stream INTELLIGENCE

Prediction of Churned Customers:
A Case of An Online Contact Lenses Store

04 November 2016

About Stream Intelligence

We are a data and analytics consultancy that answers business problems through the intelligent use of data

Analysing data intelligently

We approach our client engagements strategically, identifying the key business challenges and objectives, before diving into rigorous and robust data analysis to provide actionable insight.

Our Services

A combination of analytics and strategy

Understand Your Customers

Using a blend of analytics and strategy we help organisations understand their customers better

Predict Your Customers

Using predictive analysis and machine learning, we help organisations anticipate what their customers will do next

Influence Your Customers

We help organisations create strategies based on insights, and guide them to make data-driven decisions

About The Presenter

The Presenter

lpdp
lembaga pengelola dana pendidikan

Agus Nur Hidayat

Work Experience

- **Stream Intelligence**:
  - Senior Data Scientist
- **Surya Computing Research Lab**:
  - Research Assistant
- **Gibeon Solutions**:
  - Software Developer

Education

- **University College London (Awardee of LPDP Scholarship):**
  - Master of Science in Business Analytics
- **Institut Teknologi Sepuluh Nopember**:
  - Bachelor of Computing in Information Systems

Outline

1. The Importance of Churn
2. Methodology
3. Understanding Churned Customers
4. Predicting Churned Customers
5. Influencing Churned Customers
6. Conclusions

The Importance of Churn (1/2)

Problems faced by the client

Online Contact Lenses Store

- High number of customers who don't re-order
- Limited budget for marketing strategy

Expected solution

Clear Measurement + Interpretable Model = Efficient Strategy

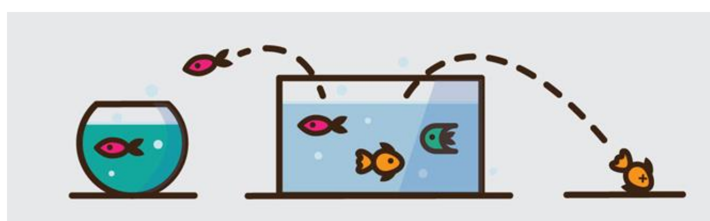
The Importance of Churn (2/2)

Why does it matter to retain existing customers?

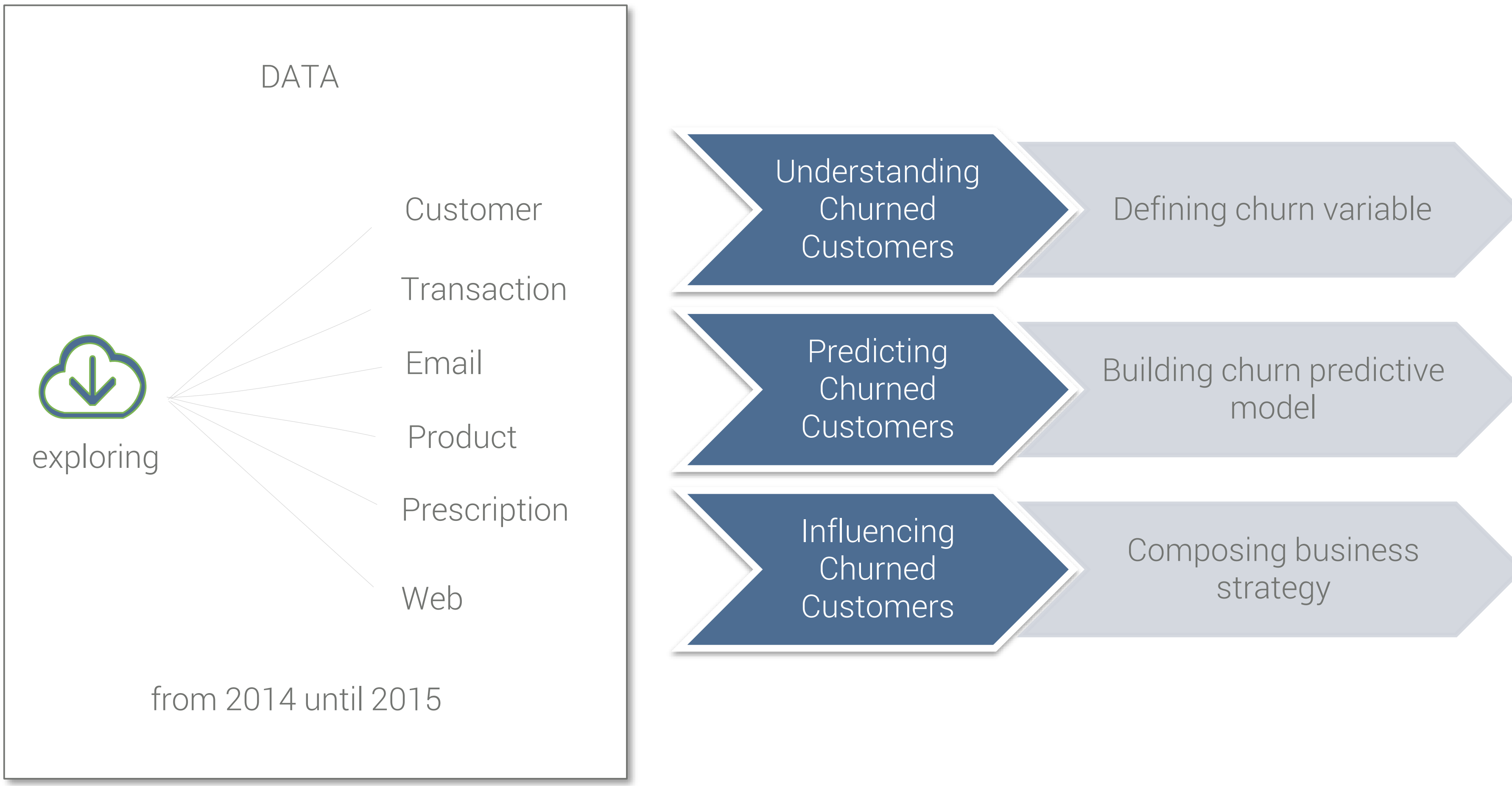
- It is five times more expensive to get a new customer compared to keeping an existing one. (Reich and Benbasat, 1990)
- Increasing the rate of customer retention by 5% increases profits by 25% to 95%. (Reichheld, 2001)

How to measure how well a company keeping its customers?

CHURN → The loss of a customer who has not re-ordered over a certain period



Methodology



Understanding Churned Customers (1/2)

- Churn can be defined by creating a threshold-rule based on the transactional activities of the customer. (Nie et al., 2009). Here is what we did:

We determined all possible bases of customers by looking at the product type and the quantity in the customer's first order.

↓

We only considered customers with at least two orders in the transaction data because we need the time difference between the first and the second orders.

↓

We defined the duration for an average customer to make their second order by measuring the number of month until 75% of customers made their second order.

The 75% coverage represents an acceptable level of returning customers to the business operations based on the client's perspective.

Understanding Churned Customers (2/2)

Customer Bases for Defining Churn

Quantities	Type A	Type B	Type C
1	6 months	6 months	6 months
2	6 months	8 months	8 months
3+	6 months	10 months	11 months

Each customer base will have a period value that can be used as the conditional value to filter churned customers. Thus, we can create a new variable called churn that shows whether a customer is a churner or not.

Predicting Churned Customers (1/4)

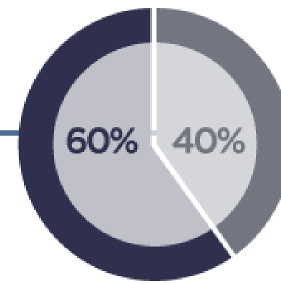
There was a study on churn which surveyed customers' motives when swapping service providers (Keaveney, 1995). It triggered the effort of recognizing the factors that drive churn and prescribing interventions based on the findings.

We used predictive modeling to understand the factors that drive churn. The features for the model can be prepared by analyzing datasets, deriving possible features on each dataset and combining these features into one master table. (Hardy and Bryman, 2004)

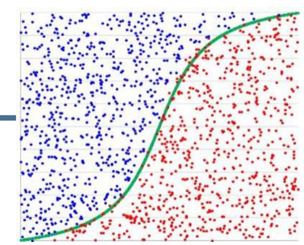
Predicting Churned Customers (2/4)

We used R as the tool and all models were fed with the master table that consisted of 272 features (categorical variables were converted to binary ones) which included 114, 708 customers.

There were 60% customers labelled as churners and the rest labelled as non-churners. Therefore, we used the ratio of 60:40 when we split the data into training and test sets.

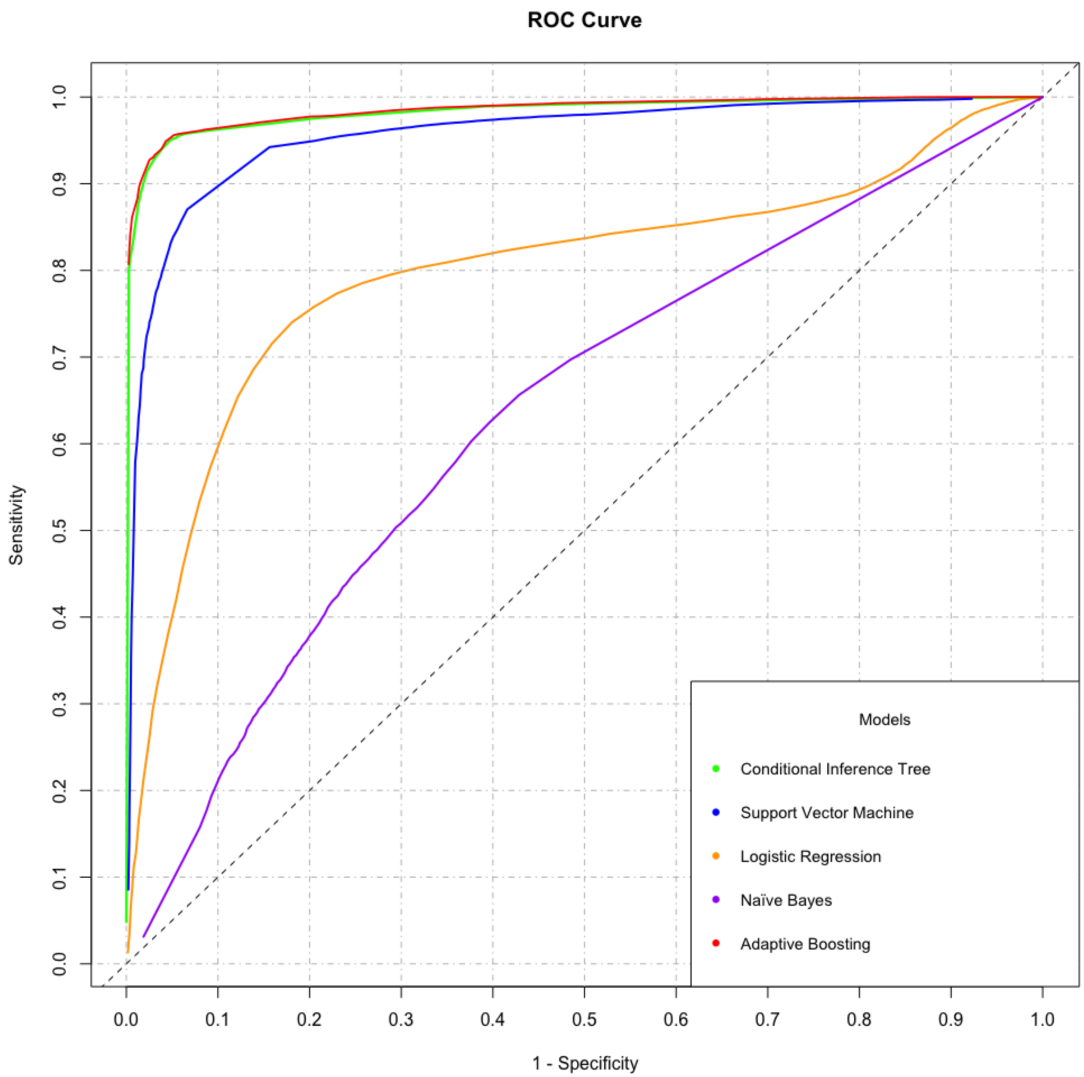


For the models, we compared the Conditional Inference Tree or CTree (Hothorn et al., 2006), Logistic Regression, Naïve Bayes, Adaptive Boosting (AdaBoost), and Support Vector Machine (SVM).



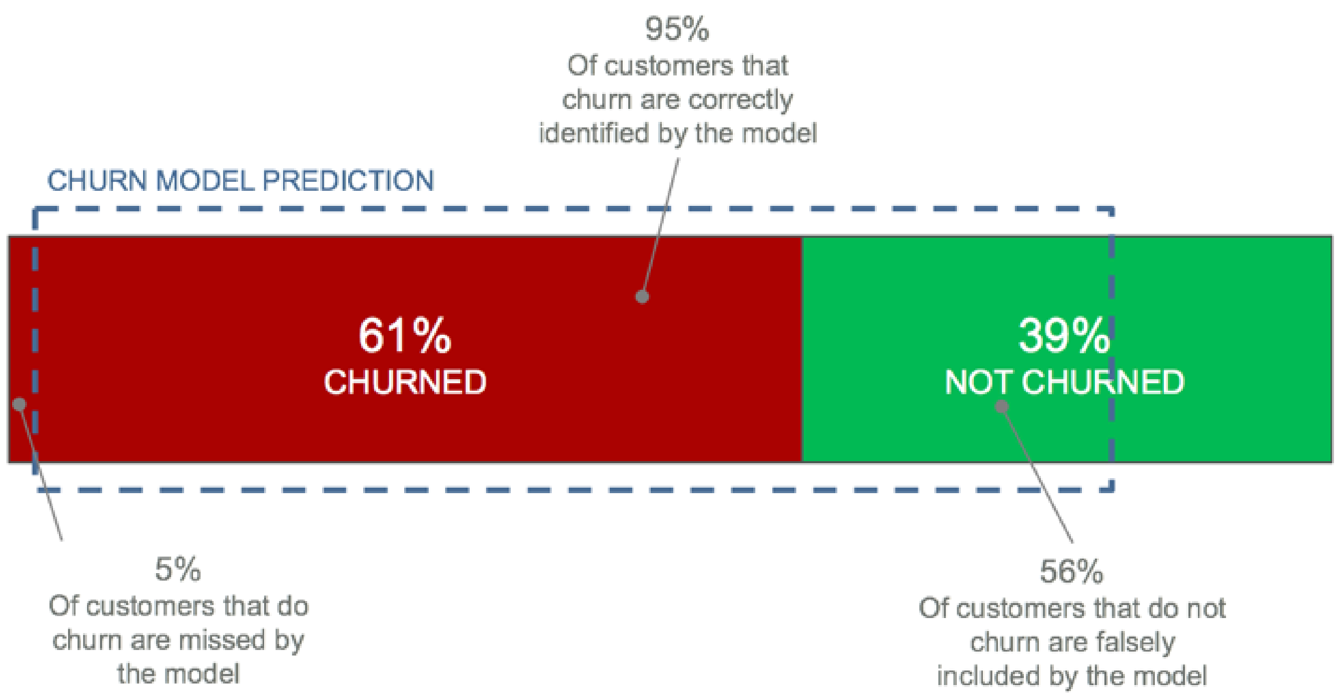
Predicting Churned Customers (3/4)

- Fawcett (2006) noted a way to compare the models easily by using a Receiver Operating Characteristic (ROC) Curve.
- Area Under the Curves (AUC) is used as the indicator of how well a model performs.
- CTree and AdaBoost give the best performance achieving AUC score of 0.95.
- CTree has the upper hand to visualize the rule of features triggering churn due to its interpretability of the tree illustration.



Predicting Churned Customers (4/4)

Illustration of Churn Prediction Result from the CTree



The model can predict with 95% accuracy those customers who will eventually churn. However, the model did not recognize 5% of churned customers and identified 56% of those not churning as having churned.

Influencing Churned Customers (1/4)

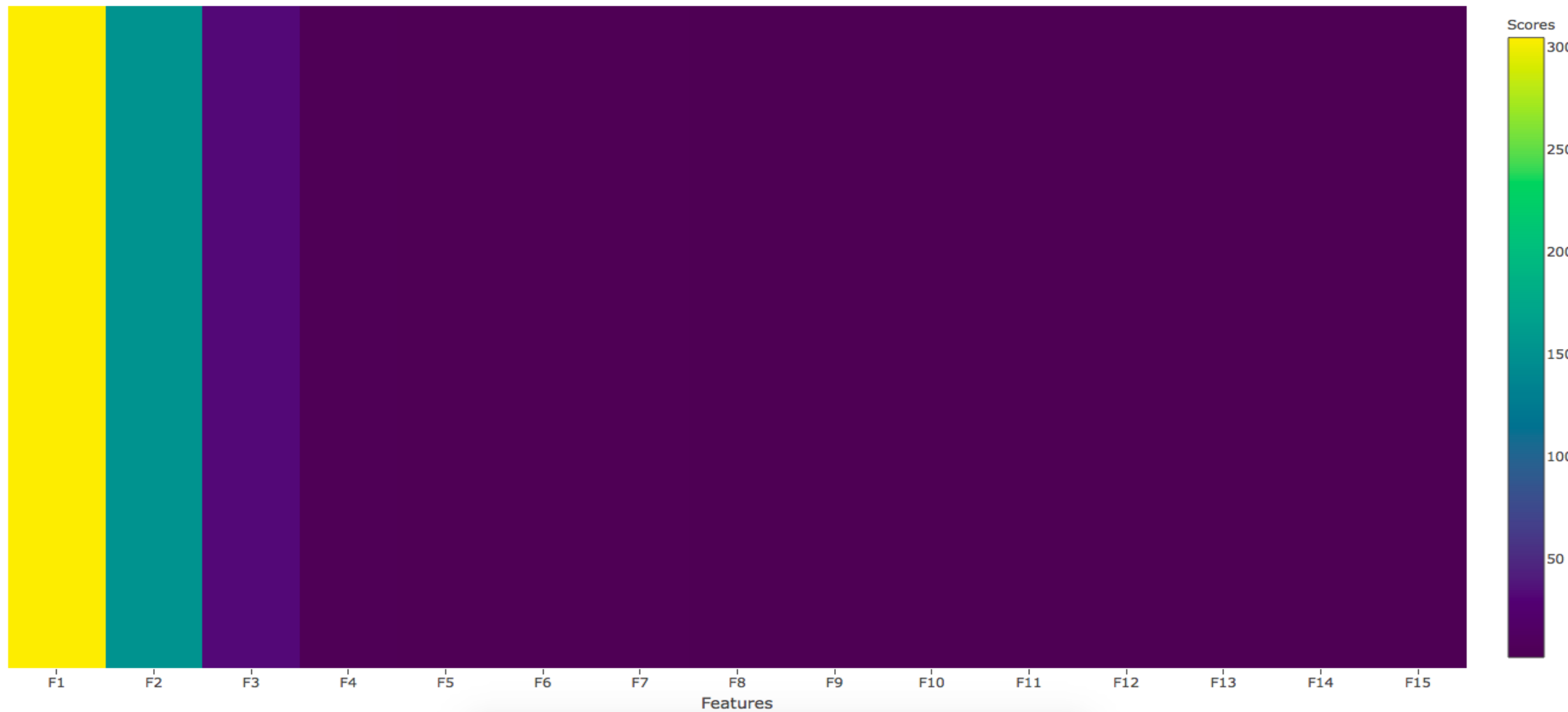
Sample of Churn Model Rule from the CTree

Churn Probability	**99.2%**
=	
Var1	>179.5
and	
Var2	>223.5
and	
Var3	0.0; 1.0; 3.0; 19.0; 5.0
and	
Var1	>239.5
and	
Var4	>8.2
and	
Var1	>328.5

The table shows a path in the tree where a customer with a combination of some features with certain values will have a 99.2% probability of churning.

Influencing Churned Customers (2/4)

Heat Map of Churn Top 15 Important Features from the CTree



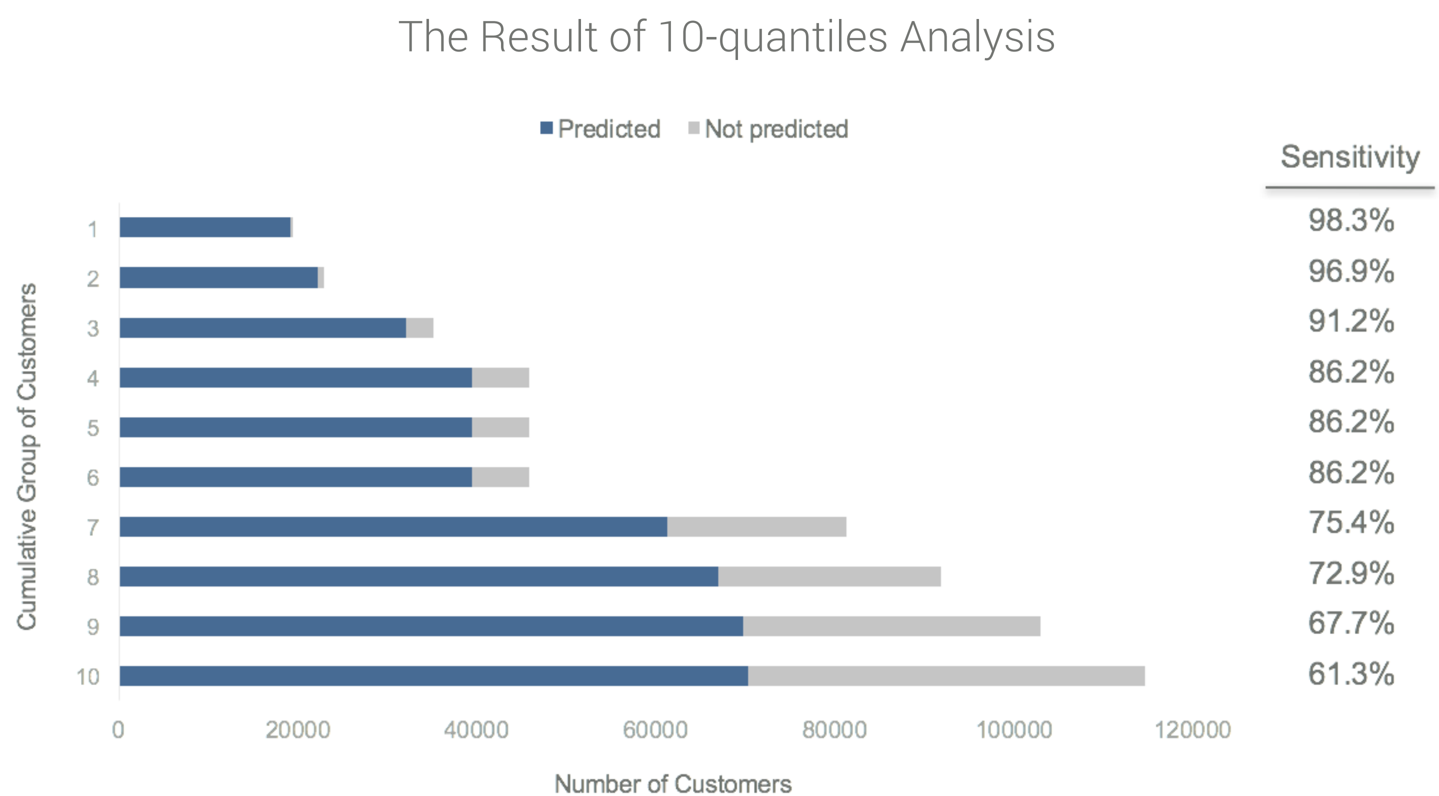
Features with significantly different color demonstrate large differences of important score between each other. Features with a slightly different color have smaller score difference with each other and features with the same color are not so different from each other.

Influencing Churned Customers (3/4)

Insights from the model can be used to isolate factors which lead individuals to churn and take remedial action to prevent that behavior from occurring (e.g. by re-designing the user interface of the website, etc.).

For the problem of limited marketing budget, we used the 10-quantiles concept from the theory of probability to rank the churn probabilities into multiple groups (Hyndman and Fan, 1996).

Influencing Churned Customers (4/4)



The larger group will cover the larger number of customers but with less accuracy in predicting churned customers. Therefore, the company can decide on the marketing targets by considering the accuracy of predicting churn on each group.

Conclusions

Thanks to the predictive model, the company now:

- Has the knowledge about customers who are likely to churn and they can influence those customers to reduce the likelihood they will leave. (As most churn events occurred six months after the transaction, there is almost a five-month window to target the customers)

- Has a metric to measure how many active customers they would have:

    - If they did nothing to reduce churn and continued with their acquisition strategy, or
    - If they put their resources into diminishing churn.

Further suggestion:

- The model can be enhanced by understanding the value of a customer. The company can be more selective by only targeting customers who have greater value.

R

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