

# Subscription Churn Analysis

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MLDS 401: Predictive Analytics I Project  
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# Outline

- Business Questions
- Subscription Churn Factor Analysis
  - Payment Effect
  - Engagement Effect
  - Content Effect
  - Device Effect
- Conclusion
  - Data Science Insights
  - Business Analytics Insights
- Actionable Advice



# **1 Business Questions**

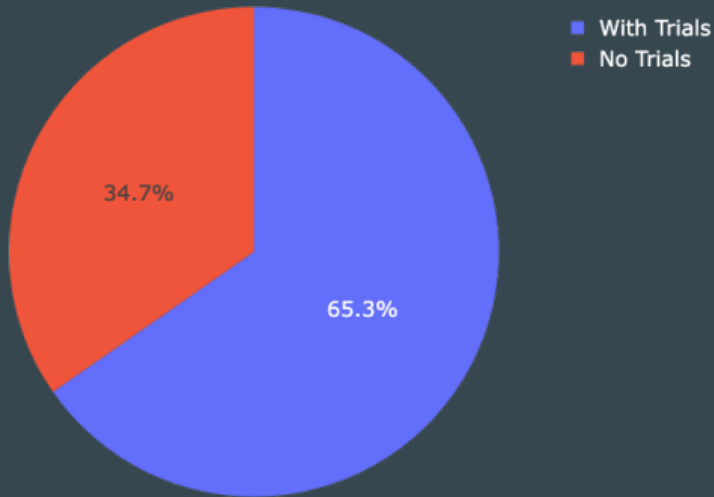
# Business Questions

- How do **different factors** such as *trial offers, subscription price, customers' engagement, content preferences, and device usage* impact customer **churn rate**?
- What **strategies** can be implemented to **minimize churn rate** and enhance **customer loyalty** in this subscription-based service?

## **2 Subscription Churn Factor Analysis**

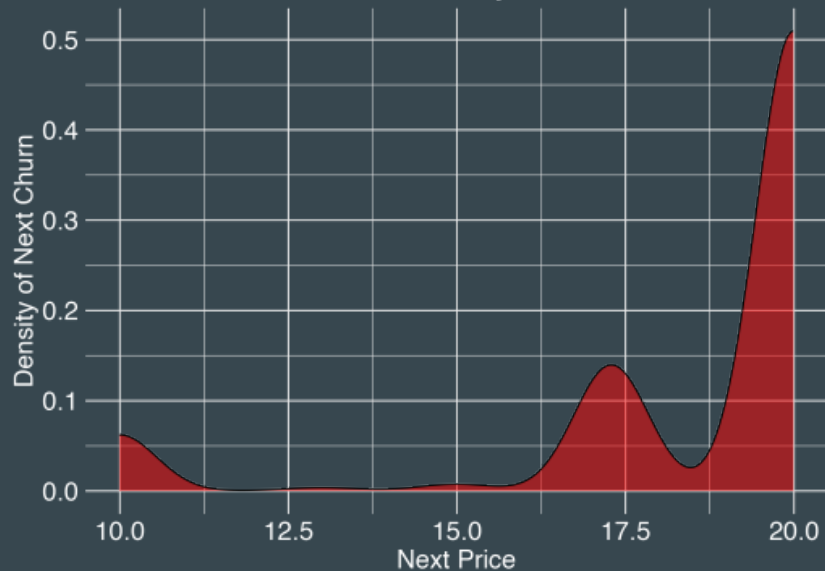
# Payment Effect: Trial & Price

Customer Segmentation by Having Trials or Not



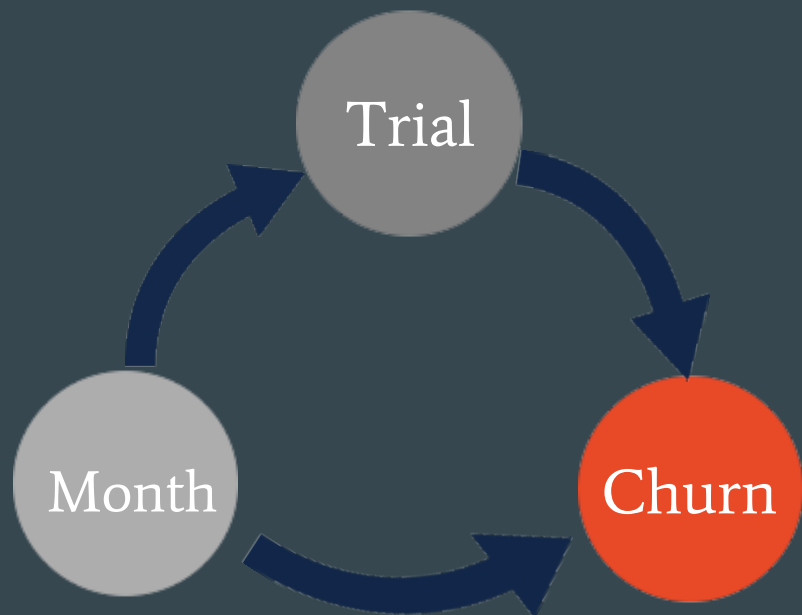
Around  $\frac{2}{3}$  of customers have *trials*, but the majority are only interested in the *trial* period and don't show long-term commitment to the subscription service

Distribution of Next Price by Next Churn



With a higher subscription *price*, customers are more likely to churn in the next month

# Do we lose some variable(s)?



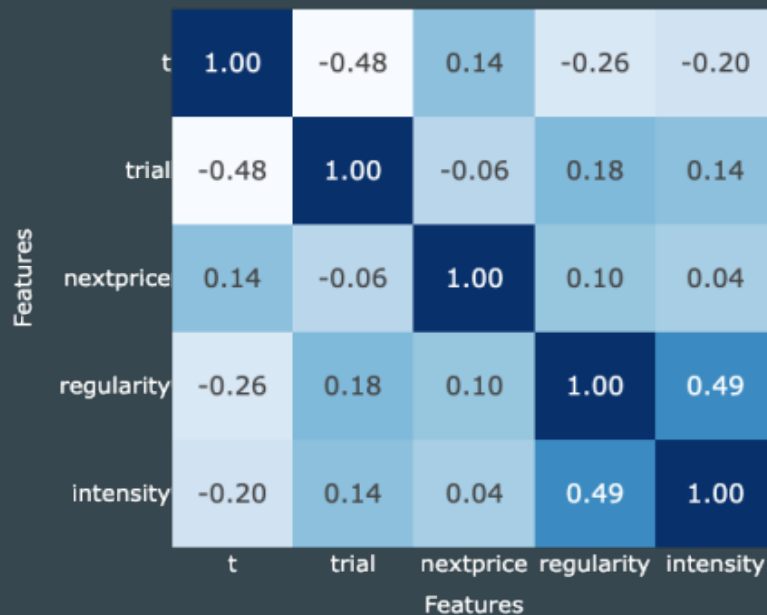
- Seasonal Patterns
- Promotions or Offers
- Trial Period Impact
- Behavior Change Over Time

Fork Structure => Keep *Month* !

# Engagement Effect: Regularity & Intensity

- Examine their correlations and VIFs
  - Correlation between *regularity* and *intensity* is **0.49**
- P-values
  - The effect of *intensity* could be partly explained by *regularity*
- The *regularity*'s **sign** is **negative**: the more frequently customer reads in a certain month, the higher probability they will retain in subscription in the following month

Correlation Heatmap





# Content Effect

- P-values & AIC
  - In the model without *regularity*, *sports* and *news* are significant, whereas they become not significant after adding in *regularity*
  - The AIC of the model without *regularity* is higher than that with *regularity*
- After adding in *regularity*, the VIFs of all *content* variables become higher
- All *content* variables are not significant in the model, this tells us that the content readers are reading has **no** significant effect on the churn rate

# Device Effect

- P-values
  - In the model without *regularity*, *desktop*, one of the device variables, is significant, whereas it becomes not significant after adding in *regularity*
- After adding in *regularity*, the VIFs of all *device* variables become higher
- All the *device* variables are not significant in the model, this tells us that the device readers are using has **no** significant effect on the churn rate



# **3 Conclusion**

# Conclusion: Data Science Insights

## Stepwise Regression Evaluation:

- Month



- Trial



- Nextprice



- News



- Crime



- Regularity



# Conclusion: Business Analytics Insights

- Loyal customers exhibit a lower tendency to churn over *months*, showing their loyalty to the service
- Customers commonly churn after their *trial* period
- *Nextprice* increase can trigger substantial customer churn
- *Regularity* has a high impact on the churn rate

=> Our Model:  $nextchurn = \beta_0 + \beta_1 month + \beta_2 trial + \beta_3 nextprice + \beta_4 regularity$

Retain Customers	Drive Customers Away	No Substantial Effect
<i>Month &amp; Regularity</i>	<i>Trial &amp; NextPrice</i>	<i>Content and Device Variables</i>

Dismiss the *intensity* factor  
due to **high collinearity**

# **4 Actionable Advice**

# Actionable Advice

- Implement a **notification system** to remind users of new articles, breaking news, or personalized
- Offer some **discounts** to retain customers to reduce the immediate loss after the *trial*
- Adjust the **gap** between the *trial* price and the *normal* price
- Introduce **loyalty programs**

**Q&A**