UNCOVERING RETAIL CUSTOMER SEGMENTATION FROM LARGE TRANSACTION RECORDS

A NUANCED COMPARISON OF CLUSTERING ALGORITHMS
USING ROUGH SET REDUCED DATASET

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PROBLEM STATEMENT

Traditional clustering methods does not take into account inherent inconsistencies in data, hence the need to explore and compare alternative clustering algorithms



TRADITIONAL K-MEANS

Clustering Comparison



FUZZY
K-MEANS

Clustering Comparison



GAUSSIAN
MIXTURE MODEL

Clustering Comparison



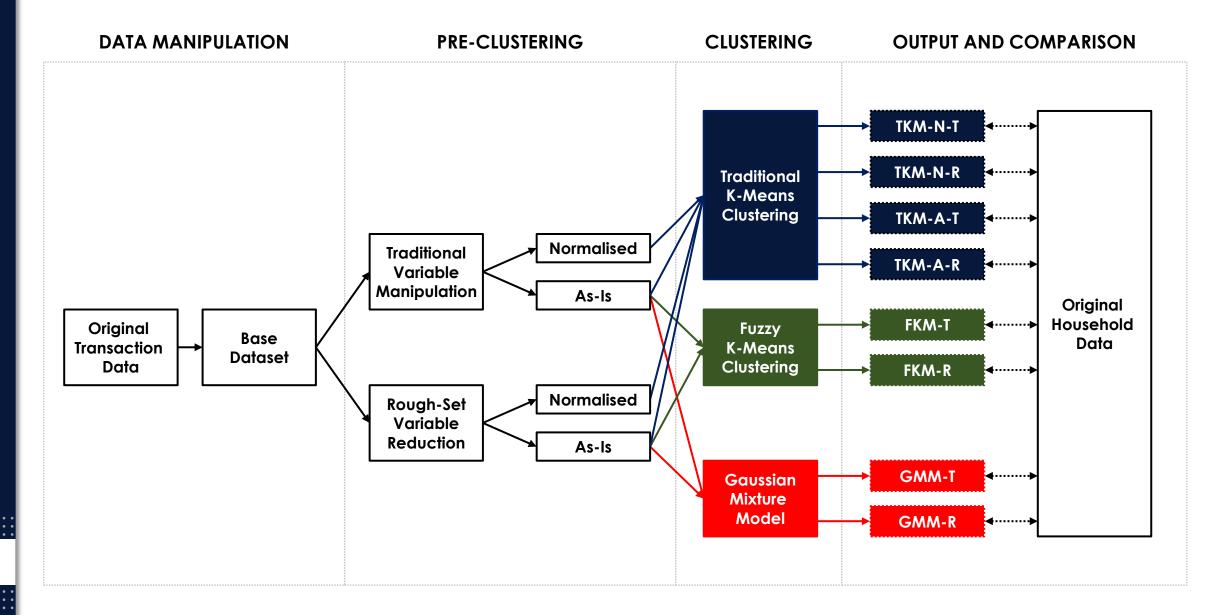
ROUGH SET

Feature Reduction

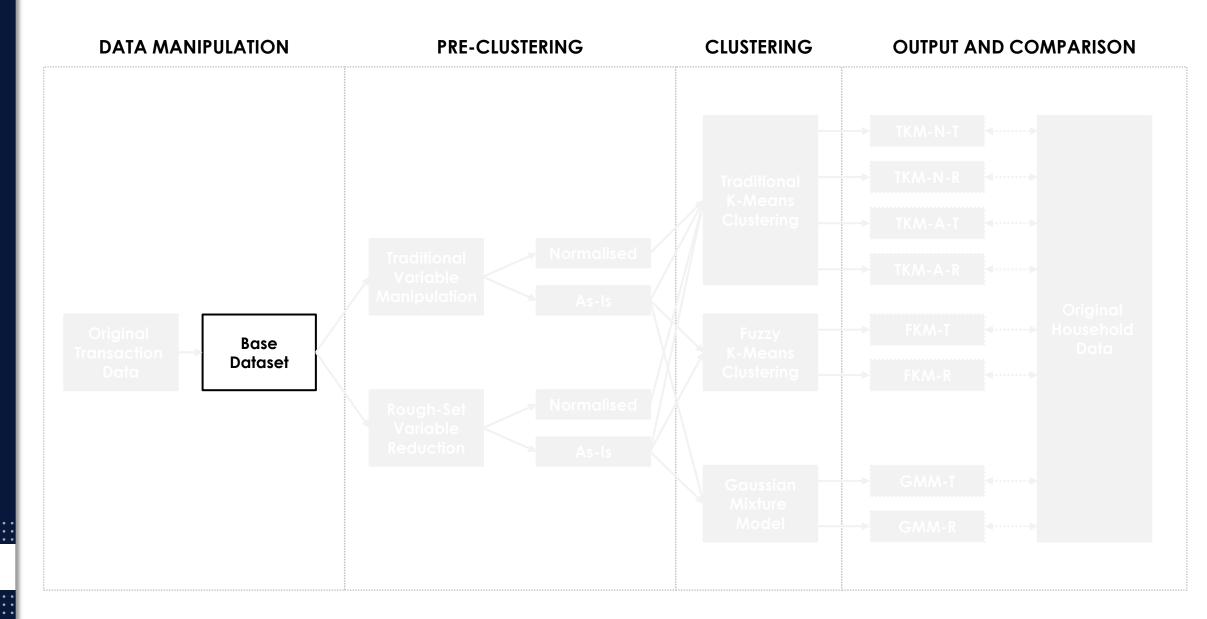
OPEN-SOURCE INTEGRATION (R)

SAS ENTERPRISE MINER 14.1





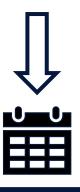






BASE DATASET (RFM MODEL INSPIRED)

DUNNHUMBY'S RETAIL SHOPPING DATASET (TXNS)







RECENCY

(How long ago were their purchase?)

- Days Since First Order
- Days Since Last Order

FREQUENCY

(How often were the purchases made?)

- Active Weekday Count
- Active Weekend Count
- Active Morning $(6 \le x < 12)$ Count
- Active Afternoon (12 ≤ x < 18) Count
- Active Evening (18 ≤ x < 0) Count
- Active Late-Night (0 ≤ x < 6) Count
- Average Basket Count Per Active Weekday
- Average Basket Count Per Active Weekend
- Average Basket Count Per Active Morning
- Average Basket Count Per Active Afternoon
- Average Basket Count Per Active Evening
- Average Basket Count Per Active Late-Night

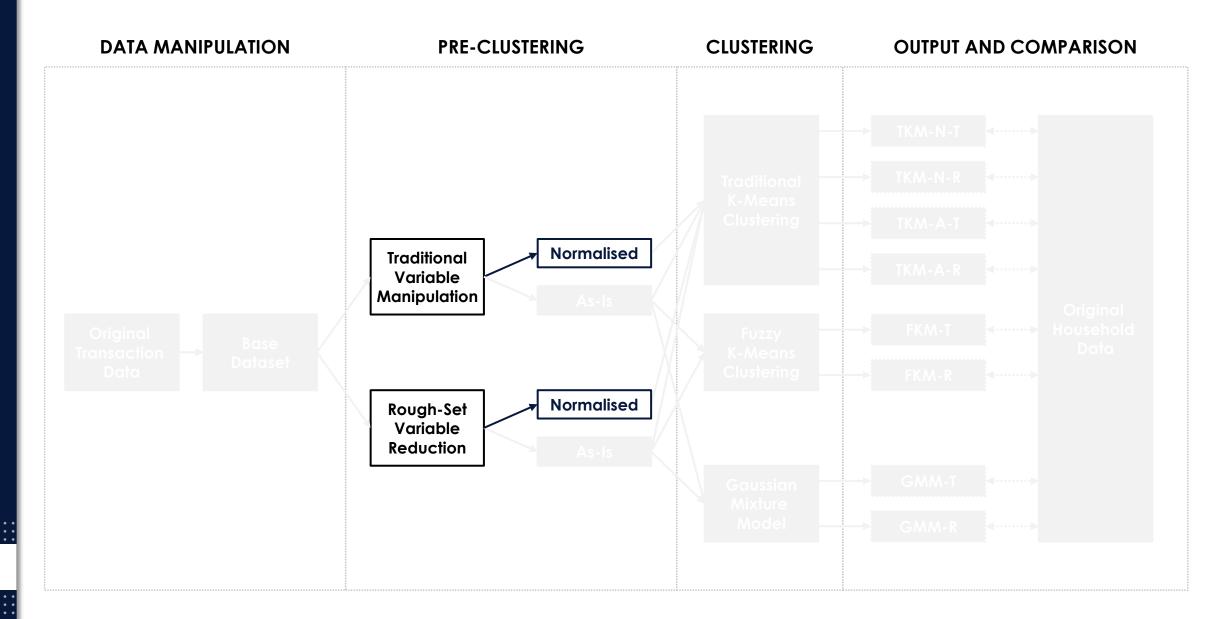
MONETARY

(How much money was spent?)

- Total Spend
- Min Spend Per Basket
- Average Spend Per Basket
- Max Spend Per Basket
- Average Sales Value Per Qty
- Min Spend Per Active Week
- Average Spend Per Active Week
- Max Spend Per Active Week
- Average Spend Per Active Morning
- Average Spend Per Active Afternoon
- Average Spend Per Active Evening
- Average Spend Per Active Late Night
- Discount Used Per Active Weekday
- Discount Used Per Active Weekend









PRE-CLUSTERING

Traditional Variable Manipulation

28
Base Dataset
Variables



16 Non-Collinear Variables



16
Normalised
Non-Collinear
Variables



16
Normalised
& Scaled
Non-Collinear
Variables

Rough-Set Variable Reduction

28
Base Dataset
Variables



2 & 3 Reduct Variables



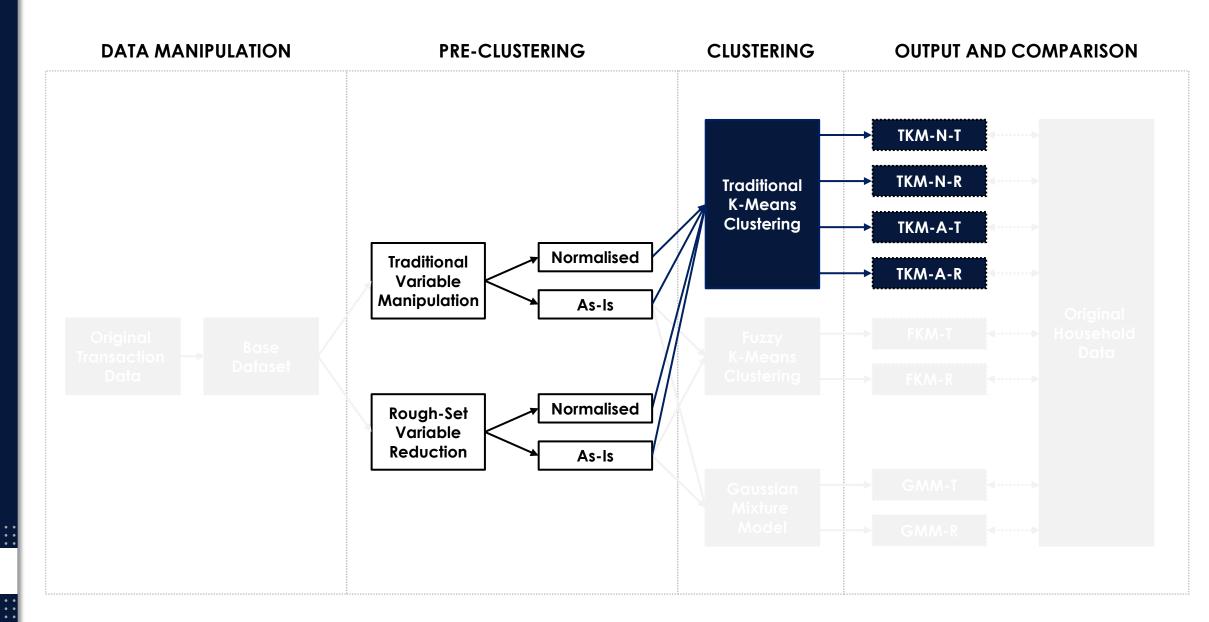
2 & 3
Normalised
Reduct
Variables



2 & 3
Normalised
& Scaled
Reduct
Variables

10







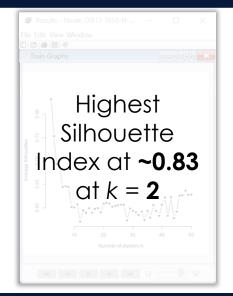
ANALYSIS & RESULTS (TRAD. K-MEANS)

TKM-N-T



Average Silhouette Index (k = 2 to 50)

TKM-N-R



TKM-N-R3



TKM-A-T



Average Silhouette Index (k = 2 to 50)

TKM-A-R

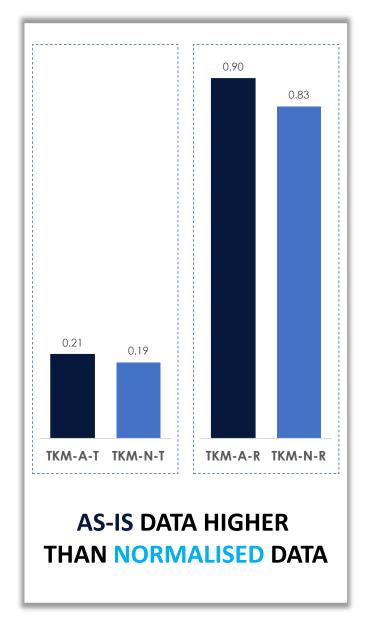


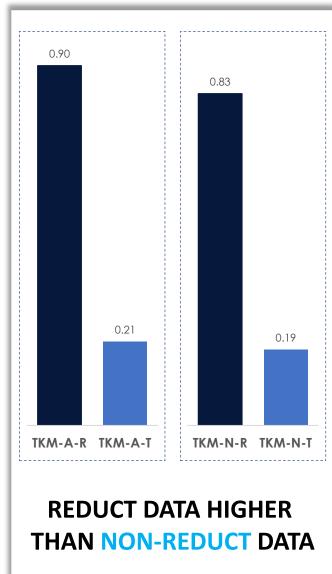
TKM-A-R3

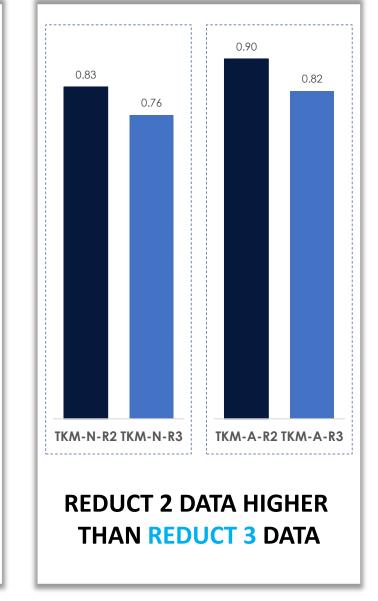




SILHOUETTE COMPARISON (TRAD. K-MEANS)



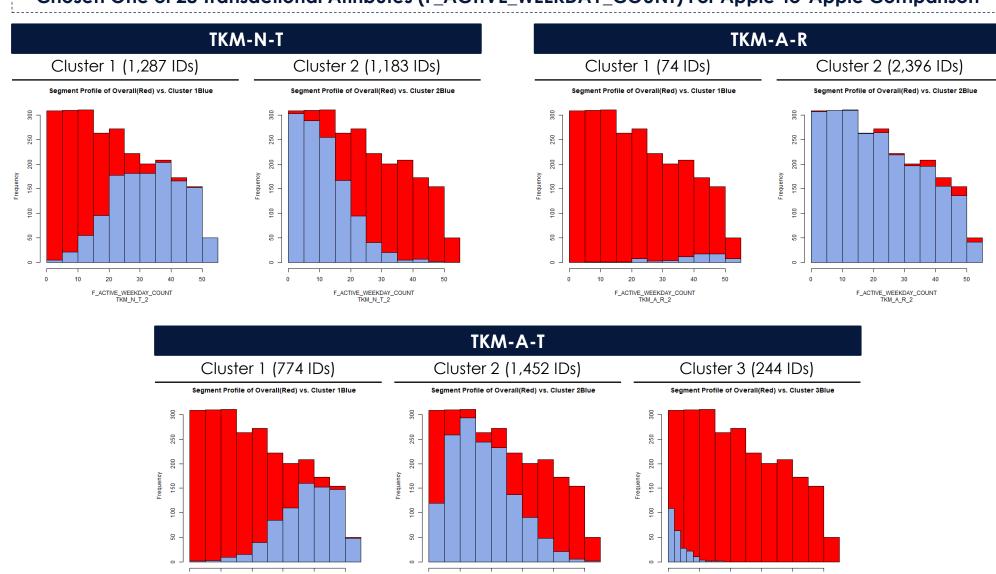






CLUSTER COMPARISON (TRAD. K-MEANS)

Chosen One of 28 Transactional Attributes (F_ACTIVE_WEEKDAY_COUNT) For Apple-to-Apple Comparison



20

30

F_ACTIVE_WEEKDAY_COUNT TKM_A_T_3 30

F_ACTIVE_WEEKDAY_COUNT TKM_A_T_3

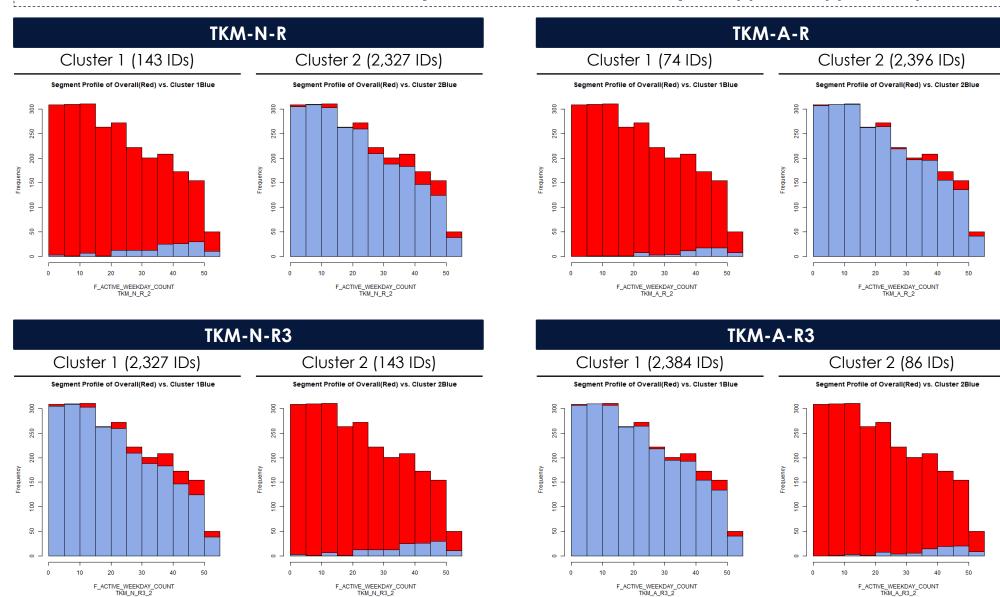
30

F_ACTIVE_WEEKDAY_COUNT TKM_A_T_3

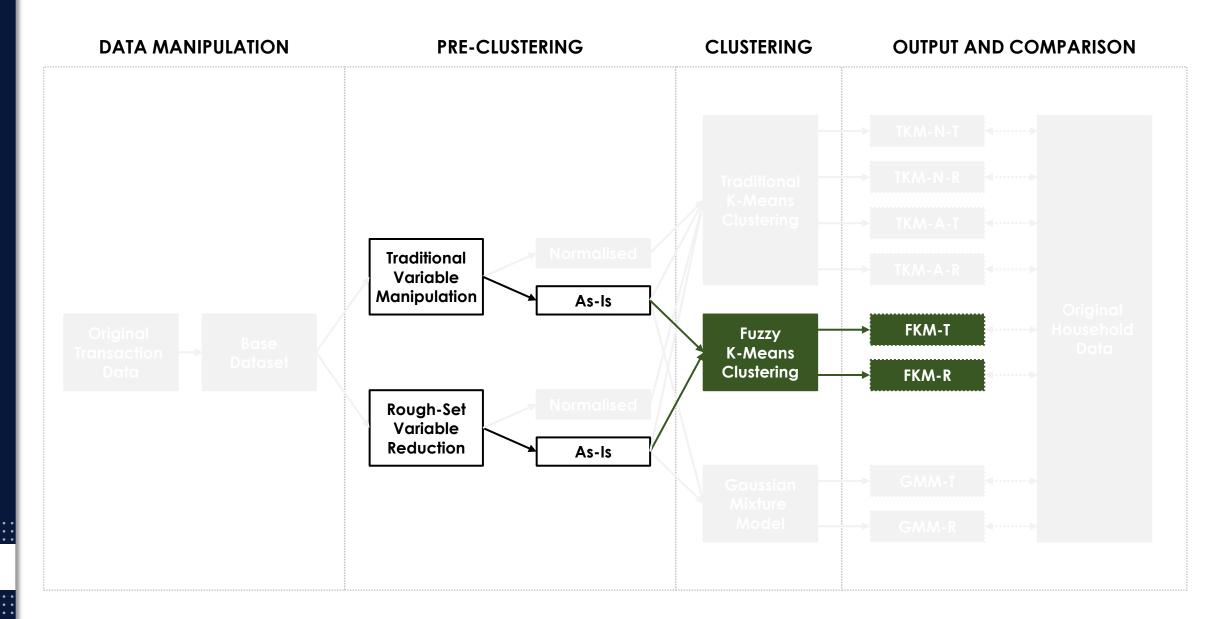


CLUSTER COMPARISON (TRAD. K-MEANS)

Chosen One of 28 Transactional Attributes (F_ACTIVE_WEEKDAY_COUNT) For Apple-to-Apple Comparison









ANALYSIS & RESULTS (FUZZY K-MEANS)

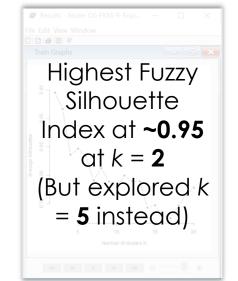
FKM-T



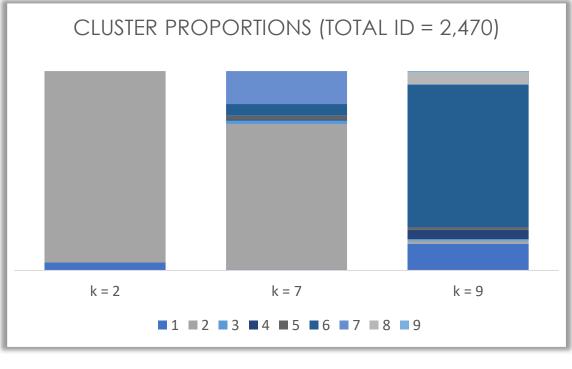
Average Silhouette Index (k = 2 to 20)



FKM-R3



FKM-R had the highest silhouette index values amongst TKM and FKM. Possibility of exploring other cluster counts than just the one with the highest silhouette value

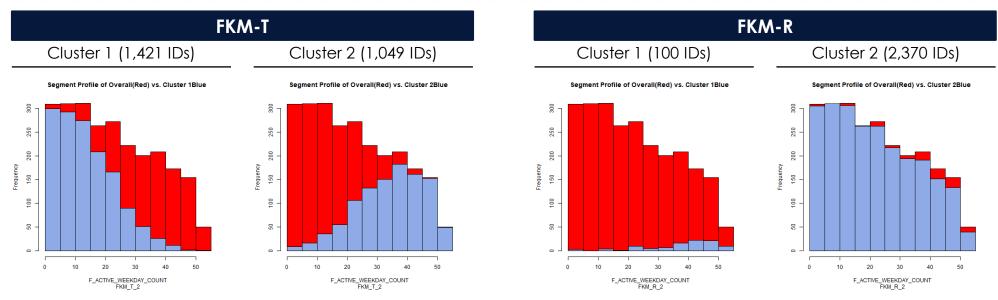


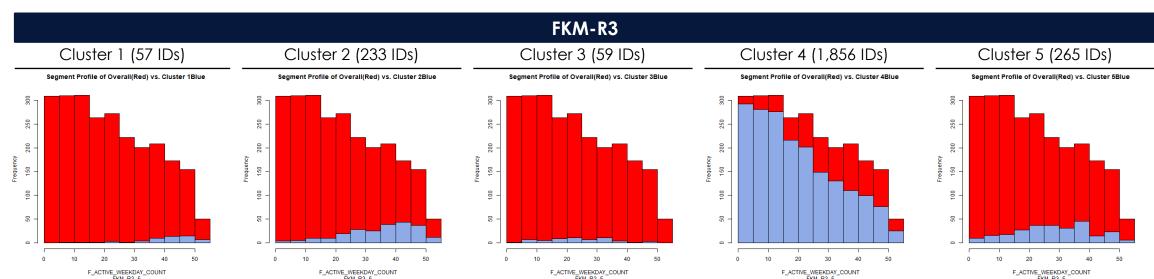
Highly uneven distribution, despite the high silhouette values



CLUSTER COMPARISON (FUZZY K-MEANS)

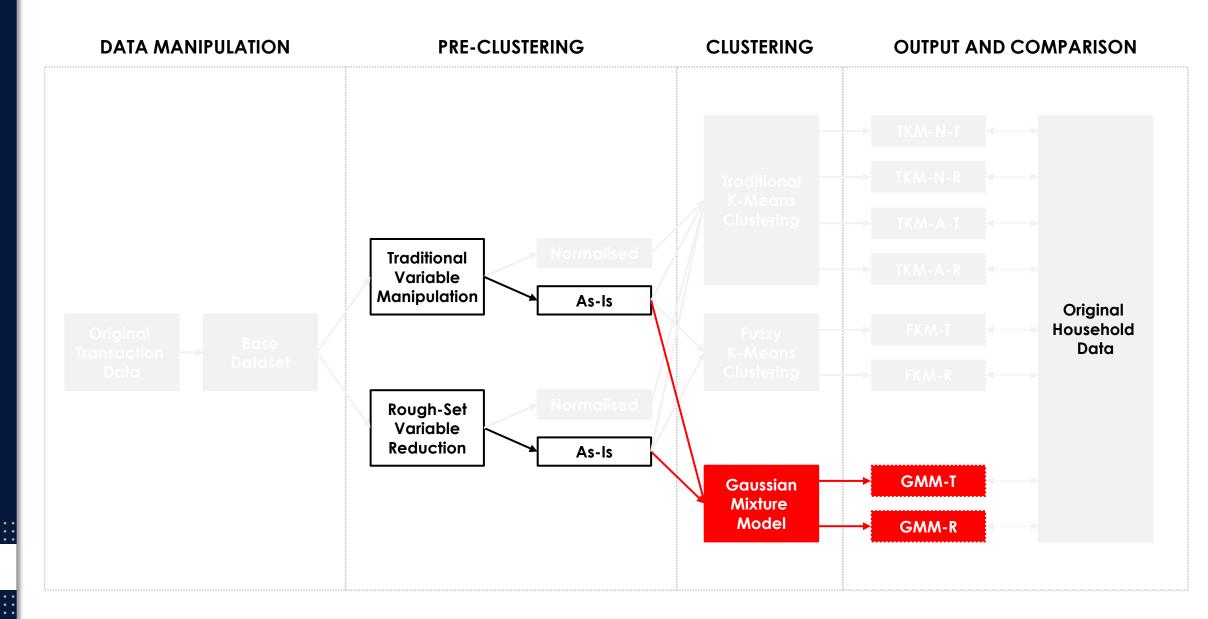
Chosen One of 28 Transactional Attributes (F_ACTIVE_WEEKDAY_COUNT) For Apple-to-Apple Comparison





18





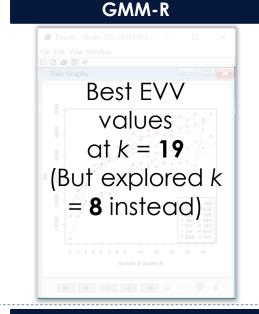


ANALYSIS & RESULTS (GAUSSIAN)

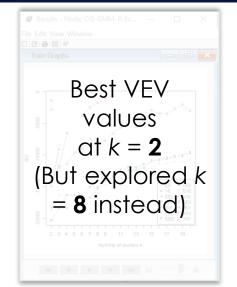
GMM-T



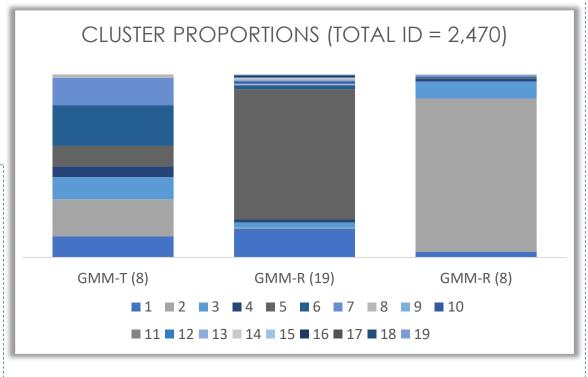
Average Silhouette Index (k = 2 to 20)



GMM-R3



GMM-R had optimal cluster count of 19, but it is too granular. Though sub-optimal, capstone super-imposed *k*=8 onto GMM-R

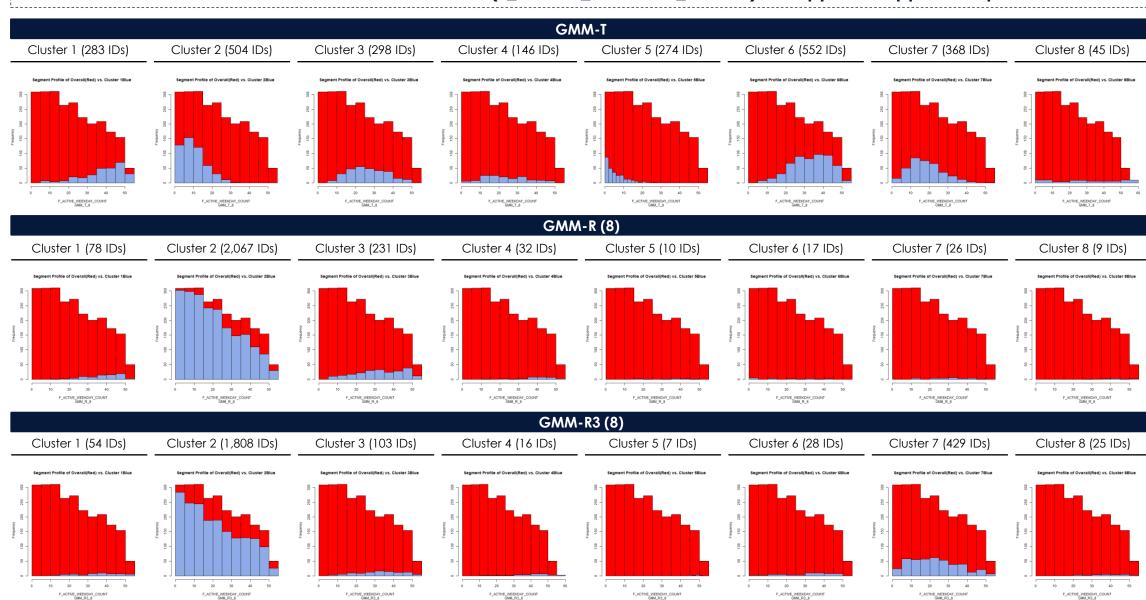


Reduct dataset had highly uneven distribution



CLUSTER COMPARISON (GAUSSIAN)

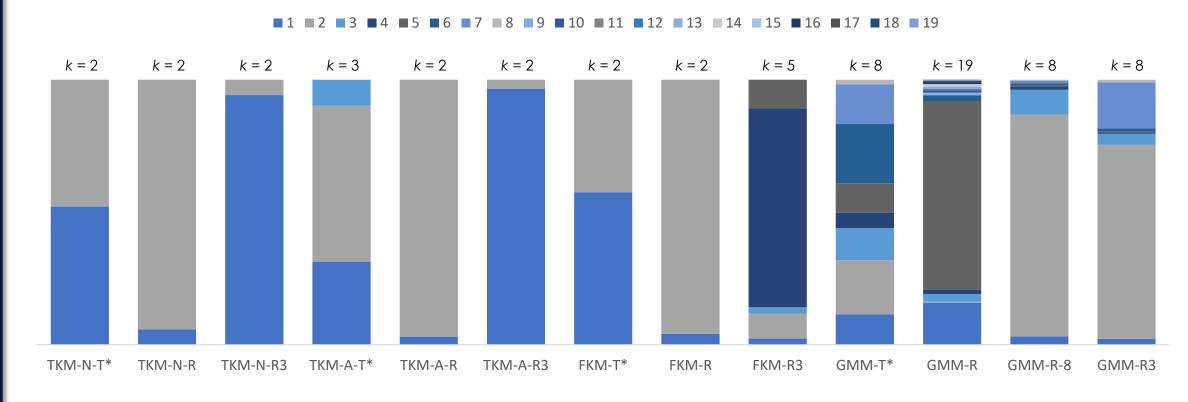
Chosen One of 28 Transactional Attributes (F_ACTIVE_WEEKDAY_COUNT) For Apple-to-Apple Comparison





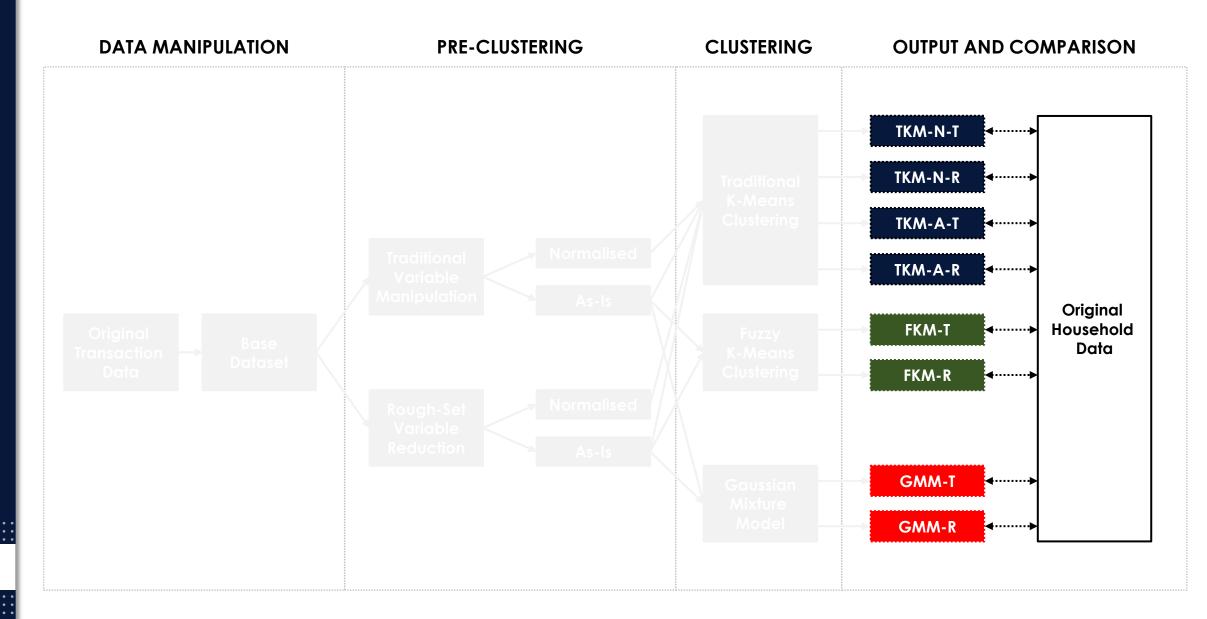
ANALYSIS & RESULTS (OVERVIEW)

CLUSTER PROPORTIONS (TOTAL ID = 2,470)



- Optimised Cluster Counts Were Higher For GMM Than Other Clustering Algos (TKM And FKM)
- Non-Reduct Data* Had More Evenly Spread Cluster Proportions Than Reduct Data
- Little Clustering
 Difference Between
 Reduct-2 and Reduct-3
 Dataset

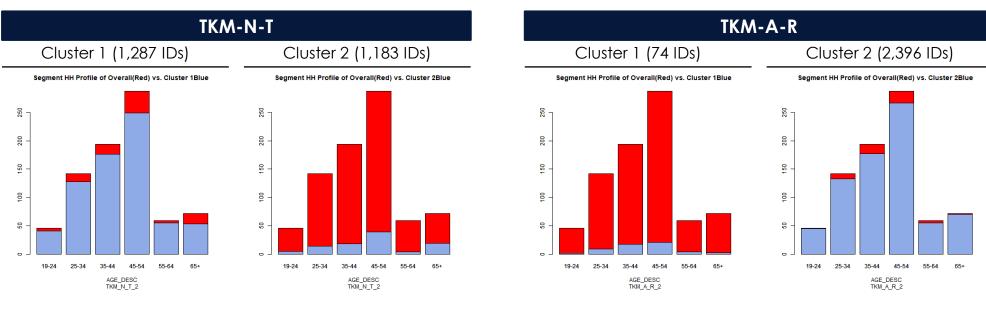


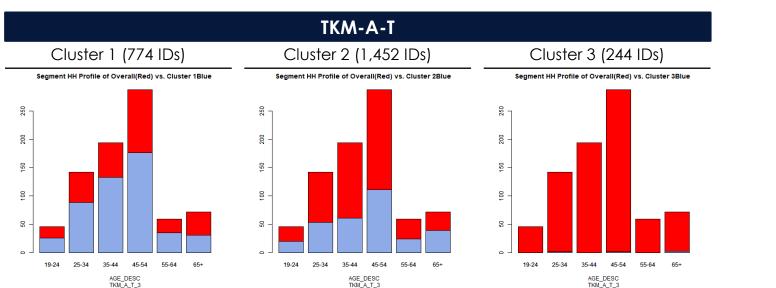




CLUSTER COMPARISON (TRAD. K-MEANS)

Chosen One of 6 Demographic Attributes (AGE_DESC) For Apple-to-Apple Comparison

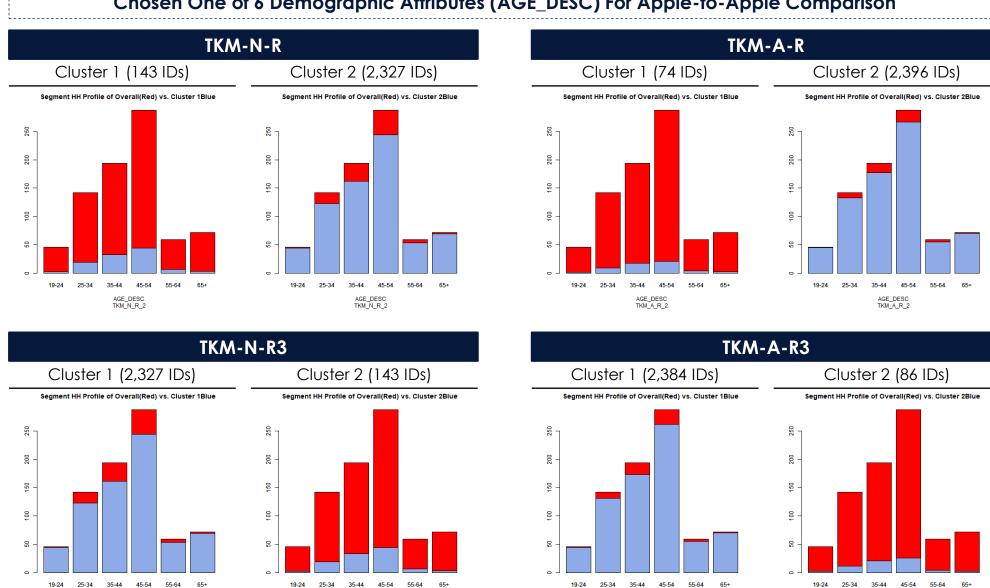






CLUSTER COMPARISON (TRAD. K-MEANS)

Chosen One of 6 Demographic Attributes (AGE_DESC) For Apple-to-Apple Comparison



19-24 25-34

35-44

35-44

45-54 AGE_DESC TKM_A_R3_2

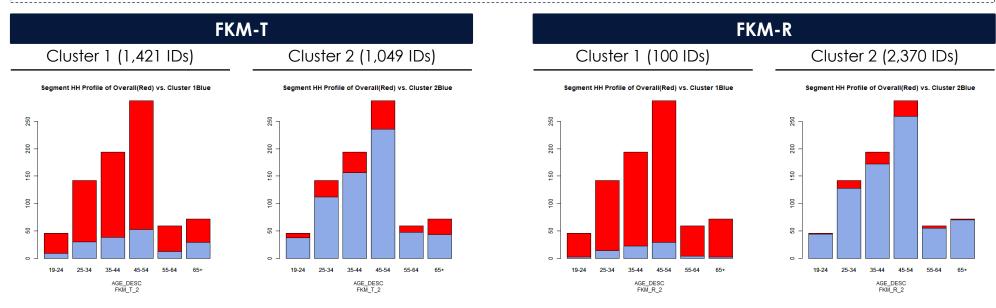
35-44

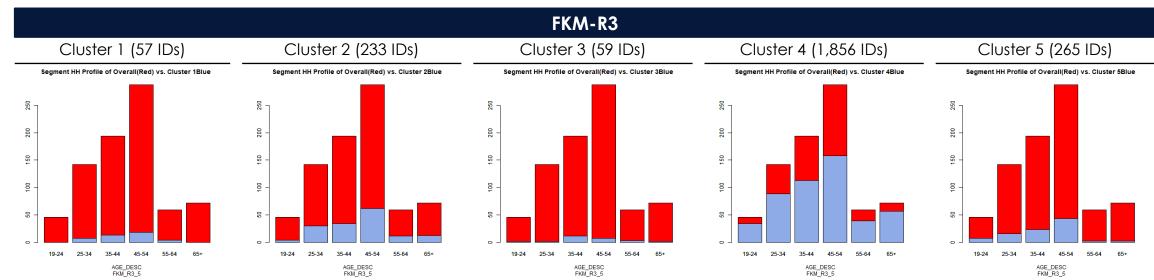
45-54



CLUSTER COMPARISON (FUZZY K-MEANS)

Chosen One of 6 Demographic Attributes (AGE_DESC) For Apple-to-Apple Comparison

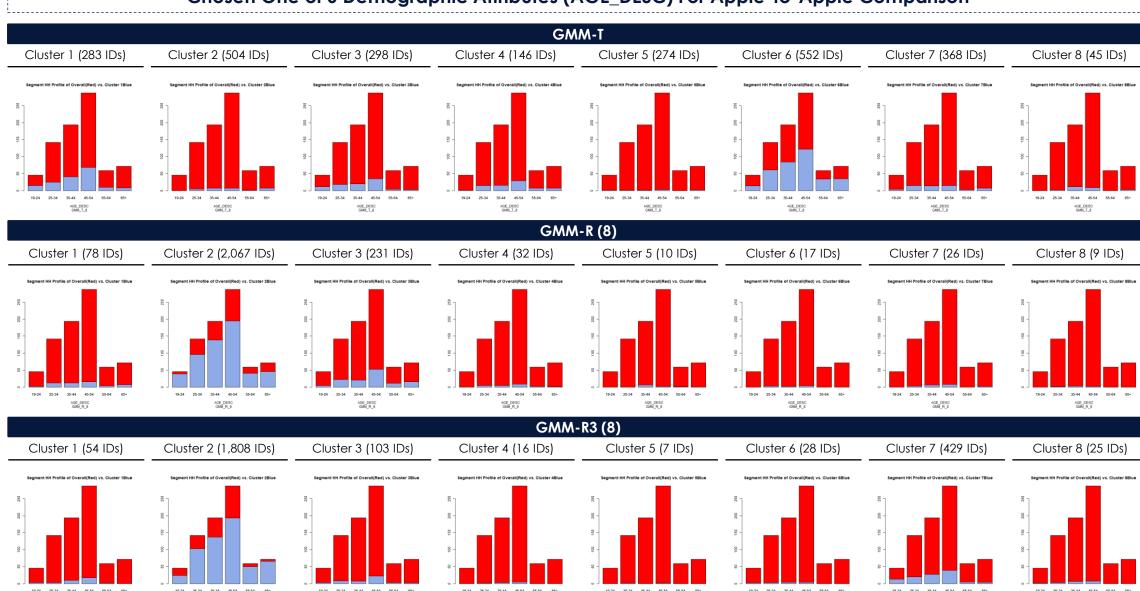






CLUSTER COMPARISON (GAUSSIAN)

Chosen One of 6 Demographic Attributes (AGE_DESC) For Apple-to-Apple Comparison



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IN SUMMARY

Data Type	Traditional k-means (TKM)	Fuzzy k-means (FKM)	Gaussian Mixture Model (GMM)
Non-Reduct Dataset	 Similar output to FKM Low optimal cluster counts of 2 and 3 Even distribution Distinct cluster traits (transactional) Distinct cluster traits (demographic) 	 Similar output to TKM Low optimal cluster count of 2 Even distribution Distinct cluster traits (transactional) Distinct cluster traits (demographic) 	 High optimal cluster counts of 8 Even distribution Somewhat distinct cluster traits (transactional) Somewhat distinct cluster traits (demographic)
Reduct Dataset	 Low optimal cluster count of 2 Uneven distribution Highly distinct cluster traits (transactional) Distinct cluster traits (demographic) Little difference seen between reduct-2 and reduct-3 	 Low optimal cluster count of 2 Uneven distribution Highly distinct cluster traits (transactional) Distinct cluster traits (demographic) Reduct-3 had more similar cluster traits than reduct-2 	 High optimal cluster counts of 19 Uneven distribution Similar cluster traits (transactional) for k = 8 Similar cluster traits (demographic) Little difference seen between reduct-2 and reduct-3



DISCUSSION



DISTINCTIVE REDUCT DATASET

Rough Set's feature reduction generated more distinctive cluster attributes



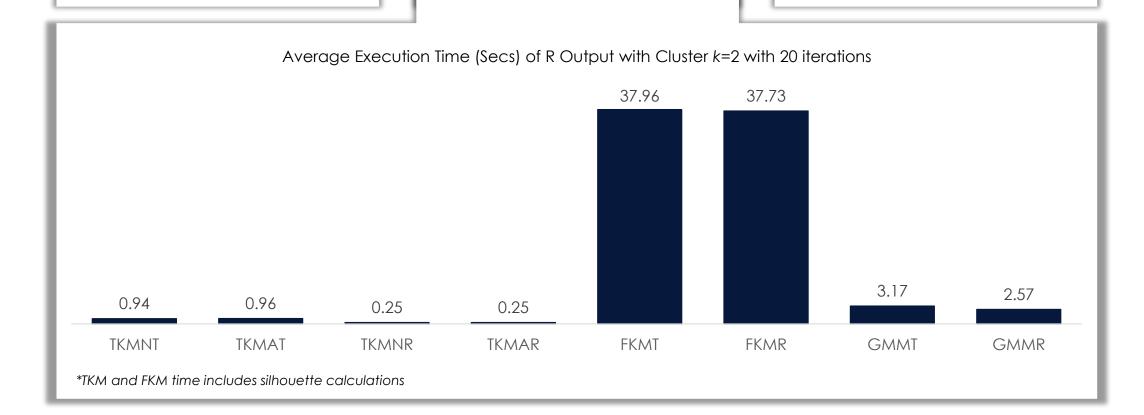
SLOWER SOFT CLUSTERING

Slower processing speed observed for FKM and GMM than TKM



HIGHER $k \neq BETTER$ & CLEAR CLUSTERS

Higher cluster counts (k>2)does not necessarily show distinctive clusters





CONCLUSION & CONTRIBUTIONS

USEFUL ADDITIONS TO A DATA ANALYST'S TOOLBOX



TRADITIONAL K-MEANS

Clustering Comparison



GAUSSIAN
MIXTURE MODEL

Clustering Comparison



FUZZY *K*-MEANS

Clustering Comparison



ROUGH SET

Feature Reduction

FUTURE WORK

- Exploring other Rough Set reduct method
 - Capstone used global discernibility
 - Available methods include local discernibility, quick reduct.rst and quick reduct.frst
- Explore use of Rough Set reduct on both pre and post clustering
 - Capstone used reduct pre clustering
 - Other journals used reduct post clustering to distil significant attributes for each cluster

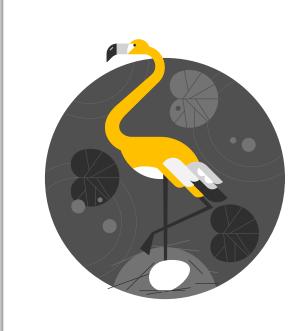


MILESTONES & REFLECTIONS



NEVER UNDER-ESTIMATE CAPSTONE RIGOUR

Taking additional courses would've sufficed as MITB course requirements, but capstone opportunity proved invaluable



JOURNEY BEGINS WITH THE FIRST STEP

Initially fuzzy; Gained clarity at every step; Where clarity was at its best, scale of work seemed daunting



SUSTAINABLE SAS & R INTEGRATION

R packages complements existing SAS environment. Challenge is to make it sustainable, amidst compatibility concerns

THANK YOU

FOR THE OPPORTUNITY!





