DEPA Final Project Document - Group 7

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Evaluation of key investment areas towards Chicago bike infrastructure to increase city bikeability and decrease road deaths

Executive summary

Goal: We aim to investigate how Chicago could improve on traffic safety and accessibility by promoting biking, specifically through analyzing Chicago's current bikeability, and identifying room for improvement towards promoting biking through infrastructure and accessibility.

Data Sources: We utilized public data from the City of Chicago, namely traffic data, bike racks/trips, and demographic data to identify biking and safety trends across socioeconomic and geographic areas.

EDA: After analysis of data distributions and univariate trends, we identified three findings that guided our final investigations:

1. Crashes are mainly caused by driver error, not by conditions or cyclist mistakes.
2. Physical infrastructure (protected bike lanes) is therefore the best way to physically separate bikes from dangerous cars.
3. Existing bike infrastructure varies across the city, and especially limited on the South and West Sides of Chicago.

Data Modeling: We utilized Google Cloud Platform (GCP) to create a central accessible database for our team, and GitHub to share DML/DDL scripts throughout the modelling process. We used Excel and Jupyter Notebooks to wrangle the data from its base form, and MySQL workbench to change the database into our desired OLAP format. We then used Tableau to create visualizations and draw insights.

We transformed our initial OLTP model into a OLAP snowflake schema, to structure our data more effectively, making it easier for us to analyze our data in Tableau to create valuable insights. We created 3 fact tables for crashes, bike trips, and bike racks, and created dimensions to link different fact tables.

Insights: We have identified 3 key problems and areas of improvements regarding biking in Chicago:

1. There are significant high-volume crash areas in Chicago, particularly downtown and key arterial roads in N Milwaukee Ave and N Clark St.
2. The city has numerous low-traffic bike areas which critically need bike access, especially in poorer, low accessibility areas in south/west Chicago.
3. Bike racks and Divvy stations are often few and far between

Recommendations: Based on our insights, we have provided several recommendations to reach out intended goal in decreasing biking injuries and encourage further ridership:

1. Protected bike lanes and lower speed limits on Clark St and Milwaukee Ave
2. Protected bike routes west from Lakefront to increase safe access to transit
3. Create safe bike paths in specific dangerous crash areas
4. Protected bike lanes in South Side
5. Influx of Divvy stations/bike racks in South/West sides

Lessons Learned: Given our team's inexperience within data engineering, we took several key lessons away from this project:

1. Using raw data from government sources is difficult
2. Collaborating on a cloud database requires careful planning
3. Working with geospatial data is strenuous

Business case and objective(s)

The City of Chicago is engaged in a Vision Zero Initiative to eliminate road deaths and injuries through various initiatives. A key way to do this is to increase bikeability around Chicago through providing accessible bike infrastructure and replacing road vehicles with bikes for two reasons:

(1) Bikes are less likely to cause road deaths and injuries as motor vehicles, as they are far smaller, lighter, and slower. We hypothesize that increasing bike use can reduce cars on the road, and lead to safer streets
(2) Cyclists on certain roads in the city are in high danger of being struck by motor vehicles, due to a lack of safe bike-friendly routes

We would like to investigate where key investments in bike infrastructure could make the greatest impact on safety and bike ridership.

Through data collected from:

(1) Traffic crashes in Chicago
(2) Existing bike infrastructure (particularly from Divvy, Chicago's largest bike sharing system)
(3) SMART demographic data from the US Census

We can draw insights from how bikes are currently used to reduce traffic incidents, and where there is room for improvement in further integrating biking into Chicago transportation.

EDA - Exploratory Data Analysis

- Data Source Information (including shape and characteristics)

Data	Source	Shape	Description	Link
Chicago Traffic Crashes	City of Chicago	CSV (23 x 11918)	Chicago biking-related traffic incidents - includes incident type, environmental variables	(1)
Chicago Bike Racks	City of Chicago	CSV (6 x 2198)	Location and type of non-Divvy bike stations in Chicago	(2)
Divvy Bike Stations	City of Chicago	CSV (5 x 1420)	Geocoded Divvy bike stations in Chicago	(3)
Divvy Bike Trips	Divvy	CSV (13 x 537114)	Record of all bike trips, - includes timestamp and start/end points	(4)
SMART Location Database	US EPA	CSV (30 x 4013)	Chicago Census-Based Demographic Data (Jan 2021)	(5)

- Key Characteristics:

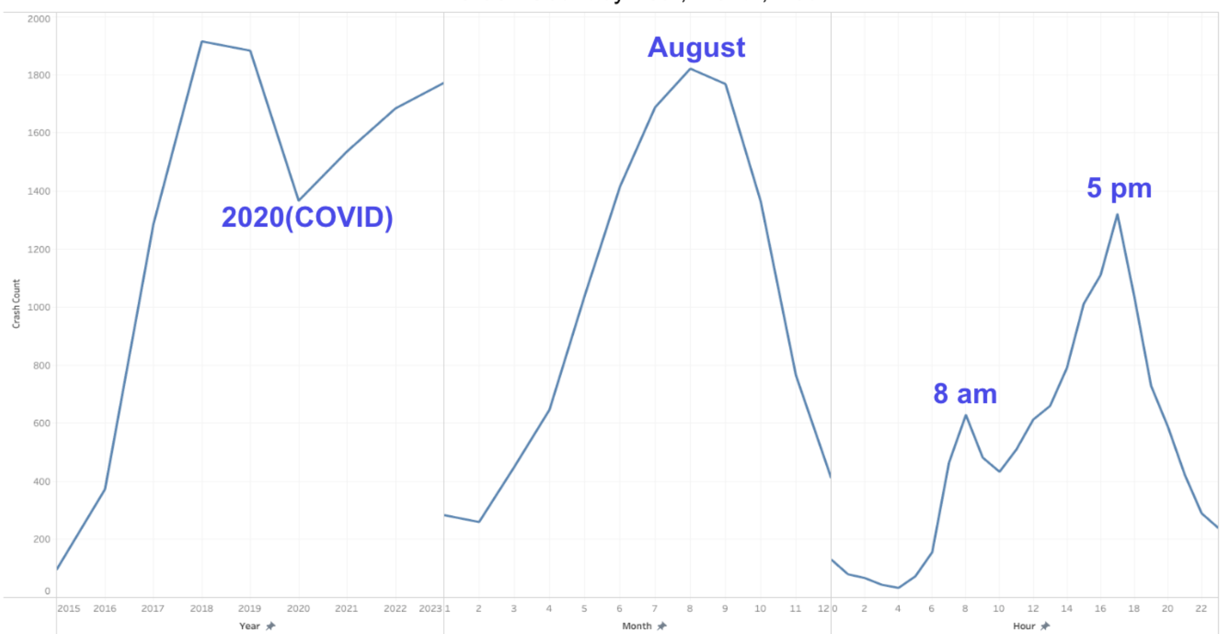
- Chicago Traffic Crashes
    - This data contains entries for traffic crashes in Chicago from 2015 through present. Each row is a separate crash.
    - For our analysis on biking in Chicago we limit the data to only crashes involving pedal cyclists.
    - Each crash has information on the time, road details, crash type, and weather during the crash.
- Chicago Bike Racks
    - This data contains entries for every bike rack installed in the city between 2015-2021
    - Key attributes include location and quantity of racks.
- Divvy Bike Stations
    - This data contains entries for every Divvy station in Chicago.
    - Key attributes include location and quantity of docks.
- Divvy Bike Trips
    - This data contains entries for every Divvy trip taken in October 2023.
    - Key attributes include start/end location/time.
- SMART Location Database
    - This dataset contains census demographic data for every block group in Chicago.
    - Key attributes include access to transit, walkability score, percentage of low income households, percentage of households with no cars.

- Visualization of the data

To seek our initial understanding of the data we examined distributions of the main variables of interest in our data.

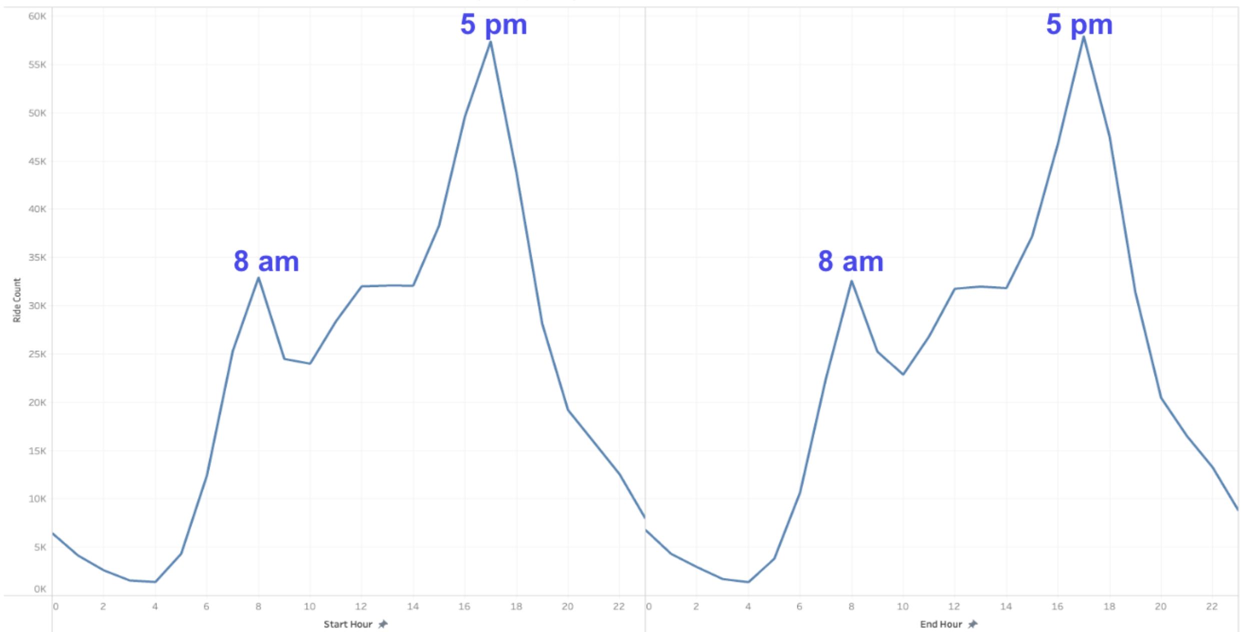
- Crash Timing
    - The season with the most accidents is summer, with peak times being during morning commutes and evening returns.

Crash Count by Year, Month, Hour



- Divvy Trip Timing
    - Peak ride frequency is the same as peak crash frequency. This implies that crashes happen irrespective of timing and occur at somewhat of a fixed rate when people are riding bikes in the city.

Divvy Trips by Start Hour and End Hour



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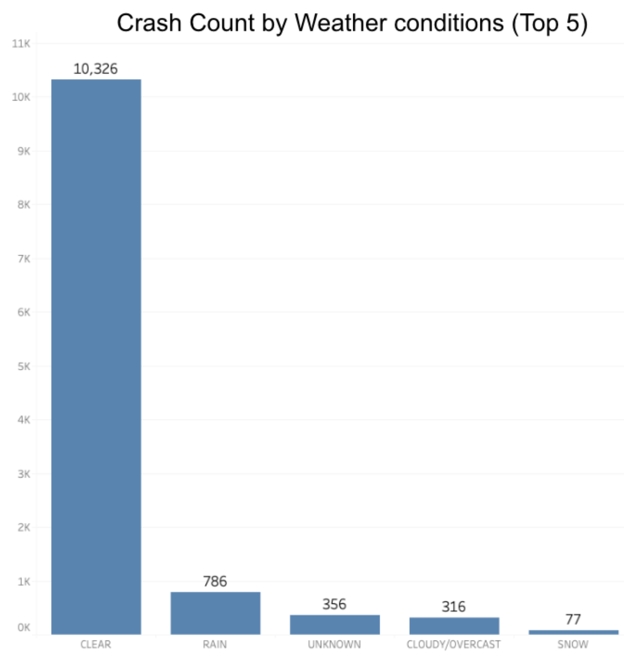
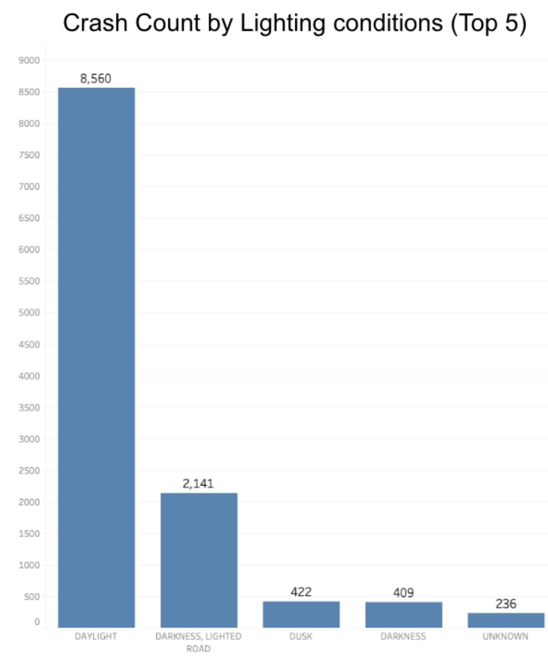
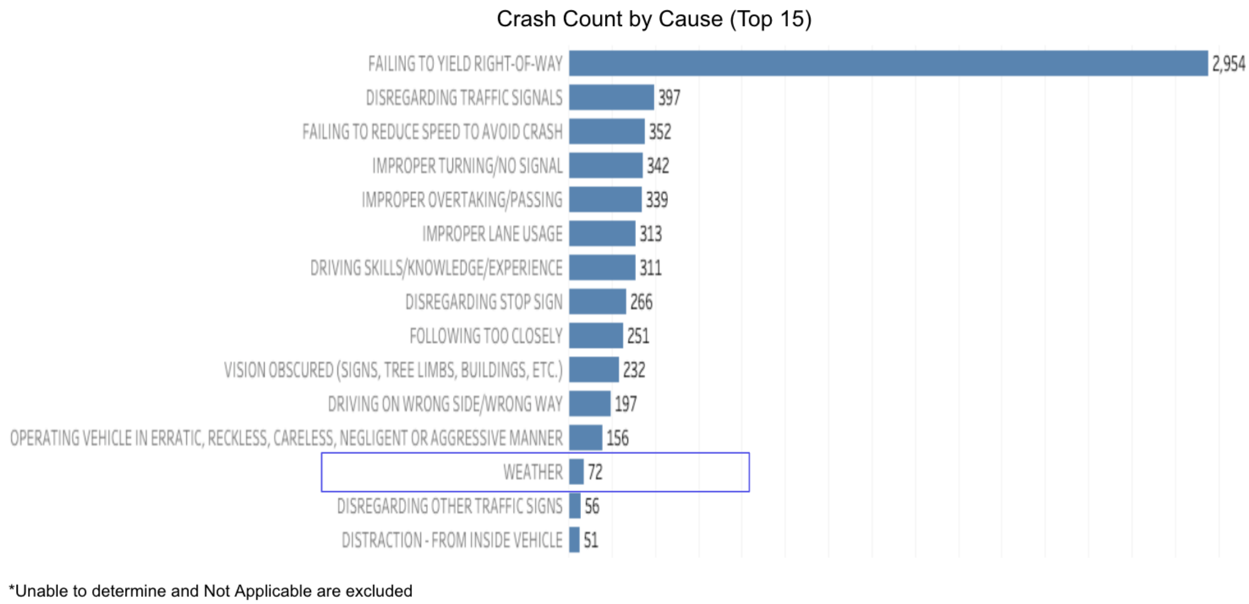
- Crashes by Weather and Lighting Condition
    - Crashes appear to happen the most often in weather/lighting conditions that are the most common for bike riding.





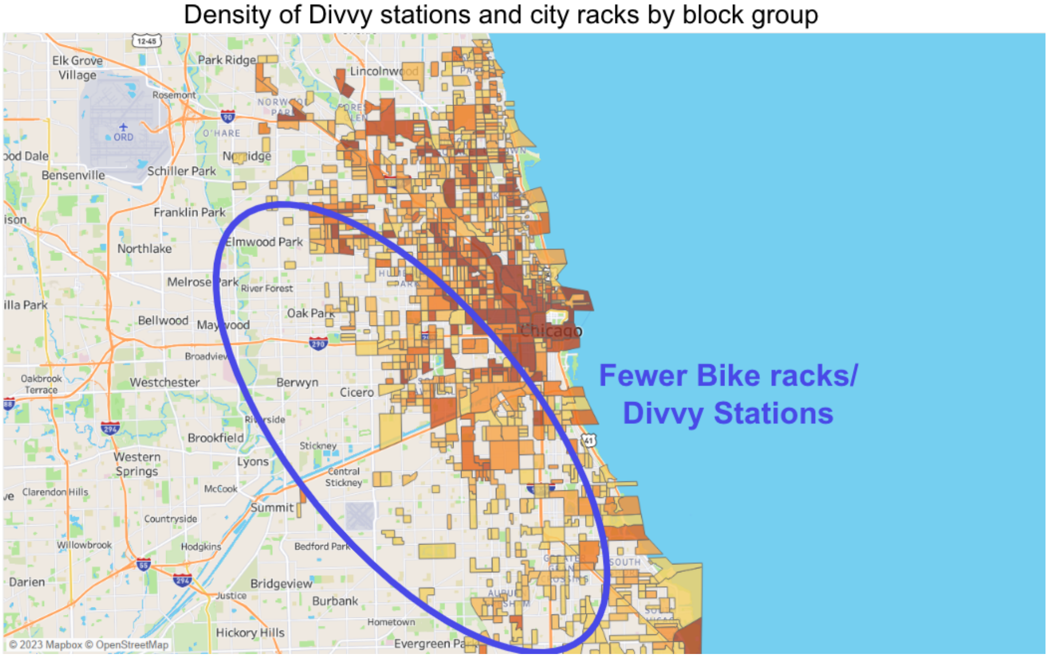
Crash Causes

- Causes seem to be mostly due to improper driving or rule violations, not the behavior of people riding their bikes.



- Bike Racks and Divvy Station Distribution
  - Racks and stations are not spread evenly across the city – they are more concentrated in the Downtown and North Side areas.

Density of Divvy stations and city racks by block group



Takeaways from our EDA:

1. Crashes are mainly caused by driver error, not by conditions or cyclist mistakes. The overwhelming majority of known crash types are reasons like “failing to yield right of way,” “disregarding traffic signals,” and “failure to reduce speed.”
2. Physical infrastructure (protected bike lanes) is therefore the best way to physically separate bikes from dangerous cars. If drivers cannot prevent themselves from hitting cyclists by driving better, people on bikes need to be protected by concrete infrastructure which physically prevents cars from hitting them.
3. Existing bike infrastructure varies across the city. Current Divvy station and rack coverage is very limited in some areas, especially on the South and West Sides of Chicago.

Data Models

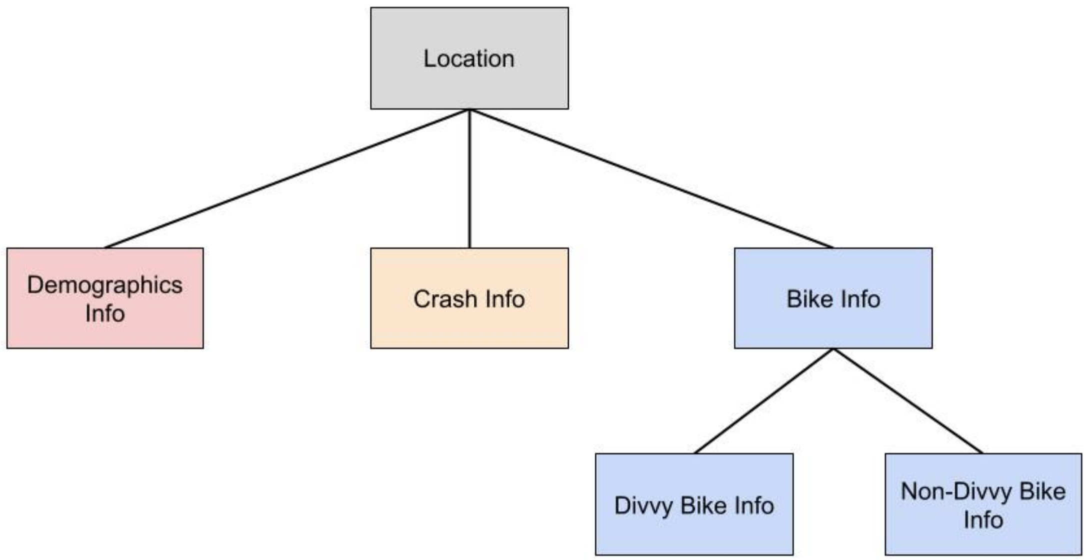
Data Model Considerations:

- Our database is wide-reaching and contains tables which relate to bike safety and accessibility in different ways.
    1. Bike Crashes
    2. Bike Infrastructure (Racks and Divvy Stations)
    3. Bike Trips (via Divvy)
- Some tables are very large and fast querying for analysis is important

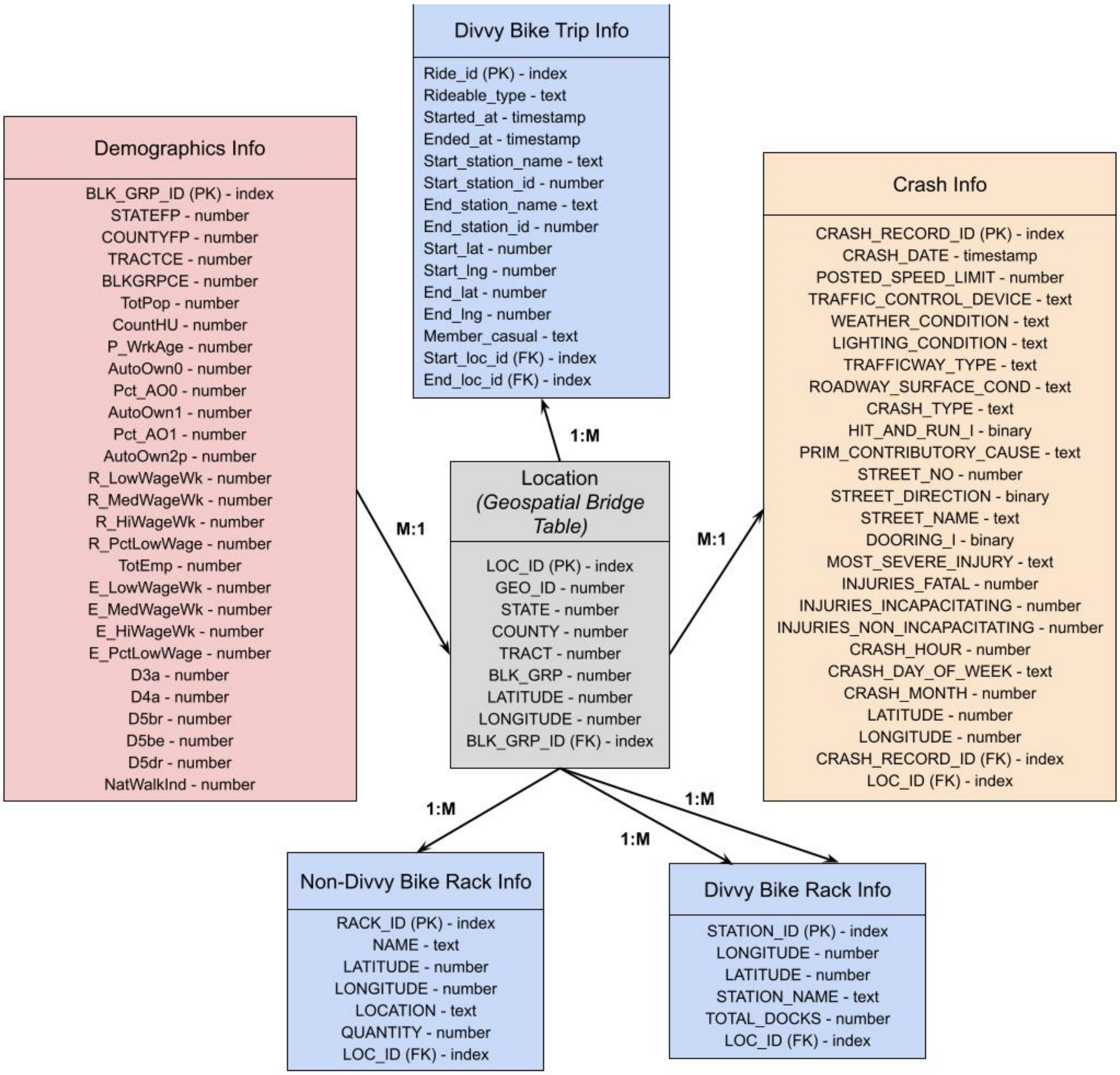
Solution:

- Convert from OLTP to OLAP model and establish three main fact tables
- Relate each fact table to location and demographic information
- Normalize by creating important dimension tables which relate to facts:
    - Crash type, road type, weather conditions, time

Original Conceptual Model

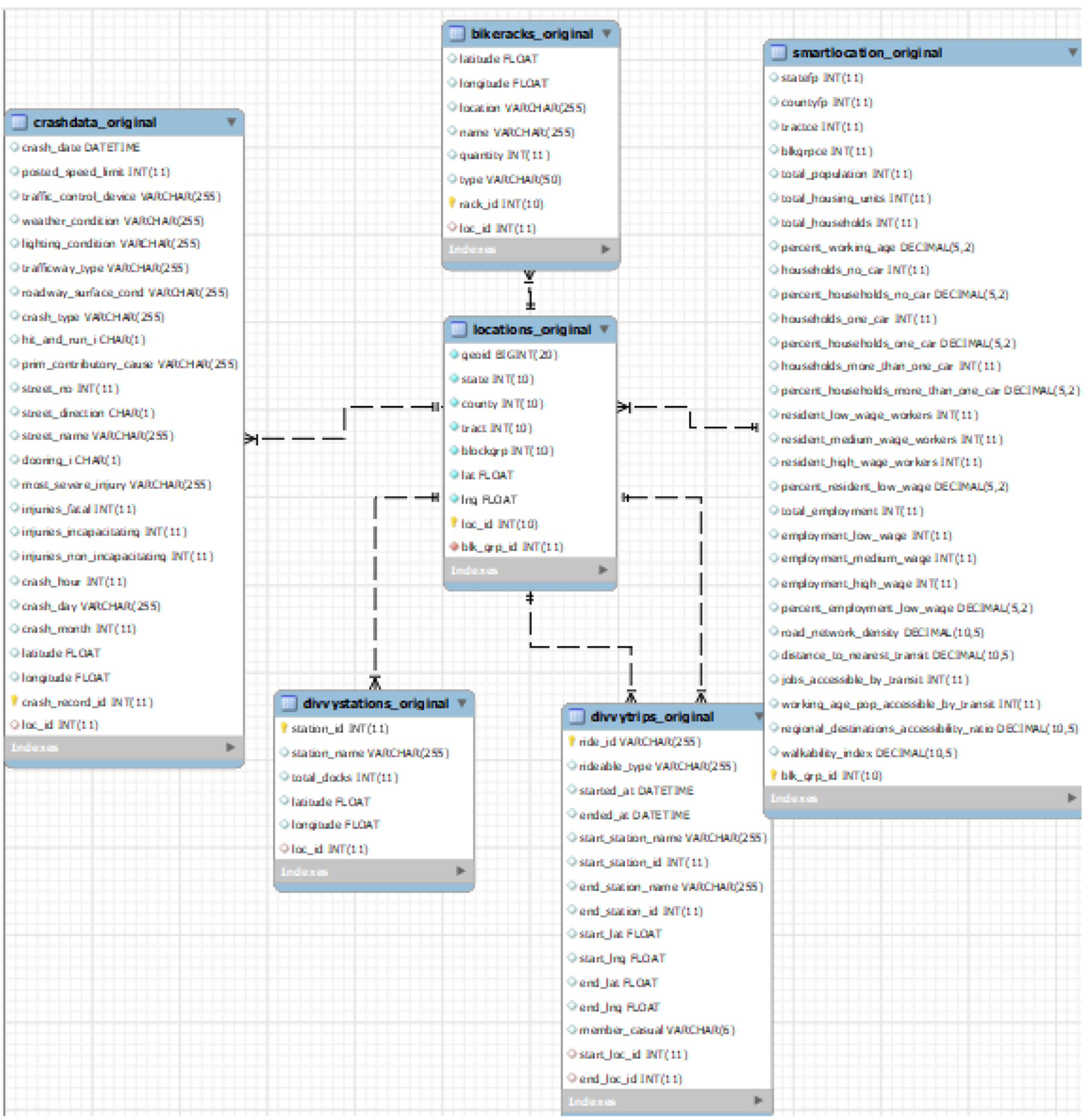


Logical Model



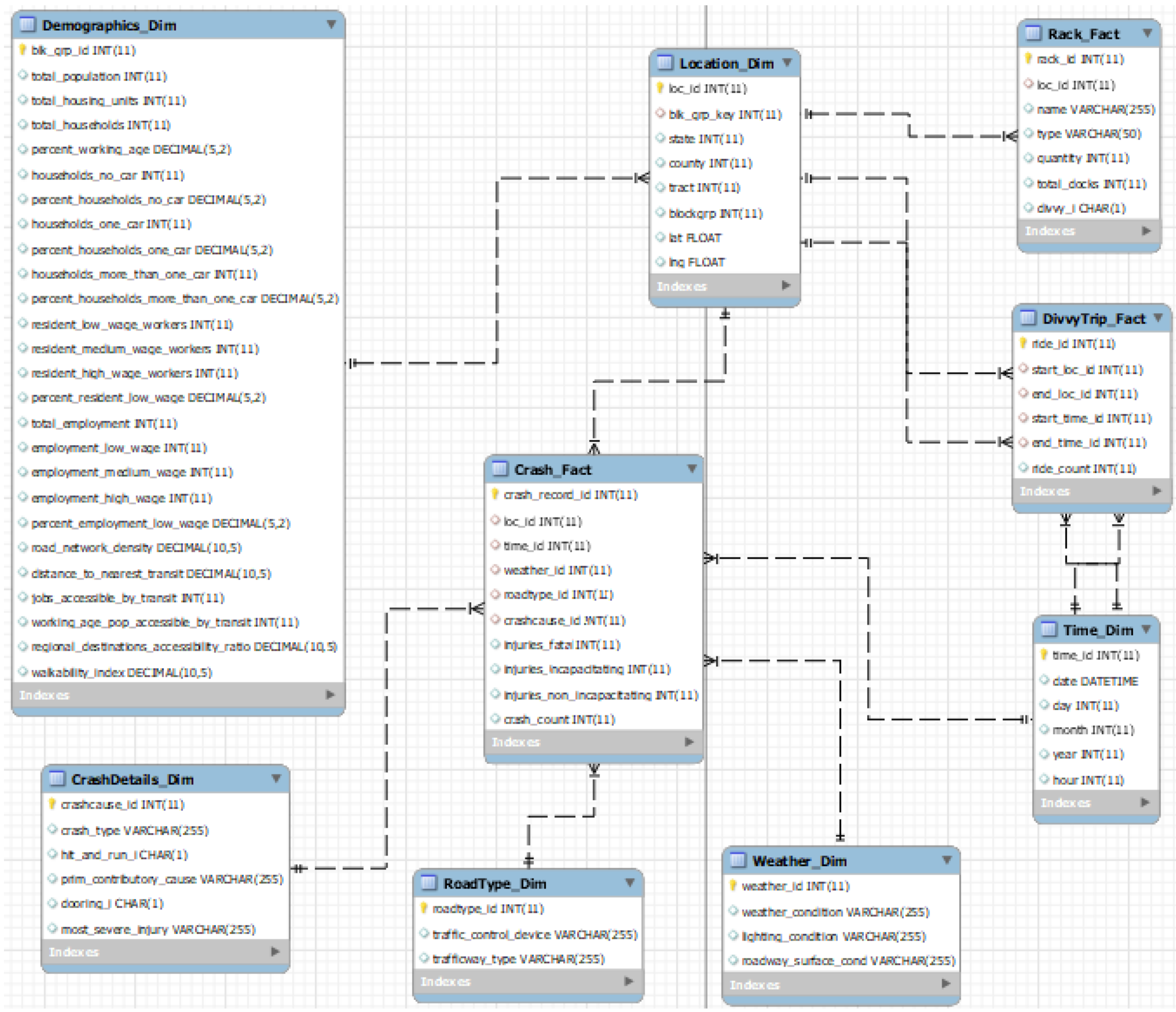
Initial Physical Model (OLTP Version)

We normalized data from the SMART demographic and crash databases for our initial model. The location table originally acted as a bridge table to connect all geospatial data from various formats across databases, allowing us to plot crash, bike rack, and trip data on a map, while getting demographical data for analysis on specific locations. To create this structure we had to create the locations_original table using Python and a government API — we compiled all locations of crashes, bike racks, Divvy trips, and Divvy stations and fed them through a program which called the US Census Geocoder API. By doing this we were able to pull the census block group of every location in our data and create the locations_original table accordingly. Using this table it was then possible to match every location and event to demographic data about its location.



Final/Converted Physical Model (OLAP Version)

We decided to convert our model into an OLAP structure to make it easier for us to analyze in Tableau to create valuable insights toward our problem of interest. Our OLAP model has three fact tables: Crash_Fact, Rack_Fact, and DivvyTrip_Fact. We decided to make these different fact tables as they all represent completely different events and things. Each fact table links to Location_Dim, which contains the longitude and latitude for each fact entry. Each location can then be linked to Demographics_Dim, a dimension table with demographic information for every Census block group. We also denormalized our crash data to make it easier to analyze specific weather, road, and crash conditions during our analysis. We also combined all racks (Divvy stations and city racks) into a single table, making it easier to analyze bike routes geographically.



Data Profiling

While our data was relatively clean and useful after importing it into our MySQL data model, we made a few calculations and removals when doing our analysis.

- Importing geographical shapefiles into Tableau to create maps
    - Unfortunately, Tableau's internal geospatial geometry extends only as deep as the zip code level in the US. In order to create detailed heatmaps of the Chicago area that were representative of our data, we had to pull geospatial shapefiles from an external source that contains geometrical breakdowns of the city according to our most granular geographical level (block groups). These shapefiles had to be related to our location data on one specific field, the external source called the 'GeoID'. Luckily our location data from the US Census Bureau contained this 'GeoID' variable through a combination of the provided fields. We performed a join calculation within Tableau to concatenate these fields together and relate these shapefiles to our data structure so we could create maps to our desired granularity.
- Outliers removed for many plots
    - There were many instances in our data where specific block groups exhibited abnormal values due to their dense populations or unique geographical locations. For example, we had to remove some data points from our plot showing the number of bike racks vs the percentage of households with no cars. There were areas in the downtown Chicago area that had extremely high quantities of racks while having an extremely low percentage of car-owning households. Removal of points such as these are crucial to uncovering the underlying trends in the data so we can understand more generally what it is telling us.
- Injury severity calculation
    - Our use of heatmaps to display the distribution of crashes across the city was helpful in understanding where the crashes are happening. However, we decided to take it a step further as we wanted to identify which areas are most dangerous for riders using the 'most severe injury' variable from our crash data. We assigned those crashes that resulted in the most severe injury of 'Fatal' a 10, 'Incapacitating Injury' a 5, 'Non Incapacitating Injury' a 1, and other records a 0. This allowed us to zero in on the exact blocks and areas within the city that maybe don't have the most crashes, but the deadliest ones. Of course, these assigned weights are subjective and maybe aren't entirely representative of the severity of the injury, but were enough to understand the general trends.

Methodology and various tools used in the process

Data Engineering/Transformation Process:

Our most intense bit of data transformation came via creating the data which eventually became our Location_Dim table. When we accessed the raw data, the crash, rack, and Divvy trip information was all at the latitude/longitude coordinate level, while the demographic information from the SMART Location Database was at the US Census Block Group level. To establish a connection between specific locations and demographics of the area, we had to map between locations and their block groups by the following steps:

- Using Python, extract all coordinates from crashes, bike racks, Divvy trips and stations data.
- Round each coordinate point to four decimals.
- Run each coordinate through the US Census Geocoder API via Python, which returned the state, county, Census Tract, and Census Block Group of every coordinate point.
- Load this data back into the MySQL Database.
- Join this information to the demographic data on state, county, tract, and block group, and to our crashes, bike rack, Divvy trip, and Divvy station data on rounded latitude and longitude coordinates.

We also had to write code to ingest the dates and times from Divvy trips and crashes, which were formatted inconsistently within their own tables in the raw data. To do this we utilized Regular Expressions to match multiple date types within each ingestion command.

Finally, within the crash, bike rack, Divvy trip, and Divvy station data, we had to round each coordinate to four decimals to ensure it matched with our created and ingested locations lookup table.

Tools used throughout the entire project:

- Excel

We used Excel to conduct initial exploration of our data, and completed several data wrangling steps in Excel directly, as it was the simplest and fastest way to filter and cut unnecessary data before uploading it into GCP. However, given several large datasets, Excel was not ideal to conduct parallel operations on 10,000+ rows, and it was difficult to share large Excel data files through Google Cloud. In future, we can use other methods for data wrangling and transfer to save time and resources instead.

- Jupyter Notebook (Python)

The main use of Python through Jupyter notebook was to create our locations lookup table by accessing the US Census Geocoder API. We compiled all locations of crashes, bike racks, Divvy trips, and Divvy stations and fed them through a program which called the API and pulled the census block group of every location in our data. We also used Jupyter Notebook to write Python code for ad-hoc data analysis and run quick experiments on our hypothesis, using the "*mysqlconnector*" package for quick queries in our database. Our team felt we did not fully capitalize on the potential of Jupyter Notebook, and we could have utilized Python for more advanced data wrangling and predictive modeling in future projects.

- MySQL Workbench

We used MySQL Workbench to query data and change our database into our desired format, and reverse engineer our EER diagrams for our physical models. Our team was proficient at the workbench's capabilities and in writing MySQL code, so we were able to stay on the same page when discussing and conducting changes to our database.

- Google Cloud Platform (GCP)

We used GCP as a cloud database solution, allowing us to store and share data remotely. Unfortunately, we had a large volume of data (even after optimization) that caused queries to take minutes to run, and our database frequently locked up when multiple people were changing our database. In the future, better TCL queries and database control system procedures can help us prevent such issues.

- Tableau

We used Tableau to visualize and find insights within our data. Given our inexperience with Tableau, we spent more time on this step as a learning opportunity, particularly when drawing findings with geospatial elements.

- GitHub

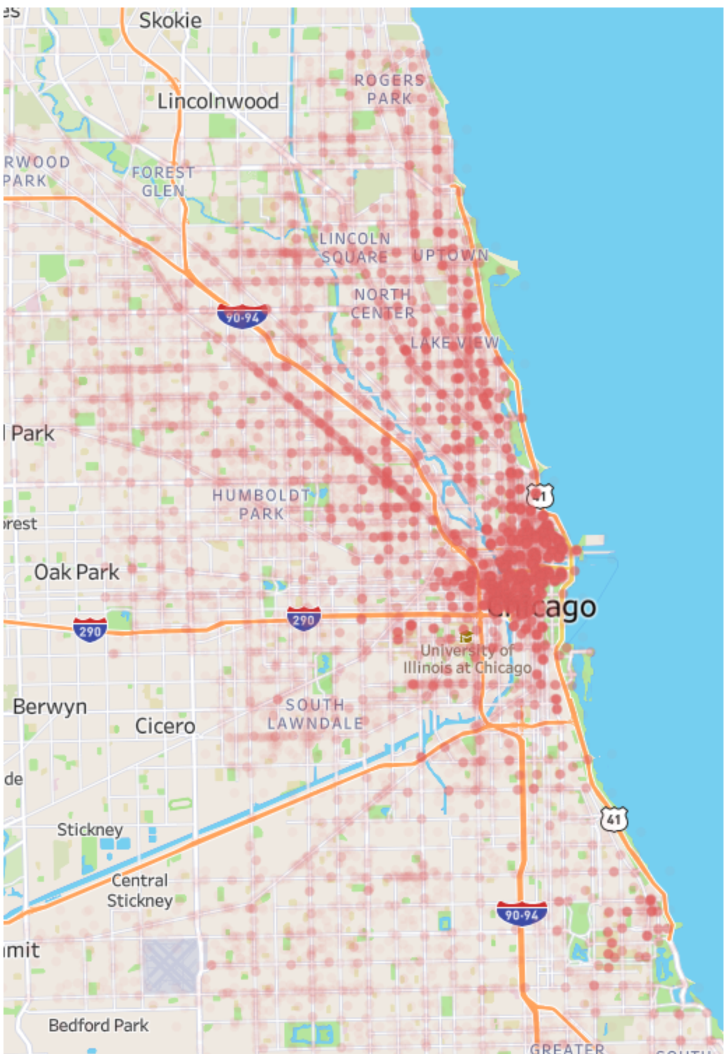
We used GitHub to store our code in a centralized repository and make sure we were always incorporating each other's edits into our DML, DDL, and Snowflake creation scripts.

Insights

1. There are significant High-Volume Crash Areas in Chicago

a. Crash high-frequency zones

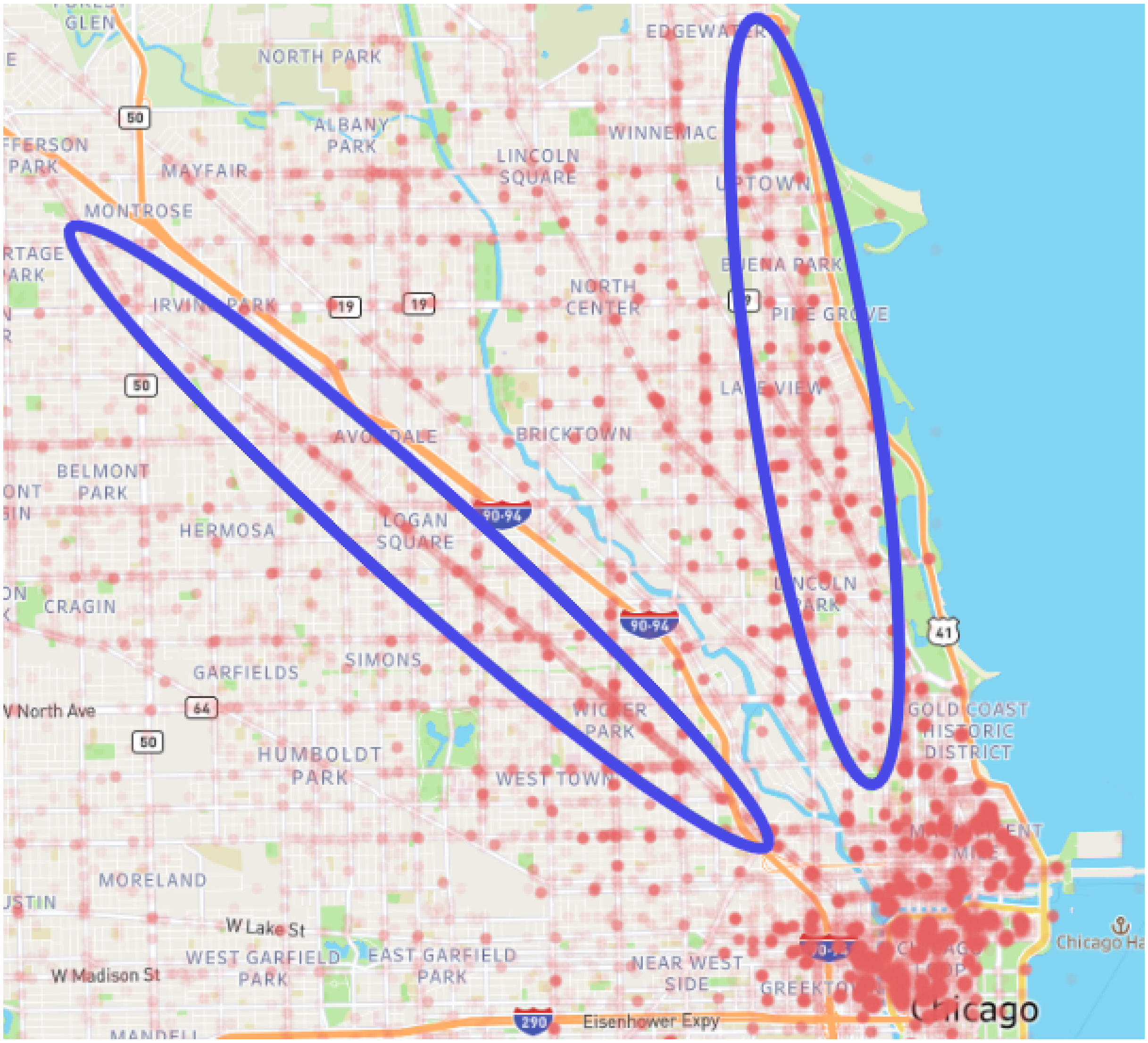
Parts of the city where crashes occur often must be the first priority in addressing bike safety in the city. Consider the plot below of crashes citywide from 2015-present:



Key corridors of crashes include:

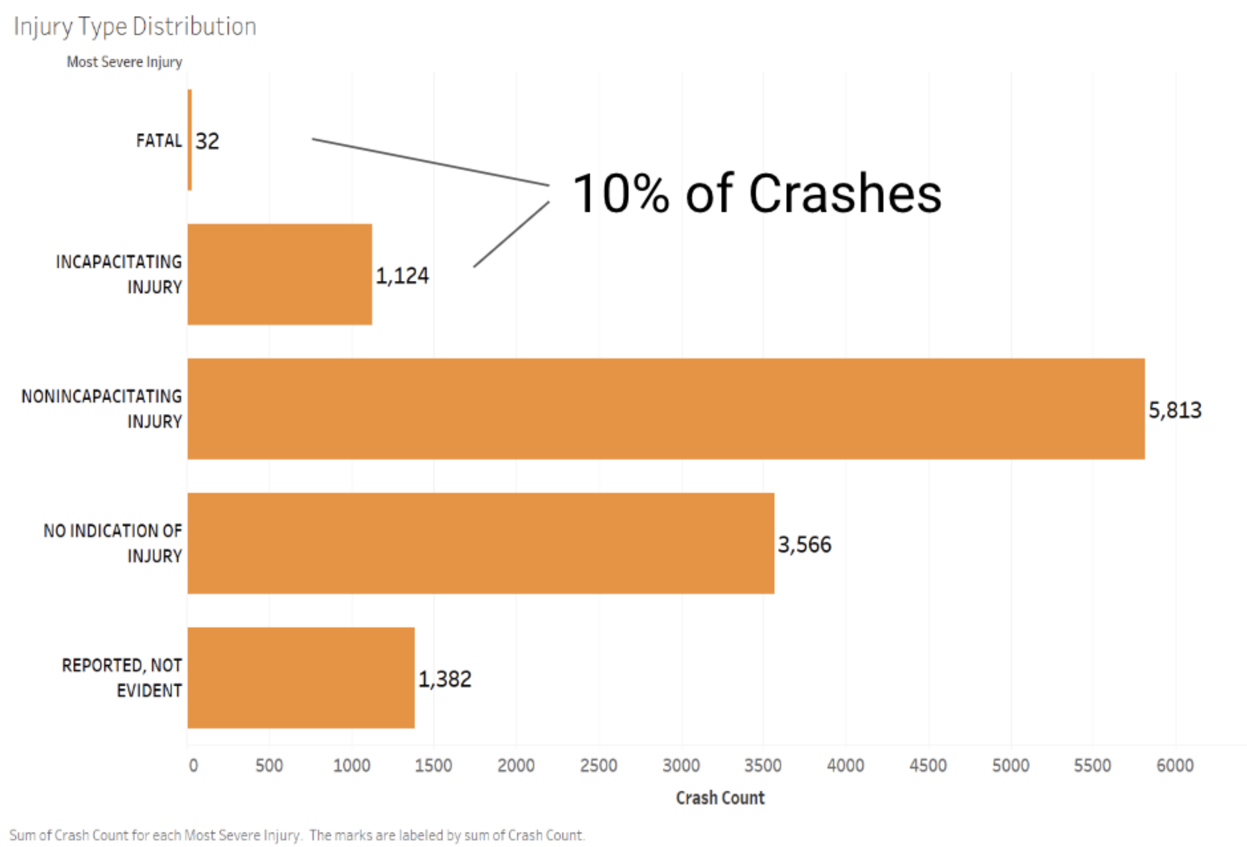
1. The entire downtown area
2. N Milwaukee Ave
3. N Clark St

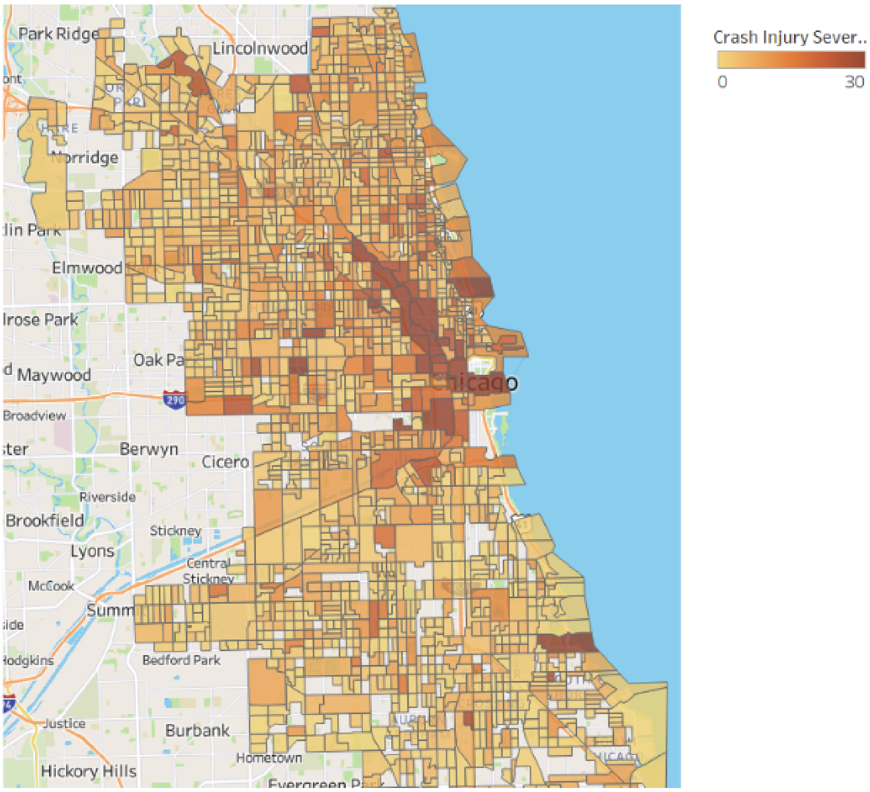
Zooming in on Milwaukee and Clark shows the massive number of cyclist-involved crashes on these thoroughfares:



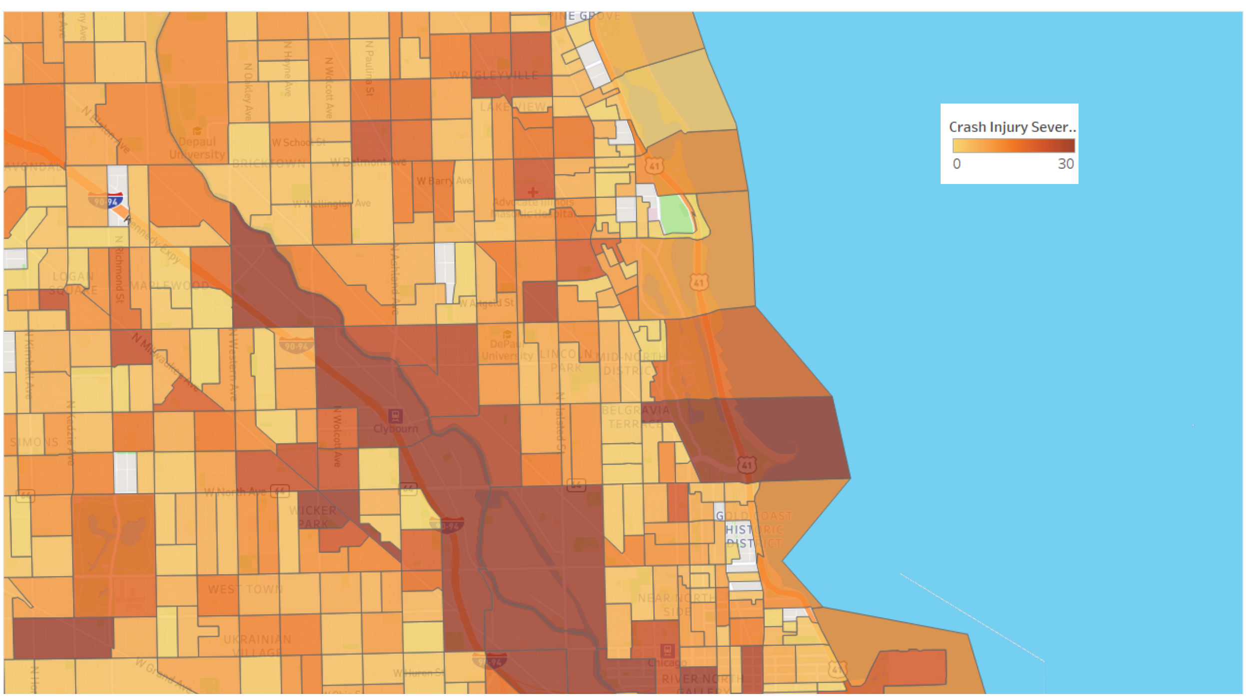
b. Critically dangerous zones

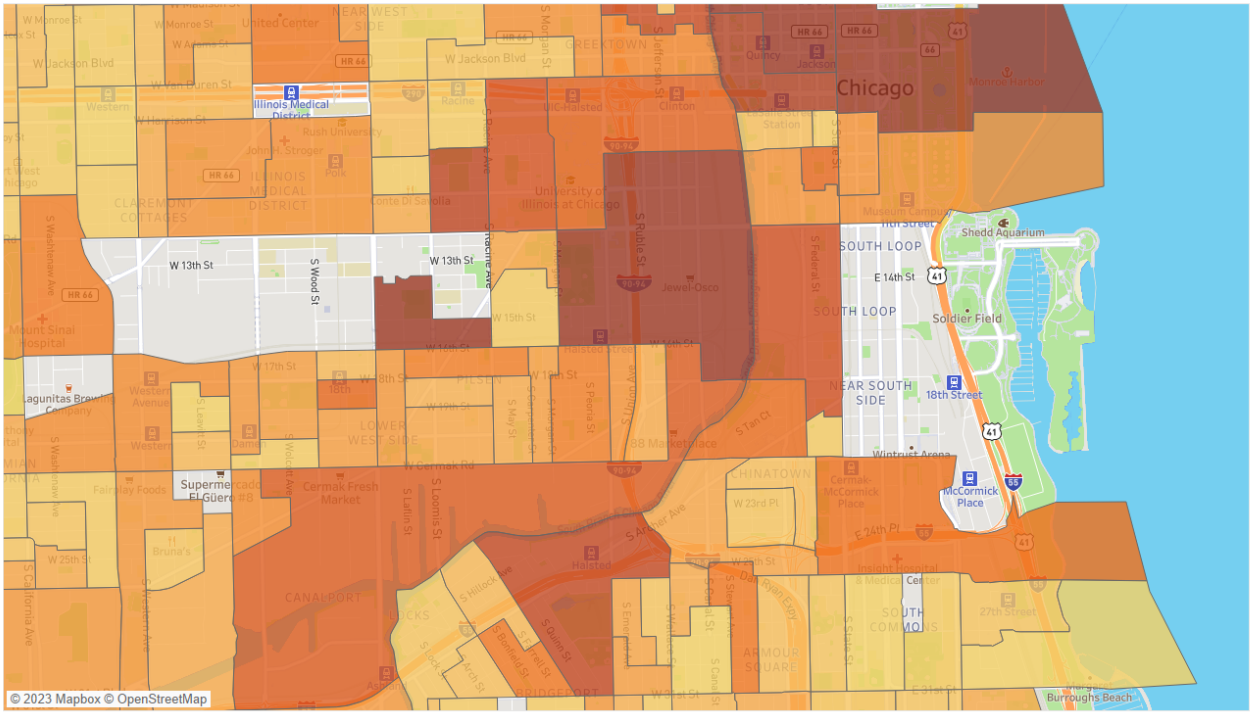
There are also areas where crashes are more likely to happen that cause serious injury. The charts below show the distribution of injury type by crash and a heat map of high-damage crashes by census block group:





Further zooming in on the above plot provides insight into some of the most dangerous areas of the city for people riding their bikes. These areas will be crucial for immediate bike safety investment to protect cyclists in these dangerous zones:

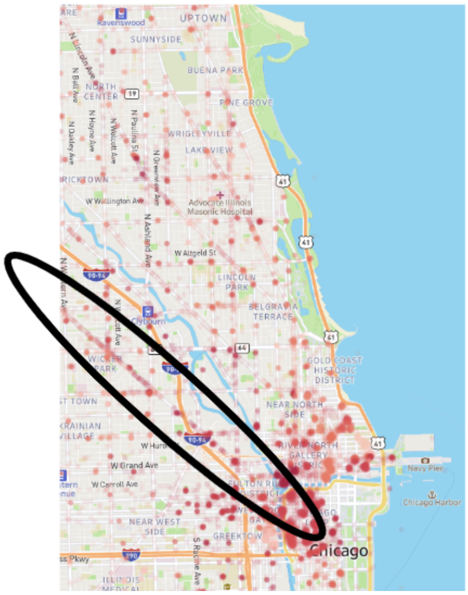




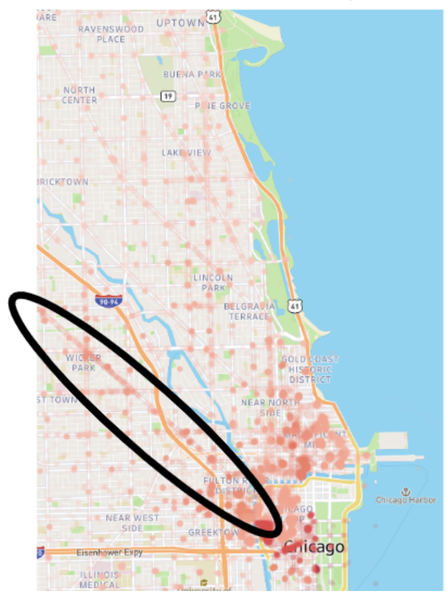
c. Crash zones by access to transit and car ownership

While crashes happen frequently on both Clark and Milwaukee, there is a specific concern related to the accessibility of people living along Clark St. As seen in the charts below, while walkability and transit access is very high along the high-crash portion of Milwaukee Ave, these metrics score much worse along Clark St. This is likely due to the Blue Line CTA rail which runs adjacent to Milwaukee Avenue on the city's Northwest Side providing strong access to the rest of the city, while bikers on Clark St have to travel a significant distance West to access the Brown/Purple/Red Line CTA Corridor.

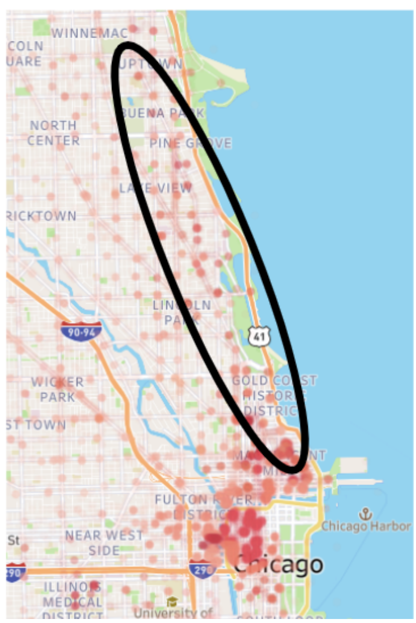
Walkability Index



Destination Accessibility Index



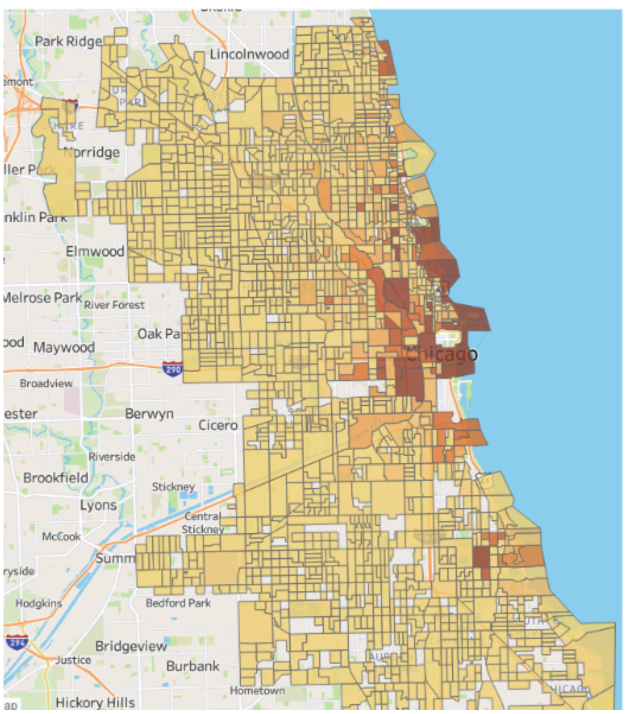
% of Households w/ No Car



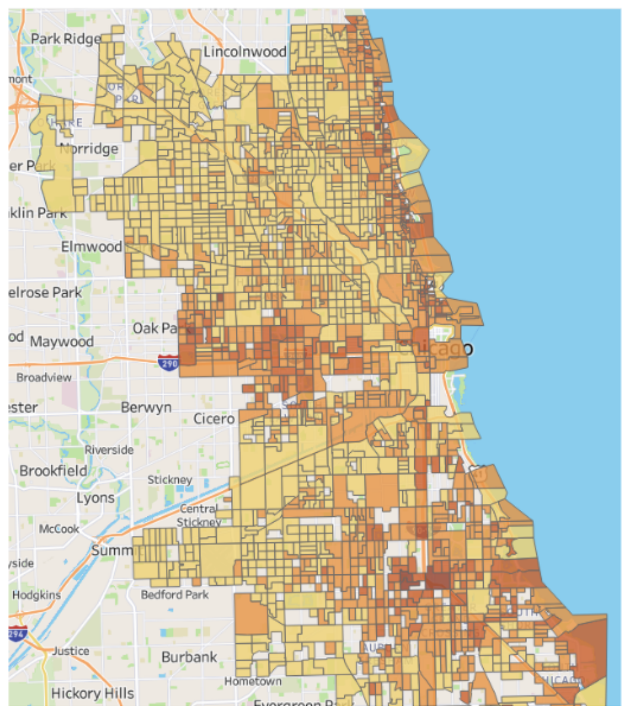
2. The City has Numerous Low-Traffic Bike Areas Which Critically Need Bike Access
    a. Divvy bike traffic is primarily focused Downtown and on the North Side, with very low traffic on South/West Sides. The areas with low bike traffic are the same areas where few people own cars.

In the chart below, it is clear that Divvy bike traffic is not widespread throughout the city. Most traffic in October 2023 was clustered downtown and on the city's North Side. Areas in the South and West Sides saw almost no traffic. Counterintuitively, in the second chart, the block groups in which many households do not own a car have very low bike activity. Since biking is such a valuable cheap alternative to driving a car, one must conclude that people are not biking in these areas because they do not have the infrastructure to keep them safe while doing so.

Divvy Trip Frequency by Block Group



% Households with no car by Block Group

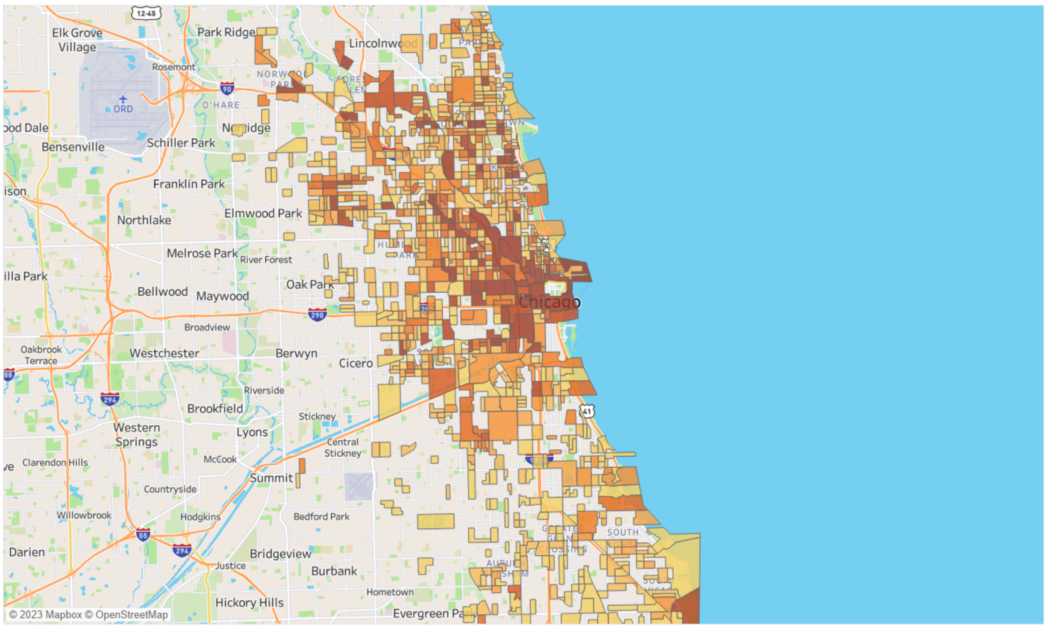


3. Limited Divvy/bike storage accessibility in many areas of the city

a. Bike racks and Divvy stations are often few and far between

The following map similarly shows how bike racks and Divvy Stations are unevenly spread across Chicago:

Rack Map

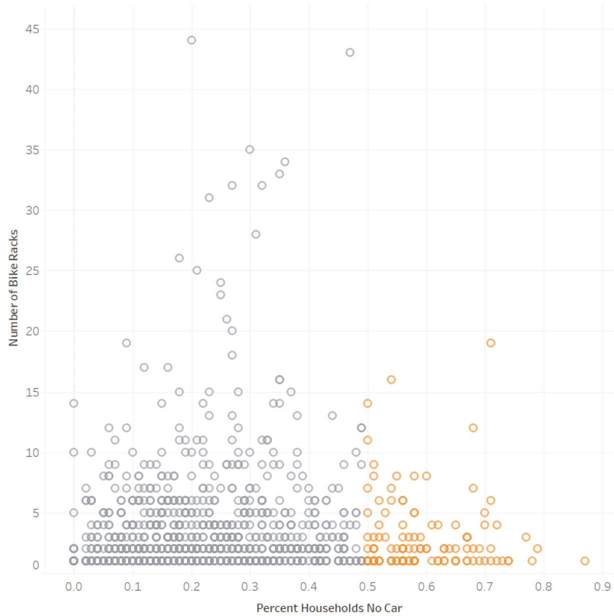


Map based on Longitude (generated) and Latitude (generated). Color shows sum of New_Quantity. Details are shown for Geoid. The view is filtered on Geoid, which keeps 1,034 of 2,104 members.

b. Racks and Stations are not present in low-wage, low-car-ownership areas

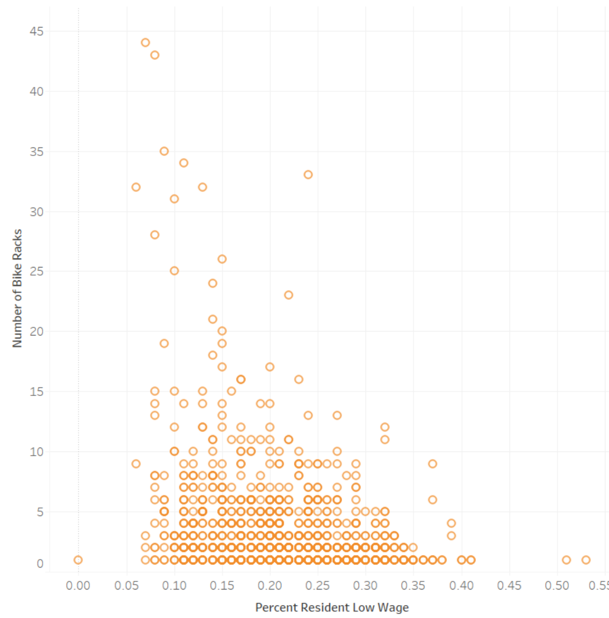
In Chicago block groups with high percentages of low wage residents and households without cars, there are less likely to be a large number of bike racks and Divvy Stations.

Racks vs HH No Car



Sum of Percent Households No Car vs. sum of New_Quantity. Color shows details about Flag. Details are shown for Geoid. The view is filtered on Geoid, which excludes Null and 170318391001.

Sheet 4



Sum of Percent Resident Low Wage vs. sum of New_Quantity. Details are shown for Geoid. The view is filtered on Geoid, which excludes Null and 170318391001.

Recommendations

Our main goals with our recommendations are to decrease the number of crashes involving people on their bikes and increase bike ridership in the city. These are important goals, as increased access to transportation increases economic mobility, and especially in many areas with current poor bike infrastructure, many people lack transportation access to jobs and other important locations and services.

Goal: To decrease the number of crashes
Recommendations:

1. Protected bike lanes and lower speed limits on Clark St and Milwaukee Ave
    a. These streets are specifically dangerous for bike riders and have an unbelievably large number of crashes along them. By creating protected bike lanes on the entirety of each street people on bikes will be physically separated from cars by concrete, which will lower the frequency of cars crashing into cyclists. Further, by lowering the speed limit, cars will be less likely to hit people on bikes.
2. Protected bike routes west from Lakefront to increase safe access to transit
    b. Our data identified that areas with high numbers of crashes along Clark St on the city's North Side also suffer from worse access to transit. By creating protected bike routes west toward the CTA's Brown/Purple/Red Line corridor people will be able to be more connected to the city via safe bike routes.
3. Create safe bike paths in specific dangerous crash areas
    c. Our data also identified specific areas where crashes with more significant injuries are more likely to occur: near the I-90/94 offramp/the Clybourn Metra Station and near the I-90/94 offramp near University of Illinois-Chicago. These are both critical areas for bike ridership – near a local transit stop and university, and the high numbers of dangerous crashes here are likely due to passengers speeding off the highway as they exit. Establishing physical barriers for cyclists in these zones is critical, as is consistent enforcement of speed limits.

Goal: Encourage further ridership
Recommendations:

1. Protected bike lanes in South Side
    a. The South Side of Chicago has very low bike ridership, as seen in the Divvy Trip data, despite many people in this region having no car. These people are very likely not using bikes for transportation because they do not feel it is safe to do so. Creating a grid-network of protected bike lanes on the South Side is critical to increase ridership and provide people a safe, convenient, and cheaper option to travel to work, grocery stores, doctor's offices, and more.
2. Influx of Divvy stations/bike racks in South/West sides

a. There is also a clear lack of existing Divvy Station and bike racks in the city's South and West sides. Establishing more stations and racks in these areas will induce demand for cycling, as it will become a more viable option for those looking to get around conveniently and cheaply.

Lessons Learned

1. **Using raw data from government sources is difficult:** Our data sources came from the City of Chicago, which had scattered data and incompatible formats across different databases, making it difficult to link together. We had to drop or find sufficient data, and rethink our initial conceptual model several times before creating the final iteration of our model. Public data requires more effort to work with, and it may be better to pay or source higher-quality/user-friendly data within an enterprise environment.

2. **Collaborating on a cloud database requires careful planning:** Given our previous inexperience with cloud databases, we had little understanding of how committing simultaneous changes to our remote database can cause issues such as mismatches and database locking. We spent a lot of time and resources resolving issues, and had to restart our database several times to unlock it. When working with larger and more interdependent data architecture, such solutions are haphazard and cannot be relied upon - it may be better to mitigate such issues beforehand through careful branching and merging of database actions.

3. **Working with geospatial data is strenuous:** Our project relied heavily on geospatial data to map out distributions and trends across Chicago. We realised that the working with geospatial data meant fine-tuning granularity for every database to ensure they linked and plotted correctly on a map. When using geospatial data in future, we can consider using geospatial packages and tools like ArcGIS to geocode and convert geospatial data to our preferred format automatically.

Appendix

Data Dictionary:

Crash Data:

- Dictionary:
    - CRASH_RECORD_ID (PK)
        - Crash key
    - CRASH_DATE
        - Date and time
    - POSTED_SPEED_LIMIT
        - Speed limit
    - TRAFFIC_CONTROL_DEVICE
        - Type of traffic control where crash occurred
    - WEATHER_CONDITION
        - Weather at crash
    - LIGHTING_CONDITION
        - Lighting at crash
    - TRAFFICWAY_TYPE
        - Road type
    - ROADWAY_SURFACE_COND
        - Road surface condition
    - CRASH_TYPE
        - Type of crash
    - HIT_AND_RUN_I
        - Hit and run indicator
    - PRIM_CONTRIBUTORY_CAUSE
        - Primary cause of crash
    - STREET_NO
        - Street number
    - STREET_DIRECTION
        - Street direction
    - STREET_NAME
        - Street name
    - DOORING_I
        - “Dooring” crash type indicator
    - MOST_SEVERE_INJURY
        - Most severe injury in crash
    - INJURIES_FATAL

        - Number of fatal injuries
    - INJURIES_INCAPACITATING
        - Number of incapacitating incjuries
    - INJURIES_NON_INCAPACITATING
        - Number of non-incapacitating injuries
    - CRASH_HOUR
        - Hour of crash
    - CRASH_DAY_OF_WEEK
        - Day of week of crash
    - CRASH_MONTH
        - Month of crash
    - LATITUDE
    - LONGITUDE
- Filter:
    - FIRST_CRASH_TYPE - filtered to PEDALCYCLIST

Bike Racks:

- Dictionary:
    - Rack_ID
        - Rack primary key
    - Latitude
    - Longitude
    - Location (Street Address)
    - Name
    - Quantity
    - Type: Decorative or Type B

Divvy Trip Data:

- Dictionary:
    - Ride_id (PK)
        - Ride primary ID
    - Rideable_type
        - Type of bike
    - Started_at
        - Start time
    - Ended_at
        - End time
    - Start_station_name
    - Start_station_id
    - End_station_name

- End_station_id
- Start_lat
    - Start latitude
- Start_lng
    - Start longitude
- End_lat
    - End latitude
- End_lng
    - End longitude
- Member_casual
    - Divvy member or casual user

SMART Location Database:

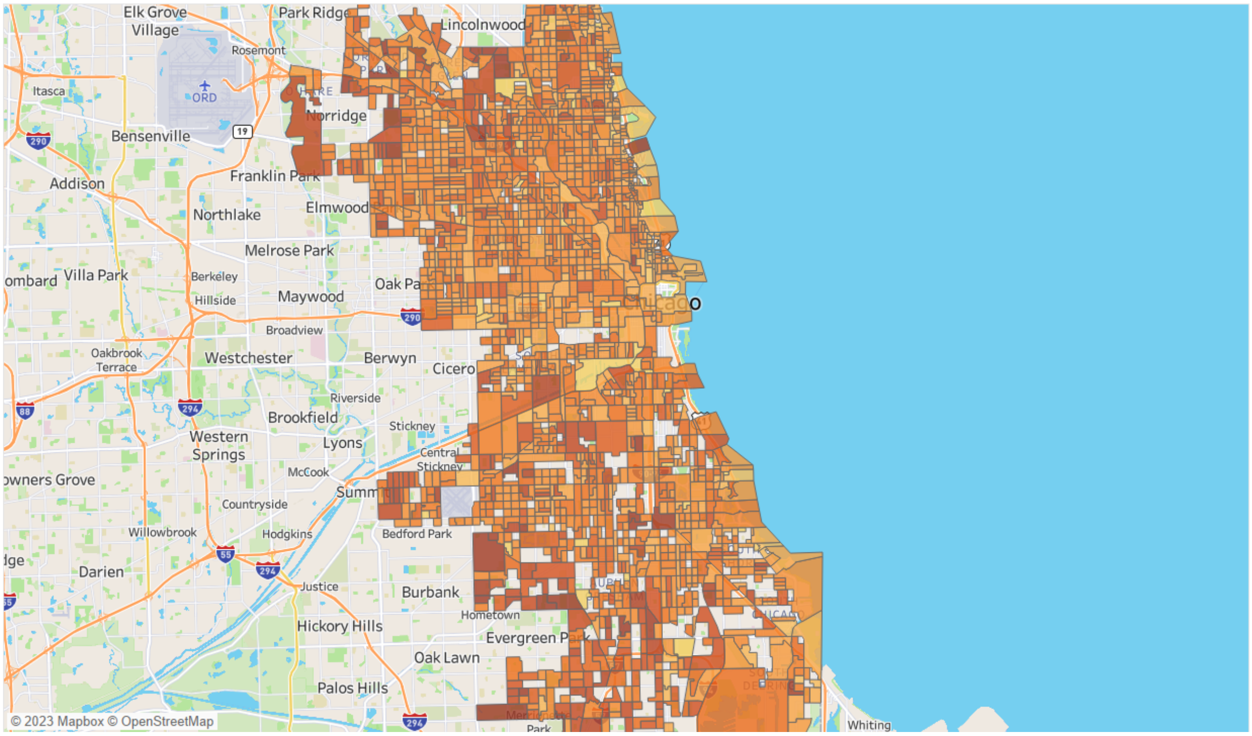
- **Dictionary:**
    - TRACTCE (PK):
        - Census tract FIPS code
    - BLKGRPCE:
        - Census Block group FIPS code
    - TotPop:
        - Population unit
    - CountHU:
        - Housing unit
    - HH:
        - Households
    - P_WrkAge:
        - % population that is working age
    - AutoOwn0:
        - Number of households that own 0 cars
    - Pct_AO0:
        - % of households that own 0 cars
    - AutoOwn1:
        - Number of households that own 1 cars
    - Pct_AO1:
        - % of households that own 1 cars
    - AutoOwn2p:
        - Number of households that own 2+ cars
    - Pct_AO2p:
        - % of households that own 2+ cars
    - R_LowWageWk:
        - Count of workers earning $1250/month or less (home location)

- R_MedWageWk:
    - Count of workers earning more than $1250/month but less than $3333/month (home location)
- R_HiWageWk:
    - Count of workers earning $3333/month or more (home location)
- R_PctLowWage:
    - Percent of low wage workers in a CBG (home location)
- TotEmp:
    - Total employment *(people working in the area)*
- E_LowWageWk:
    - # of workers earning $1250/month or less (work location)
- E_MedWageWk:
    - # of workers earning more than $1250/month but less than $3333/month (work location)
- E_HiWageWk:
    - # of workers earning $3333/month or more (work location), 2017
- E_PctLowWage:
    - % LowWageWk of total #workers in a CBG (work location), 2017
- D3a:
    - Total road network density
- D4a:
    - Distance from the population-weighted centroid to nearest transit stop (meters)
- D5br:
    - Jobs within 45-minute transit commute, distance decay (walk network travel time, GTFS schedules) weighted (-9999 placeholder values)
- D5be:
    - Working age population within 45-minute transit commute, time decay (walk network travel time, GTFS schedules) weighted (-9999 placeholder values)
- D5dr:
    - Proportional Accessibility of Regional Destinations - Transit: Employment accessibility expressed as a ratio of total MSA accessibility
- NatWalkInd:
    - Walkability index

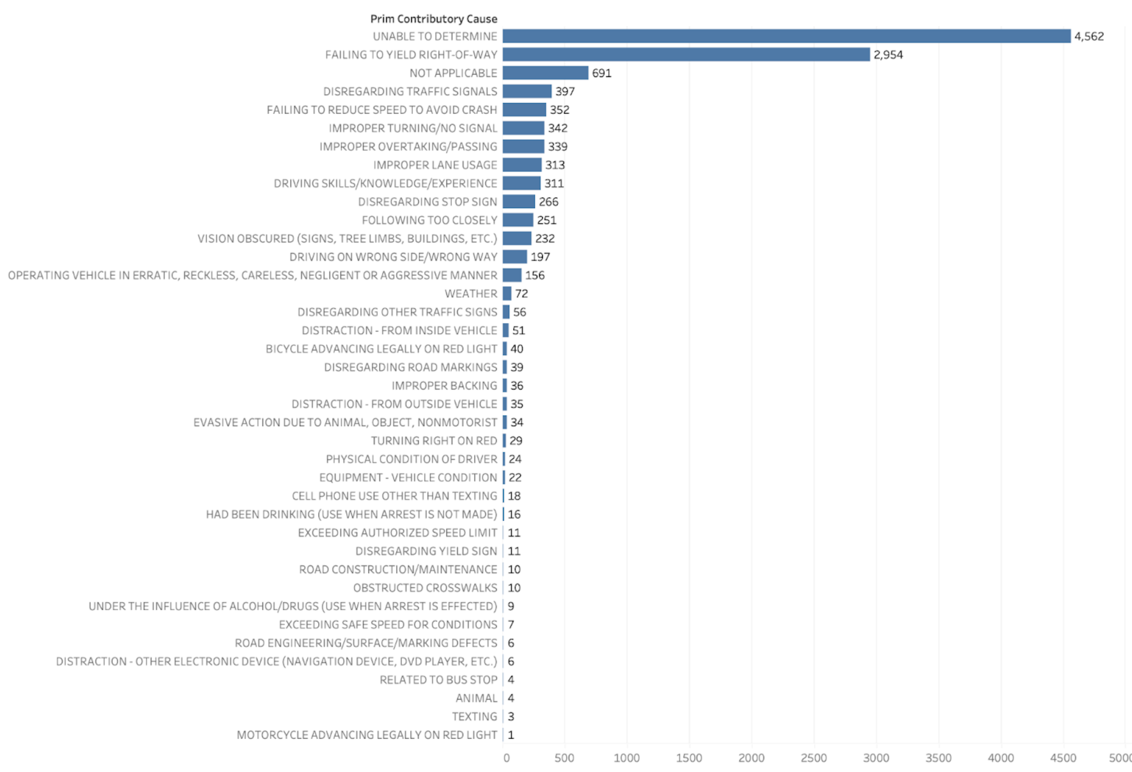
- **Filter:**
    - CSA_Name - filtered to Chicago-Naperville

Unused Charts

Distance to Transit



Crash Count by Cause



Count of Crash Record Id for each Prim Contributory Cause. The data is filtered on Crash Type, which keeps INJURY AND / OR TOW DUE TO CRASH and NO INJURY / DRIVE AWAY.