].value_counts(normalize=True)
```

```
Cochin      0.425773
Banglore    0.268884
Delhi       0.118200
New Delhi   0.086105
Hyderabad   0.065257
Kolkata    0.035780
Name: Destination, dtype: float64
```

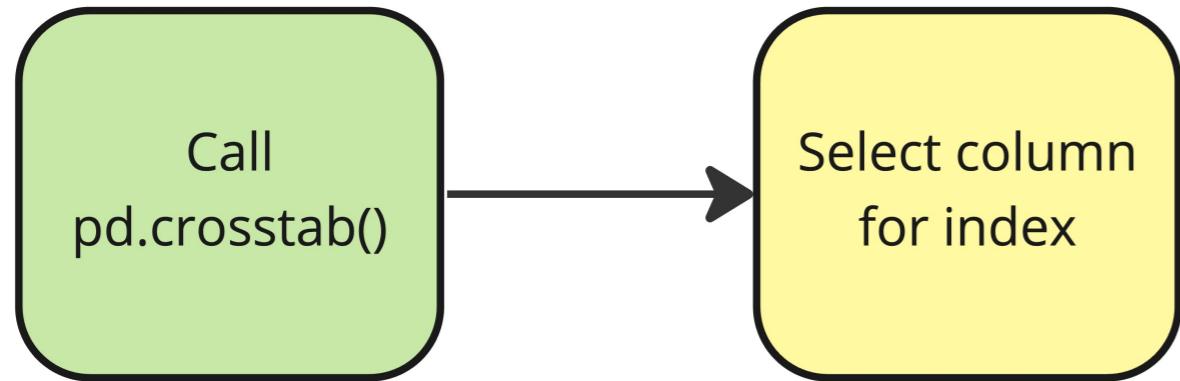
- Is our sample representative of the population (Indian internal flights)?

Cross-tabulation

Call
pd.crosstab()

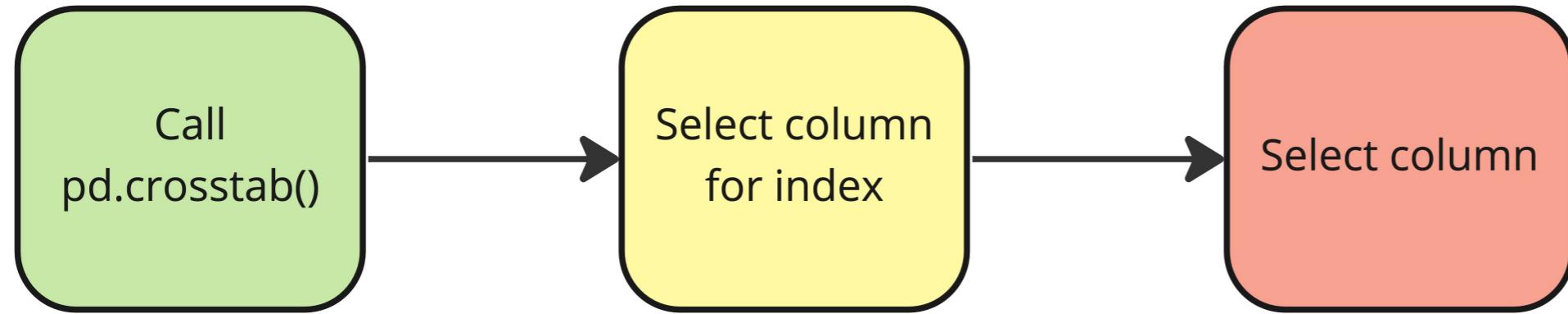
pd.crosstab(

Select index



```
pd.crosstab(planes["Source"],
```

Select columns



```
pd.crosstab(planes["Source"], planes["Destination"])
```

Cross-tabulation

| Destination | Banglore | Cochin | Delhi | Hyderabad | Kolkata | New Delhi |
|-------------|----------|--------|-------|-----------|---------|-----------|
| Source | | | | | | |
| Banglore | 0 | 0 | 1199 | 0 | 0 | 868 |
| Chennai | 0 | 0 | 0 | 0 | 364 | 0 |
| Delhi | 0 | 4318 | 0 | 0 | 0 | 0 |
| Kolkata | 2720 | 0 | 0 | 0 | 0 | 0 |
| Mumbai | 0 | 0 | 0 | 662 | 0 | 0 |

Extending cross-tabulation

| Source | Destination | Median Price (IDR) |
|----------|-------------|--------------------|
| Banglore | Delhi | 4232.21 |
| Banglore | New Delhi | 12114.56 |
| Chennai | Kolkata | 3859.76 |
| Delhi | Cochin | 9987.63 |
| Kolkata | Banglore | 9654.21 |
| Mumbai | Hyderabad | 3431.97 |

Aggregated values with pd.crosstab()

```
pd.crosstab(plan["Source"], plan["Destination"],  
            values=plan["Price"], aggfunc="median")
```

| Destination | Banglore | Cochin | Delhi | Hyderabad | Kolkata | New Delhi |
|-------------|----------|--------|---------|-----------|---------|-----------|
| Source | | | | | | |
| Banglore | | NaN | 4823.0 | NaN | NaN | 10976.5 |
| Chennai | | NaN | NaN | NaN | 3850.0 | NaN |
| Delhi | | NaN | 10262.0 | NaN | NaN | NaN |
| Kolkata | 9345.0 | | NaN | NaN | NaN | NaN |
| Mumbai | | NaN | NaN | 3342.0 | NaN | NaN |

Comparing sample to population

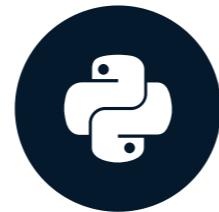
| Source | Destination | Median Price (IDR) | Median Price (dataset) |
|----------|-------------|--------------------|------------------------|
| Banglore | Delhi | 4232.21 | 4823.0 |
| Banglore | New Delhi | 12114.56 | 10976.50 |
| Chennai | Kolkata | 3859.76 | 3850.0 |
| Delhi | Cochin | 9987.63 | 10260.0 |
| Kolkata | Banglore | 9654.21 | 9345.0 |
| Mumbai | Hyderabad | 3431.97 | 3342.0 |

Let's practice!

EXPLORATORY DATA ANALYSIS IN PYTHON

Generating new features

EXPLORATORY DATA ANALYSIS IN PYTHON

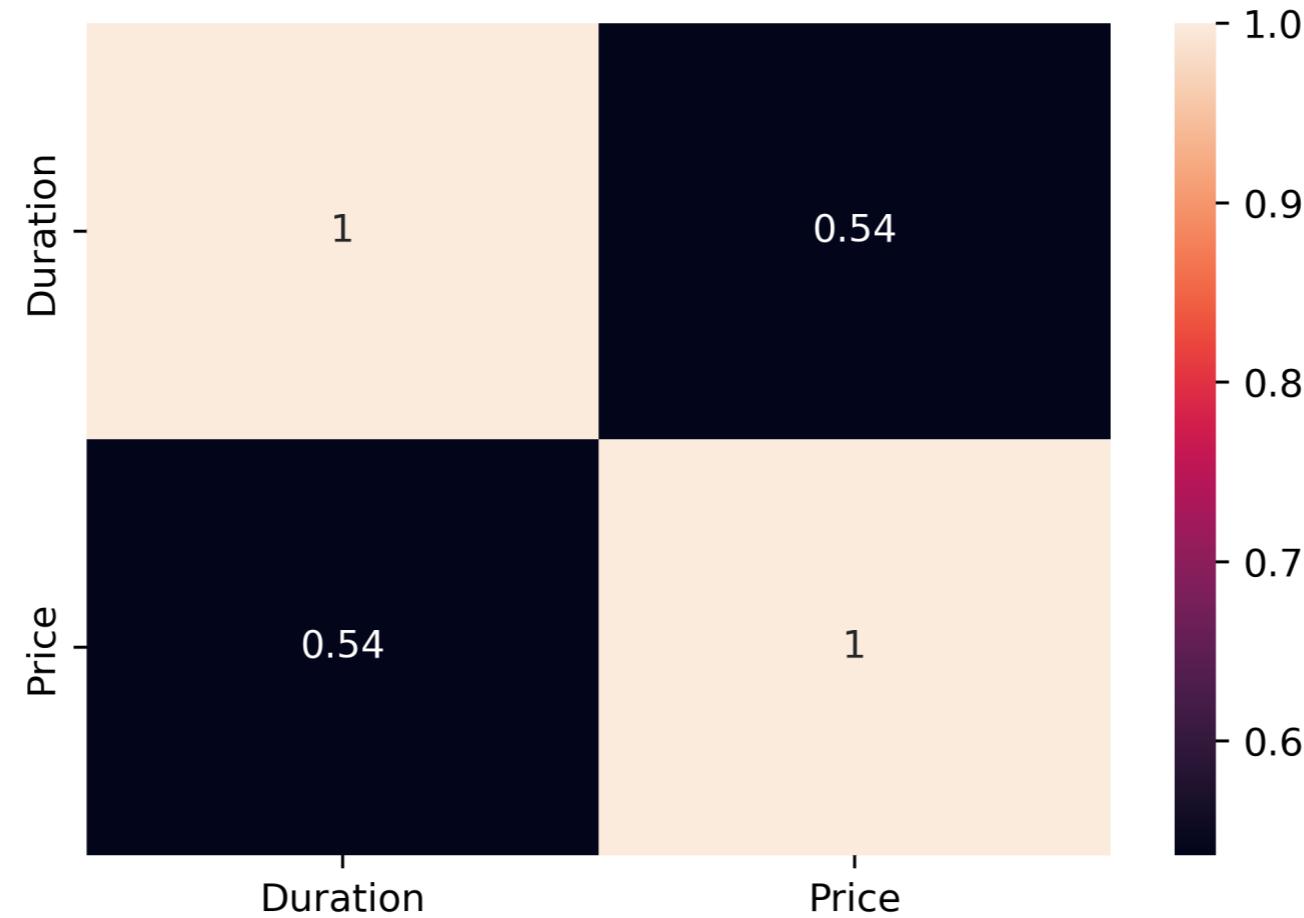


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Correlation

```
sns.heatmap(planes.corr(numeric_only=True), annot=True)  
plt.show()
```



Viewing data types

```
print(planes.dtypes)
```

```
Airline          object  
Date_of_Journey    datetime64[ns]  
Source           object  
Destination       object  
Route             object  
Dep_Time         datetime64[ns]  
Arrival_Time      datetime64[ns]  
Duration          float64  
Total_Stops        object  
Additional_Info     object  
Price             float64  
dtype: object
```

Total stops

```
print(planes["Total_Stops"].value_counts())
```

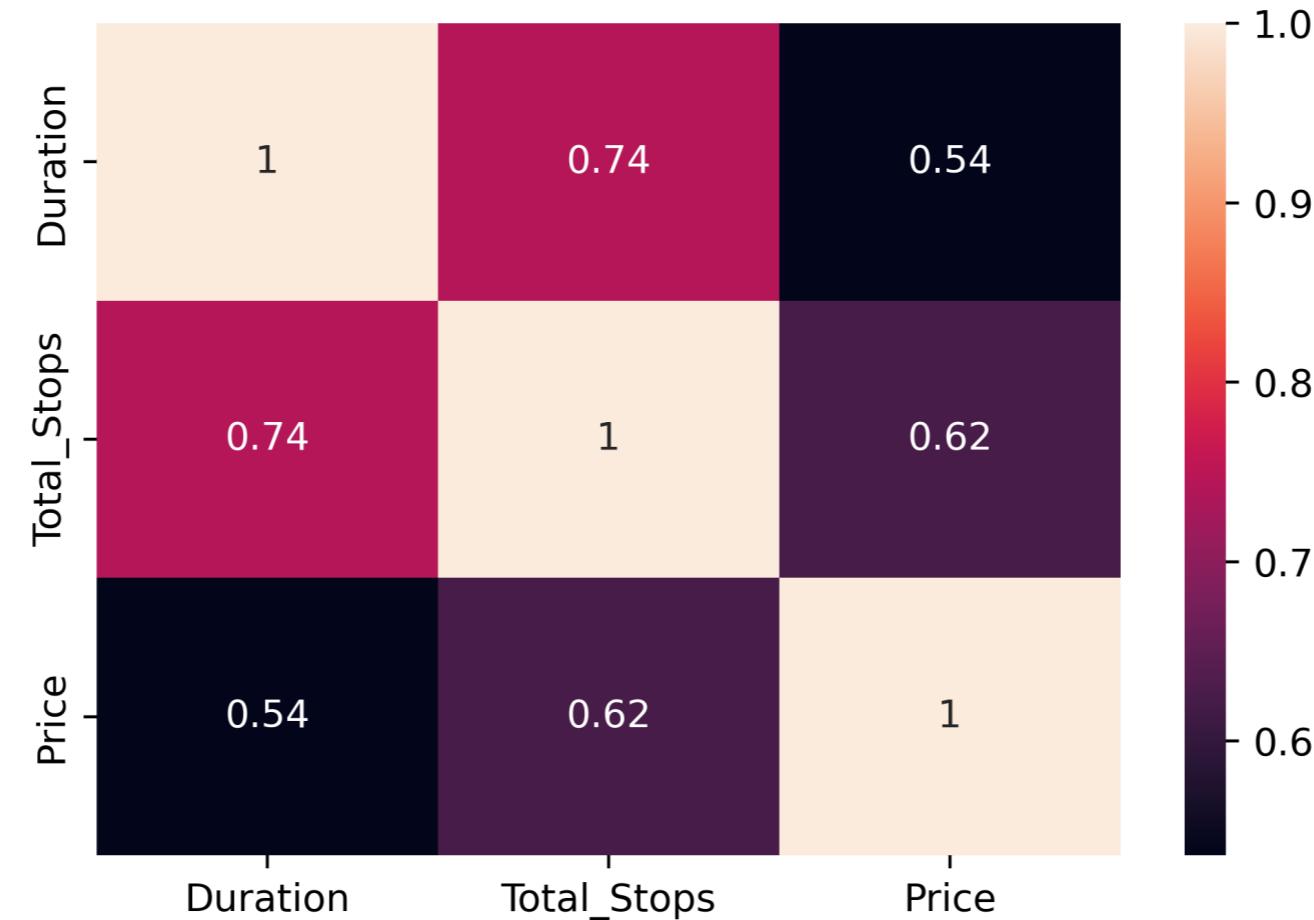
```
1 stop        4107  
non-stop     2584  
2 stops      1127  
3 stops       29  
4 stops        1  
Name: Total_Stops, dtype: int64
```

Cleaning total stops

```
planes["Total_Stops"] = planes["Total_Stops"].str.replace(" stops", "")  
planes["Total_Stops"] = planes["Total_Stops"].str.replace(" stop", "")  
planes["Total_Stops"] = planes["Total_Stops"].str.replace("non-stop", "0")  
planes["Total_Stops"] = planes["Total_Stops"].astype(int)
```

Correlation

```
sns.heatmap(planes.corr(numeric_only=True), annot=True)  
plt.show()
```



Dates

```
print(planes.dtypes)
```

```
Airline          object  
Date_of_Journey    datetime64[ns]  
Source           object  
Destination       object  
Route             object  
Dep_Time         datetime64[ns]  
Arrival_Time      datetime64[ns]  
Duration          float64  
Total_Stops        int64  
Additional_Info    object  
Price             float64  
dtype: object
```

Extracting month and weekday

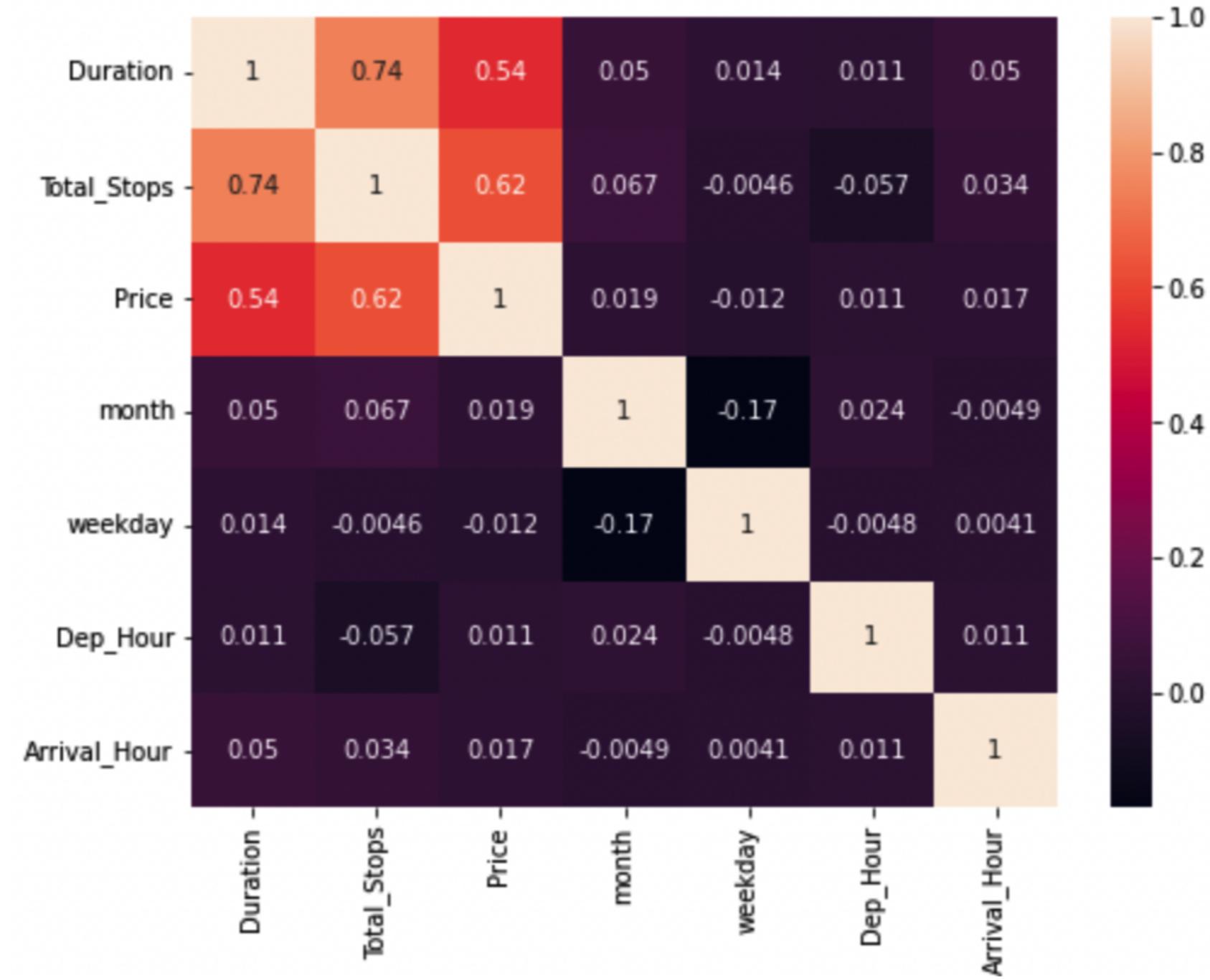
```
planes["month"] = planes["Date_of_Journey"].dt.month  
planes["weekday"] = planes["Date_of_Journey"].dt.weekday  
print(planes[["month", "weekday", "Date_of_Journey"]].head())
```

| | month | weekday | Date_of_Journey |
|---|-------|---------|-----------------|
| 0 | 9 | 4 | 2019-09-06 |
| 1 | 12 | 3 | 2019-12-05 |
| 2 | 1 | 3 | 2019-01-03 |
| 3 | 6 | 0 | 2019-06-24 |
| 4 | 12 | 1 | 2019-12-03 |

Departure and arrival times

```
planes["Dep_Hour"] = planes["Dep_Time"].dt.hour  
planes["Arrival_Hour"] = planes["Arrival_Time"].dt.hour
```

Correlation



Creating categories

```
print(planes["Price"].describe())
```

```
count      7848.000000
mean      9035.413609
std       4429.822081
min      1759.000000
25%      5228.000000
50%      8355.000000
75%     12373.000000
max     54826.000000
Name: Price, dtype: float64
```

| Range | Ticket Type |
|-----------------|-----------------|
| <= 5228 | Economy |
| > 5228 <= 8355 | Premium Economy |
| > 8355 <= 12373 | Business Class |
| > 12373 | First Class |

Descriptive statistics

```
twenty_fifth = planes["Price"].quantile(0.25)
median = planes["Price"].median()
seventy_fifth = planes["Price"].quantile(0.75)
maximum = planes["Price"].max()
```

Labels and bins

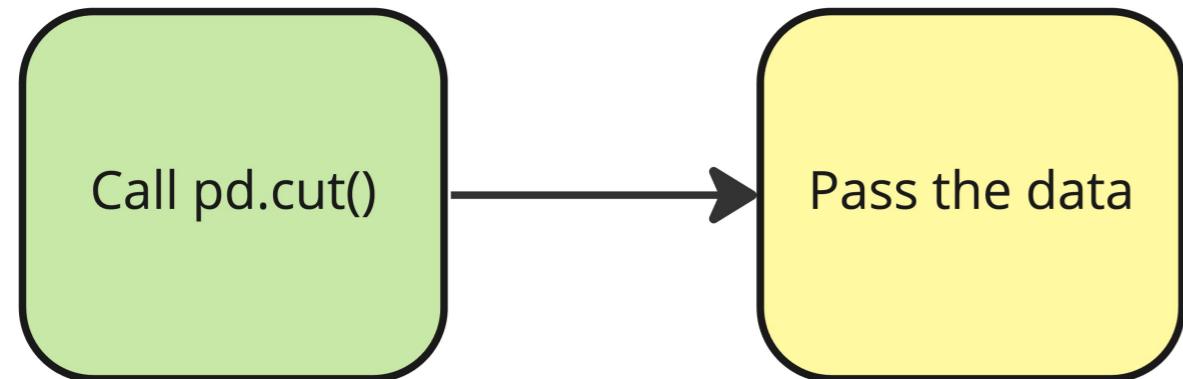
```
labels = ["Economy", "Premium Economy", "Business Class", "First Class"]  
bins = [0, twenty_fifth, median, seventy_fifth, maximum]
```

pd.cut()

Call pd.cut()

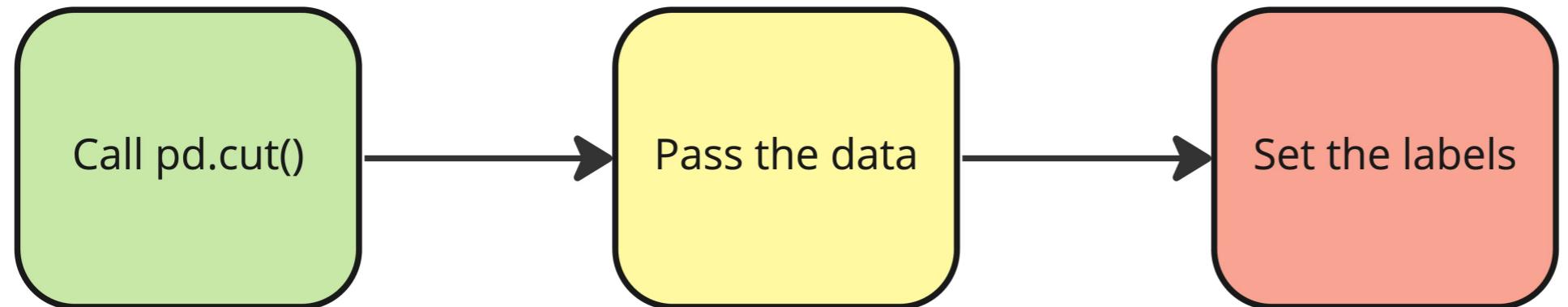
```
planes["Price_Category"] = pd.cut(
```

pd.cut()



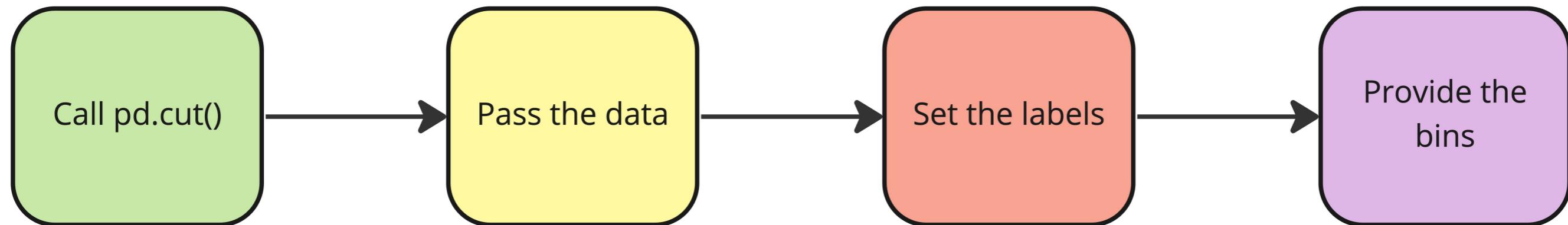
```
planes["Price_Category"] = pd.cut(planes["Price"],
```

pd.cut()



```
planes["Price_Category"] = pd.cut(planes["Price"],  
                                 labels=labels,
```

pd.cut()



```
planes["Price_Category"] = pd.cut(planes["Price"],  
                                 labels=labels,  
                                 bins=bins)
```

Price categories

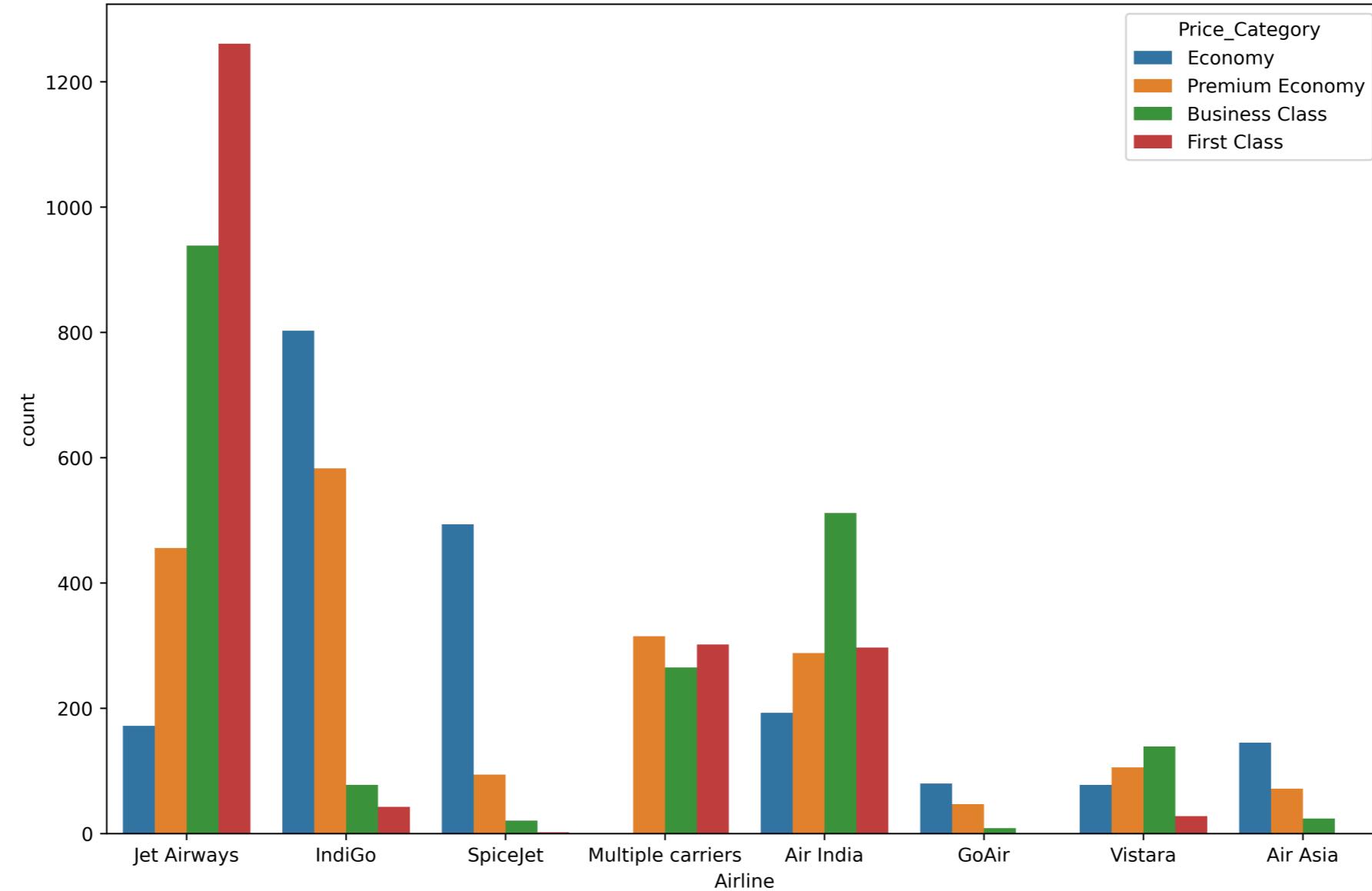
```
print(planes[["Price", "Price_Category"]].head())
```

```
   Price  Price_Category
0  13882.0      First Class
1   6218.0  Premium Economy
2  13302.0      First Class
3   3873.0        Economy
4  11087.0    Business Class
```

Price category by airline

```
sns.countplot(data=planes, x="Airline", hue="Price_Category")  
plt.show()
```

Price category by airline

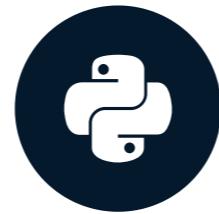


Let's practice!

EXPLORATORY DATA ANALYSIS IN PYTHON

Generating hypotheses

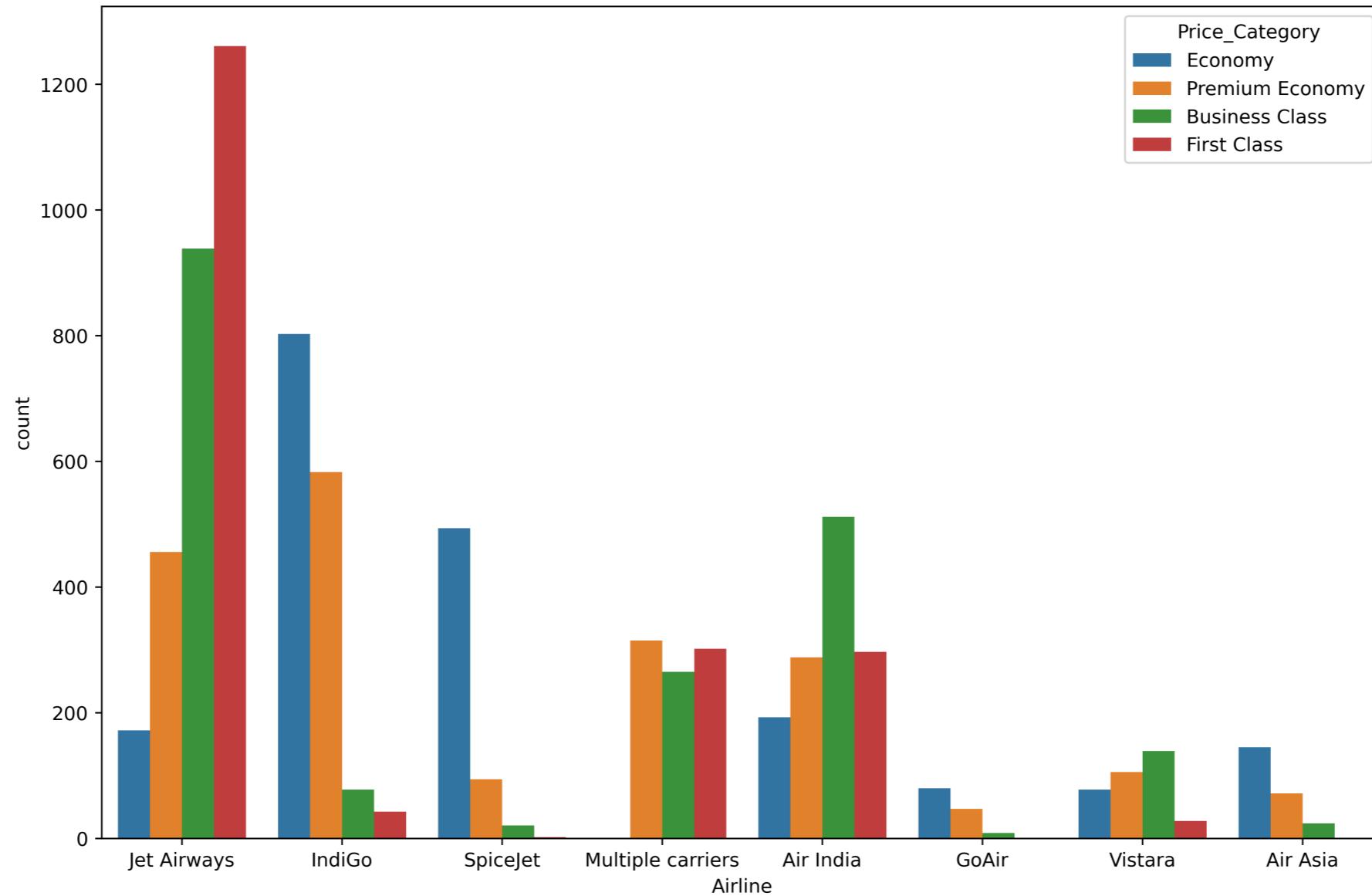
EXPLORATORY DATA ANALYSIS IN PYTHON



George Boorman

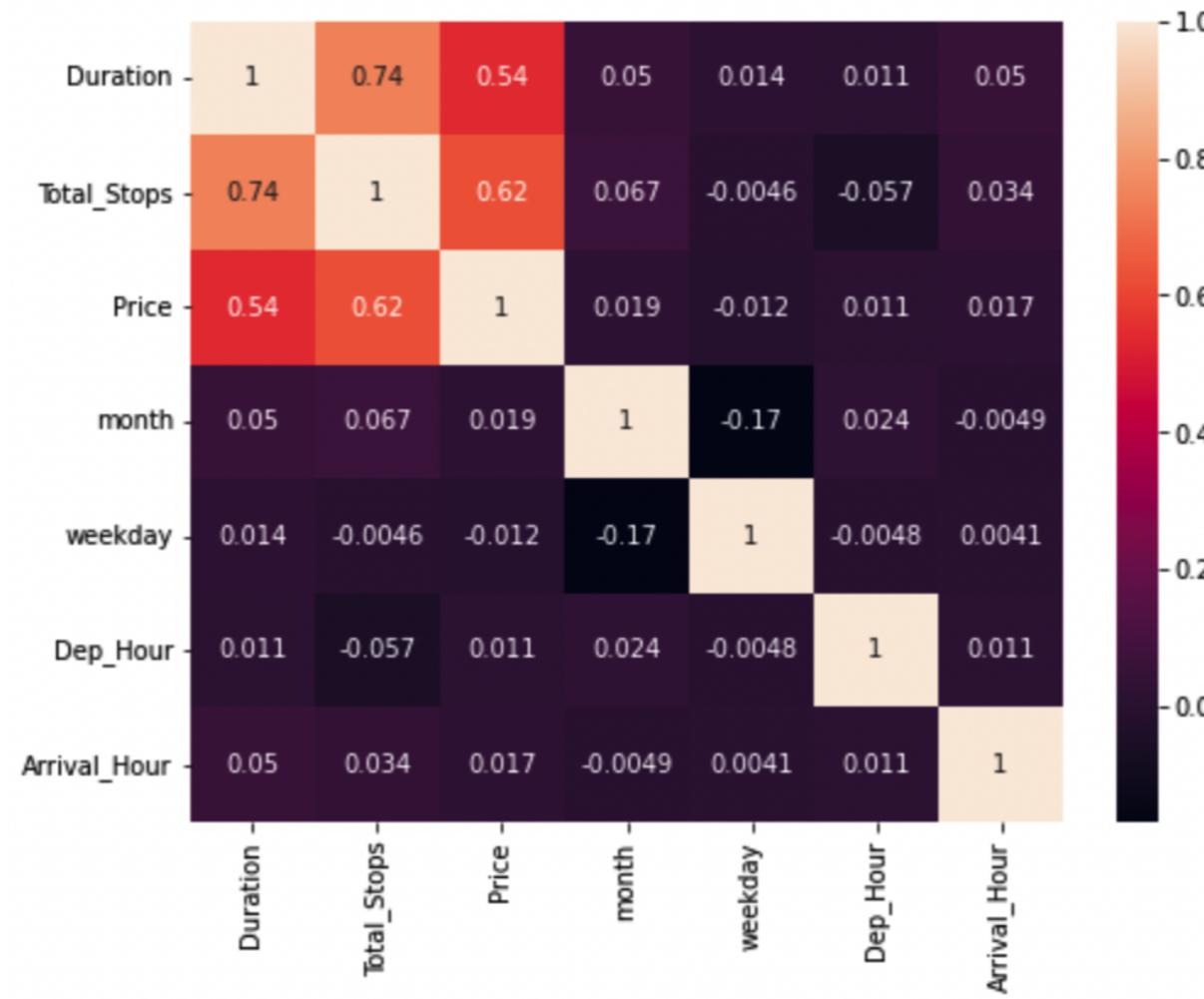
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What do we know?



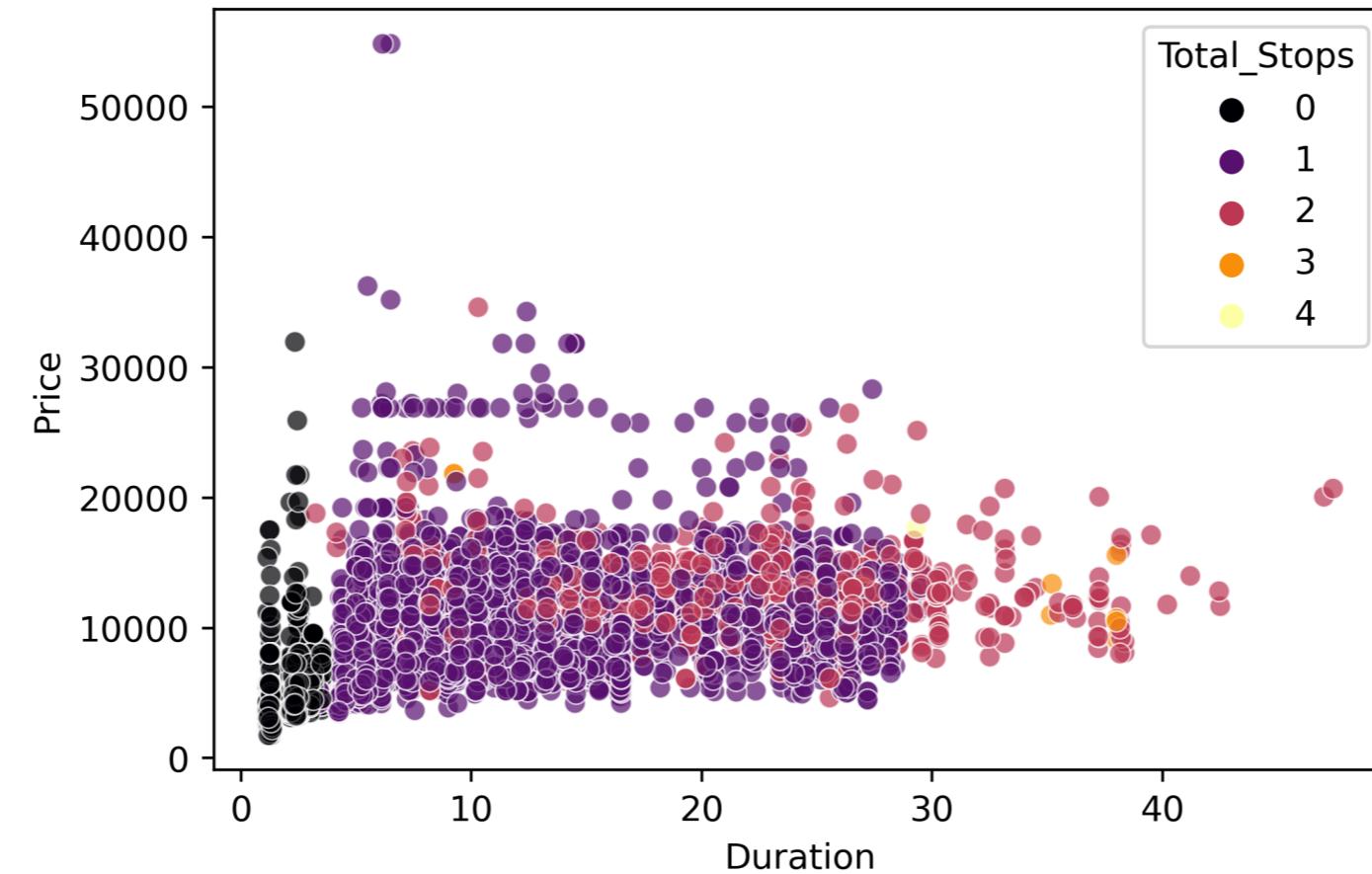
What do we know?

```
sns.heatmap(planes.corr(numeric_only=True), annot=True)  
plt.show()
```

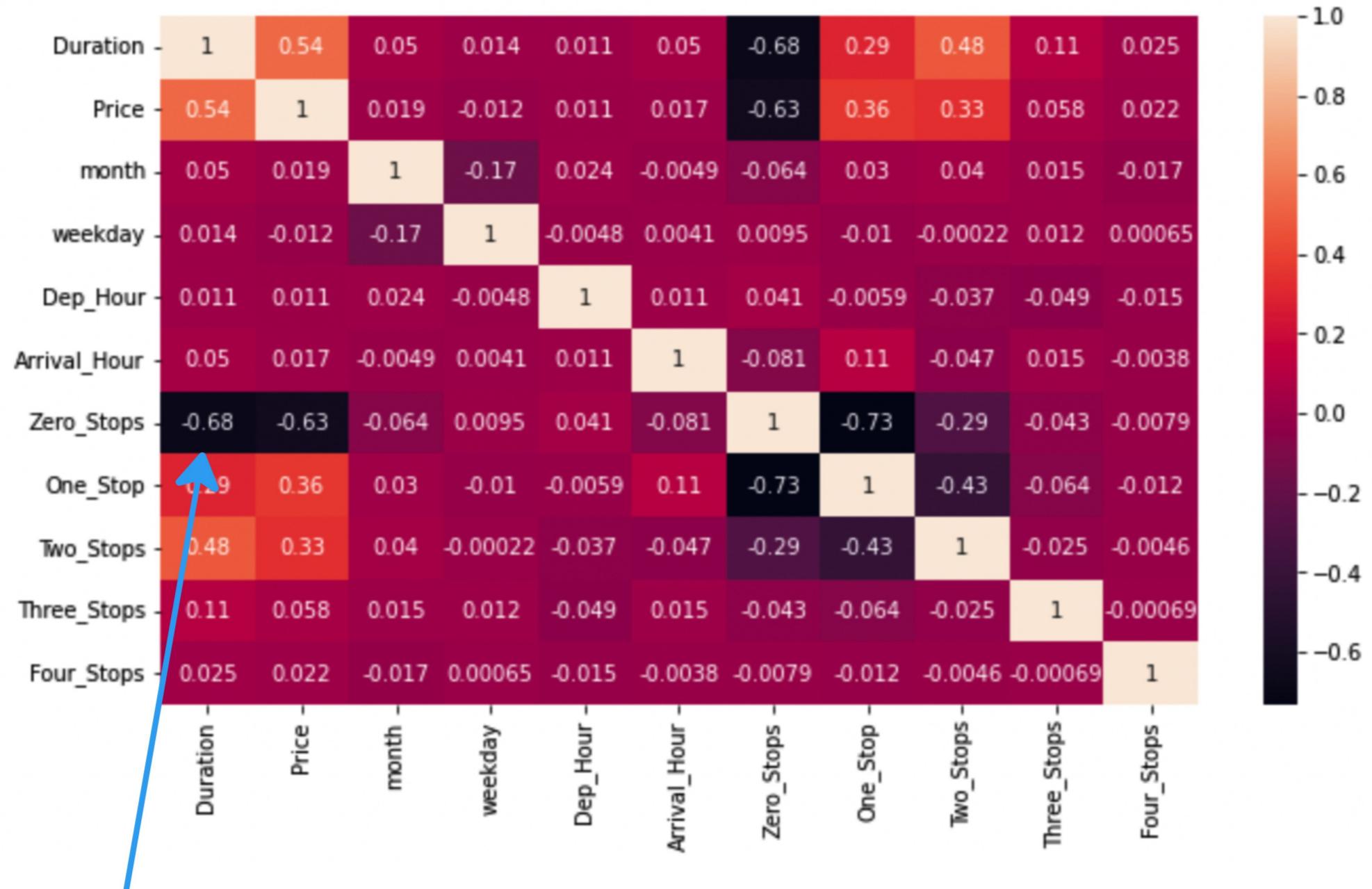


Spurious correlation

```
sns.scatterplot(data=planes, x="Duration", y="Price", hue="Total_Stops")  
plt.show()
```



How do we know?



What is true?



- Would data from a different time give the same results?
- Detecting relationships, differences, and patterns:
 - We use **Hypothesis Testing**
- Hypothesis testing requires, prior to data collection:
 - Generating a hypothesis or question
 - A decision on what statistical test to use

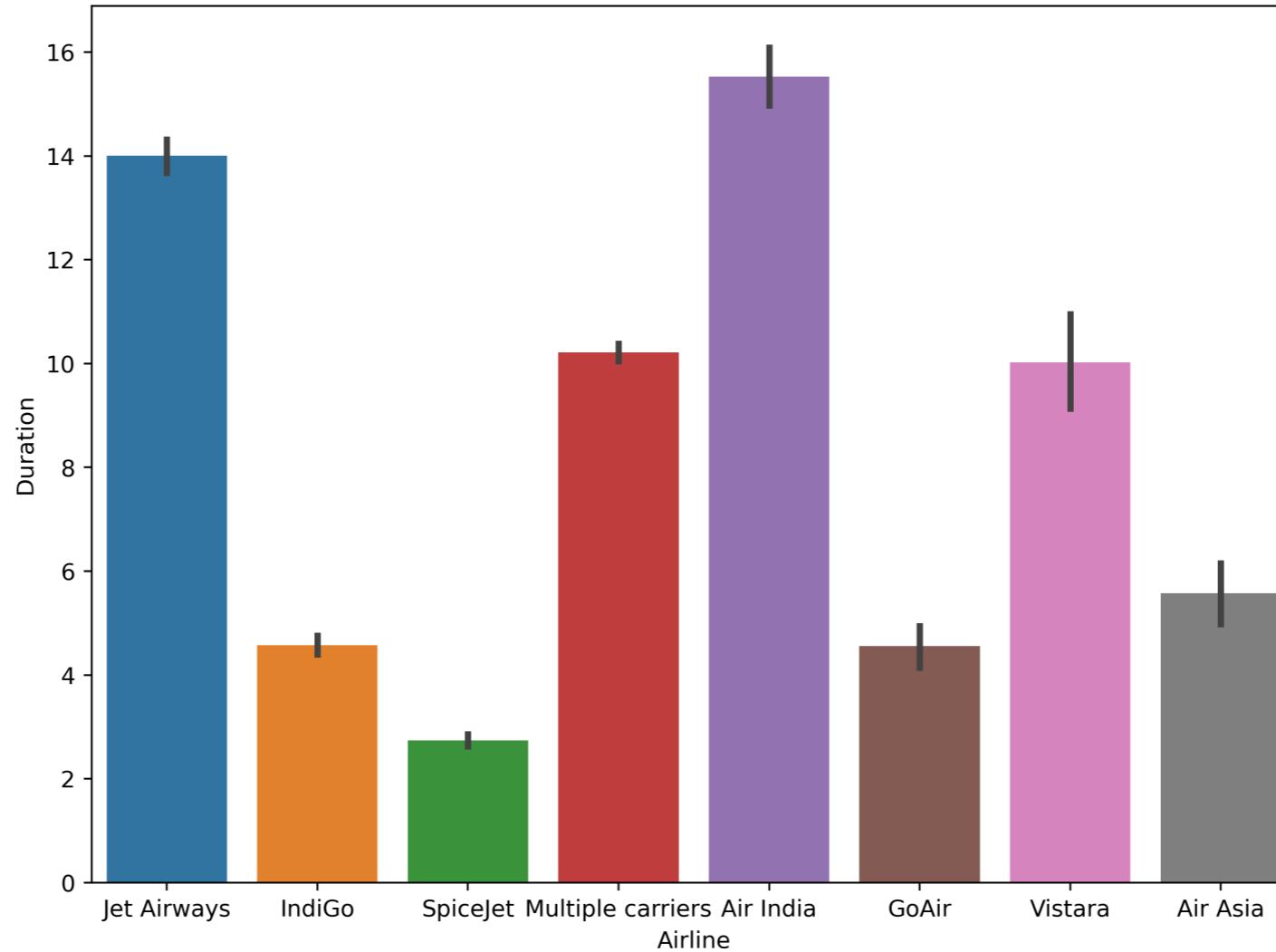
¹ Image credit: <https://unsplash.com/@markuswinkler>

Data snooping



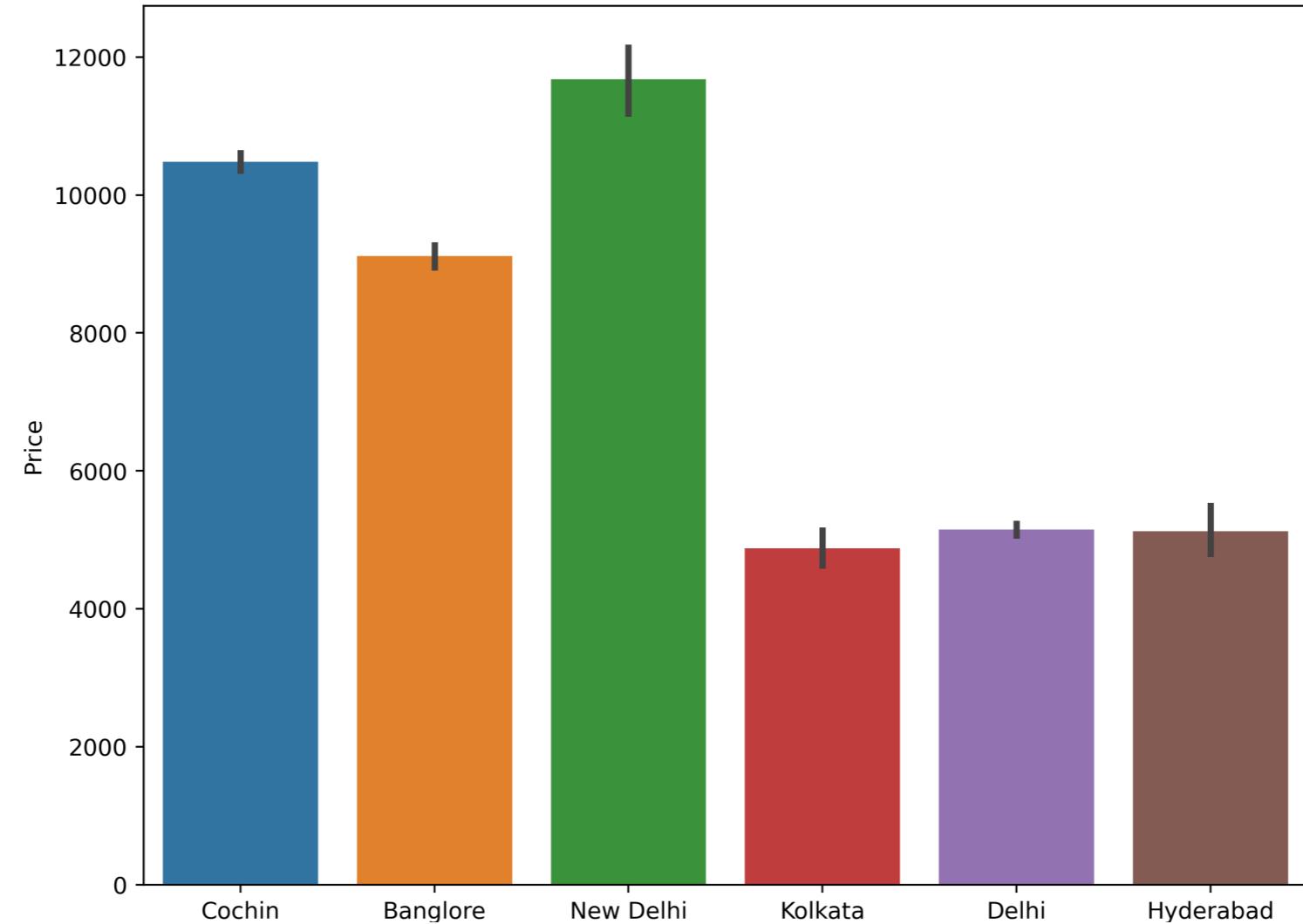
Generating hypotheses

```
sns.barplot(data=planes, x="Airline", y="Duration")  
plt.show()
```



Generating hypotheses

```
sns.barplot(data=planes, x="Destination", y="Price")  
plt.show()
```



Next steps

- Design our experiment
- Involves steps such as:
 - Choosing a sample
 - Calculating how many data points we need
 - Deciding what statistical test to run

Let's practice!

EXPLORATORY DATA ANALYSIS IN PYTHON

Congratulations

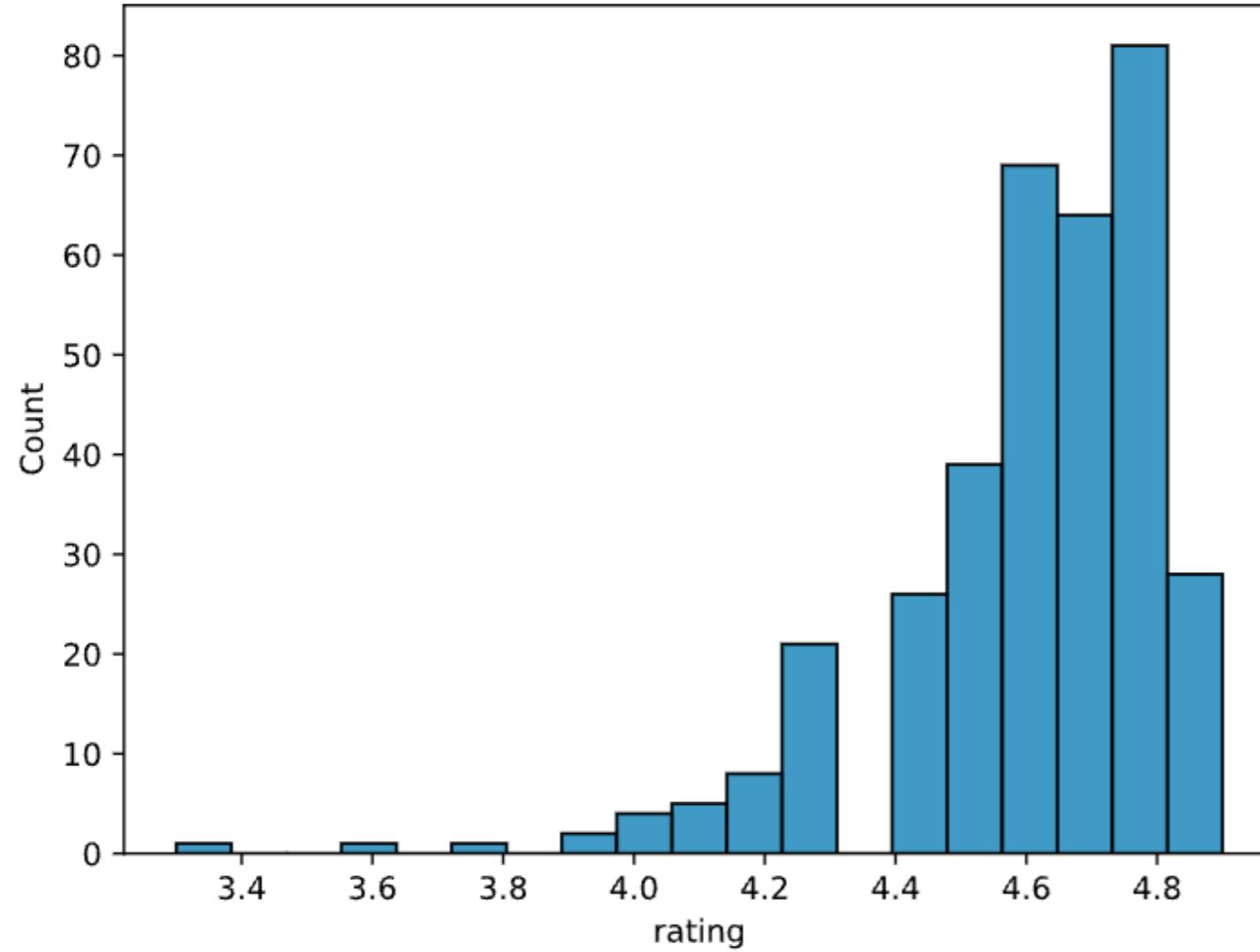
EXPLORATORY DATA ANALYSIS IN PYTHON



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Inspection and validation



```
books["year"] = books["year"].astype(int)  
books.dtypes
```

```
name          object  
author        object  
rating       float64  
year         int64  
genre        object  
dtype: object
```

Aggregation

```
books.groupby("genre").agg(  
    mean_rating=("rating", "mean"),  
    std_rating=("rating", "std"),  
    median_year=("year", "median"))  
)
```

| genre | mean_rating | std_rating | median_year |
|-------------|-------------|------------|-------------|
| Childrens | 4.780000 | 0.122370 | 2015.0 |
| Fiction | 4.570229 | 0.281123 | 2013.0 |
| Non Fiction | 4.598324 | 0.179411 | 2013.0 |

Address missing data

```
print(salaries.isna().sum())
```

```
Working_Year           12
Designation            27
Experience             33
Employment_Status      31
Employee_Location       28
Company_Size            40
Remote_Working_Ratio     24
Salary_USD              60
dtype: int64
```

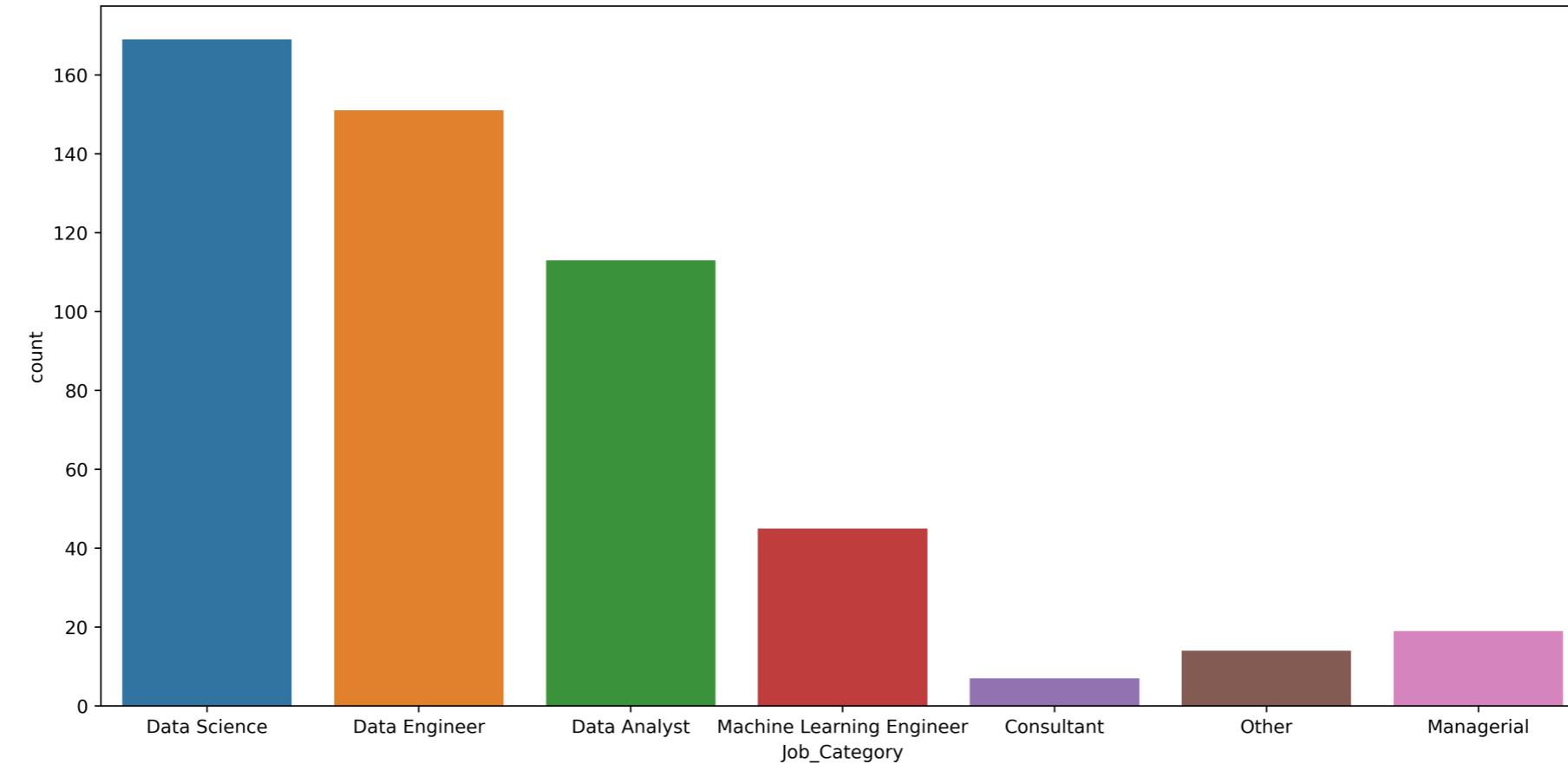
Address missing data

- Drop missing values
- Impute mean, median, mode
- Impute by sub-group

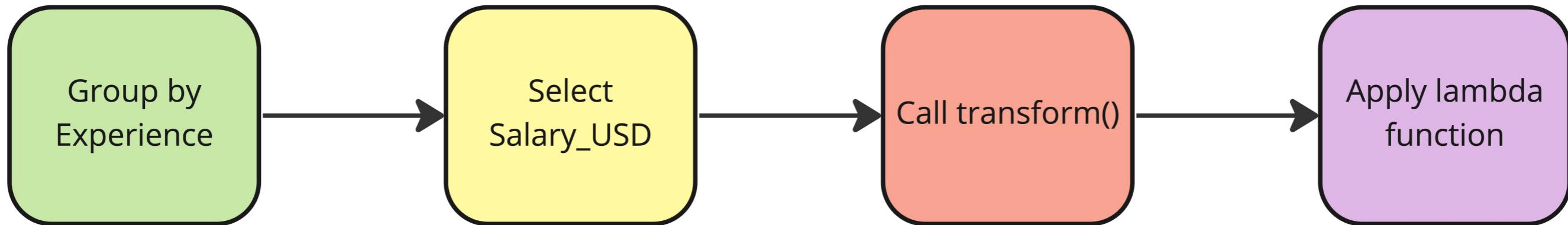
```
salaries_dict = salaries.groupby("Experience")["Salary_USD"].median().to_dict()
salaries["Salary_USD"] = salaries["Salary_USD"].fillna(salaries["Experience"].map(salaries_dict))
```

Analyze categorical data

```
salaries["Job_Category"] = np.select(conditions,  
                                    job_categories,  
                                    default="Other")
```



Apply lambda functions



```
salaries["std_dev"] = salaries.groupby("Experience")["Salary_USD"].transform(lambda x: x.std())
```

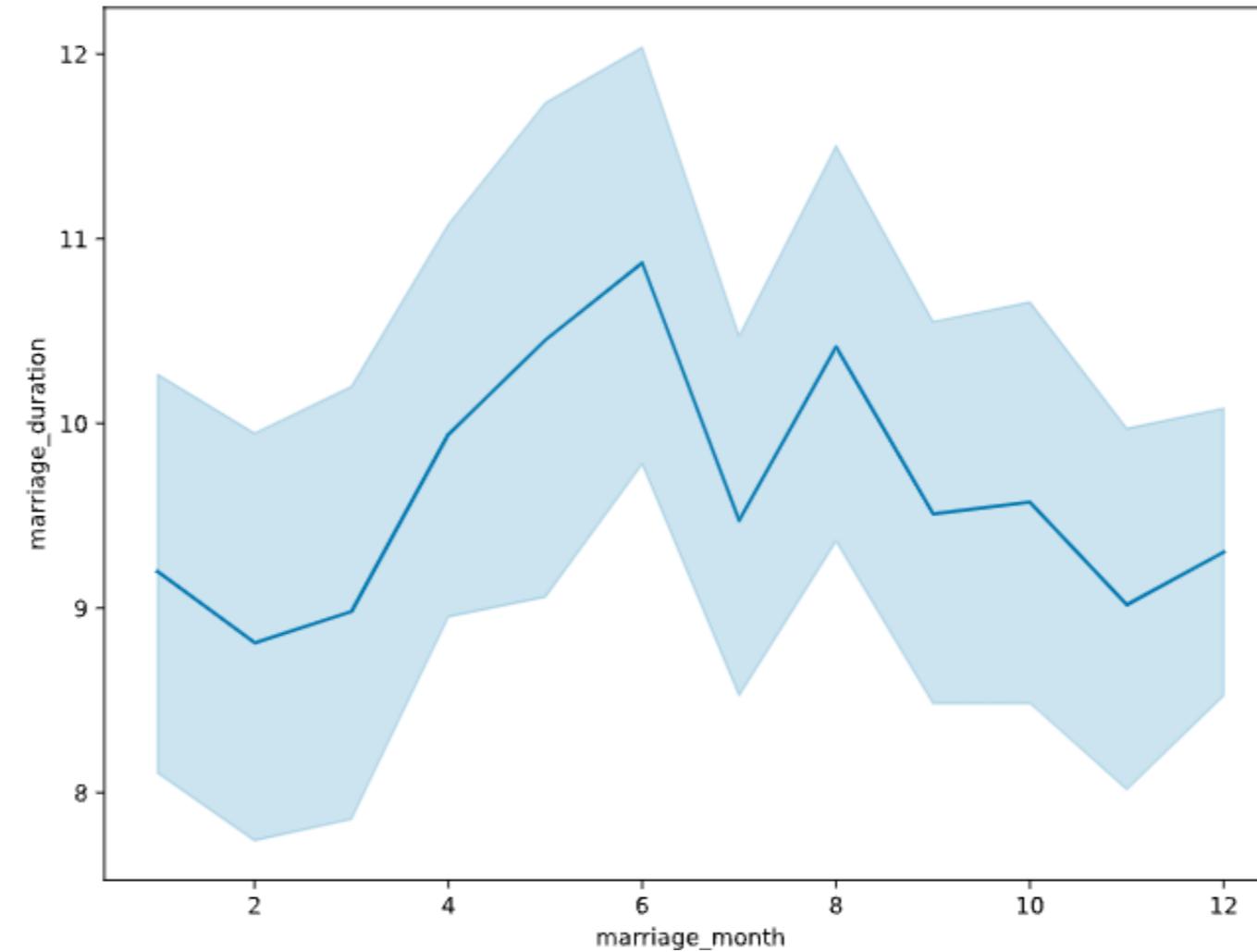
Handle outliers

```
sns.boxplot(data=salaries,  
             y="Salary_USD")  
plt.show()
```



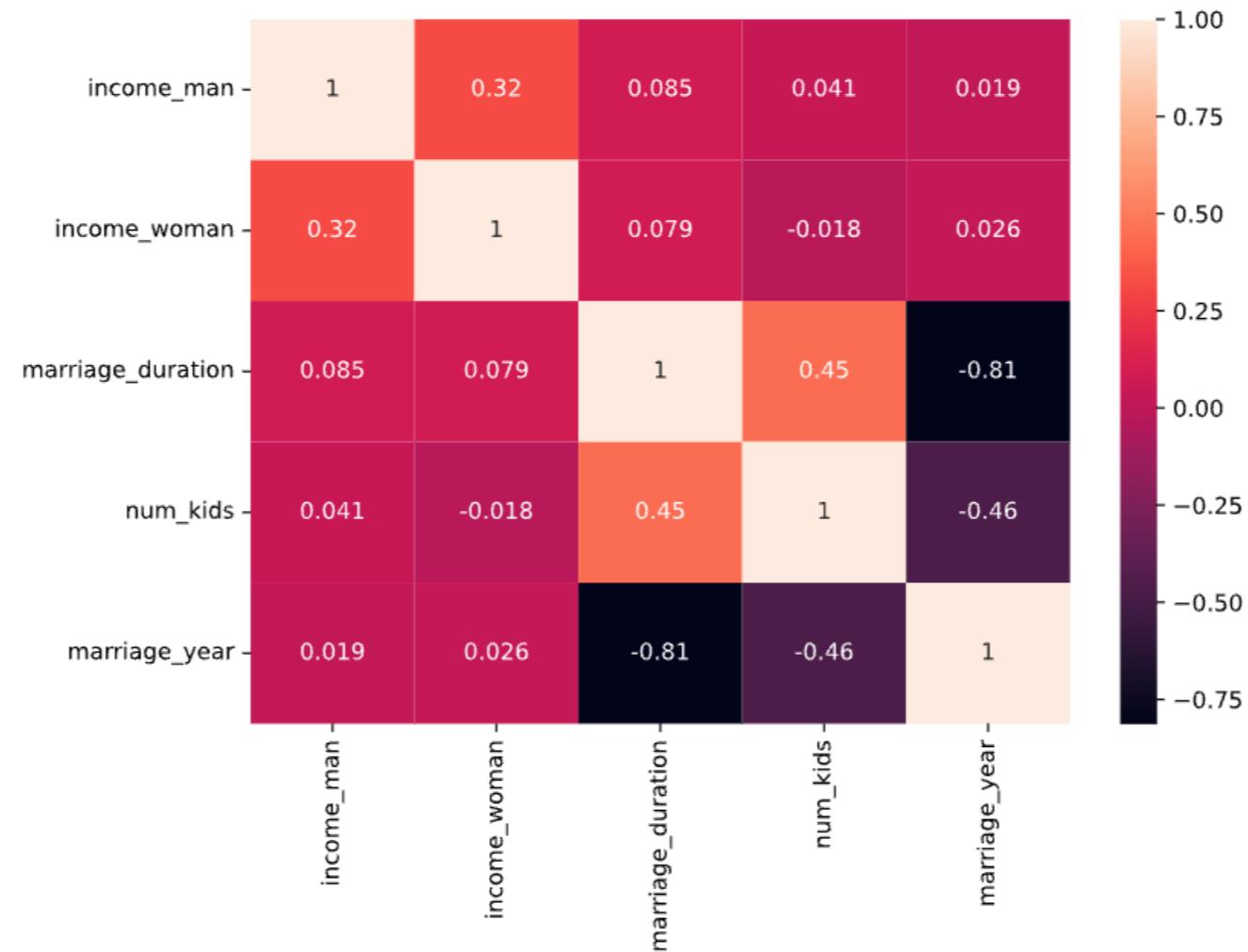
Patterns over time

```
sns.lineplot(data=divorce, x="marriage_month", y="marriage_duration")  
plt.show()
```



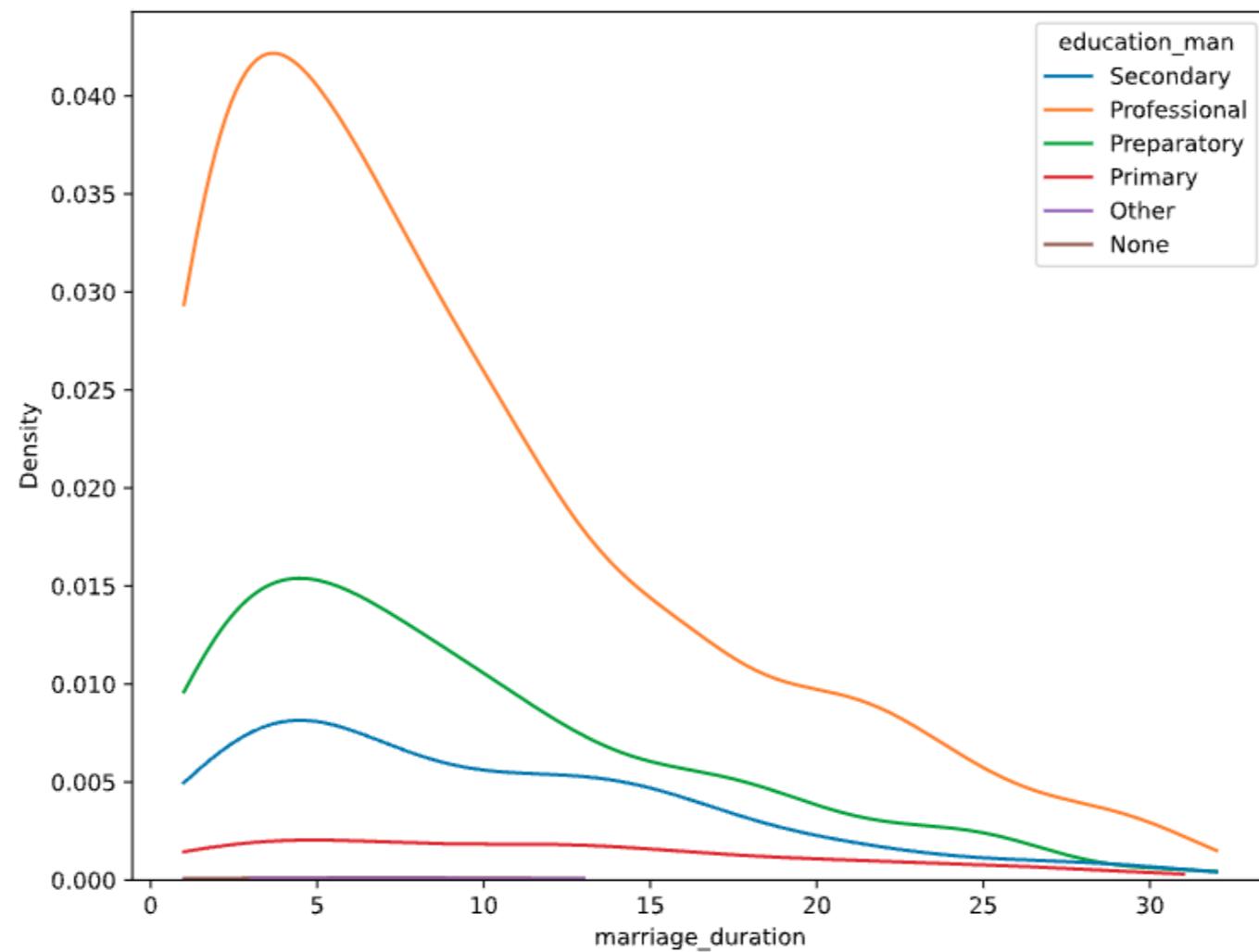
Correlation

```
sns.heatmap(divorce.corr(numeric_only=True), annot=True)  
plt.show()
```



Distributions

```
sns.kdeplot(data=divorce, x="marriage_duration", hue="education_man", cut=0)  
plt.show()
```

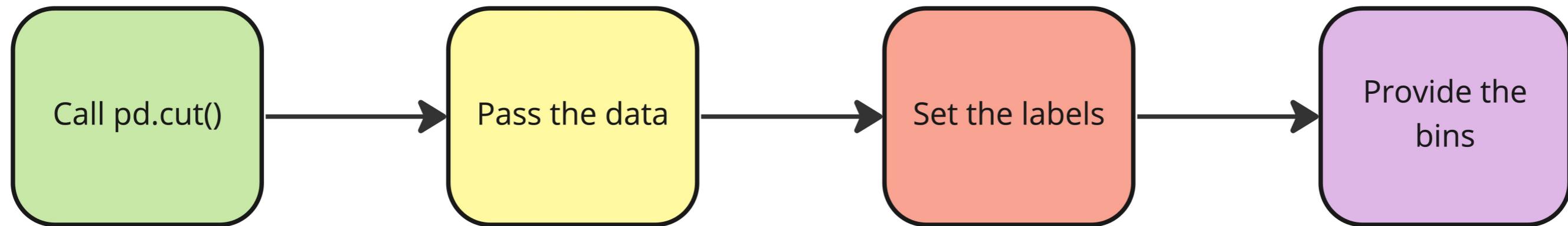


Cross-tabulation

```
pd.crosstab(plan["Source"], plan["Destination"],  
            values=plan["Price"], aggfunc="median")
```

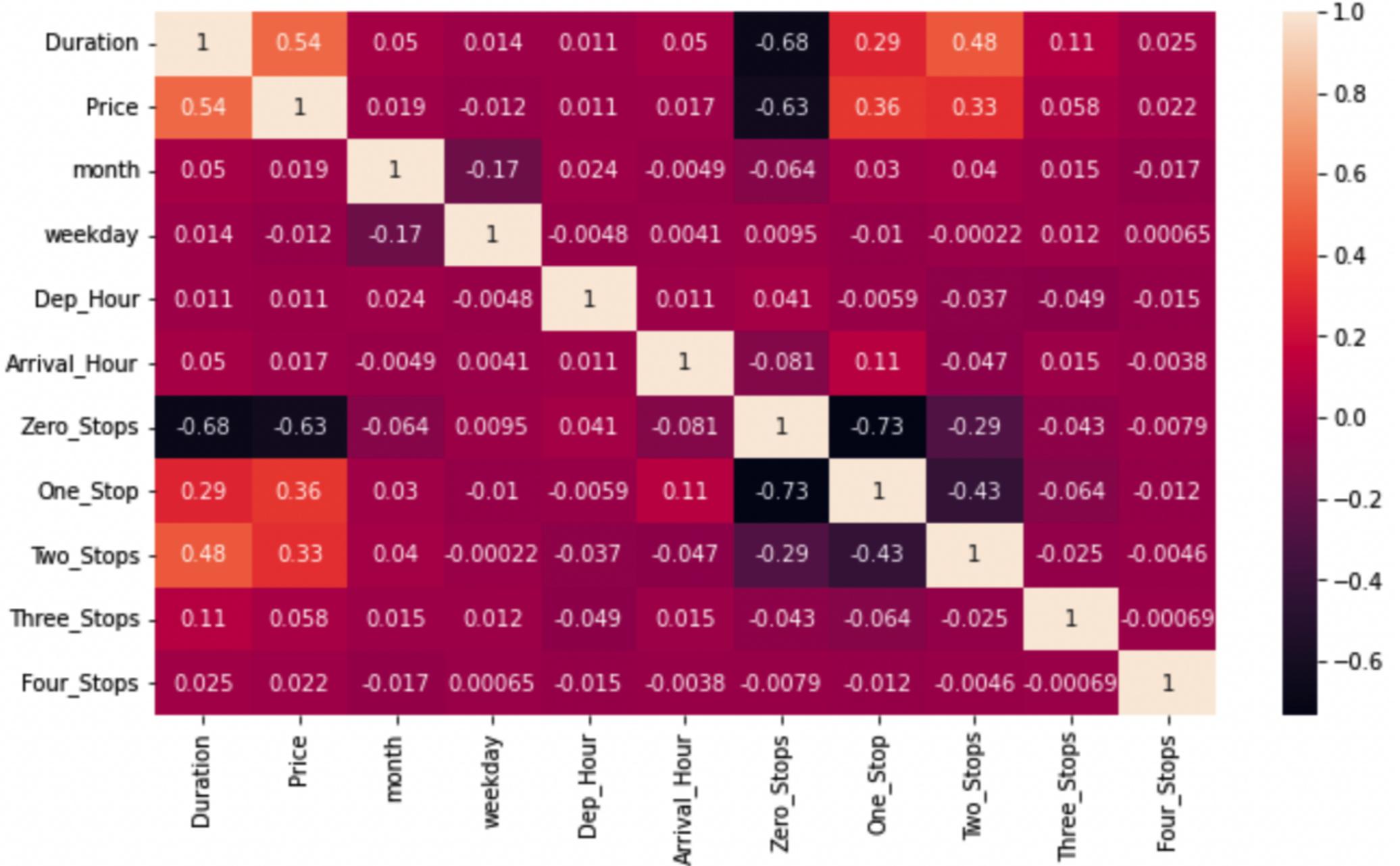
| Destination | Banglore | Cochin | Delhi | Hyderabad | Kolkata | New Delhi |
|-------------|----------|--------|---------|-----------|---------|-----------|
| Source | | | | | | |
| Banglore | | NaN | 4823.0 | NaN | NaN | 10976.5 |
| Chennai | | NaN | NaN | NaN | 3850.0 | NaN |
| Delhi | | NaN | 10262.0 | NaN | NaN | NaN |
| Kolkata | 9345.0 | | NaN | NaN | NaN | NaN |
| Mumbai | | NaN | NaN | 3342.0 | NaN | NaN |

pd.cut()



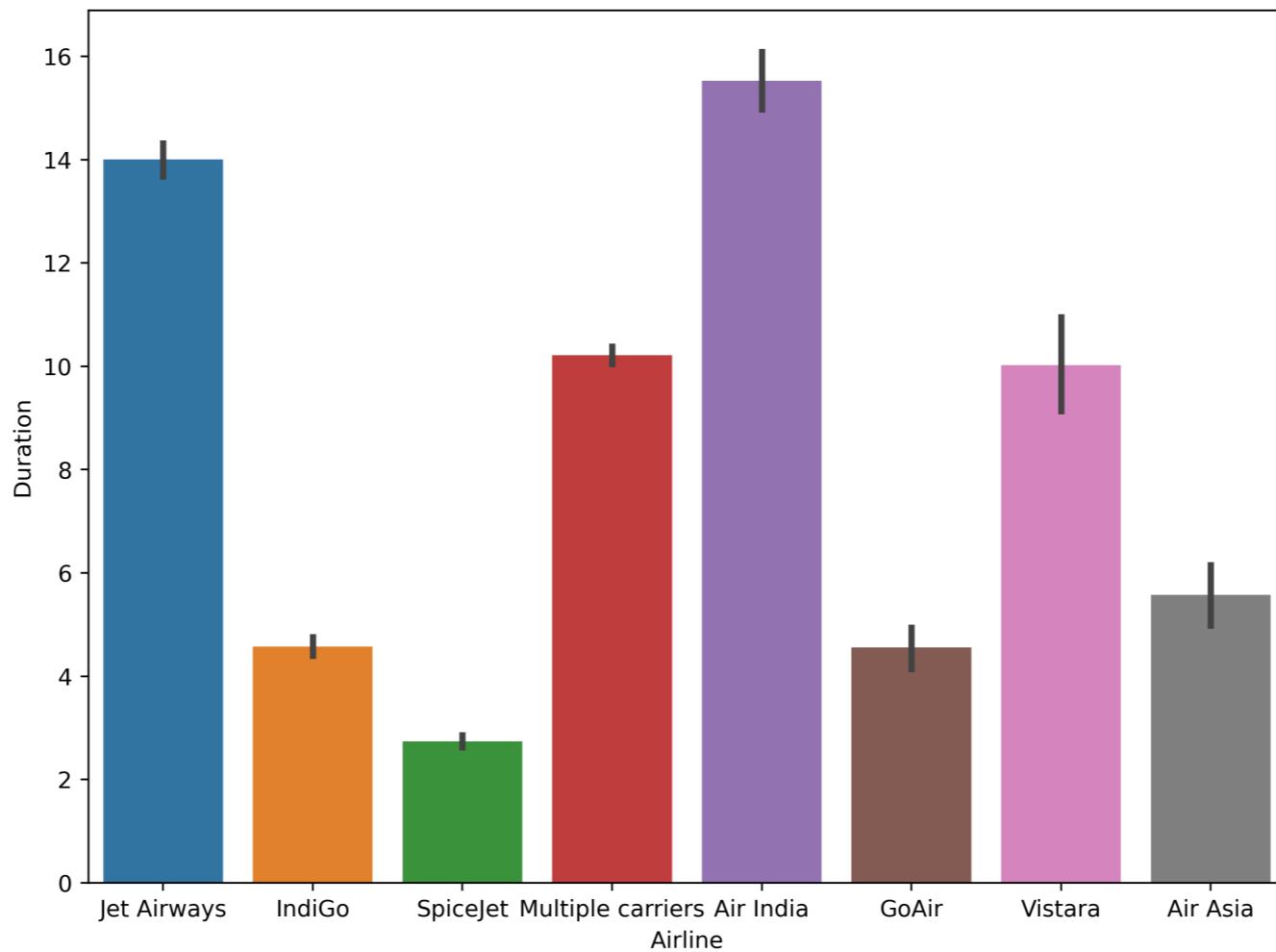
```
planes["Price_Category"] = pd.cut(planes["Price"],  
                                 labels=labels,  
                                 bins=bins)
```

Data snooping



Generating hypotheses

```
sns.barplot(data=planes, x="Airline", y="Duration")  
plt.show()
```



Next steps

- **Sampling in Python**
- **Hypothesis Testing in Python**
- **Supervised Learning with scikit-learn**

Congratulations!

EXPLORATORY DATA ANALYSIS IN PYTHON