



Economic Atlas of Rural and Small-Town America

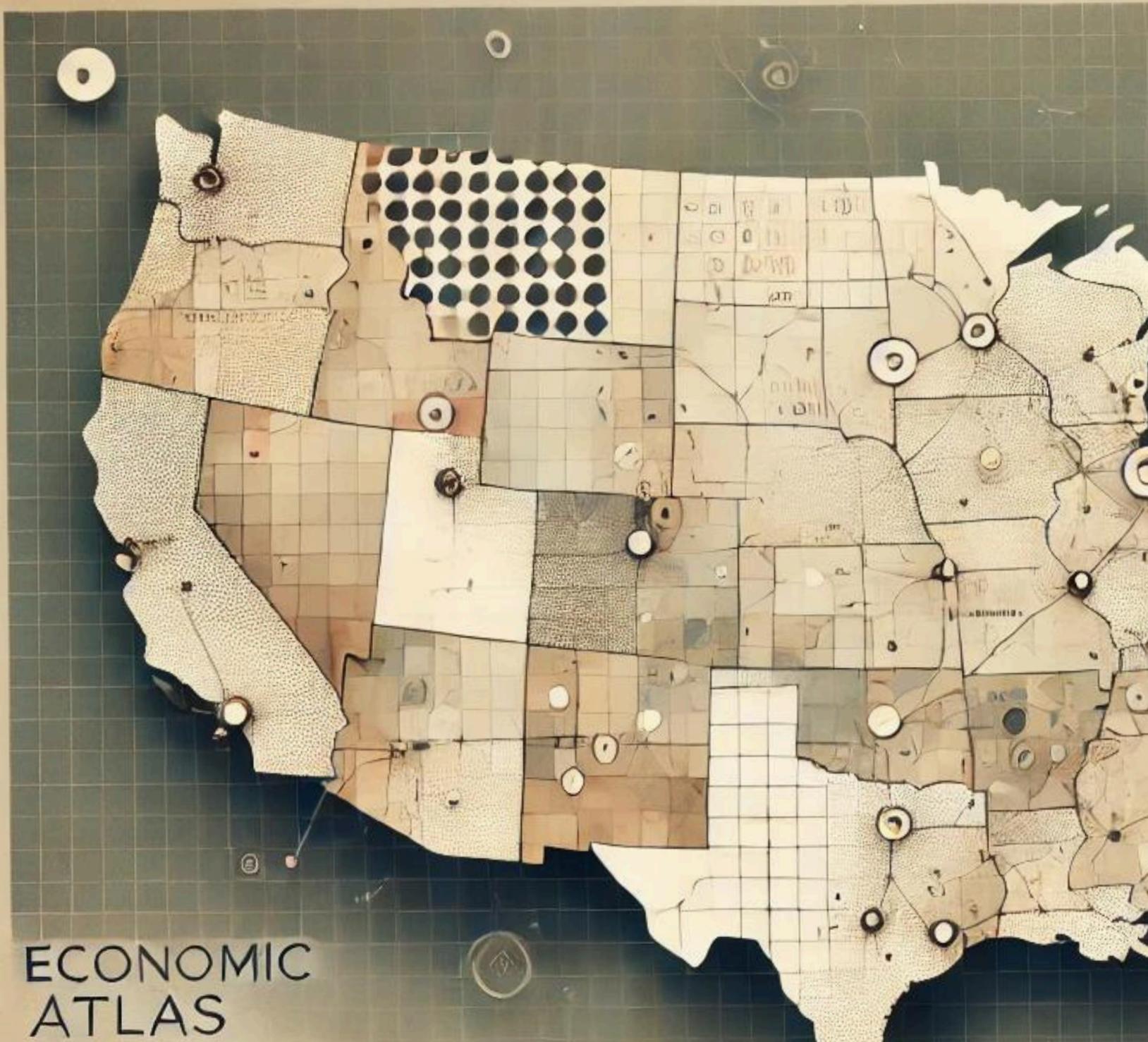
Data Science Boothcamp
Project 3 Group 12



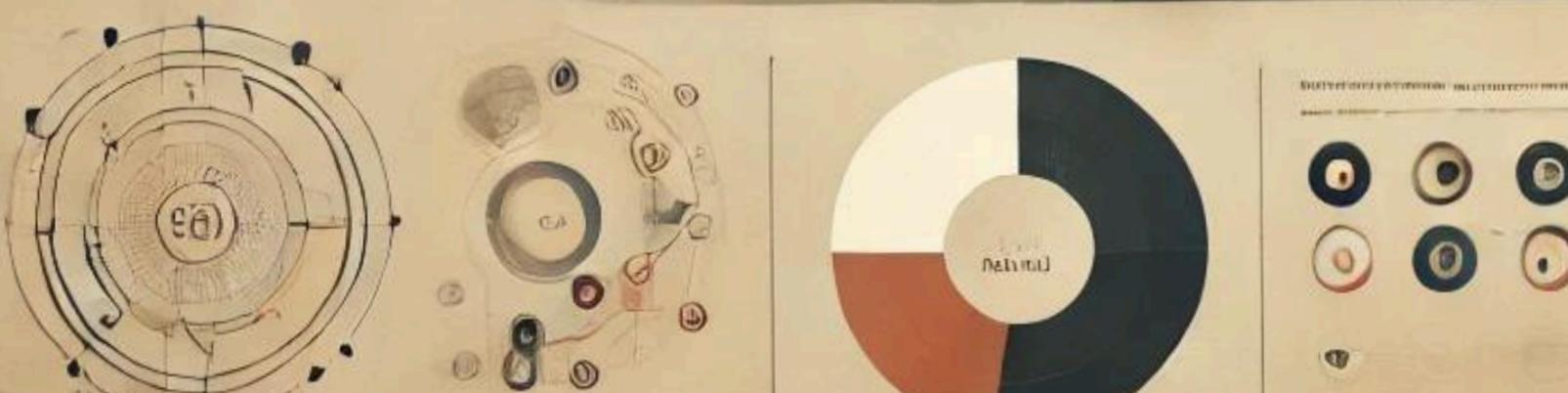
Team Members

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THE ECONOMIC ATLAS OF RURAL AND SMALL TOWNS



ECONOMIC
ATLAS
AMERICA



Introduction

- Rural and small-town America plays a vital role in the nation's socioeconomic landscape.
- The Economic Atlas of Rural and Small-Town America provides essential data on, highlighting the unique challenges and opportunities in these areas.
- Understanding and addressing these economic factors is crucial for fostering balanced national growth and improving the quality of life in rural communities.

FIPS	State	County	PctEmpAgriculture	PctEmpMining	PctEmpConstruction	PctEmpManufacturing	PctEm
0	0	US	United States	1.259202	0.512723	6.592262	10.108008
1	1000	AL	Alabama	0.993190	0.398210	6.604990	14.332569
2	1001	AL	Autauga	0.517902	0.354783	6.072099	12.951635
3	1003	AL	Baldwin	0.952772	0.257648	8.585460	9.249035
4	1005	AL	Barbour	5.717342	0.000000	6.810888	23.047664

```
j: # Get a brief summary of the crowdfunding_info DataFrame.
jobs_df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3278 entries, 0 to 3277
Data columns (total 75 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   FIPS             3278 non-null   int64  
 1   State            3278 non-null   object  
 2   County           3278 non-null   object  
 3   UnempRate2020    3193 non-null   float64
 4   PctEmpChange1920 3193 non-null   float64
 5   UnempRate2019    3272 non-null   float64
 6   PctEmpChange1819  3272 non-null   float64
 7   UnempRate2018    3272 non-null   float64
 8   UnempRate2017    3272 non-null   float64
 9   UnempRate2016    3272 non-null   float64
 10  UnempRate2015   3272 non-null   float64
 11  UnempRate2014   3272 non-null   float64
 12  UnempRate2010   3272 non-null   float64
 13  UnempRate2007   3270 non-null   float64
 14  PctEmpChange1020 3193 non-null   float64
 15  PctEmpChange0720 3188 non-null   float64
 16  PctEmpChange0710  3267 non-null   float64
 17  PctEmpAgriculture 3273 non-null   float64
 18  PctEmpMining     3273 non-null   float64
 19  PctEmpConstruction 3273 non-null   float64
 20  PctEmpManufacturing 3273 non-null   float64
 21  PctEmpTrade      3273 non-null   float64
 22  PctEmpTrans      3273 non-null   float64
 23  PctEmpInformation 3273 non-null   float64
 24  PctEmpFIRE       3273 non-null   float64
 25  PctEmpServices   3273 non-null   float64
 26  PctEmpGovt       3273 non-null   float64
 27  NumCivEmployed  3273 non-null   float64
 28  PctEmpInformation 3273 non-null   float64
```

```
jobs_cleaned_df.isnull().sum()

FIPS                      0
State                     0
County                    0
PctEmpAgriculture         0
PctEmpMining               0
PctEmpConstruction         0
PctEmpManufacturing        0
PctEmpTrade                0
PctEmpTrans                0
PctEmpInformation          0
PctEmpFIRE                 0
PctEmpServices              0
PctEmpGovt                 0
NumCivEmployed             0
dtype: int64
```

Data Cleaning

- In our analysis of the Economic Atlas of Rural and Small-Town America, we processed large datasets containing thousands of rows and multiple columns of socioeconomic data.
- Challenges
 - Large datasets
 - Missing values
 - Inconsistent data formats
- Data Cleaning
 - Dropped irrelevant columns
 - Rectified null values
 - Normalized database
 - Incorporated lat. and long. CSV into location data
 - Corrected data formats for uniformity and clarity

Sql File

```
employment_df = pd.read_sql(text(query), con=self.engine)
employment_data = employment_df.to_dict(orient="records")

return(employment_data)

def getAllData(self, econ_state):
    # allow the user to select ALL country
    if econ_state == "All":
        where_clause = f"econ_state <> 'US'"
    else:
        where_clause = f"econ_ = '{econ_state}'"

    query = f"""
        SELECT state.econ_state,
               econ_year,
               name,
               latitude,
               longitude,
               tot_num_employed,
               tot_num_unemployed,
               tot_pctemp_agriculture,
               tot_pctemp_mining,
               tot_pctemp_construction,
               tot_pctemp_manufacturing,
               tot_pctemp_trade,
               tot_pctemp_trans,
               tot_pctemp_information,
               tot_pctemp_fire,
               tot_pctemp_services,
               tot_pctemp_government,
               tot_um_civ_labor_force
        FROM
        (
        SELECT
            jobs.econ_state,
            employment.econ_year,
            sum(num_employed) as tot_num_employed,
            sum(num_unemployed) as tot_num_unemployed,
            sum(pctemp_agriculture) as tot_pctemp_agriculture,
            sum(pctemp_mining)as tot_pctemp_mining,
            sum(pctemp_construction) as tot_pctemp_construction,
            sum(pctemp_manufacturing) as tot_pctemp_manufacturing,
            sum(pctemp_trade) as tot_pctemp_trade,
            sum(pctemp_trans) as tot_pctemp_trans,
            sum(pctemp_information) as tot_pctemp_information,
            sum(pctemp_fire) as tot_pctemp_fire,
            sum(pctemp_services) as tot_pctemp_services,
            sum(pctemp_government) as tot_pctemp_government,
            sum(num_civ_labor_force) as tot_um_civ_labor_force
        FROM
            jobs
        JOIN
            employment
        ON jobs.fips = employment.fips
        JOIN
            unemployment
        ON employment.fips = unemployment.fips
        AND employment.econ_year = unemployment.econ_year
        WHERE
            {where_clause};
        GROUP BY
            jobs.econ_state,
            employment.econ_year
        ORDER BY
            jobs.econ_state,
            employment.econ_year
        ) AS JOBS
        JOIN
            state ON JOBS.econ_state = state.econ_state
        ORDER BY
            econ_state,
            econ_year
    """
    """

alldata_df = pd.read_sql(text(query), con=self.engine)
all_data = alldata_df.to_dict(orient="records")

return(all_data)
```

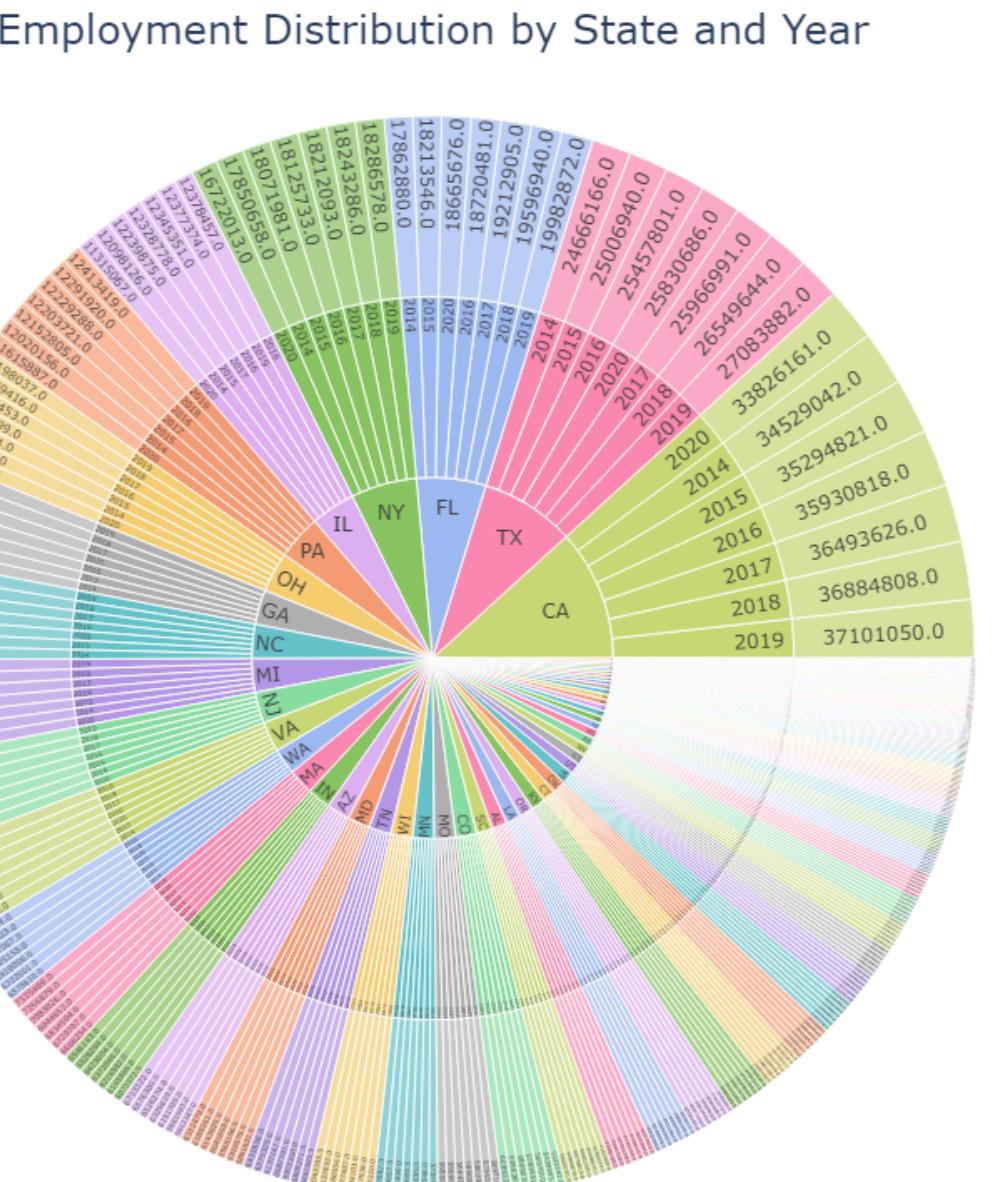


```
latitude,
longitude,
tot_num_employed,
tot_num_unemployed,
tot_pctemp_agriculture,
tot_pctemp_mining,
tot_pctemp_construction,
tot_pctemp_manufacturing,
tot_pctemp_trade,
tot_pctemp_trans,
tot_pctemp_information,
tot_pctemp_fire,
tot_pctemp_services,
tot_pctemp_government,
tot_um_civ_labor_force
FROM
(
SELECT
    jobs.econ_state,
    employment.econ_year,
    sum(num_employed) as tot_num_employed,
    sum(num_unemployed) as tot_num_unemployed,
    sum(pctemp_agriculture) as tot_pctemp_agriculture,
    sum(pctemp_mining)as tot_pctemp_mining,
    sum(pctemp_construction) as tot_pctemp_construction,
    sum(pctemp_manufacturing) as tot_pctemp_manufacturing,
    sum(pctemp_trade) as tot_pctemp_trade,
    sum(pctemp_trans) as tot_pctemp_trans,
    sum(pctemp_information) as tot_pctemp_information,
    sum(pctemp_fire) as tot_pctemp_fire,
    sum(pctemp_services) as tot_pctemp_services,
    sum(pctemp_government) as tot_pctemp_government,
    sum(num_civ_labor_force) as tot_um_civ_labor_force
FROM
    jobs
JOIN
    employment
ON jobs.fips = employment.fips
JOIN
    unemployment
ON employment.fips = unemployment.fips
AND employment.econ_year = unemployment.econ_year
WHERE
    {where_clause};
GROUP BY
    jobs.econ_state,
    employment.econ_year
ORDER BY
    jobs.econ_state,
    employment.econ_year
) AS JOBS
JOIN
    state ON JOBS.econ_state = state.econ_state
ORDER BY
    econ_state,
    econ_year
"""

alldata_df = pd.read_sql(text(query), con=self.engine)
all_data = alldata_df.to_dict(orient="records")

return(all_data)
```

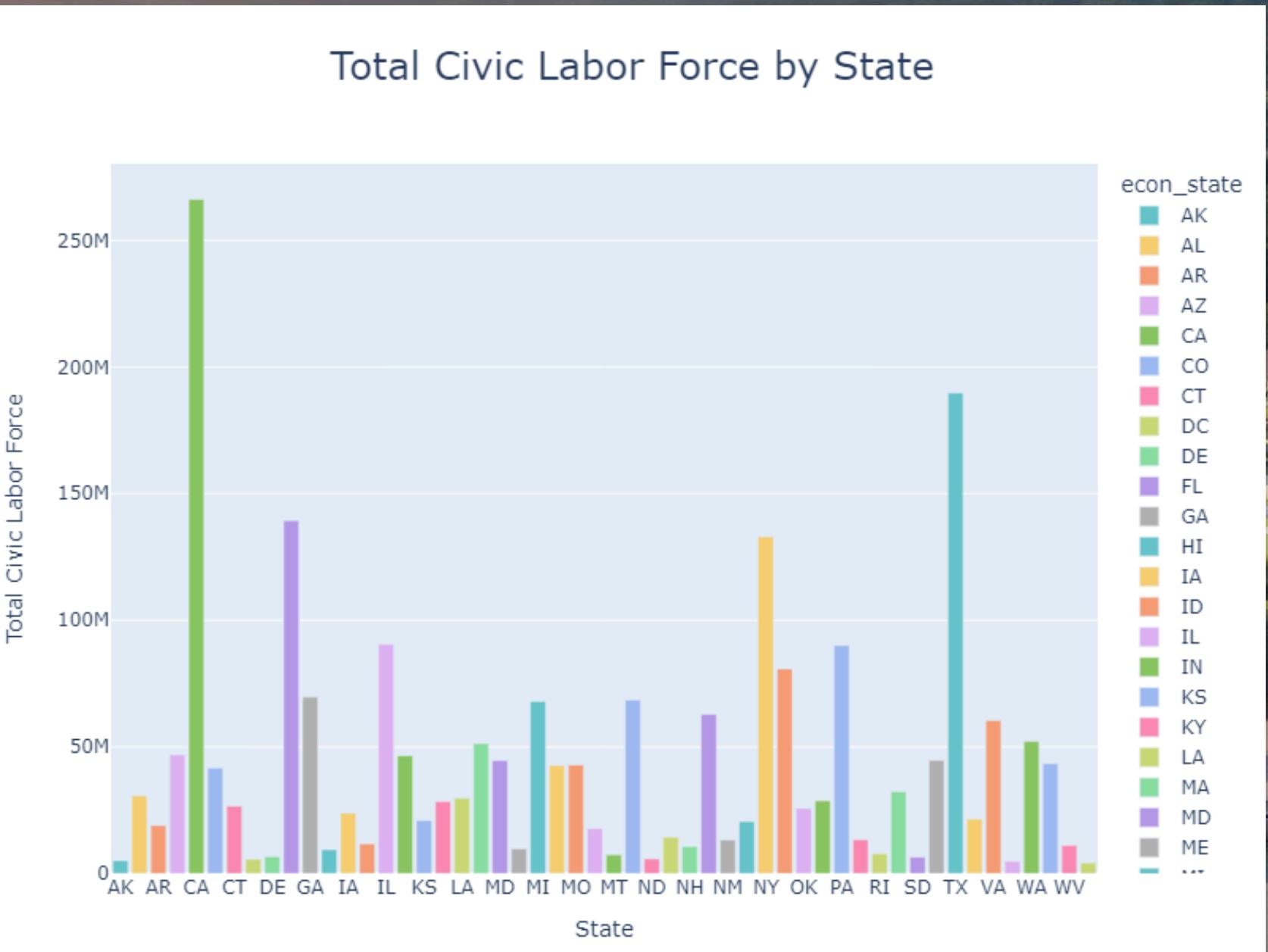
Visualizations



Visualizations



Visualizations





Analysis Findings

- **Employment Distribution:** The analysis reveals that rural and small-town areas have distinct employment patterns, with certain industries like agriculture and manufacturing being more prevalent compared to urban regions.
- **Income Levels:** There is a noticeable disparity in income levels across different rural regions, with some areas significantly lagging behind national averages, highlighting the economic challenges faced by these communities.
- **Unemployment Trends:** Unemployment rates in rural and small-town America show a varied trend, with some regions experiencing persistently high unemployment rates, suggesting structural economic issues.
- **Economic Dependence:** Many rural counties are economically dependent on specific industries, making them vulnerable to sector-specific downturns. This reliance can lead to economic instability if these industries decline.

Limitations/Bias



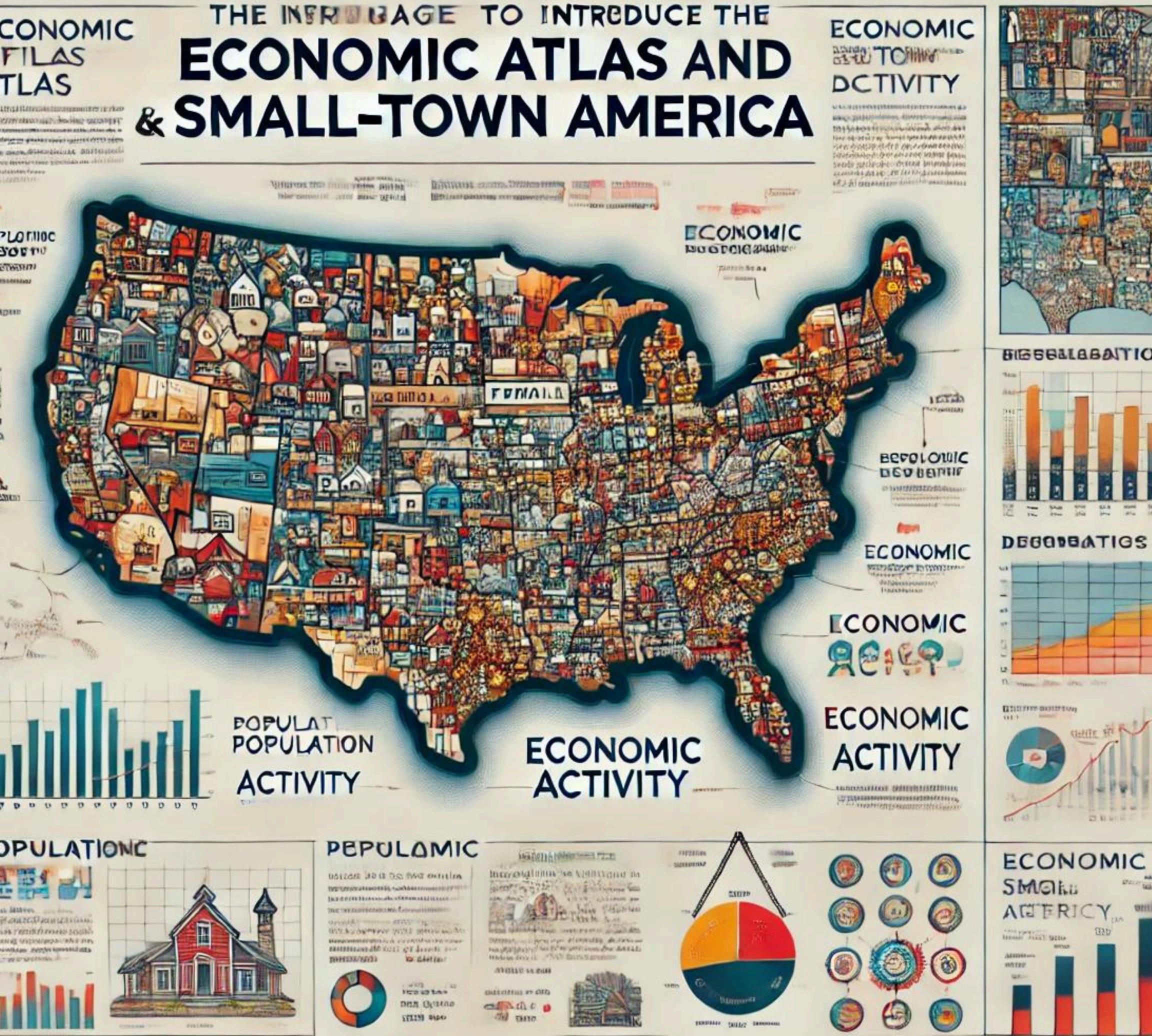
- The data itself is federal census information
 - Method of information collection is inefficient
 - Doesn't actually account for total amount of work being done or revenue being generated (especially in TX and FL with the construction industry)



Links

- Github
- Kaggle
- Xpert Learning Assistant
- <https://github.com/cisnerosjp/project3Team2/tree/main>
- <https://www.texastribune.org/2023/11/21/texas-immigrants-pew-research/#:~:text=Unauthorized%20immigrants%20make%20up%208,networks%20that%20encourage%20further%20immigration>
- <https://www.usatoday.com/story/news/politics/2023/06/21/florida-immigration-law-business-owners-fear-exodus-of-workers-construction-landscaping/70341632007/>

THE INFLUENCE TO INTRODUCE THE **ECONOMIC ATLAS AND** **& SMALL-TOWN AMERICA**



Thank you!!!!!!