



Examining Customer Purchase Intent

Predictive Analytics Project: Wong Wen Bing Y2 DAAA

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01 About

Examining the retail industry

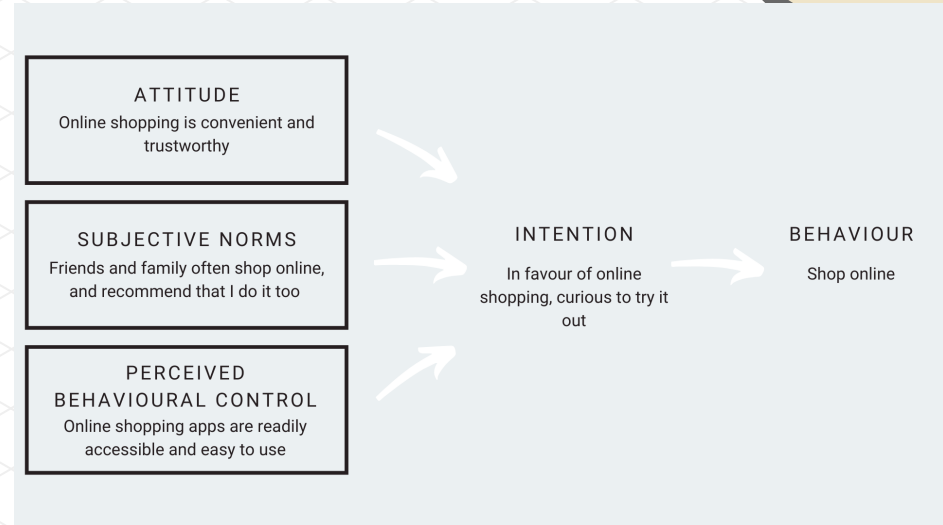


Theory of Planned Behaviour (TPB)

“The theory of planned behaviour assumes that, when an individual intends to perform a specific behaviour, they will actually do so. According to the theory of planned behaviour, behavioural intentions are formed on the basis of attitudes, subjective norms and perceived behavioural control.”

Applying TPB in Retail

- A frequently used technique by marketers to predict and understand consumer's behaviour.
- Argument for the theory's usage in retail is that behaviours are **solely determined on behavioural intentions** which are determined by **behavioural attitude, subjective norms and perceived behaviour**

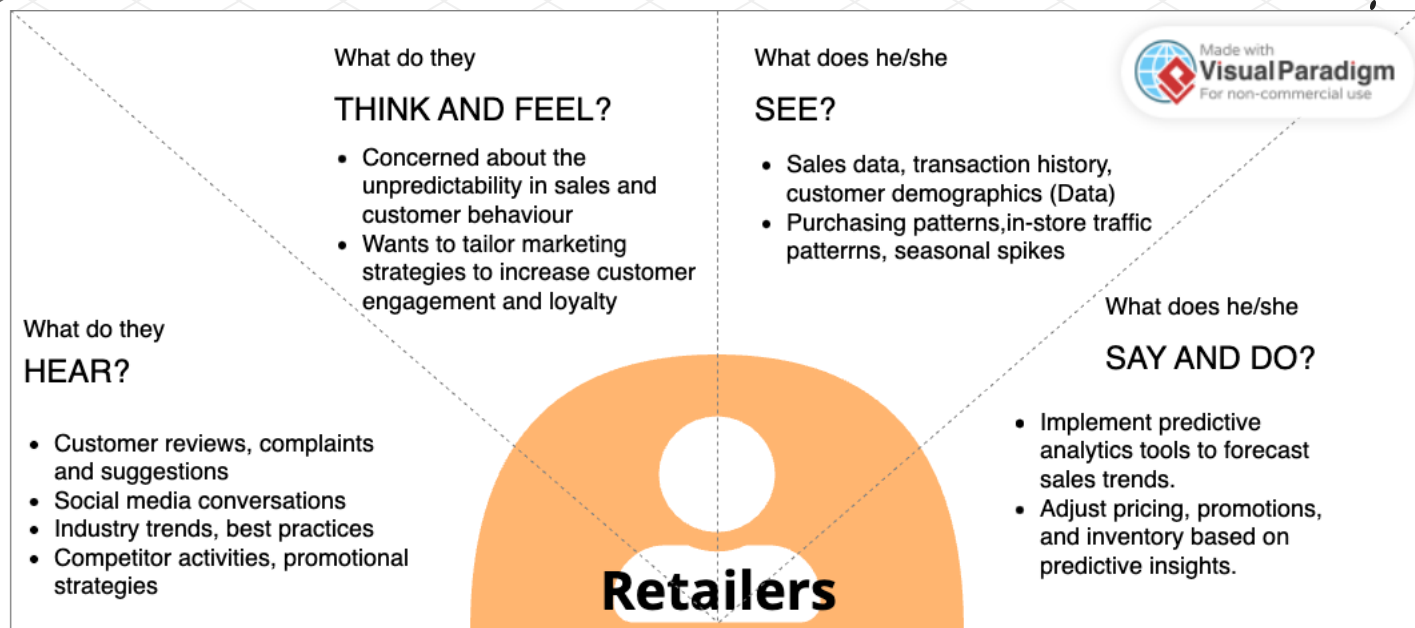


Example on Online Shopping (Blogs @NTU)

Problem for retailers

“Despite the growing attention on enhancing purchase intent, there is no coherent framework for determining retail customers’ purchase intent.”

Menidjel, Choukri & Bilgihan, Anil. (2022). The determinants of retail customers’ purchase intent. *International Journal of Consumer Studies*. 46. 10.1111/ijcs.12802.



PAIN	GAIN
<ul style="list-style-type: none">• Risk of over-reliance on historical data, leading to inaccurate predictions.• Balancing short-term sales targets with long-term customer relationship management.• Unable to keep up with industry trends.	<ul style="list-style-type: none">• Enhanced customer satisfaction through personalized experiences.• Increased profitability by optimizing marketing spend and reducing waste.

“Empowering retailers to make MORE informed decisions about their business through predictive modelling research on purchase intent.”

~Project Business Objective

02

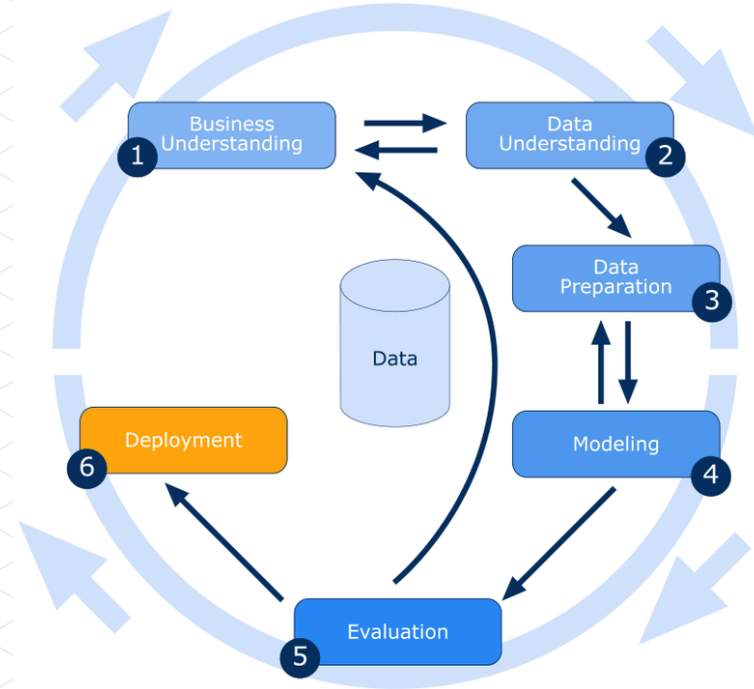
Process

CRISP-DM



CRISP-DM

- Comprehensive process of conducting a data mining project
- Structured: ensuring all aspects of this investigation are aspects of the project are thoroughly addressed
- Effective: ensures business goals are met and thorough data preparation and evaluation is conducted



03

Data Understanding and Preparation



Dataset Information – Electronic Sales Dataset

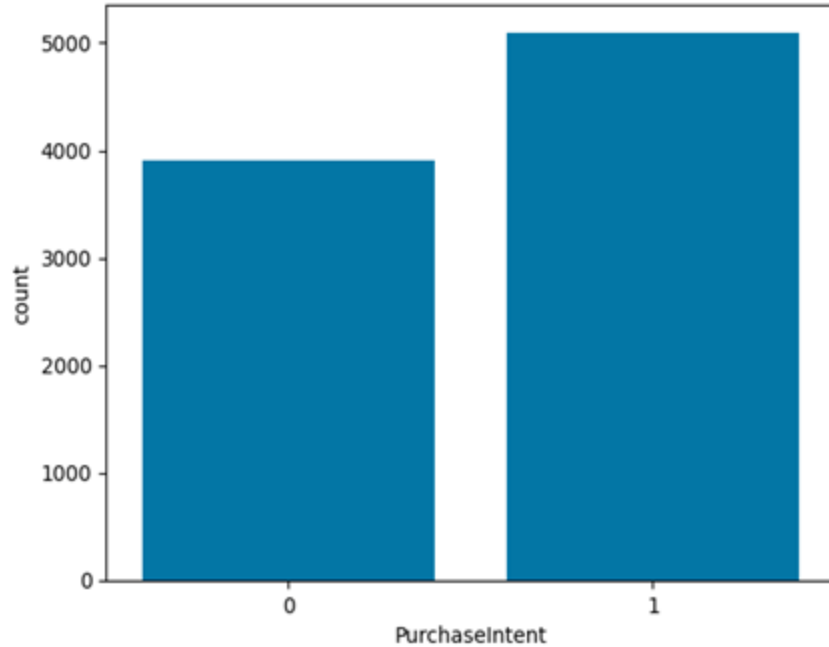
- Source: <https://www.kaggle.com/datasets/rabieelkharoua/consumer-electronics-sales-dataset/data>
- Examine customer purchase intent based on an Electronics store
- Data Information:
 - Total Data: 9000 rows
 - Total Number of Columns: 9

Data Dictionary

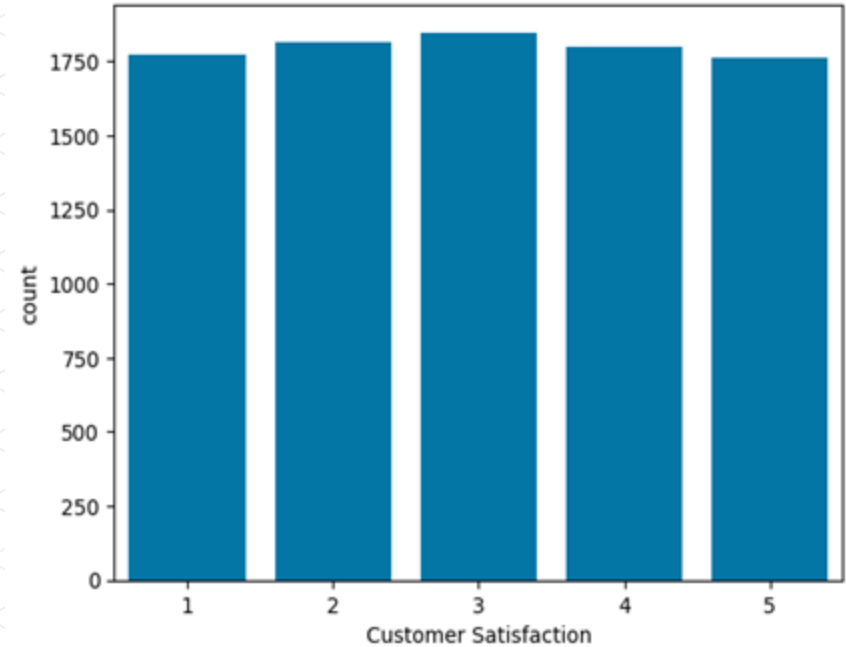
ProductID	Unique identifier for each product.
ProductCategory	Category of the consumer electronics product (e.g., Smartphones, Laptops).
ProductBrand	Brand of the product (e.g., Apple, Samsung).
ProductPrice	Price of the product (\$).
CustomerAge	Age of the customer.
CustomerGender	Gender of the customer (0 - Male, 1 - Female).
PurchaseFrequency	Average number of purchases per year.
CustomerSatisfaction	Customer satisfaction rating (1 - 5).
PurchaseIntent	Intent to purchase. (0 - no intent, 1 - intent)

Balance of Dataset

Purchase Intent Count



Customer Satisfaction Count



Data Preparation – KNIME

- Checking and removing necessary null values
- Removing unnecessary columns – ProductID
- Changing values in CustomerGender (0 to Male, 1 to Female)

Data Preparation – Reducing Overfitting

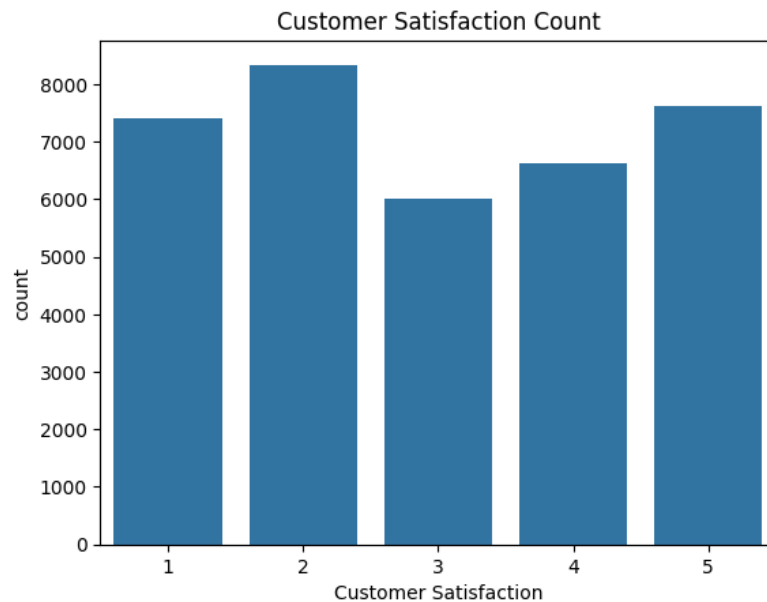
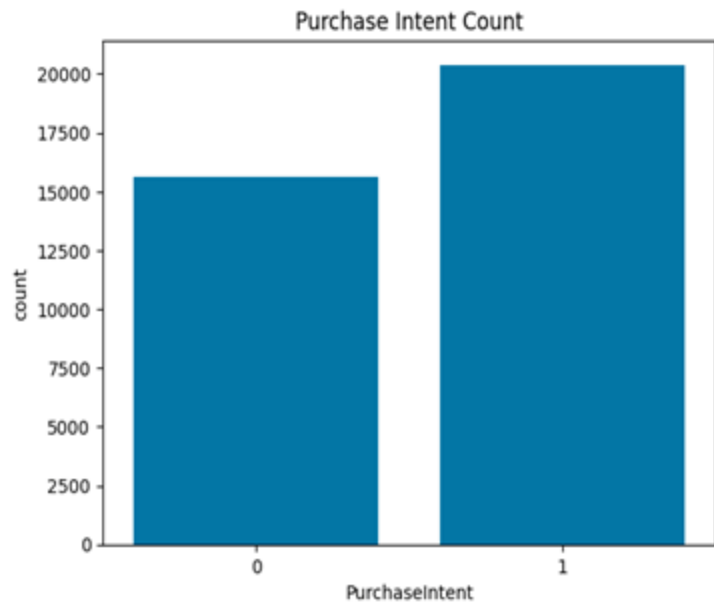
- During Data preparation: Even though dataset is balanced but there is overfitting due to data count and imbalance
- In KNIME: SMOTE node to create synthetic data
- By doing so: reduces the possibility of overfitting

Final Dataset

- Total Number of Rows: 36000
- Total Number of Features: 8

Name	Type of Variable	Description
ProductCategory	Category	Category of the consumer electronics product (e.g., Smartphones, Laptops).
ProductBrand	Category	Brand of the product (e.g., Apple, Samsung).
ProductPrice	Numeric (Aggregated as Average)	Price of the product (\$).
CustomerAge	Numeric	Age of the customer.
CustomerGender	Category	Gender of the customer (Male, Female).
PurchaseFrequency	Numeric (Aggregated as Average)	Average number of purchases per year.
CustomerSatisfaction	Category	Customer satisfaction rating (1 - 5).
PurchaseIntent	Category	Intent to purchase.

Data Balance



Partitioning

- Given the relatively well balance of the dataset, a 70-30 partition was done with SAS Viya using simple random sampling

WHY Simple Random Sampling:

- Both types of variable can have an equal and fair chance of being used as compared to stratified sampling

03

Modelling

Finding the best model possible

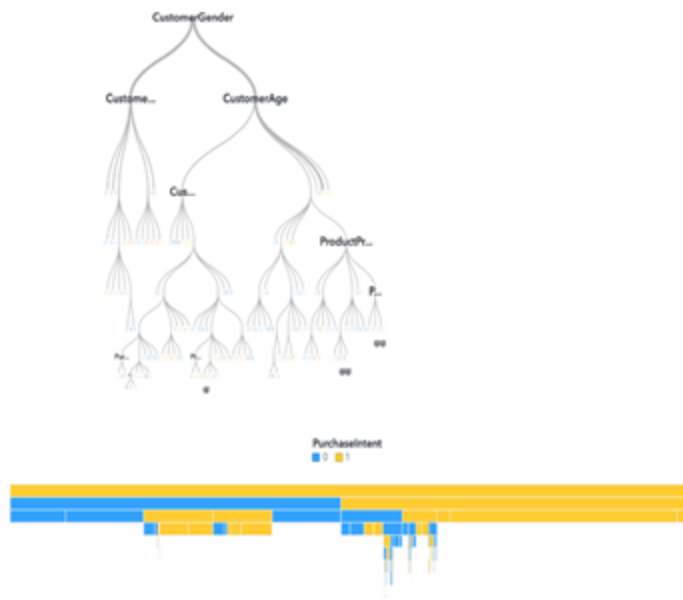


Base Model

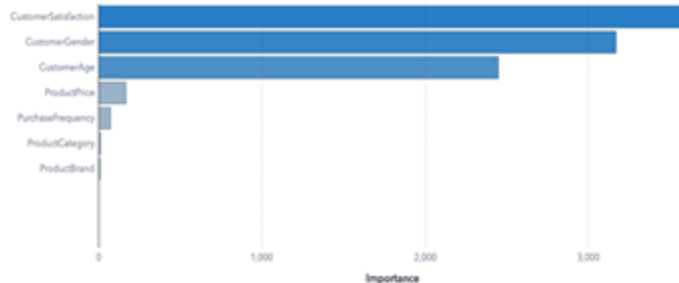
Decision Tree of PurchaseIntent

Event: 1 • Fit: Validation F1 Score 0.942 • Observations: 36K of 36K

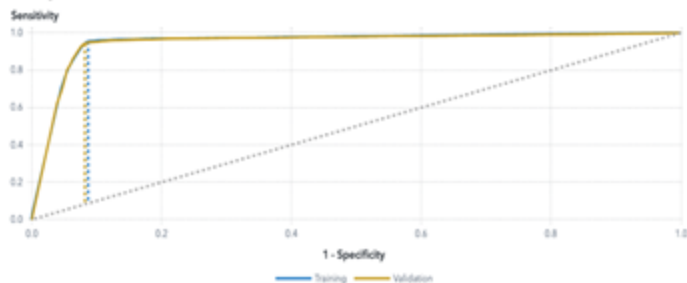
Tree



Variable Importance



ROC

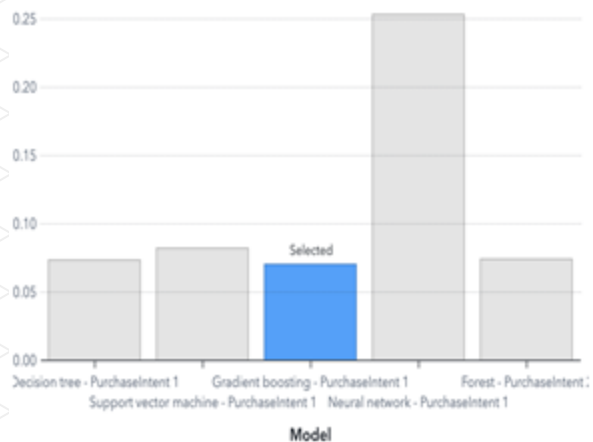


- F1 Score: 0.942
- KS-Youden: 0.8611
- Misclassification Rate: 0.0669

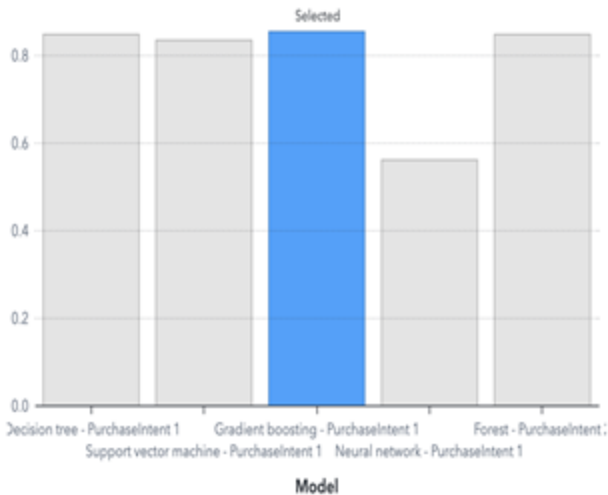
Model Comparison - Statistics

- Variety of models used to model the data: Decision Tree, Support Vector Machine, Gradient Boosting, Neural Network Random Forest

Validation Misclassification Rate (Event)

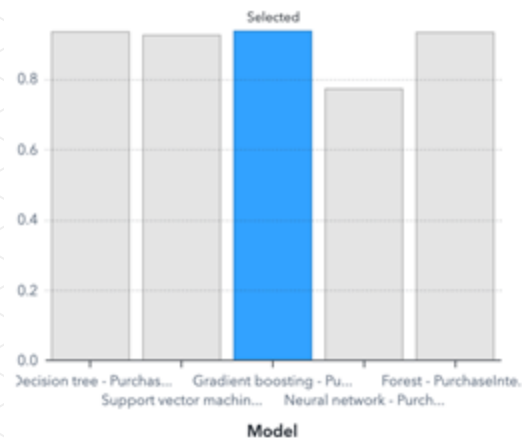


Validation KS (Youden)

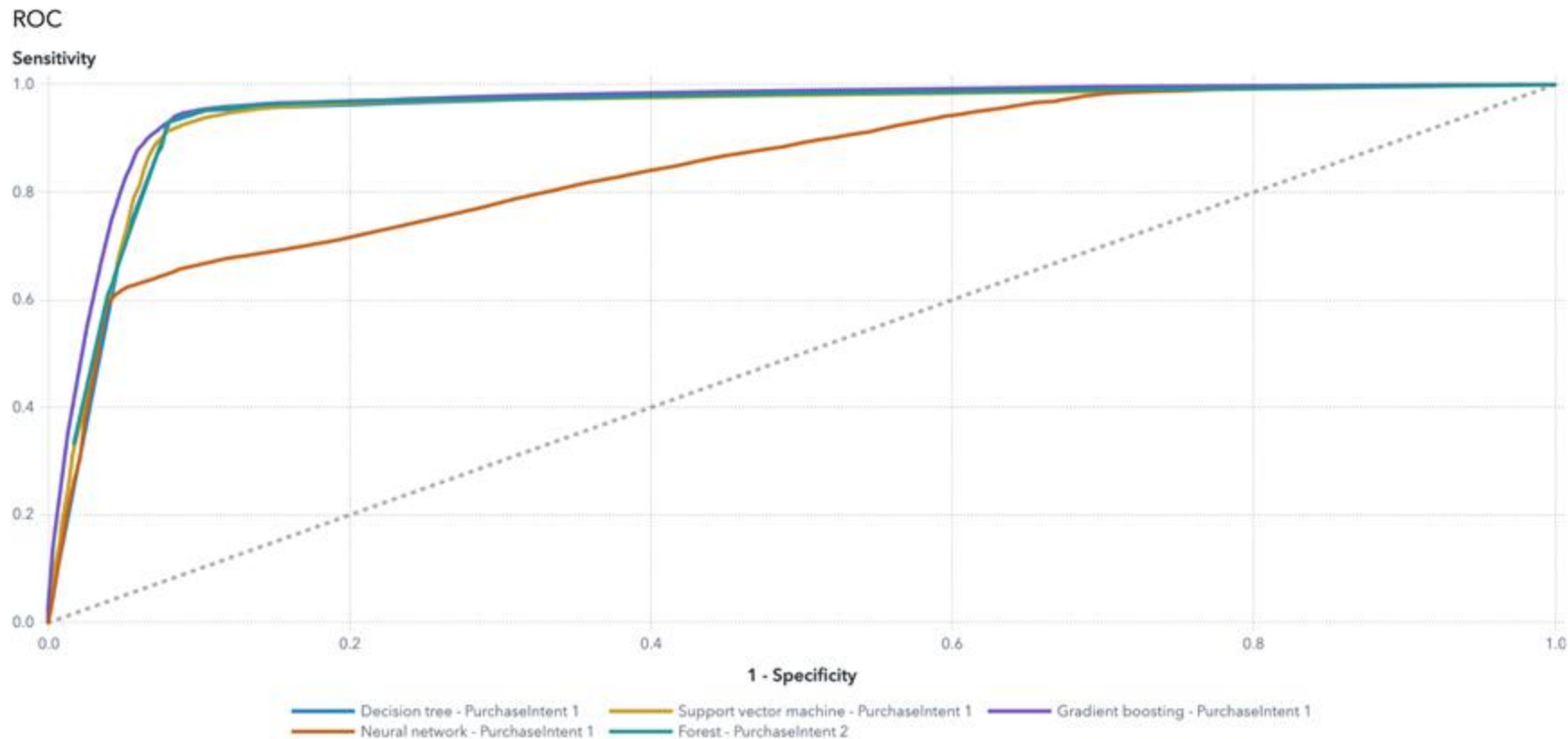


Fit Statistic @

Validation F1 Score

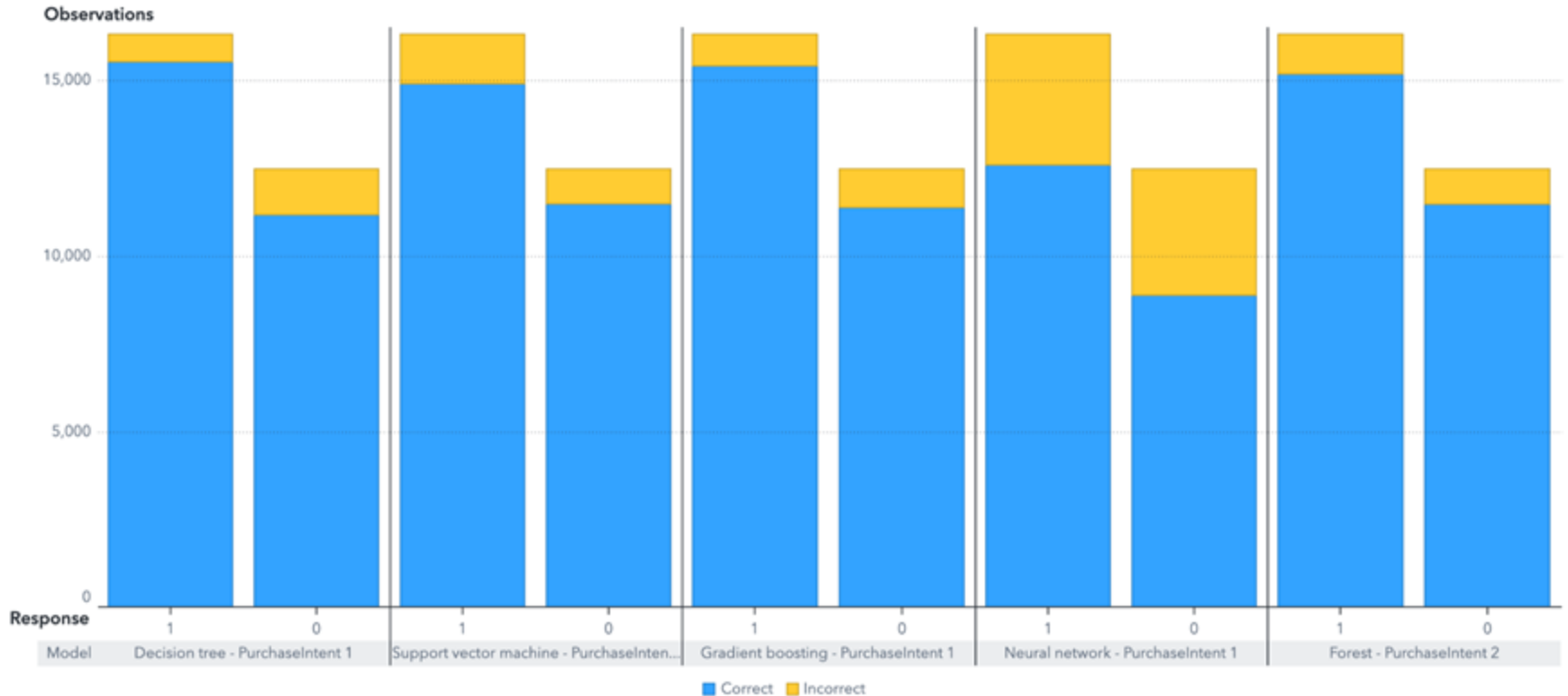


Model Comparison – ROC Curve



Model Comparison - Misclassification

Misclassification



Final Decision

Final Decision: Gradient Boosting

Model Statistics:

- F1 Score: 0.943 (good performance)
- KS Youden: 0.8982 (sensitive to data changes)
- Misclassification Rate: 0.0530 (less likely to misclassify the data)

04

FINAL MODEL

Gradient Boosting

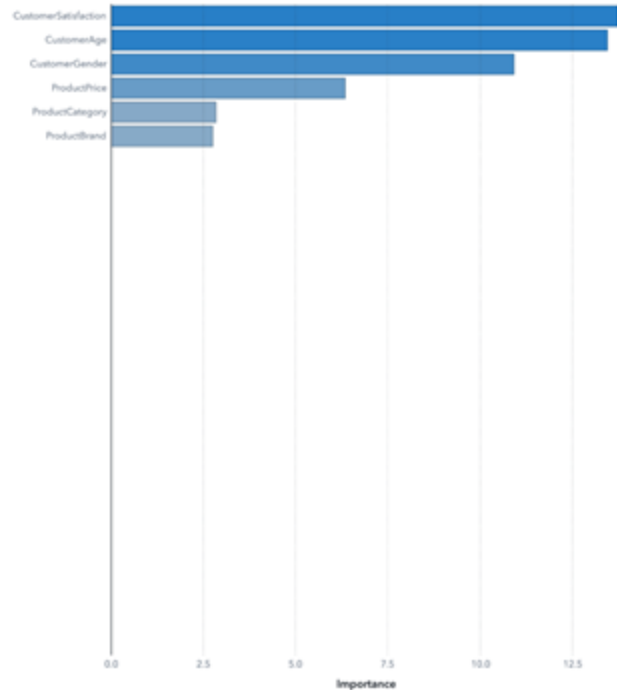


About Model

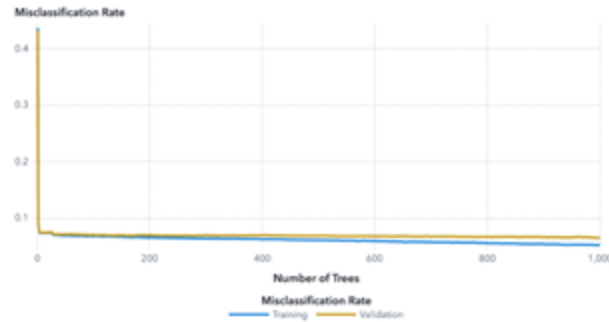
Gradient Boosting of PurchaseIntent

Event: 1 • Fit: Validation F1 Score 0.943 • Observations: 36K of 36K

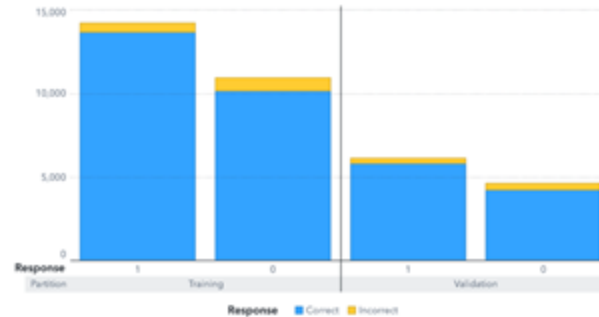
Variable Importance



Iteration Plot



Misclassification



Model Statistics:

- F1 Score: 0.942
- KS-Youden: 0.8611
- Misclassification Rate: 0.0669

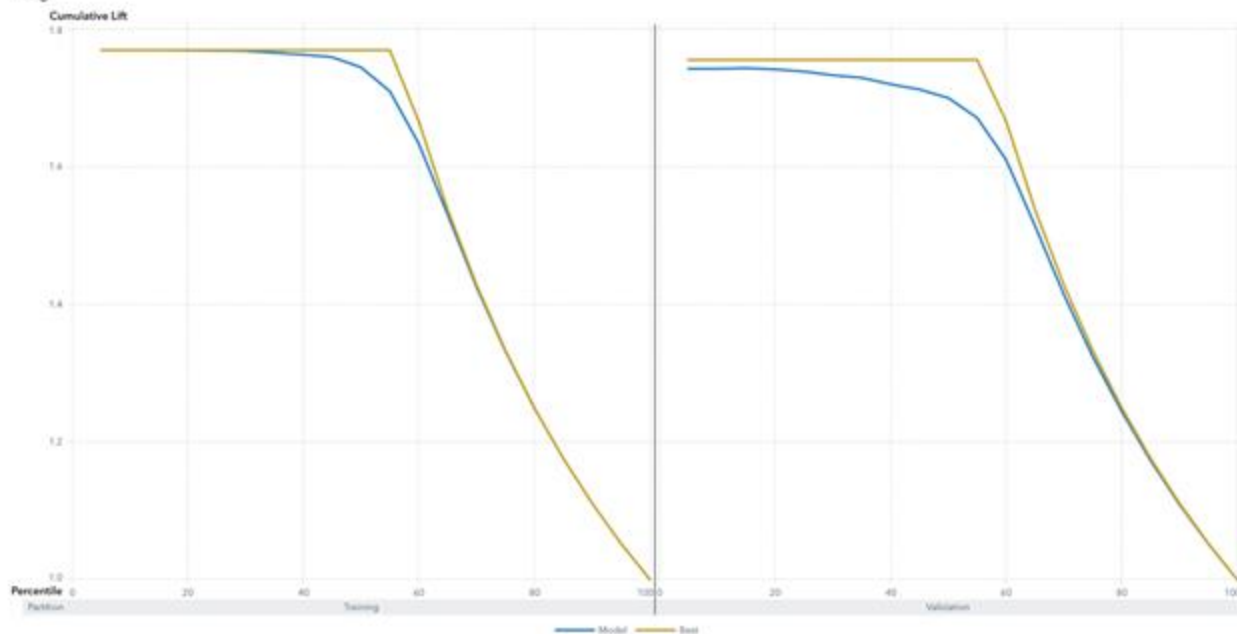
Lift Curve

Gradient Boosting of PurchaseIntent

Event: 1 • Fit: Validation F1 Score 0.943 • Observations: 36K of 36K

Variable Importance Iteration Plot Assessment

Lift



No Overfitting:

- Observation that the validation model performs relatively similar to training model

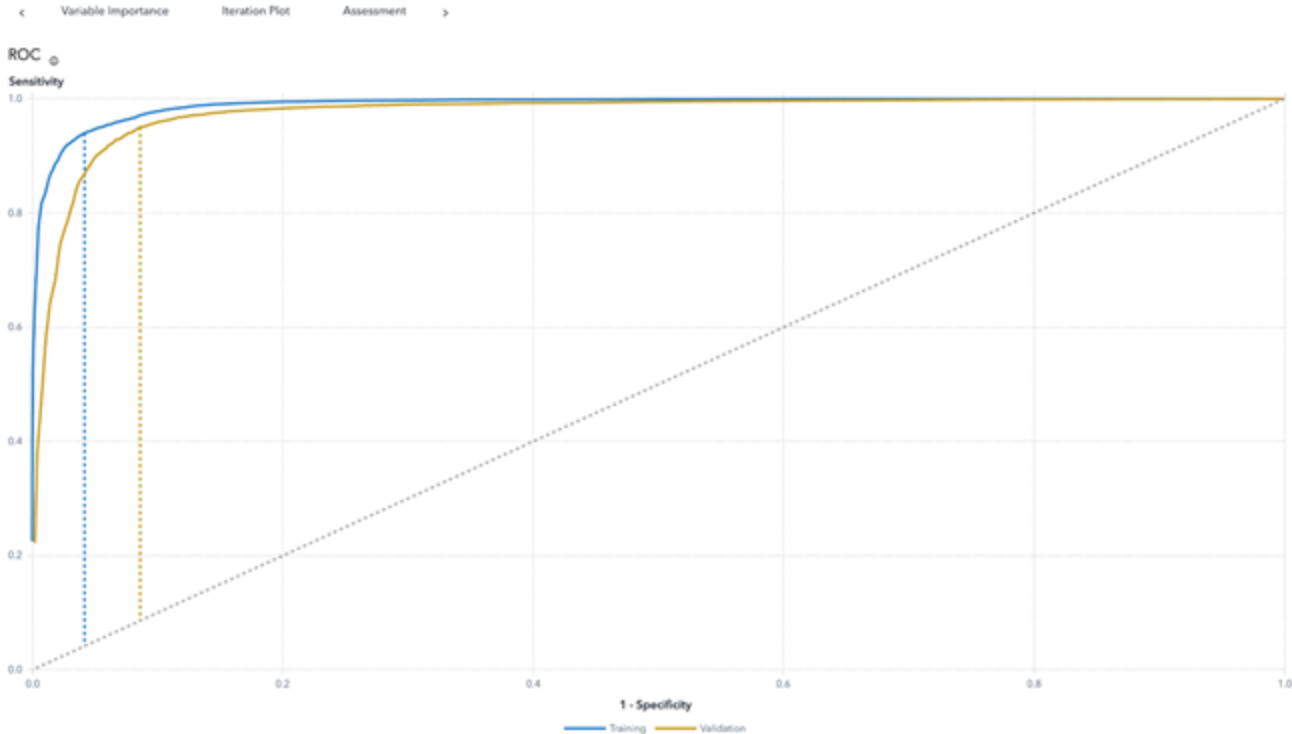
Good Model Performance:

- Model is performing relatively close to the best model

ROC Curve

Gradient Boosting of PurchaseIntent

Event: 1 • Fit: Validation F1 Score 0.943 • Observations: 36K of 36K



Insignificant Overfitting:

- Training curve is slightly sensitive than the validation

Good Model Performance:

- Curves for both models are close to the top left side which indicates a very sensitive and good model

Fine Tuning

- Higher number of trees → reducing Overfitting
- Lower number of levels → reduces the complexity of the decision tree

The image shows a user interface for configuring machine learning models. It is divided into two main sections: Gradient Boosting and Decision Tree.

Gradient Boosting

- General**
 - Event level: 1
 - Autotune: Autotune...
 - Auto-stop method: None
 - Number of trees: 1,000
 - Learning rate: 0.1
 - Subsample rate: 0.5
 - Lasso: 0
 - Ridge: 1
 - ☐ Set fixed number of predictors to split nodes
 - Number of predictors to split nodes: 6

Decision Tree

- Missing assignment: Use in search
- Minimum value: 1
- Maximum branches: 5
- Maximum levels: 5
- Leaf size: 5
- Predictor bins: 50
- ☐ High-cardinality predictors
- Bin method: Quantile

Assessment

- Number of bins: 20
- Prediction cutoff: 0.5

Model Analysis (Decision Tree)

- Demographics of customers who purchase the most: (Based on customers with the purchase intent)
 - Customer Age: 26-31/20-21
 - Gender: Female
 - Purchase Frequency: 7 to 9

06

CONCLUSION

You can enter a subtitle here if you need it



Insights

- In determining whether a customer decides to purchase the product, the below factors are important
(in descending order most → least important)
 - Customer Satisfaction
 - Customer Age
 - Customer Gender
 - Product Price
 - Product Brand
 - Product Category

Recommendations

- Ensure maximum customer satisfaction
- Tailor marketing strategies to Females aged between 26 and 31 or 20 to 21

Conclusion

- By using the model insights, effective marketing strategies could be tailored to the specific categories of people.
- Linking back to the Theory of Planned Behaviour (TPB), we can justify that the theory does work in its own mysterious ways (with customer satisfaction as a main goal)
- With the increasing use of predictive analysis in the retail fields, companies must use such a model as a baseline for future models to observe different factors – such as Customer Satisfaction determined by the different product brands and prices
- In short, whilst this model can serve as an example, it is important to use **updated** and **customised** data **based on the needs of the specific sector**

THANKS

Do you have any questions?

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