Capstone II: Forecasting US national parks visits Project

HarvardX: PH125.9x Data Science

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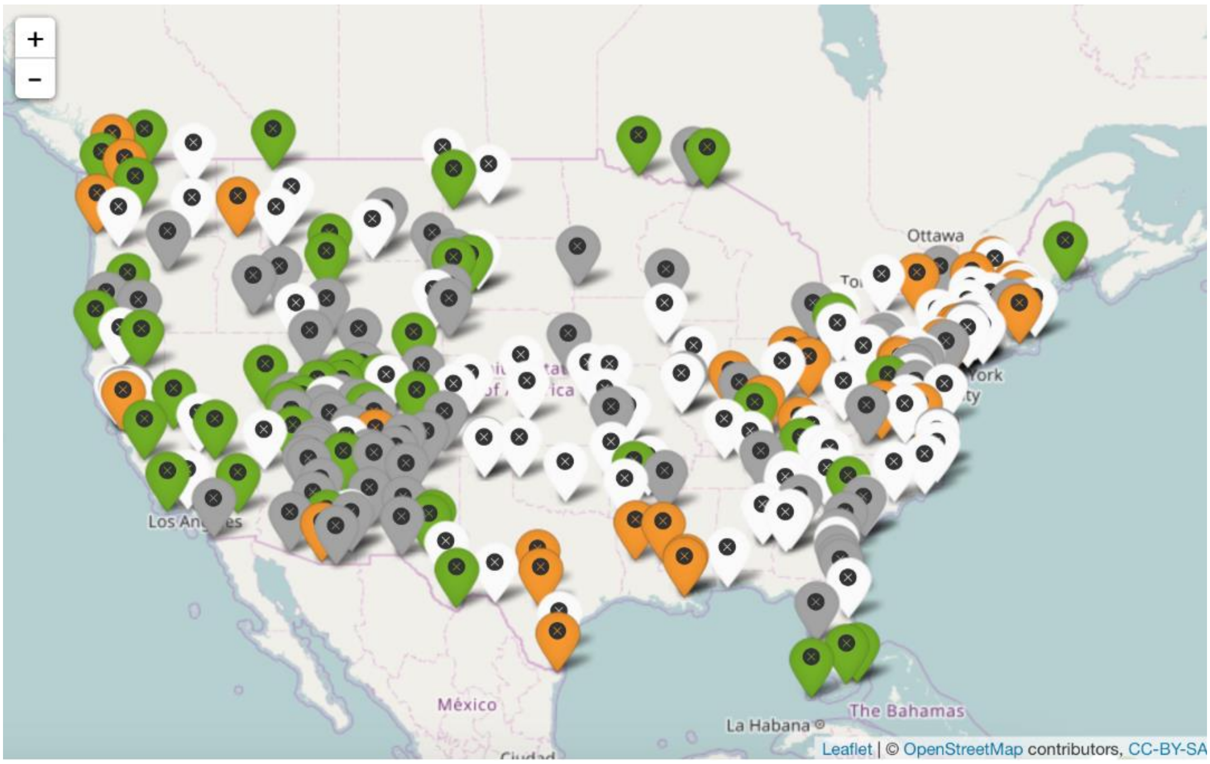
I. Introduction

The U.S. National Parks System includes 417 areas including national parks, monuments, battlefields, military parks, historical parks, historical sites, lakeshores, seashores, recreation areas, scenic rivers and trails, and the White House (see map in Figure 1). Every year, hundreds of millions of recreational visitors come to the parks. What do we know about the parks that can affect the visitor counts?



Can we forecast the monthly visits to a given park accurately? To derive insights and answer these questions, we take a look at the historical visits data and the parks information released by the National Parks Service (NPS).

For this problem, we obtained monthly visits data between 2010 and 2016 (source: https://irma.nps.gov/Stats/Reports/National). We also got park-specific data via the

NPS API (https://developer.nps.gov/api/index.htm). The aggregated dataset *park_visits.csv* results in a total of **12 variables** and **25587 observations**. Each observation contains one record per park per month. Here's a detailed description of the variables:

- **ParkName**: The full name of the park.

- **ParkType**: The type of the park. For this study we restrict ourselves to the following more frequently visited types: National Battlefield, National Historic Site, National Historical Park, National Memorial, National Monument, National Park, National Recreation Area, and National Seashore.

- **Region**: The region of the park, including Alaska, Intermountain, Midwest, National Capital, Northeast, Pacific West, and Southeast.

- **State**: The abbreviation of the state where the park resides.

- **Year, Month**: the year and the month for the visits.

- lat, long: Latitude and longitude of the park.

- **Cost**: a simple extraction of the park's entrance fee. Some parks may have multiple levels of entrance fees (differ by transportation methods, age, military status, etc.); for this problem, we only extracted the first available cost information.

- **logVisits**: Natural logarithm of the recreational visits (with one added to the visits to avoid taking logs of zero) to the park in the given year and month. **We decided to use log of number of visits here to remove right skewness of the original data in order to improve model fit.**

- **laglogVisits**: the logVisits from last month.

-**laglogVisitsYear**: the logVisits from last year.

We will follow below steps:

- loading of datasets
- pre-processing data if necessary
- exploration and visualization of data
- modeling approach
- results obtained
- conclusion

II. Analysis

1. Loading data

```
if (!require("RCurl")) install.packages("RCurl")
library(RCurl)
URL <- getURL("https://raw.githubusercontent.com/mfofanagn/Forecasting-US-national-parks-visits-/master/park_visits.csv")
visits <- read.csv(text = URL)
```

```
Loading required package: RCurl
Warning message in library(package, lib.loc = lib.loc, character.only = TRUE, logical.return = TRUE, :
“there is no package called ‘RCurl’”Installing package into ‘/srv/rlibs’
(as ‘lib’ is unspecified)
also installing the dependency ‘bitops’

Loading required package: bitops
```

```
str(visits)
```

```
'data.frame':   25587 obs. of  12 variables:
 $ ParkName        : Factor w/ 305 levels "Abraham Lincoln Birthplace NHP",..: 1 1 1 1 1 1 1 1 1 1 ...
 $ ParkType        : Factor w/ 8 levels "National Battlefield",..: 3 3 3 3 3 3 3 3 3 3 ...
 $ Region          : Factor w/ 7 levels "Alaska","Intermountain ",..: 7 7 7 7 7 7 7 7 7 7 ...
 $ State           : Factor w/ 53 levels "AK","AL","AR",..: 19 19 19 19 19 19 19 19 19 19 ...
 $ Year            : int  2010 2010 2010 2010 2010 2010 2010 2010 2010 2010 ...
 $ Month           : int  1 2 3 4 5 6 7 8 9 10 ...
 $ lat             : num  37.6 37.6 37.6 37.6 37.6 ...
 $ long            : num  -85.7 -85.7 -85.7 -85.7 -85.7 ...
 $ cost            : num  0 0 0 0 0 0 0 0 0 0 ...
 $ logVisits       : num  8.26 8.55 8.99 9.81 9.87 ...
 $ laglogVisits    : num  NA 8.26 8.55 8.99 9.81 ...
 $ laglogVisitsYear: num  NA NA NA NA NA NA NA NA NA NA ...
```

We want to predict *logVisits* which represents natural logarithm of visits to a park in a given year and month.

Visualization of data

Entrée [9]:
```
head(visits)
```

A data.frame: 6 × 12

	ParkName	ParkType	Region	State	Year	Month	lat	long	cost	logVisits	laglogVisits	laglogVisitsYear
	<fct>	<fct>	<fct>	<fct>	<int>	<int>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
13	Abraham Lincoln Birthplace NHP	National Historical Park	Southeast	KY	2011	1	37.58587	-85.67331	0	7.880048	8.315077	8.263333
14	Abraham Lincoln Birthplace NHP	National Historical Park	Southeast	KY	2011	2	37.58587	-85.67331	0	8.201934	7.880048	8.550241
15	Abraham Lincoln Birthplace NHP	National Historical Park	Southeast	KY	2011	3	37.58587	-85.67331	0	8.977904	8.201934	8.994048
16	Abraham Lincoln Birthplace NHP	National Historical Park	Southeast	KY	2011	4	37.58587	-85.67331	0	9.869931	8.977904	9.808022
17	Abraham Lincoln Birthplace NHP	National Historical Park	Southeast	KY	2011	5	37.58587	-85.67331	0	9.738554	9.869931	9.867394
18	Abraham Lincoln Birthplace NHP	National Historical Park	Southeast	KY	2011	6	37.58587	-85.67331	0	9.975483	9.738554	10.098602

2. Pre-processing

Manage missing and errors data

Entrée [4]:
```
colSums(is.na(visits))
```

ParkName	0
ParkType	0
Region	0
State	0
Year	0
Month	0
lat	84
long	84
cost	0
logVisits	0
laglogVisits	305
laglogVisitsYear	3660

We noticed that there are some NA's in the data

Variables *laglogVisits* and *laglogVisitsYear* were created by lagging the log visits by a month or by a year. These variables have missing data since earlier data is not available for the first months.

To deal with the missing and errors values:

- we will simply remove the observations with the missing values first
- then we will remove rows with logVisits equal to 0

Entrée [5]:
```
visits = visits[rowSums(is.na(visits)) == 0, ]
visits = visits[visits$logVisits != 0, ]
```

Entrée [6]:
```
str(visits)
```

```
'data.frame':	21500 obs. of  12 variables:
 $ ParkName        : Factor w/ 305 levels "Abraham Lincoln Birthplace NHP",..: 1 1 1 1 1 1 1 1 1 1 ...
 $ ParkType        : Factor w/ 8 levels "National Battlefield",..: 3 3 3 3 3 3 3 3 3 3 ...
 $ Region          : Factor w/ 7 levels "Alaska","Intermountain ",..: 7 7 7 7 7 7 7 7 7 7 ...
 $ State           : Factor w/ 53 levels "AK","AL","AR",..: 19 19 19 19 19 19 19 19 19 19 ...
 $ Year            : int  2011 2011 2011 2011 2011 2011 2011 2011 2011 2011 ...
 $ Month           : int  1 2 3 4 5 6 7 8 9 10 ...
 $ lat             : num  37.6 37.6 37.6 37.6 37.6 ...
 $ long            : num  -85.7 -85.7 -85.7 -85.7 -85.7 ...
 $ cost            : num  0 0 0 0 0 0 0 0 0 0 ...
 $ logVisits       : num  7.88 8.2 8.98 9.87 9.74 ...
 $ laglogVisits    : num  8.32 7.88 8.2 8.98 9.87 ...
 $ laglogVisitsYear: num  8.26 8.55 8.99 9.81 9.87 ...
```

Data conversion

We will convert Month variable from int to factor variable

Entrée [ ]:
```
# From data structure above, let's transform Month  variable as factor
```

Entrée [16]:
```
visits$Month = as.factor(visits$Month)
```

Entrée [17]:
```
str(visits)
```

```
'data.frame':	21855 obs. of  12 variables:
 $ ParkName        : Factor w/ 305 levels "Abraham Lincoln Birthplace NHP",..: 1 1 1 1 1 1 1 1 1 1 ...
 $ ParkType        : Factor w/ 8 levels "National Battlefield",..: 3 3 3 3 3 3 3 3 3 3 ...
 $ Region          : Factor w/ 7 levels "Alaska","Intermountain ",..: 7 7 7 7 7 7 7 7 7 7 ...
 $ State           : Factor w/ 53 levels "AK","AL","AR",..: 19 19 19 19 19 19 19 19 19 19 ...
 $ Year            : int  2011 2011 2011 2011 2011 2011 2011 2011 2011 2011 ...
 $ Month           : Factor w/ 12 levels "1","2","3","4",..: 1 2 3 4 5 6 7 8 9 10 ...
 $ lat             : num  37.6 37.6 37.6 37.6 37.6 ...
 $ long            : num  -85.7 -85.7 -85.7 -85.7 -85.7 ...
 $ cost            : num  0 0 0 0 0 0 0 0 0 0 ...
 $ logVisits       : num  7.88 8.2 8.98 9.87 9.74 ...
 $ laglogVisits    : num  8.32 7.88 8.2 8.98 9.87 ...
 $ laglogVisitsYear: num  8.26 8.55 8.99 9.81 9.87 ...
```

3. Initial Data Exploration

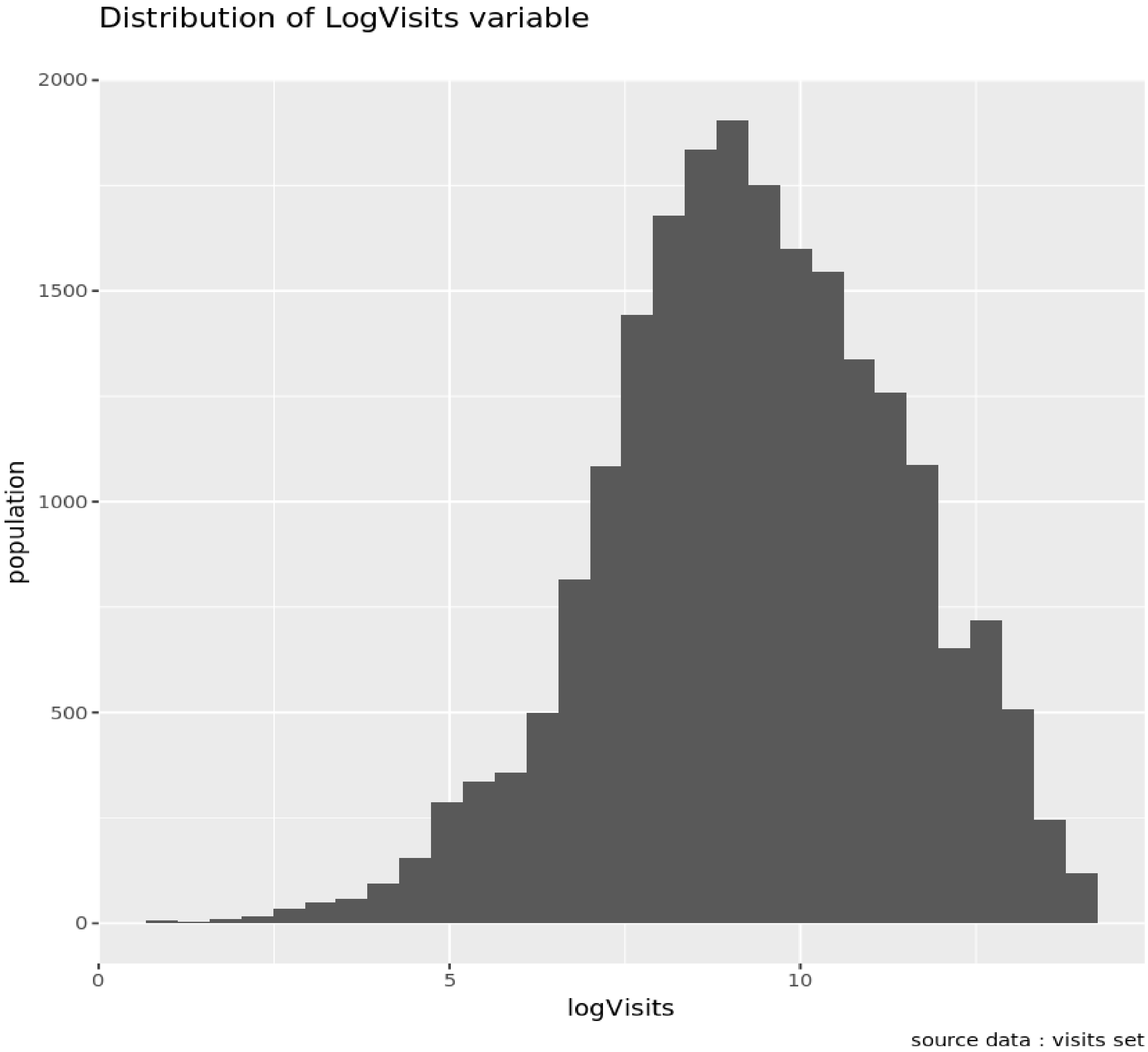
Individual Feature Statistics

Entrée [7]:
```
summary(visits)
```

```
                               ParkName                            ParkType   
 Abraham Lincoln Birthplace NHP:   72   National Historic Site   :5277  
 Acadia NP                     :   72   National Monument        :4808  
 African Burial Ground NM      :   72   National Park            :4038  
 Agate Fossil Beds NM          :   72   National Historical Park:3007  
 Alibates Flint Quarries NM    :   72   National Memorial        :1850  
 Allegheny Portage Railroad NHS:   72   National Recreation Area:1080  
 (Other)                       :21068   (Other)                  :1440  
              Region         State            Year          Month       
 Alaska          : 725   CA     : 1427   Min.   :2011   Min.   : 1.000  
 Intermountain   :5399   NY     : 1390   1st Qu.:2012   1st Qu.: 4.000  
 Midwest         :2880   AZ     : 1368   Median :2013   Median : 7.000  
 National Capital :1119   PA     :  915   Mean   :2014   Mean   : 6.503  
 Northeast       :4568   MA     :  898   3rd Qu.:2015   3rd Qu.: 9.000  
 Pacific West    :3367   NM     :  864   Max.   :2016   Max.   :12.000  
 Southeast       :3442   (Other):14638                                  
      lat              long              cost           logVisits     
 Min.   :-14.23   Min.   :-169.85   Min.   : 0.000   Min.   : 1.099  
 1st Qu.: 34.88   1st Qu.:-111.04   1st Qu.: 0.000   1st Qu.: 7.937  
 Median : 38.53   Median : -94.36   Median : 0.000   Median : 9.280  
 Mean   : 38.10   Mean   : -96.35   Mean   : 5.091   Mean   : 9.301  
 3rd Qu.: 41.67   3rd Qu.: -77.44   3rd Qu.: 8.000   3rd Qu.:10.790  
 Max.   : 67.76   Max.   : 144.69   Max.   :30.000   Max.   :14.198  

  laglogVisits     laglogVisitsYear
 Min.   : 0.000   Min.   : 0.000   
 1st Qu.: 7.929   1st Qu.: 7.888   
 Median : 9.275   Median : 9.248   
 Mean   : 9.278   Mean   : 9.213   
 3rd Qu.:10.785   3rd Qu.:10.770   
 Max.   :14.198   Max.   :14.188   
```

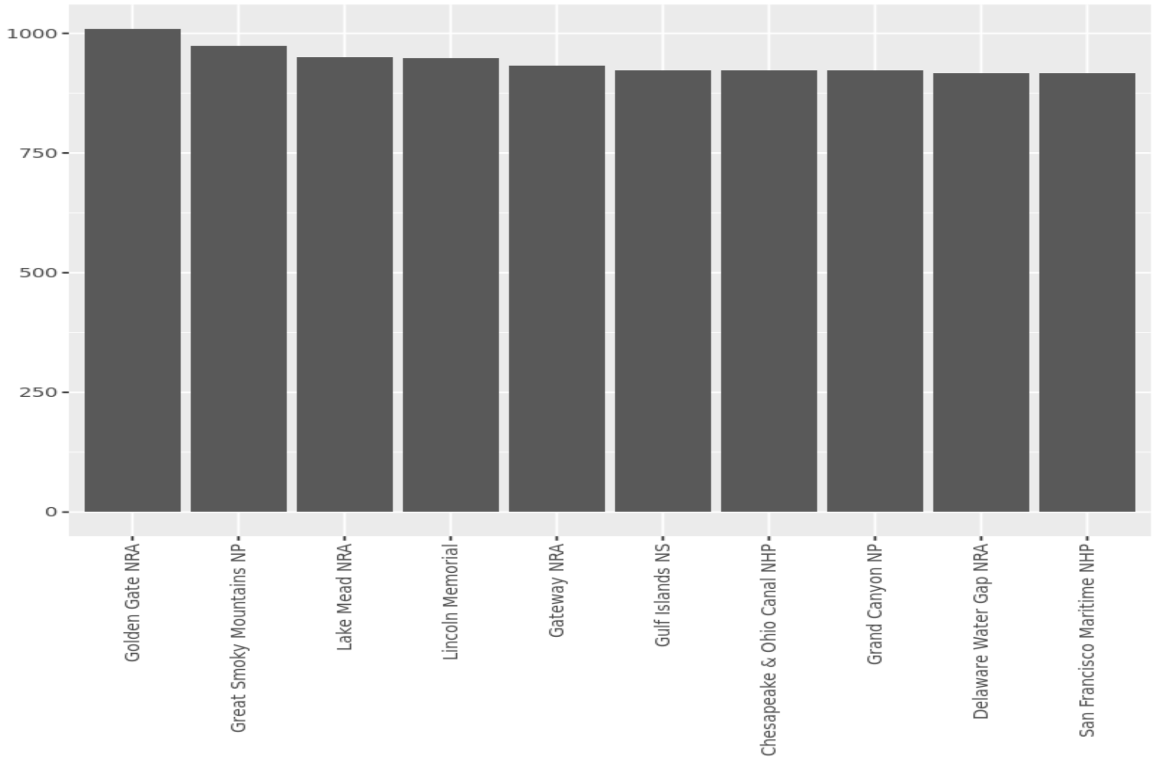
Distribution of dependant variable logVisits



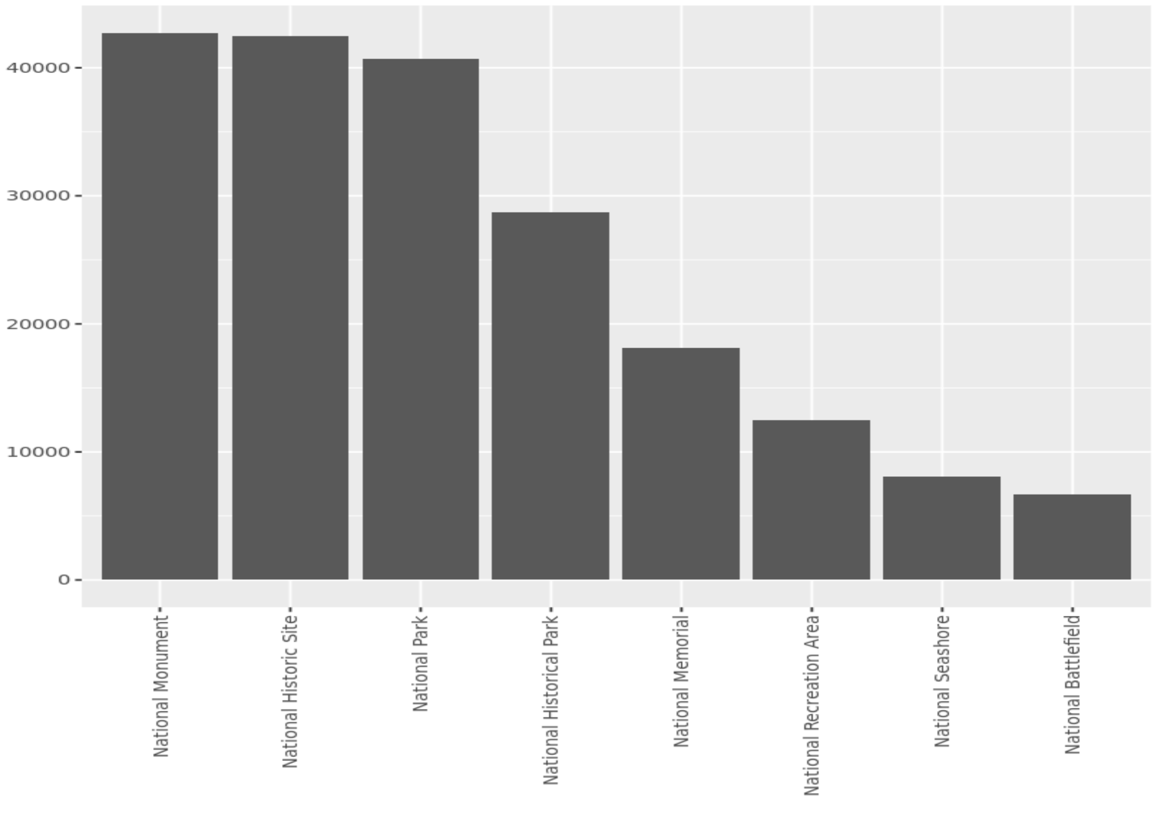
An histogram of the logVisits column shows that it has almost symetric distribution and seems to be approximatively normally distributed which could help to a better model.

Summaries interesting statistics about independant variables

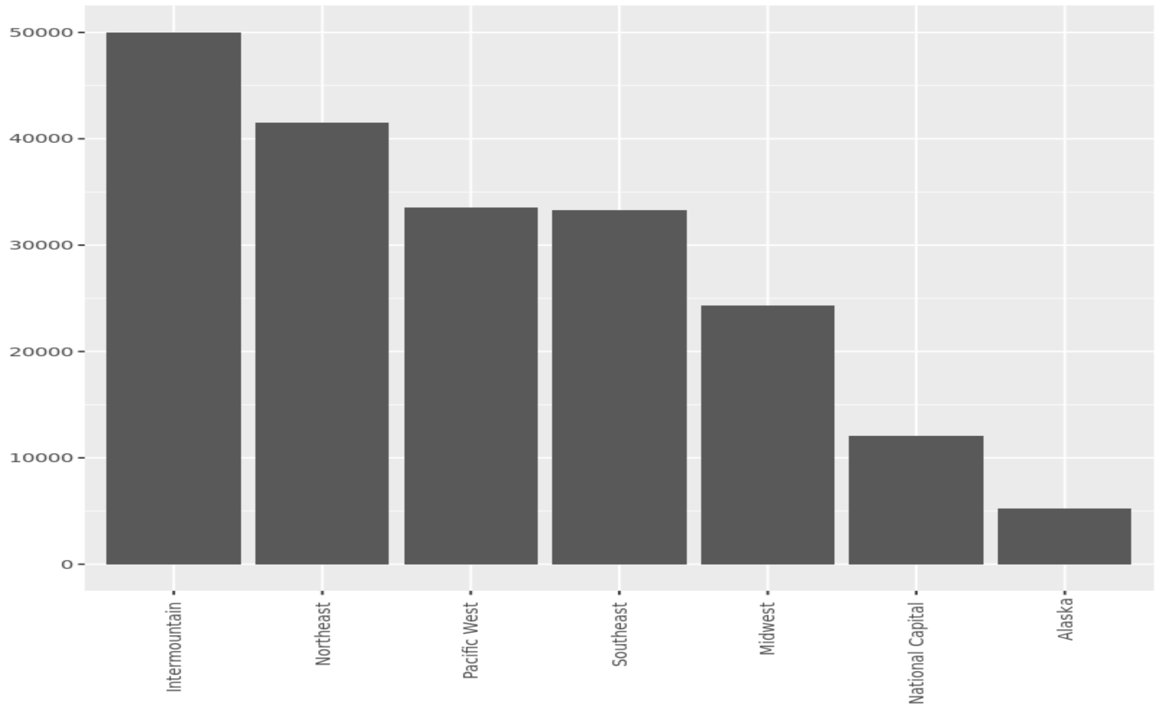
10 Most visited parks



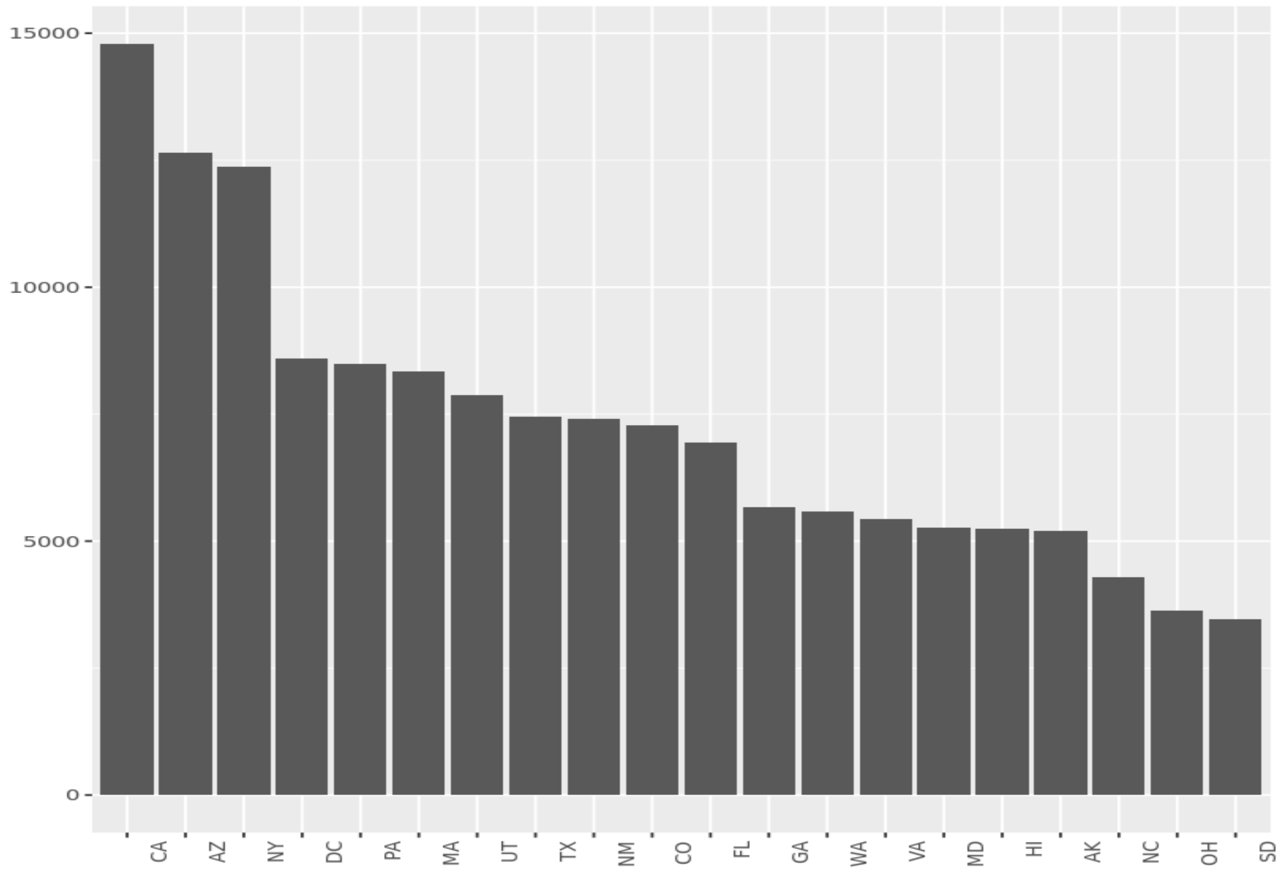
Most visited parkType



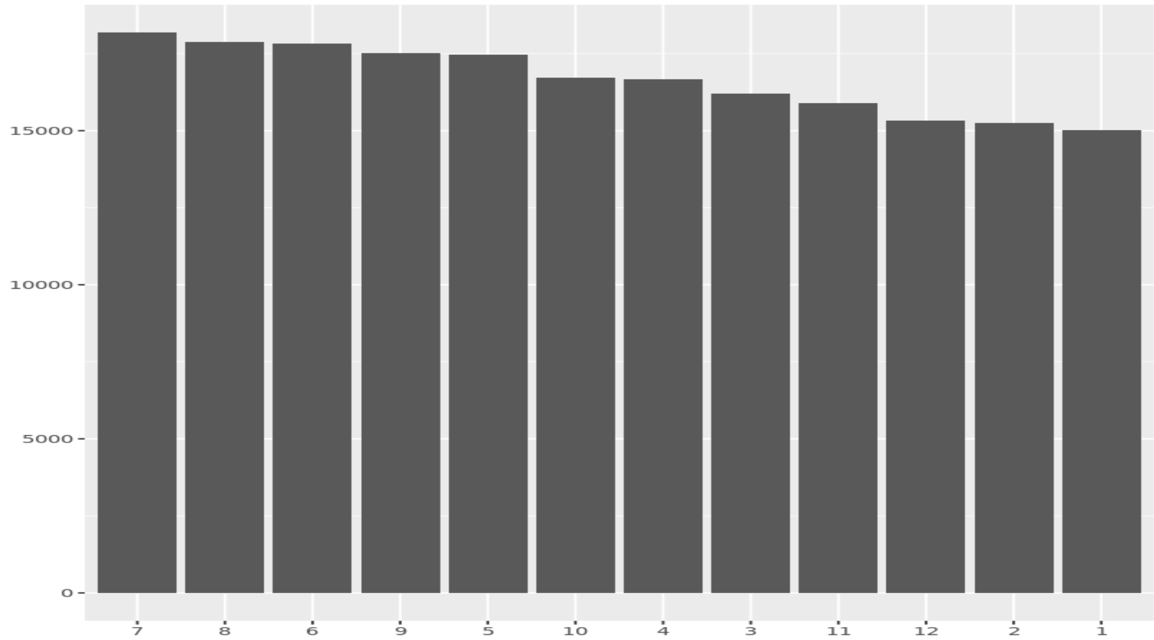
Most visited region



20 Most visited state

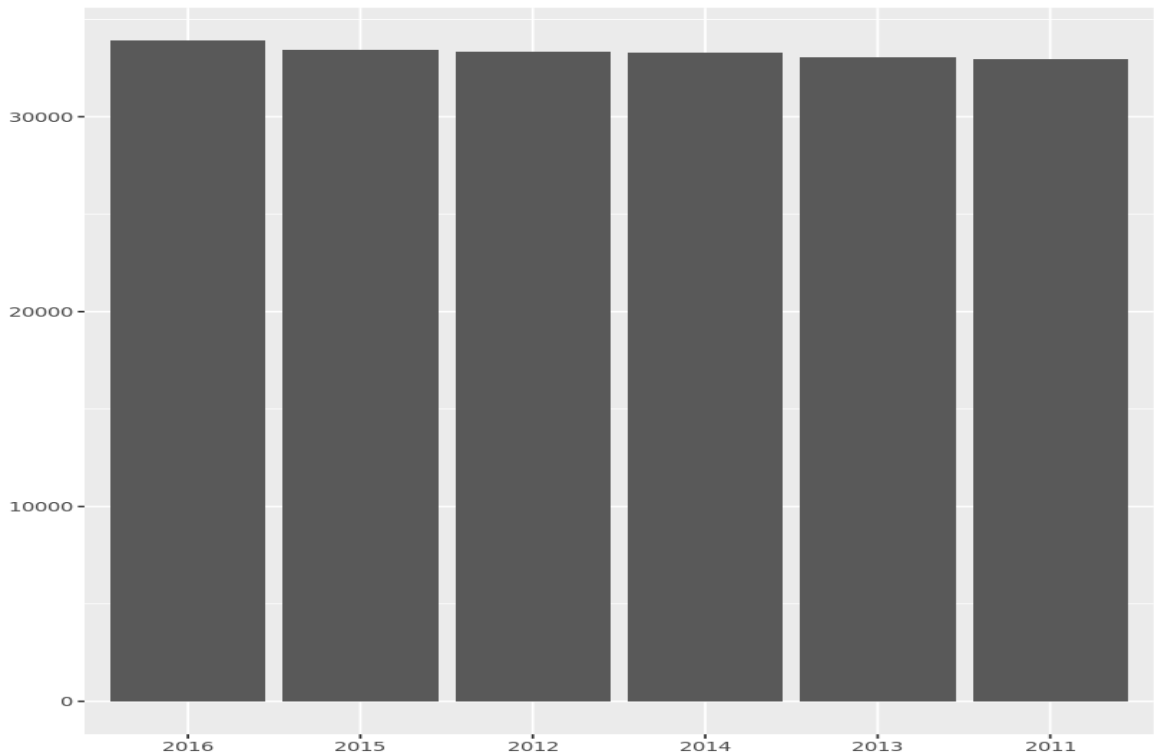


Most frequents months



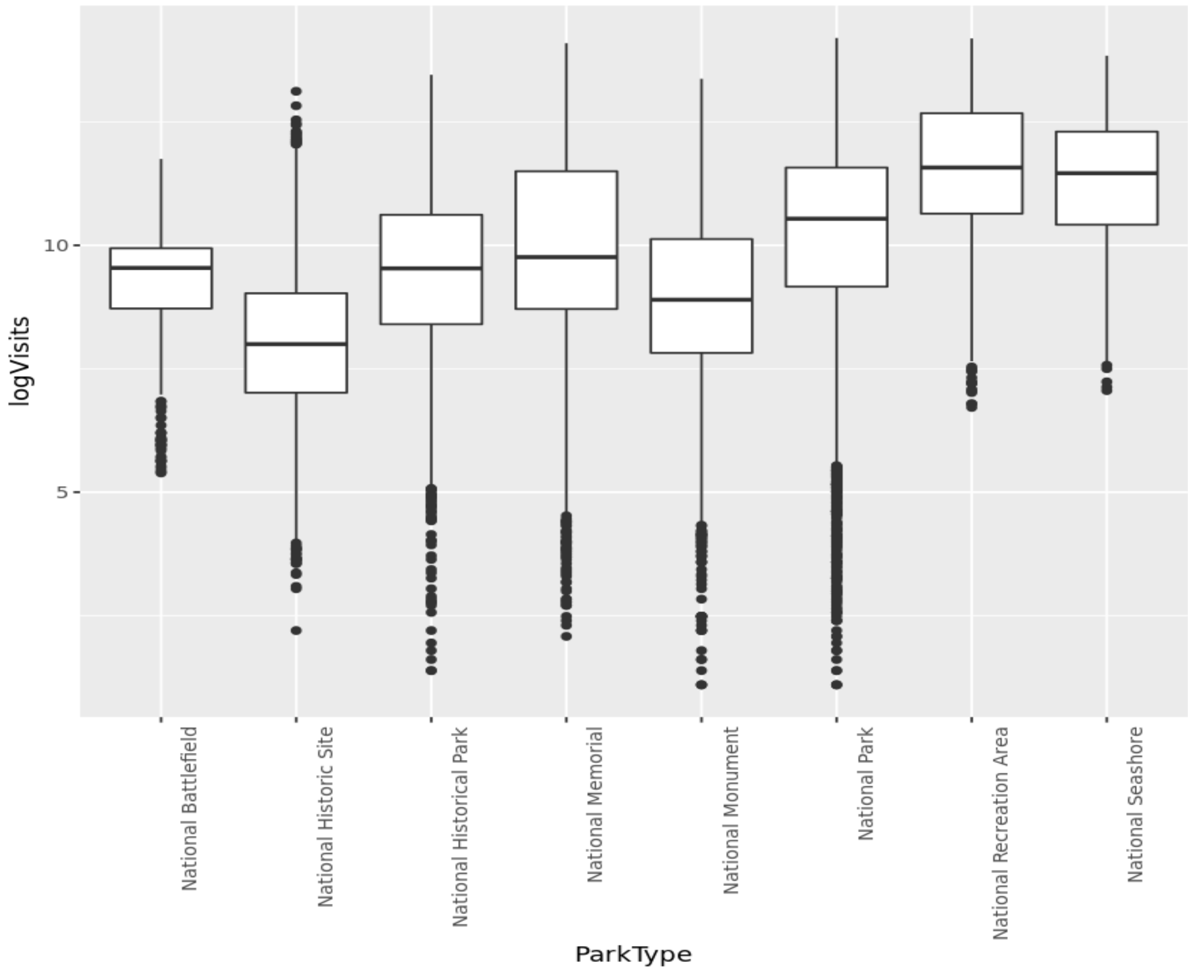
July and august seems to be months with the most visits, this could be explained by the fact that they correspond to leave period in which people have more time for tourism.

Year with most visits



We noticed here that visits are relatively constant between years

Categorical relationship



We notice within a group that the distribution of visits is quite wide and that each parkType has a different distribution from the others.

Numerical relationship between logVisits and Cost

```
Entrée [79]: cor(visits$logVisits, visits$cost)
```

0.358364241498407

There is a positive correlation between logVisits and cost, which could mean higher cost has fewer influence on frequentations likely because more expensive parks are often more popular due to other features of the parks.

Time series analysis

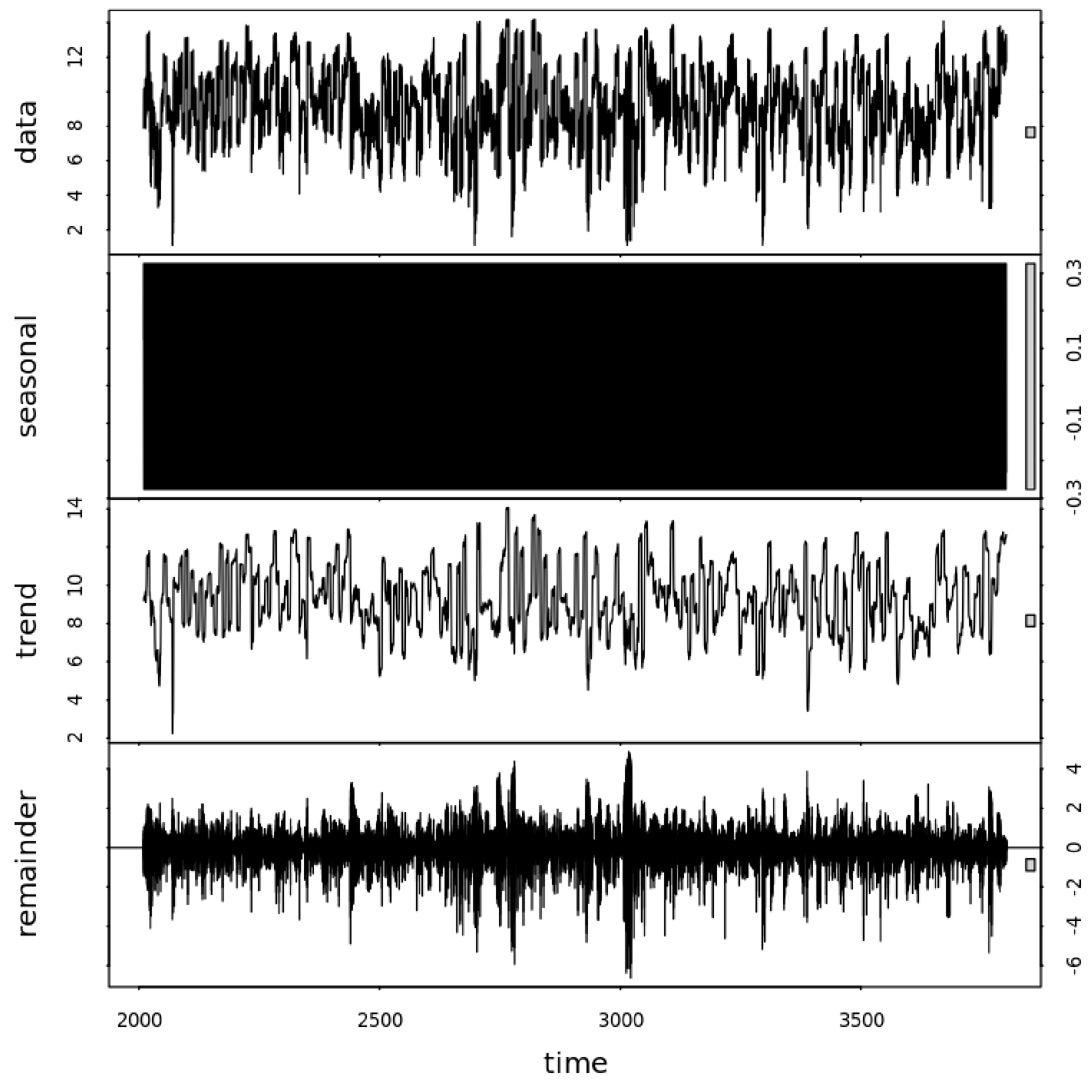
Given that our data is recorded by date, we will try to analyze it our data as time series data in order to find some interesting insights if there exists.

```
Entrée [27]: # Time serie analysis
```

```
Entrée [28]: ts=ts(visits$logVisits,start=c(2010,1),freq=12)
```

```
Entrée [29]: # Seasonal decomposition
```

```
Entrée [30]: fit <- stl(ts, s.window="period")
             plot(fit)
```



Theses graphics does not allow us to find interesting trends; maybe data need to be more processed in order to get some useful insights about eventual cyclical trend of the data.

III. Results

In this section, we are going to explain the methodology over different Machines Learning algorithms we used and present the metric (R square) for the model performance evaluation.

We are interested in predicting the log visits, let's subset our dataset into a training and a testing set by splitting based on the year:

- training would contain 2010-2014 years of data,
- and testing would be 2015-2016 data.

Entrée [40]:
```
training = subset(visits, Year >= 2010 & Year <= 2014)
dim(training)
```

14338 12

Entrée [41]:
```
testing = subset(visits, Year >= 2015 & Year <= 2016)
dim(testing)
```

7162 12

We will then try several regression algorithms:

- linear regression
- tree regression with cross validation
- randomForest regression

Those three models will be evaluated using R square metrics

1. Linear Regression Models

Let's start by a simple linear model; we will use those independents variables

laglogVisits, laglogVisitsYear, Year, Month, Region, ParkType, and cost

```
visitsLM = lm(logVisits ~ laglogVisits + laglogVisitsYear + Year + Month + Region + ParkType + cost, data = training)
summary(visitsLM)
```

```
Call:
lm(formula = logVisits ~ laglogVisits + laglogVisitsYear + Year +
    Month + Region + ParkType + cost, data = training)

Residuals:
    Min      1Q  Median      3Q     Max
-5.9725 -0.2210 -0.0020  0.2079  9.4341

Coefficients:
                                  Estimate Std. Error t value Pr(>|t|)
(Intercept)                     -5.7680775  8.6949715  -0.663 0.507097
laglogVisits                     0.5027913  0.0051052  98.485  < 2e-16 ***
laglogVisitsYear                 0.4106751  0.0048173  85.251  < 2e-16 ***
Year                             0.0031569  0.0043206   0.731 0.464994
Month2                           0.1159852  0.0237187   4.890 1.02e-06 ***
Month3                           0.3534700  0.0238852  14.799  < 2e-16 ***
Month4                           0.2538986  0.0238456  10.648  < 2e-16 ***
Month5                           0.3888252  0.0239772  16.216  < 2e-16 ***
Month6                           0.2753548  0.0240065  11.470  < 2e-16 ***
Month7                           0.2585186  0.0241000  10.727  < 2e-16 ***
Month8                           0.0717295  0.0240819   2.979 0.002901 **
Month9                           0.0193276  0.0239826   0.806 0.420314
Month10                         -0.1132568  0.0239405  -4.731 2.26e-06 ***
Month11                         -0.1116565  0.0238207  -4.687 2.79e-06 ***
Month12                         -0.0670265  0.0237596  -2.821 0.004794 **
RegionIntermountain             -0.0423104  0.0311187  -1.360 0.173964
RegionMidwest                   -0.0376482  0.0318423  -1.182 0.237094
RegionNational Capital           0.2100051  0.0393440   5.338 9.56e-08 ***
RegionNortheast                  0.1067349  0.0318246   3.354 0.000799 ***
RegionPacific West               0.0540633  0.0314565   1.719 0.085696 .
RegionSoutheast                  0.0720603  0.0320214   2.250 0.024440 *
ParkTypeNational Historic Site  -0.0424715  0.0286264  -1.484 0.137925
ParkTypeNational Historical Park 0.0822116  0.0299409   2.746 0.006044 **
ParkTypeNational Memorial        0.1554981  0.0315541   4.928 8.40e-07 ***
ParkTypeNational Monument        0.0701139  0.0295025   2.377 0.017489 *
```


ParkTypeNational Monument   0.0701139 0.0295025   2.377 0.017489 *


```
ParkTypeNational Park            0.1289505  0.0312339   4.129 3.67e-05 ***
ParkTypeNational Recreation Area 0.2243614  0.0360719   6.220 5.11e-10 ***
ParkTypeNational Seashore        0.1516997  0.0382825   3.963 7.45e-05 ***
cost                             0.0053496  0.0008207   6.519 7.33e-11 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5775 on 14309 degrees of freedom
Multiple R-squared:  0.9249,    Adjusted R-squared:  0.9248
F-statistic:  6298 on 28 and 14309 DF,  p-value: < 2.2e-16
```

Let’s predict test data

we will use metrics R square to evaluate our models

```
LM.pred = predict(visitsLM, newdata=testing)
LM.sse = sum((LM.pred - testing$logVisits)^2)
LM.ssm = sum((LM.pred - mean(training$logVisits)) ^ 2)

R2.LM =  1 - LM.sse / LM.ssm
print(R2.LM)
```

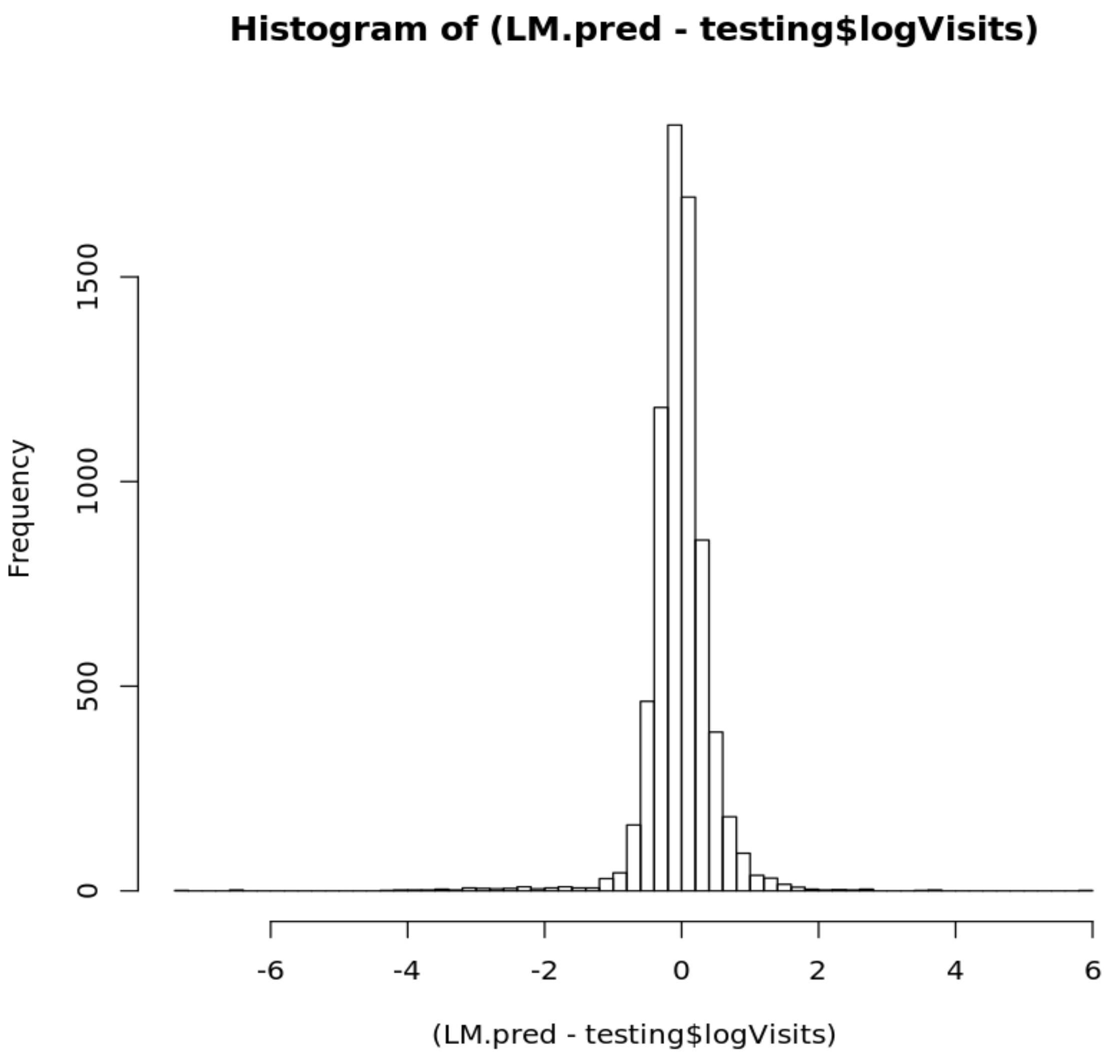
```
[1] 0.9411129
```

We got R2 = 0.94 which is already a good score

That means that our model can predict visits within 94 % of time

Let’s plot residuals to confirm our score

```
Entrée [47]: hist((LM.pred - testing$logVisits),breaks = 50)
```



Residual plot is approximatively normal, that confirm our first model perform well.

2. Regression Trees

In addition to the logistic regression model, we can also train a regression tree using the same set of variables as the previous problem

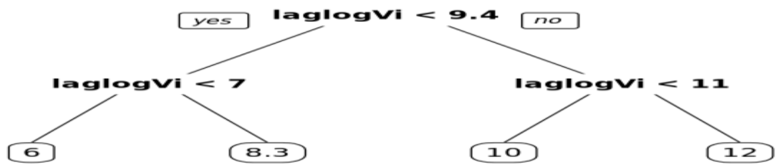
Entrée [48]:
```
# In addition to the logistic regression model, we can also train a regression tree.
# Use the same set of variables as the previous problem
# (laglogVisits, laglogVisitsYear, Year, Month, Region, ParkType, and cost), train a regression tree with cp = 0.05
```

Entrée [64]:
```
install.packages("rpart.plot")
```

```
Installing package into '/srv/rlibs'
(as 'lib' is unspecified)
```

Entrée [65]:
```
library(rpart)
library(rpart.plot)
```

Entrée [66]:
```
visitsTree = rpart(logVisits ~ laglogVisits + laglogVisitsYear + Year + Month + Region + ParkType + cost, data = training, cp=0.
prp(visitsTree)
```



Evaluate Regression tree on test data set

```
tree.pred = predict(visitsTree, newdata=testing)
tree.sse = sum((tree.pred - testing$logVisits)^2)
tree.ssm = sum((tree.pred - mean(training$logVisits))^2)

R2.tree = 1 - tree.sse / tree.ssm
print(R2.tree)
```

```
[1] 0.8326104
```

Tree model performs less well than linear regression

Let's use tree with cross validation

Entrée [54]:

```
install.packages("caret")
library(caret)
install.packages("e1071")
library(e1071)
```

```
Installing package into ‘/srv/rlibs’
(as ‘lib’ is unspecified)
also installing the dependencies ‘numDeriv’, ‘SQUAREM’, ‘lava’, ‘prodlim’, ‘iterators’, ‘data.table’, ‘gower’, ‘ipred’, ‘RcppRo
ll’, ‘timeDate’, ‘foreach’, ‘ModelMetrics’, ‘recipes’

Loading required package: lattice

Attaching package: ‘caret’

The following object is masked from ‘package:purrr’:

    lift

Installing package into ‘/srv/rlibs’
(as ‘lib’ is unspecified)
```

Entrée [55]:

```
set.seed(201)
tr.control = trainControl(method = "cv", number = 10)
numFolds = trainControl( method = "cv", number = 10 )
cpGrid = expand.grid( .cp = seq(0.0001,0.005,0.0001))
train(logVisits ~ laglogVisits + laglogVisitsYear + Year + Month + Region + ParkType + cost, data = training, method = "rpart",
```

```
CART

14338 samples
    7 predictor

No pre-processing
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 12906, 12905, 12903, 12904, 12903, 12905, ...
Resampling results across tuning parameters:

  cp      RMSE       Rsquared   MAE
  0.0001  0.4838971  0.9467770  0.2952133
  0.0002  0.4924362  0.9448958  0.3032523
  0.0003  0.4976597  0.9437303  0.3074828
  0.0004  0.5075856  0.9415064  0.3175902
  0.0005  0.5090270  0.9411936  0.3191110
  0.0006  0.5139388  0.9400830  0.3233982
  0.0007  0.5194519  0.9387892  0.3274553
  0.0008  0.5198011  0.9387014  0.3279586
  0.0009  0.5190786  0.9388980  0.3277833
  0.0010  0.5190786  0.9388980  0.3277833
  0.0011  0.5190786  0.9388980  0.3277833
  0.0012  0.5218088  0.9382561  0.3295830
  0.0013  0.5271344  0.9368804  0.3333222
  0.0014  0.5313146  0.9359253  0.3379208
  0.0015  0.5357965  0.9349171  0.3431950
  0.0016  0.5416167  0.9334610  0.3508861
  0.0017  0.5461812  0.9323744  0.3569955
  0.0018  0.5537915  0.9303121  0.3620179
  0.0019  0.5550574  0.9300059  0.3631031
  0.0020  0.5550087  0.9300239  0.3634760
  0.0021  0.5606959  0.9286402  0.3712965
  0.0022  0.5639396  0.9278474  0.3720488
  0.0023  0.5649483  0.9275849  0.3730385
  0.0024  0.5695213  0.9264489  0.3760930
```

0.0025	0.5750305	0.9250698	0.3823049
0.0026	0.5814986	0.9234595	0.3866928
0.0027	0.5839201	0.9228570	0.3896643
0.0028	0.5845562	0.9226606	0.3911005
0.0029	0.5867111	0.9220863	0.3925992
0.0030	0.5905840	0.9210462	0.3977341
0.0031	0.5922378	0.9206193	0.3996227
0.0032	0.5932963	0.9203172	0.4009069
0.0033	0.5964782	0.9193833	0.4058073
0.0034	0.5977599	0.9190425	0.4074945
0.0035	0.5992522	0.9186577	0.4091447
0.0036	0.6011586	0.9181622	0.4107840
0.0037	0.6011586	0.9181622	0.4107840
0.0038	0.6011586	0.9181622	0.4107840
0.0039	0.6011586	0.9181622	0.4107840
0.0040	0.6011586	0.9181622	0.4107840
0.0041	0.6011586	0.9181622	0.4107840
0.0042	0.6011586	0.9181622	0.4107840
0.0043	0.6011586	0.9181622	0.4107840
0.0044	0.6025489	0.9177978	0.4120021
0.0045	0.6041986	0.9173678	0.4133392
0.0046	0.6041986	0.9173678	0.4133392
0.0047	0.6041986	0.9173678	0.4133392
0.0048	0.6062630	0.9168683	0.4147676
0.0049	0.6062630	0.9168683	0.4147676
0.0050	0.6062630	0.9168683	0.4147676

```
RMSE was used to select the optimal model using the smallest value.
The final value used for the model was cp = 1e-04.
```

Final Regression Tree

Let's re-run the regression tree on the training data,

Now using the cp value equal to the one selected in the previous problem cp = 1e-04.

Entrée [69]:

```
1 : = rpart(logVisits ~ laglogVisits + laglogVisitsYear + Year + Month + Region + ParkType + cost, data = training, cp = 1e-04)
```

And evaluate tree model with cross validation on the testing data set

```
tree.pred2 = predict(visitsTree, newdata=testing)
tree.sse = sum((tree.pred - testing$logVisits)^2)
tree.sse = sum((tree.pred2 - testing$logVisits)^2)
tree.ssm = sum((testing$logVisits - mean(training$logVisits))^2)
R2.tree = 1 - tree.sse / tree.ssm
print(R2.tree)
```

```
[1] 0.960693
```

We noticed here a big improvement (R2=0.96)

3. RandomForest

We can potentially further improve the models by using a random forest.

We train a random forest model with the same set of covariates, and using just default parameters.

But the training process may take a while.

```
install.packages("randomForest")
library(randomForest)
```

```
Installing package into '/srv/rlibs'
(as 'lib' is unspecified)
randomForest 4.6-14
Type rfNews() to see new features/changes/bug fixes.

Attaching package: 'randomForest'

The following object is masked from 'package:dplyr':

    combine

The following object is masked from 'package:ggplot2':

    margin
```

```
#Model building and evaluated
```

```
set.seed(201)
RandonForest = randomForest(logVisits ~ laglogVisits + laglogVisitsYear + Year + Month + Region + ParkType + cost, data = traini
Forest.pred3 = predict(RandonForest, newdata=testing)
Forest.sse = sum((Forest.pred3 - testing$logVisits)^2)
#Forest.ssm = sum((testing$logVisits - mean(visits$logVisits))^2)
Forest.ssm = sum((Forest.pred3 - mean(training$logVisits))^2)
R2.Forest = 1 - Forest.sse / Forest.ssm
print(R2.Forest)
```

```
[1] 0.969775
```

We got a better score

IV. Conclusion

Analysing national parks visits dataset gave many interesting insights into the national park business model during data exploration. (see data exploration section).

Our three regressions models both got good R square score with 7 independents variables from 0.94 to 0.97.

However, the models did not consider enough fields that could have been interesting for our study; laglogVisits and laglogVisitsYear.

Indeed, we could have exploited in depth the temporal nature of the data to build models based on those fields only and expect to get a better and simpler predictor.

Also, we can try to get better predictions using others optimized algorithms and apply other evaluations metrics to choose the best model.