Should They Stay or Should They Go? The Prediction of Customer Churn in Energy Sector

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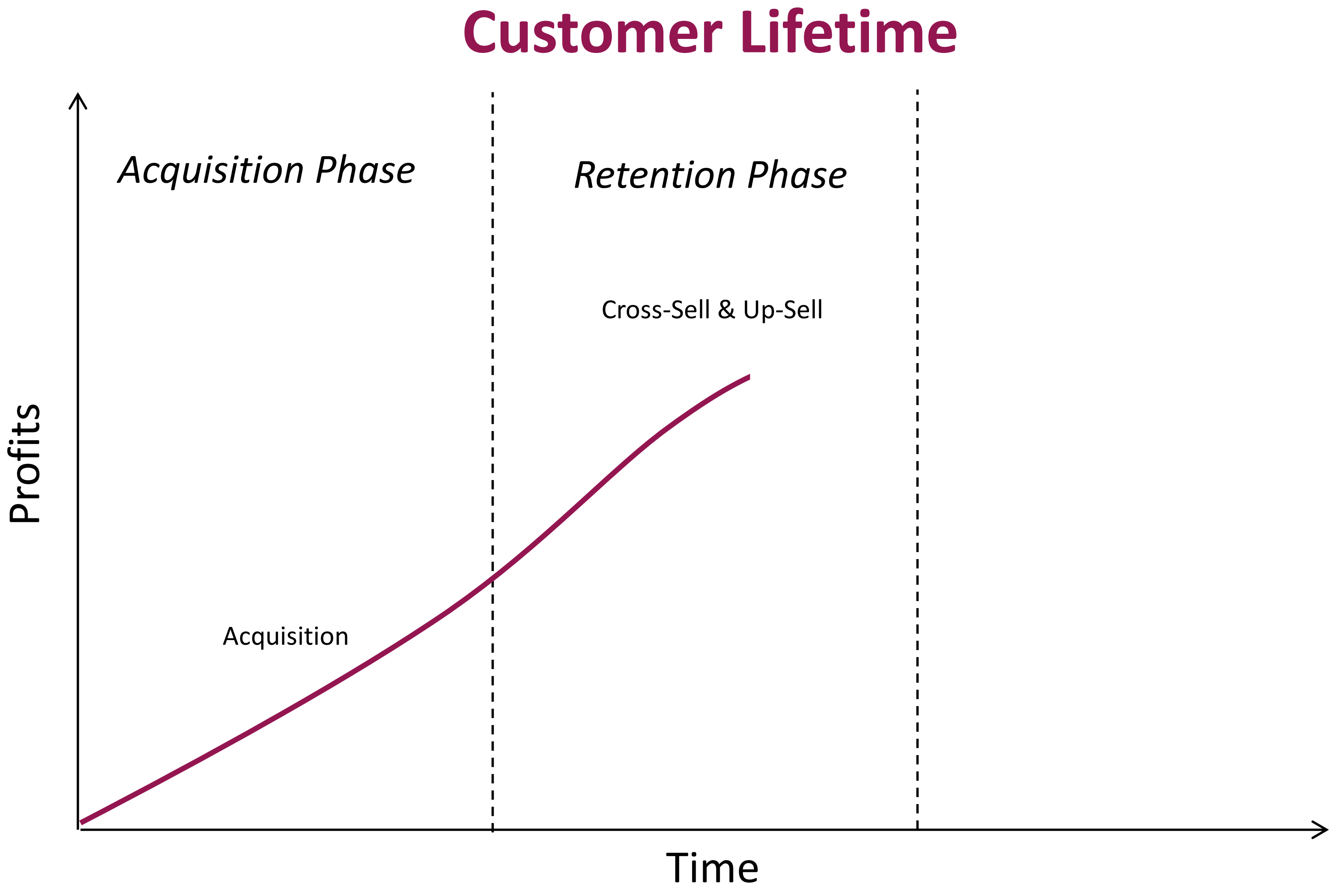
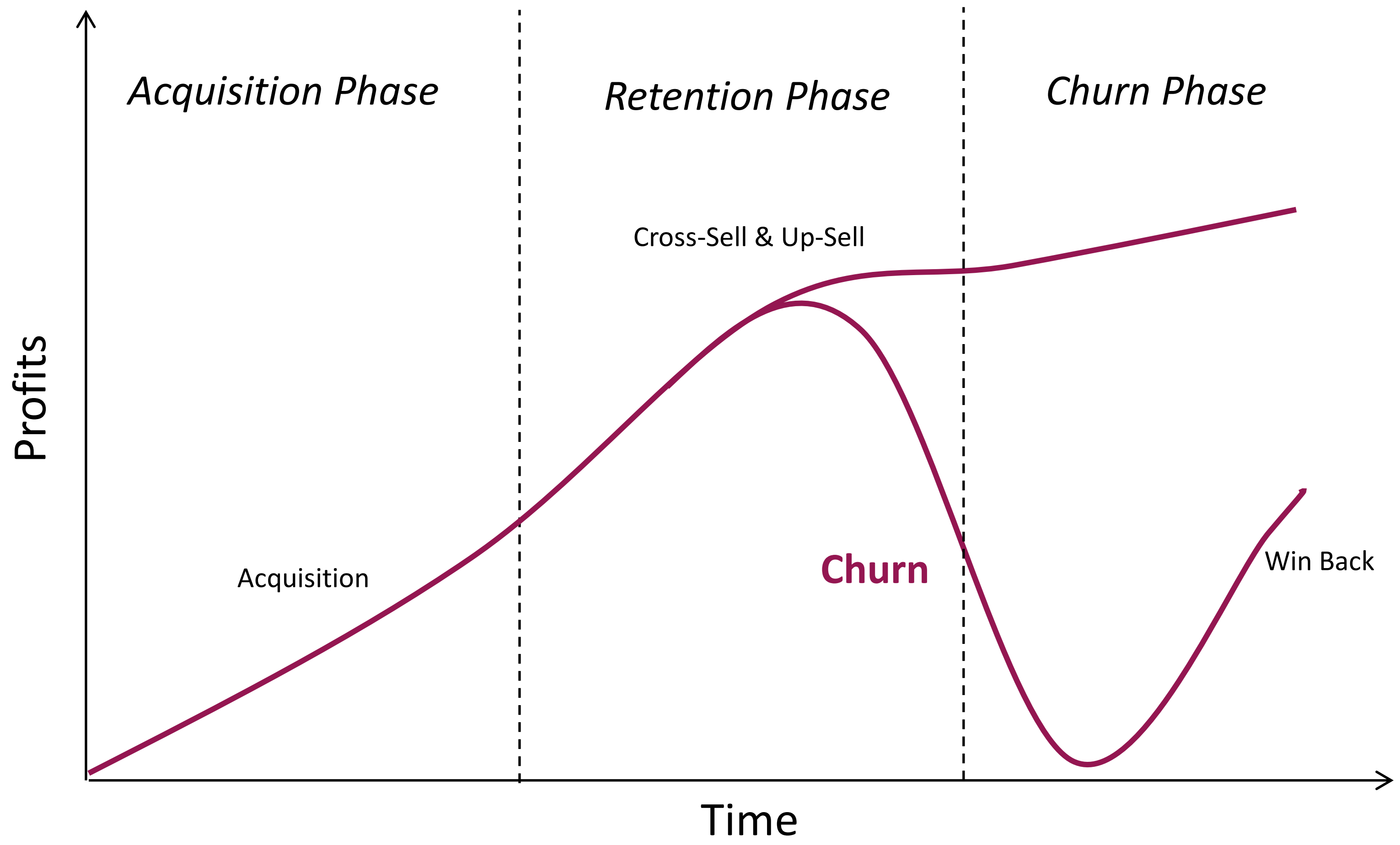
Churn Behaviour



Churn Behaviour

Customer Lifetime



Why study churn behaviour? Economic reasons

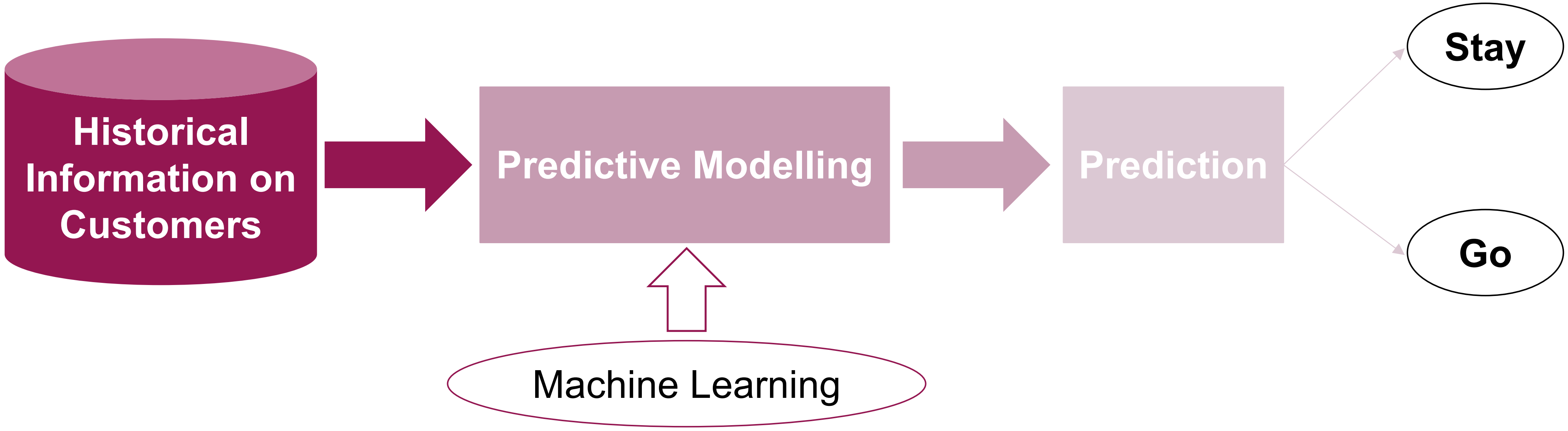
- Attracting new customers **costs 5 to 6 times more** than retaining of the existing ones
- Long-term customers generate **more profits**
- Long-term customers are **less sensitive to competitors' marketing campaigns**
- Long-term customers are **less costly** to maintain over time
- Long-term customers provide new referrals through **positive word-of-mouth**

Why study churn behaviour? Psychological reasons

"I'm sorry, sir, this is the Department of Immediate Dissatisfaction. Your appointment is with the Bureau of Eternal Frustration."

More importantly, churners are **unhappy**, **unsatisfied** and **no-more-loyal customers**

How to study Churn: Making predictions



The aims of the study

1. Develop the predictive model
2. Understand predictive relationships
3. Shed light on the consumer psychology

Methodology for developing predictive churn models

Predictive modelling turns **data into information** and **information into insight**

It does not demand a priori hypotheses → Data Driven

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The Data Mining Process

Data Acquisition

Methodology for developing predictive churn models

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The Data Mining Process

Data Acquisition → **Data Cleaning**

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The Data Mining Process

Data Acquisition → Data Cleaning → **Model Training and Tuning**

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The Data Mining Process

Data Acquisition → Data Cleaning → Model Training and Tuning → **Model Testing**

Methodology for developing predictive churn models

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The Data Mining Process

Data Acquisition → Data Cleaning → Model Training and Tuning → Model Testing → **Action**

Data acquisition and cleaning

820.123 Customers

CRM

BILLING

CAMEO

Outliers Treatment

Handling Missing Values

Defining Time Window

Feature Selection

Getting Know the Data

81.813 Customers

Electricity

Residential

Single POD

Original Datasets → Data Cleaning → Targeted Population

Predictors

Socio-Demographics

Age, Sex, Regional area

Account

Customer Type, Length of the contract, Acquisition Channel, Loyalty Program Member, Payment method, Online Billing

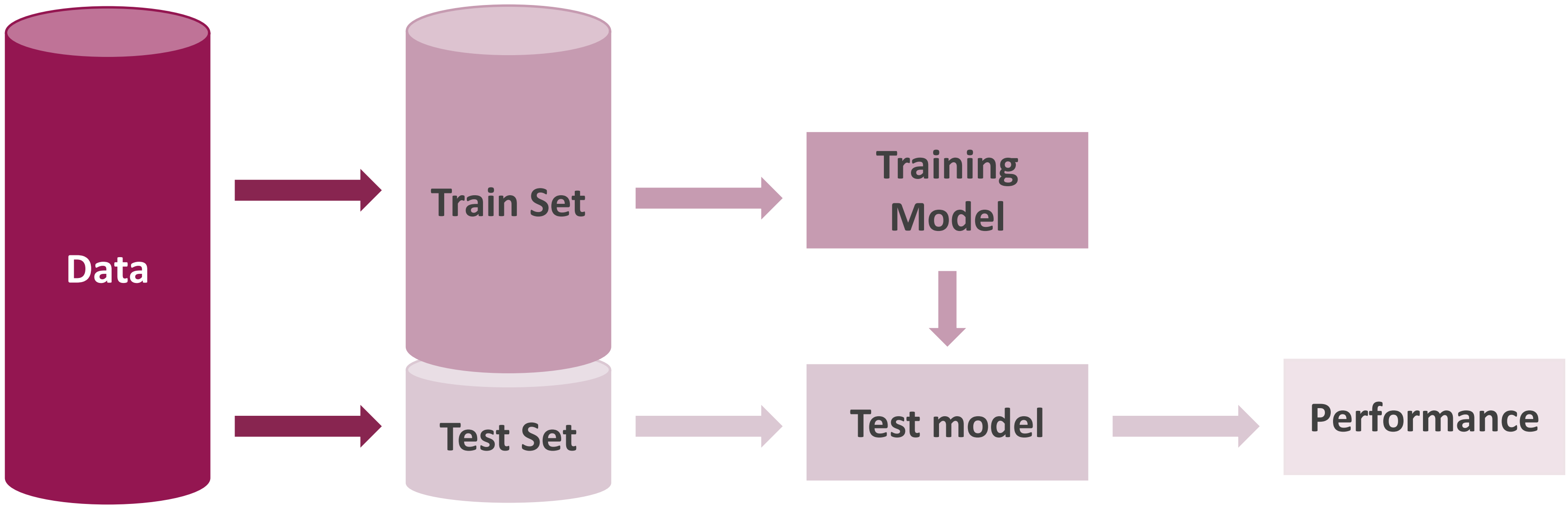
Behavioural

Number of complaints, Number of change offer, Number of contacts, Number of retention proposal, Contract starts with a transfer, Number of cross sell proposal, Digital customer, Number of previously churn

Socio-Economics

Socio-economic status, Presence of adults over 60, Presence of children, Household size, Education, Building age

Train – Test split

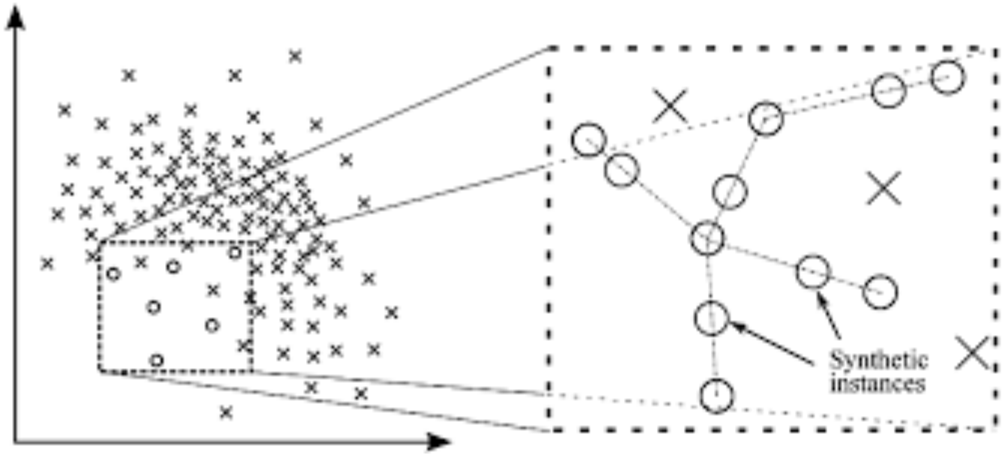


	Total Dataset	Training Set	Test Set
N of Churner (%)	6899 (8.4%)	4848 (8.5%)	2050 (8.3%)
N of Non-Churner (%)	74915 (91.6%)	54421 (91.5%)	22494 (91.7%)
Total	81836	57269	24544

Class imbalance

Number of non-churners is far higher than the number of churners

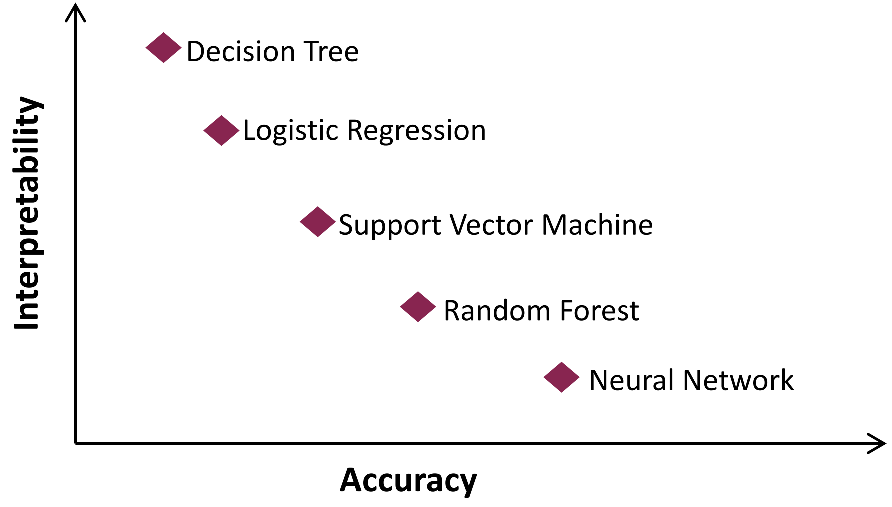
Resampling Approach: **SMOTE**



	SMOTE Training Sample
N of Churner (%)	24240 (45.5 %)
N of Non-Churner (%)	29088 (54.5 %)
Total	53328

Modelling phase: Training and testing

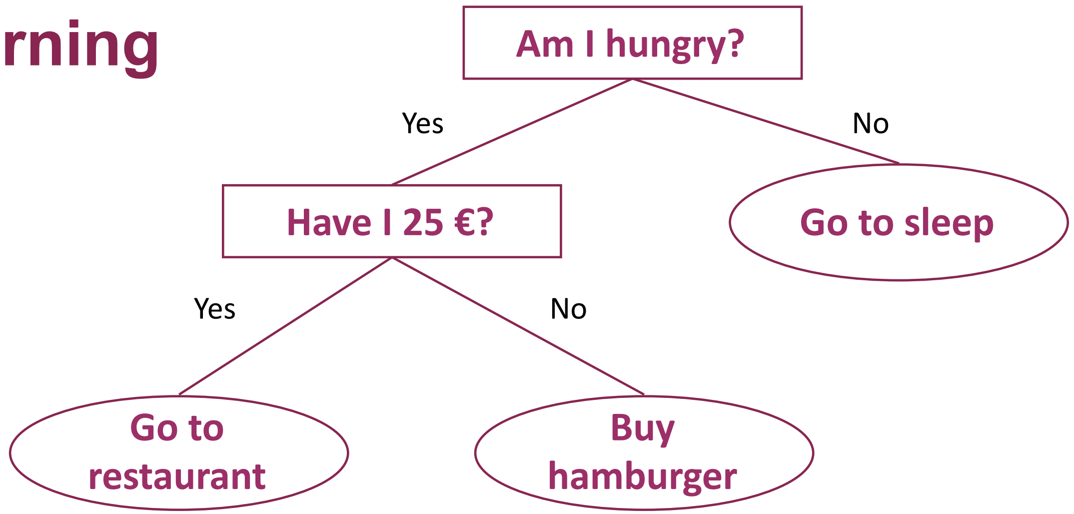
Churn prediction is a **supervised learning classification task**



Modelling phase: Training and testing

Churn prediction is a **supervised learning classification task**

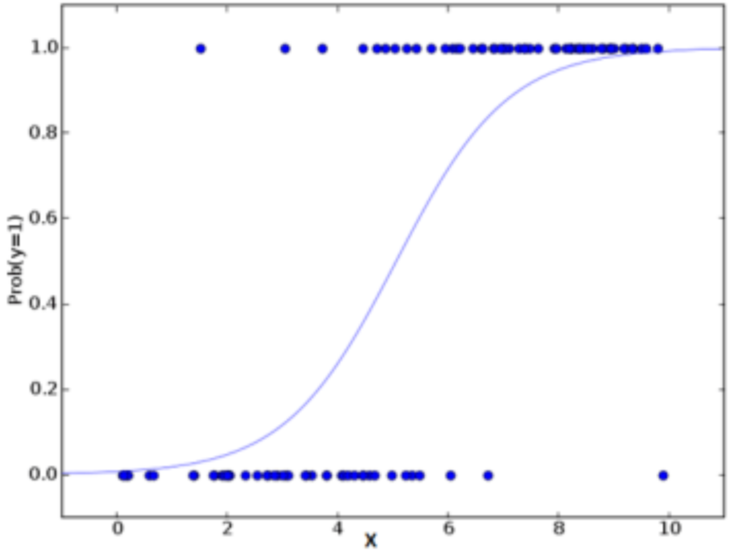
Decision Tree (**CART** and **C5.0**)



Modelling phase: Training and testing

Churn prediction is a **supervised learning classification task**

Decision Tree (**CART** and **C5.0**)
Logistic Regression



Modelling phase: Training and testing

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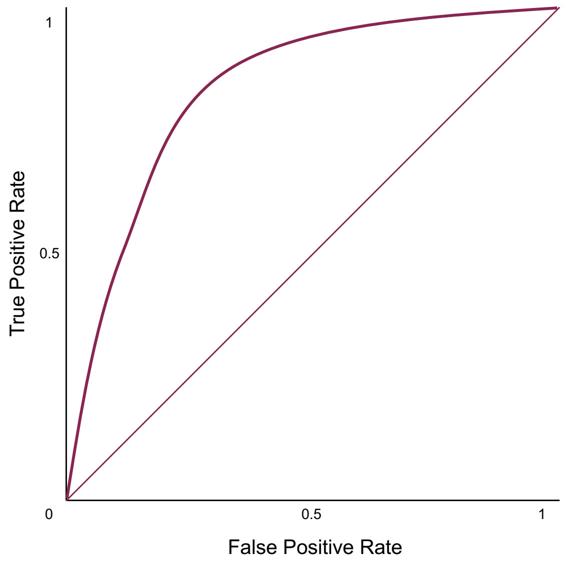

Decision Tree (**CART** and **C5.0**)

Logistic Regression

Performance measure: **Area Under the ROC Curve (AUC)**

Range values from 0.5 (random model) to 1 (perfect model)

Results

Model	AUC Train	AUC Test
CART Unbalance	0,51	0,51
CART + SMOTE	0,76	0,56
C5.0 Unbalance	0,51	0,51
C5.0 + SMOTE	0,73	0,56
Logistic Regression Unbalance	**0,67**	**0,68**
Logistic Regression + SMOTE	0,77	0,63

Odds ratio: Socio-demographic predictors

Regional Area	Center	1.17
	North East	1.01
	South	1.40
	Islands	1.14
Sex	Female	0.99
Age		0.99

- No relationship
- Decrease the likelihood of churn
- Increase the likelihood of churn

Odds ratio: Account predictors

Acquisition Channel	Agency	2.17
	Counter	0.47
	Call Center	1.09
	Web	1.18
	Tele-selling	1.25
Customer Type	Dual	0.89
Payment Method	RID	0.95

No relationship

Decrease the likelihood of churn

Increase the likelihood of churn

Odds ratio: Account predictors

Lenght of the Contract		0.986
On Line Billing	**Yes**	**0.84**
Start with Transfer	**Yes**	**0.89**
Loyalty Program Member	**Yes**	**0.78**
Digital Customer	Yes	0.95

No relationship

Decrease the likelihood of churn

Increase the likelihood of churn

Odds ratio: Behavioural predictors

Cross-Sell Proposal	0.70	Number of Contacts	1.04
Change Offer	0.449	Number of Complaints	1.36
Retention Proposal	1.478	Previously Churn	1.50

No relationship

Decrease the likelihood of churn

Increase the likelihood of churn

Odds ratio: Socio-economic predictors

Socio-Economic Status	1.08	Household Size	0.99
Presence of adults over 60	1.02	Building Age	0.97
Presence of children	1.02	Education	0.99

No relationship

Decrease the likelihood of churn

Increase the likelihood of churn

Discussion

Contributions to the knowledge on consumers’ churn behaviour

Implement machine learning techniques and data mining methodology into the consumer psychology research

Logistic regression outperformed CART and C5.0 decision trees. Moreover, the logistic regression has shown to be robust

Limitations and Developments

- Consider other predictors
- Examine multiple retailers
- Actual behaviours of electricity consumers → Ecological Validity
- Disentangle the causality of some of the effects we found