

Predicting Sales Win or Lose

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How do you know which deals will close? You've worked your territory and leads. Demonstrated the value of your product or service to your customers' businesses and it should be a done deal. But is it? All too often, determining which customers will buy is a guessing game. You have pipeline reports, regional sales figures and wins and losses that you could analyze. Unlock the information in those sources and you'll unlock more revenue and more satisfied customers. Better understanding of sales pipeline can help any sales team organization can expect win or lose based on data. In this project, I am going to be the sales manager at an automotive supply company. Any B2B company like GE, AMAZON, GOOGLE, ADP, etc can use the same approach that I demonstrated on this project to their sales team. As a manager, I'm trying to assess a sales execution issue. We have not been able to convert enough opportunities lately. As a start, I load the required packages and data for this project.

```
library(tidyverse)
```

```
## Warning: package 'tidyverse' was built under R version 3.5.2
```

```
library(caret)
```

```
## Warning: package 'caret' was built under R version 3.5.2
```

```
sales_win_loss <- read_csv("DATA/WA_Fn-UseC_-Sales-Win-Loss.csv")
```

Data for this project is publicly available from Wattson Analytic sample data. (https://community.watsonanalytics.com/wp-content/uploads/2015/04/WA_Fn-UseC_-Sales-Win-Loss.csv) The csv file contains 78K row of data and 19 columns. Each row is assigned a unique sales opportunity ID. The dependent variable is 'Opportunity Result' column with values of either 'Won' or 'Loss'. There are several independent variables from the sample data that I can use such as: 'Supplies Group', 'Region', 'Route To Market', 'Elapsed Days In Sales Stage', 'Opportunity Result', 'Sales Stage Change Count', 'Total Days Identified Through Closing', 'Total Days Identified Through Qualified', 'Opportunity Amount USD', 'Client Size By Revenue', 'Client Size By Employee Count', 'Revenue From Client Past Two Years', and 'Competitor Type'. I use 'glimpse' and 'head' to understand the data structure of my sample data.

```
glimpse(sales_win_loss, give.attr = FALSE)
```

```
## Observations: 78,025
## Variables: 19
## $ `Opportunity Number`      <int> 1641984, 1658010, 16...
## $ `Supplies Subgroup`      <chr> "Exterior Accessorie...
## $ `Supplies Group`         <chr> "Car Accessories", "...
## $ Region                   <chr> "Northwest", "Pacifi...
## $ `Route To Market`       <chr> "Fields Sales", "Res...
## $ `Elapsed Days In Sales Stage` <int> 76, 63, 24, 16, 69, ...
## $ `Opportunity Result`     <chr> "Won", "Loss", "Won"...
## $ `Sales Stage Change Count` <int> 13, 2, 7, 5, 11, 3, ...
## $ `Total Days Identified Through Closing` <int> 104, 163, 82, 124, 9...
```

```
## $ `Total Days Identified Through Qualified` <int> 101, 163, 82, 124, 1...
## $ `Opportunity Amount USD` <int> 0, 0, 7750, 0, 69756...
## $ `Client Size By Revenue` <int> 5, 3, 1, 1, 1, 5, 4,...
## $ `Client Size By Employee Count` <int> 5, 5, 1, 1, 1, 1, 5,...
## $ `Revenue From Client Past Two Years` <int> 0, 0, 0, 0, 0, 0, 0,...
## $ `Competitor Type` <chr> "Unknown", "Unknown"...
## $ `Ratio Days Identified To Total Days` <dbl> 0.696360, 0.000000, ...
## $ `Ratio Days Validated To Total Days` <dbl> 0.113985, 1.000000, ...
## $ `Ratio Days Qualified To Total Days` <dbl> 0.154215, 0.000000, ...
## $ `Deal Size Category` <int> 1, 1, 1, 1, 4, 5, 2,...
```

```
summary(sales_win_loss)
```

```
## Opportunity Number Supplies Subgroup Supplies Group
## Min. : 1641984 Length:78025 Length:78025
## 1st Qu.: 6900423 Class :character Class :character
## Median : 7545569 Mode :character Mode :character
## Mean : 7653429
## 3rd Qu.: 8228329
## Max. : 10094266
## Region Route To Market Elapsed Days In Sales Stage
## Length:78025 Length:78025 Min. : 0.0
## Class :character Class :character 1st Qu.: 19.0
## Mode :character Mode :character Median : 43.0
## Mean : 43.6
## 3rd Qu.: 65.0
## Max. : 210.0
## Opportunity Result Sales Stage Change Count
## Length:78025 Min. : 1.000
## Class :character 1st Qu.: 2.000
## Mode :character Median : 3.000
## Mean : 2.956
## 3rd Qu.: 3.000
## Max. : 23.000
## Total Days Identified Through Closing
## Min. : 0.00
## 1st Qu.: 4.00
## Median : 12.00
## Mean : 16.73
## 3rd Qu.: 24.00
## Max. : 208.00
## Total Days Identified Through Qualified Opportunity Amount USD
## Min. : 0.00 Min. : 0
## 1st Qu.: 4.00 1st Qu.: 15000
## Median : 12.00 Median : 49000
## Mean : 16.31 Mean : 91637
## 3rd Qu.: 24.00 3rd Qu.: 105099
## Max. : 208.00 Max. : 1000000
## Client Size By Revenue Client Size By Employee Count
## Min. :1.00 Min. :1.000
## 1st Qu.:1.00 1st Qu.:1.000
## Median :1.00 Median :1.000
## Mean :1.62 Mean :1.604
## 3rd Qu.:1.00 3rd Qu.:1.000
```

```
## Max. :5.00 Max. :5.000
## Revenue From Client Past Two Years Competitor Type
## Min. :0.0000 Length:78025
## 1st Qu.:0.0000 Class :character
## Median :0.0000 Mode :character
## Mean :0.3033
## 3rd Qu.:0.0000
## Max. :4.0000
## Ratio Days Identified To Total Days Ratio Days Validated To Total Days
## Min. :0.0000 Min. :0.0000
## 1st Qu.:0.0000 1st Qu.:0.0000
## Median :0.0000 Median :0.4480
## Mean :0.2031 Mean :0.4883
## 3rd Qu.:0.1972 3rd Qu.:1.0000
## Max. :1.0000 Max. :1.0000
## Ratio Days Qualified To Total Days Deal Size Category
## Min. :0.0000 Min. :1.000
## 1st Qu.:0.0000 1st Qu.:2.000
## Median :0.0000 Median :3.000
## Mean :0.1850 Mean :3.437
## 3rd Qu.:0.1886 3rd Qu.:5.000
## Max. :1.0000 Max. :7.000
```

```
head(sales_win_loss[, 1:6])
```

```
## # A tibble: 6 x 6
## `Opportunity Nu~ `Supplies Subgr~ `Supplies Group~ Region
## <int> <chr> <chr> <chr>
## 1 1641984 Exterior Access~ Car Accessories North~
## 2 1658010 Exterior Access~ Car Accessories Pacif~
## 3 1674737 Motorcycle Parts Performance & N~ Pacif~
## 4 1675224 Shelters & RV Performance & N~ Midwe~
## 5 1689785 Exterior Access~ Car Accessories Pacif~
## 6 1692390 Shelters & RV Performance & N~ Pacif~
## # ... with 2 more variables: `Route To Market` <chr>, `Elapsed Days In
## # Sales Stage` <int>
```

```
head(sales_win_loss[, 7:13])
```

```
## # A tibble: 6 x 7
## `Opportunity Re~ `Sales Stage Ch~ `Total Days Ide~ `Total Days Ide~
## <chr> <int> <int> <int>
## 1 Won 13 104 101
## 2 Loss 2 163 163
## 3 Won 7 82 82
## 4 Loss 5 124 124
## 5 Loss 11 91 13
## 6 Loss 3 114 0
## # ... with 3 more variables: `Opportunity Amount USD` <int>, `Client Size
## # By Revenue` <int>, `Client Size By Employee Count` <int>
```

```
head(sales_win_loss[, 14:19])
```

```
## # A tibble: 6 x 6
##   `Revenue From C~` `Competitor Typ~` `Ratio Days Ide~` `Ratio Days Val~`
##         <int> <chr>                <dbl>         <dbl>
## 1             0 Unknown              0.696         0.114
## 2             0 Unknown              0             1
## 3             0 Unknown              1             0
## 4             0 Known                1             0
## 5             0 Unknown              0             0.141
## 6             0 Unknown              0             0.000877
## # ... with 2 more variables: `Ratio Days Qualified To Total Days` <dbl>,
## #   `Deal Size Category` <int>
```

I checked for missing values of my dataset

```
map_dbl(sales_win_loss, ~sum(is.na(.)))
```

```
##           Opportunity Number
##                0
##           Supplies Subgroup
##                0
##           Supplies Group
##                0
##                Region
##                0
##           Route To Market
##                0
##           Elapsed Days In Sales Stage
##                0
##           Opportunity Result
##                0
##           Sales Stage Change Count
##                0
##           Total Days Identified Through Closing
##                0
##           Total Days Identified Through Qualified
##                0
##           Opportunity Amount USD
##                0
##           Client Size By Revenue
##                0
##           Client Size By Employee Count
##                0
##           Revenue From Client Past Two Years
##                0
##           Competitor Type
##                0
##           Ratio Days Identified To Total Days
##                0
##           Ratio Days Validated To Total Days
##                0
```

```
##      Ratio Days Qualified To Total Days
##                                     0
##      Deal Size Category
##                                     0
```

The next step is setting the standard theme for the charts to `theme_minimal` with legend set at the bottom of the chart.

```
theme_set(theme_minimal() + theme(legend.position = "bottom"))
```

For better data visualization on the chart, I rename the columns with long name.

```
colnames(sales_win_loss) <- c("ID", "SuppliesSubgroup", "SuppliesGroup", "Region", "Route",
                             "ElapsedDays", "Result", "SalesStageCount",
                             "TotalDaysClosing", "TotalDaysQualified",
                             "Opportunity", "ClientSizeRev", "ClientSizeCount",
                             "Revenue", "Competitor", "RDaysIdentified",
                             "RDaysValidated", "RDaysQualified",
                             "DealSize")
```

Moreover, I made several assumptions to translate the categorical columns into meaningful information.

```
sales_win_loss <- sales_win_loss %>%
  mutate(ClientSizeRev2 = case_when(
    ClientSizeRev == 1 ~ "ClientRev<$1M",
    ClientSizeRev == 2 ~ "$1M<=ClientRev<$10M",
    ClientSizeRev == 3 ~ "$10M<=ClientRev<$50M",
    ClientSizeRev == 4 ~ "$50M<=ClientRev<$100M",
    ClientSizeRev == 5 ~ "ClientRev>=$100M"))

sales_win_loss <- sales_win_loss %>%
  mutate(ClientSizeCount2 = case_when(
    ClientSizeCount == 1 ~ "Count<1K",
    ClientSizeCount == 2 ~ "1K<=Count<5K",
    ClientSizeCount == 3 ~ "5K<=Count<10K",
    ClientSizeCount == 4 ~ "10K<=Count<30K",
    ClientSizeCount == 5 ~ "Count>=30K"))

sales_win_loss <- sales_win_loss %>%
  mutate(Revenue2 = case_when(
    Revenue == 0 ~ "Rev=$0",
    Revenue == 1 ~ "$1<=Rev<$50K",
    Revenue == 2 ~ "$50K<=Rev<$400K",
    Revenue == 3 ~ "$400K<=Rev<$1.5M",
    Revenue == 4 ~ "Rev>=$1.5M"))
```

Data Dictionary

```
var_descriptions <- c(
  "A random number assigned to the opportunity",
  "Supplies Subgroup",
```

```

"Supplies Group",
"Region",
"Route to market",
"The number of days between the change in sales stages",
"A closed opportunity. Values is either won or loss",
"A count of number of times an opportunity changes sales stages",
"Total days from Identified to Gained Agreement/closing",
"Total days from Identified to Qualified Agreement",
"Sum of line item revenue estimates",
"Client size based on annual revenue",
"Client size based on number of employees",
"Revenue from client the past two years assuming after the deal is closed",
"An indicator whether or not competitor has been identified",
"Ratio of Identified/Validating over total days",
"Ratio of Qualified/Gaining Agreement over total days",
"Ratio of Validated/Qualifying over total days",
"Categorical grouping of the opportunity amount"
)

var <- colnames(sales_win_loss)
var_type <- unlist(map(sales_win_loss, class))
as_tibble(cbind(c(var, var_type, var_descriptions)))

```

```

## # A tibble: 63 x 1
##   V1
##   <chr>
## 1 ID
## 2 SuppliesSubgroup
## 3 SuppliesGroup
## 4 Region
## 5 Route
## 6 ElapsedDays
## 7 Result
## 8 SalesStageCount
## 9 TotalDaysClosing
## 10 TotalDaysQualified
## # ... with 53 more rows

```

```
as_data_frame(cbind(c(1:length(var)), var, var_type, var_descriptions))
```

```

## Warning in cbind(c(1:length(var)), var, var_type, var_descriptions): number
## of rows of result is not a multiple of vector length (arg 4)

```

```

## # A tibble: 22 x 4
##   V1    var          var_type var_descriptions
##   <chr> <chr>          <chr>    <chr>
## 1 1      ID            integer  A random number assigned to the opportuni~
## 2 2    SuppliesSubg~ charact~ Supplies Subgroup
## 3 3    SuppliesGroup charact~ Supplies Group
## 4 4      Region        charact~ Region
## 5 5      Route          charact~ Route to market
## 6 6    ElapsedDays     integer  The number of days between the change in ~

```

```
## 7 7      Result      charact~ A closed opportunity. Values is either wo~
## 8 8      SalesStageCo~ integer  A count of number of times an opportunity~
## 9 9      TotalDaysClo~ integer  Total days from Identified to Gained Agre~
## 10 10     TotalDaysQua~ integer  Total days from Identified to Qualified A~
## # ... with 12 more rows
```

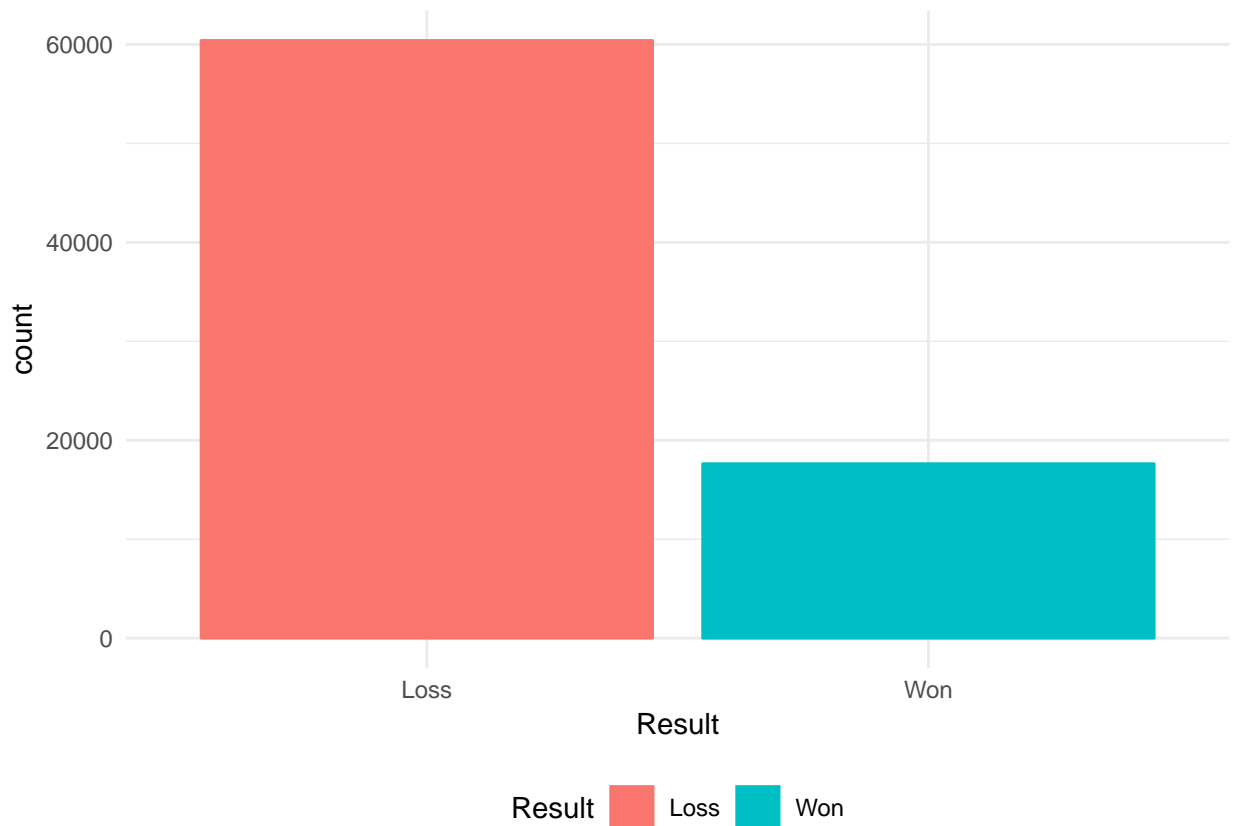
```
as_tibble(sales_win_loss)
```

```
## # A tibble: 78,025 x 22
##       ID SuppliesSubgroup SuppliesGroup Region Route ElapsedDays Result
##   <int> <chr>           <chr>      <chr> <chr>      <int> <chr>
## 1 1.64e6 Exterior Access~ Car Accessor~ North~ Fiel~        76 Won
## 2 1.66e6 Exterior Access~ Car Accessor~ Pacif~ Rese~        63 Loss
## 3 1.67e6 Motorcycle Parts Performance ~ Pacif~ Rese~        24 Won
## 4 1.68e6 Shelters & RV    Performance ~ Midwe~ Rese~        16 Loss
## 5 1.69e6 Exterior Access~ Car Accessor~ Pacif~ Rese~        69 Loss
## 6 1.69e6 Shelters & RV    Performance ~ Pacif~ Rese~        89 Loss
## 7 1.94e6 Garage & Car Ca~ Car Accessor~ Pacif~ Fiel~       111 Won
## 8 1.95e6 Exterior Access~ Car Accessor~ Pacif~ Fiel~        82 Loss
## 9 2.00e6 Batteries & Acc~ Car Accessor~ North~ Fiel~        68 Loss
## 10 2.05e6 Exterior Access~ Car Accessor~ Pacif~ Rese~        18 Loss
## # ... with 78,015 more rows, and 15 more variables: SalesStageCount <int>,
## #   TotalDaysClosing <int>, TotalDaysQualified <int>, Opportunity <int>,
## #   ClientSizeRev <int>, ClientSizeCount <int>, Revenue <int>,
## #   Competitor <chr>, RDaysIdentified <dbl>, RDaysValidated <dbl>,
## #   RDaysQualified <dbl>, DealSize <int>, ClientSizeRev2 <chr>,
## #   ClientSizeCount2 <chr>, Revenue2 <chr>
```

Data Exploration

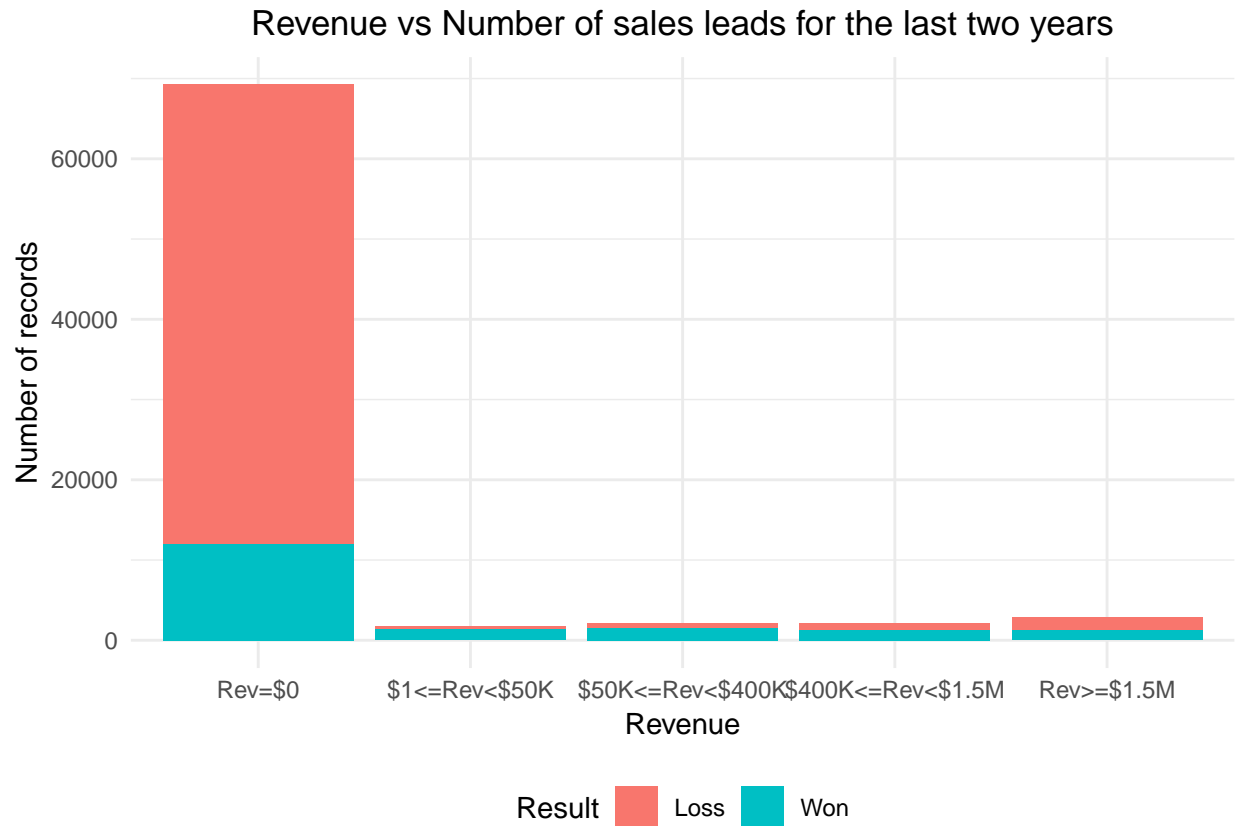
The first chart is to understand the number of sales leads that the company won versus loss in respect to revenue for the last two years.

```
ggplot(sales_win_loss, aes(x = Result, color = Result, fill = Result)) +
  geom_bar()
```



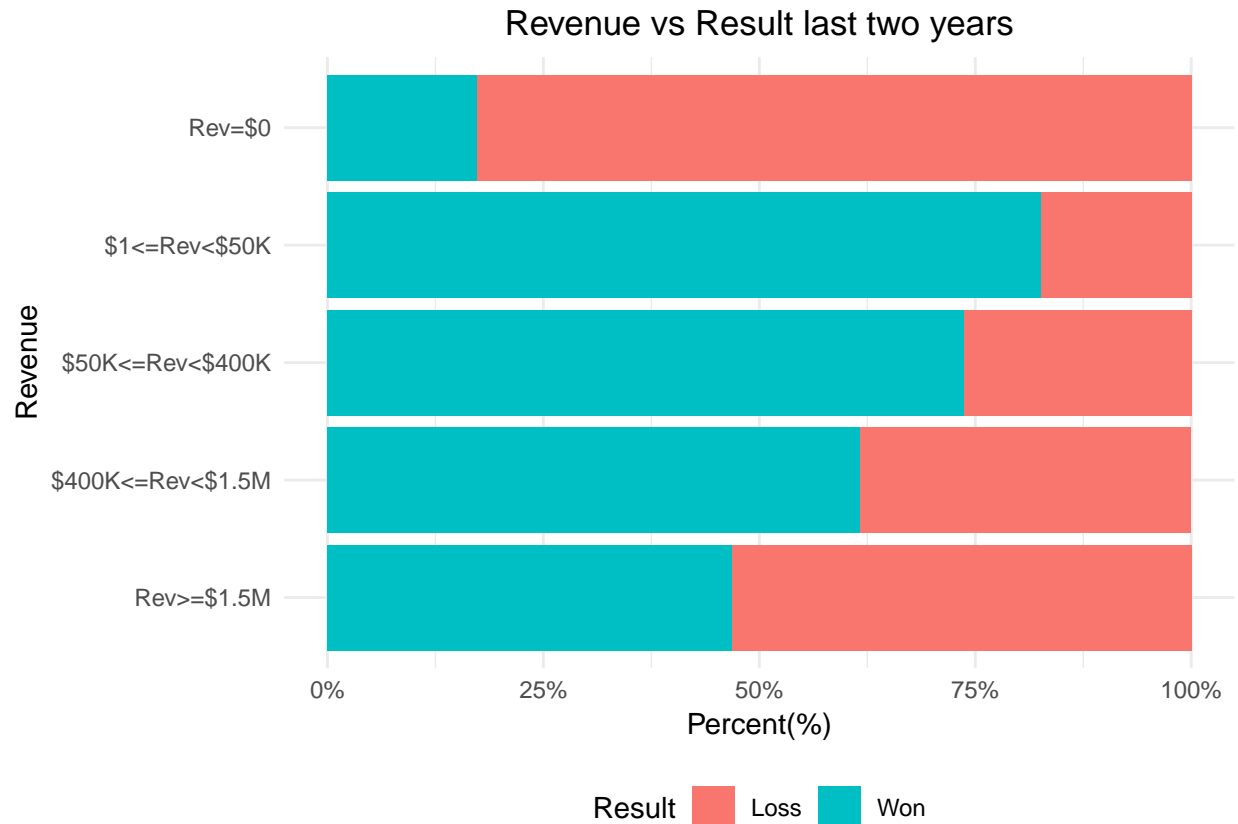
From the chart, we have ~18K records of 'Won' sales leads and ~60K 'Loss' sales leads for the last two years. Using this data, it looks the high number of loss opportunity could be attributed to business condition or we can explore deeper into the data set if there are variables that affecting the loss opportunity.

```
position <- c("Rev=$0", "$1<=Rev<$50K", "$50K<=Rev<$400K",
              "$400K<=Rev<$1.5M", "Rev>=$1.5M")
ggplot(sales_win_loss, aes(x = Revenue2, fill = Result)) +
  geom_bar() +
  scale_x_discrete(limits = position) +
  xlab("Revenue") +
  ylab("Number of records") +
  ggtitle("Revenue vs Number of sales leads for the last two years") +
  theme(plot.title = element_text(hjust = 0.5))
```

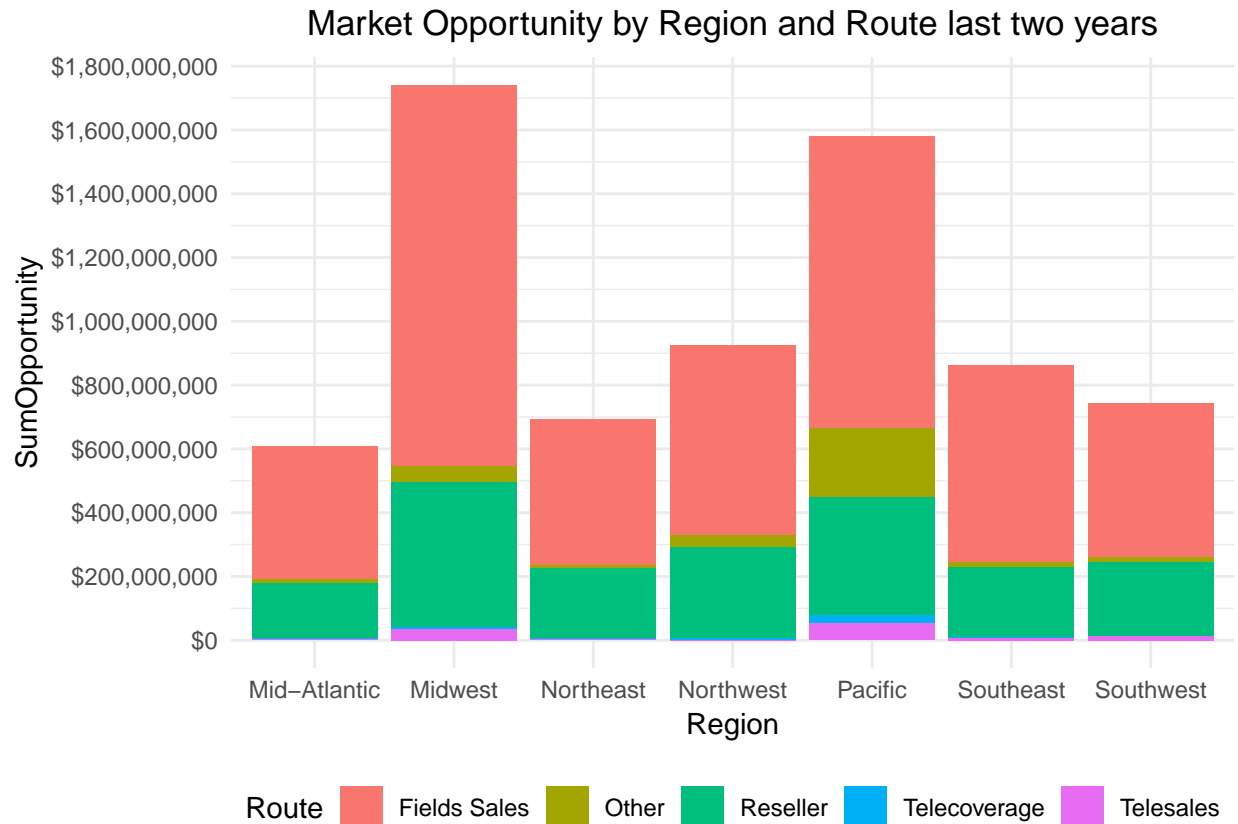
From the chart, we can see for the last two years, there are plenty of sales leads opportunity. A lot of sales leads opportunity that resulted in \$0 revenue for the last two years.

```
position <- c("Rev>=$1.5M", "$400K<=Rev<$1.5M", "$50K<=Rev<$400K", "$1<=Rev<$50K", "Rev=$0")
ggplot(sales_win_loss) +
  geom_bar(aes(x = Revenue2, fill = Result), position = "fill") +
  scale_x_discrete(limits = position) +
  scale_y_continuous(labels = scales::percent_format()) +
  coord_flip() +
  ggtitle("Revenue vs Result last two years") +
  xlab("Revenue") +
  ylab("Percent(%)" ) +
  theme(plot.title = element_text(hjust = 0.5))
```



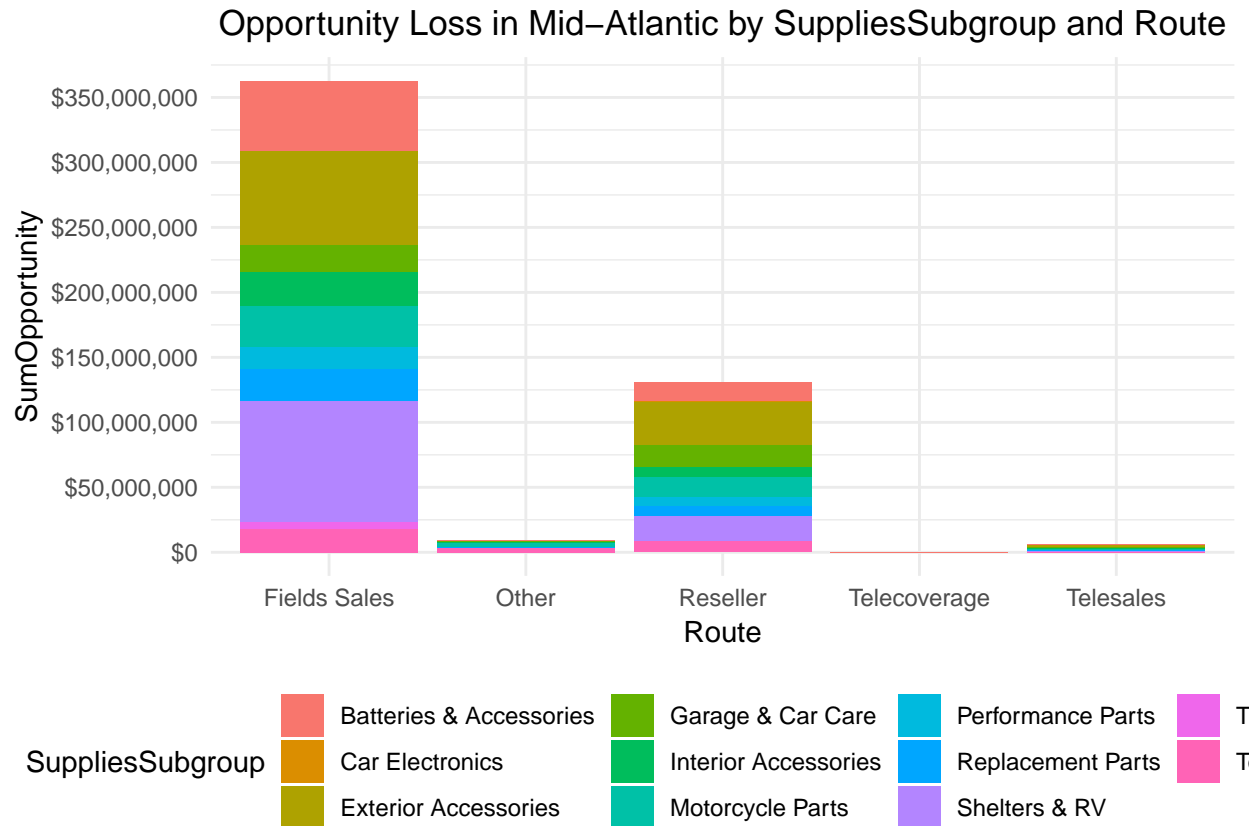
I can see that the probability of loss opportunity is higher if customer didn't buy anything in the last two years. If client purchase in the last two years, the chance of win decreases as sales deals rises

```
sales_win_loss %>%
  group_by(Region, Route) %>%
  summarise(SumOpportunity = sum(Opportunity)) %>%
  ggplot(aes(x = Region, y = SumOpportunity, fill = Route)) +
  geom_bar(stat = "identity") +
  scale_y_continuous(breaks = seq(0, 1e+11, 2e+08),
                     labels = scales::dollar_format(prefix = "$")) +
  ggtitle("Market Opportunity by Region and Route last two years") +
  theme(plot.title = element_text(hjust = 0.5))
```



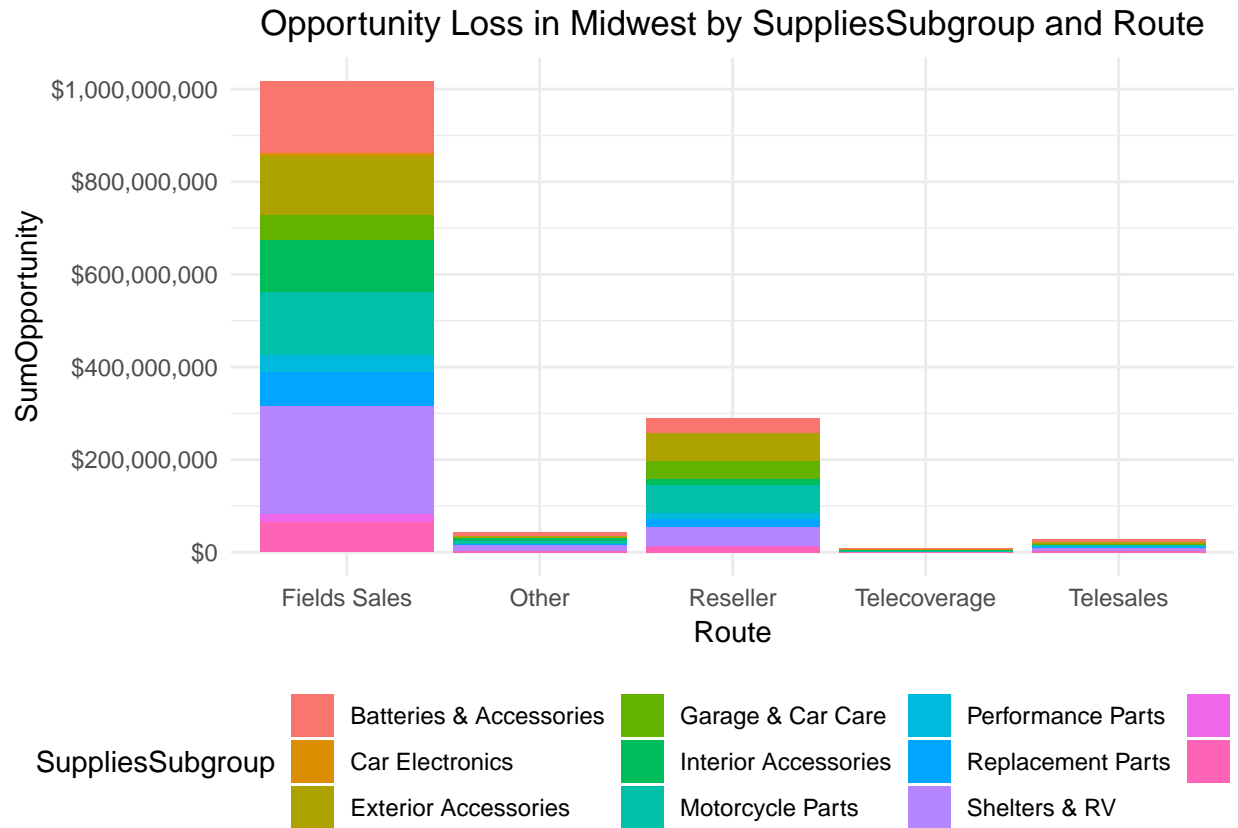
From the chart above, it's clear that the field sales and reseller are the most common channel of sales route to market across all regions. In the pacific region, other sales channel also play some role to bring in revenue in comparison to other regions. I want to see the breakdown of the 'Loss' opportunity by each region to dig deeper. The subsequent charts will show the break down of the supplies subgroup for each region where sales lead is 'Loss'

```
sales_win_loss %>% filter(Result == "Loss" & Region == "Mid-Atlantic") %>%
  group_by(Route, SuppliesSubgroup) %>%
  summarise(SumOpportunity = sum(Opportunity)) %>%
  ggplot(aes(x = Route, y = SumOpportunity, fill = SuppliesSubgroup)) +
  geom_bar(stat = "identity") +
  scale_y_continuous(breaks = seq(0, 4e+08, 5e+07),
                     labels = scales::dollar_format(prefix = "$")) +
  ggtitle("Opportunity Loss in Mid-Atlantic by SuppliesSubgroup and Route") +
  theme(plot.title = element_text(hjust = 0.5))
```



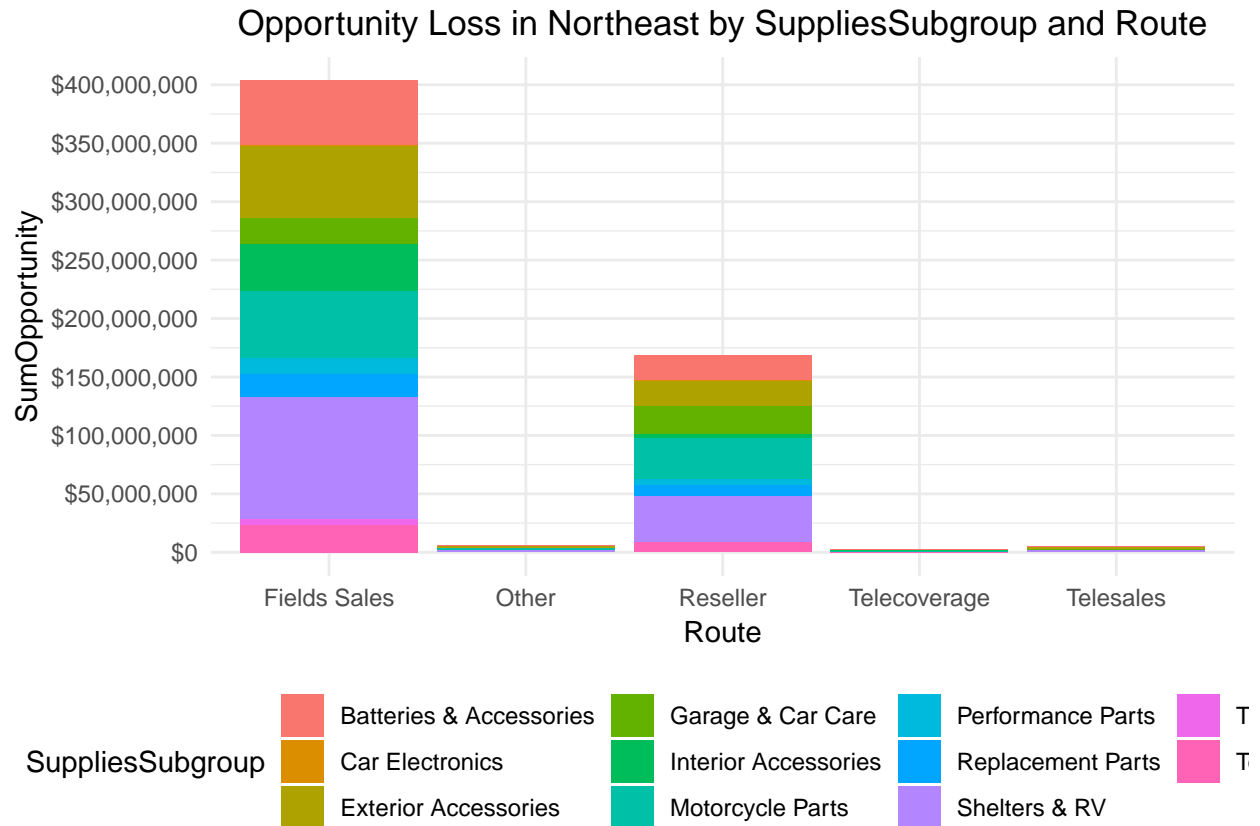
The chart above show the Mid-Atlantic region breakdown of loss opportunity by supplies subgroup. In this region, “Shelters & RV”, Batteries & Accessories“, and”Exterior Accessories" are the main supplies subgroup that contribute to the loss opportunity.

```
sales_win_loss %>% filter(Result == "Loss" & Region == "Midwest") %>%
  group_by(Route, SuppliesSubgroup) %>%
  summarise(SumOpportunity = sum(Opportunity)) %>%
  ggplot(aes(x = Route, y = SumOpportunity, fill = SuppliesSubgroup)) +
  geom_bar(stat = "identity") +
  scale_y_continuous(breaks = seq(0, 1.5e+09, 2e+08),
    labels = scales::dollar_format(prefix = "$")) +
  ggtitle("Opportunity Loss in Midwest by SuppliesSubgroup and Route") +
  theme(plot.title = element_text(hjust = 0.5))
```



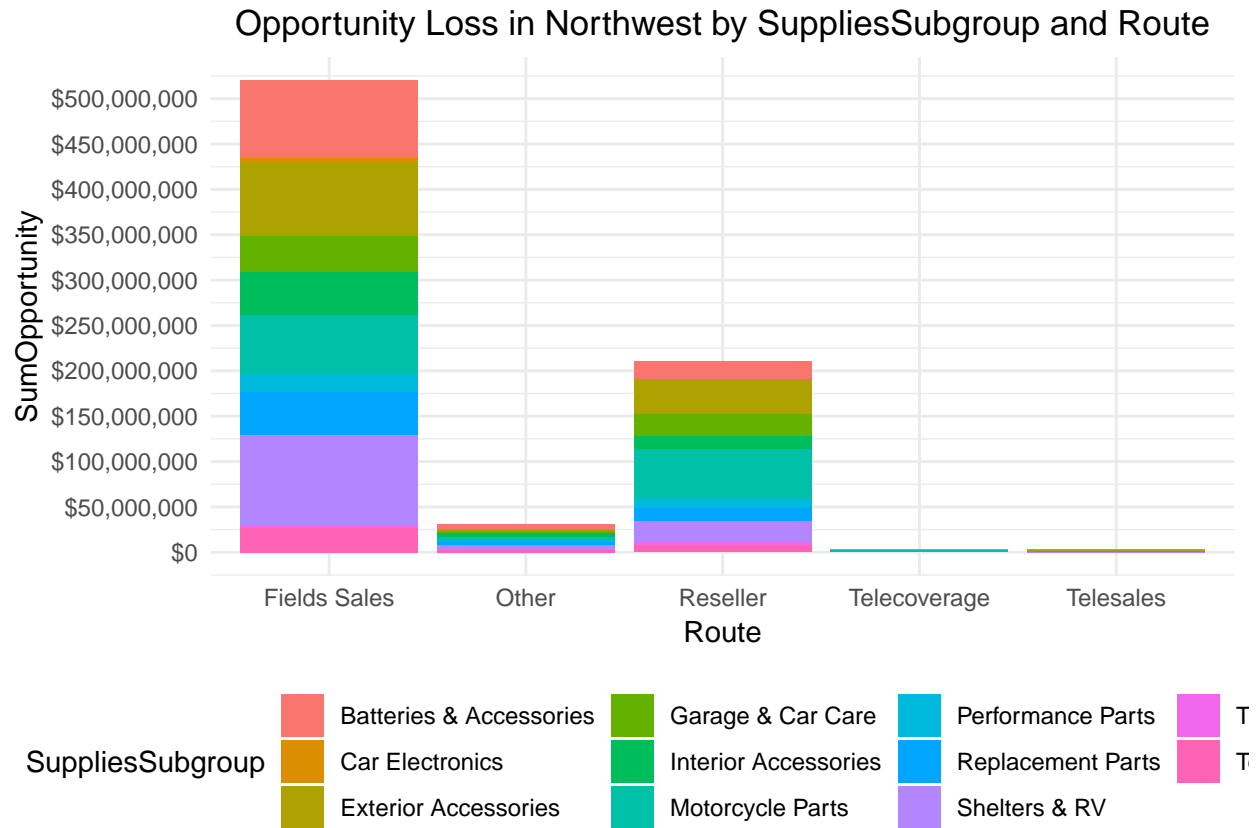
The chart above show the MidWest region breakdown of loss opportunity by supplies subgroup. In this region, “Shelters & RV”, Batteries & Accessories“, and”Exterior Accessories" are the main supplies subgroup that contribute to the loss opportunity.

```
sales_win_loss %>% filter(Result == "Loss" & Region == "Northeast") %>%
  group_by(Route, SuppliesSubgroup) %>%
  summarise(SumOpportunity = sum(Opportunity)) %>%
  ggplot(aes(x = Route, y = SumOpportunity, fill = SuppliesSubgroup)) +
  geom_bar(stat = "identity") +
  scale_y_continuous(breaks = seq(0, 5e+08, 5e+07),
    labels = scales::dollar_format(prefix = "$")) +
  ggtitle("Opportunity Loss in Northeast by SuppliesSubgroup and Route") +
  theme(plot.title = element_text(hjust = 0.5))
```



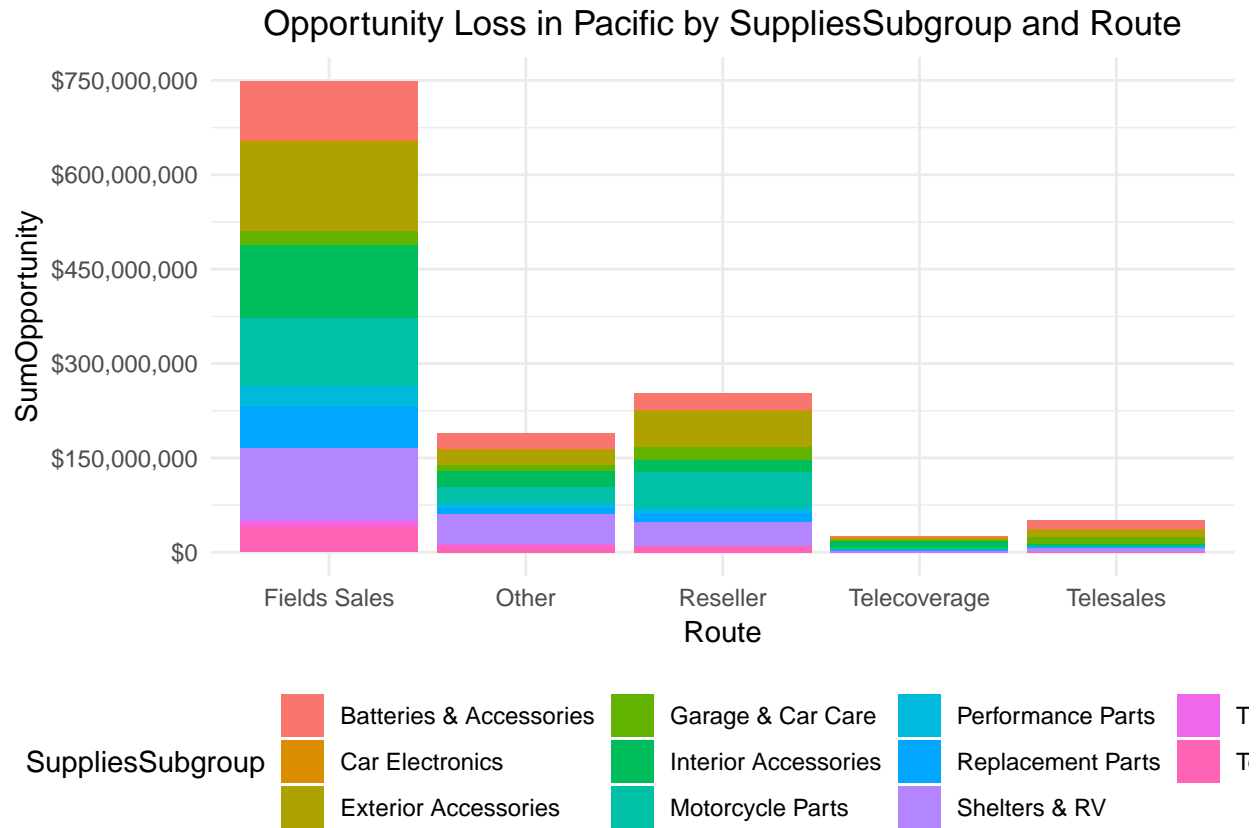
The chart above show the Northeast region breakdown of loss opportunity by supplies subgroup. In this region, “Shelters & RV” and “Motorcycle Parts” are the main supplies subgroup that contribute to the loss opportunity.

```
sales_win_loss %>% filter(Result == "Loss" & Region == "Northwest") %>%
  group_by(Route, SuppliesSubgroup) %>%
  summarise(SumOpportunity = sum(Opportunity)) %>%
  ggplot(aes(x = Route, y = SumOpportunity, fill = SuppliesSubgroup)) +
  geom_bar(stat = "identity") +
  scale_y_continuous(breaks = seq(0, 1e+11, 5e+07),
    labels = scales::dollar_format(prefix = "$")) +
  ggtitle("Opportunity Loss in Northwest by SuppliesSubgroup and Route") +
  theme(plot.title = element_text(hjust = 0.5))
```



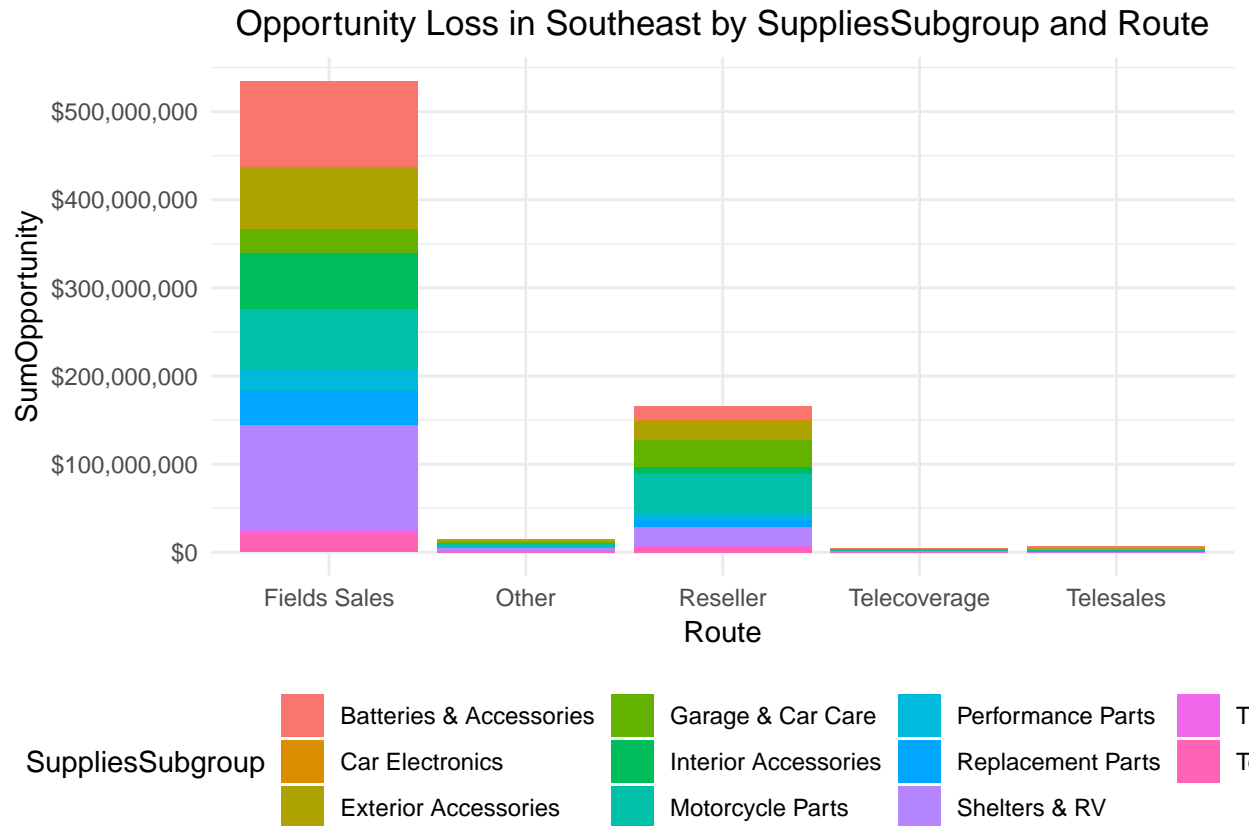
The chart above show the Northwest region breakdown of loss opportunity by supplies subgroup. In this region, “Shelters & RV”, Batteries & Accessories“, and”Exterior Accessories" are the main supplies subgroup that contribute to the loss opportunity.

```
sales_win_loss %>% filter(Result == "Loss" & Region == "Pacific") %>%
  group_by(Route, SuppliesSubgroup) %>%
  summarise(SumOpportunity = sum(Opportunity)) %>%
  ggplot(aes(x = Route, y = SumOpportunity, fill = SuppliesSubgroup)) +
  geom_bar(stat = "identity") +
  scale_y_continuous(breaks = seq(0, 1e+11, 1.5e+08),
    labels = scales::dollar_format(prefix = "$")) +
  ggtitle("Opportunity Loss in Pacific by SuppliesSubgroup and Route") +
  theme(plot.title = element_text(hjust = 0.5))
```



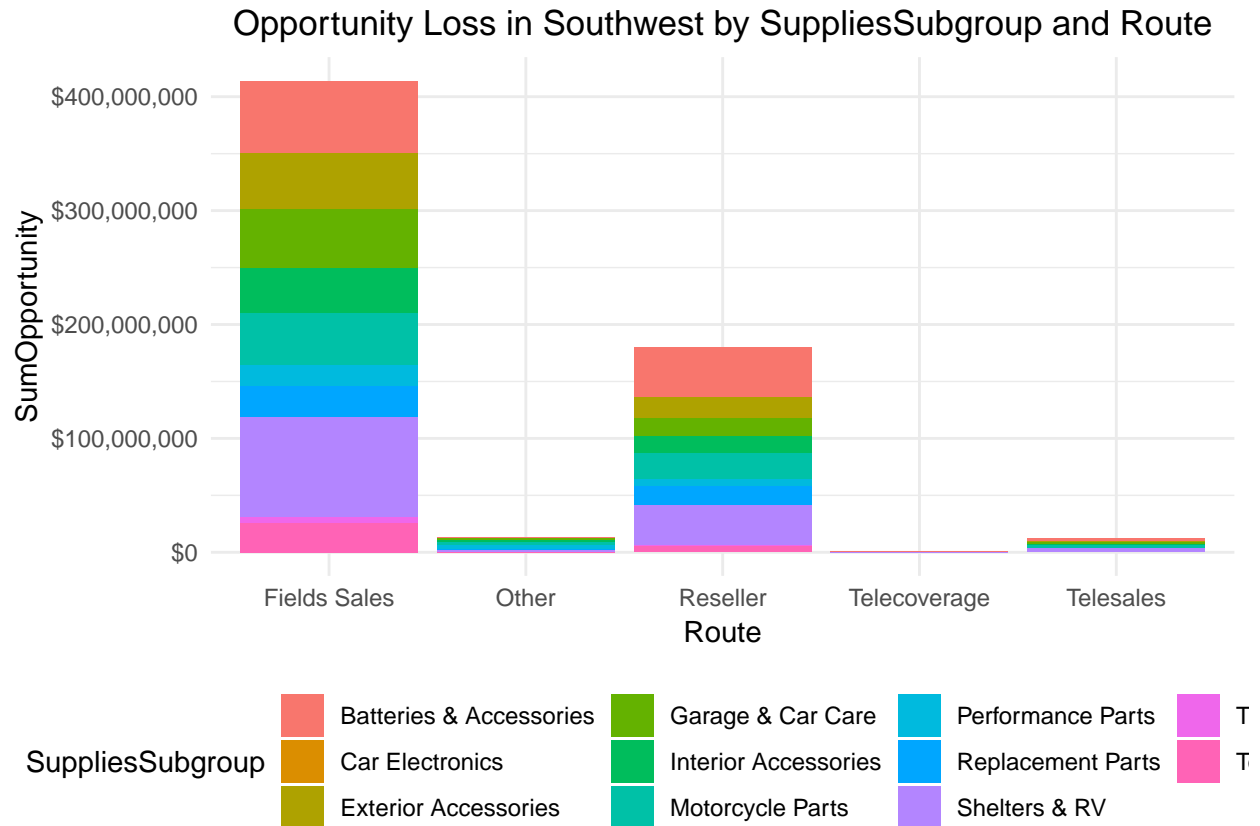
The chart above show the Pacific region breakdown of loss opportunity by supplies subgroup. In this region, “Shelters & RV”, Batteries & Accessories“, and”Exterior Accessories” are the main supplies subgroup that contribute to the loss opportunity.

```
sales_win_loss %>% filter(Result == "Loss" & Region == "Southeast") %>%
  group_by(Route, SuppliesSubgroup) %>%
  summarise(SumOpportunity = sum(Opportunity)) %>%
  ggplot(aes(x = Route, y = SumOpportunity, fill = SuppliesSubgroup)) +
  geom_bar(stat = "identity") +
  scale_y_continuous(breaks = seq(0, 1e+11, 1e+08),
    labels = scales::dollar_format(prefix = "$")) +
  ggtitle("Opportunity Loss in Southeast by SuppliesSubgroup and Route") +
  theme(plot.title = element_text(hjust = 0.5))
```

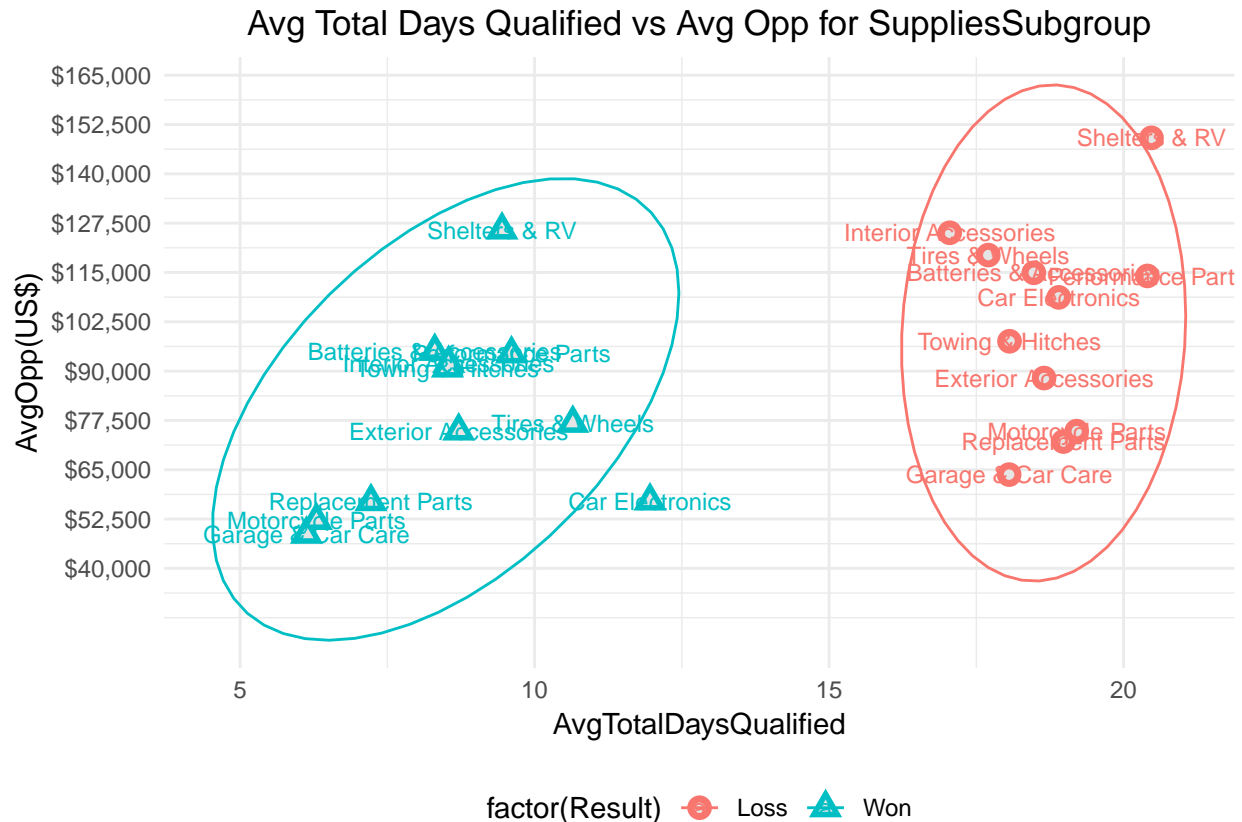
The chart above show the MidWest region breakdown of loss opportunity by supplies subgroup. In this region, “Shelters & RV”, Batteries & Accessories“, and”Exterior Accessories" are the main supplies subgroup that contribute to the loss opportunity.

```
sales_win_loss %>% filter(Result == "Loss" & Region == "Southwest") %>%
  group_by(Route, SuppliesSubgroup) %>%
  summarise(SumOpportunity = sum(Opportunity)) %>%
  ggplot(aes(x = Route, y = SumOpportunity, fill = SuppliesSubgroup)) +
  geom_bar(stat = "identity") +
  scale_y_continuous(breaks = seq(0, 1e+11, 1e+08),
    labels = scales::dollar_format(prefix = "$")) +
  ggtitle("Opportunity Loss in Southwest by SuppliesSubgroup and Route") +
  theme(plot.title = element_text(hjust = 0.5))
```



The chart above show the SouthWest region breakdown of loss opportunity by supplies subgroup. In this region, “Shelters & RV”, Batteries & Accessories“, and”Exterior Accessories" are the main supplies subgroup that contribute to the loss opportunity.

```
sales_win_loss %>%
  group_by(Result, SuppliesSubgroup) %>%
  summarise(AvgOpp = mean(Opportunity),
            AvgQual = mean(TotalDaysQualified)) %>%
  ggplot(aes(x = AvgQual, y = AvgOpp, shape = factor(Result), label = SuppliesSubgroup)) +
  geom_point(aes(colour = factor(Result)), size = 4) +
  geom_point(colour = "grey90", size = 1.5) +
  xlab("AvgTotalDaysQualified") + ylab("AvgOpp(US$)") +
  scale_x_continuous(breaks = seq(0, 30, 5)) +
  scale_y_continuous(breaks = seq(40000, 175000, 12500),
                    labels = scales::dollar_format(prefix = "$")) +
  geom_text(aes(label = SuppliesSubgroup, color = Result), size = 3) +
  stat_ellipse(aes(color = Result), type = "t") +
  ggtitle("Avg Total Days Qualified vs Avg Opp for SuppliesSubgroup") +
  theme(plot.title = element_text(hjust = 0.5))
```



Looking from left to right, this Scatter chart shows that irrespective of opportunity amounts, we start losing deals as they stay longer in the pipeline. This could help formulate threshold levels for each supplier based on how many days a deal is in the pipeline and create alert mechanisms to expedite its progression.

Machine Learning Modeling

Create Modeling Data

The next step is partitioning the data set into training, validation, and testing dataset. We start with the seed for reproducibility followed by using createDataPartition function from caret.

```
ModelData <- sales_win_loss %>% select(SuppliesSubgroup, Region, Route, TotalDaysClosing,
                                     TotalDaysQualified, Opportunity, ClientSizeRev,
                                     ClientSizeCount, Competitor, DealSize, Result)

set.seed(3456)
TrainingValidationIndex <- caret::createDataPartition(ModelData$Result, p = .80,
                                                       list = FALSE,
                                                       times = 1)

str(TrainingValidationIndex)
```

```
## int [1:62421, 1] 3 6 8 9 10 11 13 14 15 16 ...
## - attr(*, "dimnames")=List of 2
## ..$ : NULL
## ..$ : chr "Resample1"
```

```

TrainingValidation <- ModelData[ TrainingValidationIndex,]
TrainingIndex <- caret::createDataPartition(TrainingValidation$Result, p = .75,
                                             list = FALSE,
                                             times = 1)

Training <- TrainingValidation[TrainingIndex,]
Validation <- TrainingValidation[-TrainingIndex,]
Testing <- ModelData[-TrainingValidationIndex,]

```

Using glimpse function, we can see the selected variables for the model.

```
glimpse(Training)
```

```

## Observations: 46,817
## Variables: 11
## $ SuppliesSubgroup <chr> "Shelters & RV", "Batteries & Accessories",...
## $ Region           <chr> "Pacific", "Northwest", "Pacific", "Northwe...
## $ Route            <chr> "Reseller", "Fields Sales", "Reseller", "Fi...
## $ TotalDaysClosing <int> 114, 156, 50, 165, 31, 208, 138, 32, 130, 1...
## $ TotalDaysQualified <int> 0, 156, 50, 165, 31, 208, 138, 32, 130, 125...
## $ Opportunity      <int> 232522, 250000, 55003, 0, 10000, 232522, 20...
## $ ClientSizeRev     <int> 5, 1, 1, 1, 2, 1, 4, 5, 4, 1, 3, 1, 1, 5, 1...
## $ ClientSizeCount   <int> 1, 5, 1, 2, 1, 1, 5, 1, 3, 5, 5, 1, 4, 3, 5...
## $ Competitor        <chr> "Unknown", "None", "Unknown", "Unknown", "U...
## $ DealSize          <int> 5, 6, 4, 1, 2, 5, 5, 1, 4, 5, 4, 3, 4, 4, 7...
## $ Result            <chr> "Loss", "Loss", "Loss", "Loss", "Loss", "Lo...

```

Training the Logistic and Random Forest model using training dataset

Next, we setup the model parameter

```

control <- caret::trainControl(method = "cv", number = 2, classProbs = TRUE)
seed <- 7
metric <- "Accuracy"
set.seed(seed)

```

Training Logistic with training dataset

```

GLMModel <- caret::train(
  Result ~ SuppliesSubgroup + Region + Route + TotalDaysClosing + TotalDaysQualified +
    Opportunity + ClientSizeRev + ClientSizeCount + Competitor + DealSize,
  data = Training,
  method = "glm",
  trControl = control
)

```

Training Random Forest model with training dataset

```

RFModel <- caret::train(
  Result ~ SuppliesSubgroup + Region + Route + TotalDaysClosing + TotalDaysQualified +
    Opportunity + ClientSizeRev + ClientSizeCount + Competitor + DealSize,

```

```

data = Training,
method = "rf",
trControl = control
)

```

Predicting the model using validation data set

Using predict function from caret package, I will use the result to find the best model. Caret package also have the confusion matrix function to calculate sensitivity, specificity, negative predicted value, positive predicted values, and F1 score. The F1 score is a harmonic average of precision and recall to select the best model.

```

PredGLM <- predict(GLMModel, Validation)

ConfMatGLM <- caret::confusionMatrix(
  PredGLM, factor(Validation$Result), positive = "Won",
  mode = "everything")

ConfMatGLM

```

```

## Confusion Matrix and Statistics
##
##           Reference
## Prediction  Loss   Won
##           Loss 11604 2703
##           Won   475   822
##
##           Accuracy : 0.7963
##           95% CI : (0.7899, 0.8026)
##           No Information Rate : 0.7741
##           P-Value [Acc > NIR] : 9.572e-12
##
##           Kappa : 0.2498
##           McNemar's Test P-Value : < 2.2e-16
##
##           Sensitivity : 0.23319
##           Specificity : 0.96068
##           Pos Pred Value : 0.63377
##           Neg Pred Value : 0.81107
##           Precision : 0.63377
##           Recall : 0.23319
##           F1 : 0.34094
##           Prevalence : 0.22590
##           Detection Rate : 0.05268
##           Detection Prevalence : 0.08312
##           Balanced Accuracy : 0.59693
##
##           'Positive' Class : Won
##

```

The F1 score for the Logistic model is 0.3409374 Next, we did the same thing using Random Forest model with validation data set

```
PredRF <- predict(RFModel, Validation)

ConfMatRF <- caret::confusionMatrix(PredRF, factor(Validation$Result),
                                     positive = "Won",
                                     mode = "everything")
```

```
ConfMatRF
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  Loss   Won
##           Loss 11233 1893
##           Won   846 1632
##
##           Accuracy : 0.8245
##           95% CI : (0.8184, 0.8304)
##           No Information Rate : 0.7741
##           P-Value [Acc > NIR] : < 2.2e-16
##
##           Kappa : 0.4391
##           McNemar's Test P-Value : < 2.2e-16
##
##           Sensitivity : 0.4630
##           Specificity : 0.9300
##           Pos Pred Value : 0.6586
##           Neg Pred Value : 0.8558
##           Precision : 0.6586
##           Recall : 0.4630
##           F1 : 0.5437
##           Prevalence : 0.2259
##           Detection Rate : 0.1046
##           Detection Prevalence : 0.1588
##           Balanced Accuracy : 0.6965
##
##           'Positive' Class : Won
##
```

Selecting the best model

The F1 score for the Random Forest model is 0.5437281

Because the F1 score for Random Forest model is higher than the logistic model. The random forest model is selected as the better model. The next step is to evaluate the Random Forest model using testing dataset.

```
FinalPredRF <- predict(RFModel, Testing)

ConfMatFinalRF <- caret::confusionMatrix(FinalPredRF, factor(Testing$Result),
                                          positive = "Won", mode = "everything")
```

```
ConfMatFinalRF
```

```
## Confusion Matrix and Statistics
```

```

##
##           Reference
## Prediction  Loss   Won
##           Loss 11256 1855
##           Won   823 1670
##
##           Accuracy : 0.8284
##           95% CI : (0.8224, 0.8343)
##           No Information Rate : 0.7741
##           P-Value [Acc > NIR] : < 2.2e-16
##
##           Kappa : 0.4525
## Mcnemar's Test P-Value : < 2.2e-16
##
##           Sensitivity : 0.4738
##           Specificity : 0.9319
##           Pos Pred Value : 0.6699
##           Neg Pred Value : 0.8585
##           Precision : 0.6699
##           Recall : 0.4738
##           F1 : 0.5550
##           Prevalence : 0.2259
##           Detection Rate : 0.1070
##           Detection Prevalence : 0.1598
##           Balanced Accuracy : 0.7028
##
##           'Positive' Class : Won
##

```

Testing the final model

The final prediction using testing data set (0.5550017) appears to have about the same F1 score as using the validation data set (0.5437281)

Recommendations

From the exploratory data analysis, it looks like the company start losing deals as the sales lead stays longer in the pipeline more than 10 days. Using this information, the sales team should be able to formulate threshold levels for each supplier based on how many days a deal is in the pipeline and create alert mechanisms to expedite its progression.

More depth machine learning model should also be done. Especially learning the interaction of other independent variables such as RDaysValidated and RDaysQualified. The current Random Forest model accuracy is (NA) Other regression model such as clustering k-means model or other classification model that can produce higher accuracy should be explored.

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