

# Walmart Customer Trip Type Classification

## 1. 분석목적 (Purpose of Analysis)

Walmart Recruiting: Trip Type Classification 이용, Walmart 소비자 패턴을 분석하여 범주화된 Trip Type에 해당되는 VisitNumber 예측 및 분류.

## 2. 사용한 라이브러리

```
## Loading required package: grid

## Loading required package: mvtnorm

## Loading required package: modeltools

## Loading required package: stats4

## Loading required package: strucchange

## Loading required package: zoo

##
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':
##
##      as.Date, as.Date.numeric

## Loading required package: sandwich

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##      filter, lag

## The following objects are masked from 'package:base':
##
##      intersect, setdiff, setequal, union
```

```
## Loading required package: lattice
```

```
## Loading required package: ggplot2
```

```
##  
## Attaching package: 'MASS'
```

```
## The following object is masked from 'package:dplyr':  
##  
##      select
```

```
## Loading required package: Hmisc
```

```
## Loading required package: survival
```

```
##  
## Attaching package: 'survival'
```

```
## The following object is masked from 'package:caret':  
##  
##      cluster
```

```
## Loading required package: Formula
```

```
##  
## Attaching package: 'Hmisc'
```

```
## The following object is masked from 'package:e1071':  
##  
##      impute
```

```
## The following objects are masked from 'package:dplyr':  
##  
##      combine, src, summarize
```

```
## The following objects are masked from 'package:base':  
##  
##      format.pval, round.POSIXt, trunc.POSIXt, units
```

```
## funModeling v.1.6.5 :)  
## Examples and tutorials at livebook.datascienceheroes.com
```

```
##  
## Attaching package: 'kknns'
```

```
## The following object is masked from 'package:caret':  
##  
##      contr.dummy
```

```
## Type 'citation("pROC")' for a citation.
```

```
##  
## Attaching package: 'pROC'
```

```
## The following objects are masked from 'package:stats':  
##  
##      cov, smooth, var
```

```
## randomForest 4.6-12
```

```
## Type rfNews() to see new features/changes/bug fixes.
```

```
##  
## Attaching package: 'randomForest'
```

```
## The following object is masked from 'package:Hmisc':  
##  
## combine
```

```
## The following object is masked from 'package:ggplot2':  
##  
## margin
```

```
## The following object is masked from 'package:dplyr':  
##  
## combine
```

## 수정 전 데이터

```
wal_dataset <- read.csv("C:/Users/rudghksldl/Desktop/train 3.csv")  
  
head(wal_dataset, 20)
```

```
##      TripType VisitNumber Weekday      Upc ScanCount  
## 1         999          5 Friday 68113152929      -1  
## 2          30          7 Friday 60538815980       1  
## 3          30          7 Friday 7410811099       1  
## 4          26          8 Friday 2238403510       2  
## 5          26          8 Friday 2006613744       2  
## 6          26          8 Friday 2006618783       2  
## 7          26          8 Friday 2006613743       1  
## 8          26          8 Friday 7004802737       1  
## 9          26          8 Friday 2238495318       1  
## 10         26          8 Friday 2238400200      -1  
## 11         26          8 Friday 5200010239       1  
## 12         26          8 Friday 88679300501       2  
## 13         26          8 Friday 22006000000       1  
## 14         26          8 Friday 2236760452       1  
## 15         26          8 Friday 88679300501      -1  
## 16         26          8 Friday 2238400200       2  
## 17         26          8 Friday 3019294203       1  
## 18         26          8 Friday 72450408840       1  
## 19         26          8 Friday 25541500000       2  
## 20         26          8 Friday 2310010776       1  
##      DepartmentDescription FinelineNumber  
## 1      FINANCIAL SERVICES          1000  
## 2              SHOES          8931  
## 3      PERSONAL CARE          4504  
## 4 PAINT AND ACCESSORIES          3565  
## 5 PAINT AND ACCESSORIES          1017  
## 6 PAINT AND ACCESSORIES          1017  
## 7 PAINT AND ACCESSORIES          1017  
## 8 PAINT AND ACCESSORIES          2802  
## 9 PAINT AND ACCESSORIES          4501  
## 10 PAINT AND ACCESSORIES          3565  
## 11              DSD GROCERY          4606  
## 12 PAINT AND ACCESSORIES          3504  
## 13 MEAT - FRESH & FROZEN          6009  
## 14 PAINT AND ACCESSORIES           7  
## 15 PAINT AND ACCESSORIES          3504  
## 16 PAINT AND ACCESSORIES          3565  
## 17 PAINT AND ACCESSORIES          2801  
## 18 PAINT AND ACCESSORIES          1028  
## 19              DAIRY          1305  
## 20      PETS AND SUPPLIES          3300
```

## 변수 설명

TripType - a categorical id representing the type of shopping trip the customer made. This is the ground truth that you are predicting.

TripType\_999 is an “other” category. VisitNumber - an id corresponding to a single trip by a single customer

Weekday - the weekday of the trip

Upc - the UPC number of the product purchased

ScanCount - the number of the given item that was purchased. A negative value indicates a product return.

DepartmentDescription - a high-level description of the item’s department

FinelineNumber - a more refined category for each of the products, created by Walmart

## 변수 변환

```
dt <- na.omit(read.csv("C:/Users/rudghksldl/Desktop/newdata (1).csv"))
dt <- dt[,c(-1,-2,-5,-6)]
dt$striptype <- as.factor(dt$striptype)
glimpse(dt)
```

```
## Observations: 94,247
## Variables: 74
## $ num_prod <int> -1, 2, 28, 3, 3, 4, 7, 9, 4, 9, 3,...
## $ weekday <fctr> Friday, Friday, Friday, Friday, F...
## $ TotalDescCount <int> 1, 2, 22, 3, 3, 4, 7, 8, 4, 9, 2, ...
## $ max_prodrate <dbl> 1.000, 0.500, 0.727, 0.667, 0.667,...
## $ X1.HR.PHOTO <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ ACCESSORIES <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0...
## $ AUTOMOTIVE <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ BAKERY <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ BATH.AND.SHOWER <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ BEAUTY <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ BEDDING <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ BOOKS.AND.MAGAZINES <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ BOYS.WEAR <int> 0, 0, 0, 0, 0, 0, 2, 0, 0, 0, 0, 0...
## $ BRAS...SHAPEWEAR <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ CAMERAS.AND.SUPPLIES <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ CANDY...TOBACCO..COOKIES <int> 0, 0, 0, 0, 1, 0, 0, 0, 2, 0, 0, 0...
## $ CELEBRATION <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ COMM.BREAD <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ CONCEPT.STORES <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ COOK.AND.DINE <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ DAIRY <int> 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ DSD.GROCERY <int> 0, 0, 1, 0, 2, 1, 0, 0, 2, 0, 0, 0...
## $ ELECTRONICS <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ FABRICS.AND.CRAFTS <int> 0, 0, 0, 0, 0, 0, 0, 8, 0, 1, 0, 0...
## $ FINANCIAL.SERVICES <int> 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ FROZEN.FOODS <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0...
## $ FURNITURE <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ GIRLS.WEAR..4.6X..AND.7.14 <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ GROCERY.DRY.GOODS <int> 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0...
## $ HARDWARE <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ HEALTH.AND.BEAUTY.AIDS <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ HOME.DECOR <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ HOME.MANAGEMENT <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1...
## $ HORTICULTURE.AND.ACCESS <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ HOUSEHOLD.CHEMICALS.SUPP <int> 0, 0, 1, 0, 0, 0, 2, 0, 0, 0, 0, 0...
## $ HOUSEHOLD.PAPER.GOODS <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ IMPULSE.MERCHANDISE <int> 0, 0, 0, 1, 0, 2, 0, 0, 0, 2, 0, 0...
## $ INFANT.APPAREL <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ INFANT.CONSUMABLE.HARDLINES <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ JEWELRY.AND.SUNGLASSES <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0...
## $ LADIES.SOCKS <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ LADIESWEAR <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ LARGE.HOUSEHOLD.GOODS <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ LAWN.AND.GARDEN <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ LIQUOR.WINE.BEER <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ MEAT...FRESH...FROZEN <int> 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ MEDIA.AND.GAMING <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ MENS.WEAR <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 3, 0, 0...
## $ MENSWEAR <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ NULL <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ OFFICE.SUPPLIES <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ OPTICAL FRAMES <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0
```

```
## $ OPTICAL...LENSES <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ OTHER.DEPARTMENTS <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ PAINT.AND.ACCESSORIES <int> 0, 0, 16, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
## $ PERSONAL.CARE <int> 0, 1, 0, 0, 0, 0, 2, 0, 0, 0, 0, 0, 0...
## $ PETS.AND.SUPPLIES <int> 0, 0, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ PHARMACY.OTC <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ PHARMACY.RX <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ PLAYERS.AND.ELECTRONICS <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ PLUS.AND.MATERNITY <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ PRE.PACKED.DELI <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ PRODUCE <int> 0, 0, 0, 2, 0, 0, 0, 0, 0, 0, 0, 0, 1...
## $ SEAFOOD <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ SEASONAL <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ SERVICE.DELI <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0...
## $ SHEER.HOSIERY <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ SHOES <int> 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0...
## $ SLEEPWEAR.FOUNDATIONS <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ SPORTING.GOODS <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ SWIMWEAR.OUTERWEAR <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ TOYS <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ WIRELESS <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ triptype <fctr> 999, 30, 26, 8, 8, 35, 41, 21, 6,...
```

## 새로 만든 변수 설명

id - 고객 고유값

num\_prod - 구매 + 환불(-)

weekday - 방문요일

RefundCount - 고객의 총 환불량

TotalDescCount - 고객의 총 구매량

MaxDescCount - 최대값을 갖는 DepartmentDescription의 양

max\_prodrate - 최대값을 갖는 DepartmentDescription의 해당비율

DepartmentDescription의 dummy 변수(one hot 인코딩) - 68열

TripType - 예측해야할 타겟 변수

## 4. Model Accuracy 판단

```
# train / validation data
trn_idx <- sample(1:dim(dt)[1], round(0.7*dim(dt)[1]))
w_trn <- dt[trn_idx, ]
w_val <- dt[-trn_idx, ]
```

## 4.1 KNN

찾은 K 값으로 모델 적합

```
w_knn <- kknk(triptype ~ .,
             w_trn,
             w_val,
             k = 7,
             distance = 2,
             kernel = "rectangular")
```

모델 적합 후 정확도 확인

```
pima_knn_fit <- fitted(w_knn)
pima_knn_cf <- confusionMatrix(w_val$striptype, as.factor(pima_knn_fit))
pima_knn_cf
```

```
## Confusion Matrix and Statistics
##
##              Reference
## Prediction    3    4    5    6    7    8    9   12   14   15   18   19
##      3      1020    0    0    1    0   29    7    0    0    0    0    0
##      4         1    2   78    0    1    7    2    0    0    0    0    0
##      5         6    5  731    6   22   71   40    0    0    1    2    1
##      6         1    0    1  274    6   58    3    0    0    0    0    1
##      7         3    0   10    8 1208   220   24    1    0    3    2    0
```

##	8	7	0	111	70	194	2917	133	0	0	0	0	0
##	9	20	0	15	2	12	140	2102	3	0	9	16	31
##	12	0	0	0	1	9	3	10	3	0	1	2	0
##	14	0	0	0	0	0	0	0	0	0	0	0	0
##	15	2	0	3	1	8	47	49	1	0	97	1	0
##	18	0	0	0	0	0	9	49	0	0	1	66	0
##	19	0	0	0	0	0	0	43	0	0	0	1	28
##	20	1	0	2	1	1	1	69	0	0	1	0	0
##	21	0	0	2	1	1	3	46	0	0	5	2	1
##	22	2	0	2	0	0	0	91	0	0	0	1	22
##	23	2	0	0	0	0	0	22	0	0	0	0	0
##	24	5	0	3	4	7	9	151	0	0	3	1	1
##	25	8	0	3	6	5	7	175	2	0	0	2	0
##	26	2	0	1	0	1	1	57	0	0	1	0	0
##	27	3	0	1	2	2	2	55	3	0	1	2	0
##	28	1	0	2	0	2	0	63	0	0	0	0	0
##	29	3	0	4	0	0	2	51	0	0	0	13	1
##	30	2	0	2	1	2	2	123	0	0	0	0	0
##	31	4	0	0	1	0	4	36	0	0	0	0	0
##	32	5	0	6	3	9	44	31	1	0	3	6	0
##	33	3	0	0	1	6	62	11	0	0	0	0	0
##	34	1	0	2	4	4	37	12	0	0	0	0	0
##	35	11	0	12	7	34	140	28	0	0	2	4	1
##	36	10	0	44	4	7	115	35	0	0	3	2	0
##	37	6	0	8	1	126	71	13	0	0	5	1	4
##	38	2	0	5	7	80	107	20	0	0	0	2	0
##	39	21	0	115	72	292	191	130	8	0	22	13	4
##	40	0	1	14	3	22	2	4	3	0	4	4	0
##	41	1	0	1	0	0	0	36	0	0	1	3	3
##	42	2	0	1	3	2	7	85	1	0	26	18	3
##	43	7	0	5	1	2	11	62	3	0	8	6	0
##	44	0	0	8	4	3	2	12	0	0	10	6	1
##	999	221	2	39	7	54	263	374	0	0	12	6	7
##	Reference												
##	Prediction	20	21	22	23	24	25	26	27	28	29	30	31
##	3	1	0	5	1	6	0	0	1	0	1	2	0
##	4	0	0	0	0	0	0	0	0	1	1	0	0
##	5	1	3	1	0	10	6	1	2	1	1	4	1
##	6	1	1	1	0	0	0	0	0	0	0	0	0
##	7	1	1	1	0	5	5	0	3	1	1	4	0
##	8	2	1	0	0	7	3	3	2	0	1	5	2
##	9	13	5	41	16	72	60	11	15	21	7	32	54
##	12	0	1	0	0	2	2	0	14	0	2	0	0
##	14	0	1	1	0	0	0	0	0	0	0	0	0
##	15	0	7	4	0	4	5	1	1	2	0	1	1
##	18	4	4	0	0	4	2	0	0	0	25	1	0
##	19	0	0	44	1	0	0	0	0	1	0	0	0
##	20	123	0	1	0	0	1	0	0	0	0	0	0
##	21	0	111	0	0	2	0	1	1	0	1	0	0
##	22	0	1	99	7	4	4	1	0	0	0	1	8
##	23	0	0	2	17	0	0	0	0	0	0	0	0
##	24	2	6	2	0	463	10	5	3	2	0	2	0
##	25	3	2	3	1	12	775	4	3	1	0	21	1
##	26	2	2	0	0	5	0	45	0	1	1	0	0
##	27	0	1	0	0	4	0	2	144	0	0	0	0
##	28	0	1	0	0	6	2	0	1	65	16	1	0
##	29	1	0	0	0	1	4	0	0	16	8	1	0
##	30	1	2	1	0	1	27	0	1	1	0	126	1
##	31	0	0	1	1	0	0	0	0	1	0	0	139
##	32	0	5	0	0	3	10	0	1	1	1	9	0
##	33	3	3	1	0	7	3	2	2	0	2	0	1
##	34	1	0	1	0	1	0	1	1	0	0	0	0
##	35	2	3	0	0	5	3	1	1	2	1	1	0
##	36	3	7	5	0	14	22	2	11	1	0	5	1
##	37	4	0	5	0	10	7	2	1	3	0	4	0
##	38	2	1	1	0	3	5	1	3	0	1	6	0
##	39	27	9	30	2	68	72	20	19	10	9	34	3
##	40	2	5	2	1	21	46	7	7	4	0	2	2
##	41	2	0	9	0	16	37	7	1	1	2	28	1
##	42	15	29	29	3	49	96	17	27	9	4	24	4
##	43	10	21	1	0	21	22	9	8	3	1	10	1
##	44	2	13	9	1	33	71	10	17	3	2	14	2
##	aaa	a	?	??	A	5a	66	A	11	13	3	11	10

##	999	9	2	23	4	33	88	4	11	13	3	11	10
##	Reference												
##	Prediction	32	33	34	35	36	37	38	39	40	41	42	43
##	3	0	0	0	0	0	0	0	1	0	0	0	0
##	4	0	1	0	0	2	0	0	2	0	0	0	0
##	5	0	1	2	5	22	2	4	28	0	0	1	1
##	6	0	0	0	4	1	0	1	13	1	0	0	0
##	7	2	2	1	3	1	47	36	86	1	0	0	0
##	8	43	15	11	24	38	14	24	16	0	0	0	0
##	9	25	1	0	3	4	0	1	10	0	0	3	1
##	12	0	10	1	2	2	4	1	10	5	0	0	0
##	14	0	0	0	0	0	0	0	0	0	0	0	0
##	15	2	10	0	7	3	2	2	29	3	0	1	0
##	18	3	0	0	3	3	1	0	2	0	0	2	0
##	19	0	0	1	0	0	0	0	0	0	1	0	0
##	20	0	0	1	0	1	0	0	0	0	1	2	1
##	21	0	1	0	2	3	0	0	0	0	0	6	3
##	22	0	2	2	0	0	0	0	5	3	1	0	0
##	23	0	0	0	0	0	0	0	2	0	0	0	0
##	24	1	9	2	4	5	3	1	25	8	1	8	4
##	25	5	2	1	5	7	3	1	17	2	1	8	2
##	26	0	0	0	1	0	0	2	5	1	1	0	0
##	27	0	0	4	0	1	1	0	3	0	0	0	0
##	28	1	1	0	0	1	0	0	1	0	0	0	1
##	29	2	0	1	0	0	2	0	8	0	0	4	0
##	30	0	1	1	1	4	1	0	7	0	0	3	0
##	31	0	0	0	0	0	0	0	1	0	0	0	0
##	32	382	7	2	5	5	2	8	22	5	0	3	0
##	33	2	207	0	6	11	4	1	54	0	0	0	1
##	34	0	0	126	1	2	0	1	19	6	1	0	0
##	35	4	5	1	282	8	13	17	49	3	0	1	0
##	36	5	4	1	7	459	3	4	78	7	0	2	1
##	37	1	1	5	7	2	398	12	54	47	0	1	1
##	38	8	7	3	37	6	30	336	146	47	0	1	1
##	39	51	82	46	110	142	56	158	1110	26	1	6	5
##	40	11	27	21	16	34	98	88	456	914	0	2	5
##	41	6	1	0	2	1	0	0	3	0	2	6	2
##	42	24	1	2	6	3	0	1	11	3	4	38	2
##	43	4	0	1	1	9	0	1	16	0	1	3	4
##	44	13	3	5	0	10	1	1	39	11	3	17	4
##	999	20	3	4	3	17	6	15	9	0	1	3	0
##	Reference												
##	Prediction	44	999										
##	3	0	23										
##	4	0	0										
##	5	0	5										
##	6	1	1										
##	7	0	4										
##	8	0	20										
##	9	0	92										
##	12	0	2										
##	14	0	0										
##	15	0	2										
##	18	0	1										
##	19	0	8										
##	20	0	1										
##	21	0	0										
##	22	0	18										
##	23	0	2										
##	24	0	37										
##	25	4	28										
##	26	0	7										
##	27	0	2										
##	28	0	2										
##	29	0	1										
##	30	0	6										
##	31	0	1										
##	32	0	1										
##	33	0	2										
##	34	0	1										
##	35	1	1										
##	36	0	7										
##	37	0	1										

```

##          38      0    10
##          39      0      9
##          40      9      0
##          41      3      2
##          42      7      8
##          43      0      1
##          44      7      2
##          999      0 1240
##
## Overall Statistics
##
##          Accuracy : 0.5683
##          95% CI : (0.5625, 0.5741)
##          No Information Rate : 0.1621
##          P-Value [Acc > NIR] : < 2.2e-16
##
##          Kappa : 0.5371
##          McNemar's Test P-Value : NA
##
## Statistics by Class:
##
##          Class: 3  Class: 4  Class: 5  Class: 6  Class: 7
## Sensitivity      0.73753 2.000e-01 0.59383 0.552419 0.56927
## Specificity      0.99710 9.966e-01 0.99053 0.996580 0.98180
## Pos Pred Value   0.92896 2.041e-02 0.74063 0.742547 0.71734
## Neg Pred Value   0.98664 9.997e-01 0.98168 0.992044 0.96563
## Prevalence       0.04891 3.537e-04 0.04354 0.017543 0.07505
## Detection Rate   0.03608 7.074e-05 0.02585 0.009691 0.04272
## Detection Prevalence 0.03883 3.466e-03 0.03491 0.013051 0.05956
## Balanced Accuracy 0.86731 5.983e-01 0.79218 0.774500 0.77554
##          Class: 8  Class: 9  Class: 12  Class: 14  Class: 15
## Sensitivity      0.6363 0.49412 0.1034483 NA 0.442922
## Specificity      0.9685 0.96940 0.9970260 9.999e-01 0.992907
## Pos Pred Value   0.7963 0.74092 0.0344828 NA 0.327703
## Neg Pred Value   0.9323 0.91540 0.9990776 NA 0.995639
## Prevalence       0.1621 0.15046 0.0010257 0.000e+00 0.007746
## Detection Rate   0.1032 0.07434 0.0001061 0.000e+00 0.003431
## Detection Prevalence 0.1296 0.10034 0.0030770 7.074e-05 0.010469
## Balanced Accuracy 0.8024 0.73176 0.5502371 NA 0.717915
##          Class: 18  Class: 19  Class: 20  Class: 21  Class: 22
## Sensitivity      0.362637 0.2568807 0.518987 0.447581 0.306502
## Specificity      0.995942 0.9964495 0.996968 0.997110 0.993739
## Pos Pred Value   0.366667 0.2187500 0.591346 0.578125 0.361314
## Neg Pred Value   0.995871 0.9971221 0.995938 0.995121 0.992000
## Prevalence       0.006437 0.0038551 0.008382 0.008771 0.011424
## Detection Rate   0.002334 0.0009903 0.004350 0.003926 0.003501
## Detection Prevalence 0.006366 0.0045271 0.007357 0.006791 0.009691
## Balanced Accuracy 0.679290 0.6266651 0.757978 0.722345 0.650120
##          Class: 23  Class: 24  Class: 25  Class: 26  Class: 27
## Sensitivity      0.3090909 0.50436 0.56735 0.286624 0.478405
## Specificity      0.9989369 0.98816 0.98718 0.996764 0.996818
## Pos Pred Value   0.3617021 0.58831 0.69196 0.330882 0.618026
## Neg Pred Value   0.9986538 0.98345 0.97824 0.996020 0.994401
## Prevalence       0.0019453 0.03247 0.04831 0.005553 0.010646
## Detection Rate   0.0006013 0.01638 0.02741 0.001592 0.005093
## Detection Prevalence 0.0016623 0.02783 0.03961 0.004810 0.008241
## Balanced Accuracy 0.6540139 0.74626 0.77726 0.641694 0.737612
##          Class: 28  Class: 29  Class: 30  Class: 31  Class: 32
## Sensitivity      0.396341 0.0879121 0.361032 0.599138 0.62114
## Specificity      0.996371 0.9959195 0.993160 0.998217 0.99284
## Pos Pred Value   0.389222 0.0650407 0.397476 0.735450 0.65862
## Neg Pred Value   0.996478 0.9970516 0.992023 0.996689 0.99159
## Prevalence       0.005800 0.0032185 0.012343 0.008205 0.02175
## Detection Rate   0.002299 0.0002829 0.004456 0.004916 0.01351
## Detection Prevalence 0.005906 0.0043503 0.011212 0.006685 0.02051
## Balanced Accuracy 0.696356 0.5419158 0.677096 0.798677 0.80699
##          Class: 33  Class: 34  Class: 35  Class: 36  Class: 37
## Sensitivity      0.512376 0.514286 0.515539 0.56877 0.57598
## Specificity      0.993254 0.996575 0.986980 0.98507 0.98539
## Pos Pred Value   0.524051 0.567568 0.438569 0.52819 0.49688
## Neg Pred Value   0.992934 0.995758 0.990409 0.98730 0.98933
## Prevalence       0.014289 0.008665 0.019346 0.02854 0.02444
## Detection Rate   0.007321 0.004456 0.009974 0.01623 0.01408

```



```
## Detection Prevalence 0.013970 0.007852 0.022742 0.03073 0.02833
## Balanced Accuracy 0.752815 0.755430 0.751260 0.77692 0.78068
## Class: 38 Class: 39 Class: 40 Class: 41 Class: 42
## Sensitivity 0.46927 0.47497 0.83623 1.053e-01 0.314050
## Specificity 0.98033 0.92817 0.96604 9.938e-01 0.981316
## Pos Pred Value 0.38269 0.37336 0.49755 1.130e-02 0.067376
## Neg Pred Value 0.98613 0.95150 0.99323 9.994e-01 0.997005
## Prevalence 0.02532 0.08266 0.03866 6.720e-04 0.004280
## Detection Rate 0.01188 0.03926 0.03233 7.074e-05 0.001344
## Detection Prevalence 0.03105 0.10515 0.06497 6.260e-03 0.019948
## Balanced Accuracy 0.72480 0.70157 0.90114 5.495e-01 0.647683
## Class: 43 Class: 44 Class: 999
## Sensitivity 0.1025641 0.2187500 0.80103
## Specificity 0.9911812 0.9882445 0.95207
## Pos Pred Value 0.0158103 0.0206490 0.49187
## Neg Pred Value 0.9987509 0.9991051 0.98804
## Prevalence 0.0013794 0.0011318 0.05475
## Detection Rate 0.0001415 0.0002476 0.04386
## Detection Prevalence 0.0089482 0.0119898 0.08916
## Balanced Accuracy 0.5468726 0.6034972 0.87655
```

## 4.2 RandomForest

최적의 파라미터를 찾기 위한 그리드 서치

```

## 하이퍼 파라미터 정의
ntree = c(10, 20)
mtry = c(3, 5, 10)

# 결과값 넣을 매트릭스
tree_result <- matrix(0, length(ntree)*length(mtry),6)
iter_cnt = 1
i = 1
j = 1

# 위 파라미터들 다 넣는 포문
for(i in 1:length(ntree)){
  for(j in 1:length(mtry)){
    cat("ntree : ", ntree[i],
        ", mtry : ", mtry[j],
        "\n")

    ## 위 파라미터로 RF 모형 적합

    tmp_rf <- randomForest(triptype ~ .,
                           data = w_trn,
                           ntree = ntree[i],
                           mtry = mtry[j]
                           )

    ## 위 적합으로 검증데이터 예측 수행
    tmp_tree_val_pred <- predict(tmp_rf, newdata = w_val, type = "class")

    ## 혼동행렬 작성
    tmp_tree_val_cf <- confusionMatrix(as.factor(tmp_tree_val_pred), w_val$striptype)

    ## AUROC

    ### 조건들 저장
    tree_result[iter_cnt, 1] = ntree[i]
    tree_result[iter_cnt, 2] = mtry[j]
    tree_result[iter_cnt, 3] = tmp_tree_val_cf$byClass['Recall']
    tree_result[iter_cnt, 4] = tmp_tree_val_cf$byClass['Precision']
    tree_result[iter_cnt, 5] = tmp_tree_val_cf$overall['Accuracy']
    tree_result[iter_cnt, 6] = tmp_tree_val_cf$byClass['F1']

    iter_cnt = iter_cnt +1
  }
}

```

```

## ntree : 10 , mtry : 3
## ntree : 10 , mtry : 5
## ntree : 10 , mtry : 10
## ntree : 20 , mtry : 3
## ntree : 20 , mtry : 5
## ntree : 20 , mtry : 10

```

```

colnames(tree_result) <- c("ntree", "mtry", "Recall", "Precision", "Accuracy",
                           "F1")

# 어큐러시 와 F1 지표를 기준으로 정렬
tree_result.df <- data.frame(tree_result)
tree_result.df <- tree_result.df[order(tree_result.df[,5],tree_result.df[,6],decreasing = T),]
head(tree_result.df)

```

```
##      ntree mtry Recall Precision Accuracy F1
## 6      20   10     NA         NA 0.6687770 NA
## 5      20    5     NA         NA 0.6626229 NA
## 3      10   10     NA         NA 0.6569286 NA
## 2      10    5     NA         NA 0.6523661 NA
## 4      20    3     NA         NA 0.6287402 NA
## 1      10    3     NA         NA 0.6092523 NA
```

## 최적조건으로 최종적합

```
# 최적 조건으로 학습나무를 학습 with 전체 데이터
tree <- randomForest(triptype ~ .,
                     data = w_trn ,
                     ntree = 20,
                     mtry = 10)

tree_all_prediction <- predict(tree, newdata = w_val)

# 최종 완성된 결정나무의 분류 성능 확인
tree_all_cm <- confusionMatrix(tree_all_prediction, w_val$triptype)
tree_all_cm
```

```
## Confusion Matrix and Statistics
##
##              Reference
## Prediction      3      4      5      6      7      8      9     12     14     15     18     19
##      3      1038      0      0      0      0      0     20      0      0      2      1      0
##      4        0      0      0      0      0      0      0      0      0      0      0      0
##      5        0      87     727      3      7     112     32      1      0      3      0      1
##      6        0      0      4     236      6      77      2      0      0      0      0      1
##      7        0      0     11     12    1117     143     31      3      0      6      1      1
##      8       42      3     48     34     191    3092     233      1      0     27      9      0
##      9        1      0     17      4      8      85    2261      4      0      9     35     66
##     12        0      0      1      0      0      0      0      0      0      1      0      0
##     14        0      0      0      0      0      0      0      0      0      0      0      0
##     15        0      0      1      0      2      1      2      3      0     110      1      0
##     18        0      0      0      0      0      1      3      4      0      1     51      1
##     19        0      0      0      0      0      1      9      0      0      0      0     15
##     20        0      0      1      0      0      0      2      0      0      0      4      0
##     21        0      0      2      1      1      1      5      1      2      5      4      1
##     22        2      0      0      0      0      0     19      0      0      0      0     19
##     23        0      0      0      0      0      0     10      0      0      0      0      1
##     24        6      0      3      3      7      5     20      3      0      5      6      2
##     25        2      0      7      1      5      2     41      1      0      6      7      4
##     26        0      0      0      0      0      0      1      0      0      1      0      1
##     27        1      0      0      0      1      1      1      9      0      1      0      0
##     28        0      0      0      0      0      0      2      0      0      1      0      0
##     29        0      0      0      0      0      0      5      0      0      0      3      0
##     30        1      0      1      0      2      2     17      0      0      4      0      0
##     31        0      0      0      0      0      2     62      0      0      1      0      0
##     32        0      0      0      0      4     63     40      1      0      4      5      0
##     33        0      1      2      4      4      4      1      8      0      7      2      0
##     34        0      0      2      0      1      3      1      0      0      0      1      1
##     35        1      0      7      9      8      5      2      3      0     17      7      0
##     36        1      1     34      2      2     17      3      2      0      4      5      2
##     37        0      0      5      6     64      5      2      5      0     10      1      1
##     38        1      0      4      2     41     25      3      1      0      3      1      2
##     39        2      6    100     49    208     11      1     28      0     54     19      7
##     40        0      0      6      2      5      0      0      7      0      9      2      0
##     41        0      0      0      0      0      0      1      0      0      0      1      0
##     42        0      0      1      1      0      1      2      2      0      4     12      2
##     43        0      0      0      0      0      0      0      0      0      1      1      0
##     44        0      0      0      0      0      0      0      0      0      0      1      0
##     999        0      0      3      0      0      4      3      0      0      0      0      0
##
##              Reference
## Prediction     20     21     22     23     24     25     26     27     28     29     30     31
##      3         2      1      1      4      7      0      4      1      0      2      2      0
##      4         0      0      0      0      0      0      0      0      0      0      1      0
##      5         4      3      5      1      7      7      3      6      2      3      7      2
##      6         0      1      1      0      0      0      0      1      0      1      0      0
##      7         1      3      4      0      9      7      4      4      4      1      5      1
```

##	8	2	1	4	1	14	3	3	2	1	4	2	10
##	9	51	12	90	20	108	84	23	28	50	43	84	0
##	12	0	0	0	0	0	0	0	0	0	0	0	0
##	14	0	0	0	0	0	0	0	0	0	0	0	0
##	15	0	7	2	1	5	1	1	1	1	0	1	0
##	18	0	2	0	0	1	1	1	1	2	14	1	0
##	19	0	0	9	0	0	0	0	0	0	0	0	1
##	20	106	0	2	0	4	2	4	2	0	2	2	0
##	21	0	113	3	1	6	2	1	1	2	0	2	0
##	22	0	0	63	1	1	0	1	0	0	0	1	1
##	23	0	0	3	10	0	0	0	0	0	0	0	0
##	24	1	9	7	0	368	11	7	2	5	3	5	0
##	25	2	5	10	0	17	784	2	0	2	5	36	0
##	26	0	0	1	0	4	0	48	0	0	0	1	0
##	27	1	0	1	0	2	1	1	136	1	0	0	0
##	28	1	0	0	0	0	2	1	0	56	12	1	1
##	29	0	2	0	0	1	0	0	0	5	2	0	0
##	30	1	1	2	0	2	14	1	0	1	1	96	0
##	31	0	0	8	0	0	0	0	0	0	0	0	151
##	32	0	2	2	0	3	8	0	2	1	1	3	1
##	33	0	1	2	1	15	4	1	0	1	0	1	0
##	34	1	0	2	0	4	1	0	4	1	1	4	0
##	35	3	3	4	1	12	13	1	1	2	2	7	3
##	36	6	2	9	0	22	17	4	5	4	3	7	1
##	37	1	1	0	0	13	11	2	3	3	3	3	0
##	38	2	1	4	2	6	4	4	1	0	2	5	1
##	39	17	10	30	3	97	93	11	21	15	13	27	14
##	40	1	3	3	0	34	22	3	7	0	1	4	0
##	41	0	0	0	0	0	3	0	0	1	1	0	0
##	42	5	9	1	0	17	19	4	4	4	3	9	2
##	43	0	0	1	0	3	2	1	0	3	0	0	0
##	44	0	0	0	0	2	4	0	0	0	0	0	0
##	999	0	0	0	1	3	0	0	0	0	0	0	0
##	Reference												
##	Prediction	32	33	34	35	36	37	38	39	40	41	42	43
##	3	1	0	0	0	1	0	0	0	0	1	0	0
##	4	0	0	0	0	0	0	0	0	0	0	0	0
##	5	4	3	1	5	36	10	4	50	2	0	3	8
##	6	0	0	3	1	0	0	1	12	0	1	0	1
##	7	3	0	5	20	3	80	46	125	3	0	1	7
##	8	10	13	34	28	35	41	10	13	0	1	5	0
##	9	5	5	0	2	4	0	0	3	0	3	10	0
##	12	0	0	0	0	1	0	0	0	0	0	1	0
##	14	0	0	0	0	0	0	0	0	0	0	0	0
##	15	0	1	0	2	1	1	0	5	0	2	18	1
##	18	3	0	0	2	1	0	0	1	0	4	10	1
##	19	0	0	0	0	0	0	1	1	0	1	0	0
##	20	0	2	1	0	1	0	0	0	0	1	7	3
##	21	1	2	0	1	3	0	0	0	1	1	12	8
##	22	0	0	0	0	1	0	0	1	0	0	4	1
##	23	0	0	0	0	0	0	0	0	0	0	0	0
##	24	7	4	2	6	4	1	0	24	0	15	46	10
##	25	8	1	0	8	13	3	4	25	4	35	98	25
##	26	0	0	0	0	2	0	0	0	0	2	6	4
##	27	1	0	2	0	3	0	2	1	0	2	14	1
##	28	0	0	0	0	1	0	0	0	0	1	7	2
##	29	0	0	0	0	0	0	0	1	0	3	3	0
##	30	3	0	0	1	2	0	0	3	0	12	10	5
##	31	0	0	0	0	0	0	0	0	0	0	0	0
##	32	416	1	2	3	4	0	6	42	2	7	26	4
##	33	3	225	1	7	4	0	5	47	1	2	6	7
##	34	1	0	113	0	0	3	1	25	5	1	1	0
##	35	3	9	3	382	2	5	26	82	2	1	8	3
##	36	7	9	5	10	550	0	4	99	11	1	8	16
##	37	2	4	3	17	6	423	18	63	40	2	1	4
##	38	6	6	5	16	6	6	335	113	24	1	4	3
##	39	68	101	34	118	167	111	313	2181	79	38	87	115
##	40	17	8	6	9	13	115	97	46	1658	5	32	2
##	41	0	0	1	0	0	0	0	0	0	3	6	0
##	42	10	1	0	2	2	0	0	3	1	22	102	12
##	43	0	0	1	1	1	2	0	3	0	3	5	9
##	44	1	0	0	0	2	0	0	4	4	6	22	1
##	999	0	0	0	2	0	0	5	0	0	0	1	0

```

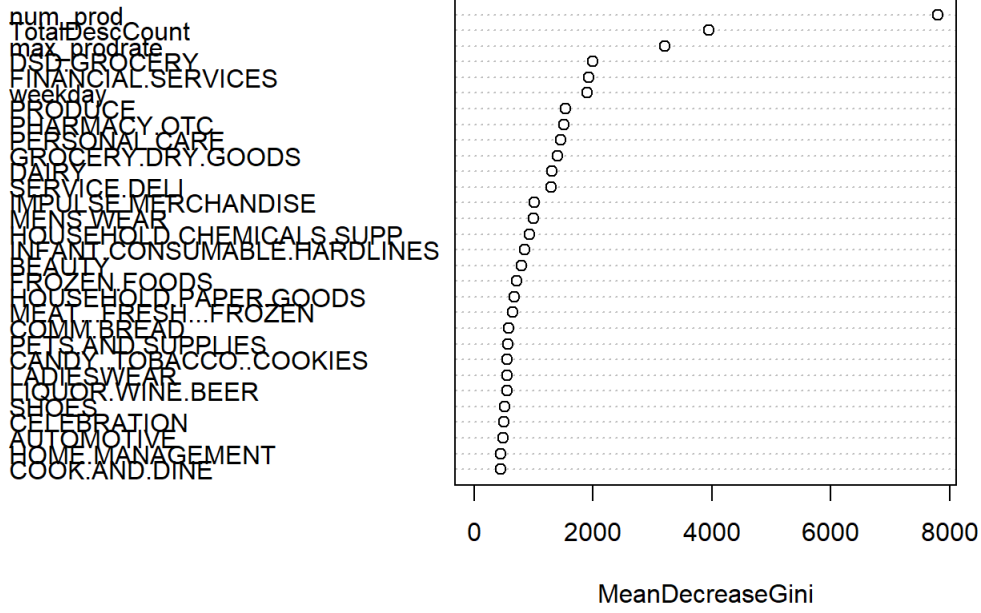
##           Reference
## Prediction  44  999
##           3      0  212
##           4      0   0
##           5      3  24
##           6      0   0
##           7      1  36
##           8      0 119
##           9      0 124
##          12      0   0
##          14      0   0
##          15      4   4
##          18      0   0
##          19      0   1
##          20      0   2
##          21      1   1
##          22      0  13
##          23      0   1
##          24      8  23
##          25     20   8
##          26      0   2
##          27      1   1
##          28      0   1
##          29      0   0
##          30      0   3
##          31      1   4
##          32      7   5
##          33      1   1
##          34      2   0
##          35      0   3
##          36      8  13
##          37      2   6
##          38      2  14
##          39     147  16
##          40     104   0
##          41      2   0
##          42      9   2
##          43      4   0
##          44     12   0
##          999     0 1882
##
## Overall Statistics
##
##           Accuracy : 0.6674
##           95% CI : (0.6619, 0.6729)
##           No Information Rate : 0.1296
##           P-Value [Acc > NIR] : < 2.2e-16
##
##           Kappa : 0.642
##           McNemar's Test P-Value : NA
##
## Statistics by Class:
##
##           Class: 3  Class: 4  Class: 5  Class: 6  Class: 7
## Sensitivity      0.94536 0.000e+00 0.73658 0.639566 0.66330
## Specificity      0.99036 1.000e+00 0.98355 0.995951 0.97815
## Pos Pred Value   0.79846 0.000e+00 0.61820 0.676218 0.65783
## Neg Pred Value   0.99778 9.965e-01 0.99041 0.995237 0.97866
## Prevalence       0.03883 3.466e-03 0.03491 0.013051 0.05956
## Detection Rate   0.03671 0.000e+00 0.02571 0.008347 0.03951
## Detection Prevalence 0.04598 3.537e-05 0.04159 0.012343 0.06006
## Balanced Accuracy 0.96786 5.000e-01 0.86006 0.817758 0.82073
##           Class: 8  Class: 9  Class: 12  Class: 14  Class: 15
## Sensitivity      0.8441 0.79697 0.0000000 0.000e+00 0.371622
## Specificity      0.9616 0.96155 0.9998581 1.000e+00 0.997534
## Pos Pred Value   0.7661 0.69805 0.0000000      NaN 0.614525
## Neg Pred Value   0.9764 0.97699 0.9969225 9.999e-01 0.993380
## Prevalence       0.1296 0.10034 0.0030770 7.074e-05 0.010469
## Detection Rate   0.1094 0.07997 0.0000000 0.000e+00 0.003891
## Detection Prevalence 0.1427 0.11456 0.0001415 0.000e+00 0.006331
## Balanced Accuracy 0.9029 0.87926 0.4999290 5.000e-01 0.684578
##           Class: 18  Class: 19  Class: 20  Class: 21  Class: 22
## Sensitivity      0.283333 0.1171875 0.509615 0.588542 0.229927

```

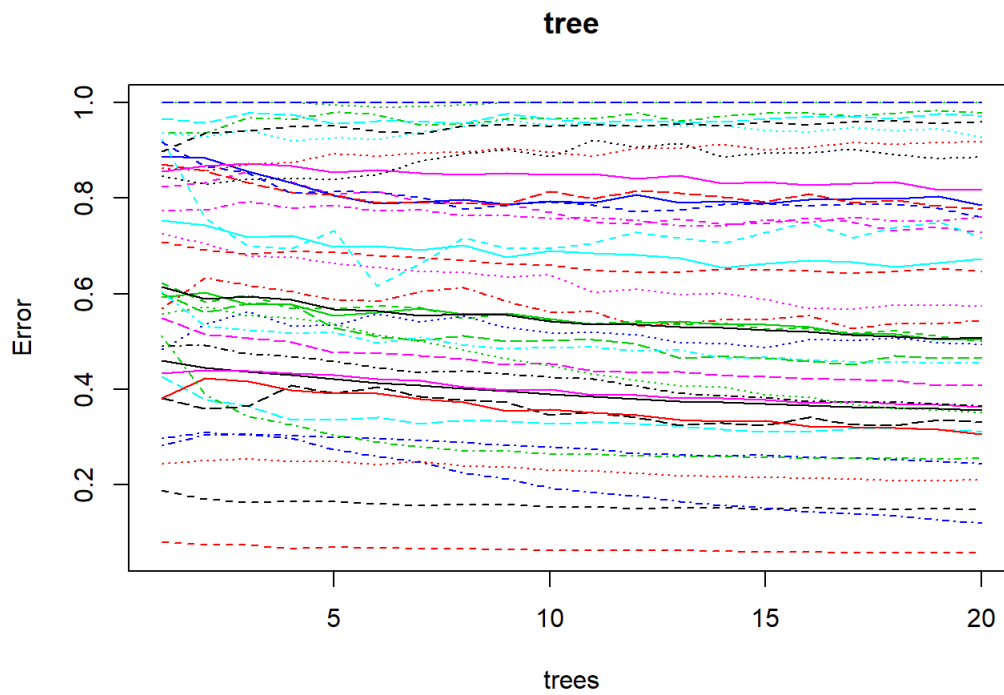
```
## Sensitivity      0.283333 0.1171875 0.309013 0.308342 0.227727
## Specificity      0.998042 0.9991473 0.998504 0.997436 0.997679
## Pos Pred Value   0.481132 0.3846154 0.716216 0.610811 0.492187
## Neg Pred Value    0.995420 0.9959979 0.996373 0.997188 0.992503
## Prevalence        0.006366 0.0045271 0.007357 0.006791 0.009691
## Detection Rate    0.001804 0.0005305 0.003749 0.003997 0.002228
## Detection Prevalence 0.003749 0.0013794 0.005234 0.006543 0.004527
## Balanced Accuracy 0.640688 0.5581674 0.754059 0.792989 0.613803
##
## Class: 23 Class: 24 Class: 25 Class: 26 Class: 27
## Sensitivity      0.2127660 0.46760 0.70000 0.352941 0.583691
## Specificity      0.9994686 0.99054 0.98501 0.999112 0.998253
## Pos Pred Value   0.4000000 0.58599 0.65827 0.657534 0.735135
## Neg Pred Value    0.9986902 0.98484 0.98759 0.996880 0.996547
## Prevalence        0.0016623 0.02783 0.03961 0.004810 0.008241
## Detection Rate    0.0003537 0.01302 0.02773 0.001698 0.004810
## Detection Prevalence 0.0008842 0.02221 0.04212 0.002582 0.006543
## Balanced Accuracy 0.6061173 0.72907 0.84251 0.676026 0.790972
##
## Class: 28 Class: 29 Class: 30 Class: 31 Class: 32
## Sensitivity      0.335329 1.626e-02 0.302839 0.798942 0.71724
## Specificity      0.998826 9.992e-01 0.996817 0.997223 0.99101
## Pos Pred Value   0.629213 8.000e-02 0.518919 0.659389 0.62556
## Neg Pred Value    0.996062 9.957e-01 0.992132 0.998645 0.99406
## Prevalence        0.005906 4.350e-03 0.011212 0.006685 0.02051
## Detection Rate    0.001981 7.074e-05 0.003395 0.005341 0.01471
## Detection Prevalence 0.003148 8.842e-04 0.006543 0.008099 0.02352
## Balanced Accuracy 0.667078 5.077e-01 0.649828 0.898082 0.85413
##
## Class: 33 Class: 34 Class: 35 Class: 36 Class: 37
## Sensitivity      0.569620 0.509009 0.59409 0.63291 0.52809
## Specificity      0.994835 0.997647 0.99066 0.98745 0.98883
## Pos Pred Value   0.609756 0.631285 0.59688 0.61521 0.57945
## Neg Pred Value    0.993908 0.996120 0.99056 0.98835 0.98628
## Prevalence        0.013970 0.007852 0.02274 0.03073 0.02833
## Detection Rate    0.007958 0.003997 0.01351 0.01945 0.01496
## Detection Prevalence 0.013051 0.006331 0.02264 0.03162 0.02582
## Balanced Accuracy 0.782228 0.753328 0.79238 0.81018 0.75846
##
## Class: 38 Class: 39 Class: 40 Class: 41 Class: 42
## Sensitivity      0.38155 0.73360 0.90256 0.0169492 0.180851
## Specificity      0.98828 0.91186 0.97870 0.9994305 0.994009
## Pos Pred Value   0.51067 0.49445 0.74651 0.1578947 0.380597
## Neg Pred Value    0.98034 0.96681 0.99313 0.9938418 0.983504
## Prevalence        0.03105 0.10515 0.06497 0.0062602 0.019948
## Detection Rate    0.01185 0.07714 0.05864 0.0001061 0.003608
## Detection Prevalence 0.02320 0.15601 0.07855 0.0006720 0.009479
## Balanced Accuracy 0.68492 0.82273 0.94063 0.5081898 0.587430
##
## Class: 43 Class: 44 Class: 999
## Sensitivity      0.0355731 0.0353982 0.74653
## Specificity      0.9988580 0.9983175 0.99915
## Pos Pred Value   0.2195122 0.2033898 0.98845
## Neg Pred Value    0.9913576 0.9884104 0.97577
## Prevalence        0.0089482 0.0119898 0.08916
## Detection Rate    0.0003183 0.0004244 0.06656
## Detection Prevalence 0.0014501 0.0020867 0.06734
## Balanced Accuracy 0.5172156 0.5168579 0.87284
```

```
# 시각화
varImpPlot(tree)
```

tree



```
plot(tree)
```



## 5. 설정 모델로 예측 및 평가