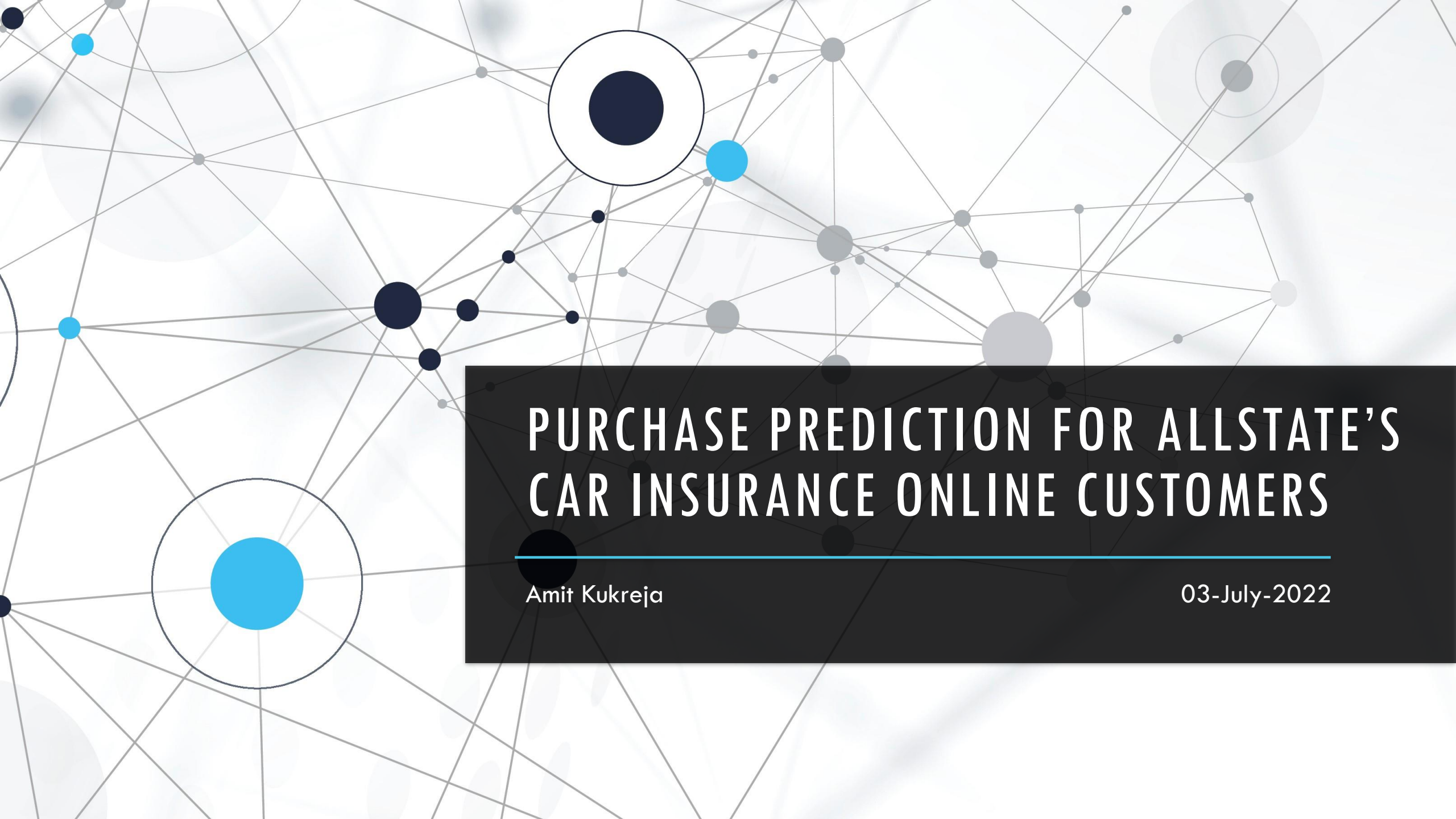


PURCHASE PREDICTION FOR ALLSTATE'S CAR INSURANCE ONLINE CUSTOMERS

Amit Kukreja

03-July-2022

Problem Statement: Develop a predictive model to predict the coverage plan that Allstate's online customer would eventually buy.

Context : AllState's online customer's make changes to product features (vectors) to generate multiple quotes. Each revision increases the probability of losing the customer. If the eventual purchase can predict sooner, the quoting process is shortened and Allstate is more likely to get the customer's business.

Criteria for Success: A model that can accurately predict customer's final vector choices early in the shopping window.

Scope: The model shall be developed based on data of approx. 97,000 customers provided by Allstate.

Constraints: The predictive power of the model would be limited by:
- Non-availability of data on competitive products
- Lack of important customer parameters like household income, car model and driving history.

Stakeholders to provide Key Insight:
1) Ben Bell – Springboard Mentor

Data Sources: Dataset of 97,000 customers provided by Allstate on Kaggle

https://www.kaggle.com/c/allstate-purchase-prediction-challenge/data

DATA WRANGLING

1. CONVERTED THE TRAINING DATASET FROM **LONG FORM** TO A **WIDE FORM**

- Training data had **665,249** observations for **97,009 unique customers.**
- Each row had quote details of a customer
- Converted this to wide form, each row containing entire purchase history of the customer

	customer_ID	shopping_pt	record_type	day	time	state	location	group_size	homeowner	car_age	.
0	10000000	1	0	0	08:35	IN	10001	2	0	2	.
1	10000000	2	0	0	08:38	IN	10001	2	0	2	.
2	10000000	3	0	0	08:38	IN	10001	2	0	2	.
3	10000000	4	0	0	08:39	IN	10001	2	0	2	.
4	10000000	5	0	0	11:55	IN	10001	2	0	2	.
5	10000000	6	0	0	11:57	IN	10001	2	0	2	.
6	10000000	7	0	0	11:58	IN	10001	2	0	2	.
7	10000000	8	0	0	12:03	IN	10001	2	0	2	.
8	10000000	9	1	0	12:07	IN	10001	2	0	2	.
9	10000005	1	0	3	08:56	NY	10006	1	0	10	.
10	10000005	2	0	3	08:56	NY	10006	1	0	10	.

A customer across multiple rows (**each observation is a QUOTE**)

	customer_ID	shopping_pt	record_type	day	time	state	location	group_size	homeowner	car_age	...	C_p
0	10000000	9	1	0	12:07	IN	10001	2	0	2	...	
1	10000005	6	1	3	09:09	NY	10006	1	0	10	...	
2	10000007	8	1	4	14:26	PA	10008	1	0	11	...	
3	10000013	4	1	4	09:31	WV	10014	2	1	3	...	
4	10000014	6	1	1	17:50	MO	10015	1	0	5	...	

5 rows × 259 columns

One customer per row (**each observation is a CUSTOMER now**)

2. UNDERSTOOD EACH FEATURE AND CATEGORIZED IT

- **25** features categorized as follows:
  - **6 numerical variables**: shopping_pt, car_age, age_oldest and age_youngest, duration_previous & cost.
  - **10 categorical variables**: day, state, location, group_size, car_value, risk_factor, C_previous, record_type, homeowner, married_couple
  - **1 datetime variable**: time
  - ***7* Response Variables or Target** : Product features (aka vectors) (A - G). They take **discrete** values.

EXPLORATORY DATA ANALYSIS

IMPORTANT NOMENCLATURE

- baseline_model : This refers to predicting the final vector choice based on the customer's selection of the vector at the most recent shopping pt, say shopping pt 2.

- 'A': Customer's **final choice** for vector **A** i.e. the target we are predicting for vector A.

- 'A_2': Customer's choice for vector **A** at shopping pt **2**.

- 'A_2_2': **One-hot encoded** feature for vector **A**, at shopping pt **2**, for class **2**.

CORRELATIONS OF CATEGORICAL FEATURES WITH TARGET VECTORS

EDA

Some vectors are co-related to each other!

- Other noticeable co-relations
  - State with vectors F & G
  - C_previous with vectors C & D

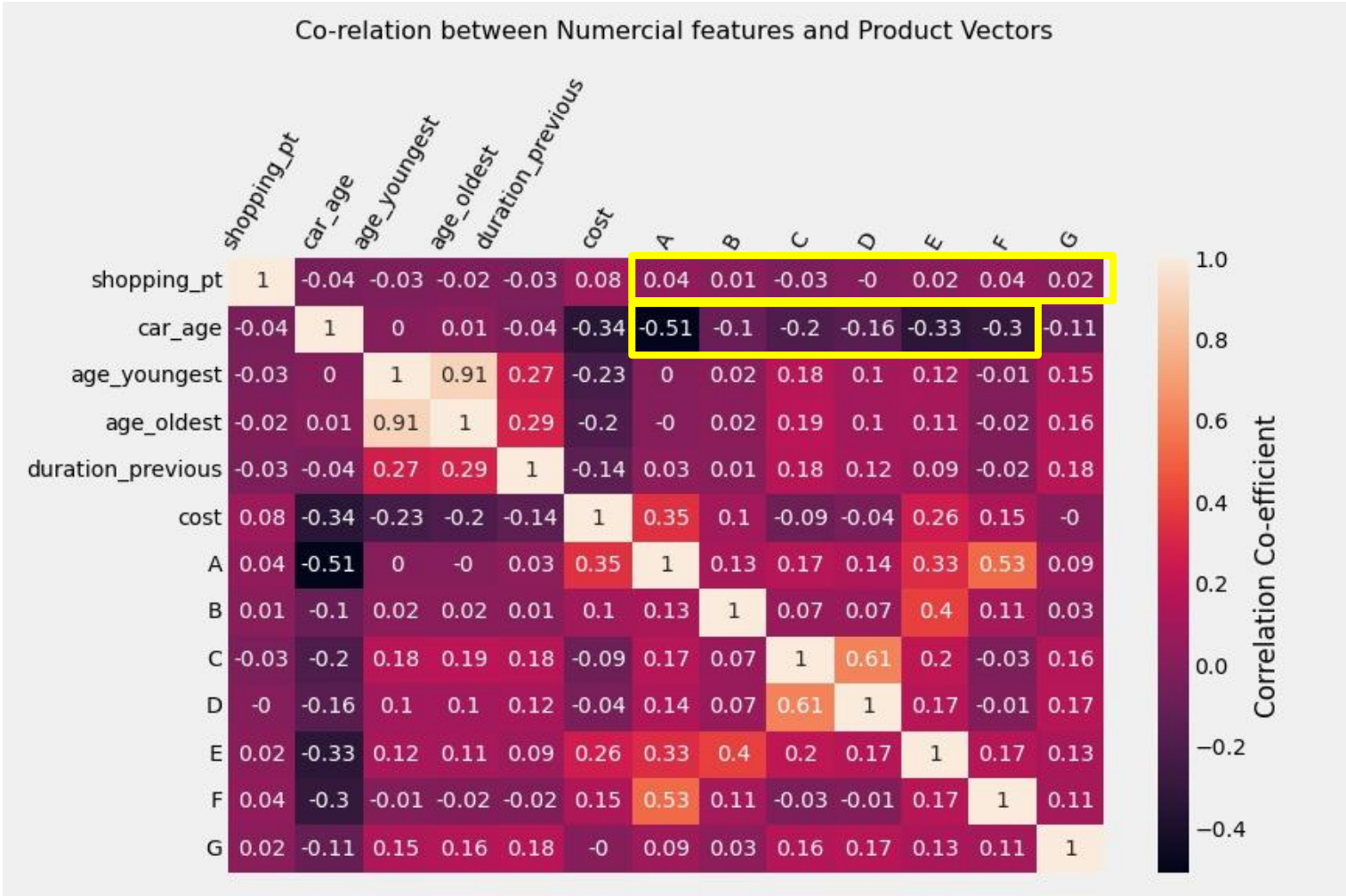
- Prioritized ***7 out of 9*** categorical variables for model development
  - state, car_value, risk_factor, C_previous, group_size, homeowner, married_couple

EDA

CORRELATIONS OF NUMERICAL FEATURES WITH TARGET VECTORS

car_age is negatively co-related with some vectors

- Final shopping pt has very little to do with vector choice
- Prioritized **5 out of 6** numerical variables for model development
  - car_age, age_youngest, age_oldest, duration_previous and cost

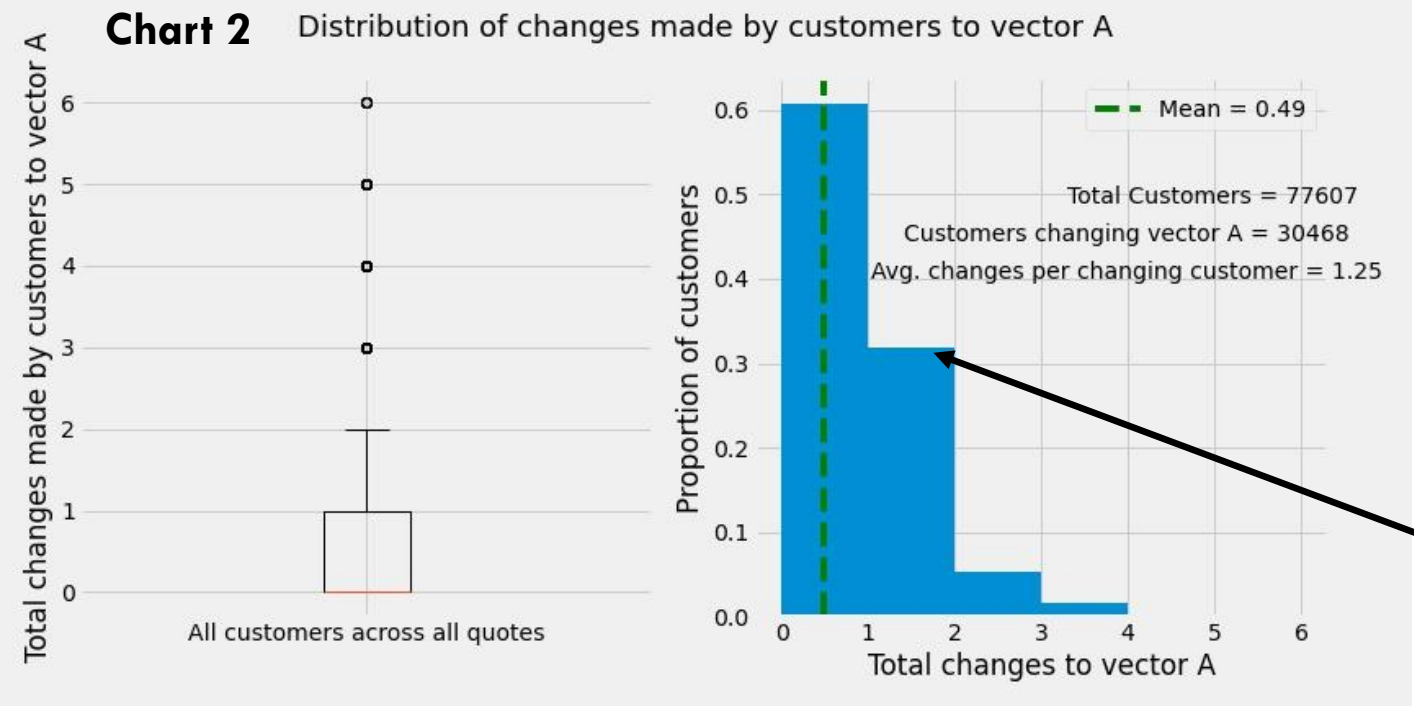


EDA

RATE OF VECTORS CHANGES IS HIGH EARLY ON, THEN SLOWS SIGNIFICANTLY

- The pattern of changes across every vector is very similar to that shown in Chart 1 & 2 for vector A
  - Most customers changes vectors early on, at shopping points 2 & 3 (Chart 1)
  - Out of those who do change the vector, approx. 80% change it only once (chart 2)

After shopping point 4, **less than 5%** of active customers change vector A at any given shopping pt.

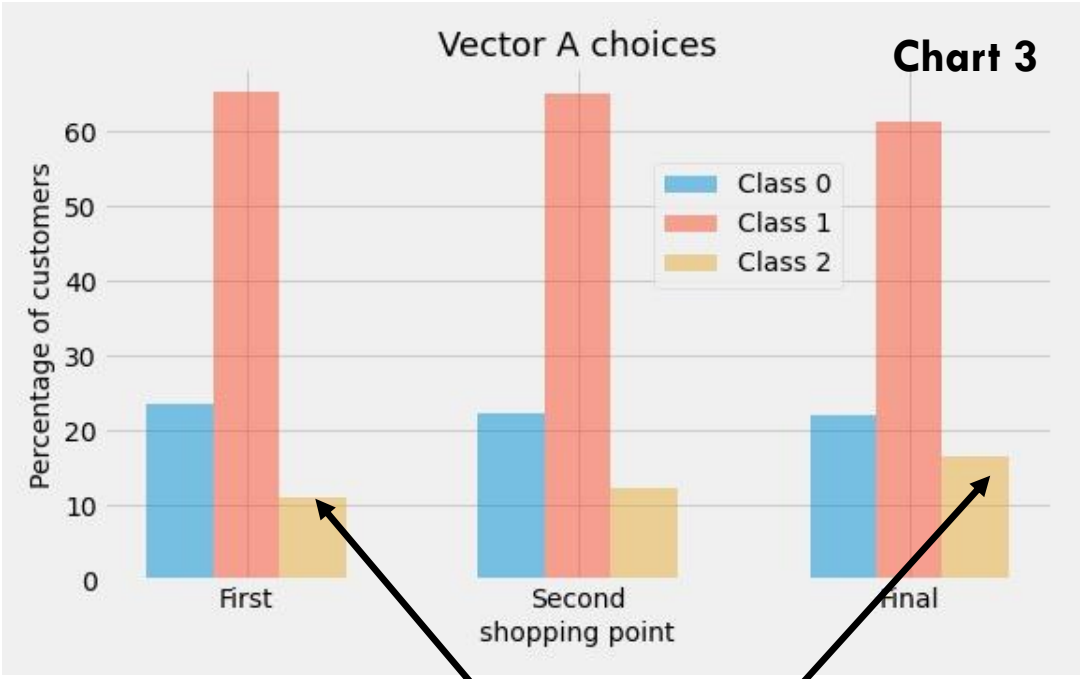


80% of customers who change vector A, change it only **once.**

EDA

VECTOR CLASSES ARE DYNAMIC THROUGHOUT QUOTING

- The footprint of different vector A classes shifts as a results of these changes
  - Classes 0 and 1 have declines from shopping point 1 through to the final shopping point (chart 3)
  - Class 2 has gains, even through it is the smallest class (chart 3)
  - But **no class is static**, there are customers entering and exiting every class (Table 1)



Customers choosing class 2 increase from **10% to 18%** of total customers during the shopping cycle

Table 1: How A_2 and A compare

A_2 →	Class 0	Class 1	Class 2	total
A ↓				
Class 0	3264	856	148	4268
Class 1	769	10785	369	11923
Class 2	258	1110	1843	3211

e.g. **856** customers moved from class 1 for **A_2**(A at shopping pt 2)
to class 0 for
A (their final A choice)

EDA

CUSTOMERS WHO TAKE LONGER TO DECIDE MAKE MORE CHANGES

- This chart shows that no. of changes made by customers increase if they stay longer in the shopping window

PRE-PROCESSING

FEATURE ENGINEERING AND TRANSFORMATIONS

- **Engineered** 2 features:
  - **changes_step_2**: No. of vectors changed by a customer at quote 2.
  - **cost_diff_step_2**: Difference in policy cost between quote 1 and 2.

- **Extracted** quote 1, 2 and final target vectors:
  - Customers make the most changes at Quote 2. So models can learn the most with quote 1 & 2 and understand how customers make further changes
- Categorical features transformed with **dummy encoding** and numerical features scaled using **Standardscaler**

- Post transformation, the final features dataset has **94 columns**

```
X.head()
```

	shopping_pt	car_age_2	age_oldest_2	age_youngest_2	duration_previous_2	cost_1	cost_2	changes_step_2	cost_diff_step_2	state_AR	...	F_1_
0	-0.929538	0.306686	1.718107	1.331208	-1.064370	-0.519793	-0.583795	-0.871664	-0.043014	0	...	
1	0.071276	-0.901461	-1.151705	-1.015758	-1.064370	-0.716734	0.867553	2.086860	2.452875	0	...	
2	0.571683	-0.211091	0.742371	0.587048	-1.064370	-0.362240	-0.352421	-0.279959	0.051766	0	...	
3	-0.929538	-1.246646	-0.061176	0.071860	1.933252	-0.657652	-0.920340	-0.871664	-0.327356	0	...	
4	0.571683	-1.246646	-1.094309	-0.958515	-0.422023	1.804113	1.750982	-0.279959	-0.264169	0	...	

5 rows × 94 columns

Engineered Features

MODELING APPROACH AND PERFORMANCE METRICS

- **Step 1**: Trained a basic model based on 3 different classifiers - Random Forest, Gradient Boost and XG Boost.
  - For binary vectors (B and E), a Logistic Regression classifier was also evaluated.
- **Step 2**: Tuned hyperparameters using 60 iterations of RandomizedSearchCV
- **Step 3**: Compared the performance of tuned classifiers on the test set to then choose the best classifier for each vector.

METRICS

The key objective is to predict **each customer's correct class** for each of the 7 vectors.

As such, the key metrics for model evaluation would be '**micro accuracy/recall**' i.e. the overall correct class predictions across all customers.

VECTOR A: BASELINE MODEL HAS SCORE OF ~82%

- 'baseline_model' as benchmark:
  - Table 1 shows that recall based on simply predicting vector A = A_2 is **81.91%**

Table 1: How A_2 and A compare

A_2 →	Class 0	Class 1	Class 2	total
A ↓				
Class 0	3264	856	148	4268
Class 1	769	10785	369	11923
Class 2	258	1110	1843	3211

A same as A_2 i.e. these customers didn't change their vector A choice from quote 2 till purchase

Total customers = sum of total column

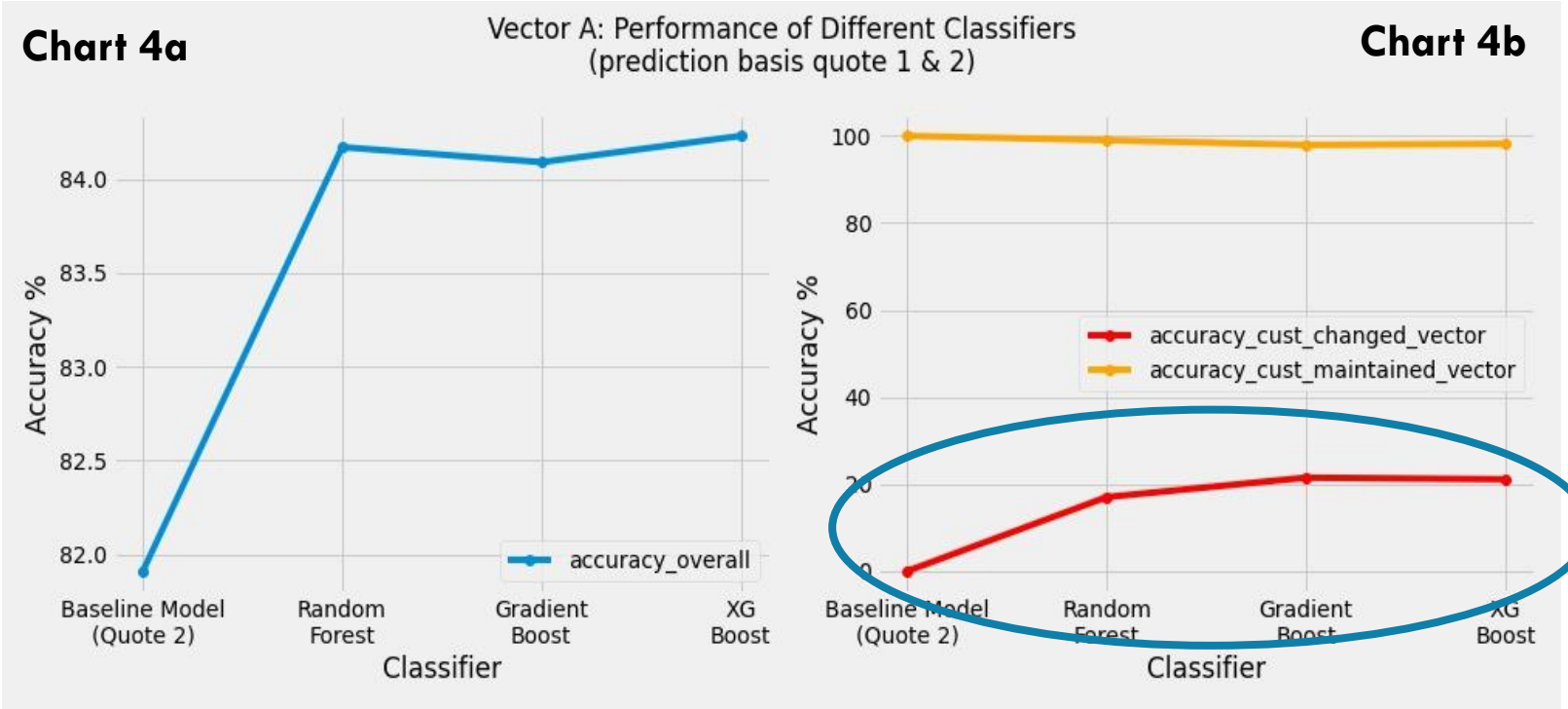
$$\text{Micro Accuracy Score} = \frac{\text{sum of diagonal}}{\text{sum of total column}}$$

$$= \frac{(3264 + 10785 + 1843)}{(4268+11923+3211)}$$

$$= \mathbf{81.91\%}$$

VECTOR A: MODELS PERFORMED MUCH BETTER THAN BASELINE IN PREDICTING CUSTOMERS WHO CHANGED THEIR CLASS

- **Chart 4a** shows that the best classifer (XGBoost) had an accuracy score of **84.23%**
- **Chart 4b** shows the score breakup between customers:
  - **98 – 99%** accuracy of classifiers for customers who **maintained** their vector A class (baseline: **100%**)
  - **18 - 22%** accuracy of classifiers for customers who **changed** their vector A class (baseline: **0%**)



VECTOR A: MODELS PERFORMED BETTER THAN BASELINE ACROSS ALL SHOPPING POINTS

- **Chart 4c** shows that the models had improved predictions for customers purchasing at all shopping points

- **Especially** noteworthy is the superior performance between shopping points 7 to 11
  - Based on knowledge of only shopping point 1 and 2, the classifiers could predict customers much further out in the shopping window

DIFFERENT MODELS LEARN FROM DIFFERENT FEATURES !

Could the models be **combined** to improve performance ?

- **Only 4** amongst top 10 features were common between XGBoost (score 84.23%) and Random Forest(score: 84.17%)
- **Engineered features** (changes_step_2) and (cost_diff_step_2) are present in top 10
- Some **correlations** seen during EDA are evident here

Chart 4d

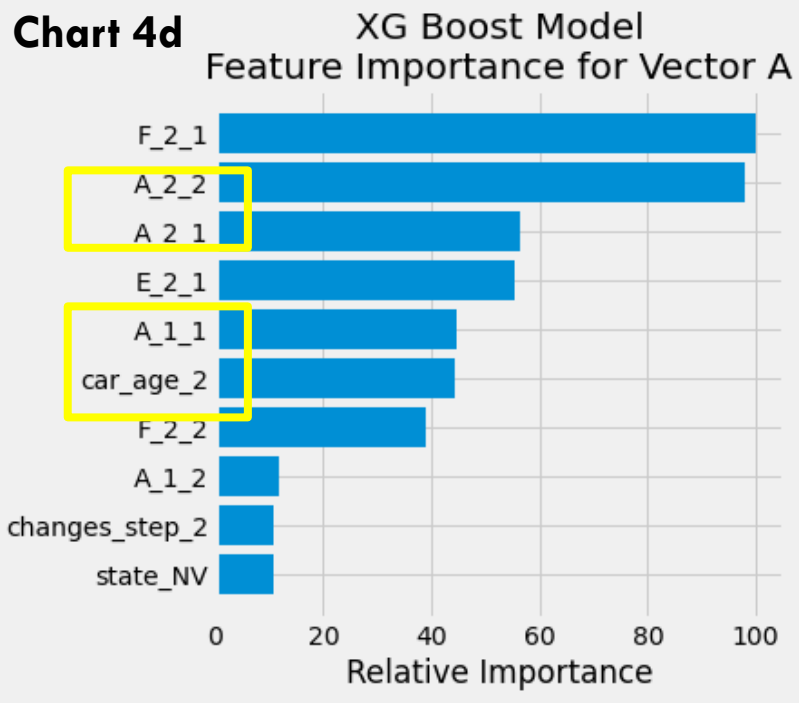
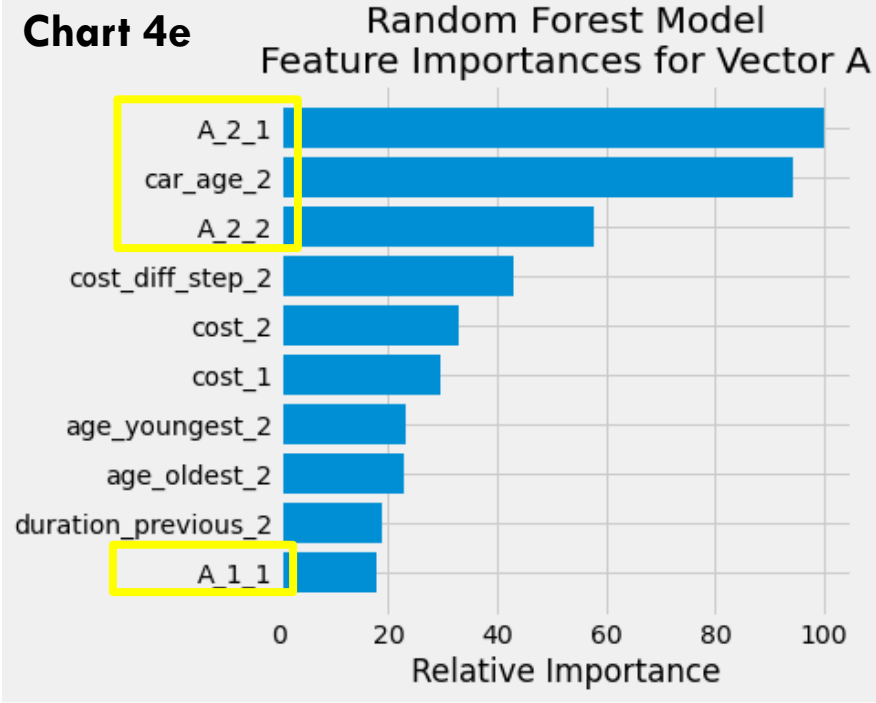
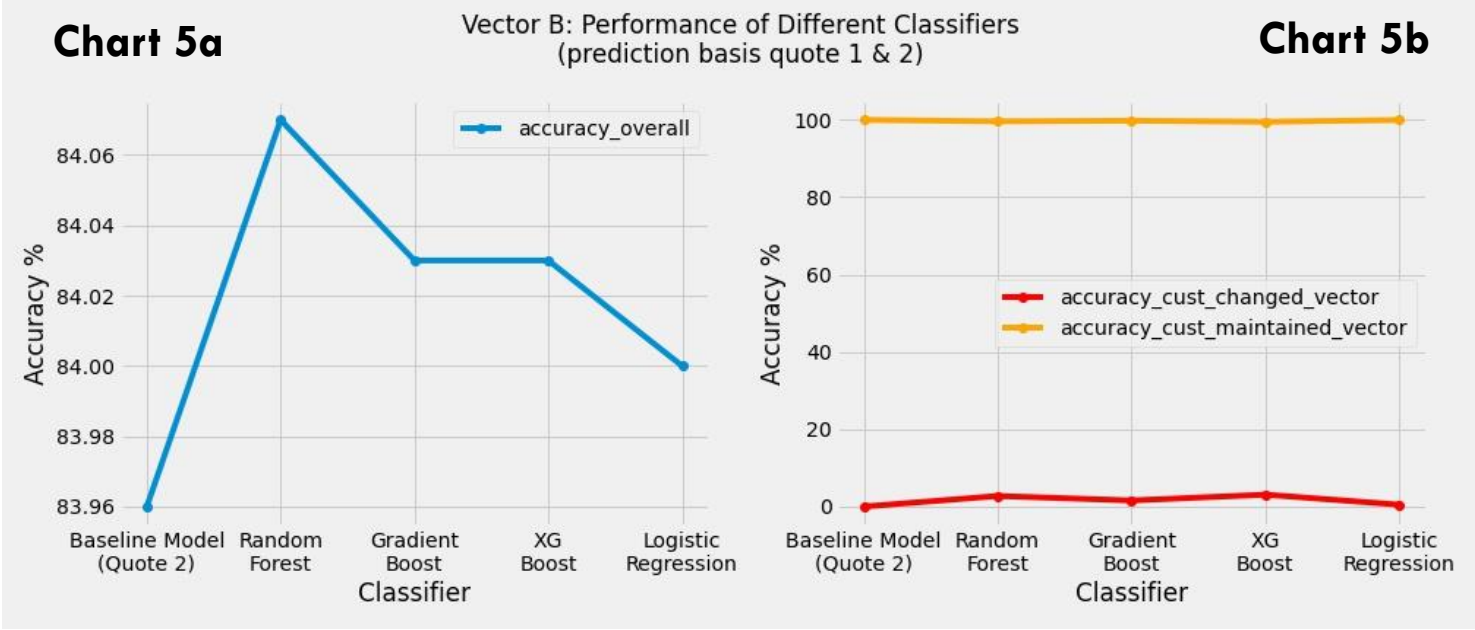


Chart 4e



VECTOR B: HARDEST TO PREDICT VECTOR

- **Chart 5a** shows that the best classifer (Random Forest) had a score of **84.07%,** only a **0.11%** improvement over baseline
- 'baseline_model' score: B = B_2 gives a **83.96%** accuracy



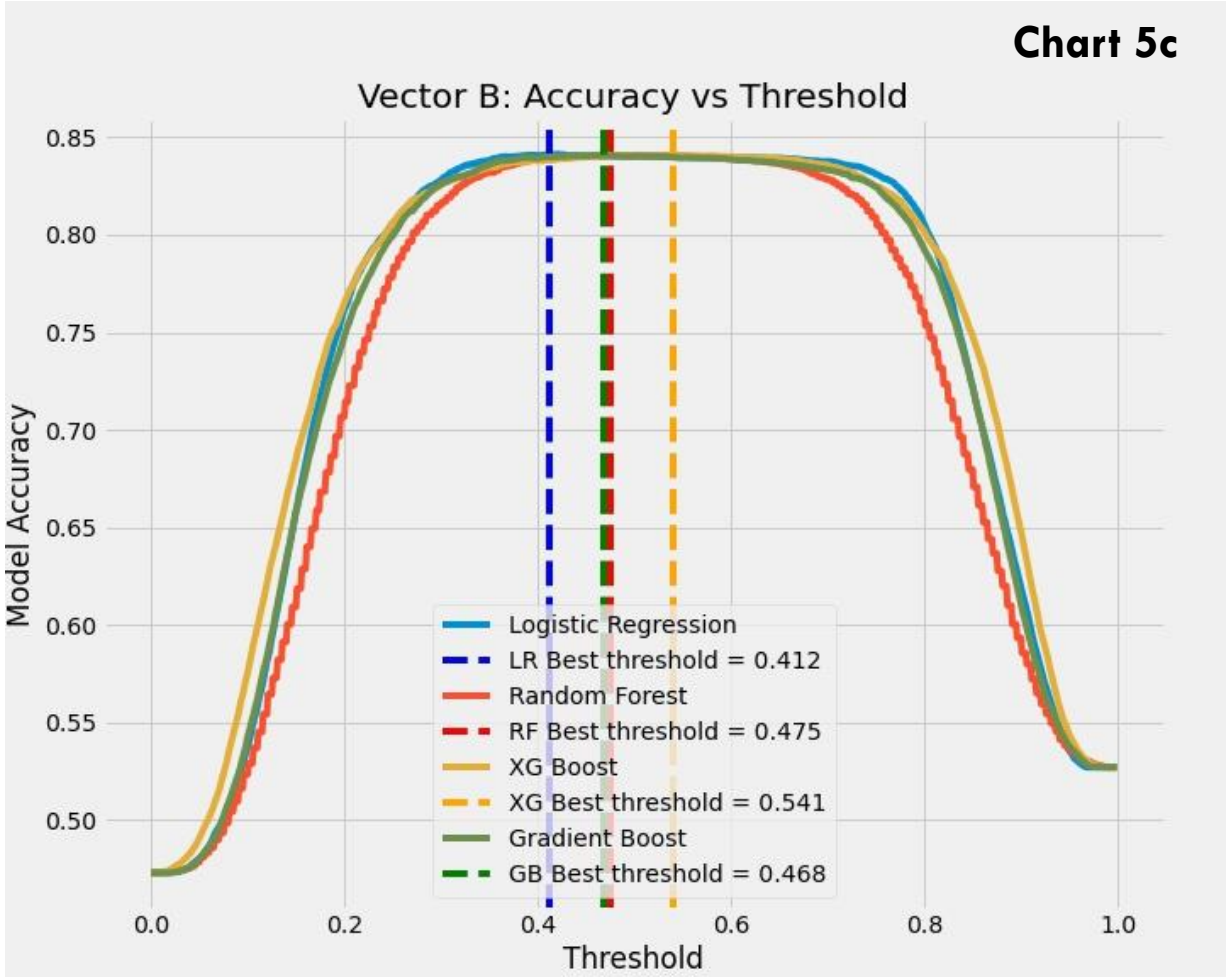
VECTOR B: THRESHOLDING PROVIDED GAINS

Turned Logistic Regression from worst to best model

- **Thresholding made improvements to all classifiers** with Logistic regression returning a score of **84.14%**, an improvement of **0.18%** over baseline.

- Accuracy plateaus for all models

Chart 5c



KEY FINDINGS: SOME MODELS ARE USEFUL!

- The models gave a performance improvement ranging from **0.18% to 2.8%** over the baseline
- The average improvement was **1.59%**, the best performance was for **vector C at 2.8%**
- For customers that changed vector choice, the performance improvement ranged from 0.48% to 27.02% for vector C. On average, the models predicted **14.72%** of such customers correctly.
- There seemed to be a **trade-off** in predicting customers who changed and customer who didn't

Table 3

vector	recall_baseline_model	best_model	recall_best_model	improvement_over_baseline	recall_cust_changed_vector	recall_cust_maintained_vector
A	81.91	xg	84.23	2.32	21.11	98.17
B	83.96	lr	84.14	0.18	0.48	99.96
C	80.18	xg	82.98	2.80	27.02	96.81
D	85.09	rf	86.71	1.62	16.29	99.04
E	83.80	xg	84.72	0.92	13.07	98.58
F	81.04	rf	82.63	1.59	11.36	99.30
G	74.31	rf	75.98	1.67	11.46	98.28

IDEAS FOR FURTHER DEVELOPMENT

- Creating an ensemble of different classifiers based on voting rules or by combining the probabilities of different models
- More engineered features: e.g. time difference between quotes
- More data to get the models to learn better about features like location