# CUSTOMER RETENTION CLASSIFICATION

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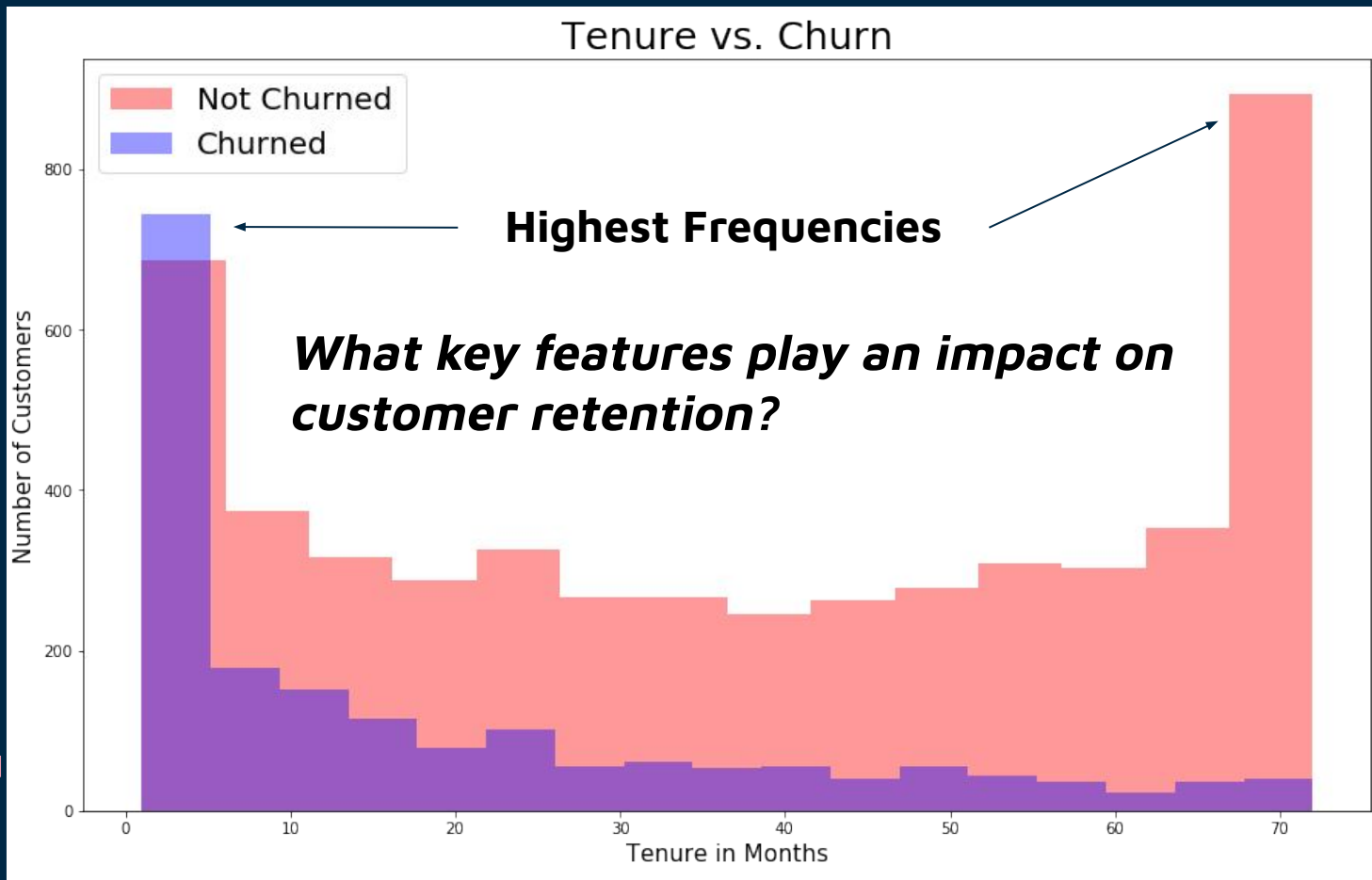
"Do what you do so well that they want to see it again and bring their friends."
–Walt Disney

# CHURN

Customer retention is a mainstay for profitability and success.

Customers who churn have a shorter transactional lifecycle



Tenure vs. Churn

Legend: Not Churned, Churned

Highest Frequencies

*What key features play an impact on customer retention?*

Y-axis: Number of Customers
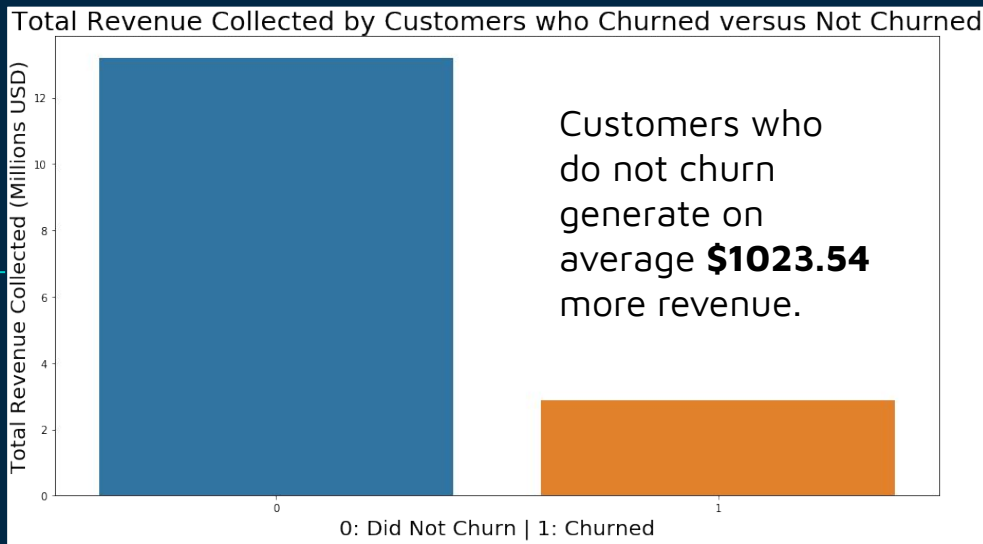
X-axis: Tenure in Months

# UNDERSTANDING THE PROBLEM

## IS IT POSSIBLE?

Can churn be explained and understood through a model? If so, which features have the strongest association?

## HOW?

Can Telco reduce churn? What can other businesses learn about what features drive churn?

**Total Revenue Collected by Customers who Churned versus Not Churned**

Customers who do not churn generate on average **$1023.54** more revenue.

Total Revenue Collected (Millions USD)

0: Did Not Churn | 1: Churned

# METHODOLOGY

Gathering the data and understanding its significance
**RESEARCH**

**PREPROCESSING**

Implementing a number of classification modeling techniques
**ITERATION**

**EVALUATING**

**LOADING**

**VISUALIZATION**
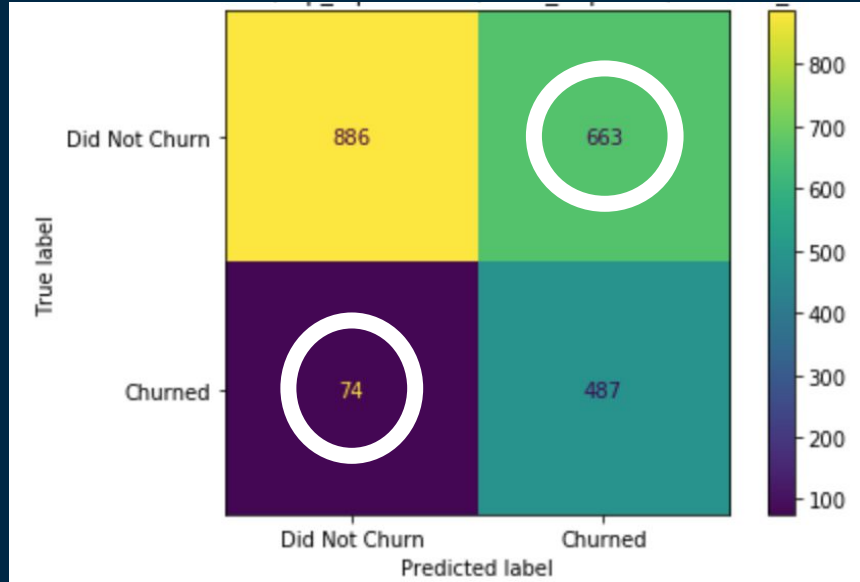Cleaning, exploring, and analyzing the relationships

**MODELING**

**RECOMMENDATION**
Weighing key metrics to best support business needs

# RESULTS: MINIMIZE COSTLY SITUATIONS



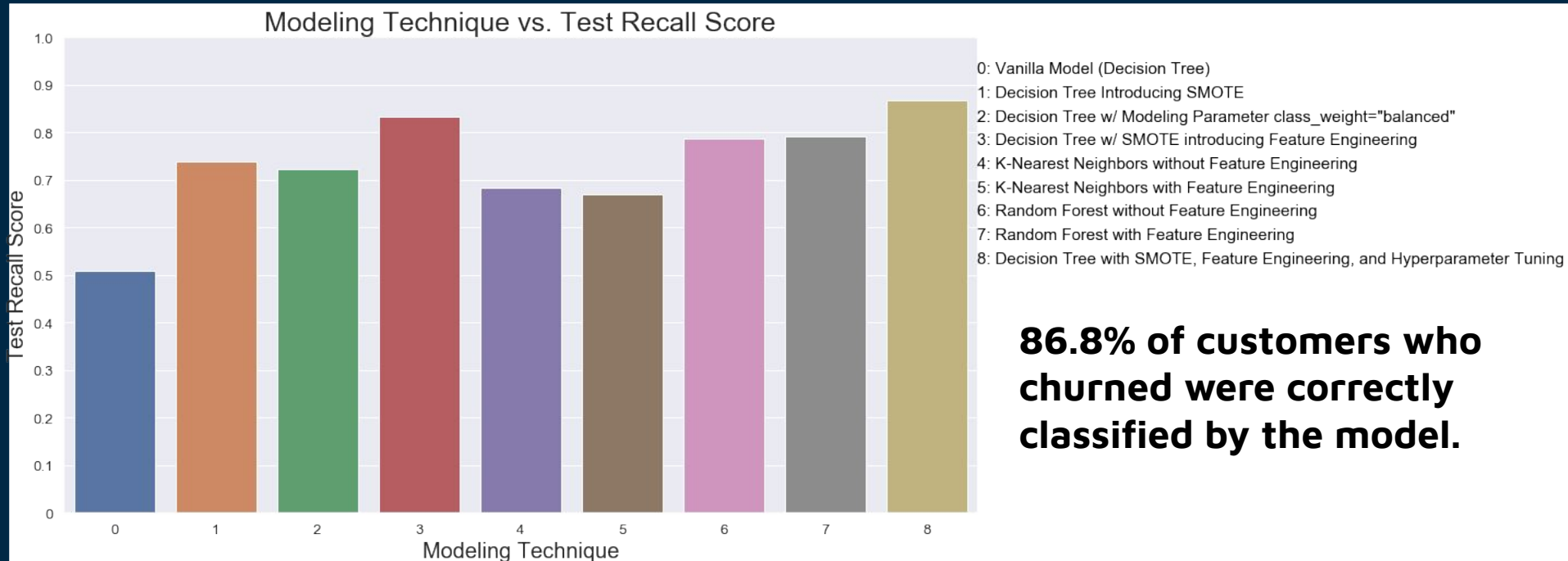## ACCURACY

Customer is satisfied with Telco's product and remained a paying customer

## RECALL

Customer is dissatisfied with Telco's product and churned

**Focusing on reducing recall minimizes costly situations where a customer churns.**

# RESULTS: FINDING THE RIGHT MODEL

## Modeling Technique vs. Test Recall Score

0: Vanilla Model (Decision Tree)
1: Decision Tree Introducing SMOTE
2: Decision Tree w/ Modeling Parameter class_weight="balanced"
3: Decision Tree w/ SMOTE introducing Feature Engineering
4: K-Nearest Neighbors without Feature Engineering
5: K-Nearest Neighbors with Feature Engineering
6: Random Forest without Feature Engineering
7: Random Forest with Feature Engineering
8: Decision Tree with SMOTE, Feature Engineering, and Hyperparameter Tuning

**86.8% of customers who churned were correctly classified by the model.**

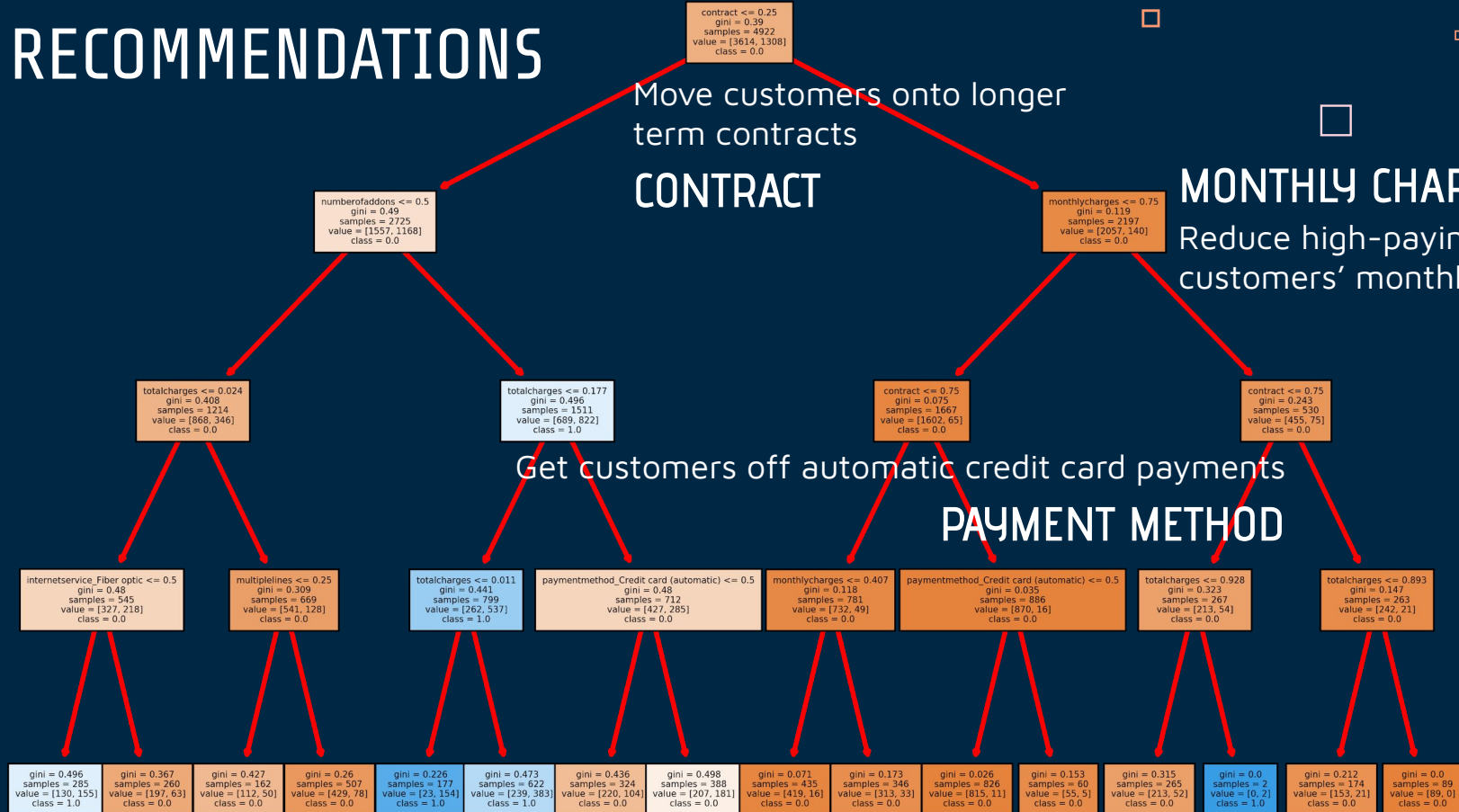# RECOMMENDATIONS

**CONTRACT**

Move customers onto longer term contracts

**MONTHLY CHARGES**

Reduce high-paying customers' monthly rates

Get customers off automatic credit card payments

**PAYMENT METHOD**

contract <= 0.25
gini = 0.39
samples = 4922
value = [3614, 1308]
class = 0.0

numberofaddons <= 0.5
gini = 0.49
samples = 2725
value = [1557, 1168]
class = 0.0

monthlycharges <= 0.75
gini = 0.119
samples = 2197
value = [2057, 140]
class = 0.0

totalcharges <= 0.024
gini = 0.408
samples = 1214
value = [868, 346]
class = 0.0

totalcharges <= 0.177
gini = 0.496
samples = 1511
value = [689, 822]
class = 1.0

contract <= 0.75
gini = 0.075
samples = 1667
value = [1602, 65]
class = 0.0

contract <= 0.75
gini = 0.243
samples = 530
value = [455, 75]
class = 0.0

internetservice_Fiber optic <= 0.5
gini = 0.48
samples = 545
value = [327, 218]
class = 0.0

multiplelines <= 0.25
gini = 0.309
samples = 669
value = [541, 128]
class = 0.0

totalcharges <= 0.011
gini = 0.441
samples = 799
value = [262, 537]
class = 1.0

paymentmethod_Credit card (automatic) <= 0.5
gini = 0.48
samples = 712
value = [427, 285]
class = 0.0

monthlycharges <= 0.407
gini = 0.118
samples = 781
value = [732, 49]
class = 0.0

paymentmethod_Credit card (automatic) <= 0.5
gini = 0.035
samples = 886
value = [870, 16]
class = 0.0

totalcharges <= 0.928
gini = 0.323
samples = 267
value = [213, 54]
class = 0.0

totalcharges <= 0.893
gini = 0.147
samples = 263
value = [242, 21]
class = 0.0

gini = 0.496
samples = 285
value = [130, 155]
class = 1.0

gini = 0.367
samples = 260
value = [197, 63]
class = 0.0

gini = 0.427
samples = 162
value = [112, 50]
class = 0.0

gini = 0.26
samples = 507
value = [429, 78]
class = 0.0

gini = 0.226
samples = 177
value = [23, 154]
class = 1.0

gini = 0.473
samples = 622
value = [239, 383]
class = 1.0

gini = 0.436
samples = 324
value = [220, 104]
class = 0.0

gini = 0.498
samples = 388
value = [207, 181]
class = 0.0

gini = 0.071
samples = 435
value = [419, 16]
class = 0.0

gini = 0.173
samples = 346
value = [313, 33]
class = 0.0

gini = 0.026
samples = 826
value = [815, 11]
class = 0.0

gini = 0.153
samples = 60
value = [55, 5]
class = 0.0

gini = 0.315
samples = 265
value = [213, 52]
class = 0.0

gini = 0.0
samples = 2
value = [0, 2]
class = 1.0

gini = 0.212
samples = 174
value = [153, 21]
class = 0.0

gini = 0.0
samples = 89
value = [89, 0]
class = 0.0
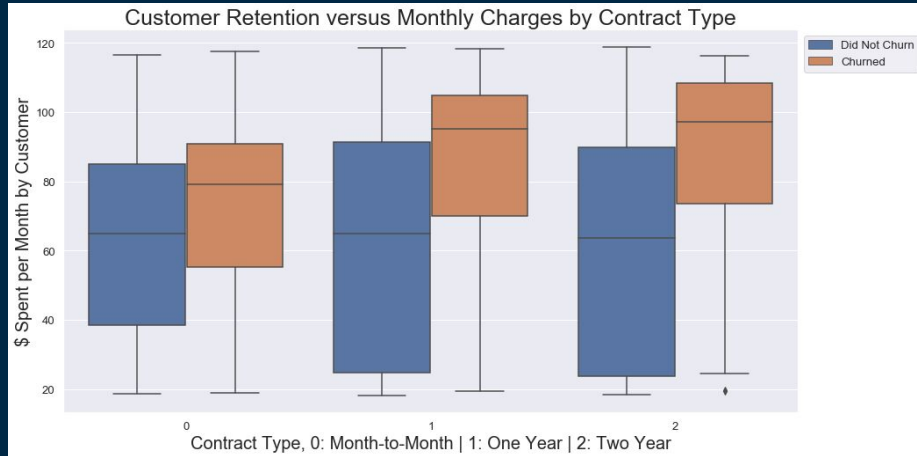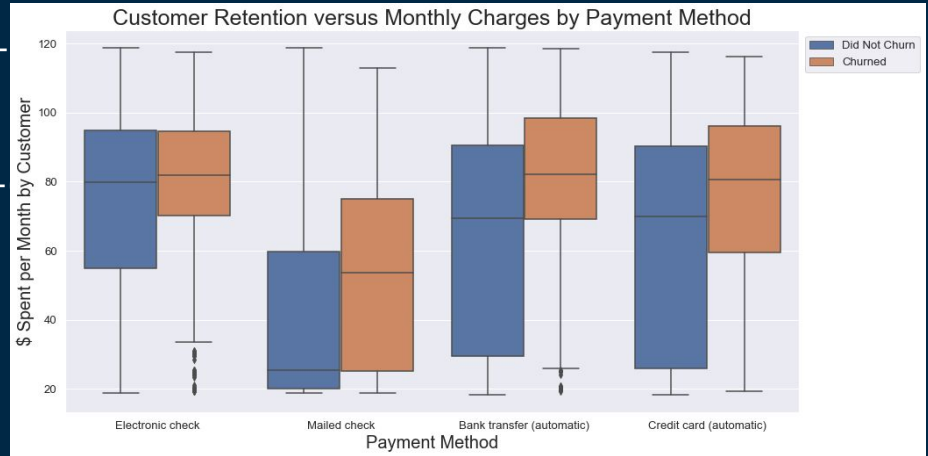
# RECOMMENDATIONS

## CONTRACT

## MONTHLY RATE

## PAYMENT METHOD



**Treat all indicators of a potential churner with urgency. Better safe than sorry.**

# FUTURE WORK

## MODEL IMPLEMENTATION

Conduct a short term study on the financial effects of converting customers onto longer term contracts, reducing monthly rates, and changing payment methods.

## FINE TUNE UNDERSTANDING OF SERVICE ADD-ONS

Through a Principle Component Analysis (PCA), investigate which service add-ons have the strongest impact on churn.

## REDUCE OVERFITTING

Increase the number of cross validations to conduct more hyperparameter tuning.

Do you have any questions?

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github.com/mattielips

# THANKS
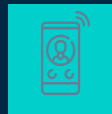
Appendix available upon request

# APPENDIX