# UMD Data Analysis: Final Project

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## Introduction

The dataset shows some variables that represent support for the people in need by Urban Ministries of Durham, whose aim is to help ending the homeless in the neighborhood.

In this project, we are provided different kind of datasets which contain the different features' statistics summary and demographic data at two different status: entry and exit. we could explore some potential phenomenon based on the summary of entry data and exit data.

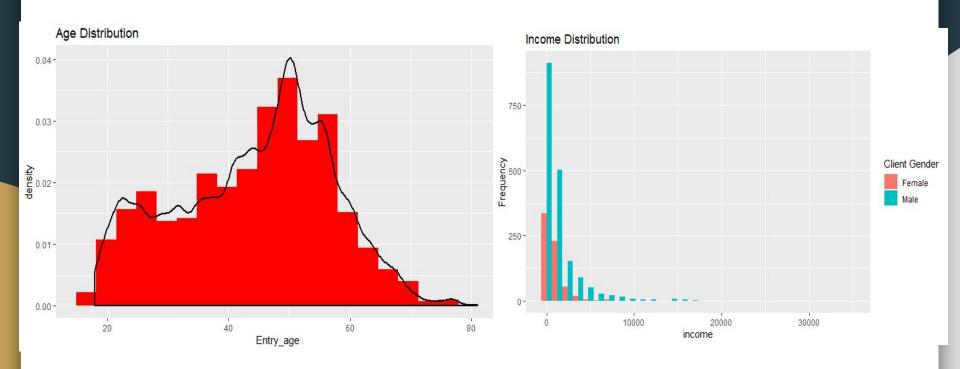
## Goals

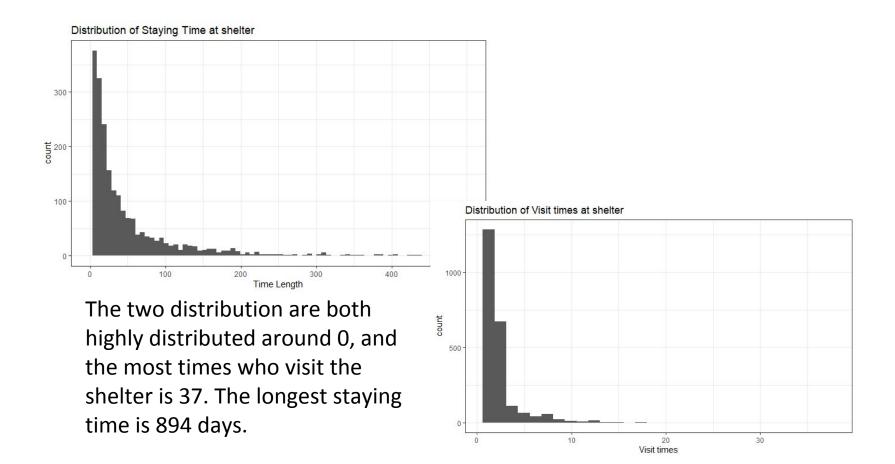
Will the Duration of Staying be affected by some features of clients, such as gender, race, ....? Try to build a linear model to see if it works well.

Explore the description and correlation among different data.

Will season affect the entry? Will some variables have influence on the clients' entry month?

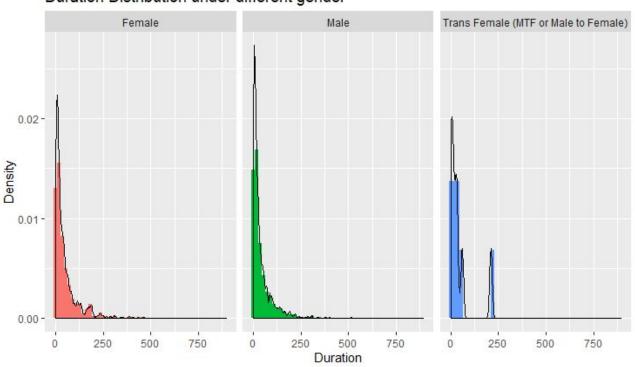
## Distribution of some variables





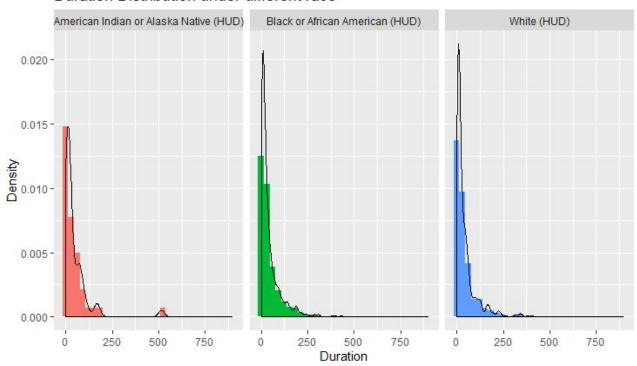
# Correlation with Duration

#### Duration Distribution under different gender



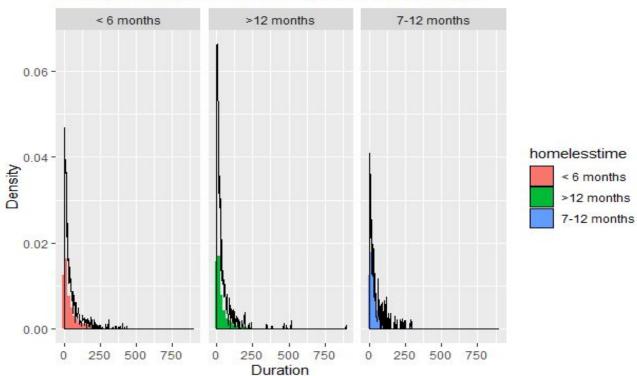
## Correlation with Duration

#### Duration Distribution under different race

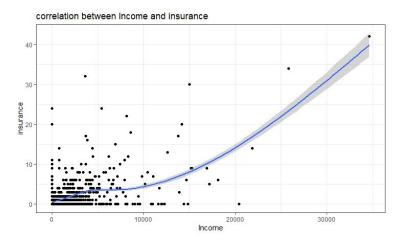


# Correlation with Duration

#### Duration Distribution under different homeless time

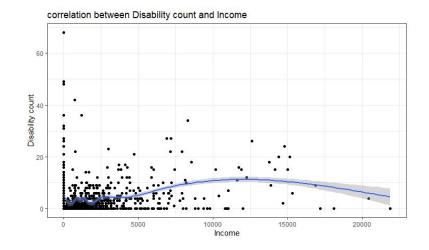


# Some interesting Correlation



For who got higher monthly income, usually they will have less disability; but for whose monthly income is small, since the cardinality is large, we found more points gathering near 0

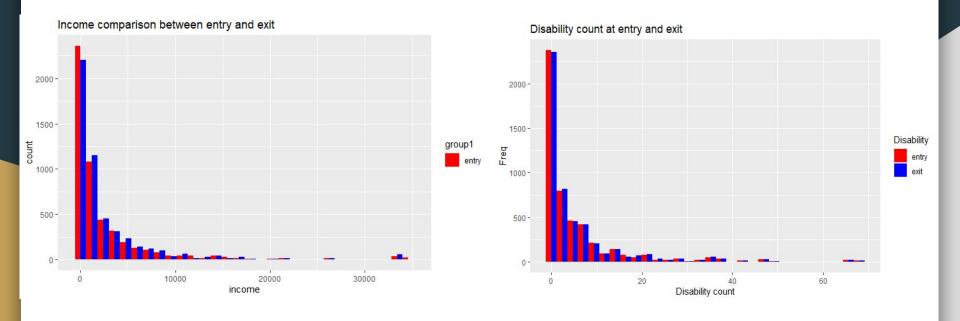
For who got higher monthly income, usually they will have more kinds of health insurance.



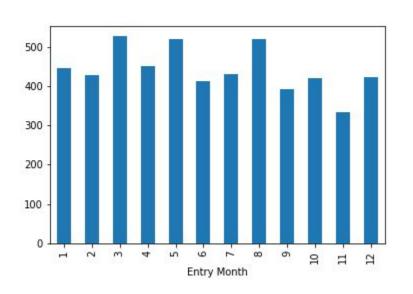
From the Correlation plot, we know that the income, disability and insurance count have moderate level linear correlation.

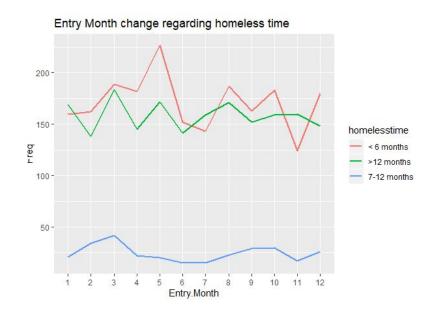


# Comparisons between entry and exit



# Any monthly trend?





We find around November is almost a time that less people enter the shelter.

## Linear Model

```
Estimate Std. Error t value Pr(>|t|)
(Intercept)
                                              18.0497254 10.1765406 1.774 0.076196 .
                                                0.5896283
                                                          0.0804013 7.334 2.7e-13
Entry_age
'Client Gender 'Male
                                               -5.7619078 2.3535638 -2.448 0.014402 *
raceBlack or African American (HUD)
                                               -2.7672987 7.8457708 -0.353 0.724323
raceWhite (HUD)
                                               -4.9020090 8.0219895 -0.611 0.541187
'Client Veteran Status Yes (HUD)
                                               -9.4855934 3.3628351 -2.821 0.004815
`Client Ethnicity`Non-Hispanic/Non-Latino (HUD) 12.0942522 5.6656433 2.135 0.032849
income month
                                                0.0002789 0.0003197 0.872 0.383093
healins
                                               -0.2051081 0.2882905 -0.711 0.476839
`Disability count`
                                               -0.5101565 0.1158894 -4.402 1.1e-05 ***
'Receiving Benefit (Entry)'
                                               0.1521957 0.3649462 0.417 0.676675
homelesstime>12 months
                                               -8.3048505 2.1536475 -3.856 0.000117 ***
homelesstime7-12 months
                                              -7.3223762 4.0636846 -1.802 0.071636 .
```

Duration of staying is our response variable, and we include all the continuous and categorical variables at first.

## Linear Model

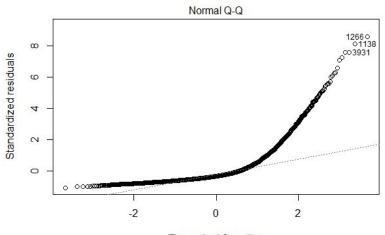
#### Coefficients:

	Estimate	Std. Error	t value Pr(> t )
(Intercept)	11.34965	6.70248	1.693 0.090466 .
Entry_age	0.62717	0.08076	7.766 1.02e-14 ***
`Client Gender`Male	-5.04849	2.35181	-2.147 0.031882 *
`Client Veteran Status`Yes (HUD)	-10.76816	3.37672	-3.189 0.001439 **
`Client Ethnicity`Non-Hispanic/Non-Latino (HUD)	13.94352	5.55068	2.512 0.012042 *
`Disability count`	-0.52480	0.10360	-5.066 4.25e-07 ***
homelesstime>12 months	-7.90170	2.17177	-3.638 0.000278 ***
homelesstime7-12 months	-6.06640	4.09788	-1.480 0.138851

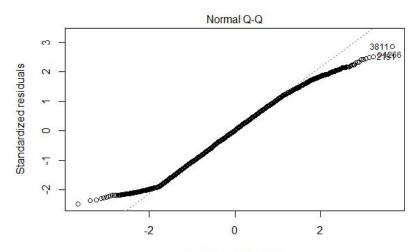
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When we drop some non-significant variables, we found gender, veteran status, ethnicity, homeless time and disability count are very important variables to be included in the model.

# Try log normal Distribution



Theoretical Quantiles Im('Time Difference' ~ Entry\_age + 'Client Gender' + race + 'Client Veteran ...



 $\label{log-cont} Theoretical Quantiles $$ Im(log(`Time Difference`) \sim Entry\_age + `Client Gender` + race + `Client Ve \dots 'Client Ve \text{ } ... $$$ 

## Conclusions

Most people are around 50-60 years old, black man. For the duration time, we found that in fact age, gender, race, ethnicity have little effect on it. But seems who are homeless for more year is more possible to stay for shorter time.

In linear regression model, We found that those who are veteran, young people usually stay less time at shelter; those who are homeless more than one year will be less possible to stay longer than those whose homeless time is less than 6 months. That is interesting since it is against our usual idea.

50% people didn't complete the program when they select to leave. I think our next step analysis is to figure out what leads to their departure, is it correlated to any other feature?