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Executive Summary

Objective: A mobile phone (service provider) company is studying factors related to customer *churn*, a term used for customers who have moved to another service provider. If we can better identify the customers most likely to churn, we can intervene and offer them the discount, thereby retaining them as customers. The company has allocated resources to review up to 15% of their customer accounts that may leave their service with the intent of offering a discount ($10) to prevent their departure (churn). Each customer pays $50 per month to the phone company, and the discount will net $40 per month in revenue. The mobile company has asked us to predict customer churn and recommend which accounts to offer a discount. Overall, this will result in higher revenue for us, as fewer customers are leaving.

Your Best Model: We tried boosting by 100 models, but then we changed to 30 models. JMP returned a better model boosted by 12 models, as we inserted 30 max. We inserted 3 for nodes and a learning rate of 0.25. We also transformed covariates in our model.

Key Insights: As the number of customer service calls increases, probability of churn increases. Most likely the majority of calls are customer complaints. People who have international calling plans are more likely to churn, and for these customers, the probability of churn increases as usage minutes for day, night, evening, and international minutes decrease. It does not make sense, unless customers who make international calls use third parties services or WhatsApp compared to using the company's international calls packages. Churn also becomes more likely for these customers as the charges for these types of calls increase, which makes business sense as no one likes to pay these types of charges. Customers who have international packages and end up talking more than 13 minutes per day in international calls, have a high probability of churning. I believe we should review our international calls packages, and offer customers better deals as they use more minutes on international calls.

Customers who have VM plans are less likely to churn. Although as night voice mail messages increase, the probability of churn increases. As day minutes increase, the probability of churn decreases. Day charge is best around 40. If day charge is too low, most likely the quality of calls are low, so probability of churn increases. As day charges get above 40, customers churn as it gets too expensive for them ($40 looks too expensive for me per day/ not sure this makes business sense.)

Why your model is better: We believe the model is both more effective than the base model and reasonably constructed relative to the available information. Considering performance, the final model produced superior revenue to the base model and had higher accuracy in every measure except for small differences in validation dataset false positive and sensitivity. Further, the variables used in the model are easily explained, selected through observations of statistical difference (standard deviations) and relatively intuitive when compiled.

Conclusion: Our model beat the JMP model in terms of revenue: ours generates a New Revenue figure of $47,135,086.13, compared with $46,030,603.06. Our model has a validation accuracy of 93.29% vs. the JMP model's 88.3%. The testing propensity for our model is 1.1366, compared to the JMP model propensity of 1.0591. Our model also had a higher lift than the JMP model: 1.103 vs. 1.076.

JMP default model

Build the Neural Network Model using JMP on the following conditions:

Learning Rate = 0.21

i) Statistical KPIs of JMP Model – From JMP Printout

Measure	Training	Validation	Definition
Entropy RSquare	0.46554	0.401639	1-Loglike(model)/Loglike(0)
Generalized RSquare	0.56804	0.5023869	(1-(L(0)/L(model))^(2/n))/(1-L(0)^(2/n))
Mean -Log p	491.315	275.075	∑ -Log(ρ[j])/n
RMSE	0.2422205	0.2587534	√ ∑(y[j]-ρ[j])²/n
Mean Abs Dev	0.1308453	0.1410139	∑ |y[j]-ρ[j]|/n
Misclassification Rate	0.0670869	0.0747075	∑ (ρ[j]≠ρMax)/n
N	2221	1111	n

Statistical KPIs of JMP Model – From Excel Printout

	Training	Validation
Accuracy %	**89.51%**	**88.30%**
True Positive Rate	**72.36%**	**68.94%**
False Positive Rate	**7.58%**	**8.42%**
Sensitivity (True Positive Rate)	**72.36%**	**68.94%**
Specificity (True Negative Rate)	**92.42%**	**91.58%**

ii) a) Business KPIs of JMP Model – Training

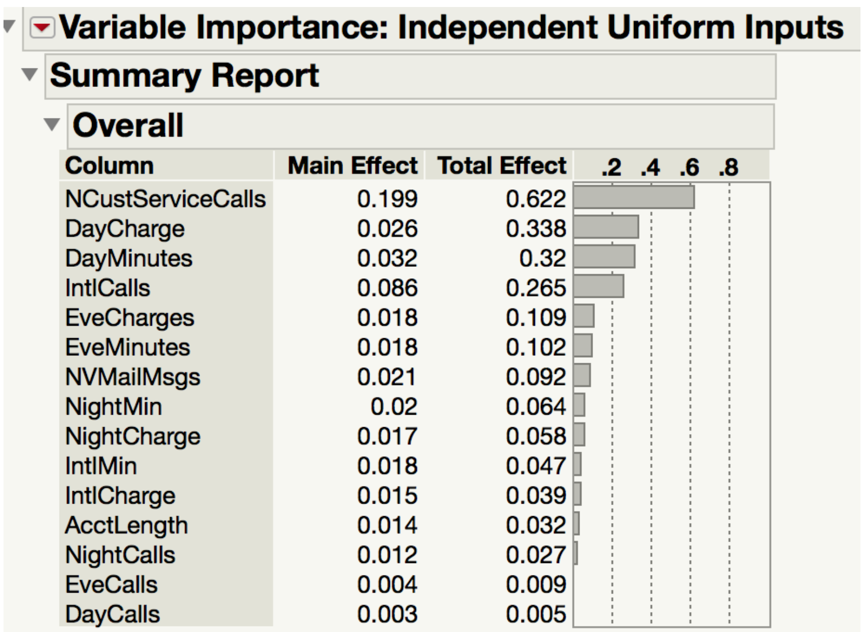
Maximum Revenue	$ 50,000,000
Bottom Line Revenue	$ 42,751,013
Assume upto 15% of the Account will be reviewed	150,000
Cost of Reviewing and making changes to prevent churn	$ (10)
New Revenue	$ 46,298,964.43

b) Business KPIs of JMP Model – Testing

Maximum Revenue	$ 50,000,000
Bottom Line Revenue	$ 42,751,013
Assume upto 15% of the Account will be reviewed	150,000
Cost of Reviewing and making changes to prevent churn	$ (10)
New Revenue	$ 46,030,603.06

iii) Interpret the Model (NN) – From Business Point of view & Profiler point of view

From Profiler, we ranked variables by importance in JMP.



Variable Importance: Independent Uniform Inputs

Summary Report

Overall

Column	Main Effect	Total Effect
NCustServiceCalls	0.199	0.622
DayCharge	0.026	0.338
DayMinutes	0.032	0.32
IntlCalls	0.086	0.265
EveCharges	0.018	0.109
EveMinutes	0.018	0.102
NVMailMsgs	0.021	0.092
NightMin	0.02	0.064
NightCharge	0.017	0.058
IntlMin	0.018	0.047
IntlCharge	0.015	0.039
AcctLength	0.014	0.032
NightCalls	0.012	0.027
EveCalls	0.004	0.009
DayCalls	0.003	0.005

Evaluating Variables:

<u>NCustServiceCall</u>

As the number of customer service calls increases, prob(churn) increases, then decreases, then increases again as the number of customer service calls approaches the maximum. From a business point of view, this makes sense: when the number of customer service calls is low, the customer is less likely to be frustrated and considering leaving. As the number of complaints increase, the probability of churn increases. As the company responds to complaints and improves its customer service to gather feedback early on, the probability of churn decreases. As the number of calls approaches the maximum, a good number of the calls would probably be complaints. So, the probability of churn increases again.

<u>DayCharge / DayMinutes /</u>

As day charges and daytime minutes increase, the probability of churn increases. If our customers use too many day minutes and day charges increase, we would expect a higher probability of churn. It makes business sense for customers to leave if charges increase, especially if they are using too many minutes.

IntlCalls
As international Calls increase, the probability of churn decreases. Common sense would dictate that customers who make a good number of international calls, purchase a package or deal in order to make those calls in a cost-effective way. If we see that customers are making many international calls, they likely have a specific plan they chose at a price they are happy with. So, they are less likely to churn. But if we look deeper into the graph, then cross-reference with our distribution graph for the international calls variable, we see that our customers who do not churn make lower than average international calls. This may mean that customers making more international calls are a relatively small group compared to those making mostly domestic calls, so it's harder to use this variable to predict churn for the entire customer base.

EveCharges / Eve Minutes
As the number of evening charges increases, the probability of churn decreases slightly, then increases slightly again. As evening minutes increase, the probability of churn decreases. For the evening minutes, it makes sense that people who talk in the evening would be satisfied with the price and are continuing / increasing talking. As for the evening charges, the prob of churn fluctuates and that must be due to an underlying reason related to packages / deals. Most providers offer free evening calls and people who talk more in evenings, must be talking for free. As most companies have limitations to the number of minutes unless it is unlimited calls, somehow the companies reaching their max are not satisfied with the service. We need to engage with those customers and encourage them to purchase unlimited service

NVMail messages
As voicemail increases, the probability of churning increases. A possible explanation is that these people like to talk rather than leave voicemails, so their calls are more likely personal than for business purposes. Those people who like to talk more and churn due to increased daytime minutes or daytime charges as interpreted above, would also churn for the same reasons.

iv) Confusion Matrix for Training

	No Churn	Churn	
No Churn	1755	144	1899
Churn	89	233	322
	1844	377	2221

iv) Confusion Matrix for Testing

	No Churn	Churn	
No Churn	870	80	950
Churn	50	111	161
	920	191	1111

Lift for training: New Revenue / Baseline= 1.0829

Lift for validation: New Revenue / Baseline = 1.076

v) Attach JMP Printout

Model NTanH(2)NTanH2(30)

Training — Churn

Measures	Value
Generalized RSquare	0.5680452
Entropy RSquare	0.46554
RMSE	0.2422205
Mean Abs Dev	0.1308453
Misclassification Rate	0.0670869
-LogLikelihood	491.31543
Sum Freq	2221

Validation — Churn

Measures	Value
Generalized RSquare	0.5023869
Entropy RSquare	0.401639
RMSE	0.2587534
Mean Abs Dev	0.1410139
Misclassification Rate	0.0747075
-LogLikelihood	275.07586
Sum Freq	1111

Your Best Neural Network Model

Your Best Model: We tried boosting by 100 models, but then we changed to 30 models. JMP returned a better model boosted by 12 models, as we inserted 30 max. We inserted 3 for nodes and a learning rate of 0.25. We also transformed covariates in our model below.

Model NTanH(3)NBoost(12)

Training — Churn

Measures	Value
Generalized RSquare	0.6929003
Entropy RSquare	0.5973107
RMSE	0.2053796
Mean Abs Dev	0.1047787
Misclassification Rate	0.0522287
-LogLikelihood	370.18205
Sum Freq	2221

Validation — Churn

Measures	Value
Generalized RSquare	0.6725443
Entropy RSquare	0.5748508
RMSE	0.2111532
Mean Abs Dev	0.1071525
Misclassification Rate	0.0522052
-LogLikelihood	195.4477
Sum Freq	1111

Neural

Model Launch

Validation Method

Excluded Rows Holdback

Reproducibility:
Random Seed 0

Hidden Layer Structure

Number of nodes of each activation type

Activation	Sigmoid	Identity	Radial
Layer	TanH	Linear	Gaussian
First	3	0	0
Second	0	0	0

Second layer is closer to X's in two layer models.

Boosting

Fit an additive sequence of models scaled by the learning rate.
Number of Models 30
Learning Rate 0.25

Fitting Options

☑ Transform Covariates
Penalty Method Squared
Number of Tours 1

Go

Key Insights:

Training

Maximum Revenue	**$ 50,000,000**
Bottom Line Revenue	**$ 42,751,013**
Assume upto 15% of the Account will be reviewed	**150,000**
Cost of Reviewing and making changes to prevent churn	**$ (10)**
New Revenue	**$47, 343, 538.95**

Validation

Maximum Revenue	**$ 50,000,000**
Bottom Line Revenue	**$ 42,751,013**
Assume upto 15% of the Account will be reviewed	**150,000**
Cost of Reviewing and making changes to prevent churn	**$ (10)**
New Revenue	**$47,137, 713.77**

iv) Confusion Matrix for Training

	No Churn	Churn	
No Churn	**1839**	**60**	**1899**

Churn	**52**	**270**	**322**
	1891	**330**	**2221**

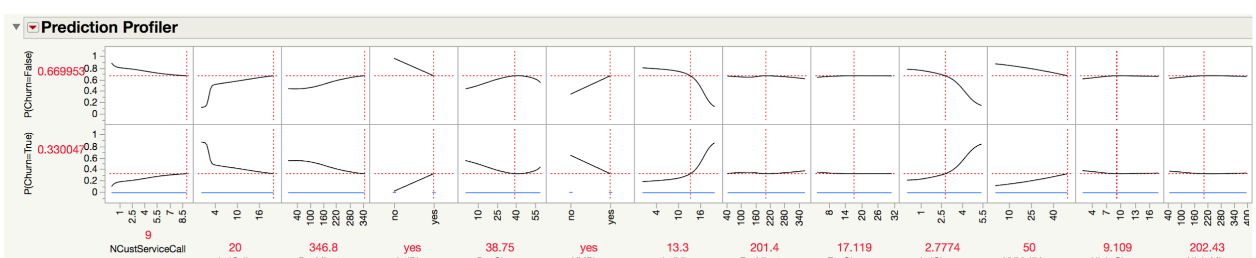
iv) Confusion Matrix for Testing

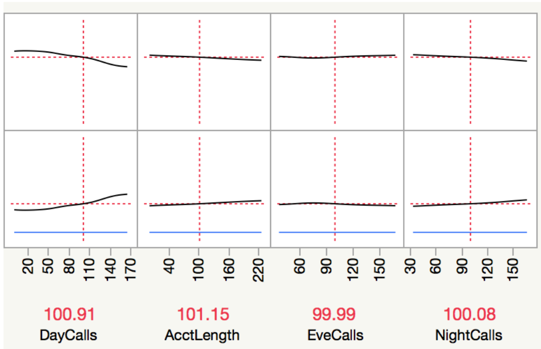
	No Churn	**Churn**	
No Churn	**913**	**37**	**950**
Churn	**30**	**131**	**161**
	943	**168**	**1111**

Lift

Lift Table in Dollars	Training	Testing
Lift with respect to Baseline - JMP Model	1.082991048	1.076631579
Lift with respect to Baseline - My Best Model	1.107424961	1.102526316
Lift with respect to JMP Model - My Contribution	1.022561509	1.024051623

Lift Table in Propensity	Training	Testing
Lift with respect to Baseline - JMP Model	1.113114392	1.105915332
Lift with respect to Baseline - My Best Model	1.137401494	1.132268795





Variable Importance: Independent Uniform Inputs

Summary Report

Overall

Column	Main Effect	Total Effect
NCustServiceCalls	0.151	0.315
IntlCalls	0.143	0.246
DayMinutes	0.028	0.235
IntlPlan	0.063	0.232
DayCharge	0.03	0.18
VMPlan	0.081	0.164
IntlMin	0.073	0.129
EveMinutes	0.021	0.092
EveCharges	0.026	0.087
IntlCharge	0.025	0.077
NVMailMsgs	0.03	0.058
NightCharge	0.02	0.046
NightMin	0.019	0.042
DayCalls	0.006	0.009
AcctLength	0.002	0.003
EveCalls	0.002	0.003
NightCalls	0.002	0.003