

Goals:

- Isolate Eastern Bluebird

We choose the Eastern Bluebird (*Sialia sialis*) due to the abundance of data as well as the ease of analysis, as they are mostly contained within the eastern states of USA.

From SpeciesList.csv, we find that the AOU code for Eastern Bluebird is 7660.

```
In [ ]: import pandas as pd

df = pd.read_csv("mourningdove.csv")
df
```

Out []:

	Country	State	Route	Year	Aou	SpeciesTotal
0	124.0	4.0	1.0	1990.0	3160.0	7.0
1	124.0	4.0	1.0	1991.0	3160.0	32.0
2	124.0	4.0	1.0	1992.0	3160.0	1.0
3	124.0	4.0	1.0	1993.0	3160.0	2.0
4	124.0	4.0	1.0	1994.0	3160.0	5.0
...
76660	840.0	92.0	901.0	2018.0	3160.0	1.0
76661	840.0	92.0	902.0	2004.0	3160.0	25.0
76662	840.0	92.0	902.0	2006.0	3160.0	13.0
76663	840.0	92.0	902.0	2015.0	3160.0	2.0
76664	840.0	92.0	902.0	2017.0	3160.0	6.0

76665 rows x 6 columns

```
In [ ]: # Grouping by State, ignoring individual routes and aggregating them to state
df_grouped = df.groupby(['State', 'Year'], as_index=False)['SpeciesTotal'].sum()
df_grouped
```

Out []:

	State	Year	SpeciesTotal
0	2.0	1990.0	1891.0
1	2.0	1991.0	1802.0
2	2.0	1992.0	1776.0
3	2.0	1993.0	2127.0
4	2.0	1994.0	2098.0
...
1720	92.0	2016.0	906.0
1721	92.0	2017.0	795.0
1722	92.0	2018.0	771.0
1723	92.0	2019.0	519.0
1724	93.0	1994.0	1.0

1725 rows x 3 columns

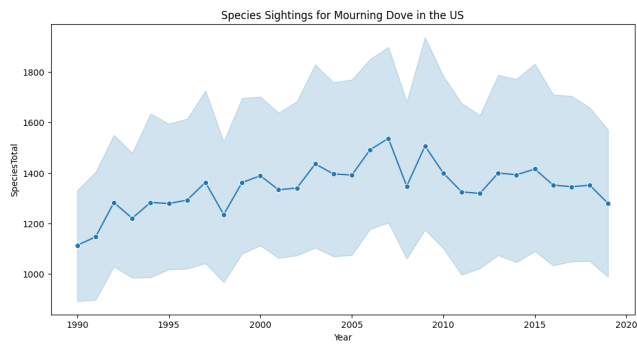
```
In [ ]: # Visualizing our data

import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(12,6))
sns.lineplot(data=df_grouped, x="Year", y="SpeciesTotal", marker="o")

plt.title("Species Sightings for Mourning Dove in the US", fontsize=12)
plt.xlabel("Year", fontsize=10)
plt.ylabel("SpeciesTotal", fontsize=10)

plt.show()
```



```
In [ ]: df_grouped["State"].unique()
```

```
Out[ ]: array([ 2.,  4.,  6.,  7., 11., 14., 17., 18., 21., 25., 27., 33., 34.,
        35., 36., 38., 39., 42., 44., 45., 46., 47., 49., 50., 51., 52.,
        53., 54., 55., 56., 57., 58., 59., 60., 61., 63., 64., 65., 66.,
        67., 68., 69., 72., 75., 76., 77., 79., 80., 81., 82., 83., 85.,
        87., 88., 89., 90., 91., 92., 93.])
```

The metadata defines each state:

```
''' 02,Alabama; 03,Alaska; 04,Alberta; 06,Arizona; 07,Arkansas; 11,British Columbia;
14,California; 17,Colorado; 18,Connecticut; 21,Delaware; 25,Florida; 27,Georgia; 33,Idaho;
34,Illinois; 35,Indiana; 36,Iowa; 38,Kansas; 39,Kentucky; 42,Louisiana; 43,Northwest
Territories; 44,Maine; 45,Manitoba; 46,Maryland; 47,Massachusetts; 49,Michigan;
50,Minnesota; 51,Mississippi; 52,Missouri; 53,Montana; 54,Nebraska; 55,Nevada;
56,New Brunswick; 57,Newfoundland and Labrador; 58,New Hampshire; 59,New Jersey;
60,New Mexico; 61,New York; 62,Nunavut; 63,North Carolina; 64,North Dakota; 65,Nova
Scotia; 66,Ohio; 67,Oklahoma; 68,Ontario; 69,Oregon; 72,Pennsylvania; 75,Prince
Edward Island; 76,Quebec; 77,Rhode Island; 79,Saskatchewan; 80,South Carolina;
81,South Dakota; 82,Tennessee; 83,Texas; 85,Utah; 87,Vermont; 88,Virginia;
89,Washington; 90,West Virginia; 91,Wisconsin; 92,Wyoming; 93,Yukon '''
```

We will use, for now, 07 Arkansas, 34 Illinois, 52 Missouri.

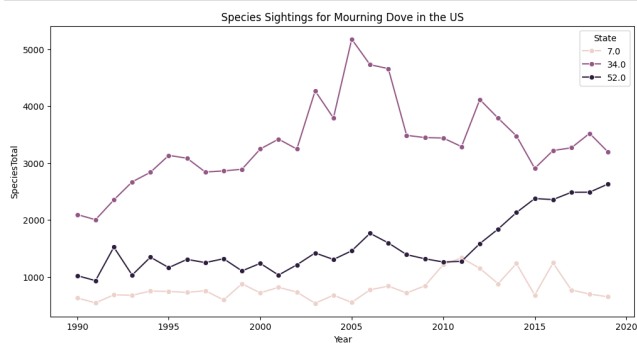
```
In [ ]: # Visualizing our data

import seaborn as sns
import matplotlib.pyplot as plt

df_filtered = df_grouped[df_grouped["State"].isin([7,34,52])]

plt.figure(figsize=(12,6))
sns.lineplot(data=df_filtered, x="Year", y="SpeciesTotal", hue="State", mark

plt.title("Species Sightings for Mourning Dove in the US", fontsize=12)
plt.xlabel("Year", fontsize=10)
plt.ylabel("SpeciesTotal", fontsize=10)
plt.show()
```



```
In [ ]: df_filtered
```

Out[]:

	State	Year	SpeciesTotal
90	7.0	1990.0	629.0
91	7.0	1991.0	542.0
92	7.0	1992.0	684.0
93	7.0	1993.0	676.0
94	7.0	1994.0	750.0
...
775	52.0	2015.0	2376.0
776	52.0	2016.0	2358.0
777	52.0	2017.0	2486.0
778	52.0	2018.0	2488.0
779	52.0	2019.0	2631.0

90 rows x 3 columns

Now comparing with emission types

```
In [ ]: import pandas as pd

df_emissions = pd.read_csv("full_data.csv")

states = {
    'Arkansas': 7,
    'Illinois': 34,
    'Missouri': 52
}

df_emissions.rename(columns={'Region': 'State', 'Value': 'Emissions'}, inplace=True)
df_emissions['State'] = df_emissions['State'].map(states)
df_emissions = df_emissions[df_emissions["State"].isin([7, 34, 52])]

df_emissions_pivoted = df_emissions.pivot_table(index=['State', 'Year'], columns=['Emissions'],
df_emissions_pivoted.columns = [col for col in df_emissions_pivoted.columns if col != 'Emissions']
df_emissions_pivoted.reset_index(inplace=True)
df_combined = pd.merge(df_filtered, df_emissions_pivoted, on=['State', 'Year'])
df_combined = df_combined.drop(columns=['Gross total', 'Net total'])

(df_combined)
```

Out[]:

	State	Year	SpeciesTotal	Carbon dioxide	Fluorinated gases	Land use and forestry carbon stock change	Methane	Nitrous oxide
0	7.0	1990.0	629.0	54.132545	1.786645	-54.692963	19.292660	6.820905
1	7.0	1991.0	542.0	52.856844	1.774128	-53.677058	20.753636	6.932789
2	7.0	1992.0	684.0	54.872688	1.784589	-53.177882	19.099499	7.071014
3	7.0	1993.0	676.0	53.910021	1.821897	-52.455692	19.912666	7.185217
4	7.0	1994.0	750.0	57.663686	1.931176	-51.678457	20.257696	7.031927
...
85	52.0	2015.0	2376.0	131.141261	3.751684	-24.649114	13.959973	16.166956
86	52.0	2016.0	2358.0	124.714462	3.251369	-23.865313	14.543042	14.071274
87	52.0	2017.0	2486.0	130.783979	3.384542	-23.793008	14.902632	15.683796
88	52.0	2018.0	2488.0	131.588221	3.078250	-24.213457	15.575442	16.136778
89	52.0	2019.0	2631.0	123.542202	3.249534	-22.699114	15.095425	14.753059

90 rows x 8 columns

Let's look at one state. We choose Arkansas for now.

```

In [ ]: import matplotlib.pyplot as plt

# Arkansas
state_data = df_combined[df_combined['State'] == 7]

fig, axes = plt.subplots(5, 1, figsize=(20, 20), sharex=True)

emission_types = ['Carbon dioxide', 'Fluorinated gases', 'Land use and fores
                  'Methane', 'Nitrous oxide']
colors = ['tab:red', 'tab:orange', 'tab:green', 'tab:purple', 'tab:brown']

for i, emission in enumerate(emission_types):
    ax = axes[i]

    # species
    ax.set_ylabel('Species Total', color='tab:blue')
    ax.plot(state_data['Year'], state_data['SpeciesTotal'], color='tab:blue')

    # emission type
    ax2 = ax.twinx()
    ax2.set_ylabel(emission, color=colors[i])
    ax2.plot(state_data['Year'], state_data[emission], color=colors[i], label=emission)

    # key
    ax.set_title(f'{emission} vs Species Total')
    ax.tick_params(axis='y', labelcolor='tab:blue')
    ax2.tick_params(axis='y', labelcolor=colors[i])
    ax2.legend(loc='upper left')

fig.tight_layout()
plt.xlabel('Year')
plt.show()

```



```

In [ ]: correlation_matrix = df_combined[['SpeciesTotal', 'Carbon dioxide', 'Fluorinated gases', 'Land use and forestry carbon stock change', 'Methane', 'Nitrous oxide']]
correlation_matrix

```

Out[]:

	SpeciesTotal	Carbon dioxide	Fluorinated gases	Land use and forestry carbon stock change	Methane	Nitrous oxide
SpeciesTotal	1.000000	0.915412	0.815209	0.814000	0.372454	0.873839
Carbon dioxide	0.915412	1.000000	0.858797	0.917618	0.430775	0.971450
Fluorinated gases	0.815209	0.858797	1.000000	0.711549	0.603259	0.794049
Land use and forestry carbon stock change	0.814000	0.917618	0.711549	1.000000	0.378159	0.936623
Methane	0.372454	0.430775	0.603259	0.378159	1.000000	0.382065
Nitrous oxide	0.873839	0.971450	0.794049	0.936623	0.382065	1.000000

```
In [ ]: import statsmodels.api as sm

X = df_combined[['Carbon dioxide', 'Fluorinated gases', 'Land use and forest
X = sm.add_constant(X)
y = df_combined['SpeciesTotal']

# regression model
model = sm.OLS(y, X).fit()
print(model.summary())
```

OLS Regression Results					
=====					
Dep. Variable:	SpeciesTotal	R-squared:	0.848		
Model:	OLS	Adj. R-squared:	0.839		
Method:	Least Squares	F-statistic:	93.52		
Date:	Sun, 13 Apr 2025	Prob (F-statistic):	7.87e-33		
Time:	14:59:10	Log-Likelihood:	-68.009		
No. Observations:	90	AIC:	72.13		
Df Residuals:	84	BIC:	87.13		
Df Model:	5				
Covariance Type:	nonrobust				
=====					
P> t	[0.025	0.975]	coef	std err	t

const			-132.6606	820.532	-0.162
0.872	-1764.378	1499.057			
Carbon dioxide			18.8798	4.155	4.544
0.000	10.617	27.142			
Fluorinated gases			35.3464	28.393	1.245
0.217	-21.116	91.809			
Land use and forestry carbon stock change			-5.3549	12.242	-0.437
0.663	-29.700	18.990			
Methane			-20.4860	15.413	-1.329
0.187	-51.137	10.165			
Nitrous oxide			-38.5389	44.114	-0.874
0.385	-126.265	49.188			
=====					
Omnibus:	4.980	Durbin-Watson:	0.532		
Prob(Omnibus):	0.083	Jarque-Bera (JB):	4.900		
Skew:	0.569	Prob(JB):	0.863		
Kurtosis:	2.894	Cond. No.	2.58e+03		
=====					
Notes:					
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.					
[2] The condition number is large, 2.58e+03. This might indicate that there are strong multicollinearity or other numerical problems.					