Development of a Detection System for Problematic Online Gambling in Quebec

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Introduction

- **People are increasingly gambling online**. This is partly due to mobile computing, and has been aggravated by COVID-19 [1,2].
- Compared to land-based gambling venues, **online gambling operators have unique opportunities to reduce problem gambling (PG)** by modifying their platforms, and providing at-risk users with additional tools.
- **These efforts first require developing algorithms** capable of identifying users who are experiencing PG.
- **Earlier studies involving machine learning** have mostly used proxy measures of PG, and researchers have called for the use of validated screening instruments [3,4].

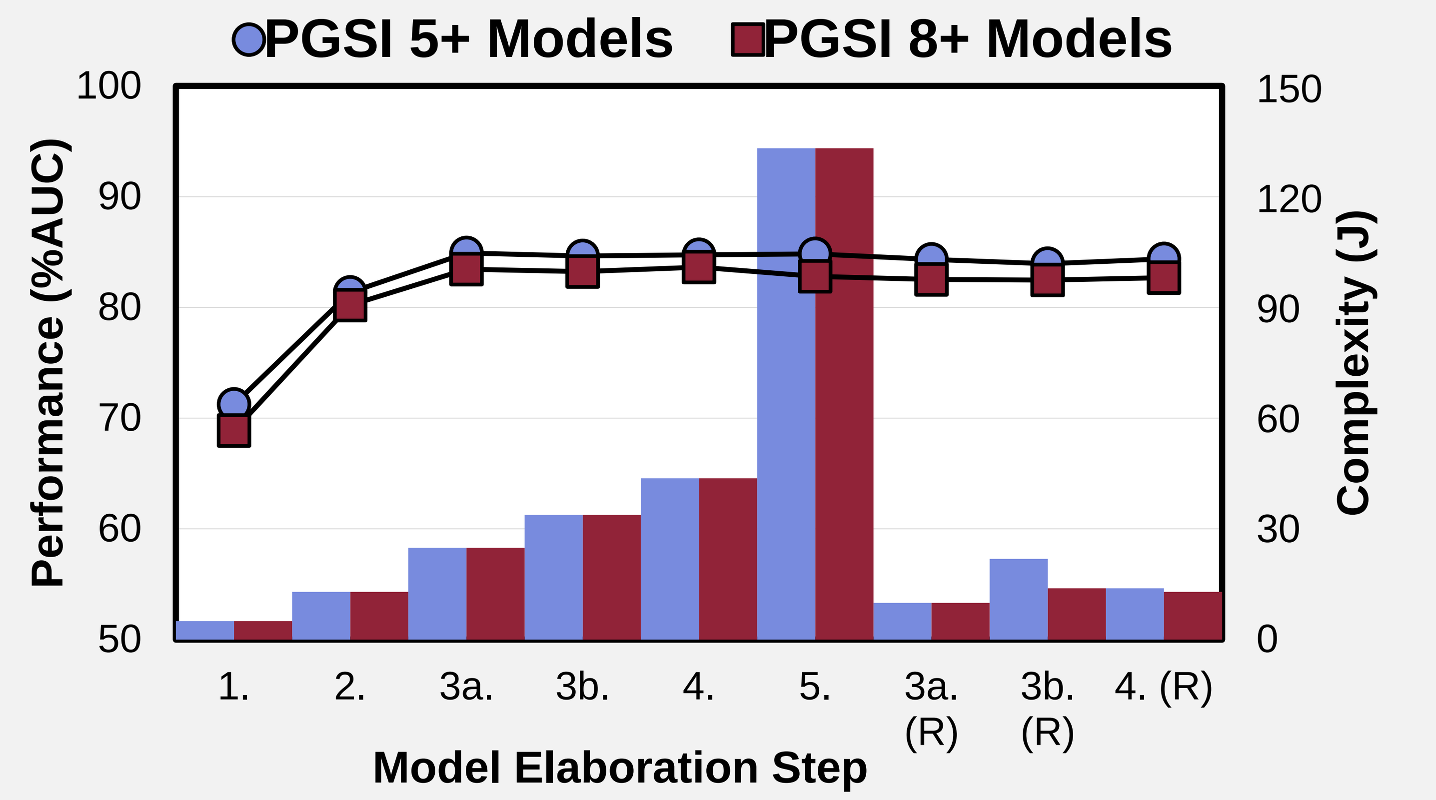
Pilot Hypothesis

Machine learning algorithms can use online gambling behaviour to predict moderate-to-high risk problem gambling, as indicated by the Problem Gambling Severity Index (PGSI).

Survey and Data Collection

- **N = 9145** online gamblers placed bets on *espacejeux.com* (now *lotoquebec.com*) prior to completing the PGSI [5].
- Participants agreed to release additional data about:
  1. **Demographics and accounts (J = 5)**
  2. **Responsible gambling tool use (J = 8)**
  3. **Overall betting behaviour (J = 10)**
  4. **Transactions and loss chasing (J = 21)**
  5. **Bets on 10 different activities (J = 100)**
- Betting data and PGSI responses referred to the same 12-month period, Sept. 2018 – Nov. 2019.
- Participants were randomly divided in to training (80%) and validation (20%) groups.

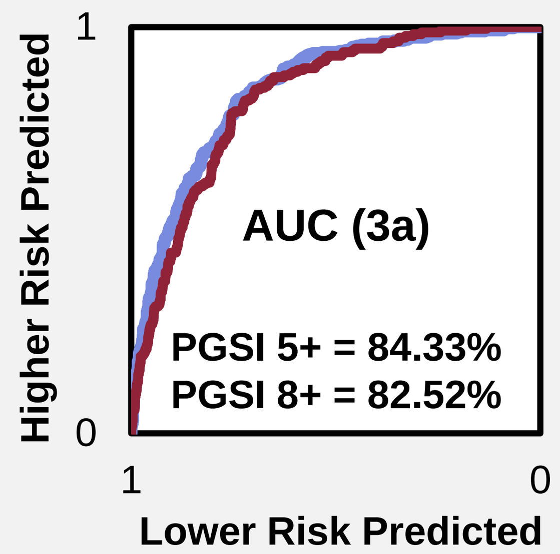
1.



1. Account information only
2. Added responsible gambling
3a. Added overall bet behaviour and loss chasing (no transactions)
3b. Added transactions and loss chasing (no bet behaviour)
4. Added transactions, bet behaviour and loss chasing
5. Stratified bet behaviour by activity type

(R) *Indicates factor reduction*

2.



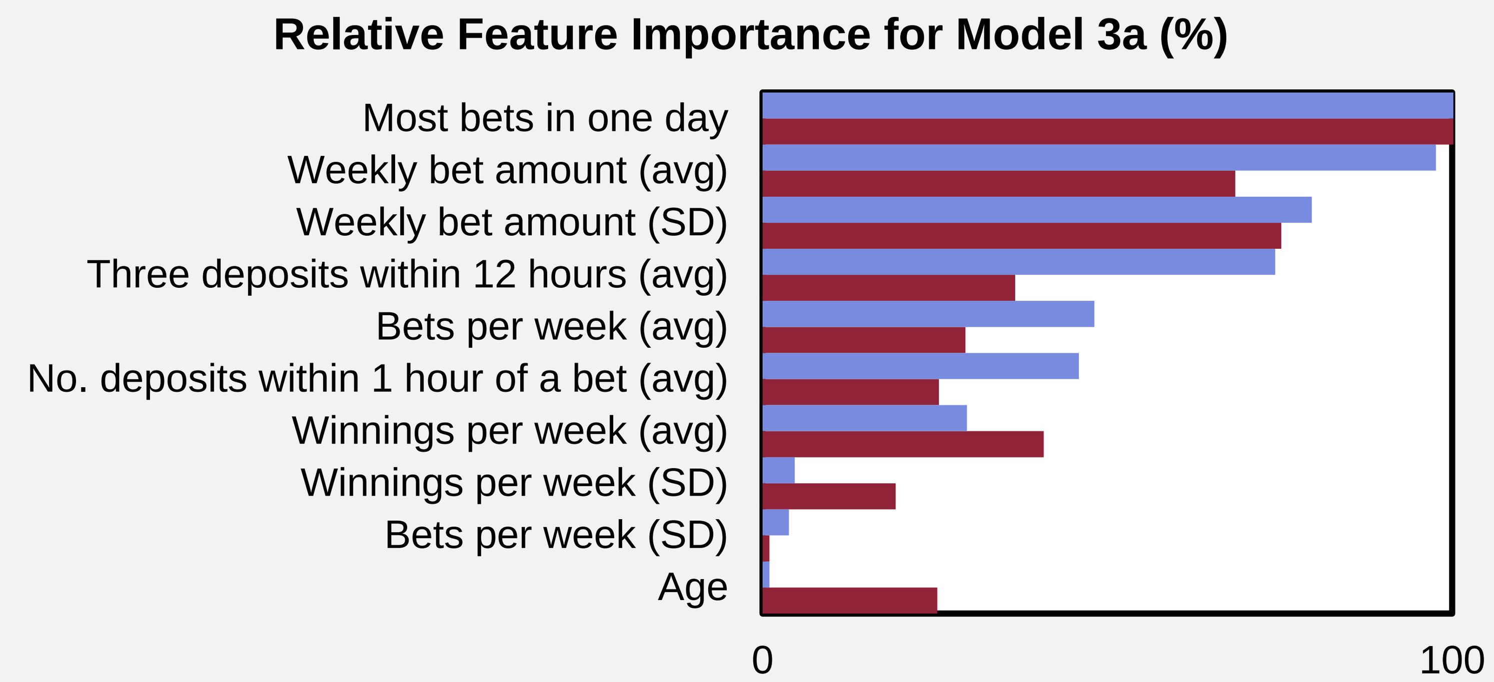
Fixed Higher Risk Prediction	Lower Risk Predicted PGSI 5+	Lower Risk Predicted PGSI 8+
99%	13.62%	24.36%
95%	45.93%	39.16%
90%	61.78%	55.03%
85%	70.26%	68.64%

Table 1. Fixed high-risk prediction performance.

Machine Learning Analyses

- Classification (dependent) variables:
  - **PGSI 8+ (high-risk PG, n = 1137)**
  - **PGSI 5+ (moderate-to-high risk PG, n = 1916)**
- We tested classification models using:
  1. Logistic Regression
  2. K-Nearest Neighbors
  3. Decision Trees and **Random Forests**
  4. Neural Networks
  5. Support Vector Machines
- Model performance was assessed using area under the ROC curve (AUC; Figure 2).
- Blocks of variables (left) were added (Figure 1). The best performing, simplest models were reduced in complexity until AUC was diminished by 1%.

3.



Results

- After reduction, Model 3a had the best ratio of performance to simplicity (Figure 1).
- Classification performance is interpreted as excellent for both PGSI 5+ and 8+ (Figure 2) [6].
- The frequency, average, and standard deviation of weekly bets were among the most important factors (Figure 3).
- A majority of lower-risk participants were correctly classified when ≤ 92% of higher-risk participants were correctly classified (see also Table 1).

Conclusion

Our pilot hypothesis was **supported**: machine learning algorithms can correctly classify at-risk users of an online gambling platform. These models may include relatively few inputs and may not require activity-specific indicators of gambling behaviour.

These algorithms can also identify people who report moderate PG risk. They may therefore be useful in primary prevention initiatives.

Machine learning algorithms such as these provide a new method for detecting harmful gambling platforms or activities, and may enable new kinds of interventions for at-risk users. With additional development and evaluation, we hope to enable new approaches to reducing gambling-related harm in Quebec.

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