

Telecom Customer Retention Analysis







Scenario

As a consultant for a telecom company how can I get more existing customers to stay and potentially attract new customer?

Data

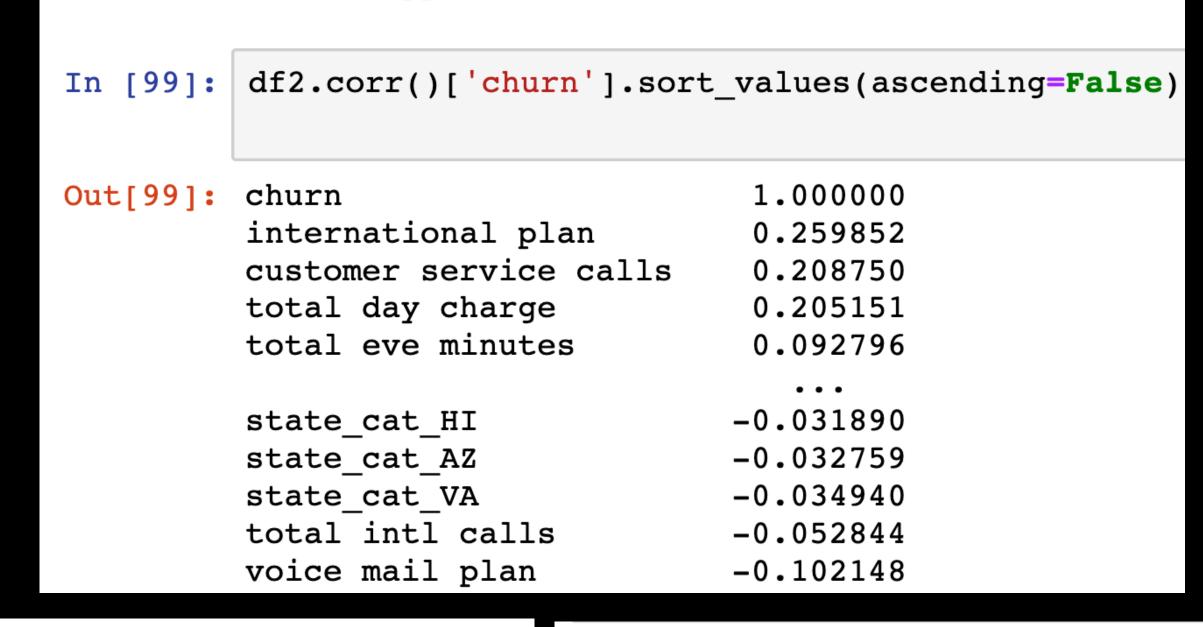
- Data: telecom churn data (provided)
- Source: https://www.kaggle.com/becksddf/churn-intelecoms-dataset
- 3300 observations with 20 atributes (including churn)
- Target Variable: Churn
- 2,850 out of 3300 observations are False

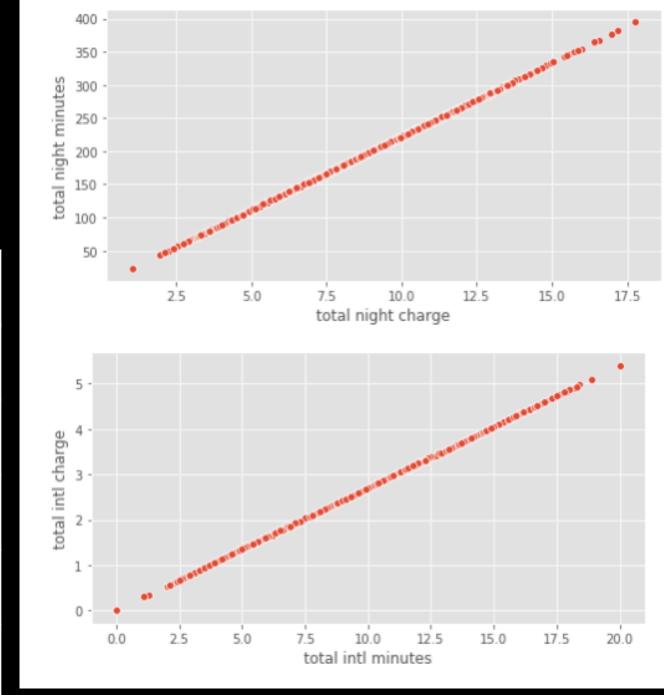
Column state account length area code phone number international plan voice mail plan number vmail messages total day minutes total day calls total day charge total eve minutes total eve calls total eve charge total night minutes total night calls total night charge total intl minutes total intl calls total intl charge customer service calls churn

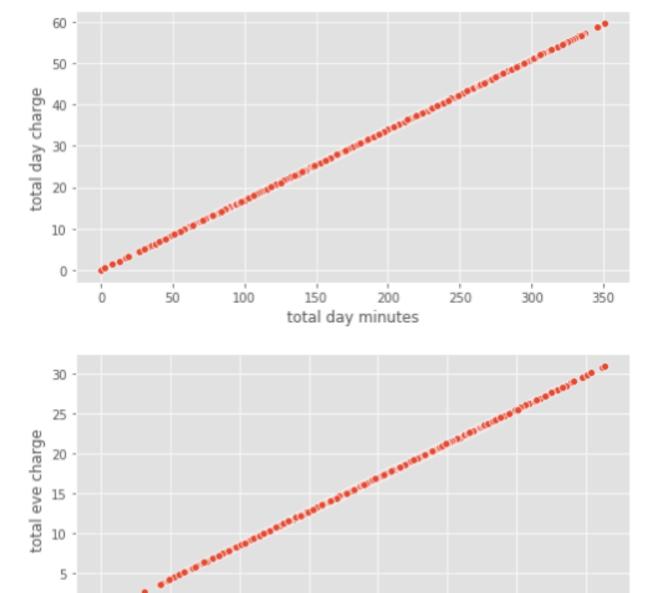
EDA

- None of the date is very correlated with churn
- Much of the data is highly correlated
- Converted states and area code to dummies
- Dropped phone number

Pairs	
(total day minutes, total day charge)	1.000000
(total eve minutes, total eve charge)	1.000000
(total night charge, total night minutes)	0.999999
(total intl minutes, total intl charge)	0.999993
(voice mail plan, number vmail messages)	0.956927







150

200

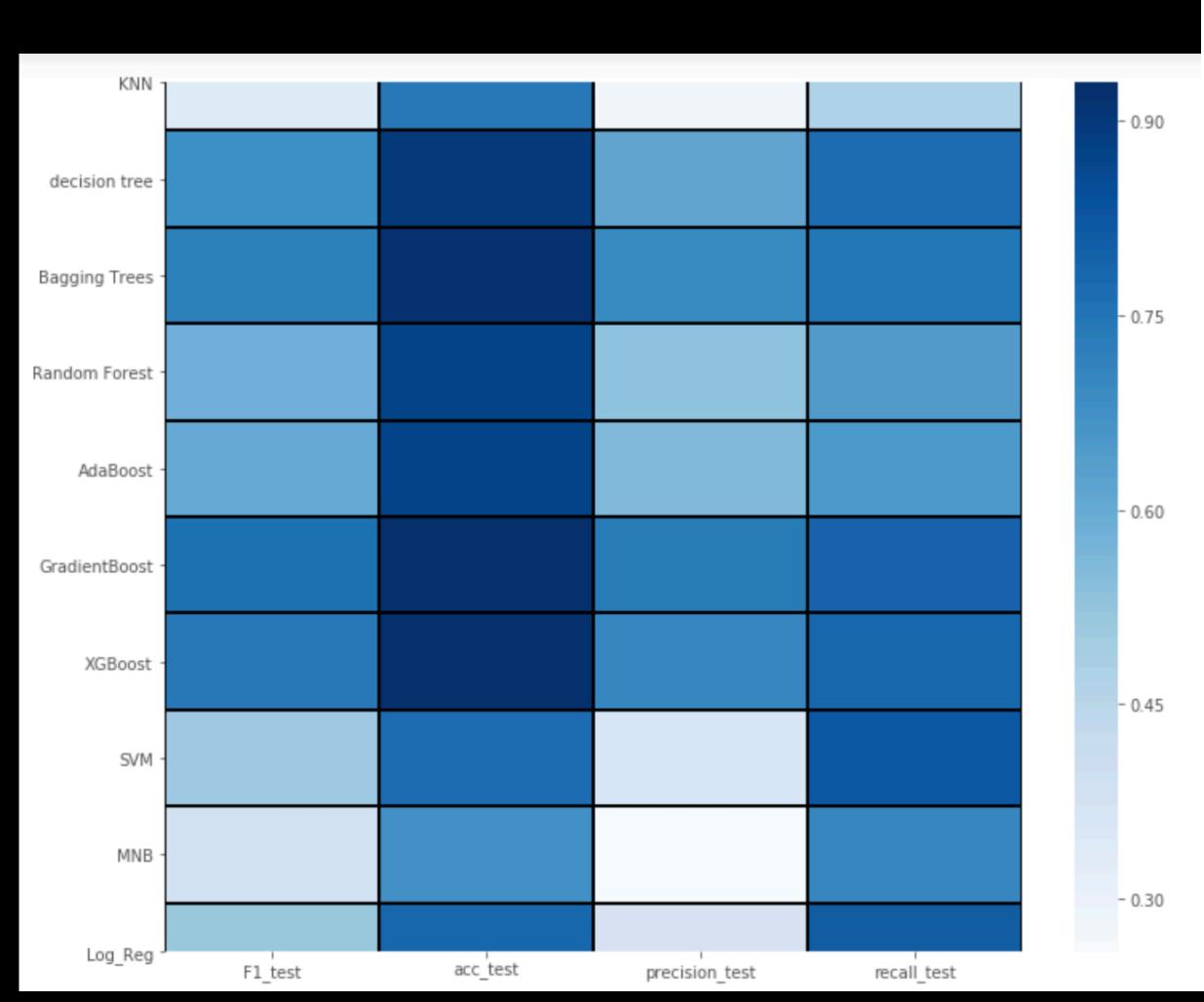
total eve minutes

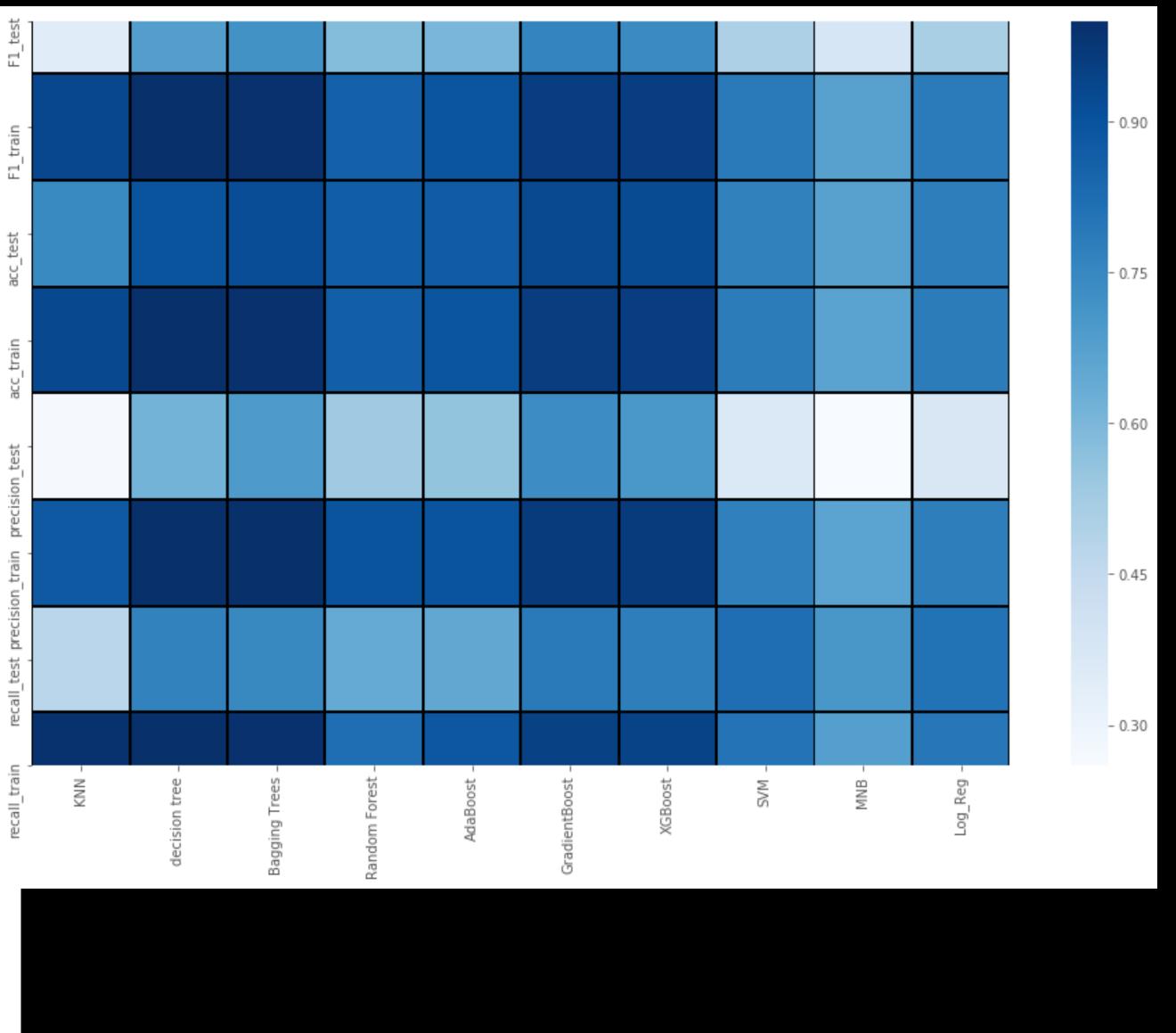
Initial Models

- KNN and Decision
 Tree over trained
- Gradient Boost and XGBoost tested the best
- KNN = baseline model

	F1_test	F1_train	acc_test	acc_train	precision_test	precision_train	recall_test	recall_train
KNN	0.344828	0.935344	0.743628	0.931299	0.271084	0.883340	0.473684	0.993854
decision tree	0.682243	1.000000	0.898051	1.000000	0.613445	1.000000	0.768421	1.000000
Bagging II	0.717172	0.996037	0.916042	0.996049	0.689320	0.999117	0.747360	U.992976
Random Forest	0.583732	0.858519	Unological			0.898704	0.642105	0.821773
Ad Loost	0.601942	0.894040	0.877061	0.894644	0.558559	0.899201	0.652632	222038
GradientBoost	0.761421	0.959328	0.929535	0.959614	0.735294	0.966162	0.789474	0.952590
XGBoost	0.740000	0.957216	0.922039	0.957638	0.704762	0.966861	0.778947	0.947761
SVIVI	0.00	0.700638	0.770615	0.785996	0.364486	N 773955		0.808165
MNB	0.379603	0.672605	0.671664	0.669227	0.259690	0.665806	0.705263	0.679543
Log_Reg	0.511628	0.787511	0.779610	0.784899	0.373786	0.778063	0.810526	0.797191

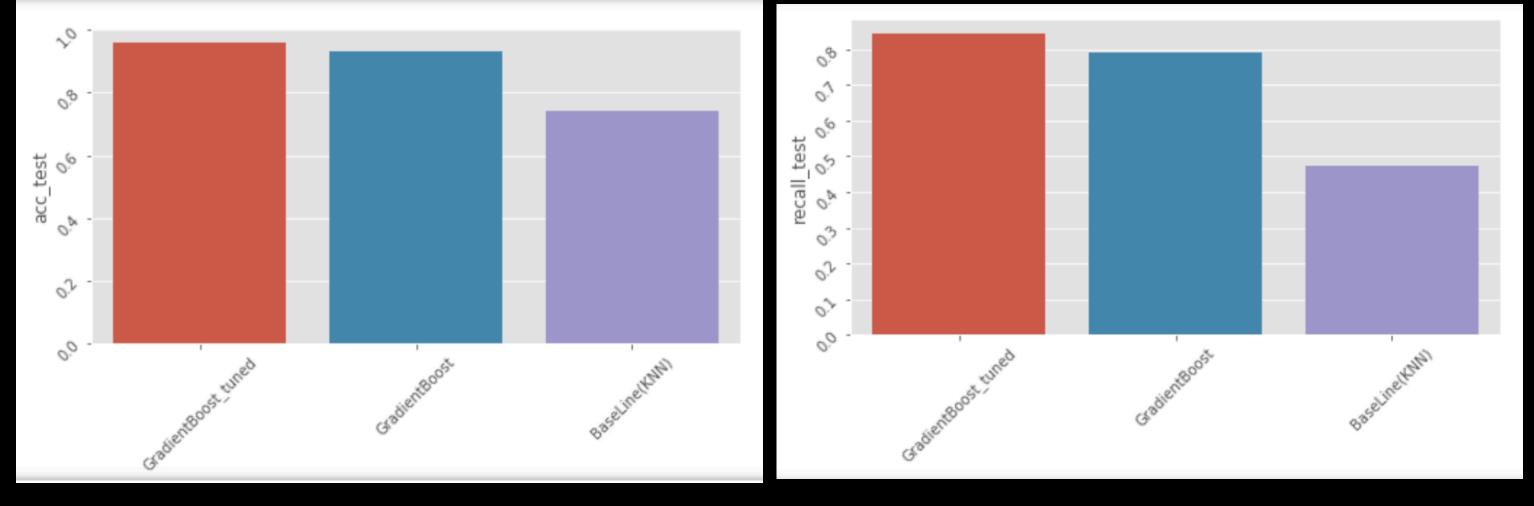
Initial Models Visuals

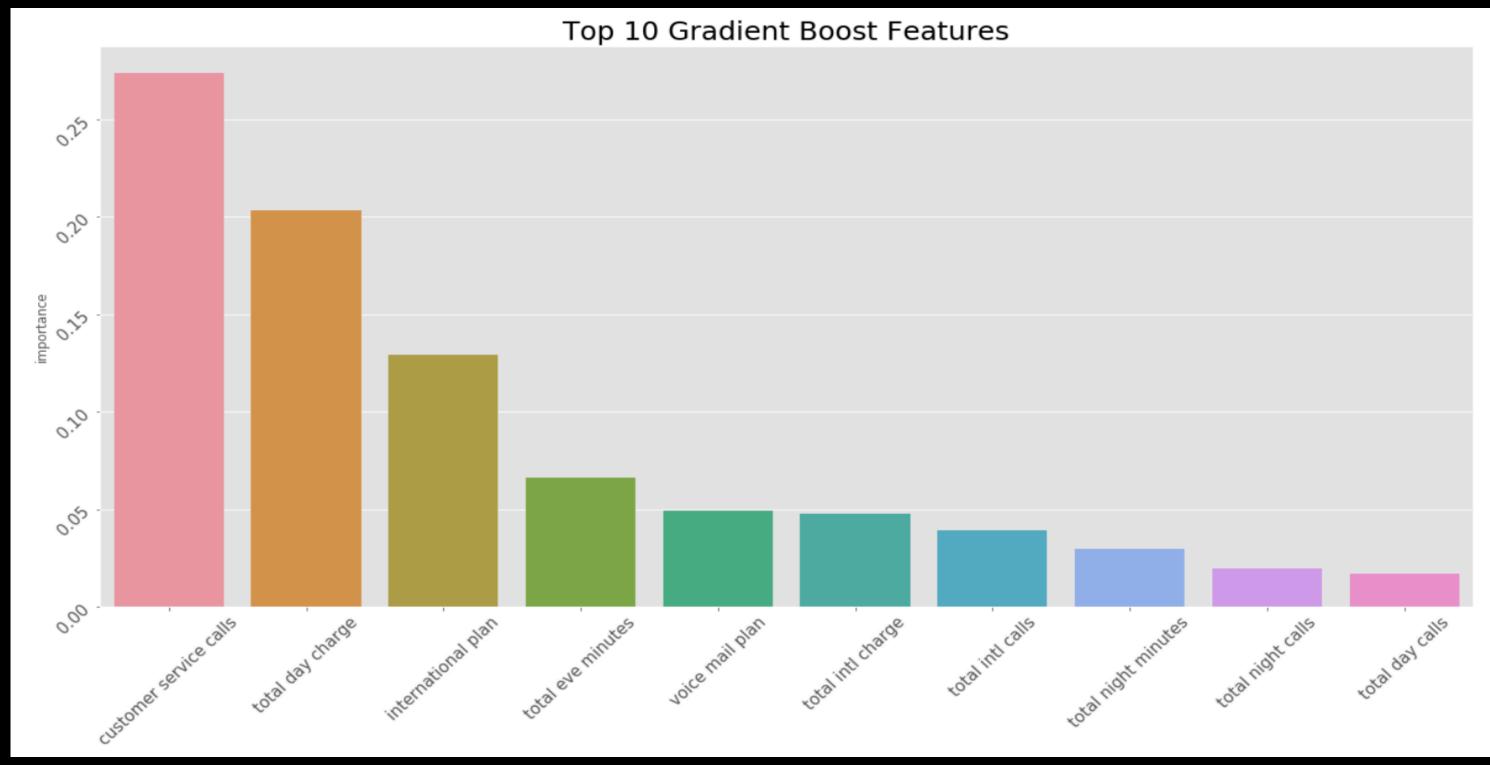




Final Models Gradient Boost

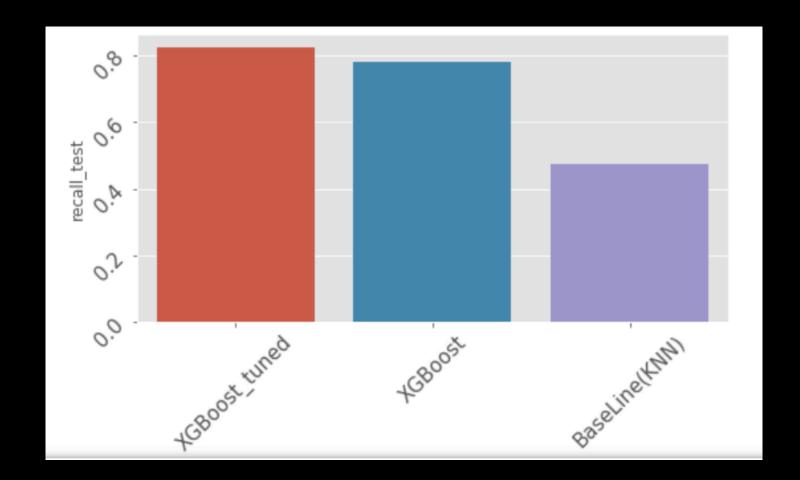
- Accuracy: up 0.03 and 0.21 from original and baseline
- Recall: up 0.05 and 0.4 from original and baseline
- Top features: customer service calls, day charge, international plan

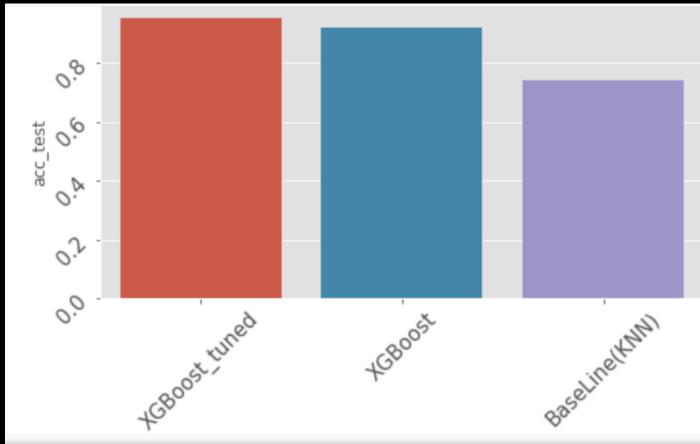


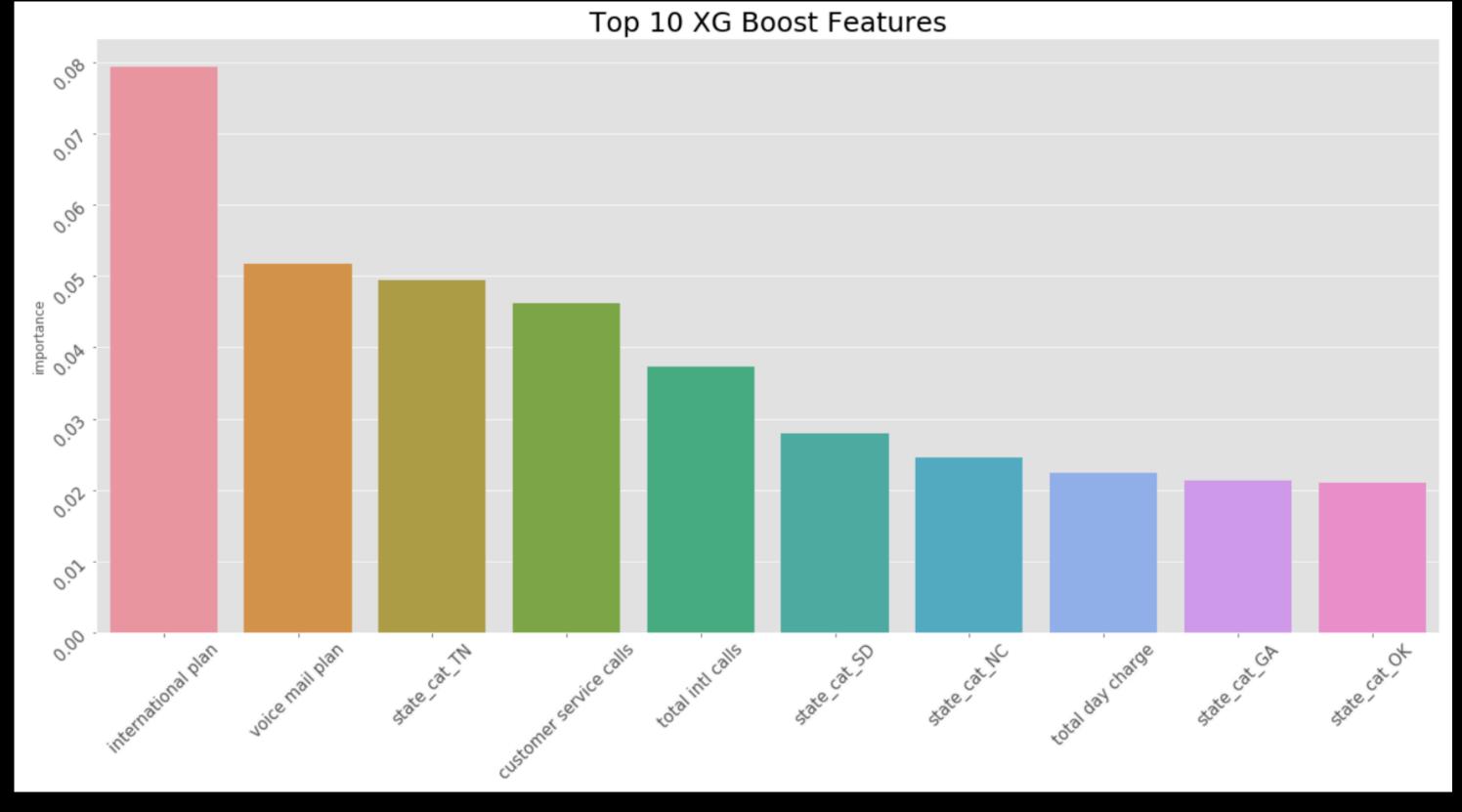


Final Models XG Boost

- Accuracy: up 0.03 and 0.22 from original and baseline
- Recall: up 0.05 and 0.35 from original and baseline
- Top features: international plan, voicemail plan, Tennessee
- No feature over 0.10



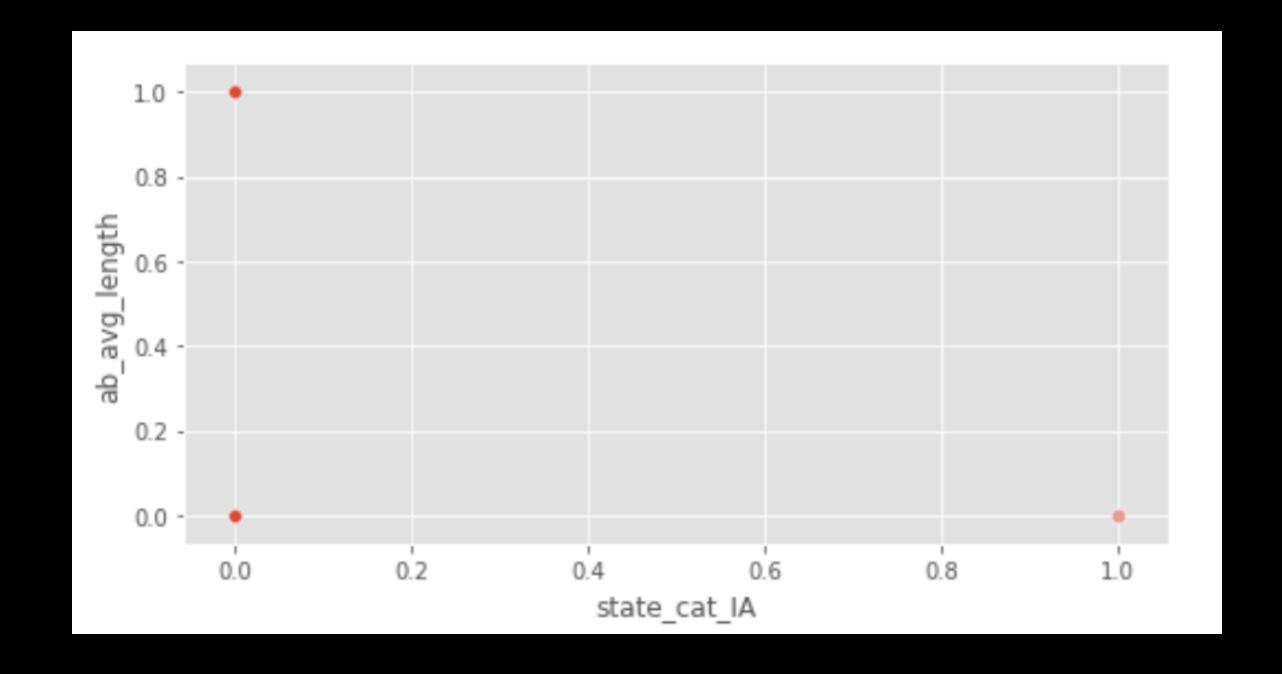




Secondary Analysis Account Length

- EDA:
 - looked only at accounts that left
 - Created binary variable 'Above_AVG_Length'
- Almost no one in RI, NM, LA stayed less than average
- No one in IA stayed longer than average

```
df3.corr()['ab_avg_length'].sort_values(ascending=False)
ab_avg_length
                       1.000000
state_cat_LA
                       0.093488
                       0.087647
state cat NY
state_cat_CO
                       0.079711
                       0.077344
state_cat_RI
areaCode 510
                      -0.066922
                      -0.077277
state_cat_IA
state_cat_KY
                      -0.094402
total night minutes
                      -0.100395
state cat ME
                      -0.111380
Name: ab_avg_length, Length: 64, dtype: float64
```



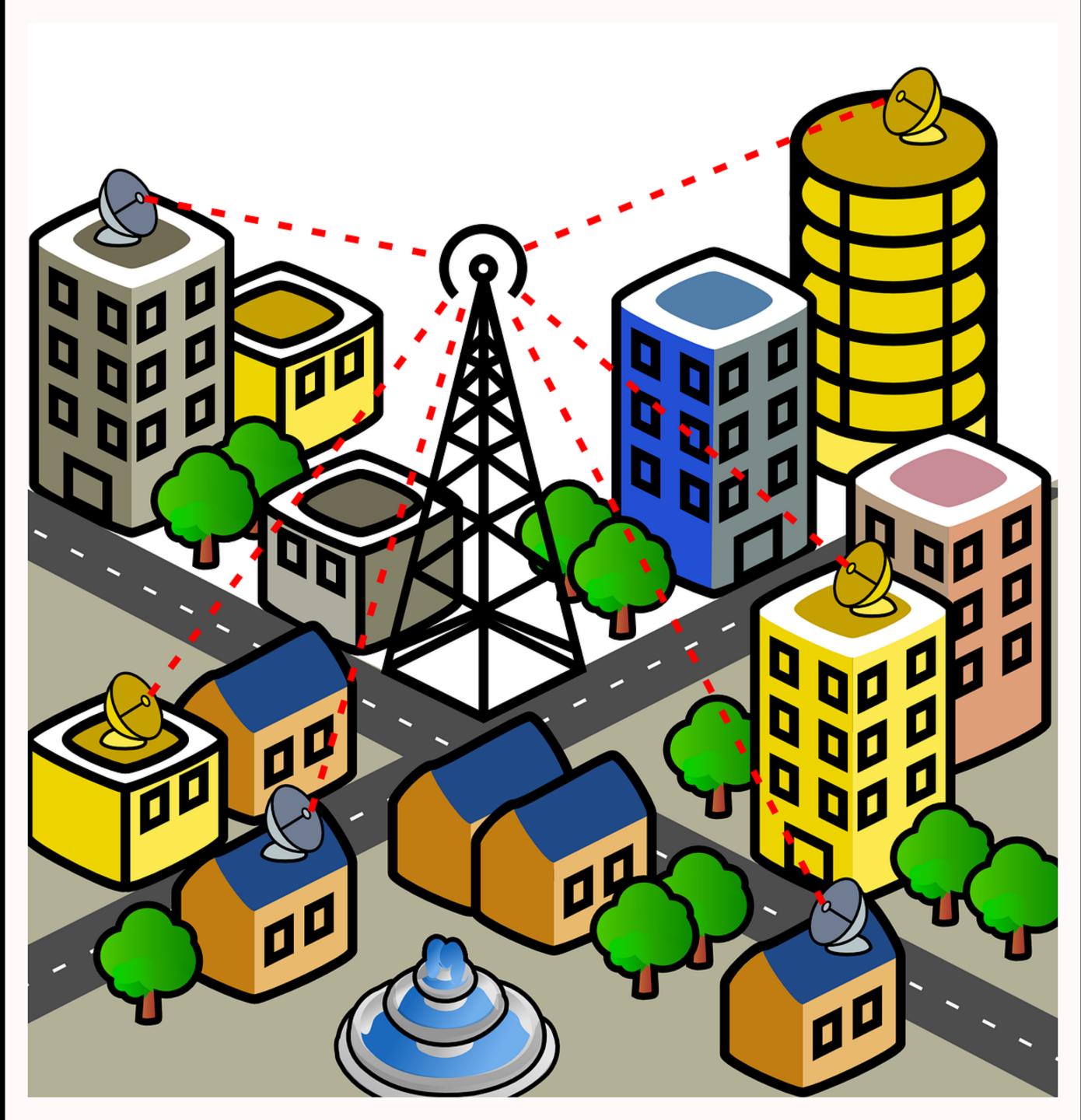
Conclusion

- Important features:
 - Number of customer service calls
 - International plan
 - Voicemail plan
- Invest in customer service
- Target domestic customers
 - potentially in RI, NM, LA
- Promote voicemail plan



Next steps

- Get more data on accounts/ customers that left (or churned).
- Find other variable about customers to analyze
- Get data on broader industry/competitors



Inank you

Questions?

Link: https://github.com/s-shader/Telecom-Customer-Retention-Analysis

Appendix Gradient boost Tuned

Train/test results: Gradient Boost Tuned Model

	GradientBoost_tuned	GradientBoost	BaseLine(KNN)
F1_test	0.851064	0.761421	0.344828
F1_train	1.000000	0.959328	0.935344
acc_test	0.958021	0.929535	0.743628
acc_train	1.000000	0.959614	0.931299
precision_test	0.860215	0.735294	0.271084
precision_train	1.000000	0.966162	0.883340
recall_test	0.842105	0.789474	0.473684
recall_train	1.000000	0.952590	0.993854

Top 10 Features

	importance
customer service calls	0.274019
total day charge	0.203235
international plan	0.129018
total eve minutes	0.066390
voice mail plan	0.049568
total intl charge	0.047704
total intl calls	0.039292
total night minutes	0.029662
total night calls	0.019661
total day calls	0.016852
total eve calls	0.016702
account length	0.015789

Appendix XG Boost

Train/test results: XG Boost Tuned Model

	XGBoost_tuned	XGBoost	BaseLine(KNN)
F1_test	0.829787	0.740000	0.344828
F1_train	1.000000	0.957216	0.935344
acc_test	0.952024	0.922039	0.743628
acc_train	1.000000	0.957638	0.931299
precision_test	0.838710	0.704762	0.271084
precision_train	1.000000	0.966861	0.883340
recall_test	0.821053	0.778947	0.473684
recall_train	1.000000	0.947761	0.993854

Top 10 Features

	importance
international plan	0.079393
voice mail plan	0.051786
state_cat_TN	0.049446
customer service calls	0.046269
total intl calls	0.037305
state_cat_SD	0.027997
state_cat_NC	0.024579
total day charge	0.022493
state_cat_GA	0.021376
state_cat_OK	0.021074