Improving Call Center Operations with Data Analytics

Part A: Descriptive Analytics, Data Visualization & Storytelling with Data

Susan Kim, Call Center Manager

"Another crisis – that's what I need today" said a visibly frustrated Susan Kim. She has just finished three months as the manager of the call center for the bank – and it has been one crisis after the other. The latest one – a call center associate having a breakdown in the cafeteria after she had to deal with a series of calls today morning where customers not just did not buy the product but were angry and abusive towards her.

Susan recalled her first few days at the call center. She was shocked by how sad and depressing the place was. Nobody smiled. Nobody did any small talk. People came, put their headphones on, made their daily quota of calls and then left. Rinse and repeat. And then they left – as in left their jobs – many within days of joining, most within a year of joining.

Susan was sent from Corporate HQ with an express message – make this call center at least break even. It has been losing money since the day it was set up. She has had 3 months to study the situation. Now is the time to figure solutions, she thought and started walking towards the conference room for her weekly meeting with Kyle Mills, the Business Analyst she had hired a month ago. Kyle has been collecting data from the call center's IT systems for the past month – maybe he will have some actionable insights to follow through.

Kyle Mills, Business Analyst

"What pit of fire have I landed myself into" thought Kyle as he waited for Susan to join him in the conference room. This was his first job after finishing his Master's in Business Analytics degree. He is the one man data analysis team here and it has been stressful – the pressure. Susan, and everyone else, has been looking to him for solutions – but he had no magic wand. Worse still, he didn't even had good data to build any solutions on.

Kyle remembered how his hopes of finally implementing in practice all the wonderful data analysis tools and methodologies he had learnt in school were dashed when he realized that there was no central repository of easily accessible data for him to work with. "We gotta do the hard part first", Kyle recalled thinking. For the past month, Kyle has been working with the IT staff to collect and collate the needed data – and he was ready today. "We can't do data driven decision making until we have data" wondered Kyle – and now we have. Kyle opened the data files on his laptop as Susan entered the room.

"So – what does your laptop has to say today" Susan asked. It was an inside joke – referring to the fact that Kyle can reliably be found staring into his laptop screen, any time of the day.

"Well – nobody buys what we are selling" said Kyle.

"I know that! Everybody knows that!! Do you think people are crying in the cafeteria because people love and welcome our calls and buy what we sell as if they are going out of style" Susan blurted out. It has been a long day already.

“Ah – but now we have data. Now we can figure exactly how many are not buying. We can dig deep and figure who is buying and who is not. We can, hopefully, figure how to change what we are doing. We can now let the data show us the way forward” defended Kyle. He clicked a button, the projector came to life and there were bunch of numbers on the screen. Kyle started his presentation.

“This is what I have managed to collect from our IT systems. This is data on our latest, ongoing, campaign to sell term deposits. As you know, we get a list of our customers from the Corporate HQ. We randomly assign people from the list to out call center associates. They all get the same one page script that they have undergone a one day training session on. They then start calling customers from the list assigned to them. Our IT system collects data about the call – and at the end of the call, our associates enter in the system whether the call was successful i.e. whether the customer committed to buying what we are selling – in this case – term deposit.”

“We had made ~41K calls in past three years. I have collected the following information for these calls” with that Kyle passed a sheet of paper with the following details of every data field (i.e columns) in his data table:

A. Bank Client Data:
1 - age (numeric)
2 - job : type of job (categorical: 'admin.','blue-collar','entrepreneur','housemaid','management','retired','self-employed','services','student','technician','unemployed','unknown')
3 - marital : marital status (categorical: 'divorced','married','single','unknown'; note: 'divorced' means divorced or widowed)
4 - education (categorical: 'basic.4y','basic.6y','basic.9y','high.school','illiterate','professional.course','university.degree','unknown')
5 - default: has credit in default? (categorical: 'no','yes','unknown')
6 - housing: has housing loan? (categorical: 'no','yes','unknown')
7 - loan: has personal loan? (categorical: 'no','yes','unknown')

B. Data related with the last contact of the current campaign
8 - contact: contact communication type (categorical: 'cellular','telephone')
9 - Date: last contact date
10 - duration: last contact duration, in seconds (numeric).

C. Other Attributes:
11 - campaign: number of contacts performed during this campaign (numeric, includes last contact)
12 - pdays: number of days that passed by after the client was last contacted from a previous campaign
13 - previous: number of contacts performed before this campaign (numeric)
14 - poutcome: outcome of the previous marketing campaign (categorical: 'failure','nonexistent','success')

D. Social and economic context attributes (in a separate table)
15 - emp.var.rate: employment variation rate - quarterly indicator (numeric)
16 - cons.price.idx: consumer price index - monthly indicator (numeric)
17 - cons.conf.idx: consumer confidence index - monthly indicator (numeric)
18 - euribor3m: euribor 3 month rate - daily indicator (numeric)
19 - nr.employed: number of employees - quarterly indicator (numeric)

E. Output variable (desired target):
20 - result - has the client subscribed a term deposit? (binary: 0: no, 1: yes)

"So what now?" asked Susan. This was a good start. There is hard data to work with – but data isn't insight. "Data is great – but – I need something actionable. Tell me what is working and what is not. Tell me what to do. Tell me what to do differently than how we are doing now".

"I am coming to it" Kyle was excited – finally some analysis rather than the drudgery of data collection and cleaning. "I am going to now do some descriptive analytics, some data exploration, some data visualization – and get you a set of recommendations".

"What's your preliminary hypothesis?" asked Susan.

"Well – I will have to check what the data says – but I think we are calling way too many people without checking whether they are likely to buy our product or not." Kyle was getting to the meat of his argument. "We should see who is likely to buy our product and target them". Let me see if the data supports this reasoning."

"How about same time next month?" suggested Susan. I will also ask MK to join that meeting. I am meeting with him later today – I will ask him to pass on any relevant bits from our meeting to you. Remember though our goal – we have to make sure that this call center is not running at a loss – we have to reach break-even. Best of luck!" with that Susan left for her meeting with Maya Krishnan – the Finance manager – everybody just called him MK.

MK, Finance Manager

MK has been around a lot longer than most in the building. He has been a steadying influence in an increasingly uncertain business climate. He knew his numbers, his numbers were reliable, he would tell you to your face if you were making a stupid decision.

"How are we doing MK" Susan tried to start the conversation on a happy, non-confrontational manner.

"We are losing money, same as always" MK was having none of it. "We are making calls, only a few are buying; meanwhile we have to absorb the cost of all this infrastructure – and to top it all, our training costs are through the roof what with nobody willing to work more than a week."

"I know – we have to improve employee retention. That will only happen if they are having a kinda sorta decent experience at least – some sense of accomplishment. Okay – listen – I have asked Kyle to analyze our call data and it would be a great help to him if we could give them some concrete financials to work with." Susan implored.

"Ah – I am glad I got my notes then" said MK and handed over an Excel printout with the following data:

- Variable cost per call: $1
- Contribution margin per successful call: $10
- Average cost of training each call associate: $1000
- Current average retention rate for call associates: 1000 calls.

“That’s great – but how about fixed cost, and any idea what will move the needle on retention of call associates?” said Susan.

KM was quick to point out that there are no other meaningful cost that the call center needs to absorb. Then he thought for a minutes and explained – “I have been here long enough to remember when call associates used to stay for longer. If I remember right – the most important difference was the call success rate. We had done a bit of data crunching and it seemed like every 1% increase in call success rate increased the average retention rate by 100 calls.”

“That’s great insight” Susan could see a way out of the current mess. “Could you please share the numbers with Kyle – and ask him to create a financial model for our current profitability – and his projected profitability for any recommendations he might have on how we should have approached these calls differently.”

“We will meet again next month and discuss Kyle’s recommendations. Kyle has promised to do Data Exploration/Cleaning, Descriptive Analytics and most importantly, Data Visualization to develop a set of recommendations.” Susan was hopeful. “Let’s see what Kyle comes up with”. Susan added “I have asked Kyle to make a 10 minute presentation with a maximum of 5 slides – with an emphasis on visualizing the data and communicating his solution on how we can improve our profitability”.

“Let’s hope Kyle tells a persuasive story” MK said as he left Susan’s office.

Part B – Unsupervised Learning

“That worked out well” thought Kyle. He had presented his preliminary analysis to Susan and MK – and they seemed receptive to his message that the call center needed to target specific groups of people who are more receptive to buying the product rather than calling every person in the customer list.

After a bit of silence in the room, MK spoke up. “I like where Kyle’s mind is at. We target people with higher propensity to buy, we make less calls but they will be more successful. We will have lower employee turnover – and we will finally be bottom-line positive.”

“I like the sound of that.” Everybody was waiting for Susan to chime in. She sounded hesitant. “I am worried though how to implement this insight. Right now our process is simple – we have a list of customer – we pass that list to our associated and they call everybody on the list. Simple and easy.”

“I need something *that* easy to figure out who our associates should be calling” Susan looked at Kyle with a questioning face. “Any ideas?”

“I do have an idea. This is a multi-dimensional problem – we need to combine all the data elements we have to get to an overall picture of a customer group. Once we have these groups figured out then we can calculate which customer groups have higher propensity to buy our product – and the prioritize calling the groups with the highest propensity” Kyle was trying to not make this complicated and was failing.

“Wait – do you mean clustering? We want to create clusters of customers?” Susan was wrapping her head around the idea.

“Yes – exactly” Kyle was relieved.

“Great. Let’s meet win a week again. I would like to see a breakdown of customers into clusters – and your evaluation of which clusters are the best targets for us to call” Susan was wrapping up.

“One last thing” MK wanted his priorities here too. “Could you also calculate our profitability for your recommendations of which clusters to call?”

Kyle was loving it. Finally an opportunity to use all the data science he had learnt in school for a real business problems. To make a difference, design a new process and directly affect the bottom-line. “Time to fire up RStudio. Let’s go!

Part C – Supervised Learning

“Here we go again” thought Kyle. He had presented the Unsupervised Learning approach last time – it was well received. “Not sure why we are meeting again. Well I guess I figured wrong that we had a workable solution”. It has been some time since he started working on this problem – and all he has done since was present in meetings. “When will things actually change? When will we implement anything” Kyle wondered.

MK was in the meeting room before Susan. He was positively beaming. “We ran the numbers for your Unsupervised Learning approach. It does seem like if we only called the groups you identified then we will indeed be profitable.”

“They are called ‘clusters’ not groups” Kyle grumbled.

“Yes – let’s be precise in our language” Susan had overheard their conversation. “So we can go ahead with Kyle’s last suggestion about *clusters*” Susan emphasized.

Susan looked at MK – he was quiet. “Can we? Go ahead I mean?” Susan asked MK.

“Yes…. But…” said MK. “It’s a good stop gap plan – but I would really like to explore what’s happening in clusters that we don’t plan to call.”

“What’s happening is that there aren’t enough people in those clusters who will buy our product” Kyle shot back.

“Not enough but not zero either!” KM was a little defensive now. “I don’t like that we are just leaving money on the table in those clusters we are not calling.”

Kyle jumped in – seemed liked he had a lightbulb moment. “I got it. How about I build an individual prediction model – which individual customer is likely to buy our product and only call those customers that are predicted to buy. Will that work” Kyle looked at MK.

“Yes – that should work” KM was relieved. “As long as you make a financial for this approach as well – and compare with the previous cluster approach to tell us which is better.”

“Sure thing!” Kyle was thinking aloud: “seems like Logistic Regression, K-Nearest Neighbor and Artificial Neural Networks will work great. Time to spend some time with RStudio again.”