Econ294A - Final Exam

Feng Hong

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Extract raw data from sqlite

```
Here comes to your word, Here comes to your word,
Here comes to your word, Here comes to your word
```

```
nycflights13_sqlite()
```

```
## src:  sqlite 3.8.6 [/var/folders/sv/knpls9wx0fddp_m5lh8y139w0000gn/T//RtmpVLmUCx/nycflights13.sqlite]
## tbls: airlines, airports, flights, planes, sqlite_stat1, weather
```

```
flights_sqlite <- tbl(nycflights13_sqlite(), "flights")
airlines_sqlite <- tbl(nycflights13_sqlite(), "airlines")
airports_sqlite <- tbl(nycflights13_sqlite(), "airports")
planes_sqlite <- tbl(nycflights13_sqlite(), "planes")
weather_sqlite <- tbl(nycflights13_sqlite(), "weather")
```

join flights and planes data

```
inner_flights_planes <- inner_join(flights, planes, by = "tailnum") %>% tbl_df
colnames(inner_flights_planes)[1] <- "flight_year"
colnames(inner_flights_planes)[15] <- "dep_hour"
colnames(inner_flights_planes)[17] <- "plane_year"
#names(inner_flights_planes)
```

create the date index

```
inner_flights_planes <- inner_flights_planes %>%
  mutate(
    date = paste(flight_year, month, day, sep = "-"),
    date = as.Date(date, format = "%Y-%m-%d"), # create date to merge with weather
    cancelled = ifelse(is.na(arr_time), 1, 0)  # question requires this
  )
```

select columns needed from the inner_flights_planes dataset

```
flights_planes <- inner_flights_planes %>%
  dplyr::select(
    cancelled, date, month, day, dep_hour,
    dep_time, dep_delay, arr_time, arr_delay,
    carrier, flight, origin, dest, air_time, distance,
    plane_year, manufacturer, seats)
```

- change character variable to factor variable
- change integer variable to factor variable

```
flights_planes$carrier <- as.factor(flights_planes$carrier)
flights_planes$origin <- as.factor(flights_planes$origin)
flights_planes$dest <- as.factor(flights_planes$dest)
flights_planes$manufacturer <- as.factor(flights_planes$manufacturer)
flights_planes$month <- as.factor(flights_planes$month)
flights_planes$flight <- as.factor(flights_planes$flight)
```

refine weather data

```
weather <- weather_sqlite %>%
  collect() %>%
  mutate(
    date = paste(year, month, day, sep = "-"),
    date = as.Date(date, format = "%Y-%m-%d"),
    weekday = weekdays(date),
    weekday = as.factor(weekday) # add the weekday variable
  )
```

```
weather_mean <- weather %>% group_by(date) %>%
  summarise(
    weekday = first(weekday),
    mean_temp = mean(temp),
    mean_dewp = mean(dewp),
    mean_humid = mean(humid),
    # mean_wind_dir = mean(wind_dir), wind direction has too many NA's.
    # mean_wind_speed = mean(wind_speed),
    # mean_wind_gust = mean(wind_gust), excluded because their effects depending on direction.
    mean_precip = mean(precip),
    # mean_pressure = mean(pressure), pressure has too many NA's.
    mean_visib = mean(visib)
  )
```

identify the highly correlated data

```
corr_weather_mean <- cor(na.omit(weather_mean[,3:7]))
print(corr_weather_mean)
```

```
##               mean_temp  mean_dewp mean_humid mean_precip mean_visib
## mean_temp    1.00000000  0.9472446  0.2452670 -0.01067683  0.1110659
## mean_dewp    0.94724465  1.0000000  0.5393149  0.11526017 -0.1050222
## mean_humid   0.24526696  0.5393149  1.0000000  0.40771500 -0.6731405
## mean_precip -0.01067683  0.1152602  0.4077150  1.00000000 -0.4625583
## mean_visib   0.11106590 -0.1050222 -0.6731405 -0.46255832  1.0000000
```

delete columns that are highly correlated from weather_mean

```
weather2 <- weather_mean %>%
  dplyr::select(date, weekday, mean_temp, mean_precip, mean_visib)
```

join flights, planes and weather data

```
final_data <- inner_join(flights_planes, weather2, by = "date")
length(final_data[final_data$cancelled == 1])
```

```
## [1] 4547
```

```
#names(final_data)
```

OLS for *dep_delay

```
model.delay <- lm(dep_delay ~ month + as.factor(weekday) + carrier + origin +
                plane_year + seats + mean_precip + mean_visib,
               data = final_data)
summary(model.delay)
```

```
##
## Call:
## lm(formula = dep_delay ~ month + as.factor(weekday) + carrier +
##     origin + plane_year + seats + mean_precip + mean_visib, data = final_data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
##  -77.67  -18.12  -10.08    0.48 1302.36
##
## Coefficients:
##                             Estimate Std. Error t value Pr(>|t|)
## (Intercept)               205.755670  34.704574   5.929 3.06e-09 ***
## month2                      0.916951   0.389117   2.356 0.018449 *
## month3                      6.049689   0.374667  16.147  < 2e-16 ***
## month4                      6.838469   0.376252  18.175  < 2e-16 ***
## month5                      3.312550   0.371874   8.908  < 2e-16 ***
## month6                     12.417621   0.380368  32.646  < 2e-16 ***
## month7                     15.555095   0.374606  41.524  < 2e-16 ***
## month8                      5.528696   0.374189  14.775  < 2e-16 ***
## month9                      0.026098   0.379965   0.069 0.945241
## month10                    -0.694563   0.372429  -1.865 0.062189 .
## month11                    -1.791855   0.378258  -4.737 2.17e-06 ***
## month12                     6.462775   0.378077  17.094  < 2e-16 ***
## as.factor(weekday)Monday   -0.854723   0.277070  -3.085 0.002037 **
## as.factor(weekday)Saturday  -6.991724   0.296295 -23.597  < 2e-16 ***
## as.factor(weekday)Sunday   -3.292526   0.281827 -11.683  < 2e-16 ***
```

```
## as.factor(weekday)Thursday    2.329743   0.277379   8.399  < 2e-16 ***
## as.factor(weekday)Tuesday    -4.330445   0.277813 -15.588  < 2e-16 ***
## as.factor(weekday)Wednesday  -3.689374   0.277307 -13.304  < 2e-16 ***
## carrierAA                    -9.560631   0.619017 -15.445  < 2e-16 ***
## carrierAS                   -12.181077   1.542126  -7.899 2.82e-15 ***
## carrierB6                    -4.620915   0.355492 -12.999  < 2e-16 ***
## carrierDL                    -9.326508   0.413355 -22.563  < 2e-16 ***
## carrierEV                     2.189111   0.406559   5.384 7.27e-08 ***
## carrierF9                     2.457422   1.618348   1.518 0.128896
## carrierFL                     0.858047   0.818992   1.048 0.294784
## carrierHA                   -13.771479   2.308885  -5.965 2.46e-09 ***
## carrierMQ                   -11.363331   1.416456  -8.022 1.04e-15 ***
## carrierOO                    -0.555190   7.347354  -0.076 0.939767
## carrierUA                    -6.782975   0.430371 -15.761  < 2e-16 ***
## carrierUS                   -14.324738   0.463010 -30.938  < 2e-16 ***
## carrierVX                    -4.874944   0.652174  -7.475 7.75e-14 ***
## carrierWN                    -0.225239   0.512890  -0.439 0.660549
## carrierYV                     1.526848   1.741014   0.877 0.380494
## originJFK                    -0.682926   0.253037  -2.699 0.006957 **
## originLGA                    -0.782260   0.232691  -3.362 0.000774 ***
## plane_year                   -0.081739   0.017291  -4.727 2.28e-06 ***
## seats                         0.006086   0.001413   4.306 1.66e-05 ***
## mean_precip                 246.102409   9.817433  25.068  < 2e-16 ***
## mean_visib                   -2.973681   0.061364 -48.460  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 39.51 on 274122 degrees of freedom
##   (9358 observations deleted due to missingness)
## Multiple R-squared:  0.05255,    Adjusted R-squared:  0.05242
## F-statistic: 400.1 on 38 and 274122 DF,  p-value: < 2.2e-16
```

GLS for *cancel*

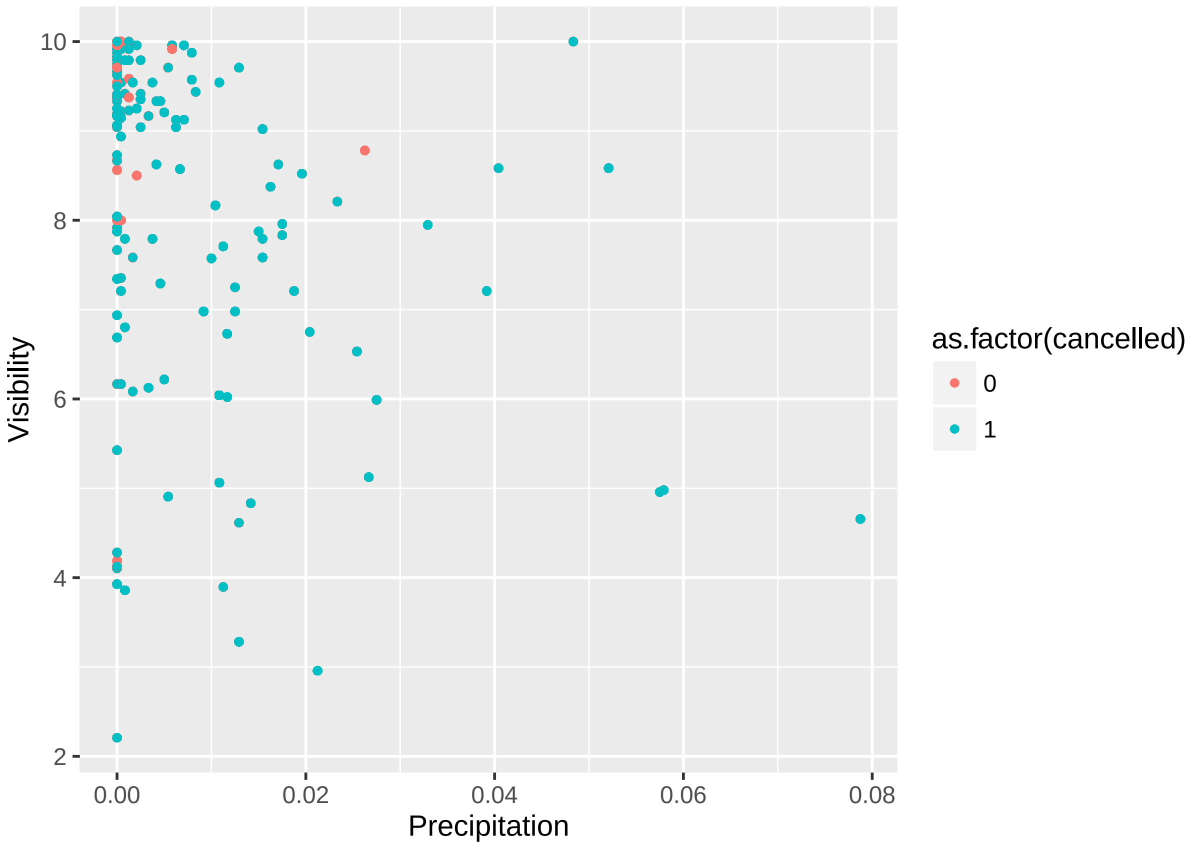
```r
model.cancel <- glm(cancelled ~ month + as.factor(weekday) + carrier + origin +
                      seats +  mean_visib,
                    data = final_data, family=binomial(link="logit"))
summary(model.cancel)
```

```
##
## Call:
## glm(formula = cancelled ~ month + as.factor(weekday) + carrier +
##     origin + seats + mean_visib, family = binomial(link = "logit"),
##     data = final_data)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.3304  -0.1698  -0.0952  -0.0522   4.2731
##
## Coefficients:
##                               Estimate Std. Error z value Pr(>|z|)
## (Intercept)                 -2.4393036  0.1562902 -15.608  < 2e-16 ***
```

```
## month2                        1.2048077  0.0746512  16.139  < 2e-16 ***
## month3                        0.8599651  0.0789870  10.887  < 2e-16 ***
## month4                        0.6527097  0.0856683   7.619 2.56e-14 ***
## month5                        0.2789271  0.0836728   3.334 0.000857 ***
## month6                        1.0834795  0.0784206  13.816  < 2e-16 ***
## month7                        1.2298009  0.0794558  15.478  < 2e-16 ***
## month8                        0.3539360  0.0915396   3.866 0.000110 ***
## month9                        0.3244573  0.0946035   3.430 0.000604 ***
## month10                      -0.5761280  0.1134244  -5.079 3.79e-07 ***
## month11                      -0.3623568  0.1110580  -3.263 0.001103 **
## month12                       0.6810983  0.0768904   8.858  < 2e-16 ***
## as.factor(weekday)Monday     -0.4322734  0.0538827  -8.022 1.04e-15 ***
## as.factor(weekday)Saturday   -0.3774389  0.0620898  -6.079 1.21e-09 ***
## as.factor(weekday)Sunday     -0.6874177  0.0631751 -10.881  < 2e-16 ***
## as.factor(weekday)Thursday    0.2302250  0.0504070   4.567 4.94e-06 ***
## as.factor(weekday)Tuesday    -0.3688324  0.0556339  -6.630 3.37e-11 ***
## as.factor(weekday)Wednesday  -0.3249462  0.0543958  -5.974 2.32e-09 ***
## carrierAA                     1.6964487  0.1450800  11.693  < 2e-16 ***
## carrierAS                    -0.3015237  0.7226137  -0.417 0.676482
## carrierB6                     0.8911258  0.1290850   6.903 5.08e-12 ***
## carrierDL                     0.5303609  0.1377119   3.851 0.000118 ***
## carrierEV                     2.4170370  0.1290509  18.729  < 2e-16 ***
## carrierF9                    -1.2785345  1.0108560  -1.265 0.205942
## carrierFL                     1.2479201  0.1762006   7.082 1.42e-12 ***
## carrierHA                    -9.2171723 75.4569783  -0.122 0.902779
## carrierMQ                     1.9384151  0.1901058  10.197  < 2e-16 ***
## carrierOO                     3.1923504  0.6351356   5.026 5.00e-07 ***
## carrierUA                    -1.3228198  0.1851520  -7.145 9.03e-13 ***
## carrierUS                    -1.1994161  0.2207254  -5.434 5.51e-08 ***
## carrierVX                     0.7939935  0.2123517   3.739 0.000185 ***
## carrierWN                     1.0108355  0.1510457   6.692 2.20e-11 ***
## carrierYV                     2.7750120  0.1930360  14.376  < 2e-16 ***
## originJFK                    -0.2453609  0.0633199  -3.875 0.000107 ***
## originLGA                     0.3986579  0.0430716   9.256  < 2e-16 ***
## seats                        -0.0024326  0.0004009  -6.068 1.30e-09 ***
## mean_visib                   -0.3539327  0.0079566 -44.483  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 46604  on 283518  degrees of freedom
## Residual deviance: 37218  on 283482  degrees of freedom
## AIC: 37292
##
## Number of Fisher Scoring iterations: 14
```

(a) weather

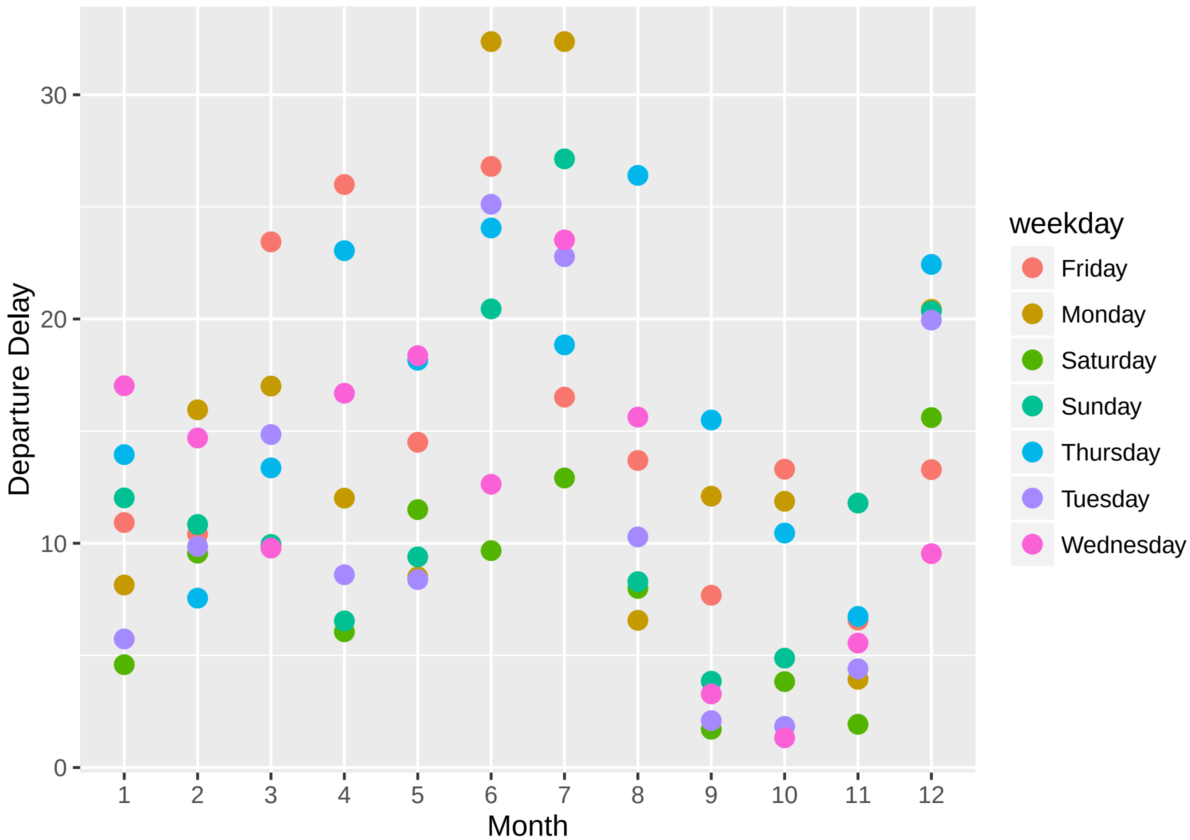
```r
plot_weather <- ggplot(data = final_data, aes(mean_precip, mean_visib))
plot_weather + geom_point( aes(color = as.factor(cancelled)),size = 1) +
  xlab("Precipitation") + ylab("Visibility")
```



(b) day of week and time of year

```
month_weekday <- final_data %>%
  group_by(month, weekday) %>%
  summarise(mean.dep_delay = mean(dep_delay, na.rm = T))

plot_time <- ggplot(month_weekday, aes(x = month, y= mean.dep_delay))
plot_time + geom_point(aes(color = weekday), size = 3) +
  xlab("Month") + ylab("Departure Delay")
```


Departure Delay
30
20
10
0
1
2
3
4
5
6
7
8
9
10
11
12
Month
weekday
Friday
Monday
Saturday
Sunday
Thursday
Tuesday
Wednesday