Final Write-Up

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Introduction

In 2015, 35092 people died in motor vehicle accidents according to the National Highway Traffic Safety Association (NHTSA). This is increase of 2348 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. The CDC reports that around 31% of traffic fatalities include a drunk driver and that alcohol impaired vehicle accidents costs around $44 billion.

Identifying the risk factors and the behavior of drunk drivers could go a long way in reducing drunk driving. Knowing who is more likely to drunk drive gives information about who to target with intervention methods. In addition, if we are able to identify the times that driver are more likely to be drunk, the general public could be informed (e.g. if there are more alcohol immpaired drivers during weekends, the general public should be aware and would then be able to be more viligant while driving during the weekend).

Furthermore, although the dangers of and facts concerning drunk driving are well documented, the known risk factors are generally only known at the individual level. What we mean is that 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. The difference between the two counties is massive. But what makes Fremont County so different from Wyoming? Why is the rate of traffic fatalities including drunk drivers much higher in county than in another? What economic and demographic differences of the two counties explain why?

Determining the factors that could help explain the discrepancy in the rates of fatal traffic accidents involving a drunk driver could pinpoint the risk factors of drunk driving at the county level. This in turn would indicate which geographic areas would benefit the most from different types of intervention.

For our project we are looking to determine what predictors/factors at the individual and county level are good predictors for whether a driver involved in a fatal traffic accident was alcohol impaired or not. In addition we would also like to see what behaviors are good predictors as well. Specifically, if a fatal accident occurs during the night or the weekend, is it more likely that the drivers were drinking?

Data

In order to answer our questions we used data from two different sources. The first and primary source of data came from the Fatality Accident Report Service (FARS) managed by the 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 as a service is an analytics warehouse with the ability to process data on the petabyte scale. It provides a serverless and infrastructure-less environment since it deviates the need of a database administrator given that the data is processed and stored on the cloud. 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 Person, Vehicle and Accident 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. Data can be uploaded in BigQuery by first creating a project from the ProjectsPage and enable billing as well as the BigQuery API. Once a project has been created, it can be selected on the Google BigQuery platform and 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 the data types for each variable. The variable names and data types should match the original file that is being exported to BigQuery. Once the data is exported in a table, it can be previewed and queried through the 'compose query tab' on the left. Tables can additionally be joined given specification of a unique key. Past query and job history can be viewed on the left.

After the data is queried, the resulting dataset can be exported out to the Cloud. This export can be achieved by first creating a bucket from the Cloud console. Buckets can be created by selecting the Storage option from the tabbed main Cloud Platform console page. After a bucket is created, the queried data can be exported to that bucket with file name and format specified.

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, drug use and death scence status. 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. 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, previous speeding convictions and suspensions and revocations (PrevDWIConvictions, PrevSpeeding, PrevSuspensions), driver's police reported drug use and death scene status (ReportedDrugs, DeathSceneStatus), vehicle level attributes like speed before crash (VehicleSpeed), accident level atributes like number of fatalities, weekday status and say 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).

Results/Analysis

The dataset was then split in test and training sets with a 70/30 split (70% data in training and 30% in test set). Logistic regression was used first to assess whether drunk driving incidence can be predicted by the above mentioned predictors.

Predictors associated with increased drunk driving incidence

Predictors accounting for the driver's previous suspensions and revocations, previous DWI convictions, previous speeding convictions, reported drug use, vehicle speed, death enroute to a medical facility, weekend, nighttime and total population all increased the odds of driver being drunk.

The coefficient for PrevSuspensions indicates that holding other variables constant, the odds of a driver involved in a fatal accident being drunk increase by 1.07 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 1.05 holding other variables fixed. In regards to police reported drug involvement, the odds of a driver being drunk given police reported drug use by the driver is about 2.32 higher than the odds of the driver being drunk given no police reported drug use. The odds of a driver being drunk are about 1.00 higher given a one unit increase in the vehicle speed holding other variables constant. There is about a 1.45 higher odds of a driver being drunk if the driver dies enroute to a medical facility than if the driver dies at scene of accident. If the day of crash is a weekend, then there is about a 1.93 odds of a drunk driver incidence in comparison to is the crash occurred on a weekday. If the time occurred during night, then there is about a 5.08 odds of the driver being drunk than if the crash occurred during the day. Lastly the odds of a drunk driver increase by about 1.00 given a one unit increase in the total population holding other variables fixed.

```r
data1 <- read.csv("DriversData.csv") #only data for the drivers selected

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

small <- data1 %>% 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)

filter <- unique(small)
small <- filter

#Counting the county frequency by fips code

small$A_STATE <- as.numeric(small$A_STATE)
small$A_COUNTY <- as.numeric(small$A_COUNTY)
small <- small %>% mutate(FIPSCode = ((1000*A_STATE) + A_COUNTY)) #fips code


countiesL <- tally(small$FIPSCode) #tally by FIPSCode
data4 <- data.frame(countiesL)
data6 <- rename(data4, FIPSCode = X)
data7 <- merge(data6, small)
data7 <- unique(data7)

#create new variable here: only counties
```

```
data8 <- data7 %>%
  filter(Freq > 10)

data8$P_SEX = as.factor(data8$P_SEX)
data8$P_DRUGS = as.factor(data8$P_DRUGS)
data8$P_DOA = as.factor(data8$P_DOA)
data8$V_DR_DRINK = as.factor(data8$V_DR_DRINK)

data8 <- rename(data8, state = A_STATE)
data8 <- rename(data8, county = A_COUNTY)
data8$state = as.factor(data8$state)
data8$county = as.factor(data8$county)

data8 <- data8 %>% mutate(TravSpeed = as.numeric(V_TRAV_SP),
                          Age = as.numeric(P_AGE),
                          PDWI = as.numeric(V_PREV_DWI),
                          PSuspension = as.numeric(V_PREV_SUS),
                          PCrash = as.numeric(V_PREV_ACC),
                          PSpeed = as.numeric(V_PREV_SPD))

data9 <- data8

ACS <- load("CensusFinalD1.Rda")
CensusFinalD1$FIPSCode <- as.factor(CensusFinalD1$FIPSCode)
FinalMerge2<- CensusFinalD1 %>% right_join(data9, by = "FIPSCode") #40422 observations
```

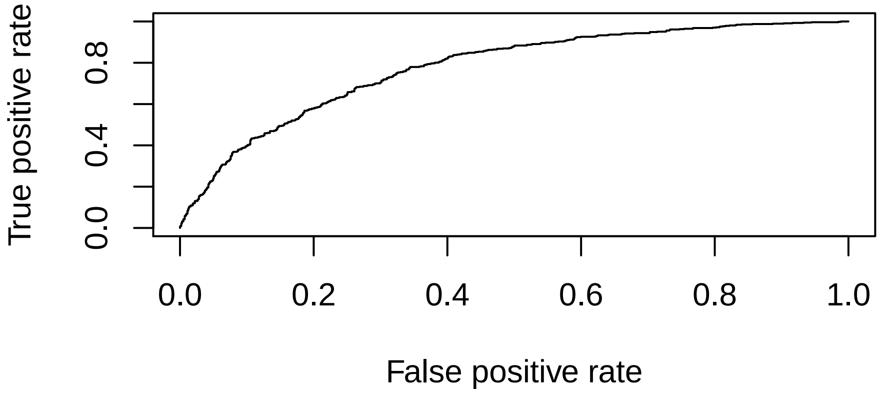
```
## Warning in right_join_impl(x, y, by$x, by$y, suffix$x, suffix$y): joining
## factors with different levels, coercing to character vector
```

```
FinalMerge2 <- na.omit(FinalMerge2)

########Build training and test models here
FinalMerge2 <- rename(FinalMerge2, IncomeToPovRatio = C17002_001) #Quant
FinalMerge2 <- rename(FinalMerge2, TotalPopulation = B01003_001) #Quant
FinalMerge2 <- rename(FinalMerge2, Sex = P_SEX) #Cat
FinalMerge2 <- rename(FinalMerge2, PrevDWIConvictions = PDWI) #Quantitative
FinalMerge2 <- rename(FinalMerge2, PrevSpeeding = PSpeed) #Quantitative
FinalMerge2 <- rename(FinalMerge2, PrevSuspensions = PSuspension) #Quant
FinalMerge2 <- rename(FinalMerge2, VehicleSpeed = TravSpeed) #Quant
FinalMerge2 <- rename(FinalMerge2, ReportedDrugs = P_DRUGS) #Cat
FinalMerge2 <- rename(FinalMerge2, NumFatalities = A_FATALS) #Quant
FinalMerge2 <- rename(FinalMerge2, DeathSceneStatus = P_DOA) #Cat
FinalMerge2 <- rename(FinalMerge2, DriverDrinking = V_DR_DRINK) #Cat

FinalMerge2 <- FinalMerge2 %>% filter(Sex == '1' | Sex == '2')
FinalMerge2$Sex <- droplevels(FinalMerge2$Sex)
levels(FinalMerge2$Sex) <- c("Male", "Female")

FinalMerge2 <- FinalMerge2 %>% filter(ReportedDrugs == '0' | ReportedDrugs == '1')
FinalMerge2$ReportedDrugs <- droplevels(FinalMerge2$ReportedDrugs)
levels(FinalMerge2$ReportedDrugs) <- c("No", "Yes")

FinalMerge2 <- FinalMerge2 %>% filter(DeathSceneStatus == '7' | DeathSceneStatus == '8')
```

```r
FinalMerge2$DeathSceneStatus <- droplevels(FinalMerge2$DeathSceneStatus)
levels(FinalMerge2$DeathSceneStatus) <- c("DiedAtScence", "DiedAtEnroute")

#Creating weekend/weekday predictor
FinalMerge2 <- FinalMerge2 %>%
  mutate(WeekdayStatus = ifelse(A_DAY_WEEK == '1' | A_DAY_WEEK == '7', "Weekend", "Weekday"))
FinalMerge2$WeekdayStatus <- as.factor(FinalMerge2$WeekdayStatus)

FinalMerge2 <- FinalMerge2 %>%
  mutate(DayStatus = ifelse(A_HOUR < 6 | A_HOUR > 18, "Night", "Day"))
FinalMerge2$DayStatus <- as.factor(FinalMerge2$DayStatus)

test <- FinalMerge2 %>% select(A_HOUR, DayStatus, A_DAY_WEEK, WeekdayStatus) #6908 observations in tota


#Creating training and test results
mergeData <- FinalMerge2
n <- nrow(mergeData)
shuffled <- mergeData[sample(n),]
train <- shuffled[1:round(0.7 * n),]
test <- shuffled[(round(0.7 * n) + 1):n,]

logmod <- glm(formula = DriverDrinking ~ Sex + Age + PrevSuspensions + PrevDWIConvictions + PrevSpeedin
              + ReportedDrugs + VehicleSpeed + DeathSceneStatus
              + NumFatalities + WeekdayStatus + DayStatus + IncomeToPovRatio + TotalPopulation,
              family=binomial(link='logit'), data = train)

logTable <- tidy(logmod)
logTable <- logTable %>% mutate(ExpEstimate = exp(estimate))
logTable <- logTable %>% dplyr::select(term, estimate, ExpEstimate, std.error, p.value)
logTable <- rename(logTable, Estimate = estimate)
logTable <- rename(logTable, Term = term)
logTable <- rename(logTable, StdError = std.error)
logTable <- rename(logTable, PValue = p.value)
logTable  #added exponentiated estimate column in the model summary
```

```
##                              Term      Estimate ExpEstimate     StdError
## 1                     (Intercept) -9.257775e-01   0.3962232 1.721147e-01
## 2                       SexFemale -4.309692e-01   0.6498789 9.835134e-02
## 3                             Age -1.580206e-02   0.9843221 2.433465e-03
## 4                 PrevSuspensions  3.948994e-02   1.0402800 1.937579e-02
## 5              PrevDWIConvictions  1.045708e-01   1.1102340 4.788995e-02
## 6                    PrevSpeeding -1.460204e-01   0.8641400 4.632500e-02
## 7                ReportedDrugsYes  8.686824e-01   2.3837679 9.957522e-02
## 8                    VehicleSpeed  9.869137e-05   1.0000987 8.451302e-05
## 9  DeathSceneStatusDiedAtEnroute  2.723390e-01   1.3130321 2.781458e-01
## 10                  NumFatalities -2.640409e-01   0.7679421 8.048599e-02
## 11           WeekdayStatusWeekend  7.113098e-01   2.0366572 8.110285e-02
## 12                 DayStatusNight  1.580983e+00   4.8597287 8.110198e-02
## 13               IncomeToPovRatio -1.582330e-05   0.9999842 6.383072e-06
## 14                TotalPopulation  1.557079e-05   1.0000156 6.291227e-06
##          PValue
## 1  7.496751e-08
## 2  1.176296e-05
## 3  8.378343e-11
## 4  4.153920e-02
## 5  2.899428e-02
## 6  1.621080e-03
## 7  2.688247e-18
## 8  2.429015e-01
## 9  3.275190e-01
## 10 1.035929e-03
## 11 1.779272e-18
## 12 1.240227e-84
## 13 1.317707e-02
## 14 1.332359e-02
```

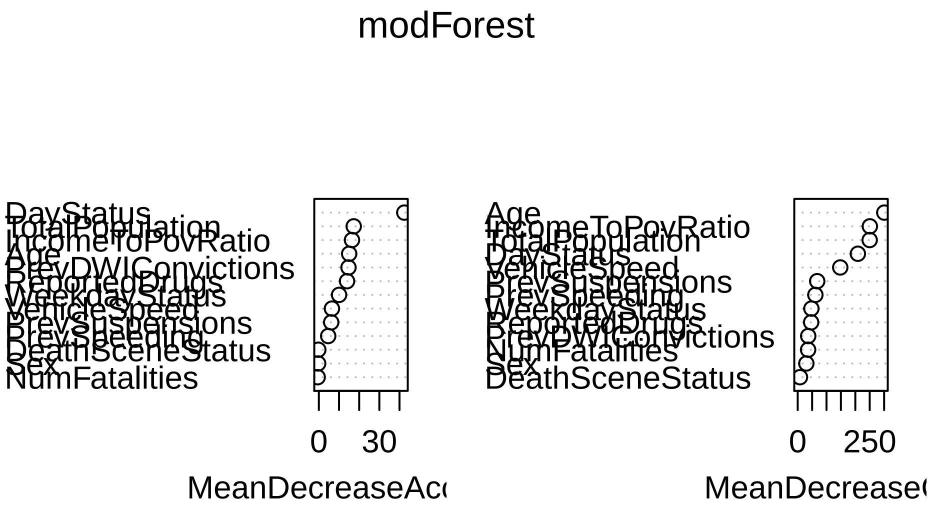
```r
prob <- predict(logmod, newdata=test, type="response")
pred <- prediction(prob, test$DriverDrinking)
perf <- performance(pred, measure = "tpr", x.measure = "fpr")
plot(perf)
```



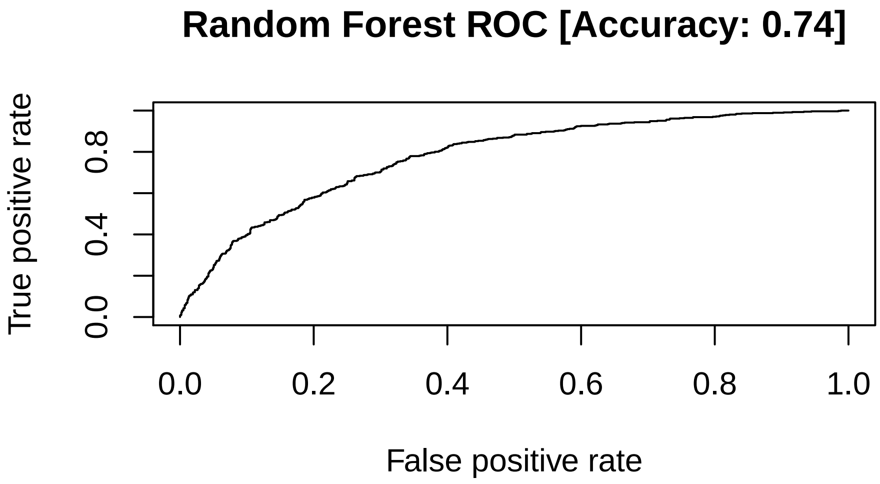
```r
#Accuracy assessment
auc <- performance(pred, measure = "auc")
auc <- auc@y.values[[1]]
auc #75% accurate
```

```
## [1] 0.777159
```

```r
set.seed(1000)
modForest <- randomForest(DriverDrinking ~ Sex + Age + PrevSuspensions + PrevDWIConvictions +
                          PrevSpeeding + ReportedDrugs + VehicleSpeed + DeathSceneStatus +
                          NumFatalities + WeekdayStatus + DayStatus + IncomeToPovRatio +
                          TotalPopulation, data = train, ntree = 100, mtry = 4,
                        keep.forest = FALSE, importance = TRUE)
#Importance plots
varImpPlot(modForest)
```



```
#Assessing model accuracy
modForest1 <- randomForest(DriverDrinking ~ Sex + Age + PrevSuspensions + PrevDWIConvictions +
                            PrevSpeeding + ReportedDrugs + VehicleSpeed + DeathSceneStatus +
                            NumFatalities + WeekdayStatus + DayStatus + IncomeToPovRatio +
                            TotalPopulation, data = train, ntree = 100, mtry = 4,
                          keep.forest = TRUE, importance = FALSE)

test.forest = predict(modForest1, type = "prob", newdata = test)
forestpred = prediction(test.forest[,2], test$DriverDrinking)
forestperf = performance(forestpred, "tpr", "fpr")
plot(perf, main="Random Forest ROC [Accuracy: 0.74]")
```



```
conf <- modForest$confusion
print(sum(diag(conf)) / sum(conf))
```

```
## [1] 0.7280471
```