Telecom Services and Churn

Summer Malone
UCLA Extension 450.4

Background

Company

TelCo is a telecommunications company that offers customers a variety of subscriptions (phone, internet, tv)

Problem

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.

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

Tools for analysis and reporting

```
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
```
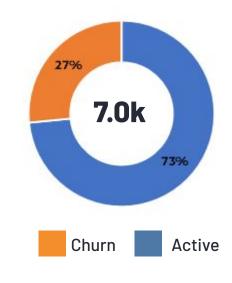
Represents end of Oct. accounts/status

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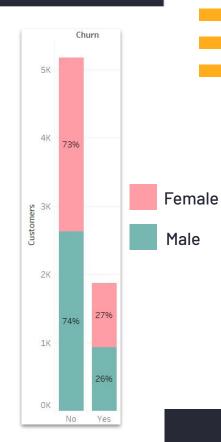
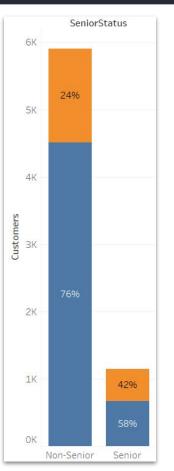# Exploratory Analysis

Telco Customers

Churned Customers

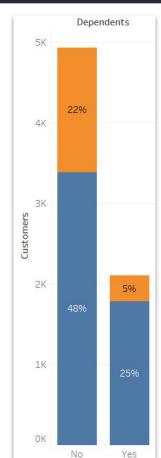## Churn - customers who left within the last month

🌐 About ⅓ of customers churned within the last month

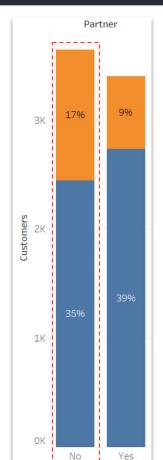🌐 The customer base is 50/50 split for both current/churn customers

27%

7.0k

73%

■ Churn ■ Active

Churn

5K

4K

73%

Customers

3K

2K

74%   27%

1K

26%

0K

No   Yes

■ Female
■ Male

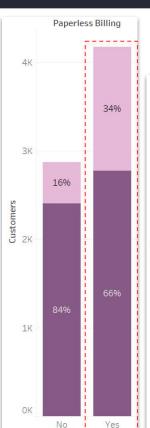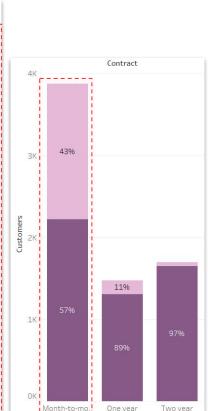Dates: 10/1/18 - 10/31/18

Demographics

Churn

Active

🌐 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

Payment Method

Customers

- Bank transfer ..: 17% / 83%
- Credit card (au..: 15% / 85%
- Electronic check: 45% / 55%
- Mailed check: 19% / 81%

Paperless Billing

Customers

- No: 16% / 84%
- Yes: 34% / 66%

Contract

Customers

- Month-to-mo.: 43% / 57%
- One year: 11% / 89%
- Two year: 97%

Churn

Active

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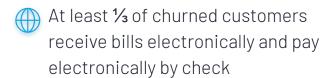
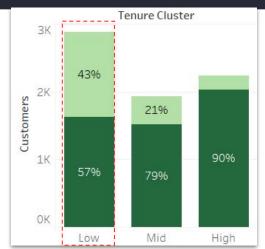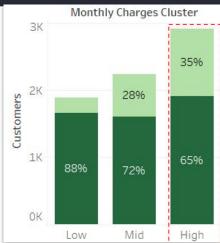🌐 43% of month-to-month contracts churned within the last month
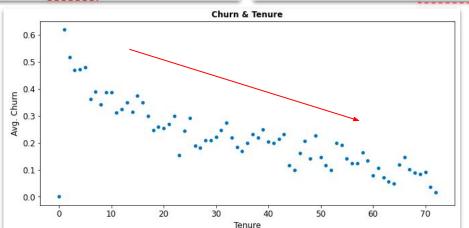
📡 A/B test with CRM team to find optimal time to email billing statement

Dates: 10/1/18 – 10/31/18

Tenure and Spending

Tenure Cluster

Monthly Charges Cluster

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
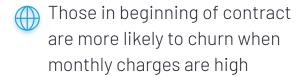

Churn & Tenure

📡 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
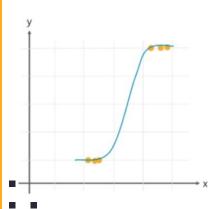
Dates: 10/1/18 – 10/31/18

Model Comparison
Predicting Churn

Model Implementations – Predicting Churn

33% test size & random state activated across all models

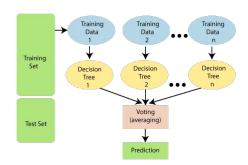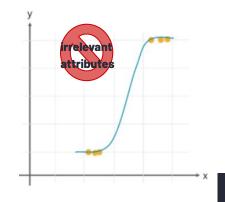## Logistic Regression

★ Simplest

Random Forest

★ Handles more features

LR + Feature Elimination

★ Reduces noise for LR

Dates: 10/1/18 – 10/31/18
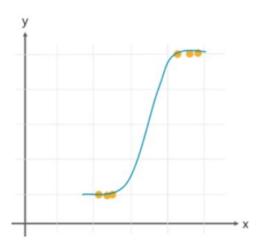
🌐 F1 score closest to 1 is the goal, so .64 is great start

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

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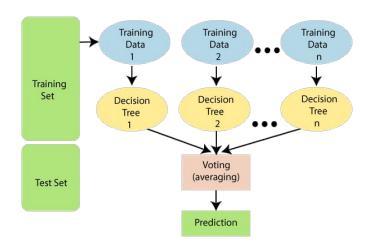
	precision	recall	f1-score	support
0	0.91	0.77	0.83	1714
1	0.54	0.77	0.64	611
accuracy			0.77	2325
macro avg	0.72	0.77	0.73	2325
weighted avg	0.81	0.77	0.78	2325

⭐ Dataset is 30% churn, so added more weight to these to compensate for majority active 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        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
```
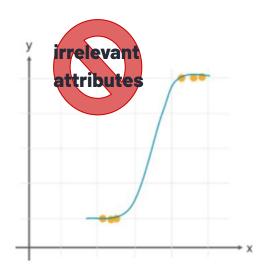
Random Forest Classifier

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
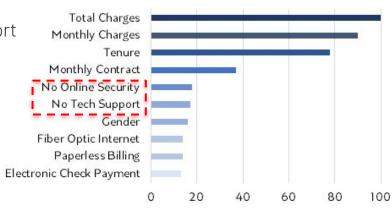
RFE – Feature Importance

🌐 'Additionals' like online security and tech support increase likelihood of attrition

📡 Collaborate with sales/marketing teams to bundle these additional services to early subscribers

Feature Importance

Feature	
Total Charges	100
Monthly Charges	90
Tenure	78
Monthly Contract	38
No Online Security	18
No Tech Support	17
Gender	16
Fiber Optic Internet	14
Paperless Billing	13
Electronic Check Payment	12

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

Linkedin: Summer Malone

github.com/malonesum

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/