biodiversity_parks

September 14, 2021

1 Biodiversity In National Parks

1.1 Introduction

In this project, we will seek to discover more about the health of species that reside in the United States' National Parks.

First we will define and scope our project. Then we can analyze our data, prepare it, plot it, and lastly, discuss and evaluate our findings.

- 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?

1.2 Scoping

Whenever starting a project it is pertinent to define its boundaries and end points. 1. We will discuss our project goals and intentions. 2. We will discuss our data and its viability in achieving our objectives. 3. We will analyze our data. 4. We will evaluate and discuss our findings.

1.2.1 Project Goals

The viewpoint we will be taking in this endeavor is that of a biodiversity analyst for the National Parks Service. In order ensure the biodiversity of their parks it is necessary for the service to know which species are at risk and what their park distribution is.

As such, our primary goals in the project will be to answer the following questions: - What is the distribution of conservation status for our available species? - Are certain species more likely to be endangered? - If differences exist between species and their conservation status, is it significant? - What are the most prevalent species and what is their park distribution?

1.2.2 Data

Our data is comprised of two csv files containing: - `species_info.csv`: Species information including type, name, and conservation status - `observations.csv`: Sightings of species in the past 7 days, organized by park Given our previous questions it appears we can at least partially achieve our objectives.

1.2.3 Analysis

We will utilize descriptive statistics and visualizations of the data to better understand it. Following this, we will test the observed values for significance. Some of these metrics include:

1. Data Distribution
2. Counts
3. The Relationship Between Species
4. The Conservation Status of Various Species
5. The Observations of Species in the Parks

1.2.4 Evaluation

Finally, we will revisit our previous questions and discuss the impact of our findings. Additionally, we will discuss the limitations of our research and investigate areas of future study.

1.2.5 Imports

[90]:
```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns
from scipy.stats import chi2_contingency
from itertools import chain
import string
%matplotlib inline
# setting pandas options
pd.set_option('display.max_columns', 500)
```

1.3 Data Analysis

We can start by loading in our data and checking its columns and first few rows in order to describe it.

species `species_info.csv` contains information on the observed species and contains the following columns: - **category** - The taxonomy category of a species, categorical variable - **scientific_name** - The scientific name of each species, categorical variable - **common_names** - The common names of each species, categorical variable - **conservation_status** - The species conservation status, ordinal variable

observations `observations.csv` details recorded sightings of different species in the parks over the past 7 days. The columns it includes are: - **scientific_name** - Each species scientific name, categorical variable - **park_name** - The name of the associated national park, categorical variable - **observations** - Observations in the past week, continuous variable

[91]:
```
species = pd.read_csv('species_info.csv', encoding='utf-8')
species.head()
```

[91]:
```
  category                scientific_name  \
0   Mammal  Clethrionomys gapperi gapperi
1   Mammal                      Bos bison
2   Mammal                     Bos taurus
3   Mammal                     Ovis aries
4   Mammal                  Cervus elaphus

                                    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
```

[92]:
```
observations = pd.read_csv('observations.csv', encoding='utf-8')
observations.head()
```

[92]:
```
            scientific_name                            park_name  observations
0        Vicia benghalensis  Great Smoky Mountains National Park            68
1            Neovison vison  Great Smoky Mountains National Park            77
2         Prunus subcordata               Yosemite National Park           138
3      Abutilon theophrasti                  Bryce National Park            84
4  Githopsis specularioides  Great Smoky Mountains National Park            85
```

Data Characteristics The dimensions of our data sets can tell us how much about our data. `species` contains 5,284 rows and 4 columns and `observations` contains 23,296 rows and 3 columns.

[93]:
```
print(f'Species Columns: {species.columns}')
print(f'Observations Columns: {observations.columns}')
print(f'Species Shape: {species.shape}')
print(f'Observations Shape: {observations.shape}')
```

```
Species Columns: Index(['category', 'scientific_name', 'common_names',
'conservation_status'], dtype='object')
Observations Columns: Index(['scientific_name', 'park_name', 'observations'],
dtype='object')
Species Shape: (5824, 4)
Observations Shape: (23296, 3)
```

There are 5,541 unique species available in our data.

[94]:
```
print(f'Number of species:{species.scientific_name.nunique()}')
```

```
Number of species:5541
```

There are 7 categories comprised of both animal and plant life.

[95]:
```
## species_info.csv overview
# getting the number of categories in species
```

```
print(f'Number of categories in Species: {species.category.nunique()}')
print(f'Category types: {species.category.unique()}')
```

```
Number of categories in Species: 7
Category types: ['Mammal' 'Bird' 'Reptile' 'Amphibian' 'Fish' 'Vascular Plant'
 'Nonvascular Plant']
```

We see that there are 4,470 species of vascular plants and only 79 species of reptile.

[96]:
```
# determining the size of each category in species
print(species.groupby('category').size())
```

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

Now let's look at our primary indicator of species endangerment, `conservation status`. There are 5 main values: `Endangered`, `In Recovery`, `Species of Concern`, `Threatened`, and `nan`. These 5,633 values mostly consist of null entries, which in this case indicates no conservation status.

[97]:
```
# conservation statues exploration
print(f'Number of conservation statuses:{species.conservation_status.
 ↪nunique()}')
print(f'Conservation statuses:{species.conservation_status.unique()}')
# Note: nan values indicate species not in threat of extinction due to no␣
 ↪conservation status
print(f'nan values: {species.conservation_status.isna().sum()}')
print(species.groupby('conservation_status').size())
```

```
Number of conservation statuses:4
Conservation statuses:[nan 'Species of Concern' 'Endangered' 'Threatened' 'In
Recovery']
nan values: 5633
conservation_status
Endangered             16
In Recovery             4
Species of Concern    161
Threatened             10
dtype: int64
```

The observations data contains 4 main parks: `Great Smoky Mountains National Park`, `Yosemite National Park`, `Bryce National Park`, and `Yellowstone National Park`. Over the past week there were 3,314,739 observations.

[98]:
```
## observations.csv overview
# determining the number of parks in the set
print(f'Number of parks: {observations.park_name.nunique()}')
print(f'Unique parks: {observations.park_name.unique()}')
```

```
Number of parks: 4
Unique parks: ['Great Smoky Mountains National Park' 'Yosemite National Park'
 'Bryce National Park' 'Yellowstone National Park']
```

[99]:
```
# getting the total observations in the past week
print(f'Number of observations: {observations.observations.sum()}')
```

```
Number of observations: 3314739
```

1.3.1 Analysis

After exploring our data we need to clean it. First we will take care of the null values in `conservation status` by changing them to `No Concern`.

[100]:
```
# changing the nan values in species to a new status 'No Concern'
species.fillna('No Concern', inplace=True)
print(species.groupby('conservation_status').size())
```

```
conservation_status
Endangered              16
In Recovery              4
No Concern            5633
Species of Concern     161
Threatened              10
dtype: int64
```

Since our data is now cleaned, we explore the breakdown of species in conservation status.

[101]:
```
# filtering species based on status and then pivoting the table
conservationCategory = species[species.conservation_status != 'No Concern']\
        .groupby(['conservation_status', 'category'])['scientific_name']\
        .count()\
        .unstack()
print(conservationCategory)
```

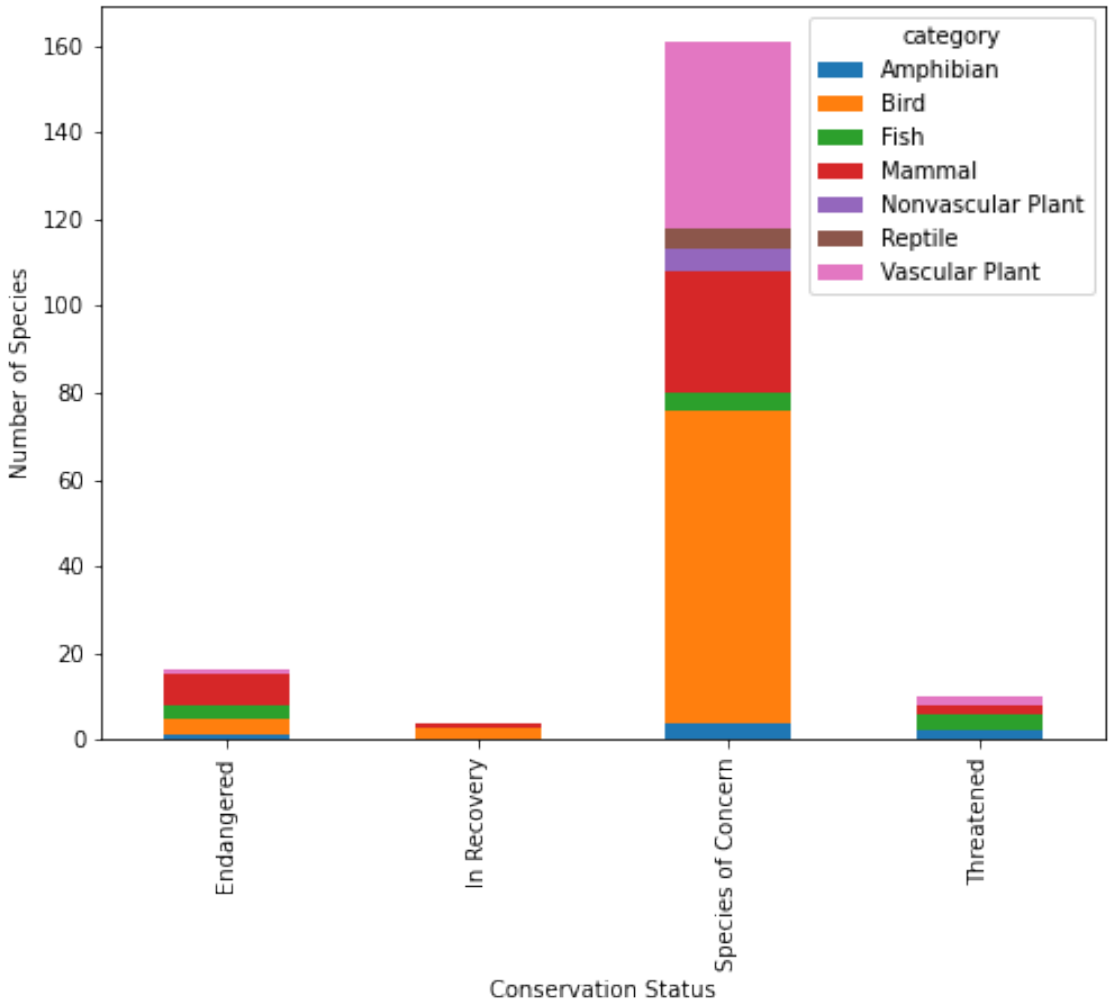
```
category             Amphibian  Bird  Fish  Mammal  Nonvascular Plant  \
conservation_status
Endangered                 1.0   4.0   3.0     7.0                NaN
In Recovery                NaN   3.0   NaN     1.0                NaN
Species of Concern         4.0  72.0   4.0    28.0                5.0
Threatened                 2.0   NaN   4.0     2.0                NaN

category             Reptile  Vascular Plant
conservation_status
Endangered               NaN             1.0
```

```
In Recovery              NaN             NaN
Species of Concern       5.0            43.0
Threatened               NaN             2.0
```

This data can be made easier to understand graphically. We will use a stacked bar plot of conservation status vs. the number of species, and segment each bar by species category.

[102]:
```
# visualizing species based on conservation status
ax = conservationCategory.plot(kind = 'bar', figsize=(8,6),
                               stacked=True)
ax.set_xlabel("Conservation Status")
ax.set_ylabel("Number of Species")
```

[102]: Text(0, 0.5, 'Number of Species')



1.3.2 Conservation

Now we will determine if a species is more likely to be endangered in comparison to another. First we will class species without a conservation status as `is_protected`.

[103]:
```
## Are different species more likely to be protected on a per category basis?
# creating a column 'is_protected' based on exclusion of 'No Concern'
species['is_protected'] = species.conservation_status != 'No Concern'
```

We then use this binary classifier to show which species categories are protected by total numbers.

[104]:
```
category_counts = species.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
```

[104]:

	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

Let's also look at what percent of each category is considered `protected`.

[105]:
```
# determining percent protected per category
category_counts['percent_protected'] = category_counts.protected / \
                                       (category_counts.protected +␣
 ↪category_counts.not_protected) * 100
category_counts
```

[105]:

	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

1.3.3 Statistical Significance

We will primarly be using chi-squared tests on our categorical variables to determine if there is a significant difference between species in regards to conservation status rates. We will be using a standard p-value cutoff of 0.05 to test our hypothesis.

When comparing `Mammal` and `Bird` we get a p-value = 0.69, far above our cutoff and thus likely independent of each other.

[106]:
```
contingency1 = [
    [category_counts.at[3,'protected'], category_counts.at[3,'not_protected']],
    [category_counts.at[1,'protected'], category_counts.at[1,'not_protected']]
    ]
chi2_contingency(contingency1)
```

[106]:
```
(0.1617014831654557,
 0.6875948096661336,
 1,
 array([[ 27.8313253, 148.1686747],
        [ 77.1686747, 410.8313253]]))
```

However, in the comparison of `Mammal` and `Reptile` we get a p-value = 0.039. This provides evidence that when compared to reptiles, mammals are in significantly higher need of protection.

[107]:
```
contingency2 = [
    [category_counts.at[3,'protected'], category_counts.at[3,'not_protected']],
    [category_counts.at[5,'protected'], category_counts.at[5,'not_protected']]
    ]
chi2_contingency(contingency2)
```

[107]:
```
(4.289183096203645,
 0.03835559022969898,
 1,
 array([[ 24.2519685, 151.7480315],
        [ 10.7480315,  67.2519685]]))
```

1.3.4 Park Species

Now we can look at the observations recorded amongst the various parks.

From our inspection earlier it's apparent that the names need some cleaning.

[108]:
```
# creating a method for taking the punctuation out of text
def del_punctuation(text):
    for punctuation in string.punctuation:
        text = text.replace(punctuation, '')
        return text

# generating basic names
common_names = species[species.category == 'Mammal']\
```

```
    .common_names\
    .apply(del_punctuation)\
    .str.split().tolist()

print(common_names[:6])
```

```
[["Gapper's", 'Red-Backed', 'Vole'], ['American', 'Bison,', 'Bison'],
['Aurochs,', 'Aurochs,', 'Domestic', 'Cattle', '(Feral),', 'Domesticated',
'Cattle'], ['Domestic', 'Sheep,', 'Mouflon,', 'Red', 'Sheep,', 'Sheep',
'(Feral)'], ['Wapiti', 'Or', 'Elk'], ['White-Tailed', 'Deer']]
```

We also have to eliminate duplicate words in the rows, since they should only be counted once per species.

[109]:
```
cleaned_rows = []

# taking only one from each
for item in common_names:
    item = list(dict.fromkeys(item))
    # adding each to list
    cleaned_rows.append(item)

print(cleaned_rows[:6])
```

```
[["Gapper's", 'Red-Backed', 'Vole'], ['American', 'Bison,', 'Bison'],
['Aurochs,', 'Domestic', 'Cattle', '(Feral),', 'Domesticated'], ['Domestic',
'Sheep,', 'Mouflon,', 'Red', 'Sheep', '(Feral)'], ['Wapiti', 'Or', 'Elk'],
['White-Tailed', 'Deer']]
```

Then we collapse all the words into one list.

[110]:
```
# using list comprehension
simple_list = list(chain.from_iterable(i if isinstance(i, list) else [i] for i␣
 ↪in cleaned_rows))
print(simple_list)
```

```
["Gapper's", 'Red-Backed', 'Vole', 'American', 'Bison,', 'Bison', 'Aurochs,',
'Domestic', 'Cattle', '(Feral),', 'Domesticated', 'Domestic', 'Sheep,',
'Mouflon,', 'Red', 'Sheep', '(Feral)', 'Wapiti', 'Or', 'Elk', 'White-Tailed',
'Deer', 'Feral', 'Hog,', 'Wild', 'Pig', 'Coyote', 'Gray', 'Wolf', 'Red', 'Wolf',
'Common', 'Gray', 'Fox,', 'Fox', 'Black', 'Fox,', 'Cross', 'Red', 'Silver',
'Fox', 'Red', 'Fox', 'Mountain', 'Lion', 'Wild', 'Cat,', 'Wildcat', 'Bobcat',
'Panther', '(Mountain', 'Lion)', 'Striped', 'Skunk', 'Eastern', 'Spotted',
'Skunk', 'River', 'Otter', 'Northern', 'River', 'Otter', 'Fisher', 'Mink',
'(Or', 'Weasel)', 'Long-Tailed', 'Weasel', 'Least', 'Weasel', 'Mink', 'Common',
'Raccoon,', 'Raccoon', 'Black', 'Bear', "Rafinesque's", 'Big-Eared', 'Bat',
'Big', 'Brown', 'Bat', 'Silver-Haired', 'Bat', 'Eastern', 'Red', 'Bat,', 'Bat',
'Hoary', 'Bat', 'Mississippi', 'Myotis,', 'Southeastern', 'Myotis', 'Gray',
'Myotis', "Keen's", 'Myotis', 'Eastern', 'Small-Footed', 'Bat,', 'Myotis',
'Little', 'Brown', 'Bat,', 'Myotis', 'Northern', 'Long-Eared', 'Bat,', 'Myotis',
```

'Indiana', 'Bat,', 'Or', 'Social', 'Myotis', 'Evening', 'Bat', 'Eastern',
'Pipistrelle', 'Virginia', 'Opossum,', 'Oppossum', 'Snowshoe', 'Hare',
'Eastern', 'Cottontail', 'Appalachian', 'Cottontail', 'New', 'England',
'Cottontail', 'Feral', 'Horse,', 'Horse', 'Human,', 'Humans,', 'Man',
'American', 'Beaver,', 'Beaver', 'Southern', 'Red-Backed', 'Vole', 'Rock',
'Vole,', 'Southern', 'Vole', 'Meadow', 'Vole', 'Woodland', 'Vole', 'Eastern',
'Woodrat', 'Allegheny', 'Woodrat,', 'Appalachian', 'Woodrat', 'Golden', 'Mouse',
'Muskrat', 'Marsh', 'Rice', 'Rat', 'Marsh', 'Rice', 'Rat', 'Cotton', 'Mouse',
'White-Footed', 'Mouse', 'Deer', 'Mouse', 'Eastern', 'Harvest', 'Mouse',
'Southern', 'Bog', 'Lemming', "Stone's", 'Southern', 'Bog', 'Lemming',
'Woodland', 'Jumping', 'Mouse', 'Meadow', 'Jumping', 'Mouse', 'Common',
'Porcupine,', 'Porcupine', 'House', 'Mouse', 'Norway', 'Rat', 'Black', 'Rat',
'Carolina', 'Northern', 'Flying', 'Squirrel,', 'Squirrel', 'Southern', 'Flying',
'Squirrel', 'Woodchuck', 'Eastern', 'Gray', 'Squirrel,', 'Squirrel', 'Eastern',
'Fox', 'Squirrel,', 'Squirrel', 'Eastern', 'Chipmunk', 'Red', 'Squirrel',
'Northern', 'Short', 'Tailed', 'Shrew,', 'Short-Tailed', 'Shrew', 'Least',
'Shrew', 'Common', 'Shrew,', 'Masked', 'Shrew', 'Long-Tailed', 'Or', 'Rock',
'Shrew,', 'Shrew', 'Smoky', 'Shrew', 'Pygmy', 'Shrew', 'Southeastern', 'Shrew',
'Water', 'Shrew', 'Star-Nosed', 'Mole', 'Hairy-Tailed', 'Mole', 'Eastern',
'Mole', 'Antelope,', 'Pronghorn', 'Bison,', 'Buffalo', 'Mountain', 'Goat,',
'Rocky', 'Goat', 'Bighorn', 'Sheep,', 'Sheep', 'Eurasian', 'Elk,', 'Moose',
'Yellowstone', 'Moose', 'Rocky', 'Mountain', 'Elk', 'Mule', 'Deer,', 'Deer',
'White-Tailed', 'Deer,', 'Deer', 'Gray', 'Wolf,', 'Wolf', 'Canada', 'Lynx,',
'Canadian', 'Lynx', 'Cougar,', 'Mountain', 'Lion,', 'Puma', 'Western',
'Spotted', 'Skunk', 'Wolverine', 'River', 'Otter', 'Pine', 'Marten', 'Ermine,',
'Short', 'Tailed', 'Weasel', 'American', 'Mink,', 'Mink', 'American', 'Badger,',
'Badger', 'Common', 'Raccoon,', 'Northern', 'Raccoon', 'American', 'Black',
'Bear,', 'Bear', 'Grizzly', 'Bear', 'Pallid', 'Bat,', 'Bat', 'Mule-Eared',
'Bat,', 'Pacific', "Townsend's", 'Big-Eared', 'Western', 'Long-Eared', 'Lump-
Nosed', 'Bat', 'Big', 'Brown', 'Bat,', 'Bat', 'Spotted', 'Bat,', 'Bat', 'Silver-
Haired', 'Bat,', 'Bat', 'Hoary', 'Bat,', 'Bat', 'California', 'Myotis,',
'Californian', 'Myotis', 'Small-Footed', 'Myotis,', 'Western', 'Bat,', 'Myotis',
'Long-Eared', 'Myotis,', 'Myotis', 'Little', 'Brown', 'Bat,', 'Myotis,',
'Myotis', 'Fringed', 'Myotis,', 'Myotis', 'Long-Legged', 'Myotis,', 'Myotis',
'Yuma', 'Myotis,', 'Myotis', 'White-Tailed', 'Jack', 'Rabbit,', 'Jackrabbit',
'Desert', 'Cottontail', 'Mountain', 'Cottontail', 'American', 'Pika,', 'Pika',
'American', 'Beaver', 'Sagebrush', 'Vole', 'Coronation', 'Island', 'Vole,',
'Long-Tailed', 'Vole', 'Montane', 'Vole', 'Richardson', 'Water', 'Vole', 'Bushy-
Tailed', 'Woodrat', 'Common', 'Muskrat,', 'Muskbeaver,', 'Muskrat', 'Deer',
'Mouse,', 'North', 'American', 'Deermouse', 'Heather', 'Vole,', 'Western',
'Vole', 'Western', 'Jumping', 'Mouse', 'Northern', 'Pocket', 'Gopher',
'Northern', 'Flying', 'Squirrel', 'Yellow-Bellied', 'Marmot', 'Yellow', 'Pine',
'Chipmunk', 'Least', 'Chipmunk', 'Uinta', 'Chipmunk', 'Uinta', 'Ground',
'Squirrel', 'Golden-Mantled', 'Ground', 'Squirrel', 'Yellow-Pine', 'Chipmunk',
'Least', 'Chipmunk', 'Uinta', 'Chipmunk', 'Cinereus', 'Shrew,', 'Common',
'Masked', 'Shrew', 'American', 'Pygmy', 'Shrew,', 'Shrew', 'Dusky', 'Shrew',
'Dwarf', 'Shrew,', 'Rocky', 'Mountain', 'Shrew', 'American', 'Water', 'Shrew,',
'Northern', 'Shrew', 'Malheur', 'Shrew,', "Preble's", 'Shrew', 'Sierra',

```
'Nevada', 'Bighorn', 'Sheep', 'Pig,', 'Pig', '(Feral),', 'Wild', 'Boar,',
'Boar', 'Gray', 'Wolf,', 'Wolf', 'Gray', 'Fox', 'Sierra', 'Nevada', 'Red',
'Fox', 'Mountain', 'Lion', 'Spotted', 'Skunk', 'American', 'Marten,', 'Marten',
'Ermine', 'American', 'Mink', 'Fisher', 'Badger', 'Ringtail', 'Raccoon',
'Brown', 'Bear,', 'Grizzly', 'Bear', 'Western', 'Mastiff', 'Bat', 'Mexican',
'Free-Tailed', 'Bat', "Townsend's", 'Big-Eared', 'Bat', 'Western', 'Red', 'Bat',
'California', 'Myotis', 'Small-Footed', 'Myotis', 'Little', 'Brown', 'Myotis',
'Canyon', 'Bat', 'Virginia', 'Opossum', 'Sierra', 'Nevada', 'Snowshoe', 'Hare',
'Western', 'White-Tailed', 'Jackrabbit', 'Brush', 'Rabbit', 'Pika', 'Sierra',
'Nevada', 'Mountain', 'Beaver', 'Beaver', 'California', 'Meadow', 'Mouse',
'Long-Tailed', 'Vole', 'Big-Eared', 'Woodrat', 'Big-Eared', 'Woodrat', 'Brush',
'Deermouse,', 'Mouse', 'California', 'Mouse', 'Pi_On', 'Deermouse,', 'Mouse,',
'Pinyon', 'Mouse', 'Western', 'Harvest', 'Mouse', 'Porcupine', "Botta's",
'Pocket', 'Gopher', 'Mountain', 'Pocket', 'Gopher', 'California', 'Pocket',
'Mouse', 'Golden-Mantled', 'Ground', 'Squirrel', 'California', 'Ground',
'Squirrel', 'Western', 'Gray', 'Squirrel', 'Alpine', 'Chipmunk', "Merriam's",
'Chipmunk', 'Long-Eared', 'Chipmunk', "Allen's", 'Chipmunk,', 'Shadow',
'Chipmunk', 'Lodgepole', 'Chipmunk', 'Inyo', 'Chipmunk', 'Chickaree',
"Belding's", 'Ground', 'Squirrel', 'Mount', 'Lyell', 'Shrew', 'Montane',
'Shrew', 'Inyo', 'Shrew', "Trowbridge's", 'Shrew', 'Broad-Footed', 'Mole']
```

Now we can count our observations!

[111]:
```
word_counts = []
for i in simple_list:
    n = simple_list.count(i)
    word_counts.append((i,n))

# making a df from our words and counts
df = pd.DataFrame(set(word_counts), columns=['Animal', 'Count']).
 ↪sort_values('Count', ascending=False)
df.head()
```

[111]:

	Animal	Count
54	Shrew	18
69	Myotis	17
90	Bat	17
33	Mouse	15
201	Chipmunk	13

Since there are several scientific names for each species of animal, we need to check if they are all the same species. We do this using str.contains and regex. We will use bats as an example.

[112]:
```
species['is_Bat'] = species.common_names.str.contains(r'\bBat\b', regex=True)
species.head(10)
```

[112]:

	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          No Concern
1                             American Bison, Bison          No Concern
2  Aurochs, Aurochs, Domestic Cattle (Feral), Dom…          No Concern
3  Domestic Sheep, Mouflon, Red Sheep, Sheep (Feral)          No Concern
4                                    Wapiti Or Elk          No Concern
5                                White-Tailed Deer          No Concern
6                              Feral Hog, Wild Pig          No Concern
7                                           Coyote  Species of Concern
8                                       Gray Wolf          Endangered
9                                        Red Wolf          Endangered

   is_protected  is_Bat
0         False   False
1         False   False
2         False   False
3         False   False
4         False   False
5         False   False
6         False   False
7          True   False
8          True   False
9          True   False
```

Now we can select the rows where a species `is_Bat`.

[113]:
```
species[species.is_Bat]
```

[113]:
```
     category            scientific_name  \
28     Mammal   Corynorhinus rafinesquii
29     Mammal           Eptesicus fuscus
30     Mammal  Lasionycteris noctivagans
31     Mammal          Lasiurus borealis
32     Mammal          Lasiurus cinereus
36     Mammal              Myotis leibii
37     Mammal           Myotis lucifugus
38     Mammal     Myotis septentrionalis
39     Mammal             Myotis sodalis
40     Mammal       Nycticeius humeralis
```

```
3033   Mammal         Antrozous pallidus
3034   Mammal    Corynorhinus townsendii
3035   Mammal           Eptesicus fuscus
3036   Mammal          Euderma maculatum
3037   Mammal  Lasionycteris noctivagans
3038   Mammal          Lasiurus cinereus
3040   Mammal         Myotis ciliolabrum
3042   Mammal           Myotis lucifugus
4461   Mammal             Eumops perotis
4462   Mammal      Tadarida brasiliensis
4463   Mammal    Corynorhinus townsendii
4464   Mammal      Lasiurus blossevillii
4468   Mammal      Parastrellus hesperus

                                          common_names conservation_status  \
28                          Rafinesque's Big-Eared Bat          No Concern
29                                       Big Brown Bat  Species of Concern
30                                 Silver-Haired Bat  Species of Concern
31                           Eastern Red Bat, Red Bat          No Concern
32                                        Hoary Bat          No Concern
36   Eastern Small-Footed Bat, Eastern Small-Footed…  Species of Concern
37               Little Brown Bat, Little Brown Myotis  Species of Concern
38            Northern Long-Eared Bat, Northern Myotis          Threatened
39               Indiana Bat, Indiana Or Social Myotis          Endangered
40                                     Evening Bat          No Concern
3033                         Pallid Bat, Pallid Bat  Species of Concern
3034  Mule-Eared Bat, Pacific Townsend's Big-Eared B…          No Concern
3035                      Big Brown Bat, Big Brown Bat  Species of Concern
3036                          Spotted Bat, Spotted Bat  Species of Concern
3037               Silver-Haired Bat, Silver-Haired Bat  Species of Concern
3038                             Hoary Bat, Hoary Bat          No Concern
3040  Small-Footed Myotis, Western Small-Footed Bat,…          No Concern
3042  Little Brown Bat, Little Brown Myotis, Little …  Species of Concern
4461                              Western Mastiff Bat          No Concern
4462                           Mexican Free-Tailed Bat          No Concern
4463                          Townsend's Big-Eared Bat          No Concern
4464                                   Western Red Bat  Species of Concern
4468                                        Canyon Bat          No Concern

     is_protected  is_Bat
28          False    True
29           True    True
30           True    True
31          False    True
32          False    True
36           True    True
37           True    True
```

```
38            True    True
39            True    True
40           False    True
3033          True    True
3034         False    True
3035          True    True
3036          True    True
3037          True    True
3038         False    True
3040         False    True
3042          True    True
4461         False    True
4462         False    True
4463         False    True
4464          True    True
4468         False    True
```

Now that we know where our bats exist we can combine this with our observations to get a bit more information.

[114]:
```
Bat_observations = observations.merge(species[species.is_Bat])
Bat_observations
```

[114]:
```
              scientific_name                          park_name  \
0       Lasiurus blossevillii                 Bryce National Park
1       Lasiurus blossevillii  Great Smoky Mountains National Park
2       Lasiurus blossevillii              Yosemite National Park
3       Lasiurus blossevillii           Yellowstone National Park
4    Corynorhinus rafinesquii              Yosemite National Park
..                        …                                  …
139           Myotis sodalis           Yellowstone National Park
140            Myotis leibii              Yosemite National Park
141            Myotis leibii                 Bryce National Park
142            Myotis leibii  Great Smoky Mountains National Park
143            Myotis leibii           Yellowstone National Park

     observations category                                       common_names  \
0             113   Mammal                                     Western Red Bat
1              70   Mammal                                     Western Red Bat
2             123   Mammal                                     Western Red Bat
3             221   Mammal                                     Western Red Bat
4             188   Mammal                       Rafinesque's Big-Eared Bat
..            …      …                                                    …
139            68   Mammal             Indiana Bat, Indiana Or Social Myotis
140           132   Mammal  Eastern Small-Footed Bat, Eastern Small-Footed…
141            84   Mammal  Eastern Small-Footed Bat, Eastern Small-Footed…
142            49   Mammal  Eastern Small-Footed Bat, Eastern Small-Footed…
143           233   Mammal  Eastern Small-Footed Bat, Eastern Small-Footed…
```

```
    conservation_status  is_protected  is_Bat
0    Species of Concern          True    True
1    Species of Concern          True    True
2    Species of Concern          True    True
3    Species of Concern          True    True
4            No Concern         False    True
..                  …           …     …
139          Endangered          True    True
140  Species of Concern          True    True
141  Species of Concern          True    True
142  Species of Concern          True    True
143  Species of Concern          True    True

[144 rows x 8 columns]
```

Therefore, in the past week we had 18,992 bat sightings! Most in Yellowstone National Park.

[115]:
```
Bat_observations.groupby('park_name').observations.sum().reset_index()
```

[115]:
```
                           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
```

We can also break down sightings between protected and not_protected sightings.

[116]:
```
obs_by_park = Bat_observations.groupby(['park_name', 'is_protected']).
↪observations.sum().reset_index()
obs_by_park
```

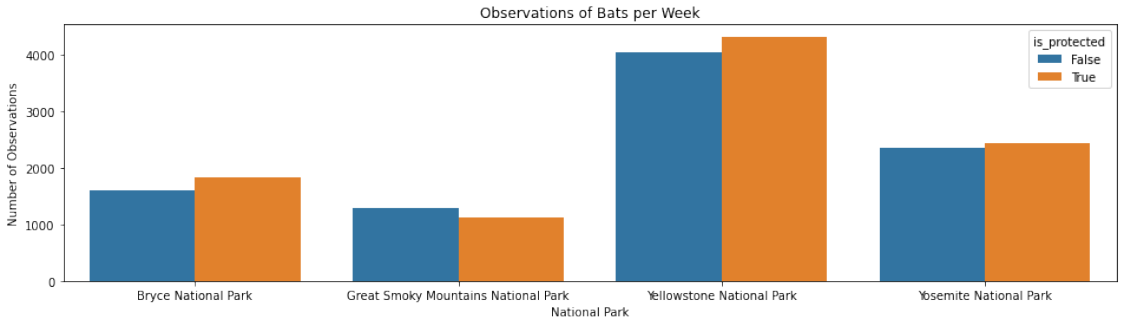
[116]:
```
                           park_name  is_protected  observations
0                 Bryce National Park         False          1596
1                 Bryce National Park          True          1837
2  Great Smoky Mountains National Park         False          1299
3  Great Smoky Mountains National 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
```

Finally, we will plot the data of these sightings. We can compare the numbers of protected to non protected to determine how well each parks conservation efforts are doing.

[117]:
```
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 Park')
plt.ylabel('Number of Observations')
plt.title('Observations of Bats per Week')
```

[117]: `Text(0.5, 1.0, 'Observations of Bats per Week')`



1.4 Conclusions

We made several visualizations and derived new insights into the species available in the data of these four National Parks.

Lets look again at the questions we seeked to answer at the start of this project: - What is the distribution of conservation status for our available species? - Most of the species were not of conservation status (5,633 vs. 191) - Are certain species more likely to be endangered? - Birds and Mammals had the highest protection percentage. - If differences exist between species and their conservation status, is it significant? - Reptiles and Mammals have a significant difference in protected status, while Mammals and Birds do not show such a difference. - What are the most prevalent species and what is their park distribution? - The most prevalence species is bats, and they have the highest prevalency in Yellowstone National Park.

1.5 Further Research

Further analyses could include larger datasets (such as observations from older than the past week) and look at the change in specie's protection over time. This dataset also is ignorant of the size of each park, which likely has a correlation with the prevalence of species observed. Finally, if we had location data of each observation we could make correlations between species observations and their spatial distribution.

Data sources Both csv files (`Observations.csv`, `Species_info.csv`) were provided by Codecademy.com.