Seattle Food Inspections

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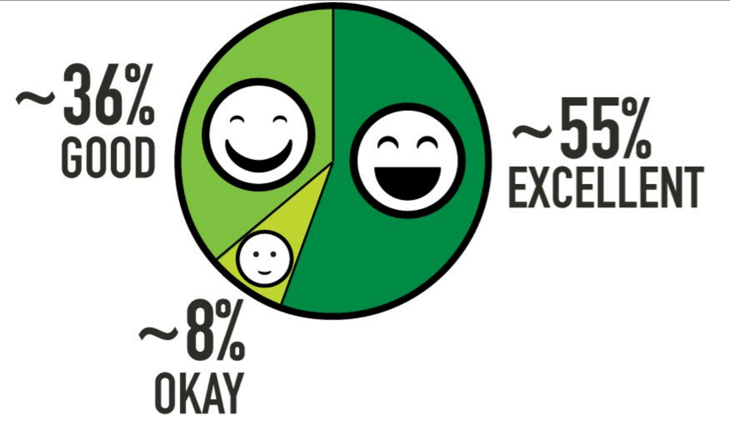
Introduction

- Starting 2012, jurisdictions across the country including King County have begun publishing **health inspection scores** using a standardized scoring system called LIVES.
- This open data allowed restaurant consumers to make informed decisions based on **where they want to eat** and motivated a lot of restaurant establishments to **improve their inspection score** in the hopes of attracting a bigger customer base.



Brief overview of the objectives

1. **Location Specific Contributions**: Where are the specific regions in Seattle that have the most high risk food safety violations?
2. **Interactive Map**: showing food inspection ratings in Seattle.
3. Then overlay these **ratings with demographic** information in the areas around restaurants.
4. Users will be able to explore **correlations** between the demographics and health inspection ratings to help make decisions about where to eat.

Package Dependency

Folium

GeoPandas
in Python

Pandas

Altair
Declarative Visualization in Python

NumPy

Dataset

1. Food Establishment Inspection Data - ***King County Open Data***

	Name	Program Identifier	Inspection Date	Description	Address	City	Zip Code	Phone	Longitude	Latitude	Inspection Business Name	Inspection Type
0	@ THE SHACK, LLC	SHACK COFFEE	08/03/2019	Seating 0-12 - Risk Category III	2920 SW AVALON WAY	Seattle	98126	(206) 938-5665	-122.370913	47.570425	@ THE SHACK, LLC	Routine Inspection/Field Review

2. Median Income 5-Year Estimates (S1903) - ***American Community Survey***
3. Marital Status (S1201) - ***American Community Survey***

	zipcode	Population	No_Married(%)	Widowed(%)	Divorced(%)	Separated(%)	Never_Married(%)	No_Married	Widowed	Divorced	Separated	Never_Marriec
0	83501	28808	52.0	6.7	13.5	1.1	26.7	14980	1930	3889	316	7691
1	83822	1625	52.1	8.2	14.2	2.0	23.5	846	133	230	32	381

Data Cleaning

- Detecting **missing values** (tolerance)
  - (✓)Missing Violation
  - (✕)Missing Name / Grade
  - (✕)Unnecessary Identifiers
- Extracting desired **columns**
- Modifying the data (i.e. **type**, caps, etc.)
- Joining the census data by **zip codes**

```
SEATTLE          136455
BELLEVUE          19689
KENT              13705
RENTON            11805
FEDERAL WAY       11695
REDMOND           11159
KIRKLAND          10654
AUBURN             7752
ISSAQUAH           5846
SHORELINE          5185
Name: City, dtype: int64
```

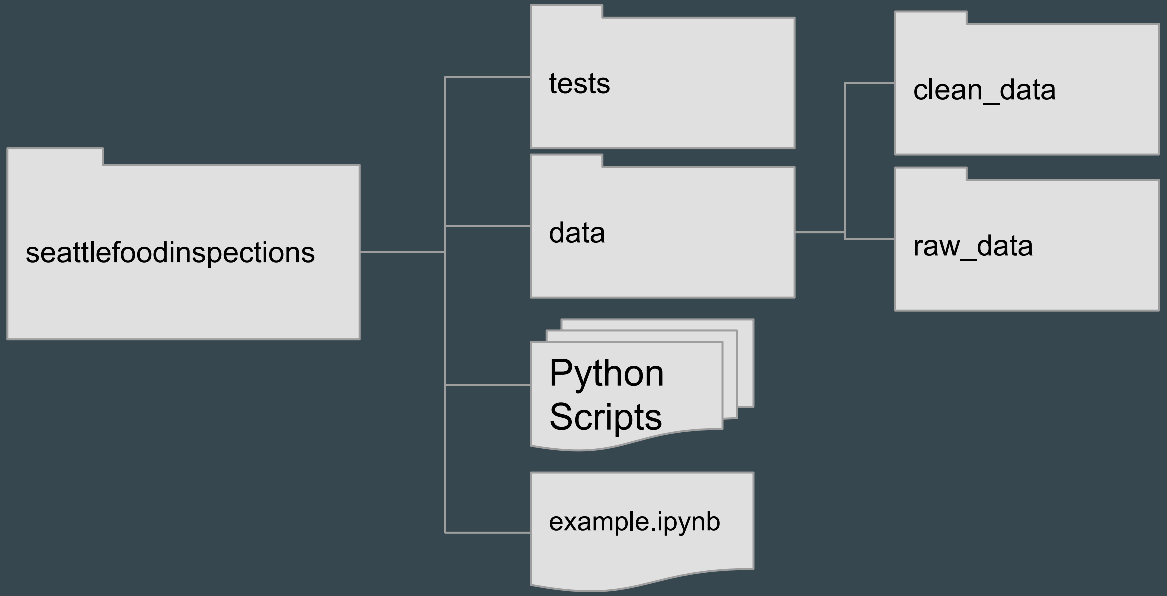
Data Cleaning

- Shape: **(274970, 22)** >>> **(8413, 12)**
- Columns & Types

```
RangeIndex: 274970 entries, 0 to 274969
Data columns (total 22 columns):
Name                          274970 non-null object
Program Identifier            274970 non-null object
Inspection Date               274423 non-null object
Description                   274970 non-null object
Address                       274970 non-null object
City                          274970 non-null object
Zip Code                      274970 non-null object
Phone                         192911 non-null object
Longitude                     274959 non-null float64
Latitude                      274959 non-null float64
Inspection Business Name      274423 non-null object
Inspection Type               274423 non-null object
Inspection Score              274369 non-null float64
Inspection Result             274423 non-null object
Inspection Closed Business    274423 non-null object
Violation Type                156246 non-null object
Violation Description         156246 non-null object
Violation Points              274970 non-null int64
Business_ID                   274970 non-null object
Inspection_Serial_Num         274423 non-null object
Violation_Record_ID           156246 non-null object
Grade                         215640 non-null float64
dtypes: float64(4), int64(1), object(17)
```

```
Int64Index: 8413 entries, 134890 to 208625
Data columns (total 12 columns):
Name                          8413 non-null object
Inspection Date               8413 non-null datetime64[ns]
Description                   8413 non-null object
Zip Code                      8413 non-null int64
Inspection Type               8413 non-null object
Inspection Score              8413 non-null float64
Inspection Result             8413 non-null object
Inspection Closed Business    8413 non-null object
Violation Type                3853 non-null object
Violation Description         3853 non-null object
Violation Points              8413 non-null int64
Grade                         8413 non-null float64
dtypes: datetime64[ns](1), float64(2), int64(2), object(7)
```

(Partial) File Structure



Use Case

BMC Public Health

BMC

BMC Public Health. 2014; 14: 571. PMCID: PMC4057591
Published online 2014 Jun 7. doi: 10.1186/1471-2458-14-571 PMID: 24908104

Factors affecting food handling Practices among food handlers of Dangila town food and drink establishments, North West Ethiopia

Ayehu Gashe Tessema,[1] Kassahun Alemu Gelaye,[1] and Daniel Haile Chercos[1]

- At least in NW Ethiopia, **certain demographic information** of the workers is associated with food handling practices.
- Users can see visually if such **correlation** between restaurant locations and some of the same demographic information (median income and various marital statuses) in Seattle.
- Users can use these **demographic statistics** to find what zip codes in Seattle to explore for new restaurants.

Demo

(transition to JupyterLab for demonstration)

Design

Data collection from URLs (inspections, census and geographic)

↓

Cleaning datasets (remove null/NaN etc, erroneous locations ...)

↓

Merging datasets (merge on restaurant zip code)

↓

Visualizing (chloropleth of census data with interactive histograms, associated trend analysis charts)

Lessons Learned & Future Work

- Data sets are inherently “dirty” -> data science software requires significant data cleaning and preparation
- Modulation and generalization has up-front costs that pay for themselves in the long run
  - It’s easy to write functions that work for one instance but which break easily

- Incorporate more robust census data
- Generalize functions to be used for any city/region

Questions?

Thank you