CS513: Theory & Practice of Data Cleaning

Individual Submission: Nadia Wood (nadiaw2)

Team115

Git repo: https://github.com/nadiawoodninja/cs513-data-cleaning

Tableau Dashboard: https://public.tableau.com/app/profile/nadia.wood/viz/cs513/Dashboard1

# 1. Dataset of interest:

- **Initial dataset**: farmersmarkets.csv. The source of this data is https://www.ams.usda.gov/local-food-directories/farmersmarkets
- There is an API available to download the farmers market data at this URL: `https://www.usdalocalfoodportal.com/api/farmersmarket/`
- According to the website "The Farmers Market Directory lists markets that feature two or more farm vendors selling agricultural products directly to customers at a common, recurrent physical location. Maintained by the Agricultural Marketing Service, the Directory is designed to provide customers with convenient access to information about farmers market listings to include: market locations, directions, operating times, product offerings, accepted forms of payment, and more."
- **Output dataset:**
  - **farmersmarkets_output.csv**

- **farmersMarket_location.csv**
- **farmeresmarkets_payments.csv**
- **farmersmarkets_products.csv**

## 2. Initial Data Profiling:

I used the Pandas profiling library to develop a profile of the data to understand it better.
**Link to the data profiling report**:
https://htmlpreview.github.io/?https://github.com/nadiawoodninja/cs513-data-cleaning/blob/main/DataProfiling/farmersDataStats.html

Overview | Alerts 115 | Reproduction

**Dataset statistics**

| | |
|---|---|
| Number of variables | 59 |
| Number of observations | 8665 |
| Missing cells | 185185 |
| Missing cells (%) | 36.2% |
| Duplicate rows | 0 |
| Duplicate rows (%) | 0.0% |
| Total size in memory | 3.9 MiB |
| Average record size in memory | 472.0 B |

**Variable types**

| | |
|---|---|
| Numeric | 3 |
| Categorical | 22 |
| Boolean | 34 |

Names of all the columns in the csv

```
In [8]: my_list = list(df_m)
        print (my_list)

['FMID', 'MarketName', 'Website', 'Facebook', 'Twitter', 'Youtube', 'OtherMedia', 'street', 'city', 'County', 'Stat
e', 'zip', 'Season1Date', 'Season1Time', 'Season2Date', 'Season2Time', 'Season3Date', 'Season3Time', 'Season4Date',
'Season4Time', 'x', 'y', 'Location', 'Credit', 'WIC', 'WICcash', 'SFMNP', 'SNAP', 'Organic', 'Bakedgoods', 'Cheese',
'Crafts', 'Flowers', 'Eggs', 'Seafood', 'Herbs', 'Vegetables', 'Honey', 'Jams', 'Maple', 'Meat', 'Nursery', 'Nuts',
'Plants', 'Poultry', 'Prepared', 'Soap', 'Trees', 'Wine', 'Coffee', 'Beans', 'Fruits', 'Grains', 'Juices', 'Mushroom
s', 'PetFood', 'Tofu', 'WildHarvested', 'updateTime']
```

## 3. Project Use Cases

### 3.1. U1 (main target)

Given the popularity and usage of credit cards (Apple Pay, Android Pay etc.), an interesting use case to develop would be to identify the markets that accept credit card in a certain geo location. A heatmap could be created to show which geo locations are using credit cards most and which ones are using least. This can be done with some data cleaning efforts given the current dataset.

## 3.2. U0 use case that requires "zero data cleaning":

A possible use case without data cleaning would be to determine the most and least popular products sold by markets by summing the 'Y' for each product's column. This can be pivoted in various other columns such as location of the market.

## 3.3. U2 is a use case data "never (good) enough":

Any use cases surrounding the Season2, Season3 and Season4 columns are never going to be useful due to a lot of missing data. No amount of wrangling, cleaning will be able to give us any insights into the data.

# 4. Initial Assessment of the dataset

There are 8665 entries in the dataset and 59 columns. Further details can be found in the data profiling report generated by pandas_profiling report.

```
In [24]: df_m.info(verbose=True)

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8665 entries, 0 to 8664
Data columns (total 59 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   FMID           8665 non-null   int64
 1   MarketName     8665 non-null   object
 2   Website        5207 non-null   object
 3   Facebook       3796 non-null   object
 4   Twitter        997 non-null    object
 5   Youtube        161 non-null    object
 6   OtherMedia     638 non-null    object
 7   street         8380 non-null   object
 8   city           8625 non-null   object
 9   County         8127 non-null   object
 10  State          8665 non-null   object
 11  zip            7721 non-null   object
 12  Season1Date    5386 non-null   object
 13  Season1Time    5525 non-null   object
 14  Season2Date    429 non-null    object
 15  Season2Time    414 non-null    object
 16  Season3Date    79 non-null     object
 17  Season3Time    75 non-null     object
 18  Season4Date    7 non-null      object
 19  Season4Time    7 non-null      object
 20  x              8636 non-null   float64
 21  y              8636 non-null   float64
 22  Location       2936 non-null   object
 23  Credit         8665 non-null   object
 24  WIC            8665 non-null   object
 25  WICcash        8665 non-null   object
 26  SFMNP          8665 non-null   object
 27  SNAP           8665 non-null   object
 28  Organic        8665 non-null   object
 29  Bakedgoods     5642 non-null   object
 30  Cheese         5642 non-null   object
 31  Crafts         5642 non-null   object
 32  Flowers        5642 non-null   object
 33  Eggs           5642 non-null   object
 34  Seafood        5642 non-null   object
 35  Herbs          5642 non-null   object
 36  Vegetables     5642 non-null   object
 37  Honey          5642 non-null   object
 38  Jams           5642 non-null   object
 39  Maple          5642 non-null   object
 40  Meat           5642 non-null   object
 41  Nursery        5642 non-null   object
 42  Nuts           5642 non-null   object
 43  Plants         5642 non-null   object
 44  Poultry        5642 non-null   object
 45  Prepared       5642 non-null   object
 46  Soap           5642 non-null   object
 47  Trees          5642 non-null   object
 48  Wine           5642 non-null   object
 49  Coffee         5642 non-null   object
 50  Beans          5642 non-null   object
 51  Fruits         5642 non-null   object
 52  Grains         5642 non-null   object
 53  Juices         5642 non-null   object
 54  Mushrooms      5642 non-null   object
 55  PetFood        5642 non-null   object
 56  Tofu           5642 non-null   object
 57  WildHarvested  5642 non-null   object
 58  updateTime     8665 non-null   object
```

## 4.1. Columns and their description:

- FMID – a 7 digit integer unique identifier for each farmers' market

- MarketName - a string containing the name of the farmers' market
- Website, Facebook, Twitter, Youtube, OtherMedia - a string containing URL or other information that identifies the social media information
- street, city, County, State, zip - strings containing data corresponding to the column name that identifies the location of the farmers' market
- Season1Date, Season1Time, Season2Date, Season2Time, Season3Date, Season3Time, Season4Date, Season4Time - date fields representing the start date and end date for the given farmers' market or the times in which the farmers' markets are opened
- x, y - latitude and longitude coordinates
- location - a string describing the location of the farmers' market
- Credit, WIC, WICcash, SFMNP, SNAP - Y/N (boolean) character to indicate whether or not a given payment method is accepted
- Organic, Bakedgoods, Cheese...PetFood, Tofu, WildHarvested (30 columns) - Y/N (boolean) column to indicate whether or not a given product is offered

## 4.2. Data quality problems

***U1**: Given the popularity and usage of credit cards (Apple Pay, Android Pay etc.), an interesting use case to develop would be to identify the markets that accept **credit card** in a certain **geo location**.*

Let's observe the missing values by looking at the nullity matrix of the data generated by pandas_profiling. The nullity matrix is a data-dense display which allows one to quicky visually pick out patterns in data completion.


Doing a quick visual analysis, we can see that there are some missing data fields in the **street**, **city**, **county** and **zip** columns. Credit column does not have any missing data and seems to have either true or false values for each entry. Let's deep dive into these columns.

**Street Column:** It has 285 missing values. To generate a geo heatmap it would this column is not crucial to have. We can also look at other markets which may have similar address and infer the street address.

**street**
Categorical

HIGH CARDINALITY
MISSING
UNIFORM

| | |
|---|---|
| Distinct | 8188 |
| Distinct (%) | 97.7% |
| Missing | 285 |
| Missing (%) | 3.3% |
| Memory size | 67.8 KiB |

| | |
|---|---|
| Main Street | 30 |
| Courthouse Square | 20 |
| City Park | 13 |
| Main St. | 12 |
| Main St | 6 |
| Other values (8183) | 8299 |

**City:** This column has 40 missing values. We would have to look at other location related columns to determine the city.

**city**
Categorical

HIGH CARDINALITY

| | |
|---|---|
| Distinct | 5015 |
| Distinct (%) | 58.1% |
| Missing | 40 |
| Missing (%) | 0.5% |
| Memory size | 67.8 KiB |

| | |
|---|---|
| Chicago | 51 |
| Washington | 45 |
| New York | 45 |
| Philadelphia | 43 |
| Brooklyn | 42 |
| Other values (5010) | 8399 |

**County:** There is 6.2% missing data in this column. Again, looking at other location columns, the data would have to be imputed.

**County**
Categorical

HIGH CARDINALITY
MISSING

| | |
|---|---|
| Distinct | 1487 |
| Distinct (%) | 18.3% |
| Missing | 538 |
| Missing (%) | 6.2% |
| Memory size | 67.8 KiB |

| | |
|---|---|
| Los Angeles | 122 |
| Cook | 95 |
| Washington | 94 |
| Jefferson | 93 |
| Middlesex | 77 |
| Other values (1482) | 7646 |

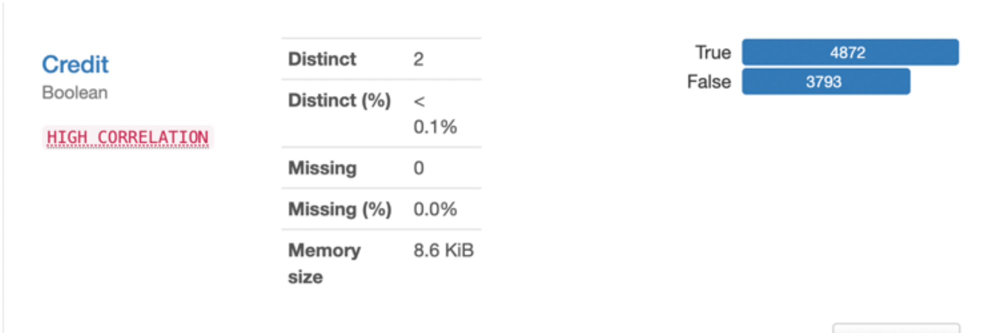
**Zip:** There is 10.9% of the data missing in this column. Again, the data would have be imputed based on other location columns.

**zip**
Categorical

HIGH CARDINALITY
MISSING
UNIFORM

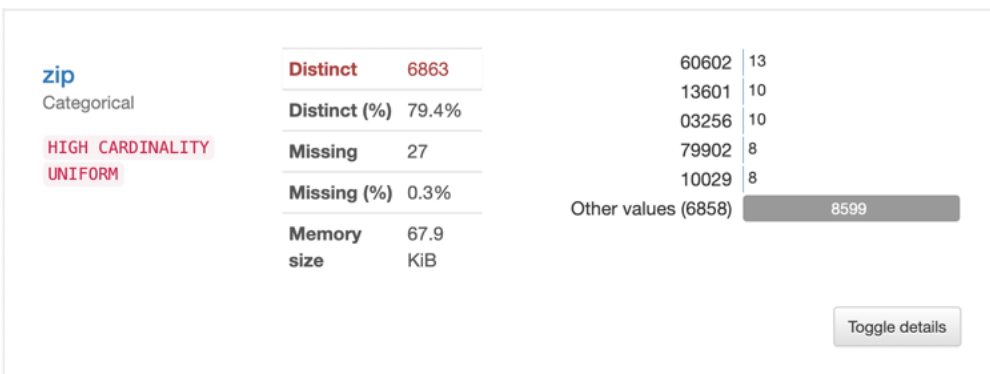
| | |
|---|---|
| Distinct | 6281 |
| Distinct (%) | 81.3% |
| Missing | 944 |
| Missing (%) | 10.9% |
| Memory size | 67.8 KiB |

| | |
|---|---|
| 60602 | 13 |
| 79902 | 8 |
| 95814 | 7 |
| 53703 | 6 |
| 20032 | 6 |
| Other values (6276) | 7681 |



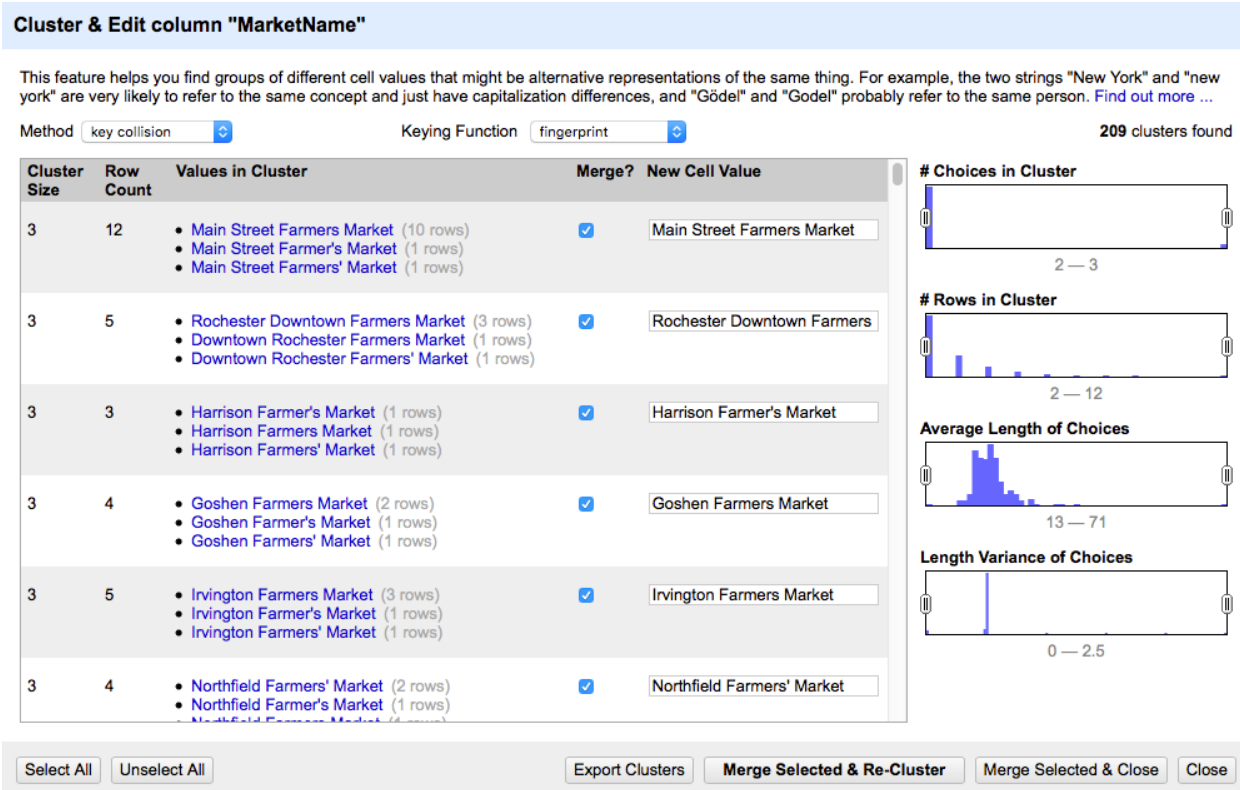

## 5. Data Cleaning methods and process

5.1. Zip Code: Records were filtered where zip was missing and geo attributes (Longitude & Latitude) available. TomTom's Reverse Geocode API was used to derive zip code. (See farmersmarket_impute_zip.ipynb). After this step, I had only 0.3% missing zip code vs. 10.9%. The resulting dataset only had 3 records where it did not have any geographics attributes such as street, city, state or longitude, latitude.

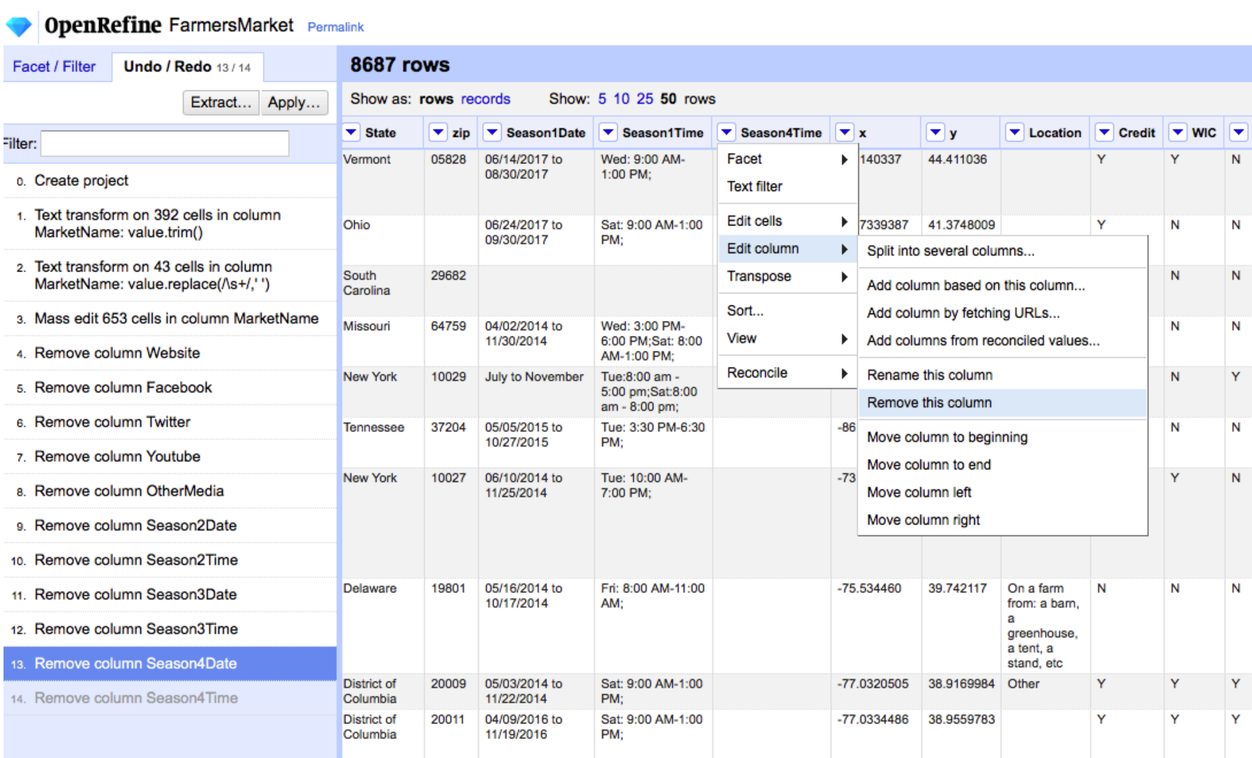



5.2. I used OpenRefine to clean the data. Please note that the tool works for smaller datasets and not large datasets

5.3. Cleaning started with MarketName column by first trimming the leading and trailing whitespace and then collapsing any consecutive whitespaces. Then a text facet was used and clustering to group similar MarketNames together. As seen below, the key collision method and the fingerprint keying function was used.

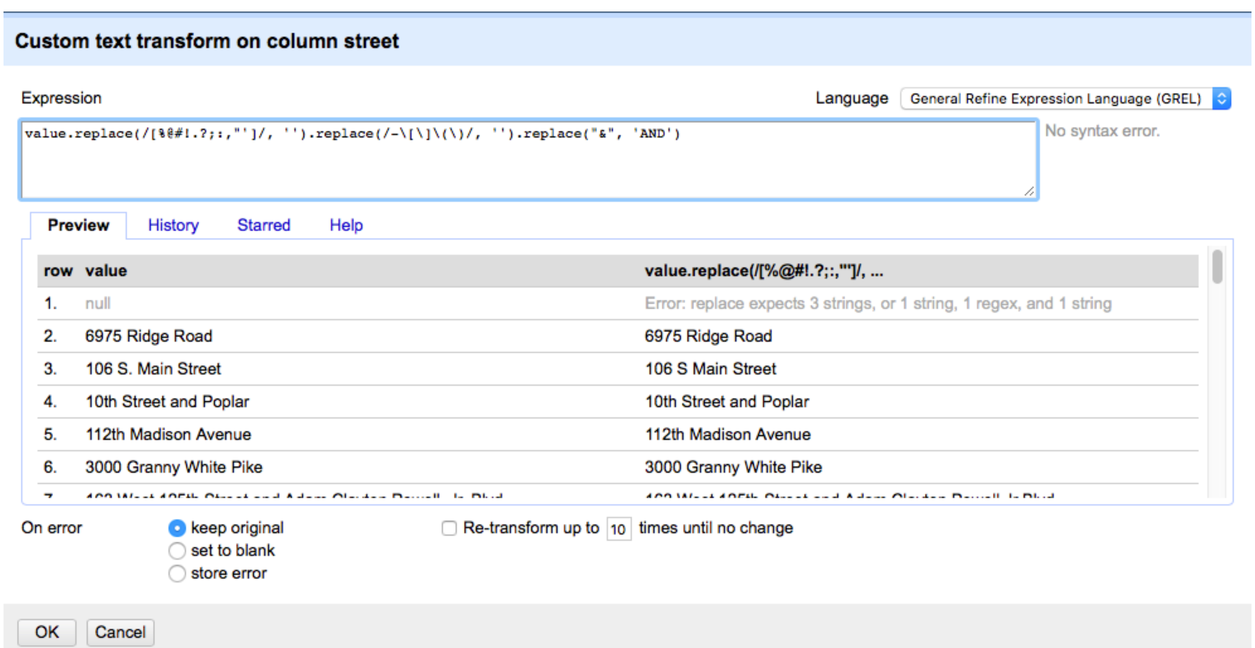



5.4. Next, removed some of the columns that are **irrelevant** to both main use case and other potential use cases. The social media data quality was very poor and so those columns were also removed: Website, Facebook, Twitter, Youtube, OtherMedia. The time and date columns for Season2 onwards were also removed because there was very little data for these columns.

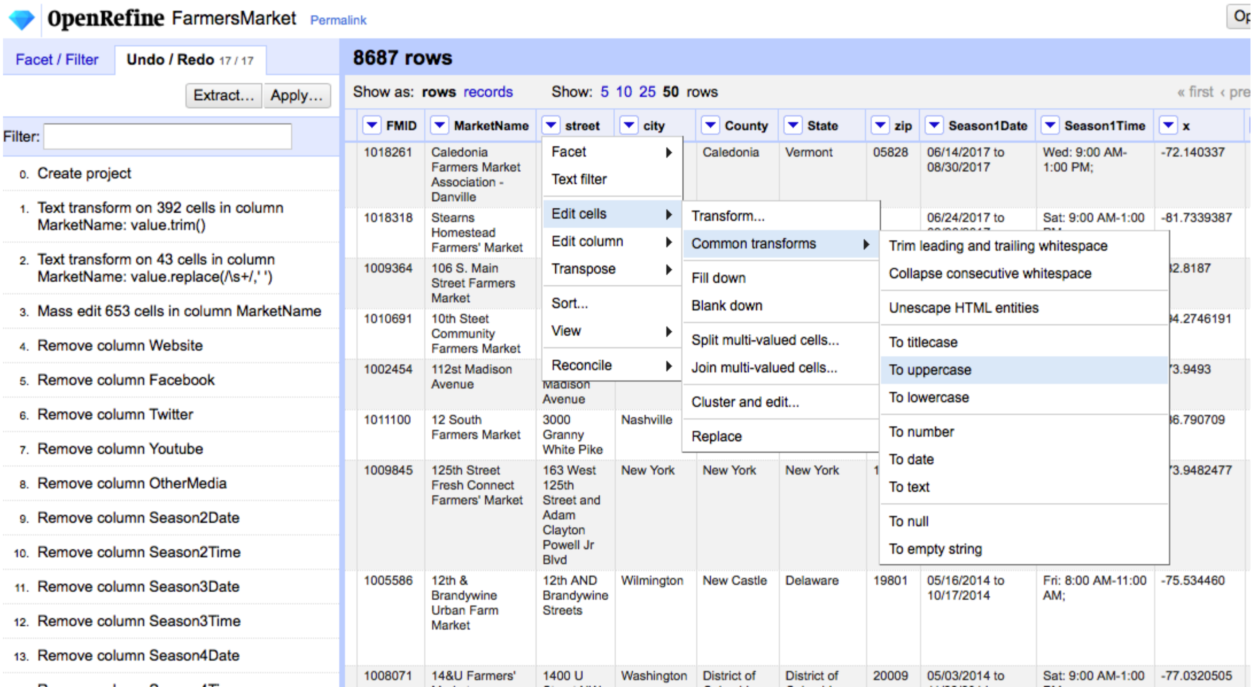



5.5. Next. Switching the focus to the location columns - street, city, County, State, and zip. For street, GREL expressions were used to remove any special characters and substitute the ampersand with 'AND':

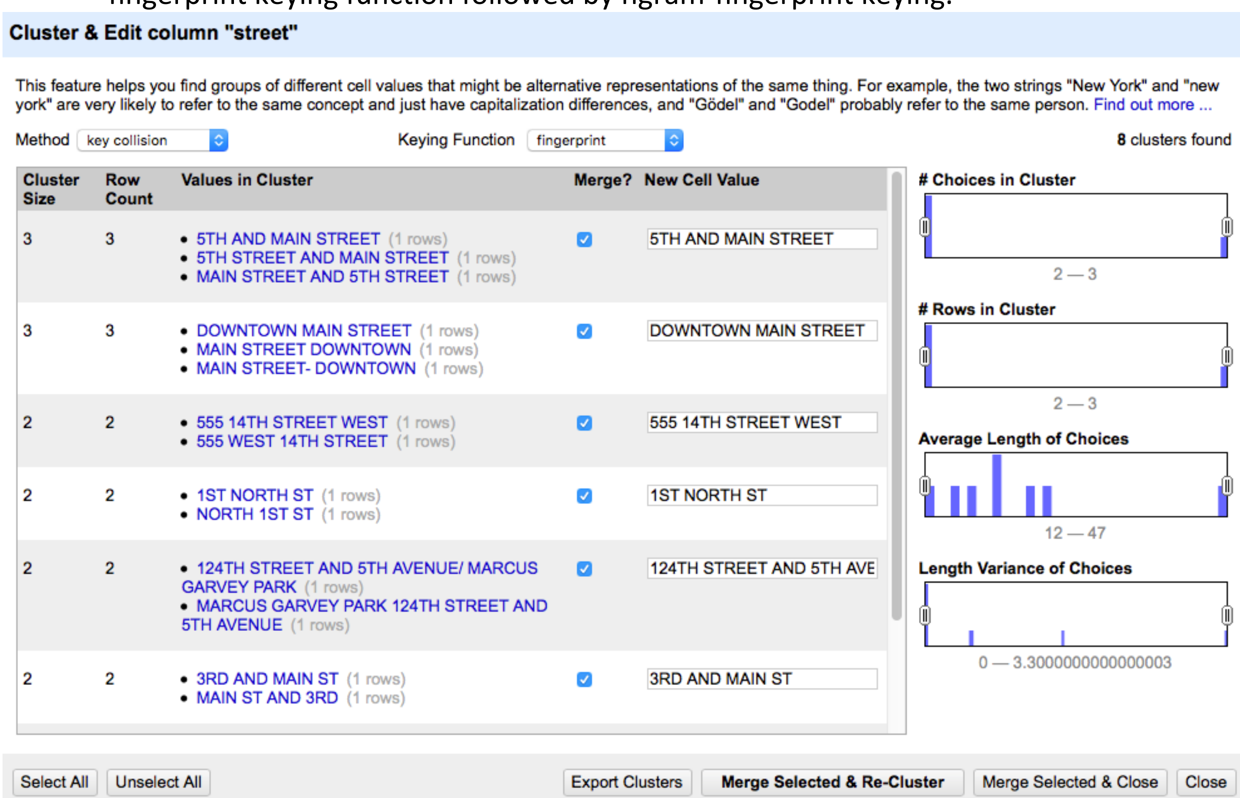
```
value.replace(/[%@#!.?;:,"']/, '').replace(/-\[\]\(\)/,
'').replace("&", 'AND')
```

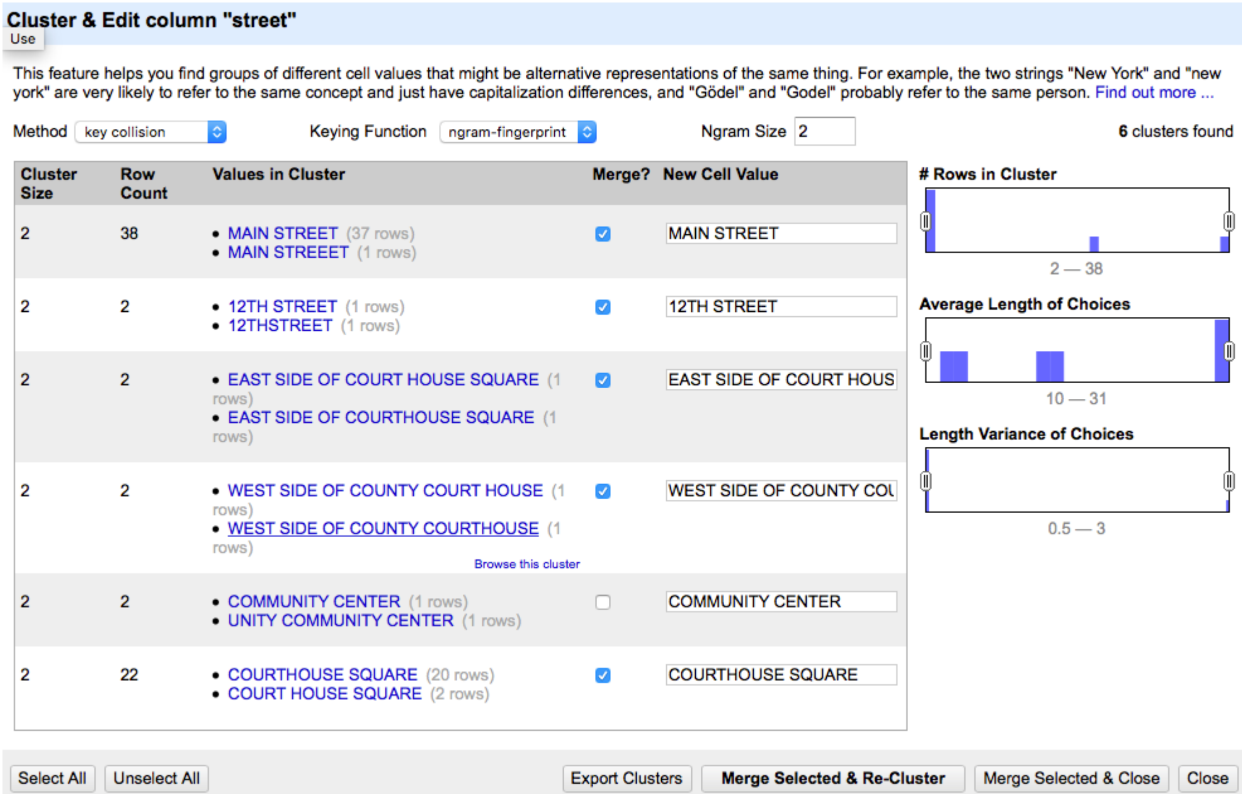


5.6. Then, the leading and trailing whitespace were trimmed and collapsed any consecutive whitespaces and converted to uppercase.

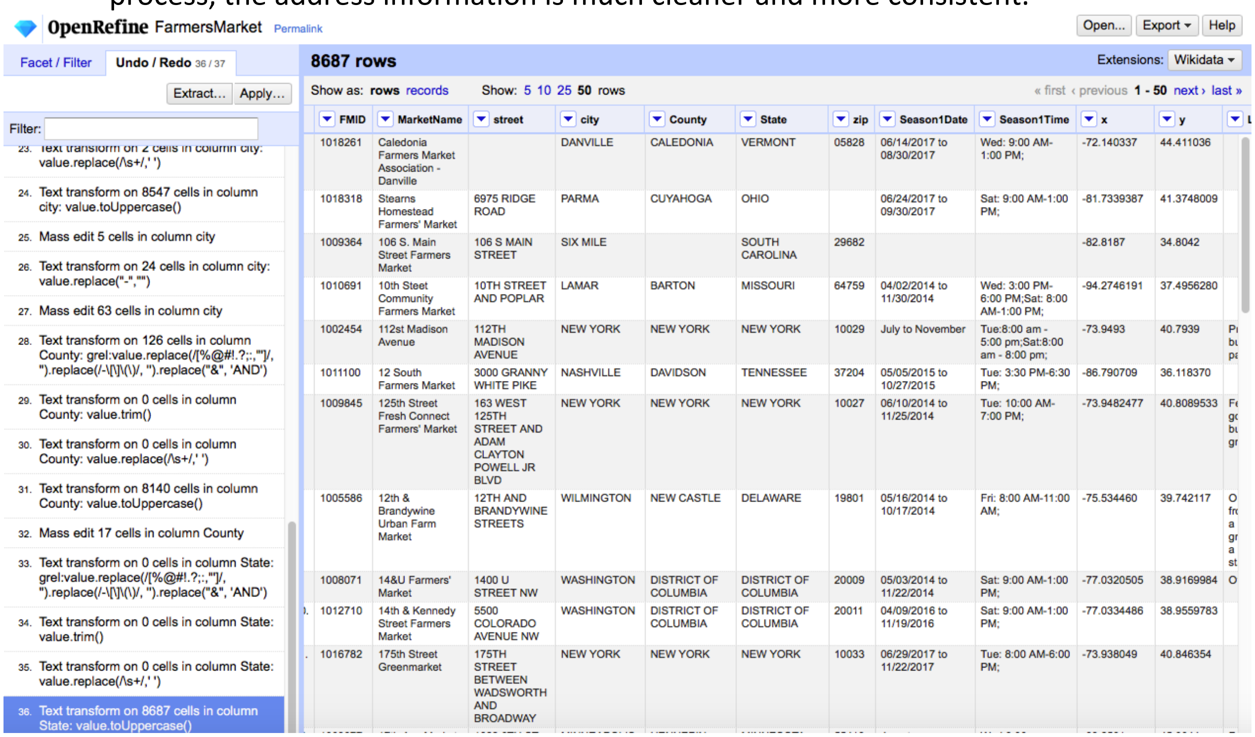



5.7. Next step was to merge any logical clusters together using the key collision method and fingerprint keying function followed by ngram-fingerprint keying.






5.8. Same steps were used (remove special characters, trim and collapse whitespace, convert to uppercase, clustering) for the city, County, and State columns. After this process, the address information is much cleaner and more consistent.




5.9. Next step was to switch focus to Season1Date and Season1Time. These columns were removed as they are not relevant to the use case in focus.

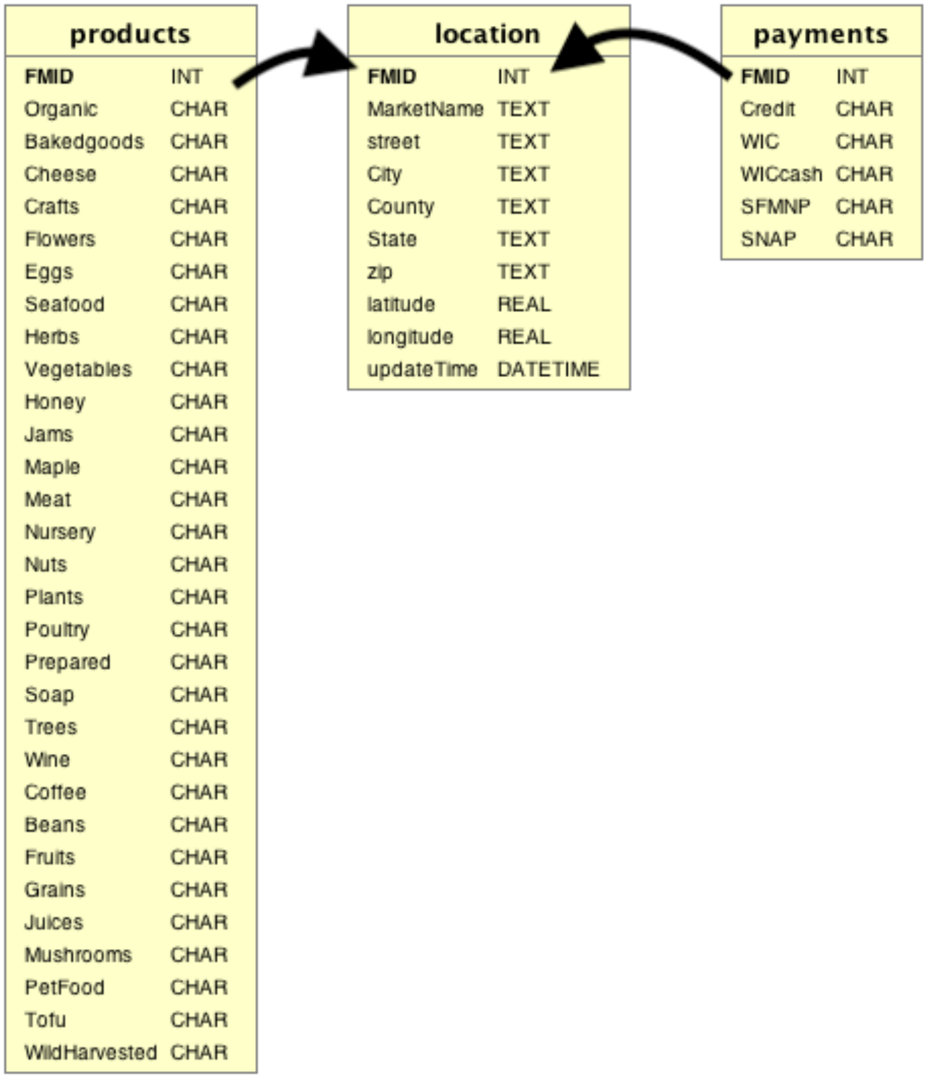
5.10. The x and y columns were renamed to latitude and longitude respectively, and then convert to numeric. The Location column was removed as it is not helpful for our purposes and is generally blank.

5.11. The values in the updateTime column were converted to ISO format using the GREL expression: value.toDate('d/M/y H:m:s') after trimming and collapsing whitespace.

# 6. Final Dataset

## 6.1. Relational Database Schema

The following Entity Relationship shows the schema developed for the final dataset. The cleaned dataset was broken into three separate tables (found in 2CleanedData): location, payments, and products, with the FMID as the primary key for all of them. This ER diagram was generated using DBVisualizer after loading the separate tables into sqllite.




Then, a few integrity constraints were developed using in sql-lite/sql-lite.ipynb notebook.

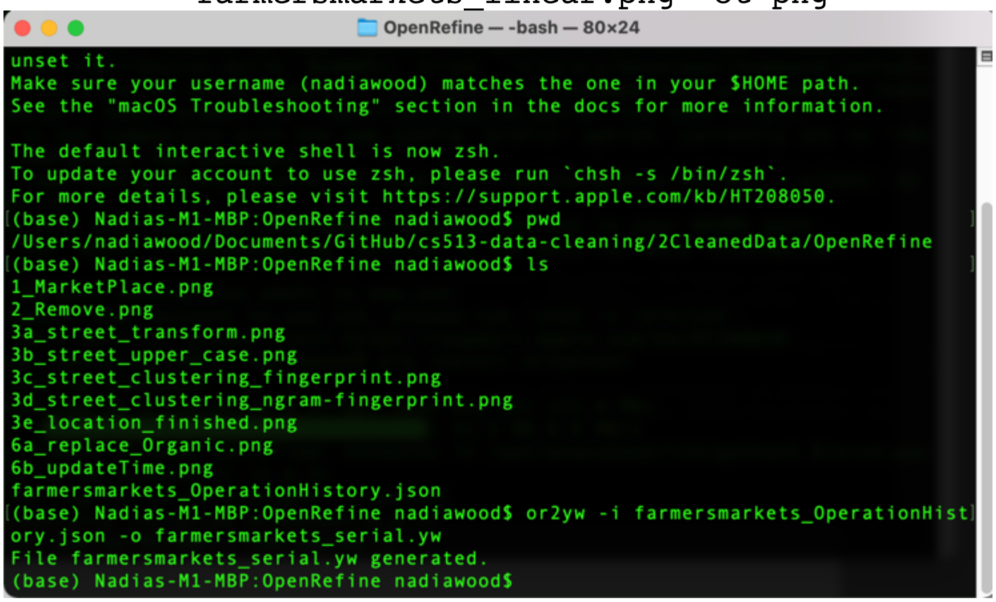
- Ensure that FMID is an appropriate primary non-null and unique key
- Ensure that data for my use case is non-null (specifically latitude, longitude, state)
- Ensure latitude is between [0,90] and longitude is between [-180, 180]
- Ensure FMID has unique address (street, City, County, State, zip) if it exists

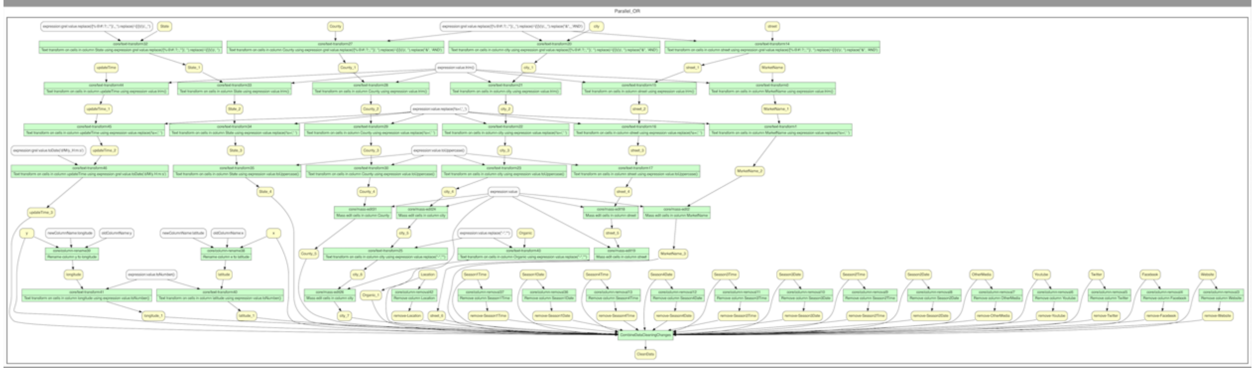
## 6.2. Modeling the Workflow

I modeled the workflow using or2yw tool, and the instructions found at https://pypi.org/project/or2ywtool/, I was able to create a workflow model of our data cleaning process very easily. I used the operations history json file from the OpenRefine Data Cleaning steps. Here the commands that I used:

1. pip install of the or2yw tool:
   ```
   >pip install or2ywtool
   ```
2. Then, we generate both a serial and parallel yw file
   ```
   >or2yw -i farmersmarkets_OperationHistory.json -o farmersmarkets_serial.yw
   >or2yw -i farmersmarkets_OperationHistory.json -o farmersmarkets_parallel.yw -t parallel
   ```
3. Install graphviz:
   ```
   >brew install graphviz
   ```

   and then generate the model using the following commands:
   ```
   >or2yw -i farmersmarkets_OperationHistory.json -o farmersmarkets_parallel.png -ot png -t parallel
   > or2yw -i farmersmarkets_OperationHistory.json -o farmersmarkets_linear.png -ot png
   ```





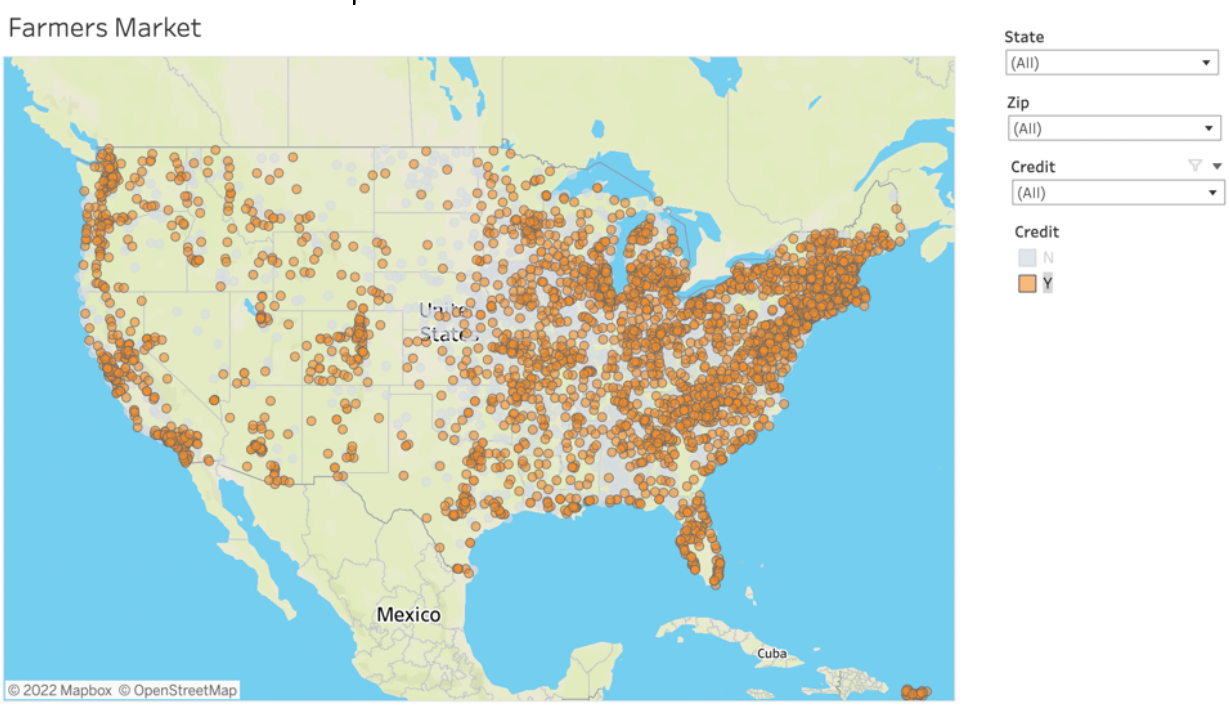
## 6.3. Overview of changes

| | |
|---|---|
| FMID | |
| MarketName | 392 leading/trailing whitespaces trimmed; 43 whitespace collapsed;653 clustered |
| Website, Facebook, Twitter, Youtube, OtherMedia | columns removed |
| street, city, County, State, zip | street: 3175 cells had special characters removed/replaced; 305 had whitespaces trimmed, and 108 had whitespace collapsed, and 8301 were converted to uppercase, and 84 total were clustered<br>city: 917 had whitespaces trimmed and 2 had whitespace collapsed; 68 total clustered cells clustered, 24 had "-" replaced,<br>County: 126 cells had punctuation/special characters removed or replaced; 8140 were converted to uppercase<br>State: all converted to uppercase<br>zip: |
| Season1Date, Season1Time, Season2Date, Season2Time, Season3Date, Season3Time, Season4Date, Season4Time | Removed |
| x, y | columns renamed to latitude and longitude, and 8658 cells converted to |

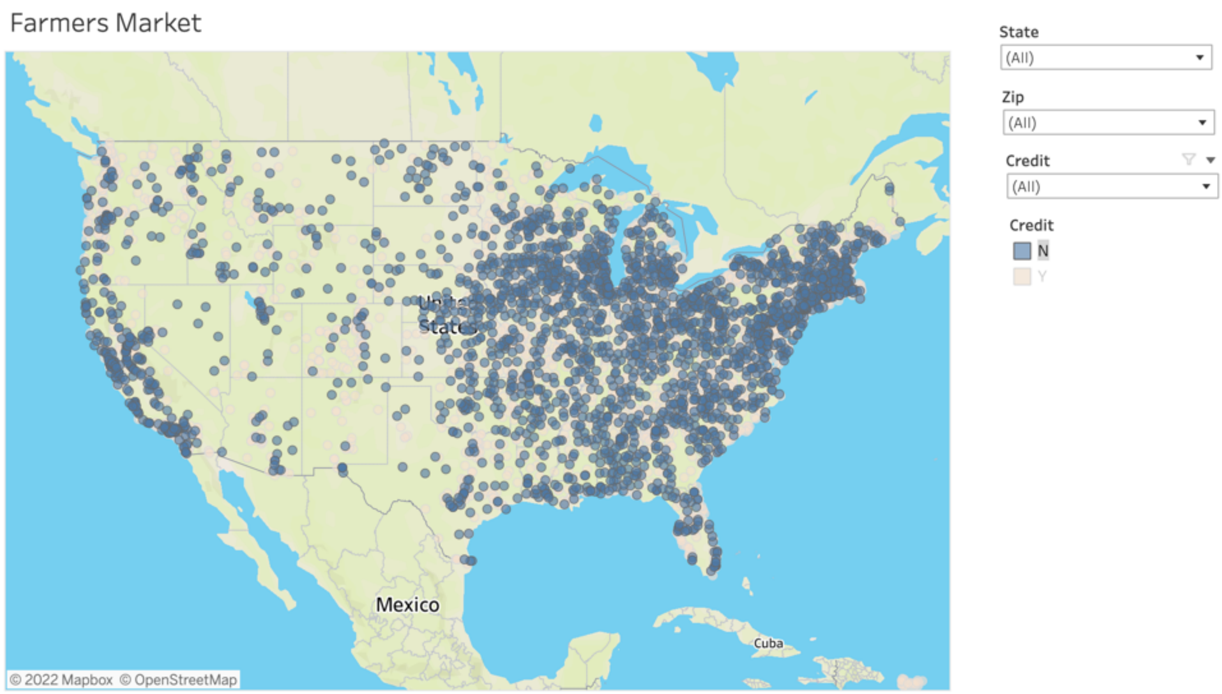
| | Numeric |
|---|---|
| location | removed |
| Credit, WIC, WICcash, SFMNP, SNAP | No change |
| Organic, Bakedgoods, Cheese...PetFood, Tofu, WildHarvested (30 columns) | 5043 cells had "-" replaced in Organic column |
| updateTime | 219 cells had whitespace collapsed; 8384 cells changed to ISO date |

## 7. Conclusion

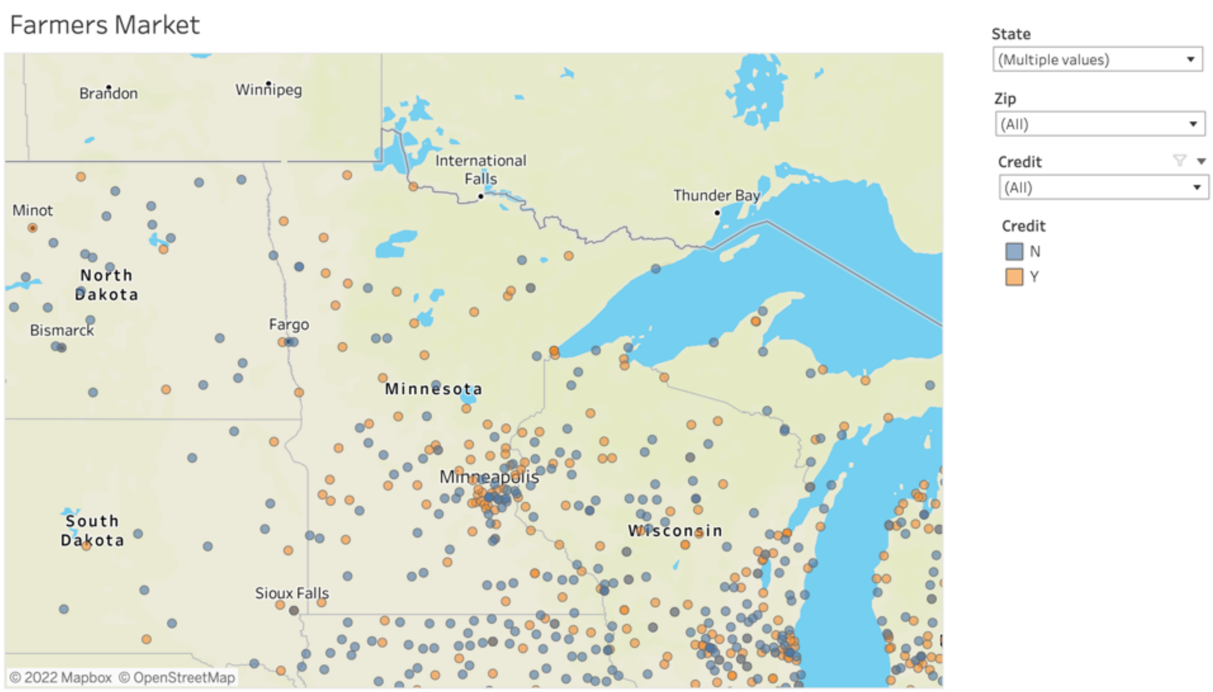
Now that we have a clean dataset, we can dive into our focus use case. I used tableau to create a dashboard (https://public.tableau.com/app/profile/nadia.wood/viz/cs513/Dashboard1) with drop downs (State, Zip Code and Credit card yes or no) . This will allow us to explore the data. From visualization, we can see that East coast, West coast and some parts of Midwest are dense with credit card acceptance.



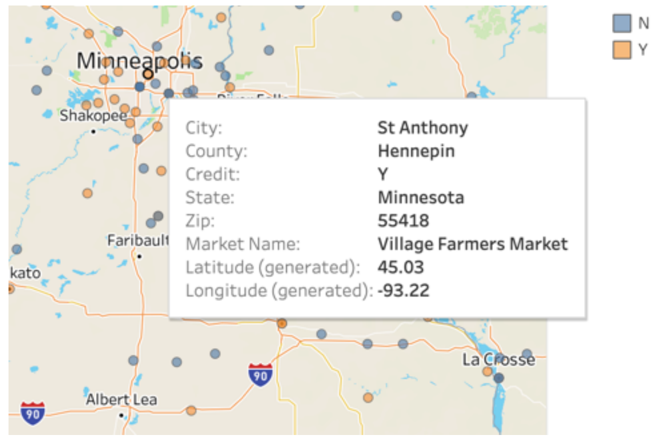

Here is another visualization of the zip codes that do not accept credit card. Comparing the two visualizations, it is hard to determine the difference between the two cases. So let's break it down by state.




Here we observe just the state of Minnesota. The places closer to bigger cities like Minneapolis and Rochester accept credits cards vs. some of the smaller cities do not.




Within Minnesota, even within Hennepin County, there are markets which do not accept credit card. See below.


## 8. Future Considerations

The data can allow to slice and dice information based on products, credit cards, city, zip code etc. The data can also be enriched by population data. There are many different permutations of the data that can be done to understand the data. Another thing to note that Tableau itself, gives the ability to clean and manipulate the data as well. The downside of cleaning the data in tableau is that there is no tracking history of changes unlike OpenRefine and Yesworkflow. These tools are great to be able to reproduce the steps taken to clean and manipulate the data. Datasets can also be used to develop predictive models based on population growth and credit card acceptance rate.