Bird: Mourning Dove

```
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 **1** 124.0 4.0 1.0 1991.0 3160.0 32.0 124.0 4.0 1.0 1992.0 3160.0 1.0 **3** 124.0 4.0 1.0 1993.0 3160.0 2.0 124.0 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

76665 rows × 6 columns

In []: # Grouping by State, ignoring individual routes and aggregating them to stat

df_grouped = df.groupby(['State', 'Year'], as_index=False)['SpeciesTotal'].s
 df_grouped

6.0

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 × 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()
```

Species Sightings for Mourning Dove in the US

```
1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 1800 - 18
```

```
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,Newada; 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 '''

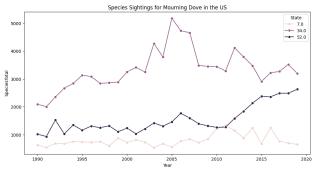
We will use, for now, 07 Arkansas, 34 Illinois, 52 Missouri.

```
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
                   2358.0
776 52.0 2016.0
                    2486.0
777 52.0 2017.0
                   2488.0
778 52.0 2018.0
                    2631.0
779 52.0 2019.0
```

90 rows × 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'}, inpla
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'], col
df_emissions_pivoted.columns = [col for col in df_emissions_pivoted.columns]
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
	1 2 3 4 85 86 87 88	0 7.0 1 7.0 2 7.0 3 7.0 4 7.0 85 52.0 86 52.0 87 52.0	0 7.0 1990.0 1 7.0 1991.0 2 7.0 1992.0 3 7.0 1993.0 4 7.0 1994.0 85 52.0 2015.0 86 52.0 2016.0 87 52.0 2017.0 88 52.0 2018.0	0 7.0 1990.0 629.0 1 7.0 1991.0 542.0 2 7.0 1992.0 684.0 3 7.0 1993.0 676.0 4 7.0 1994.0 750.0 85 52.0 2015.0 2376.0 86 52.0 2016.0 2358.0 87 52.0 2017.0 2486.0 88 52.0 2018.0 2488.0	State Vear SpeciesTotal dioxide 0 7.0 1990.0 629.0 54.132545 1 7.0 1991.0 542.0 52.856844 2 7.0 1992.0 684.0 54.872688 3 7.0 1993.0 676.0 53.910021 4 7.0 1994.0 750.0 57.663686 85 52.0 2015.0 2376.0 131.141261 86 52.0 2016.0 2358.0 124.714462 87 52.0 2017.0 2486.0 130.78397 88 52.0 2018.0 2488.0 131.588221	State Vear SpeciesTotal dioxide gases 0 7.0 1990.0 629.0 54.132545 1.786645 1 7.0 1991.0 542.0 52.856844 1.774128 2 7.0 1992.0 684.0 54.872688 1.784589 3 7.0 1993.0 676.0 53.910021 1.821897 4 7.0 1994.0 750.0 57.663686 1.931176 85 52.0 2015.0 2376.0 131.141261 3.751684 86 52.0 2016.0 2358.0 124.714462 3.251369 87 52.0 2017.0 2486.0 130.783979 3.384542 88 52.0 2018.0 2488.0 131.588221 3.078250	State Year SpeciesTotal Carbon dioxide Fubrinate gases and reget from carbon carbon stock to the constance 0 7.0 1990.0 629.0 54.132545 1.786645 -54.692963 1 7.0 1991.0 54.20 52.856844 1.774128 -53.67708 2 7.0 1992.0 684.0 54.872688 1.784589 -53.177882 3 7.0 1993.0 676.0 53.910021 1.821897 -52.455692 4 7.0 1994.0 750.0 57.663686 1.931176 -51.678457 5 2.0 2015.0 2376.0 131.141261 3.751684 -24.649114 8 5 2016.0 2358.0 124.714462 3.25136 -23.865313 8 5 2017.0 2486.0 130.78397 3.38454 -23.79308 8 5 2018.0 2486.0 131.58821 3.07825 -24.213487	State Year SpeciesTotal Carbon dioxide Fluorinated gases and present prese

90 rows × 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)
```



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

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

OLS Regression Results

_____ Dep. Variable: SpeciesTotal transformed R-squared: 0.850 Model: OLS Adj. R-squared: 0.845 Method: Least Squares F-statistic: 163.2 Sun, 13 Apr 2025 Prob (F-statistic): Date: 1.80e-57 15:59:32 Log-Likelihood: Time: 22.300 No. Observations: -32.60 150 AIC: Df Residuals: 144 BIC: -14.54 Df Model: nonrobust Covariance Type:

P> t	[0.025	0 9751		coef	std err	t
const				6.7145	0.222	30.307
0.000 Carbon d	6.277	7.152		0.0070	0.001	8.854
0.000	0.005	0.009		0.0070	0.001	0.034
Fluorina	ted gases			-0.0181	0.004	-4.071
0.000		-0.009				
	and forestr		tock char	nge 0.0124	0.004	3.202
0.002 Methane	0.005	0.020		-0.0029	0.005	-0.572
	-0.013	0.007		010023	0.003	01372
Nitrous o	oxide			0.0106	0.007	1.512
0.133	-0.003	0.025				
====						
Omnibus:			0.394	Durbin-Watson:		0.
833						
Prob(Omn:	ibus):		0.821	Jarque-Bera (JE	3):	0.
547 Skew:			0.083	Prob(JB):		0.
761			0.003	1100(30).		۷.
Kurtosis	:		2.755	Cond. No.		1.90e
+03						

=== Notes

- Notes: [1] Standard Errors assume that the covariance matrix of the errors is correctly specified. [2] The condition number is large, 1.9e+03. This might indicate that there
- [2] The condition number is large, 1.9e+03. This might indicate that there are strong multicollinearity or other numerical problems.

In []: from sklearn.model_selection import cross_val_score, KFold
 from sklearn.linear_model import LinearRegression
 from sklearn.metrics import make_scorer, mean_squared_error
 import numpy as np

 df_train = df_combined[df_combined['State'].isin([7, 34, 52])]

 features = ['Carbon dioxide', 'Fluorinated gases', 'Land use and forestry ca
 X_train = df_train[features]
 y_train = df_train['SpeciesTotal']

 model = LinearRegression()

 cv = KFold(n_splits=5, shuffle=True, random_state=1)

 r2_scores = cross_val_score(model, X_train, y_train, cv=cv, scoring='r2')

print("Cross-validated R² scores:", np.round(r2_scores, 4))

print("Average R²:", np.round(np.mean(r2_scores), 4))

Cross-validated R² scores: [0.7801 0.798 0.8297 0.8017 0.6416]

Average R²: 0.7702