Predicting Drunk Driving Incidents

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Introduction

In 2015, 35,092 people died in motor vehicle accidents according to the National Highway Traffic Safety Association (NHTSA). This is an increase of 2,348 fatalities from 2014. Part of the reason that there was an increase in the number of fatal traffic accidents overall is that the number of fatal traffic accidents involving alcohol impaired drivers increased by 322. This increase in the number of fatal traffic accidents involving drunk drivers is important because CDC reports that around 31% of traffic fatalities include a drunk driver and that alcohol impaired vehicle accidents cost around $44 billion. Of course the primary concern with the increase in drunk driving fatalities is the increased loss of life, but these accidents also have detrimental monetary implications as well.

Although the dangers of drunk driving are well documented at an individual level, the risk factors associated with drunk driving are generally not well known at an aggregate level. There is relatively little literature exploring why there are large discrepancies in rate of drunk driving between different U.S. counties. For example, in 2015, Fremont County, Wyoming, had 27 fatal traffic accidents involving alcohol per 100,000 people whereas the same statistic for Morris County, New Jersey is only 0.2. This difference in drunk driving incidence between the two counties is vast though there is little understanding of how and why these disparities are accentuated based on socioeconomic differences or additional factors.

Identifying risk factors associated with drunk driving could help develop intervention methods. More specifically, if individual level risk factors can be determined then we know who to target with drunk driving precaution campaign. On a separate note educational programs can be developed for the general public to spread awareness about how drunk drivers behave (Do they drive more at night? Do they drive more during the weekends?) equipping citizens with the knowledge to better avoid drunk drivers. Moreover pinpointing county level disparities in drunk driving related accidents could lead to geographic level government policy implementations like increased budget allocation to spread awareness about safe driving practices in counties with high rates of drunk driving and fatalities.

In this project, we plan to determine what factors at individual and county level predict whether or not the driver involved in a fatal traffic accident was alcohol impaired. Individual level predictors include driver's sex, age and past driving related convictions. County level predictors of interest include population and income to poverty ratio. Lastly, we also analyze accident level attribute like time of day, week status (weekday/weekend) and number of fatalities in the crash in potentially explaning drunk driving incidence related to fatal accidents.

Data

We used data from two different sources to identify potential risk factors associated with drunk driving related fatal accidents. Our primary source of data was from the Fatality Accident Report Service (FARS) managed by the National Highway Traffic Safety Administration (NHTSA). FARS provides information concerning every vehicle and person involved in a fatal traffic accident. The data is provided at an accident, vehicle, and person level. Each accident is given a unique identifier, and each row of the vehicle and person datasets includes the unique ID indicating which accident that the vehicle or person was a part of. This allowed us to seamlessly join the data together. The manual provided in this link contains information about each variable within the datasets.

The second and supplementary source of data came from the American Community Survey (ACS) conducted by the U.S. Census Bureau. The ACS provides social, economic, and demographic data at the county, state, and national level. The FARS data contains geographic information like latitude, longitude, county, and state.

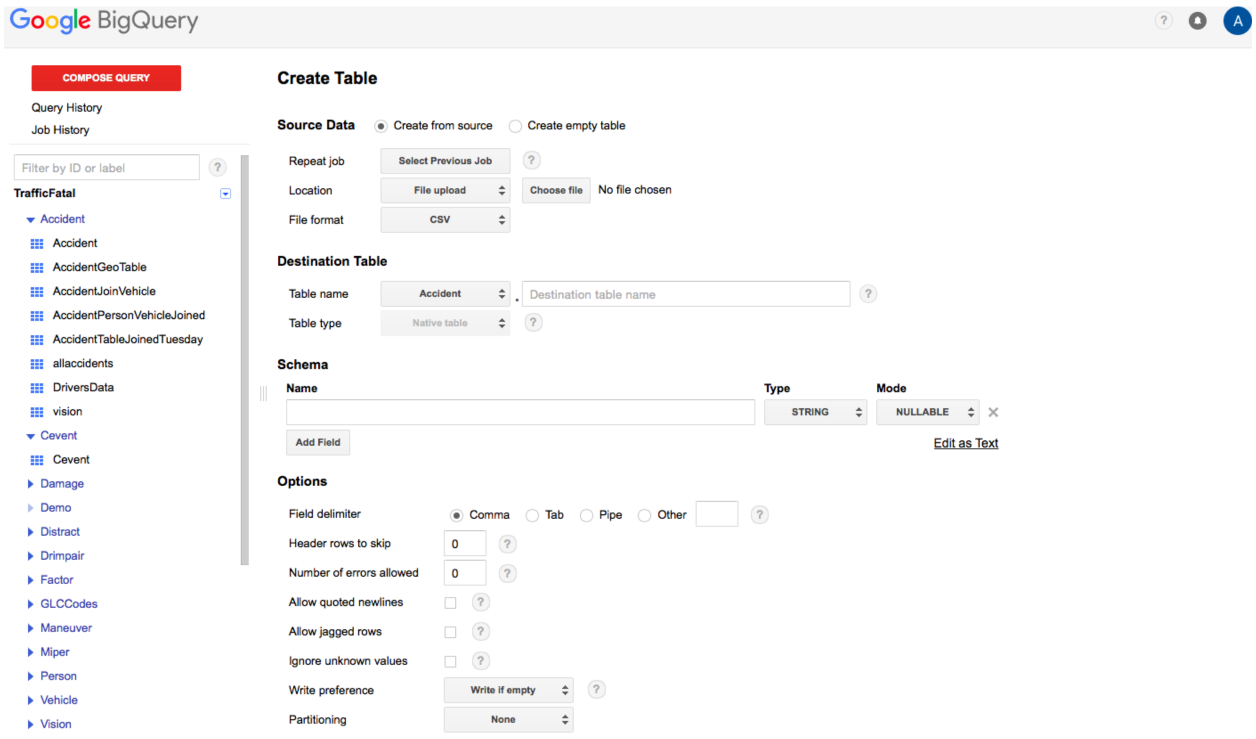
By calculating FIPS codes, we were able to match the county level data we were looking for to each accident, vehicle and person. Information about the ACS can be found here.

Data Wrangling

BigQuery

We used Google's BigQuery as a hosting platform for our datasets. BigQuery is an analytics warehouse with the ability to process data on the petabyte scale accessible at here. It provides a serverless and infrastructure-less environment through its cloud data storage, thereby further reducing the need for a database administrator. Its features include the ability to ingest data from different sources including Google Cloud Storage, Cloud Datastore, and livestream. Data can be read and written via Cloud Dataflow, Spark, and Hadoop and exported out in the Cloud. A key feature of BigQuery is the ability to collaborate and share queries as well as data by adding members to a project. Since we used accident, vehicle and person level data, BigQuery provided a cohesive and structured environment for managing all three. Additionally the user-friendly interface was conducive to basic exploratory analysis with SQL as well as for performing variety of joins.

Most basic and preliminary use of BigQuery entails navigating between two environments: Google BigQuery and Google Cloud Platform (accesible at here). Data can be uploaded in BigQuery by first creating a project and enabling both billing and the BigQuery API. Once a project is created, datasets can be added from the 'create a new dataset drop down option' on the highlighted project (available on the left side of the inteface). After specifying a dataset, it is populated by tables of interest. The specification of the table entails defining a schema (structure or data skeleton), which involves defining the variable names as well as the data types for each variable as shown by Figure 1.



Create Table

Source Data: [✓ Create from source] Create empty table

Repeat job

Location: File upload — No file chosen

File format: CSV

Destination Table

Table name: Accident . Destination table name

Table type: Native table

Schema

Name	Type	Mode
	STRING	NULLABLE

Options

Field delimiter: [✓ Comma] Tab Pipe Other

Header rows to skip: 0

Number of errors allowed: 0

Allow quoted newlines ☐

Allow jagged rows ☐

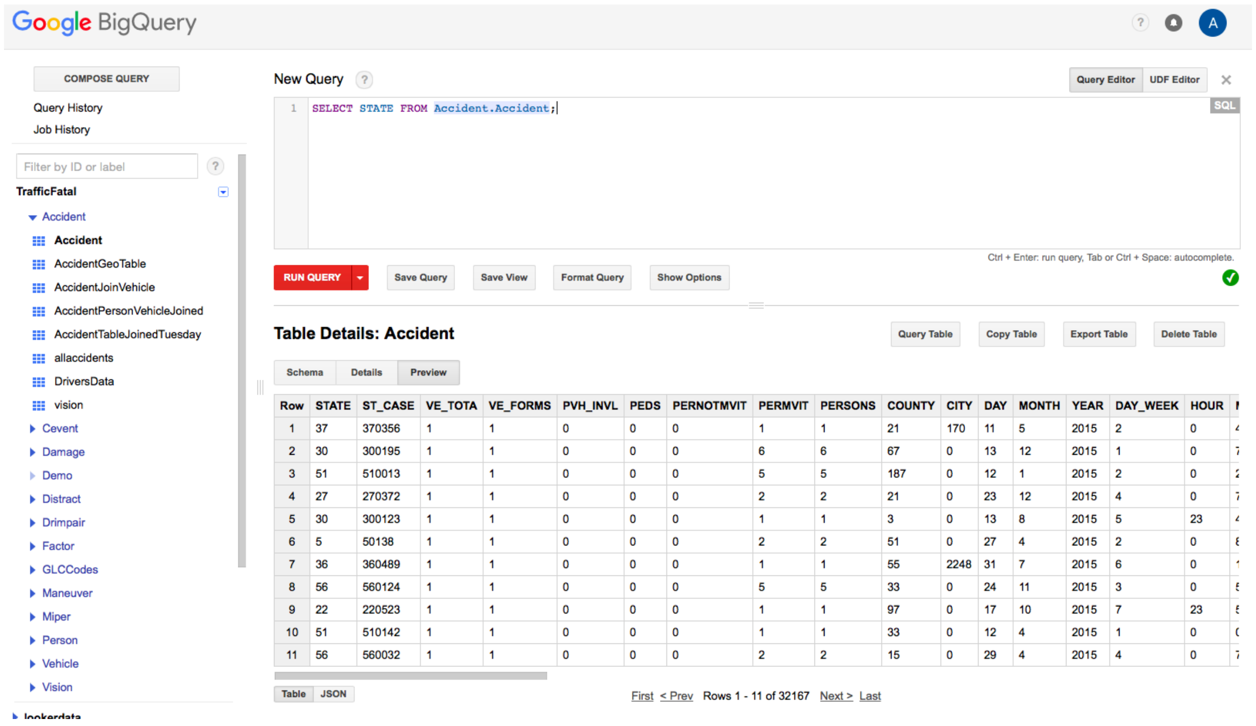
Ignore unknown values ☐

Write preference: Write if empty

Partitioning: None

Figure 1: Google BigQuery Interface for Creating Table

Once the data is exported in a table, it can be previewed and queried through the 'compose query tab' on the left (see Figure 2).



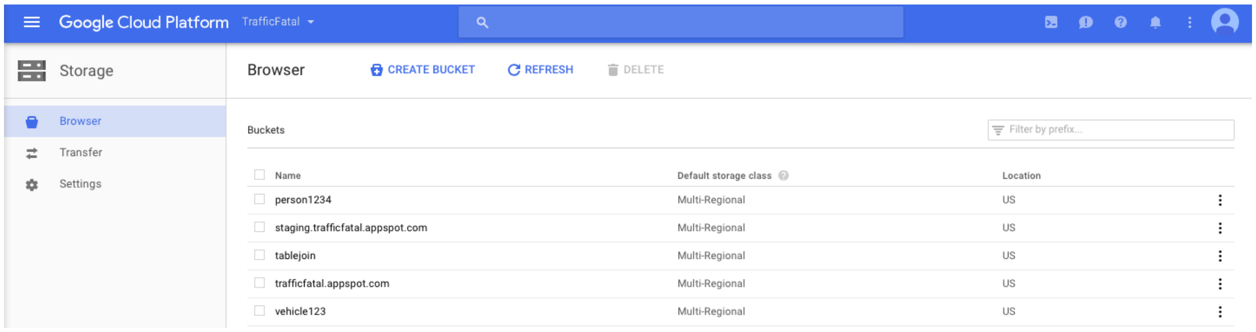
```
SELECT STATE FROM Accident.Accident;
```

Table Details: Accident

Row	STATE	ST_CASE	VE_TOTA	VE_FORMS	PVH_INVL	PEDS	PERNOTMVIT	PERMVIT	PERSONS	COUNTY	CITY	DAY	MONTH	YEAR	DAY_WEEK	HOUR
1	37	370356	1	1	0	0	0	1	1	21	170	11	5	2015	2	0
2	30	300195	1	1	0	0	0	6	6	67	0	13	12	2015	1	0
3	51	510013	1	1	0	0	0	5	5	187	0	12	1	2015	2	0
4	27	270372	1	1	0	0	0	2	2	21	0	23	12	2015	4	0
5	30	300123	1	1	0	0	0	1	1	3	0	13	8	2015	5	23
6	5	50138	1	1	0	0	0	2	2	51	0	27	4	2015	2	0
7	36	360489	1	1	0	0	0	1	1	55	2248	31	7	2015	6	0
8	56	560124	1	1	0	0	0	5	5	33	0	24	11	2015	3	0
9	22	220523	1	1	0	0	0	1	1	97	0	17	10	2015	7	23
10	51	510142	1	1	0	0	0	1	1	33	0	12	4	2015	1	0
11	56	560032	1	1	0	0	0	2	2	15	0	29	4	2015	4	0

Figure 2: BigQuery Interface for Queries

After the data is queried, the resulting table can be exported out to the Cloud by first creating a bucket from the Cloud console. Buckets can be created by selecting the Storage option from the main Cloud Platform console page. After a bucket is created, the queried data can be exported to that bucket with the name of the bucket and filename specified in format: gs://tablejoin/accident.csv where tablejoin is the name of the folder and accident is the name of the csv formatted table (see Figure 3).



Name	Default storage class	Location
person1234	Multi-Regional	US
staging.trafficfatal.appspot.com	Multi-Regional	US
tablejoin	Multi-Regional	US
trafficfatal.appspot.com	Multi-Regional	US
vehicle123	Multi-Regional	US

Figure 3: Google Cloud Platform for Storing Data

BigQuery has additional features worth highlighting like the publicly available datasets, which include the National Oceanic and Atmospheric Administration (NOAA) global data obtained from the USAF Climatology Center, US Disease Surveillance data from the CDC, NYC Taxi and Limousine Commission (TLC) Trip Data and GDELT Internet Archive Book Data.

FARS/ACS datasets

The FARS dataset was cleaned to remove any observations with unreported sex, previous DWI conviction, previous suspensions, and age. Observations with nonsensical values were also removed. An example of this is an observation where the driver was listed at 500 and 600 years old which of course is impossible. Other implausible outliers included a driver with over 40 previous suspensions. As someone gets in more and more trouble with the law, the punishments escalate and licenses are generally revoked before 40 suspensions are given.

A FIPS code column was created and used as the basis for joining the FARS and the ACS datasets so that each driver is matched with the county and state aggregate population and income to poverty ratio measures. We also created weekday and day status predictors. The data given from FARS already had information about the day of the week the accident occurred as well as the time. In the FARS dataset, the variable for day equaled 1 for Sunday and 7 for Saturday. The weekend variable was therefore coded as a binary indicator of weekend using the day of week variable. We coded night for if the accident occurred between the hours of 6pm and 6am and day otherwise. Final predictors of interest as a measure of driver's drunk incidence included the driver's sex (Sex), age (Age), history of previous DWI convictions and driving suspensions (PrevDWIConvictions, PrevSuspensions), accident level atributes like number of fatalities, weekday status and day status (NumFatalities, WeekdayStatus, DayStatus) and county level variables like total population and income to poverty ratio in the past 12 months of the driver's state and county (TotalPopulation, IncomeToPovRatio).

Data Visualization/Exploration

In order to visualize and explore the data, the shiny, leaflet and choroplethr packages were used. The findings from the shiny app will be detailed below, but the app itself can be found at this link. The shiny app was made up of three components: a marker map made using leaflet and two choropleth maps with different forms of interactivity.

Marker Map

The first of three components was the marker map. For every fatal accident in the year 2015, there was a circle representing the accident at the location of the accident on the map (using latitude and longitude). The user could choose whether to color code the circles by whether a drunk driver was involved or not, whether it was a weekend or weekday, or whether it was night (between 6pm and 6am) or day. The user could also choose to scale the dot size by the number of fatilities or the number of people involved in the accident.

Another feature of the marker map is that if a circle is clicked, a pop-up display will show up. The pop-up displays relevant information regarding the accident including whether a drunk driver was involved, the number of vehicles, the number of people, and the number of fatalities. The most important feature of the pop-up is that it displays the unique ID given to each accident. If there is a particularly interesting accident displayed on the marker map and the user would like to look into it, the ID provided the pop-up is essential. The user could take the ID, and match the accident from the map to the corresponding row in the dataset.

The first map displayed on the next page is the marker map where the color is based on whether a drunk driver or not and the size is based on the number of fatilities in the accident. The second map displayed is the marker map where the color is based on whether a drunk driver or not and the size is based on the number of people in the accident.

In the first map, the yellow dots are easy to make out whereas in the second map, the yellow dots are muted. This indicates that a drunk driver was not present in the accidents with largest number of people involved. On the other hand, a drunk driver was present in some of the accidents with the largest number of people who died. This indicates that there maybe a direct relationship between whether a drunk driver was involved in an accidents and the number of fatalities or an inverse relationship between whether a drunk driver was involved and the number of people who were involved. This is something we explore later.

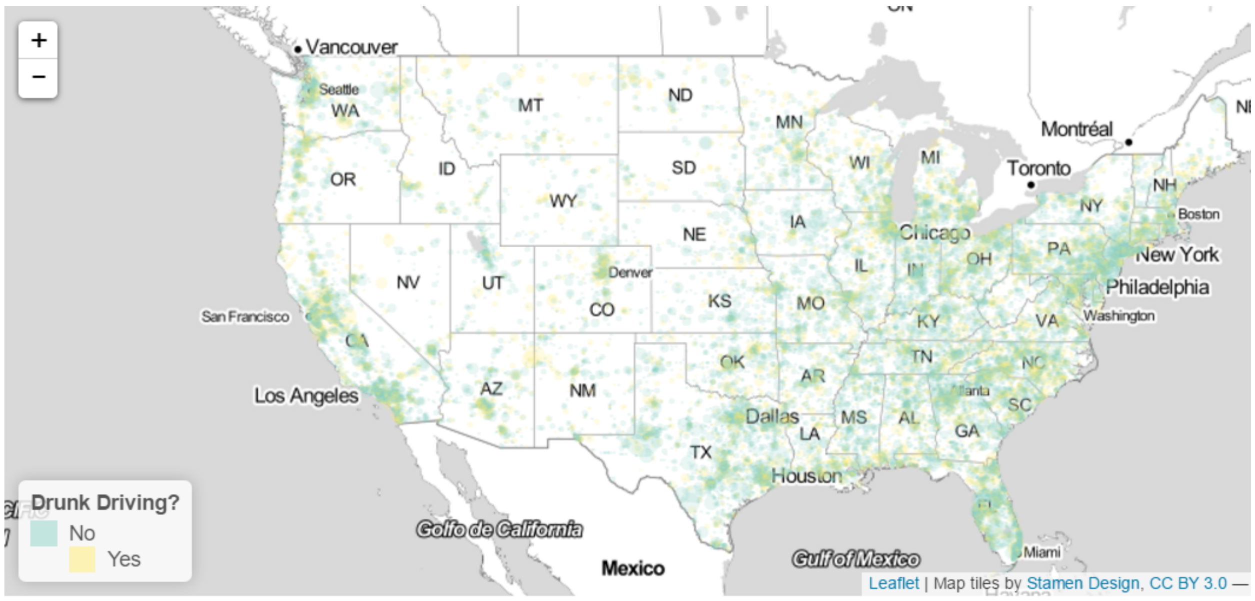


Figure 4: Marker map - Marker size based on number of fatalities

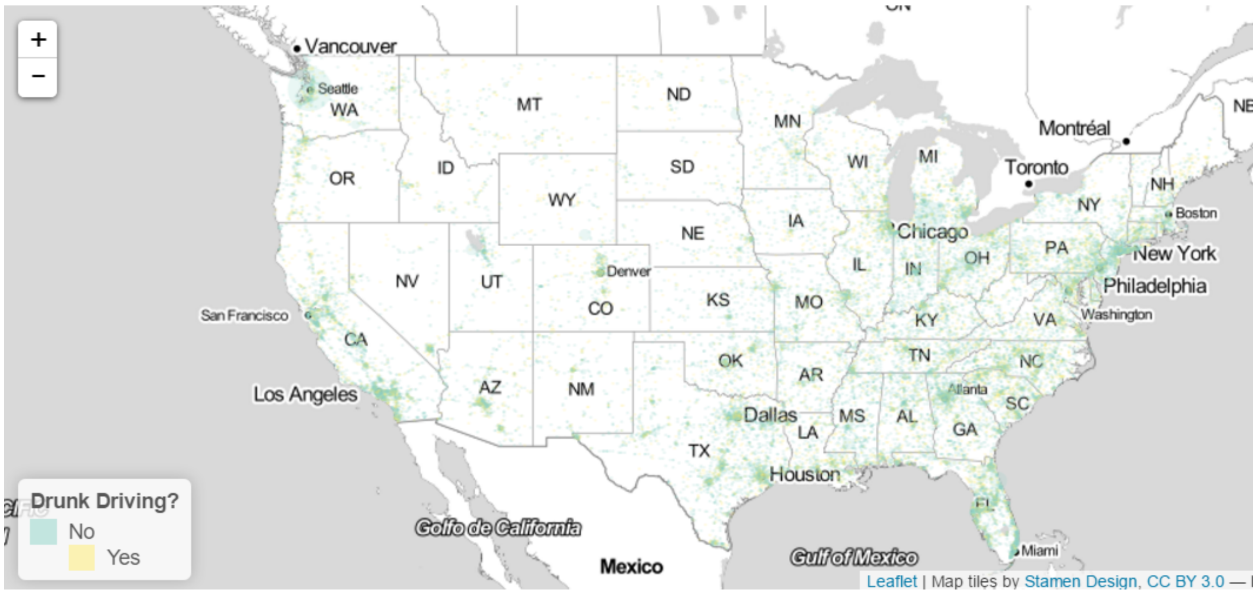


Figure 5: Marker map - Marker size based on number of people involved

Choropleth Map 1

The second of the three components was a choropleth map. The primary use of this component is to see how fatal traffic accidents involving drunk drivers varies from county to county and to explore possible relationships between drunk driving and other predictors. The user could select they wanted a state or a county level choropleth map. The user could also select whether they wanted the choropleth to be based on raw count of accidents or number of accidents per 100,000. Other features include selecting whether the data contained all accidents or only those involving drunk driver; whether to include accidents occurring during the weekend, the weekday, or both; and whether to include accidents occurring during the night, the day, or both. A convenient feature of the second component of the shiny app is that it allows the users to zoom in on states they wish to explore further.

Displayed below is a county level choropleth map of the number of fatal accidents involving drunk drivers per 100,000 inhabitants. This was to normalize for population as the larger counties are expected to have larger raw counts. The darker the green the higher the rate of fatal accidents involving a drunk driver in that county.

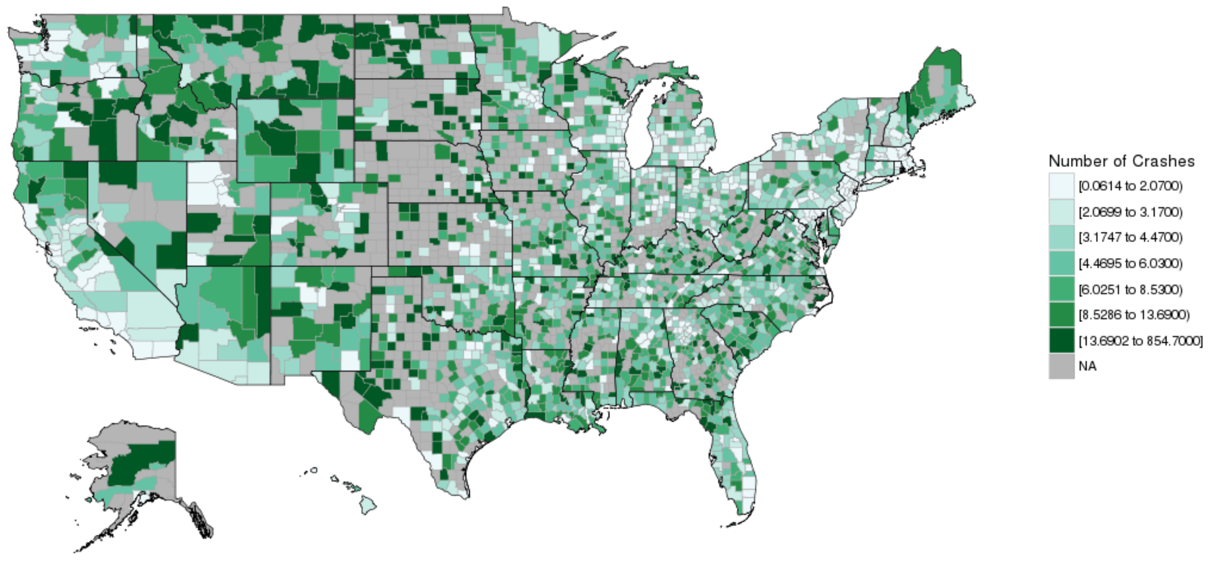


Figure 6: Number of Fatal Accidents Involving Drunk Driver per 100,000 people - County Level

The visual above confirms that fatal accidents involving drunk drivers is not uniformly distributed. It seems that counties with large populations (and therefore more raw accidents) seem to have more stable and lower rates of fatal accidents involving drunk drivers. This display also serves to point out the counties and regions with abnormally high rates of fatal traffic accidents involving drunk drivers. In particular, the Mountain West region seems to have the highest share of counties that are very green (and so have the largest rates of accidents involving drunk drivers).

The state level display confirms that the Mountain West region has high rates of accidents involving drunk drivers. In addition, the states in the South also seem to have relatively high rates of accidents involving drunk drivers. The Mountain Northwest and the South regions happens to be two of the poorer and less populated regions of America. This indicates that perhaps population and some measure of income at the county or state level could be valuable predictors for whether a driving involved in an accident was drunk or not.

The last component of the shiny app will be discussed after our algorithmic/model analysis.

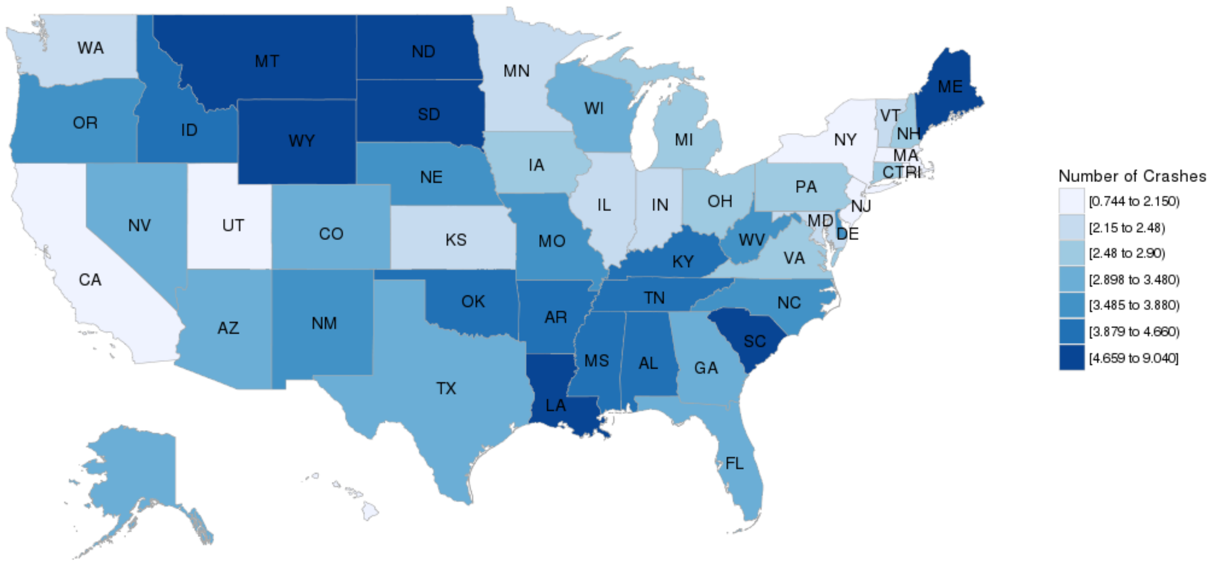


Figure 7: Number of Fatal Accidents Involving Drunk Driver per 100,000 people - State Level

```
#options(warn = -1)
set.seed(495)
load("FinalDataUpdate.Rda")
n <- nrow(Update1)
shuffled <- Update1[sample(n),]
train <- shuffled[1:round(0.7 * n),]
test <- shuffled[(round(0.7 * n) + 1):n,]
```

Data Modeling (Logistic and Random Forest)

Logistic Regression Conditions Assessment

Binary dependent response variable (drunk or not drunk) was used, which satisfies the condition that response variable be dichotomous for binary logistic regression. A correlation matrix was used to assess whether the quantitative explanatory variables (Age, PrevSuspensions, PrevDWIConvictions, NumFatalities, IncomeToPovRatio and TotalPopulation) were independent or had some underlying unaccounted dependence structure. As the correlation matrix shows below, there does not appear to be much correlation between the explanatory predictors aside from the correlation between total population and income to poverty ratio variables, which seems understandable given that a county with a high total population may have a high income to poverty ratio. Therefore the explanatory predictors mostly satisfied the independence assumption.

```
modelAssess <- Update1 %>% dplyr::select(Age, PrevSuspensions, PrevDWIConvictions,
                                         NumFatalities, IncomeToPovRatio, TotalPopulation)
modelAssess$NumFatalities <- as.numeric(modelAssess$NumFatalities)
modelAssess <- modelAssess %>% rename(PreDWI = PrevDWIConvictions)
modelAssess <- modelAssess %>% rename(PreSusp = PrevSuspensions)
modelAssess <- modelAssess %>% rename(NumFatal = NumFatalities)
modelAssess <- modelAssess %>% rename(TotalPop = TotalPopulation)

corTable <- cor(modelAssess)
```

```r
print(xtable(corTable, caption =
              'Assessing Independence Assumption',
             caption.placement = 'top', scalebox='0.75'))
```

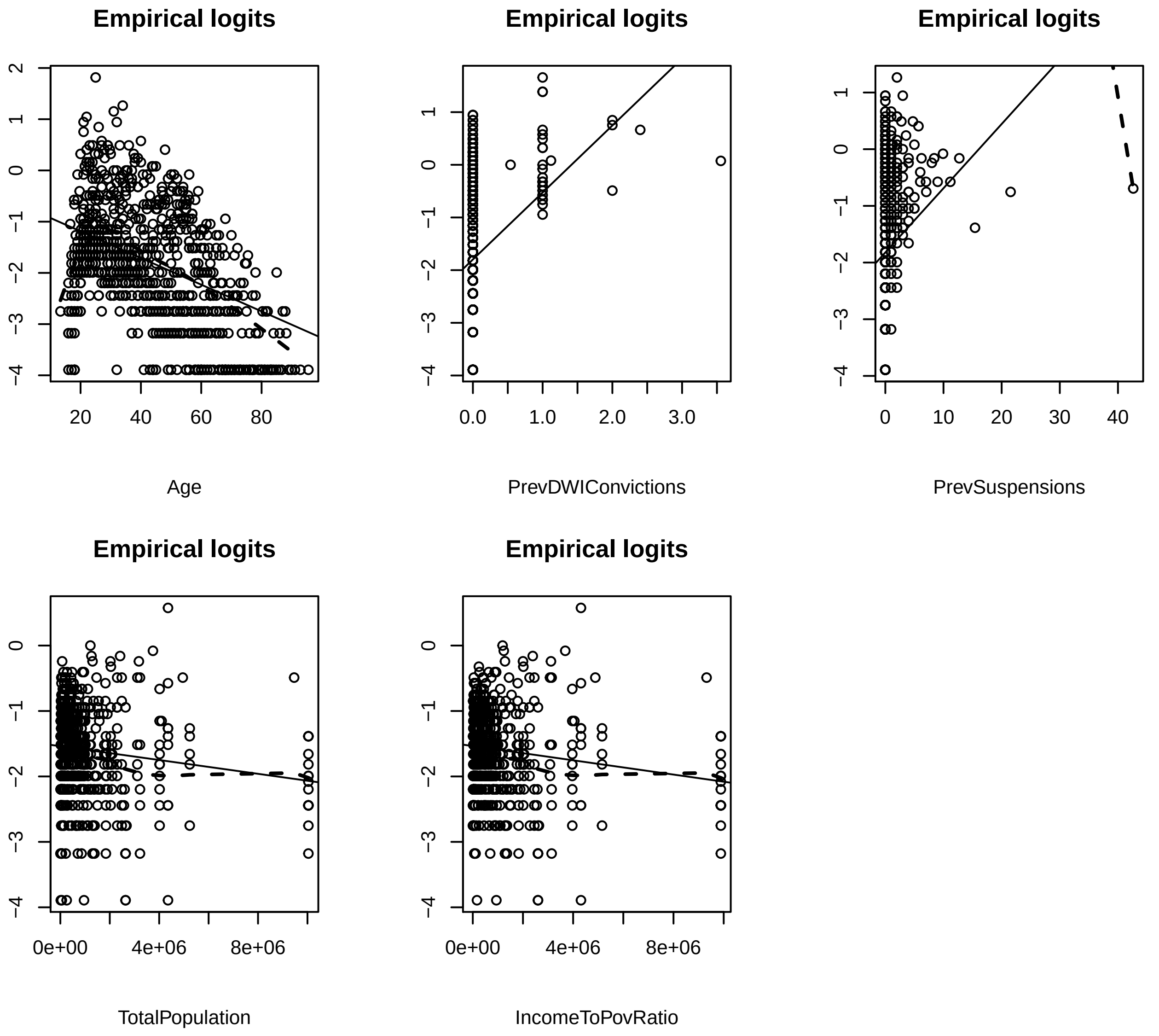
	Age	PreSusp	PreDWI	NumFatal	IncomeToPovRatio	TotalPop
Age	1.00	-0.10	-0.06	-0.03	-0.05	-0.05
PreSusp	-0.10	1.00	0.23	-0.00	0.02	0.02
PreDWI	-0.06	0.23	1.00	-0.00	-0.02	-0.02
NumFatal	-0.03	-0.00	-0.00	1.00	-0.02	-0.02
IncomeToPovRatio	-0.05	0.02	-0.02	-0.02	1.00	1.00
TotalPop	-0.05	0.02	-0.02	-0.02	1.00	1.00

Table 1: Assessing Independence Assumption

Note: In the table above: PreDWI = PreDWIConvictions, PreSusp = PrevSuspensions, NumFatal = NumFatalities and TotalPop = TotalPopulation.

Next we assessed the linearity assumption of logistic regression. Linearity assumption was satisfied for binary predictors like Sex, WeekdayStatus and DayStatus. For quantitative predictors, empirical logit plots were used to assess linearity. As the plots show, linearity assumption is mostly satisfied for these predictors. PrevDWIConvictions and PrevSuspensions predictors show some deviation from normality though the deviation is not especially great.

```r
emplogit = function(x, y, binsize = NULL, ci = FALSE, probit = FALSE,
                    prob = FALSE, main = NULL, xlab = "", ylab = ""){
  if (length(x) != length(y))
    stop("x and y lengths differ")
  if (any(y < 0 | y > 1))
    stop("y not between 0 and 1")
  if (length(x) < 100 & is.null(binsize))
    stop("Less than 100 observations: specify binsize manually")

  if (is.null(binsize)) binsize = min(round(length(x)/10), 50)

  if (probit){
    link = qnorm
    if (is.null(main)) main = "Empirical probits"
  } else {
    link = function(x) log(x/(1-x))
    if (is.null(main)) main = "Empirical logits"
  }

  sort = order(x)
  x = x[sort]
  y = y[sort]
  a = seq(1, length(x), by=binsize)
  b = c(a[-1] - 1, length(x))

  prob = xmean = ns = rep(0, length(a)) # ns is for CIs
  for (i in 1:length(a)){
    range = (a[i]):(b[i])
    prob[i] = mean(y[range])
    xmean[i] = mean(x[range])
    ns[i] = b[i] - a[i] + 1 # for CI
  }

  extreme = (prob == 1 | prob == 0)
  prob[prob == 0] = min(prob[!extreme])
  prob[prob == 1] = max(prob[!extreme])

  g = link(prob) # logits (or probits if probit == TRUE)

  linear.fit = lm(g[!extreme] ~ xmean[!extreme])
  b0 = linear.fit$coef[1]
  b1 = linear.fit$coef[2]

  loess.fit = loess(g[!extreme] ~ xmean[!extreme])

    plot(xmean, g, main=main, xlab=xlab, ylab=ylab)
    abline(b0,b1)
    lines(loess.fit$x, loess.fit$fitted, lwd=2, lty=2)
}

FinalData <- Update1
par(mfrow=c(2,3))
FinalData$DriverDrinking <- as.numeric(FinalData$DriverDrinking)
FinalData$DriverDrinking <- as.numeric(FinalData$DriverDrinking)
FinalData$DriverDrinking[FinalData$DriverDrinking == 1] <- 0
FinalData$DriverDrinking[FinalData$DriverDrinking == 2] <- 1

emplogit(FinalData$Age, FinalData$DriverDrinking)
title(sub = "Age")
emplogit(FinalData$PrevDWIConvictions, FinalData$DriverDrinking)
title(sub = "PrevDWIConvictions")
emplogit(FinalData$PrevSuspensions, FinalData$DriverDrinking)
title(sub = "PrevSuspensions")
emplogit(FinalData$TotalPopulation, FinalData$DriverDrinking)
title(sub = "TotalPopulation")
emplogit(FinalData$IncomeToPovRatio, FinalData$DriverDrinking)
title(sub = "IncomeToPovRatio")
```



Lastly, logistic regression also demands independence between observations. Given that we are incorporating county level data, it may be the case that drivers from a particular county may have similar driving and drunk driving experience based on the rules and regulations enforced by that county. Therefore some correlation at the county level may be present, which our model does not fully account for (see the Limitations and Future Work section for further explication on the issue).

Test and Training Sets

The dataset was then split in test and training sets with a 70/30 split (70% data in training and 30% in test set) where the training set had 27,214 observations while the test set had 11,663 observations. Logistic regression was used first to assess whether drunk driving incidence can be predicted by the above mentioned predictors followed by random forest. Both models were built on the training data and then assessed on the test data via accuracy.

Results and Model Analysis

Predictors associated with increased drunk driving incidence Predictors accounting for the driver's previous suspensions and revocations, previous DWI convictions, number of fatalities in the accident, the day of the crash being a weekend and time being night and total population all increase the odds of a driver being drunk.

Exponential of the coefficient estimates was assessed in the column labeled ExpEstimate (since logistic model is used, exponentiating the coefficients allows for a more intuitive interpretation). The coefficient for PrevSuspensions indicates that holding other variables constant, the odds of a driver involved in a fatal accident being drunk increase by 4% given an increase in the previous suspension record by one. Coefficient for PreDWIConvictions indicates that an increase in the previous DWI convictions by one produces an increase in the odds of the driver being drunk by about 174% holding other variables fixed.

In regards to accident and county level attributes, increase in number of fatalities by one inceases the odds of a driver involved in fatal accident being drunk by about 2%. If the day of crash is a weekend, then there is about a 96% increase in odds of a drunk driver incidence in comparison to if the crash occurred on a weekday. If the time occurred during night, then there is about a 301% odds increase of the driver being drunk than if the crash occurred during the day. Lastly the odds of a drunk driver increase by about 0.38% given a one thousand unit increase in the total population holding other variables fixed.

Predictors associated with decreased drunk driving incidence Predictors like the driver's sex, age, history of previous speeding suspensions, number of fatalities and income to poverty ratio all decreased the odds of a driver being drunk.

The coefficient for Sex indicates that holding other variables constant, if the driver is female, then there is about a 44% decrease in odds of a driver being drunk than if the driver was a male. Age indicates that the odds of a driver being drunk are about 2% lower given a one year increase in age. Lastly an increase in income to poverty ratio of one thousand is associated with a .4% decrease in odds of the driver being drunk.

```r
logmodnew <- glm(formula = DriverDrinking ~ Sex + Age + PrevSuspensions +
                PrevDWIConvictions + NumFatalities + WeekdayStatus + DayStatus +
                IncomeToPovRatio + TotalPopulation,
              family=binomial(link='logit'), data = train)
#save(logmodnew, file = "logisticmodFinal.Rda")
logmod <- logmodnew
logTable <- tidy(logmod)
logTable <- logTable %>% mutate(ExpEstimate = exp(estimate)) %>%
  dplyr::select(term, estimate, ExpEstimate, std.error, p.value) %>%
  rename(Estimate = estimate, Term = term,
         StdError = std.error, PValue = p.value)
#logTable  #added exponentiated estimate column in the model summary
print(xtable(logTable, caption =
               'Logistic Regression with Exponentiated Estimates'
             ,caption.placement = 'top'))
```

Logistic Regression Model Accuracy

Logistic regression was assessed with model accuracy. Cross validation with k = 20 (data is iteratively split in training and test sets 100 times and accuracy is computed and averaged) was used. The accuracy from cross validation was about about 0.82. Given the noisiness in the data, a 0.82 accuracy shows that our model performs very well.

```r
#Cross-validation for model assessment
dat <- FinalData
k <- 20
acc <- NULL
```

	Term	Estimate	ExpEstimate	StdError	PValue
1	(Intercept)	-1.88	0.15	0.07	0.00
2	SexFemale	-0.58	0.56	0.04	0.00
3	Age	-0.02	0.98	0.00	0.00
4	PrevSuspensions	0.04	1.04	0.01	0.00
5	PrevDWIConvictions	1.01	2.74	0.06	0.00
6	NumFatalities	0.02	1.02	0.04	0.70
7	WeekdayStatusWeekend	0.67	1.96	0.03	0.00
8	DayStatusNight	1.39	4.01	0.04	0.00
9	IncomeToPovRatio	-0.00	1.00	0.00	0.11
10	TotalPopulation	0.00	1.00	0.00	0.12

Table 2: Logistic Regression with Exponentiated Estimates

```r
set.seed(123)

for(i in 1:k)
{
  smp_size <- floor(0.70 * nrow(dat))
  index <- sample(seq_len(nrow(dat)),size=smp_size)
  train <- dat[index, ]
  test <- dat[-index, ]
  model <- glm(formula = DriverDrinking ~ Sex + Age + PrevSuspensions +
                 PrevDWIConvictions + NumFatalities + WeekdayStatus +
                 DayStatus + IncomeToPovRatio + TotalPopulation,
               family=binomial(link='logit'), data = train)
  results_prob <- predict(model,newdata=test,type='response')
  results <- ifelse(results_prob > 0.5,1,0)
  answers <- test$DriverDrinking
  misClasificError <- mean(answers != results)
  acc[i] <- 1-misClasificError
}
LogisticAcc <- mean(acc)
#save(LogisticAcc, file = "LogisticAcc.Rda")
```

```r
meanAccuracyLog <- load("LogisticAcc.Rda")
print(LogisticAcc)
```

```
## [1] 0.8192473
```

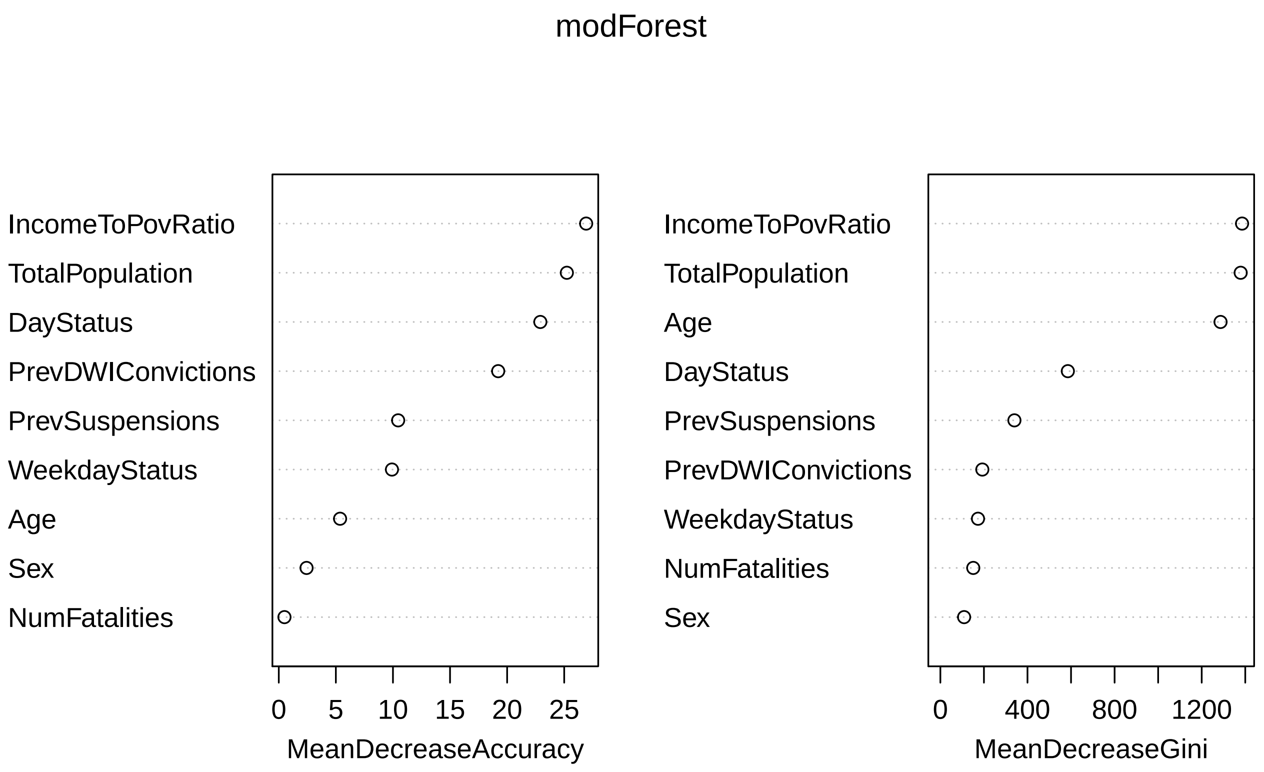
Random Forest

Variable Importance In addition to logistic regression, random forest was built to assess variable importance. Random forest is an ensemble modeling approach where output from many bootstrapped decision trees is aggregated to provide an estimate. About 50 trees were grown for the random forest model and the same predictors were regressed to predict drunk driving incidence as used for the logistic regression (Sex, Age, PrevDWIConvictions, PrevSuspensions, NumFatalities, WeekdayStatus, DayStatus, TotalPopulation, IncomeToPovRatio).

Variable importance plot was constructed to assess which features are highly predictive in forecasting drunk driving incidence. Mean decrease in accuracy and mean decrease in gini index (measure of the model misclassification rate) were used to assess importance. County level income to poverty ratio was the most important predictor according to the mean decrease accuracy index which means that exclusion of this predictor from the model would result in the highest decrease in accuracy. In comparison, total population was the most important predictor according to the mean decrease gini index indicating that total population results in the highest node purity, which signifies a low rate of misclassifying the driver as drunk. Additionally day status and previous driving suspension history were the next important predictors according to both the mean decrease accuracy and the mean decrease gini indices.

Least important predictors in predicting the drunk driving incident included the driver's sex and number of fatalities according to both mean decrease accuracy and mean decrease gini indices. Weekday status also does not appear to be a very informative predictor in predicting drunk driving incidence.

```r
set.seed(1000)
train$DriverDrinking <- as.factor(train$DriverDrinking)
modForest <- randomForest(DriverDrinking ~ Sex + Age + PrevSuspensions +
                          PrevDWIConvictions + NumFatalities + WeekdayStatus +
                          DayStatus + IncomeToPovRatio + TotalPopulation,
                          data = train, ntree = 50, mtry = 4,
                          keep.forest = TRUE, importance = TRUE)
#save(modForest, file = "modForest.Rda")
#Importance plots
varImpPlot(modForest)
```



Random Forest Model Assessment

Random forest model was assessed with accuracy validated through cross-validation. K value of 20 was specified in cross-validation, indicating that the data was split in a test and training set 20 times and accuracy was calculated each time, producing an aggregate estimate of accuracy of about 0.80. Again, given the noisiness in the data, a 0.80 accuracy shows that our random forest performs very well. The logistic regression model and the random forest are about the same in terms of accuracy.

```r
dat <- FinalData
k <- 20
acc2 <- NULL
set.seed(123)
for(i in 1:k)
{
  smp_size <- floor(0.70 * nrow(dat))
  index <- sample(seq_len(nrow(dat)),size=smp_size)
  train <- dat[index, ]
  test <- dat[-index, ]
  modForest1 <- randomForest(DriverDrinking ~ Sex + Age + PrevSuspensions +
                             PrevDWIConvictions + NumFatalities + WeekdayStatus +
                            DayStatus + IncomeToPovRatio + TotalPopulation,
                            data = train, ntree = 25, mtry = 4,
                            keep.forest = TRUE, importance = FALSE)
  conf <- modForest1$confusion
  acc2[i] <- (sum(diag(conf)) / sum(conf))
}
meanRandom <- mean(acc2)
#save(meanRandom, file = "meanRandom.Rda")
```

```r
meanAccuracy <- load("meanRandom.Rda")
print(meanRandom)
```

```
## [1] 0.8030427
```

Discussion

According to the results above, county level predictors like income to poverty ratio in the past 12 months and total population appear to be the most important predictors in predicting whether or not the driver is drunk. In regards to county level predictors, a more affluent county as indicated by a high income to poverty ratio may be more able to purchase and consume alcohol. High total population may be a confounding variable since there might naturally be an increase in the number of accidents as the population increases, irrelevant to the driver's drinking status. Additionally day status predictor is important, which seems intuitive since alcohol consumption typically occurs at night, resulting in increased drunk driving incidence during the night. Previous suspensions and DWI convictions appear to be somewhat important in predicting drunk driving incidence.

Driver's sex does not appear to be relevant in predicting drunk driving incidence although being male is listed as a risk factor of drunk driving by the CDC. Age does however seem to important to both models (according to p value and gini index). We believe that age is an important individual level risk factor for drunk driving (although this has been well documented). Number of fatalities is not an important variable indicating that the intensity of the crash as measured by the number of deaths in an accident does not predict the drunk driving incidence.

Model Assessment Using Visualization

The third component of the shiny app was another choropleth map. For this map, the focus shifted from data exploration to model assessment. For each county, the actual number of drunk drivers who were in a fatal traffic accident in 2015 was aggreated. Using the models, we also calculated the expected such drivers. The user can toggle between the logistic regression model and the random forest. In addition, the choropleth map can display the actual number of drunk drivers, the expected number, the difference between the numbers (actual - expected), and a scaled difference ([actual - expected]/actual). Using this interactive map, the user can easily visualize how the model performed in each county.

Displayed below are the choropleth maps for both the logistic regression model and the random forest with the scaled difference statistic.

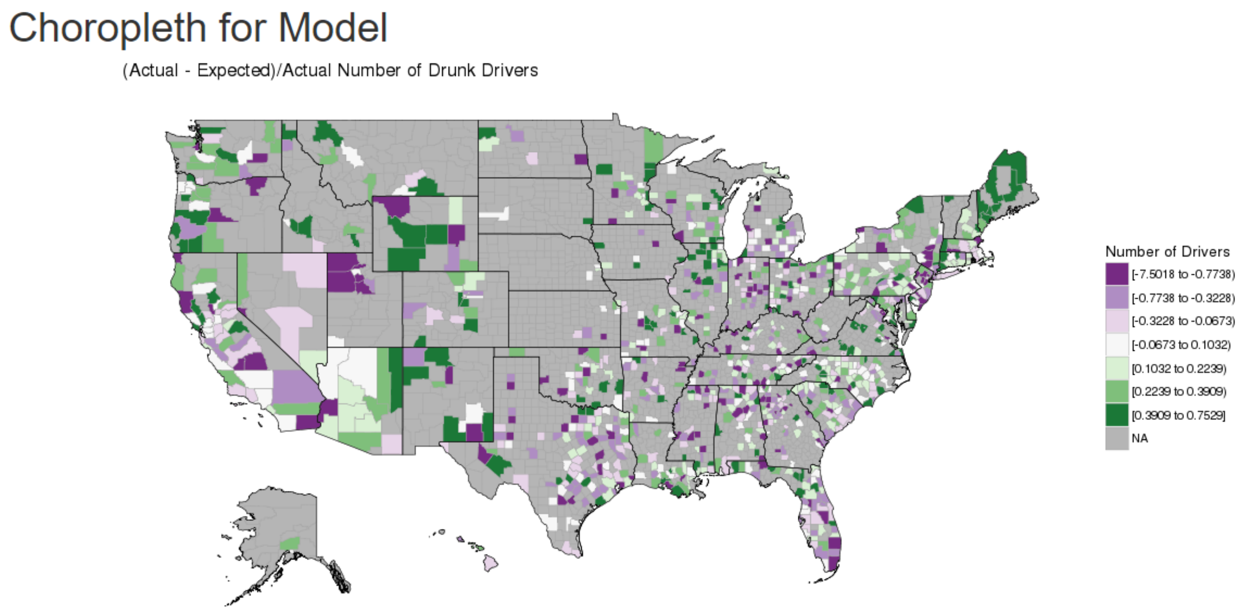


Figure 8: Scaled Difference - Logistic Regression

A quick scan at the two choropleth maps show that overall, the logistic regression model and the random forest perform similarly across counties. If the county is dark to medium purple than the model overestimated in that county. If the county is a very faint purple or white, the model estimated almost correctly within that county. And if the county is green, the model underestimated in the county. Based on the scale of the choropleth plots, the number of counties that were underestimated the models is larger than the number of counties that were overestimated by the models.

With the exception of just a few counties, if one model overpredicted than the other one did as well and if one model underpredicted than the other one did as well. There is not an obvious pattern of the magnitude or direction of the errors. In certain large metropolitan areas like Atlanta, both models seemed to overestimate, and in others like Chicago, both models underestimated. In addition, there is a healthy smattering of green, purple, and white all across the map. Although, both models underestimate the actual values more than they should, the lack of geographic pattern in the magnitude/direction of the errors affirms our earlier assessment that the models have good predictive value.

Limitations and Future Work

There are a few important limitations to our work. First, the FARS dataset only accounts for accidents leading to fatalities. So our models are technically predicting whether a driver involved in a fatal accident was drunk or not. The models may lose predictive value if used to determine drunk driving incidence for a driver involved in any accident (not necessarily one that involved a fatality). Second, we do not believe that observations in our dataset are independent from each other. As we noticed, there was a large difference in rates of drunk driving between certain counties. This indicates that there is some county level effect with a high chance of correlation between county level observations. This is a violation of the assumptions of logistic regression. In the future, generalized estimating equations (GEE) can be used to address this violation.

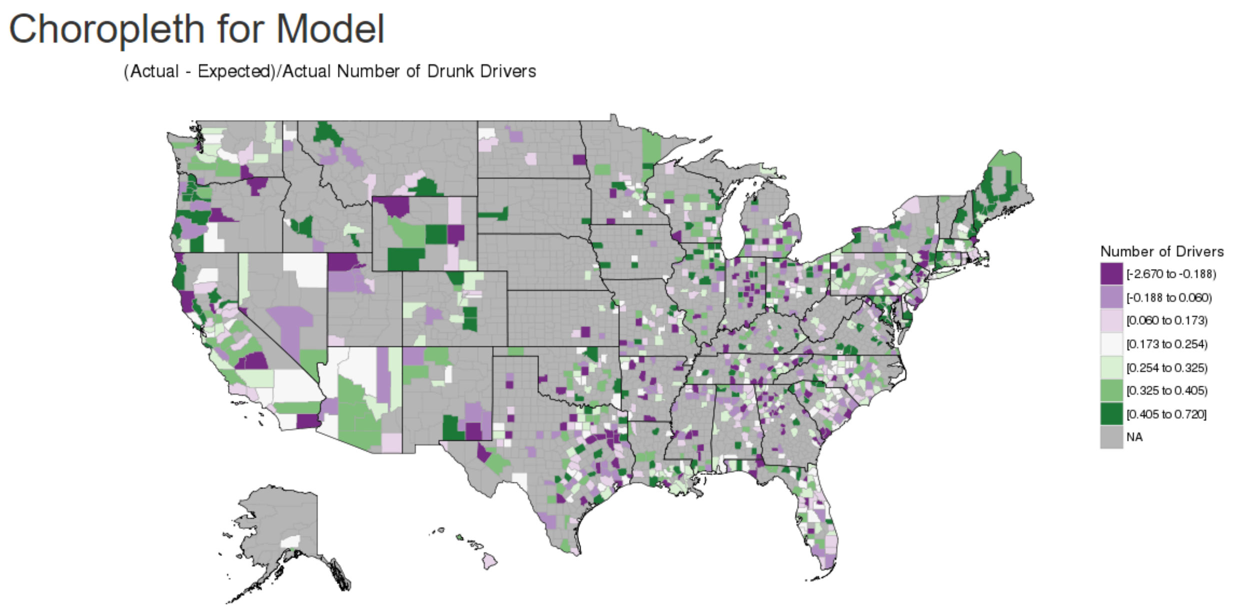


Figure 9: Scaled Difference - Random Forest

There are several natural extensions of this project that can be taken. Due to computational constraints we only included data from the year 2015 in our current analysis but would like to include additional years in consideration. Cross-validation would have been exponentially more taxing by adding several thousand more observations. Since we only included observations from counties where there were at least 10 fatal accidents, by adding more observations from different years, more counties could have been included in the analysis. The choropleth maps in the shiny app suffered as a result of many counties not hitting the 10 accident benchmark required. Additionally, a different set of questions could have been answered by adding more years. For example, as indicated in the motivation/introduction section, there was an increase in the number of fatal traffic accidents (both overall and alcohol induced). By adding more years, one could try to ascertain why 2015 saw an increase in fatal accidents when previous years observed a decrease.

In our current model, we aggregated individual level driver attributes like age and sex to allow for modeling the county level estimates. Future exploration could include analyzing how the model estimates change if the data is only fit at a county level instead of an aggregation from an individual level.

Summary and Takeaway

In summary, our study aims to predict drunk driving incidence based on individual level attributes like the driver's sex, age and previous DWI convictions and driving suspensions, accident level factors like number of fatalities in the crash as well as the day of week and time of day of the accident and county level attributes like the total population and the income to poverty level ratio. We use Google BigQuery as a platform for housing our data as well as for performing the initial table joins. Logistic regression and random forest is then used to predict a driver's drunk driving incidence (whether the driver involved in a fatal accident is drunk or not) based on these features.

We concluded that fatal traffic accidents involving drunk drivers are likely to occur at night and on weekends. In addition, we find that being young, having previous DWI convictions, and having previous driving suspensions are important personal level risk factors for drunk driving. Although much of what we learned is common knowledge, there are still some important novel takeaways from this project. With our results, we believe that risk factors at the county level (high population and low income to poverty ratio) are very important to predicting who is drunk driving or not than individual level risk factors (and maybe even more so). Also, sex is perhaps not as good of a predictor of drunk driving incidence in fatal traffic accidents as it is believed to be. In the future, this project could lead to policy implementations to address disparities in the number of fatal accidents caused by drunk driving. Government interventions can include educating the general public about safe driving habits as well as allocating specific amounts of budget to a county to aim to reduce the number of fatal crash incidents inspired by drunk driving.

Technical Appendix

```
####Creating the ACS dataset && wrangling
data("fips.state")
data("fips.county")

######Pulling in population data
mygeo <- geo.make(state = "*", county = "*")
pop <- acs.fetch(endyear=2015, geography = mygeo,
                table.number = "B01003",
                key = "3dbabece4401ad72afa36a118e2cf777efa2afb3")
countypop <- as.data.frame(estimate(pop))
countypopT <- setDT(countypop, keep.rownames = TRUE)[]
countypopT <- countypopT %>% rename(StateCounty = rn) %>%
  mutate(StateCounty = as.factor(StateCounty))
levels(countypopT$StateCounty)[levels(countypopT$StateCounty)
                               =="Doña Ana County, New Mexico"] <- "Dona Ana County,
                                                                     New Mexico"

countypopT <- countypopT %>%
  separate(StateCounty, c("County.Name", "STATE_NAME"), ", ") %>%
  mutate(STATE_NAME = as.factor(STATE_NAME))

#merge county and state data
fips.state <- fips.state %>% mutate(STATE_NAME = as.factor(STATE_NAME)) %>%
  rename(State = STUSAB)

#joinedData merge state and county by state
joinedData <- right_join(fips.state, fips.county, by = "State")
joinedData <- joinedData %>% mutate(County.Name = as.factor(County.Name))
countypopT <- countypopT %>% mutate(County.Name = as.factor(County.Name))

FinalPop <- inner_join(joinedData, countypopT, by = c("County.Name", "STATE_NAME")) %>%
  mutate(FIPSCode = ((1000*State.ANSI) + County.ANSI)) #find fips encoding

#####Pulling in Poverty to Income ratio data
income <- acs.fetch(endyear=2015, geography = mygeo,
                table.number = "C17002",
                key = "3dbabece4401ad72afa36a118e2cf777efa2afb3")

income <- as.data.frame(estimate(income))
income <- income %>% dplyr::select(C17002_001)
incomeT <- setDT(income, keep.rownames = TRUE)[]
incomeT <- incomeT %>% rename(StateCounty = rn) %>%
  mutate(StateCounty = as.factor(StateCounty))
```

```r
levels(incomeT$StateCounty)[levels(incomeT$StateCounty)
                              =="Doña Ana County, New Mexico"] <- "Dona Ana County,
                                                                     New Mexico"

incomeT <- incomeT %>%
  separate(StateCounty, c("County.Name", "STATE_NAME"), ", ") %>%
  mutate(STATE_NAME = as.factor(STATE_NAME), County.Name = as.factor(County.Name))

FinalIncome <- inner_join(joinedData, incomeT, by = c("County.Name", "STATE_NAME")) %>%
  mutate(FIPSCode = ((1000*State.ANSI) + County.ANSI)) #find fips encoding


######Now merge FinalIncom1 and FinalPop1 by FipsCode
FinalCensus <- inner_join(FinalIncome, FinalPop, by = "FIPSCode")
CensusFinalD1 <- FinalCensus %>% dplyr::select(FIPSCode, C17002_001, B01003_001)
#save(CensusFinalD1, file = "CensusFinalD1.Rda")
```

```r
####FARS Dataset wrangling
drivers <- read.csv("DriversData.csv") #only data for the drivers selected

#should get around 30000 observations: if more than person involved in an accident

drivers <- drivers %>% select(V_V_CONFIG, V_TRAV_SP, V_DEFORMED, V_DR_DRINK, V_PREV_ACC,
                              V_PREV_SUS, V_PREV_DWI, V_PREV_SPD, V_VALIGN, V_VPAVETYP,
                              V_VSURCOND, A_LGT_COND, A_FATALS, A_DRUNK_DR, A_WEATHER,
                              A_WEATHER1, A_WEATHER2, A_WRK_ZONE, A_MAN_COLL, P_AGE,
                              P_SEX, P_INJ_SEV, P_SEAT_POS, P_AIR_BAG, P_EJECTION,
                              P_EJ_PATH, P_DRINKING, P_DRUGS, P_LAG_HRS, P_DOA, A_COUNTY,
                              A_STATE, A_CITY, A_DAY_WEEK, A_HOUR)

#Counting the county frequency by fips code
drivers <- drivers %>% unique() %>%
  mutate(A_STATE = readr::parse_number(A_STATE),
         A_COUNTY = readr::parse_number(A_COUNTY)) %>%
  mutate(FIPSCode = ((1000*A_STATE) + A_COUNTY)) #fips code

countiesL <- tally(drivers$FIPSCode) #tally by FIPSCode
filtereddrivers <- data.frame(countiesL) %>%
  rename(FIPSCode = X) %>%
  mutate(FIPSCode = readr::parse_number(FIPSCode)) %>%
  right_join(drivers)

#create new variable here: only counties
filtereddrivers <- filtereddrivers %>%
  filter(Freq > 10) %>%
  mutate(P_SEX = as.factor(P_SEX), P_DRUGS = as.factor(P_DRUGS),
         P_DOA = as.factor(P_DOA), V_DR_DRINK = as.factor(V_DR_DRINK),
         A_STATE = as.factor(A_STATE), A_COUNTY = as.factor(A_COUNTY)) %>%
  rename(state = A_STATE, county = A_COUNTY) %>%
  mutate(TravSpeed = readr::parse_number(V_TRAV_SP),
         Age = readr::parse_number(P_AGE),
         PDWI = readr::parse_number(V_PREV_DWI),
         PSuspension = readr::parse_number(V_PREV_SUS),
         PCrash = readr::parse_number(V_PREV_ACC),
         PSpeed = readr::parse_number(V_PREV_SPD))

ACS <- load("CensusFinalD1.Rda")
FinalData <- CensusFinalD1 %>% mutate(FIPSCode = readr::parse_number(FIPSCode)) %>%
  right_join(filtereddrivers, by = "FIPSCode") #40422 observations
FinalData <- na.omit(FinalData)

FinalData <- FinalData %>%
  rename(IncomeToPovRatio = C17002_001, #Quant
         TotalPopulation = B01003_001, #Quant
         Sex = P_SEX, #Categorical
         PrevDWIConvictions = PDWI, #Quantitative
         PrevSpeeding = PSpeed, #Quantitative
         PrevSuspensions = PSuspension, #Quant
         VehicleSpeed = TravSpeed, #Quant
         ReportedDrugs = P_DRUGS, #Categorical
         NumFatalities = A_FATALS, #Quant
         DeathSceneStatus = P_DOA, #Categorical
         DriverDrinking = V_DR_DRINK) %>% #Categorical
  filter(Sex == '1' | Sex == '2')

FinalData$Sex <- droplevels(FinalData$Sex)
levels(FinalData$Sex) <- c("Male", "Female")

#Creating weekend/weekday predictor
FinalData <- FinalData %>%
  mutate(WeekdayStatus = ifelse(A_DAY_WEEK == '1' | A_DAY_WEEK == '7',
                                "Weekend", "Weekday"))
FinalData$WeekdayStatus <- as.factor(FinalData$WeekdayStatus)

FinalData <- FinalData %>%
  mutate(DayStatus = ifelse(A_HOUR < 6 | A_HOUR >= 18, "Night", "Day"))
FinalData$DayStatus <- as.factor(FinalData$DayStatus)

FinalData <- FinalData %>% filter(Age < 99)
FinalData <- FinalData %>% filter(PrevDWIConvictions < 99)
FinalData <- FinalData %>% filter(PrevSuspensions < 99)
save(FinalData, file = "FinalDataDec22.Rda")
```