

Understanding proposal win rates

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Executive summary

In management consulting competitiveness is high. Our firm competes actively with the ‘Big 4’ consultancies. Better understanding of the reasons why we win and lose proposal will give us an advantage.

Our business makes decisions on our proposal management practice with the view to increase win rates. Until recently those decisions were made based on experience and perception of what works and what doesn’t.

In this assignment my aim is to apply machine learning approaches to gain insights into what the data tells us about the relevant features that are good predictors of win and lose rates.

Given the low number of transactions and limited cleanliness of the data, the analysis of features that should underpin decisions around proposals is relatively ambiguous. This is the main challenge to work with.

Cleaning data

The data set is a raw export from the system we use to manage opportunities. A csv export was obtained with the following structure:

```
names(proposals) # obtain the column names
```

```
## [1] "Opportunity Name"
## [2] "Account Name"
## [3] "Stage"
## [4] "Amount Currency"
## [5] "Amount"
## [6] "Created Date"
## [7] "Close Date"
## [8] "Primary Practice"
## [9] "Business Offer"
## [10] "Sector"
```

```
## [11] "Segment"
## [12] "Proposal director"
## [13] "Proposal manager"
## [14] "Source"
## [15] "Competitive or sole sourced (compulsory)"
```

```
tibble(proposals) # show structure of data
```

```
## # A tibble: 3,562 x 1
##   proposals$`Oppo~ $`Account Name` $`Stage $`Amount Curren~ $Amount
##   <chr>           <chr>           <chr> <chr>           <dbl>
## 1 USY 1803 Sydney~ University of ~ Clie~ AUD           300000
## 2 UOW 1803 Academ~ University of ~ Opp s~ AUD           81735
## 3 NAU 1803 - HSF ~ Nous Australia Opp s~ GBP             1
## 4 DHV 1608 Improv~ Dept of Health~ Opp s~ AUD          99134.
## 5 NUK 1701 - CCS ~ Nous UK           Opp s~ AUD             0
## 6 DHG 1803 NW Abo~ Dept of Commun~ Clie~ AUD          15000
## 7 UNS 1803 Refine~ University of ~ Opp s~ AUD          220000
## 8 UNS 1803 Market~ University of ~ Opp u~ AUD          150000
## 9 LTU 1803 Accom~ La Trobe Unive~ Opp u~ AUD          125000
## 10 DTF 1802 Major ~ Dept of Treasu~ Opp u~ AUD          300000
## # ... with 3,552 more rows, and 10 more variables: $`Created Date` <chr>,
## #   $`Close Date` <chr>, $`Primary Practice` <chr>, $`Business
## #   Offer` <chr>, $`Sector` <chr>, $`Segment` <chr>, $`Proposal
## #   director` <chr>, $`Proposal manager` <chr>, $`Source` <chr>,
## #   $`Competitive or sole sourced (compulsory)` <chr>
```

The data needs cleaning up. The following changes are made:

- Rename the columns with names more suitable for analysis
- Factorise features to enable certain type analyses
- Convert dates and proposal amounts from strings to dates and integers
- To facilitate Principle Component Analysis (PCA) columns reflecting people directing and managing the opportunities will be converted using one hot encoding. This will be done after data exploration and at the appropriate stage of analysis

```
# Rename columns to increase readability and facilitate analysis
```

```
proposals <- proposals %>%
  rename(
    name = `Opportunity Name`,
    account = `Account Name`,
    stage = Stage,
    currency = `Amount Currency`,
    amount = Amount,
    practice = `Primary Practice`,
    offer = `Business Offer`,
    sector = Sector,
    director = `Proposal director`,
    manager = `Proposal manager`,
    source = Source,
    competitiveness = `Competitive or sole sourced (compulsory)`,
    amount = Amount,
    segment = Segment,
    creationDate = `Created Date`,
    closeDate = `Close Date`
  )
```

```

# Factorise columns to facilitate certain type analyses (with exception of regression)
proposals$account <- factor(proposals$account)
proposals$stage <- factor(proposals$stage)
proposals$currency <- factor(proposals$currency)
proposals$practice <- factor(proposals$practice)
proposals$offer <- factor(proposals$offer)
proposals$sector <- factor(proposals$sector)
proposals$director <- factor(proposals$director)
proposals$manager <- factor(proposals$manager)
proposals$source <- factor(proposals$source)
proposals$competitiveness <- factor(proposals$competitiveness)
proposals$segment <- factor(proposals$segment)

# Convert amount column from char to integer
proposals$amount <- as.integer(proposals$amount)

# Convert date columns from char to date types
proposals$creationDate <- as.Date(proposals$creationDate, "%d/%m/%Y")
proposals$closeDate <- as.Date(proposals$closeDate, "%d/%m/%Y")

```

Exploration

Data integrity

The following table shows NA values in the dataset. It is clear that some work is to be done to prepare the dataset for analysis.

```

# Show a table summary of the NA values in the dataset
colSums(is.na(proposals))

```

##	name	account	stage	currency
##	2	7	7	7
##	amount	creationDate	closeDate	practice
##	82	7	7	118
##	offer	sector	segment	director
##	9	1693	604	22
##	manager	source	competitiveness	
##	24	1328	3331	

The following approaches to addressing the NA values are proposed.

- Drop the column “Competitive or sole sourced (compulsory)”. Although it would be interesting to see the impact of competitiveness on proposals, too many data points are missing to make it useful
- Amount: investigate if missing amounts can be replaced with amount group means for “account”, “primary practice” and “business offer”
- Proposal director / manager: create “unknown” category for relevant observations. Doing this will retain observations for analysis and will not interfere with PCA
- Outline other wrangling to be conducted

```

# Drop "Competitive or sole sourced (compulsory)" column
proposals <- select(proposals, -competitiveness)

```

Method

Analysis

Conclusions