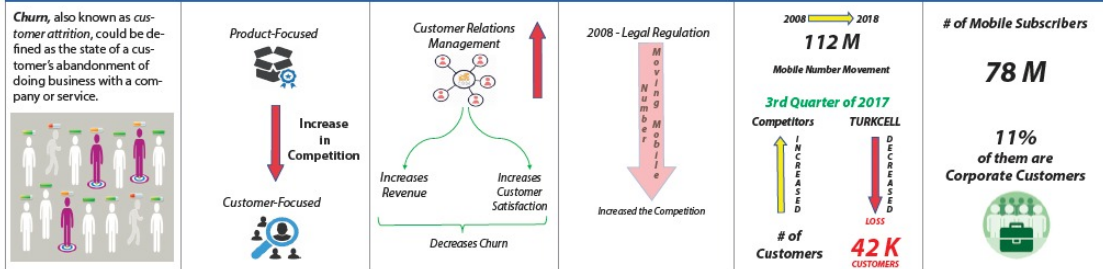


INTRODUCTION



PROBLEM DEFINITION

ARPA < **ARPC**

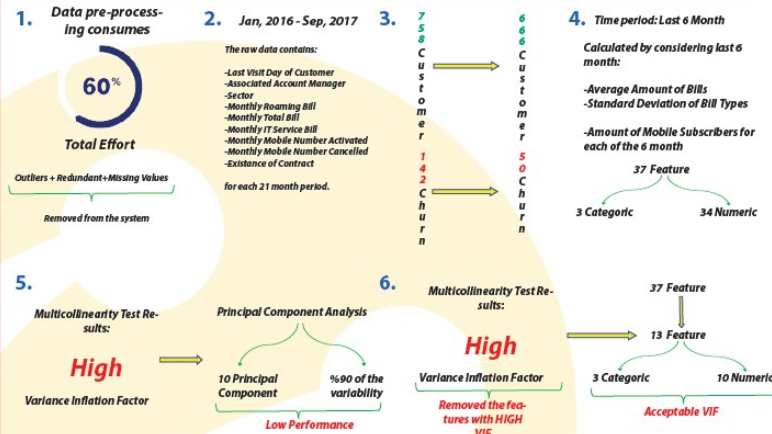
Revenue per New Customer < Loss per Customer Churn

Since attracting new customers require sacrifices in the company side, such as relatively low price than existing customers, the ARPC value is expected to be greater than the ARPA value.

TURKCELL does not have automated system to indicate the risk of churn for corporate customers, the managers use their judgment and experience for prediction.

CUSTOMER CHURN Causes **%2 REVENUE LOSS**

DATA PRE-PROCESSING



LEARNING MODELS

Artificial Neural Network (ANN)	Support Vector Machine (SVM)	Naive Bayes (NB)	Random Forest (RF)
<ul style="list-style-type: none"> The objective of the neural network is to transform the inputs into meaningful outputs. Each input value is multiplied by the corresponding weighting layers, then summed and a scalar parameter called bias is added. There are three types of transfer functions used commonly in literature such as sigmoid, rectifier*, hyperbolic tangent and linear. <p>* transfer function which is used in our model</p>	<ul style="list-style-type: none"> A learning model that is based on structural risk minimization, controlled by associated learning algorithms that analyze data and define patterns. A support vector machine attempts to find the line that "best" separates two classes of points. By "best", it means the line that results in the largest margin between the two classes. The points that lie on this margin are the support vectors. 	<ul style="list-style-type: none"> Naive Bayes methods are a set of supervised learning algorithms based on applying Bayes' theorem with the "naive" assumption of independence between every pair of features. The result of Naive Bayes modeling technique became acceptable when the high dimensional data was transformed into low dimension (Huang, Kechadi, & Buckley 2012). 	<ul style="list-style-type: none"> It is a model of multiple decision trees created using more than one decision tree. It has been improved by adding randomness feature to bagging method. (Breiman 2001) This model breaks each node into branches using the best among randomly selected features in each node, instead of dividing each node by using the best parameter among all features.

EVALUATION

EVALUATION

Confusion Matrix			Accuracy		Sensitivity		Model/Metric					
		Predicted		Accuracy = $\frac{TN + TP}{TN + TP + FP + FN}$		Sensitivity = $\frac{TP}{TP + FN}$		Model/Metric				
		-	+					Model/Metric	Accuracy	Recall	Sensitivity	F-measure
Real	-	TN	FP	+	FN	TP	ANN	94%	75%	25%	37.5%	
TN: Predicted true but do not leave the system												
FP: Predicted the customer will the system but it does not leave												
FN: The customer leave the system but model predict it wrong												
TP: Model predicted correct and customer leaves the system												
		Recall		F-measure = $2 \times \frac{\text{Recall} \times \text{Sensitivity}}{\text{Recall} + \text{Sensitivity}}$				SVM				
		-	+					Model/Metric	Accuracy	Recall	Sensitivity	F-measure
Real	-	TN	FP	+	FN	TP	SVM	95.2%	100%	33%	50%	
Recall = $\frac{TP}{TP + FP}$												
F-measure = $2 \times \frac{\text{Recall} \times \text{Sensitivity}}{\text{Recall} + \text{Sensitivity}}$												
NB												
RF												

RESULTS

The Random Forest model predicted customer loss with an accuracy of 96.3%. In addition, the features with the highest effect on the prediction are identified by using feature importance.

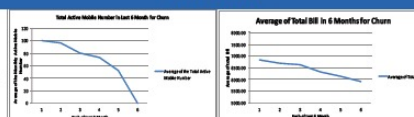
The Company uses this information to revise customer relationship management strategies.

FEATURE IMPORTANCE

Feature importances are measured for learning models which have highest accuracies. SVM and RF models approximately gives the same results. The most important 5 Features are:

- Average # of Roaming Bill
- Total # of Cancelled Mobile Numbers
- Std.Deviation of Roaming Bill
- Average of the Total Bill
- Number of port-out mobile number in the last 6 months

INSIGHTS



REFERENCES

Breiman, 2001; Breiman, <http://oz.berkeley.edu/users/breiman/randomforests.html>

Huang, B., Kechadi, M. T., & Buckley, B. (2012). Customer churn prediction in telecommunications. Expert Systems with Applications, 39(1), 1414-1425.