2025_teaching_pylibs

November 5, 2025

1 2025 Python libraries

- Presenter: Jake Krol
- Notebook contents inspired by Erik Johnson and Michael Bradshaw

1.1 Purpose

- Gain hands-on experience with NumPy, Pandas, Matplotlib, and other libraries

1.2 Methods

- Regression
- Hypothesis testing
- Gini Coefficient and Lorenz curve

1.3 Topics

- Climate change
- Population equilibrium
- Rice production "wealth"

1.4 Related work

- Lecture slides: https://docs.google.com/presentation/d/1eq1OidZWZSqgBQHWibpLE_m3-_NNYqYcCeVR95GhkMc/edit?usp=sharing

1.5 Setup

- Upload `agrofood_co2_emission.csv` file

1.6 Scenario

You work for a data science consulting firm, and your supervisor sends you some data with minimal context. Your task is to understand what the data encodes and what insights are attainable purely from the dataset.

[36]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import sklearn as skl
```

```python
import re
import scipy.stats as stats
```

1.7 Basic inspection

[37]:
```python
# read
# view shape
df = pd.read_csv('agrofood_co2_emission.csv')
print('# shape ', df.shape)
```

```
# shape  (6965, 31)
```

[38]:
```python
# preview
df.head()
```

[38]:
```
          Area  Year  Savanna fires  Forest fires  Crop Residues  \
0  Afghanistan  1990        14.7237        0.0557       205.6077
1  Afghanistan  1991        14.7237        0.0557       209.4971
2  Afghanistan  1992        14.7237        0.0557       196.5341
3  Afghanistan  1993        14.7237        0.0557       230.8175
4  Afghanistan  1994        14.7237        0.0557       242.0494

   Rice Cultivation  Drained organic soils (CO2)  Pesticides Manufacturing  \
0            686.00                          0.0                 11.807483
1            678.16                          0.0                 11.712073
2            686.00                          0.0                 11.712073
3            686.00                          0.0                 11.712073
4            705.60                          0.0                 11.712073

   Food Transport  Forestland  …  Manure Management  Fires in organic soils  \
0         63.1152   -2388.803  …           319.1763                     0.0
1         61.2125   -2388.803  …           342.3079                     0.0
2         53.3170   -2388.803  …           349.1224                     0.0
3         54.3617   -2388.803  …           352.2947                     0.0
4         53.9874   -2388.803  …           367.6784                     0.0

   Fires in humid tropical forests  On-farm energy use  Rural population  \
0                              0.0                 NaN         9655167.0
1                              0.0                 NaN        10230490.0
2                              0.0                 NaN        10995568.0
3                              0.0                 NaN        11858090.0
4                              0.0                 NaN        12690115.0

   Urban population  Total Population - Male  Total Population - Female  \
0         2593947.0                5348387.0                  5346409.0
1         2763167.0                5372959.0                  5372208.0
2         2985663.0                6028494.0                  6028939.0
```

```
3         3237009.0                 7003641.0                  7000119.0
4         3482604.0                 7733458.0                  7722096.0

   total_emission  Average Temperature °C
0     2198.963539                0.536167
1     2323.876629                0.020667
2     2356.304229               -0.259583
3     2368.470529                0.101917
4     2500.768729                0.372250

[5 rows x 31 columns]
```

[39]:
```python
# count column data types
df.dtypes.value_counts()
```

[39]:
```
float64    29
object      1
int64       1
Name: count, dtype: int64
```

checkpoint - Agricultural data - For various (area,year) combinations, there exists numeric features - e.g., Afghan 1990 rice cultivation questions - How many distinct countries exist in df? - What is the year span? - What are the units of measurement for these columns? - What are mean/expected values in each numeric column?

[40]:
```python
# distinct areas
print(df['Area'].nunique())
print(df['Area'].unique()[:10])
```

```
236
['Afghanistan' 'Albania' 'Algeria' 'American Samoa' 'Andorra' 'Angola'
 'Anguilla' 'Antigua and Barbuda' 'Argentina' 'Armenia']
```

[41]:
```python
# year span
print(
    df['Year'].min(),
    df['Year'].max()
)
```

```
1990 2020
```

[42]:
```python
df[df.columns.drop(['Area', 'Year'])].describe().T['mean'].round(2)
```

[42]:
```
Savanna fires                      1188.39
Forest fires                        919.30
Crop Residues                       998.71
Rice Cultivation                   4259.67
Drained organic soils (CO2)        3503.23
Pesticides Manufacturing            333.42
```

```
Food Transport                          1939.58
Forestland                            -17828.29
Net Forest conversion                  17605.64
Food Household Consumption              4847.58
Food Retail                             2043.21
On-farm Electricity Use                 1626.68
Food Packaging                          1658.63
Agrifood Systems Waste Disposal         6018.44
Food Processing                         3872.72
Fertilizers Manufacturing               3035.72
IPPU                                   19991.50
Manure applied to Soils                  923.23
Manure left on Pasture                  3518.03
Manure Management                       2263.34
Fires in organic soils                  1210.32
Fires in humid tropical forests          668.45
On-farm energy use                      3008.98
Rural population                    17857735.39
Urban population                    16932296.97
Total Population - Male             17619629.63
Total Population - Female           17324469.29
total_emission                         64091.24
Average Temperature °C                     0.87
Name: mean, dtype: float64
```

questions - why is forestland negative? is change in forestland measured? - given this data, what hypotheses could we form? - let's get a frame of reference by inspecting one area/country

[43]:
```python
df_usa=df[df['Area'] == 'United States of America']
df_usa.head()
```

[43]:
```
                          Area  Year  Savanna fires  Forest fires  \
6591  United States of America  1990      1391.1481     1999.5617
6592  United States of America  1991      1391.1481     1999.5617
6593  United States of America  1992      1391.1481     1999.5617
6594  United States of America  1993      1391.1481     1999.5617
6595  United States of America  1994      1391.1481     1999.5617

      Crop Residues  Rice Cultivation  Drained organic soils (CO2)  \
6591     19193.1314         11195.520                   50713.3546
6592     17574.1126         11029.312                   50713.3546
6593     20964.8025         12421.402                   50713.3546
6594     16761.5327         11235.602                   50566.2744
6595     21370.6468         13151.110                   50418.1314

      Pesticides Manufacturing  Food Transport   Forestland  …  \
6591                   13772.0      45410.2673 -520573.1593  …
6592                   13139.0      44566.9408 -520573.1593  …
```

```
6593                    14109.0      46198.5933 -520573.1593  …
6594                    12948.0      45175.6740 -520573.1593  …
6595                    14401.0      46739.0889 -520573.1593  …

      Manure Management  Fires in organic soils  \
6591         47024.7024                     0.0
6592         48206.0451                     0.0
6593         48416.2439                     0.0
6594         48426.0899                     0.0
6595         49165.7227                     0.0

      Fires in humid tropical forests  On-farm energy use  Rural population  \
6591                           9.8513          54454.7092        62373717.0
6592                           9.8513          54565.6091        61957131.0
6593                           9.8513          57469.9273        61539241.0
6594                           9.8513          54689.3180        61136396.0
6595                           9.8513          55539.8937        60759735.0

      Urban population  Total Population - Male  Total Population - Female  \
6591       190156233.0              121451448.0                126632284.0
6592       193017688.0              123229931.0                128330258.0
6593       195915032.0              125081499.0                130093840.0
6594       198883790.0              126914111.0                131865642.0
6595       201981831.0              128685441.0                133588147.0

      total_emission  Average Temperature °C
6591     463050.9394                0.733583
6592     473285.7816                0.706333
6593     486026.3425                0.253000
6594     484238.6197                0.153500
6595     509412.4984                0.470250

[5 rows x 31 columns]
```

questions - we have savannas in the USA? - does avg. temp support climate warming hypotheses? - are urban/rural populations shrinking/growing?

[44]:
```python
# graph avg temp over time in the US
# plt.plot(df_usa['Year'], df_usa['AvgTemp'])
# plt.show()
```

- oh, that's very annoying. the temperature column uses the '°' character …
- what's a simple way to resolve this?

[45]:
```python
# let's clean up column names
def cln(x):
    x = x.replace('°','')
    # whitespace
```

```
    x = re.sub(r"\s+", "_", x)
    # hyphens
    x = x.replace('-','_')
    # parentheses
    x = x.replace('(', '')
    x = x.replace(')', '')
    # redundant '_' removal
    x = re.sub(r"_+", "_", x)
    # lower
    return x.lower()
df.columns = [cln(x) for x in df.columns]
df.head()
```

[45]:

```
          area  year  savanna_fires  forest_fires  crop_residues  \
0  Afghanistan  1990        14.7237        0.0557       205.6077
1  Afghanistan  1991        14.7237        0.0557       209.4971
2  Afghanistan  1992        14.7237        0.0557       196.5341
3  Afghanistan  1993        14.7237        0.0557       230.8175
4  Afghanistan  1994        14.7237        0.0557       242.0494

   rice_cultivation  drained_organic_soils_co2  pesticides_manufacturing  \
0            686.00                        0.0                 11.807483
1            678.16                        0.0                 11.712073
2            686.00                        0.0                 11.712073
3            686.00                        0.0                 11.712073
4            705.60                        0.0                 11.712073

   food_transport  forestland  …  manure_management  fires_in_organic_soils  \
0         63.1152   -2388.803  …           319.1763                     0.0
1         61.2125   -2388.803  …           342.3079                     0.0
2         53.3170   -2388.803  …           349.1224                     0.0
3         54.3617   -2388.803  …           352.2947                     0.0
4         53.9874   -2388.803  …           367.6784                     0.0

   fires_in_humid_tropical_forests  on_farm_energy_use  rural_population  \
0                              0.0                 NaN         9655167.0
1                              0.0                 NaN        10230490.0
2                              0.0                 NaN        10995568.0
3                              0.0                 NaN        11858090.0
4                              0.0                 NaN        12690115.0

   urban_population  total_population_male  total_population_female  \
0         2593947.0              5348387.0                5346409.0
1         2763167.0              5372959.0                5372208.0
2         2985663.0              6028494.0                6028939.0
3         3237009.0              7003641.0                7000119.0
4         3482604.0              7733458.0                7722096.0
```

```
   total_emission  average_temperature_c
0     2198.963539               0.536167
1     2323.876629               0.020667
2     2356.304229              -0.259583
3     2368.470529               0.101917
4     2500.768729               0.372250

[5 rows x 31 columns]
```

[46]:

```python
# clean usa subset
df_usa.columns = [cln(x) for x in df_usa.columns]
df_usa.head()
```

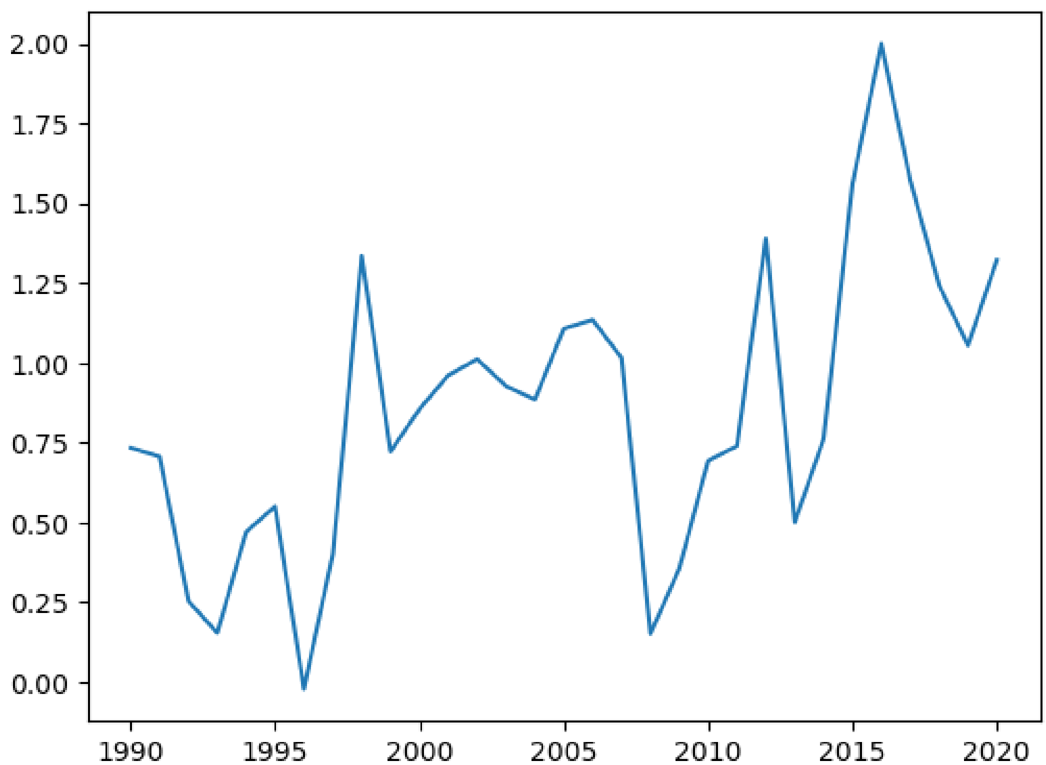
[46]:

```
                          area  year  savanna_fires  forest_fires  \
6591  United States of America  1990      1391.1481     1999.5617
6592  United States of America  1991      1391.1481     1999.5617
6593  United States of America  1992      1391.1481     1999.5617
6594  United States of America  1993      1391.1481     1999.5617
6595  United States of America  1994      1391.1481     1999.5617

      crop_residues  rice_cultivation  drained_organic_soils_co2  \
6591     19193.1314         11195.520                 50713.3546
6592     17574.1126         11029.312                 50713.3546
6593     20964.8025         12421.402                 50713.3546
6594     16761.5327         11235.602                 50566.2744
6595     21370.6468         13151.110                 50418.1314

      pesticides_manufacturing  food_transport   forestland  …  \
6591                   13772.0      45410.2673 -520573.1593  …
6592                   13139.0      44566.9408 -520573.1593  …
6593                   14109.0      46198.5933 -520573.1593  …
6594                   12948.0      45175.6740 -520573.1593  …
6595                   14401.0      46739.0889 -520573.1593  …

      manure_management  fires_in_organic_soils  \
6591         47024.7024                     0.0
6592         48206.0451                     0.0
6593         48416.2439                     0.0
6594         48426.0899                     0.0
6595         49165.7227                     0.0

      fires_in_humid_tropical_forests  on_farm_energy_use  rural_population  \
6591                           9.8513          54454.7092        62373717.0
6592                           9.8513          54565.6091        61957131.0
6593                           9.8513          57469.9273        61539241.0
6594                           9.8513          54689.3180        61136396.0
```

```
6595                         9.8513          55539.8937        60759735.0

      urban_population  total_population_male  total_population_female  \
6591       190156233.0            121451448.0              126632284.0
6592       193017688.0            123229931.0              128330258.0
6593       195915032.0            125081499.0              130093840.0
6594       198883790.0            126914111.0              131865642.0
6595       201981831.0            128685441.0              133588147.0

      total_emission  average_temperature_c
6591     463050.9394               0.733583
6592     473285.7816               0.706333
6593     486026.3425               0.253000
6594     484238.6197               0.153500
6595     509412.4984               0.470250

[5 rows x 31 columns]
```

[47]:
```
# is climate warming hypothesis supported by USA data?
x = df_usa['year']
y = df_usa['average_temperature_c']
plt.plot(x,y)
```

[47]:
```
[<matplotlib.lines.Line2D at 0x7f8171643d10>]
```



interesting, there's an upward trend.

Q: how could we simply, numerically quantify this trend?

Click to reveal spoiler

linear regression

1.8 Climate change regression

[48]:
```
# regression with OLS objective
# using scipy
slope, intercept, r_value, p_value, std_err = stats.linregress(
    x,
    y,
    alternative='greater'
)
print(
    'slope: ', slope,
    '\nintercept: ', intercept,
    '\nr_value: ', r_value,
    '\np_value: ', p_value,
    '\nstd_err: ', std_err
)
```

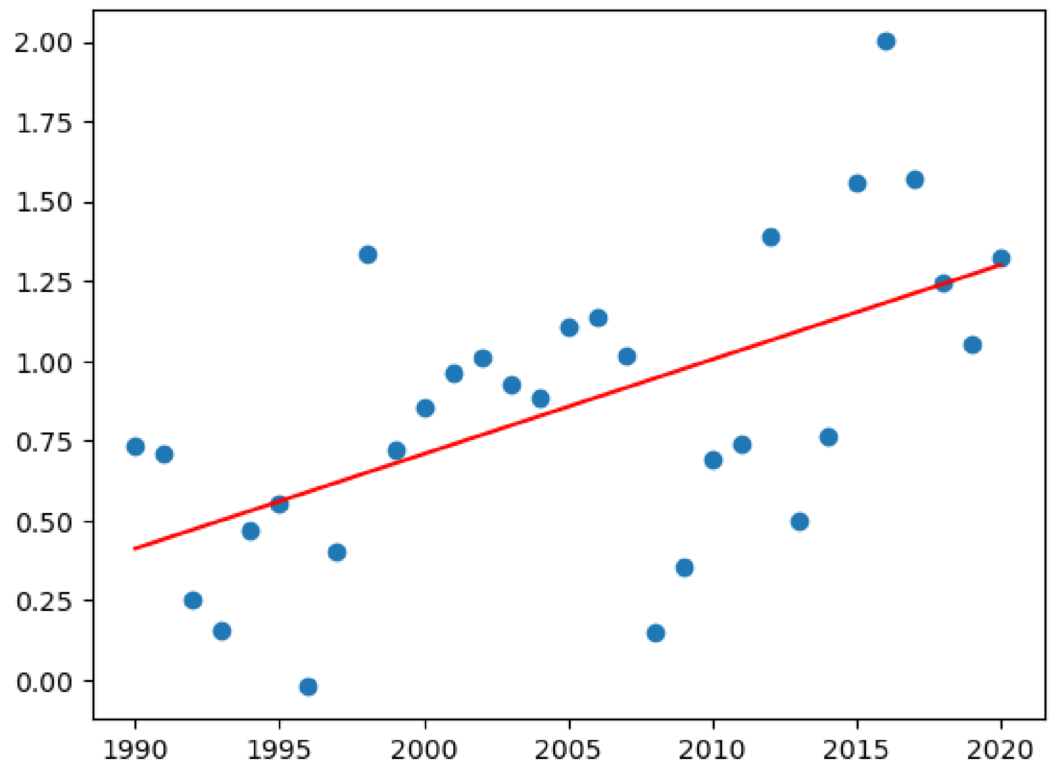
```
slope:  0.029624798387096774
intercept:  -58.5416320564516
r_value:  0.5784210865537276
p_value:  0.0003266897078220169
std_err:  0.007758239185112271
```

checkpoint: regression analysis - how can we visualize our regression line - why did we get a p-value? how do we interpret it in this context? (hint: what did we talk about in monte carlo hypothesis testing?)

Click to reveal spoiler

- slope and intercept provide the linear equation; therefore, we can plug in arbitrary inputs in the domain $x \in R$. we're interested

[49]:
```
# plot fit regression line and data
plt.plot(x, y, 'o')
plt.plot(x, intercept + slope*x, 'r')
plt.show()
```



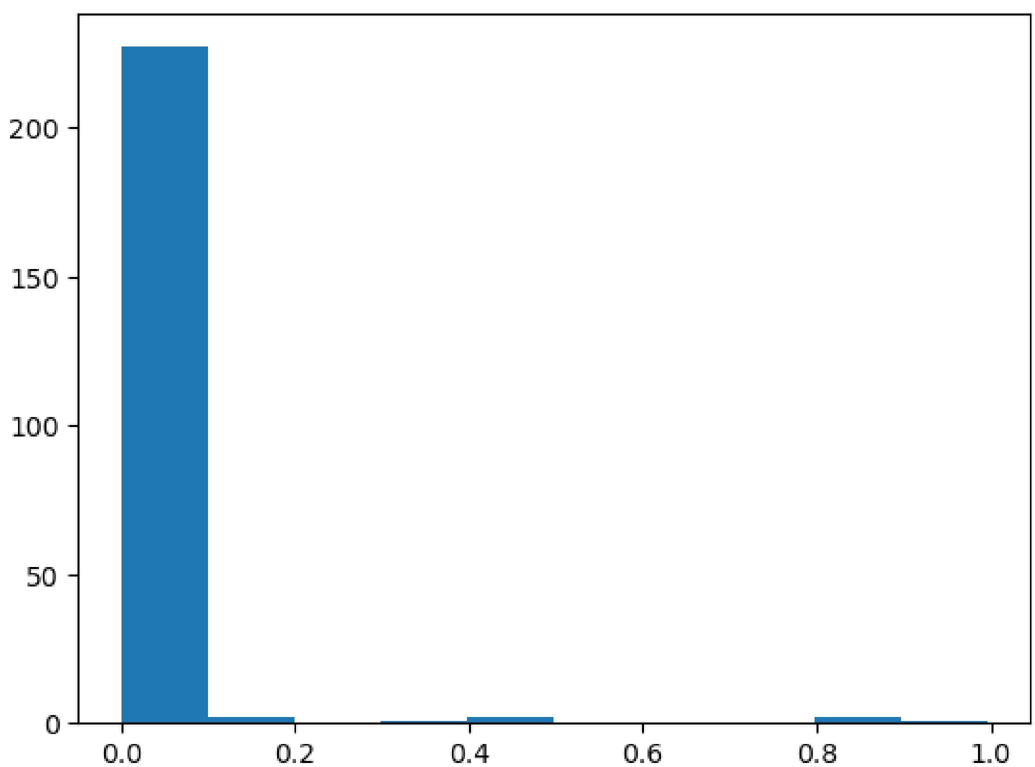
Yes, from the data, we can **reject the null hypothesis** ($p = .00032$) that average temperature is non-increasing over time … in the USA.

What about other countries? How would you design and implement this experiment on a larger scale?

[50]:
```
def gwarm_exp(years, avg_temps):
    slope, _, _, p_value, _ = stats.linregress(
      years,
      avg_temps,
      alternative='greater'
    )
    return p_value, slope
# apply this experiment to all areas
p_values = []
slopes = []
for group, df_group in df.groupby('area'):
    p_value, slope = gwarm_exp(df_group['year'],␣
  ↪df_group['average_temperature_c'])
    p_values.append(p_value)
    slopes.append(slope)
# plot distribution of p-values
plt.hist(p_values)
```

```
/data/jake/miniconda3/lib/python3.12/site-
packages/scipy/stats/_stats_py.py:10729: RuntimeWarning: invalid value
encountered in scalar divide
  slope = ssxym / ssxm
/data/jake/miniconda3/lib/python3.12/site-
packages/scipy/stats/_stats_py.py:10743: RuntimeWarning: invalid value
encountered in sqrt
  t = r * np.sqrt(df / ((1.0 - r + TINY)*(1.0 + r + TINY)))
/data/jake/miniconda3/lib/python3.12/site-
packages/scipy/stats/_stats_py.py:10749: RuntimeWarning: invalid value
encountered in scalar divide
  slope_stderr = np.sqrt((1 - r**2) * ssym / ssxm / df)
```

[50]:
```
(array([227.,   2.,   0.,   1.,   2.,   0.,   0.,   0.,   2.,   1.]),
 array([0.        , 0.09962106, 0.19924212, 0.29886318, 0.39848424,
        0.49810531, 0.59772637, 0.69734743, 0.79696849, 0.89658955,
        0.99621061]),
 <BarContainer object of 10 artists>)
```

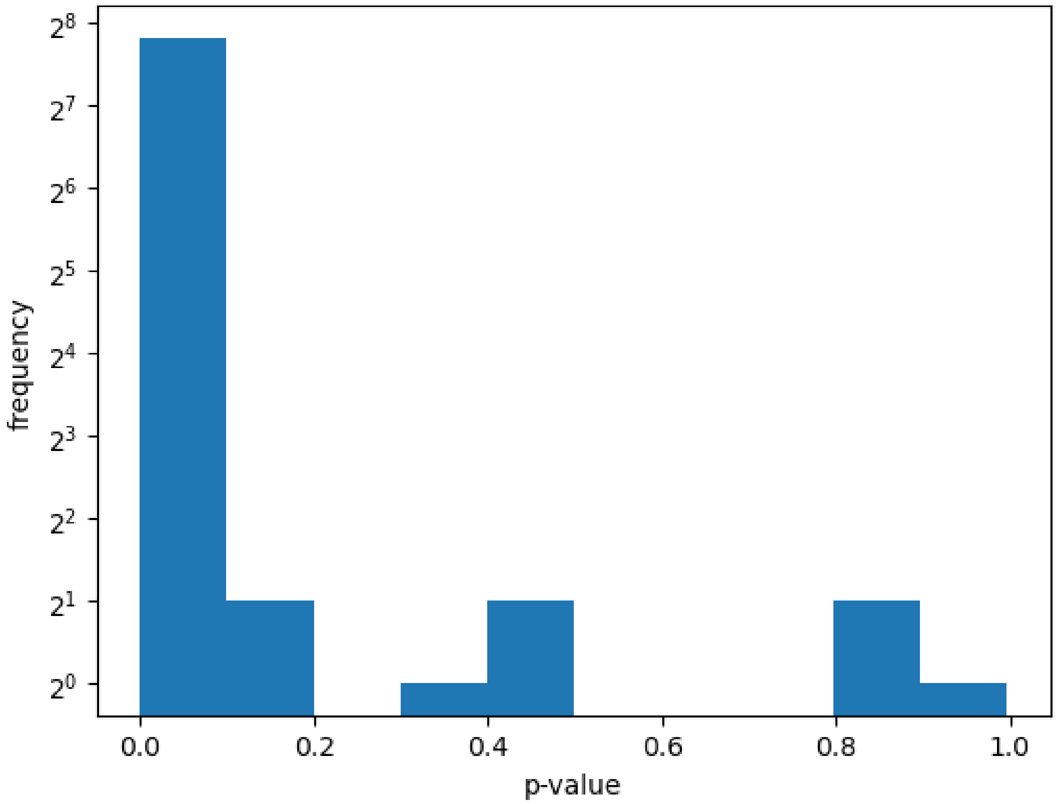


most p-values are close to zero. But, $\exists$ some $p >> 0$.

How can we make this plot better?

[51]:

```
plt.hist(p_values)
plt.yscale("log", base = 2)
plt.xlabel("p-value")
plt.ylabel("frequency")
plt.show()
```



now, high p-values can easily be counted (cases where climate warming hyp was not supported).

i counted 8.

let's be more precise

[52]:

```
# what fraction of areas support climate warming hypothesis
# try diff alpha and see how fraction changes
alpha = 0.05
n = len(p_values)
num = [p < alpha for p in p_values].count(True)
print(num/n)
```

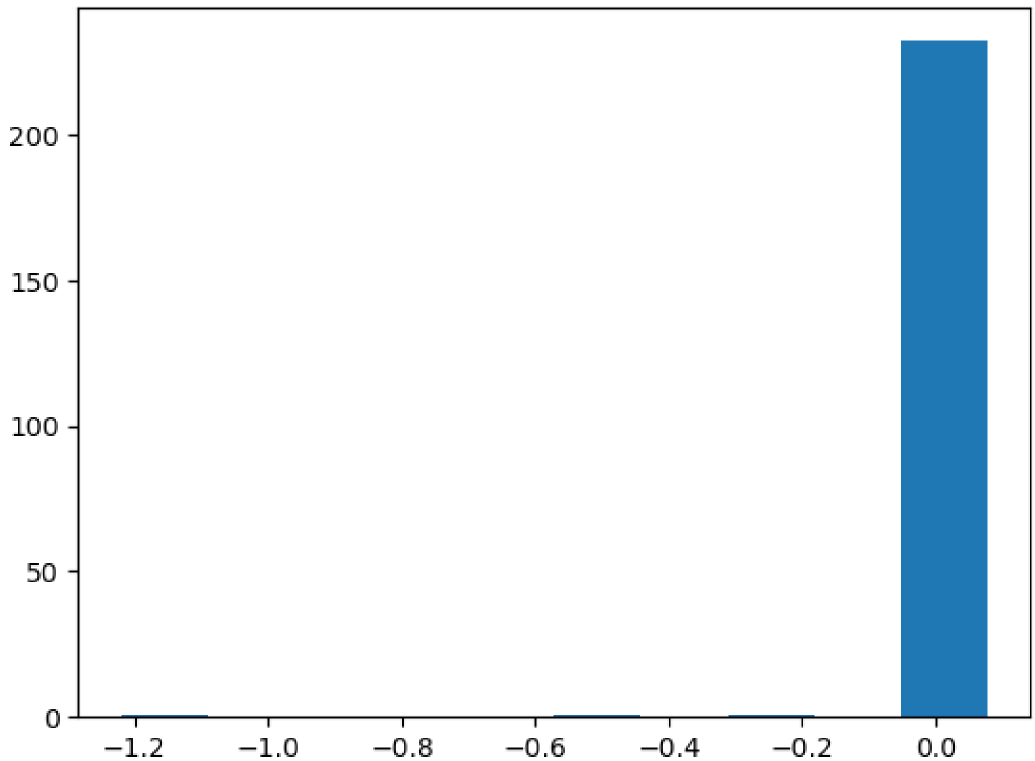
```
0.940677966101695
```

conclusion: 94% of areas in our dataset support a climate warming hypothesis

we showed that temperature is rising, but to what degree and in which places?

[53]:
```
plt.hist(slopes)
```

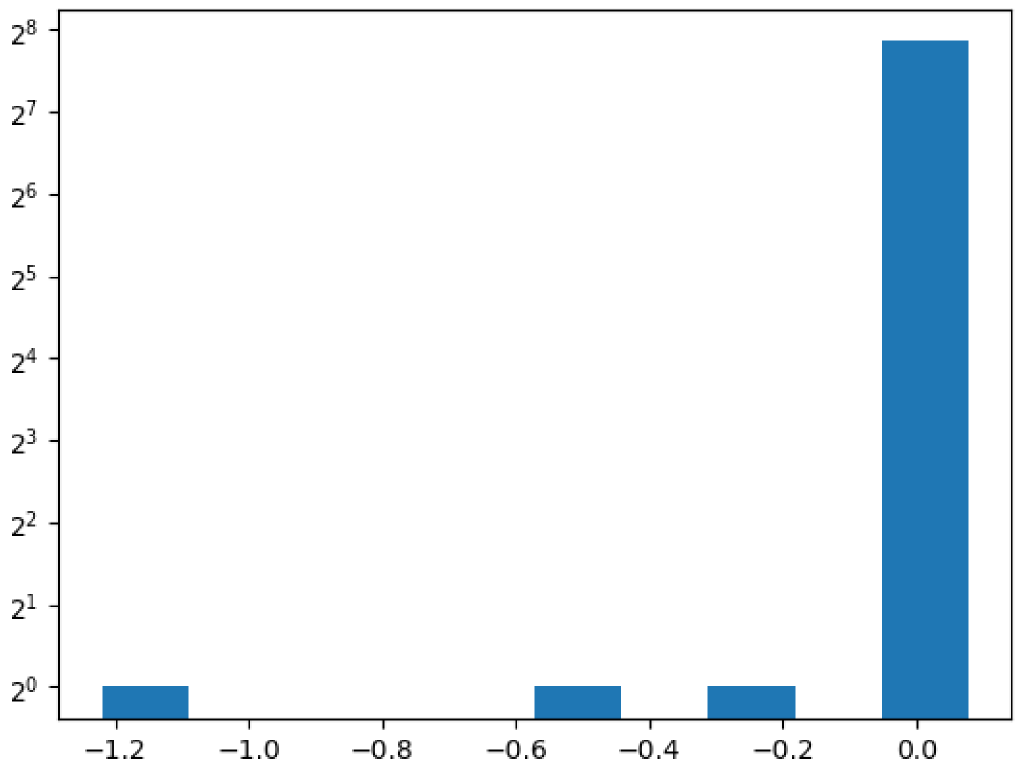
[53]:
```
(array([  1.,   0.,   0.,   0.,   0.,   1.,   0.,   1.,   0., 232.]),
 array([-1.21991667, -1.09021346, -0.96051025, -0.83080704, -0.70110383,
        -0.57140062, -0.44169741, -0.3119942 , -0.18229099, -0.05258778,
         0.07711544]),
 <BarContainer object of 10 artists>)
```



clearly many slopes are close to zero, … however, the tail of this distribution is interesting.

some places have a strong decrease in temp over the years

[54]:
```
# again we scale y-axis for better view of dist. tail
plt.hist(slopes)
plt.yscale("log", base = 2)
plt.show()
```



two paths 1. i want to show evidence against climate warming 2. i want to show evidence supporting climate warming

[55]:
```
# path 1
# goal: find outlier areas where avg temp is decreasing sharply
p_values_cherry = []
slopes_cherry = []
groups_cherry = []
for group, df_group in df.groupby('area'):
    p_value, slope = gwarm_exp(df_group['year'],␣
 ↪df_group['average_temperature_c'])
    if slope < -0.1:
        p_values_cherry.append(p_value)
        slopes_cherry.append(slope)
        groups_cherry.append(group)
groups_cherry
```

```
/data/jake/miniconda3/lib/python3.12/site-
packages/scipy/stats/_stats_py.py:10729: RuntimeWarning: invalid value
encountered in scalar divide
  slope = ssxym / ssxm
/data/jake/miniconda3/lib/python3.12/site-
packages/scipy/stats/_stats_py.py:10743: RuntimeWarning: invalid value
```

```
encountered in sqrt
  t = r * np.sqrt(df / ((1.0 - r + TINY)*(1.0 + r + TINY)))
/data/jake/miniconda3/lib/python3.12/site-
packages/scipy/stats/_stats_py.py:10749: RuntimeWarning: invalid value
encountered in scalar divide
  slope_stderr = np.sqrt((1 - r**2) * ssym / ssxm / df)
```

[55]:

```
['Ethiopia PDR', 'USSR', 'Yugoslav SFR']
```

[56]:

```
# path 1 cont.
df_cherry = df[df['area'].isin(groups_cherry)]
df_cherry.head()
```

[56]:

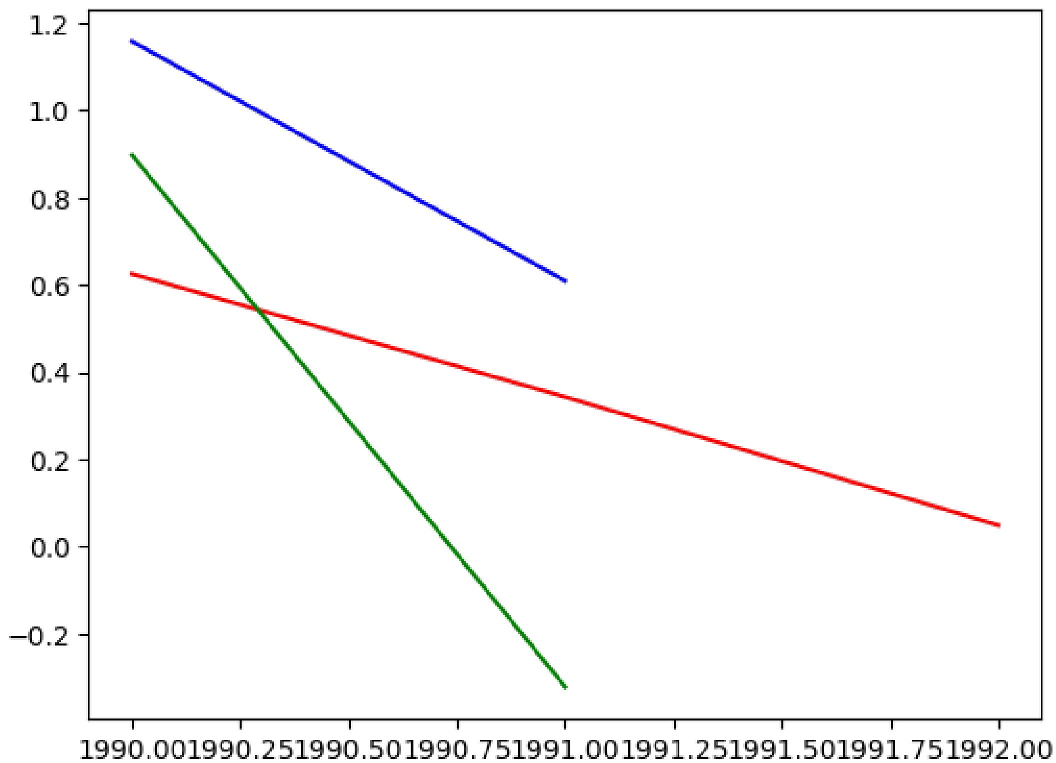
```
              area  year  savanna_fires  forest_fires  crop_residues  \
2152  Ethiopia PDR  1990      3851.3866     1509.6419       349.6276
2153  Ethiopia PDR  1991      3851.3866     1509.6419       286.8652
2154  Ethiopia PDR  1992      3851.3866     1509.6419       270.0245
6684          USSR  1990      8405.2264     7262.4148     14854.7660
6685          USSR  1991      8405.2264     7262.4148     11900.4386

      rice_cultivation  drained_organic_soils_co2  pesticides_manufacturing  \
2152       3391.507802                  5513.0102                 12.850182
2153       3309.287814                  5513.0102                 12.098396
2154       3586.696796                  5513.0102                 11.606165
6684       4813.760000                131838.2352               1169.000000
6685       4699.296000                131838.2352               1301.000000

      food_transport   forestland  …  manure_management  \
2152        100.5070    -107.2750  …          1543.7229
2153         98.8585    -107.2750  …          1554.3704
2154         33.8336    -107.2750  …          1594.3863
6684      32821.6716 -605722.9991  …         60407.5004
6685      32500.3786 -605722.9991  …         59296.5706

      fires_in_organic_soils  fires_in_humid_tropical_forests  \
2152                     0.0                         416.3368
2153                     0.0                         416.3368
2154                     0.0                         416.3368
6684                     0.0                           0.0000
6685                     0.0                           0.0000

      on_farm_energy_use  rural_population  urban_population  \
2152             80.8401        44542203.0         6657624.0
2153             82.1289        45925516.0         7022864.0
2154             41.6932        47359180.0         7407170.0
6684         248879.1769        99158922.0       188910774.0
6685         246785.4967        99725999.0       189602194.0
```

```
      total_population_male  total_population_female  total_emission  \
2152             24890395.0               25137639.0    65914.320714
2153             25886400.0               26090250.0    61115.468490
2154             26890139.0               27042568.0    61654.073430
6684            136777703.0              153126995.0   524473.945541
6685            137641632.0              153853429.0   520480.833615

      average_temperature_c
2152               0.625000
2153               0.342667
2154               0.048444
6684               1.158250
6685               0.609000

[5 rows x 31 columns]
```

[57]:

```python
# path 2 cont.
x_eth = df_cherry[df['area'] == 'Ethiopia PDR']['year']
y_eth = df_cherry[df['area'] == 'Ethiopia PDR']['average_temperature_c']
plt.plot(x_eth, y_eth, 'r')
x_ussr = df_cherry[df['area'] == 'USSR']['year']
y_ussr = df_cherry[df['area'] == 'USSR']['average_temperature_c']
plt.plot(x_ussr, y_ussr, 'b')
x_yugo = df_cherry[df['area'] == 'Yugoslav SFR']['year']
y_yugo = df_cherry[df['area'] == 'Yugoslav SFR']['average_temperature_c']
plt.plot(x_yugo, y_yugo, 'g')
plt.show()
```

```
/tmp/ipykernel_3250460/3954201872.py:2: UserWarning: Boolean Series key will be
reindexed to match DataFrame index.
  x_eth = df_cherry[df['area'] == 'Ethiopia PDR']['year']
/tmp/ipykernel_3250460/3954201872.py:3: UserWarning: Boolean Series key will be
reindexed to match DataFrame index.
  y_eth = df_cherry[df['area'] == 'Ethiopia PDR']['average_temperature_c']
/tmp/ipykernel_3250460/3954201872.py:5: UserWarning: Boolean Series key will be
reindexed to match DataFrame index.
  x_ussr = df_cherry[df['area'] == 'USSR']['year']
/tmp/ipykernel_3250460/3954201872.py:6: UserWarning: Boolean Series key will be
reindexed to match DataFrame index.
  y_ussr = df_cherry[df['area'] == 'USSR']['average_temperature_c']
/tmp/ipykernel_3250460/3954201872.py:8: UserWarning: Boolean Series key will be
reindexed to match DataFrame index.
  x_yugo = df_cherry[df['area'] == 'Yugoslav SFR']['year']
/tmp/ipykernel_3250460/3954201872.py:9: UserWarning: Boolean Series key will be
reindexed to match DataFrame index.
  y_yugo = df_cherry[df['area'] == 'Yugoslav SFR']['average_temperature_c']
```



the data available for these countires is only from a few years

[58]:
```
# observe year span of 1990-1991/1992
df_cherry
```

[58]:

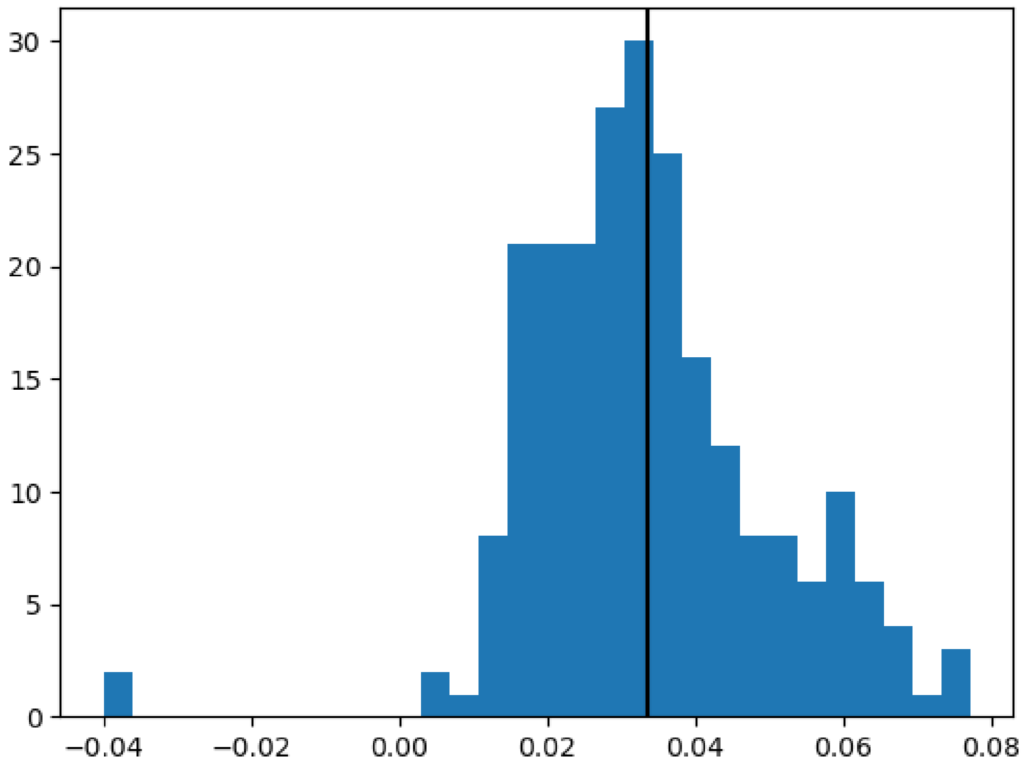
	area	year	savanna_fires	forest_fires	crop_residues	\
2152	Ethiopia PDR	1990	3851.3866	1509.6419	349.6276	
2153	Ethiopia PDR	1991	3851.3866	1509.6419	286.8652	
2154	Ethiopia PDR	1992	3851.3866	1509.6419	270.0245	
6684	USSR	1990	8405.2264	7262.4148	14854.7660	
6685	USSR	1991	8405.2264	7262.4148	11900.4386	
6901	Yugoslav SFR	1990	17.5124	27.8984	844.4150	
6902	Yugoslav SFR	1991	17.5124	27.8984	1047.9798	

	rice_cultivation	drained_organic_soils_co2	pesticides_manufacturing	\
2152	3391.507802	5513.0102	12.850182	
2153	3309.287814	5513.0102	12.098396	
2154	3586.696796	5513.0102	11.606165	
6684	4813.760000	131838.2352	1169.000000	
6685	4699.296000	131838.2352	1301.000000	
6901	69.619200	276.0991	40.000000	
6902	68.145300	276.0991	34.000000	

```
      food_transport   forestland  …  manure_management  \
2152        100.5070    -107.2750  …          1543.7229
2153         98.8585    -107.2750  …          1554.3704
2154         33.8336    -107.2750  …          1594.3863
6684      32821.6716 -605722.9991  …         60407.5004
6685      32500.3786 -605722.9991  …         59296.5706
6901       1874.2445  -10843.0573  …          4584.6630
6902       1727.6882  -10843.0573  …          4502.9731

      fires_in_organic_soils  fires_in_humid_tropical_forests  \
2152                     0.0                         416.3368
2153                     0.0                         416.3368
2154                     0.0                         416.3368
6684                     0.0                           0.0000
6685                     0.0                           0.0000
6901                     0.0                           0.0000
6902                     0.0                           0.0000

      on_farm_energy_use  rural_population  urban_population  \
2152             80.8401        44542203.0         6657624.0
2153             82.1289        45925516.0         7022864.0
2154             41.6932        47359180.0         7407170.0
6684         248879.1769        99158922.0       188910774.0
6685         246785.4967        99725999.0       189602194.0
6901            836.4433        11929250.0        11445927.0
6902            776.2953        11824752.0        11526722.0

      total_population_male  total_population_female  total_emission  \
2152             24890395.0               25137639.0    65914.320714
2153             25886400.0               26090250.0    61115.468490
2154             26890139.0               27042568.0    61654.073430
6684            136777703.0              153126995.0   524473.945541
6685            137641632.0              153853429.0   520480.833615
6901             10758632.0               11248553.0    28161.400700
6902             10733004.0               11229798.0    24271.147832

      average_temperature_c
2152               0.625000
2153               0.342667
2154               0.048444
6684               1.158250
6685               0.609000
6901               0.897500
6902              -0.322417

[7 rows x 31 columns]
```

[59]:
```
# path 2
# slope distribution excluding outliers
slopes_filt = [i for i in slopes if i > -0.1]
plt.hist(slopes_filt,bins=30)
plt.axvline(x=np.mean(slopes_filt),color='black')
```

[59]: <matplotlib.lines.Line2D at 0x7f8167a5e780>



using regression analysis,

average temperature is rising in most areas after we filter out areas with small year span

what's next? we have many other dimensions to understand and formulate hypotheses with

[60]:
```
df.head()
```

[60]:
```
          area  year  savanna_fires  forest_fires  crop_residues  \
0  Afghanistan  1990        14.7237        0.0557       205.6077
1  Afghanistan  1991        14.7237        0.0557       209.4971
2  Afghanistan  1992        14.7237        0.0557       196.5341
3  Afghanistan  1993        14.7237        0.0557       230.8175
4  Afghanistan  1994        14.7237        0.0557       242.0494
```

```
   rice_cultivation  drained_organic_soils_co2  pesticides_manufacturing  \
0            686.00                        0.0                 11.807483
1            678.16                        0.0                 11.712073
2            686.00                        0.0                 11.712073
3            686.00                        0.0                 11.712073
4            705.60                        0.0                 11.712073

   food_transport  forestland  …  manure_management  fires_in_organic_soils  \
0         63.1152   -2388.803  …           319.1763                     0.0
1         61.2125   -2388.803  …           342.3079                     0.0
2         53.3170   -2388.803  …           349.1224                     0.0
3         54.3617   -2388.803  …           352.2947                     0.0
4         53.9874   -2388.803  …           367.6784                     0.0

   fires_in_humid_tropical_forests  on_farm_energy_use  rural_population  \
0                              0.0                 NaN         9655167.0
1                              0.0                 NaN        10230490.0
2                              0.0                 NaN        10995568.0
3                              0.0                 NaN        11858090.0
4                              0.0                 NaN        12690115.0

   urban_population  total_population_male  total_population_female  \
0         2593947.0              5348387.0                5346409.0
1         2763167.0              5372959.0                5372208.0
2         2985663.0              6028494.0                6028939.0
3         3237009.0              7003641.0                7000119.0
4         3482604.0              7733458.0                7722096.0

   total_emission  average_temperature_c
0     2198.963539               0.536167
1     2323.876629               0.020667
2     2356.304229              -0.259583
3     2368.470529               0.101917
4     2500.768729               0.372250

[5 rows x 31 columns]
```

regression experiment showed the year span varies for diff areas.

these outliers may confound our analysis

what is the distribution of year span for each area?

1.9 Exercise 1

- goal: make a single figure to visualize and understand the year spans in the dataset
- time: 5m
- hint: you can use either 1D or 2D input for your plot

1.10 Population equilibrium

questions: - are male/female populations in equilibrium? - what is the rate of change of urban and rural populations?

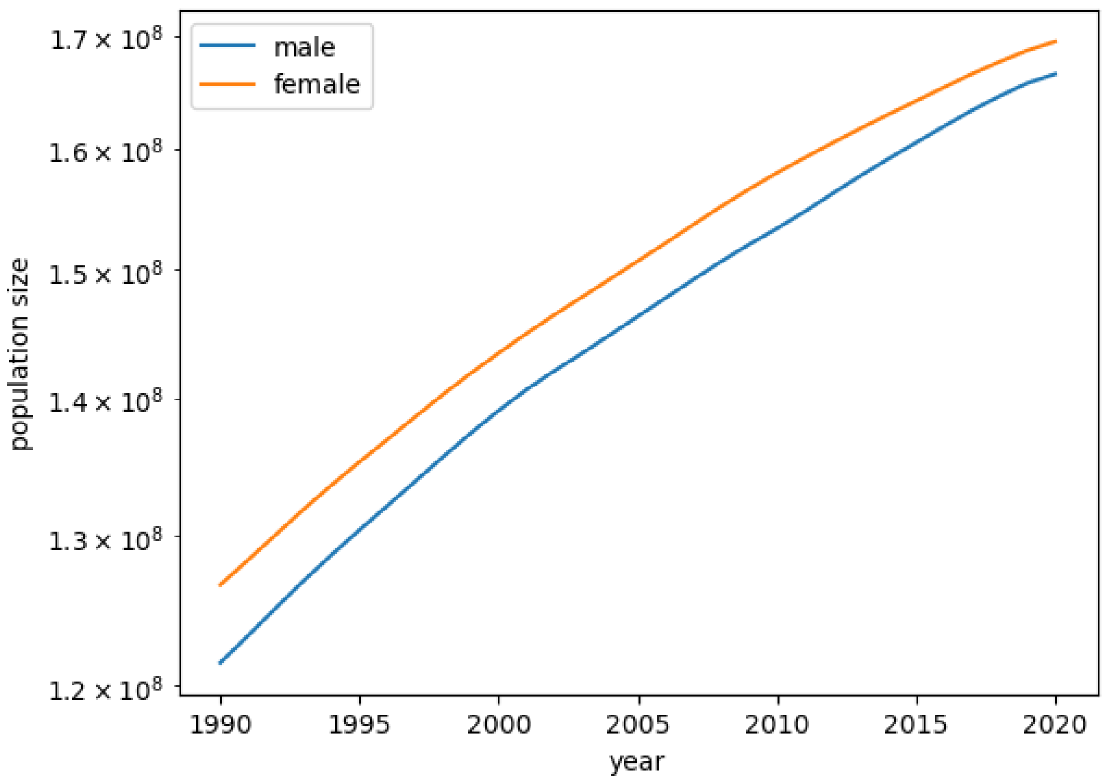
[61]:
```
df.head()
```

[61]:
```
          area  year  savanna_fires  forest_fires  crop_residues  \
0  Afghanistan  1990        14.7237        0.0557       205.6077
1  Afghanistan  1991        14.7237        0.0557       209.4971
2  Afghanistan  1992        14.7237        0.0557       196.5341
3  Afghanistan  1993        14.7237        0.0557       230.8175
4  Afghanistan  1994        14.7237        0.0557       242.0494

   rice_cultivation  drained_organic_soils_co2  pesticides_manufacturing  \
0            686.00                        0.0                 11.807483
1            678.16                        0.0                 11.712073
2            686.00                        0.0                 11.712073
3            686.00                        0.0                 11.712073
4            705.60                        0.0                 11.712073

   food_transport  forestland  …  manure_management  fires_in_organic_soils  \
0         63.1152   -2388.803  …           319.1763                     0.0
1         61.2125   -2388.803  …           342.3079                     0.0
2         53.3170   -2388.803  …           349.1224                     0.0
3         54.3617   -2388.803  …           352.2947                     0.0
4         53.9874   -2388.803  …           367.6784                     0.0

   fires_in_humid_tropical_forests  on_farm_energy_use  rural_population  \
0                              0.0                 NaN         9655167.0
1                              0.0                 NaN        10230490.0
2                              0.0                 NaN        10995568.0
3                              0.0                 NaN        11858090.0
4                              0.0                 NaN        12690115.0

   urban_population  total_population_male  total_population_female  \
0         2593947.0              5348387.0                5346409.0
1         2763167.0              5372959.0                5372208.0
2         2985663.0              6028494.0                6028939.0
3         3237009.0              7003641.0                7000119.0
4         3482604.0              7733458.0                7722096.0

   total_emission  average_temperature_c
0     2198.963539               0.536167
1     2323.876629               0.020667
2     2356.304229              -0.259583
3     2368.470529               0.101917
4     2500.768729               0.372250
```

```
[5 rows x 31 columns]
```

[62]:
```
# plot male and female populations over time in us
x = df_usa['year']
y_male = df_usa['total_population_male']
y_female = df_usa['total_population_female']
plt.plot(x,y_male,label='male')
plt.plot(x,y_female,label='female')
plt.yscale("log",base=10)
plt.xlabel('year')
plt.ylabel('population size')
plt.legend()
```

[62]:
```
<matplotlib.legend.Legend at 0x7f81727c21b0>
```

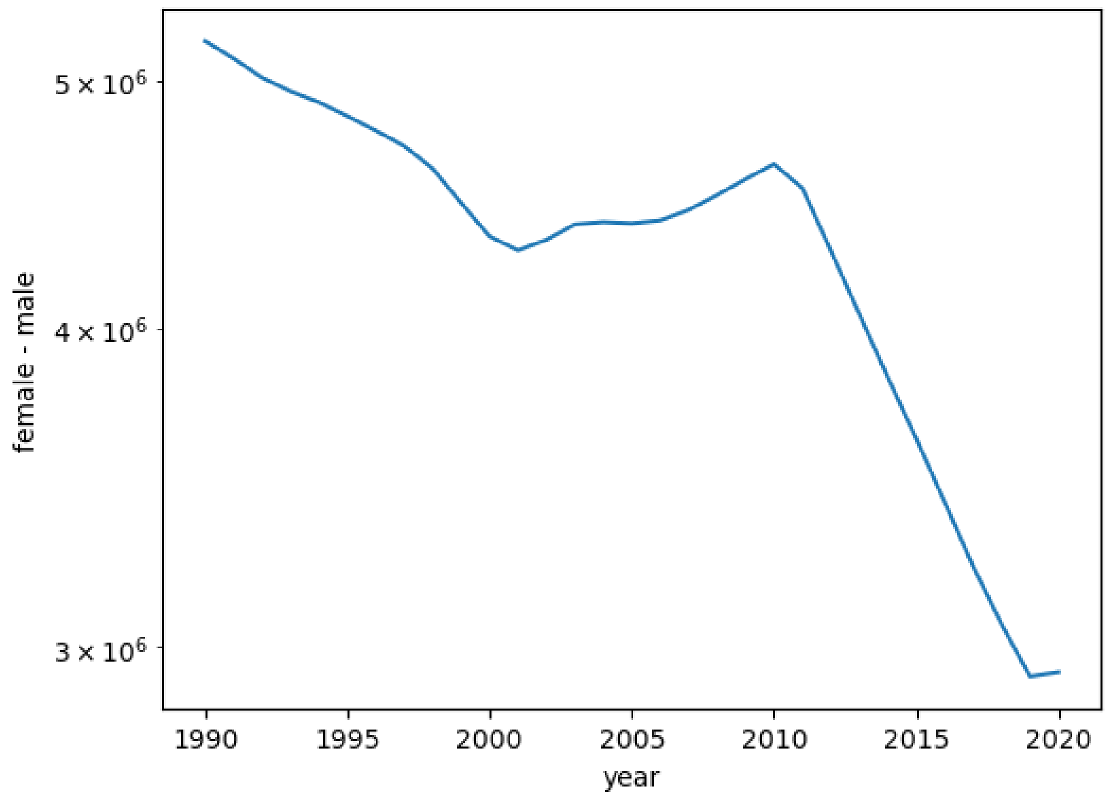


more females than males, but what is the gap here? hard to tell by this plot

[63]:
```
# plot difference of males and females
y_diff = y_female - y_male
plt.plot(x,y_diff)
plt.yscale("log",base=10)
```

```
plt.ylabel('female - male')
plt.xlabel('year')
```

[63]: Text(0.5, 0, 'year')



- 1990: 5M more females than males
- 2020: only 3M more females than males
- the difference (females - males) is decreasing over time

1.11 Exercise 2

- goal: quantify the balance and rate of change between rural and urban populations in the USA
- produce two line plots

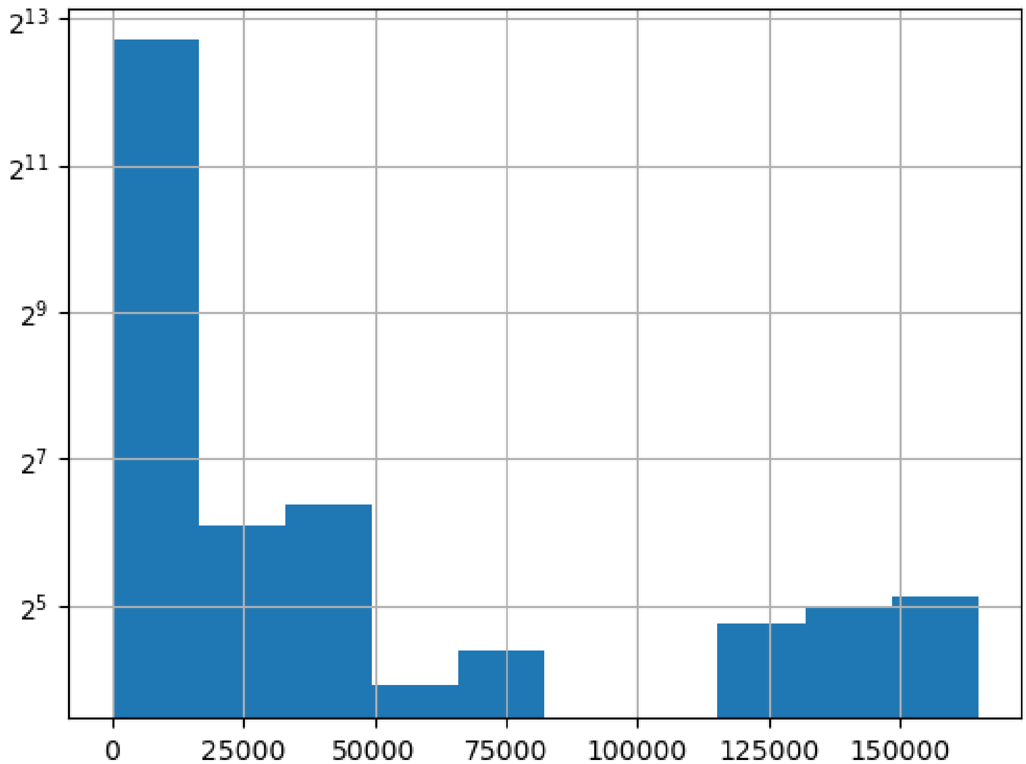
1. Urban and rural population sizes over time
2. The difference urban and rural populations over time

Write a 1 sentence hypothesis based on your plots

1.12 Rice cultivation dominated by few areas

the majority of human wealth and power is held by a small fraction of people what about rice?

```
[64]: df['rice_cultivation'].hist()
      plt.yscale('log',base=2)
```



most areas produce a small amount of rice while relatively few produce a lot of rice

heavy-tailed distributions are infamous in social sciences and empirical network dataset

in fact, many non-negative count data sets (natural numbers [$\mathbb{N}_0$]) are heavy-tailed

let's quantify how important the areas are on the right-hand tail of distribution

The **Gini coefficient** and **Lorenz curve** will quantify the degree of inequality in a distribution.

Lorenz curve

sort $x_1, \ldots, x_n$ from least to most "wealthy" - x-axis: cumulative fraction of the population - y-axis: cumulative fraction of total wealth

Gini coefficient - $x \in \mathbb{R}^n :=$ data - $\bar{x} :=$ empirical mean

$G = \frac{\sum_{i=1}^n \sum_{j=1}^n |x_i - x_j|}{2n^2 \bar{x}}$

- numerator is sum of pairwise differences
- divide by 2 bc we double count
- divide by n^2 to average

  - I feel like we should use $\binom{n}{2}$ instead ...
  - $G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}|x_i - x_j|}{2n(n-1)\bar{x}}$
- divide by $\bar{x}$ s.t. $Range(G) \in [0,1]$ (normalization)
- interpretation
  - $G = 0 \rightarrow$ wealth is equally distributed (one for all)
  - $G = 1 \rightarrow$ maximal inequality (all for one)

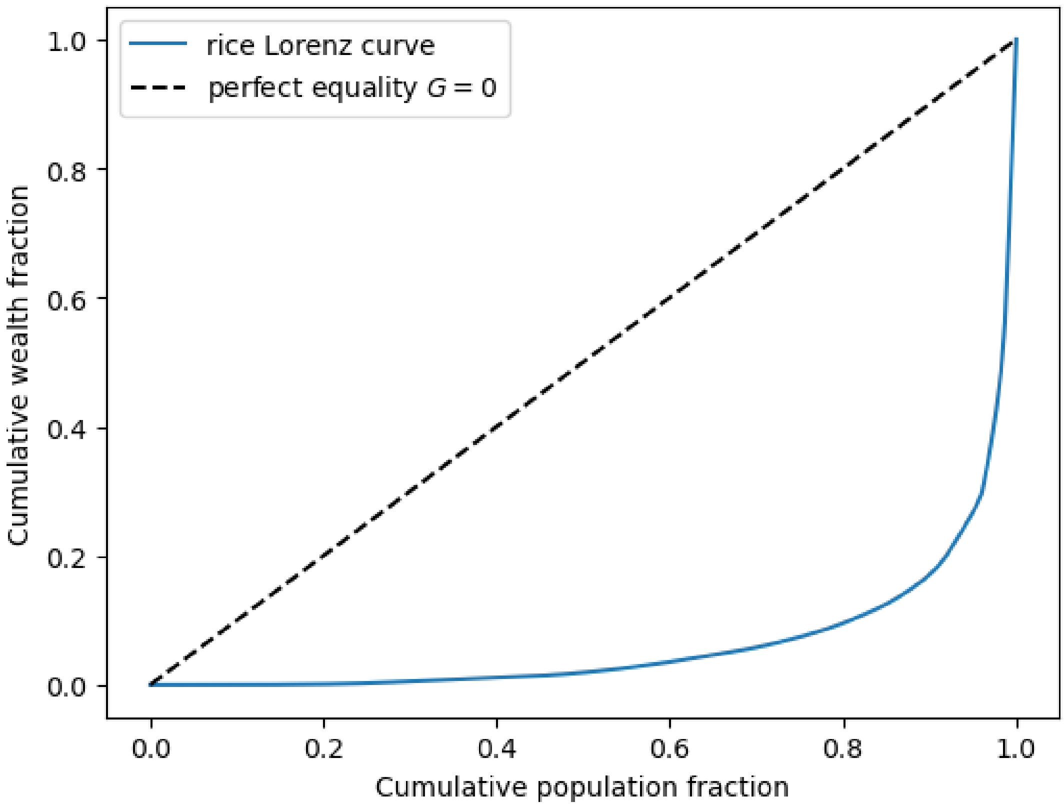
[65]:
```
def gini(x, avg='nchoose2'):
  # there are more efficient ways to compute this
  # but the form used above is most interpretable
  n = len(x)
  num = 0
  mean = np.mean(x)
  for i in range(n):
    for j in range(n):
      num += np.abs(x[i] - x[j])
  if avg == 'nchoose2':
      denom = 2*n*(n-1) * mean
  elif avg == 'quad':
      denom = 2*(n**2)*mean
  else:
      raise ValueError('use "nchoose2" or "quad" for denominator scale')
  return num / denom
# takes about 1 min
gini(df['rice_cultivation'].values)
```

[65]: 0.8707302318270593

[66]:
```
# plot lorenz curve
x = np.sort(df['rice_cultivation'].values)
n = len(x)
# cumulaitve sum vector
cs = np.cumsum(x)
# add 0,0
cs = np.insert(cs, 0, 0)
# normalize cs to [0,1]
cs = cs / cs[-1]
# space our population along the line segment [0,1]
pop = np.linspace(0,1,n+1) # +1 because we added 0,0
# plot
# lorenz curve
plt.plot(pop, cs, label='rice Lorenz curve')
# perfect equality line (G=0)
plt.plot([0,1], [0,1], label="perfect equality $G=0$", color = 'black',␣
↪linestyle='--')
plt.xlabel('Cumulative population fraction')
plt.ylabel('Cumulative wealth fraction')
```

```
plt.legend()
```

[66]: <matplotlib.legend.Legend at 0x7f81678aee70>



interpretation of rice Lorenz curve - 20% of areas produce \$ 90y 0.1\$ of Lorenz curve)

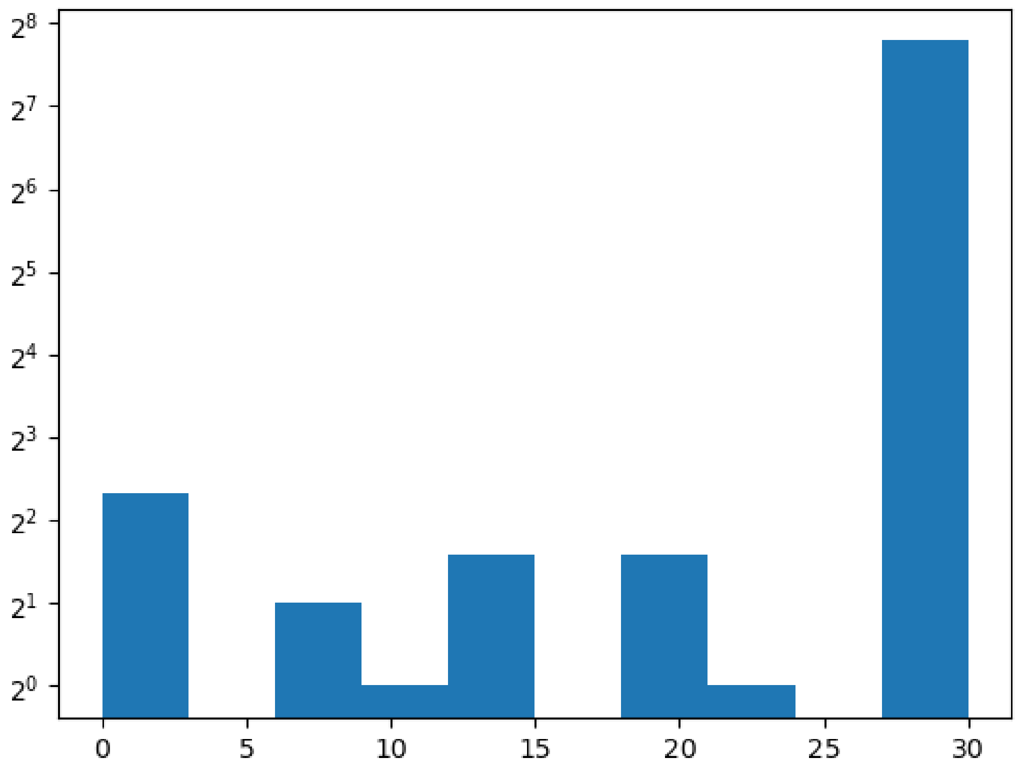
1.13 Exercise 3

- goal: compute Gini coef. for simulated data
- approach:
  - for zipf and powerlaw distributions (hint: use np.random)
    - sample 1000 values
    - compute Gini coef. and plot Lorenz curve
- time: 10m

2 Exercise solutions

2.1 Excerise 1

[67]:
```
# histogram solution
spans = []
for group, df_group in df.groupby('area'):
    spans.append(df_group['year'].max() - df_group['year'].min())
plt.hist(spans)
plt.yscale('log',base=2)
```

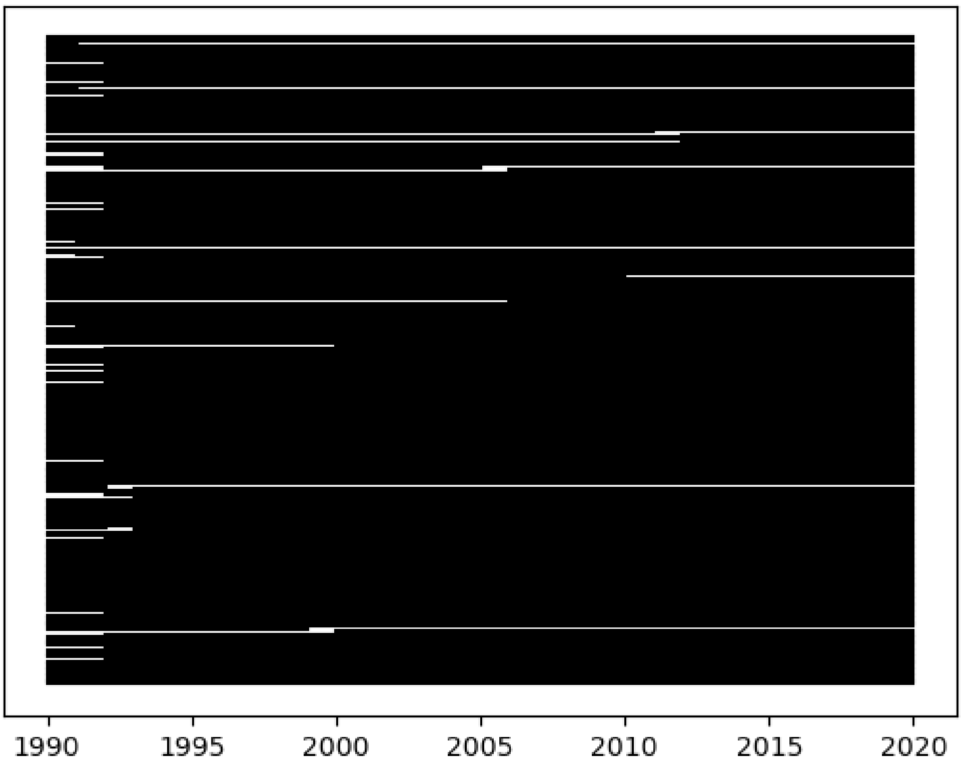


histogram collapses year data for each area into a single integer: span length.

does not indicate which years are missing

[71]:
```
# interval line solution
fig,ax = plt.subplots()
ticks = []
spacing = 1
i=-2
i_prev=0
for group, df_group in df.groupby('area'):
    i = i_prev + spacing
```

```
    years = df_group['year'].values
    ax.plot(years, np.repeat(i, len(years)),color='black')
    ticks.append(group)
    i_prev = i
# hide yticks
ax.yaxis.set_visible(False)
# set y axis label
ax.set_ylabel('Countries')
fig.show()
```



interval plot has fine grain resolution on which years are missing

2.2 Exercise 2

[72]:
```
df_usa.head()
```

[72]:

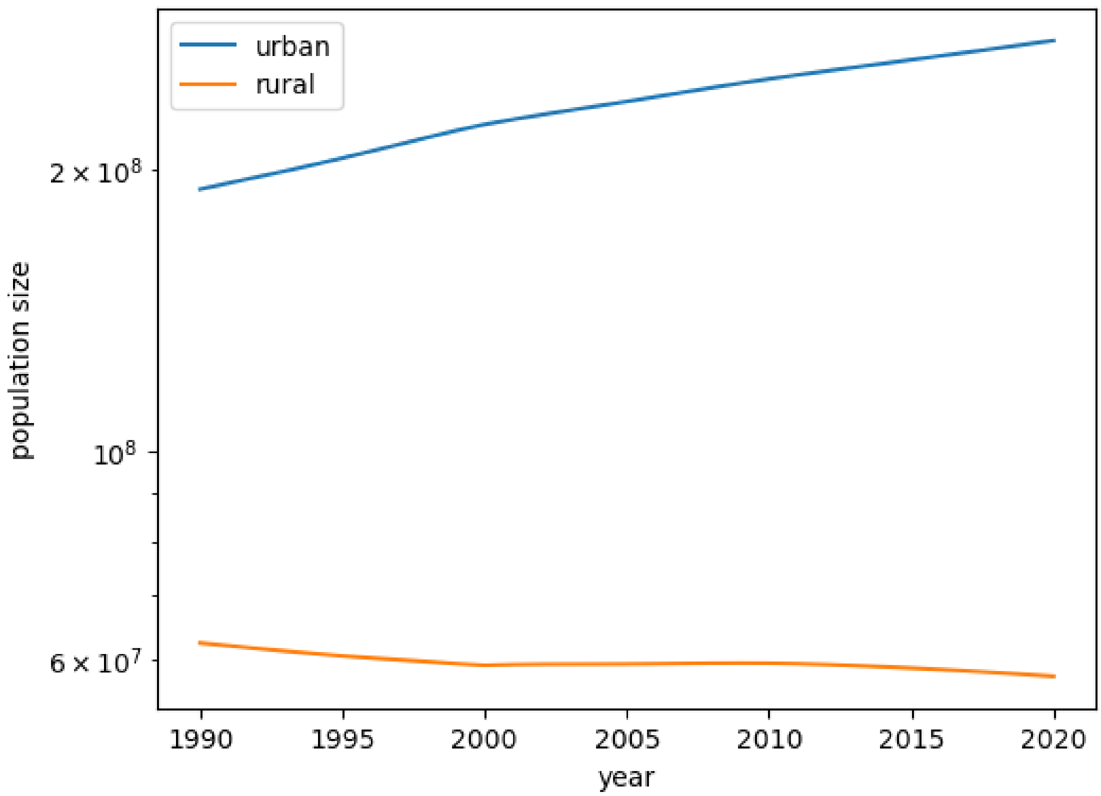
	area	year	savanna_fires	forest_fires	\
6591	United States of America	1990	1391.1481	1999.5617	
6592	United States of America	1991	1391.1481	1999.5617	
6593	United States of America	1992	1391.1481	1999.5617	
6594	United States of America	1993	1391.1481	1999.5617	
6595	United States of America	1994	1391.1481	1999.5617	

```
      crop_residues  rice_cultivation  drained_organic_soils_co2  \
6591     19193.1314         11195.520                 50713.3546
6592     17574.1126         11029.312                 50713.3546
6593     20964.8025         12421.402                 50713.3546
6594     16761.5327         11235.602                 50566.2744
6595     21370.6468         13151.110                 50418.1314

      pesticides_manufacturing  food_transport   forestland  …  \
6591                   13772.0      45410.2673 -520573.1593  …
6592                   13139.0      44566.9408 -520573.1593  …
6593                   14109.0      46198.5933 -520573.1593  …
6594                   12948.0      45175.6740 -520573.1593  …
6595                   14401.0      46739.0889 -520573.1593  …

      manure_management  fires_in_organic_soils  \
6591         47024.7024                     0.0
6592         48206.0451                     0.0
6593         48416.2439                     0.0
6594         48426.0899                     0.0
6595         49165.7227                     0.0

      fires_in_humid_tropical_forests  on_farm_energy_use  rural_population  \
6591                           9.8513          54454.7092        62373717.0
6592                           9.8513          54565.6091        61957131.0
6593                           9.8513          57469.9273        61539241.0
6594                           9.8513          54689.3180        61136396.0
6595                           9.8513          55539.8937        60759735.0

      urban_population  total_population_male  total_population_female  \
6591       190156233.0            121451448.0              126632284.0
6592       193017688.0            123229931.0              128330258.0
6593       195915032.0            125081499.0              130093840.0
6594       198883790.0            126914111.0              131865642.0
6595       201981831.0            128685441.0              133588147.0

      total_emission  average_temperature_c
6591     463050.9394               0.733583
6592     473285.7816               0.706333
6593     486026.3425               0.253000
6594     484238.6197               0.153500
6595     509412.4984               0.470250

[5 rows x 31 columns]
```

[73]:
```
# plot urban and rural populations over time in us
x = df_usa['year']
```

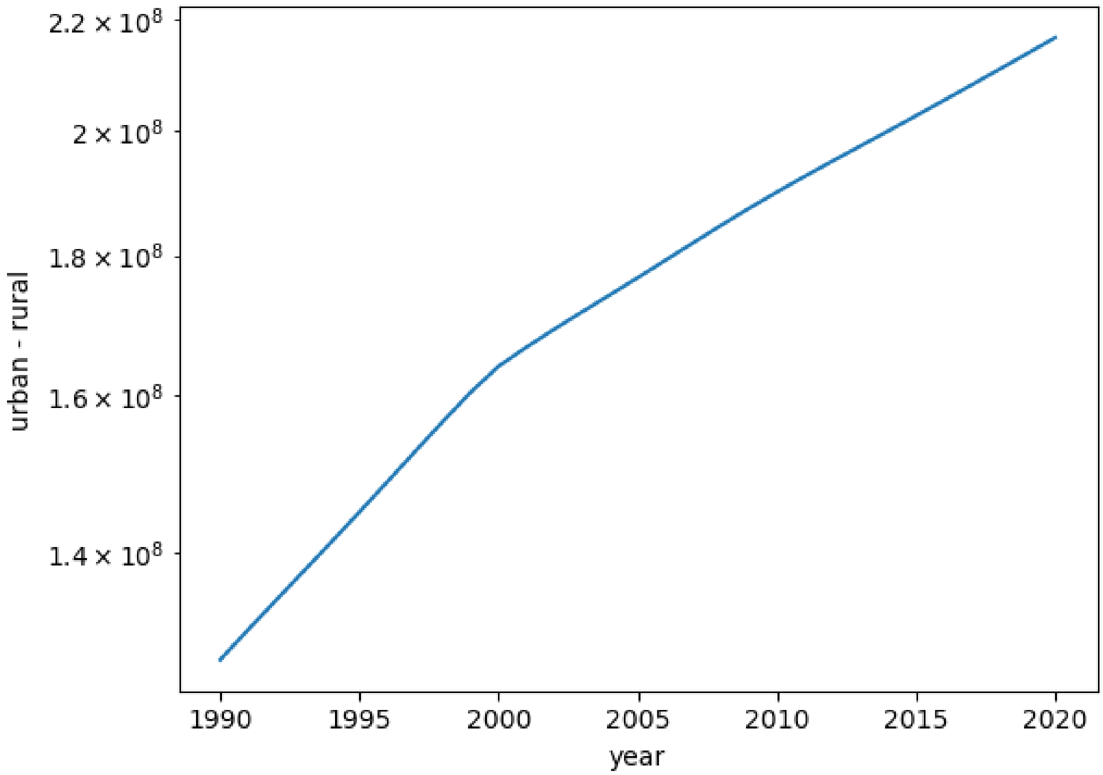
```
y_urban = df_usa['urban_population']
y_rural = df_usa['rural_population']
plt.plot(x,y_urban,label='urban')
plt.plot(x,y_rural,label='rural')
plt.yscale("log",base=10)
plt.xlabel('year')
plt.ylabel('population size')
plt.legend()
```

[73]: <matplotlib.legend.Legend at 0x7f8171481d00>



[74]:
```
# plot difference of males and females
y_diff = y_urban - y_rural
plt.plot(x,y_diff)
plt.yscale("log",base=10)
plt.ylabel('urban - rural')
plt.xlabel('year')
```

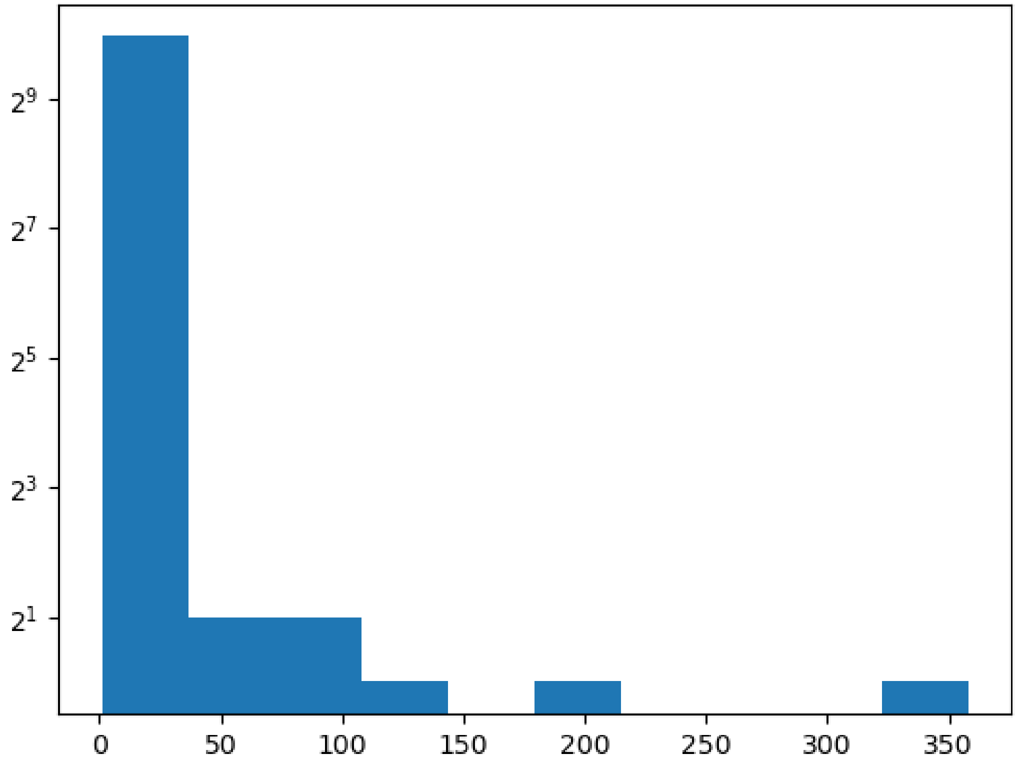
[74]: Text(0.5, 0, 'year')



hypothesis: in the last three decades of the USA, people have been migrating from rural to urban areas

2.3 Exercise 3

[75]:
```
x_zipf = np.random.zipf(a=2,size=1000)
plt.hist(x_zipf)
plt.yscale("log",base=2)
```



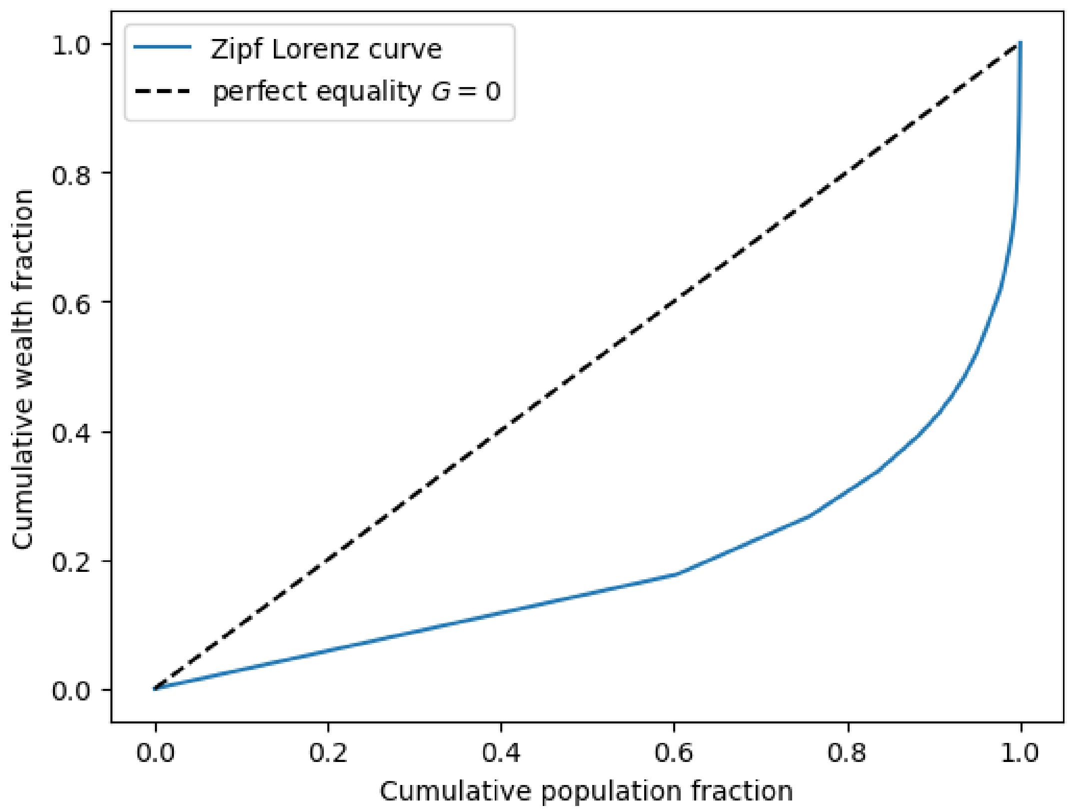
[76]:
```
# zipf Gini
gini_zipf = gini(x_zipf)
print("zipf gini: ", gini_zipf)
```

```
zipf gini:  0.6202736694539973
```

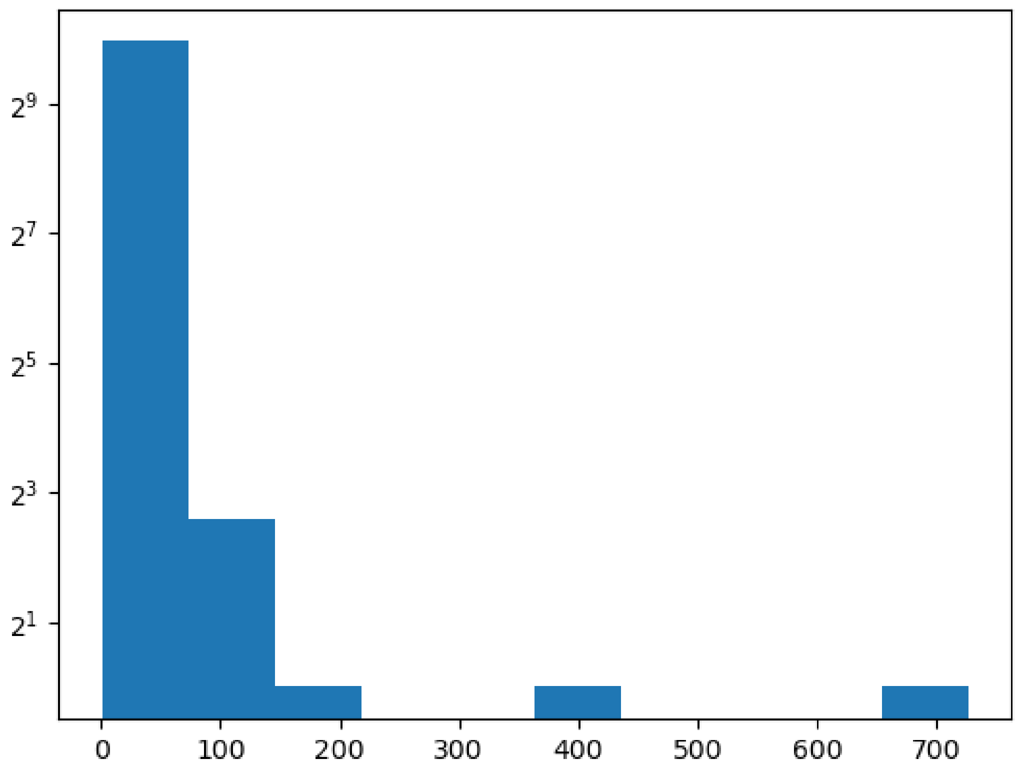
[77]:
```
# zipf Lorenz
x_zipf_sort = np.sort(x_zipf)
n = len(x_zipf_sort)
# cumulaitve sum vector
cs = np.cumsum(x_zipf_sort)
# add 0,0
cs = np.insert(cs, 0, 0)
# normalize cs to [0,1]
cs = cs / cs[-1]
# space our population along the line segment [0,1]
pop = np.linspace(0,1,n+1) # +1 because we added 0,0
# plot
# lorenz curve
plt.plot(pop, cs, label='Zipf Lorenz curve')
# perfect equality line (G=0)
```

```
plt.plot([0,1], [0,1], label="perfect equality $G=0$", color = 'black',␣
    ↪linestyle='--')
plt.xlabel('Cumulative population fraction')
plt.ylabel('Cumulative wealth fraction')
plt.legend()
```

[77]: <matplotlib.legend.Legend at 0x7f8171735430>



[78]:
```
# zipf a = 2
x_zipf = np.random.zipf(2,1000)
plt.hist(x_zipf)
plt.yscale("log",base=2)
```



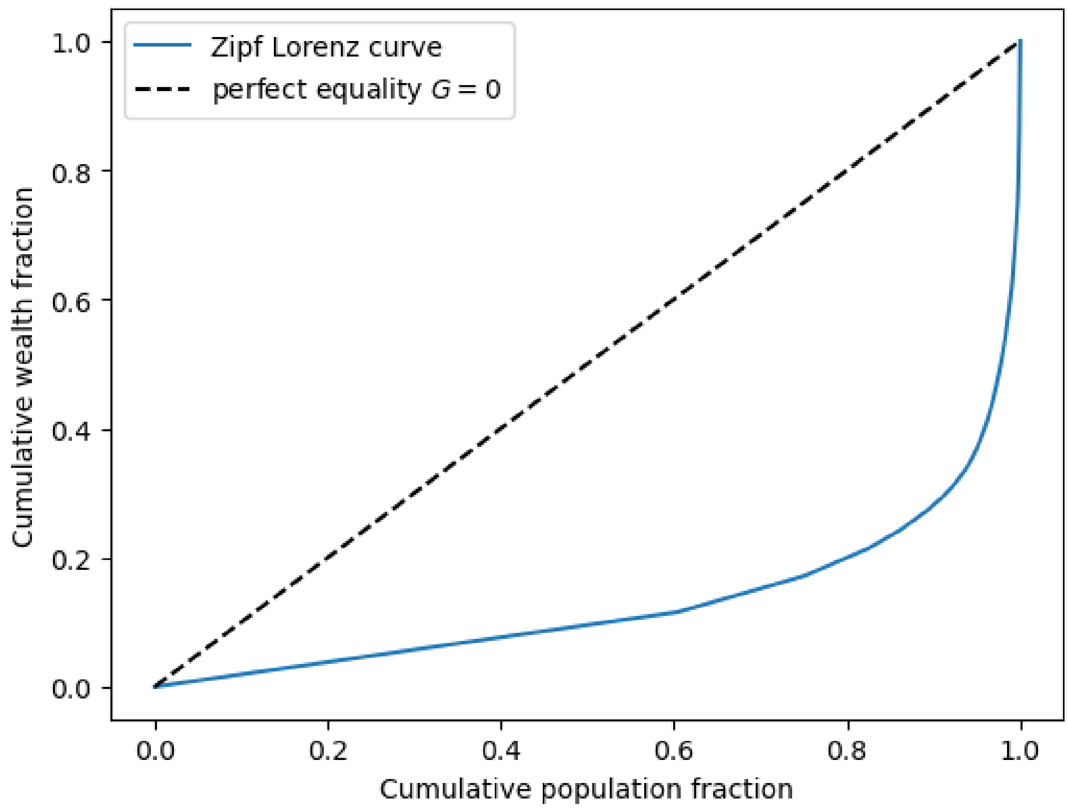
[79]:
```
# zipf Gini
gini_zipf = gini(x_zipf)
print("zipf gini: ", gini_zipf)
```

```
zipf gini:  0.739825818556948
```

[80]:
```
# zipf Lorenz
x_zipf_sort = np.sort(x_zipf)
n = len(x_zipf_sort)
# cumulaitve sum vector
cs = np.cumsum(x_zipf_sort)
# add 0,0
cs = np.insert(cs, 0, 0)
# normalize cs to [0,1]
cs = cs / cs[-1]
# space our population along the line segment [0,1]
pop = np.linspace(0,1,n+1) # +1 because we added 0,0
# plot
# lorenz curve
plt.plot(pop, cs, label='Zipf Lorenz curve')
# perfect equality line (G=0)
```

```
plt.plot([0,1], [0,1], label="perfect equality $G=0$", color = 'black',␣
    ↪linestyle='--')
plt.xlabel('Cumulative population fraction')
plt.ylabel('Cumulative wealth fraction')
plt.legend()
```

[80]: <matplotlib.legend.Legend at 0x7f8167279640>



increasing the a parameter increased the Gini Coefficient and changed the shape of Lorenz curve.

3 Instructor notes

from command-line

`jupyter server`

copy link into web browser