Biodiversity in Four US National Parks

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This project is an exploration of several biodiversity markers for various plant and animal species in four US national parks.

Throughout the project, we will explore, analyze, visualize, and make conclusions about the conservation efforts being made by the National Parks Service.

`Note: The datasets used for this project were provided by Codecademy.com. While they are inspired by real conservation data, they are mostly fictional, and have been provided for educational and demonstrative purposes only.`

Introduction

The US National Parks Service is the organization responsible for maintaining and preserving many nature reserves and heritage sites in the US. They're not just nature's custodians though; the parks service is responsible for closely monitoring the health and wellbeing of all the wildlife in our national parks. This analysis will take a look at some data from four US national parks and assess a few key markers of biodiversity.

The goal of this analysis will be to determine the following:

- What are the most common animals at each national park?
- How are the various conservation efforts distributed among different wildlife classifications?
- Are there significant differences in conservation efforts for different classifications of animals?
- How do rates of concervation efforts compare between plants and animals?

Setting Up

Start by importing the python libraries that will be used, adjusting some pandas output settings, and loading the datasets.

In [ ]:
```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
```

```python
from scipy.stats import chi2_contingency

pd.options.display.width = 0
pd.options.display.expand_frame_repr = False
pd.options.display.colheader_justify = 'left'

observations_raw = pd.read_csv('observations.csv')
species_raw = pd.read_csv('species_info.csv')
```

Data

Next, begin cleaning up the data, and take a look at how it is structured.

The `observations.csv` file contains 22164 unique observations of three variables, which are:

- scientific name
- park name
- number of observations

And the `species_info.csv` file contains 5541 unique observations of four variables, which are:

- category
- scientific name
- common name
- conservation status

In addition, we can also go ahead and merge our two dataframes, observations and species, into one dataframe containing all six variables.

`About duplicate values: Several animal and park combinations in observations.csv have duplicate entries with different observation counts. No clarification on these duplicate values was available, however it is assumed that these duplicate entries were meant to be updated after subsequent observation; as such the lower observation count entries are removed for the purpose of analysis. Duplicates in species_info.csv are 1:1 duplicates, and can therefore be removed without cause for concern.`

In [ ]:

```python
observations = observations_raw.sort_values('observations').drop_duplicates(['scien
species = species_raw.drop_duplicates(['scientific_name'])

print(f'observations: {observations.shape} {observations.columns}')
print(f'species: {species.shape} {species.columns}')

data = pd.merge(observations, species, on='scientific_name')
```

```
observations: (22164, 3) Index(['scientific_name', 'park_name', 'observations'], dty
pe='object')
species: (5541, 4) Index(['category', 'scientific_name', 'common_names', 'conservati
on_status'], dtype='object')
```

Next, assign a label to the missing values in our conservation status variable. Each Species is given an conservation status, with species which are not the focus of a conservation effort being unlabeled. For clarity, we will replace these missing values with 'No Intervention'.

In [ ]:
```
data.fillna('No Intervention', inplace = True)
```

Now that the missing values have been labeled, create two separate dataframes for plants and animals.

In [ ]:
```
plants = data[(data.category == 'Vascular Plant') | (data.category == 'Nonvascular
animals = data[(data.category != 'Vascular Plant') & (data.category != 'Nonvascular
```

Exploration

Now that the environment has been configured and the dataframes are set up, it's time to begin exploring the dataset. First, take a look at the number of plant and animal species, and the groups they're catgorized into.

Starting off, check the number of species of plants and animals, without breaking them down into further categorizations.

In [ ]:
```
print(f'Species of plants: {plants.scientific_name.nunique()}')
print(f'Species of animals: {animals.scientific_name.nunique()}')
```

```
Species of plants: 4595
Species of animals: 946
```

Taking a closer look, vascular plants, or plants with veins, are by far the most common specimine found in the national parks, with 4262 different species of vascular plant. The most common type of animal are birds, at 488 different species; the least common are reptiles with 78 different species, narrowly beating out amphibians which have 79.

In [ ]:
```
print(species.groupby(species.category).scientific_name.count())
```

```
category
Amphibian              79
Bird                  488
Fish                  125
Mammal                176
Nonvascular Plant     333
Reptile                78
Vascular Plant       4262
Name: scientific_name, dtype: int64
```

Next, we'll take a look at the most common animal at each park.

- Yellowstone National Park: Western Painted Turtle (307 sightings)
- Yosemite National Park: Red Knot (207 sightings)
- Bryce National Park: American Marten (167 sightings)
- Great Smoky Mountains National Park: Cackling Goose (139 sightings)

In [ ]:
```
print(animals.sort_values(['observations'], ascending = False).groupby(['park_name'
```

```
      scientific_name        park_name                            observations cat
egory common_names                        conservation_status
22155  Chrysemys picta bellii           Yellowstone National Park  307           Re
ptile              Western Painted Turtle  No Intervention
16770        Calidris canutus              Yosemite National Park  207
Bird                             Red Knot  No Intervention
15409           Bubulcus ibis                 Bryce National Park  164
Bird  Cattle Egret, Western Cattle Egret  No Intervention
12770        Branta hutchinsii  Great Smoky Mountains National Park  139
Bird                       Cackling Goose  No Intervention
```

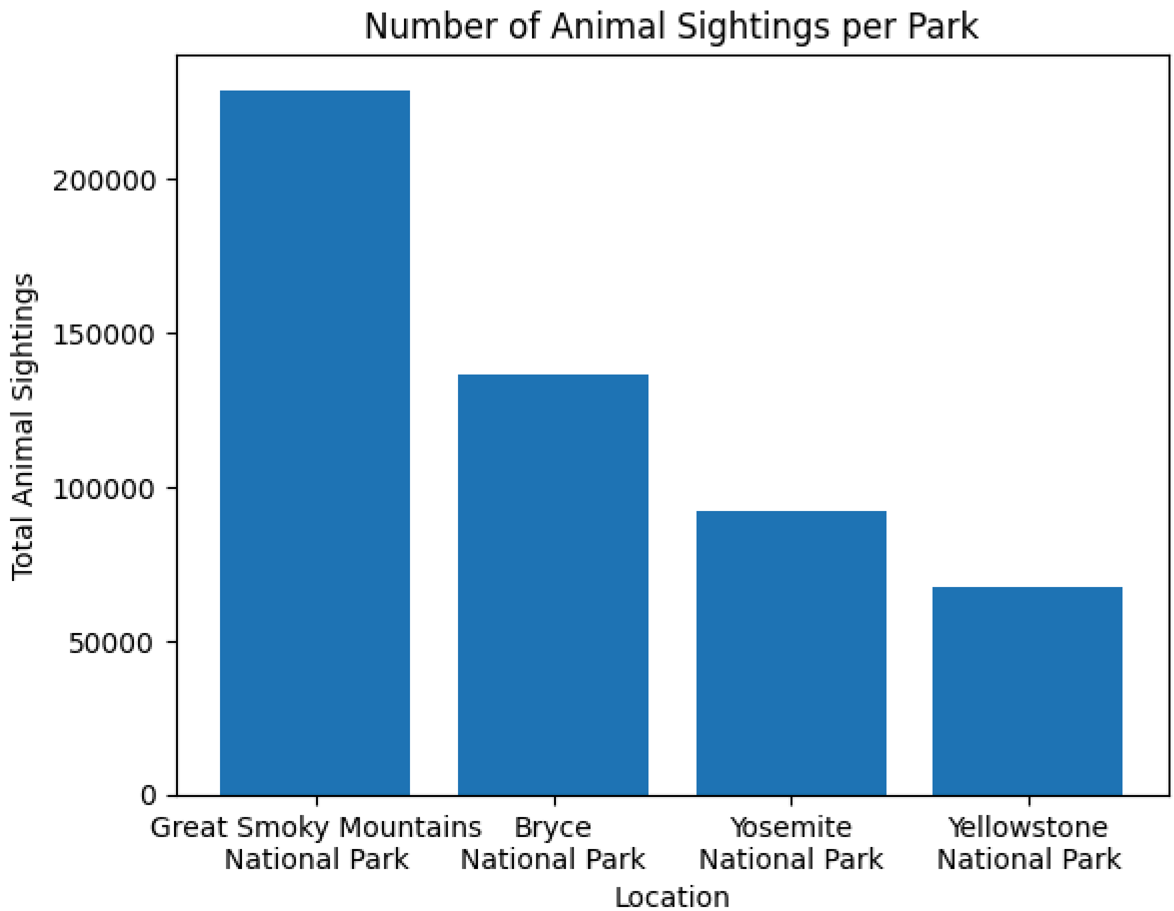
Interestingly, there is a sizeable gap in number of observations among the most popular animal at each park.

Taking a closer look, we can see that this trend is simply a reflection of overall animal populations for each area.

In [ ]:
```
print(animals.groupby('park_name').sum('observations').sort_values(by='observations

plt.bar(animals.park_name.unique(), animals.observations.groupby(animals.park_name)
plt.ticklabel_format(useOffset=False,style = 'plain', axis='y')
plt.xticks(animals.park_name.unique(), ['Great Smoky Mountains\nNational Park', 'Br
plt.xlabel('Location')
plt.ylabel('Total Animal Sightings')
plt.title('Number of Animal Sightings per Park')
plt.show(); plt.close()
```

```
                                     observations
park_name
Yellowstone National Park            228776
Yosemite National Park               136376
Bryce National Park                   91666
Great Smoky Mountains National Park   67099
```



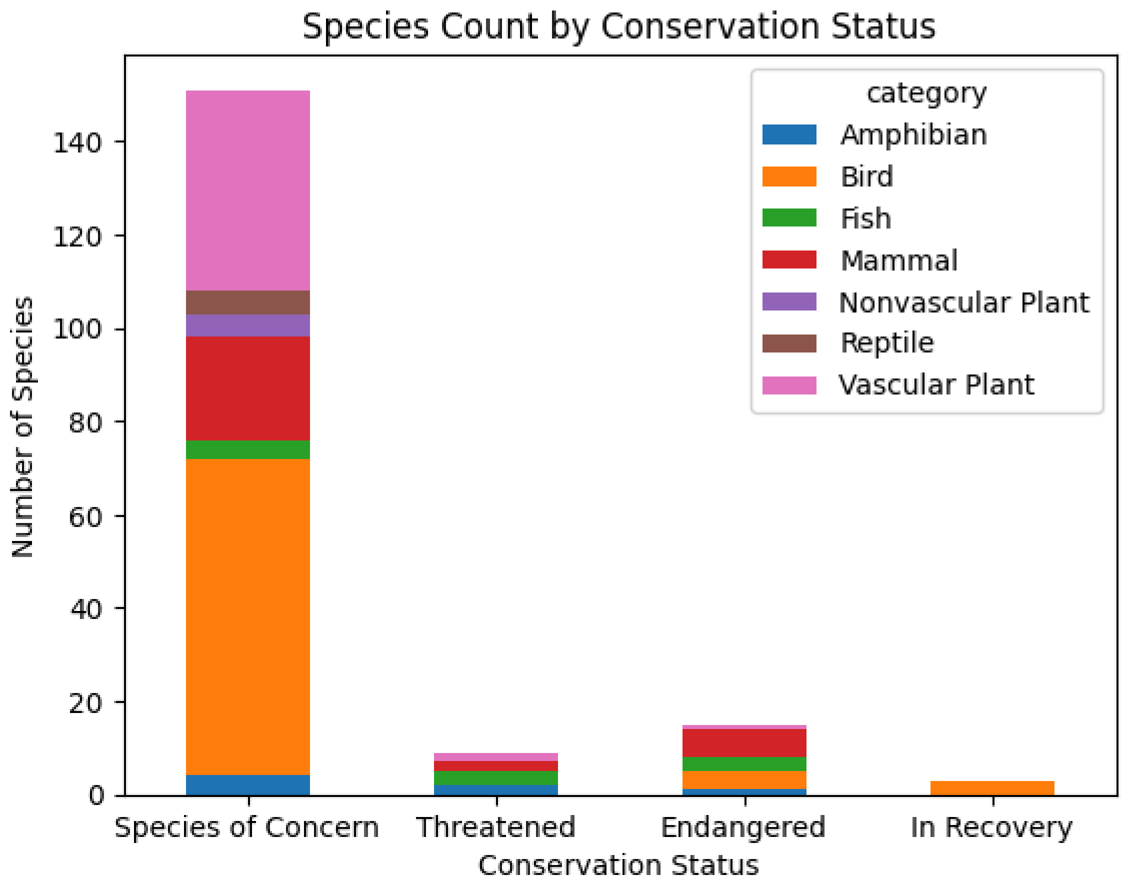
Analysis

Rates of Conservation Efforts

To begin the analysis, take a look at the distribution of conservation efforts for the various species classifications.

In [ ]:
```
category_threat = data[data['conservation_status'] != 'No Intervention'].groupby(['
category_threat.index = ([2,3,0,1])
category_threat.sort_index(inplace=True)
category_threat.index = (['Species of Concern','Threatened','Endangered','In Recove
category_threat.plot(kind = 'bar', stacked = True, title = 'Species Count by Conser
plt.xticks(rotation=0)
category_threat.fillna(0, inplace=True)
print(category_threat)
plt.show(); plt.close()
```

```
category            Amphibian   Bird  Fish  Mammal  Nonvascular Plant  Reptile  Vascu
lar Plant
Species of Concern  4.0         68.0  4.0   22.0    5.0                5.0      43.0
Threatened          2.0          0.0  3.0    2.0    0.0                0.0       2.0
Endangered          1.0          4.0  3.0    6.0    0.0                0.0       1.0
In Recovery         0.0          3.0  0.0    0.0    0.0                0.0       0.0
```



You might remember that there were 488 species of birds accounted for in our dataset. Looking at this distribution of conservation efforts, we can see that there are 75 species of bird that are seeing some kind of conservation effort, more than 15% of our total bird species. Let's check if birds are the largest concentration of conservation efforts.

While birds do have the second highest rate of conservation efforts, at ~15.3%, the top spot is actually taken by mammals, which sit at ~17%.

In [ ]:

```
threat_percentages = data.groupby('category').nunique()
threat_percentages['species'] = data.groupby('category').scientific_name.nunique()
threat_percentages['threatened'] = data[data['conservation_status'] != 'No Interven
threat_percentages['percentage'] = (data[data['conservation_status'] != 'No Interve
threat_percentages = threat_percentages[['species','threatened','percentage']]
print(threat_percentages)
```

```
                   species  threatened  percentage
category
Amphibian               79           7    0.088608
Bird                   488          75    0.153689
Fish                   125          10    0.080000
Mammal                 176          30    0.170455
Nonvascular Plant      333           5    0.015015
Reptile                 78           5    0.064103
Vascular Plant        4262          46    0.010793
```

Proportions of Conservation Efforts

While the percentage of each species group that needs conservation is certainly interesting, it's not the only metric that can be analyzed. Next we can find the proportion of conservation efforts each category accounts for.

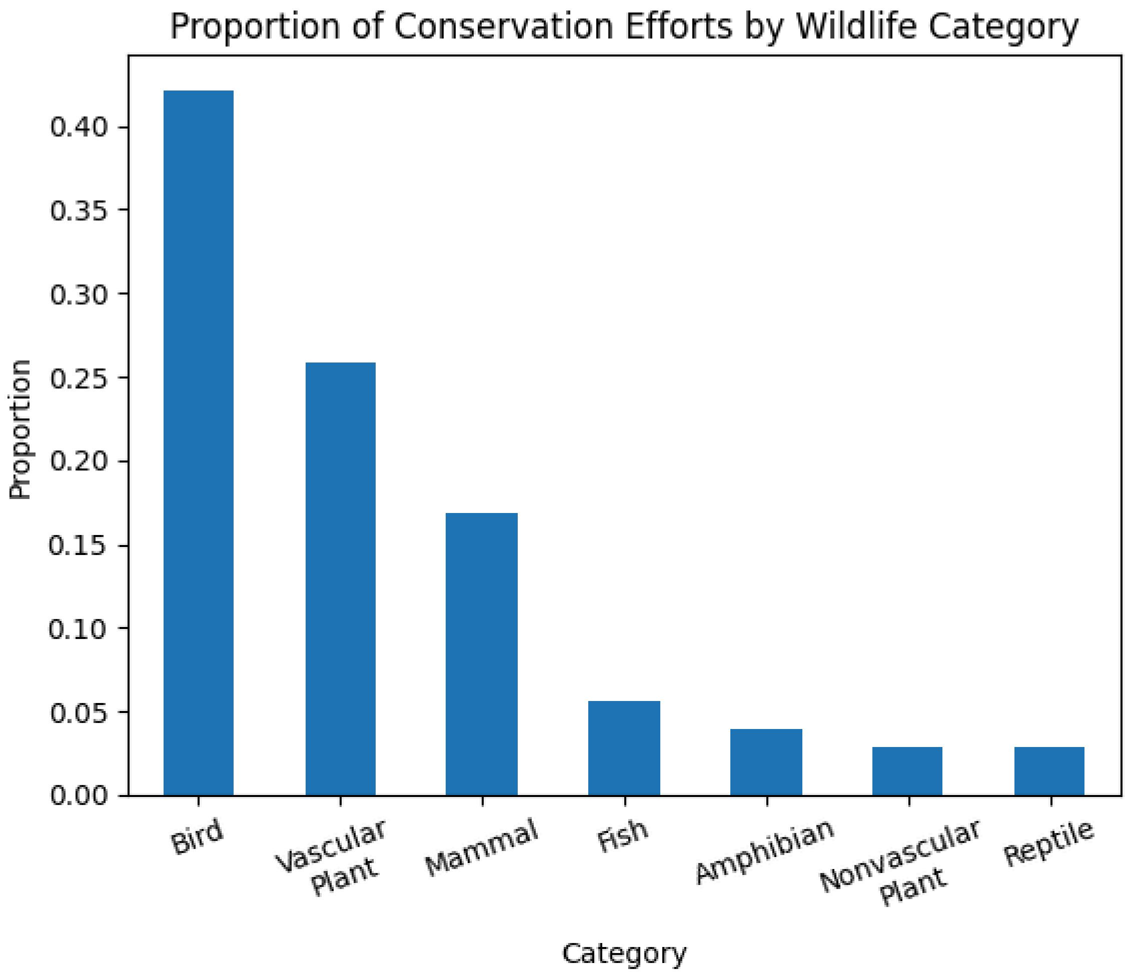
The highest of these is, as one might expect, birds, accounting for 42% of all conservation efforts.

In [ ]:
```
threat_percentages['proportion'] = (threat_percentages.threatened)/(threat_percenta
threat_percentages.sort_values('proportion', ascending = False, inplace = True)

category_labels = threat_percentages.index.tolist()
for x in range(len(category_labels)):
    category_labels[x] = category_labels[x].replace(' Plant', '\nPlant')

threat_percentages.plot(kind = 'bar', y='proportion', legend = None, title = 'Propo
plt.xticks(range(len(threat_percentages.index)), category_labels, rotation=20)
print(threat_percentages.proportion)
plt.show(); plt.close()
```

```
category
Bird                 0.421348
Vascular Plant       0.258427
Mammal               0.168539
Fish                 0.056180
Amphibian            0.039326
Nonvascular Plant    0.028090
Reptile              0.028090
Name: proportion, dtype: float64
```



Conservation Efforts Between Plants and Animals

The proportions we just calculated another good point: there seems to be a large disparity between the conservation efforts needed for plants and animals.

Calculating the ratio of conservation efforts for plants and animals shows that there are 2.5x more conservation efforts for animals than plants. Additionally, while only 1% of plant species are the focus of conservation efforts, conservation efforts are being made for 13% of animal species.

In [ ]:
```
ancount =  animals.groupby('category').scientific_name.nunique().sum()
anthreat = animals[animals['conservation_status'] != 'No Intervention'].groupby('ca
plcount = plants.groupby('category').scientific_name.nunique().sum()
plthreat = plants[plants['conservation_status'] != 'No Intervention'].groupby('cate

print(anthreat/plthreat)
print(anthreat/ancount)
print(plthreat/plcount)
```

```
2.4901960784313726
0.13424947145877378
0.011099020674646356
```

That's quite a difference. Let's check to make sure it is statistically significant.

After checking the Chi Squared statistic (329.77) and p-value (<0.000), large, statistically significant difference between the rates of conservation efforts for plants and animals.

In [ ]:
```
threat_ratios = np.array([[anthreat, plthreat],[ancount, plcount]])
result = chi2_contingency(threat_ratios)
print(f'Chi Squared Statistic (correlation): {result.statistic}\nP-value (significa
```

```
Chi Squared Statistic (correlation): 329.7662280127497
P-value (significance): 1.0806952989706841e-73
```

Conclusions

This analysis began with the goal to answer four questions. Having finished our analysis, the results are as follows:

- What are the most common animals at each national park?

The most prevalent animal at each park were the western painted turtle, red knot, american marten and cackling goose. The population size of these animals displayed a trend in overall animal populations at each of their respective parks.

- Are there significant differences in conservation efforts for different classifications of animals?

Conservation efforts for various animal classifications range from ~6.5% to ~17%.

- How are the various conservation efforts distributed among different wildlife classifications?

Birds are the most group of species to be the subject of conservation, with ~42% of conservation efforts being for birds. They are followed by vascular plants at ~25% and mammals at ~17%.

- How do rates of concervation efforts compare between plants and animals?

Conservation efforts are focused primarily on animals, with 2.5x the number of animal species receiving conservation efforts compared to plants. Additionally, 1% of all plant species recieve conservation efforts, whereas the same is true for 13% of animals.

Future Research

Being that this is cross-sectional data, it is not possible to determine any sort of change over time regarding what types of species need concentration efforts. The incorporation of time-series data would allow for the assessment of effectiveness of ongoing conservation efforts. Additionally, this dataset is only for four national parks, of which there are several hundred;

incorporating data from a larger selection of parks may reveal different trends in biodiversity.