```
In [125]:
```

```
import pandas as pd
import numpy as np
```

In [126]:

```
visitor_park = pd.read_csv("july4_snapshot.csv")
```

In []:

```
#1: Exploratory Data Analysis
```

In [127]:

```
#A:
```

visitor_park.head()

Out[127]:

	visitor	day_pass	season_ticket	domestic	state	country	gender	age	maine_res	stay_1
0	1	1	No	1	NY	USA	0	32	No	
1	2	0	Yes	1	Other	USA	1	43	No	
2	3	1	No	1	ME	USA	1	28	Yes	
3	4	0	Yes	1	NH	USA	1	35	No	
4	5	1	No	0	NaN	MEX	1	44	No	
4										•

There are 5 rows of data seen from the head function

In [128]:

```
#Looking at Shape Attribute with .shape
```

In []:

```
visitor_park.shape
```

Out[]:

(5216, 19)

There are 5216 columns and 19 rows

```
#D:
visitor_park.info()
```

RangeIndex: 5216 entries, 0 to 5215 Data columns (total 19 columns): Column Non-Null Count Dtype ---------_ _ _ ----0 visitor 5216 non-null int64 1 day_pass 5216 non-null int64 2 season_ticket 5216 non-null object 5216 non-null 3 domestic int64 4 state 4127 non-null object 5 5160 non-null country object 5216 non-null int64 6 gender 7 age 5216 non-null int64 5216 non-null 8 maine_res object 9 stay_four 5216 non-null int64 10 payment_method 5216 non-null int64 11 ice_cream_purch 5216 non-null int64 12 ice_cream_flavor 5216 non-null object

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

15 lobster_claw 5216 non-null int64 16 lobster_junior 5216 non-null int64 17 merch_spend 5216 non-null float64 18 lobsterama_spend 5216 non-null float64

5216 non-null

5216 non-null

dtypes: float64(2), int64(12), object(5)

memory usage: 774.4+ KB

13 sky_chair

14 ferris_wheel

Gender, age and payment method are categorical data and other values from 11-18 would be numeric

int64

int64

```
#E = Rounding of values to 2 decimals
visitor_park.round({"merch_spend":2})
```

Out[]:

	visitor	day_pass	season_ticket	state	country	gender	age	main_per	stay_four	pay
0	1	1	No	NY	USA	0	15	No	1	
1	2	0	Yes	Other	USA	1	15	No	1	
2	3	1	No	ME	USA	1	15	Yes	1	
3	4	0	Yes	NH	USA	1	15	No	0	
4	5	1	No	NaN	MEX	1	15	No	1	
5211	5212	0	Yes	NH	USA	0	15	No	1	
5212	5213	1	No	NaN	UK	1	15	No	1	
5213	5214	0	Yes	NH	USA	1	15	No	0	
5214	5215	0	Yes	ME	USA	0	15	Yes	1	
5215	5216	1	No	MA	USA	0	15	No	1	

5216 rows × 18 columns

→

In []:

```
#F:
visitor_park.isna().sum()
```

Out[]:

```
visitor
                        0
day_pass
                        0
season_ticket
                        0
domestic
                         0
                     1089
state
                       56
country
gender
                        0
                         0
age
maine_res
                         0
stay four
                         0
payment_method
                         0
ice_cream_purch
                         0
ice_cream_flavor
                         0
sky_chair
                        0
ferris_wheel
                        0
                        0
lobster_claw
lobster_junior
                        0
merch_spend
                         0
                         0
lobsterama_spend
dtype: int64
```

Total of 1145 values are missing

```
In [ ]:
```

```
#F(a):
visitor_park.isna().sum() * 100 / len(visitor_park)
```

Out[]:

21.95168711656442

In []:

```
#F(b):
visitor_park.isna().sum() * 100 / len(visitor_park)
```

Out[]:

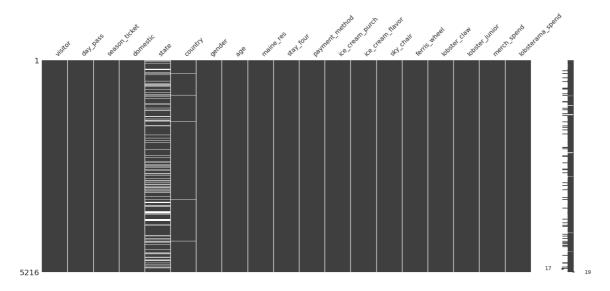
visitor 0.000000 0.000000 day_pass season_ticket 0.000000 domestic 0.000000 state 20.878067 country 1.073620 gender 0.000000 age 0.000000 maine_res 0.000000 stay_four 0.000000 payment_method 0.000000 ice_cream_purch 0.000000 ice_cream_flavor 0.000000 sky_chair 0.000000 ferris wheel 0.000000 lobster_claw 0.000000 lobster_junior 0.000000 merch_spend 0.000000 lobsterama_spend 0.000000

dtype: float64

```
#F(c):
import missingno as msno
msno.matrix(visitor_park)
```

Out[]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f9448fd6490>

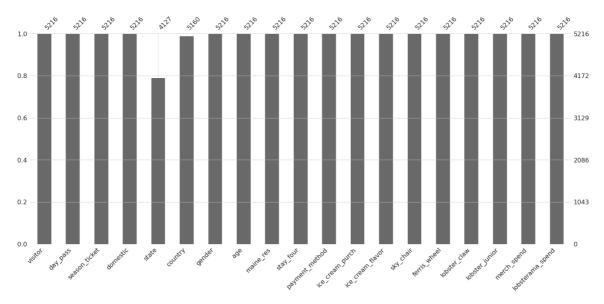


In []:

```
#F(d):
msno.bar(visitor_park)
```

Out[]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f944c0ff8b0>



```
#F(e):
visitor_park[visitor_park["state"].isna()]
```

Out[]:

	visitor	day_pass	season_ticket	domestic	state	country	gender	age	maine_res	sta
4	5	1	No	0	NaN	MEX	1	44	No	
10	11	1	No	0	NaN	CAN	1	37	No	
12	13	1	No	0	NaN	CHN	1	38	No	
14	15	1	No	0	NaN	BRA	1	40	No	
17	18	1	No	0	NaN	CAN	0	31	No	
5202	5203	1	No	0	NaN	CAN	0	34	No	
5205	5206	1	No	0	NaN	CAN	1	39	No	
5206	5207	1	No	0	NaN	CHN	0	38	No	
5207	5208	1	No	0	NaN	CAN	1	35	No	
5212	5213	1	No	0	NaN	UK	1	30	No	

1089 rows × 19 columns

file:///C:/Users/aravind/Desktop/marketing analytics/Aravindrao_assignment1.html

```
#G(a):
visitor_park["age"] = np.where(visitor_park["age"] < 15, 15, visitor_park["age"])
visitor_park['age'] = visitor_park['age'].where(visitor_park['age']<15,15)
print(visitor_park)</pre>
```

,	visitor	day_pass	season_ti	.cket	state	count	ry	gender	age	main_per
\	1	1		No	MV		IC A	α.	1 -	No
0 1	1 2	1 0		No Yes	NY Other		JSA JSA	0 1	15 15	No No
2	3	1		No	ME		JSA	1	15	Yes
3	4	0		Yes	NH		JSA	1	15	No
4	5	1		No	NaN		1EX	1	15	No
		•••		•••	• • •			• • •	• • •	• • •
5211	5212	0		Yes	NH		JSA	0	15	No
5212	5213	1		No	NaN		UK	1	15	No
5213	5214	0		Yes	NH		JSA	1	15	No
5214	5215	0		Yes	ME		JSA	0	15	Yes
5215	5216	1		No	MA	U	JSA	0	15	No
	stay_fou	ın navmen	t_method	ica c	ream ni	ırch i	CO (crosm fl	avor	sky_cha
ir \	stay_rou	n paymen	t_iiie triou	106_0	ı eaiii_pi	ai Cii 1		ci eaiii_i i	avoi	SKy_Ciia
0		1	0			1		Van	illa	
1		_	Ū			_		• • • • • • • • • • • • • • • • • • • •		
1		1	0			1		Choco	late	
0		-	Ü			_		CHOCO	1000	
2		1	0			0			None	
1		-	J			· ·			Nonc	
3		0	0			0			None	
0		· ·	J			· ·			NOTIC	
4		1	0			1		Van	illa	
0		_	O			-		van	111 <i>a</i>	
• • •										
• • •										
5211		1	0			0			None	
0										
5212		1	0			1		Van	illa	
1										
5213		0	0			1		Choco	late	
1										
5214		1	0			0			None	
1		4	0			^			NI	
5215 0		1	0			0			None	
O										
	ferris_w	heel lob	ster_claw	lobs	ter_jur	nior	mer	ch_spend	\	
0	_	0	_ 0		_3	1		4.529611		
1		0	1			0		3.811135		
2		1	0			1		9.231936		
3		1	1			0		5.508722		
4		1	0			0		1.019885		
5211		1	0			0	5:	1.132212		
5212		1	0			0		3.170379		
5213		0	0			0		7.488318		
5214		1	0			0		5.340795		
5215		0	0			0		5.312087		
	lobstera	ma_spend								
0		24.95								
1		16.58								
2		29.94								
3		49.95								
4		36.62								
• • •		•••								
5211		22.17								
5212		23.71								

```
      5213
      48.33

      5214
      34.59

      5215
      27.02
```

[5216 rows x 18 columns]

In []:

```
#H(a):
visitor_park[visitor_park["stay_four"]==1]
count = (visitor_park["stay_four"] == 1).sum()
total = len(visitor_park["stay_four"])
percentage = count / total * 100
print(percentage)
```

59.93098159509203

In []:

```
#H(b):
visitor_park_usa = visitor_park[visitor_park["country"] == "USA"]
count = (visitor_park_usa["stay_four"] == 1).sum()
total = len(visitor_park_usa["stay_four"])
percentage_usa = count / total * 100
print(percentage_usa)
```

52.047492125030296

domestic visitors who stayed more than 4 years

In []:

```
#H(b):
park_other = visitor_park[visitor_park["country"] != "USA"]
count = (park_other["stay_four"] == 1).sum()
total = len(park_other["stay_four"])
percentage_other = count / total * 100
print(percentage_other)
```

89.80716253443526

Percentage of international visitors stayed more than 4 years

In [129]:

```
#I(a):
park_visitor = visitor_park.drop(columns=["domestic"])
park_visitor.head()
```

Out[129]:

	visitor	day_pass	season_ticket	state	country	gender	age	maine_res	stay_four	paym
0	1	1	No	NY	USA	0	32	No	1	
1	2	0	Yes	Other	USA	1	43	No	1	
2	3	1	No	ME	USA	1	28	Yes	1	
3	4	0	Yes	NH	USA	1	35	No	0	
4	5	1	No	NaN	MEX	1	44	No	1	
4										•

Column country already gives us the information regarding domestic and international visitors information

```
In [ ]:
```

```
#J(a):
visitor_park = visitor_park.rename(columns={"maine_res" : "main_per"})
visitor_park.head(20)
```

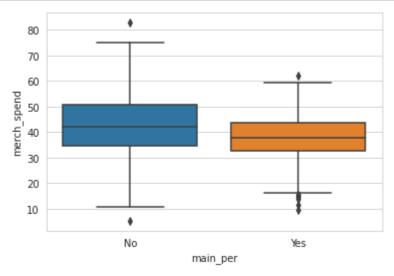
Out[]:

	visitor	day_pass	season_ticket	state	country	gender	age	main_per	stay_four	paym
0	1	1	No	NY	USA	0	15	No	1	
1	2	0	Yes	Other	USA	1	15	No	1	
2	3	1	No	ME	USA	1	15	Yes	1	
3	4	0	Yes	NH	USA	1	15	No	0	
4	5	1	No	NaN	MEX	1	15	No	1	
5	6	1	No	NY	USA	0	15	No	0	
6	7	1	No	Other	USA	1	15	No	0	
7	8	0	Yes	VT	USA	0	15	No	1	
8	9	0	Yes	NH	USA	0	15	No	0	
9	10	1	No	NH	USA	0	15	No	0	
10	11	1	No	NaN	CAN	1	15	No	1	
11	12	1	No	NY	USA	1	15	No	1	
12	13	1	No	NaN	CHN	1	15	No	1	
13	14	0	Yes	ME	USA	0	15	Yes	0	
14	15	1	No	NaN	BRA	1	15	No	1	
15	16	1	No	ME	USA	1	15	Yes	1	
16	17	1	No	NH	USA	0	15	No	0	
17	18	1	No	NaN	CAN	0	15	No	1	
18	19	1	No	MA	USA	1	15	No	0	
19	20	1	No	NaN	FRA	1	15	No	1	
4										•

In []:

#2: Data Visualization

```
#K:
import seaborn as sns
sns.boxplot(x = "main_per", y = "merch_spend", data = visitor_park);
```

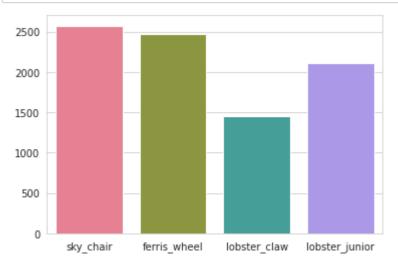


In []:

#K(a):

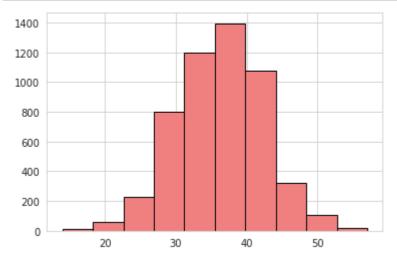
In []:

```
#L:
ride_names = visitor_park[["sky_chair", "ferris_wheel", "lobster_claw", "lobster_junio
r"]]
sns.barplot(x = ride_names.columns, y = ride_names.sum(), palette='husl');
```



In [130]:

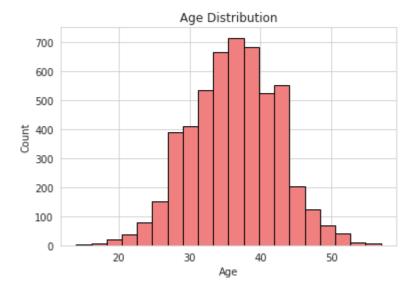
```
#M:
import matplotlib.pyplot as plt
plt.hist(visitor_park["age"], color = "lightcoral", edgecolor = "black");
```



In []:

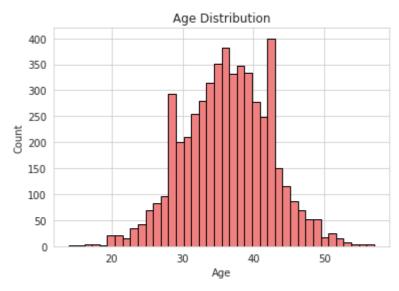
In [131]:

```
#M(b):
plt.hist(visitor_park["age"], bins = 20, color = "lightcoral", edgecolor = "black")
plt.xlabel('Age')
plt.ylabel('Count')
plt.title('Age Distribution');
```



In [132]:

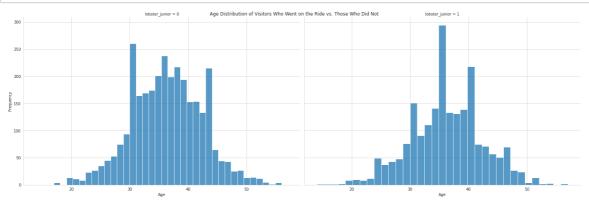
```
plt.hist(visitor_park["age"], bins = 40, color = "lightcoral", edgecolor = "black")
plt.xlabel('Age')
plt.ylabel('Count')
plt.title('Age Distribution');
```



increasing the number of makes the data more concentrated and normally distributed

In [136]:

```
#M(d):
g = sns.FacetGrid(visitor_park, col = "lobster_junior", height = 7, aspect = 1.5)
g.map(sns.histplot, "age", kde = False)
g.set_axis_labels("Age", "Frequency")
g.fig.suptitle("Age Distribution of Visitors Who Went on the Ride vs. Those Who Did No t");
```

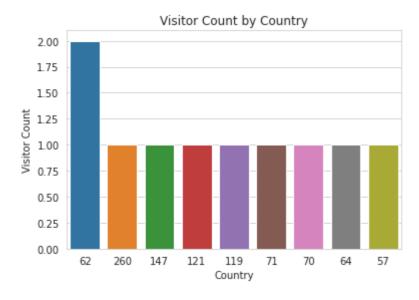


For me it does because both the data have different frequency, especially the ones who went were 35 years and shows the maximum frewuncy compared to ones who didnt . the ones who didnt have a much higher frequency

In [137]:

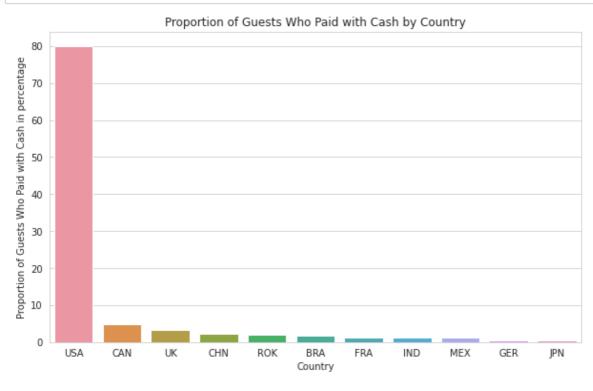
```
#N:
country_visitor_sum = visitor_park.groupby(["country"])["visitor"].count()
country_visitor_sum = country_visitor_sum[country_visitor_sum.index != "USA"]
print(country_visitor_sum)
country_visitor_sum = country_visitor_sum.sort_values(ascending = False)
country_visitor_sum_df = country_visitor_sum.to_frame()
print(country_visitor_sum_df)
sns.countplot(x=country_visitor_sum_df.index, data= country_visitor_sum, order= country_visitor_sum.value_counts().index)
plt.xlabel("Country")
plt.ylabel("Visitor Count")
plt.title("Visitor Count by Country");
```

```
country
BRA
        121
CAN
        260
CHN
        147
FRA
         70
GER
         57
         71
IND
         62
JPN
         64
MEX
ROK
         62
UK
        119
Name: visitor, dtype: int64
          visitor
country
CAN
               260
CHN
               147
BRA
               121
UK
               119
               71
IND
FRA
                70
MEX
                64
JPN
                62
                62
ROK
                57
GER
```



This data shows the number of visitors for the certain international visitor and the visitor_count for the data. South korea has the most visitors compared to other countries.

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
# Load the data into a DataFrame
df = pd.read_csv('july4_snapshot.csv') # replace with your file name
# Filter the data to only include guests who paid with cash
cash_df = df[df['payment_method'] == 1]
# Group the data by country and calculate the proportion of guests who paid with cash
country_proportions = cash_df.groupby('country').size() / len(cash_df)*100
# Sort the countries in descending order of proportion of guests who paid with cash
country_proportions = country_proportions.sort_values(ascending=False)
# Create a bar plot using seaborn
sns.set_style("whitegrid")
plt.figure(figsize=(10, 6))
sns.barplot(x=country_proportions.index, y=country_proportions.values)
plt.title('Proportion of Guests Who Paid with Cash by Country')
plt.xlabel('Country')
plt.ylabel('Proportion of Guests Who Paid with Cash in percentage')
plt.show()
```



In []: !pip install nbconvert Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/col ab-wheels/public/simple/ Requirement already satisfied: nbconvert in /usr/local/lib/python3.8/distpackages (5.6.1) Requirement already satisfied: jinja2>=2.4 in /usr/local/lib/python3.8/dis t-packages (from nbconvert) (2.11.3) Requirement already satisfied: bleach in /usr/local/lib/python3.8/dist-pac kages (from nbconvert) (6.0.0) Requirement already satisfied: pandocfilters>=1.4.1 in /usr/local/lib/pyth on3.8/dist-packages (from nbconvert) (1.5.0) Requirement already satisfied: pygments in /usr/local/lib/python3.8/dist-p ackages (from nbconvert) (2.6.1) Requirement already satisfied: defusedxml in /usr/local/lib/python3.8/dist -packages (from nbconvert) (0.7.1) Requirement already satisfied: jupyter-core in /usr/local/lib/python3.8/di st-packages (from nbconvert) (5.2.0) Requirement already satisfied: testpath in /usr/local/lib/python3.8/dist-p ackages (from nbconvert) (0.6.0) Requirement already satisfied: entrypoints>=0.2.2 in /usr/local/lib/python 3.8/dist-packages (from nbconvert) (0.4) Requirement already satisfied: nbformat>=4.4 in /usr/local/lib/python3.8/d ist-packages (from nbconvert) (5.7.3) Requirement already satisfied: mistune<2,>=0.8.1 in /usr/local/lib/python 3.8/dist-packages (from nbconvert) (0.8.4) Requirement already satisfied: traitlets>=4.2 in /usr/local/lib/python3.8/ dist-packages (from nbconvert) (5.7.1) Requirement already satisfied: MarkupSafe>=0.23 in /usr/local/lib/python3.

8/dist-packages (from jinja2>=2.4->nbconvert) (2.0.1)

Requirement already satisfied: fastjsonschema in /usr/local/lib/python3.8/ dist-packages (from nbformat>=4.4->nbconvert) (2.16.2)

Requirement already satisfied: jsonschema>=2.6 in /usr/local/lib/python3.

8/dist-packages (from nbformat>=4.4->nbconvert) (4.3.3)

Requirement already satisfied: webencodings in /usr/local/lib/python3.8/di st-packages (from bleach->nbconvert) (0.5.1)

Requirement already satisfied: six>=1.9.0 in /usr/local/lib/python3.8/dist -packages (from bleach->nbconvert) (1.15.0)

Requirement already satisfied: platformdirs>=2.5 in /usr/local/lib/python 3.8/dist-packages (from jupyter-core->nbconvert) (3.0.0)

Requirement already satisfied: attrs>=17.4.0 in /usr/local/lib/python3.8/d ist-packages (from jsonschema>=2.6->nbformat>=4.4->nbconvert) (22.2.0)

Requirement already satisfied: pyrsistent!=0.17.0,!=0.17.1,!=0.17.2,>=0.1 4.0 in /usr/local/lib/python3.8/dist-packages (from jsonschema>=2.6->nbfor

mat>=4.4->nbconvert) (0.19.3) Requirement already satisfied: importlib-resources>=1.4.0 in /usr/local/li

b/python3.8/dist-packages (from jsonschema>=2.6->nbformat>=4.4->nbconvert) (5.10.2)

Requirement already satisfied: zipp>=3.1.0 in /usr/local/lib/python3.8/dis t-packages (from importlib-resources>=1.4.0->jsonschema>=2.6->nbformat>=4. 4->nbconvert) (3.13.0)

In [135]:

```
!jupyter nbconvert -- to html Aravindrao_assignment1.ipynb
```

```
[NbConvertApp] WARNING | pattern 'to' matched no files
[NbConvertApp] WARNING | pattern 'html' matched no files
[NbConvertApp] Converting notebook Aravindrao_assignment1.ipynb to html
[NbConvertApp] Writing 690440 bytes to Aravindrao assignment1.html
```

The data shows that there are a lot USA visitors in general when comapred to other countries. USA visitors have paid around 80 percent in cash compared to other country visitors.

Part III: Wildcard: Metrics and "Quantified Self"

I chose to keep track of my daily steps for three days in a row as both a researcher and a subject. I measured and kept track of my daily step totals using the health app on my iphone. According to the results, I walked 2,900 steps on the first day, 3,8456 steps on the second, and 5,198 steps on the third.

My daily physical activity varied substantially from day to day as I discovered by keeping track of my steps. Due to doing errands and finishing home duties, the second day saw a marked increase in the number of steps I took compared to the previous two. I became more aware of my physical activity as a result of seeing the numbers in front of me, and I was inspired to exercise more on the third day. I chose to use the stairs rather than the elevator when I went for a walk in the park. Also, I discovered that keeping track of my steps helped me become more conscious of my daily routine and ways to include more exercise.

No one nearby responded to me tracking my steps throughout the course of the three days. The outcomes, though, were significant to me and gave me a chance to consider my routines. I'd definitely think about continuing this experiment for a while, maybe for a week or a month, to gain a better grasp of my daily physical activity patterns. Overall, this experiment served as a great reminder to emphasize exercise in my daily routine and to keep active.