Telecom Services and Churn

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UCLA Extension 450.4

Background

TelCo saw subscription services decline in the last quarter. They would like to understand more about their customers and any indicators that could prevent churn in the future.

Dataset - IBM fictional dataset

Agenda

- Data Overview
- Exploratory Analysis
- Model Comparison
- Next Steps and Recommendations

Data Overview

Structure and Cleaning

TelCo Dataset and Execution

7,043 entries across 21 fields

- Account information
- Demographics
- Services enrolled

0	customerID
1	gender
2	SeniorCitizen
3	Partner
4	Dependents
5	tenure
6	PhoneService
7	MultipleLines
8	InternetService
9	OnlineSecurity
10	OnlineBackup
11	DeviceProtection
12	TechSupport
13	StreamingTV
14	StreamingMovies
15	Contract
16	PaperlessBilling
17	PaymentMethod
18	MonthlyCharges
19	TotalCharges
20	Churn

Dataset: https://www.kaggle.com/farazrahman/telco-customer-churn-logisticregression

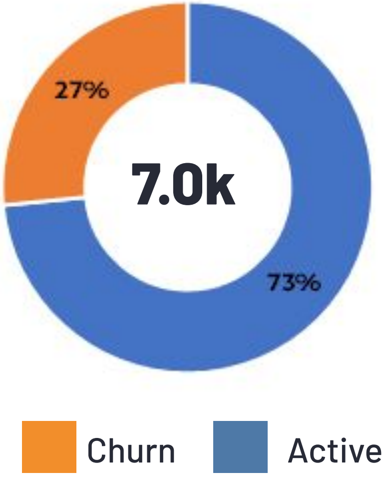
Exploratory Analysis

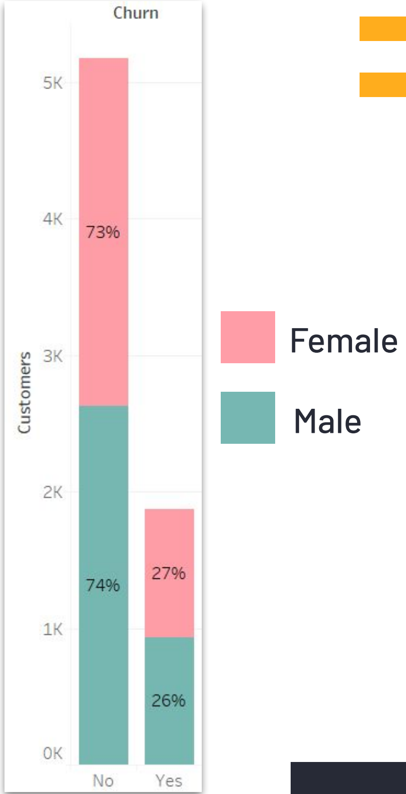
Telco Customers

Churned Customers

Churn - customers who left within the last month

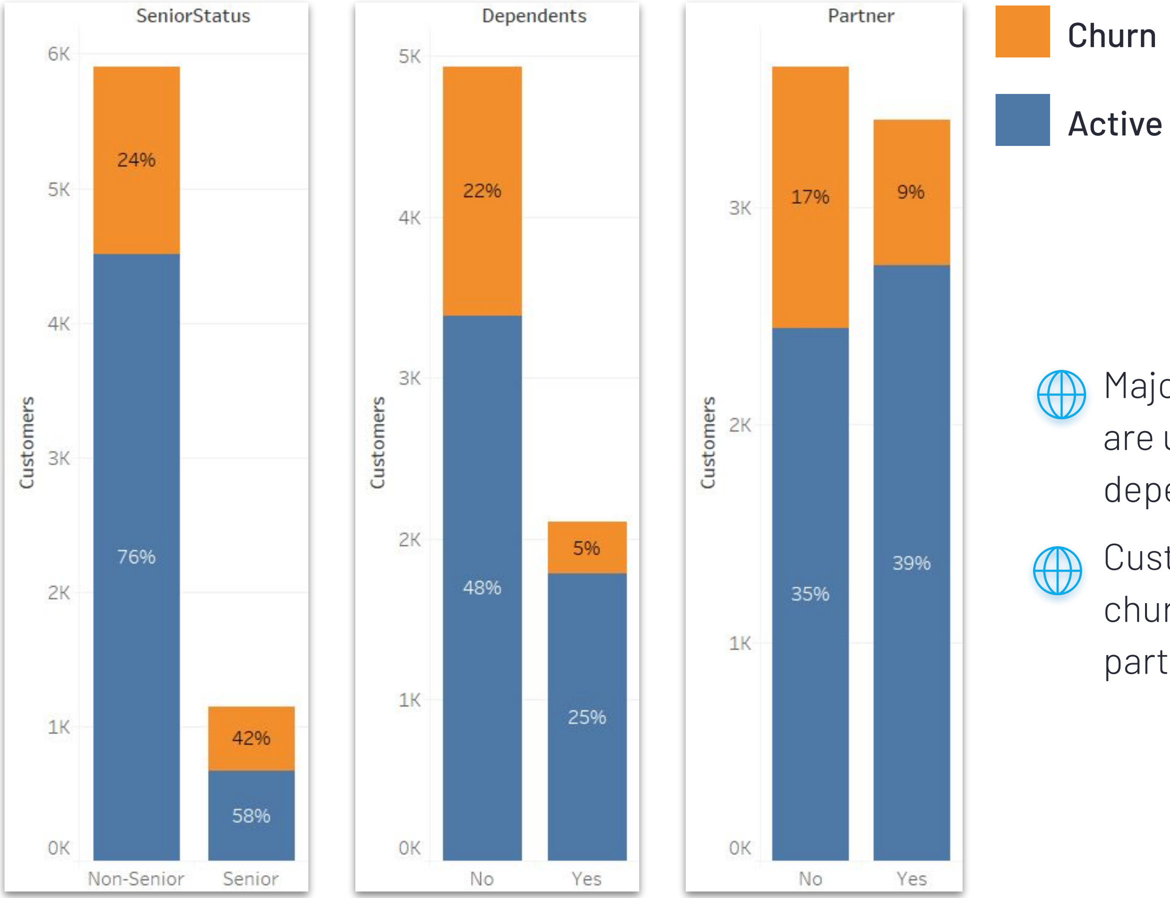
- About ⅓ of customers churned within the last month
- The customer base is 50/50 split for both current/churn customers





Dates: 10/1/18 - 10/31/18

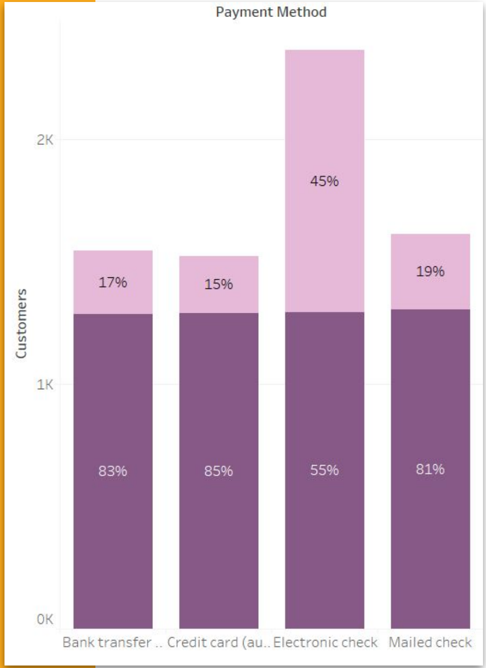
Demographics

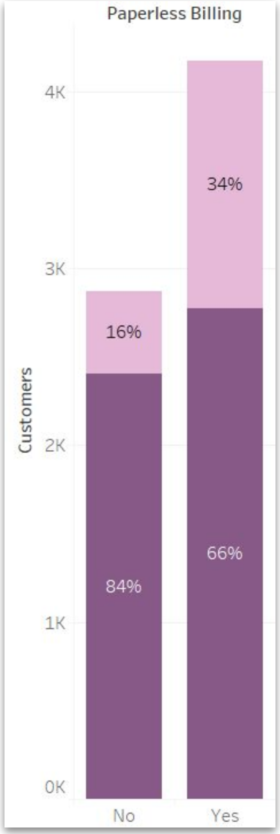


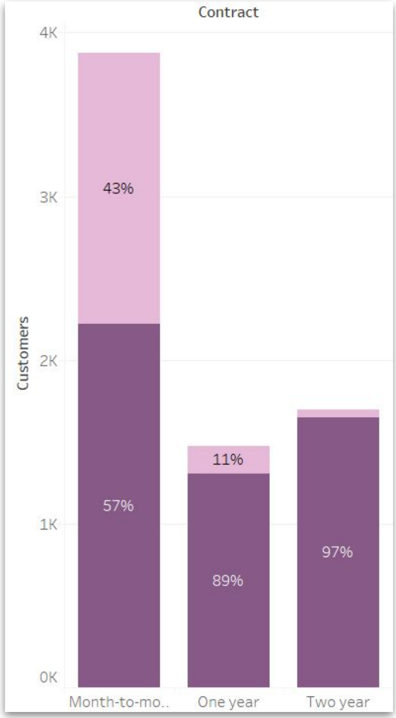
- Majority of customers with Telco are under 65 and do not have any dependents
- Customers without partners churned 2x more than those with partners

Dates: 10/1/18 - 10/31/18

Contracts and Billing







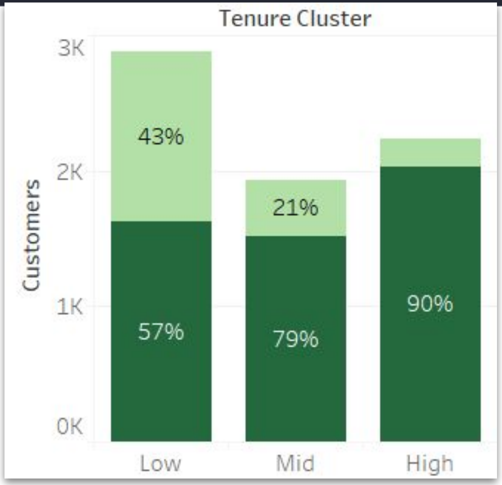
Churn

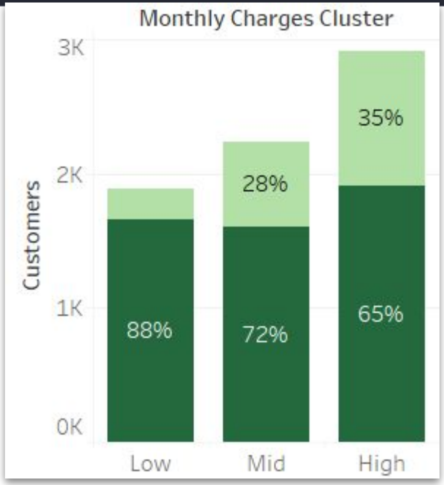
Active

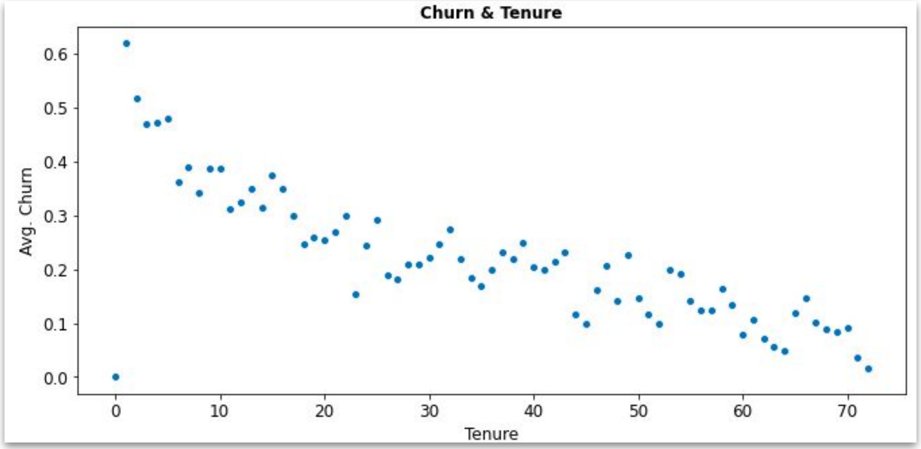
- At least ⅓ of churned customers receive bills electronically and pay electronically by check
- 43% of month-to-month contracts churned within the last month
- A/B test with CRM team to find optimal time to email billing statement

Dates: 10/1/18 - 10/31/18

Tenure and Spending







Churn

Active

- 43%+ of customers who have low tenure churned within last month
- Those in beginning of contract are more likely to churn when monthly charges are high

- Explore opportunities/ROI to add free/discount services to reduce monthly charges for new customers (i.e, internet upgrade)

Clusters split into 3 groups based on elbow curve of KMeans algorithm

Dates: 10/1/18 - 10/31/18

Model Comparison

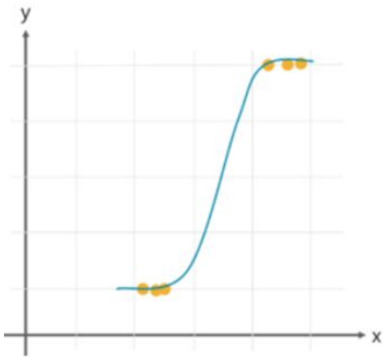
Predicting Churn

Model Implementations - Predicting Churn

33% test size & random state activated across all models

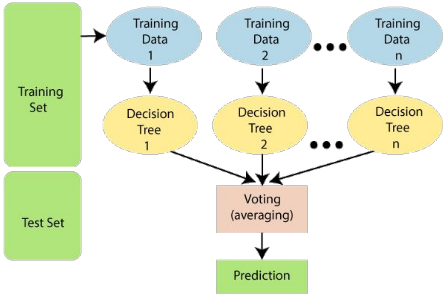
Logistic Regression

★ Simplest



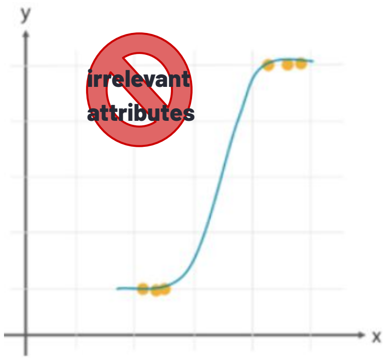
Random Forest

★ Handles more features



LR + Feature Elimination

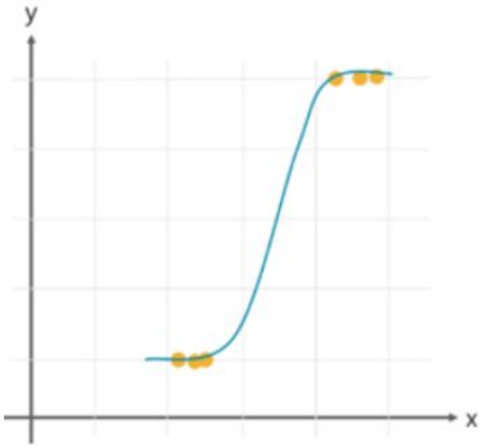
★ Reduces noise for LR



Dates: 10/1/18 - 10/31/18

F1 score closest to 1 is the goal, so .64 is great start

Consider altering different parameters to improve model (i.e, solver, penalty)



LR Classification report:

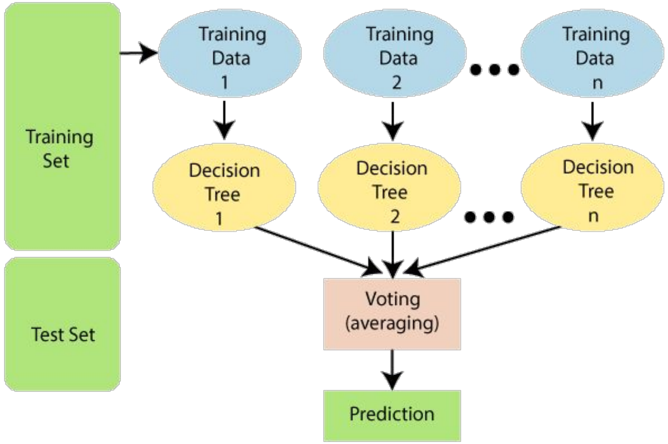
	precision	recall	f1-score	support
0	0.91	0.77	0.83	1714
1	0.54	0.77	0.64	611
accuracy			0.77	2325
macro avg	0.72	0.77	0.73	2325
weighted avg	0.81	0.77	0.78	2325

Dataset is 30% churn, so added more weight to these to compensate for majority customers

Logistic Regression

Dates: 10/1/18 - 10/31/18

- LR F1 score was .64, so .37 is disappointing
- There is too much noise, which is mudding the results (49 features total)



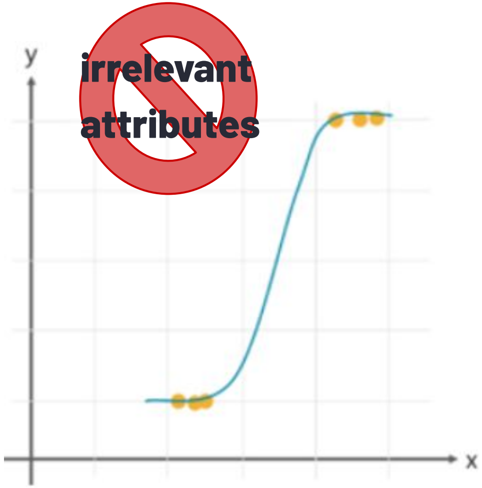
RF Classification report:

	precision	recall	f1-score	support
0	0.78	0.97	0.87	1714
1	0.73	0.25	$\boxed{0.37}$	611
accuracy			0.78	2325
macro avg	0.76	0.61	0.62	2325
weighted avg	0.77	0.78	0.74	2325

Random Forest Classifier

Dates: 10/1/18 - 10/31/18

- F1 score .52, which is better than RF (.34), but LR with weights performed best (.64)
- Consider implementing other ensemble models like XGBoost



RFE Classification report:

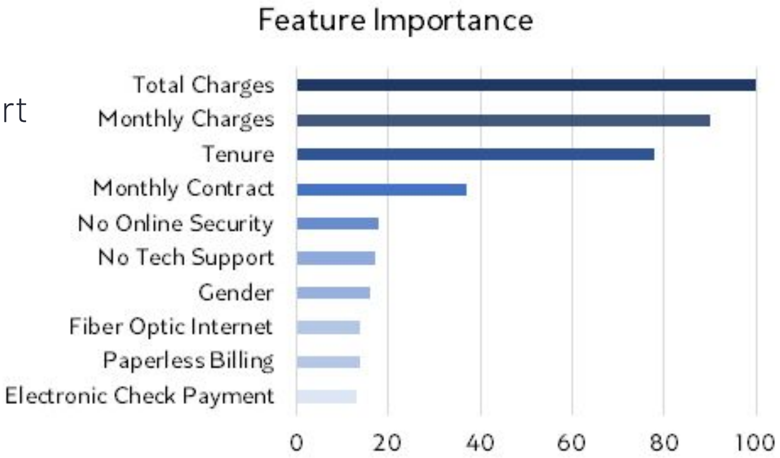
	precision	recall	f1-score	support
0	0.82	0.89	0.85	1714
1	0.60	0.47	0.52	611
accuracy			0.78	2325
macro avg	0.71	0.68	0.69	2325
weighted avg	0.76	0.78	0.77	2325

Logistic Regression + Recursive Feature Elimination

Dates: 10/1/18 - 10/31/18

RFE - Feature Importance

- 'Additionals' like online security and tech support increase likelihood of attrition
- Collaborate with sales/marketing teams to bundle these additional services to early subscribers



Dates: 10/1/18 - 10/31/18

Next Steps

- Monitor seasonality and offers
- Observe competitors and partnerships
- Dive into and understand LTV

Recommendations

- Explore opportunities to add free/discounted services for new customers to reduce monthly payments (i.e, internet upgrade)
- A/B test with CRM team to find optimal time to email billing statement
- Continue model iteration - XGBoost Classifier, parameter tweaking
- Collaborate with sales/marketing teams to bundle these additional services to early subscribers

Thank you

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Deck template from Slides Carnival

https://www.slidescarnival.com/

Appendix

Dataset: https://www.kaggle.com/blastchar/telco-customer-churn

Utilized and edited code from various sources:

https://github.com/irinhwng/Consumer-Insights-Metrics_and_Predictions

https://github.com/akshayr89/Telecom_Churn_Model

https://scikit-learn.org/