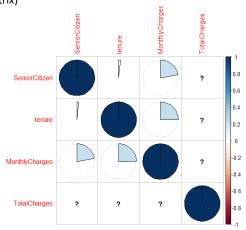
Aryan Sharma TelcoChurn

Exploratory Data Analysis & Processing

The data has 21 variables and 7043 observations. Out of the 21 variables a lot of the variables are character variables, we can either change them to factor variables or can change them in numeric sequences. Here I have changed the character variables into numeric variables, for e.g.: Partner, Dependents, etc. From the main dataset I have created subsets defined by whether a customer is only having internet, telephone connection or both. We are predicting the churn rate of the customers of the telco services and there are 2 different services and some customers have opted for both the services.

Correlation:

There are only 4 variables in the data which are numeric. Hence, we are calculating whether they have any correlation between them or not. correlation_matrix <- cor(data[c("SeniorCitizen", "tenure", "MonthlyCharges", "TotalCharges")]) correlation_matrix, method = "pie") print(correlation_matrix)



There is a correlation between total charges and monthly charges, hence we are only taking Monthly charges the variables.

Predictor table:

	Phone	Internet	Both	
	Connection	Connection	Connections	
Predictor	only	only		Rationale
		+/-	+/-	Gender can be a factor in churning rate and
				can be classified as a human factor as some
Gender	+/-			gender may take quick decision
Partner & Dependents		+/-	+/-	The number of family member can lead to
				more lines and hence changing a family plan
	+/-			can be taxing and may lead to sustaining
Streaming movies		-	-	If extra services like streaming is offered by
	-			provider, then it can lead to less churn rate
		-	-	Having a backup of data might help in
				retaining customers and it won't be helpful
Online Backup	+			for phone connection only customers
		-	-	If the service provider is providing good
				security over data and other services then
				churn rate might decrease as security is a
Online Security	-			major factor in data privacy nowadays
		()	-	Generally, multiple lines only effect phone
				connection and intenet is not there, multiple
				lines mean family plan & attrition rate is less
Multiplelines	-			when customer has family plan

Contract		+/-	+/-	If the contract is for a longer duration, then	
				the churn rate of customer is less which is	
	+/-			good and vice versa is also true	
Techsupport		-	-	If the tech support is good and solve all the	
				customer related problems then the churn	
	-			rate would be less	
SeniorCitzen		-	-	Churn rate should be less in senior citizens	
				as they do not want to change what they	
	-			have	
Monthly charges		+	+	If the monthly bill amount is more then the	
	+			churn rate can be higher	
Paperlessbilling and		+/-	+/-	This can be an indivilusitic factor depending	
Paymentmethod				upon a person whether or not they want a	
				type of service and they might churn if that	
	+/-			service is not available	

Regression Analysis

tenure*MultipleLines + OnlineSecurity + OnlineBackup + DeviceProtection +
TechSupport + StreamingTV + StreamingMovies + Contract +
PaperlessBilling + PaymentMethod + MonthlyCharges,
data=trainset_internet, family=binomial (link="logit"))

Dependent variable: Churn (1) (2) (3) genderMale SeniorCitizen1 Partner Dependents tenure MultipleLines -1.247 (1.422) -0.099 (0.141) OnlineSecurity -0.610*** (0.103) -0.106 (0.812) -0.038 (0.831) 0.109 (0.830) -0.289*** (0.096) OnlineBackup -0.147 (0.099) DeviceProtection -1.252*** (0.447) -0.671* (0.384) -0.490*** (0.138) -1.532** (0.635) -1.809** (0.795) -1.176*** (0.234) ContractOne year ContractTwo vear 0.285 (0.265) 0.141 (0.277) 0.346 (0.423) PaperlessBilling 0.355*** (0.098) 0.444 (0.358) -0.184 (0.155) PaymentMethodBank transfer (automatic) -0.184 (0.155) -0.031 (0.154) 0.274** (0.128) 0.035*** (0.004) -0.541*** (0.105) PaymentMethodCredit card (automatic) -0.999* (0.545)
PaymentMethodElectronic check 0.355 (0.380) -0.036 (0.423) PaymentMethodElectronic check 0.645* (0.332) 0.035 (0.237) -0.024 (0.157) MonthlyCharges -0.498 (0.854) TechSupport -0.087 (0.110) StreamingTV 0.530 (1.601) StreamingMovies 0.545 (1.566) -0.141 (0.109) 0.646 (0.789) 0.037 (0.025) -0.366 (0.677) 0.126 (0.247) Partner:Dependents 0.011** (0.005) 0.256 (3.917) -2.061*** (0.271) tenure:MultipleLines -1.769 (4.733) Constant 511 Log Likelihood -223.812 453.902 -1,738.440 3,520.881 Akāike Inf. Crit. 479.625 Note: *p<0.1; **p<0.05; ***p<0.01

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Interpretation

1. Only Phone Line Customers

Predictor	Beta	Exp Beta	Rationale	
		0.2873	Churn rate of customer with multiple lines would be	
Multiple Lines	-1.247		reduced to 71.27%	
		0.2858	Churn rate of customer with multiple lines would be	
Contract Year One	-1,252		reduced to 71.42%	
		0.2160	Churn rate of customer with multiple lines would be	
Contract Year two	-1.532		reduced to 78.4%	

2. Only Internet Line Customers

Predictor	Beta	Exp Beta	Rationale	
		0.6083	Churn rate of customer with multiple lines would be	
Dependents	-0.497		reduced to 78.4%	
		0.5112	Churn rate of customer with multiple lines would be	
Contract Year One	-0.671		reduced to 78.4%	
		0.1637	Churn rate of customer with multiple lines would be	
Contract Year two	-1.809		reduced to 78.4%	

3. Customers who have both internet as well as phone line

Predictor	Beta	Exp Beta	Rationale	
		0.5432	Churn rate of customer with multiple lines would be	
Online Security	-0.610		reduced to 46.68%	
		0.6125	Churn rate of customer with multiple lines would be	
Contract Year One	-0.490		reduced to 39.75%	
		0.3086	Churn rate of customer with multiple lines would be	
Contract Year two	-1.176		reduced to 69.14%	

4. F1 Score and Precision/Recall

Predictor	Precision Score	Recall	F1 Score	AUC Score
Phone Service User Only	0.9186	0.9971	0.9562	0.7094
Internet Service User Only	0.8201	0.9268	0.8702	0.6528
Both Internet and Phone		0.8279	0.8279	0.6797
Service user	0.8142			

Recommendations:

Explore additional features or transform existing ones to capture more complex relationships in the data. Consider interaction terms, polynomial features, or domain-specific transformations to better represent the underlying patterns. Regularization helps control model complexity and prevents extreme parameter estimates, leading to better performance on unseen data.