

CUSTOMER CHURN PREDICTION

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INTRODUCTION AND OVERVIEW

A telecommunications company wanted to reduce customer churn. By analyzing customer behavior data using SQL and Excel, and applying statistical models, they identified key churn predictors. Power BI was used to create a dashboard that monitored churn risk in real-time. As a result, the company implemented targeted retention strategies, reducing churn by 12% within six months.

Customer churn is the phenomenon where customer stops doing business with a company or switches companies.

Here, the data was taken from kaggle telecom churn prediction data set.

The columns in the dataset are as follows:

- customerID: unique value
- Gender: Male or Female
- SeniorCitizen: yes or no
- Partner: yes or no
- Dependents: yes or no
- Tenure: in months
- PhoneService: Yes or no
- MultipleLines: No phone service, yes or no
- InternetService: DSL FiberOptics or no service
- OnlineSecurity: Yes or no or no internet service
- OnlineBackup: Yes or no No internet
- DeviceProtection: Yes or no or no internet service
- TechSupport: Yes or no or no internet service
- StreamingTV: Yes or no or no internet service
- StreamingMovies: Yes or no or no internet service
- Contract: month-to-month, one year, two year
- PaperlessBilling: Yes or No
- PaymentMethod: electronic, mailcheck, bank transfer, credit card
- MonthlyCharges: Dollar
- TotalCharges: Dollar
- Churn: yes or no

EXCEL

First, the data was processed on Excel. Here, relevant groupings were done and categorical data was converted to numerical data for the purpose of applying machine learning models.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q		
1	Gender	SeniorDisc	Senior	Repurchase	Phone	Mail	Electronic	Internet	Contract	Month	Year	Month	Year	Month	Year	Month	Year		
2	Female	0	1	0	0	0	0	1	0	0	0	0	0	1	1	DSL	Month-to-month Electronic check		
3	Male	0	0	0	1	0	1	0	1	0	0	0	0	0	14	DSL	One year Mailed check		
4	Male	0	0	0	1	0	1	1	2	DSL	1	0	0	0	0	0	Mailed check		
5	Male	0	0	0	0	0	1	0	1	0	1	1	0	0	45	DSL	One year Bank transfer (automatic)		
6	Female	0	0	0	1	0	0	0	0	0	0	0	0	0	1	2	Fiber optic Month-to-month Electronic check		
7	Female	0	0	0	1	1	0	0	1	1	1	1	1	1	1	8	Fiber optic Month-to-month Electronic check		
8	Male	0	0	1	1	1	1	0	1	0	0	0	1	0	1	22	Fiber optic Month-to-month Credit card (automatic)		
9	Female	0	0	0	0	0	1	0	0	0	0	0	0	0	10	DSL	Month-to-month Mailed check		
10	Female	0	1	0	1	1	1	0	0	1	1	1	1	1	1	28	Fiber optic Month-to-month Electronic check		
11	Male	0	0	0	1	0	0	1	0	0	0	0	0	0	0	42	DSL	One year Bank transfer (automatic)	
12	Male	0	1	1	1	0	1	0	0	0	0	0	0	0	1	13	DSL	Month-to-month Mailed check	
13	Male	0	0	0	1	0	0	0	0	0	0	0	0	0	0	16	No	Two year Credit card (automatic)	
14	Male	0	0	0	1	0	0	0	0	0	0	0	0	0	0	58	Fiber optic One year Credit card (automatic)		
15	Male	0	0	0	1	1	0	0	1	1	0	0	1	1	1	49	Fiber optic Month-to-month Bank transfer (automatic)		
16	Male	0	0	0	1	0	1	0	1	0	1	1	1	1	1	25	Fiber optic Month-to-month Electronic check		
17	Female	0	1	1	1	1	1	1	1	1	1	1	1	1	0	69	Fiber optic Two year Credit card (automatic)		
18	Female	0	0	0	1	0	0	0	0	0	0	0	0	0	0	32	No	One year Mailed check	
19	Male	0	0	1	1	1	1	1	0	1	0	0	1	1	0	71	Fiber optic Two year Bank transfer (automatic)		
20	Female	0	1	1	1	0	0	0	0	1	1	1	0	0	0	18	DSL	Month-to-month Credit card (automatic)	
21	Female	0	0	0	1	0	0	0	0	0	0	0	0	0	0	21	Fiber optic Month-to-month Electronic check		
22	Male	1	0	0	0	0	0	0	0	1	0	0	0	1	1	1	DSL	Month-to-month Electronic check	
23	Male	0	1	0	1	0	0	0	0	0	0	0	0	0	0	12	No	One year Bank transfer (automatic)	
24	Male	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	No	Month-to-month Mailed check	
25	Female	0	1	0	1	0	1	0	1	0	1	0	0	0	0	18	DSL	Two year Credit card (automatic)	
26	Male	0	1	1	1	1	0	1	1	0	1	1	0	0	0	49	DSL	Month-to-month Credit card (automatic)	
27	Female	0	0	0	1	0	0	1	1	0	1	0	0	0	0	1	30	DSL	Month-to-month Bank transfer (automatic)
28	Male	0	1	1	1	0	0	0	0	0	0	0	0	0	0	47	Fiber optic Month-to-month Electronic check		
29	Male	0	1	1	0	0	0	0	0	0	0	0	0	0	0	1	DSL	Month-to-month Electronic check	
30	Male	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	72	DSL	Two year Credit card (automatic)
31	Female	0	0	0	1	0	0	0	0	0	0	0	0	0	0	17	DSL	Month-to-month Mailed check	
32	Female	1	1	0	1	1	1	1	1	1	1	1	1	0	0	1	71	Fiber optic Two year Credit card (automatic)	
33	Male	1	1	0	0	1	0	0	0	1	0	1	0	1	1	1	2	Fiber optic Month-to-month Credit card (automatic)	
34	Female	0	0	0	1	0	0	0	0	0	0	0	0	0	0	27	DSL	One year Mailed check	
35	Male	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	No	Month-to-month Bank transfer (automatic)	
36	Male	1	0	0	1	0	0	0	0	0	0	0	0	0	0	1	DSL	Month-to-month Bank transfer (automatic)	
37	Female	0	1	1	1	1	1	1	1	0	1	1	0	0	0	72	Fiber optic Two year Bank transfer (automatic)		
38	Male	0	0	0	1	0	0	0	0	0	0	0	0	0	0	2	Fiber optic Month-to-month Electronic check		

	R	S	T	U	V	W	X	Y	Z	AA
1	Monthly charges	Total charges	Contract type	Contract type	Contract type	Contract type	Contract type	Contract type	Contract type	Contract type
2	not automatic	29.85	29.85	0	1	0	1	1	1	0
3	1 DSL	56.95	1889.5	0	1	0	1	0	1	0
4	not automatic	53.85	108.15	1	1	0	1	1	0	0
5	automatic	42.3	1540.75	0	1	0	1	0	1	0
6	not automatic	70.7	151.65	1	1	0	1	0	0	0
7	not automatic	99.65	820.5	1	1	0	1	0	1	0
8	automatic	69.5	2460.4	0	1	1	0	1	0	0
9	not automatic	29.75	801.9	0	1	0	1	1	0	0
10	not automatic	104.8	3046.05	1	1	0	1	1	0	0
11	automatic	56.15	1487.95	0	1	0	1	1	0	0
12	not automatic	49.95	147.45	0	1	0	1	1	0	0
13	automatic	18.95	126.8	0	0	0	0	0	0	1
14	automatic	100.35	5681.1	0	1	0	0	1	0	0
15	automatic	103.7	5036.3	1	1	0	1	0	1	0
16	not automatic	105.5	2686.05	0	1	0	1	0	1	0
17	automatic	113.25	7895.15	0	1	0	0	1	0	1
18	not automatic	20.65	3022.95	0	0	0	0	1	0	0
19	automatic	106.7	7182.25	0	1	0	1	0	1	1
20	automatic	55.2	528.35	1	1	0	1	1	0	0
21	not automatic	90.05	1862.9	0	1	0	1	0	0	0
22	not automatic	39.65	39.65	1	1	0	1	1	0	0
23	automatic	19.8	202.25	0	0	0	0	1	0	0
24	not automatic	20.15	20.15	1	0	0	0	1	0	0
25	automatic	59.9	2505.1	0	1	0	1	0	1	0
26	automatic	99.6	2970.3	0	1	0	1	1	0	0
27	automatic	55.3	1530.6	0	1	0	1	1	0	0
28	not automatic	99.35	4749.15	1	1	0	1	1	0	0
29	not automatic	30.2	30.2	1	1	0	1	1	0	0
30	automatic	90.25	6369.45	0	1	0	1	0	1	0
31	not automatic	64.7	1093.1	1	1	0	1	1	0	0
32	automatic	96.55	6766.55	0	1	0	0	1	0	0
33	automatic	95.5	181.65	0	1	0	1	0	0	0
34	not automatic	66.15	1874.45	0	1	0	1	0	1	0
35	automatic	20.2	20.2	0	0	0	1	0	0	0
36	automatic	43.25	43.25	0	1	0	1	1	0	0
37	automatic	99.9	7251.7	0	1	0	0	0	1	0
38	not automatic	69.7	316.9	1	1	1	0	1	0	0

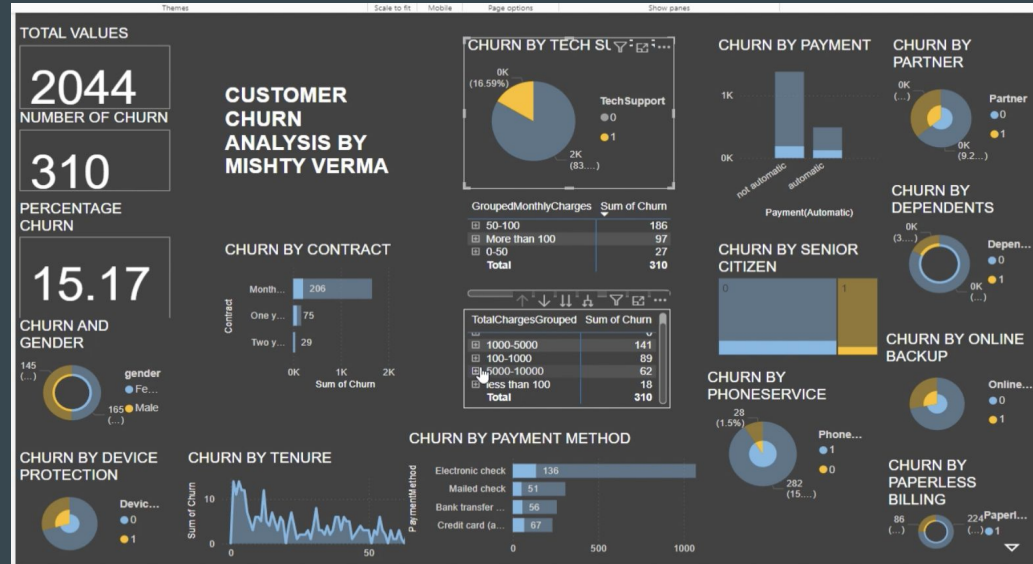
Irrelevant columns were also deleted and files were saved in two formats, csv(for machine learning model, and Excel file for power BI analysis.

MonthlyCharges	TotalCharges	Churn	InternetService(num)	InternetService(fiber optic)	InternetService(DSL)	Contract(Monthly)	Contract(One year)	Contract(two year)	Payment(Automatic_num)	Gender(num)	GroupedMonthlyCharges	TotalChargesGrouped
29.85	29.85	0	1	0	1	1	0	0	0	0	0 0-50	less than 100
56.95	1889.5	0	1	0	1	0	1	0	0	0	1 50-100	1000-5000
53.85	108.15	1	1	0	1	1	0	0	0	0	1 50-100	100-1000
42.3	1840.75	0	1	0	1	0	1	0	0	1	1 0-50	1000-5000
70.7	151.65	1	1	1	0	1	0	0	0	0	0 50-100	100-1000
99.65	820.5	1	1	1	0	1	0	0	0	0	0 50-100	100-1000
89.1	1949.4	0	1	1	0	1	0	0	0	1	1 50-100	1000-5000
29.75	301.9	0	1	0	1	1	0	0	0	0	0 0-50	100-1000
104.8	3046.05	1	1	1	0	1	0	0	0	0	0 More than 100	1000-5000
56.15	3487.95	0	1	0	1	0	1	0	0	1	1 50-100	1000-5000
49.95	587.45	0	1	0	1	1	0	0	0	0	1 0-50	100-1000
18.95	326.8	0	0	0	0	0	0	0	1	1	1 0-50	100-1000
100.35	5681.1	0	1	1	0	0	1	0	0	1	1 More than 100	5000-10000
103.7	5036.3	1	1	1	0	1	0	0	0	1	1 More than 100	5000-10000
105.5	2686.05	0	1	1	0	1	0	0	0	0	1 More than 100	1000-5000
113.25	7895.15	0	1	1	0	0	0	0	1	1	0 More than 100	5000-10000
20.65	1022.95	0	0	0	0	0	1	0	0	0	0 0-50	1000-5000
106.7	7382.25	0	1	1	0	0	0	0	1	1	1 More than 100	5000-10000
55.2	528.35	1	1	0	1	1	0	0	0	1	0 50-100	100-1000
90.05	1862.9	0	1	1	0	1	0	0	0	0	0 50-100	1000-5000
39.65	39.65	1	1	0	1	1	0	0	0	0	1 0-50	less than 100
19.8	202.25	0	0	0	0	0	1	0	0	1	1 0-50	100-1000
20.15	20.15	1	0	0	0	1	0	0	0	0	1 0-50	less than 100
59.9	3505.1	0	1	0	1	0	0	1	0	1	0 50-100	1000-5000
59.6	2970.3	0	1	0	1	1	0	0	0	1	1 50-100	1000-5000
55.3	1530.6	0	1	0	1	1	0	0	0	1	0 50-100	1000-5000
99.35	4749.15	1	1	1	0	1	0	0	0	0	1 50-100	1000-5000
30.2	30.2	1	1	0	1	1	0	0	0	0	1 0-50	less than 100
90.25	6369.45	0	1	0	1	0	0	1	0	1	1 50-100	5000-10000
64.7	1093.1	1	1	0	1	1	0	0	0	0	0 50-100	1000-5000
96.35	6766.95	0	1	1	0	0	0	0	1	1	0 50-100	5000-10000
95.5	181.65	0	1	1	0	1	0	0	0	1	1 50-100	100-1000
66.15	1874.45	0	1	0	1	0	1	0	0	0	0 50-100	1000-5000
20.2	20.2	0	0	0	0	1	0	0	0	1	1 0-50	less than 100
45.25	45.25	0	1	0	1	1	0	0	0	1	1 0-50	less than 100
99.9	7251.7	0	1	1	0	0	0	1	0	1	0 50-100	5000-10000
69.7	316.9	1	1	1	0	1	0	0	0	0	1 50-100	100-1000

POWER BI

A dynamic dashboard was created to find the key performance indicators. Relevant conclusions were made from the dashboard.

<https://drive.google.com/file/d/1UIQLn-gL2cFJkEnfQneTjFPHeiLNGWW8/view?usp=s>
haring



Conclusions made from dashboard

Out of 7043 customers, 1869 or 26.5% customers churned in the past month.

Gender did not significantly affect the churn rate.

For no device protection, tech support, and online backup, churn was higher than that for customers with these services.

Customers with automatic mode of payment churned less than those without it.

People without dependents or partners churned more than those with dependents and partners.

People with paperless billing churned more.

Lower the tenure, higher was the churn and similarly people with month to month contract churned more and people with 2 year contract churned less.

Customers with monthly charges of 50-100 dollars churned more.

Logistic Regression Model

Logistic regression uses sigmoid function to map values to different classes. Unlike linear regression, which gives a continuous outcome, logistic regression predicts classes of values. The equation for logistic regression is

$$\text{logit}(p) = \ln(p/1-p) = \beta_0 + \beta_1 x_1 + \dots + \beta_n x_n$$

Where:

p is the probability of the outcome of interest (probability of churn), x_1, x_2, \dots, x_n are the independent variables, β_0 is the intercept, β_1, \dots, β_n are coefficients of the independent variables.

The logistic function (or sigmoid function) is used to transform the logit (linear combination of inputs) into a probability:

$$p = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \dots + \beta_n x_n)}}$$

Logistic regression Model

Logistic regression was used to classify the value and predict churn(1) or no churn (0)

https://drive.google.com/file/d/1nUU8s4b2aGJFwjEmbjPK_wsXabN2vqbu/view?usp=drive_link

https://drive.google.com/file/d/1T4TWPrVMT7zMwBRoRxfNylwR8ZWDXPv-/view?usp=drive_link

Here are the links to my logistic regression models

