SPRING 2025

Random Forest Analysis of Health and Poverty Dynamics in the US (2015-2025)

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CSc 59866 L
Senior Project I - Modeling of Complex Systems

AGENDA

01 PROBLEM STATEMENT

02 DATASETS / DATA SOURCES

03 EXPLORATORY DATA ANALYSIS (EDA)

04 RANDOM FOREST

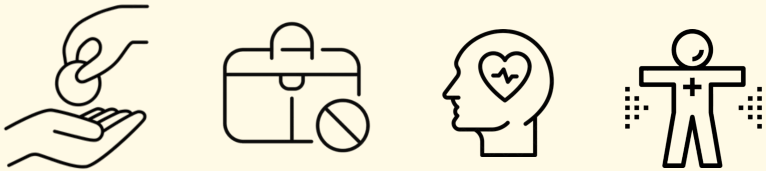
05 DISCUSSION & NEXT STEPS

01

PROBLEM STATEMENT

This project analyzes county-level health and socioeconomic data across the United States from 2015–2025.

It examines trends in poverty, unemployment, and mental and physical health to identify key areas for improving quality of life nationwide.



DATASETS / DATA SOURCES

HEALTH, POVERTY, UNEMPLOYMENT, LOCATION

Population Dynamics Foundation Model (PDFM) Embeddings

- conus27.csv
- county_unemployment.csv
- zcta_poverty.csv

Google Research

11.9k followers · Earth · https://research.google

github.com/google-research

HEALTH, UNEMPLOYMENT, DEMOGRAPHICS, LOCATION

County-Level Population Health and Well-being and Community Conditions

2015 CHR CSV Analytic Data
2016 CHR CSV Analytic Data
2017 CHR CSV Analytic Data
2018 CHR CSV Analytic Data
2019 CHR CSV Analytic Data
2020 CHR Analytic Data (CSV)
2021 CHR CSV Analytic Data
2022 CHR CSV Analytic Data
2023 CHR CSV Analytic Data
2024 CHR CSV Analytic Data
2025 CHR CSV Analytic Data

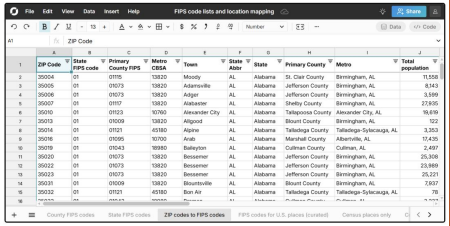
County Health Rankings & Roadmaps

ZIP CODES, FIPS CODES, STATES

FIPS codes for all U.S. locations in a spreadsheet

ZIP codes to FIPS codes mapping

The ZIP codes to FIPS codes sheet provides the list of USPS ZIP codes with their population and maps each ZIP code to state FIPS code and county FIPS code as well as CBSA codes for metropolitan statistical areas. You can use this sheet to lookup FIPS codes by ZIP code or conversely filter to lookup ZIP codes by FIPS code. Note that this sheet includes the primary county for each ZIP code. The ZIP code to county mapping below includes all unique ZIP to county relationships (some ZIP codes overlap with multiple counties).



row zero

FIPS CODES, STATES

USPS State Abbreviations and FIPS Codes

State	Postal Abbr.	FIPS Code	State	Postal Abbr.	FIPS Code
Alabama	AL	01	Nebraska	NE	31
Alaska	AK	02	Nevada	NV	32
Arizona	AZ	04	New Hampshire	NH	33
Arkansas	AR	05	New Jersey	NJ	34
California	CA	06	New Mexico	NM	35
Colorado	CO	08	New York	NY	36
Connecticut	CT	09	North Carolina	NC	37
Delaware	DE	10	North Dakota	ND	38
District of Columbia	DC	11	Ohio	OH	39
Florida	FL	12	Oklahoma	OK	40
Georgia	GA	13	Oregon	OR	41
Hawaii	HI	15	Pennsylvania	PA	42
Idaho	ID	16	Puerto Rico	PR	72
Illinois	IL	17	Rhode Island	RI	44
Indiana	IN	18	South Carolina	SC	45
Iowa	IA	19	South Dakota	SD	46
Kansas	KS	20	Tennessee	TN	47
Kentucky	KY	21	Texas	TX	48
Louisiana	LA	22	Utah	UT	49
Maine	ME	23	Vermont	VT	50
Maryland	MD	24	Virginia	VA	51
Massachusetts	MA	25	Virgin Islands	VI	78
Michigan	MI	26	Washington	WA	53
Minnesota	MN	27	West Virginia	WV	54
Mississippi	MS	28	Wisconsin	WI	55
Missouri	MO	29	Wyoming	WY	56
Montana	MT	30			

U.S. BUREAU OF LABOR STATISTICS

EXPLORATORY DATA ANALYSIS (EDA)


```
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RangeIndex: 35126 entries, 0 to 35125
Data columns (total 32 columns):
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 0   fips5                           35126 non-null  object
 1   year                            35126 non-null  int64
 2   poor_mental_health_days         24983 non-null  float64
 3   poor_physical_health_days       25201 non-null  float64
 4   uninsured                       35107 non-null  float64
 5   ratio_primary_care_physicians   12222 non-null  float64
 6   ratio_mental_health_providers   11568 non-null  float64
 7   unemployment                    35105 non-null  float64
 8   population                      35117 non-null  float64
 9   suicides                        14822 non-null  float64
 10  crude_suicide_rate              14822 non-null  float64
 11  frequent_mental_distress        9580 non-null   float64
 12  frequent_physical_distress      9580 non-null   float64
 13  poor_or_fair_health             9580 non-null   float64
 14  life_expectancy                 9363 non-null   float64
 15  diabetes_prevalence             9580 non-null   float64
 16  hiv_prevalence                  8208 non-null   float64
 17  drug_overdose_deaths            5859 non-null   float64
 18  insufficient_sleep              9577 non-null   float64
 19  adult_smoking                   9580 non-null   float64
 20  adult_obesity                   9580 non-null   float64
 21  physical_inactivity             9580 non-null   float64
 22  excessive_drinking              9580 non-null   float64
 23  preventable_hospital_stays      9366 non-null   float64
 24  children_in_poverty             9579 non-null   float64
 25  median_household_income         9578 non-null   float64
 26  income_inequality               9538 non-null   float64
 27  air_pollution_pm                6332 non-null   float64
 28  drinking_water_violations       9431 non-null   float64
 29  traffic_volume                  9366 non-null   float64
 30  pct_below_18                    9582 non-null   float64
 31  pct_65_and_older                9582 non-null   float64
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memory usage: 8.6+ MB
```

```
--------------MISSING--------------
 fips5                              0
year                                0
poor_mental_health_days         10143
poor_physical_health_days        9925
uninsured                          19
ratio_primary_care_physicians   22904
ratio_mental_health_providers   23558
unemployment                       21
population                          9
suicides                        20304
crude_suicide_rate              20304
frequent_mental_distress        25546
frequent_physical_distress      25546
poor_or_fair_health             25546
life_expectancy                 25763
diabetes_prevalence             25546
hiv_prevalence                  26918
drug_overdose_deaths            29267
insufficient_sleep              25549
adult_smoking                   25546
adult_obesity                   25546
physical_inactivity             25546
excessive_drinking              25546
preventable_hospital_stays      25760
children_in_poverty             25547
median_household_income         25548
income_inequality               25588
air_pollution_pm                28794
drinking_water_violations       25695
traffic_volume                  25760
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pct_65_and_older                25544
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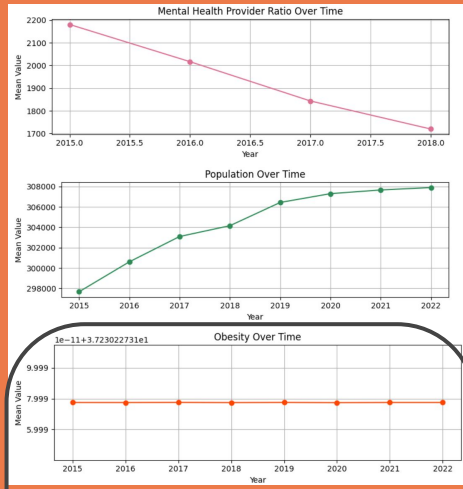
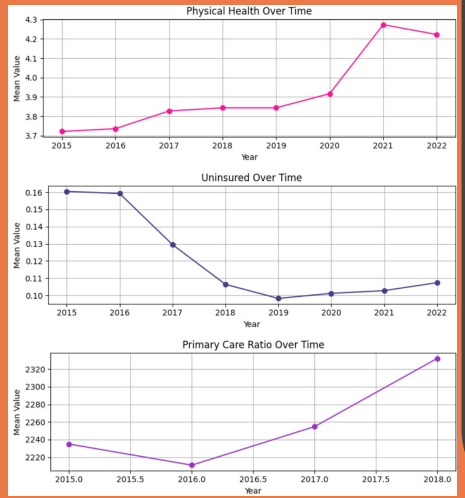
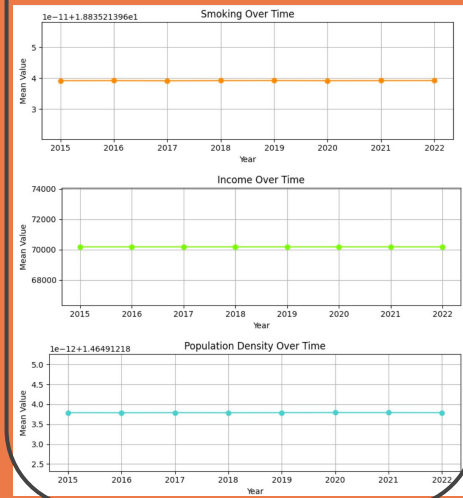
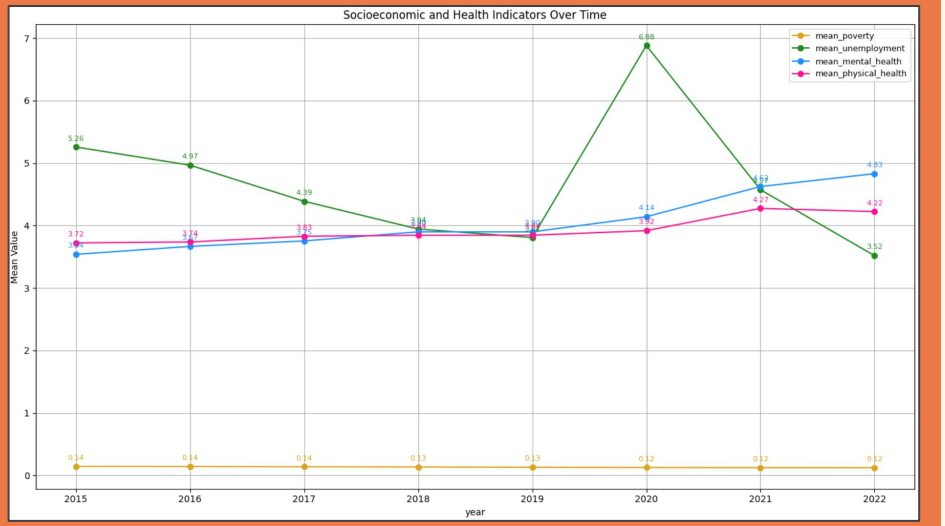
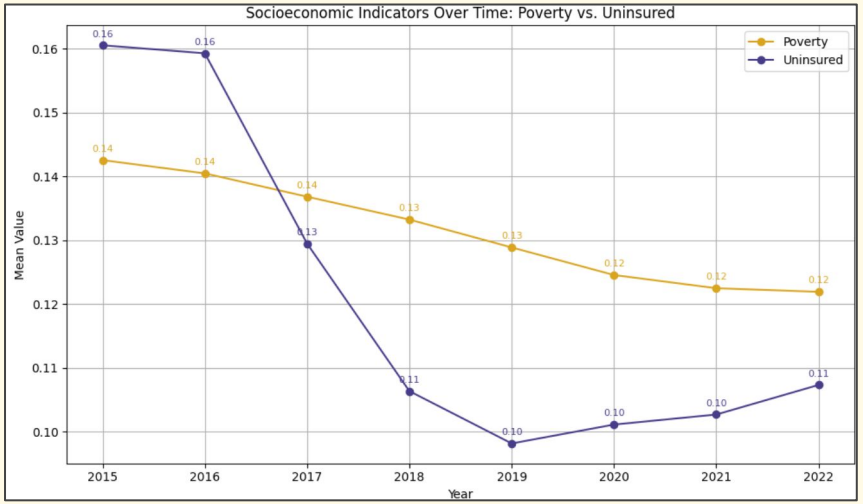


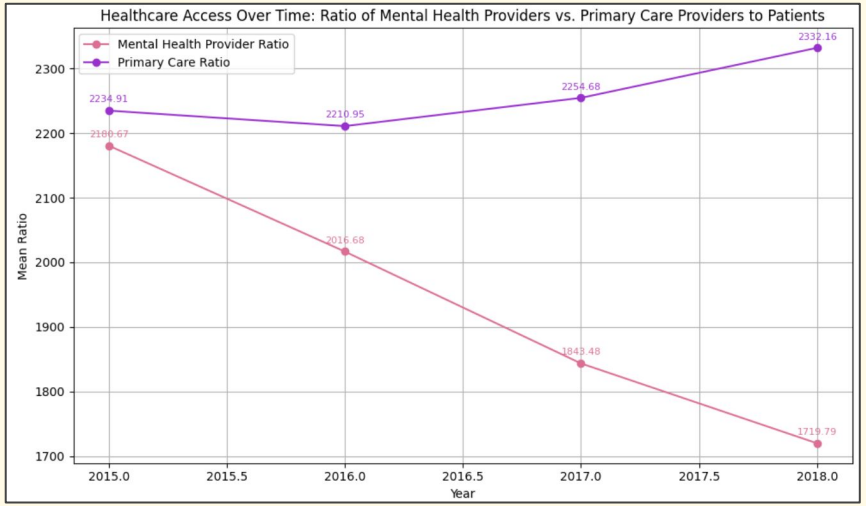




TIME SERIES (EDA)







03

STRONG POSITIVE RELATIONSHIPS, >= +0.50

poor_mental_health_days & **poor_physical_health_days: 0.94**
Percent_Person_Obesity & **Percent_Person_Smoking: 0.75**
poor_physical_health_days & **Percent_Person_Smoking: 0.70**
poor_mental_health_days & **Percent_Person_Smoking: 0.66**

MODERATE POSITIVE RELATIONSHIPS, >= 0

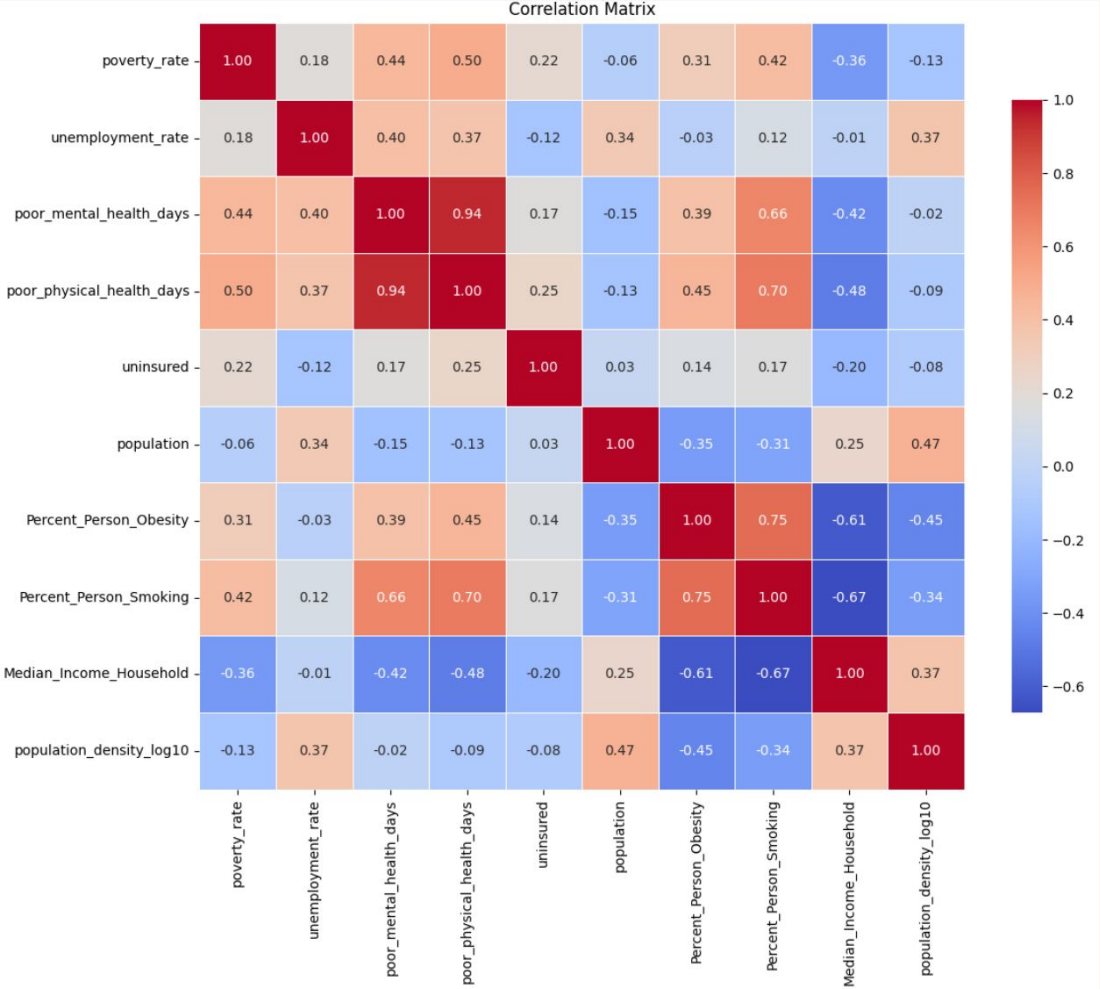
poverty_rate & poor_physical_health_days: 0.50
poverty_rate & poor_mental_health_days: 0.44
poverty_rate & Percent_Person_Smoking: 0.42
unemployment_rate & poor_mental_health_days: 0.40
poor_physical_health_days & Percent_Person_Obesity: 0.45
poor_mental_health_days & Percent_Person_Obesity: 0.39

MODERATE NEGATIVE RELATIONSHIPS, <= 0

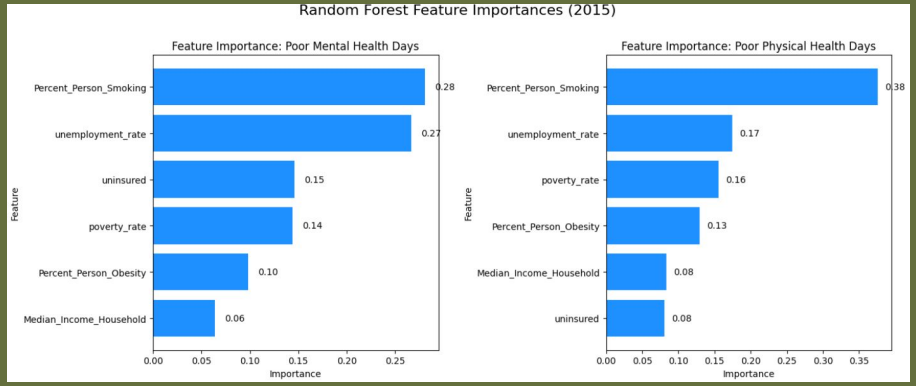
poor_physical_health_days & Median_Income_Household: -0.48
Percent_Person_Obesity & population_density_log10: -0.45
poor_mental_health_days & Median_Income_Household: -0.42

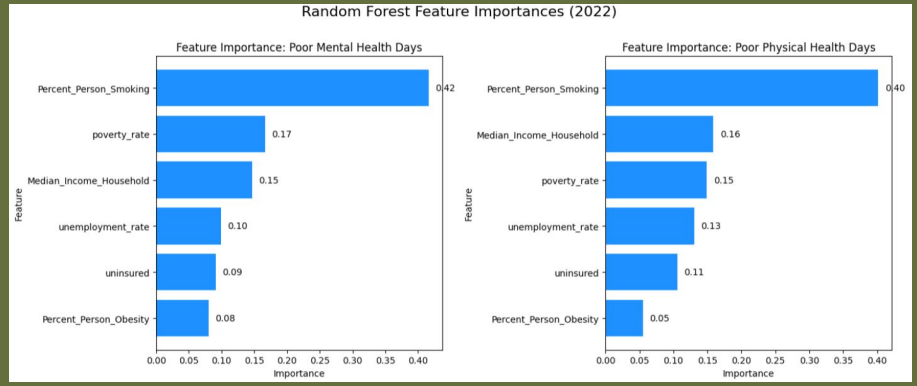
STRONG NEGATIVE RELATIONSHIPS, <= −0.50

Percent_Person_Smoking & Median_Income_Household: -0.67
Percent_Person_Obesity & Median_Income_Household: -0.61



RANDOM FOREST FEATURE IMPORTANCES






```
Processing year: 2023
No data for year 2023
Processing year: 2024
No data for year 2024
Processing year: 2025
No data for year 2025
```

MENTAL & PHYSICAL HEALTH CONTRIBUTORS

Top Feature: Percent_Person_Smoking increases from 2015-2022.

Economic hardship (poverty, unemployment, low income) **consistently predicts worse health**.

Less important: lack of insurance & obesity rates are less predictive of poor health days.

DISCUSSION &Next Steps

Smoking prevention and **rehabilitation** could have the biggest impact on reducing the frequency of poor mental & physical health days.

Economic improvements (addressing poverty, unemployment, and income) **remain important**, but their relative influence shifts with time.

Policy and intervention focus should **prioritize smoking reduction**, alongside **economic support**, for community health improvement.

01 IMPROVE DATA QUALITY

comprehensive data leads to more accurate and trustworthy analysis, pattern recognition, predictions

02 EXPLORE ADDITIONAL VARIABLES & FACTORS

might improve model performance or explain data variance and trends

03 EXAMINE CAUSALITY BETWEEN PATTERNS

understand reasons for observed associations, perceived relationships & trends