

## Project 2.1

*Project - Churn Prediction*

## ABSTRACT

Customer value analysis is critical for a good marketing and a customer relationship management strategy. An important component of this strategy is the customer retention rate. Customer retention rate has a strong impact on the customer lifetime value, and understanding the true value of a possible customer churn will help the company in its customer relationship management. Conventional statistical methods are very successful in predicting a customer churn. The goal of this study is to apply logistic regression techniques to predict a customer churn and analyze the churning and no-churning customers by using data provided for the project

## Introduction

The subject of customer retention, loyalty, and churn is receiving attention in many industries. This is important in the customer lifetime value context. A company will have a sense of how much is really being lost because of the customer churn and the scale of the efforts that would be appropriate for retention campaign. The mass marketing approach cannot succeed in the diversity of consumer business today. Customer value analysis along with customer churn predictions will help marketing programs target more specific groups of customers. Personal retail banking sector is characterized by customers who stays with a company very long time. Customers usually give their financial business to one company and they won't switch the provider of their financial help very often. In the company's perspective this produces a stable environment for the customer relationship management. Although the continuous relationships with the customers the potential loss of revenue because of customer churn in this case can be huge.

This paper will present a customer churn analysis for the data provided in the project 2. The goal of this paper is twofold. First the churning customers are analyzed in R – Logistic Regression model after applying appropriate preprocessing techniques. The second stage we need to connect with Tableau and R for visualization, probability and prediction in Tableau using the trained and testing set.

Logistic regression Binomial (binary) logistic regression is a form of regression which is used in a situation when dependent is not a continuous variable but a state which may or may not happen, or a category in a specific classification. Logistic regression can be used to predict a discrete outcome on the basis of continuous and/or categorical variables. Multinomial logistic regression exists to handle the case of dependents with more classes than two. In the logistic regression there can be only one dependent variable. Logistic regression applies maximum likelihood estimation after transforming the dependent into a logistic variable [8]. Unlike the normal regression model the dependent variable in logistic regression is usually dichotomous: the dependent variable can take value 1 with probability  $q$  and value 0 with probability  $1-q$ .

## **Preprocessing**

The Churn data provided for the project 2 is checked for the preprocessing requirements if any. Normally, the missing values requires creates many problems during analysis and this requires preprocessing and imputation etc., In this project the Amelia library is used to identify the missing values and as per the graph given below there is no missing value in the data.

```
library(Amelia)
```

```
## Loading required package: Rcpp

## ##
## ## Amelia II: Multiple Imputation
## ## (Version 1.7.5, built: 2018-05-07)
## ## Copyright (C) 2005-2018 James Honaker, Gary King and Matthew Blackwell
## ## Refer to http://gking.harvard.edu/amelia/ for more information
## ##

any(is.na(Churn))

## [1] FALSE

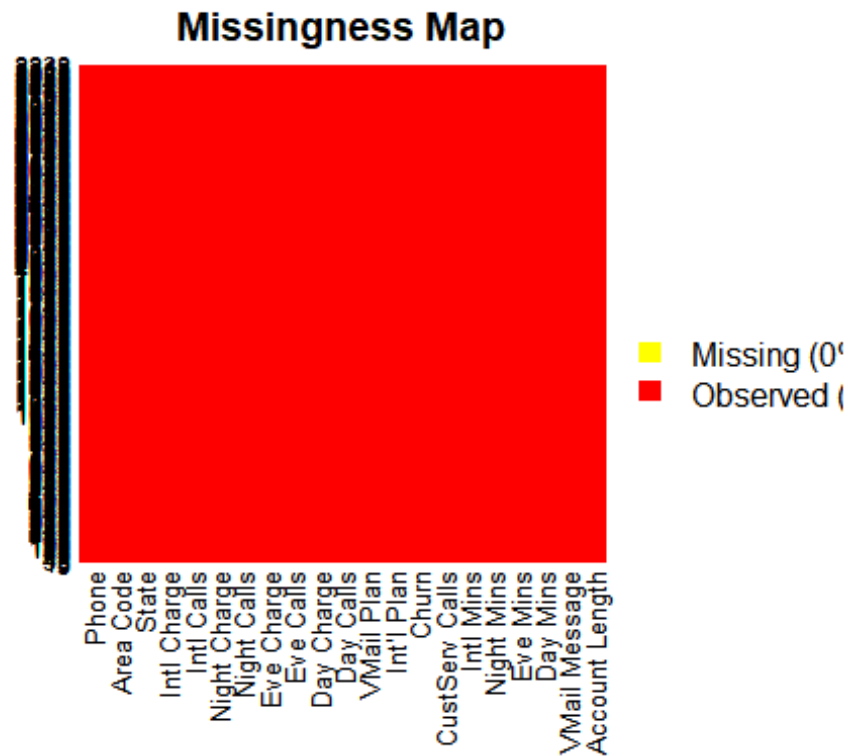
# visualize the missing values using the missing map from the Amelia package
missmap(Churn,col=c("yellow","red"))

## Warning in if (class(obj) == "amelia") {: the condition has length > 1 and
## only the first element will be used

## Warning: Unknown or uninitialised column: 'arguments'.

## Warning: Unknown or uninitialised column: 'arguments'.

## Warning: Unknown or uninitialised column: 'imputations'.
```



Excluding phone and state from the data set as they are not very important

```
mydata2<-Churn[, -21]
mydata<-mydata2[, -19]
sapply(mydata, function(x) sum(is.na(x)))
```

```
## Account Length  VMail Message      Day Mins      Eve Mins      Night Mins
##              0              0              0              0              0
##      Intl Mins  CustServ Calls      Churn      Int'l Plan      VMail Plan
##              0              0              0              0              0
##      Day Calls      Day Charge      Eve Calls      Eve Charge      Night Calls
##              0              0              0              0              0
```

```

## Night Charge      Intl Calls      Intl Charge      Area Code
##              0              0              0              0

mydata <- mydata[complete.cases(mydata), ]
intrain<- createDataPartition(mydata$Churn,p=0.8,list=FALSE)
set.seed(2017)
training<- mydata[intrain,]
testing<- mydata[-intrain,]
dim(training); dim(testing)

## [1] 2667   19
## [1] 666   19

library (data.table)

library (plyr)
library (stringr)

##
## Attaching package: 'stringr'

## The following object is masked from 'package:strucchange':
##
##      boundary

LogModel <- glm(Churn ~ .,family=binomial(link="logit"),data=training)
print(summary(LogModel))

##
## Call:
## glm(formula = Churn ~ ., family = binomial(link = "logit"), data = training)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.1332  -0.5222  -0.3425  -0.1992   3.2941
##
## Coefficients:

```

```

##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)   -7.420e+00  1.024e+00  -7.249  4.2e-13 ***
## `Account Length` 1.141e-03  1.533e-03   0.744 0.456828
## `VMail Message`  4.207e-02  2.027e-02   2.075 0.037983 *
## `Day Mins`      -1.341e+00  3.624e+00  -0.370 0.711274
## `Eve Mins`      -6.519e-01  1.813e+00  -0.360 0.719209
## `Night Mins`    -4.968e-01  9.739e-01  -0.510 0.610007
## `Intl Mins`     -7.267e-01  5.875e+00  -0.124 0.901560
## `CustServ Calls` 5.299e-01  4.387e-02  12.079 < 2e-16 ***
## `Int'l Plan`    2.096e+00  1.610e-01  13.022 < 2e-16 ***
## `VMail Plan`    -2.319e+00  6.533e-01  -3.550 0.000385 ***
## `Day Calls`      2.586e-03  3.042e-03   0.850 0.395283
## `Day Charge`     7.962e+00  2.132e+01   0.373 0.708808
## `Eve Calls`      8.044e-04  3.055e-03   0.263 0.792319
## `Eve Charge`     7.744e+00  2.133e+01   0.363 0.716583
## `Night Calls`    -2.353e-03  3.160e-03  -0.745 0.456435
## `Night Charge`   1.109e+01  2.164e+01   0.513 0.608260
## `Intl Calls`     -1.044e-01  2.812e-02  -3.712 0.000206 ***
## `Intl Charge`    2.960e+00  2.176e+01   0.136 0.891786
## `Area Code`     -6.509e-05  1.462e-03  -0.045 0.964500
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##    Null deviance: 2230.1  on 2666  degrees of freedom
## Residual deviance: 1755.5  on 2648  degrees of freedom
## AIC: 1793.5
##
## Number of Fisher Scoring iterations: 6

anova(LogModel, test="Chisq")

## Analysis of Deviance Table
##
## Model: binomial, link: logit

```

```
##
## Response: Churn
##
## Terms added sequentially (first to last)
##
##
```

	Df	Deviance	Resid. Df	Resid. Dev	Pr(>Chi)
## NULL			2666	2230.1	
## `Account Length`	1	1.550	2665	2228.6	0.2132053
## `VMail Message`	1	26.557	2664	2202.0	2.559e-07 ***
## `Day Mins`	1	92.031	2663	2110.0	< 2.2e-16 ***
## `Eve Mins`	1	17.926	2662	2092.1	2.297e-05 ***
## `Night Mins`	1	1.924	2661	2090.1	0.1654485
## `Intl Mins`	1	9.890	2660	2080.2	0.0016614 **
## `CustServ Calls`	1	130.903	2659	1949.3	< 2.2e-16 ***
## `Int'l Plan`	1	163.266	2658	1786.1	< 2.2e-16 ***
## `VMail Plan`	1	14.094	2657	1772.0	0.0001739 ***
## `Day Calls`	1	0.719	2656	1771.3	0.3966047
## `Day Charge`	1	0.051	2655	1771.2	0.8214162
## `Eve Calls`	1	0.017	2654	1771.2	0.8948703
## `Eve Charge`	1	0.132	2653	1771.1	0.7158769
## `Night Calls`	1	0.536	2652	1770.5	0.4641722
## `Night Charge`	1	0.190	2651	1770.3	0.6629360
## `Intl Calls`	1	14.804	2650	1755.5	0.0001193 ***
## `Intl Charge`	1	0.019	2649	1755.5	0.8911511
## `Area Code`	1	0.002	2648	1755.5	0.9644909

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

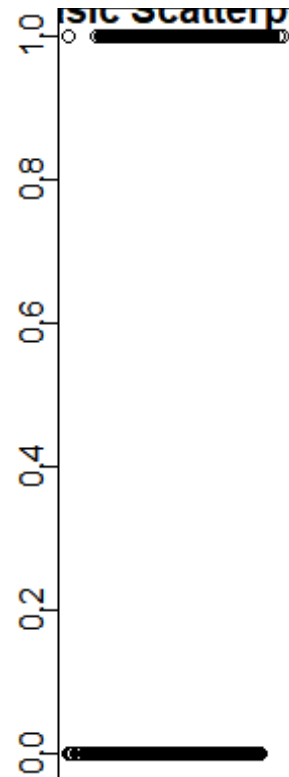
```
testing$Churn <- as.character(testing$Churn)
testing$Churn[testing$Churn=="No"] <- "0"
testing$Churn[testing$Churn=="Yes"] <- "1"
fitted.results <- predict(LogModel,newdata=testing,type='response')
fitted.results

sapply(mydata, sd)
```

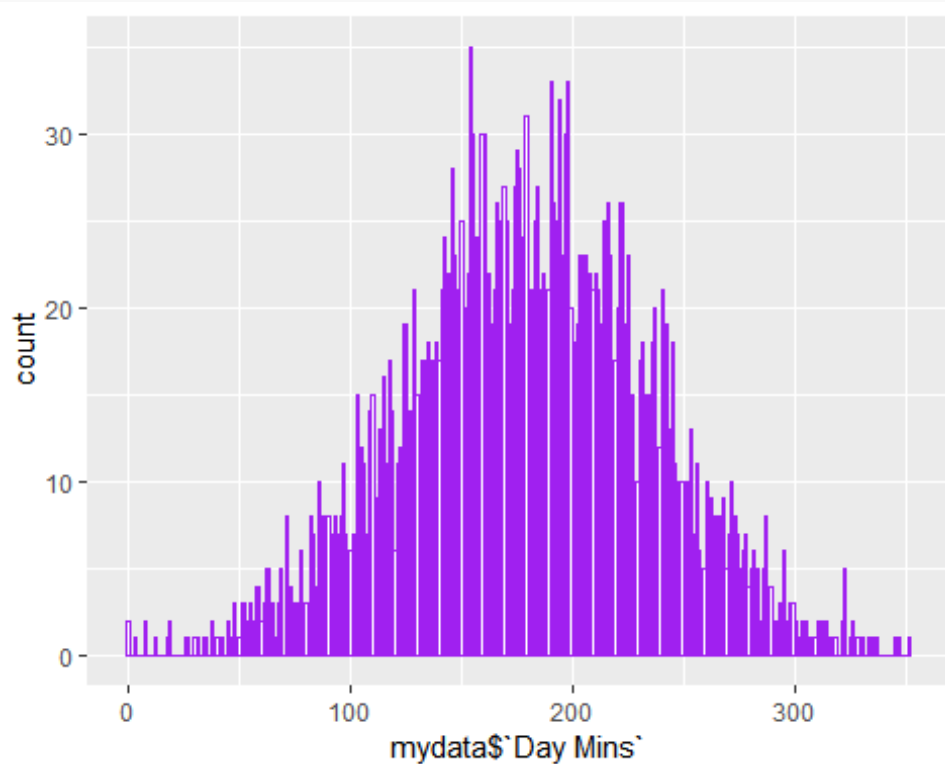


## Account Length	VMail Message	Day Mins	Eve Mins	Night Mins
## 39.8221059	13.6883654	54.4673892	50.7138444	50.5738470
## Intl Mins	CustServ Calls	Churn	Int'l Plan	VMail Plan
## 2.7918395	1.3154910	0.3520674	0.2958791	0.4473979
## Day Calls	Day Charge	Eve Calls	Eve Charge	Night Calls
## 20.0690842	9.2594346	19.9226253	4.3106676	19.5686093
## Night Charge	Intl Calls	Intl Charge	Area Code	
## 2.2758728	2.4612143	0.7537726	42.3712905	

```
plot.new()
plot(mydata$Churn ~mydata$`Day Mins`)
title('Basic Scatterplot')
```



```
ggplot(mydata, aes(x=mydata$`Day Mins`)) + geom_histogram(binwidth = 1, fill = "white", color = "purple")
```

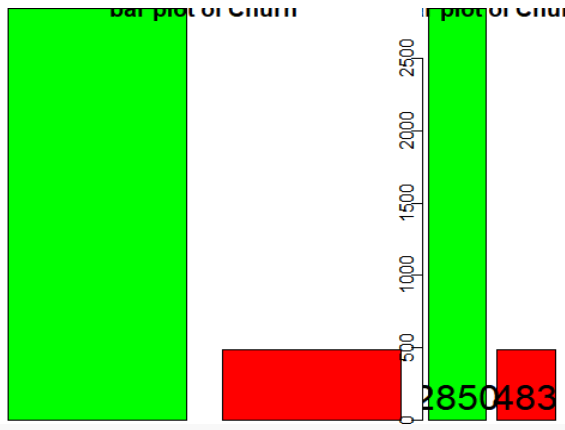


```
#Randomly split data into train and test set
```

```
#80% will be signed to train set, 20% will be assigned to tst set
```

```
barplot(table(mydata$Churn), col= c("green", "red"), main='bar plot of Churn')
```

```
text(barplot(table(mydata$Churn), col =c('green' , 'red'), main='bar plot of Churn'), 0,table(mydata$Churn),  
cex =2 , pos =3)
```



```
#proportion
round(prop.table(table(mydata$Churn))*100,digits = 2)
```

```
##
##      0      1 (As per this churn is around 15%)
## 85.51 14.49
```

```
mydata_train<-mydata_n[1:2666,]
mydata_test<-mydata_n[2667:3333,]
mydata_train_labels<-mydata_n[1:2666,7]
mydata_test_labels<-mydata_n[2667:3333,7]
```

```
sapply(mydata_n, sd)
```

```
## Account.Length  VMail.Message      Day.Mins      Eve.Mins      Night.Mins
##      0.1645542      0.2683993      0.1552662      0.1394387      0.1360243
##      Intl.Mins  CustServ.Calls      Churn      Int.l.Plan      VMail.Plan
##      0.1395920      0.1461657      0.3520674      0.2958791      0.4473979
##      Day.Calls   Day.Charge      Eve.Calls      Eve.Charge      Night.Calls
##      0.1216308      0.1552554      0.1171919      0.1394587      0.1378071
##      Night.Charge Intl.Calls      Intl.Charge
##      0.1360354      0.1230607      0.1395875
```

*#Forward elimination*

*#Lower AIC indicates a better model*

```
forward <- step(glm(Churn ~ 1, data = mydata_train), direction = 'forward', scope = ~Account.Length+VMail.Message+Day.Mins + Eve.Mins +  
                Night.Mins + Intl.Mins + CustServ.Calls + Int.l.Plan + VMail.Plan +  
                Day.Calls + Day.Charge + Eve.Calls + Eve.Charge + Night.Calls +  
                Night.Charge + Intl.Calls + Intl.Charge)
```

```
logit<- glm(Churn ~Account.Length+Day.Mins+ Day.Charge +CustServ.Calls+VMail.Plan +Eve.Mins+ Eve.Charge+VMail.Message+Day.Calls +Eve.Calls+ Intl.Mins + Night.Calls+Intl.Calls, data = mydata_train, family = "binomial")
```

```
summary(logit)
```

```
##
```

```
## Call:
```

```
## glm(formula = Churn ~ Account.Length + Day.Mins + Day.Charge +  
##     CustServ.Calls + VMail.Plan + Eve.Mins + Eve.Charge + VMail.Message +  
##     Day.Calls + Eve.Calls + Intl.Mins + Night.Calls + Intl.Calls,  
##     family = "binomial", data = mydata_train)
```

```
##
```

```
## Deviance Residuals:
```

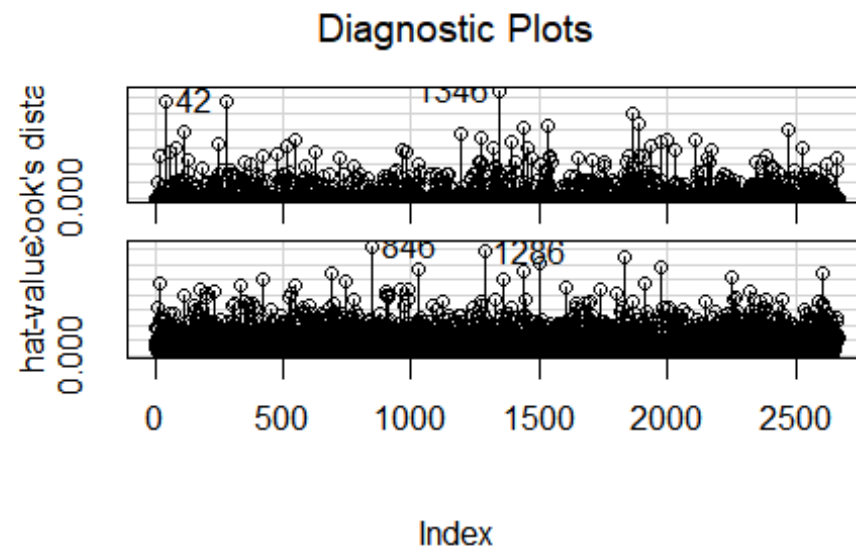
```
##      Min       1Q   Median       3Q      Max  
## -1.7136  -0.5583  -0.3989  -0.2492   3.0223
```

```
##
```

```
## Coefficients:
```

```
##              Estimate Std. Error z value Pr(>|z|)  
## (Intercept)   -7.4168    0.6846  -10.834  < 2e-16 ***  
## Account.Length    0.1336    0.3696    0.362  0.71771  
## Day.Mins       191.3463  1231.6229    0.155  0.87654  
## Day.Charge    -187.0655  1231.7103   -0.152  0.87929  
## CustServ.Calls    3.9702    0.3798   10.455  < 2e-16 ***  
## VMail.Plan      -1.7024    0.6098   -2.792  0.00524 **  
## Eve.Mins        462.5882   642.8816    0.720  0.47180  
## Eve.Charge     -460.1275   642.7876   -0.716  0.47410  
## VMail.Message    1.5122    0.9823    1.539  0.12371  
## Day.Calls        0.3629    0.4940    0.735  0.46264
```

```
## Eve.Calls      0.4090      0.5063      0.808  0.41921
## Intl.Mins      2.0353      0.4447      4.576 4.73e-06 ***
## Night.Calls    0.1657      0.4403      0.376  0.70665
## Intl.Calls     -1.6524      0.5357     -3.085  0.00204 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##    Null deviance: 2162.0  on 2665  degrees of freedom
## Residual deviance: 1867.4  on 2652  degrees of freedom
## AIC: 1895.4
##
## Number of Fisher Scoring iterations: 5
```



*# Confidence interval using Log-Likelihood*

```
confint(logit)

## Waiting for profiling to be done...

##              2.5 %      97.5 %
## (Intercept)  -8.7761881 -6.0914407
## Account.Length -0.5919165  0.8578438
## Day.Mins      -2224.7782913 2605.8924991
## Day.Charge    -2601.7748293 2229.2388877
## CustServ.Calls  3.2299992  4.7198281
## VMail.Plan     -2.9307458 -0.5373346
## Eve.Mins       -796.3103582 1725.2392867
## Eve.Charge     -1722.5889512  798.5919581
```

```
## VMail.Message      -0.4038228    3.4527140
## Day.Calls          -0.6043867    1.3330979
## Eve.Calls          -0.5823325    1.4036271
## Intl.Mins           1.1687246    2.9129356
## Night.Calls        -0.6973052    1.0293210
## Intl.Calls         -2.7201822   -0.6195282
```

```
exp(logit$coefficients)
```

```
##      (Intercept) Account.Length      Day.Mins      Day.Charge CustServ.Calls
## 6.010934e-04    1.142977e+00    1.260826e+83    5.734114e-82    5.299764e+01
##      VMail.Plan      Eve.Mins      Eve.Charge VMail.Message      Day.Calls
## 1.822392e-01    7.933806e+20    1.476321e-200    4.536688e+00    1.437439e+00
##      Eve.Calls      Intl.Mins      Night.Calls      Intl.Calls
## 1.505333e+00    7.654355e+00    1.180211e+00    1.915949e-01
```

```
# Logistic regression model:
```

```
fit <- glm(Churn~.,data =mydata_train ,family = binomial(link='logit'))
```

```
summary(fit)
```

```
##
```

```
## Call:
```

```
## glm(formula = Churn ~ ., family = binomial(link = "logit"), data = mydata_train)
```

```
##
```

```
## Deviance Residuals:
```

```
##      Min      1Q   Median      3Q      Max
## -1.9680  -0.5111  -0.3376  -0.1979   3.1864
```

```
##
```

```
## Coefficients:
```

```
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)   -8.42021    0.76774 -10.967  < 2e-16 ***
## Account.Length  0.01841    0.38853   0.047  0.962208
## VMail.Message  1.53996    1.01473   1.518  0.129114
## Day.Mins       213.42834  1293.28315   0.165  0.868922
## Eve.Mins       592.02181   674.48943   0.878  0.380088
## Night.Mins    -110.40724   368.95516  -0.299  0.764755
## Intl.Mins     -287.85749  120.73173  -2.384  0.017113 *
```

```

## CustServ.Calls      4.51834      0.40343      11.200 < 2e-16 ***
## Int.l.Plan          2.06924      0.16257      12.729 < 2e-16 ***
## VMail.Plan          -1.87056      0.63215      -2.959 0.003086 **
## Day.Calls           0.44168      0.51623       0.856 0.392222
## Day.Charge          -209.05873 1293.37170     -0.162 0.871590
## Eve.Calls           0.43463      0.53648       0.810 0.417852
## Eve.Charge          -589.41466  674.38935     -0.874 0.382120
## Night.Calls         0.01869      0.46116       0.041 0.967668
## Night.Charge        111.62067  368.91878       0.303 0.762224
## Intl.Calls          -1.92925      0.56673      -3.404 0.000664 ***
## Intl.Charge         289.76049  120.71956       2.400 0.016383 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 2162.0  on 2665  degrees of freedom
## Residual deviance: 1702.5  on 2648  degrees of freedom
## AIC: 1738.5
##
## Number of Fisher Scoring iterations: 6

library(MASS)
step_fit <- stepAIC(fit,method='backward')

summary(step_fit)

##
## Call:
## glm(formula = Churn ~ VMail.Message + Day.Mins + Eve.Mins + Intl.Mins +
##      CustServ.Calls + Int.l.Plan + VMail.Plan + Night.Charge +
##      Intl.Calls + Intl.Charge, family = binomial(link = "logit"),
##      data = mydata_train)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.9778  -0.5124  -0.3392  -0.2020   3.1476

```



```
##
## Coefficients:
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)   -7.8769     0.5686 -13.853  < 2e-16 ***
## VMail.Message    1.5052     1.0120   1.487 0.136929
## Day.Mins       4.4084     0.4297  10.259  < 2e-16 ***
## Eve.Mins       2.5099     0.4622   5.430 5.64e-08 ***
## Intl.Mins     -291.5210    120.5655  -2.418 0.015608 *
## CustServ.Calls  4.5206     0.4022  11.240  < 2e-16 ***
## Int.l.Plan     2.0630     0.1622  12.721  < 2e-16 ***
## VMail.Plan     -1.8555     0.6300  -2.945 0.003230 **
## Night.Charge    1.2494     0.4652   2.686 0.007235 **
## Intl.Calls     -1.9404     0.5652  -3.433 0.000596 ***
## Intl.Charge    293.4337    120.5539   2.434 0.014931 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##    Null deviance: 2162.0  on 2665  degrees of freedom
## Residual deviance: 1704.9  on 2655  degrees of freedom
## AIC: 1726.9
##
## Number of Fisher Scoring iterations: 6
```

```
confint(step_fit)
```

```
## Waiting for profiling to be done...
```

```
##           2.5 %      97.5 %
## (Intercept)   -9.0107622  -6.7808248
## VMail.Message  -0.4650469   3.5078770
## Day.Mins       3.5752571   5.2606938
## Eve.Mins       1.6088317   3.4218238
## Intl.Mins     -528.7346134 -55.8150001
## CustServ.Calls  3.7372142   5.3151528
## Int.l.Plan     1.7458847   2.3822001
```

```
## VMail.Plan      -3.1260647 -0.6530832
## Night.Charge    0.3391697  2.1636548
## Intl.Calls      -3.0675068 -0.8511819
## Intl.Charge     57.7541777 530.6286565
```

*#ANOVA on base model*

```
anova(fit,test = 'Chisq')
```

```
## Analysis of Deviance Table
```

```
##
```

```
## Model: binomial, link: logit
```

```
##
```

```
## Response: Churn
```

```
##
```

```
## Terms added sequentially (first to last)
```

```
##
```

```
##
```

```
##           Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
```

```
## NULL                2665      2162.0
```

```
## Account.Length    1    0.277      2664      2161.8 0.5985480
```

```
## VMail.Message     1   19.675      2663      2142.1 9.180e-06 ***
```

```
## Day.Mins          1  103.623      2662      2038.5 < 2.2e-16 ***
```

```
## Eve.Mins          1   23.581      2661      2014.9 1.197e-06 ***
```

```
## Night.Mins        1    3.199      2660      2011.7 0.0736818 .
```

```
## Intl.Mins         1   17.379      2659      1994.3 3.062e-05 ***
```

```
## CustServ.Calls    1  111.293      2658      1883.0 < 2.2e-16 ***
```

```
## Int.l.Plan        1  152.056      2657      1730.9 < 2.2e-16 ***
```

```
## VMail.Plan        1    8.313      2656      1722.6 0.0039361 **
```

```
## Day.Calls         1    1.004      2655      1721.6 0.3164303
```

```
## Day.Charge        1    0.101      2654      1721.5 0.7509001
```

```
## Eve.Calls         1    0.705      2653      1720.8 0.4010942
```

```
## Eve.Charge        1    0.752      2652      1720.1 0.3857120
```

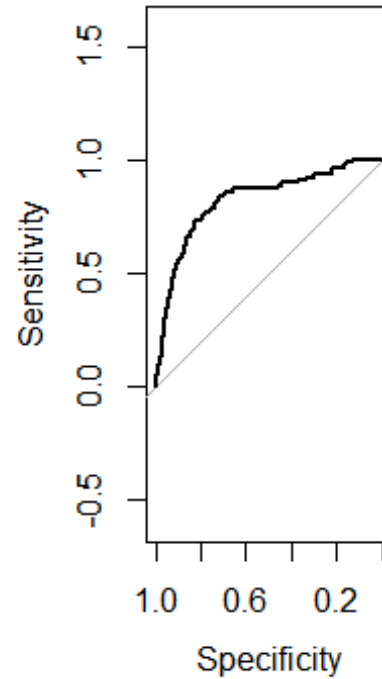
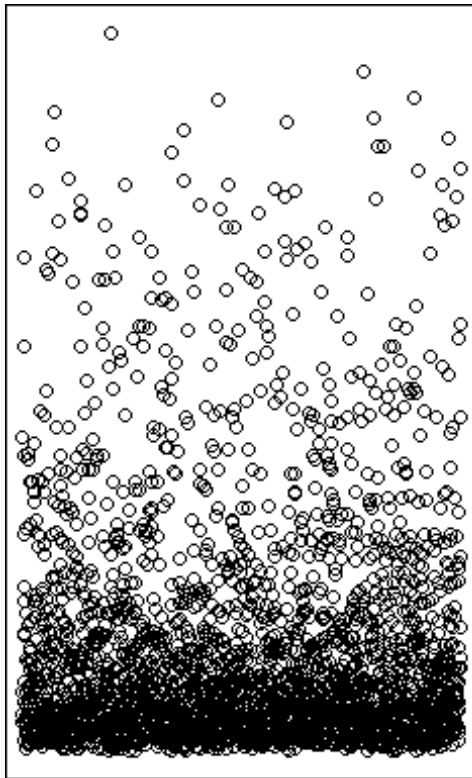
```
## Night.Calls       1    0.000      2651      1720.1 0.9948372
```

```
## Night.Charge      1    0.088      2650      1720.0 0.7668220
```

```
## Intl.Calls        1   11.638      2649      1708.3 0.0006464 ***
```

```
## Intl.Charge       1    5.795      2648      1702.5 0.0160706 *
```

```
## ---  
pred <- predict(fit,newdata = mydata_test,type = 'response')  
#check the AUC curve  
library(pROC)  
  
g <- roc( Churn~ pred, data = mydata_test)  
g  
  
##  
## Call:  
## roc.formula(formula = Churn ~ pred, data = mydata_test)  
##  
## Data: pred in 558 controls (Churn 0) < 109 cases (Churn 1).  
## Area under the curve: 0.8266  
  
plot(g)
```



```
library(caret)
#with default prob cut 0.50
mydata_test$pred_Churn <- ifelse(pred<0.8,'yes','no')

table(mydata_test$pred_Churn,mydata_test$Churn)

##
##      0    1
## no    1    3
## yes 557 106

#training split of churn classes
round(table(mydata_train$Churn)/nrow(mydata_train),2)*100
```

```

##
## 0 1
## 86 14

# test split of churn classes
round(table(mydata_test$Churn)/nrow(mydata_test),2)*100

##
## 0 1
## 84 16

#predicted split of churn classes
round(table(mydata_test$pred_Churn)/nrow(mydata_test),2)*100

##
## no yes
## 1 99

#create confusion matrix
#confusionMatrix(mydata_test$Churn,mydata_test$pred_Churn)
#how do we create a cross validation scheme
control <- trainControl(method = 'repeatedcv',
                        number = 10,
                        repeats = 3)

seed <- 7
metric <- 'Accuracy'
set.seed(seed)
fit_default <- train(Churn~.,
                    data = mydata_train,
                    method = 'glm',
                    metric = NaN,
                    trControl = control)

## Warning in train.default(x, y, weights = w, ...): You are trying to do
## regression and your outcome only has two possible values Are you trying to
## do classification? If so, use a 2 level factor as your outcome column.

```

```
## Warning in train.default(x, y, weights = w, ...): The metric "NaN" was not
## in the result set. RMSE will be used instead.
```

```
print(fit_default)
```

```
## Generalized Linear Model
```

```
##
```

```
## 2666 samples
```

```
## 17 predictor
```

```
##
```

```
## No pre-processing
```

```
## Resampling: Cross-Validated (10 fold, repeated 3 times)
```

```
## Summary of sample sizes: 2399, 2400, 2399, 2399, 2400, 2399, ...
```

```
## Resampling results:
```

```
##
```

	RMSE	Rsquared	MAE
##	0.3171573	0.1668586	0.2165651

```
library(caret)
```

```
varImp(step_fit)
```

```
## Overall
```

```
## VMail.Message 1.487325
```

```
## Day.Mins 10.258636
```

```
## Eve.Mins 5.429922
```

```
## Intl.Mins 2.417948
```

```
## CustServ.Calls 11.239954
```

```
## Int.l.Plan 12.720766
```

```
## VMail.Plan 2.945000
```

```
## Night.Charge 2.685836
```

```
## Intl.Calls 3.433245
```

```
## Intl.Charge 2.434045
```

```
varImp(fit_default)
```

```
## glm variable importance
```

```
##
```

```
## Overall
## Int.l.Plan 100.00000
## CustServ.Calls 79.36943
## Intl.Calls 21.54437
## VMail.Plan 17.99874
## Intl.Charge 15.22120
## Intl.Mins 15.11822
## VMail.Message 6.87083
## Day.Calls 5.43601
## Eve.Mins 5.43158
## Eve.Charge 5.40848
## Eve.Calls 4.87659
## Night.Charge 3.45603
## Night.Mins 3.43761
## Day.Mins 1.44730
## Day.Charge 1.42506
## Account.Length 0.02108
## Night.Calls 0.00000
```

```
library(devtools)
library(woe)
```

```
library(riv)
```

```
iv_df <- iv.mult(mydata_train, y="Churn", summary=TRUE, verbose=TRUE)
```

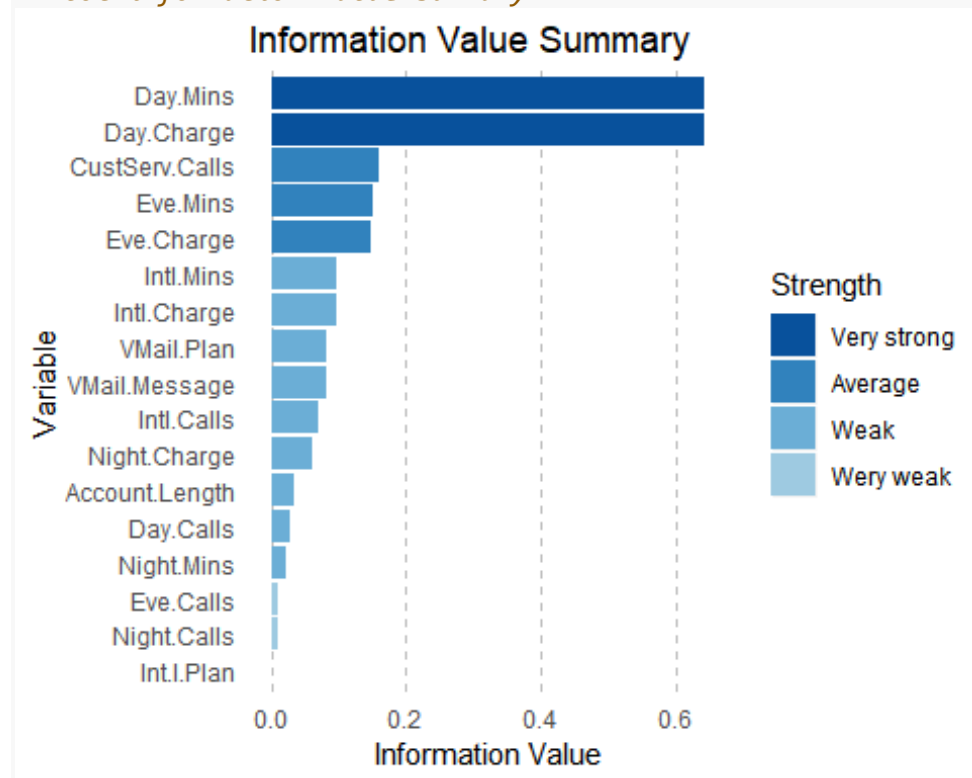
```
iv_df
```

##	Variable	InformationValue	Bins	ZeroBins	Strength
## 1	Day.Charge	0.643151413	6	0	Very strong
## 2	Day.Mins	0.643151413	6	0	Very strong
## 3	CustServ.Calls	0.158681659	2	0	Average
## 4	Eve.Mins	0.149576165	5	0	Average
## 5	Eve.Charge	0.149310982	5	0	Average
## 6	Intl.Charge	0.097357797	4	0	Weak
## 7	Intl.Mins	0.097357797	4	0	Weak
## 8	VMail.Message	0.081622650	2	0	Weak

```
## 9      VMail.Plan      0.081622650      2      0      Weak
## 10     Intl.Calls      0.068633851      2      0      Weak
## 11     Night.Charge    0.060709508      6      0      Weak
## 12 Account.Length      0.033794008      4      0      Weak
## 13      Day.Calls      0.028673937      3      0      Weak
## 14      Night.Mins      0.022784889      2      0      Weak
## 15      Eve.Calls      0.010611328      2      0      Wery weak
## 16      Night.Calls    0.009978104      2      0      Wery weak
## 17      Int.l.Plan      0.000000000      1      0      Wery weak
```

```
iv <- iv.mult(mydata_train, y="Churn", summary=FALSE, verbose=TRUE)
```

```
# Plot information value summary
```

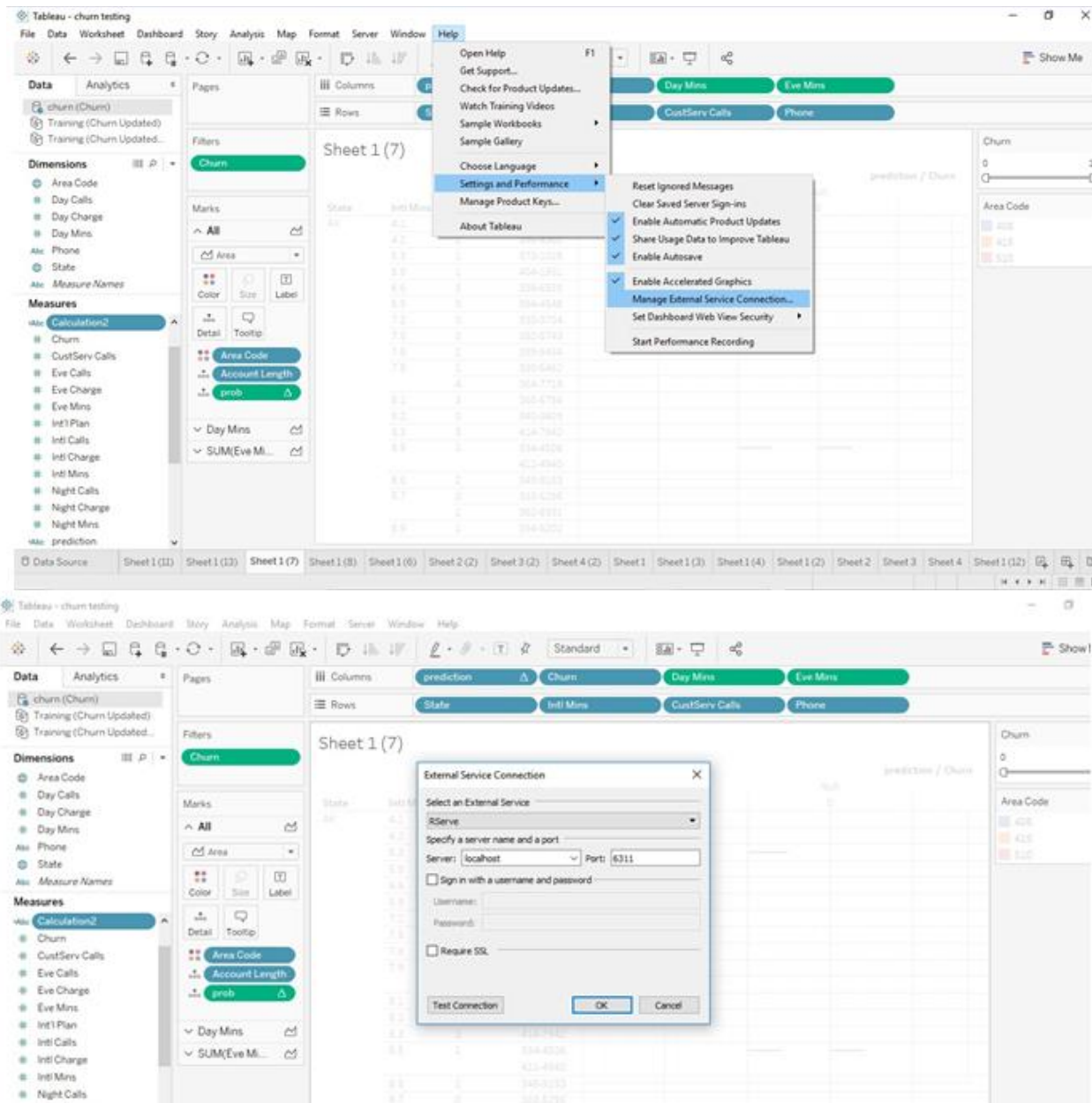


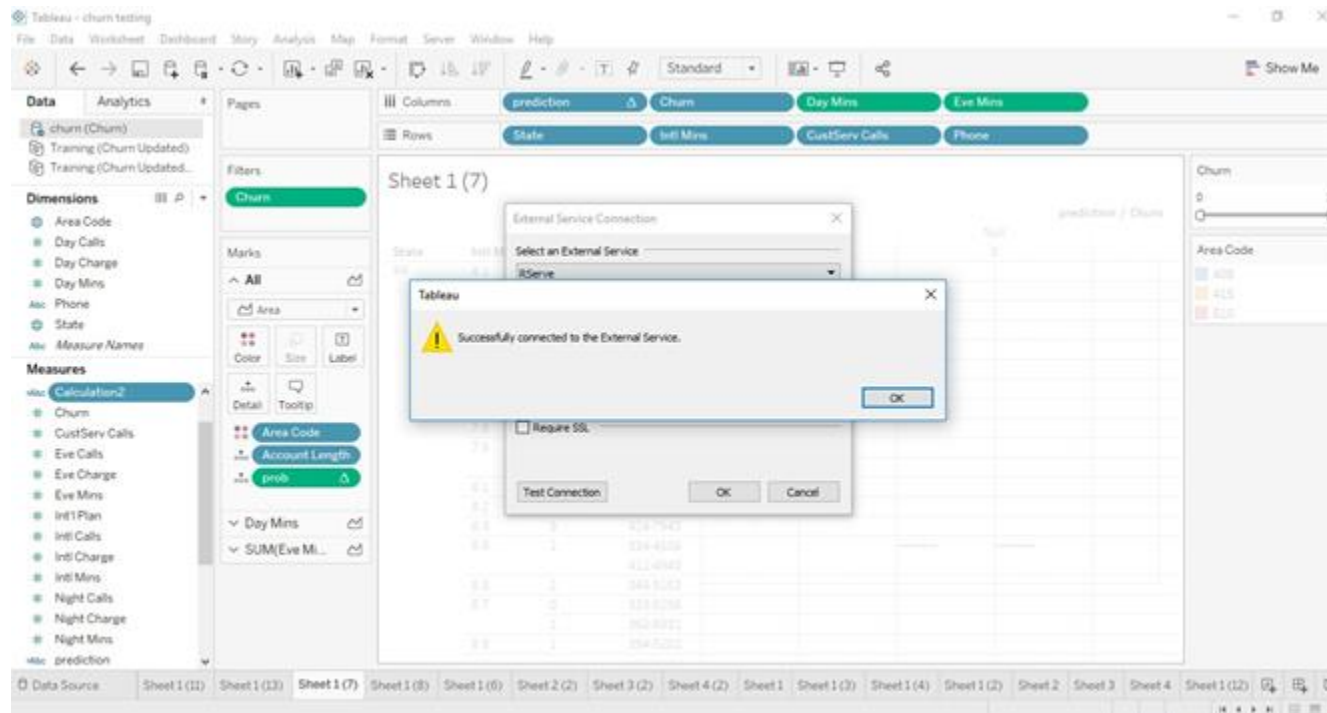


## TABALEAU VISUALIZATION

Library(Rserve)

Rserve()





```
Calculated field (prob) SCRIPT_REAL('library(dplyr);
mydata <- data.frame(churn=.arg1, day_mins=.arg2, day_charge=.arg3, custServ_call=.arg4, int_mins=.arg5);
lmodel <- glm(churn ~ day_mins + day_charge + custServ_call+int_mins, data = mydata, family = "binomial"); prob <- predict(lmodel, newdata =
mydata, type = "response");
AVG([Churn]),AVG([Day Mins]),AVG([Day Charge]),AVG([CustServ Calls]),AVG([Intl Mins]))
```

Data Analytics

- churn (Churn)
- Training (Churn Updated)
- Training (Churn Updated...

Dimensions

- Area Code
- Day Calls
- Day Charge
- Day Mins
- Phone
- State
- Measure Names

Measures

- Account Length
- Calculation1 (Sum)
- Churn
- churn\_predicted
- churn\_transformed
- CustServ Calls
- Eve Calls
- Eve Charge
- Eve Mins
- Intl Plan
- Intl Calls
- Intl Charge
- Intl Mins
- Night Calls

Pages

Filters

prediction

Marks

Automatic

Color Size Label

Detail Tooltip

Eve Mins

Eve Mins

State

Phone

prediction

Churn

CustServ Calls

Intl Mins

Day Mins

Columns

Rows

Sheet 1 (12)

prob churn (Churn)

Results are computed along Table (across).

```
arg1, day_mins=.arg2, day_charge=.arg3, custServ_call=.arg  
mins + day_charge + custServ_call+intl_mins, data = mydata,  
data = mydata, type = "response")',  
,AVG([Day Charge]),AVG([CustServ Calls]),AVG([Intl Mins]))
```

The calculation is valid.

12 Dependencies

Default Table Calculation

Apply

OK

AGG(prediction)

☒ (All)☒ 0☒ 1

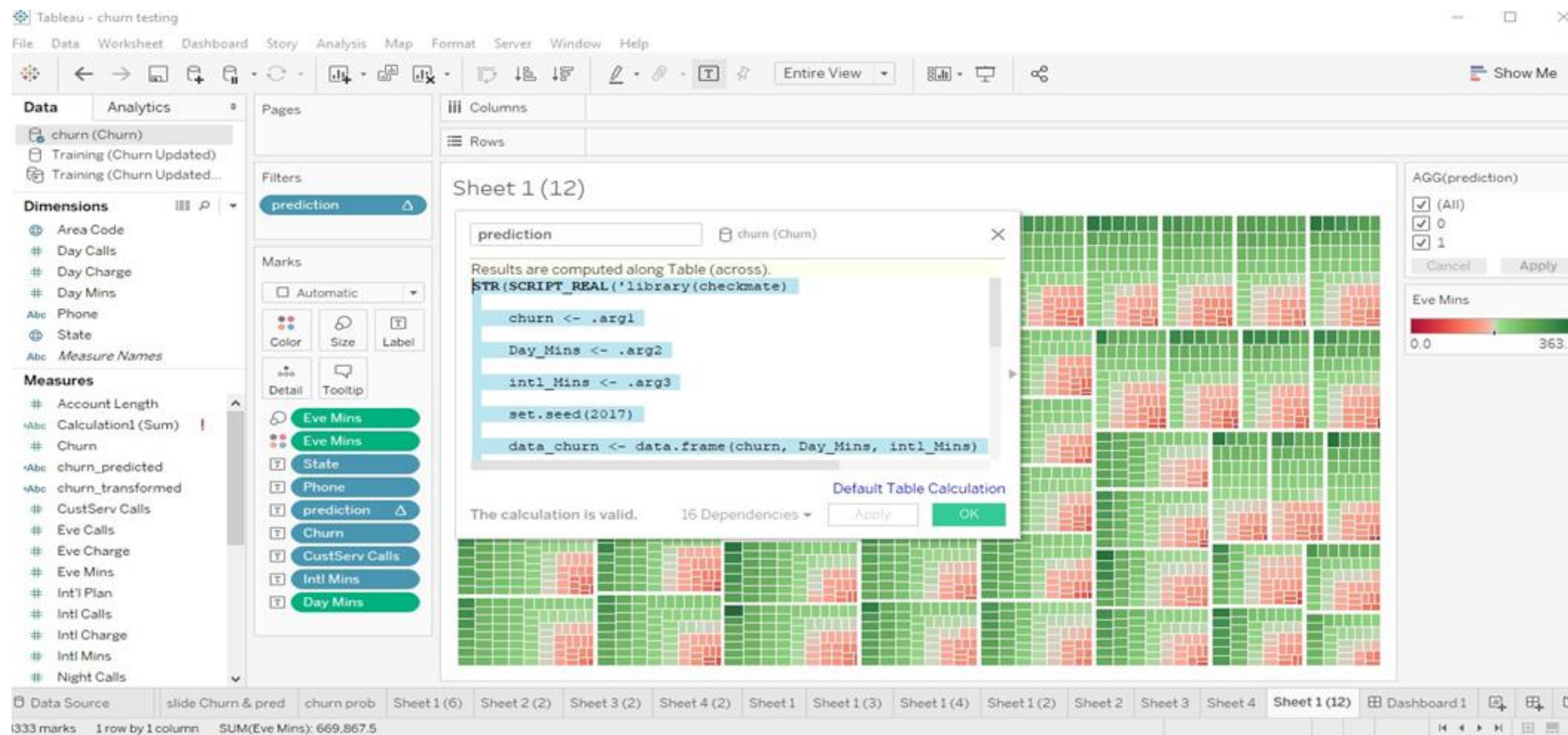
Cancel

Apply

Eve Mins

Data Source slide Churn &amp; pred churn prob Sheet 1 (6) Sheet 2 (2) Sheet 3 (2) Sheet 4 (2) Sheet 1 Sheet 1 (3) Sheet 1 (4) Sheet 1 (2) Sheet 2 Sheet 3 Sheet 4 Sheet 1 (12) Dashboard 1

3333 marks 1 row by 1 column SUM(Eve Mins): 669,867.5



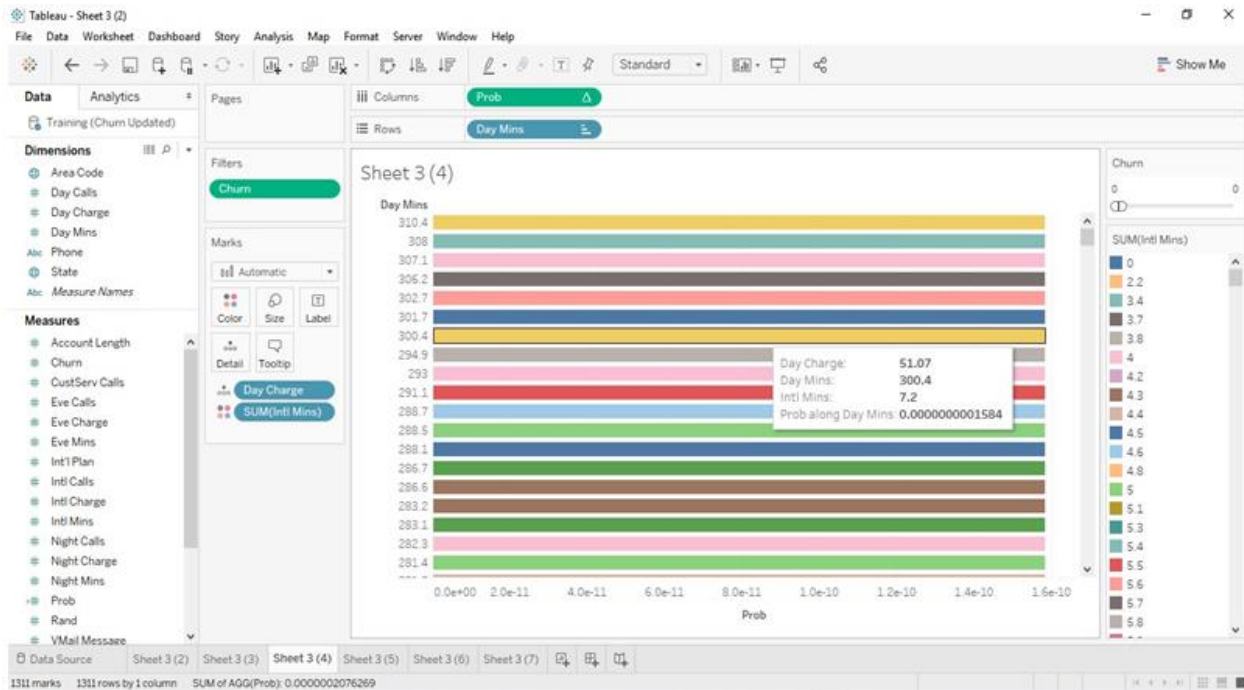
```

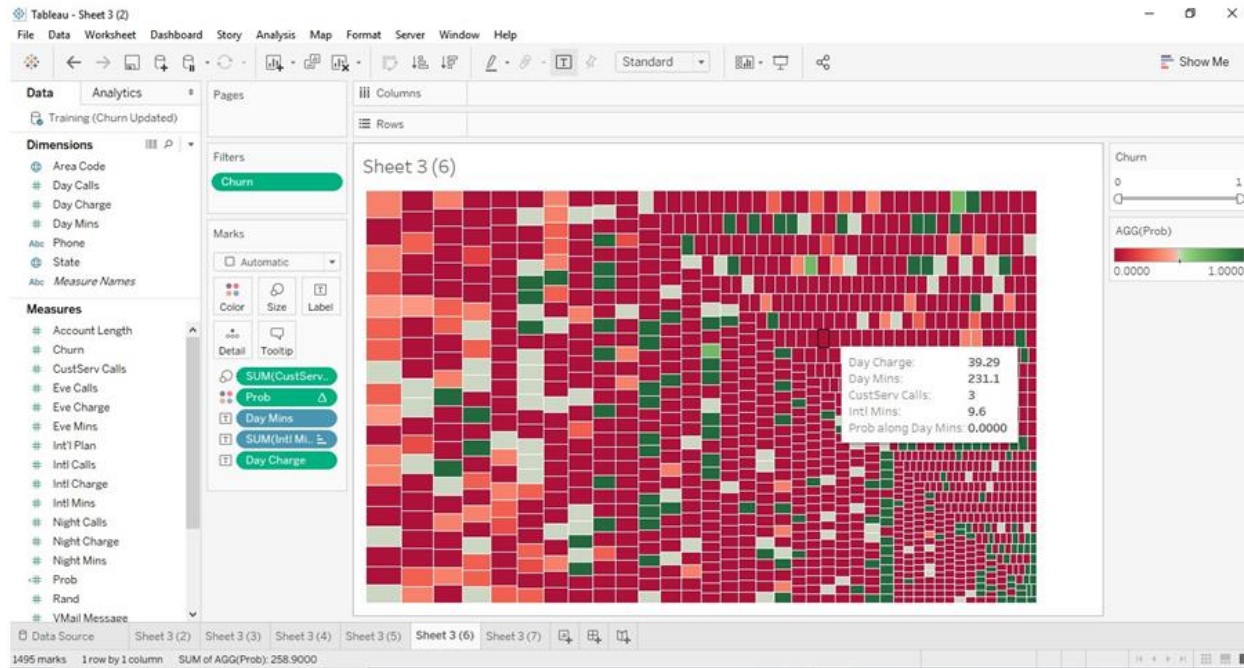
STR(SCRIPT_REAL('library(checkmate)
churn <- .arg1 Day_Mins <- .arg2 intl_Mins <- .arg3 set.seed(2017)
data_churn <- data.frame(churn, Day_Mins, intl_Mins) intrain<-sample(1:nrow(data_churn),.7*nrow(data_churn))training<- data_churn[intrain,]
testing<- data_churn[-intrain,] new_data<-rbind(training,testing)
LogModel <- glm(churn ~ .,family=binomial(link="logit"),data=training) fitted.results <- predict(LogModel,newdata=new_data,type="response")
pred_val <- ifelse(fitted.results>0.5,1,0)
pred_val',ATTR([Churn]),SUM([Day Mins]),sum([Intl Mins]))

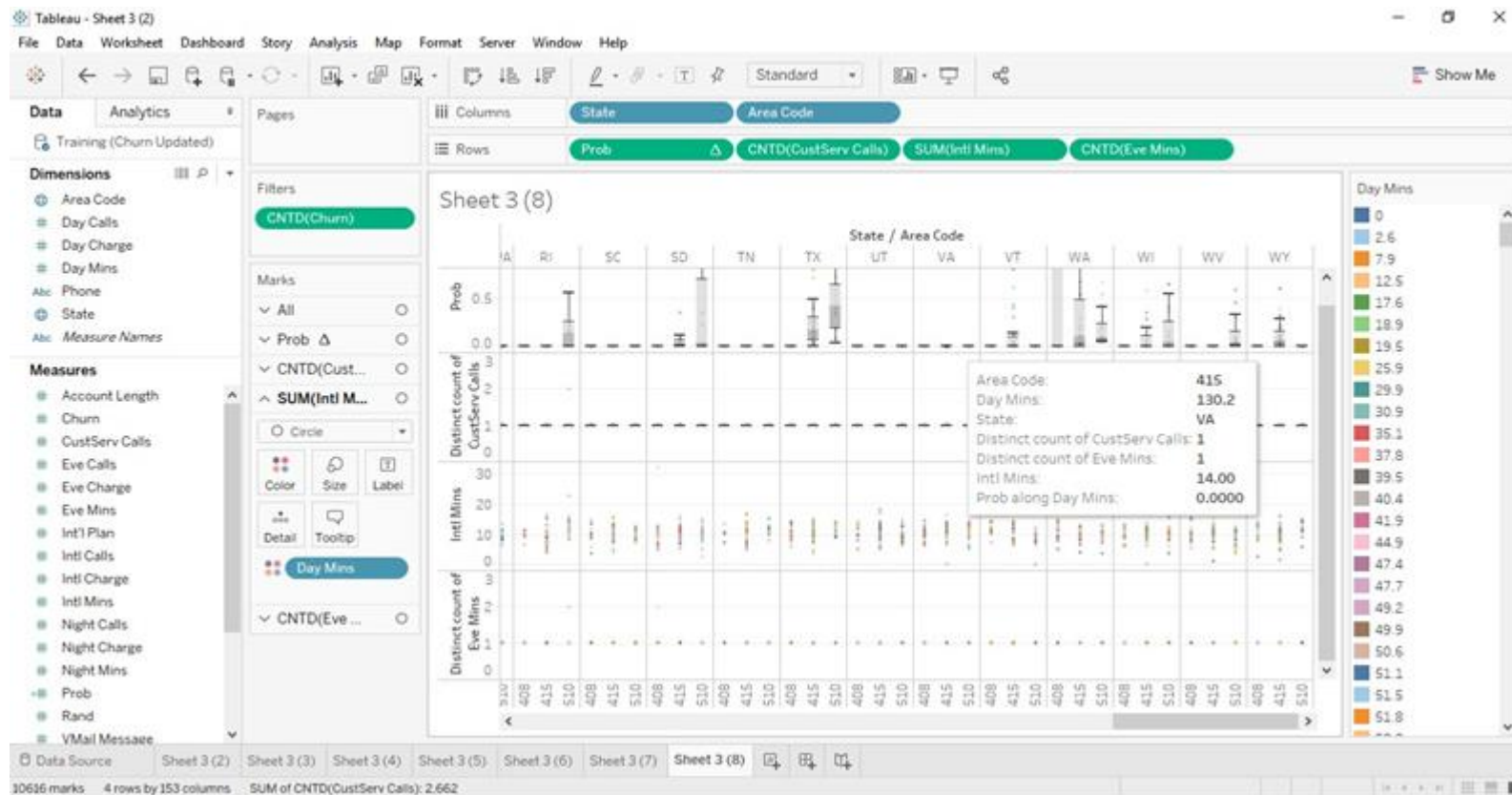
```



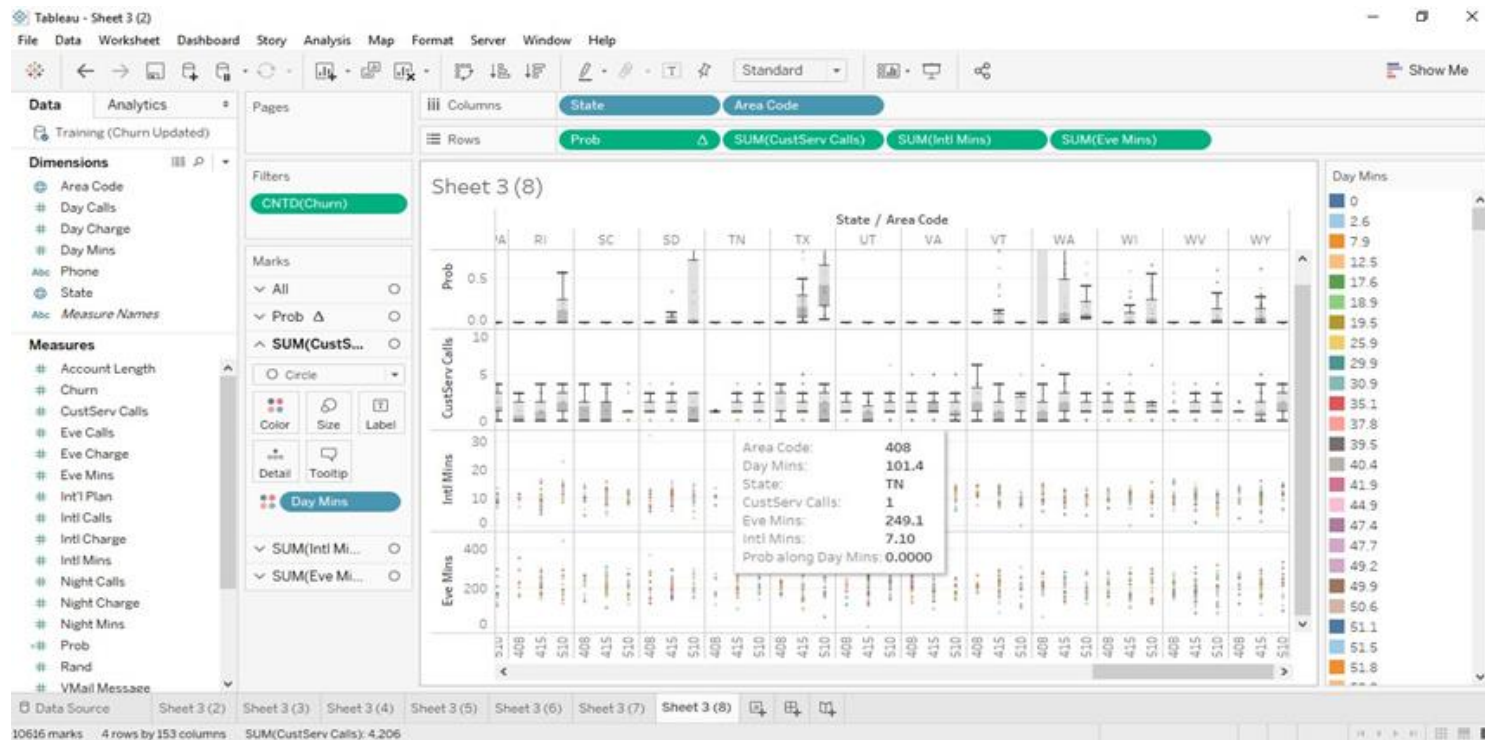


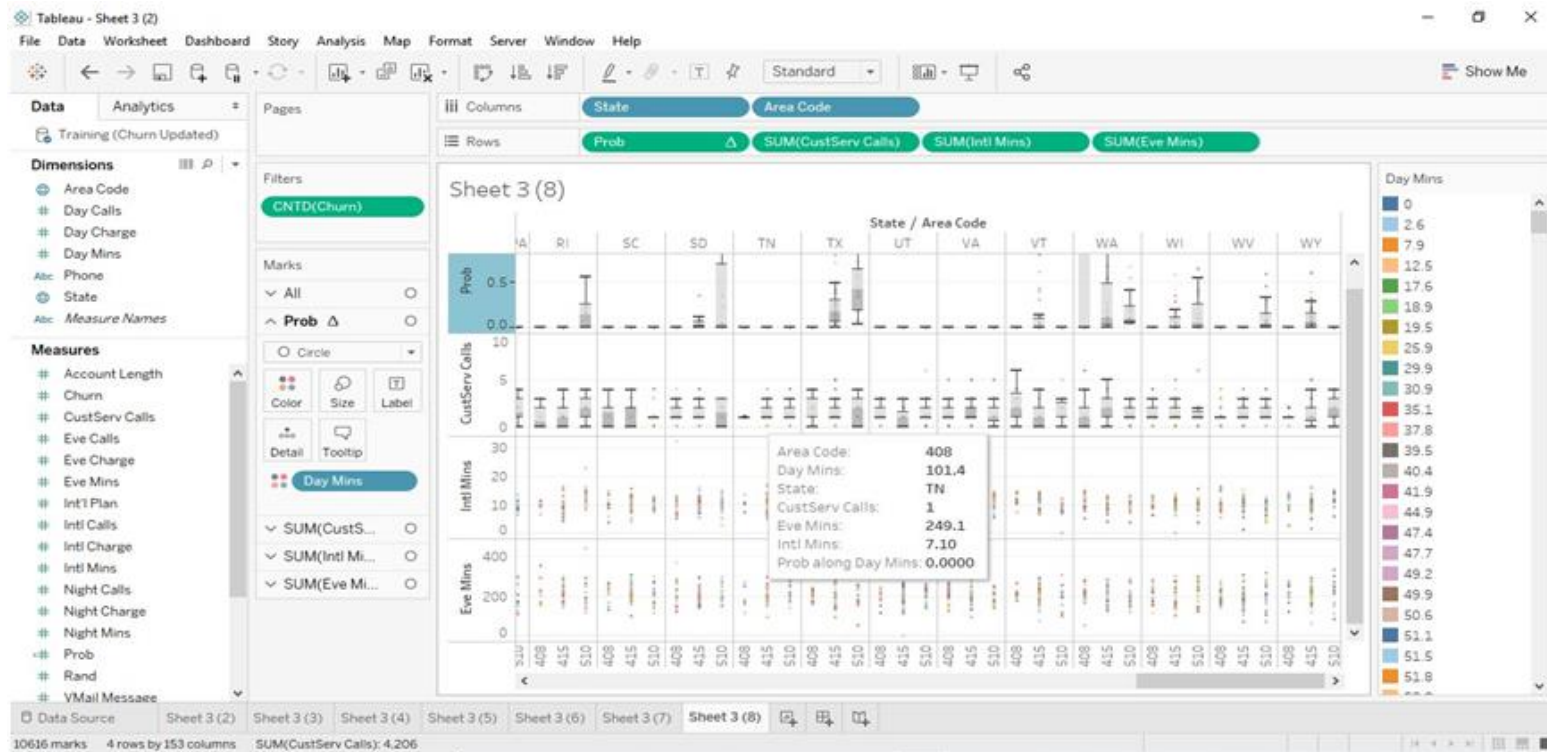




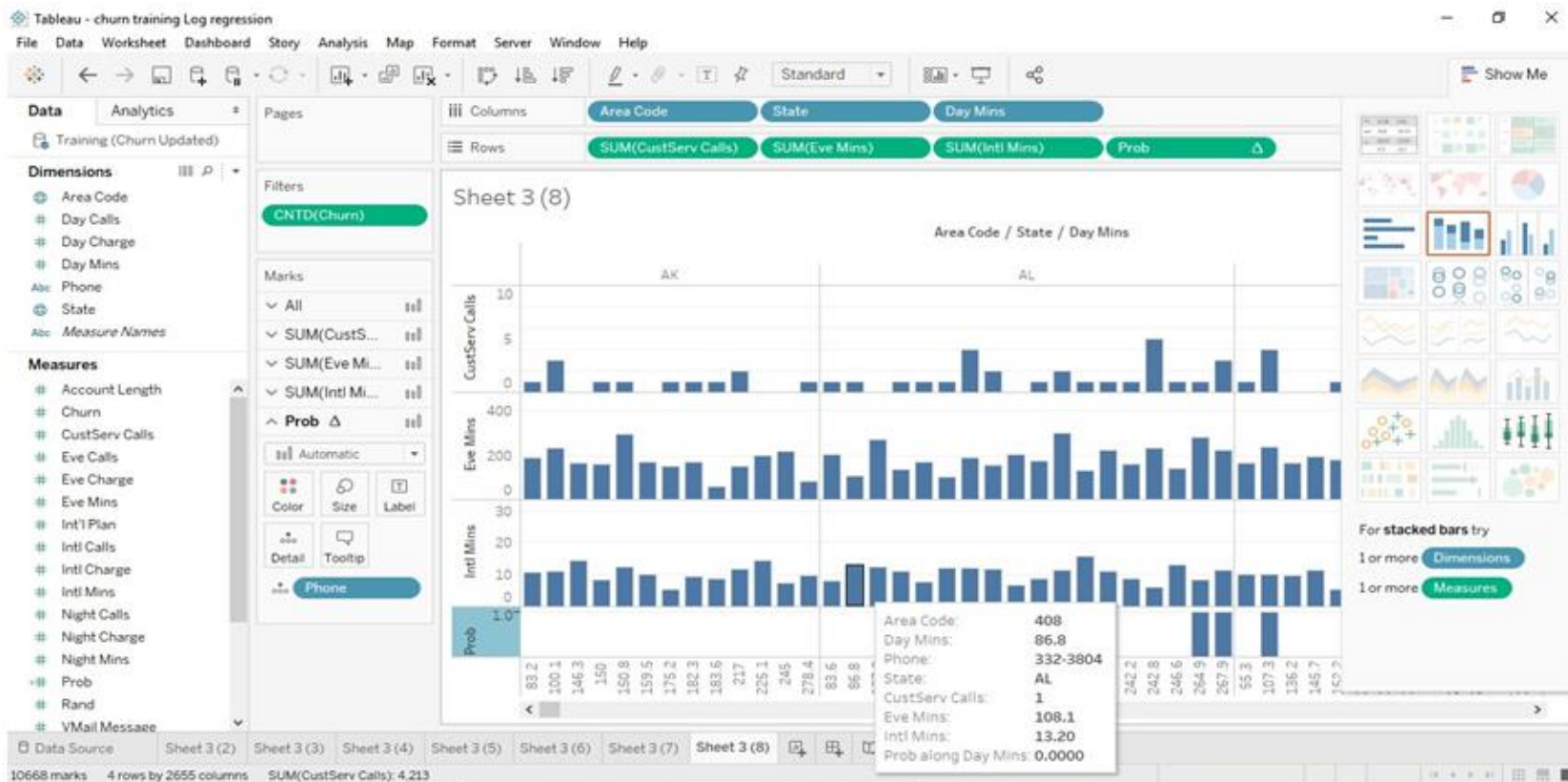


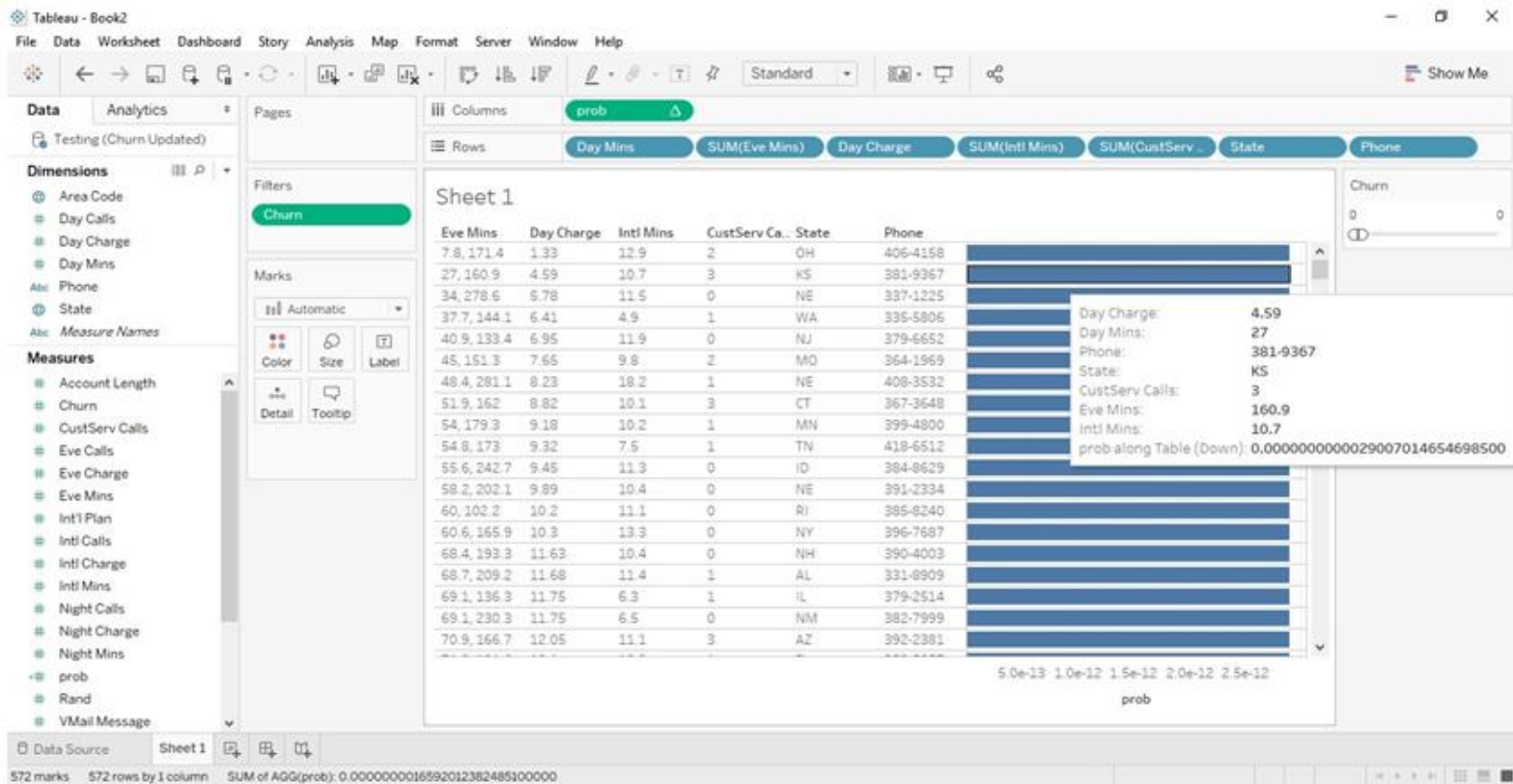


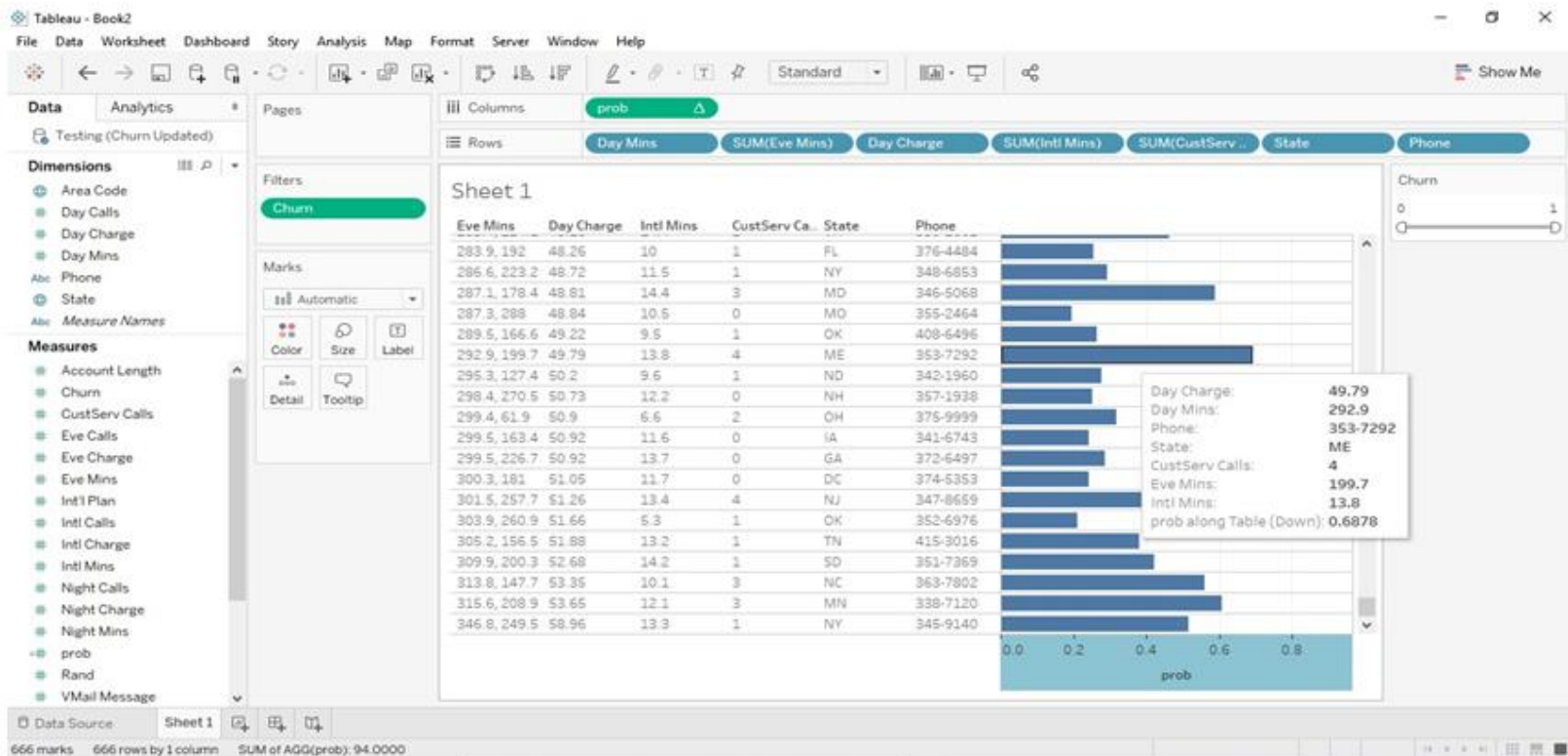




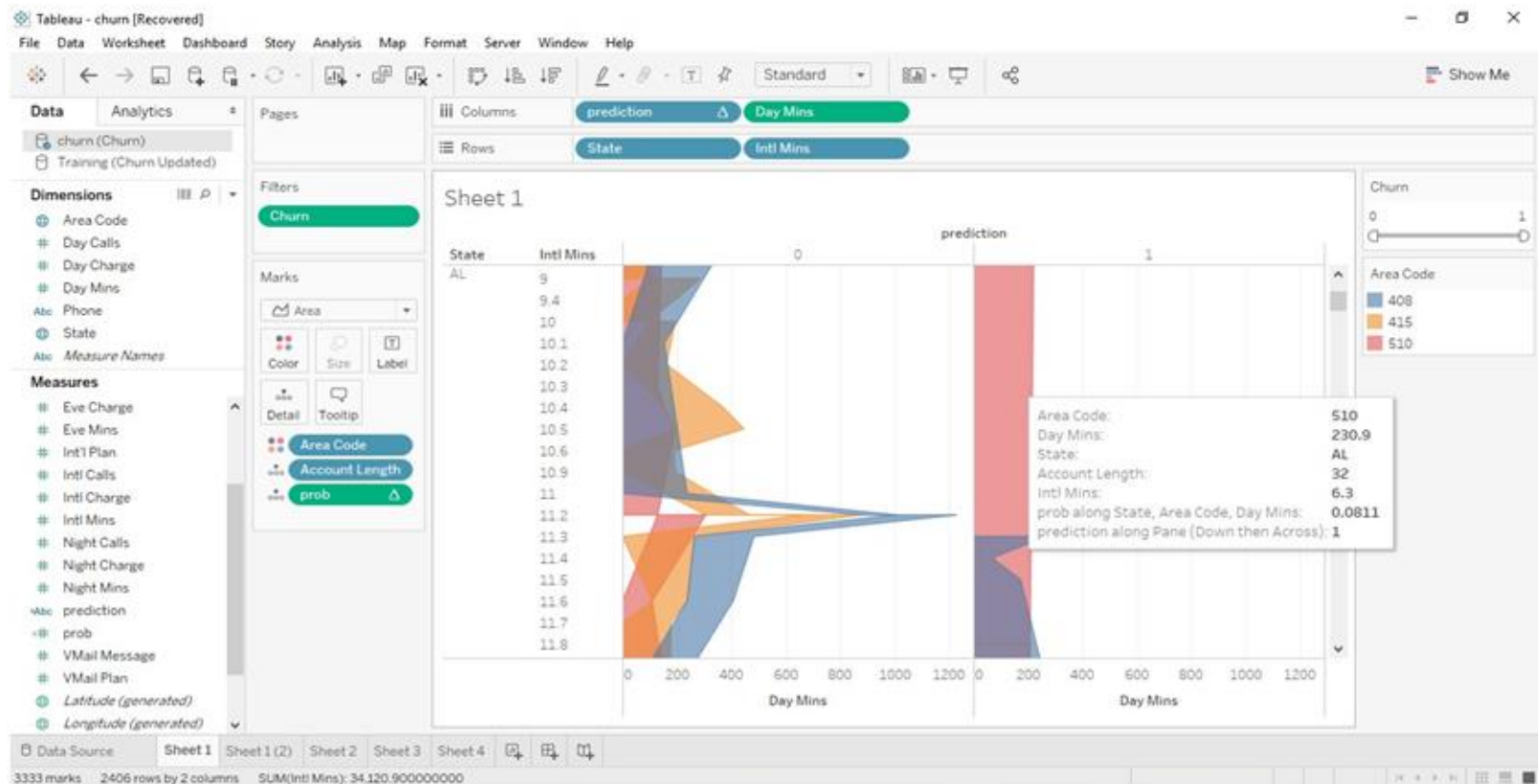


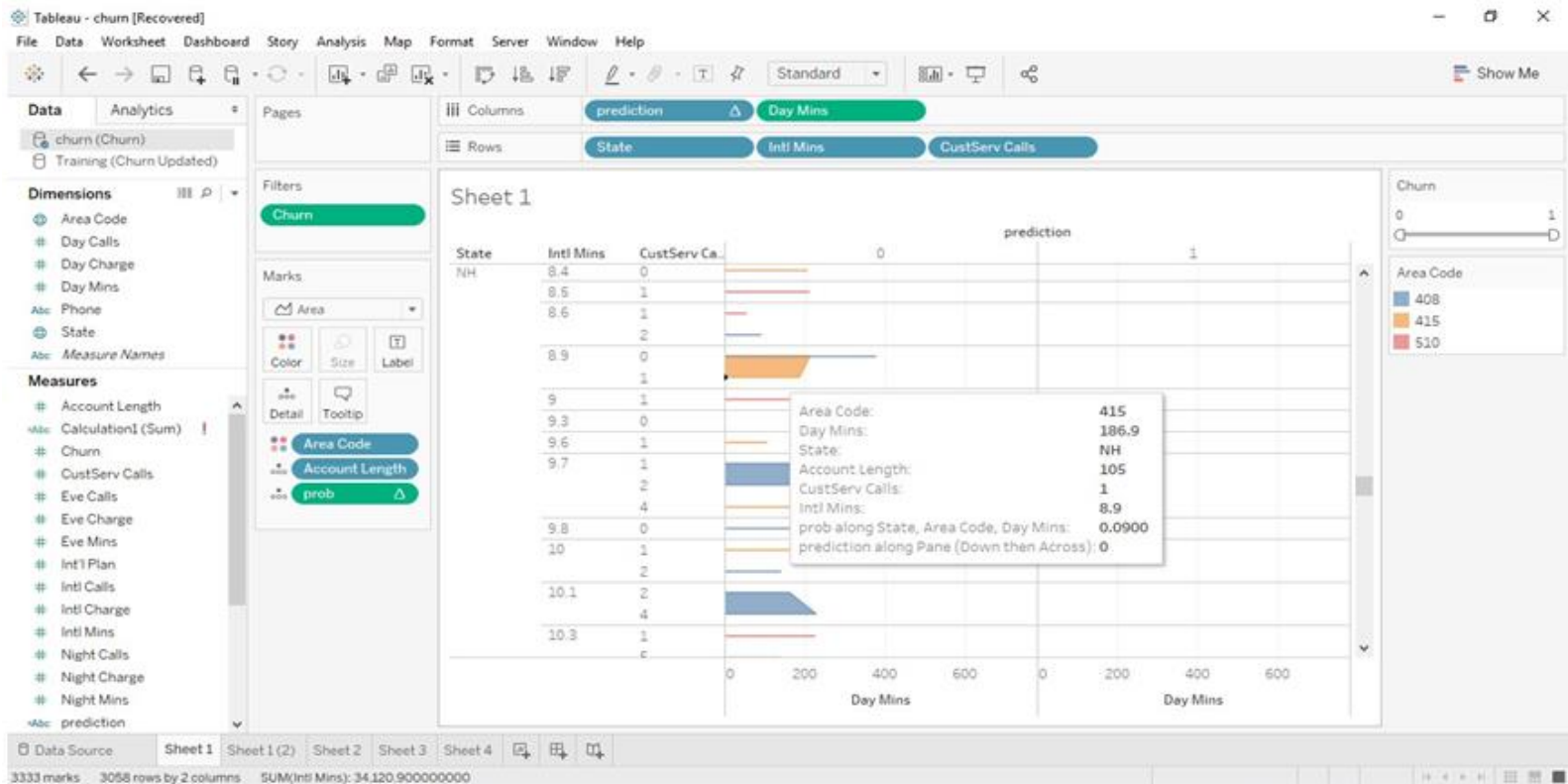




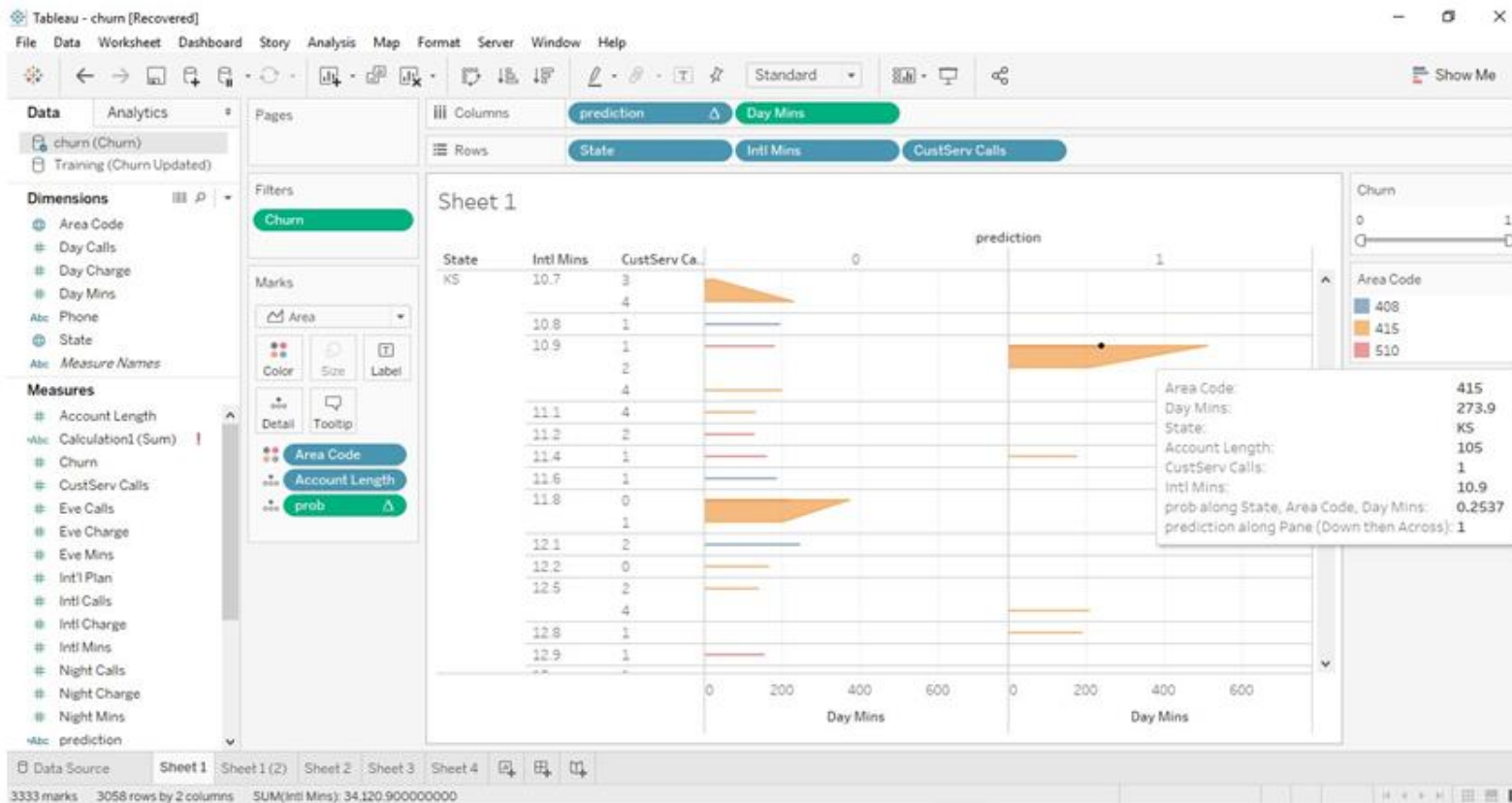


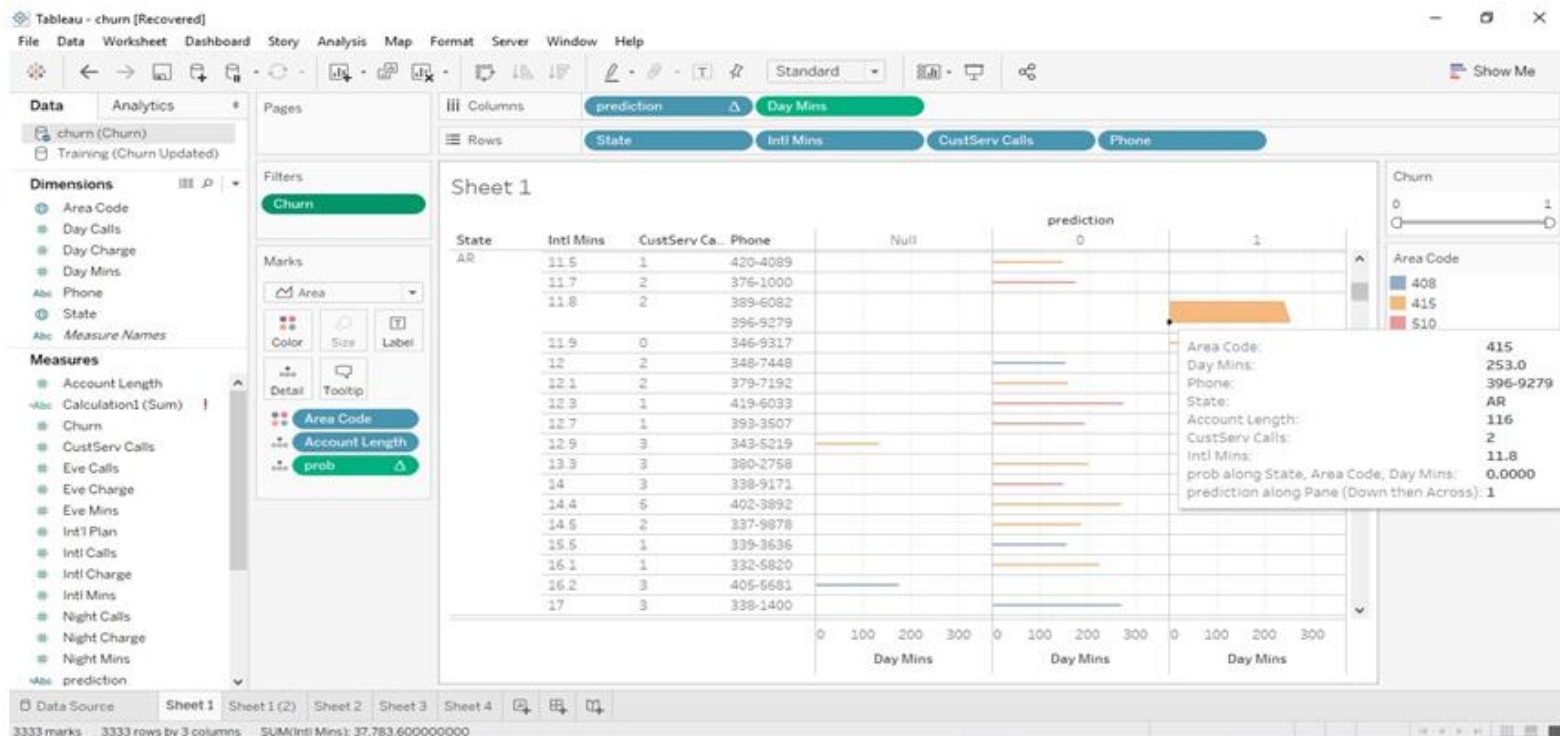


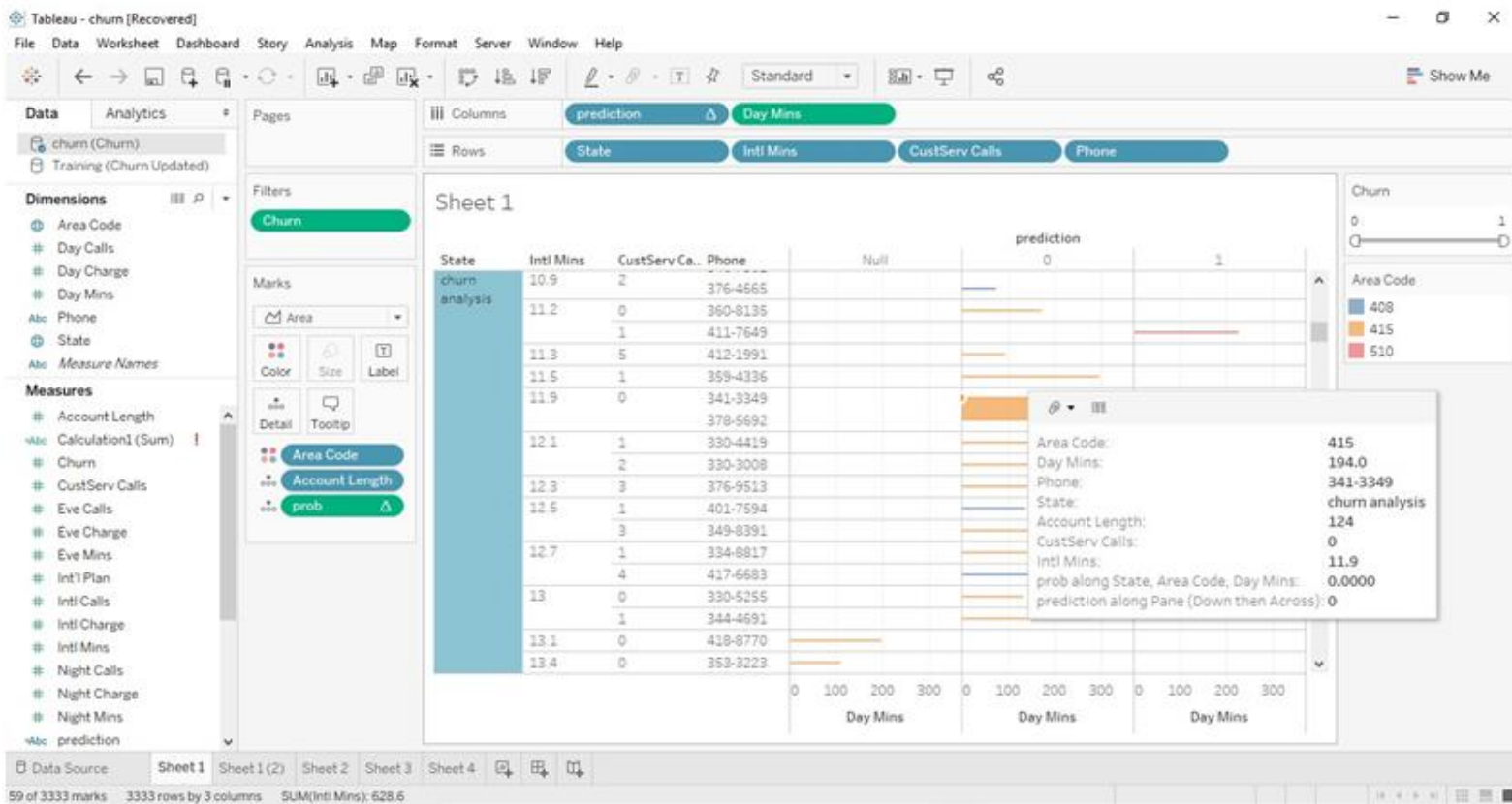


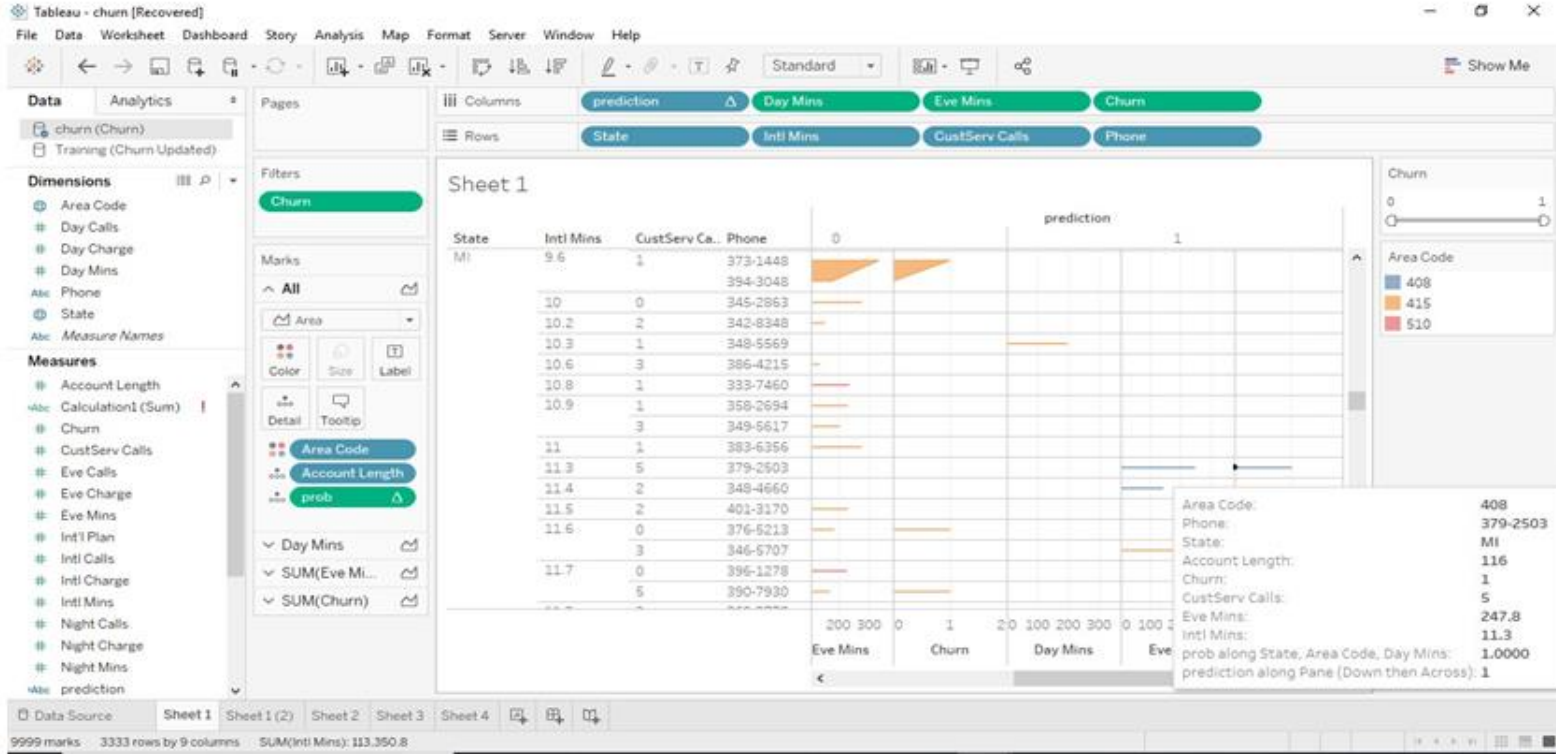


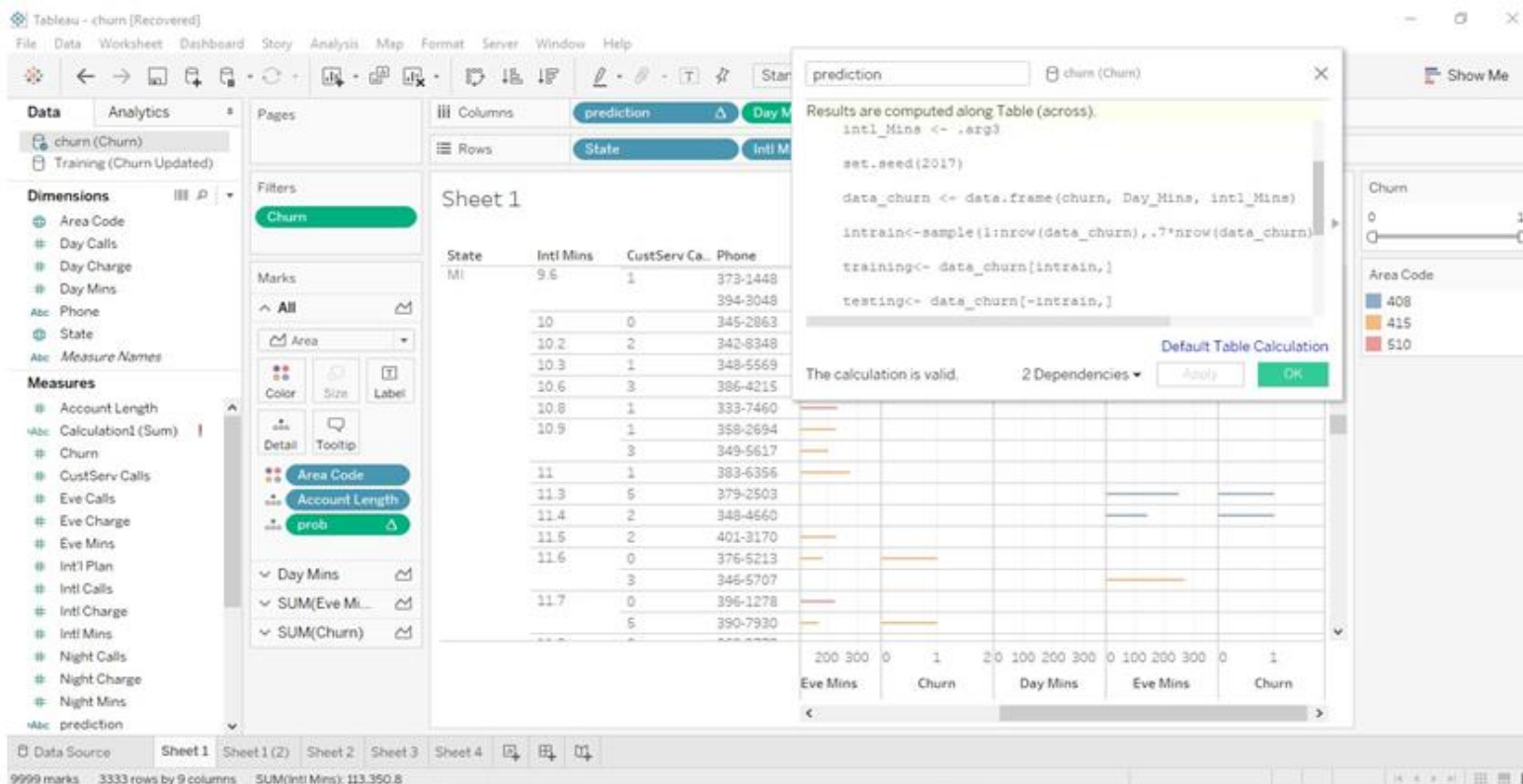


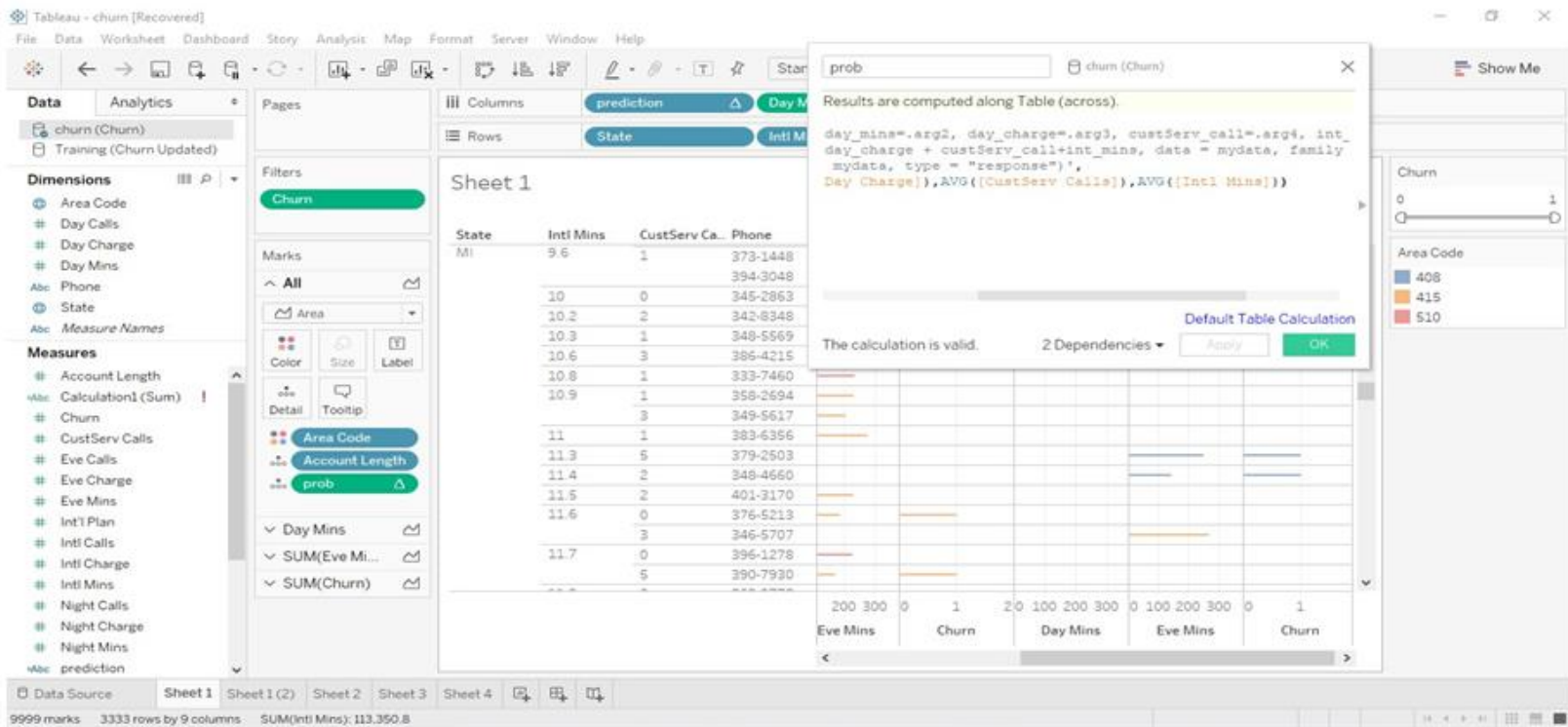


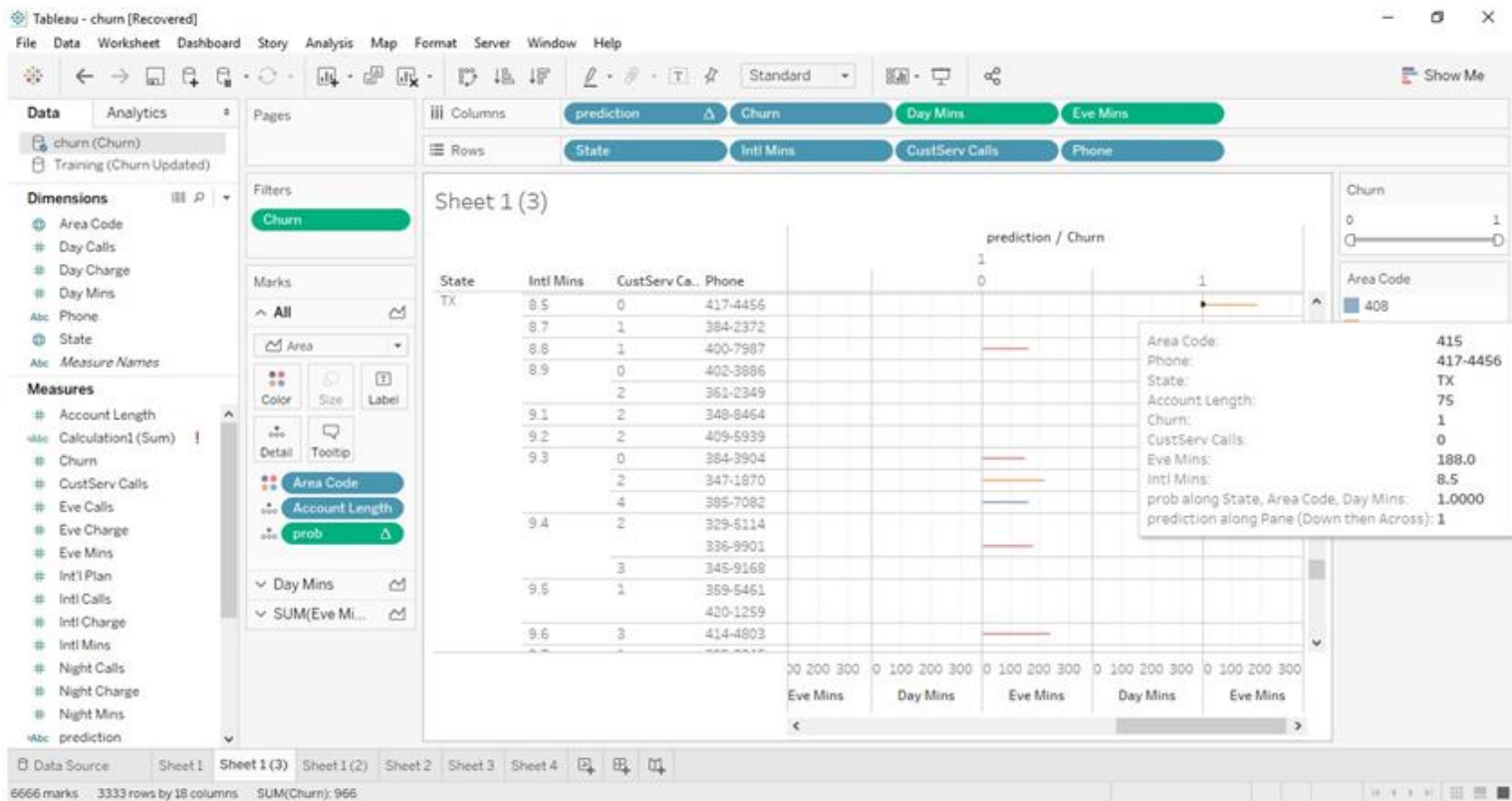




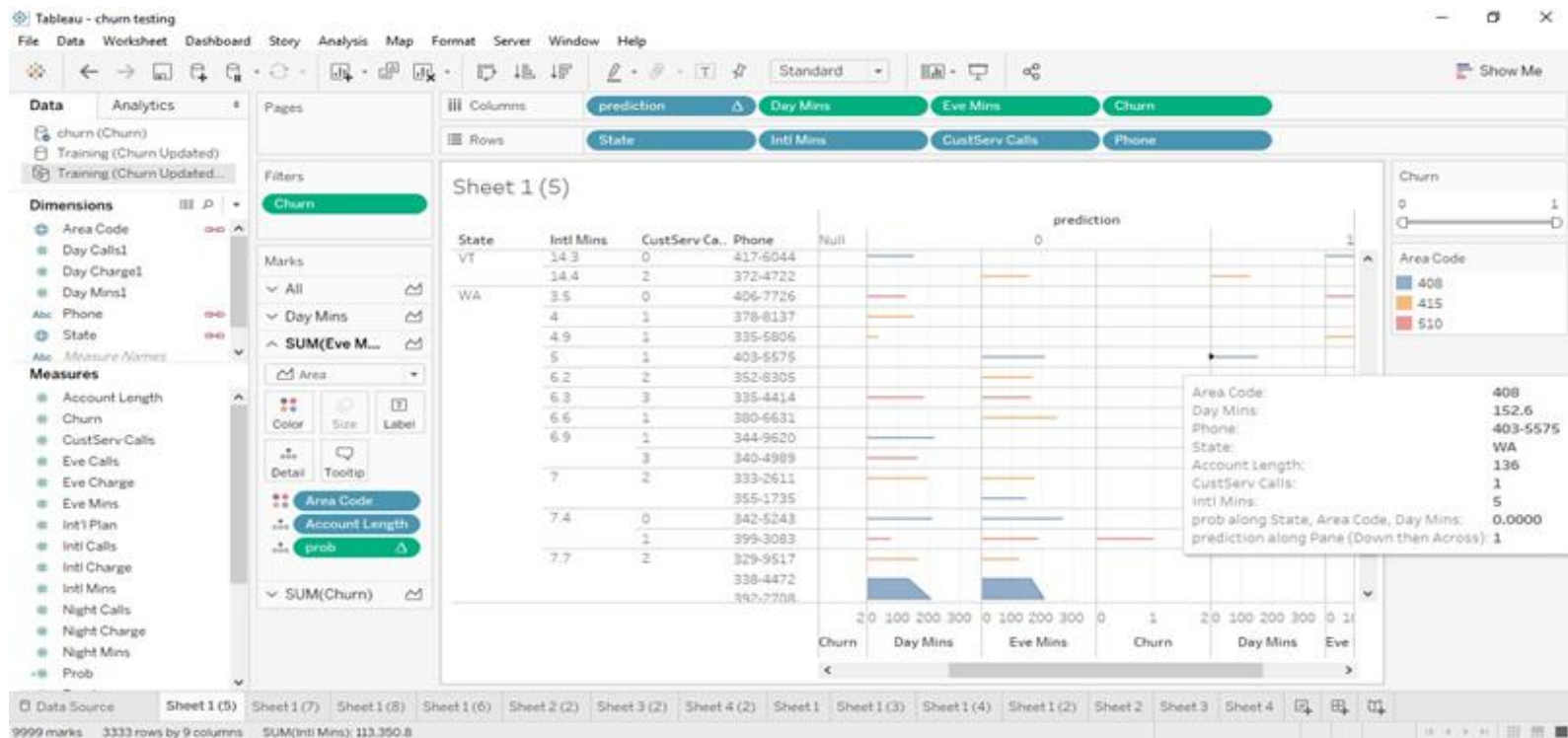




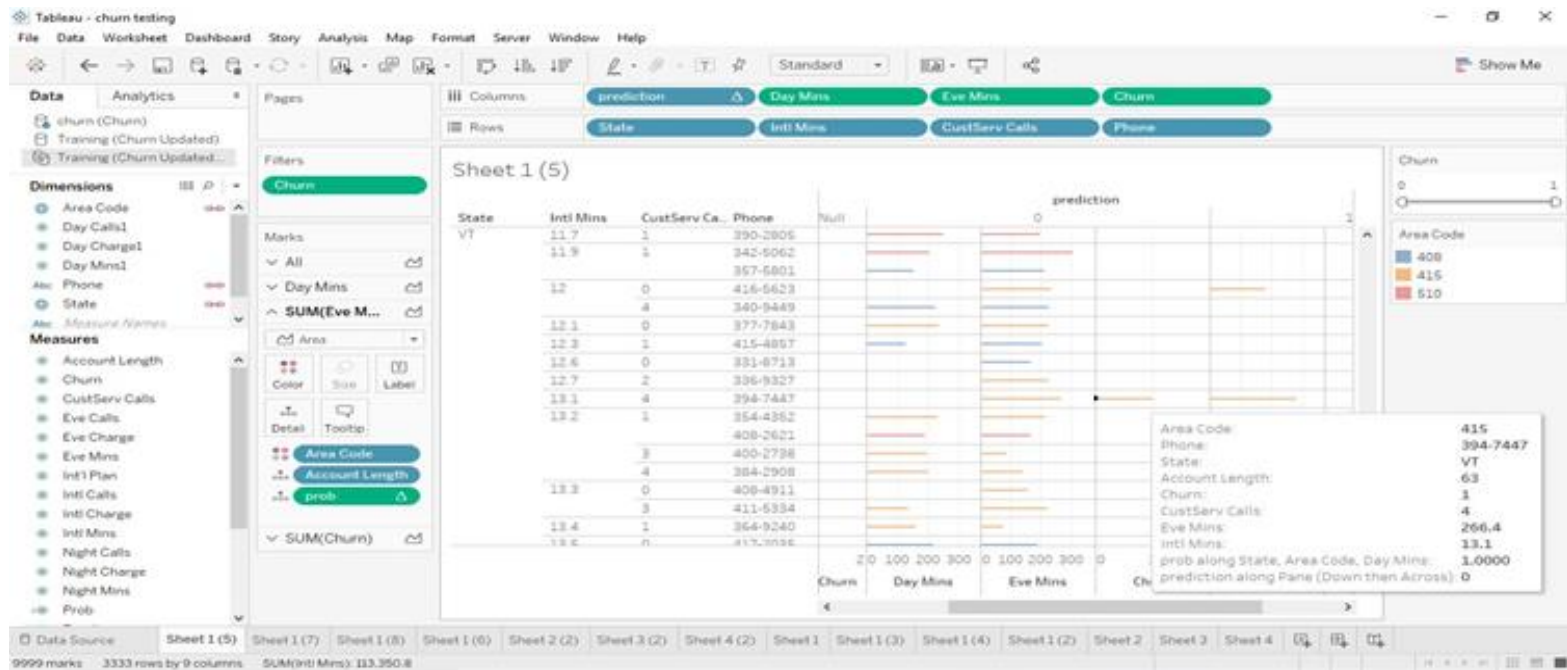


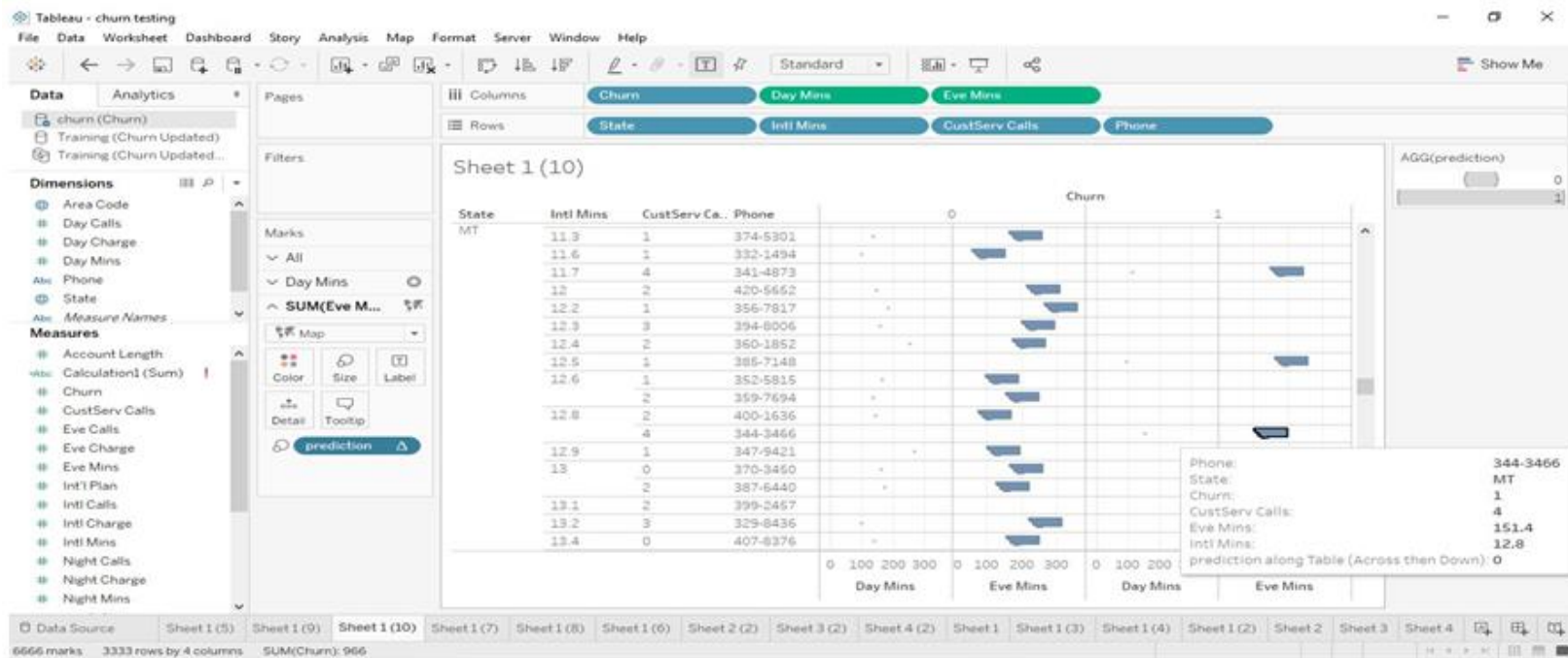




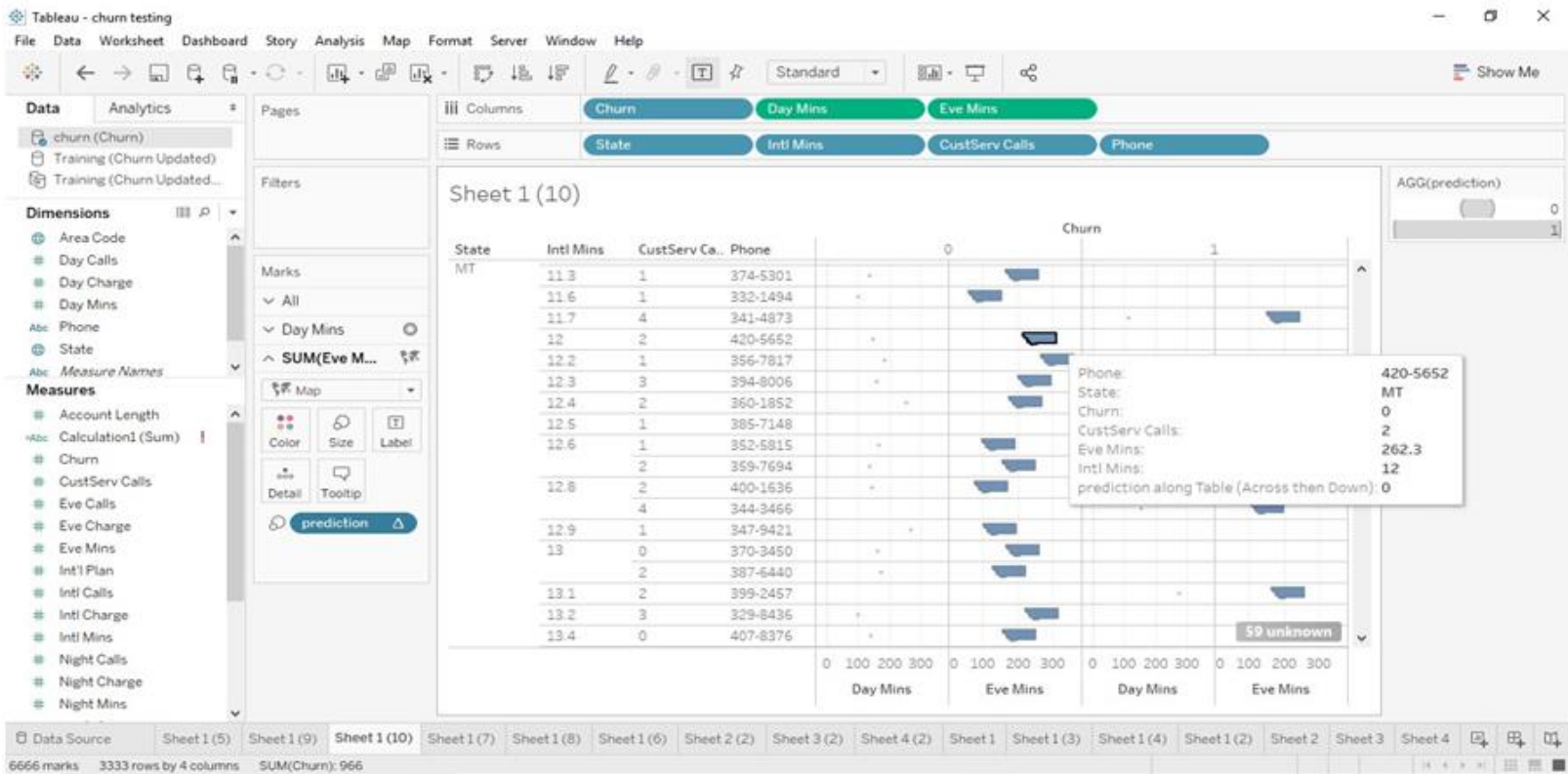


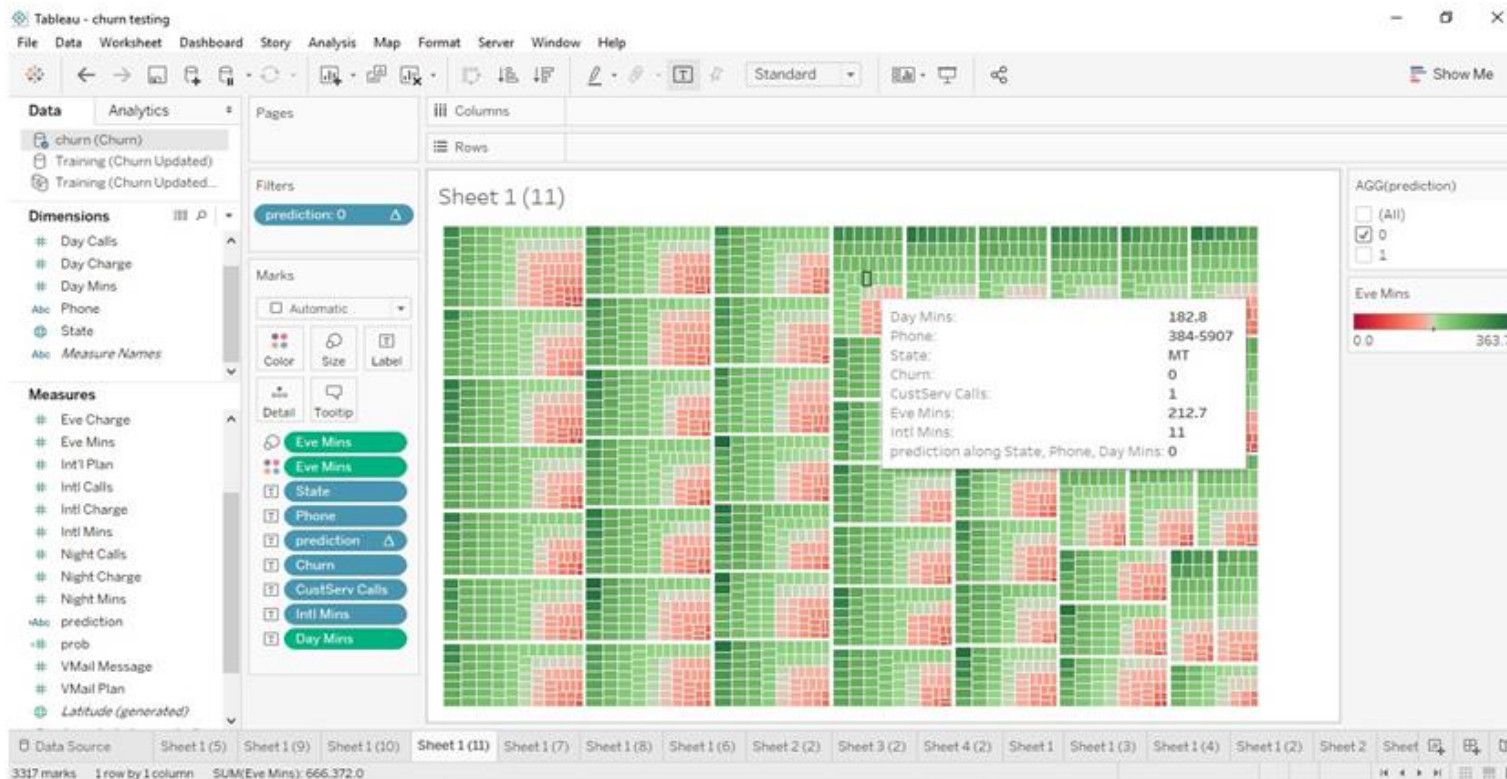


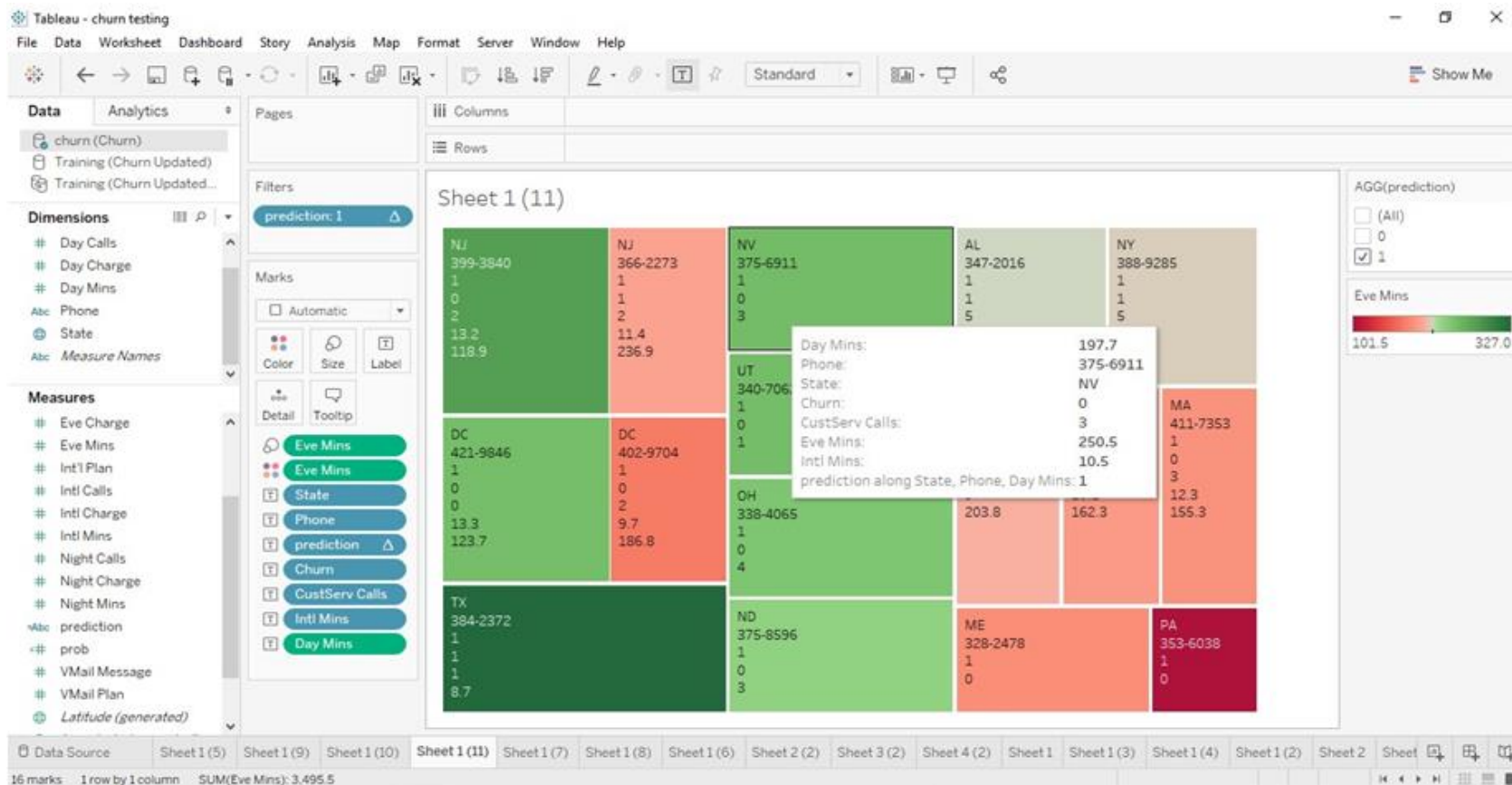








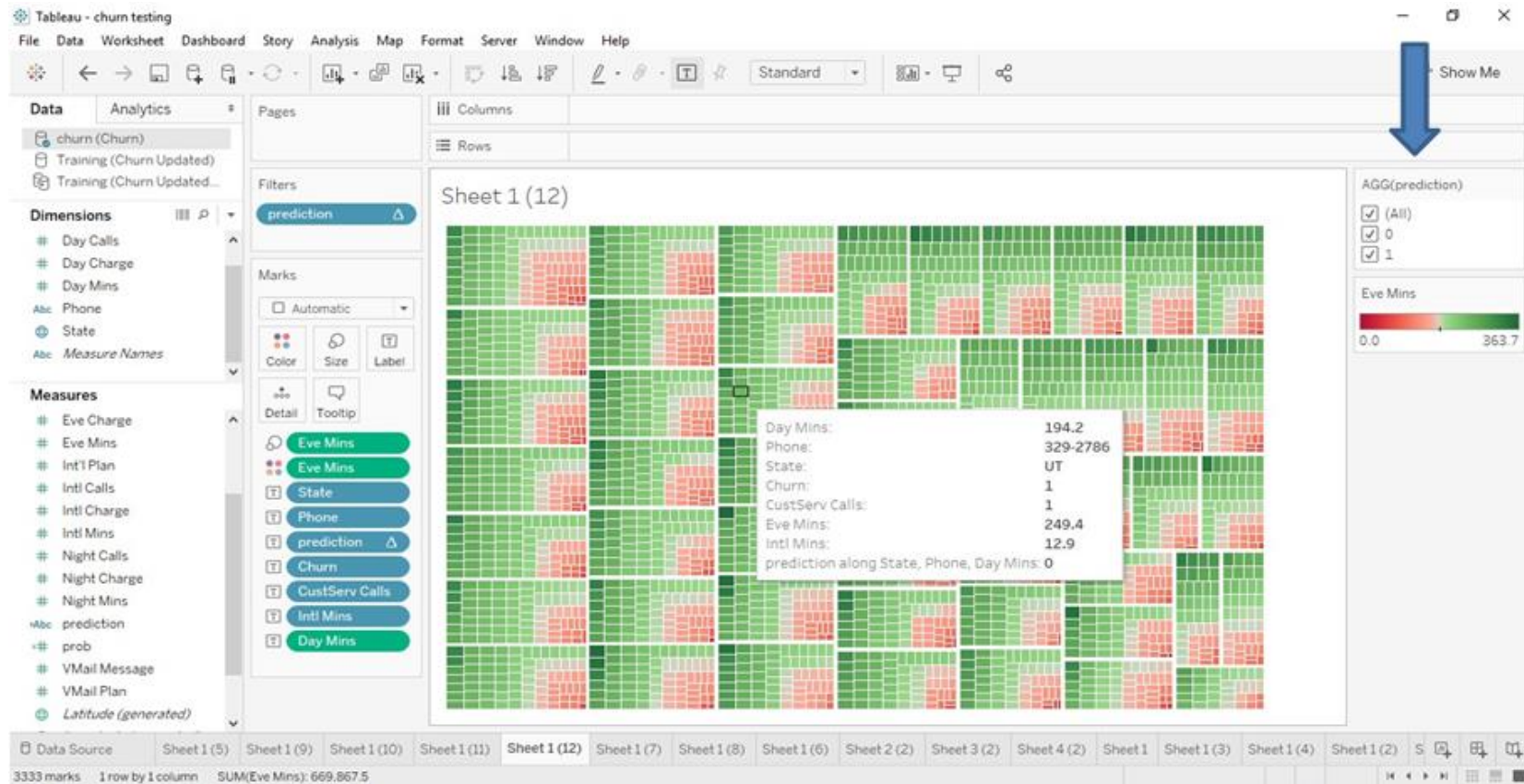


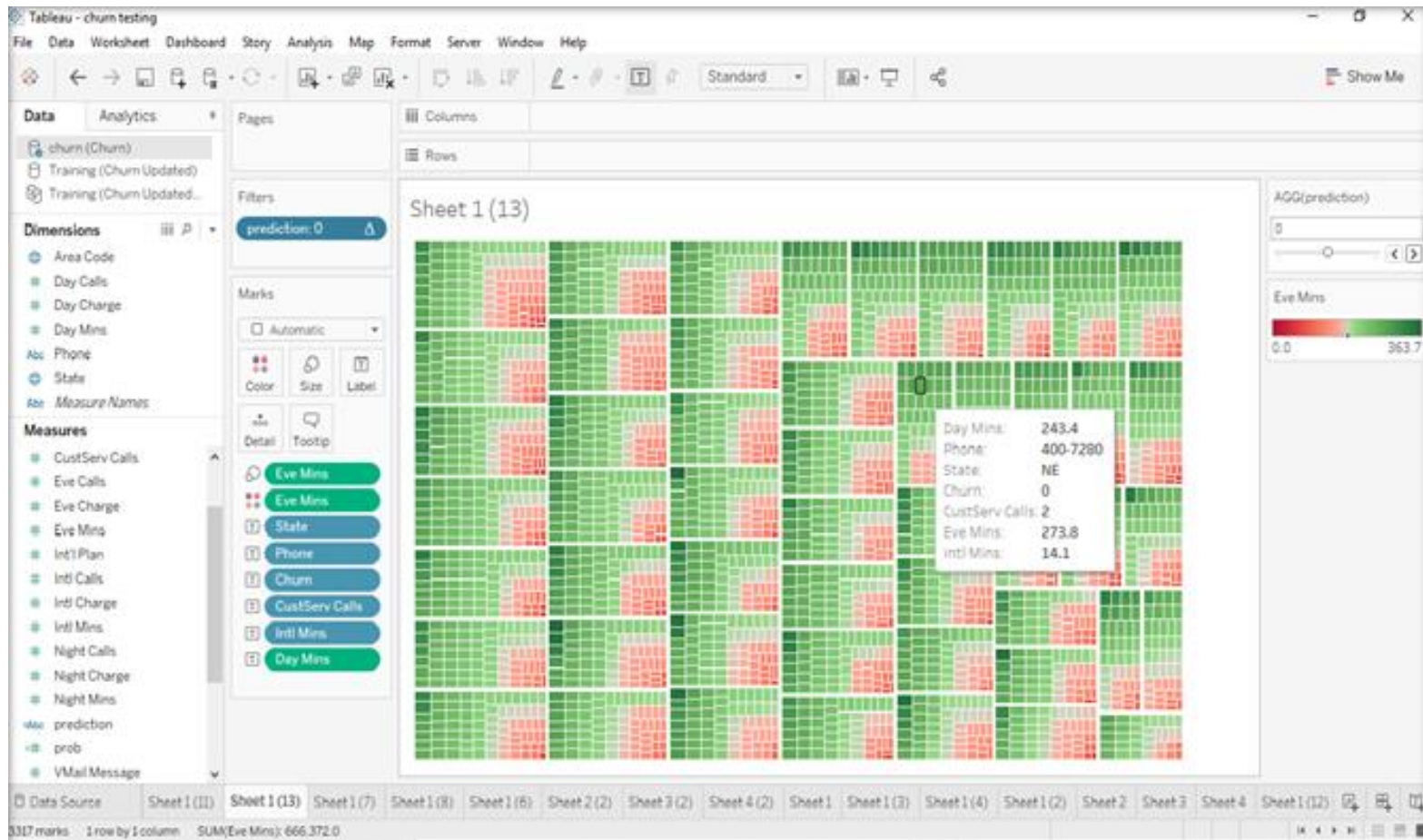




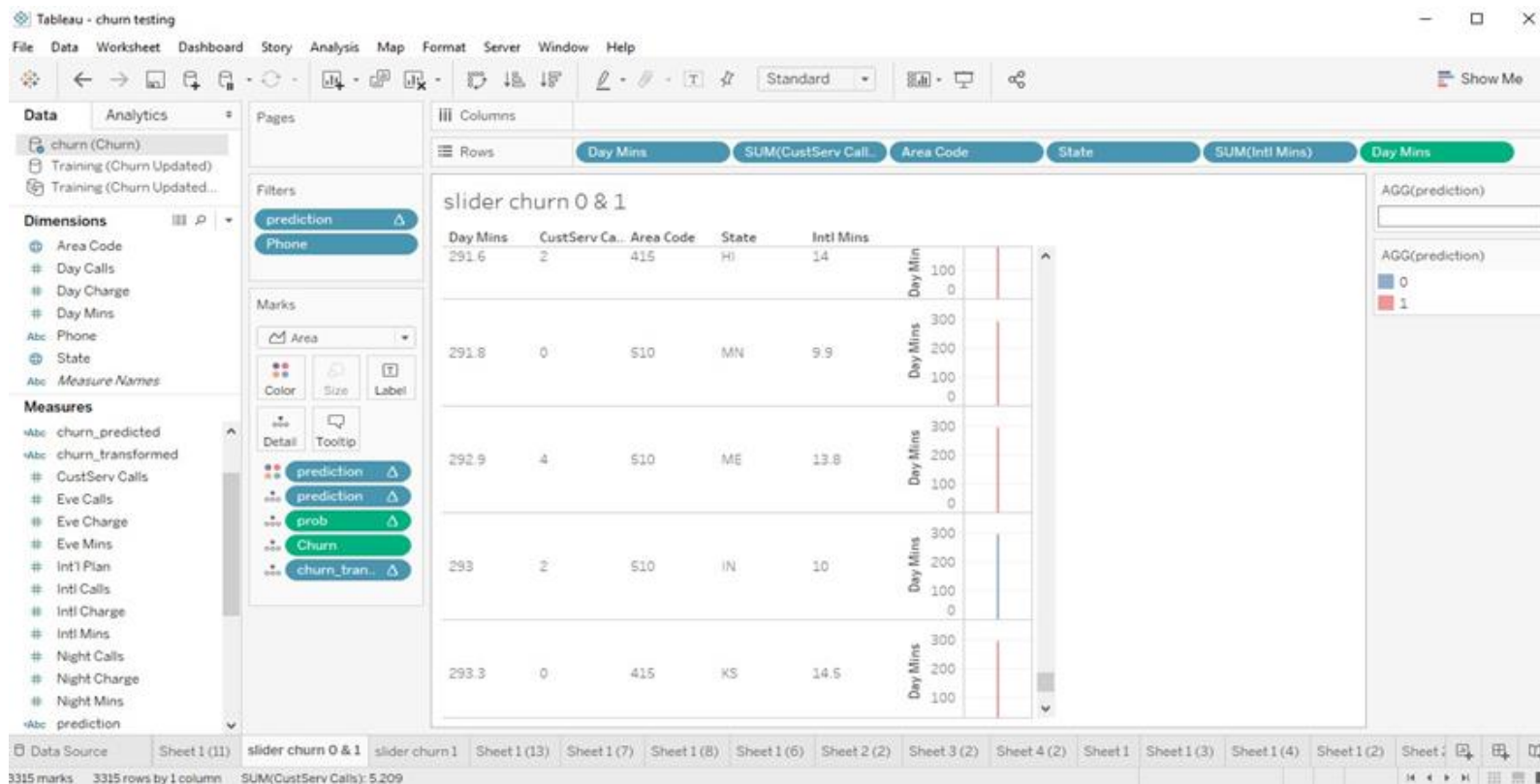
## Prediction in slider

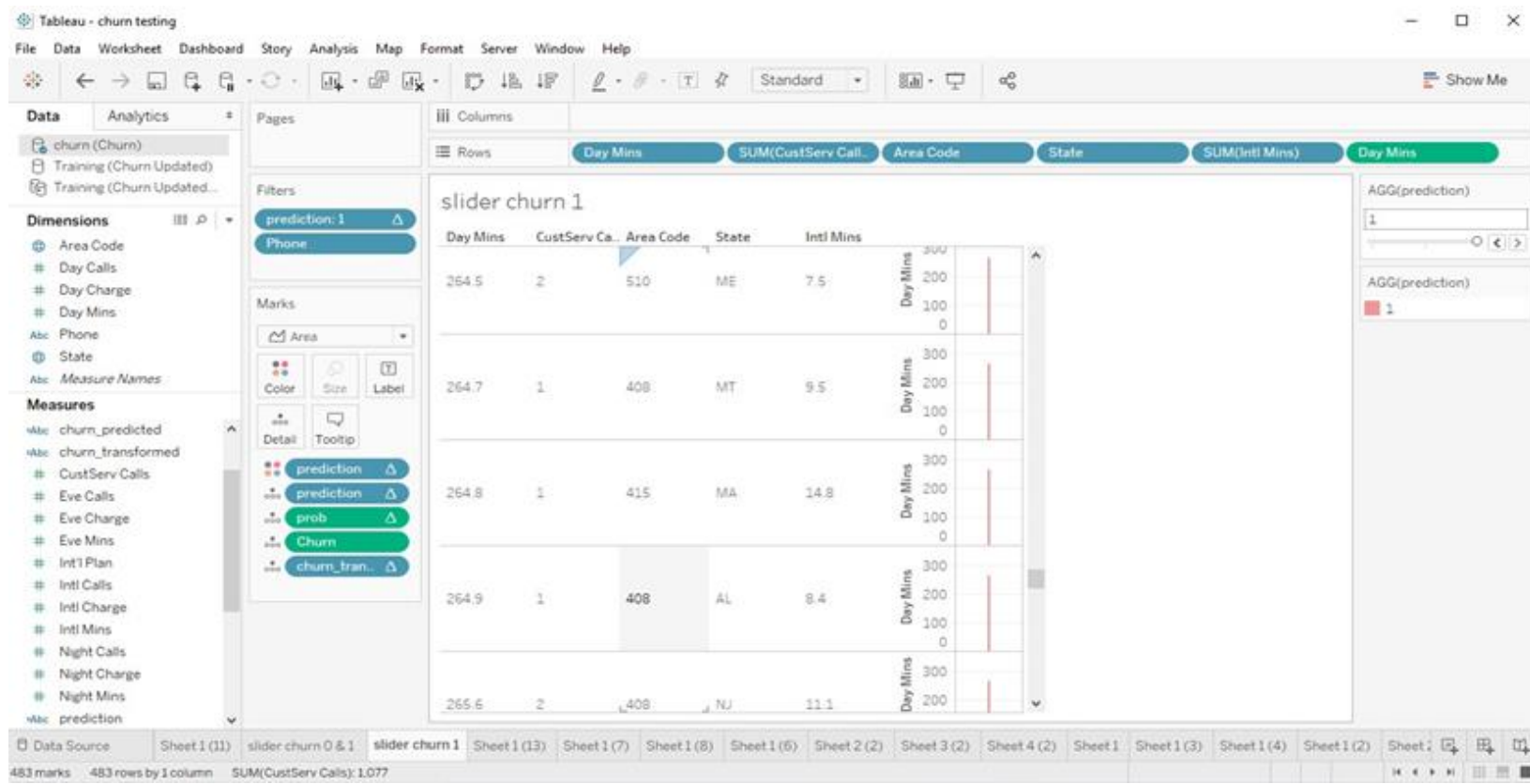
we can select 0,1 or All











In this project a customer churn analysis was presented for churn data provided in the project 2. The analysis focused on churn prediction based on logistic regression. The different models predicted the actual churners relatively well.

The differences between the models input data (the significance level in case of each of the variables) indicates the dynamic nature of the churning customer profile. This makes it hard to formulate one standard model that could be used as the predictive model in the future. The findings of this study indicate that, in case of logistic regression model, the user should update the model to be able to produce predictions with high accuracy. It is interesting for a company's perspective whether the churning customers are worth retaining or not. And also in marketing perspective what can be done to retain them. For Visualization Tableau desktop is used. Calculated fields are used to calculate the probability and the fitted results prediction. Using the Library Reserve in R Logistic regression model is connected with Tableau.

Through this model we can identify easily the churn 1 or 0 and the probabilities through a slider to visualize the churn 1, churn 0 and all. The visualization in Tableau provides separately state wise, Area code, specific telephone no and their probability to predict and visualize them nicely. The data can be imported and stored as excel data for further analysis and churn predictions. These files are exported and stored and attached in this project file.

### Acknowledgement

This is a quite interesting project and I have gained a lot of knowledge about breast cancer and the identification of tumors through Machine Learning classification Model. I thank the institute Acadgild and the Mentors, Mr. Mohit & Mr. Gaurav, who taught us the R and related subjects to understand the Analytics.

Thank you Acadgild!