MANNING SCHOOL OF BUSINESS

OVERALL RISK PROFILE ANALYSIS AND INDICATORS

MSBA Capstone Project Spring 2021 - Report

Abstract

An agile, scalable, and flexible methodology based on a mathematical approach, using Analytical techniques that can analyze, evaluate, and substantiate various risk program ratings. The utilitarian output is showcased through an interactive Tableau Dashboard.

By: Ashwini Agnihotri, Peter Neal

Contents

Acknowledgement

We want to express our gratitude and appreciation to all the wonderful people who were instrumental in the materialization of this project.

Thank you, Santander team, for giving us the opportunity to work on this amazing use case! This was an enriching experience for us!

First and foremost, we want to thank Ryan Morrissey, Director, Business Control & Risk Management, Consumer & Business Banking at Santander Bank, N.A. for proposing this project in the MSBA capstone course. This use case was unique and opened great learning vistas for us.

A special token of gratitude to Michael Donahue, Sr. Associate, Business Control & Risk Management & Bao Duong, Associate, Business Intelligence & Reporting at Santander Bank, N.A. for being such amazing mentors throughout the process. The insights shared by you both gave us the clarity and impetus at every step of the project. Both of you were always reachable; the ease of communication and idea exchange was remarkable. We appreciate this guidance immensely!

We are thankful to Prof. Asil Oztekin, our faculty advisor for being our guiding compass and providing his pivotal inputs at every critical juncture of the project. Last but not the least, we are grateful to Prof. Luvai Motiwalla for coordinating this course and providing us with this platform to work with an esteemed organization like Santander.

Best,

Ashwini Agnihotri

Peter Neal

About Santander

Santander Bank, N.A. is one of the country's largest retail and commercial banks with $74.5 billion in assets. With its corporate offices in Boston, the Bank's approximately 9,600 employees, over 600 branches, more than 2,000 ATMs and 2.1 million customers are principally located in Massachusetts, New Hampshire, Connecticut, Rhode Island, New York, New Jersey, Pennsylvania, and Delaware. The Bank is a wholly-owned subsidiary of Madrid-based Banco Santander, S.A. (NYSE: SAN) – one of the most respected banking groups in the world with more than 125 million customers in the U.S., Europe, and Latin America. It is managed by Santander Holdings USA, Inc. (SHUSA), Banco Santander's intermediate holding company in the U.S.

Project Overview

As part of the Operational Risk Management function, various Risk Programs like Key Risk Indicators, Material Risk, Risk Control Self-Assessments (RCSA), Issue Management and Event Escalation are managed. The data for above risk programs exists in various disparate, disconnected systems of record. The risk program owners and business line owners assess the overall risk profile for their programs/businesses on at least a monthly basis. Overall risk profile ratings are currently measured subjectively via a cursory review of the various risk program results presented in various reports.

Project Objectives & Scope

Our objective was to develop an agile, scalable, and flexible methodology based on a mathematical approach, using analytical techniques to analyze, evaluate and authenticate the risk ratings for various risk programs at the bank. The idea was to develop an adaptable and scalable model that can cater to various programs and provide consumable insights. The utilitarian output was to be presented using an interactive Tableau Dashboard.

We mainly focused on KRIs and Issue Management programs for the scope of this project.

Program Summaries

- KRIs - The objective of the Operational Risk Key Risk Indicator (KRI) Program is to develop and monitor metrics that inform management of risks prior to materialization so that mitigating actions can be taken to avoid or minimize potential impacts.

- Issue Management - The Issue Management program objective is to identify, and document known issues that drive risk exposure within the bank and to develop mitigating actions to remediate those issues, or temporarily accept the risks with the proper level of approval. The Issue Management team is responsible for coordination and oversight of the program including adherence to all standard requirements.

Project Data

Data was provided by Santander for KRIs and Issue Management. It contained fields like KRI codes, AD IDs, and various risk ratings associated with them.

Snapshot of KRIs data and Issue Management data is given in the Appendix.

The data provided for the Risk Programs KRIs and Issue Management did not have any numeric or quantifiable data. To build a mathematical approach to evaluate the overall risk profile ratings, it was essential to put some numbers behind the various types of ratings available in the data. These ratings which are the outcome of meticulous internal evaluation at the bank serve as an input to our model. The various ratings are the decision criteria for our model. So, it was prudent that the numbers we use in our solution resonate the significance of the underlying rating parameters. That was key to building a robust process.

Approach

We combed through the literature and various research papers as a guideline to get the numeric weights for various decision parameters in the data that could be relevant to banking or finance.

We wanted a method that would be rational and give consistent results. Also, adaptability, flexibility and scalability of the method were also in our awareness when we searched for an analytical method to get numeric weights of multiple decision-making criteria.

After due deliberation, we decided to use the Analytical Hierarchy Process better known as AHP to get appropriate numeric weights for the various underlying parameters of the risk ratings. Under the Multi criteria decision making methods, AHP is a tried and tested approach. We catered this method effectively to our use case.

Analytical Hierarchy Process (AHP)

- Developed by Thomas L Satty in the 1970s, AHP is a structured technique used to analyze complex decision-making problems
- It is a mathematical method that incorporates qualitative judgement as well as quantitative analysis
- It gives the numeric weights of various parameters of the decision criteria while maintaining the relative relevance of each parameter
- A specifically designed questionnaire is used

Choice of AHP

- In our use case, we had multiple incommensurable decision criteria for risk analysis in KRIs and Issue Management, all of which contributed to the cumulative result
- All these elements had to be treated consistently
- AHP has this distinguished ability to address a diverse array of elements contributing to decision making in a rational and consistent way
- Using AHP, we got the numeric weights for all the parameters with their relative relevance maintained
- As it is a structured technique, we could replicate it for multiple risk programs

Calculations for AHP

Using AHP, we got the numeric weights for Value Score and Severity Rating in KRIs and AD Status and Priority Rating in Issue Management. The AHP calculations were done in an Excel file, the steps followed are illustrated below.

These AHP weights were used for data preparation and were instrumental in the methodology. In the last step of the AHP calculations, we also check if the results are consistent. If the resultant numeric weights are not consistent, we revisit the definitions in Step 1 and Step 2 and modify the answers in pursuit of getting consistent numeric weights for various decision-making criteria.

In-depth domain knowledge comes in handy while implementing Step 1 and Step 2.

Step 1: Define scale for relative concern for decision-making parameters:

We start by defining the level of concern, quantified in the table below:

Level of concern:	
low	**3**
moderate	**5**
high	**7**
extreme	**9**
intermediate	**4,6,8**

Step 2: Create pairwise comparison matrix

If there are *n* parameters in a decision-making criterion, it gives a *n* X *n* resultant parameter matrix.

In our use case, for Value Score, we have 3 parameters: Red, Amber, Green

To determine the relative importance of these 3 parameters, we start by asking questions as given in table 2.2.

The level of concern is referenced from the table 2.1 in Step 1

We consider every possible combination of the parameters and get the pairwise comparison matrix given in table 2.3

Table 2.2

How concerning is the change from:			
Red to Amber	9	upon	5
Red to green	9	upon	3
Amber to Red	5	upon	9
Amber to Green	6	upon	3
Green to Red	3	upon	9
Green to Amber	3	upon	6

Table 2.3

Pair-wise comparison matrix			
	Red	**Amber**	**Green**
Red	1.00	1.80	3.00
Amber	0.56	1.00	2.00
Green	0.33	0.50	1.00
Sum	**1.89**	**3.30**	**6.00**

For *n* parameters, we get *n* X *n* pairwise comparison matrix.

Step 3: Normalized Pairwise comparison matrix

Normalized values are calculated by dividing each cell value by the column sum (given in **blue**)

Criteria Weights are calculated as the row-wise average (Refer Table 2.4)

Table 2.4

Normalized pair-wise matrix				
	Red	**Amber**	**Green**	**Criteria Wts.**
Red	0.53	0.55	0.50	0.52
Amber	0.29	0.30	0.33	0.32
Green	0.18	0.15	0.17	0.16

Step 4: Calculate the consistency

This step is to check whether the calculated values are correct or not (Refer Table 2.4)

Multiply each cell value in the Non-normalized pairwise matrix by the respective Criteria Weights

Weighted Sum is calculated as the row wise sum.

Ratio = Weighted Sum / Criteria Weights

λmax = 3.00 ➔ Average of Ratio

Consistency Index CI = 0.001848 **Formula:** λmax - n/n – 1, n = 3 (Number of Parameters)

Table 2.5

Calculating consistency						
Criteria weights	0.52	0.31	0.16			
	Red	**Amber**	**Green**	**Wt. Sum**	**Criteria Wts.**	**Ratio**
Red	0.52	0.56	0.49	1.58	0.52	**3.01**
Amber	0.29	0.31	0.33	0.93	0.31	**3.00**
Green	0.17	0.16	0.16	0.49	0.16	**3.00**

The Consistency Index CI is compared with the Standard Consistency Index for 3 parameters (refer Table 2.6). For the weights to be reasonably consistent, the calculated CI must be less than standard CI.

In our case, for *n* = 3, CI = 0.001848

CI Value for 3 parameters (refer Table 2.6) = 0.58

0.001848 < 0.58 ➔ Weights are consistent

Thus, we got the numeric weights that maintain consistency of the underlying parameters.

Table 2.6

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

***Table 2.6 shows the Standard Consistency Index calculated for up to 10 parameters.*

AHP Weights and Rank

Using AHP, we got the numeric weights for different parameters of the various risk ratings. A notable fact about these numbers is, lower is better. This means that the lower the numeric weight is, the better the parameter rating is. The way we modelled the questions for AHP results in this.

After putting the numbers in the mix, it was essential to consume these numbers effectively to get some actionable insights out of them. We calculated ***Rank*** as the combination of various parameters across

different rating criteria. The Rank contains the essence of all the underlying decision-making criteria in the form of numbers.

For KRIs,

If Value Score = Green, **Rank** = Value Score weight - Severity Rating weight

Else, **Rank** = Value Score weight + Severity Rating weight

Here, for Value Score of Green, subtraction keeps the Rank value remains as low as possible, which ensured that the subsequent value conveyed least concern in the ratings. This indicated that the performance was good. This asserted "lower is better" pattern and in a way helped authenticate the model results.

For Issue Management,

If AD Status = Complete or On Track, **Rank** = AD Status weight - Priority Rating weight

Else, **Rank** = AD Status weight + Priority Rating weight

Here, the subtraction holds same significance as that in KRIs.

Combinations

We had multiple decision-making criteria in the form of Risk ratings in both KRIs and Issue Management. We calculated the Rank values for all the possible combinations of the underlying rating parameters.

In KRIs, 3 types of Value Score and 4 types of Severity Ratings gave us 12 combinations. We normalized these values to maintain the relative relevance of numbers throughout for consistency.

Similarly, for Issue Management, 5 types of AD Status and 4 types of Priority Ratings gave us 20 combinations.

These combinations along with the normalized values are listed in the appendix.

Inference from the numbers

Average

Effective use of these Ranks and combinations to assess the overall Area performance was the vital piece of the puzzle. The Fact that data was present at the KRI code/ AD ID level aided the model. We used it to get the aggregate at the Area level in the form of ***Area Average***.

For an Area, for a given Submission month, with *n* KRI Codes/ AD IDs,

Area Average = Σ Rank for *n* KRIs / *n*

Percentiles

Now we had the measure of Area Performance, but we still needed a benchmark for performance assessment. The methodical design ensured that Rank value for every KRI Code/AD ID was found in the underlying 12 and 20 respective parameter combinations.

The measure of performance for Area, the Average was the aggregate of the KRI codes/AD IDs within.

The respective parameter combinations were used to get the performance benchmarks by the virtue of Percentiles.

We considered 10^{th} and 20^{th} Percentile mark such that:

Area Average < 10^{th} Percentile ➔ performance is Good

Area Average between 10^{th} & 20^{th} Percentile ➔ performance is Moderate/Acceptable

Area Average > 20^{th} Percentile ➔ performance is Bad

Methodology

All the above steps are illustrated as workflow below. Meticulous, sequential execution of these steps gave us the desired results.

Data preparation

We used Python for data preparation. The excel files provided by the Santander team were worked upon using Pandas library in Python. Using the AHP weights (calculated using Excel), we performed the various calculations as per the methodology explained above in Python. The remodeled data was exported into Excel files that served as data input to the Tableau Dashboards.

The Python code can be referenced and reused to remodel the data for other risk programs in future implementations as well.

Results

Our goal was to develop a utilitarian solution that was flexible, adaptable, and scalable was met by this methodology. Use of AHP to get the numeric weights for different parameter of Risk ratings ensured that the model remained consistent throughout. The methodology was first developed and tested on the KRIs data. Later, it was successfully adapted to the Issue Management data, which testified for the flexibility, adaptability, and scalability.

Use of Python for data preparation provided handy data export in excel/csv files that served as plug and play input for the Tableau Dashboards.

Even if the number of rating criteria change in future implementations or this model is used for other risk programs, AHP will ensure that the resulting numeric output will remain rational and consistent, thereby aptly capturing the sentiment of the ratings.

The utilitarian results for KRIs and Issue Management were effectively showcased using interactive Tableau dashboard (refer appendix for snapshots).

Recommendations and Future Scope

We recommend using this approach for Risk profile analysis of other risk programs at the bank as the model is scalable and adaptable. The ingenuity of the model will ensure that it is always rational and consistent.

It is possible to incorporate subjectivity at Business Line/Area levels. The Rank calculation can be modelled to favor or ignore certain risk criteria within a Business Line/Area levels in consensus with the domain expertise.

Dynamic percentile benchmarks can be implemented at Business Line/Area levels with the help of domain expertise.

An interesting extension would be quantifying the effect of one risk program on another.

Appendix

Project Proposal

Final Presentation

Snapshot of KRIs data

Snapshot of Issue Management data

Combinations for KRIs

Combinations for Issue Management

Resources referred

Tableau Dashboard snapshots

Santander, Team 2, Capstone Project Proposal for 2020

❖ **Project Title:** SANTANDER BANK: OVERALL RISK PROFILE ANALYSIS AND INDICATORS

❖ **Team Members:**

- Ashwini Agnihotri
- Peter Neal

❖ **Project Company Sponsor Team:**

- Michael Donahue
- Bao Duong

❖ **About Santander:**

Santander Bank, N.A. is one of the country's largest retail and commercial banks with $74.5 billion in assets. With its corporate offices in Boston, the Bank's approximately 9,600 employees, over 600 branches, more than 2,000 ATMs and 2.1 million customers are principally located in Massachusetts, New Hampshire, Connecticut, Rhode Island, New York, New Jersey, Pennsylvania, and Delaware. The Bank is a wholly-owned subsidiary of Madrid-based Banco Santander, S.A. (NYSE: SAN) – one of the most respected banking groups in the world with more than 125 million customers in the U.S., Europe, and Latin America. It is managed by Santander Holdings USA, Inc. (SHUSA), Banco Santander's intermediate holding company in the U.S.

❖ **Project Overview:**

As part of the Operational Risk Management function, Risk Programs like Key Risk Indicators, Material Risk, Risk Control Self-Assessments (RCSA), Issue Management and Event Escalation are managed. The data for above risk programs exists in various disparate, disconnected systems of record. The risk program owners and business line owners assess the overall risk profile for their programs/businesses on at least a monthly basis. Overall risk profile ratings are currently measured subjectively via a cursory review of the various risk program results presented in various reports.

❖ **Project Objectives & Scope:**

- To leverage descriptive analytics to assess the universe of risk program data, with Key risk Indicators and Issue management programs being the priority, by developing a methodology to normalize all risk program data and use a mathematical approach to substantiate the risk profile ratings.

- To develop a flexible, agile, and scalable model/methodology to evaluate overall risk profile rating using analytical applications such as R and Python.
- To design an interactive dashboard in Tableau to incorporate the above model and analysis.

❖ **Project Data & Other Resources:**

Santander Bank has provided us with a comprehensive dataset containing information about KRI type and rating, Escalation Tracker, RCM RCSA and Action Driver – Issues.

❖ **Research/Background Sources:**

The following sample Tableau dashboards elucidate some elements that our final product could incorporate.

https://public.tableau.com/profile/nisoni2701#!/vizhome/CreditRiskMonitoring/Dashboard1

https://public.tableau.com/profile/sathya.sridharan#!/vizhome/KeyPerformanceIndicators_0/KeyPerformanceIndicators

https://public.tableau.com/profile/manas.mohanty#!/vizhome/EnterpriseRisk-RiskRegister/RiskRegister

❖ **Approach/technique to be used:**

We will use R/Python to perform statistical analysis and incorporate predictive analytics methodology to understand the patterns and relationships in the data. Combining the inputs from the Santander team with our comprehension and interpretation of the business, we will analyze the results to get utilitarian descriptive analytics as output, showcased on an interactive Tableau dashboard. The utility of this dashboard would be to track and deliver efficient risk profile analysis information to support and improve decision making specifically around an overall program risk rating.

❖ P**roject Milestone / Proposal Submission Date:**

OCT/NOV 2020	Milestone 1: Meeting with Santander sponsor and exchange on the project Collect the dataset
DEC 2020	Milestone 2: Understanding the data definitions
JAN/FEB 2021	Milestone 3: Explore the data and add more variables aiding the analysis Finalize on model use and get approvals
MAR/APR 2021	Milestone 4: Build data analysis and models Provide drafts of possible solutions Prepare final project presentation
MAY 2021	Milestone 5: Submit all project deliverables with approvals from Sponsor and Faculty Mentor

❖**Responsibilities of each team member:**

Ashwini & Peter: Data exploration and analysis, adding variables aiding the analysis. Build data analysis and models. Prepare project deliverables.

❖ **MSBA faculty mentor:**

Dr. Asil Oztekin

University of Massachusetts Lowell
Master of Science in Business Analytics
Capstone Project

Overall Risk Profile Analysis and Indicators

By: Ashwini Agnihotri & Peter Neal

Faculty Advisor: Dr. Asil Oztekin

Project Sponsors: Ryan Morrissey, Michael Donahue & Bao Duong

Outline

- About Santander
- Project objective
- Data
- Analytical Hierarchy Process (AHP)
- Why AHP?
- AHP weights & Rank, Average and Percentiles
- Methodology
- Tableau Demo
- Recommendations and Future scope

About Santander

- Madrid-based Banco Santander
- Founded in 1857
- Globally respected Banking group

- 16^{th} largest banking institution in the world
- Has 125 million+ customers in the U.S., Europe, and Latin America

- One of the largest commercial and retail banks in the US
- Has $74.5 billion in assets, corporate offices in Boston
- Has over 600 branches and more than 2000 ATMs

- Has approximately 9600 employees
- Serves 2.1 million customers
- Principally located in MA, NH, CT, RI, NY, NJ, PA, DE

Project Objective

Under Operational Risk Management Function various risk programs are managed

KRIs

Issue Management

Material Risk

Data for these programs exists in disparate, disconnected systems

Program owners access the risk ratings by reviewing various reports created subjectively

Use mathematical approach to develop an agile, flexible & scalable methodology to analyze the risk program data with focus on KRIs and IM

Data for KRIs

Submission Month	KRI Code	Value Score	Unit	Frequency	Area Name	Risk Type	Severity Rating
Jun-2020	CI28824	Green	Percentage	Monthly	Analytics & Decision Science	Compliance	High
Jul-2020	CI28824	Green	Percentage	Monthly	Analytics & Decision Science	Compliance	High
Aug-2020	CI28824	Green	Percentage	Monthly	Analytics & Decision Science	Compliance	High
Sep-2020	CI28824	Green	Percentage	Monthly	Analytics & Decision Science	Compliance	High
Oct-2020	CI28824	Green	Percentage	Monthly	Analytics & Decision Science	Compliance	High

NO NUMERIC/QUANTIFIABLE DATA

JAN 2018-OCT 2020
SUBMISSION MONTH

253
KRI CODE

3
VALUE SCORE

13
AREA NAME

4
SEVERITY RATING

Data for Issue Management

AD Due Date by Month	Area	Department	AD ID	AD Target Due Date	AD Status	Priority Rating	Resolution Status	Current Target Date	Number of MA	Date of Creation	Products	Regulatory Hashtags	Vendor	Application	Issues opened by Month	Issues Closed/Abandoned by Month
Apr-21	Business Banking	NaN	005056A0614D1EDB85F8030A82F98364	2021-04-01	On Track	Moderate	Remediate	2021-04-01	1.0	2020-10-26	No	Yes	No	No	Oct-20	NaN
Complete	Consumer Lending	Home Loans	005056A0614D1ED8BCBBD2D9FAE5230B	2019-08-30	Complete	Moderate	Remediate	2019-08-30	4.0	2018-11-27	Yes	Yes	No	No	Created 13 Months Ago	Closed 13 Months Ago
Complete	Consumer Lending	Home Loans	005056A0614D1EDA96B3BDE076BEE563	2020-04-30	Complete	Moderate	Remediate	2020-04-30	1.0	2020-02-27	Yes	Yes	Yes	Yes	Feb-20	Apr-20
Complete	Operations	Payments	005056A0614D1EE8AEBF72AD6B4A0EED	2020-12-31	Complete	Moderate	Remediate	2020-12-31	1.0	2018-09-16	Yes	No	No	Yes	Created 13 Months Ago	Dec-20
Complete	FLOD & Bus. Controls	NaN	005056A008D11EDAA3DA9DCAF13A707E	2020-11-30	Complete	Low	Remediate	2020-11-30	3.0	2020-05-05	Yes	No	No	No	May-20	Dec-20

NO NUMERIC OR QUANTIFIABLE DATA

3187
AD ID

12
AREA NAME

5
AD STATUS

4
PRIORITY RATING

NOV 2017- JAN 2021
DATE OF CREATION

Analytical Hierarchy Process (AHP)

- AHP was developed by Thomas L Saaty in 1970s
- Structure technique to organize, analyze complex decisions
- Based on Mathematics, Qualitative judgement and Quantitative analysis
- Uses a specially designed questionnaire to get the quantified weights of decision criteria
- Considers the relative relevance of each parameter to compute the numeric weightage

Why AHP?

No Numeric or Quantifiable data

Multiple decision criteria for risk analysis in all risk programs

Relative relevance of every parameter is maintained in numeric weights

Adaptable to other risk verticals as well

Structured technique that can be replicated

AHP weights & Rank for KRIs

For Issue Management, Rank = AD -/+ PR

12 combinations

Value Score

Green	0.16
Amber	0.32
Red	0.52

Severity Rating

Critical	0.43
High	0.32
Moderate	0.18
Negligible	0.08

12 Combinations

Green_Moderate	0.02	0.003384
Green_Negligible	0.08	0.013536
Green_High	0.16	0.027073
Green_Critical	0.27	0.045685
Amber_Negligible	0.40	0.067682
Amber_Moderate	0.50	0.084602
Red_Negligible	0.60	0.101523
Amber_High	0.64	0.108291
Red_Moderate	0.70	0.118443
Amber_Critical	0.75	0.126904
Red_High	0.84	0.142132
Red_Critical	0.95	0.160745

Average and Percentile

Average

Area

Submission Month

n KRIs

Avg. = Σ Ranks of all *n* KRIs / *n*

Percentile

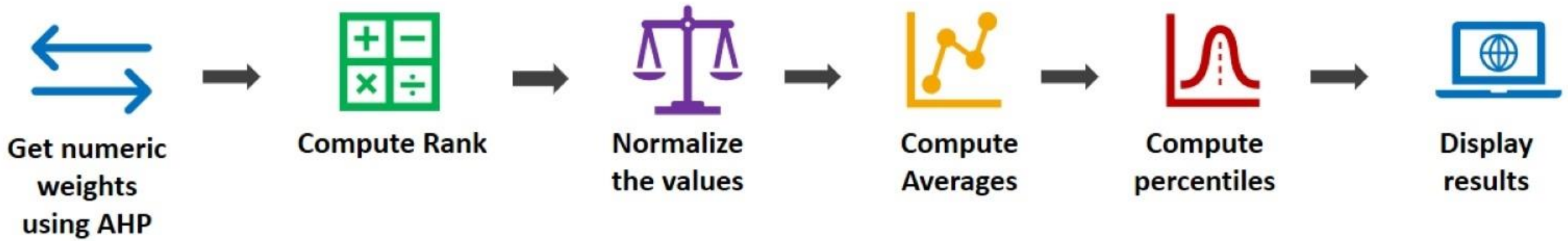
12 combinations

Avg. < 10th Percentile

10th Percentile < Avg. < 20th Percentile

Avg. > 20th Percentile

Methodology



Overall Risk Profile Analysis and Indicators - KRIs

Santander I AM Risk • Identify • Assess • Manage • Report

0.01489
10th Percentile

Value
Between 10th & 20th Percentile

0.03079
20th Percentile

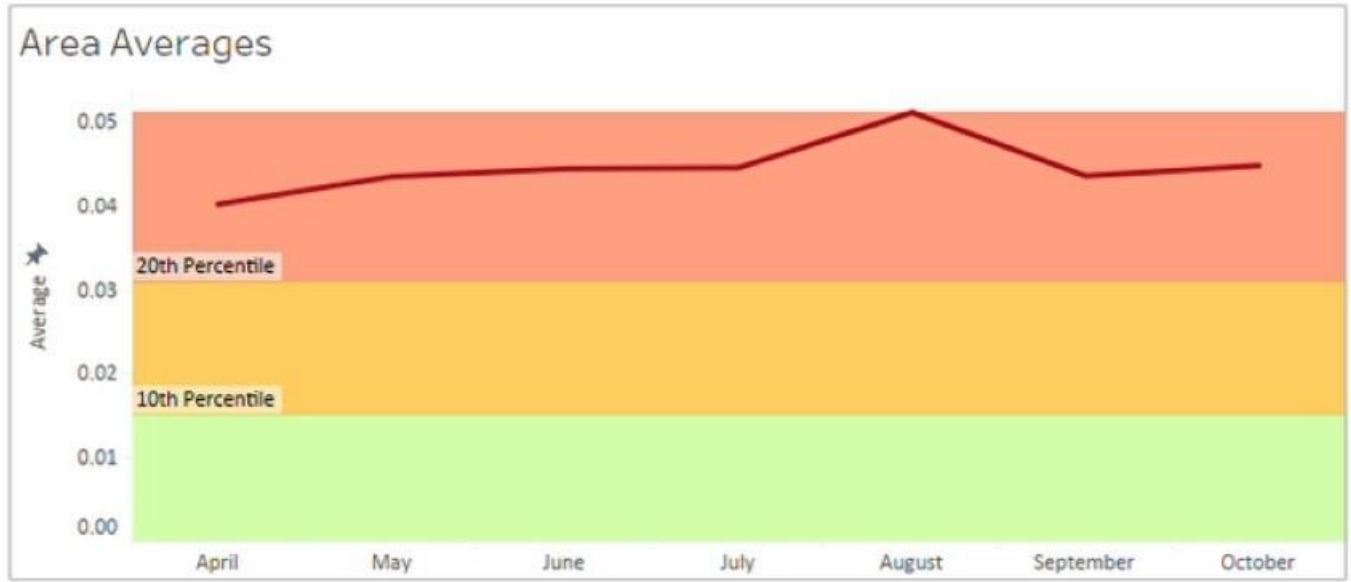
Month: October 2020

Area Name: Home Loans

0.04482	0.04360	-0.00122
Current Avg.	Prev. Avg.	Change

PROCESS FLOW

- Using AHP, get numeric weights
  for Value Score (VS) & Severity Rating (SR)
- Compute Rank
  For Value Score = Green
  Rank = VS – SR Else, Rank = VS + SR
- Normalize the values
  to maintain relative relevance
- Compute Averages
- Compute Percentiles
  to access the performance



KRI_sev_counts | KRI_counts | KRI_avg | KRIs | IM | Curr.Avg | Prev.Avg | Change | IM_Priority | IM_counts | IM_Avg | Curr. Avg. IM | Prev. Avg. IM | Change IM | Capstone_KRI_IM

Recommendations and Future scope

- Applying this methodology to other Risk programs at the Bank
- Incorporate subjectivity at Business Line level
- Quantify how each risk program affects others
- Dynamic percentiles for performance assessment

Thank You!

Snapshot of KRIs data

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Snapshot of Issue Management data

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Combinations for KRIs

Value Score

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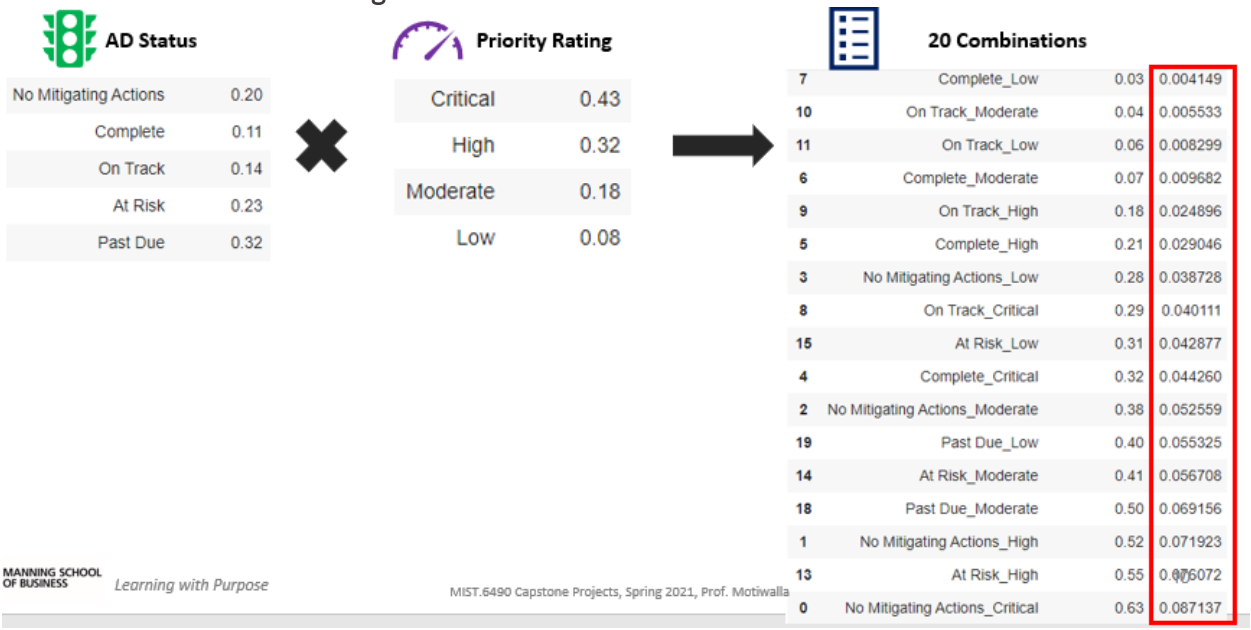
Red_Critical	0.95	0.160745

Combinations for Issue Management



AD Status

No Mitigating Actions	0.20
Complete	0.11
On Track	0.14
At Risk	0.23
Past Due	0.32

Priority Rating

Critical	0.43
High	0.32
Moderate	0.18
Low	0.08

20 Combinations

7	Complete_Low	0.03	0.004149
10	On Track_Moderate	0.04	0.005533
11	On Track_Low	0.06	0.008299
6	Complete_Moderate	0.07	0.009682
9	On Track_High	0.18	0.024896
5	Complete_High	0.21	0.029046
3	No Mitigating Actions_Low	0.28	0.038728
8	On Track_Critical	0.29	0.040111
15	At Risk_Low	0.31	0.042877
4	Complete_Critical	0.32	0.044260
2	No Mitigating Actions_Moderate	0.38	0.052559
19	Past Due_Low	0.40	0.055325
14	At Risk_Moderate	0.41	0.056708
18	Past Due_Moderate	0.50	0.069156
1	No Mitigating Actions_High	0.52	0.071923
13	At Risk_High	0.55	0.076072
0	No Mitigating Actions_Critical	0.63	0.087137

Resources referred

https://en.wikipedia.org/wiki/Analytic_hierarchy_process

https://www.arpnjournals.org/jeas/research_papers/rp_2016/jeas_0616_4416.pdf

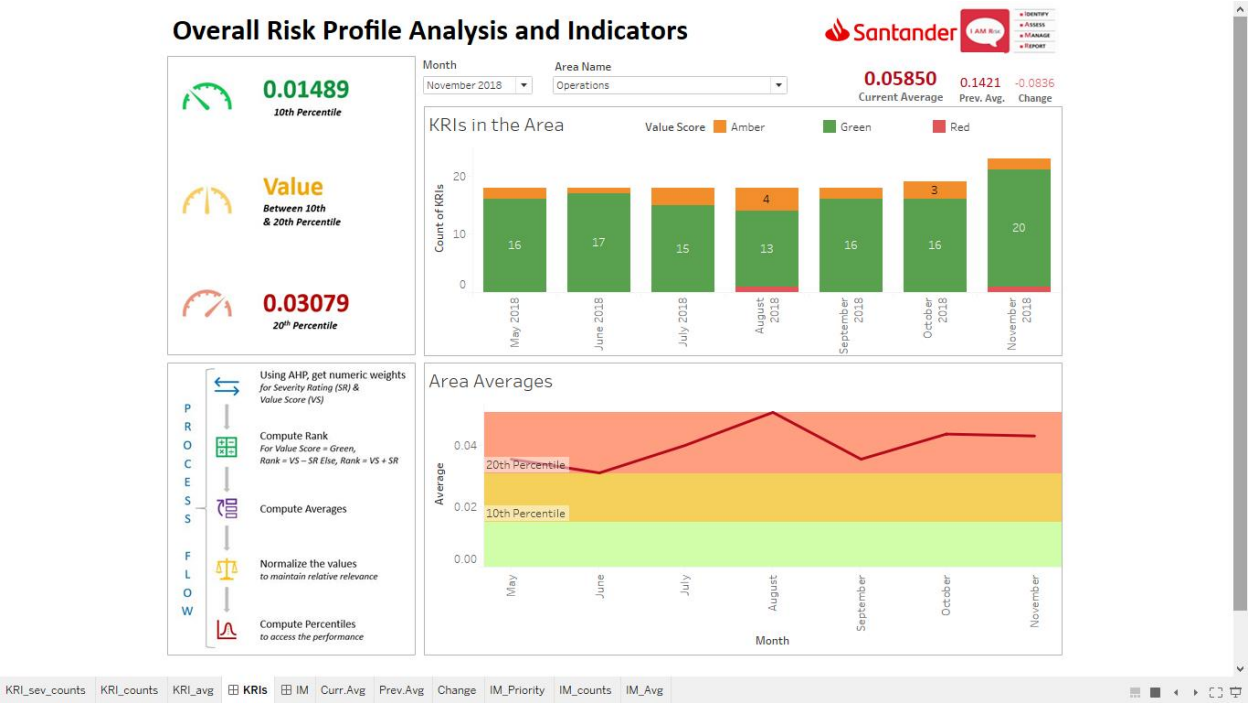
https://training.fws.gov/courses/references/tutorials/geospatial/CSP7306/Readings/AHP-Technique.pdf

https://www.youtube.com/watch?v=J4T70o8gjlk

https://www.hindawi.com/journals/ads/2016/8963214/

Tableau Dashboard snapshots

KRI Tab



Issue Management