Biodiversity Project

1 Introduction

The goal of this project is to analyze biodiversity data from the National Parks Service, particularly around various species observed in different national park locations.

This project will scope, analyze, prepare, plot data, and seek to explain the findings from the analysis.

Here are a few questions that this project has sought to answer:

- What is the distribution of conservation status for species?
- Are certain types of species more likely to be endangered?
- Are the differences between species and their conservation status significant?
- Which animal is most prevalent and what is their distribution amongst parks?

Data sources:

Both `Observations.csv` and `Species_info.csv` was provided by https://www.codecademy.com/.

The data for this project is *inspired* by real data.

1.1 Import Python Modules

Here are the primary modules that will be used in this project:

[105]:
```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns

%matplotlib inline
```

1.2 Getting data to know

species The `species_info.csv` contains information on the different species in the National Parks. The columns in the data set include: - **category** - The category of taxonomy for each species - **scientific_name** - The scientific name of each species - **common_names** - The common names of each species - **conservation_status** - The species conservation status

[147]:
```
species = pd.read_csv('species_info.csv',encoding='utf-8')
print("Columns:",species.columns)
```

```
species.head().style.set_caption("Species DataFrame Head").
  ↪background_gradient(cmap='viridis')
```

```
Index(['category', 'scientific_name', 'common_names', 'conservation_status'],
dtype='object')
```

[147]: <pandas.io.formats.style.Styler at 0x12f2b2cf0>

observations The `Observations.csv` contains information from recorded sightings of different species throughout the national parks in the past 7 days. The columns included are:

- **scientific_name** - The scientific name of each species
- **park_name** - The name of the national park
- **observations** - The number of observations in the past 7 days

[172]:
```
observations=pd.read_csv('observations.csv',encoding='utf-8')
print("Columns:",observations.columns)
observations.head().style.set_caption("Conservations DataFrame Head").
  ↪background_gradient(cmap='viridis')
```

```
Columns: Index(['scientific_name', 'park_name', 'observations'], dtype='object')
```

[172]: <pandas.io.formats.style.Styler at 0x1414f0230>

Data Characteristics Dimensions of the data sets, for `species` there are 5,824 rows and 4 columns while `observations` has 23,296 rows and 3 columns.

[150]:
```
print(f"species shape: {species.shape}")
print(f"observations shape: {observations.shape}")
```

```
species shape: (5824, 4)
observations shape: (23296, 3)
```

2 Exploring data

Exploring the `species` data a little more in depth.Finding the number of distinct species in the data.Column `scientific_name` have 5,541 unique species. There seems to be a lot of species in the national parks!

[170]:
```
print(f"number of species:{species.scientific_name.nunique()}")
```

```
number of species:5541
```

Unique `categories`

[158]:
```
print(f"nnumber of categories:{species.category.nunique()}")
print(f"categories:{species.category.unique()}")
```

```
nnumber of categories:7
categories:['Mammal' 'Bird' 'Reptile' 'Amphibian' 'Fish' 'Vascular Plant'
 'Nonvascular Plant']
```

Amount of each category

```
[161]: species.groupby("category").size()
```

```
[161]: category
Amphibian              80
Bird                  521
Fish                  127
Mammal                214
Nonvascular Plant     333
Reptile                79
Vascular Plant       4470
dtype: int64
```

Combining both tables together and create one table depending on their scientific name

```
[174]: combined = pd.merge(observations, species, on='scientific_name', how='left')
combined.head()
print("Columns:",combined.columns)
```

```
Columns: Index(['scientific_name', 'park_name', 'observations', 'category',
       'common_names', 'conservation_status'],
      dtype='object')
```

Lets find out Least observed and Most observed animal

```
[167]: least_obs_idx = combined['observations'].idxmin()
most_obs_idx = combined['observations'].idxmax()

least_observed = combined.loc[least_obs_idx]
most_observed = combined.loc[most_obs_idx]

print("Least Observed Animal:")
print(least_observed[['common_names', 'scientific_name', 'observations',␣
 ↪'park_name', 'category', 'conservation_status']])
print("\nMost Observed Animal:")
print(most_observed[['common_names', 'scientific_name', 'observations',␣
 ↪'park_name', 'category', 'conservation_status']])
```

```
Least Observed Animal:
common_names           Golden Corydalis, Scrambled Eggs
scientific_name                         Corydalis aurea
observations                                          9
park_name                           Bryce National Park
category                                 Vascular Plant
conservation_status                                 NaN
Name: 10368, dtype: object

Most Observed Animal:
common_names           Deep-Root Clubmoss, Ground Cedar
```

```
scientific_name                 Lycopodium tristachyum
observations                                       321
park_name                    Yellowstone National Park
category                                Vascular Plant
conservation_status                                NaN
Name: 12447, dtype: object
```

Lets check conservation status to find out is there any endangered species out there,and what kind of conservation status is existing

[181]:
```
not_nan_conservation = combined[combined['conservation_status'].notna()]

print("Number of rows with conservation_status values:", not_nan_conservation.
 ↪shape[0])

print("Unique conservation statuses:",␣
 ↪not_nan_conservation['conservation_status'].unique())
```

```
Number of rows with conservation_status values: 880
Unique conservation statuses: ['Species of Concern' 'Threatened' 'Endangered'
'In Recovery']
```

The column has 4 categories, `Species of Concern`, `Endangered`, `Threatened`, `In Recovery`, and `nan` values.

Finding out exact amount of each conservation status

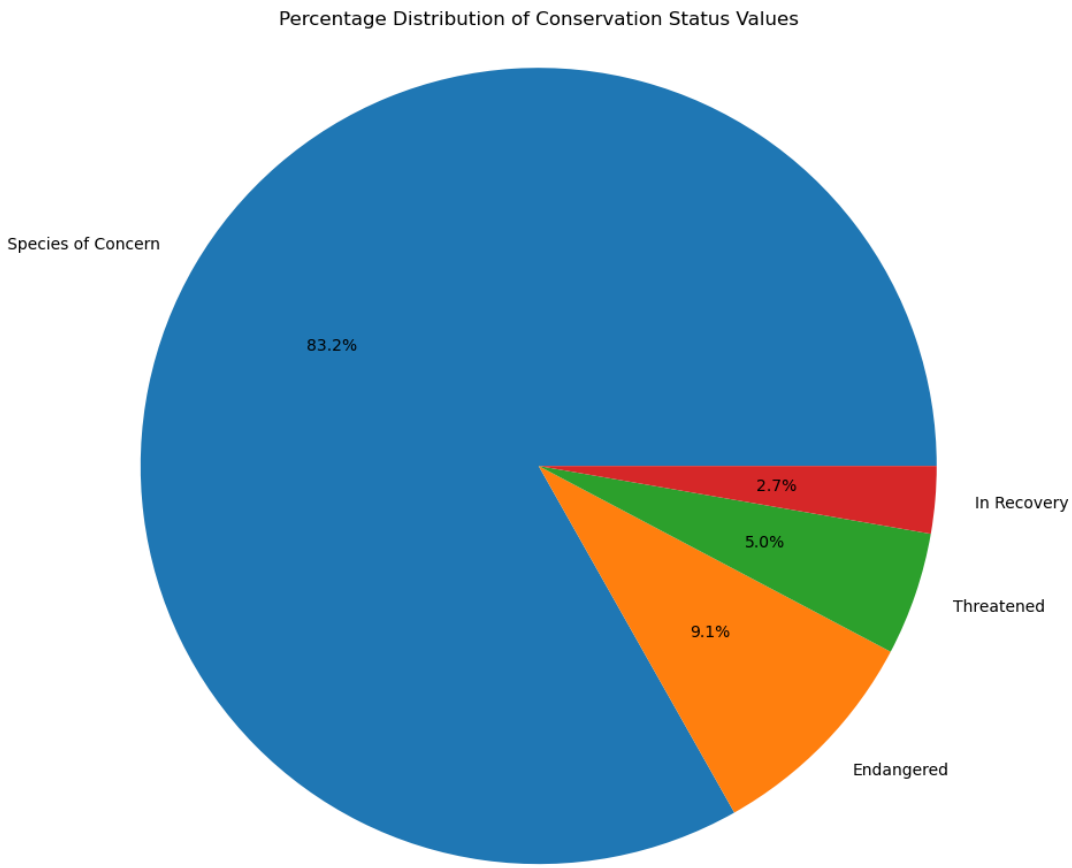
A lot of values is `NaN` so i convert them to `No Intervention`

[284]:
```
combined.fillna('No Intervention', inplace=True)
combined.groupby("conservation_status").size()
```

[284]:
```
conservation_status
Endangered                80
In Recovery               24
No Intervention        24752
Species of Concern       732
Threatened                44
dtype: int64
```

[ ]:
```
Building a pie chart having this data including only info that we have
```

[186]:
```
status_counts = not_nan_conservation['conservation_status'].value_counts()
plt.figure(figsize=(10, 8))
plt.pie(status_counts.values,labels=status_counts.index,autopct='%1.1f%%')
plt.title("Percentage Distribution of Conservation Status Values")
plt.axis('equal')
plt.tight_layout()
plt.show()
```



Finding out which category of animals in each conservation status

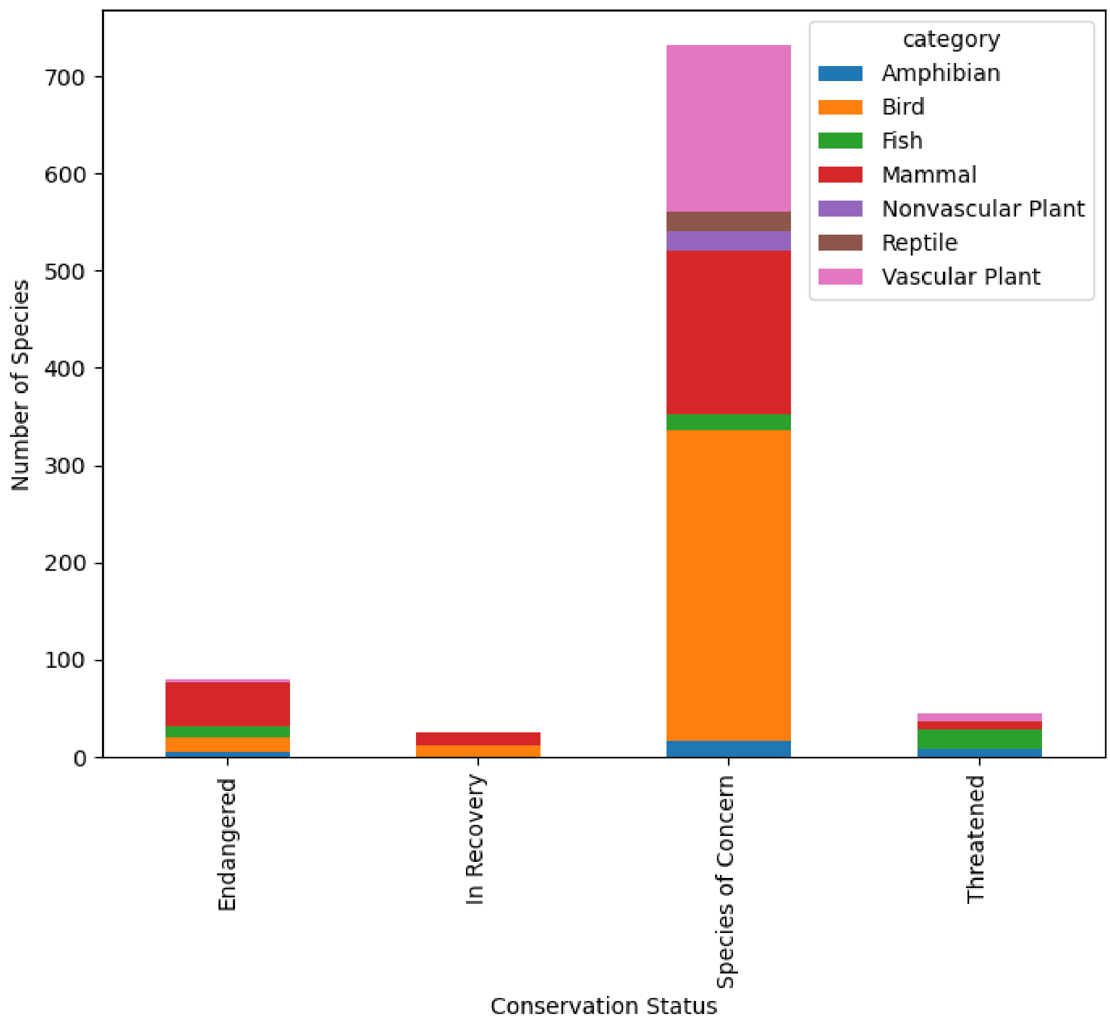
[286]:
```
conservationCategory = combined[combined.conservation_status != "No␣
↪Intervention"]\
    .groupby(["conservation_status", "category"])['scientific_name']\
    .count()\
    .unstack()

conservationCategory
```

[286]:
```
category             Amphibian   Bird  Fish  Mammal  Nonvascular Plant  \
conservation_status
Endangered                 4.0   16.0  12.0    44.0                NaN
In Recovery                NaN   12.0   NaN    12.0                NaN
Species of Concern        16.0  320.0  16.0   168.0               20.0
Threatened                 8.0    NaN  20.0     8.0                NaN

category             Reptile  Vascular Plant
conservation_status
```

```
Endangered                NaN            4.0
In Recovery               NaN            NaN
Species of Concern       20.0          172.0
Threatened                NaN            8.0
```

Building stacked bar chart depending on this

[219]:
```
ax = conservationCategory.plot(kind = 'bar', figsize=(8,6),stacked=True)
ax.set_xlabel("Conservation Status")
ax.set_ylabel("Number of Species")
plt.show();
```



Finding if certain types of species are more likely to be endangered.To do so I created new column called `is_protected` that will include any species that had value other than no `No Intevention`

[222]:
```
combined['is_protected'] = combined.conservation_status != 'No Intervention'
```

Once the new column is created, group by `category` and `is_protected` to show the break down of each species type and protection status.

It's easy to see that Birds, Vascular Plants, and Mammals have a higher absolute number of species protected.

[228]:
```
category_counts = combined.groupby(['category', 'is_protected'])\
                        .scientific_name.nunique()\
                        .reset_index()\
                        .pivot(columns='is_protected',
                                      index='category',
                                      values='scientific_name')\
                        .reset_index()
category_counts.columns = ['category', 'not_protected', 'protected']

category_counts
```

[228]:

	category	not_protected	protected
0	Amphibian	72	7
1	Bird	413	75
2	Fish	115	11
3	Mammal	146	30
4	Nonvascular Plant	328	5
5	Reptile	73	5
6	Vascular Plant	4216	46

Calculating rate of protection

[233]:
```
category_counts['percent_protected'] = category_counts.protected /\
(category_counts.protected + category_counts.not_protected) * 100

category_counts
```

[233]:

	category	not_protected	protected	percent_protected
0	Amphibian	72	7	8.860759
1	Bird	413	75	15.368852
2	Fish	115	11	8.730159
3	Mammal	146	30	17.045455
4	Nonvascular Plant	328	5	1.501502
5	Reptile	73	5	6.410256
6	Vascular Plant	4216	46	1.079305

Statistical Significance This section will run some chi-squared tests to see if different species have statistically significant differences in conservation status rates. The first test will be called `contingency1` and will need to be filled with the correct numbers for mammals and birds.

The results from the chi-squared test returns many values, the second value which is 0.69 is the p-value. The standard p-value to test statistical significance is 0.05. For the value retrieved from this test, the value of 0.69 is much larger than 0.05. In the case of mammals and birds there doesn't seem to be any significant relationship between them i.e. the variables independent.

[237]:
```
from scipy.stats import chi2_contingency

contingency1 = [[30, 146],
               [75, 413]]
chi2_contingency(contingency1)
```

[237]:
```
Chi2ContingencyResult(statistic=0.1617014831654557, pvalue=0.6875948096661336,
dof=1, expected_freq=array([[ 27.8313253, 148.1686747],
       [ 77.1686747, 410.8313253]]))
```

The next pair, is going to test the difference between `Reptile` and `Mammal`. This time the p-value is 0.039 which is below the standard threshold of 0.05 which can be take that the difference between reptile and mammal is statistically significant. Mammals are shown to have a statistically significant higher rate of needed protection compared with Reptiles.

[240]:
```
contingency2 = [[30, 146],
                [5, 73]]
chi2_contingency(contingency2)
```

[240]:
```
Chi2ContingencyResult(statistic=4.289183096203645, pvalue=0.038355590229699,
dof=1, expected_freq=array([[ 24.2519685, 151.7480315],
       [ 10.7480315,  67.2519685]]))
```

2.1 National Parks

Lets see all unique national parks and everything related to it

[197]:
```
unique_categories = combined.groupby('park_name')['category'].nunique()
print(f"All Parks:{combined.park_name.unique()}")
print(f"Total number of observations:{combined.observations.sum()}")
```

```
All Parks:['Great Smoky Mountains National Park' 'Yosemite National Park'
 'Bryce National Park' 'Yellowstone National Park']
Total number of observations:3645247
```

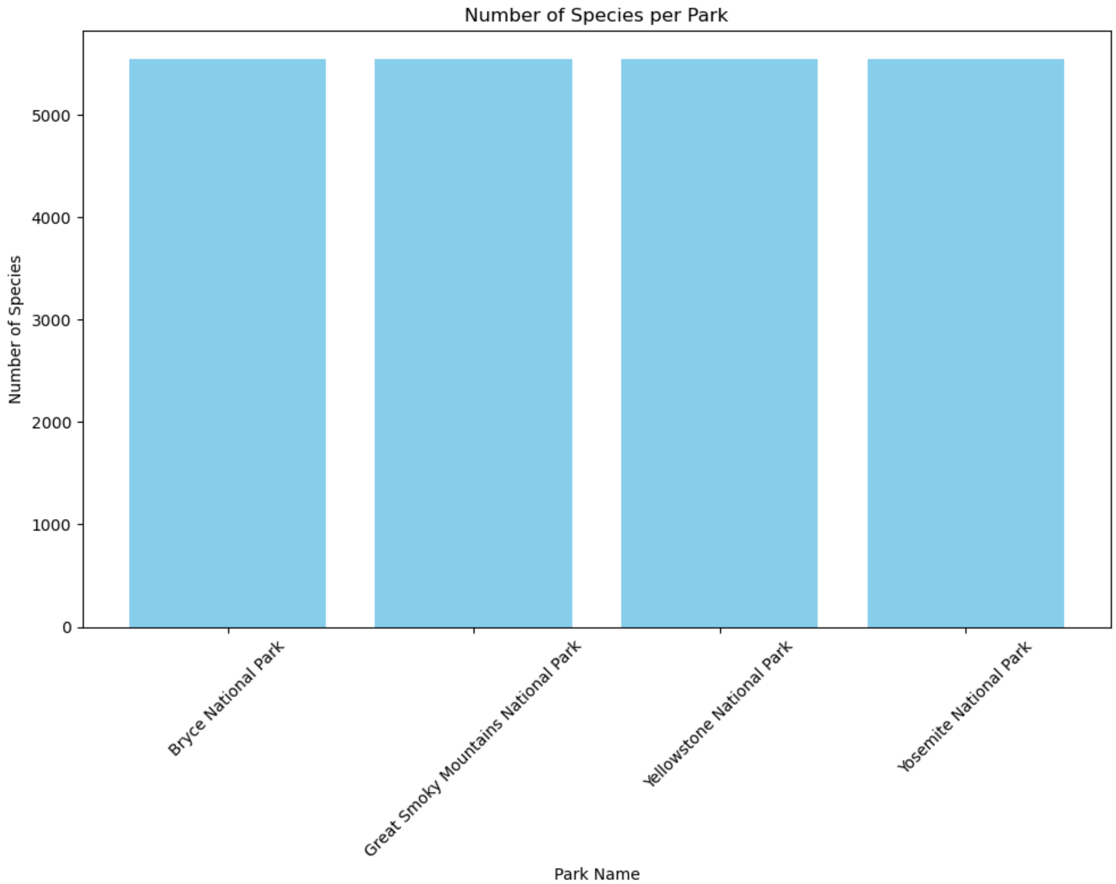
Lets make bar chart from them:

Bar Chart: Unique Parks and Amount of different species per each park

As we can see that each park have same amount of species per park which can happen beacause the data is artificial in other case that would be really strange on real data.

[82]:
```
species_count = combined.groupby('park_name')['scientific_name'].nunique()

plt.figure(figsize=(10, 8))
plt.bar(species_count.index, species_count.values, color='skyblue')

plt.xlabel("Park Name")
plt.ylabel("Number of Species")
```

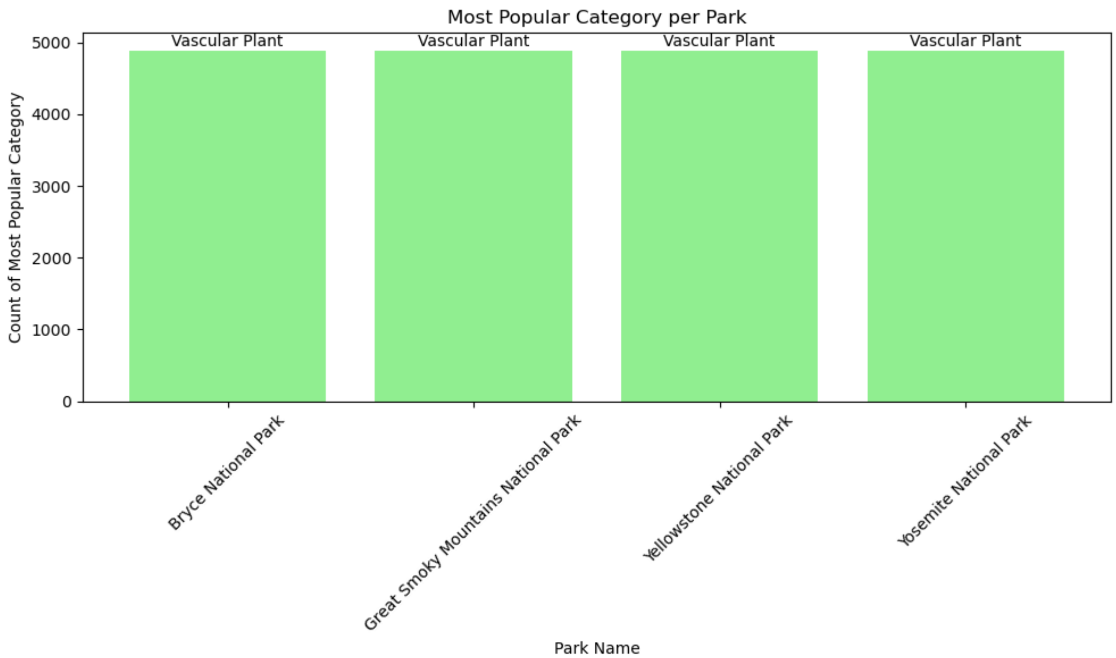
```
plt.title("Number of Species per Park")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



Bar Chart: Unique Parks vs. Most Popular Category Count Same thing here but for plants to be popular is explainable

[86]:
```
category_counts = combined.groupby(['park_name', 'category']).size().
↪reset_index(name='count')

most_popular = category_counts.loc[category_counts.
↪groupby('park_name')['count'].idxmax()]

plt.figure(figsize=(10, 6))
bars = plt.bar(most_popular['park_name'], most_popular['count'],␣
↪color='lightgreen')

plt.xlabel("Park Name")
```

```
plt.ylabel("Count of Most Popular Category")
plt.title("Most Popular Category per Park")
plt.xticks(rotation=45)


for index, row in most_popular.iterrows():
    plt.text(row['park_name'],row['count'] +␣
 ↪5,row['category'],ha='center',va='bottom')

plt.tight_layout()
plt.show()
```



So making our observations we can say that most popular category per park is `Vascular plant` and each park has over `5000 species`

Species in Parks The next set of analysis will come from data from the conservationists as they have been recording sightings of different species at several national parks for the past 7 days. The first step is to look at the the common names from `species` to get an idea of the most prevalent animals in the dataset. The data will be need to be split up into individual names.

[268]:
```
from itertools import chain
import string

def remove_punctuations(text):
    for punctuation in string.punctuation:
```

```
        text = text.replace(punctuation, '')
    return text

common_Names = combined[combined.category == "Mammal"]\
    .common_names\
    .apply(remove_punctuations)\
    .str.split().tolist()

common_Names[:6]
```

[268]:
```
[['American', 'Mink'],
 ['Northern', 'Short', 'Tailed', 'Shrew', 'Northern', 'ShortTailed', 'Shrew'],
 ['WhiteTailed', 'Deer'],
 ['WhiteTailed', 'Deer', 'WhiteTailed', 'Deer'],
 ['Panther', 'Mountain', 'Lion'],
 ['Cougar', 'Mountain', 'Lion', 'Puma']]
```

Clean duplicates

[271]:
```
cleanRows = []

for item in common_Names:
    item = list(dict.fromkeys(item))
    cleanRows.append(item)

cleanRows[:6]
```

[271]:
```
[['American', 'Mink'],
 ['Northern', 'Short', 'Tailed', 'Shrew', 'ShortTailed'],
 ['WhiteTailed', 'Deer'],
 ['WhiteTailed', 'Deer'],
 ['Panther', 'Mountain', 'Lion'],
 ['Cougar', 'Mountain', 'Lion', 'Puma']]
```

Putting everything into one list,and the counting most popular

[274]:
```
res = list(chain.from_iterable(i if isinstance(i, list) else [i] for i in␣
 ↪cleanRows))
res
res[:6]
```

[274]:
```
['American', 'Mink', 'Northern', 'Short', 'Tailed', 'Shrew']
```

[276]:
```
words_counted = []

for i in res:
    x = res.count(i)
    words_counted.append((i,x))
```

```
pd.DataFrame(set(words_counted), columns =['Word', 'Count']).
 ↪sort_values("Count", ascending = False).head(10)
```

[276]:

```
         Word  Count
21        Bat    144
32     Myotis    108
98      Shrew    104
54   American     96
184     Mouse     72
80   Mountain     68
74     Common     64
144      Gray     64
119  Chipmunk     60
33      Brown     56
```

From this analysis, it seems that most popular is `Bats`,`Myotis` and `Shrews`, so `Bat` occurred 144 times, `Myotis` 108 times while `Shrew` came up 104 times.

In the data, there are several different scientific names for different types of bats. The next task is to figure out which rows of `species` are referring to bats. A new column made up of boolean values will be created to check if `is_bat` is `True`.

[293]:

```
combined['is_bat'] = combined.common_names.str.contains(r"\bBat\b", regex =␣
 ↪True)

species.head(10)
```

[293]:

```
  category                scientific_name  \
0   Mammal  Clethrionomys gapperi gapperi
1   Mammal                      Bos bison
2   Mammal                     Bos taurus
3   Mammal                    Ovis aries
4   Mammal                Cervus elaphus
5   Mammal         Odocoileus virginianus
6   Mammal                    Sus scrofa
7   Mammal                 Canis latrans
8   Mammal                   Canis lupus
9   Mammal                   Canis rufus

                                        common_names conservation_status  \
0                           Gapper's Red-Backed Vole                 NaN
1                              American Bison, Bison                 NaN
2  Aurochs, Aurochs, Domestic Cattle (Feral), Dom…                 NaN
3  Domestic Sheep, Mouflon, Red Sheep, Sheep (Feral)                 NaN
4                                      Wapiti Or Elk                 NaN
5                                  White-Tailed Deer                 NaN
6                                Feral Hog, Wild Pig                 NaN
```

```
7                                              Coyote  Species of Concern
8                                           Gray Wolf          Endangered
9                                            Red Wolf          Endangered

   is_bat
0   False
1   False
2   False
3   False
4   False
5   False
6   False
7   False
8   False
9   False
```

Here is a subset of the data where is_bat is true, returning see the rows that matched. There seems to be a lot of species of bats and a mix of protected vs. non-protected species.

[295]:
```
combined[combined.is_bat]
```

[295]:
```
                 scientific_name                            park_name  \
286        Lasiurus blossevillii                  Bryce National Park
331      Corynorhinus rafinesquii              Yosemite National Park
450         Nycticeius humeralis            Yellowstone National Park
670        Lasiurus blossevillii  Great Smoky Mountains National Park
827           Lasiurus borealis              Yosemite National Park
…                            …                                    …
25460          Eptesicus fuscus                   Bryce National Park
25461          Eptesicus fuscus                   Bryce National Park
25476             Myotis leibii             Yellowstone National Park
25530  Lasionycteris noctivagans                  Bryce National Park
25531  Lasionycteris noctivagans                  Bryce National Park

       observations category  \
286             113   Mammal
331             188   Mammal
450             219   Mammal
670              70   Mammal
827             134   Mammal
…               …      …
25460            72   Mammal
25461            72   Mammal
25476           233   Mammal
25530           128   Mammal
25531           128   Mammal

                                        common_names conservation_status  \
```

```
286                                        Western Red Bat  Species of Concern
331                             Rafinesque's Big-Eared Bat     No Intervention
450                                            Evening Bat     No Intervention
670                                        Western Red Bat  Species of Concern
827                                  Eastern Red Bat, Red Bat     No Intervention
…                                                        …                   …
25460                                        Big Brown Bat  Species of Concern
25461                             Big Brown Bat, Big Brown Bat  Species of Concern
25476  Eastern Small-Footed Bat, Eastern Small-Footed…  Species of Concern
25530                                     Silver-Haired Bat  Species of Concern
25531                  Silver-Haired Bat, Silver-Haired Bat  Species of Concern

       is_protected  is_bat
286            True    True
331           False    True
450           False    True
670            True    True
827           False    True
…             …     …
25460          True    True
25461          True    True
25476          True    True
25530          True    True
25531          True    True

[144 rows x 8 columns]
```

Let's see how many total bat observations(across all species) were made at each national park.

The total number of bats observed in each park over the past 7 days are in the table below. Yellowstone National Park seems to have the largest with 8,362 observations and the Great Smoky Mountains National Park having the lowest with 2,411.

[298]:
```
combined[combined.is_bat].groupby('park_name').observations.sum().reset_index()
```

[298]:

	park_name	observations
0	Bryce National Park	3433
1	Great Smoky Mountains National Park	2411
2	Yellowstone National Park	8362
3	Yosemite National Park	4786

Now let's see each park broken down by protected bats vs. non-protected bat sightings. It seems that every park except for the Great Smoky Mountains National Park has more sightings of protected bats than not. This could be considered a great sign for bats.

[303]:
```
obs_by_park = combined[combined.is_bat].groupby(['park_name', 'is_protected']).
 ↪observations.sum().reset_index()
obs_by_park
```

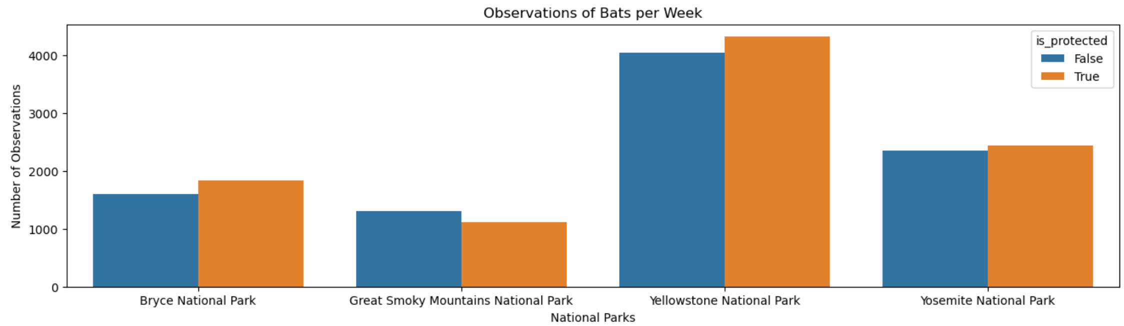
[303]:

```
                         park_name  is_protected  observations
0             Bryce National Park         False          1596
1             Bryce National Park          True          1837
2  Great Smoky Mountains National Park    False          1299
3  Great Smoky Mountains National Park     True          1112
4        Yellowstone National Park        False          4044
5        Yellowstone National Park         True          4318
6           Yosemite National Park        False          2345
7           Yosemite National Park         True          2441
```

Creating a bar chart based on this data

[306]:

```python
plt.figure(figsize=(16, 4))
sns.barplot(x=obs_by_park.park_name, y= obs_by_park.observations,
 ↪hue=obs_by_park.is_protected)
plt.xlabel('National Parks')
plt.ylabel('Number of Observations')
plt.title('Observations of Bats per Week')
plt.show()
```



2.2 Conclusions

The project was able to make several data visualizations and inferences about the various species in four of the National Parks that comprised this data set.

This project was also able to answer some of the questions first posed in the beginning:

- What is the distribution of conservation status for species?
  - The vast majority of species were not part of conservation.(24752 vs 880)
- Are certain types of species more likely to be endangered?
  - Mammals and Birds had the highest percentage of being in protection.
- Are the differences between species and their conservation status significant?
  - While mammals and Birds did not have significant difference in conservation percentage, mammals and reptiles exhibited a statistically significant difference.
- Which animal is most prevalent and what is their distribution amongst parks?
  - the study found that bats occurred the most number of times and they were most likely to be found in Yellowstone National Park.

- Found that number of species per park and most popular category is the same for all parks which proves that data is most likely to be artificial because its hard to imagine in real life

2.3 Further Research

This dataset only included observations from the last 7 days which prohibits analyze changes over time. It would be curious to see how the conservation status for various species changes over time. Another piece that is missing is the Area of each park, it can be assumed that Yellowstone National Park might be much larger than the other parks which would mean that it would exhibit more observations and greater biodiversity. Lastly, if precise locations were recorded, the spatial distribution of the species could also be observed and test if these observations are spatially clustered.

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