

2019 Teradata Analytics Challenge Finalist Presentations

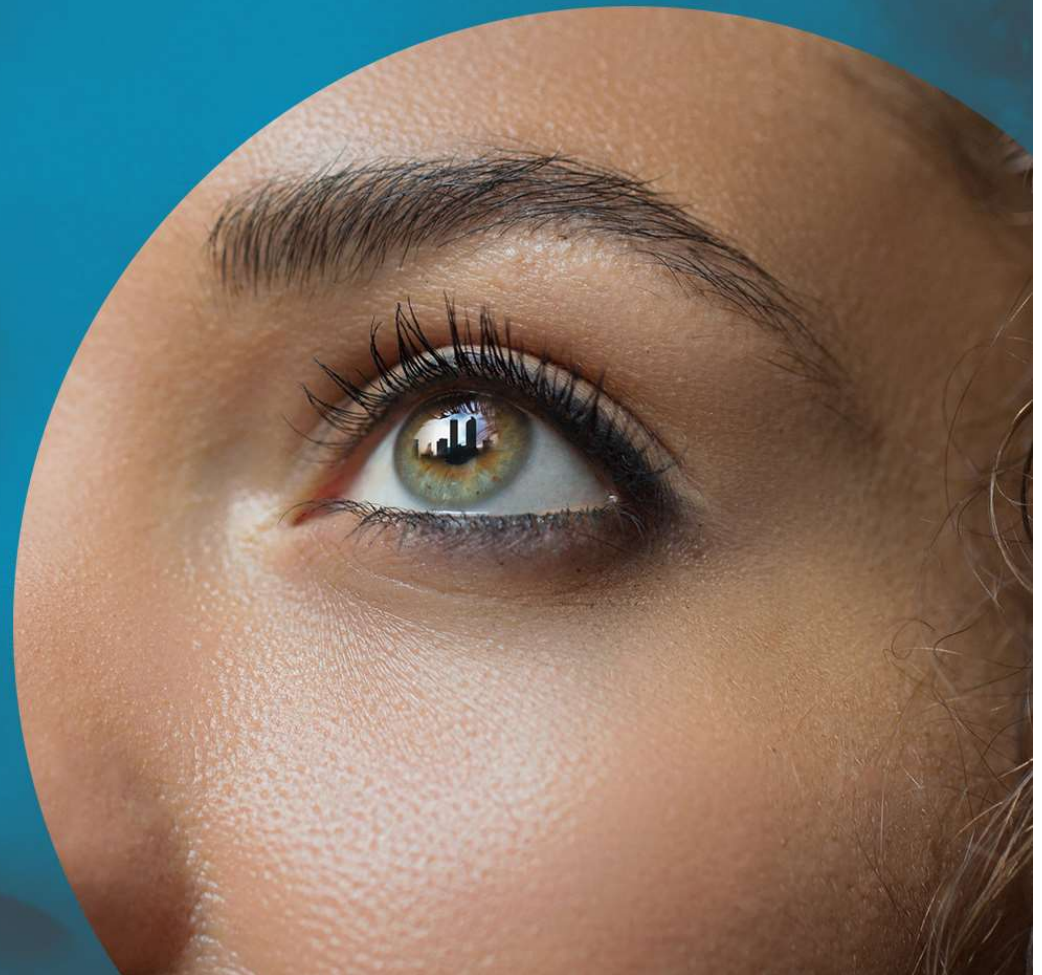
TEAM A1-A6

Yenny Yang – Teradata

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Format for Session

- Finalist Presentations (Team A1-A6)
- Wrap Up

Analytics Challenge Finalists

A1 - Asia Pacific University Malaysia

A2 - Auburn University

A3 - Lawrenceville High School

A4- Loyola University Chicago

A5- Southern New Hampshire University

A6- University of Minnesota Duluth

A1- Asia Pacific University of Technology and Innovation Malaysia

Dynamic Pricing in E-commerce Sector

Vijaya Shree Raja Sekaran
October, 2019

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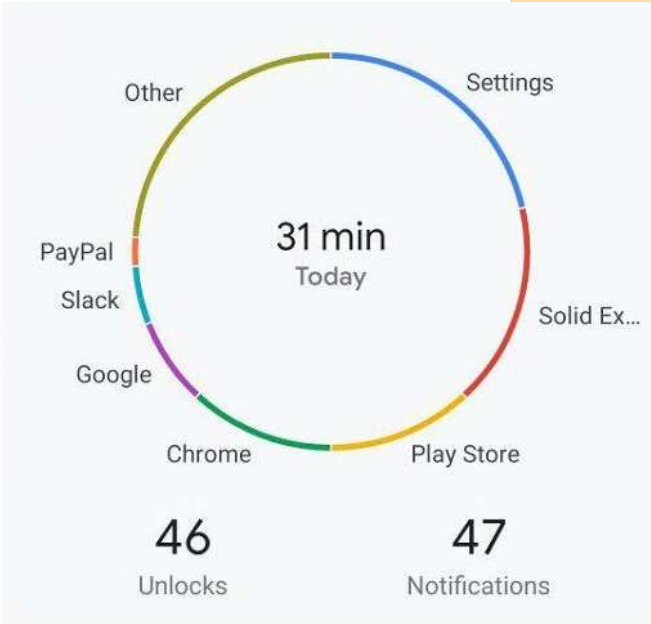


E-Commerce @ Present...!

Data Data Data...



Prices must be low
customers happy & satisfied

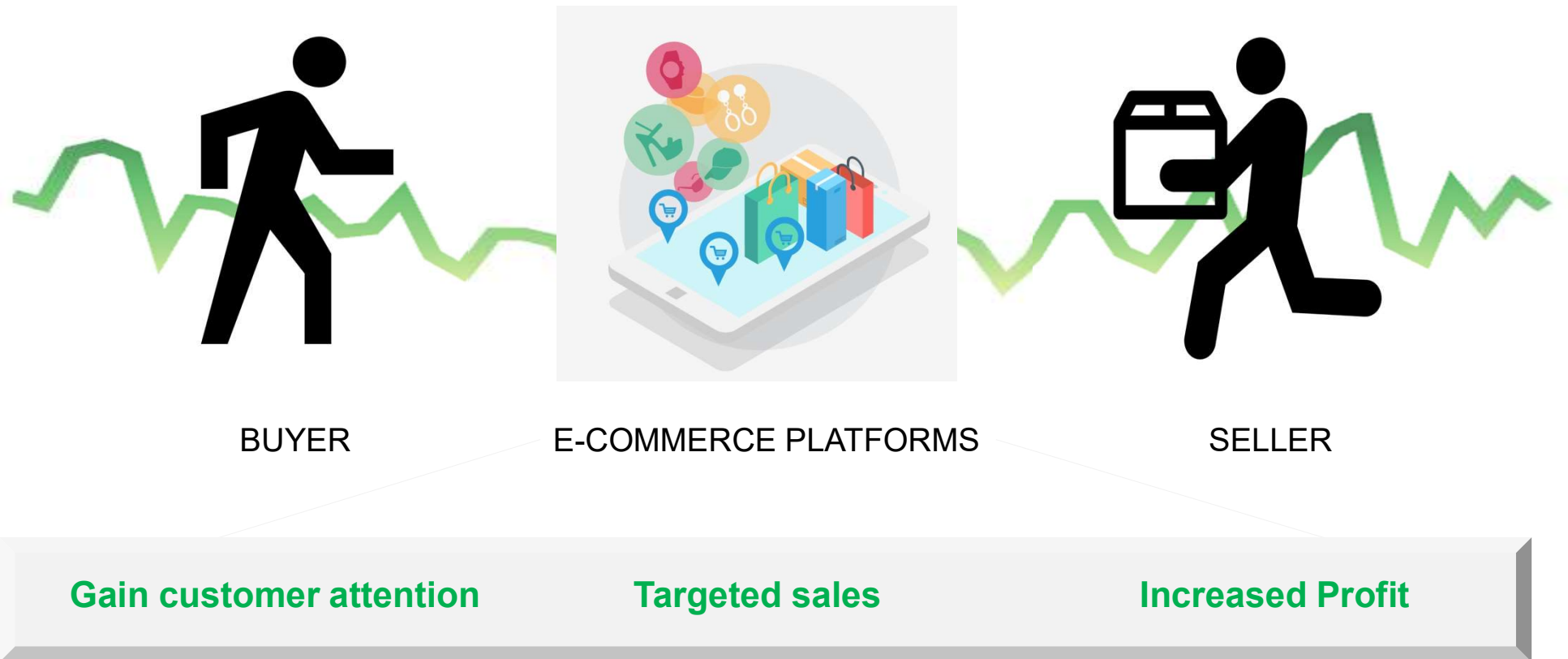


Decision
ing

Problem & Motivation



Benefiters of Dynamic Pricing



Methodology



Tools & Software



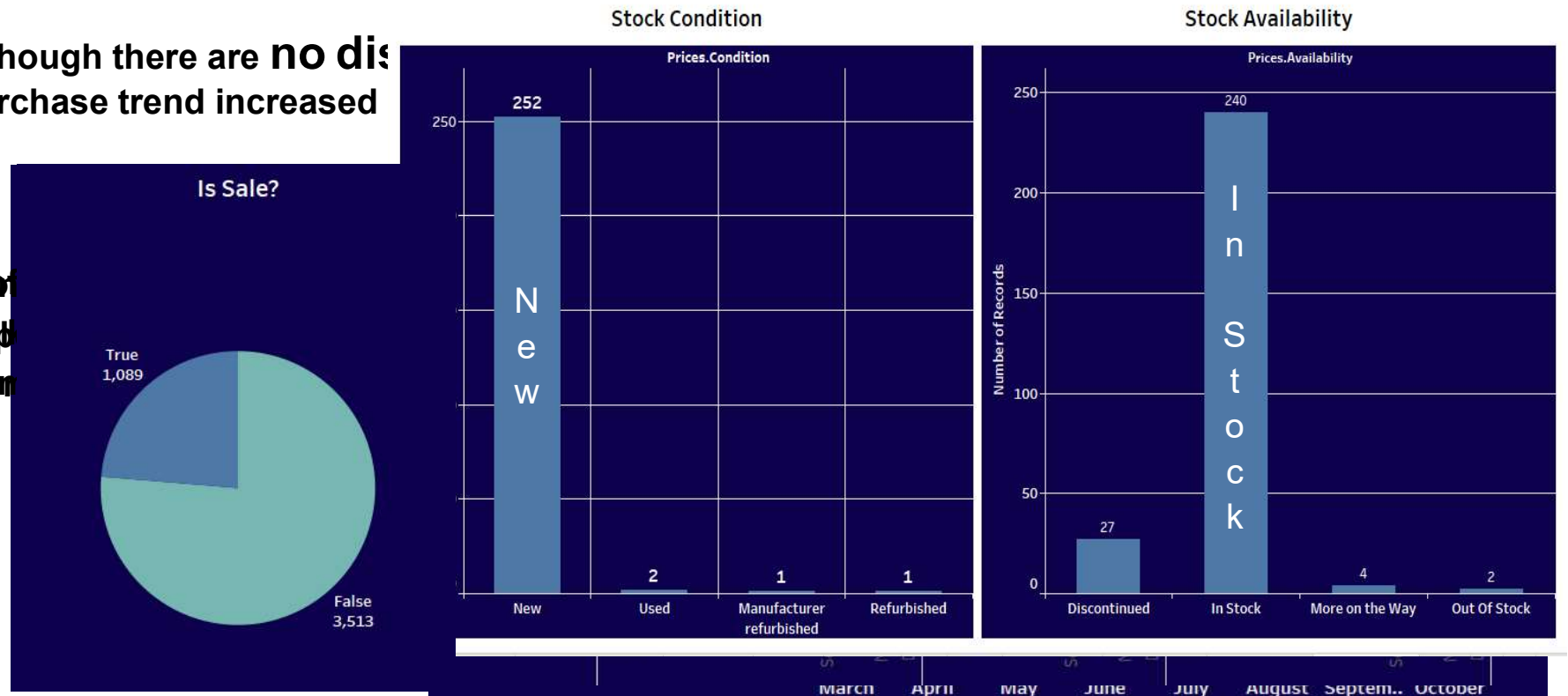
Implication of data analysis

#2

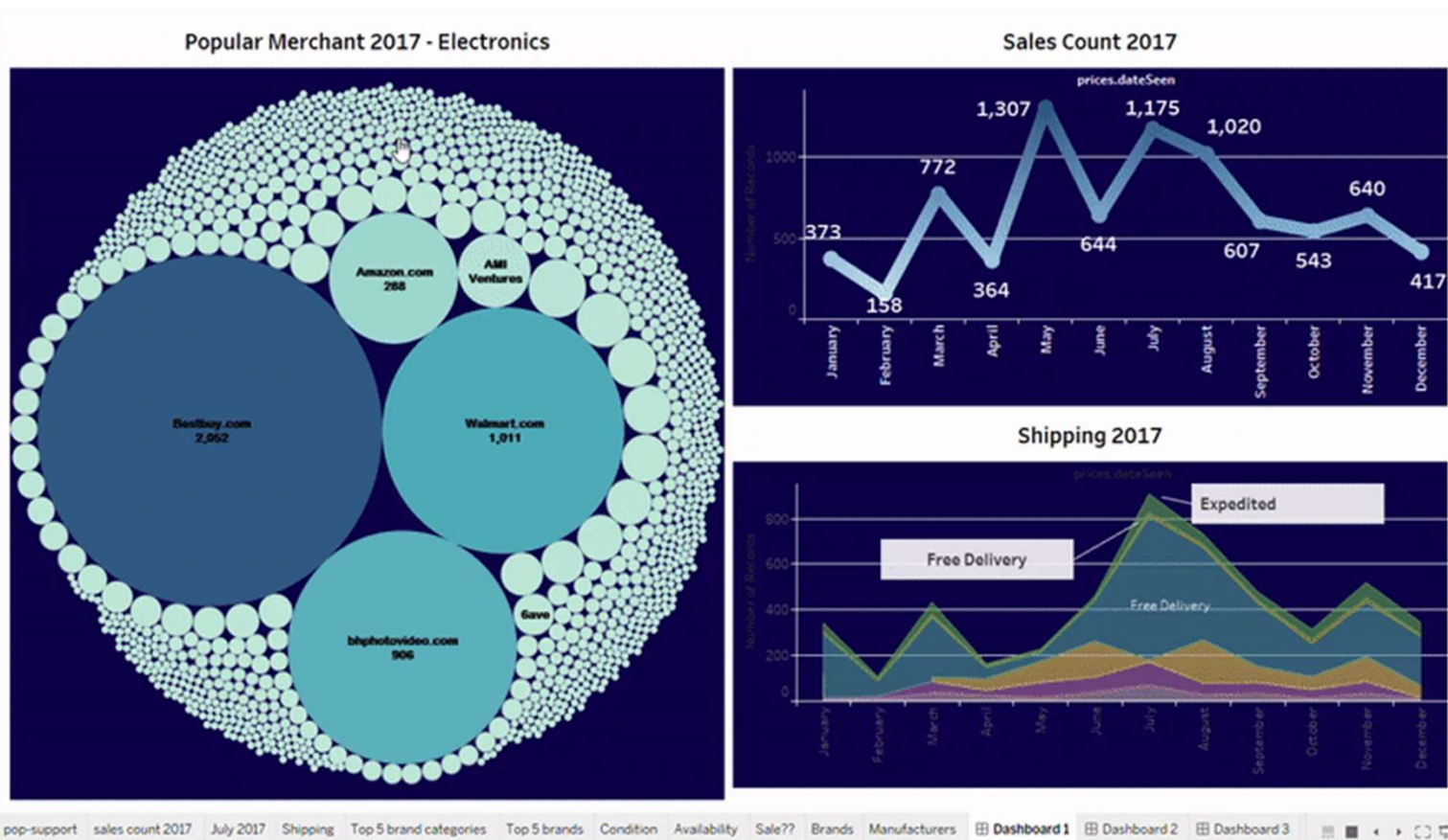
Even though there are no discounts, the purchase trend increased

#1

Support
increased
platform



Trends & Patterns in Data



Checkout the
interactive dashboard
(Tableau)



8 Significant Factors of this analysis



Analysis on customer behavior & dynamics



Customer Behavior



Customer Dynamics



Recommendation

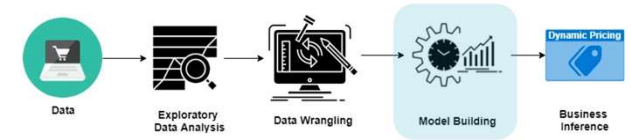
Search the products	Enters search term	Track their interest
Add to wishlist	Saves the preference	Match the products in wishlist
Add to cart	Chooses the most probable item to buy	Send the notification of the lowest prices from dynamic pricing strategy
Purchase	Place the order	Add the trait to their dynamics

Recommendation

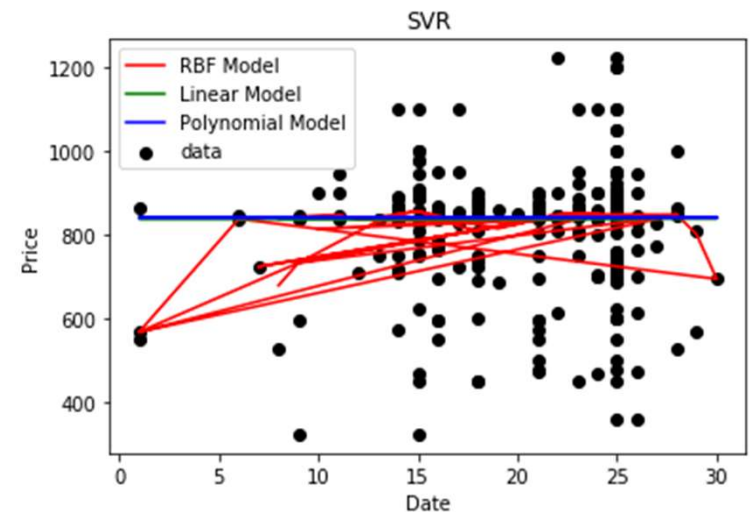
Implementation of predictive ML model

- ✓ Features: Date Seen & Previous price
- ✓ Product: MacBook2017
- ✓ Technique: Support vector machine
- ✓ Kernels: Radial basis Function, Linear, Polynomial

RBF	$Y(X_i, X_j) = \exp(-\gamma X_i - X_j ^2)$
Linear	$Y = mx + c$
Polynomial	$Y(X_i, X_j) = (X_i \cdot X_j + 1)^d$



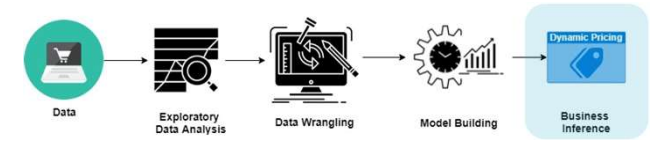
Output of ML model



```
print(predicted_price)
(850.0897439618172, 839.9500000004048, 840.0900000197965)
```

Dynamic pricing

This strategy can highly optimize the profit !



The way forward..



- ✓ Deployment of this model in the cloud
- ✓ Real-time analytics and price optimization with new features
- ✓ Plug-in development



Thank you

For Demo of the model, Credits & Acknowledgement – Please visit:
[Http://MyAnalyticsCompetition.online](http://MyAnalyticsCompetition.online)



Mentor
Mr. Raheem Mafas



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Presenter
Vijaya Shree Raja Sekaran



A2 – Auburn University USA

The Government Shutdown
(2018-2019) as seen
through Twitter

Maia MacDonald

Lauren Fuller, Avery Lawrence

October, 2019

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Introduction

- Between December 22, 2018 and January 25, 2019, the United States government shutdown
 - Longest shutdown in American history
- Began over funding for a wall along the southern US border
- Impacted 800,000 Americans who were working without pay during the shutdown
- Interested in Twitter sentiment relating to furloughed federal employees, management of TSA and air traffic control, and destruction of National Parks

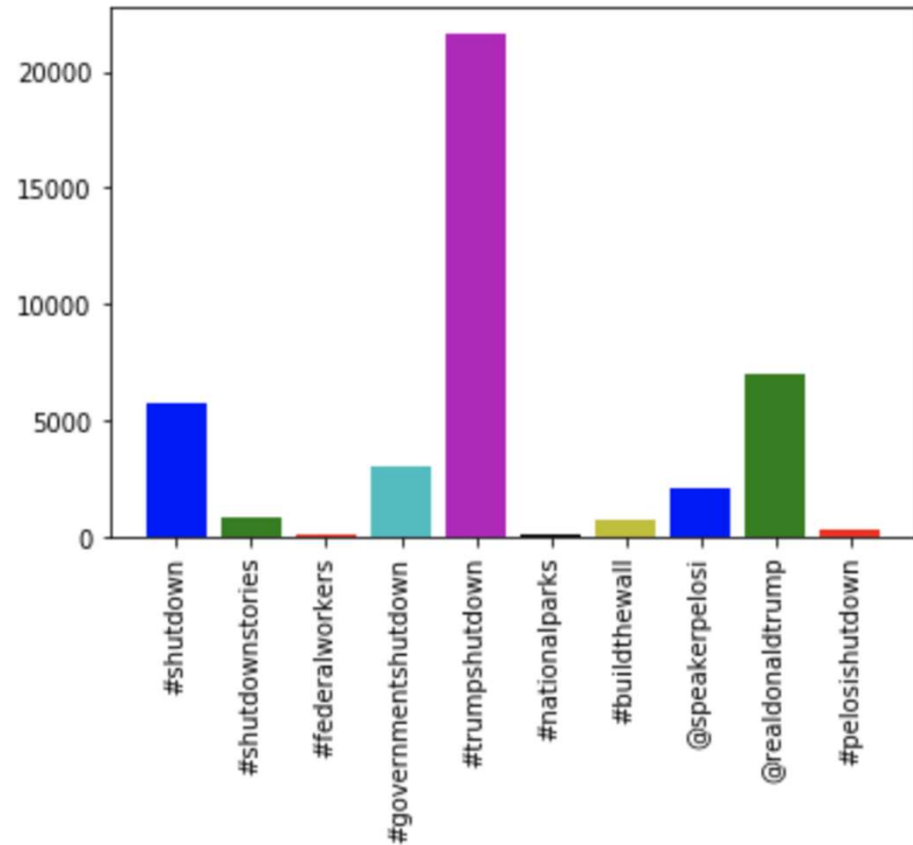
Topic Research & Analytics

- Using Amazon Web Service's Elastic MapReduce (EMR), we queried the listed hashtags from 3 months of Twitter data
 - Collected between December 3, 2018, and February 4, 2019
 - Generated roughly 100,000 tweets
- The data created a considerable amount of noise, so we cut the list down to only **#shutdown** during our analysis
 - The change reduced the number of tweets to 39,262

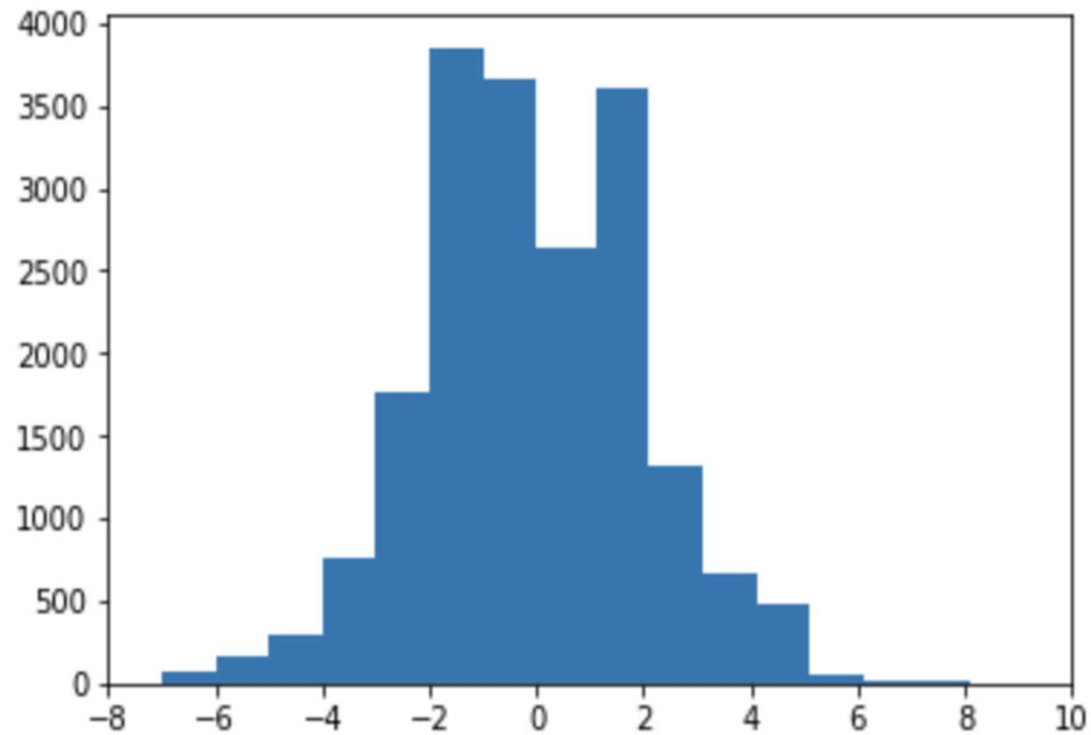
#shutdown
#governmentshutdown
#endtheshutdown
#tsa
#shutdownstories
#federalemmployees
#federalworkers
#scienceshutdown
#airtrafficcontrol
#nationalparks
#coastguard
#nasa

Hashtag Frequency

- Frequency of hashtags and usernames relating to politics:
 - #trumpshutdown – 21,528
 - @realdonaldtrump – 6,981
 - @speakerpelosi – 2,041
 - #buildthewall – 711
- Frequency of hashtags relating to the effects of the shutdown:
 - #shutdownstories – 823
 - #federalworkers – 58
 - #nationalparks – 35



Aggregate Sentiment



Sentiment Scores for each Hashtag & Username

Fig. 1: Average Raw Sentiment Scores

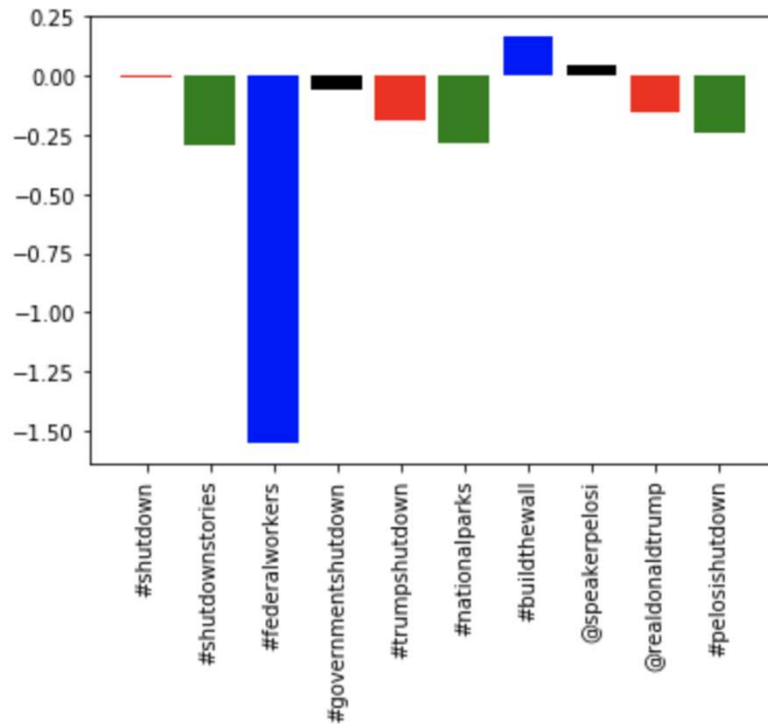
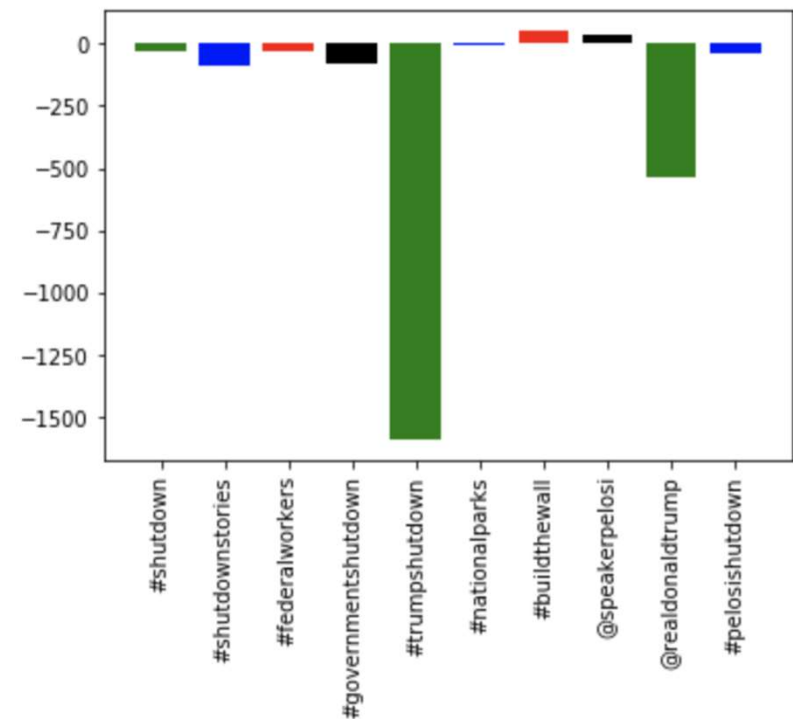


Fig. 2: Aggregate Raw Sentiment Scores



Proportion of Positive & Negative Sentiment Scores

Fig.1: #federalworkers

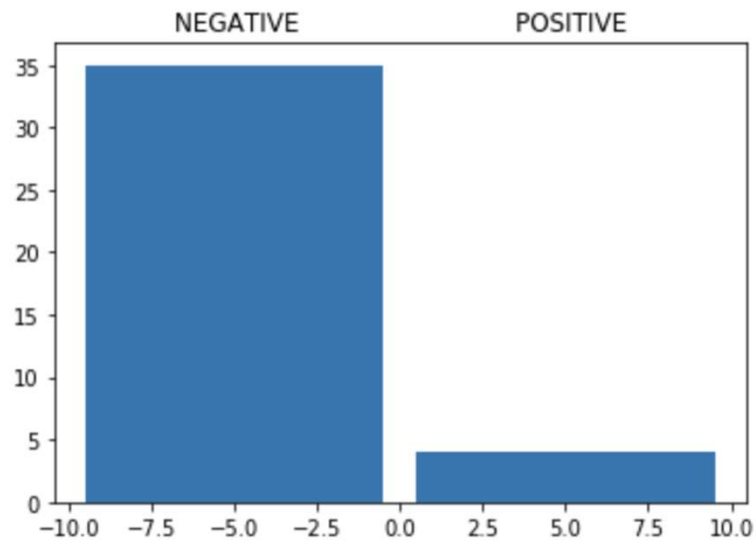
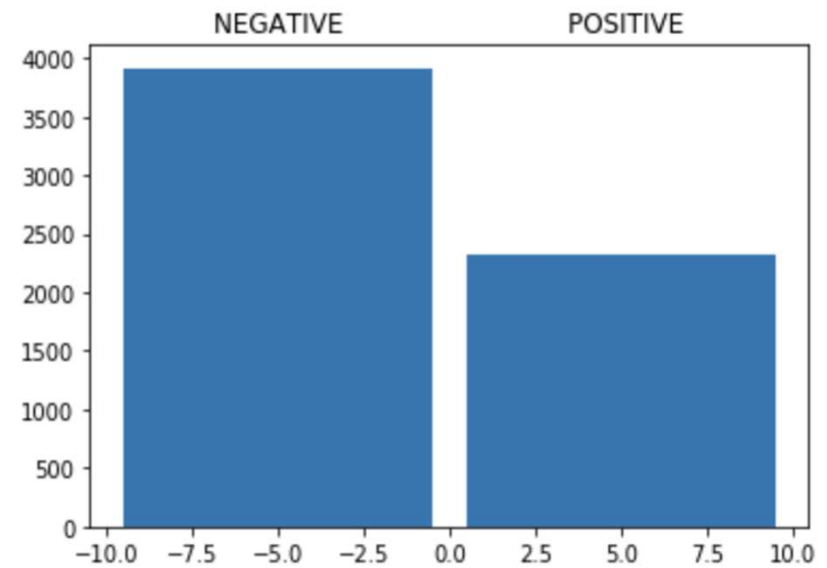
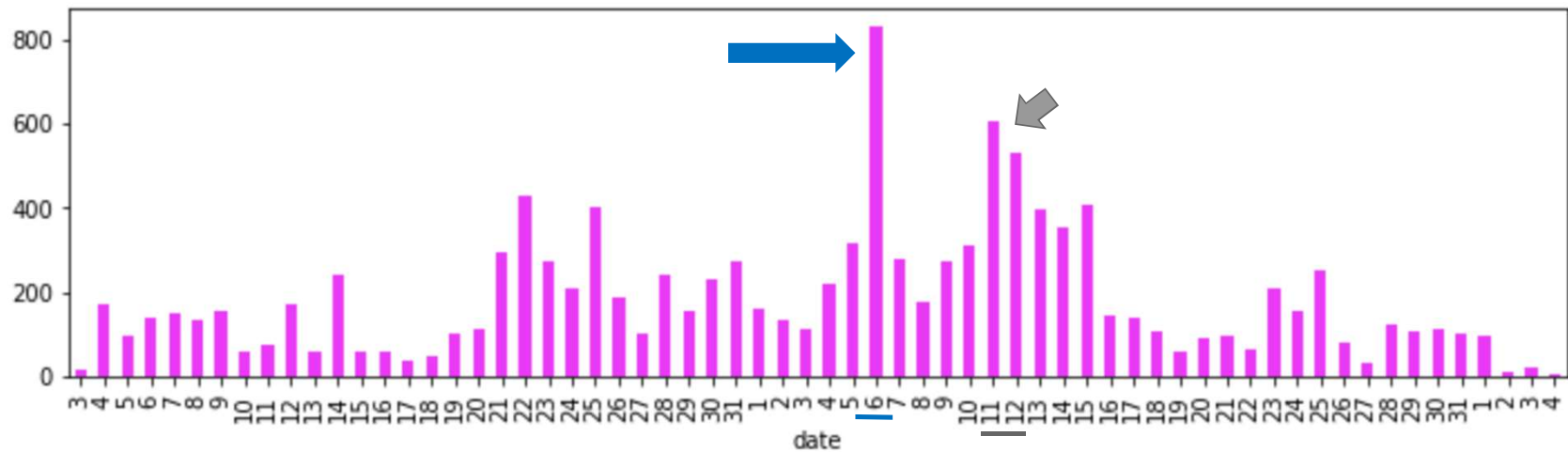


Fig. 2: #trumpshutdown



Frequency of Tweets on Queried Dates



Highest Frequency Hashtags

Fig. 1: January 6, 2019

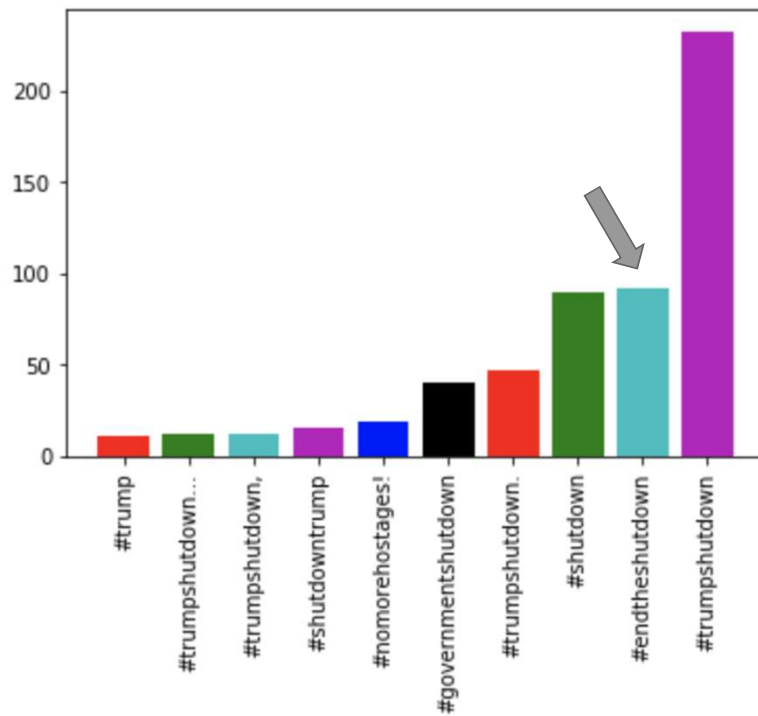
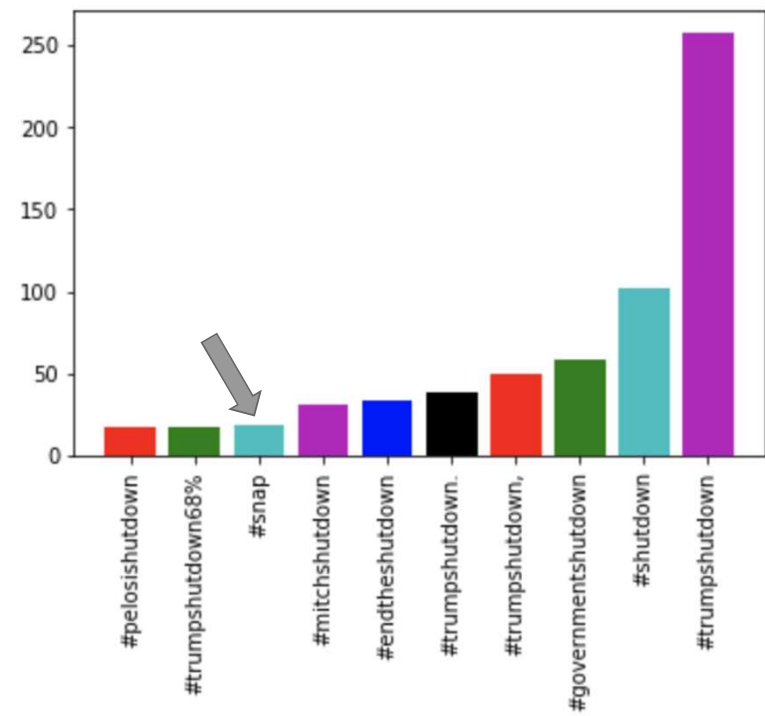
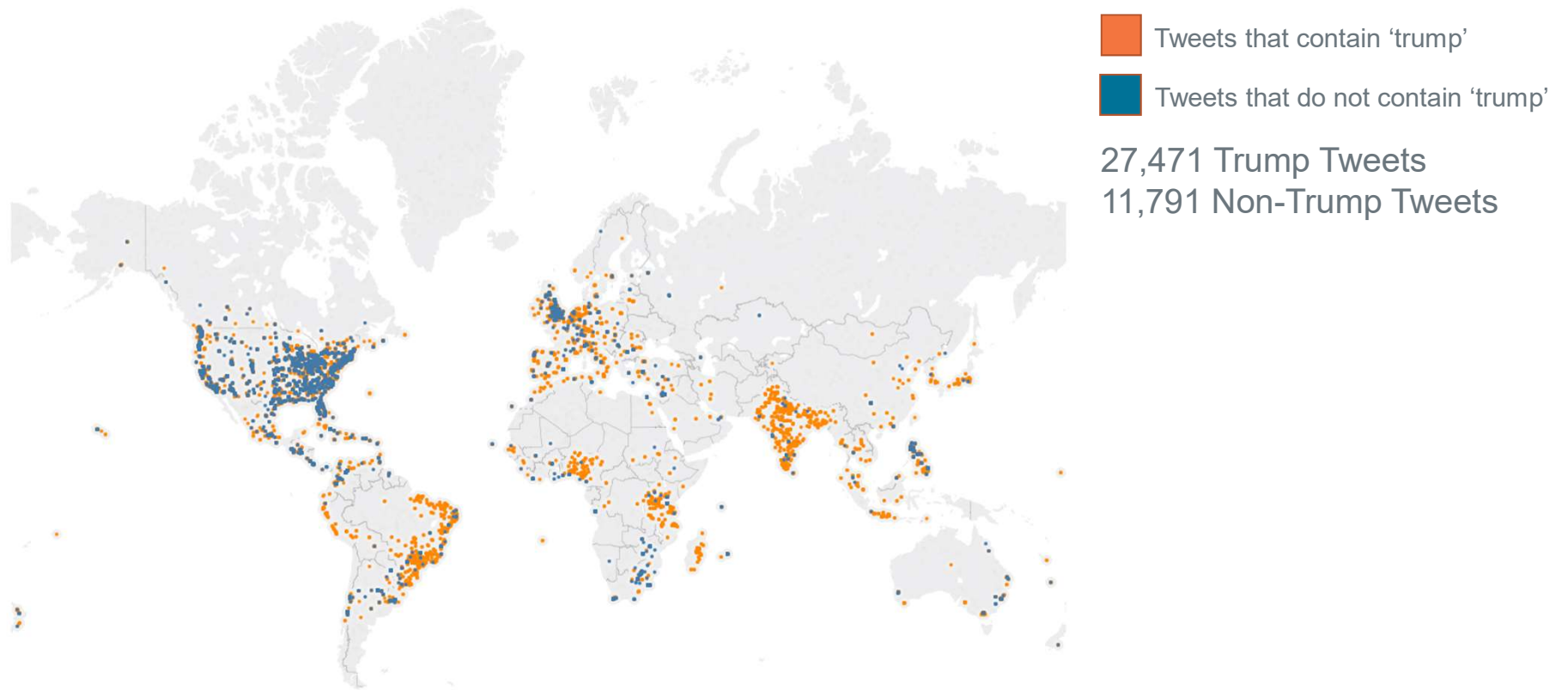


Fig. 2: January 12, 2019



Trump vs. Non-Trump Tweets



Conclusion

- We expected people to express concerns with their jobs and paying their bills
- Instead, people direct their anger towards political figures
 - Because of this, analytics techniques become difficult to use for assessing socioeconomic impacts of government actions
- Twitter should be avoided for business analytics purposes when the issue is related to politics
 - Other forms of social media may be more useful

Thank you.

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A3- Lawrenceville School (HS) USA

Is Legalisation of Cannabis for
Adults Harming Teenagers?

Johann Lee

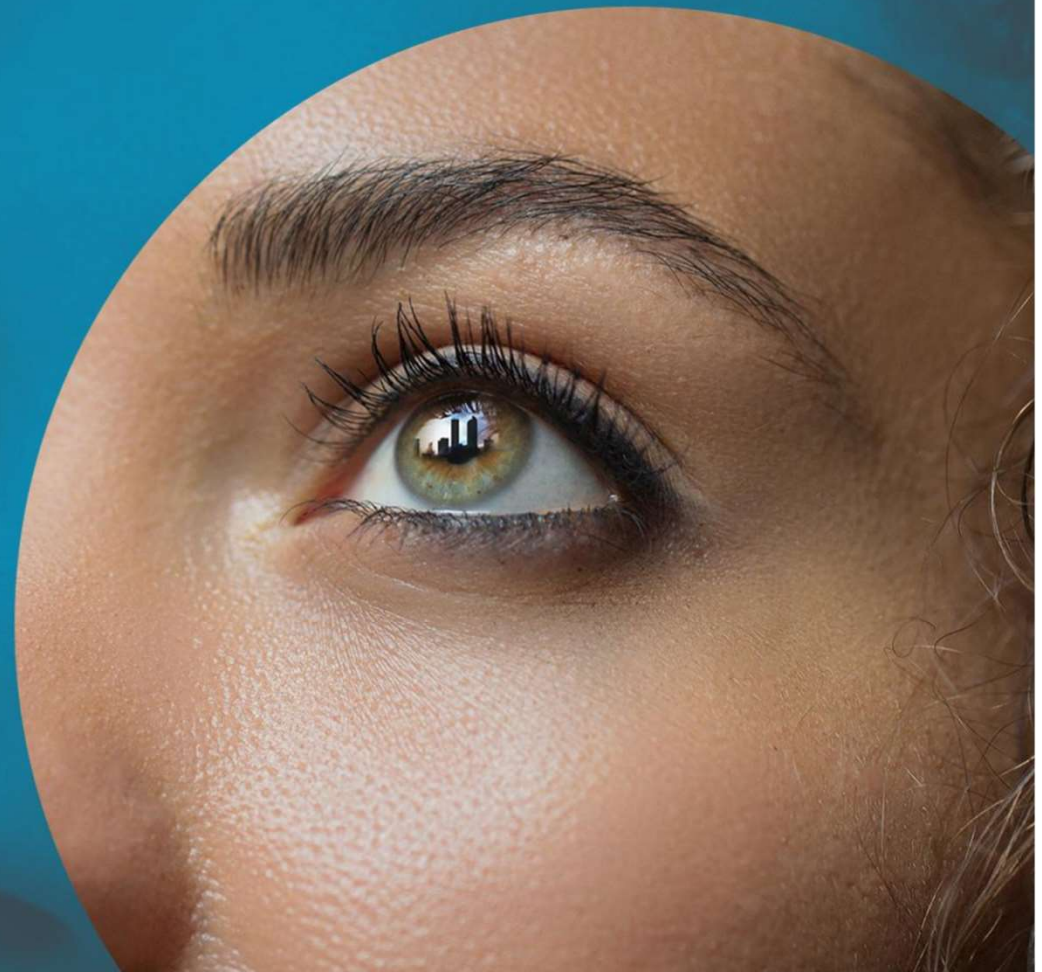
Alen Alshinbayev

October, 2019

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Our Motivation



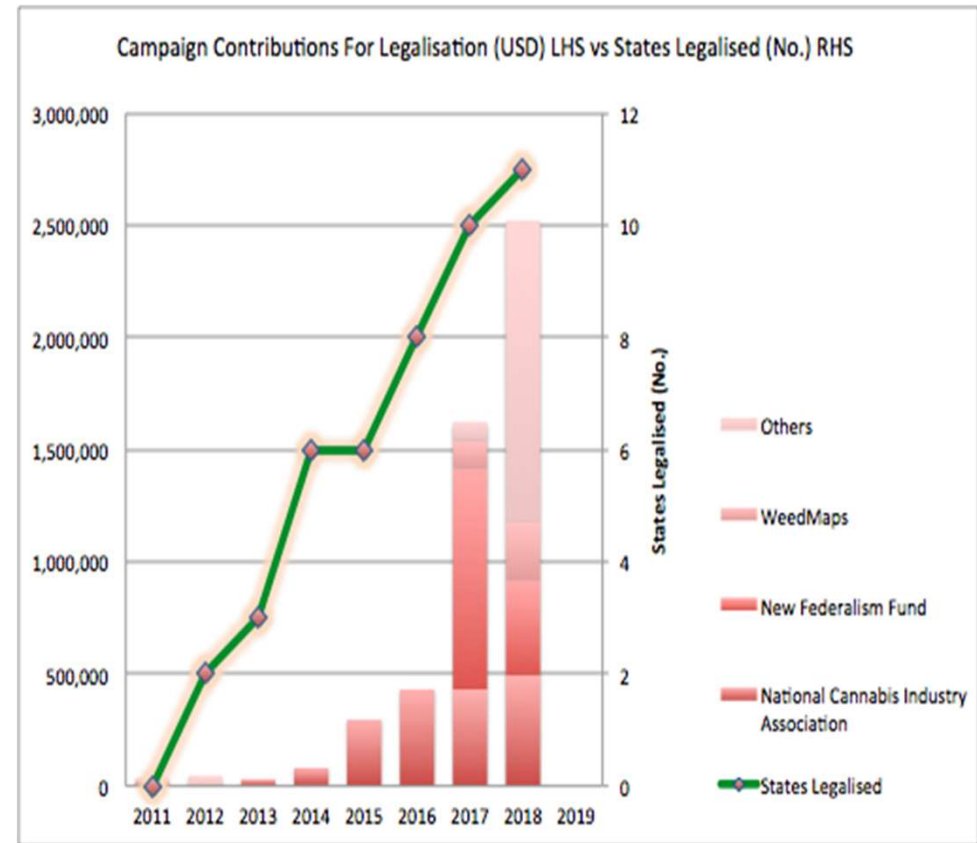
Is
**Cannabis
Legalisation
for Adults
Harming
Teenagers?**

Medical Research shows Major Health Risks

To Teenagers:

- Poorer education/employment achievements
- Impeded cognitive abilities
- Increased car accidents
- Increased addiction to hard drugs in later life

Note: "Adverse Health Effects of Marijuana Use" by Volkow et al. published in New England Journal of Medicine (2014) and many other research papers



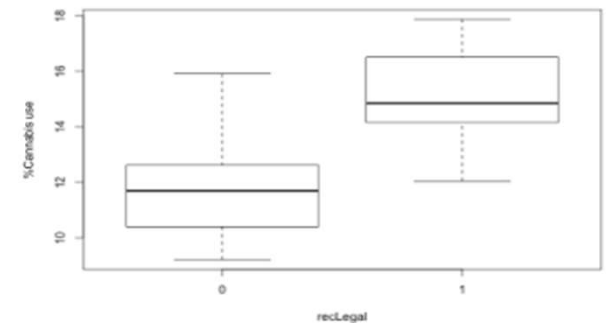
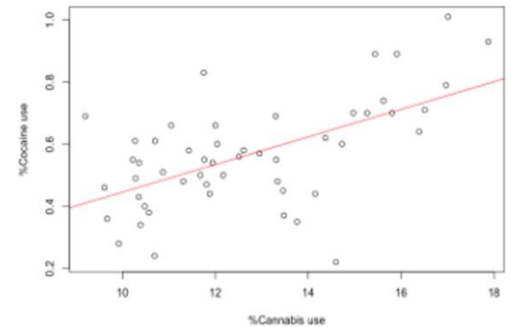
Data and Tools - What did we look at?

Clean Datasets

Apply Tools

Analyse for Correlation and anomalies

- Scatterplots
- Box plots



SAMHSA
Substance Abuse and Mental Health
Services Administration

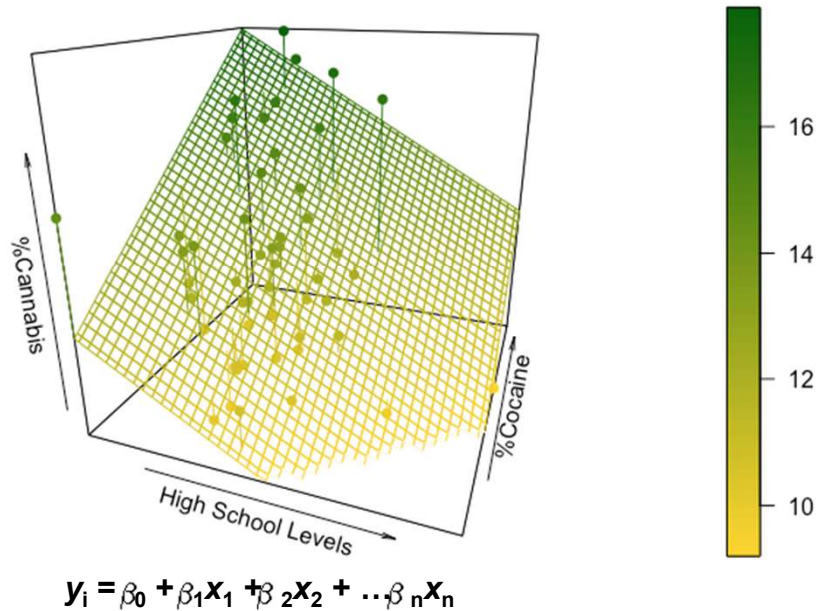
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Results: What did we find?

Best Model - 4 factors (legal status, cocaine usage, high school levels, depression level)

(F-statistic 26.35 on 46 Degrees of Freedom, R-squared 0.70, overall p-value of < 0.0001)

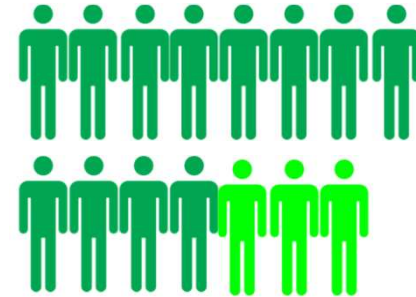
Multiple Linear Regression
3D Plot of 4 Factor Model



When we legalize:

Teenage Cannabis Use:
+22%

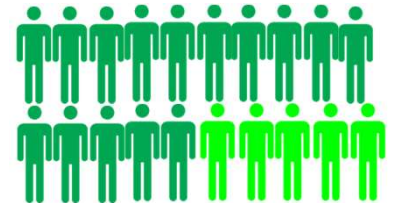
For every 100,000 teenagers



Teenage Cocaine Use:
+21%



High School Dropout rates:
+30%



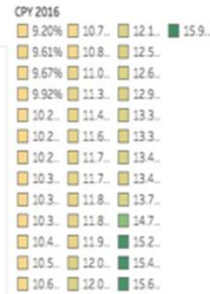
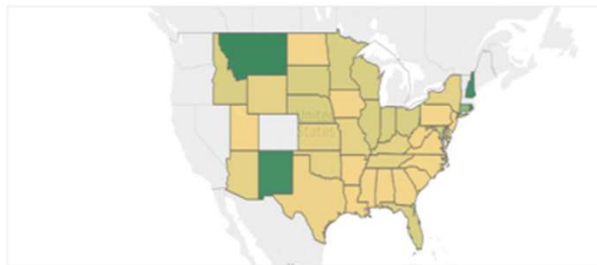
*Each person represents 1000, except cocaine (100)

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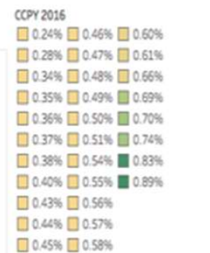
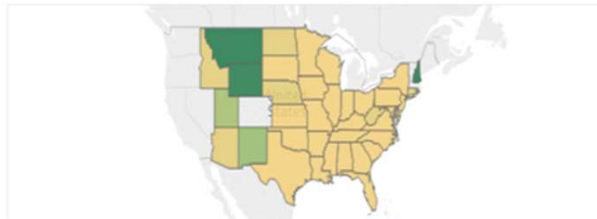
Results: Visualisation

Illegal States (excluding Hawaii)

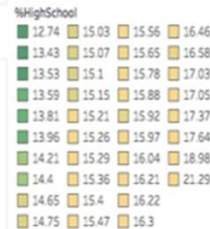
2016 Cannabis Past Year



2016 Cocaine Past Year

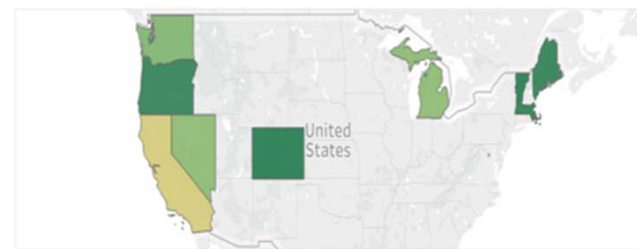


2016 %HighSchool

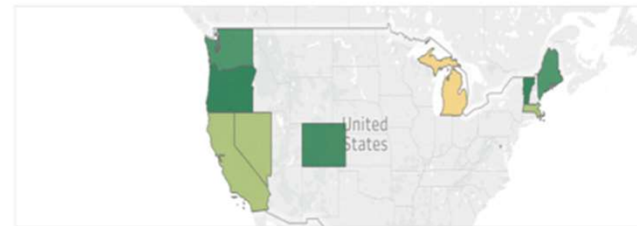


Legal States (excluding

2016 Cannabis Past Year



2016 Cocaine Past Year by State

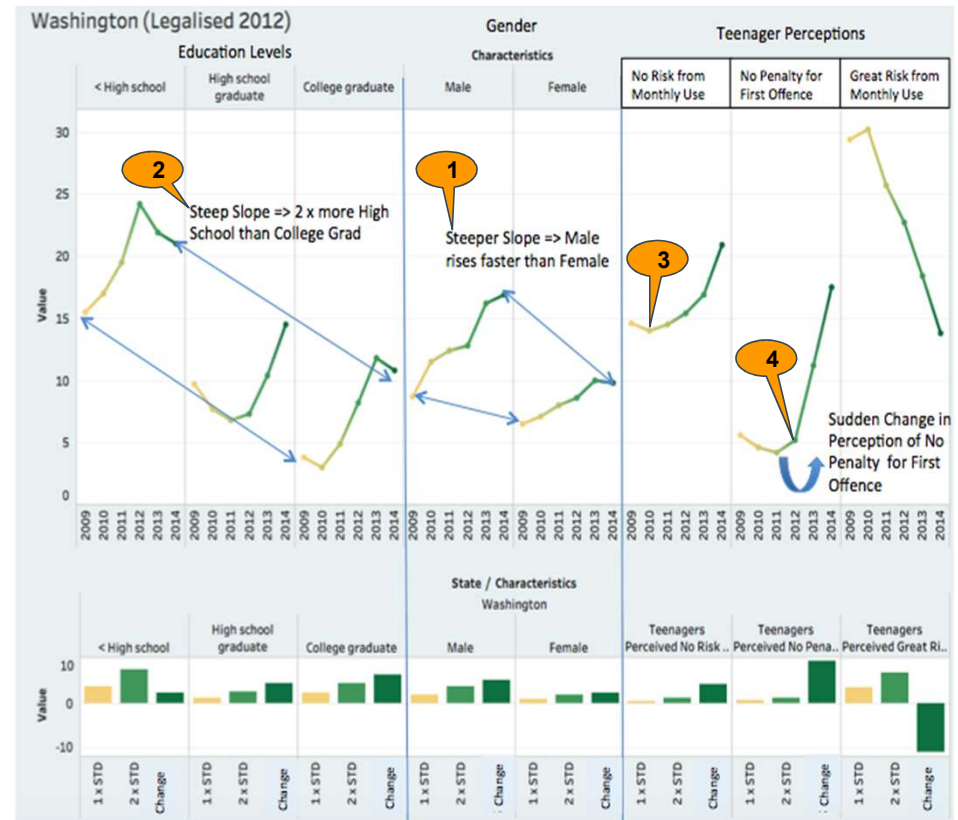
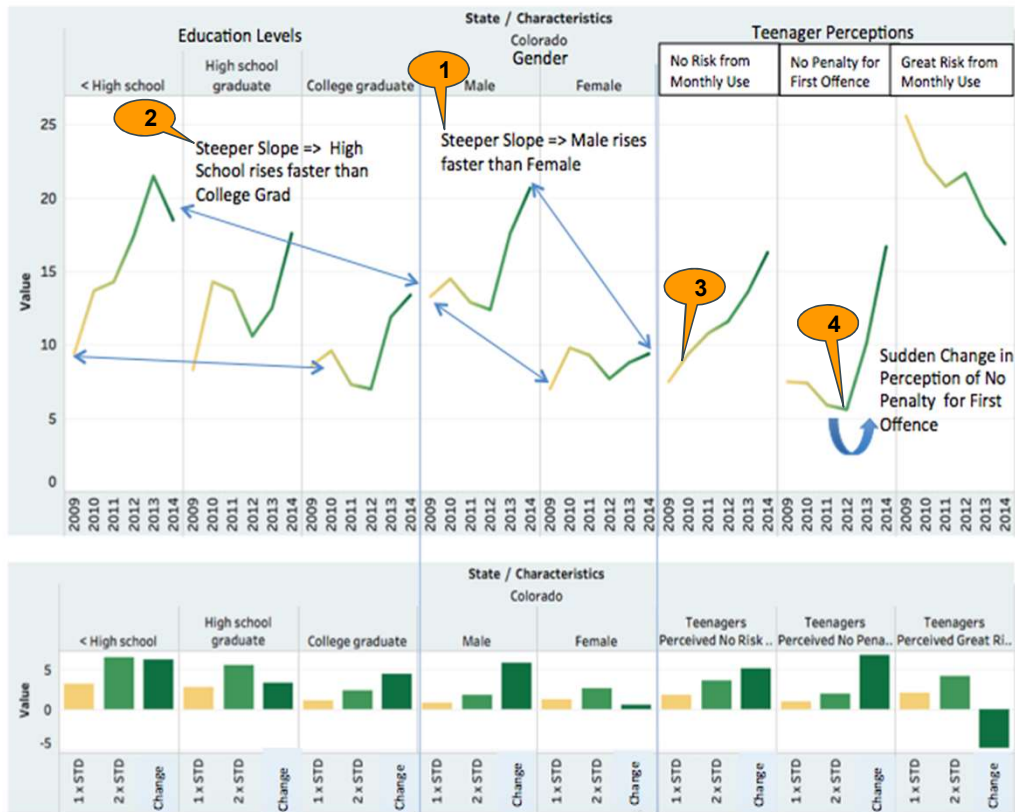


2016 %HighSchool



Results: Changes in CO and WA over 5 years

Colorado (Legalised 2012)



Recommendations

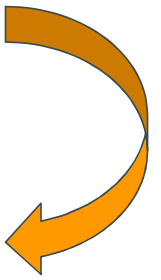
Teenage Males with Poor Education

- Doubling usage
- Misconceptions of:
 - no health risks
 - no legal penalties

VS

Teenage Tobacco Use:

- Falling steadily from 12% (2008) to 6% (2016)



- Increase
 - Taxes
 - Education
 - Legal Enforcement
- Support from influencers

Thank you.

THANK YOU
TO ALL

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A4- Loyola University Chicago USA

What Bike-sharing Data Reveals
about Chicago's Socio-Economic
Landscape

Nick Damato and Grace Sperr

Allison Heithoff, Varsha Kalangari, and
Eric Stepanovic

October, 2019

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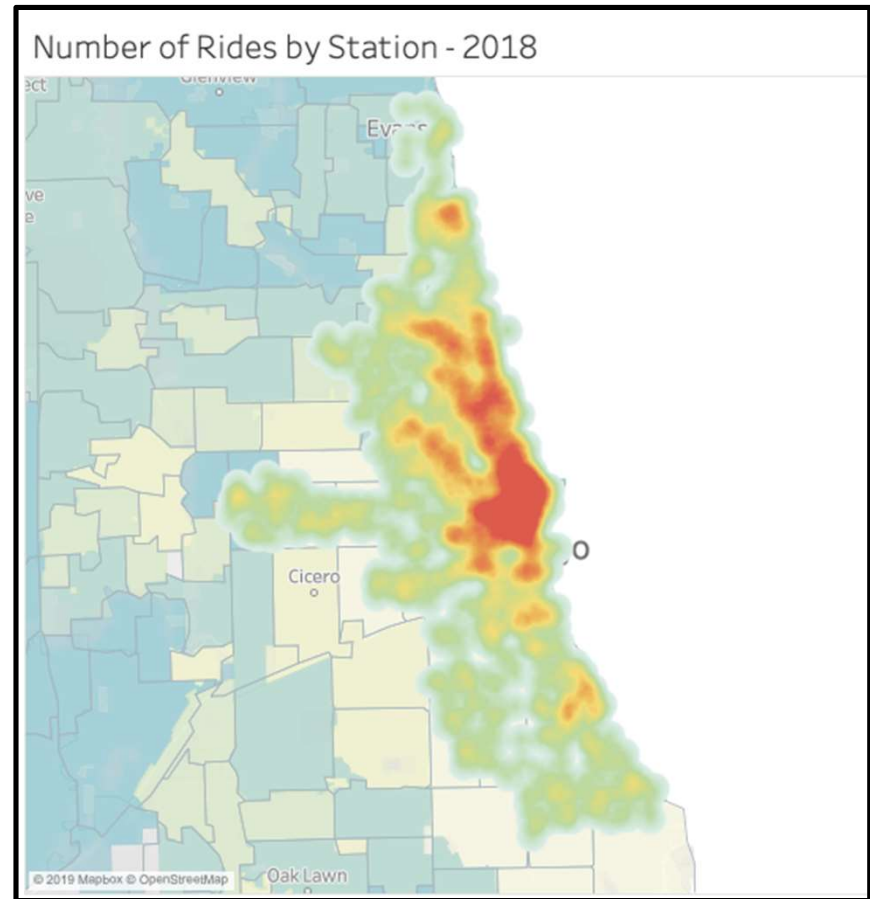
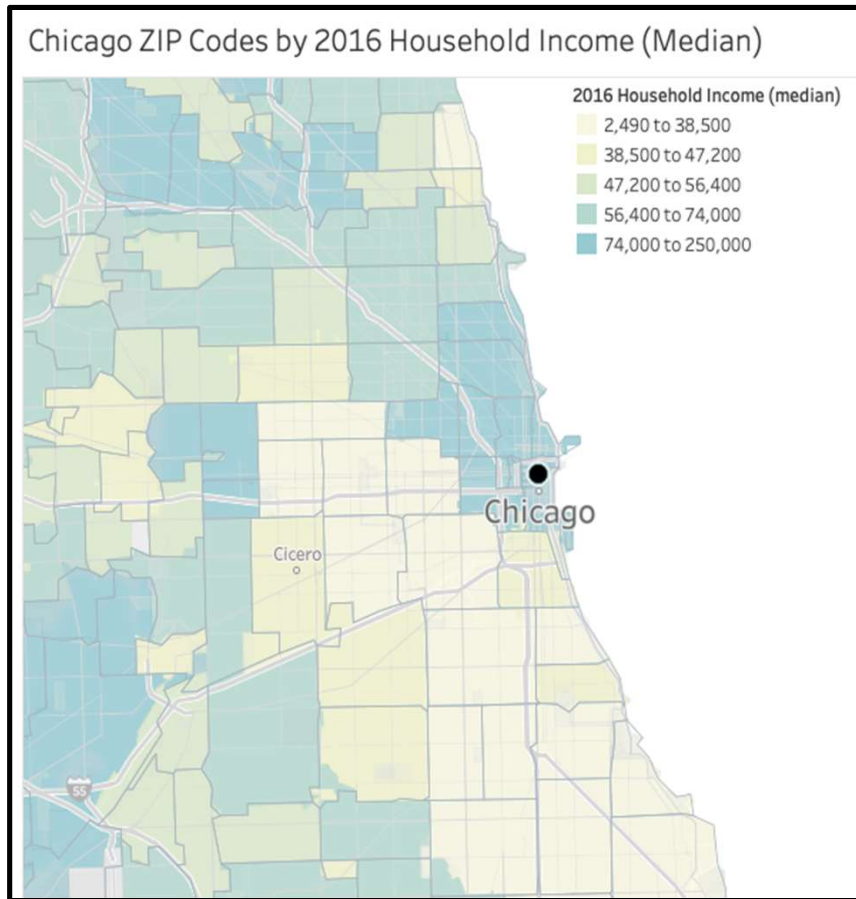
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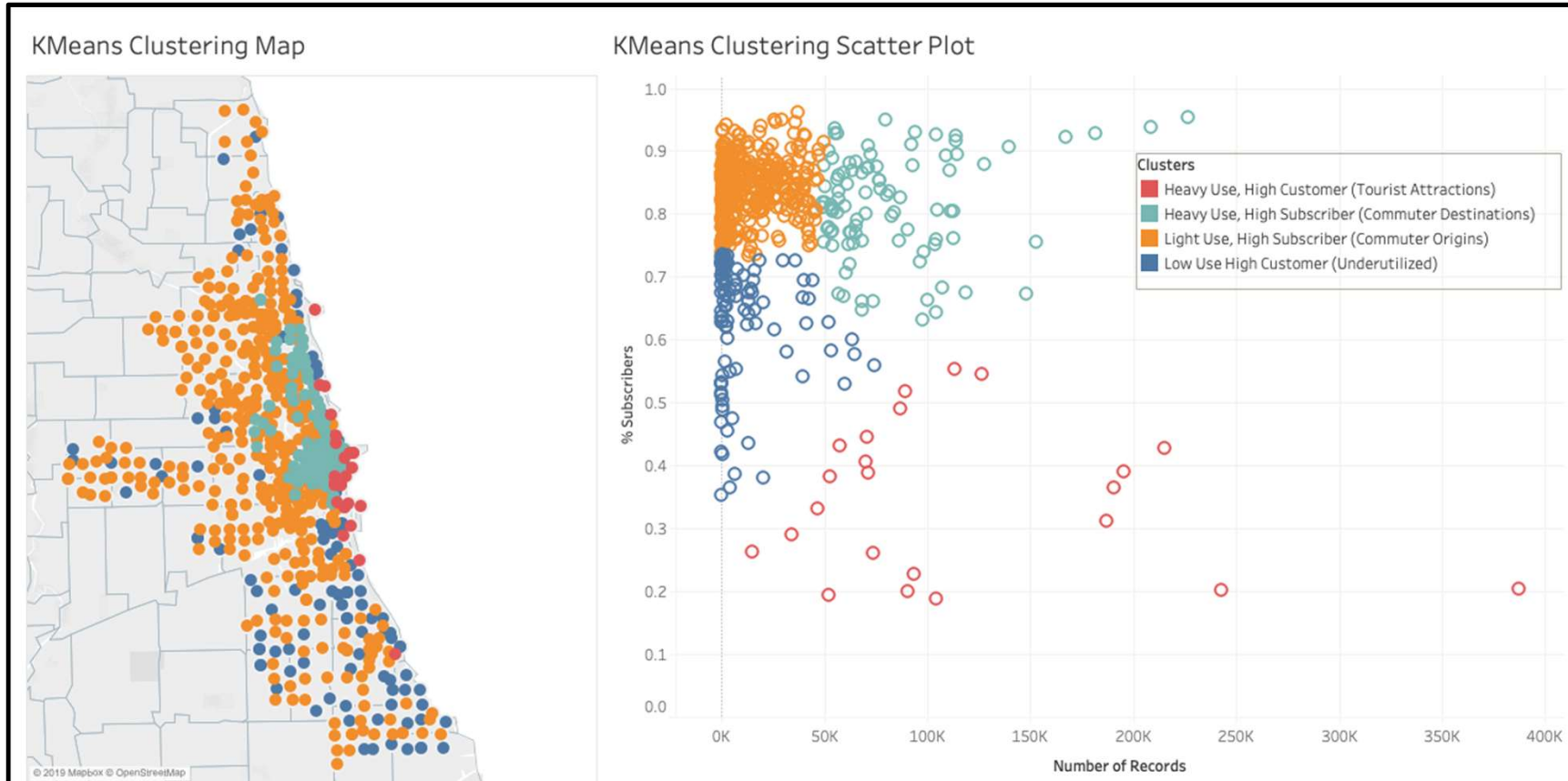
Problem: Bike-sharing ride trends reflect the same inequality as Chicago's socio-economic landscape

In 2018 majority of rides occurred in affluent areas of the city



Station Clusters

When clustered using K-Means clustering in R, based on non-location attributes, the 4 groups mirrored the same socioeconomic landscape as Chicago income data



Motivation: Understand the barriers to bike-sharing in low-income areas and explore how the city, organizations, and local communities can overcome these barriers to create a more equitable city through bike sharing

Data Sources



2013 - 2018 Trip Dataset
17 million records
9 dimensions

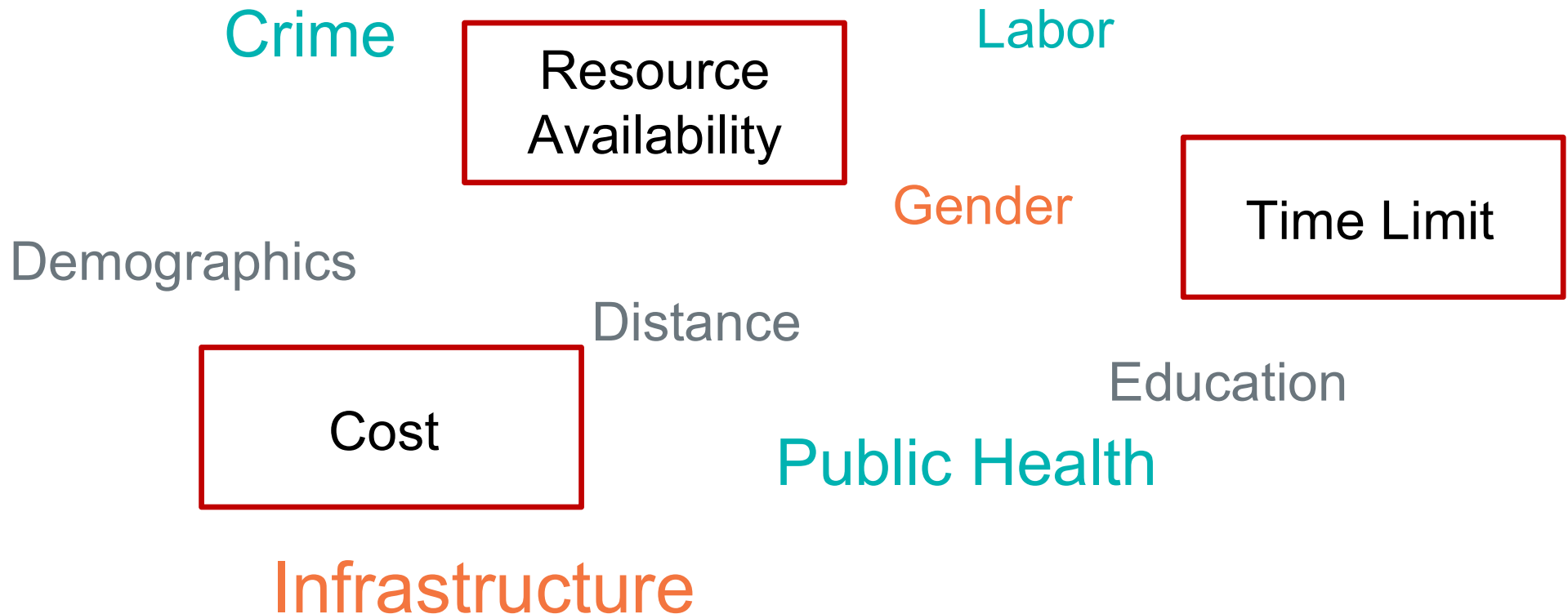


**CHICAGO
DATA PORTAL**

Analytics Tools



Approach: Brainstormed potential barriers, before choosing 3 focus areas to explore



Resources

Hypothesis: Low-Income areas have less stations, therefore increasing stations will increase ridership

Number of Rides by Station - 2013

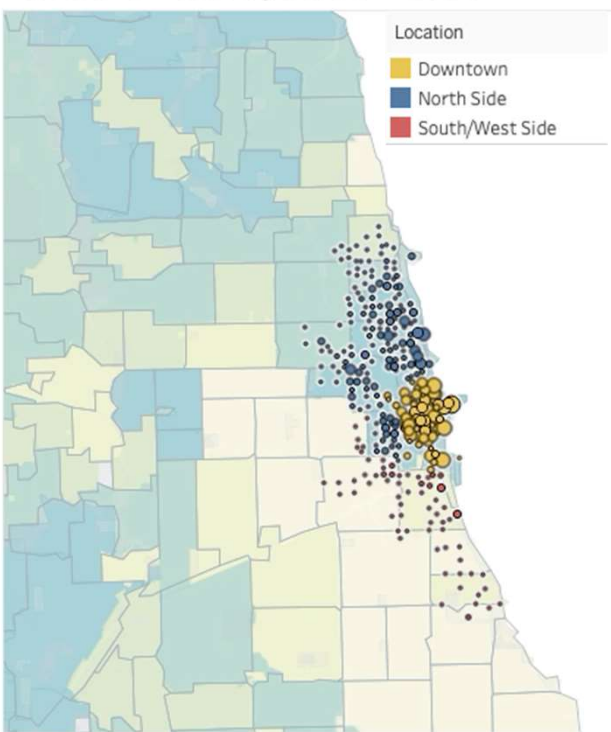


Figure 1 (video)

Figure 1 shows Divvy's explosive growth over the past 5 years, both geographically and in usage

Figure 2 shows that as the number of stations increased in South Side ZIP Codes, ridership remained low over 5 years

Number of Trips vs. Number of Stations by ZIP Code - 2013

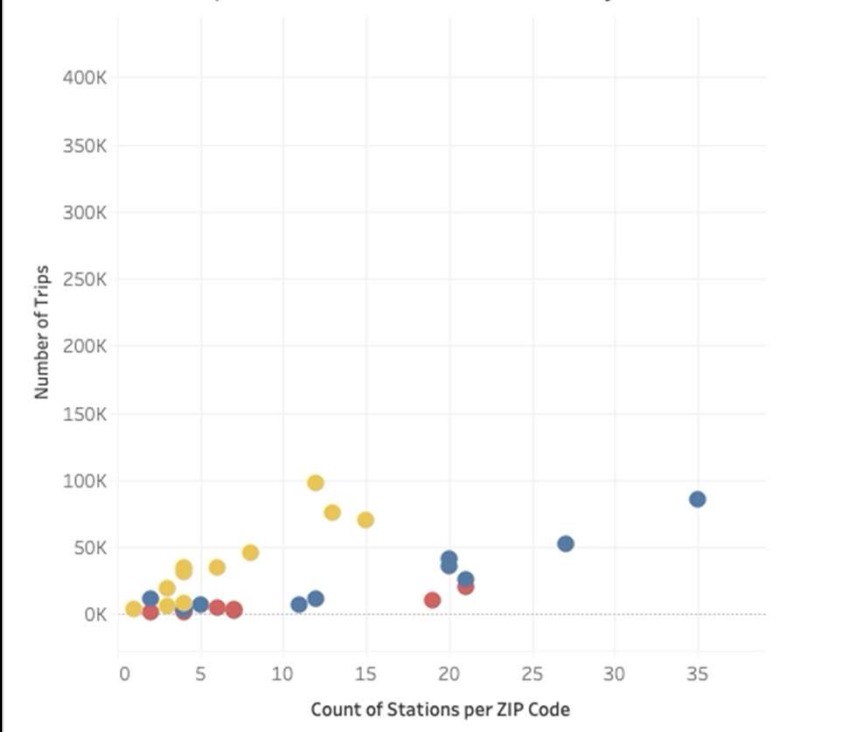


Figure 2 (video)



Increasing the number of stations alone did not increase ridership

Price

Hypothesis: Riders in low-income areas may not be able to afford \$99 annual subscription, therefore decreasing the price would increase ridership

Divvy for Everyone (D4E) launched in July 2015

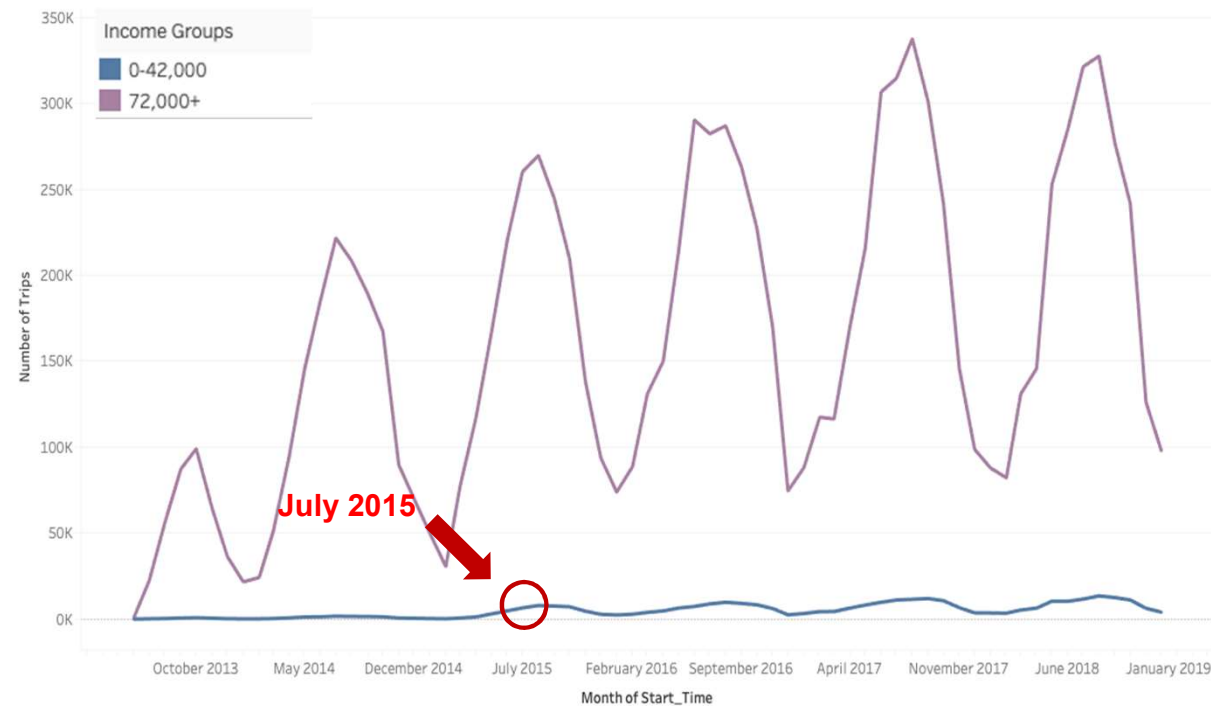
- Initiative started by Divvy to encourage usage by low income riders
- \$5 subscription for first year, gradual increase in price until Year 4, subscription capped at \$75

Figure 3 shows the trend of subscriber rides in low income areas and high income areas

Small increase in low-income rides after D4E launched, but all income groups saw slight growth from 2014 to 2015

Program didn't make large impact closing the gap between income groups

Ridership Trends by Income Group



Lowering the price for a subscription did not result in any significant increase in rides in low-income areas

Time Limit

Hypothesis: Low-Income areas are less concentrated than the downtown area and rides may take longer than the allotted time resulting in overage charges

Time Limits

- Customer (1-time rider): 30 minutes
- Subscriber (annual pass): 45 minutes

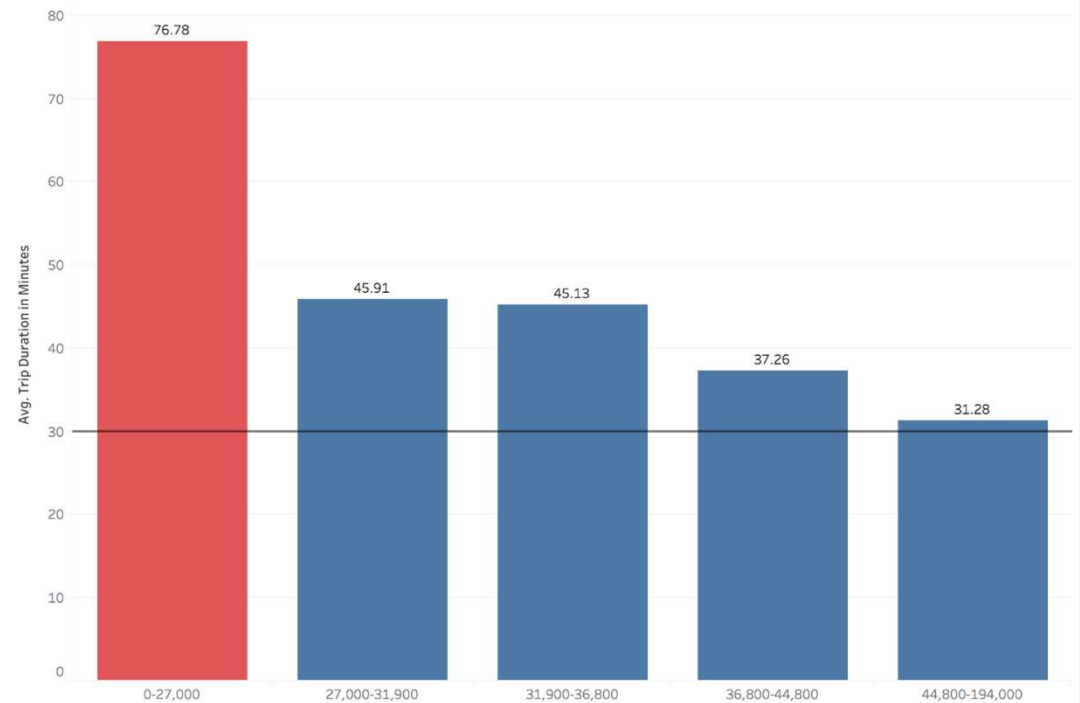
Customer trips cost \$3 per 30 minute ride, with an addition \$3 charge for every 30 minutes over limit

Figure 4 shows that trips occurring in low income areas last about 77 minutes, more than double the time limit, making the average trip costing \$9

*train or bus ticket costs \$2.50 - \$3.00

Average Customer Trip Duration By Per Capita Income

(excludes trips greater than 24 hours)



Customer trips in low-income areas are more than double the time limit of 30 minutes

Identifying these barriers in isolation and only addressing some of them has not proven effective, instead a multifaceted approach is required that considers a variety of factors



Divvy's South Side Tour

By Courtney Jennings | JULY 22, 2019



CBS Chicago

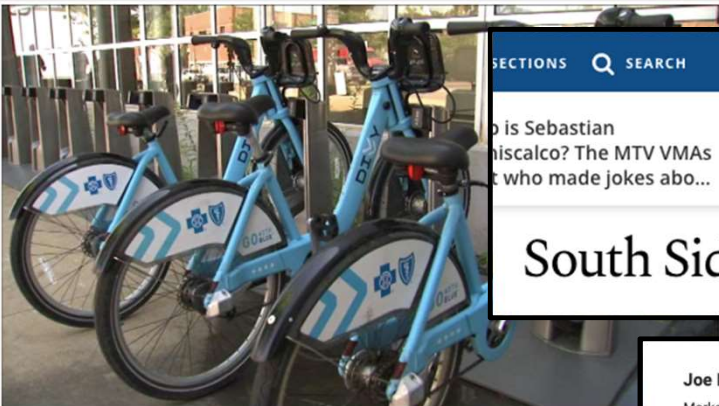
NEWS WEATHER SPORTS VIDEO BEST OF MORE

Adults Can Take Divvy Bike Lessons This Summer

May 17, 2019 at 4:02 pm Filed Under: CDOT, Chicago, Chicago Bike Riding Classes, Chicago Department Of Transportation, City of Chicago, Divvy

COMMUNITY & EVENTS

CDOT, Divvy offering bike riding lessons this summer



AP



Friday, May 17, 2019

CHICAGO (WLS) -- The Chicago Department of Transportation and Divvy are offering free riding classes this summer.

SECTIONS Q SEARCH

Chicago Tribune

ONLY \$2 FOR 20 WEEKS
SALE OFFER

Who is Sebastian
Miscalco? The MTV VMAs
who made jokes abo...



Cubs Q&A: What's wrong
with this team? Which
players will be traded? Wil...



Your DIY home renovation
project may actually lower
its value. 10 things to kno...



Leslie Jones to leave
'Saturday Night Live'



South Side dockless bike program was most popular in or near Beverly

Joe Barnas
Marketing Intern



/ JOBS + GROWTH

JUNE 21, 2019

Thousands of electric scooters have arrived in Chicago as part of a four-month pilot program.

Chicago is the latest major city to open the door to shareable electric scooters, bringing a total of 2,500 e-scooters to city streets. The city's pilot program for dockless e-scooters launched June 15, tallying 11,000 rides in its first weekend alone.

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Thank you.

THANK YOU
TO ALL

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A5- Southern New Hampshire University USA

Food Insecurity and Waste

Presenter - Mitchell Beckner

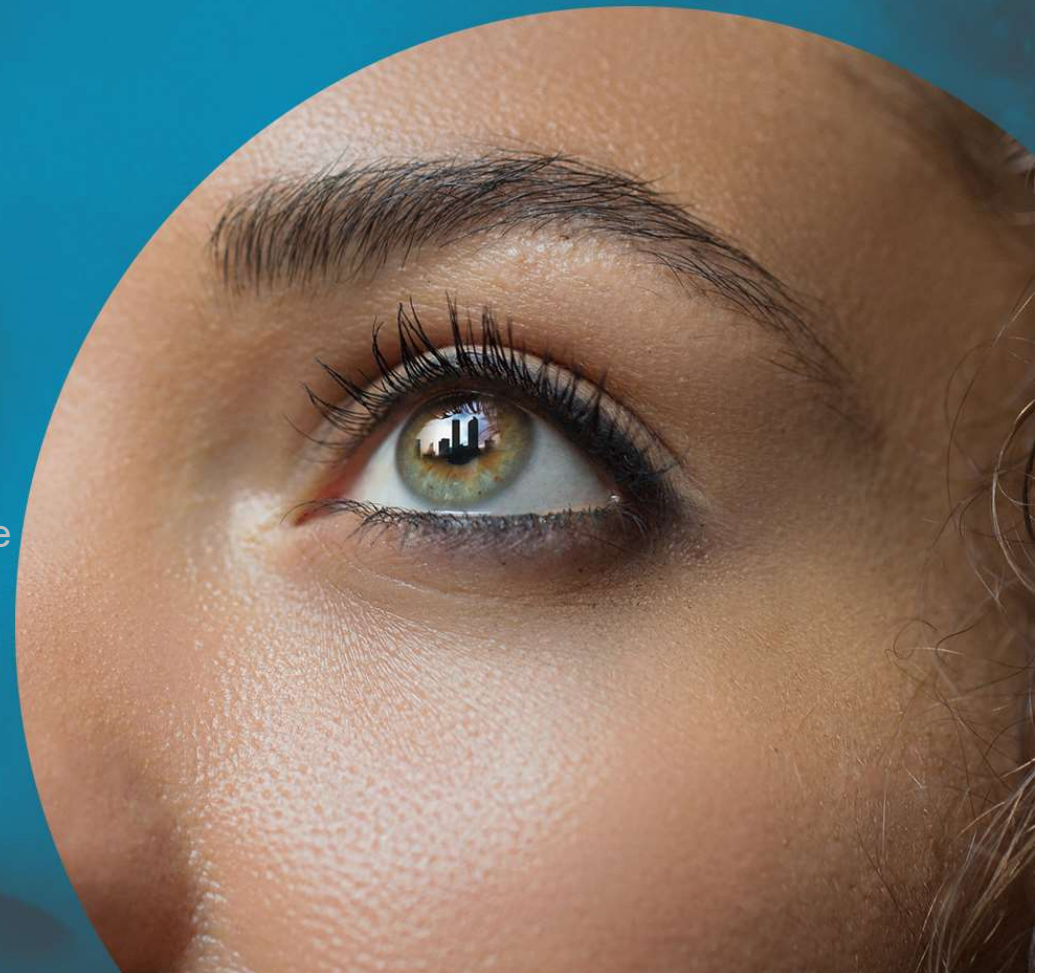
Team members – Alexander Hilton, Jonathan Squire

Faculty Advisor – Matt Keane

October 2019

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snhu



Our Vision

*To create a strategy that builds a better, properly fed world,
reducing waste and bringing meals to those in need*



US Food Supply

- Current world population is 7.7 billion
- Global food production is enough to feed 10 billion
- Current US population is 327.2 million
- The US is the world's 3rd largest food producer

Is there enough?



Food Insecurity

What is it?

The state of being without reliable access to a sufficient quantity of affordable, nutritious food

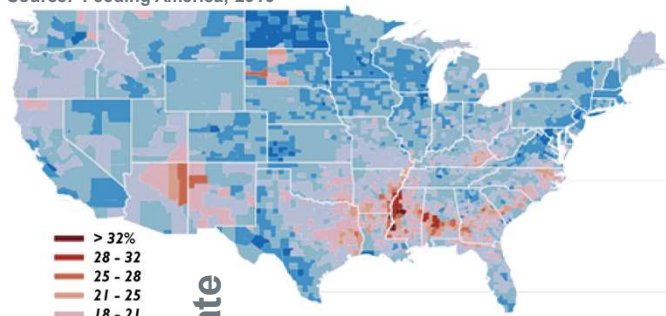
Is it a problem?

1 in 8 Americans are affected;
in some communities, 1 in 6



The Influence of Poverty on Food Insecurity

Source: Feeding America, 2016



Food Insecurity Rate

15%
10%
5%

Source: Feeding America, US Census Bureau, 2016

0%

10%

20%

Poverty Rate

30%

40%

50%

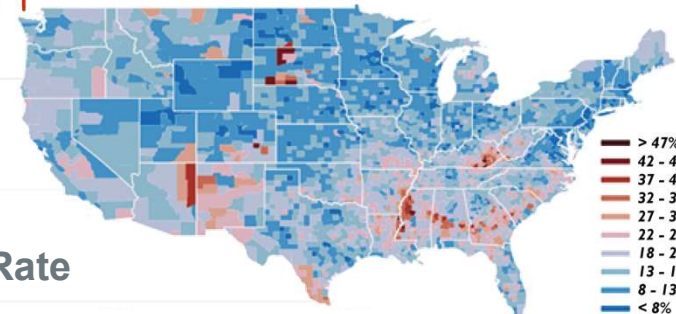
35%

30%

25%

20%

15%

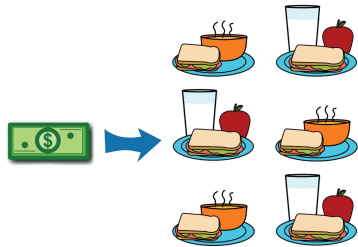


Source: US Census Bureau, 2016

There is a direct, positive correlation between poverty rates and food insecurity

Reducing the Costs

Donations of Money



“A dollar can go a long way. For every dollar donated, we provide six meals.”

- Lora D. – The Foodbank

Donations of Time



“Volunteering saves \$2.5 million annually. [That] money could be spent on groceries.”

- Maureen M – Second Harvest

Is Food Waste a Problem?

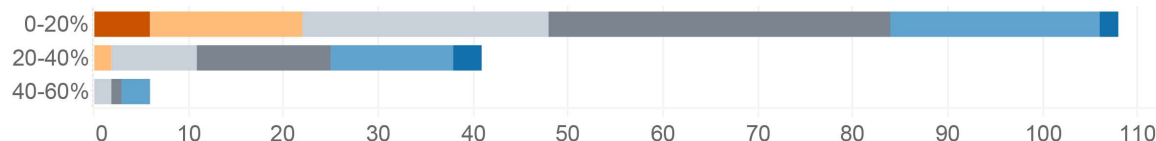
Most commonly wasted foods

Source: IT476 Food Waste Survey

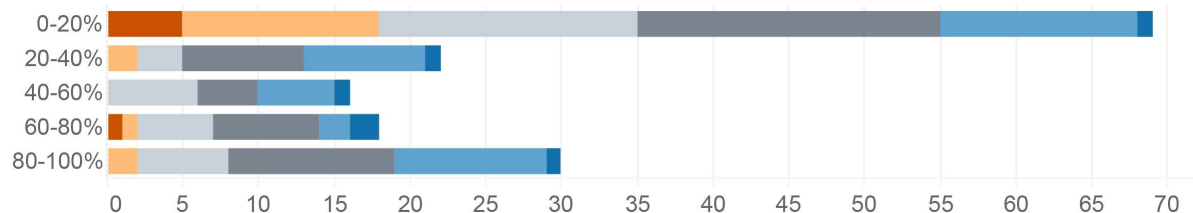


Age	Respondants
18-24	6
25-34	39
35-44	51
45-54	37
55-64	18
65-74	6
Total 157	

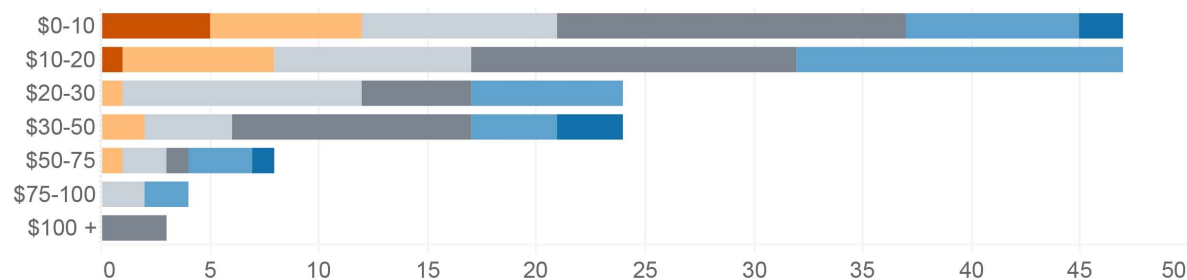
How much do we waste?



How much could we prevent?

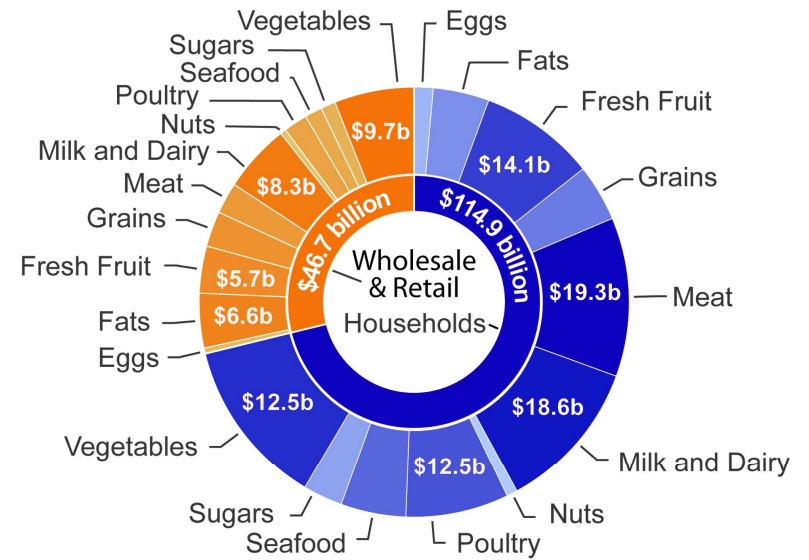
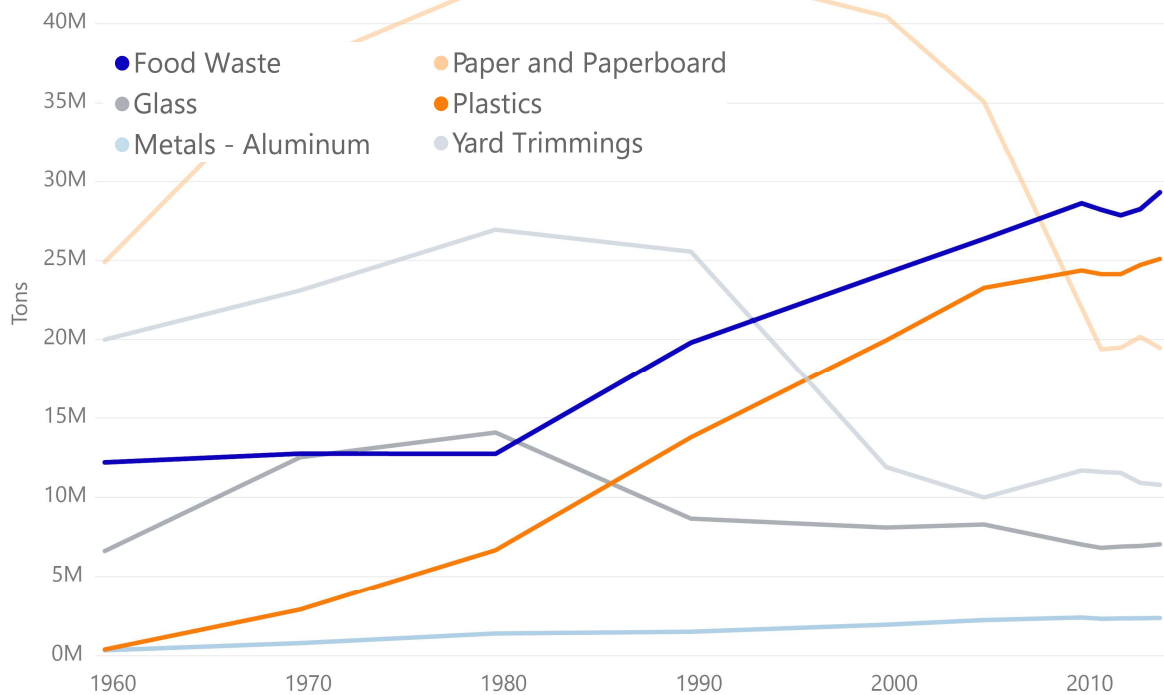


How much could we save?



US Food Waste Figures

A growing trend



Source: Buzby et al., 2014

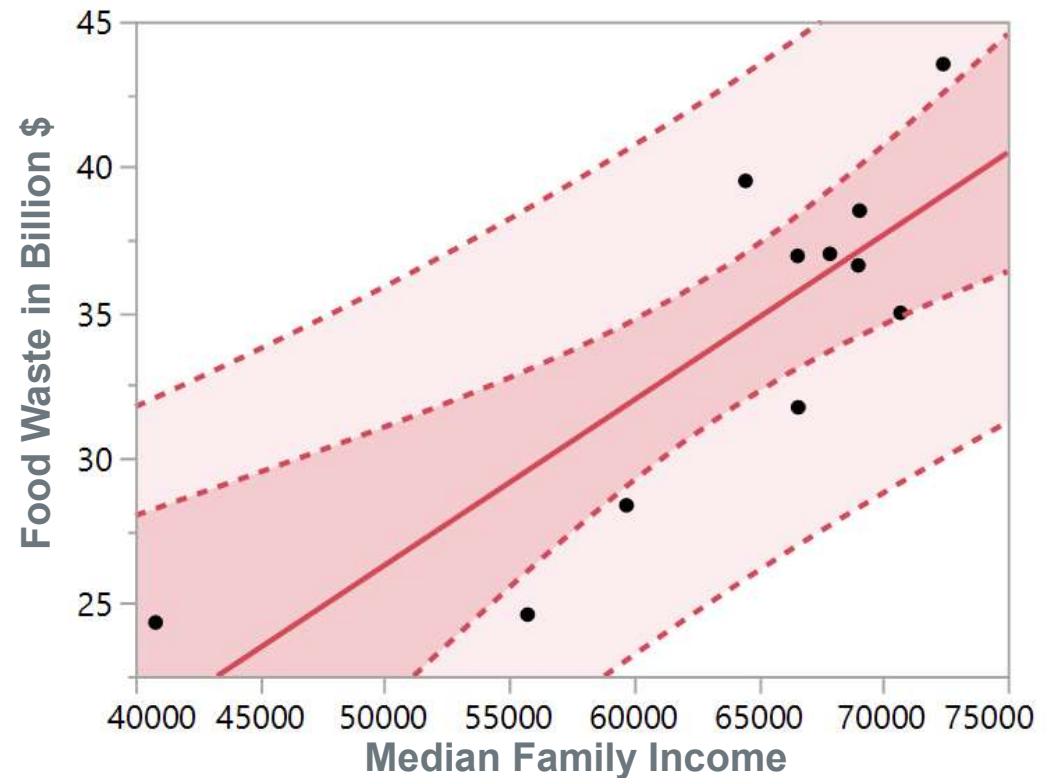
Americans waste 150,000 tons of food per day

Food waste is estimated at 30-40% of the total food supply

The Influence of Income on Food Waste

As median family income increases, so does the amount of food wasted

Individuals with healthier diets are often the most wasteful



Sources: US Census Bureau, Food and Agriculture Organization of the United Nations

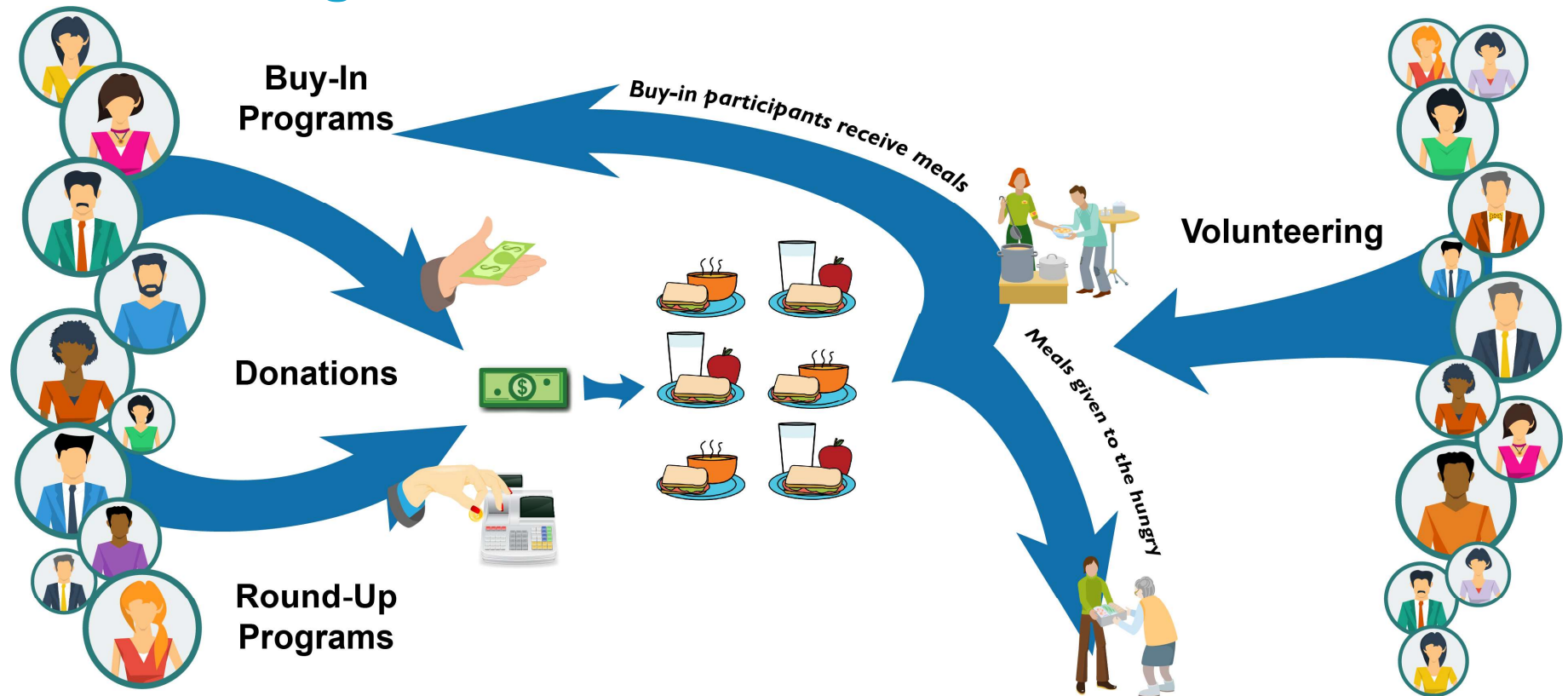
Taking Action!

Actions everyone can take

- Support standardization of regulations
- Volunteer your time
- Shop wisely
- Donate what and when you can



Our Challenge to You!



Thank you.

- Lora Davenport, Advocacy & Programs Manager at The Foodbank Inc. in Dayton, OH
Lora provided insightful firsthand information on the challenges of food insecurity and the various ways that her organization helps those in need in the Dayton area.
- Maureen Mikel, Development Manager at Second Harvest Food Bank of Central Florida in Orlando, FL
Maureen advised of ways that Second Harvest helps those in need in the community, including programs specifically aimed at ensuring children of families in need receive meals both in school and on the weekend between school.
- The Foodbank Inc: thefoodbankdayton.org
- Second Harvest Food Bank of Central Florida: www.feedhopenow.org
- To the 169 friends, family, and fellow students from SNHU who filled out the survey

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A6- University of Minnesota Duluth USA

**Impact of Health Disparities on
the Economy and Communities
in Duluth, Minnesota**

Noah Lahr

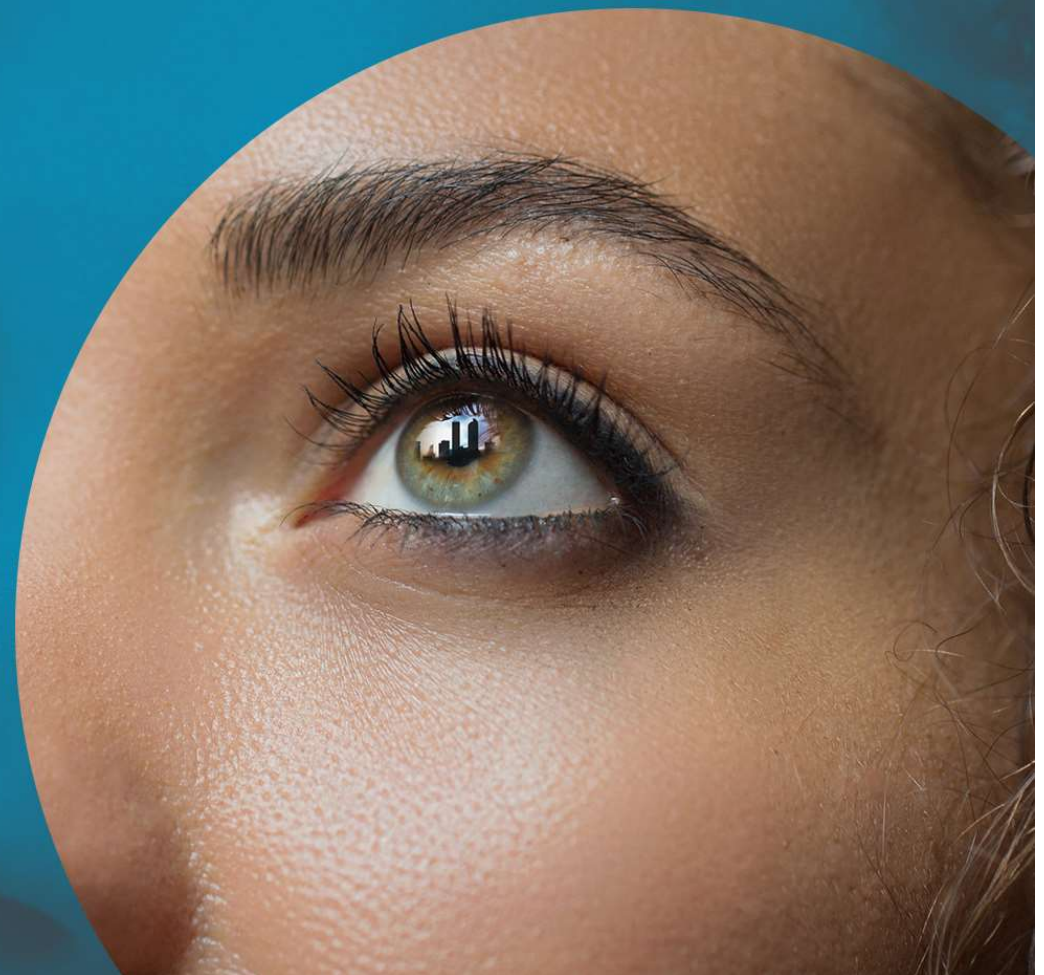
Patrick O'Brien

October, 2019

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Agenda

- Project Significance
- Defining Health Status
- Analytics Approach – Ideation, Data and Analysis
- Cluster Analysis
- Analytic Insights
- Moving Forward

Project Significance

“Minnesota is one of the healthiest states in the country, but it has some of the worst health disparities”. The Cost: \$2.26 Billion Annually.

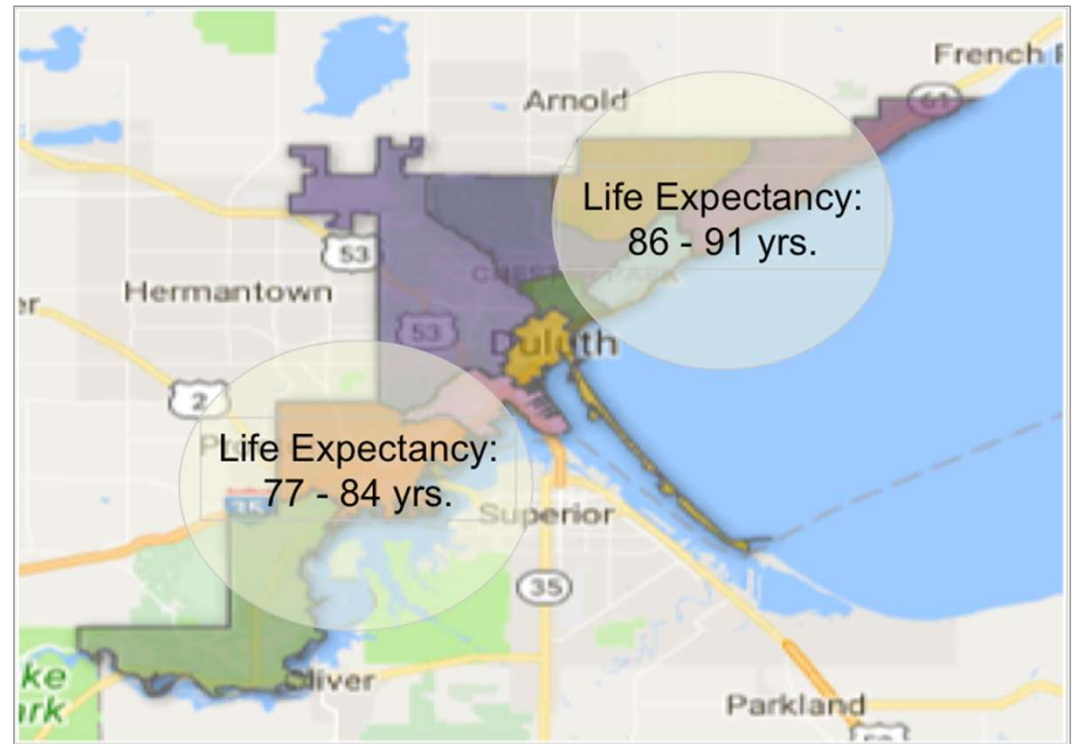
– BlueCross BlueShield MN
2018 Technical Report



Project Significance

In Duluth, health disparities have persisted over the last decade. Where you live in Duluth can lessen your life expectancy by as much as 14 years.*

**2017 Health Status Report Update to the Community. Life expectancies determined by confidence intervals of geographically defined neighborhoods.*



Defining Health Status

WHERE HEALTH HAPPENS



Social Determinants of Health:

- Income
- Poverty
- Employment
- Education
- Preventable Diseases
- Poverty
- Cost Burden Households
- Race/Ethnicity

Figure from

https://www.bluecrossmn.com/healthy/public/portalcomponents/PublicContentServlet?contentId=P11GA_16928228

Analytics Approach

Cluster analysis on census data factors of social determinants of health to remove artificial construct of geographically connected neighborhoods.

Use clusters to model variance of health disparities across the city of Duluth and provide insight into resource/access disparity.

Use State level analysis methodology of economic loss to approximate the impact on an annual basis to Duluth.

Data

- **2005 – 2017 Mortality Data**
(Minnesota DPH)



Data included addresses of decedents, causes of death (as up to 20 ICD10 codes), and extensive demographic information (gender, age, race, occupation, industry)

- **U.S. Census Bureau ACS 5-year estimates (2013-2017)**



Population demographics, social, and housing/household characteristics for all census tracts in Duluth

- **St. Louis County Geospatial Data**



Housing prices, residential density, geography of parks, community use land/buildings, grocery, gas, convenience, and liquor stores.

- **Nutritional Assistance Data**
(St. Louis County DPH)



Information on locations where Supplemental Nutrition Assistance Program benefits could be used (EBT stores).

Data Cleaning

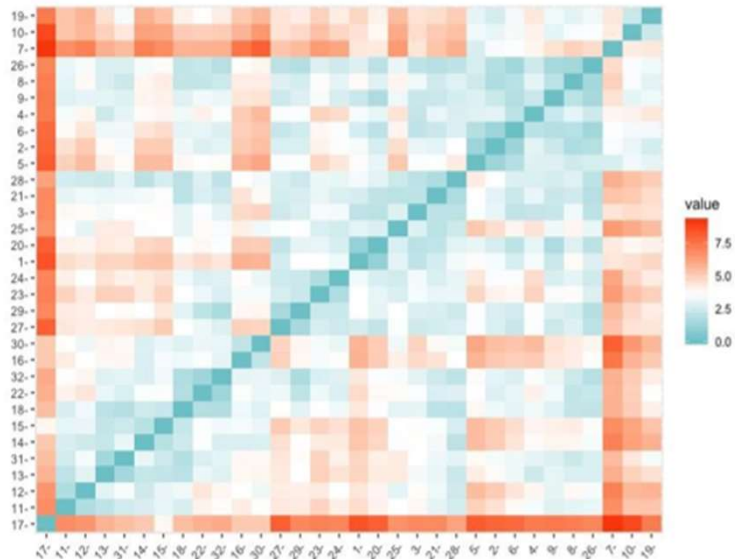
- Geocode decedents to census tracts to identify Duluth residents
- Coded occupation/wage data using NAICS Standards
- Coded cause of death
- Normalized Social Determinant Factors



Analytics

- Probability modeling - life expectancies/economic impact
- Principal component analysis, regression, and correlation were used to validate variable selection used to perform k-Means clustering on census tract data.

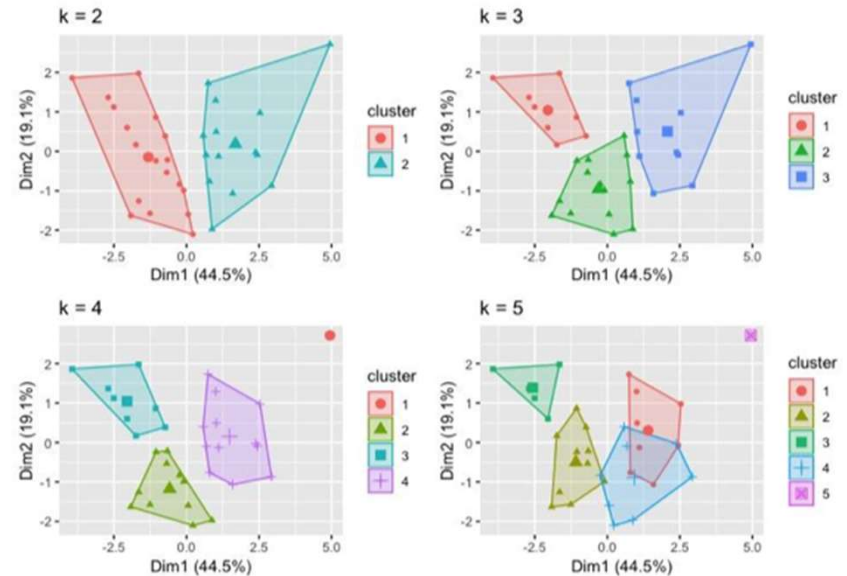
Cluster Analysis



Distance Matrix:

Red = large difference between census tracts
Teal = large similarity between tracts

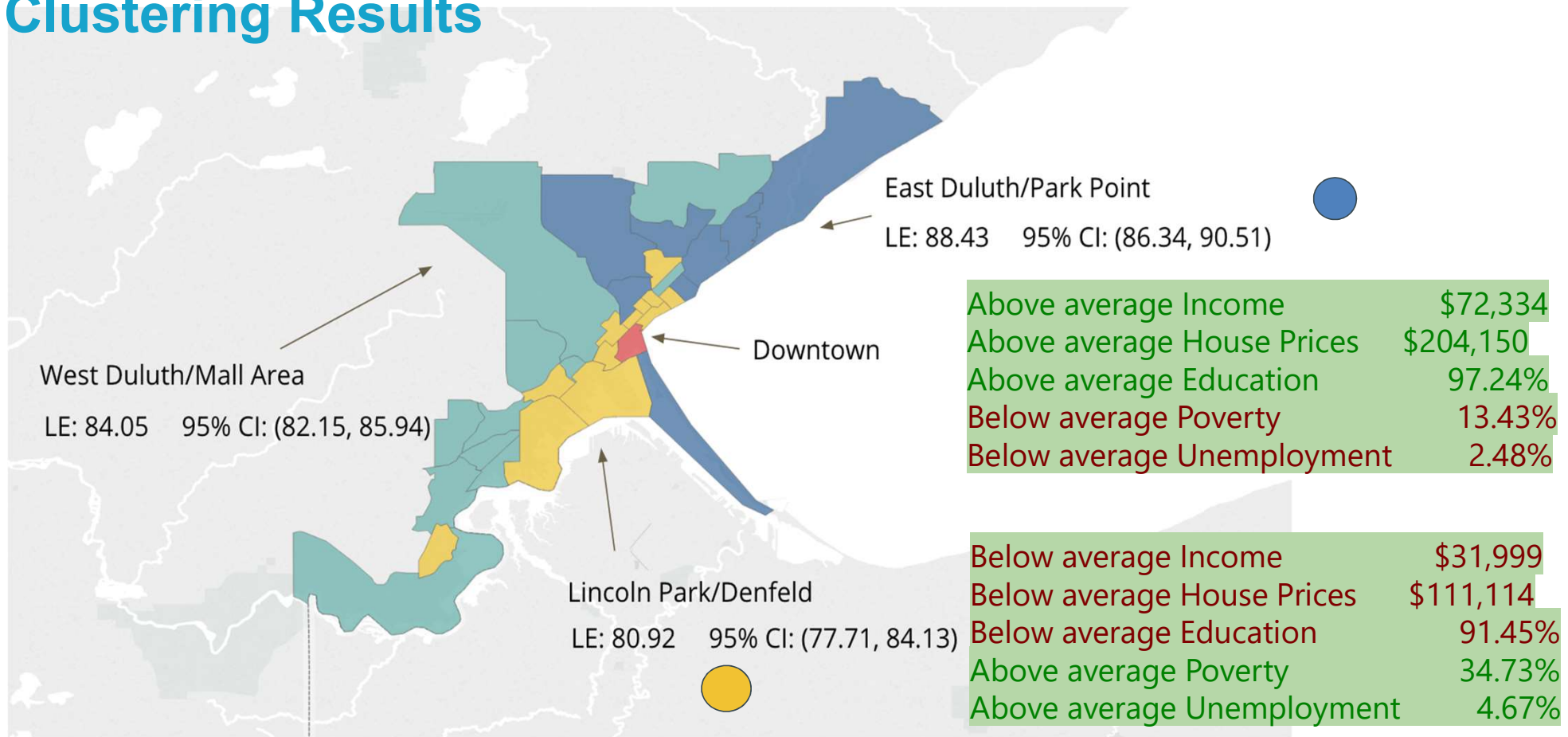
Result: Clustering is useful.



Optimal: 4 clusters

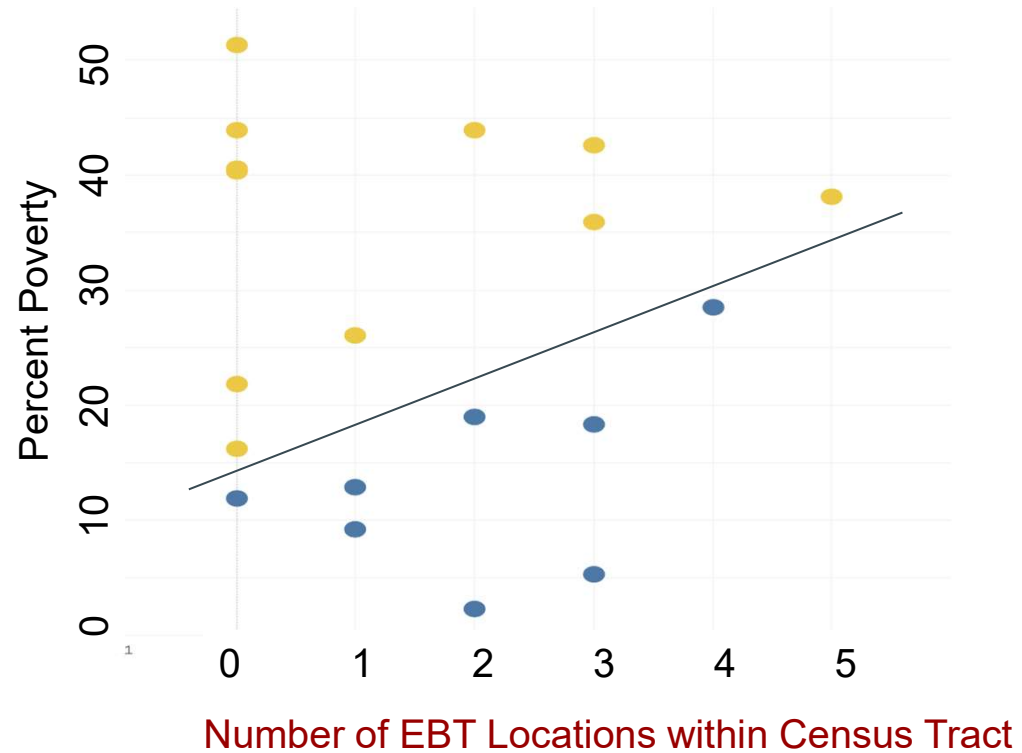
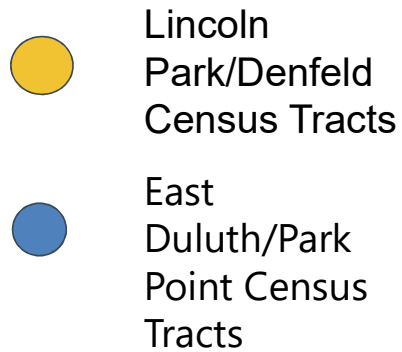
Principal component to determine the optimal number of clusters.

Clustering Results

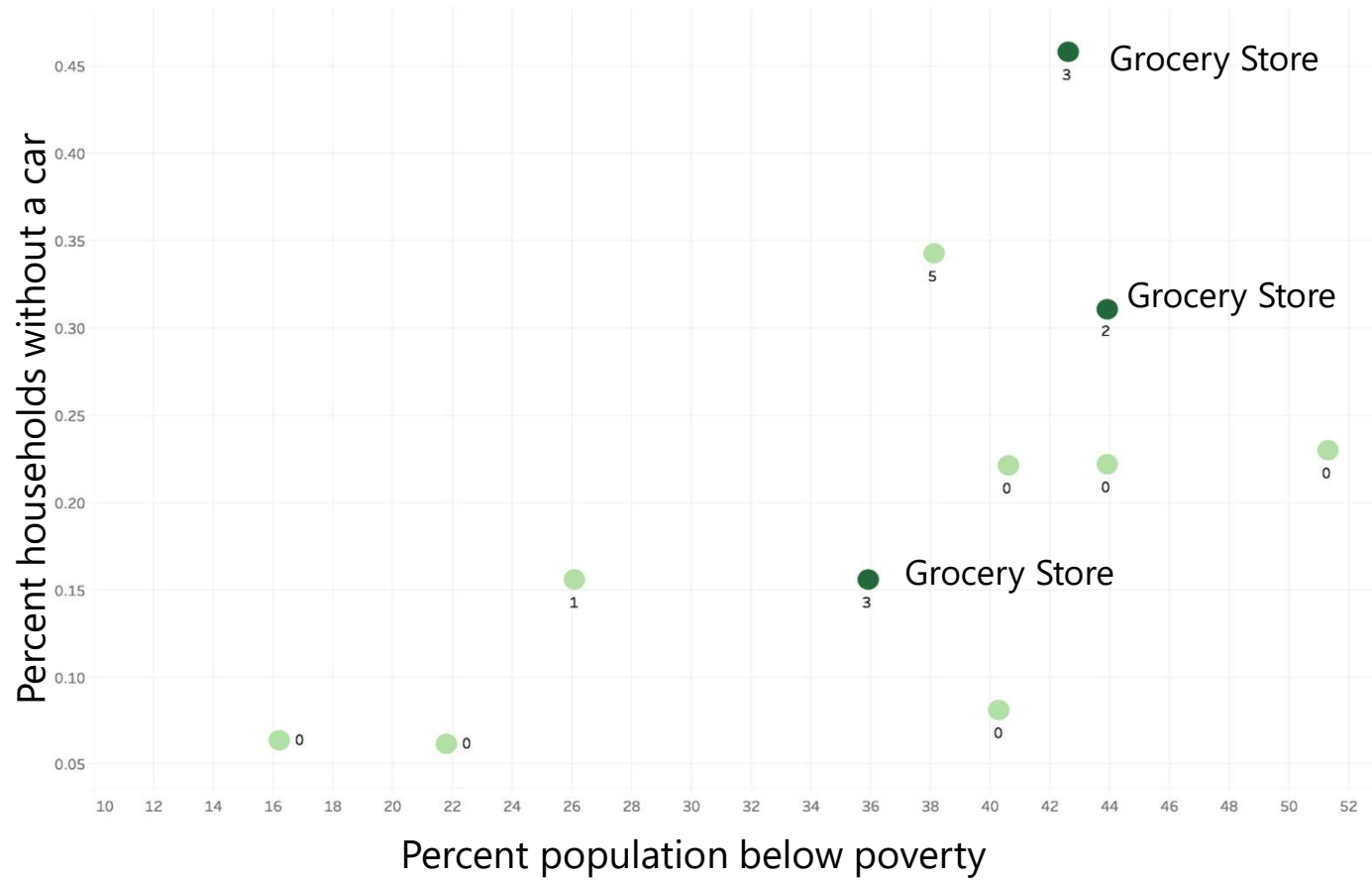


Resource Analysis

Food Scarcity:



Resource Analysis

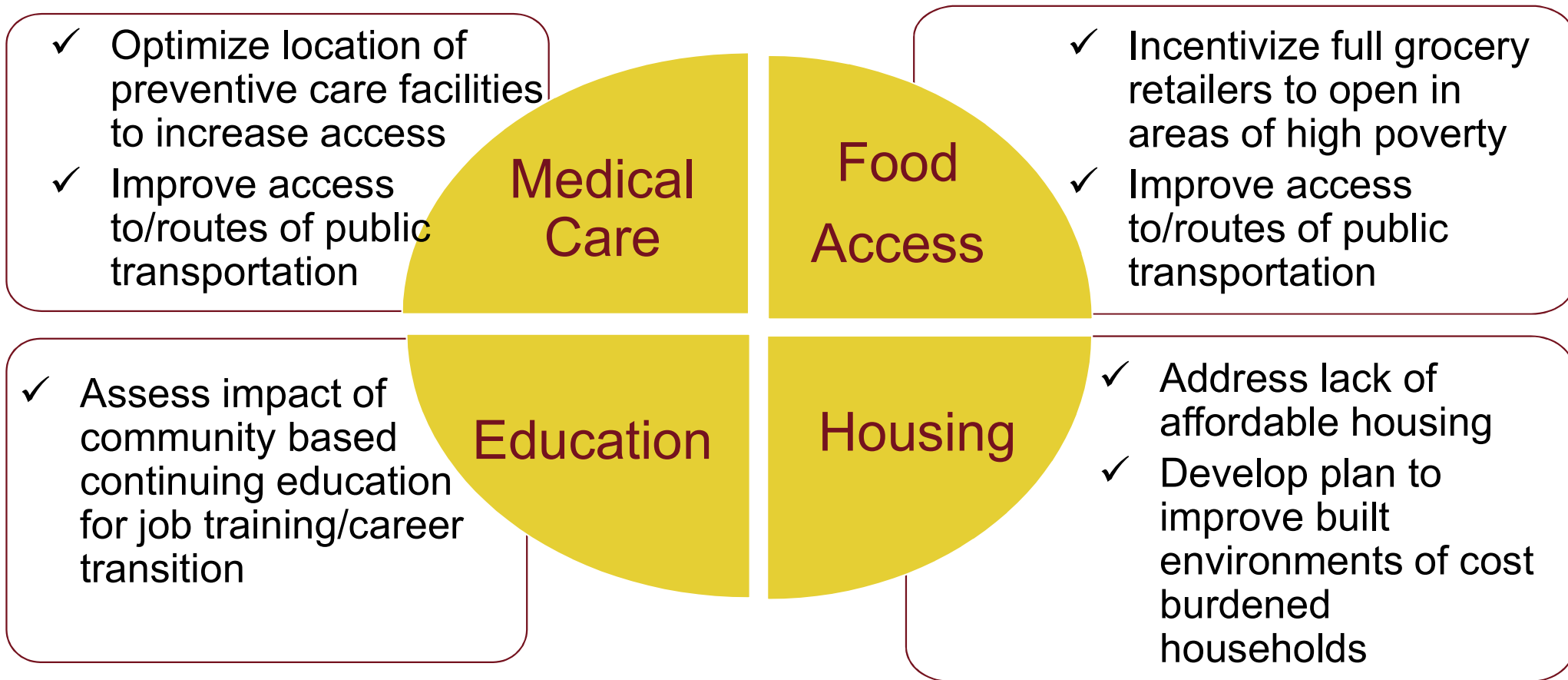


Economic Analysis

2017 Economic Loss Analysis*	Average Age of Death	Average Annual Income	Gross Annual Economic Loss
East Duluth/ Park Point	67	\$58,985	\$1.8 Million
Lincoln Park/ Denfeld	59	\$57,445	\$2.8 Million
City of Duluth	62	\$51,317	\$8.1 Million

*Age: 25-74 (working aged defined by Bureau Labor & Statistics)
Cause of Death = Heart Disease, Cancer, Diabetes, Alcohol Abuse, Suicide

Moving Forward



Thank you.

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ANALYTICS CHALLENGE WRAP UP

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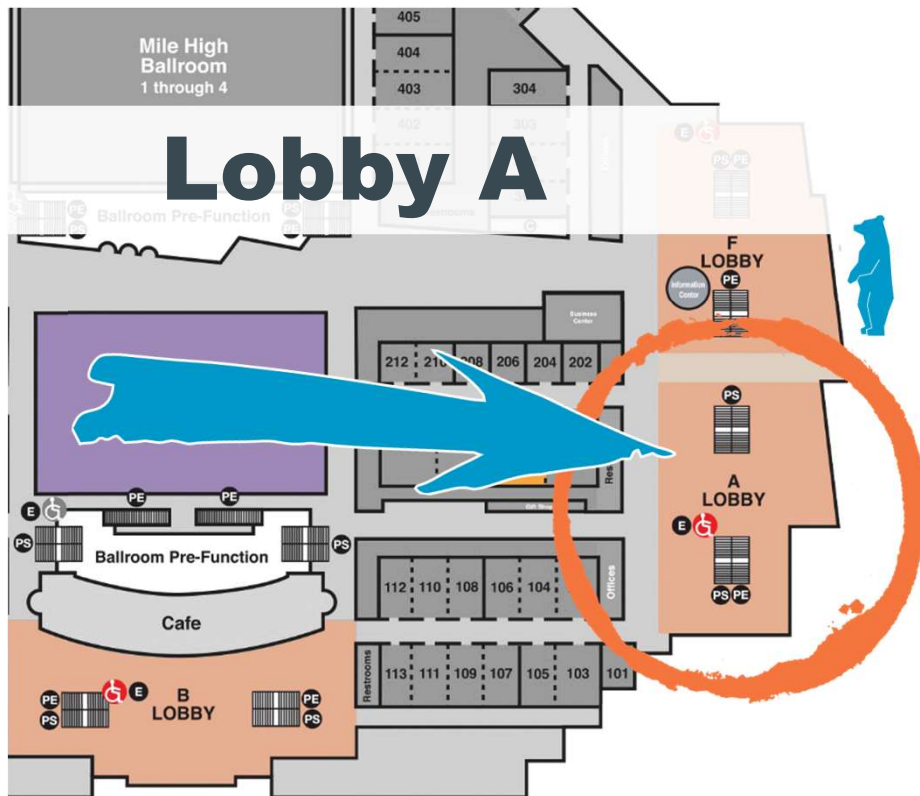
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Student Poster Presentations

Meet All Finalists and
Honorable Mention teams!!



Sunday
Oct 20

6:30 – 8:00pm

SUNDAY

MONDAY

Monday
Oct 21

8 – 8:45am

11:00am – 1:45pm

Award Categories

Data Challenge

- **People's Choice - Best Presentation**
- Overall Winner
- Best Value to Hire Heroes USA

Attendees vote

Academic vote

Hire Heroes USA vote

Analytics Challenge

- **People's Choice - Best Presentation**
- **Best Use of Analytics and Visualization Tools**
- Overall Winner

Attendees vote

Attendees vote

Academic vote

Teradata Technology Award

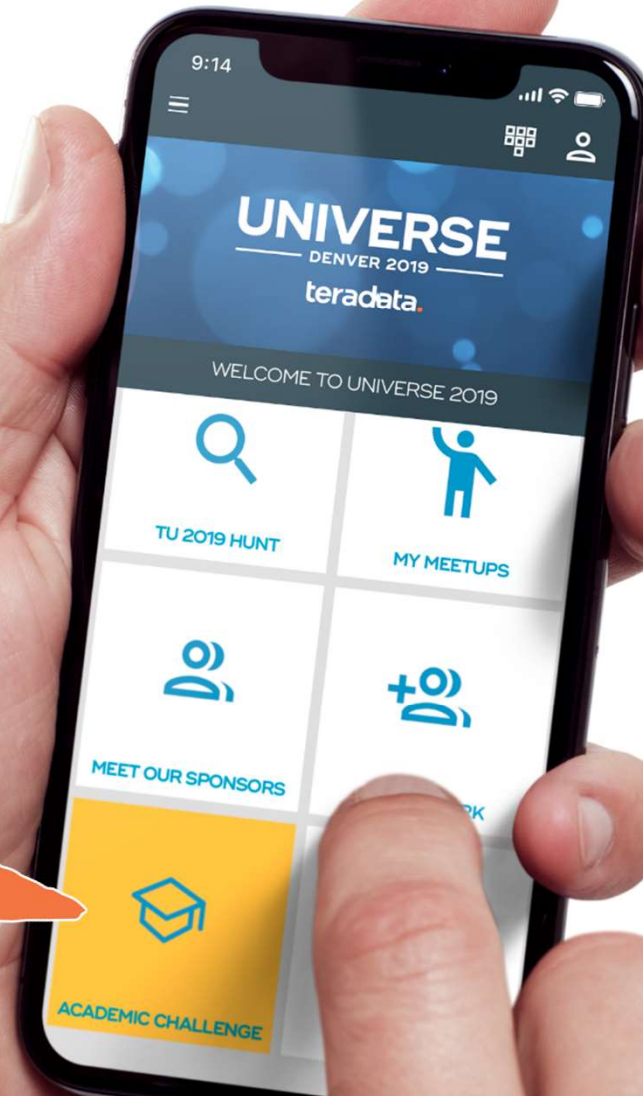
- Best Use of Teradata Technology

Academic vote

VOTE

for your
FAVORITE teams!

It's in the app!



Voting opens
on **Sunday**
at 3pm

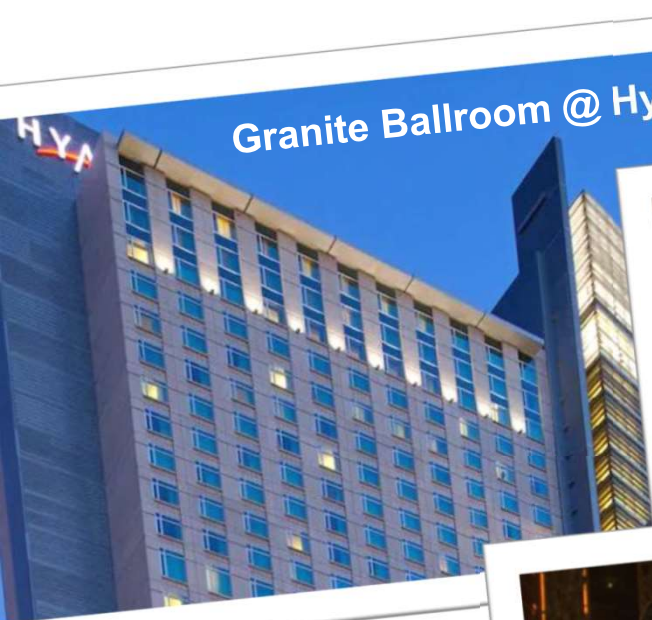
Voting closes
on **Monday**
at 2pm

Student Celebration Event

Monday, October 21, 6:30-8:30pm

Granite Ballroom @ Hyatt Regency Denver

All
attendees
invited!



Thank you.

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