CAPSTONE FINAL REPORT

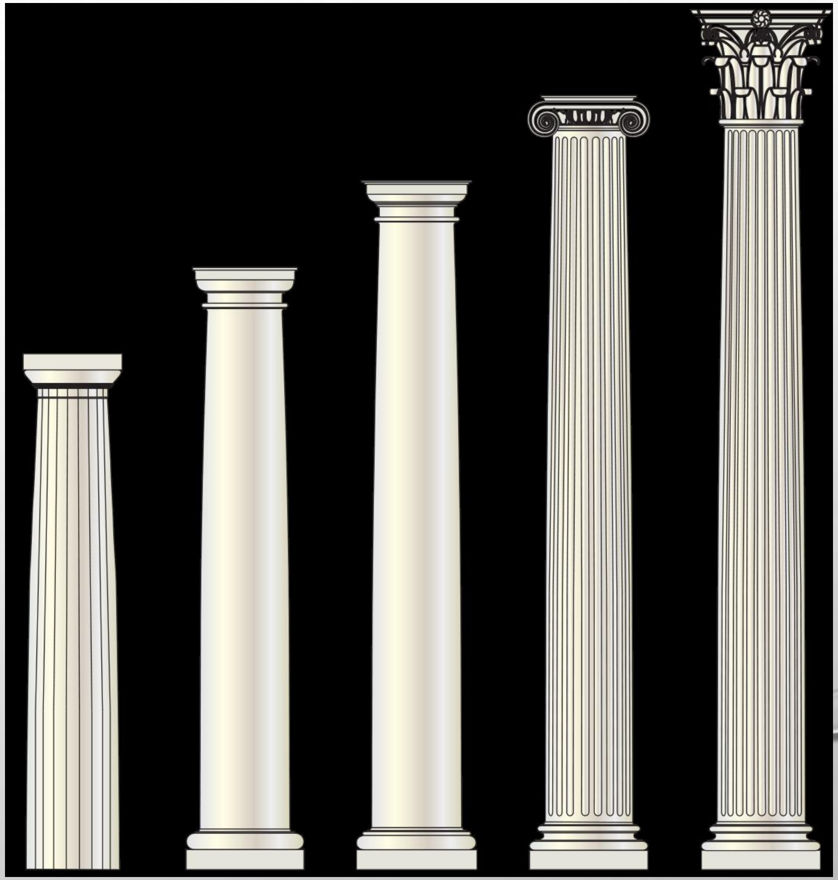
JUAN J. NUNEZ

MAY 2019

PROJECT PLAN

- GOALS:

1. EXPERIENCE WITH DATAMONTGOMERY DATA
2. DATA STATE (I.E., CAPABILITY)
3. KINDS OF VARIABLES (I.E., COLUMNS)
4. DEVELOP INTERESTING VISUALIZATIONS AND REPORTS



PROJECT PLAN

- TOOLS:

1. R AND R STUDIO FOR DATA PROCESSING + VISUALIZATIONS
2. TABLEAU PUBLIC FOR VISUALIZATIONS
3. OFFICE
4. GOOGLE

PROJECT PLAN

- **DATASETS:**

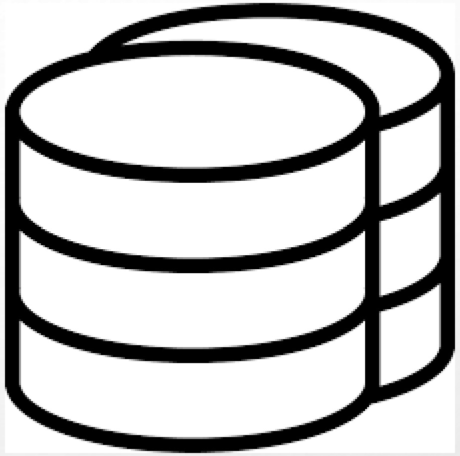
1. TRAFFIC VIOLATIONS
2. CRIME
3. TUITION ASSISTANCE
4. MONTGOMERY COLLEGE ENROLLMENT
5. ALCOHOL LICENSE VIOLATIONS
6. NOISE COMPLAINTS
7. BIAS INCIDENTS

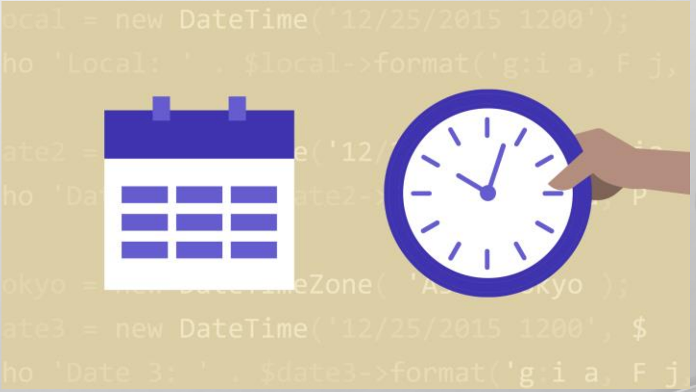
MONTGOMERY COLLEGE

DATA STATE + CLEANING

1. ALL DATASETS:

- COLUMNS WITH SAME INFORMATION DIFFER(E.G., COLUMN NAMES, CATEGORIES)
- COLUMN NAMES HAVE SPACES
- CHANGE DATE/TIME COLUMNS TYPE IN R
- UNUSABLE COLUMNS





TRAFFIC

- **IMPORTANT CHANGES:**

1. GEOLOCATION BOTTOM AND TOP CODE
2. DROPPED MAKE
3. COLLAPSED CATEGORIES (OTHER)

Female	Male
487,115	992,508

Asian	Black	Hispanic	White	Other
86,804	469,316	315,896	525,855	83,570

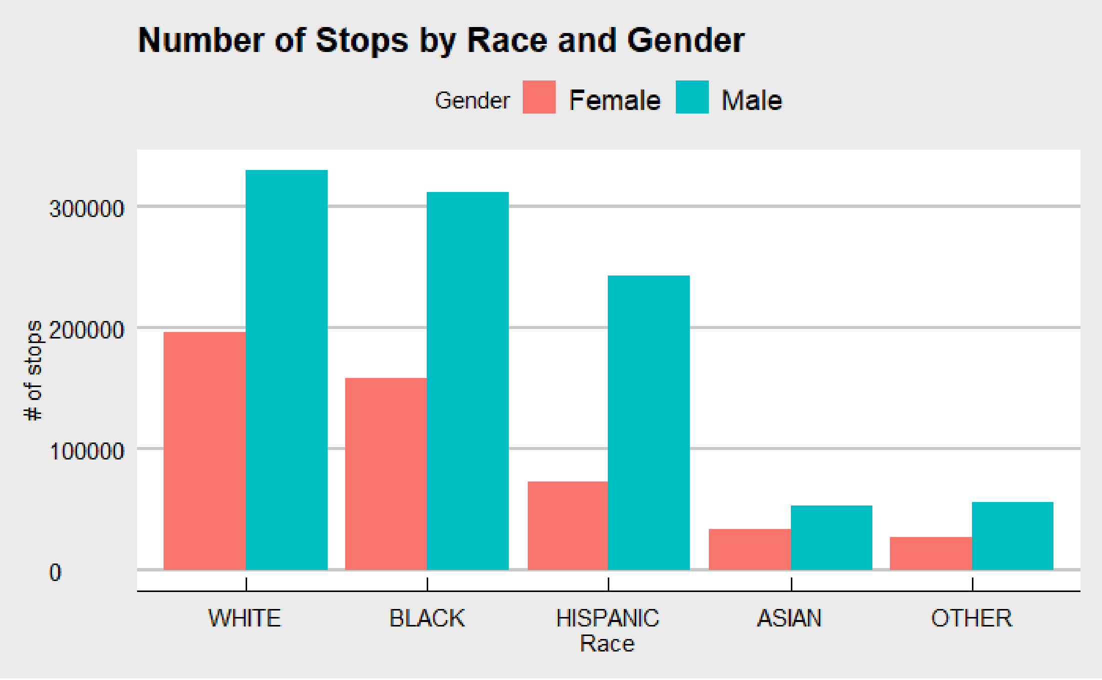
1D Rockville	2D Bethesda	3D Silver Spring	4D Wheaton	5D Germantown	6D Gaithersburg
177,628	235,207	291,705	367,336	169,374	191,104

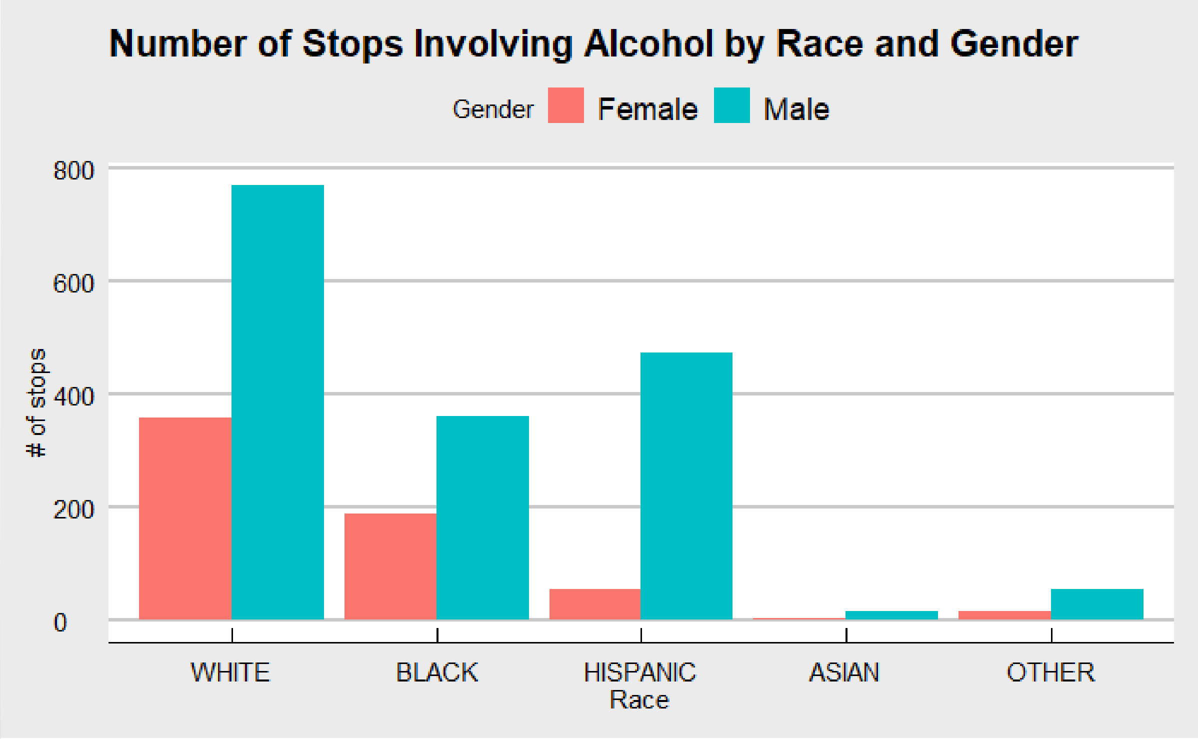
TRAFFIC

	Alcohol	No	Yes
Contributed to accident			
No		144,3812	2,127
Yes		35,337	165

- PEARSON'S CHI-SQUARED TEST:

P-VALUE < 0.001

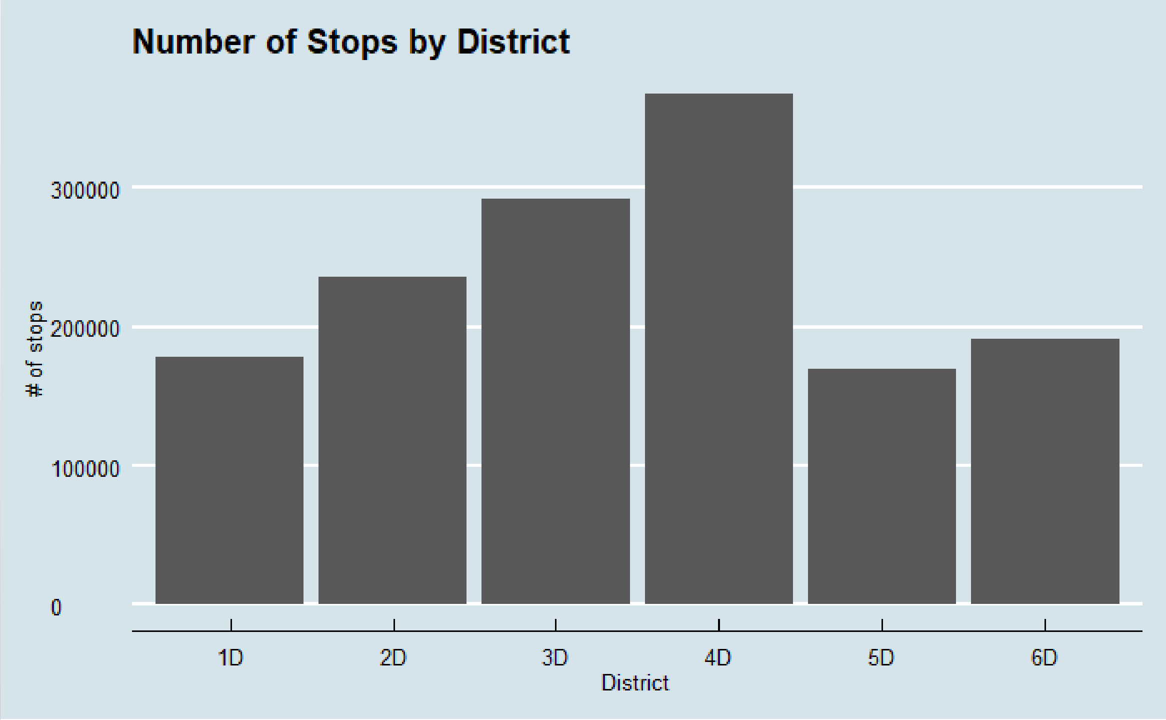


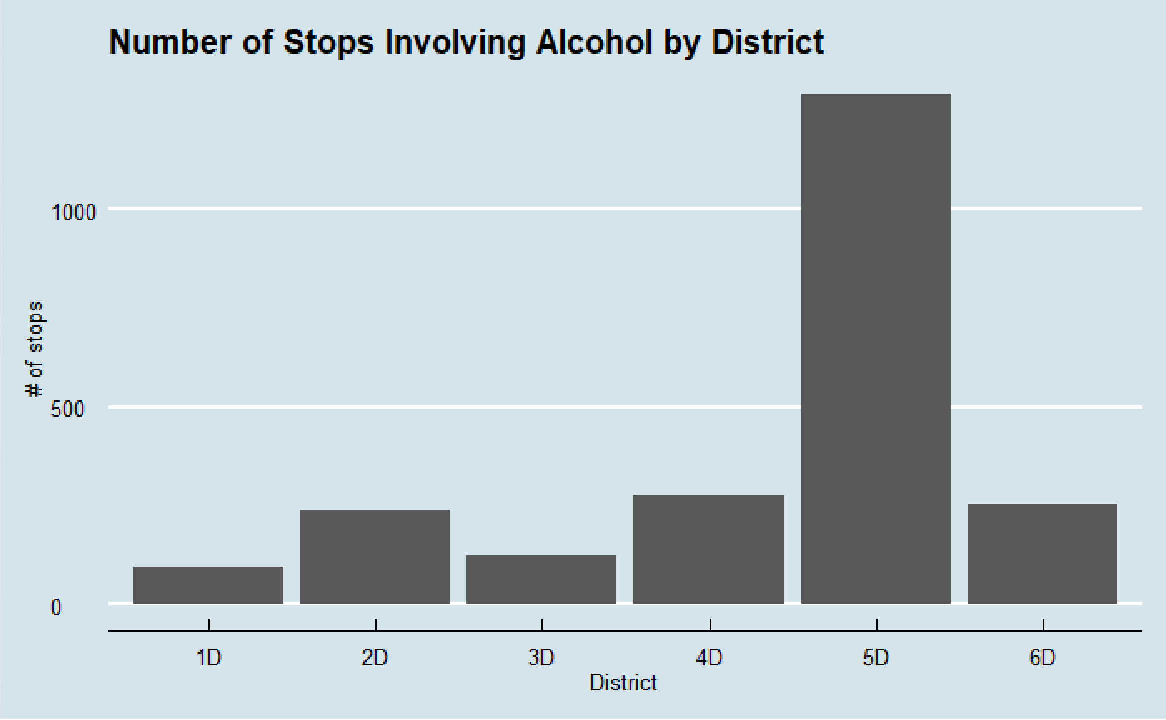


MD demographic estimates:
43 % white, 20% black, 20% Hispanic, 16% Asian

Source:
https://www.census.gov/quickfacts/montgomerycountymaryland

TRAFFIC

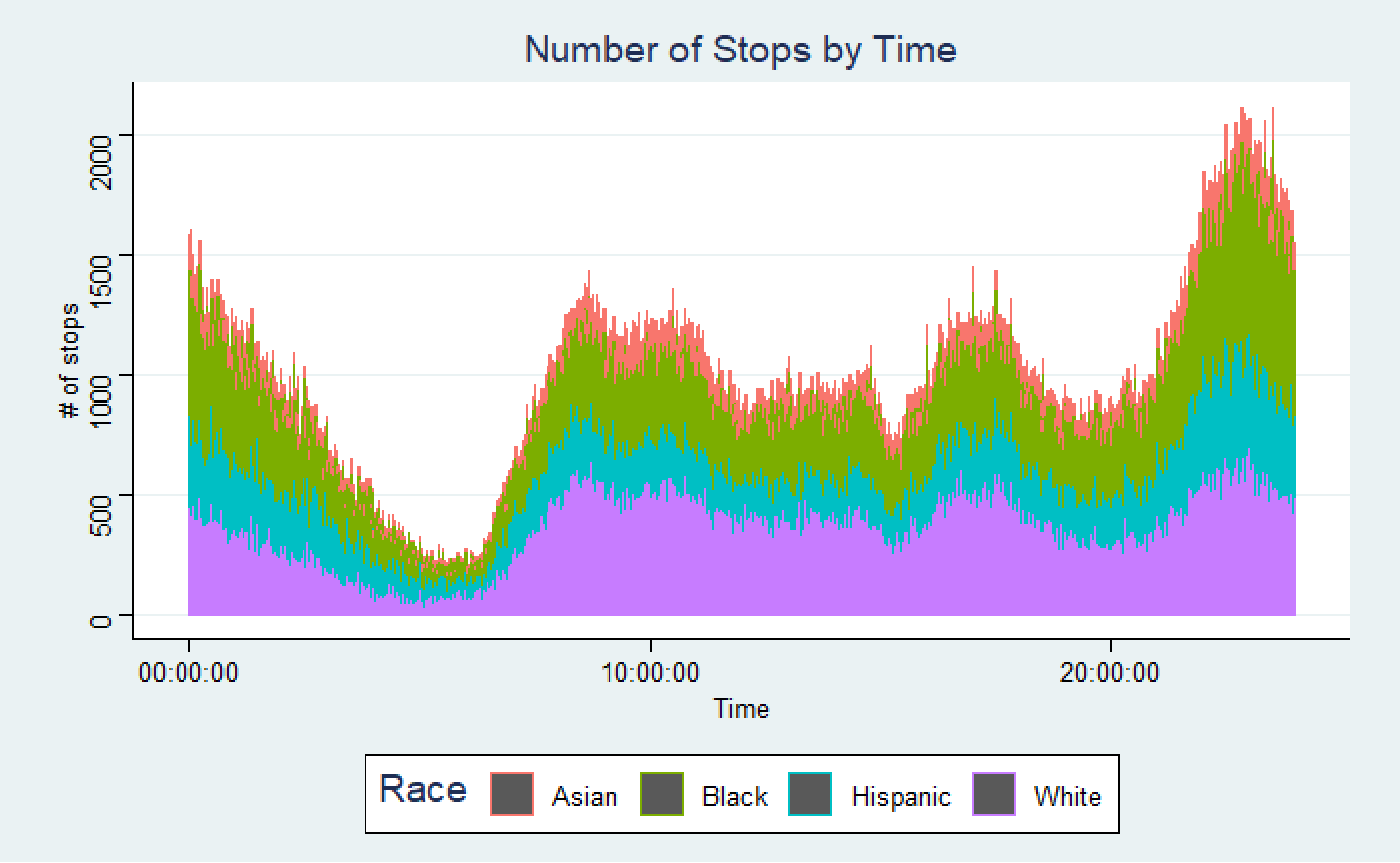




The Police District with the lowest number of stops has the most stops involving alcohol.

1D Rockville	2D Bethesda	3D Silver Spring	4D Wheaton	5D Germantown	6D Gaithersburg

TRAFFIC



There is within variable difference in the number of stops after 8:00 pm.

Map of Stops per District

CRIME

Person	Property	Society	Other
7,335	30,312	21,535	16,026

Drugs	Violent	Other
8,858	8,722	57,652

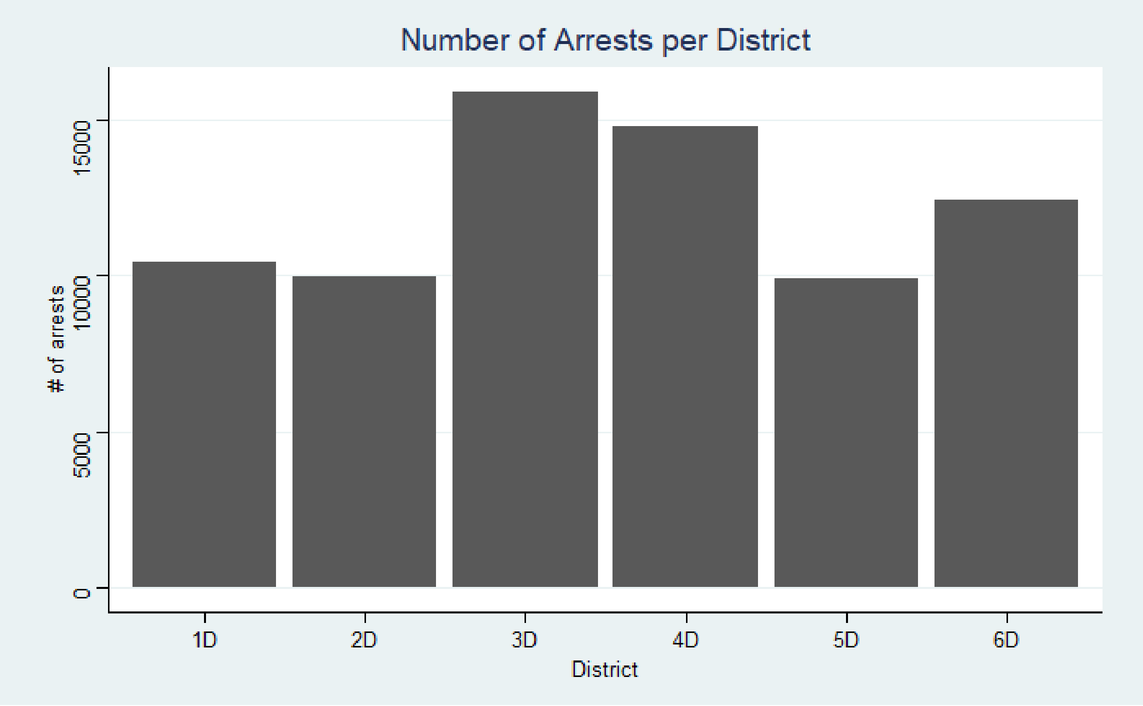
Victims		
One	Two	Three of more
73,923	1,108	201

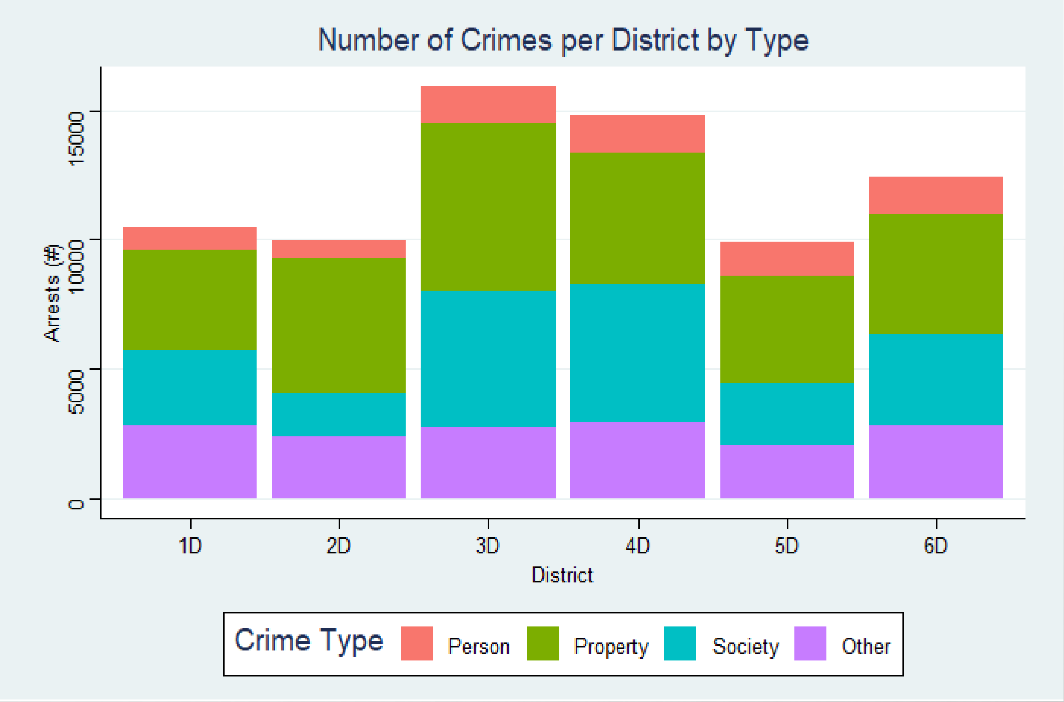
1D Rockville	2D Bethesda	3D Silver Spring	4D Wheaton	5D Germantown	6D Gaithersburg
10,448	9,974	15,915	14,788	9,905	12,413

- IMPORTANT CHANGES:

1. DATE AND TIME ARE IN ONE COLUMN
2. TIME IS NOT IN MILITARY TIME
3. MAKE CRIME TYPE CATEGORIES MANUALLY
4. COLLAPSED CATEGORIES

CRIME



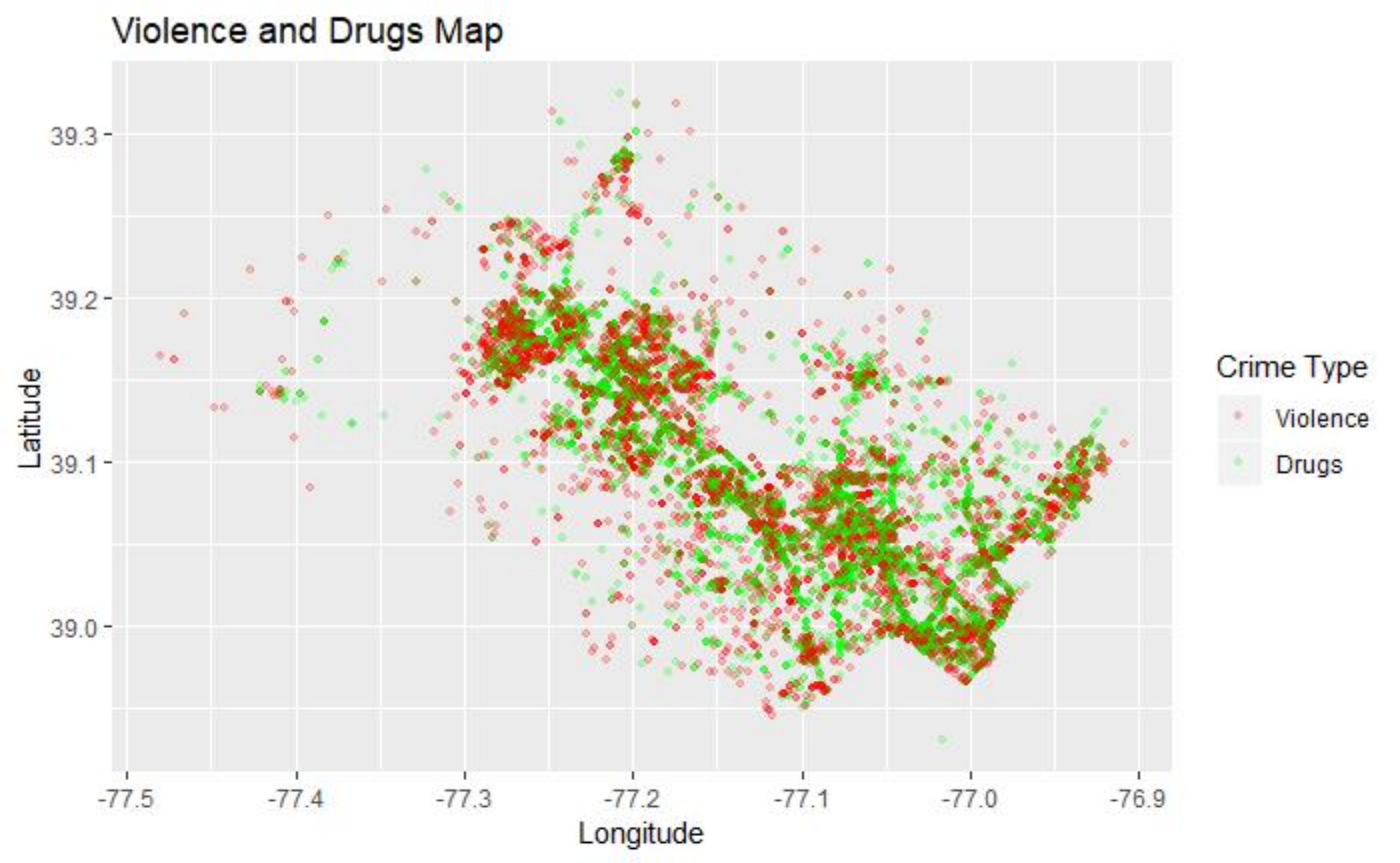


1D Rockville	2D Bethesda	3D Silver Spring	4D Wheaton	5D Germantown	6D Gaithersburg

It appears that Bethesda is afflicted with a higher percentage of property crimes.

[crime zip code] [Crime per hour]

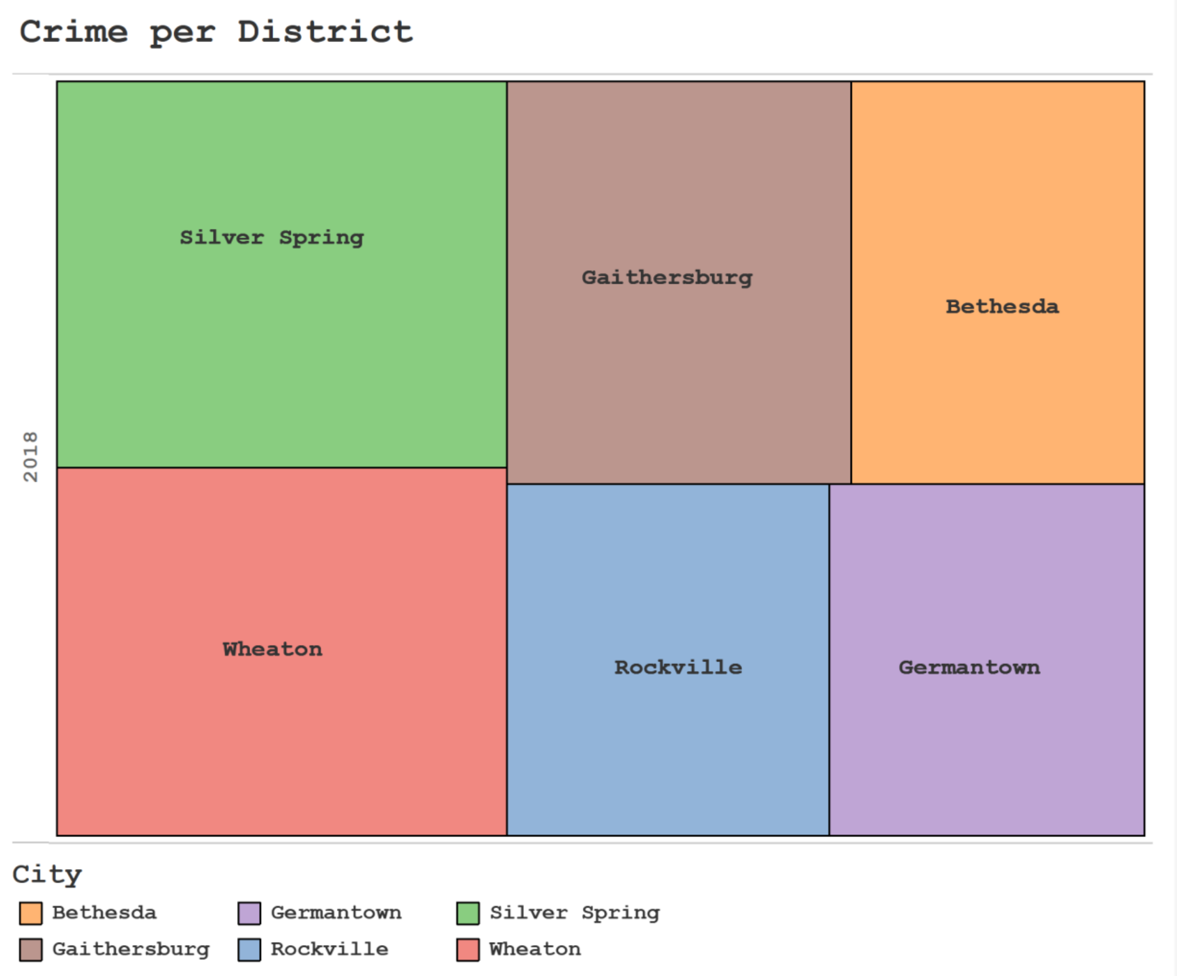
CRIME

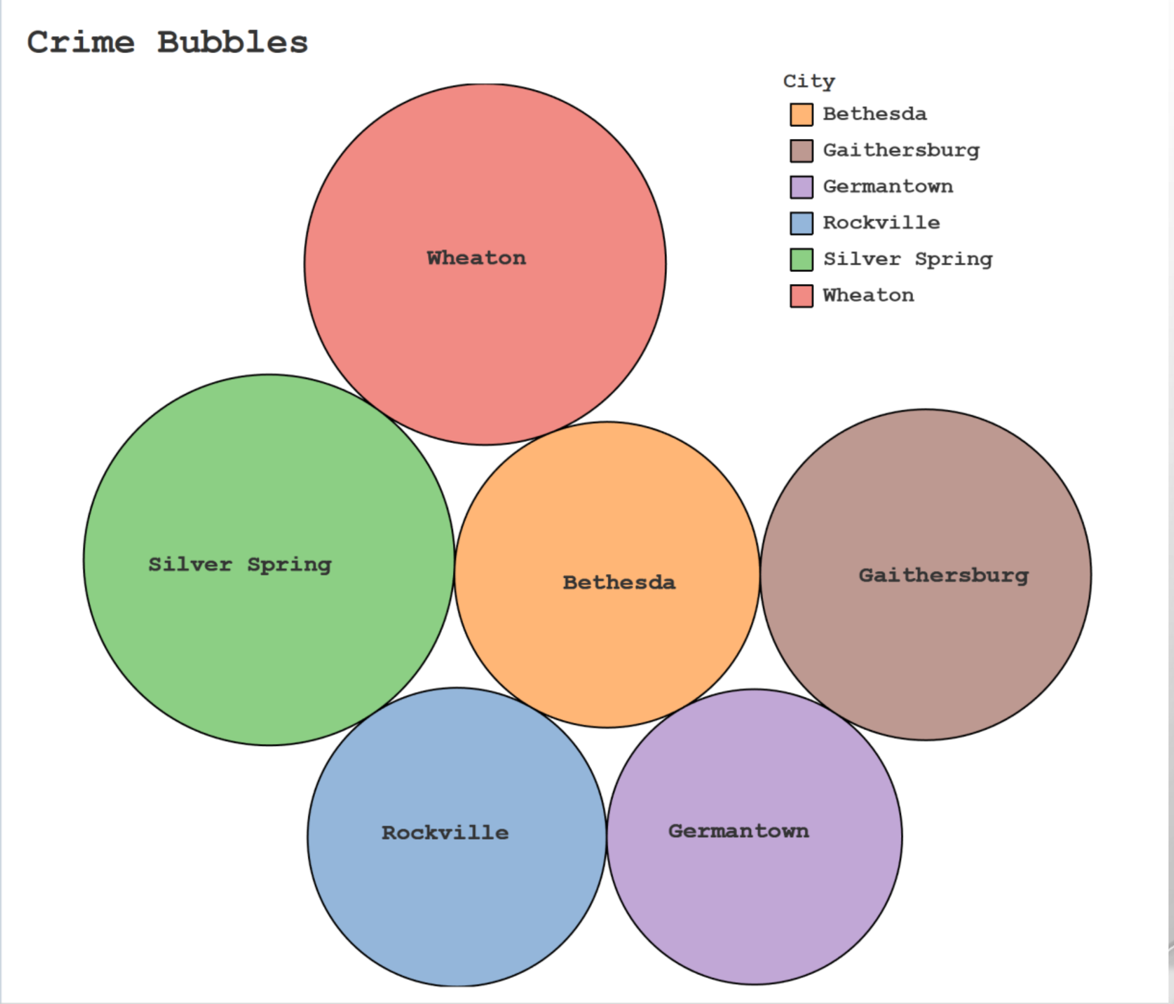


Violence seems to be more spread out than the drug crimes.

[Tableau Crime Map]

CRIME





Which differences are more perceptible?

Rockville	Bethesda	Silver Spring	Wheaton	Germantown	Gaithersburg
6,005	6,281	9,242	6,873	5,861	7,354

TUITION ASSISTANCE

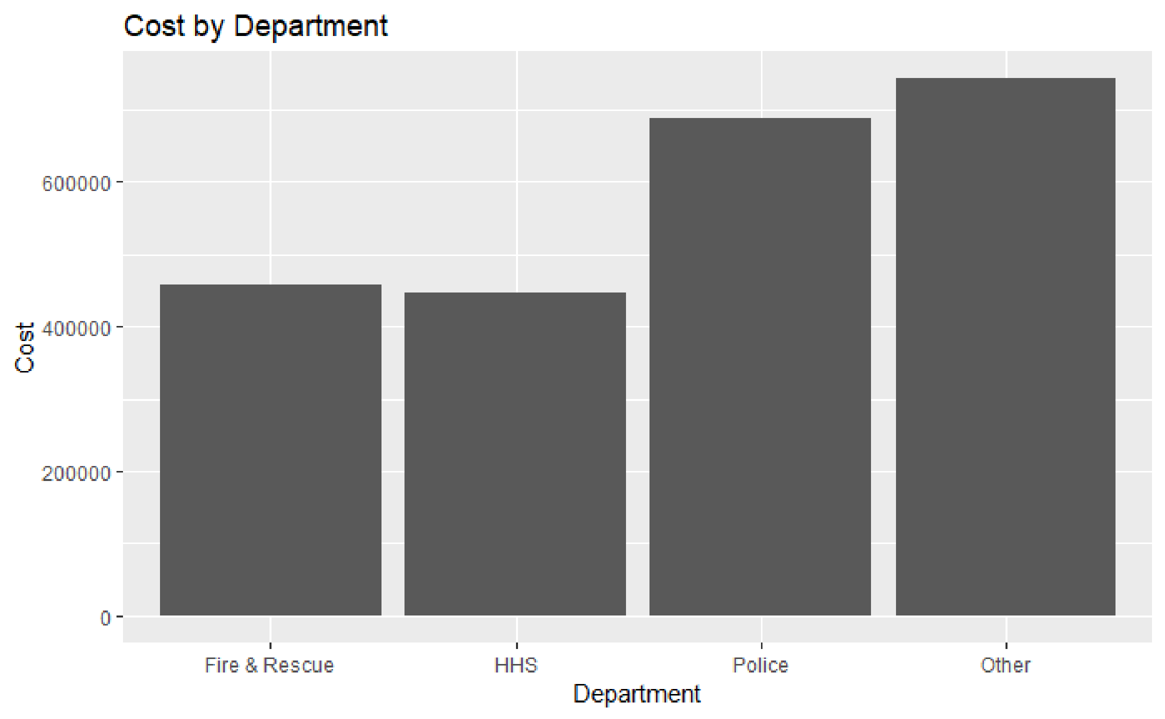
Department			
Fire & Rescue	HHS	Police	Other
633	578	859	1,023

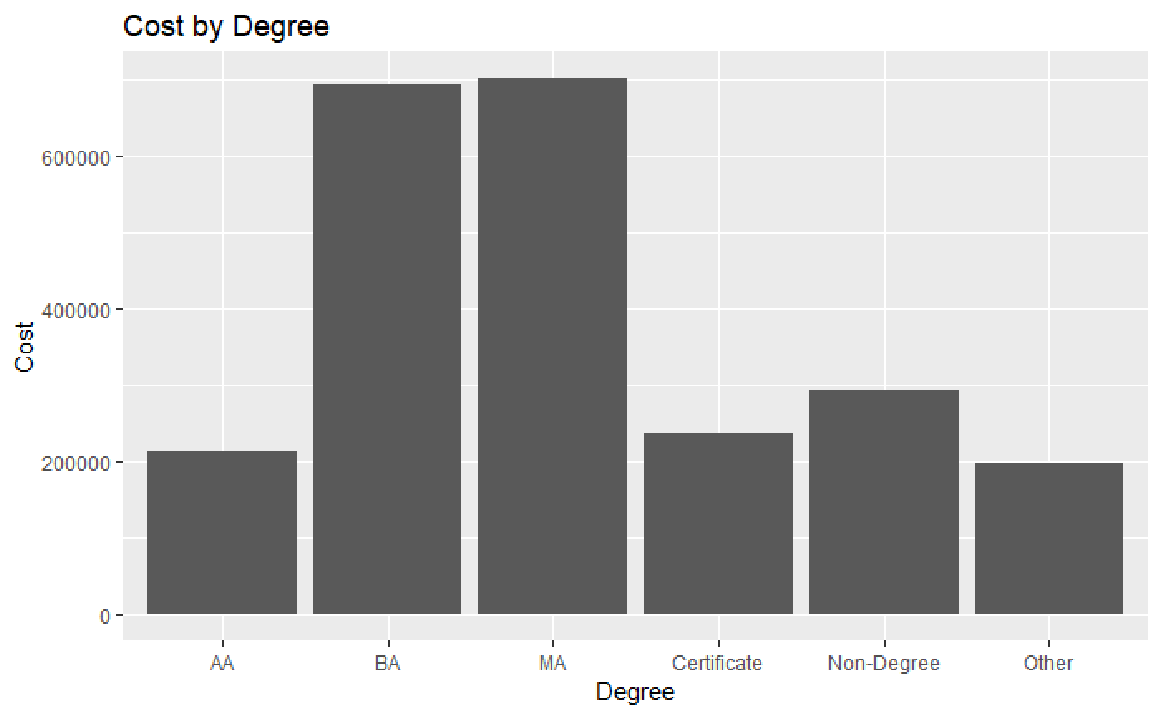
Degree					
AA	BA	MA	Cert.	Non-degree	Other
533	994	606	333	391	236

Tuition Cost ($)			
Mean	SD	Min	Max
755.53	522.7	0	2,130

- **IMPORTANT CHANGES:**

1. **CREATED NEW CATEGORIES FOR ALMOST ALL VARIABLES**





MC ENROLLMENT (FALL 2015)

Status	
Full-time	Part-time
8,890	16,430

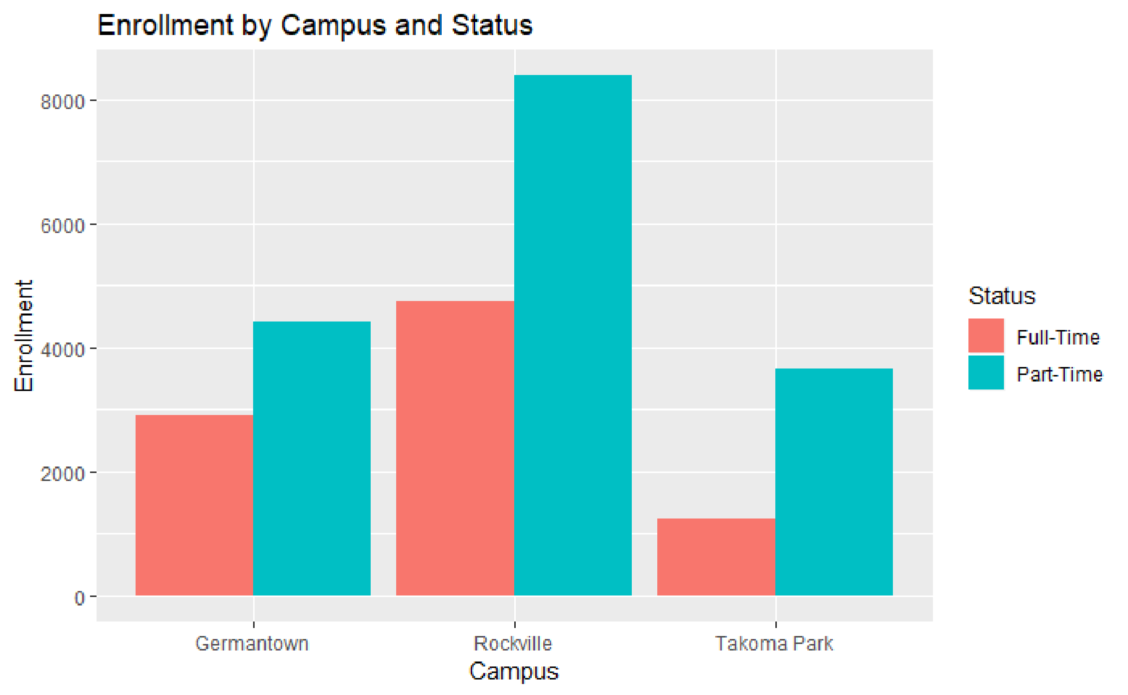
Age Groups			
<21	21-24	25-29	<29
10,533	6,349	3,320	5,116

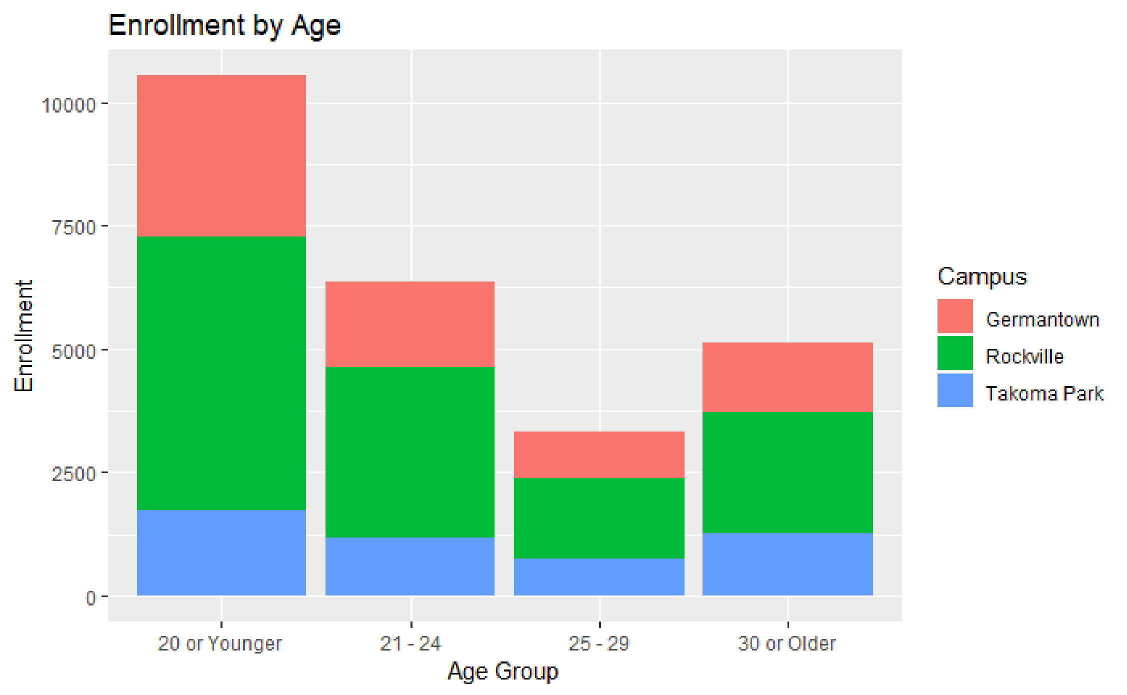
Asian	Black	Hispanic	White	Other
3,538	8,217	2,028	9,831	1,706

Rockville	Germantown	Takoma Park
13,110	7,307	4,903

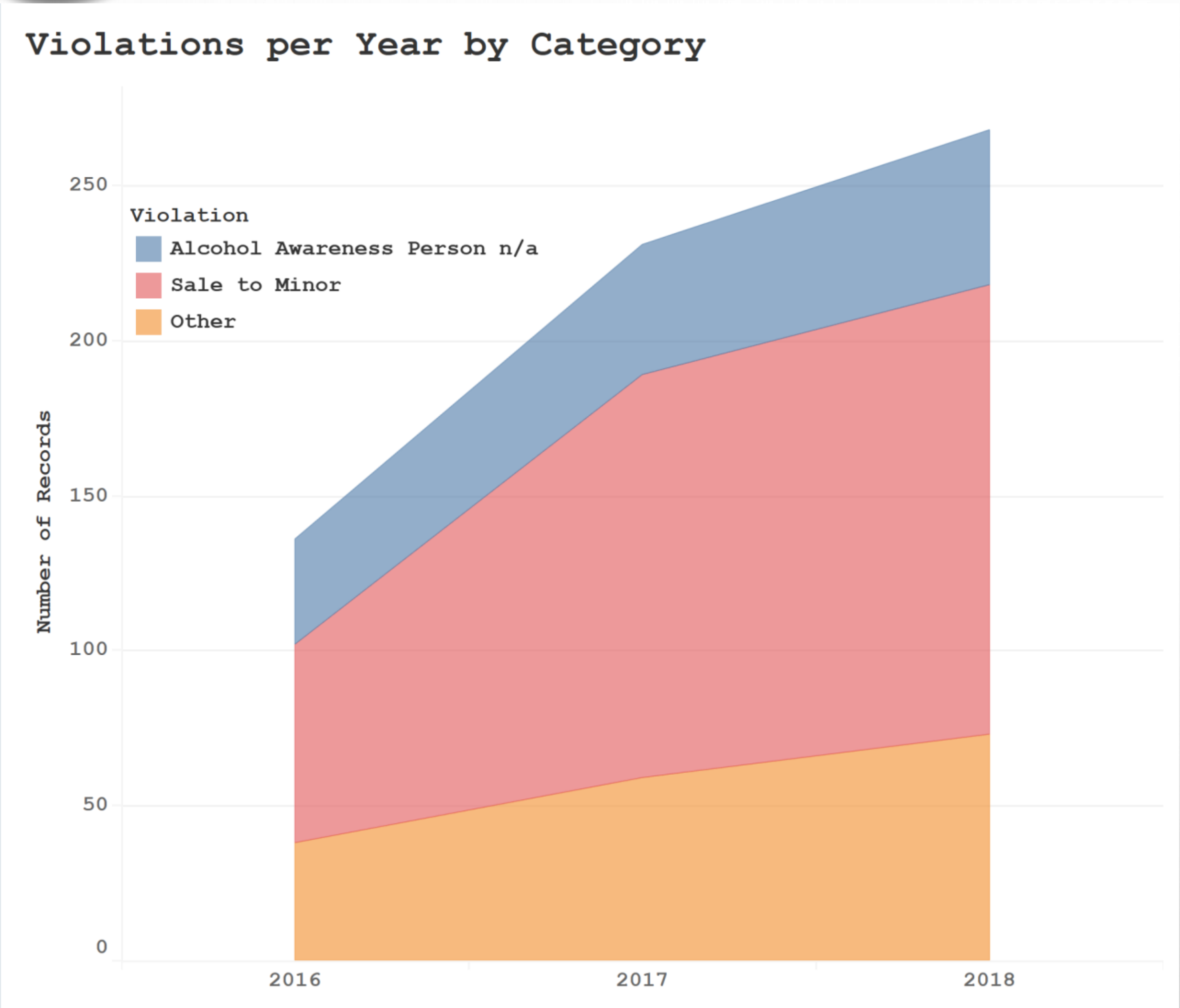
- **IMPORTANT CHANGES:**

1. CREATED NEW CATEGORIES FOR ALMOST ALL VARIABLES





ALCOHOL LICENSE VIOLATIONS



Each category increases every year.

- IMPORTANT CHANGES:
  1. ADDRESS -> MULTIPLE COLUMNS
  2. TYPOS WITHIN COLUMNS
  3. SOME ZIP CODES ARE ZIP+4

Violation		
Alc. Awareness Person n/a	Sale to Minor	Other
126	348	174

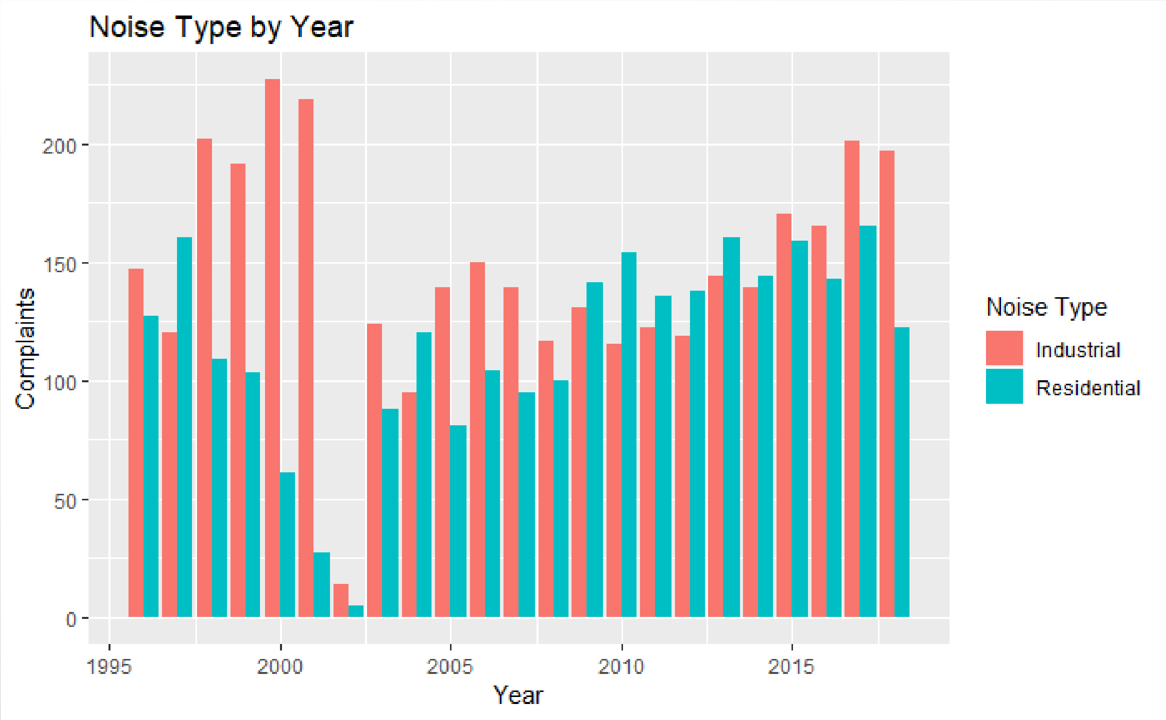
ALC_violations_map

NOISE COMPLAINTS

Noise Type		
Industrial	Residential	Other
3,802	2,815	337

[Noise Complaints Map]

- IMPORTANT CHANGES:
  1. CREATED NEW VARIABLES WITH NEW CATEGORIES
  2. FIXED COLUMN NAMES EVEN AFTER ADDING UNDERSCORE



BIAS INCIDENTS

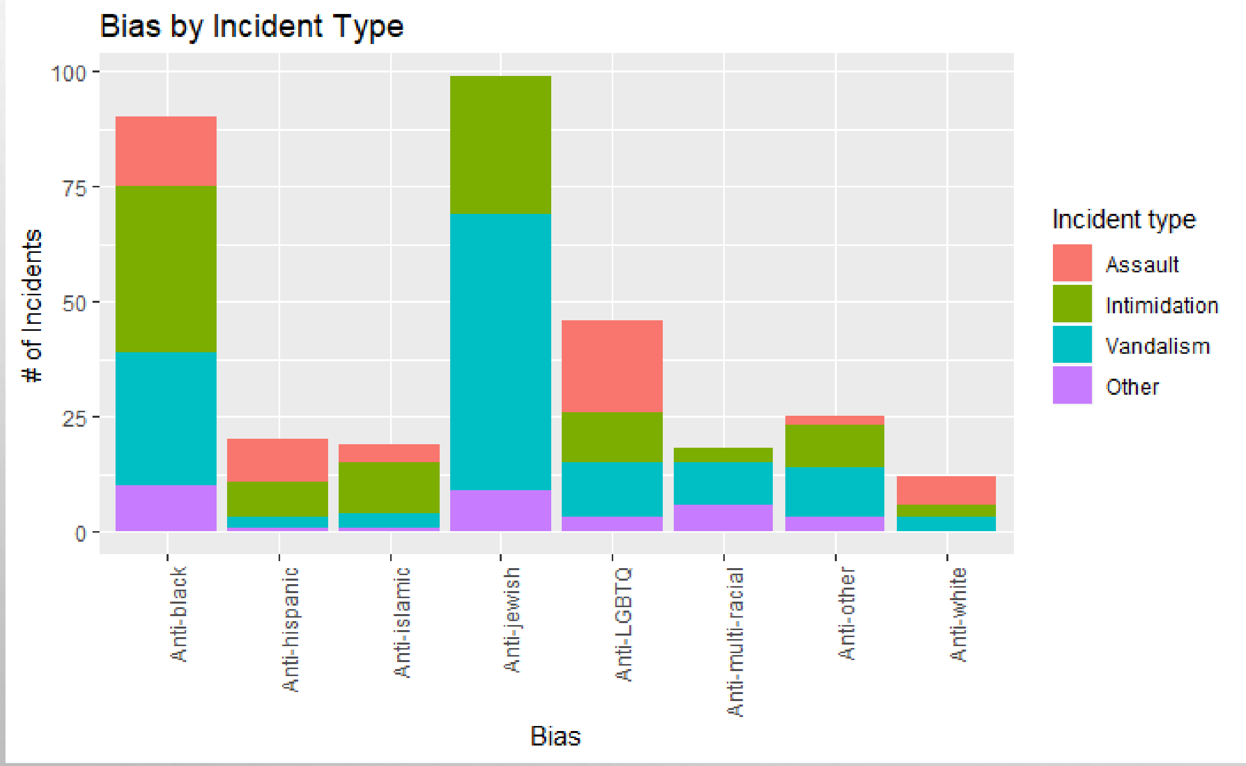
Incident			
Assault	Intimidation	Vandalism	Other
56	111	129	33

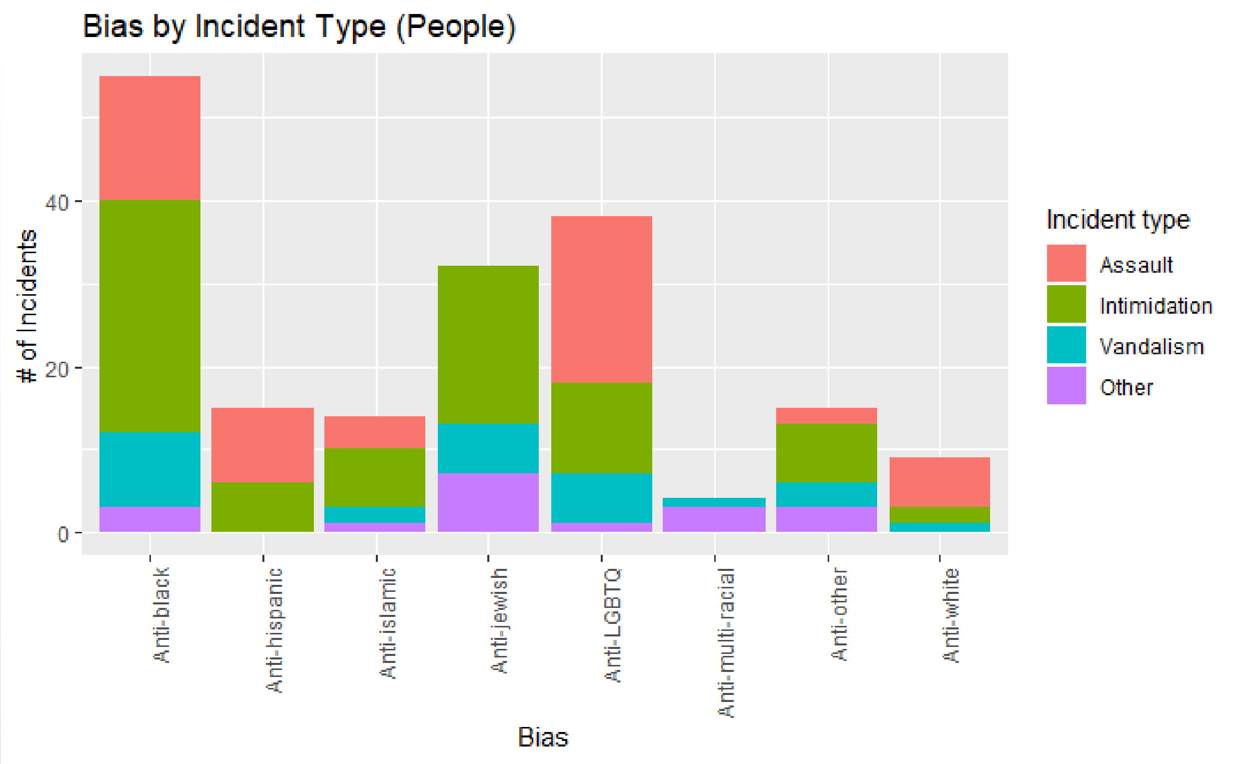
Incident By Victim Type

- IMPORTANT CHANGES:

Victim Type	
Person	Other
182	147

1. CREATED NEW VARIABLES WITH NEW CATEGORIES





1D Rockville	2D Bethesda	3D Silver Spring	4D Wheaton	5D Germantown	6D Gaithersburg
53	70	36	54	36	34

OVERALL EXPERIENCE + FUTURE DIRECTIONS

- PROS:

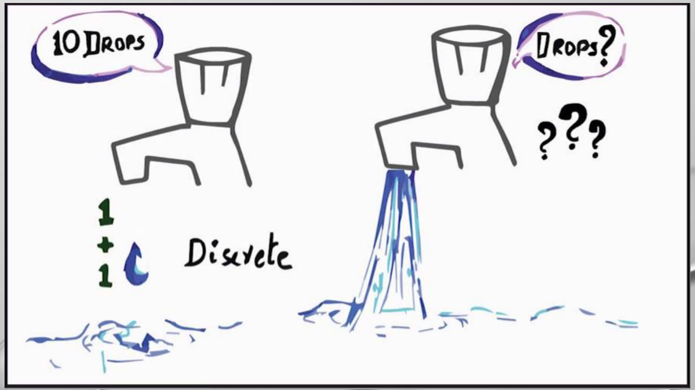
1. GREAT EXPERIENCE WITH REAL-WORLD DATA
2. GREAT EXPERIENCE VISUALIZING DATA
3. GREAT TO BE PART OF A BURGEONING FIELD

- CONS:

1. MOST VARIABLES ARE CATEGORICAL
2. A LOT OF TYPOS WITHIN COLUMNS
3. DATA MINING AND SIFTING SKILLS ARE REQUIRED FOR MOST OF THE DATA

- LOOKING AHEAD:

1. GOING THROUGH THE REST OF THE DATASETS COULD BE VERY HELPFUL
2. FIXING THE COLUMN NAMES BEFORE THEY ARE MADE PUBLIC
3. ADDING CONTINUOUS VARIABLES FOR STATISTICS AND VISUALIZATION (HOW LONG THE STOP LASTED, E.G.)
4. CODEBOOKS WOULD BE VERY HELPFUL



ACKNOLEDGMENTS

THANK YOU

- DENNIS LINDERS AND THE MONTGOMERY COUNTY GOVERNMENT FOR THE OPPORTUNITY
- DATAMONTGOMERY FOR UNDERTAKING THIS WONDERFUL PROJECT
- KATHERYN LINEHAN AND MONTGOMERY COLLEGE FOR ALL OF THE GUIDANCE THEY PROVIDED
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Juan J. Nunez
DATA 205