Predicting Player Churn in the Wild

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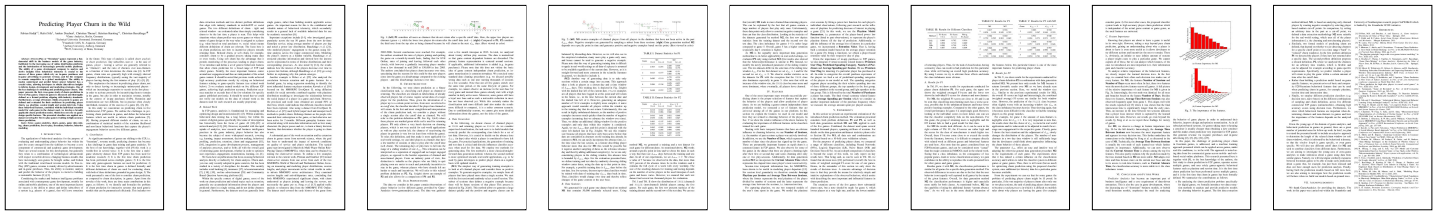
For the Impatient



Take Away Message

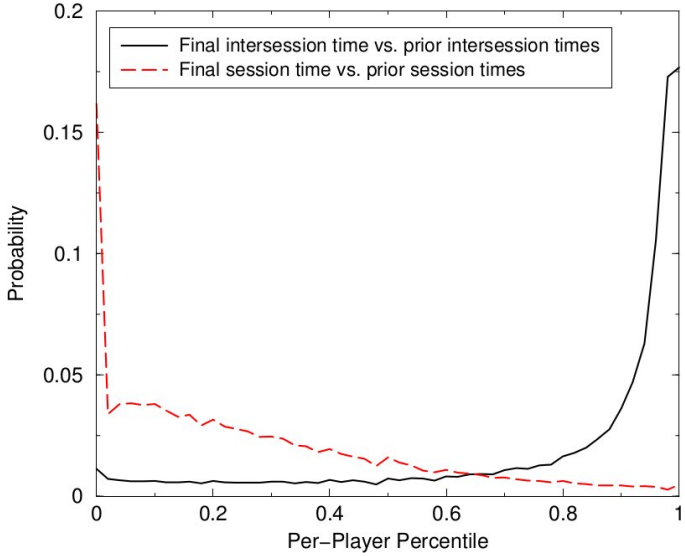
Churn prediction for mobile games can be realized with decision trees and game independent features

What is Churn Analysis?

- Generally: detect and define subscribers of a system that will leave in the future
  - e.g. players of a game
- Churn starts with players losing interest in the game

Playtime, Intersession Time & Churn

- For the final session it has been observed that session time decreases while intersession time increases [Feng et al., 2007, Workshop at ACM SIGCOMM]



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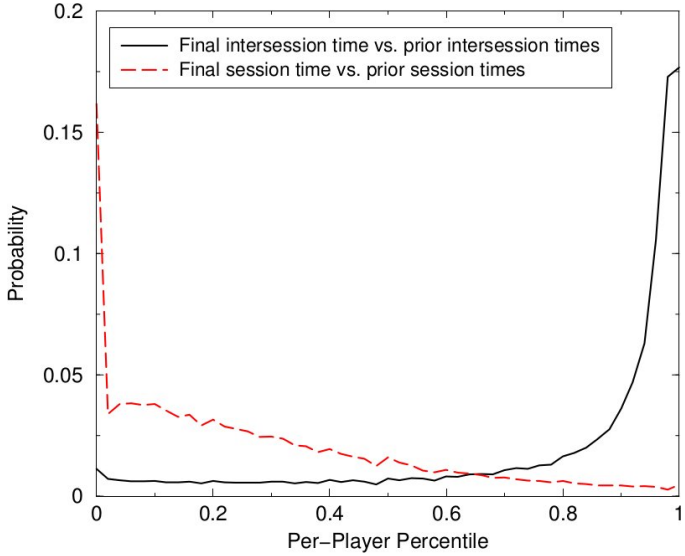

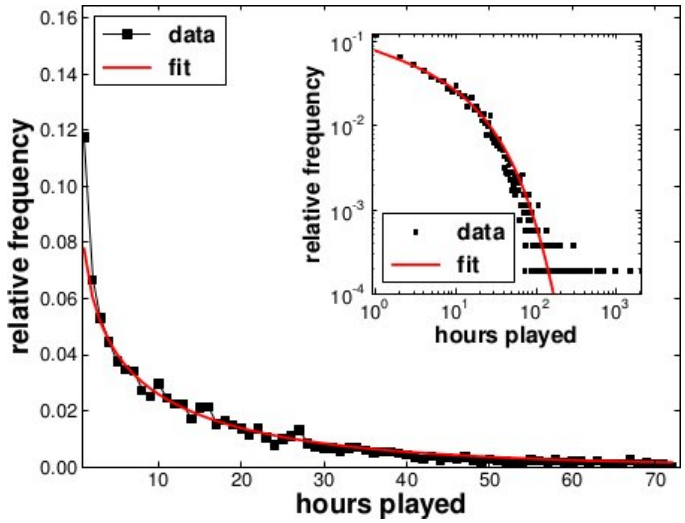

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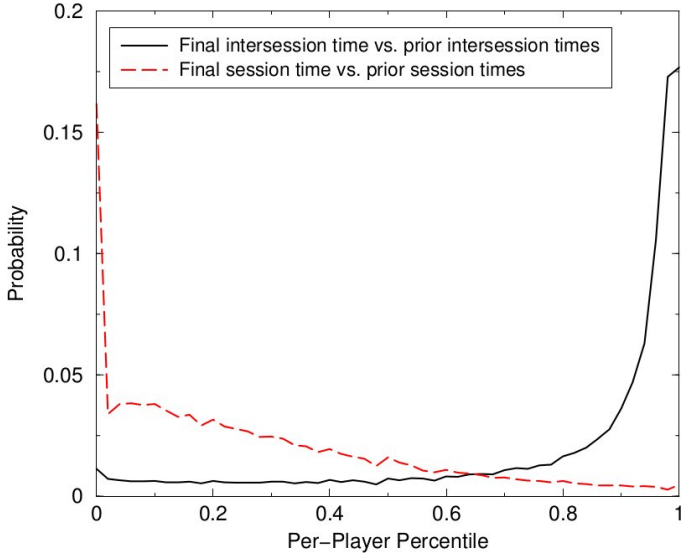
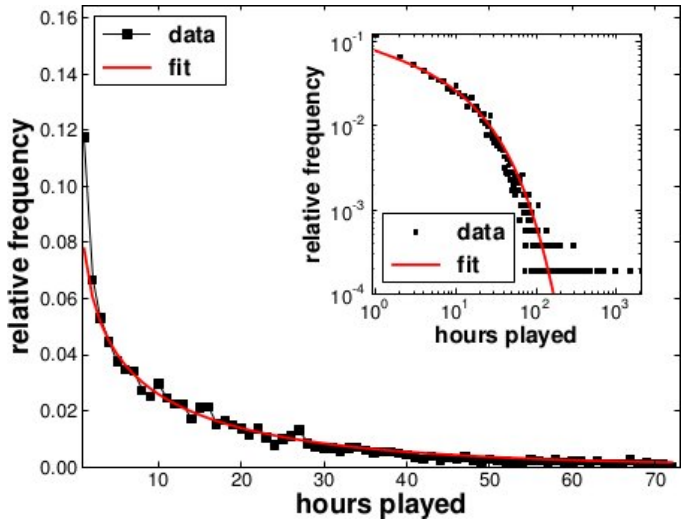
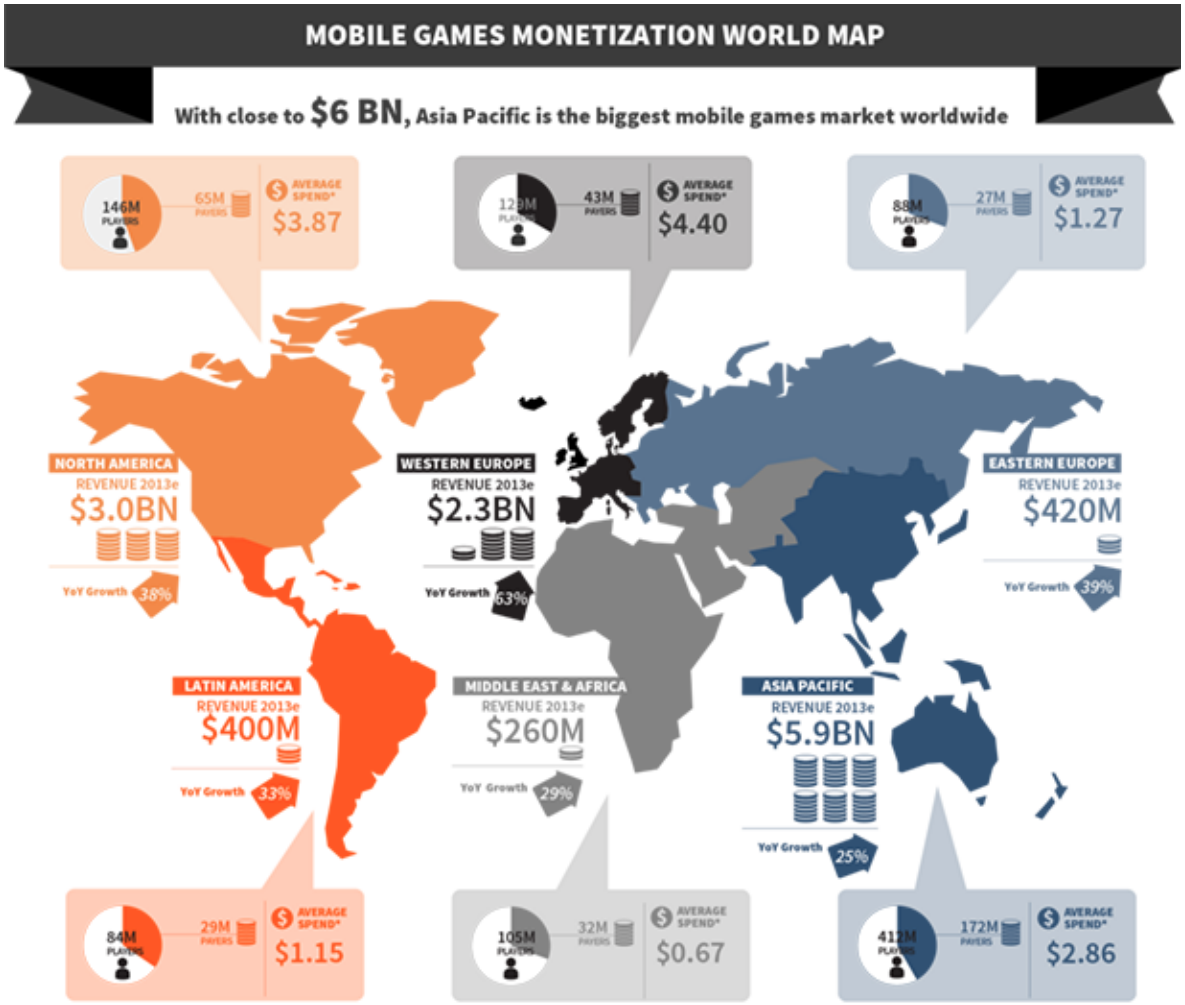
- Here, we seek for a classifier for individual players, possibly exploiting these regularities





Why is Churn Analysis important?



www.newzoo.com/infographics/infographic-the-global-mobile-landscape/

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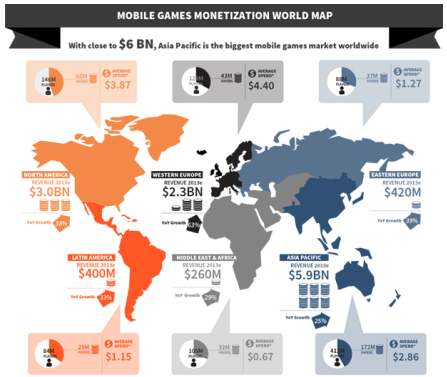

- New revenue model for mobile games is Free-to-Play (F2P)
  - The mobile game market is worth billions of dollars across the entire world
  - Monetization is based on advertisement or in-game purchases
  - Churn prediction can improve re-targeting campaigns
  - **Decreasing the churn rate increases revenue**

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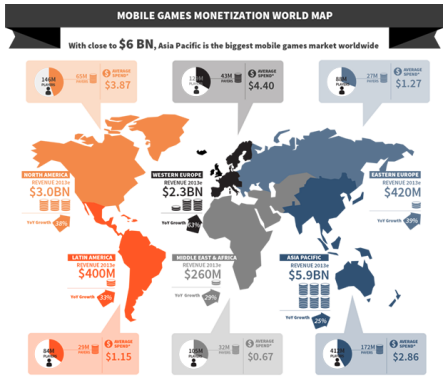

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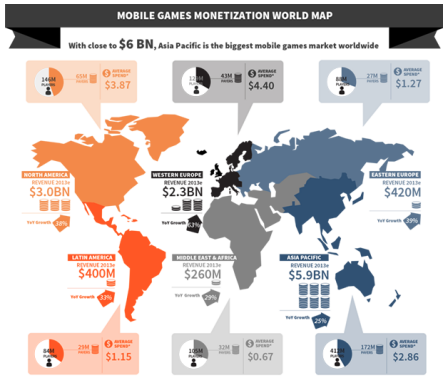

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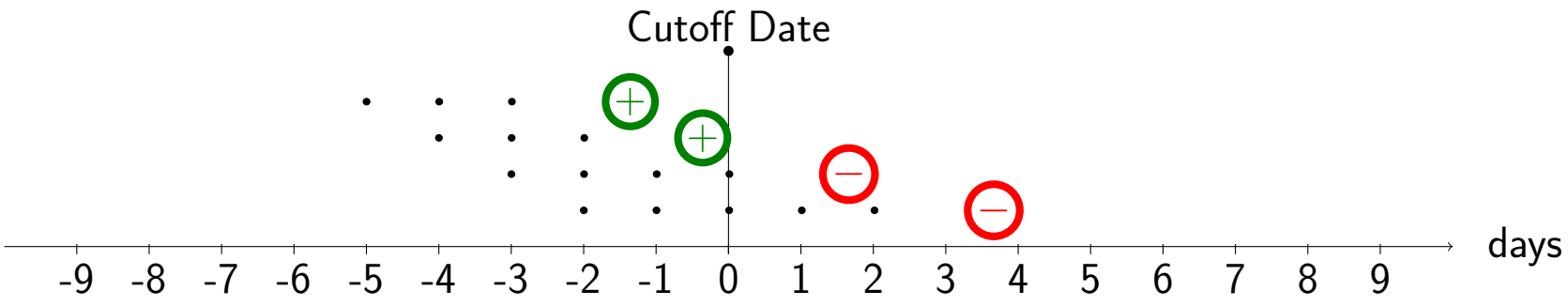
- Obtain data-driven insights to inform design and development
- See also [Runge et al., 2014, CIG]

Player Churn More Precisely

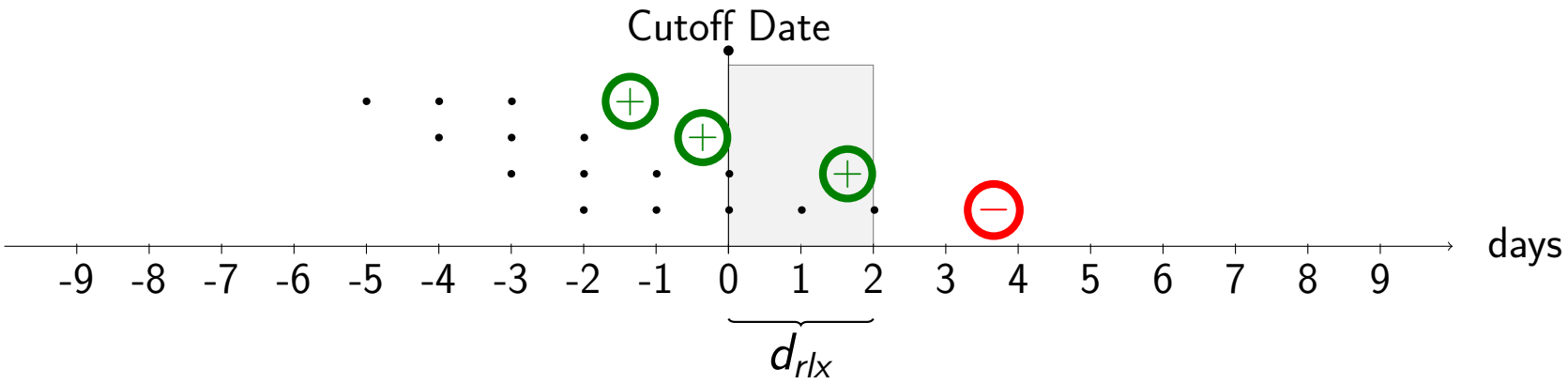
- F2P does most often not require a subscription
- Therefore, churn is not explicitly visible
- Makes a precise definition of churn necessary
- Learn a binary classifier that labels players as churners or non-churners

Churn Definition (P1)



- Churner: a player without a single session after the cutoff date
- No chance to reactivate these players again in mobile games

Churn Definition (P2)

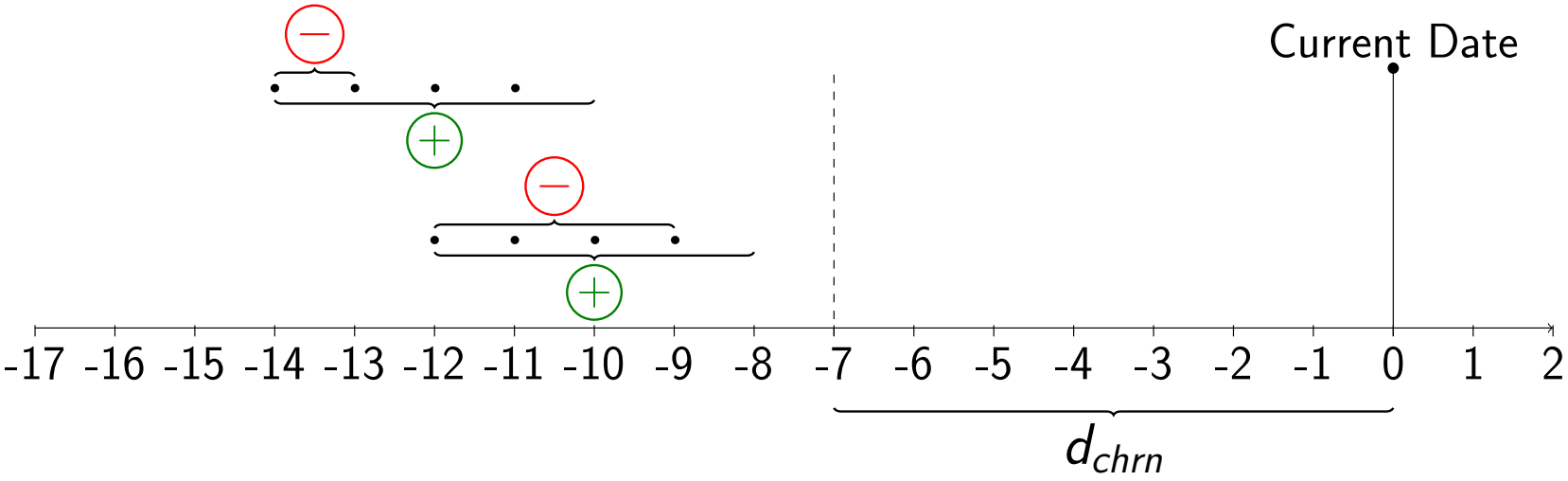


- Churner: a player with a low number of sessions to play after the cutoff date
- Introduces sliding window d_{rlx}
- Transition to separate engaged and no longer engaged players

Dataset

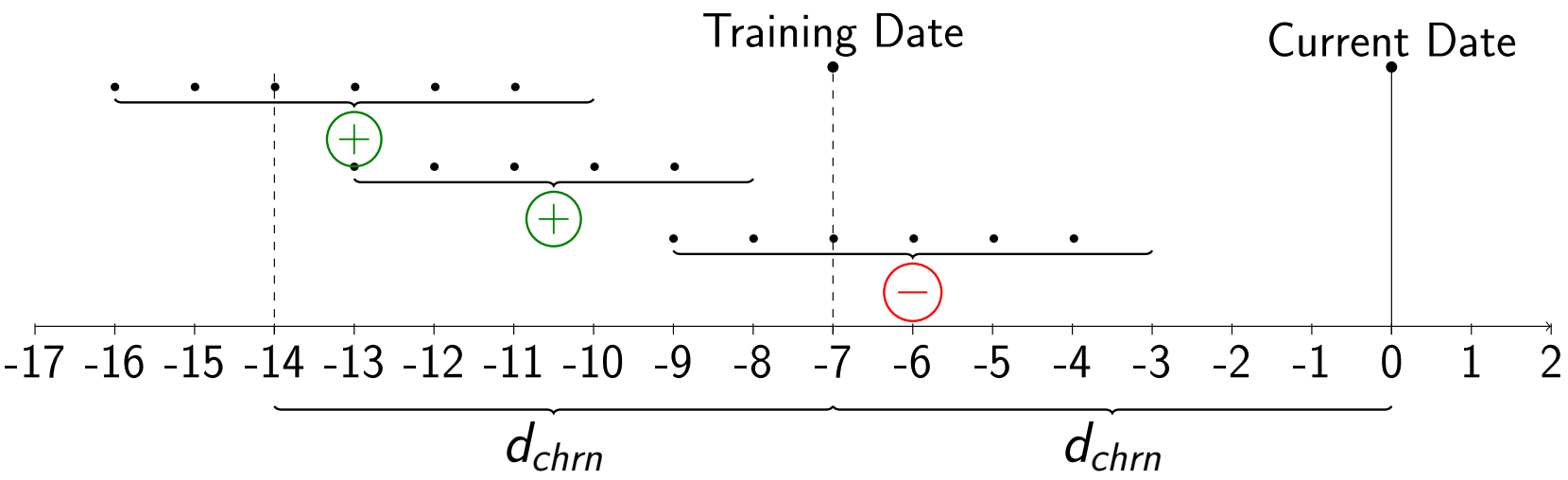
- Data was provided by GameAnalytics (`www.gameanalytics.com`)
- Game developer can transmit various kinds of messages
- Observations of player behavior in 5 different games
- Data contains about twenty million sessions
- Data also contains in-game purchase information
- We normalize these raw messages to make them game-independent and to generate training/test instances

Data Generation (M1)



- We chose $d_{chrn} = 7$ to cover every weekday
- $< 5\%$ of the players in our dataset return after a 7-day absence
- Negative instances are randomly sampled from positive ones
- Classical Machine Learning point of view

Data Generation (M2)



- Choose training date and split user in churners and non-churners
- We can easily incorporate "absence time" as feature
- Respects overall game life-cycle
- More suitable in real-world scenario

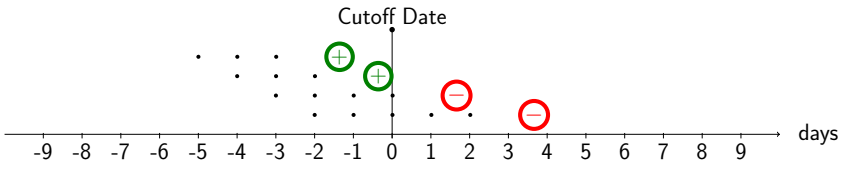
Building a Classifier

- Binary classification task
- Compared different classifiers (Logistic Regression, Neural Networks, Naive Bayes & Decision Trees)
- We found that Decision Trees to perform best
- For M1, we used a cross-validation with $50,000$ users per game
- For M2, training- and test-datasets were chosen according to a training date for each game
- For each user, we generated a feature vector

Features

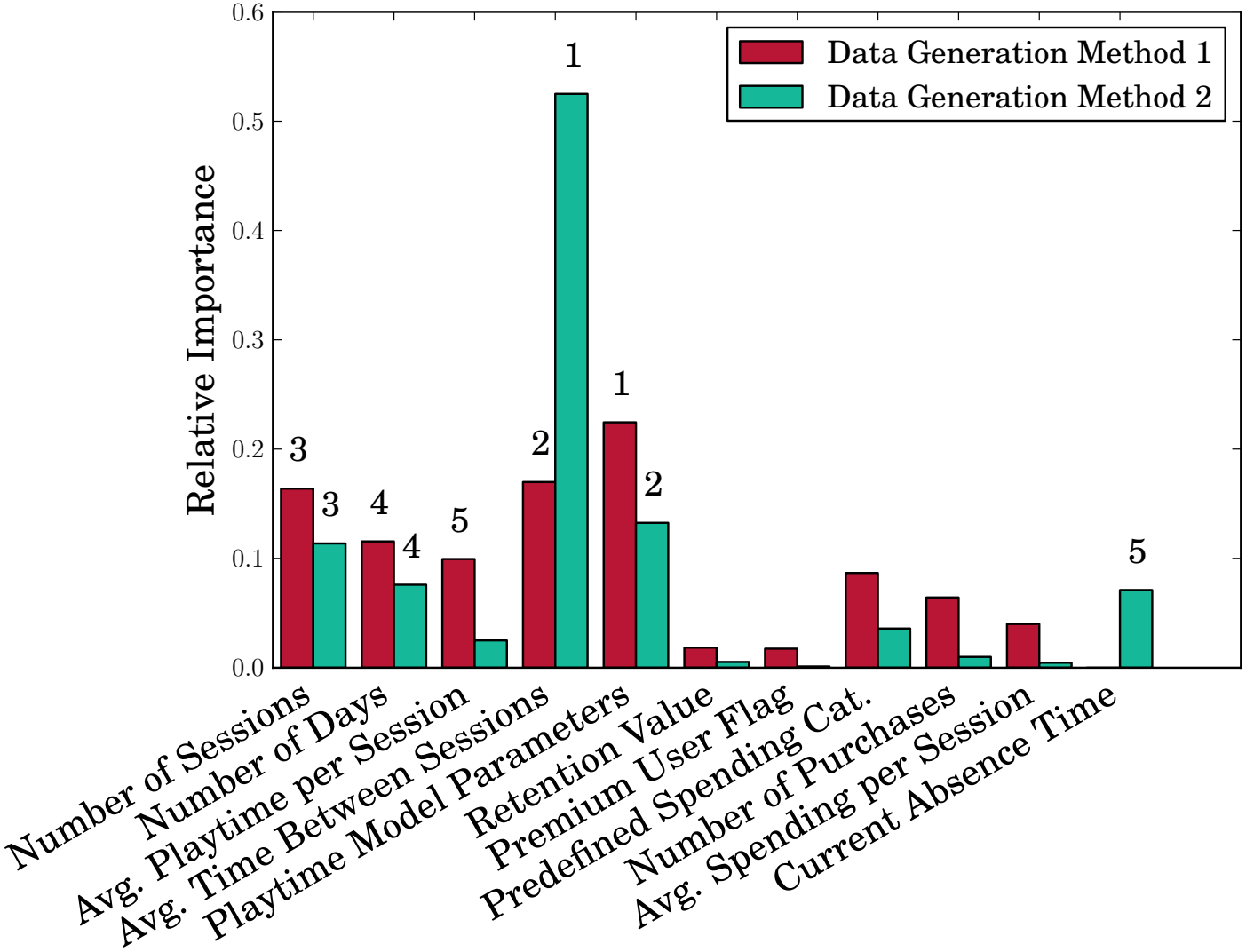
- Focus on game-design independent features to maximize applicability
- Temporal features
  - `Number of Sessions`, `Number of Days`
- Session-wise temporal information
  - `Average Playtime per Session`, `Average Time Between Sessions`
- Playtime models
  - `Playtime Model Parameters`, `Retention Value`
- Virtual economy features
  - `Premium User Flag`, `Predefined Spending Category`, `Number of Purchases` & `Average Spending per Session`
- With M2: `absence time`

Experimental Results for P1



- Generally, the classes are not balanced (typical for F2P)
- M1
  - About 71% churners
  - Decision Trees with M1-based training achieve an average F1-score of 0.64
  - However, fails to capture the negative class well (F1-score 0.14)
- M2
  - About 75% churners
  - Decision Trees with M2-based training achieve an average F1-score of 0.91
  - Shows to be balanced in both classes (0.92/0.81)
- M2 with "absence time" feature is more effective

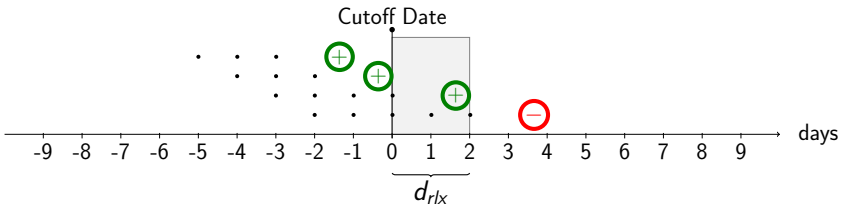
Feature Importance for P1 (I)



Feature Importance for P1 (II)

- Besides the number of occurrences, the position in the tree matters as well
  - for M1 "`Number of Days`" was always the root node
  - for M2 "`Average Time Between Sessions`" was most often the root node

Experimental Results for P2



- With increasing size of the window d_{rlx}, the class imbalance becomes more extreme

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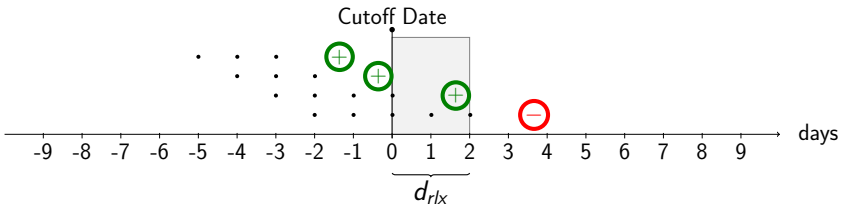

- With increasing size of the window d_{rlx}, the class imbalance becomes more extreme
- $d_{rlx} = 1$
  - 86% of players in the test-set churn in the window
  - the averaged F1-score over 5 games is 0.91, however, F1-score for the non-churners drops to 0.41

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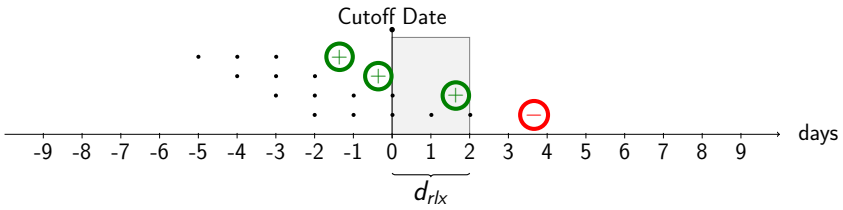

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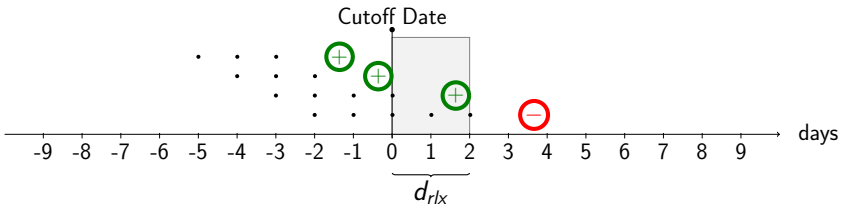

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  - the averaged F1-score over 5 games is 0.93, however, F1-score for the non-churners is at 0.39
- Except for one game, the games suffer from high churn rates and finding characteristics of the few non-churners is challenging

Conclusion

- Two definitions of churn
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  - M1: sampling based
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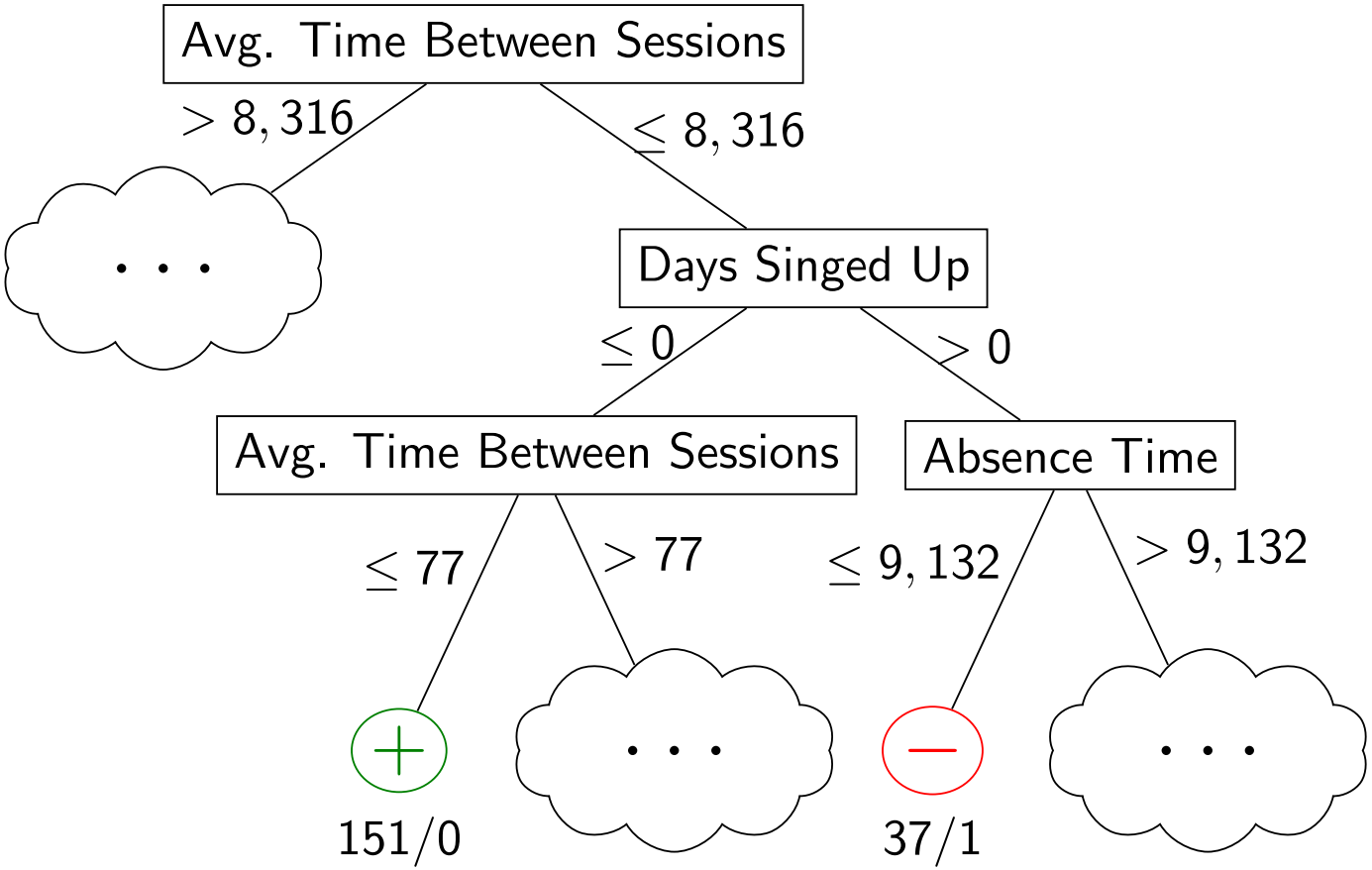
- Not only descriptive, but also predictive
- Evaluation on 5 different mobile games achieves high quality results (F1-scores between 86% and 91%)

Take Away Message — Revised



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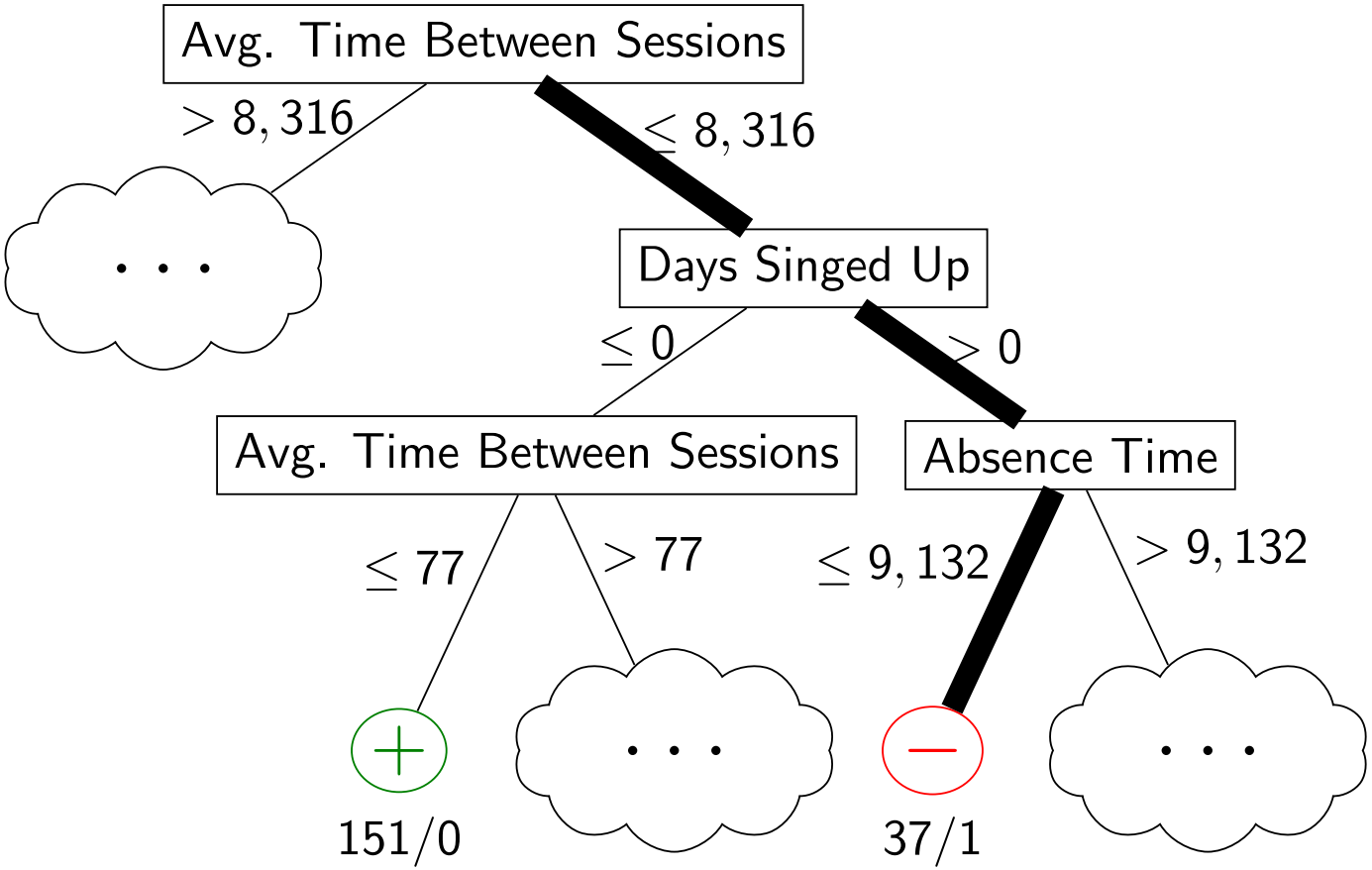

"Players who have been playing with a low average time between sessions for a few days are likely to be non-churners if they have been playing in the last hours."

Thank You For Your Attention!

Questions?

References I

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