HarvardX - Data Science Capstone: Win/Loss Analysis Project

1. Introduction

Let's consider a real life scenario where we play the role of a sales executive at an automotive supply wholesaler and investigate a sales execution issue.

We have not been converting enough opportunities lately. We want to better **understand our sales pipeline and which deals our sales teams can expect to win or lose** based on data that we've pulled out of our CRM database.

We want to find the patterns in sales wins and losses and uncover what can lead to successful sales opportunities and better anticipate performance gaps.

2. Data

The dataset is a sample provided by IBM in their Watson Analytics community that can be downloaded here (https://www.ibm.com/communities/analytics/watson-analytics-blog/guide-to-sample-datasets/). The "WA*Fn UseC* Sales Win Loss.csv" file is a dataset that covers sales activities for, amongst others, carrying out a win/loss analysis, to generate the **insights to increase revenues and grow the business**.

Dataset Features

Column name	**Description**
Client Size by Employee Count	Employee sized by number of clients: • 1: < 1K • 2: [1K, 5K] • 3: [5K, 10K] • 4: [10K, 30K] • 5: ≥ 30K
Client Size by Revenue	Client size based on annual revenue in USD: • 1: < 1M • 2: [1M, 10M] • 3: [10M, 50M] • 4: [50M, 100M] • 5: ≥ 100M
Competitor Type	An indicator if a competitor has been identified:

	Known, Unknown, None
Deal Size by Category	Categorical grouping of the opportunity amount (OpportunityAmountUSD) • 1: < 10K • 2: [10K, 25K] • 3: [25K, 50K] • 4: [50K, 100K] • 5: [100K, 250K] • 6: [250K, 500K] • 7: ≥ 500K
Opportunity Number	A unique generated number assigned to the opportunity
Opportunity Results	A closed opportunity is won or loss. Values could be Win/Loss
Region	Name of the Region: Mid-Atlantic, Midwest, Northeast, Northwest, Pacific, Southeast, Southwest
Route to Market	The opportunities' route to market: Fields Sales, Other, Reseller, Telecoverage, Telesales
Supplies Group	Reporting supplies group: Car Accessories, Car Electronics, Performance & Non-auto, Tires & Wheels
Supplies SubGroup	Reporting supplies subgroup: Batteries & Accessories, Car Electronics, Exterior Accessories, Garage & Car Care, Interior Accessories, Motorcycle Parts, Performance Parts, Replacement Parts, Shelters & RV, Tires & Wheels, Towing & Hitches
Opportunity Amount (USD)	Sum of line item revenue estimates by sales representative in American currency
Sales Stage Change Count	Actually a count of number of times an opportunity changes sales stages (back and forwards)
Elapsed Days In Sales Stage	The number of days between the change in sales stages. The counter is reset for each new sales stage
Ratio Days Identified To Total Days	Ratio of total days the opportunity has spent in sales stage: Identified/Validating over total days in sales process
Ratio Days Qualified To Total Days	Ratio of total days the opportunity has been spent in sales stage: Qualified/Gaining Agreement over total days in sales process
Ratio Days Validated To Total Days	Ratio of total days the Opportunity has presence in sales stage: Validated/Qualifying over total days in sales process
Revenue From Client Past Two Years	Revenue identified from this client in past two years • 0: 0 • 1: [1K, 50K] • 2: [50K, 400K] • 3: [400K, 1.5M] • 4: ≥ 1.5M
Total Days Identified Through Closing	Total days the opportunity has spent in Sales Stages from Identified/Validating to Gained Agreement/closing

Total Days Identified Through Qualified	Total days the opportunity has spent in CRM Stages from Identified/Validating to Qualified/Gaining Agreement

3. Methodology

3.1 Exploratory Data Analysis

In this section, we explore the data in two main steps:

- **Initial exploration**
    - Dataset structure, variable formats,
    - Missing values,
    - Duplicated information,
    - Correlation analysis.
- **In-depth exploration for first insights**

3.2 Create subsets for the project

We want to create two subsets as follows:

- sales dataset, which contains 90% of our sample dataset, to analyze our sales wins and losses.
- validation dataset, which is the remaining 10%, for the purpose of validation of our predictive model.

3.3 Predictive Model

In this section, we will go through a couple of Machine Learning methods to build a model to support our decisions.

4. Results and Discussion

4.1 Exploratory Data Analysis

Initial data exploration

In [1]:

```
# --- LIBRARIES ---------------------------------------------------
-------------

if(!require(tidyverse)) install.packages("tidyverse", repos = "http
://cran.us.r-project.org")
if(!require(caret)) install.packages("caret", repos = "http://cran.
us.r-project.org")
if(!require(gridExtra)) install.packages("gridExtra", repos = "http
://cran.r-project.org")
if(!require(rpart)) install.packages("rpart", repos = "http://cran.
r-project.org")
if(!require(rpart.plot)) install.packages("rpart.plot", repos = "ht
tp://cran.r-project.org")
if(!require(randomForest)) install.packages("randomForest", repos =
"http://cran.r-project.org")
if(!require(rpart)) install.packages("rpart", repos = "http://cran.
r-project.org")
if(!require(rpart.plot)) install.packages("rpart.plot", repos = "ht
tp://cran.r-project.org")
if(!require(randomForest)) install.packages("randomForest", repos =
"http://cran.r-project.org")
```

```
Loading required package: tidyverse
── Attaching packages ─────────────────────────────────────── tidy
verse 1.2.1 ──
✔ ggplot2 3.0.0     ✔ purrr   0.2.5
✔ tibble  1.4.2     ✔ dplyr   0.7.6
✔ tidyr   0.8.1     ✔ stringr 1.3.1
✔ readr   1.1.1     ✔ forcats 0.3.0
── Conflicts ────────────────────────────────────────── tidyverse_
conflicts() ──
✖ dplyr::filter() masks stats::filter()
✖ dplyr::lag()    masks stats::lag()
Loading required package: caret
Loading required package: lattice

Attaching package: 'caret'

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

    lift

Loading required package: gridExtra

Attaching package: 'gridExtra'

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

    combine

Loading required package: rpart
Loading required package: rpart.plot
Loading required package: randomForest
randomForest 4.6-14
Type rfNews() to see new features/changes/bug fixes.

Attaching package: 'randomForest'

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

    combine

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

    combine

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

    margin
```

In [2]:
```
# --- ORIGINAL DATASET ------------------------------------------------------
-------------

# Read csv file from IBM Watson Analytics sample datasets
# https://www.ibm.com/communities/analytics/watson-analytics-blog/g
uide-to-sample-datasets/

crm <- read.csv(url("https://community.watsonanalytics.com/wp-conte
nt/uploads/2015/04/WA_Fn-UseC_-Sales-Win-Loss.csv?cm_mc_uid=3220088
6596915345345263&cm_mc_sid_50200000=88110211548169944710&cm_mc_sid_
52640000=47085071548169944717"),
              header = TRUE)
```

In [3]:
```
# --- INITIAL EXPLORATION OF THE DATASET ---------------------------
-------------

# Let's have a look at our crm dataset
head(crm)
```

Opportunity.Number	Supplies.Subgroup	Supplies.Group	Region	Route.To.Mark
1641984	Exterior Accessories	Car Accessories	Northwest	Fields Sales
1658010	Exterior Accessories	Car Accessories	Pacific	Reseller
1674737	Motorcycle Parts	Performance & Non-auto	Pacific	Reseller
1675224	Shelters & RV	Performance & Non-auto	Midwest	Reseller
1689785	Exterior Accessories	Car Accessories	Pacific	Reseller
1692390	Shelters & RV	Performance & Non-auto	Pacific	Reseller

In [4]:
```
# Let's see the structure of our dataset and the types of variables
that it contains
str(crm)
```

```
'data.frame':	78025 obs. of  19 variables:
 $ Opportunity.Number                       : int  1641984 1658010 1
674737 1675224 1689785 1692390 1935837 1952571 1999486 2052337 ...
 $ Supplies.Subgroup                        : Factor w/ 11 levels "B
atteries & Accessories",..: 3 3 6 9 3 9 4 3 1 3 ...
 $ Supplies.Group                           : Factor w/ 4 levels "Ca
r Accessories",..: 1 1 3 3 1 3 1 1 1 1 ...
 $ Region                                   : Factor w/ 7 levels "Mi
d-Atlantic",..: 4 5 5 2 5 5 5 5 4 5 ...
 $ Route.To.Market                          : Factor w/ 5 levels "Fi
elds Sales",..: 1 3 3 3 3 3 1 1 1 3 ...
 $ Elapsed.Days.In.Sales.Stage              : int  76 63 24 16 69 89
111 82 68 18 ...
 $ Opportunity.Result                       : Factor w/ 2 levels "Lo
ss","Won": 2 1 2 1 1 1 2 1 1 1 ...
 $ Sales.Stage.Change.Count                 : int  13 2 7 5 11 3 12
6 8 7 ...
 $ Total.Days.Identified.Through.Closing    : int  104 163 82 124 91
114 112 70 156 50 ...
 $ Total.Days.Identified.Through.Qualified: int  101 163 82 124 13
0 112 70 156 50 ...
 $ Opportunity.Amount.USD                   : int  0 0 7750 0 69756
232522 20001 450000 250000 55003 ...
 $ Client.Size.By.Revenue                   : int  5 3 1 1 1 5 4 1 1
1 ...
 $ Client.Size.By.Employee.Count            : int  5 5 1 1 1 1 5 1 5
1 ...
 $ Revenue.From.Client.Past.Two.Years       : int  0 0 0 0 0 0 0 0 0
0 ...
 $ Competitor.Type                          : Factor w/ 3 levels "Kn
own","None",..: 3 3 3 1 3 3 3 1 2 3 ...
 $ Ratio.Days.Identified.To.Total.Days      : num  0.696 0 1 1 0 ...
 $ Ratio.Days.Validated.To.Total.Days       : num  0.114 1 0 0 0.141
...
 $ Ratio.Days.Qualified.To.Total.Days       : num  0.154 0 0 0 0 ...
 $ Deal.Size.Category                       : int  1 1 1 1 4 5 2 6 6
4 ...
```

In [5]:
```
# We note that some features have the wrong type as integer instead
of factor

# Let's convert them to the right type
cols <- c("Client.Size.By.Employee.Count", "Client.Size.By.Revenue"
, "Deal.Size.Category", "Revenue.From.Client.Past.Two.Years")
crm[, cols] <- data.frame(apply(crm[cols], 2, as.factor))

# Let's check again the types of our variables
str(crm)
```

```
'data.frame':	78025 obs. of  19 variables:
 $ Opportunity.Number                     : int  1641984 1658010 1
674737 1675224 1689785 1692390 1935837 1952571 1999486 2052337 ...
 $ Supplies.Subgroup                      : Factor w/ 11 levels "B
atteries & Accessories",..: 3 3 6 9 3 9 4 3 1 3 ...
 $ Supplies.Group                         : Factor w/ 4 levels "Ca
r Accessories",..: 1 1 3 3 1 3 1 1 1 1 ...
 $ Region                                 : Factor w/ 7 levels "Mi
d-Atlantic",..: 4 5 5 2 5 5 5 5 4 5 ...
 $ Route.To.Market                        : Factor w/ 5 levels "Fi
elds Sales",..: 1 3 3 3 3 3 1 1 1 3 ...
 $ Elapsed.Days.In.Sales.Stage            : int  76 63 24 16 69 89
111 82 68 18 ...
 $ Opportunity.Result                     : Factor w/ 2 levels "Lo
ss","Won": 2 1 2 1 1 1 2 1 1 1 ...
 $ Sales.Stage.Change.Count               : int  13 2 7 5 11 3 12
6 8 7 ...
 $ Total.Days.Identified.Through.Closing  : int  104 163 82 124 91
114 112 70 156 50 ...
 $ Total.Days.Identified.Through.Qualified: int  101 163 82 124 13
0 112 70 156 50 ...
 $ Opportunity.Amount.USD                 : int  0 0 7750 0 69756
232522 20001 450000 250000 55003 ...
 $ Client.Size.By.Revenue                 : Factor w/ 5 levels "1"
,"2","3","4",..: 5 3 1 1 1 5 4 1 1 1 ...
 $ Client.Size.By.Employee.Count          : Factor w/ 5 levels "1"
,"2","3","4",..: 5 5 1 1 1 1 5 1 5 1 ...
 $ Revenue.From.Client.Past.Two.Years     : Factor w/ 5 levels "0"
,"1","2","3",..: 1 1 1 1 1 1 1 1 1 1 ...
 $ Competitor.Type                        : Factor w/ 3 levels "Kn
own","None",..: 3 3 3 1 3 3 3 1 2 3 ...
 $ Ratio.Days.Identified.To.Total.Days    : num  0.696 0 1 1 0 ...
 $ Ratio.Days.Validated.To.Total.Days     : num  0.114 1 0 0 0.141
...
 $ Ratio.Days.Qualified.To.Total.Days     : num  0.154 0 0 0 0 ...
 $ Deal.Size.Category                     : Factor w/ 7 levels "1"
,"2","3","4",..: 1 1 1 1 4 5 2 6 6 4 ...
```

In [6]:
```
# Let's check if our dataset has missing values
cat("Do we have any missing value?", any(is.na(crm)),"\n")

# Let's check if our dataset has duplicated rows
cat("We have", n_distinct(crm$Opportunity.Number), "unique opportun
ity numbers out of a total of", nrow(crm),
    "so the percentage of duplicated rows is:", (1-n_distinct(crm$O
pportunity.Number)/nrow(crm))*100)
```

```
Do we have any missing value? FALSE
We have 77829 unique opportunity numbers out of a total of 78025 s
o the percentage of duplicated rows is: 0.2512015
```

In [7]:
```
# So we have 0.25% of our dataset that is duplications. Let's see w
hat rows are duplicated and how they are duplicated.
n_occur <- data.frame(table(crm$Opportunity.Number))
head(crm[crm$Opportunity.Number %in% n_occur$Var1[n_occur$Freq > 1]
,], 10)
```

	Opportunity.Number	Supplies.Subgroup	Supplies.Group	Region	Route.To
93	4947042	Exterior Accessories	Car Accessories	Midwest	Fields Sa
94	4947042	Towing & Hitches	Car Accessories	Midwest	Fields Sa
453	5629727	Shelters & RV	Performance & Non-auto	Northwest	Fields Sa
454	5629727	Shelters & RV	Performance & Non-auto	Northwest	Fields Sa
725	5799657	Interior Accessories	Car Accessories	Pacific	Fields Sa
726	5799657	Batteries & Accessories	Car Accessories	Pacific	Fields Sa
1105	5934206	Garage & Car Care	Car Accessories	Pacific	Fields Sa
1106	5934206	Batteries & Accessories	Car Accessories	Pacific	Fields Sa
1153	5943944	Batteries & Accessories	Car Accessories	Midwest	Fields Sa
1154	5943944	Batteries & Accessories	Car Accessories	Midwest	Fields Sa

In [8]:
```
# Some duplications are simple row duplication but some others look like an update of the opportunity (mostly the USD amount) in a new row.
# As we don't have any date information to identify the update, we will just delete the duplications.
crm <- crm[!duplicated(crm["Opportunity.Number"]), ]

# Let's check if our new dataset has missing values
cat("Do we have any missing value?", any(is.na(crm)),"\n")

# Let's check if our new dataset has duplicated rows
cat("We have", n_distinct(crm$Opportunity.Number), "unique opportunity numbers out of a total of", nrow(crm),
    "so the percentage of duplicated rows is:", (1-n_distinct(crm$Opportunity.Number)/nrow(crm))*100)
```

```
Do we have any missing value? FALSE
We have 77829 unique opportunity numbers out of a total of 77829 so the percentage of duplicated rows is: 0
```

In [9]:
```
# Correlation for numeric features
cor(crm[,unlist(lapply(crm,is.numeric))])
```

	Opportunity.Number	Elapsed.Days.In.Sales
Opportunity.Number	1.000000000	-0.76497109
Elapsed.Days.In.Sales.Stage	-0.764971087	1.00000000
Sales.Stage.Change.Count	-0.253592731	-0.02533635
Total.Days.Identified.Through.Closing	-0.445872151	-0.02267760
Total.Days.Identified.Through.Qualified	-0.435432828	-0.02339319
Opportunity.Amount.USD	-0.014999049	-0.01392492
Ratio.Days.Identified.To.Total.Days	0.002240132	-0.01826893
Ratio.Days.Validated.To.Total.Days	-0.057535839	0.01582840
Ratio.Days.Qualified.To.Total.Days	-0.048404076	0.02040566

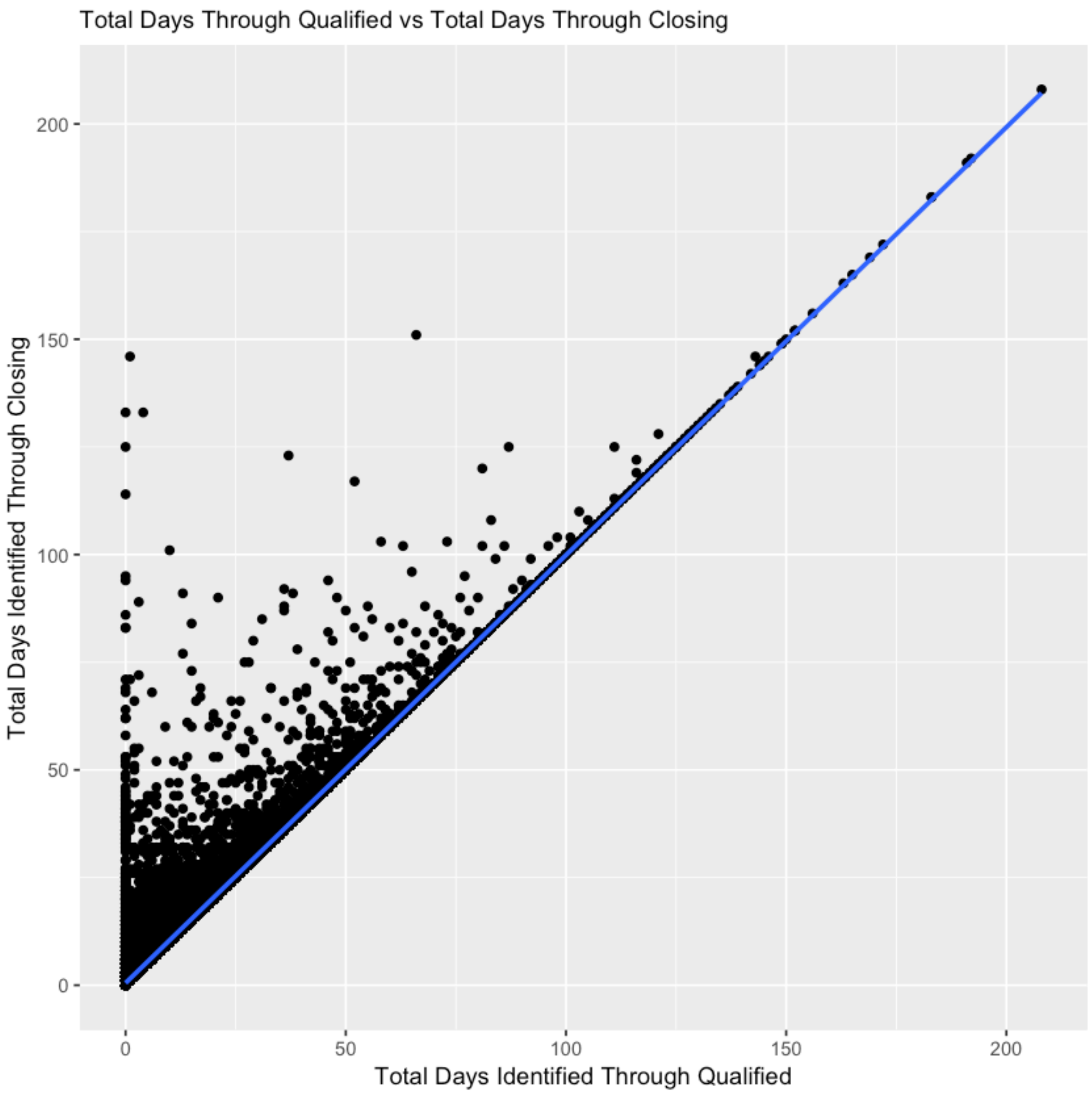
Let's have a look at the variables that are significantly correlated (say correlation coefficient either greater than 0.8 or less than -0.8).

We note that `Total.Days.Identified.Through.Qualified` and `Total.Days.Identified.Through.Closing` are strongly correlated (0.98), which is not surprising as these two variables are related in such that an opportunity stay in the pipeline from identification, through qualification and validation, to closing.

None of the other numeric features are strongly correlated.

In [10]:

```
# Correlation between "Total Days Identified Through Qualified" and
"Total Days Identified Through Closing"

crm %>%
    select(Total.Days.Identified.Through.Closing, Total.Days.Identi
fied.Through.Qualified) %>%

    ggplot(aes(x = Total.Days.Identified.Through.Qualified, y = Tot
al.Days.Identified.Through.Closing)) +
    geom_point() +
    geom_smooth(method = "lm") +
    labs(subtitle = "Total Days Through Qualified vs Total Days Thr
ough Closing", x = "Total Days Identified Through Qualified", y = "
Total Days Identified Through Closing")
```



In [11]:

```
# Chi-squared test for factor/categorical features

ssg = chisq.test(crm$Supplies.Subgroup, crm$Supplies.Group, simulat
e.p.value = TRUE)$p.value
sr = chisq.test(crm$Supplies.Subgroup, crm$Region)$p.value
srm = chisq.test(crm$Supplies.Subgroup, crm$Route.To.Market, simula
te.p.value = TRUE)$p.value
```

```
scsr = chisq.test(crm$Supplies.Subgroup, crm$Client.Size.By.Revenue
)$p.value
scse = chisq.test(crm$Supplies.Subgroup, crm$Client.Size.By.Employe
e.Count)$p.value
sy = chisq.test(crm$Supplies.Subgroup, crm$Revenue.From.Client.Past
.Two.Years, simulate.p.value = TRUE)$p.value
sc = chisq.test(crm$Supplies.Subgroup, crm$Competitor.Type)$p.value
sd = chisq.test(crm$Supplies.Subgroup, crm$Deal.Size.Category)$p.va
lue

gr = chisq.test(crm$Supplies.Group, crm$Region)$p.value
grm = chisq.test(crm$Supplies.Group, crm$Route.To.Market, simulate.
p.value = TRUE)$p.value
gcsr = chisq.test(crm$Supplies.Group, crm$Client.Size.By.Revenue)$p
.value
gcse = chisq.test(crm$Supplies.Group, crm$Client.Size.By.Employee.C
ount)$p.value
gy = chisq.test(crm$Supplies.Group, crm$Revenue.From.Client.Past.Tw
o.Years, simulate.p.value = TRUE)$p.value
gc = chisq.test(crm$Supplies.Group, crm$Competitor.Type)$p.value
gd = chisq.test(crm$Supplies.Group, crm$Deal.Size.Category)$p.value

rrm = chisq.test(crm$Region, crm$Route.To.Market)$p.value
rcsr = chisq.test(crm$Region, crm$Client.Size.By.Revenue)$p.value
rcse = chisq.test(crm$Region, crm$Client.Size.By.Employee.Count)$p.
value
ry = chisq.test(crm$Region, crm$Revenue.From.Client.Past.Two.Years)
$p.value
rc = chisq.test(crm$Region, crm$Competitor.Type)$p.value
rd = chisq.test(crm$Region, crm$Deal.Size.Category)$p.value

mcsr = chisq.test(crm$Route.To.Market, crm$Client.Size.By.Revenue)$
p.value
mcse = chisq.test(crm$Route.To.Market, crm$Client.Size.By.Employee.
Count)$p.value
my = chisq.test(crm$Route.To.Market, crm$Revenue.From.Client.Past.T
wo.Years)$p.value
mc = chisq.test(crm$Route.To.Market, crm$Competitor.Type)$p.value
md = chisq.test(crm$Route.To.Market, crm$Deal.Size.Category)$p.valu
e

ccse = chisq.test(crm$Client.Size.By.Revenue, crm$Client.Size.By.Em
ployee.Count)$p.value
cy = chisq.test(crm$Client.Size.By.Revenue, crm$Revenue.From.Client
.Past.Two.Years)$p.value
cc = chisq.test(crm$Client.Size.By.Revenue, crm$Competitor.Type)$p.
value
cd = chisq.test(crm$Client.Size.By.Revenue, crm$Deal.Size.Category)
$p.value

ey = chisq.test(crm$Client.Size.By.Employee.Count, crm$Revenue.From
.Client.Past.Two.Years)$p.value
ec = chisq.test(crm$Client.Size.By.Employee.Count, crm$Competitor.T
ype)$p.value
ed = chisq.test(crm$Client.Size.By.Employee.Count, crm$Deal.Size.Ca
tegory)$p.value
```

```
yc = chisq.test(crm$Revenue.From.Client.Past.Two.Years, crm$Competi
tor.Type)$p.value
yd = chisq.test(crm$Revenue.From.Client.Past.Two.Years, crm$Deal.Si
ze.Category)$p.value

td = chisq.test(crm$Competitor.Type, crm$Deal.Size.Category)$p.valu
e

cormatrix = matrix(c(0, ssg, sr, srm, scsr, scse, sy, sc, sd,
                     ssg, 0, gr, grm, gcsr, gcse, gy, gc, gd,
                     sr, gr, 0, rrm, rcsr, rcse, ry, rc, rd,
                     srm, grm, rrm, 0, mcsr, mcse, my, mc, md,
                     scsr, gcsr, rcsr, mcsr, 0, ccse, cy, cc, cd,
                     scse, gcse, rcse, mcse, ccse, 0, ey, ec, ed,
                     sy, gy, ry, my, cy, ey, 0, yc, yd,
                     sc, gc, rc, mc, cc, ec, yc, 0, td,
                     sd, gd, rd, md, cd, ed, yd, td, 0),
                   9, 9, byrow = TRUE)

row.names(cormatrix) = colnames(cormatrix) = c("Supplies.Subgroup",
"Supplies.Group", "Region", "Route.To.Market", "Client.Size.By.Reve
nue",
                                              "Client.Size.By.Emplo
yee.Count", "Revenue.From.Client.Past.Two.Years", "Competitor.Type"
, "Deal.Size.Category")
cormatrix
```

	Supplies.Subgroup	Supplies.Group	Region
Supplies.Subgroup	0.000000e+00	4.997501e-04	0.000000
Supplies.Group	4.997501e-04	0.000000e+00	1.838690
Region	0.000000e+00	1.838690e-65	0.000000
Route.To.Market	4.997501e-04	4.997501e-04	0.000000
Client.Size.By.Revenue	2.366019e-119	1.658829e-04	0.000000
Client.Size.By.Employee.Count	2.549308e-94	5.520897e-01	0.000000
Revenue.From.Client.Past.Two.Years	4.997501e-04	4.997501e-04	2.677537
Competitor.Type	4.915601e-283	1.561020e-05	0.000000
Deal.Size.Category	0.000000e+00	1.329050e-110	1.490902 171

Null hypothesis assumes that there is no association between two variables.

Here, we have all p-values < 0.05, so we reject the null hypothesis and conclude that all the variables are dependent to each other.

In-depth data exploration for first insights

In [12]:
```
# Let's see the frequencies for our variable of interest, the win/l
oss opportunities
table(crm$Opportunity.Result)
```

```
 Loss   Won 
60281 17548 
```

In [13]:
```
# Let's see the rates of win/loss opportunities
round(table(crm$Opportunity.Result)/nrow(crm), 2)
```

```
Loss  Won 
0.77 0.23 
```

The success rate is quite low, **only 23% of our opportunities are converted into revenues**.

Now, as sales people, we rather focus on revenues and want to first check how we perform:

- across areas,
- by deal sizes,
- across sales channels.

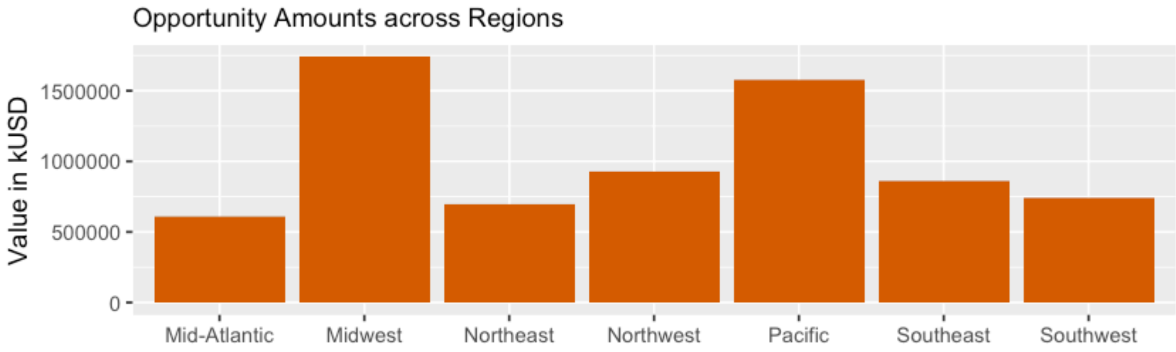
Deal conversions accross areas

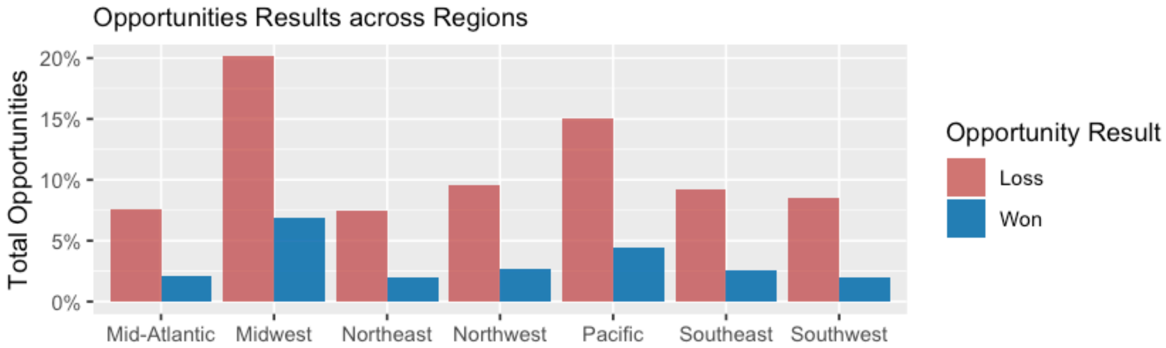
How do the `Opportunity.Amount` and `Opportunity.Result` compare by `Region`?

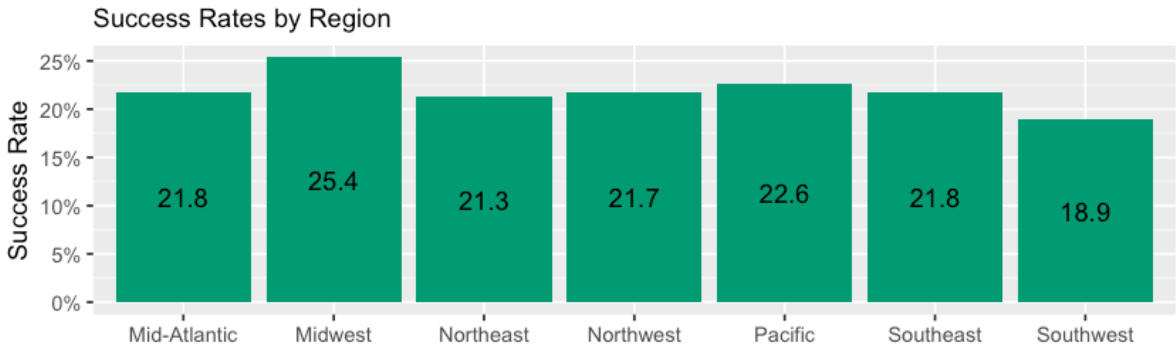
In [14]:
```
cat("The maximum opportunity amount is", max(crm$Opportunity.Amount
.USD)/1000, "thousand USD, the average is",
    round(mean(crm$Opportunity.Amount.USD)), "thousand USD, and the
median is",
    median(crm$Opportunity.Amount.USD), "thousand USD.")
```

```
The maximum opportunity amount is 1000 thousand USD, the average i
s 91665 thousand USD, and the median is 49000 thousand USD.
```

In [15]:
```
# --- OPPORTUNITY AMOUNTS AND OPPORTUNITY RESULTS BY REGION -------
--------------------------------------------------------------

# Opportunity amounts by region
par <- ggplot(data = crm, aes(x = Region, y = Opportunity.Amount.US
D/1000)) +
            geom_bar(stat = "identity", fill = "#D55E00") +
            theme(axis.text.x = element_text()) +
            labs(subtitle = "Opportunity Amounts across Regions", x
= "", y = "Value in kUSD")


# Opportunity results by region
prr <- ggplot(data = crm, aes(Region, fill = Opportunity.Result)) +
            geom_bar(aes(y = (..count..)/sum(..count..)), alpha = 0
.9, position = "dodge") +
            scale_fill_manual(name = "Opportunity Result", values =
c("#CC6666", "#0072B2")) +
            scale_y_continuous(labels = scales::percent) +
            theme(axis.text.x = element_text()) +
            labs(subtitle = "Opportunities Results across Regions",
x = "", y = "Total Opportunities")

# Success rates by region
psr <- crm %>%
        group_by(Region, Opportunity.Result) %>%
        summarise(count = n()) %>%
        spread(key = "Opportunity.Result", value = "count", convert
= TRUE) %>%
        mutate(success_rate = Won / (Won + Loss)) %>%

        ggplot(aes(x = Region, y = success_rate)) +
            geom_bar(stat = "identity", fill = "#009E73") +
            geom_text(aes(label = round(success_rate*100, 1)), posi
tion = position_stack(vjust = 0.5)) +
            scale_y_continuous(labels = scales::percent) +
            theme(axis.text.x = element_text()) +
            labs(subtitle = "Success Rates by Region", x = "", y =
"Success Rate")

grid.arrange(par, prr, psr, layout_matrix = rbind(c(1, 1, 1), c(2,
2, 2), c(3, 3, 3)))
```





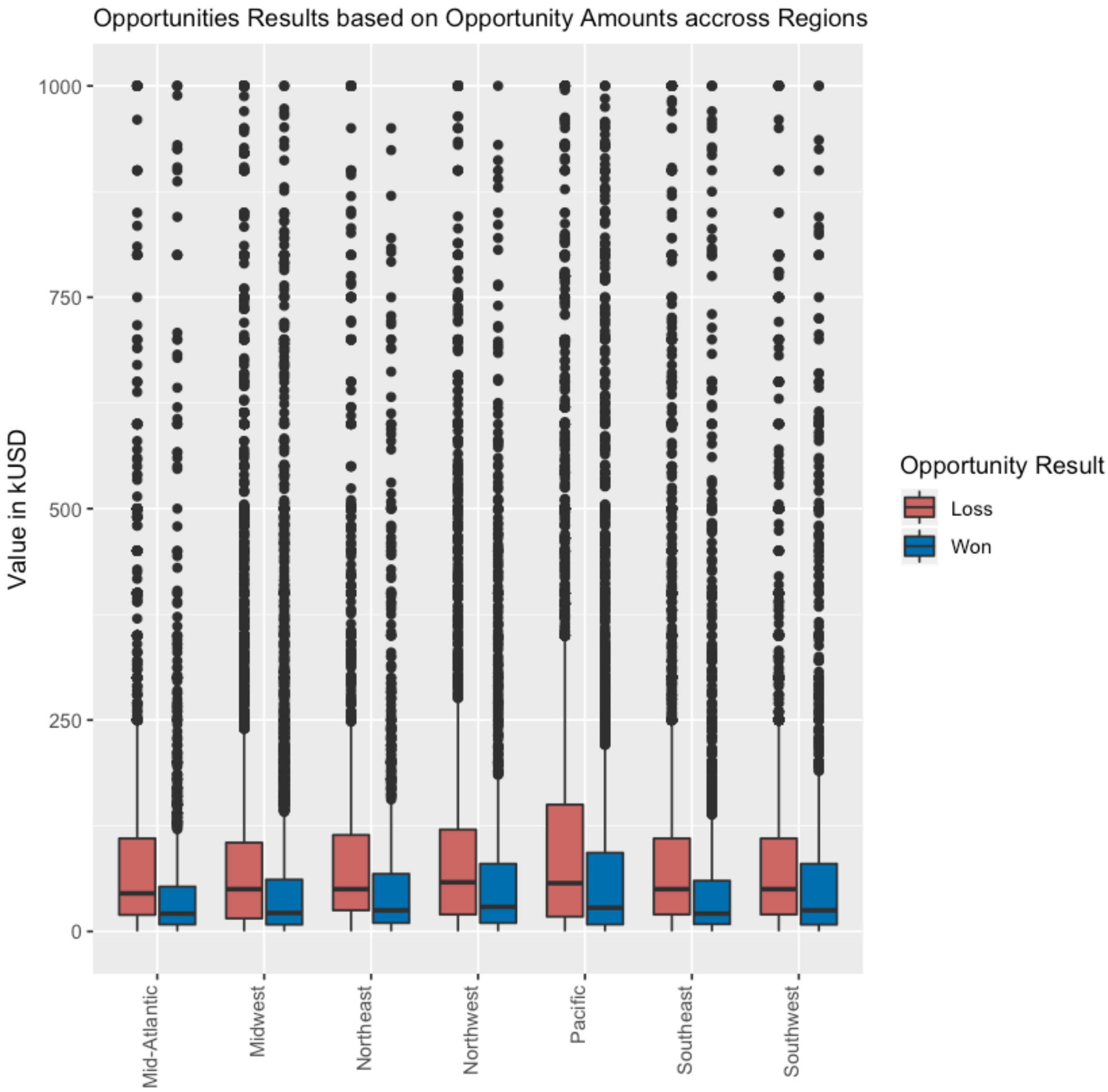


Midwest and Pacific are our biggest areas in terms of opportunity amounts.

Our deal conversion rates across all regions are similarly low, so there is surely room for improving our sales efficiency!

In [16]:

```
# --- OPPORTUNITY RESULTS BASED ON OPPORTUNITY AMOUNTS BY REGION --
-------------------------------------------------------------

# Let's see how the opportunity amount influences our deal outcome
ggplot(data = crm, aes(x = Region, y = Opportunity.Amount.USD/1000,
fill = Opportunity.Result)) +
    geom_boxplot() +
    scale_fill_manual(name = "Opportunity Result", values = c("#CC6
666", "#0072B2")) +
    theme(axis.text.x = element_text(angle = 90, hjust = 1, vjust =
0)) +
    labs(subtitle = "Opportunities Results based on Opportunity Amo
unts accross Regions", x = "", y = "Value in kUSD")
```



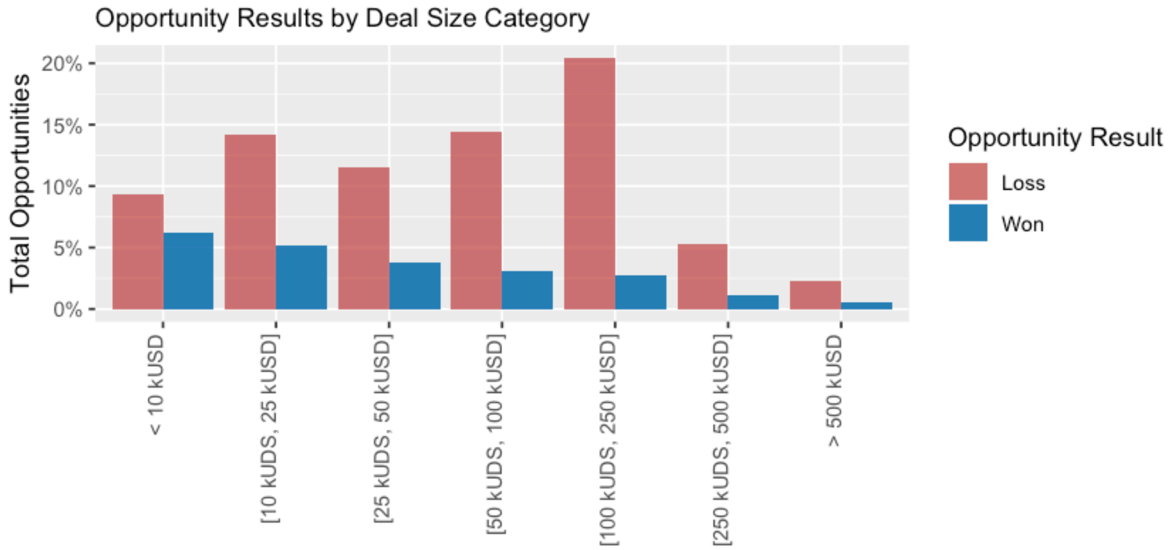
The majority of the opportunities are skewed on the low amounts. Interestingly, we note that the medians of won opportunities are with deals lower than 25 kUSD!

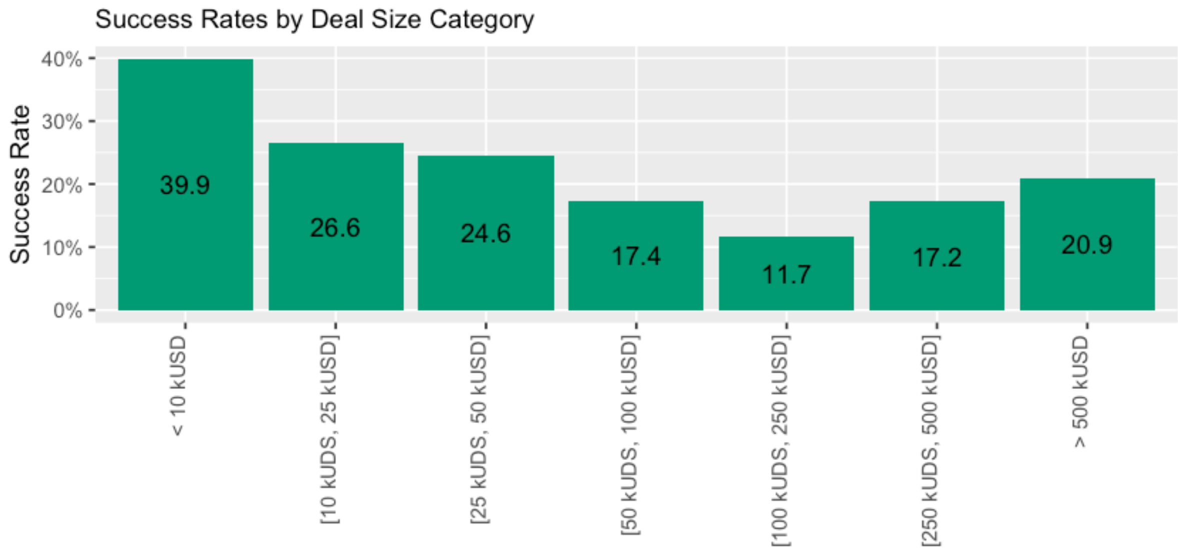
Let's see further how the `Opportunity.Result` compare by `Deal.Size.Category`.

Win / Loss opportunities by deal size categories

How do the `Opportunity.Result` compare by `Deal.Size.Category`?

In [17]:
```
# --- OPPORTUNITY RESULTS BY DEAL SIZE CATEGORY -------------------
--------------------------------------------------------------

# Opportunity results by deal size category
prd <- ggplot(data = crm, aes(Deal.Size.Category, fill = Opportunit
y.Result)) +
        geom_bar(aes(y = (..count..)/sum(..count..)), alpha = 0.9,
position = "dodge") +
        scale_fill_manual(name = "Opportunity Result", values = c("
#CC6666", "#0072B2")) +
        scale_y_continuous(labels = scales::percent) +
        scale_x_discrete(labels = c("1" = "< 10 kUSD", "2" = "[10 k
UDS, 25 kUSD]", "3" = "[25 kUDS, 50 kUSD]",
                                    "4" = "[50 kUDS, 100 kUSD]", "5
" = "[100 kUDS, 250 kUSD]",
                                    "6" = "[250 kUDS, 500 kUSD]", "
7" = "> 500 kUSD")) +
        theme(axis.text.x = element_text(angle = 90, hjust = 1, vju
st = 0)) +
        labs(subtitle = "Opportunity Results by Deal Size Category"
, x = "", y = "Total Opportunities")

# Success rates by deal size category
psd <- crm %>%
        group_by(Deal.Size.Category, Opportunity.Result) %>%
        summarise(count = n()) %>%
        spread(key = "Opportunity.Result", value = "count", convert
= TRUE) %>%
        mutate(success_rate = Won / (Won + Loss)) %>%

        ggplot(aes(x = Deal.Size.Category, y = success_rate)) +
            geom_bar(stat = "identity", fill = "#009E73") +
            geom_text(aes(label = round(success_rate*100, 1)), posi
tion = position_stack(vjust = 0.5)) +
            scale_y_continuous(labels = scales::percent) +
            scale_x_discrete(labels = c("1" = "< 10 kUSD", "2" = "[
10 kUDS, 25 kUSD]", "3" = "[25 kUDS, 50 kUSD]",
                                        "4" = "[50 kUDS, 100 kUSD]"
, "5" = "[100 kUDS, 250 kUSD]",
                                        "6" = "[250 kUDS, 500 kUSD]
", "7" = "> 500 kUSD")) +
            theme(axis.text.x = element_text(angle = 90, hjust = 1,
vjust = 0)) +
            labs(subtitle = "Success Rates by Deal Size Category",
x = "", y = "Success Rate")

grid.arrange(prd, psd, layout_matrix = rbind(c(1, 1), c(2, 2)))
```



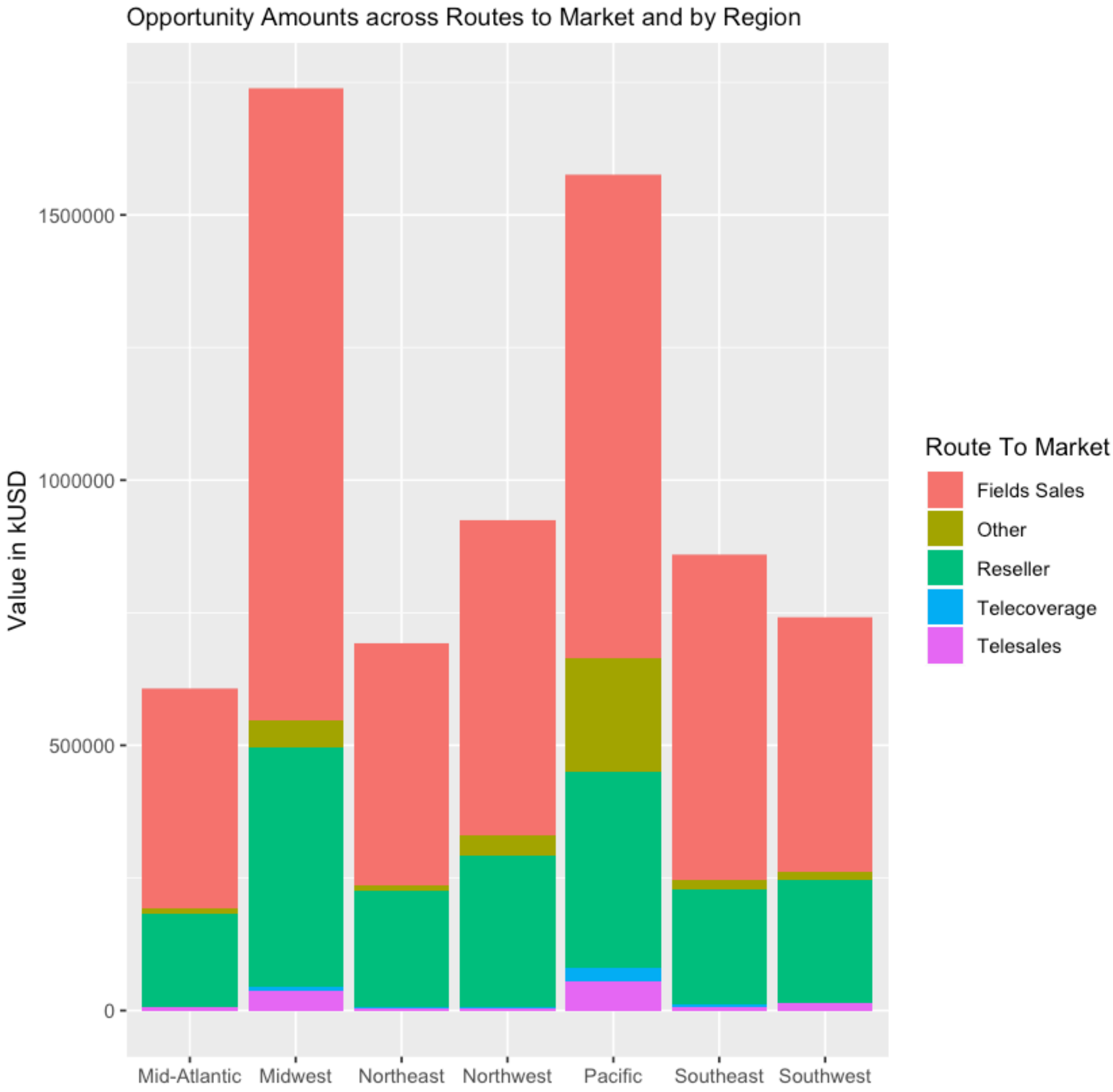


We won more opportunities for deal size < 10 kUSD and our success rate decreases as the deal size increases until a level of 100 to 250 kUSD.

Opportunity amount accross regions and sales channels

How do the `Opportunity.Amount` compare by `Region` and `Route.To.Market`?

In [18]:
```
# --- OPPORTUNITY AMOUNTS BY REGION AND ROUTE TO MARKET -----------
-------------------------------------------------------------

# Routes to Market by Region
ggplot(data = crm, aes(x = Region, y = Opportunity.Amount.USD/1000,
fill = Route.To.Market), alpha = 0.9) +
    geom_bar(stat = "identity", position = "stack") +
    scale_fill_discrete(name = "Route To Market") +
    labs(subtitle = "Opportunity Amounts across Routes to Market an
d by Region", x = "", y = "Value in kUSD")
```

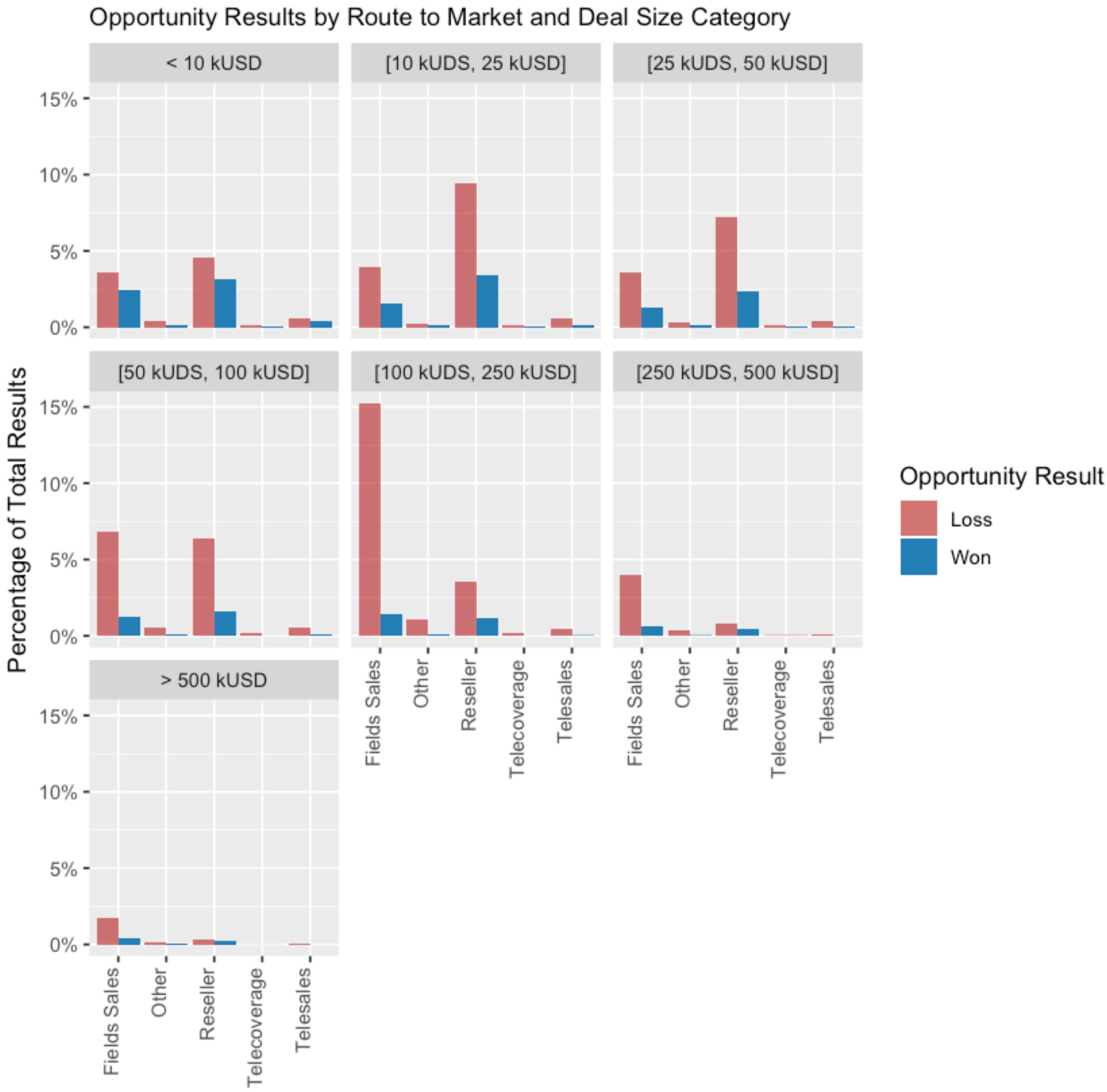


Field Sales and Reseller are our two main sales channels accross regions, but how do these sales channels perform?

Win / Loss opportunities accross sales channels and by deal size category

How do the `Opportunity.Result` compare by `Route.To.Market` and `Deal.Size.Category`?

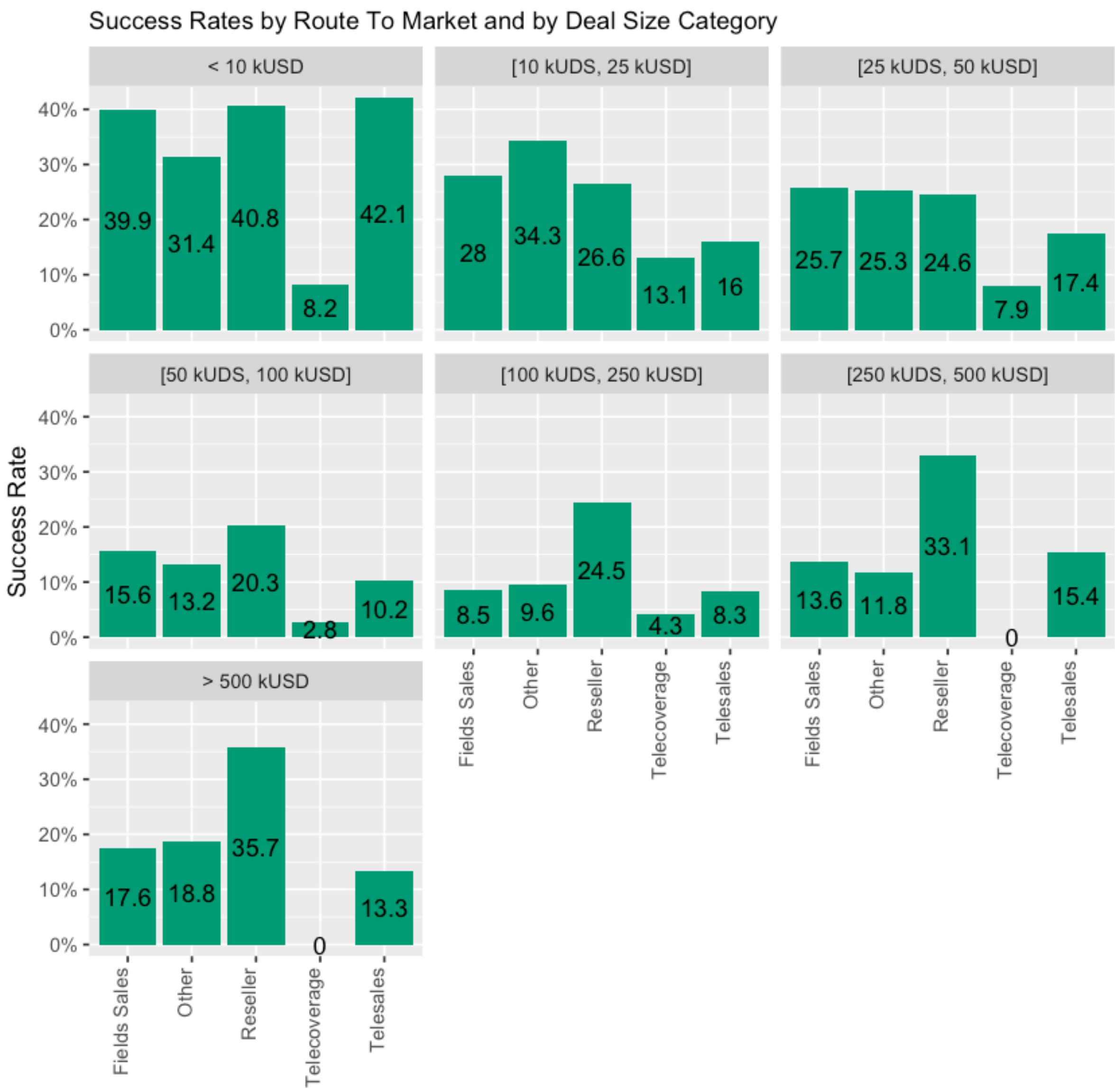
In [19]:
```
# --- OPPORTUNITY RESULTS BY ROUTE TO MARKET AND DEAL SIZE CATEGORY
-------------------------------------------------------------

# Opportunity results by route to market and deal size category

labels <- c("1" = "< 10 kUSD", "2" = "[10 kUDS, 25 kUSD]", "3" = "[
25 kUDS, 50 kUSD]", "4" = "[50 kUDS, 100 kUSD]",
            "5" = "[100 kUDS, 250 kUSD]", "6" = "[250 kUDS, 500 kUS
D]", "7" = "> 500 kUSD")

ggplot(data = crm, aes(Route.To.Market, fill = Opportunity.Result))
+
        geom_bar(aes(y = (..count..)/sum(..count..)), alpha = 0.9,
position = "dodge") +
        scale_fill_manual(name = "Opportunity Result", values = c("
#CC6666", "#0072B2")) +
        scale_y_continuous(labels = scales::percent) +
        facet_wrap(~Deal.Size.Category, labeller = labeller(Deal.Si
ze.Category = labels)) +
        theme(axis.text.x = element_text(angle = 90, hjust = 1, vju
st = 0)) +
        labs(subtitle = "Opportunity Results by Route to Market and
Deal Size Category", x = "", y = "Percentage of Total Results")
```



Opportunity Results by Route to Market and Deal Size Category
< 10 kUSD
[10 kUDS, 25 kUSD]
[25 kUDS, 50 kUSD]
[50 kUDS, 100 kUSD]
[100 kUDS, 250 kUSD]
[250 kUDS, 500 kUSD]
> 500 kUSD
Percentage of Total Results
15%
10%
5%
0%
Fields Sales
Other
Reseller
Telecoverage
Telesales
Opportunity Result
Loss
Won

In [20]:

```
# Success rates by route to market and deal size category

crm %>%
    group_by(Route.To.Market, Deal.Size.Category, Opportunity.Resul
t) %>%
    summarise(count = n()) %>%
    spread(key = "Opportunity.Result", value = "count", fill = 0, c
onvert = TRUE) %>%
    mutate(success_rate = Won / (Won + Loss)) %>%

    ggplot(aes(x = Route.To.Market, y = success_rate)) +
        geom_bar(stat = "identity",  fill = "#009E73") +
        geom_text(aes(label = round(success_rate*100, 1)), position
= position_stack(vjust = 0.5)) +
        scale_y_continuous(labels = scales::percent) +
        facet_wrap(~Deal.Size.Category, labeller = labeller(Deal.Si
ze.Category = labels)) +
        theme(axis.text.x = element_text(angle = 90, hjust = 1, vju
st = 0)) +
        labs(subtitle = "Success Rates by Route To Market and by De
al Size Category", x = "", y = "Success Rate")
```



There is no clear trend of successful routes to market across deal sizes.

- Field Sales performance trend follows the general trend accross the deal size categories as seen before. So, we note that slight rebound for opportunities above 250 kUSD. Field Sales could be refocused on bigger deals to increase efficiency.
- Reseller channel performs well and best for all deals > 50 kUSD. We should further develop and support our resellers network.
- Other routes to market efficiency could be somewhat compared to Field Sales.
- Telecoverage performance is poor, it might not be relevant for our business.
- Telesales is the best channel for deals < 10 kUSD.

Based on this finding, we may consider shifting our sales resources as:

- Telesales for opportunities ≤ 10 kUSD,
- Field Sales for opportunities > 250 kUSD,
- Reseller for all opportunities,
- Other for all opportunities,
- Telecoverage should be discontinued.

Understanding what drives our sales

With a simple managerial approach, looking at a few variables (`Opportunity.Amount`, `Region`, `Deal.Size.Category` and `Route.To.Market`), we have not been able to uncover the patterns that allow us to determine the successful sales profiles. The best performance we could achieve was a modest 40% of deals conversion with Telesales for opportunities < 10 kUSD.

We want to understand what drives our sales, which deals our sales team can expect to win or loose. In other terms, we want to understand the **why** behind what's happening.

With such a large dataset including 19 variables (so as many as 18 possible sales drivers), we can't manually explore each and every variable, not even talking about possible combinations. That is where we bring in **Machine Learning approaches to help us to identify the most significant variables and predict the opportunity results**.

Methods to perform a dimension reduction of our dataset so that we can identify the most significant variables

Two very common methods for identifying significant variables are **Decision Tree** and **Random Forests**.

- The **Decision Tree** best feature for analytics is that it is very **easy to interpret** and **results are actionable**!
- **Random Forests** improve the robustness of our predictions as they aggregate many Decision Trees.

4.2 Create subsets for the project

In [21]:
```
# --- CREATE DATASETS FOR THE PROJECT ------------------------------
------------------------------------------------------------

# Sales set is 90% of the crm data and Validation set is the remain
ing 10%
set.seed(1)
test_index <- createDataPartition(y = crm$Opportunity.Result, times
= 1, p = 0.1, list = FALSE)
sales <- crm[-test_index,]
validation <- crm[test_index,]
```

4.3 Predictive Models

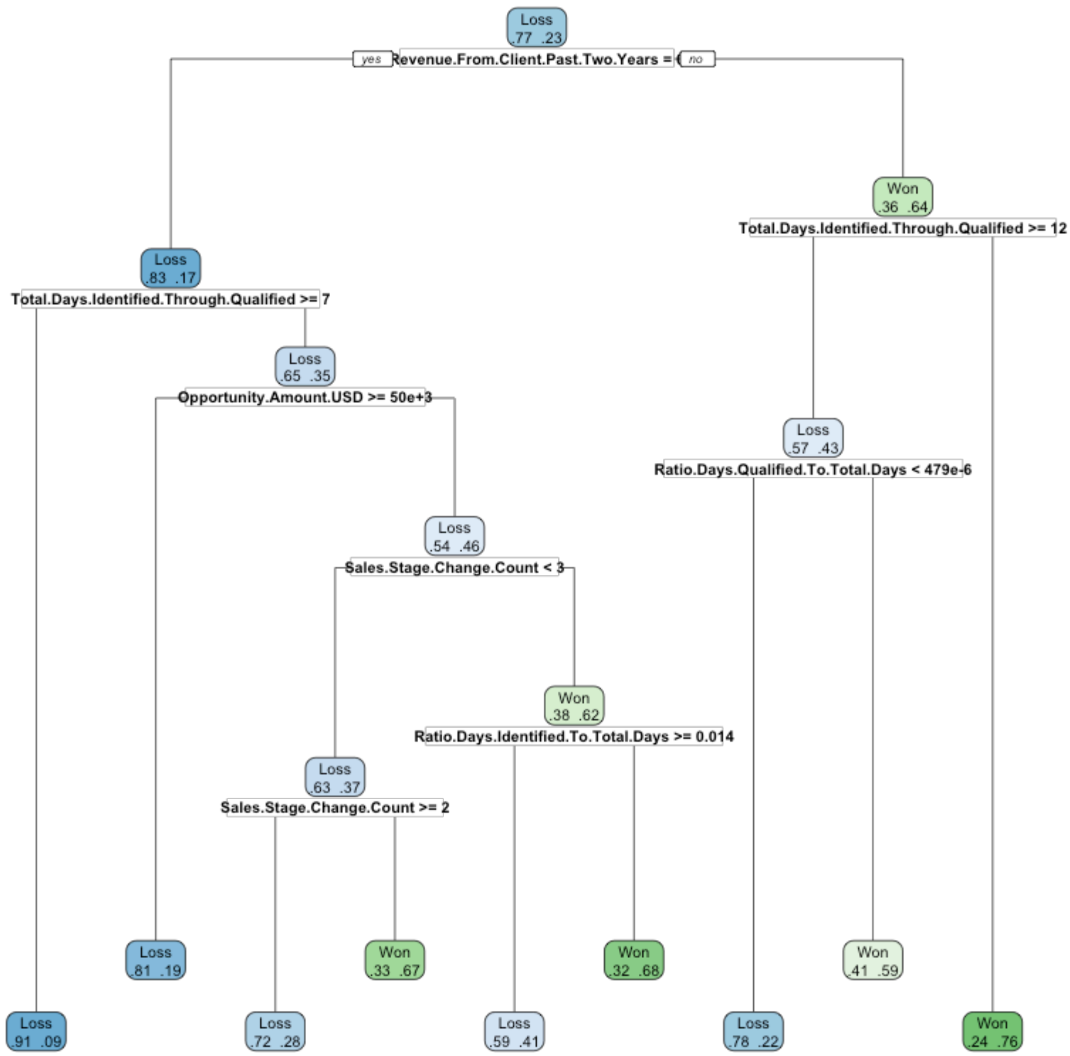
In [22]:
```
# --- SPLIT TRAIN/TEST SETS ---------------------------------------
------------------------------------------------------------

set.seed(699)
test_index <- createDataPartition(y = sales$Opportunity.Result, tim
es = 1, p = 0.2, list = FALSE)
train_set <- sales[-test_index,]
test_set <- sales[test_index,]
```

Decision Tree

In [23]:
```
# --- DECISION TREE WITH RPART PACKAGE ---------------------------
-------------------------------------------------------------

library(rpart)
library(rpart.plot)

# Fitting decision tree (rpart package) to the train set
# Note that we remove the Opportunity Number as it cannot be an act
ual cause of our Opportunity Result
rpa_tree_fit <- rpart(Opportunity.Result ~ . -Opportunity.Number, d
ata = train_set, method = "class")

# Display the results
printcp(rpa_tree_fit)
```

```
Classification tree:
rpart(formula = Opportunity.Result ~ . - Opportunity.Number,
    data = train_set, method = "class")

Variables actually used in tree construction:
[1] Opportunity.Amount.USD
[2] Ratio.Days.Identified.To.Total.Days
[3] Ratio.Days.Qualified.To.Total.Days
[4] Revenue.From.Client.Past.Two.Years
[5] Sales.Stage.Change.Count
[6] Total.Days.Identified.Through.Qualified

Root node error: 12634/56035 = 0.22547

n= 56035

        CP nsplit rel error  xerror      xstd
1 0.140019      0   1.00000 1.00000 0.0078298
2 0.025566      1   0.85998 0.85998 0.0074075
3 0.021002      2   0.83442 0.84439 0.0073560
4 0.019550      6   0.73468 0.74861 0.0070180
5 0.011477      7   0.71513 0.71545 0.0068916
6 0.010000      8   0.70366 0.70659 0.0068569
```

In [24]:
```
# Tree visualization
rpart.plot(rpa_tree_fit, extra = 4)
```



In [25]:
```
# Detailed summary of splits
summary(rpa_tree_fit)
```

```
Call:
rpart(formula = Opportunity.Result ~ . - Opportunity.Number,
    data = train_set, method = "class")
  n= 56035

          CP nsplit rel error    xerror        xstd
1 0.14001900      0 1.0000000 1.0000000 0.007829783
2 0.02556593      1 0.8599810 0.8599810 0.007407461
3 0.02100153      2 0.8344151 0.8443882 0.007355987
4 0.01955042      6 0.7346842 0.7486148 0.007018024
5 0.01147697      7 0.7151338 0.7154504 0.006891600
6 0.01000000      8 0.7036568 0.7065854 0.006856927

Variable importance
     Revenue.From.Client.Past.Two.Years Total.Days.Identified.Thro
ugh.Qualified
```

```
21
  Total.Days.Identified.Through.Closing                Sales.Stage
.Change.Count
                                     21
10
                 Opportunity.Amount.USD      Ratio.Days.Qualified.
To.Total.Days
                                      7
3
    Ratio.Days.Identified.To.Total.Days      Ratio.Days.Validated.
To.Total.Days
                                      3
3
                      Supplies.Subgroup                         Ro
ute.To.Market
                                      1
1
                        Competitor.Type
                                      1

Node number 1: 56035 observations,    complexity param=0.140019
  predicted class=Loss  expected loss=0.2254662  P(node) =1
    class counts: 43401 12634
   probabilities: 0.775 0.225
  left son=2 (49730 obs) right son=3 (6305 obs)
  Primary splits:
      Revenue.From.Client.Past.Two.Years      splits as  LRRRR, im
prove=2444.9720, (0 missing)
      Total.Days.Identified.Through.Qualified < 6.5       to the r
ight, improve=2157.3690, (0 missing)
      Total.Days.Identified.Through.Closing   < 8.5       to the r
ight, improve=1903.3660, (0 missing)
      Ratio.Days.Qualified.To.Total.Days      < 0.0167765 to the l
eft,  improve=1161.7860, (0 missing)
      Sales.Stage.Change.Count                < 1.5       to the r
ight, improve= 884.6567, (0 missing)
  Surrogate splits:
      Total.Days.Identified.Through.Closing   < 187       to the l
eft,  agree=0.887, adj=0, (0 split)
      Total.Days.Identified.Through.Qualified < 187       to the l
eft,  agree=0.887, adj=0, (0 split)

Node number 2: 49730 observations,    complexity param=0.02100153
  predicted class=Loss  expected loss=0.1728735  P(node) =0.887481
    class counts: 41133  8597
   probabilities: 0.827 0.173
  left son=4 (33535 obs) right son=5 (16195 obs)
  Primary splits:
      Total.Days.Identified.Through.Qualified < 6.5       to the r
ight, improve=1462.8840, (0 missing)
      Total.Days.Identified.Through.Closing   < 6.5       to the r
ight, improve=1297.2330, (0 missing)
      Sales.Stage.Change.Count                < 1.5       to the r
ight, improve= 706.7389, (0 missing)
      Ratio.Days.Qualified.To.Total.Days      < 0.0167765 to the l
eft,  improve= 596.8093, (0 missing)
      Opportunity.Amount.USD                  < 19997     to the r
```

```
ight, improve= 571.3677, (0 missing)
  Surrogate splits:
      Total.Days.Identified.Through.Closing < 6.5       to the rig
ht, agree=0.989, adj=0.966, (0 split)
      Sales.Stage.Change.Count              < 1.5       to the rig
ht, agree=0.715, adj=0.125, (0 split)
      Ratio.Days.Validated.To.Total.Days    < 0.0007405 to the rig
ht, agree=0.697, adj=0.069, (0 split)
      Opportunity.Amount.USD                < 2962.5    to the rig
ht, agree=0.680, adj=0.019, (0 split)
      Ratio.Days.Qualified.To.Total.Days    < 0.9996015 to the lef
t,  agree=0.679, adj=0.015, (0 split)

Node number 3: 6305 observations,    complexity param=0.02556593
  predicted class=Won   expected loss=0.3597145  P(node) =0.112519
    class counts:  2268  4037
   probabilities: 0.360 0.640
  left son=6 (2321 obs) right son=7 (3984 obs)
  Primary splits:
      Total.Days.Identified.Through.Qualified < 11.5      to the r
ight, improve=323.5650, (0 missing)
      Total.Days.Identified.Through.Closing   < 11.5      to the r
ight, improve=277.2564, (0 missing)
      Opportunity.Amount.USD                  < 98842     to the r
ight, improve=252.2435, (0 missing)
      Deal.Size.Category                      splits as  RRRRLLL,
improve=251.5352, (0 missing)
      Ratio.Days.Identified.To.Total.Days     < 0.0022035 to the r
ight, improve=209.8633, (0 missing)
  Surrogate splits:
      Total.Days.Identified.Through.Closing < 11.5      to the rig
ht, agree=0.980, adj=0.944, (0 split)
      Ratio.Days.Identified.To.Total.Days   < 0.0009805 to the rig
ht, agree=0.688, adj=0.152, (0 split)
      Sales.Stage.Change.Count              < 4.5       to the rig
ht, agree=0.677, adj=0.123, (0 split)
      Opportunity.Amount.USD                < 94972.5   to the rig
ht, agree=0.647, adj=0.041, (0 split)
      Competitor.Type                       splits as  LRR, agree=
0.647, adj=0.041, (0 split)

Node number 4: 33535 observations
  predicted class=Loss  expected loss=0.08859401  P(node) =0.59846
52
    class counts: 30564  2971
   probabilities: 0.911 0.089

Node number 5: 16195 observations,    complexity param=0.02100153
  predicted class=Loss  expected loss=0.3473912  P(node) =0.289015
8
    class counts: 10569  5626
   probabilities: 0.653 0.347
  left son=10 (6754 obs) right son=11 (9441 obs)
  Primary splits:
      Opportunity.Amount.USD              < 49967.5   to the right,
improve=568.8962, (0 missing)
      Deal.Size.Category                  splits as  RRRLLLL, impro
```

```
ve=568.8962, (0 missing)
      Route.To.Market                    splits as  LLRLL, improve
=502.3970, (0 missing)
      Sales.Stage.Change.Count           < 2.5       to the left,
improve=462.8220, (0 missing)
      Ratio.Days.Qualified.To.Total.Days < 0.004385  to the left,
improve=348.3002, (0 missing)
  Surrogate splits:
      Supplies.Subgroup                   splits as  RRRRLRLRLLL,
agree=0.625, adj=0.101, (0 split)
      Route.To.Market                     splits as  LRRLR, agree=
0.621, adj=0.090, (0 split)
      Ratio.Days.Identified.To.Total.Days < 0.145286  to the right
, agree=0.612, adj=0.070, (0 split)
      Competitor.Type                     splits as  LRR, agree=0.
604, adj=0.051, (0 split)
      Client.Size.By.Employee.Count       splits as  RRRRL, agree=
0.588, adj=0.012, (0 split)

Node number 6: 2321 observations,    complexity param=0.01955042
  predicted class=Loss  expected loss=0.4304179  P(node) =0.041420
54
    class counts:  1322   999
   probabilities: 0.570 0.430
  left son=12 (1016 obs) right son=13 (1305 obs)
  Primary splits:
      Ratio.Days.Qualified.To.Total.Days  < 0.000479  to the left,
improve=160.79180, (0 missing)
      Sales.Stage.Change.Count            < 3.5       to the left,
improve=103.11550, (0 missing)
      Ratio.Days.Identified.To.Total.Days < 0.9794605 to the right
, improve= 60.33883, (0 missing)
      Revenue.From.Client.Past.Two.Years  splits as  -RRLL, improv
e= 51.42239, (0 missing)
      Opportunity.Amount.USD              < 71182     to the right
, improve= 50.62278, (0 missing)
  Surrogate splits:
      Ratio.Days.Validated.To.Total.Days    < 0.871351  to the rig
ht, agree=0.789, adj=0.519, (0 split)
      Sales.Stage.Change.Count              < 2.5       to the lef
t,  agree=0.762, adj=0.457, (0 split)
      Ratio.Days.Identified.To.Total.Days   < 0.881062  to the rig
ht, agree=0.660, adj=0.223, (0 split)
      Opportunity.Amount.USD                < 11921     to the lef
t,  agree=0.569, adj=0.016, (0 split)
      Total.Days.Identified.Through.Closing < 14.5      to the lef
t,  agree=0.566, adj=0.009, (0 split)

Node number 7: 3984 observations
  predicted class=Won   expected loss=0.2374498  P(node) =0.071098
42
    class counts:   946  3038
   probabilities: 0.237 0.763

Node number 10: 6754 observations
  predicted class=Loss  expected loss=0.1907018  P(node) =0.120531
8
```

```
    class counts:  5466  1288
   probabilities: 0.809 0.191

Node number 11: 9441 observations,    complexity param=0.02100153
  predicted class=Loss  expected loss=0.4594852  P(node) =0.168484
    class counts:  5103  4338
   probabilities: 0.541 0.459
  left son=22 (6029 obs) right son=23 (3412 obs)
  Primary splits:
      Sales.Stage.Change.Count            < 2.5       to the left,
improve=263.9407, (0 missing)
      Ratio.Days.Qualified.To.Total.Days  < 0.016287  to the left,
improve=182.9088, (0 missing)
      Ratio.Days.Identified.To.Total.Days < 0.9622505 to the right
, improve=132.9027, (0 missing)
      Route.To.Market                     splits as  LLRLL, improv
e=131.7445, (0 missing)
      Elapsed.Days.In.Sales.Stage         < 91.5      to the left,
improve=112.6910, (0 missing)
  Surrogate splits:
      Ratio.Days.Qualified.To.Total.Days    < 0.0007585 to the lef
t,  agree=0.767, adj=0.356, (0 split)
      Ratio.Days.Validated.To.Total.Days    < 0.0003995 to the lef
t,  agree=0.685, adj=0.129, (0 split)
      Total.Days.Identified.Through.Closing < 6.5       to the lef
t,  agree=0.672, adj=0.091, (0 split)
      Ratio.Days.Identified.To.Total.Days   < 0.0015175 to the lef
t,  agree=0.658, adj=0.055, (0 split)
      Competitor.Type                       splits as  RLL, agree=
0.648, adj=0.025, (0 split)

Node number 12: 1016 observations
  predicted class=Loss  expected loss=0.2194882  P(node) =0.018131
52
    class counts:   793   223
   probabilities: 0.781 0.219

Node number 13: 1305 observations
  predicted class=Won   expected loss=0.405364  P(node) =0.0232890
2
    class counts:   529   776
   probabilities: 0.405 0.595

Node number 22: 6029 observations,    complexity param=0.02100153
  predicted class=Loss  expected loss=0.3705424  P(node) =0.107593
5
    class counts:  3795  2234
   probabilities: 0.629 0.371
  left son=44 (4643 obs) right son=45 (1386 obs)
  Primary splits:
      Sales.Stage.Change.Count                < 1.5       to the r
ight, improve=317.17690, (0 missing)
      Route.To.Market                         splits as  LLRLL, im
prove=127.59050, (0 missing)
      Elapsed.Days.In.Sales.Stage             < 91.5      to the l
eft,  improve= 92.07853, (0 missing)
      Opportunity.Amount.USD                  < 2.5       to the l
```

```
eft,  improve= 89.70116, (0 missing)
      Total.Days.Identified.Through.Qualified < 0.5       to the r
ight, improve= 86.47074, (0 missing)
  Surrogate splits:
      Elapsed.Days.In.Sales.Stage < 93.5      to the left,  agree=
0.771, adj=0.006, (0 split)
      Opportunity.Amount.USD      < 49502     to the left,  agree=
0.771, adj=0.003, (0 split)

Node number 23: 3412 observations,    complexity param=0.01147697
  predicted class=Won   expected loss=0.3833529  P(node) =0.060890
51
    class counts:  1308  2104
   probabilities: 0.383 0.617
  left son=46 (791 obs) right son=47 (2621 obs)
  Primary splits:
      Ratio.Days.Identified.To.Total.Days     < 0.0137925 to the r
ight, improve=89.35948, (0 missing)
      Total.Days.Identified.Through.Qualified < 2.5       to the r
ight, improve=48.82247, (0 missing)
      Total.Days.Identified.Through.Closing   < 4.5       to the r
ight, improve=33.91275, (0 missing)
      Ratio.Days.Qualified.To.Total.Days      < 0.0413815 to the l
eft,  improve=30.10667, (0 missing)
      Opportunity.Amount.USD                  < 9999.5    to the r
ight, improve=22.64671, (0 missing)
  Surrogate splits:
      Supplies.Subgroup        splits as  RRRRRRRRRLR, agree=0.768
, adj=0.001, (0 split)
      Supplies.Group           splits as  RRRL, agree=0.768, adj=0
.001, (0 split)
      Sales.Stage.Change.Count < 8.5       to the right, agree=0.7
68, adj=0.001, (0 split)

Node number 44: 4643 observations
  predicted class=Loss  expected loss=0.2819298  P(node) =0.082858
93
    class counts:  3334  1309
   probabilities: 0.718 0.282

Node number 45: 1386 observations
  predicted class=Won   expected loss=0.3326118  P(node) =0.024734
54
    class counts:   461   925
   probabilities: 0.333 0.667

Node number 46: 791 observations
  predicted class=Loss  expected loss=0.4083439  P(node) =0.014116
18
    class counts:   468   323
   probabilities: 0.592 0.408

Node number 47: 2621 observations
  predicted class=Won   expected loss=0.3204884  P(node) =0.046774
34
    class counts:   840  1781
   probabilities: 0.320 0.680
```

In [26]:
```
# Predicting the test set results
rpa_tree_pred <- predict(rpa_tree_fit, newdata = test_set[-7], type
= "class") # remove "Opportunity Result" for prediction

# Confusion matrix
confusionMatrix(rpa_tree_pred, test_set$Opportunity.Result)
```

```
Confusion Matrix and Statistics

          Reference
Prediction  Loss   Won
      Loss 10132  1555
      Won    719  1604

               Accuracy : 0.8377
                 95% CI : (0.8315, 0.8438)
    No Information Rate : 0.7745
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.4872
 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.9337
            Specificity : 0.5078
         Pos Pred Value : 0.8669
         Neg Pred Value : 0.6905
             Prevalence : 0.7745
         Detection Rate : 0.7232
   Detection Prevalence : 0.8342
      Balanced Accuracy : 0.7207

       'Positive' Class : Loss
```

We have achieved a decent overall accuracy of 84% with a negative predictive value (the proportion of predicted won opportunities which are real won deals) of 69%.

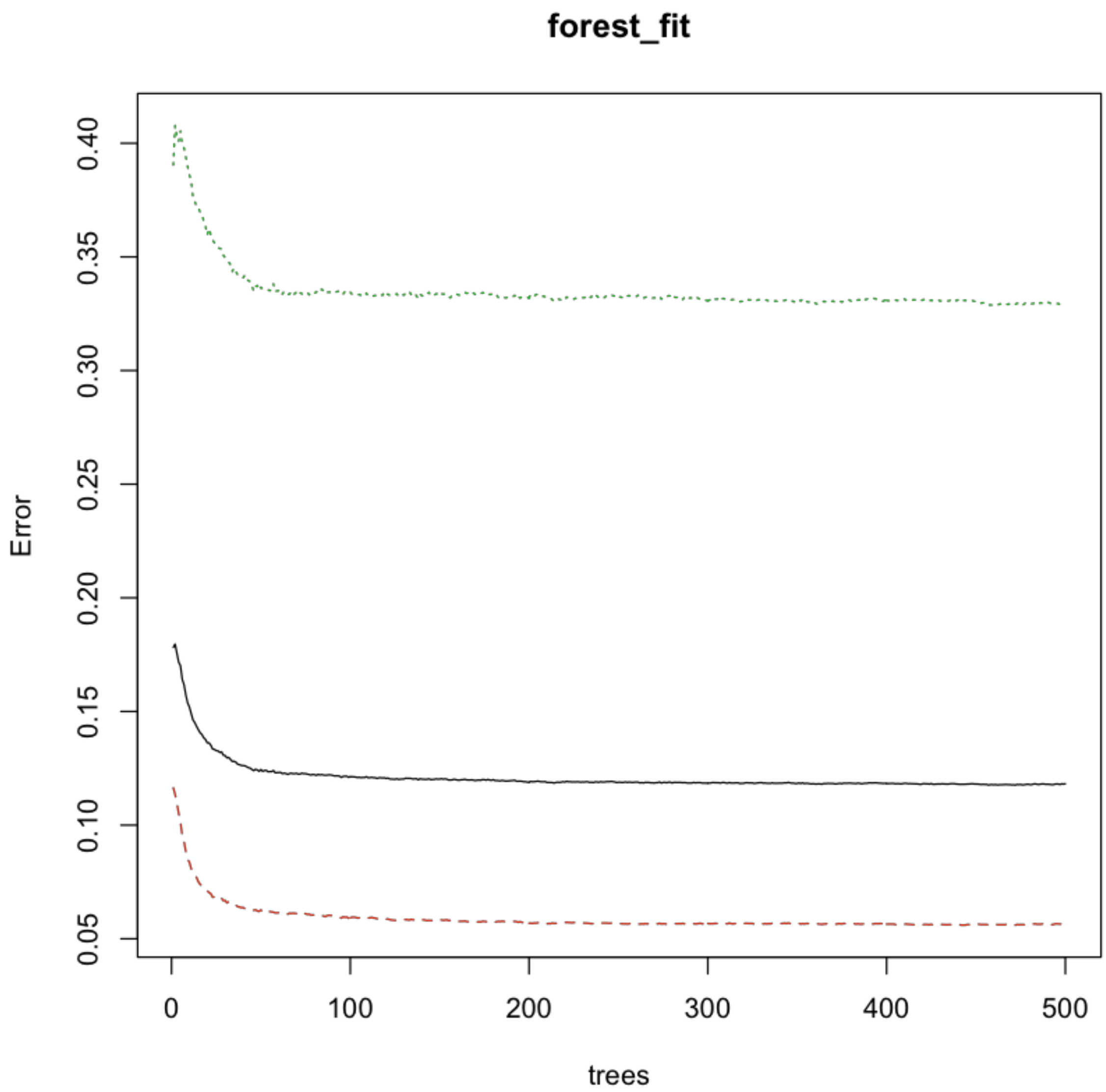
More importantly, the Decision Tree helped us to understand not only the relationships and associations between features but also the decision rules to generate that tree.

So the feature of first importance is `Revenue.From.Client.Past.Two.Years`, i.e. the business that we've had with that Customer during the past two years, then the second feature is `Total.Days.Identified.Through.Qualified`, i.e. the number of days to qualify an opportunity from its identification. We may note that `Total.Days.Identified.Through.Closing` can be used as a second feature too. These two variables are strongly correlated as we have seen before and basically bear the same information. The third significant feature is `Sales.Stage.Change.Count`, i.e. the number of times an opportunity changes sales stages (back and forwards) in the sales pipeline.

We will focus on two or three features only as we want to keep our insights interpretable and above all actionable.

Random Forest

In [27]:
```
# --- RANDOM FOREST WITH RANDOMFOREST PACKAGE ---------------------
-------------------------------------------------------------

library(randomForest)

# Fitting random forest to the train set
# Note that we remove the Opportunity Number as it cannot be an act
ual cause of our Opportunity Result
forest_fit = randomForest(Opportunity.Result ~ .-Opportunity.Number
, data = train_set)

# Choosing the number of trees
plot(forest_fit)
```



The green, black and red lines represent error rate for Loss, overall and Won, respectively. The overall error rate converges (no further decrease) to around 12%, so the default setting of 500 trees in the randomForest function is fine.

In [28]:
```
# Variables of importance
apply(importance(forest_fit), 2, sort, decreasing = TRUE)
```

	MeanDecreaseGini
Revenue.From.Client.Past.Two.Years	2026.8183
Total.Days.Identified.Through.Qualified	2014.5458
Elapsed.Days.In.Sales.Stage	1985.6999
Opportunity.Amount.USD	1917.6508
Total.Days.Identified.Through.Closing	1671.7124
Sales.Stage.Change.Count	1402.7043
Ratio.Days.Qualified.To.Total.Days	1324.6450
Supplies.Subgroup	1123.4961
Region	1070.7206
Ratio.Days.Validated.To.Total.Days	917.7806
Deal.Size.Category	733.1814
Route.To.Market	684.2728
Ratio.Days.Identified.To.Total.Days	683.1925
Client.Size.By.Employee.Count	372.3142
Client.Size.By.Revenue	366.5809
Competitor.Type	336.6062
Supplies.Group	157.0041

In [29]:
```
# Predicting the test set results
forest_pred = predict(forest_fit, newdata = test_set[-7]) # remove
"Opportunity Result" for prediction

# Confusion matrix
confusionMatrix(forest_pred, test_set$Opportunity.Result)
```

```
Confusion Matrix and Statistics

          Reference
Prediction  Loss   Won
      Loss 10190  1021
      Won    661  2138

               Accuracy : 0.8799
                 95% CI : (0.8744, 0.8853)
    No Information Rate : 0.7745
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.6418
 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.9391
            Specificity : 0.6768
         Pos Pred Value : 0.9089
         Neg Pred Value : 0.7638
             Prevalence : 0.7745
         Detection Rate : 0.7273
   Detection Prevalence : 0.8002
      Balanced Accuracy : 0.8079

       'Positive' Class : Loss
```

With a Random Forest model, we have improved our overall accuracy to 88% with a negative predictive value of 76%.

Our top 3 predictors are:

- `Revenue.From.Client.Past.Two.Years`,
- `Total.Days.Identified.Through.Qualified`,
- `Elapsed.Days.In.Sales.Stage`, i.e. the number of days between the change in sales stages (the counter is reset for each new sales stage).

Note: The two first predictors are the same as given by the Decision Tree.

Validation

In [30]:

```
# --- VALIDATION OF RANDOM FOREST MODEL --------------------------
----------------------------------------------------------------

# Fitting random forest to the sales set
val_forest_fit = randomForest(Opportunity.Result ~ .-Opportunity.Nu
mber, data = sales)

# Variables of importance
apply(importance(val_forest_fit), 2, sort, decreasing = TRUE)
```

	MeanDecreaseGini
Total.Days.Identified.Through.Qualified	2576.4643
Revenue.From.Client.Past.Two.Years	2544.4756
Elapsed.Days.In.Sales.Stage	2471.0120
Opportunity.Amount.USD	2447.5164
Total.Days.Identified.Through.Closing	2014.2339
Sales.Stage.Change.Count	1702.8337
Ratio.Days.Qualified.To.Total.Days	1645.0344
Supplies.Subgroup	1380.1869
Region	1319.9473
Ratio.Days.Validated.To.Total.Days	1144.1849
Deal.Size.Category	873.2417
Ratio.Days.Identified.To.Total.Days	858.3467
Route.To.Market	856.7560
Client.Size.By.Revenue	459.6488
Client.Size.By.Employee.Count	459.3147
Competitor.Type	430.4977
Supplies.Group	198.4108

In [31]:
```
# Predicting the validation set results
val_forest_pred = predict(val_forest_fit, newdata = validation[, -7
]) # remove "Opportunity Result" for prediction

# Confusion matrix
confusionMatrix(val_forest_pred, validation$Opportunity.Result)
```

```
Confusion Matrix and Statistics

          Reference
Prediction Loss  Won
      Loss 5680  547
      Won   349 1208

               Accuracy : 0.8849
                 95% CI : (0.8776, 0.8919)
    No Information Rate : 0.7745
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.6567
 Mcnemar's Test P-Value : 4.663e-11

            Sensitivity : 0.9421
            Specificity : 0.6883
         Pos Pred Value : 0.9122
         Neg Pred Value : 0.7759
             Prevalence : 0.7745
         Detection Rate : 0.7297
   Detection Prevalence : 0.8000
      Balanced Accuracy : 0.8152

       'Positive' Class : Loss
```

So we valid an **overall accuracy of 88% with a negative predictive value of 77%**.

Note that **we didn't try to optimize accuracy by tuning our models, as our main goal was to reduce the dimension of our dataset and identify the most significant variables with their predictive strengths**.

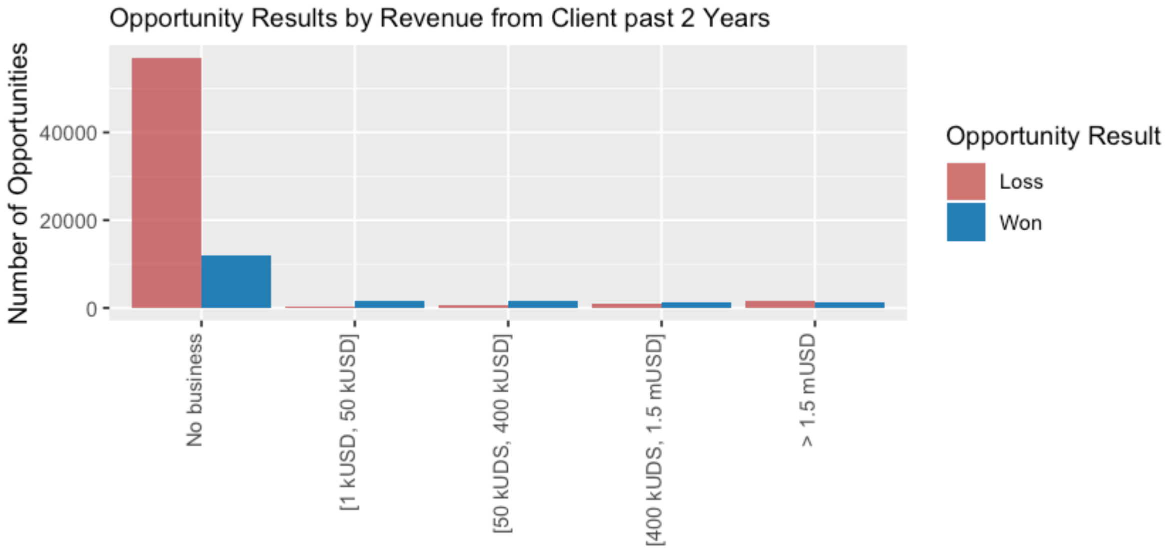
Let's see the insights we can gain from our predictive model.

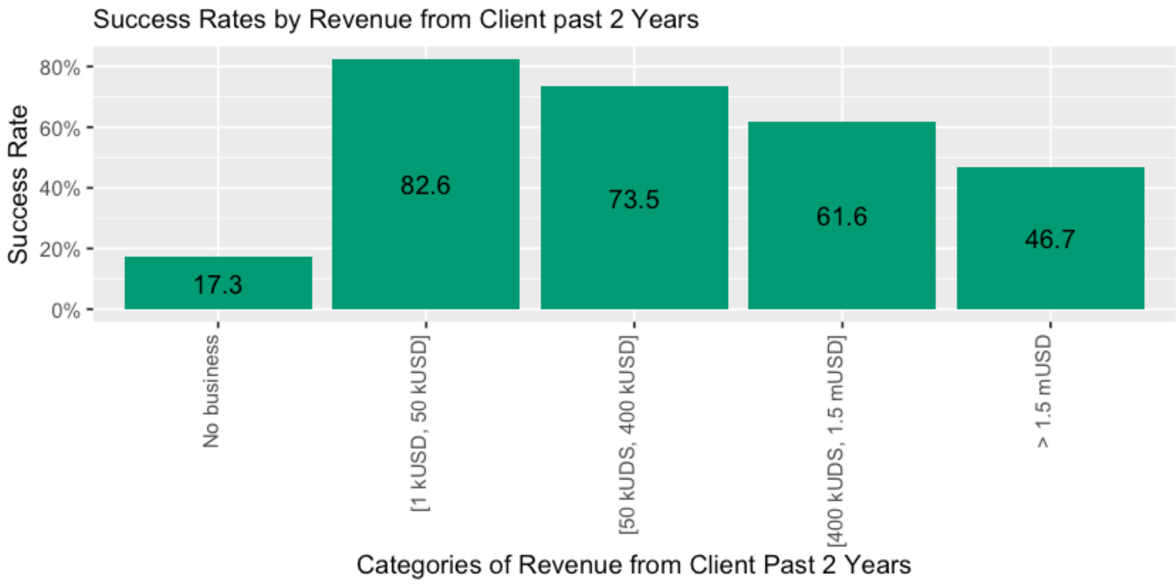
Insights With One Predictor

We use the most significant predictor identified by our models, i.e. `Revenue.From.Client.Past.Two.Years`.

In [32]:

```
# --- OPPORTUNITY RESULTS BY REVENUE FROM CLIENT PAST 2 YEARS -----
--------------------------------------------------------------

# Opportunity results by revenue from client past 2 years
prc <- ggplot(data = crm, aes(Revenue.From.Client.Past.Two.Years, f
ill = Opportunity.Result)) +
        geom_bar(aes(y = (..count..)), alpha = 0.9, position = "dod
ge") +
        scale_fill_manual(name = "Opportunity Result", values = c("
#CC6666", "#0072B2")) +
        scale_x_discrete(labels = c("0" = "No business", "1" = "[1
kUSD, 50 kUSD]", "2" = "[50 kUDS, 400 kUSD]",
                                    "3" = "[400 kUDS, 1.5 mUSD]", "
4" = "> 1.5 mUSD")) +
        theme(axis.text.x = element_text(angle = 90, hjust = 1, vju
st = 0)) +
        labs(subtitle = "Opportunity Results by Revenue from Client
past 2 Years", x = "", y = "Number of Opportunities")


# Success rates by revenue from client past 2 years
psc <- crm %>%
        group_by(Revenue.From.Client.Past.Two.Years, Opportunity.Re
sult) %>%
        summarise(count = n()) %>%
        spread(key = "Opportunity.Result", value = "count", convert
= TRUE) %>%
        mutate(success_rate = Won / (Won + Loss)) %>%

        ggplot(aes(x = Revenue.From.Client.Past.Two.Years, y = succ
ess_rate)) +
            geom_bar(stat = "identity", fill = "#009E73") +
            geom_text(aes(label = round(success_rate*100, 1)), posi
tion = position_stack(vjust = 0.5)) +
            scale_y_continuous(labels = scales::percent) +
            scale_x_discrete(labels = c("0" = "No business", "1" =
"[1 kUSD, 50 kUSD]", "2" = "[50 kUDS, 400 kUSD]",
                                        "3" = "[400 kUDS, 1.5 mUSD]
", "4" = "> 1.5 mUSD")) +
            theme(axis.text.x = element_text(angle = 90, hjust = 1,
vjust = 0)) +
            labs(subtitle = "Success Rates by Revenue from Client p
ast 2 Years", x = "Categories of Revenue from Client Past 2 Years",
y = "Success Rate")

grid.arrange(prc, psc, layout_matrix = rbind(c(1, 1, 1), c(2, 2, 2)
))
```





Looking at the Client purchase history, if they have bought from us less than 50,000 USD in the past 2 years, we have an **83% chance to successfully close the deal**.

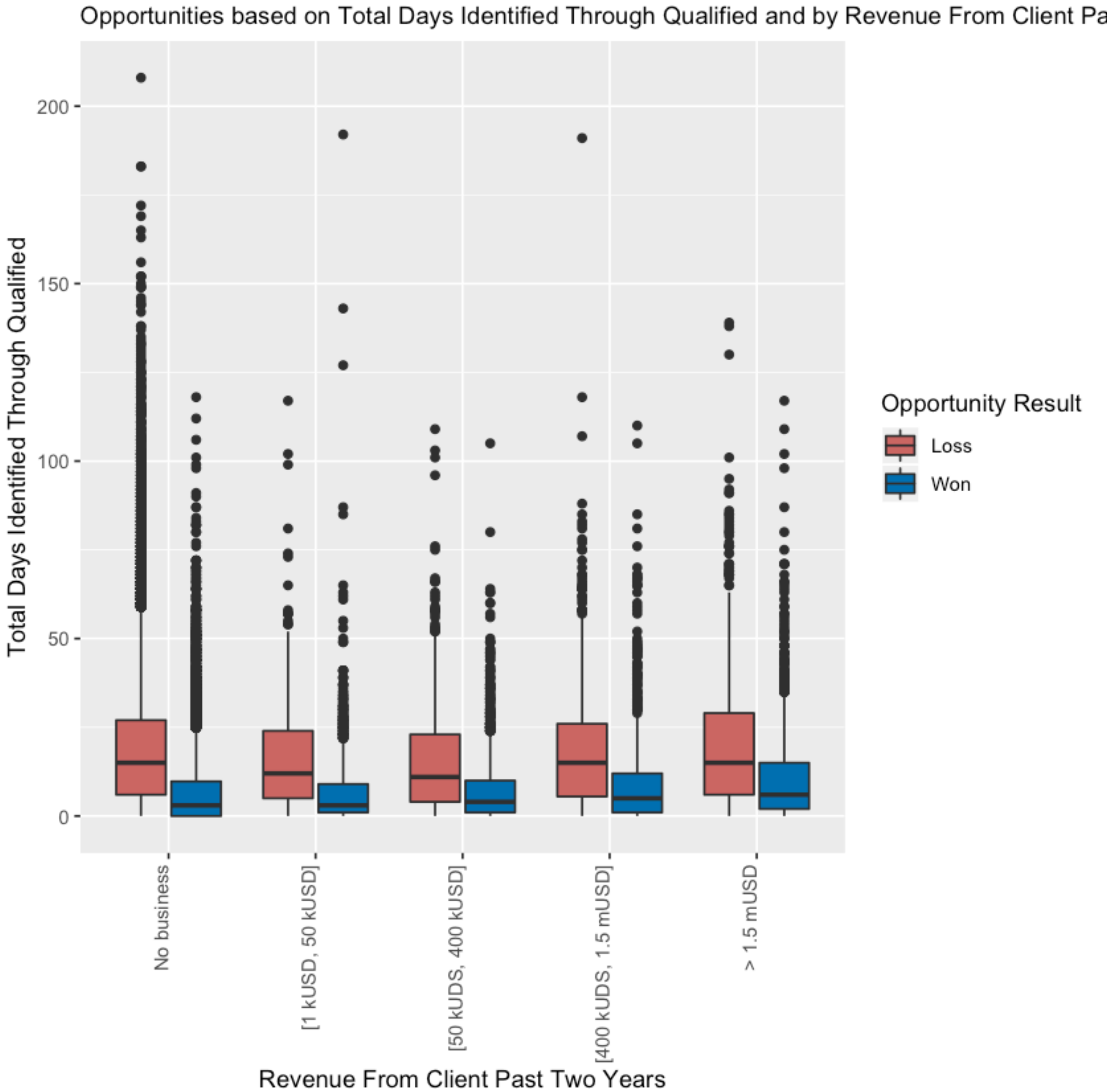
When it comes to very big opportunities (≥ 1.5 mUSD), we close the deal half the time. On the other end, gaining new customers is a real challenge with a success rate of only 17%.

Insights With Two Predictors

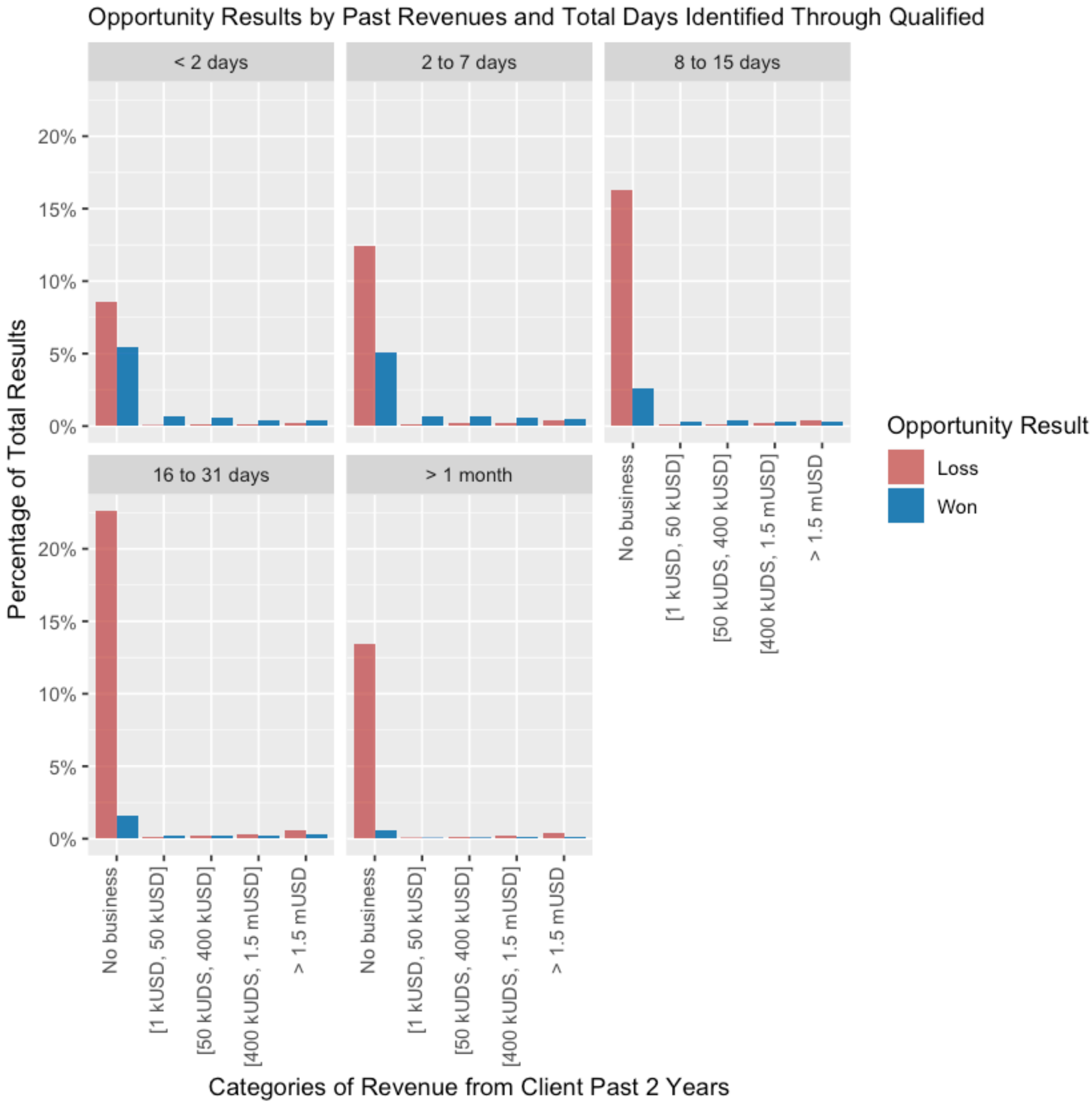
We use the two most important predictors identified by our models, i.e. `Revenue.From.Client.Past.Two.Years` and `Total.Days.Identified.Through.Qualified`.

In [34]:

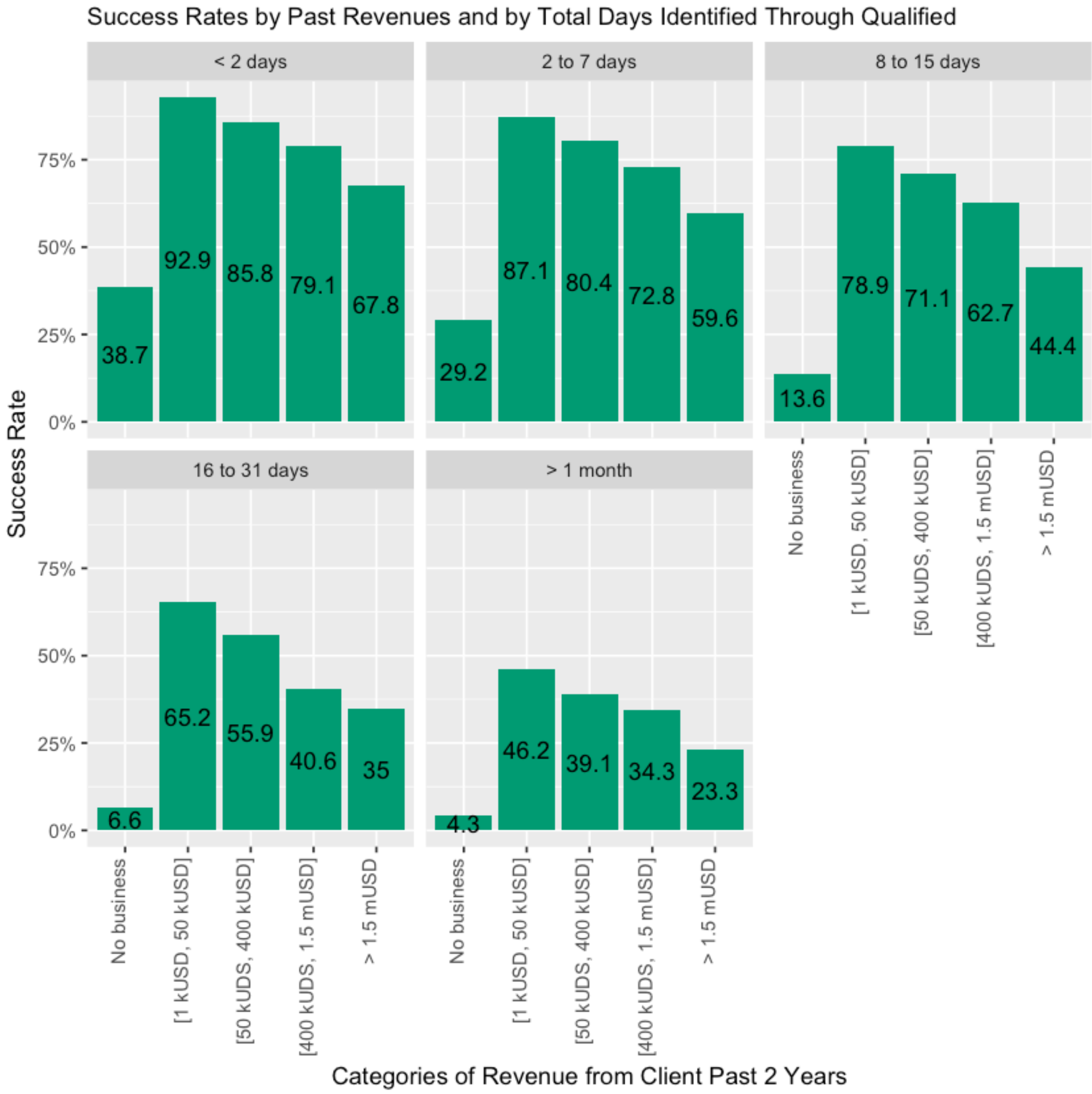
```
# --- OPPORTUNITY RESULTS BY REVENUE FROM CLIENT PAST 2 YEARS AND T
OTAL DAYS IDENTIFIED THROUGH QUALIFIED -----------------------

# Opportunity results by past revenues and total days identified th
rough qualified
ggplot(data = crm, aes(x = Revenue.From.Client.Past.Two.Years, y =
Total.Days.Identified.Through.Qualified, fill = Opportunity.Result)
) +
    geom_boxplot() +
    scale_fill_manual(name = "Opportunity Result", values = c("#CC6
666", "#0072B2")) +
    scale_x_discrete(labels = c("0" = "No business", "1" = "[1 kUSD
, 50 kUSD]", "2" = "[50 kUDS, 400 kUSD]",
                                "3" = "[400 kUDS, 1.5 mUSD]", "4" =
"> 1.5 mUSD")) +
    theme(axis.text.x = element_text(angle = 90, hjust = 1, vjust =
0)) +
    labs(subtitle = "Opportunities based on Total Days Identified T
hrough Qualified and by Revenue From Client Past Two Years ",
         x = "Revenue From Client Past Two Years", y = "Total Days
Identified Through Qualified")
```



In [35]:
```
# Opportunity results by past revenues and total days identified th
rough qualified

labels_1 <- c("0" = "No business", "1" = "[1 kUSD, 50 kUSD]", "2" =
"[50 kUDS, 400 kUSD]", "3" = "[400 kUDS, 1.5 mUSD]", "4" = "> 1.5 m
USD")
labels_2 <- c("1" = "< 2 days", "2" = "2 to 7 days", "3" = "8 to 15
days", "4" = "16 to 31 days", "5" = "> 1 month")

crm %>%
    mutate(Total.Days.Identified.Through.Qualified.Category = cut(c
rm$Total.Days.Identified.Through.Qualified, c(0, 2, 8, 16, 32, 366)
,
                                                                   r
ight = FALSE, labels = c(1:5))) %>%

    ggplot(aes(Revenue.From.Client.Past.Two.Years, fill = Opportuni
ty.Result)) +
        geom_bar(aes(y = (..count..)/sum(..count..)), alpha = 0.9,
position = "dodge") +
        scale_fill_manual(name = "Opportunity Result", values = c("
#CC6666", "#0072B2")) +
        scale_y_continuous(labels = scales::percent) +
        scale_x_discrete(labels = labels_1) +
        facet_wrap(~Total.Days.Identified.Through.Qualified.Categor
y, labeller = labeller(Total.Days.Identified.Through.Qualified.Cate
gory = labels_2)) +
        theme(axis.text.x = element_text(angle = 90, hjust = 1, vju
st = 0)) +
        labs(subtitle = "Opportunity Results by Past Revenues and T
otal Days Identified Through Qualified",
         x = "Categories of Revenue from Client Past 2 Years", y =
"Percentage of Total Results")
```


Opportunity Results by Past Revenues and Total Days Identified Through Qualified
< 2 days
2 to 7 days
8 to 15 days
16 to 31 days
> 1 month
Percentage of Total Results
0%
5%
10%
15%
20%
No business
[1 kUSD, 50 kUSD]
[50 kUDS, 400 kUSD]
[400 kUDS, 1.5 mUSD]
> 1.5 mUSD
Categories of Revenue from Client Past 2 Years
Opportunity Result
Loss
Won

In [36]:
```
# Success rates by past revenues and total days identified through
qualified

crm %>%
    mutate(Total.Days.Identified.Through.Qualified.Category = cut(c
rm$Total.Days.Identified.Through.Qualified, c(0, 2, 8, 16, 32, 366)
,

right = FALSE, labels = c(1:5))) %>%
    group_by(Revenue.From.Client.Past.Two.Years, Total.Days.Identif
ied.Through.Qualified.Category, Opportunity.Result) %>%
    summarise(count = n()) %>%
    spread(key = "Opportunity.Result", value = "count", convert = T
RUE) %>%
    mutate(success_rate = Won / (Won + Loss)) %>%

ggplot(aes(x = Revenue.From.Client.Past.Two.Years, y = success_rate
)) +
    geom_bar(stat = "identity",  fill = "#009E73") +
    geom_text(aes(label = round(success_rate*100, 1)), position = p
osition_stack(vjust = 0.5)) +
    scale_y_continuous(labels = scales::percent) +
    scale_x_discrete(labels = labels_1) +
    facet_wrap(~Total.Days.Identified.Through.Qualified.Category, l
abeller = labeller(Total.Days.Identified.Through.Qualified.Category
= labels_2)) +
    theme(axis.text.x = element_text(angle = 90, hjust = 1, vjust =
0)) +
    labs(subtitle = "Success Rates by Past Revenues and by Total Da
ys Identified Through Qualified", x = "Categories of Revenue from C
lient Past 2 Years", y = "Success Rate")
```



If we can qualify, within 2 days, an opportunity with customers having purchased for less than 50,000 USD in the last 2 years, we reach **a probability of 93% to successfully close the deal**.

As a general rule, **the chances of winning a deal decreases as it stays longer in the pipeline**. This could help to formulate thresholds based on how many days a deal is in a pipeline and create alert mechanisms to expedite qualification.

We also see the **same decrease trend with the increase of purchase history value, for a given qualification time frame**. For example, with an opportunity qualification of 2 to 7 days, we have an 87% chance of successful deal with customers valued at less than 50,000 USD and 60% with those at more than 1.5 mUSD.

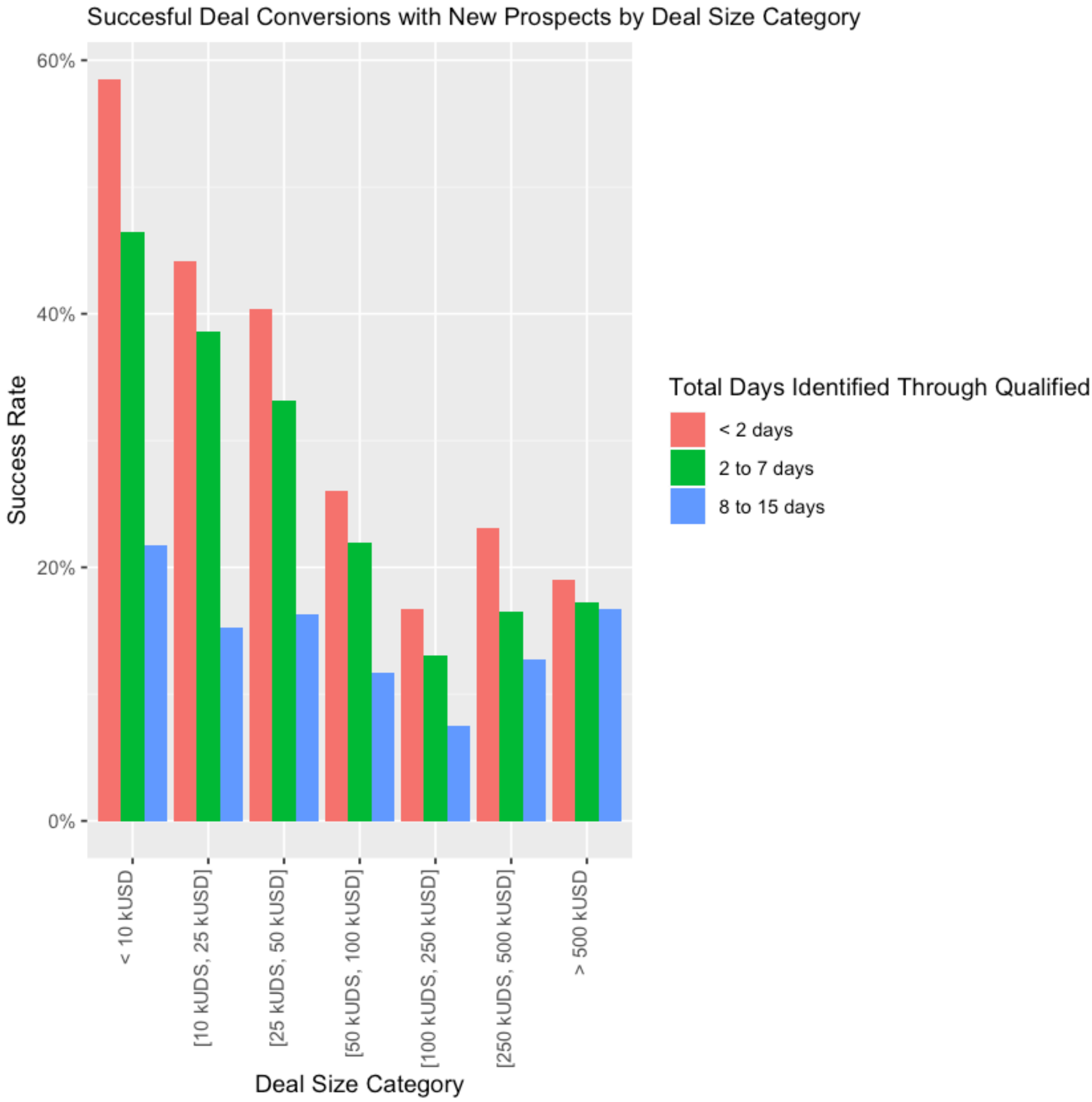
We may also note that **an opportunity is more likely to result in a loss if the client didn't buy anything from us within the last 2 years** but if we are able to qualify a deal within a week with a new customer, we have more chance of success than our global (over the whole dataset) rate of 23%, as seen in the beginning of our analysis.

Insights With Three Predictors

We may want to uncover more complex relationships by adding more features, for example with three predictors as `Revenue.From.Client.Past.Two.Years`, `Total.Days.Identified.Through.Qualified` and `Opportunity.Amount.USD`.

Let's say we want to know how we perform with new prospects, with whose we managed to qualify the opportunities, regardless of the USD value, within two weeks.

In [37]:
```
# --- OPPORTUNITY RESULTS BY REVENUE FROM CLIENT PAST 2 YEARS, TOTA
L DAYS IDENTIFIED THROUGH QUALIFIED AND DEAL SIZE CATEGORY ---

# Success rates by past revenues, total days identified through qua
lified and deal size category
crm %>%
    mutate(Total.Days.Identified.Through.Qualified.Category = cut(c
rm$Total.Days.Identified.Through.Qualified, c(0, 2, 8, 16, 32, 366)
,
                                                                   r
ight = FALSE, labels = c(1:5))) %>%
    group_by(Revenue.From.Client.Past.Two.Years, Total.Days.Identif
ied.Through.Qualified.Category, Deal.Size.Category, Opportunity.Res
ult) %>%
    summarise(count = n()) %>%
    spread(key = "Opportunity.Result", value = "count", fill = 0, c
onvert = TRUE) %>%
    mutate(success_rate = Won / (Won + Loss)) %>%
    filter(Revenue.From.Client.Past.Two.Years == 0 & Total.Days.Ide
ntified.Through.Qualified.Category %in% c(1, 2, 3)) %>%

ggplot(aes(x = Deal.Size.Category, y = success_rate,
                      group = interaction(Revenue.From.Client.Past.
Two.Years, Total.Days.Identified.Through.Qualified.Category, Deal.S
ize.Category),
                      fill = Total.Days.Identified.Through.Qualifie
d.Category), alpha = 0.9) +
        geom_bar(stat = "identity", position = "dodge") +
        scale_fill_discrete(name = "Total Days Identified Through Q
ualified", breaks = c(1, 2, 3), labels = c("< 2 days", "2 to 7 days
", "8 to 15 days")) +
        scale_y_continuous(labels = scales::percent) +
        scale_x_discrete(labels = c("1" = "< 10 kUSD", "2" = "[10 k
UDS, 25 kUSD]", "3" = "[25 kUDS, 50 kUSD]",
                                    "4" = "[50 kUDS, 100 kUSD]", "5
" = "[100 kUDS, 250 kUSD]",
                                    "6" = "[250 kUDS, 500 kUSD]", "
7" = "> 500 kUSD")) +
        theme(axis.text.x = element_text(angle = 90, hjust = 1, vju
st = 0)) +
        labs(subtitle = "Succesful Deal Conversions with New Prospe
cts by Deal Size Category", x = "Deal Size Category", y = "Success
Rate")
```



As we know by now, the chances of successfully closing a deal are higher if we expedite the qualification of the opportunity. Nevertheless, this finding is balanced by the size of the deal. For higher value deals, the impact of qualification speed show a more nuanced picture.

More predictors?

At this stage, adding more predictors won't help much but may degrade the interpretability of our findings. Let's keep in mind that we want, above all, **insights that are relevant and actionable!**

5. Conclusion

We started with a set of 78,000 rows and 19 variables of data extracted from our CRM and tried to intuitively interpret it with a managerial approach. We tried to understand what drives our sales and why we have not been converting enough deals.

We looked at some variables that could be strong indicators of our sales performance. We looked at sales results by sales amounts, region, deal size category and route to market. We gained some interesting insights but none of them uncovered success patterns. The best performance we could achieve was a modest 42% deals conversion with Telesales route to market and opportunities of less than 10,000 USD.

With such a large dataset, we couldn't realistically explore each and every variable to gain insights about what opportunities we can expect to win. We had to automatize our exploration process to determine the most significant features, which could strongly predict the opportunities results, specifically the won deals.

We tried Decision Tree and Random Forests models and achieved very good results. Random Forest yields an overall prediction accuracy of 88% and 77% accuracy on won deals. More importantly, Random Forest could drastically reduce the dimension of our dataset and provide the most significant features for predicting the opportunities results. **Random Forest is a great fit for the job that we had in hands!**

So, we could interpret our large initial dataset in terms that our sales managers can understand.

We uncovered patterns about our opportunities, sales pipeline and what drives our win and losses. We built easy visualizations to help to **understand the profiles of the most likely successful sales opportunities**. For example, we realized that the chances of winning a deal decreases as it stays longer in the pipeline or that an opportunity is more likely to result in a win if the Client has purchased from us up to 50,000 USD.

These sales profiles are extremely valuable and more importantly, actionable in the hands of our sales teams. When reviewing their deal pipeline, our managers can anticipate gaps and correct their sales strategies accordingly. They can focus on the right deals and optimize their progression through the pipeline.

We can uncover more complex relationships by adding predictors according to their significance given by our predictive model, nevertheless we should always keep in mind the need of interpretability and at the end of the day, we want our **insights to be actionable by our sales managers!**

Note: In this project, we covered typical Data Science aspects with data wrangling (data collection, data tidying, feature engineering), data visualization, and machine learning.

Thank you for reading this report!