

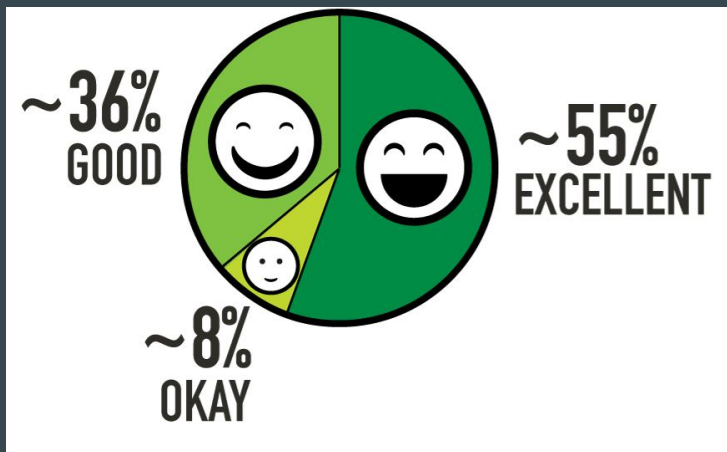
Seattle Food Inspections

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David Clancy, Sadra Fardhosseini, Greg Talpey, Harry Xie

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.

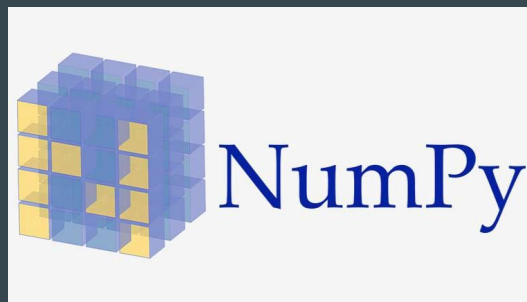


Brief overview of the objectives

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



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_Married
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)
```

Use Case



[BMC Public Health](#). 2014; 14: 571.

Published online 2014 Jun 7. doi: [10.1186/1471-2458-14-571](#)

PMCID: PMC4057591

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 ...)

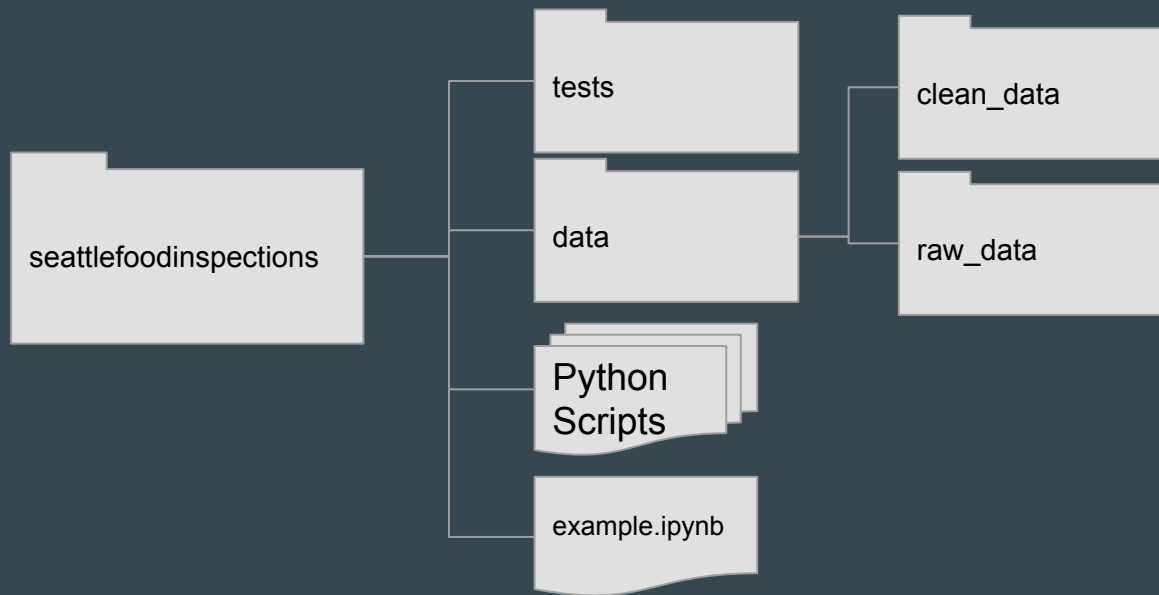


Merging datasets (merge on restaurant zip code)



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

(Partial) File Structure



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