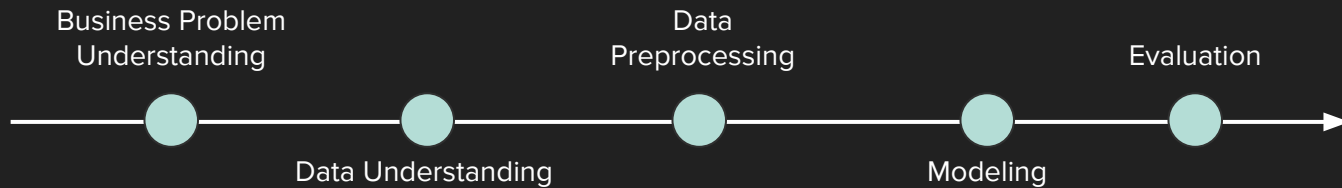


PREVENTING CHURN,
Keeping Customers Happy



Data Understanding

*Telecom Dataset from
Kaggle*

kaggle

*3333 customers from all
50 states*

*Length, frequency, & cost of
calls, subscription to
international plan, voicemail
plan*

CHURN

5 to 25 more expensive to acquire new customers, compared to retaining current customers

Increasing retention rates by 5% can increase **profit rates by 25-95%**

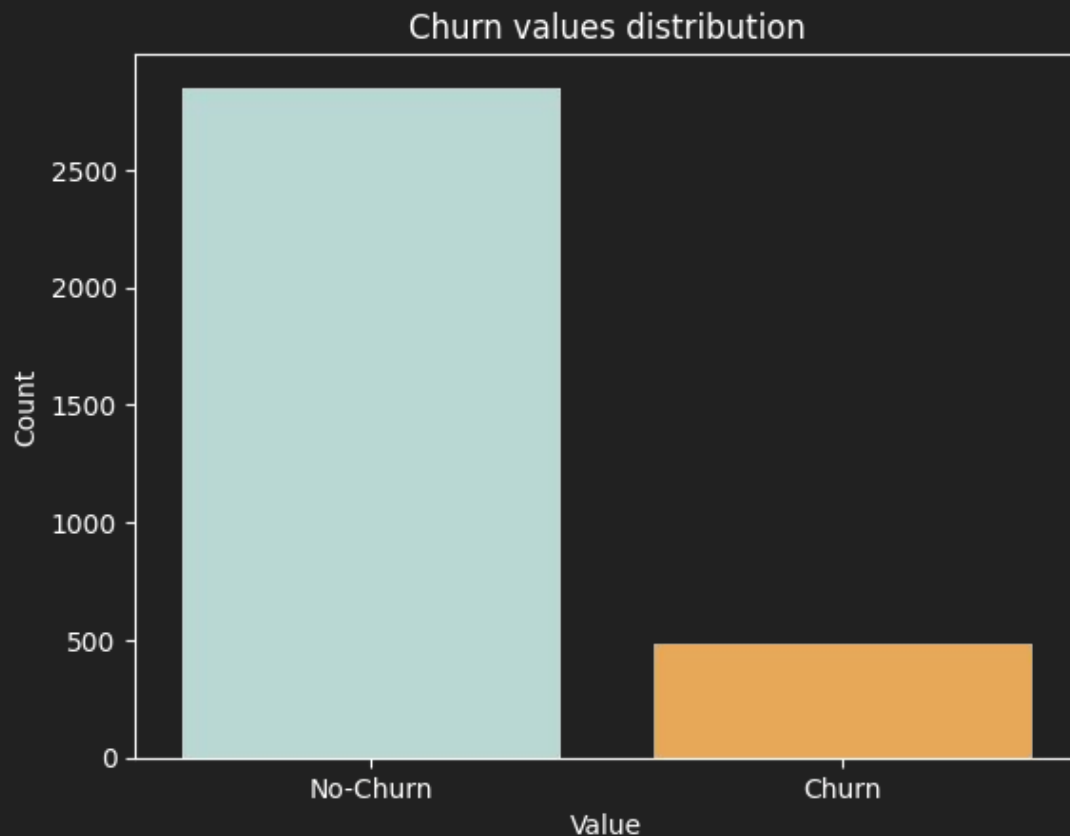
86%

*of data is no-churn
customers*

14%

*of the data is churn
customers*

*SMOTE (Synthetic Minority
Over-sampling Technique)*

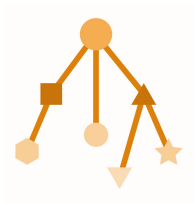


MODELING

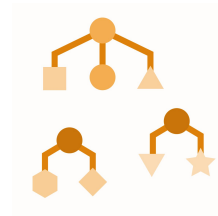
Logistic regression



Decision tree



Random forest



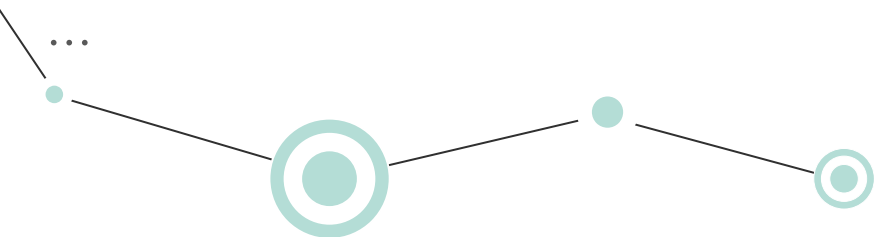
EVALUATION METRICS

RECALL

PRECISION

F1 SCORE

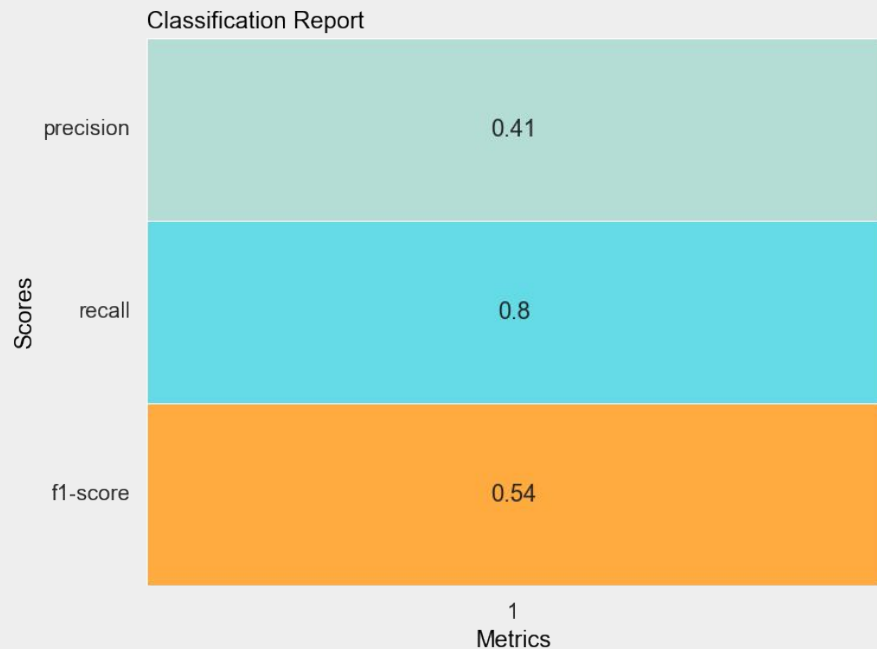
ROC-AUC





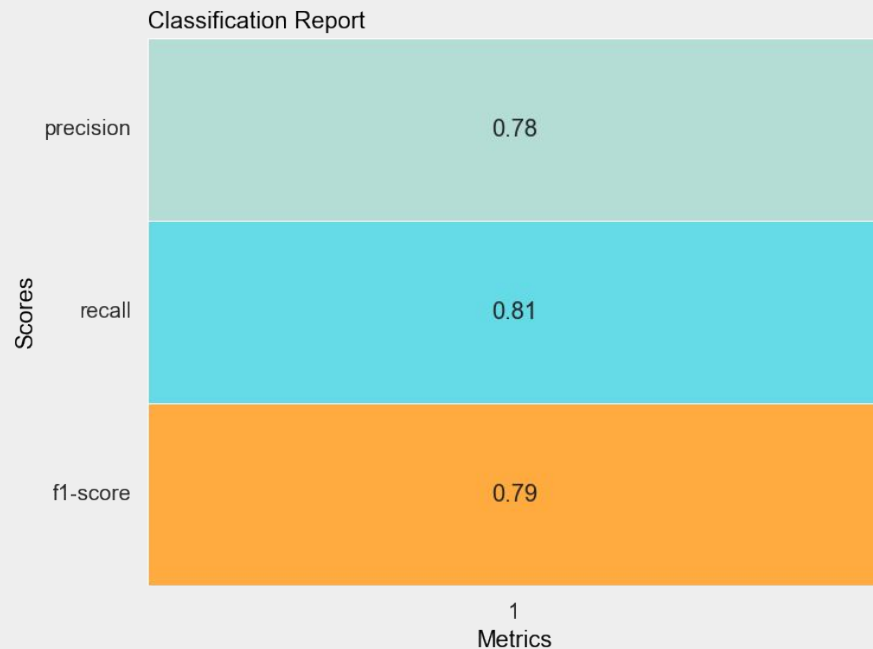
Logistic Regression

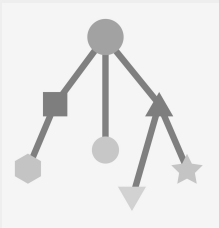
RAW SCORES



FINAL SCORES

(Cross-validated, hyper-tuned)

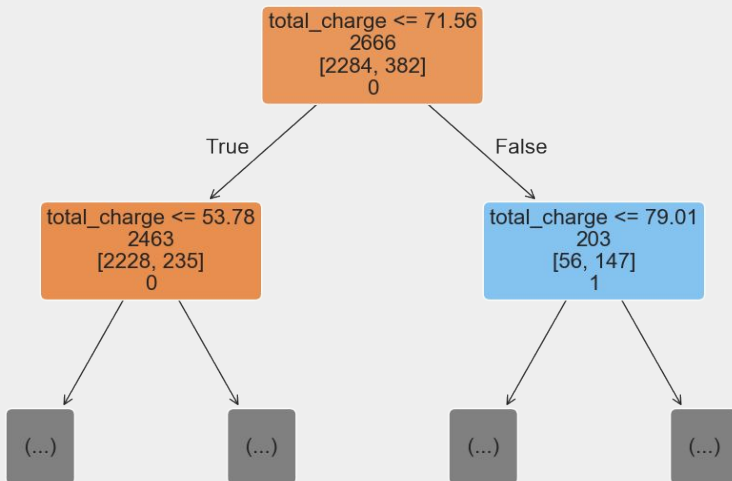




Decision Tree

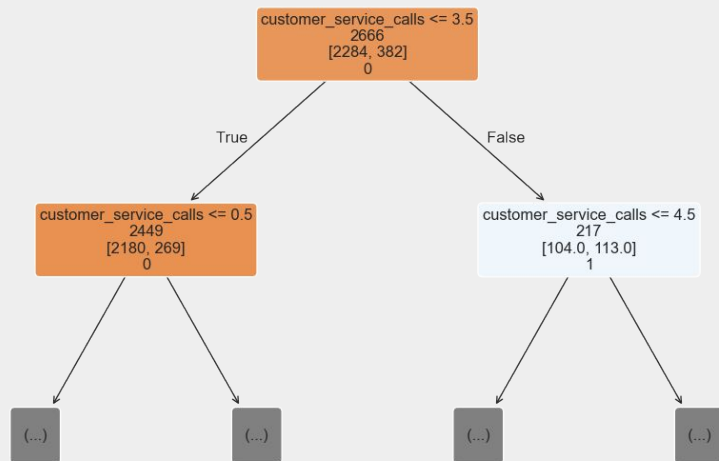
*“customers with a total-charge **less** than 71.56 are likely to **not** churn”*

Decision Tree for total_charge



*“customers with a customer-service call count **less** than 3.5 are likely to **not** churn”*

Decision Tree for customer_service_calls

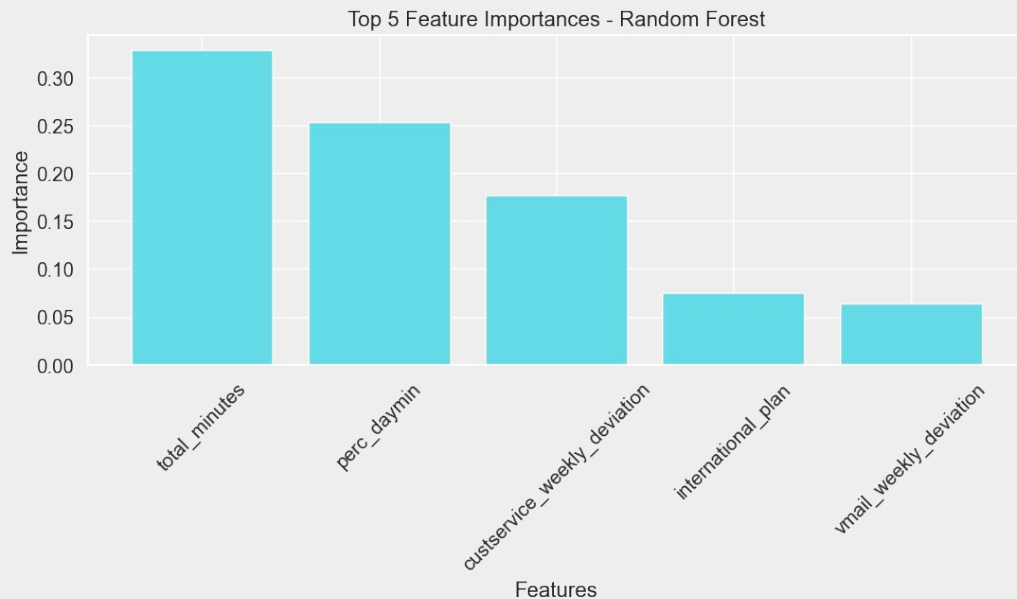


Feature Selection



Random Forest: Feature Selection

- Less sensitive to multicollinearity, captures non-linear relationships
- Ensembling method: combines predictions of multiple base models (decision trees)
- Measures reduction in purity across all decision trees in the forest



Logistic Regression

- Coefficient values
- Impact scale of 0-1

customer
service: **0.77**

total
minutes: **0.76**

international
plan: **0.68**

voice-mail
plan: **-0.36**

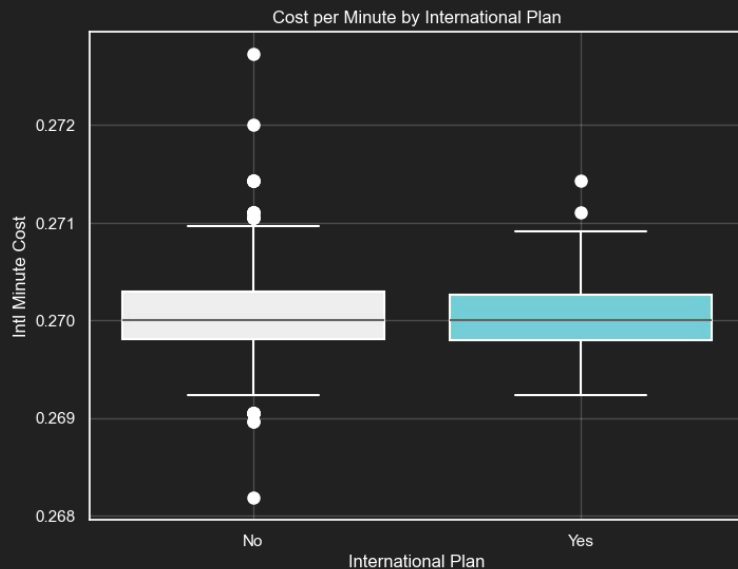
INTERNATIONAL PLAN

#3

Most important feature in final
logistic regression model

0.68 coefficient

(subscribers likely to **churn**)



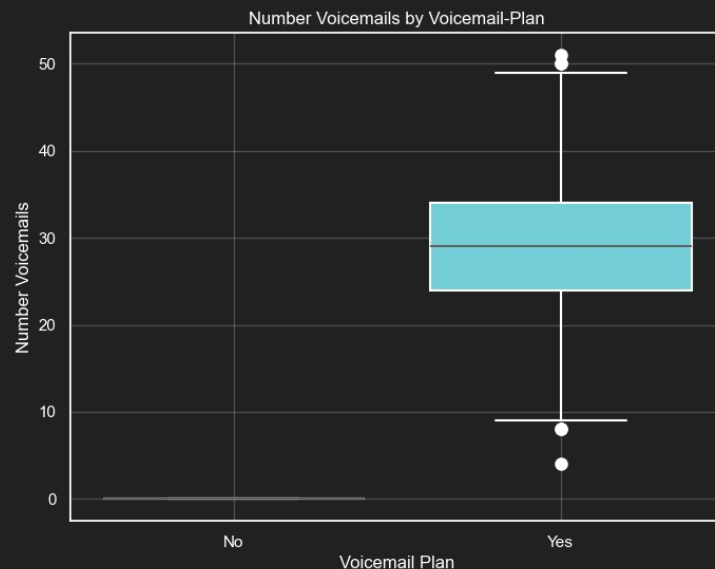
VOICEMAIL PLAN

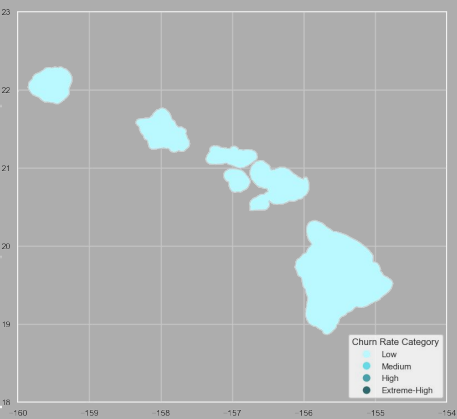
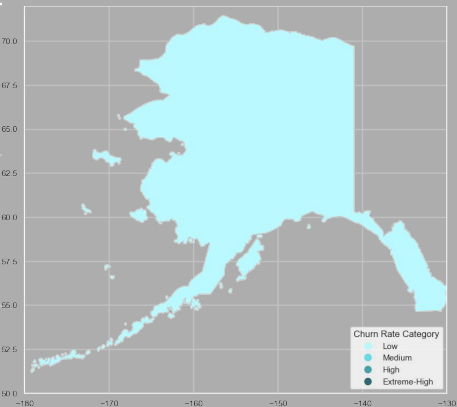
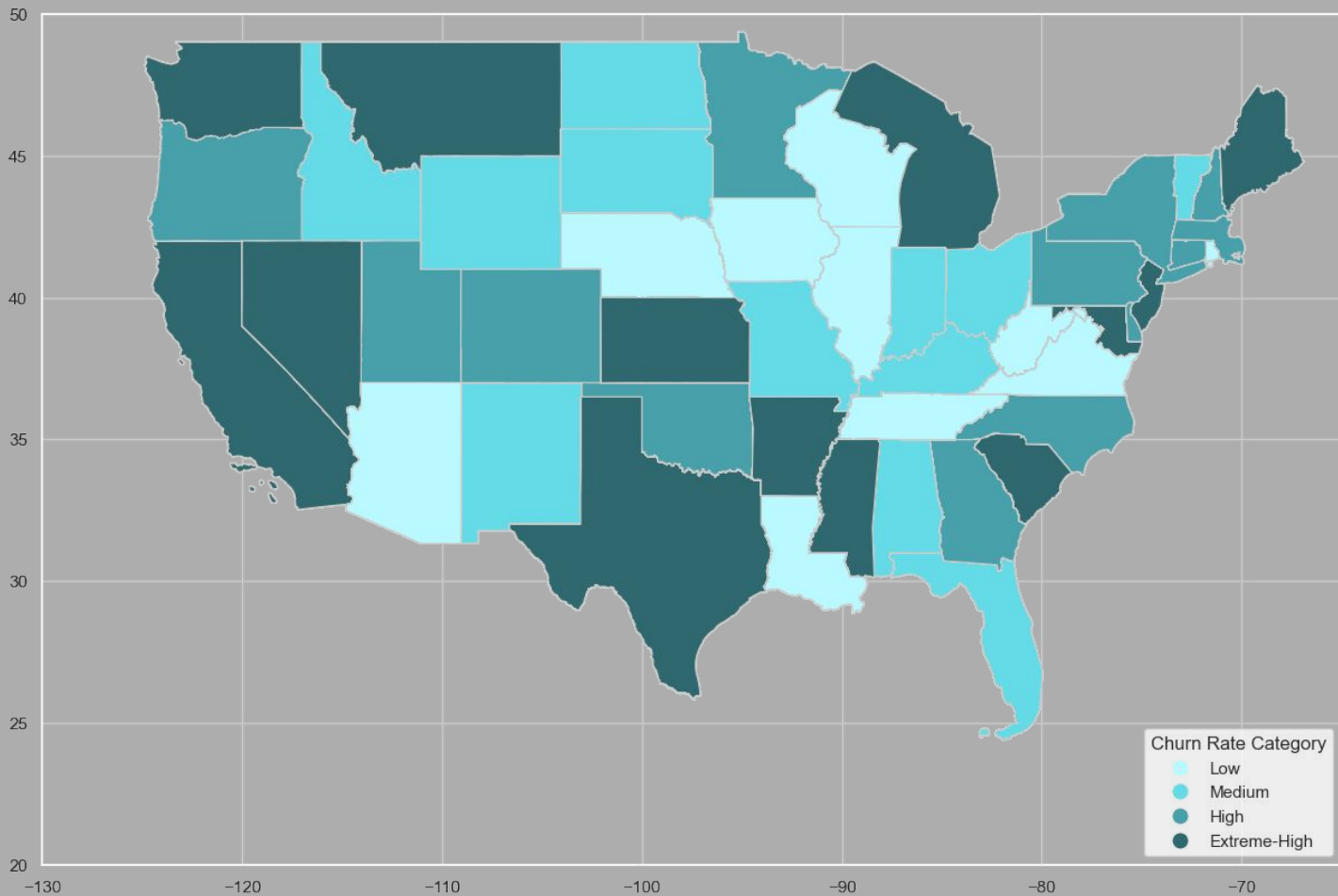
#4

Most important feature in final
logistic regression model

-0.36 coefficient

(subscribers likely to **not churn**)





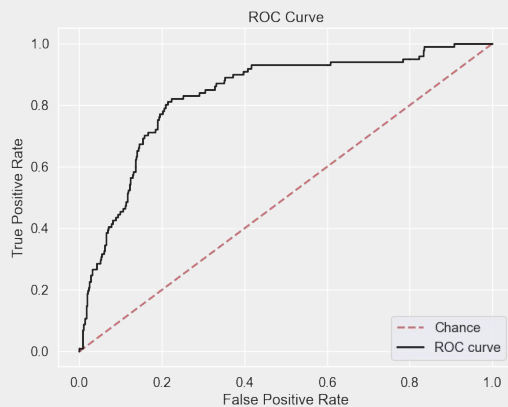


BEST MODEL: LOGISTIC REGRESSION

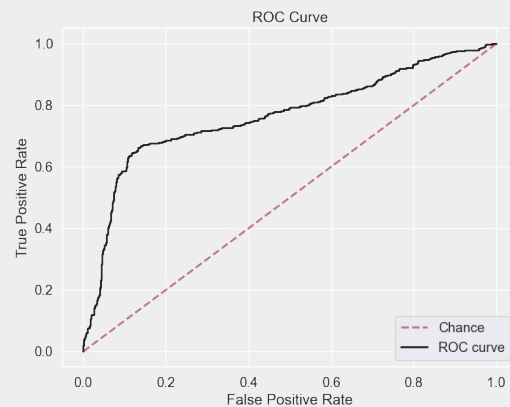




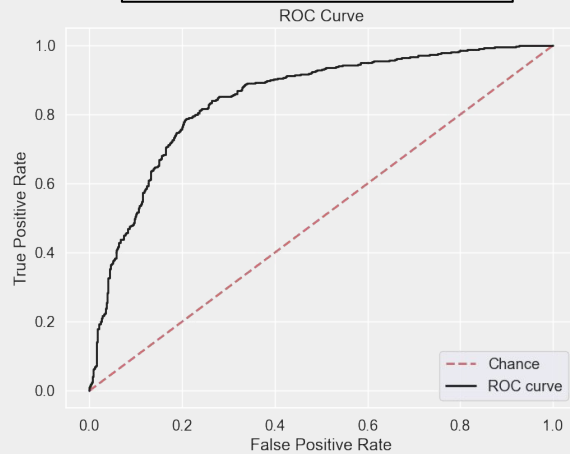
RAW
ROC-AUC: 0.83



MID-ENGINEERING
ROC-AUC: 0.85



FINAL
ROC-AUC: 0.85



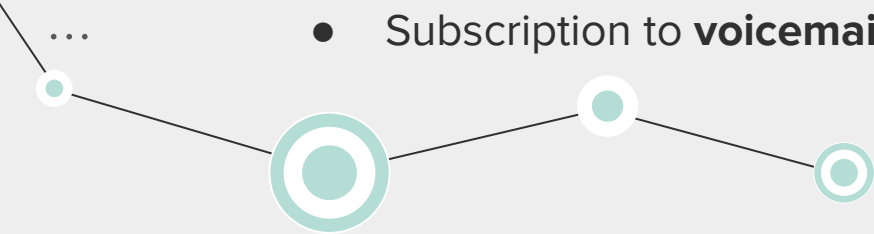
CONCLUSIONS



Key behaviors predictive of churn:

- 2+ **customer service calls**
- Increased **number of call-time minutes**, particularly during the **daytime** (most likely related to *increased charges*)
- Subscription to **international plan**
- Residing in a **high churn-rate state**

Key behaviors prediction of *no* churn:

- Subscription to **voicemail plan**
- 

NEXT STEPS

Duration of Call & Daytime Calling

PRICE-PER-MINUTE (by time of day)

DAY: 0.17

EVENING: 0.085

NIGHT: 0.045

- **Reduce the rates for daytime minutes**
- Introduce more **flexible customisable pricing plans**

International Plan

- Differentiate the international plan
- Gather feedback from current international plan users
- Develop tailored international plans



NEXT STEPS

Customer Service Calls

- Collect and analyse data on customer service calls:
 - reason for call
 - type of issue
 - was the issue resolved
 - customer service experience satisfaction

State

- Collect and analyze additional data (feedback from customers) on reasons for churn in each state



Further Recommendations

Introduce new features for analysis, including Internet data usage and Internet data services

Introduce new features on customers demographics (age, sex, family plan or not, number of people in family)

Include qualitative analysis for customer feedback to broaden understanding of features correlations

THANK YOU

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Dolgor Purbueva: github.com/dolgorp