EASG Conference 2018

InBrief: What’s new in the research arena? Who has a Vision?

Where will the value come from data analytics?

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Disclosures

- **Current:**
  - Employed by BetBuddy, a wholly owned subsidiary of Playtech Plc, a significant industry supplier and operator
  - External supervisor at City, University of London
    - One research project funded by Kindred Group.
- **Previous research funded by:**
  - InnovateUK
  - EPSRC
  - ESRC
  - DSTL.
Where will the value come from data analytics?

1. Are current approaches capable of detecting harm?

2. Have we reached a plateau of improvements?
   - Examining vertically-focused machine learning i.e., highly specialised algorithms (or narrow AI)

3. Where will significant improvements come in the next 5-10 years?
   - Combining player insights with product insights
   - Explaining algorithmic decisioning to drive personalised communications
Are current approaches capable of detecting harm?

- A supervised problem is solved if:
  - A human can tell you the right answer many times e.g., 1,000 penguins
  - Machine learning is a tool to teach a machine known things.
Today’s most promising applications of machine learning still struggle

A piece of cake on a plate with a fork

A couple of people that are standing in the snow

An airplane parked on the tarmac of an airport

Image captions generated by NeuralTalk (Karpathy)
Despite challenges, vertically focused algorithms are effective at detecting patterns of harm

- Detecting gambling related harm is a much harder problem to solve using machine learning
- Nonetheless, it has much potential to supplement humans and existing RG options and features
- However, it needs to be implemented carefully
- We need to develop human-in-the-loop in an empowering way.
What do we mean by vertically focused algorithms?
Well-designed narrow AI can still outperform humans at pattern matching

Markers of harm

16. By far the most important starting point when applying analytics to identify problematic gambling behaviour is to decide which markers of harm to monitor.

17. As these guidelines are designed to be implementable by all operators the markers of harm described here are based on information which is available to them all.

18. The following lists the key markers of harm that as a minimum operators could use:

- Staking levels/volume of gambling (spend that goes beyond an identifiable norm for that customer).
- Speed of play/velocity (frequency of play, time spent gambling, session periods, unusual high-termed wagers etc.)
- Deposits (frequency of deposits, per session deposits, use of multiple payment methods etc.)
- Withdrawals (eg changes in withdrawal patterns and reverse of withdrawals which might indicate loss infusing).
- Customer initiated contact (increased complaints, bonus requests, comments in live chat, frequent interactions etc)
- Time of play (gambling late at night has been identified as a common denominator amongst problem gamblers, but there could also be other times which, when combined with other factors, might indicate problematic behaviour).
- Product choice and play (use of multiple betting and gaming products, change in behaviours, modes of use etc)
- Use of player management tools (deposit limits, time outs, self-exclusion etc.)

...frequency of deposits...

...frequency of play...
Best practice suggests players who play frequently and deposit frequently are at-risk, but the data...?

Regular play: Variation of gap between gambling days

If I have large gaps in my play, I'm a stronger pattern match to self-excluders.

Regular players are less likely to self-exclude.

Frequency of deposit days:

Infrequent deposit days point to a stronger pattern match in self-excluder behaviour.

Frequent depositors have a poorer pattern match to self-excluders.
Even the more obvious markers are not always clearly-defined with simple, linear patterns.

...gambling late at night...
...multiple betting products...
Whilst engaging in games is a somewhat linear pattern, playing at night is not.

Number of game types played

Night time play ratio

Engaging in higher numbers of side games leads to a higher pattern match for self-excluders.

Those engaged in only bingo are less likely to get a strong pattern match.

Even a very small percentage of play during the night increases your chances of a pattern match by ~15%, but after that the effect is limited.

Still over 50% of those self-excluders play predominantly during the day and evening.
Have we reached a plateau in applying narrow AI to assessing gambling related harm?

Some narrow AI models on high quality datasets already predicting self-exclusion at 96% accuracy.
Have we reached a plateau in applying narrow AI to assessing gambling related harm?

**Today:**
Improved pattern matching will provide incremental improvements

- Better harm labelling
- Bigger data sets
- Continued improvements e.g., comparative analysis to other approaches

**Tomorrow:**
Artificial General Intelligence (AGI) is probably many years off

- Addition of ‘Human-like’ intelligence;
  - Reasoning e.g., e.g., relational
  - Planning e.g., temporal
  - Interacting e.g., questioning
Are there new opportunities to combine product data with behavioural data?

- E.g. RTP, volatility
- sensory design and theme, ...

Game Design

Player Behaviour

- how much staked
- how often played,
- ....

Risk of Player Harm

- spending more money or time on gambling than you wish you did, ...

Play Environment

Player Circumstances

- income/wealth/debt
- co-morbidities,
- ...

- stimulating/disinhibiting environment
- access to alcohol
- ...

Game design risk – Four categories of game related data

<table>
<thead>
<tr>
<th>Maths &amp; Timing</th>
<th>Look &amp; Feel</th>
<th>Options &amp; Interactions</th>
<th>Site Design</th>
</tr>
</thead>
<tbody>
<tr>
<td>RTP (low/high/variable/high at start)</td>
<td>Stimulating imagery</td>
<td>Autoplay</td>
<td>Ability to play multiple games simultaneously</td>
</tr>
<tr>
<td>Stake (min/max/variable)</td>
<td>Colour / sound</td>
<td>Turboplay</td>
<td>Practice game (esp. if has better player outcomes)</td>
</tr>
<tr>
<td>Volatility (min/max/variable)</td>
<td>Near misses visible/common</td>
<td>Player involvement features</td>
<td>Free spins/bonuses</td>
</tr>
<tr>
<td>Win frequency (any size)</td>
<td>Losses cued as wins</td>
<td>Positive feedback from game</td>
<td>Testimonials (live/static/implied)</td>
</tr>
<tr>
<td>Event duration (spin time)</td>
<td>Game complexity</td>
<td>In game chat</td>
<td>Complex withdrawal process</td>
</tr>
<tr>
<td>Reset time (bet result known → next chance to spin)</td>
<td>Unreal setting</td>
<td>Other players</td>
<td></td>
</tr>
<tr>
<td>Jackpot (availability/size)</td>
<td>...</td>
<td>Secrets / clues</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Multiple stakes per spin</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Continuity of play</td>
<td></td>
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</tr>
</tbody>
</table>

So how to link game features to intermediate drivers of harm? Work-in-progress....
We are starting to map game features through to potential risk drivers [excerpt]
Operators can market to players more appropriate games.
Industry is under increasing scrutiny to interact with customers

The Commission has confirmed that it will undertake consultations on the following potential changes to the LCCP:

- Further protection for children by banning operators from providing free-to-play demo games until a consumer’s age has been determined;
- Improving the speed and effectiveness of age verification processes;
- Ensuring operators set limits on consumers’ spending until affordability checks have been conducted;
- Tackling unacceptable marketing and advertising and unfair terms, and improving complaints and disputes procedures; and
- Strengthening requirements to interact with consumers who may be experiencing, or are at risk of developing, problems with their gambling.

There are also areas where the Commission will be undertaking further investigation before deciding whether to consult on any changes to the LCCP. These are:

- Assessing the effectiveness of the current tools available to consumers to manage their gambling;
- Reviewing gambling product characteristics to identify whether particular features pose greater risk of harm than others;
- Reviewing requirements on the protection of customer funds and consider whether there are sufficient protections around dormant accounts;
- Consider whether gambling on credit should continue to be permitted; and
- Consider whether we need to make changes to ensure that consumers can withdraw funds more easily.
Best practice suggests players should receive different interactions based on level of risk.

Adapted from Wiebe 2011, Informed Decision Making Framework.
8 studies since 2014 suggest personalised interactions can be useful

<table>
<thead>
<tr>
<th>Source</th>
<th>Location</th>
<th>Gambling mechanism</th>
<th>Gambler type</th>
<th>Sample size</th>
<th>Research method</th>
<th>Intervention / message type</th>
<th>Resulting change in behaviour</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wohl MJ, Gainsbury S, Stewart MJ, Sztainert T.</td>
<td>Canada</td>
<td>VR Electronic Gaming Machine</td>
<td>Students who are also regular gamblers - non-problem/low risk</td>
<td>73</td>
<td>Quantitative</td>
<td>V small quant group with control group</td>
<td>Comparison of effect of educational animated video vs pop-up messages about deposit limits</td>
</tr>
<tr>
<td>Blaszczynski, A., Gainsbury, S., &amp; Karlov, L.</td>
<td>Australia</td>
<td>Electronic Gaming Machine</td>
<td>Regular players clubs/casinos</td>
<td>299</td>
<td>Quantitative</td>
<td>V small quant group with control group</td>
<td>Range of RG functions including messages displayed on the machine (not pop-up)</td>
</tr>
<tr>
<td>Auer, M., Griffiths, M.</td>
<td>Europe</td>
<td>Online slots</td>
<td>Online gamblers (anonymised data)</td>
<td>1.6 million play sessions, approx 70,000 players</td>
<td>Quantitative</td>
<td>V small quant group with control group</td>
<td>Pop-up messages helped players stay within limits. Those who watched the educational video more likely to stay within limits.</td>
</tr>
<tr>
<td>Hyson S. Kim, Michael E. A. Wohl, Melissa J. Stewart, Travis Sztainert &amp; Sally M. Gainsbury</td>
<td>Canada</td>
<td>VR Electronic Gaming Machine</td>
<td>Students who are also regular gamblers - non-problem/low risk</td>
<td>43</td>
<td>Quantitative</td>
<td>V small quant group with control group</td>
<td>Pop-up message invited player to set a time limit</td>
</tr>
<tr>
<td>Wood, R. &amp; Wohl, M.</td>
<td>Australia</td>
<td>Online lottery, bingo, sports betting, poker</td>
<td>Regular online gamblers</td>
<td>770 (matched to control sample of 779)</td>
<td>Quantitative</td>
<td>Behavioural feedback via email</td>
<td>Participants given the option to set a time limit prior to play were significantly more likely to do so and gambled for significantly less time than participants who received no such instruction. In addition the majority of participants in the time limit condition gambled for less time than their indicated limit</td>
</tr>
<tr>
<td>Ginley, M., Whelan, J., Keating, H., &amp; Meyers, A.</td>
<td>USA</td>
<td>Slots machines in simulated casino environment</td>
<td>University students</td>
<td>154</td>
<td>Quantitative</td>
<td>Participants were randomly assigned to one of four groups: warning message-win condition, warning message-loss condition, control-win condition, and control-loss condition.</td>
<td>Winning or losing during slot machine play appears to have significant consequences on the impact of a warning message. Those in the message-win condition placed the smallest number of bets, made the fewest bets, and did not speed up their bet rate as much as participants in other conditions. Those in the message-loss condition decreased the size of their bets over the course of play compared with those in the message-win condition, but not their number of bets, spins, or rate of betting</td>
</tr>
<tr>
<td>Du Preez, K., Landon, J., Bellringer, M., Garrett, M., Abbott, N.</td>
<td>New Zealand</td>
<td>Electronic Gaming Machine</td>
<td>Regular players clubs/casinos</td>
<td>460</td>
<td>Quantitative</td>
<td>Pop-up info message with play duration, amount spent, win/loss amount. No explicit encouragement/discouragement</td>
<td>25% said that the messages helped them control their gambling, but only 8% actually reduced their play</td>
</tr>
<tr>
<td>Auer, M., Griffiths, M.</td>
<td>Norway</td>
<td>Online slots</td>
<td>Those that had played at least one game for money on the Norsk Tipping online platform in April 2015</td>
<td>17,452</td>
<td>Quantitative</td>
<td>1 year study</td>
<td>During the course of the study, players (excluding the control group) received information about their losses over the past 6-month period and/or, recommendations about existing responsible gaming tools, and/or normative information. Message retrieval was voluntary</td>
</tr>
</tbody>
</table>

This table contains a summary of studies suggesting that personalized interactions can be useful in reducing gambling behavior. The studies were conducted in various locations and used different methods, including pop-up messages, educational videos, and behavioural feedback tools, to encourage responsible gambling. The interventions were effective in reducing gambling expenditure and time spent, as well as helping players to control their gambling.
8 studies since 2014 suggest personalised interactions can be useful

- Pop up messages helped players stay within limits
- Those who watched the educational video more likely to stay within limits
- 7% said messages made them stop and think, 4% said had influence on behaviour
- Those who set a time limit prior to play gambled for significantly less time
- Deposits reduced a significant amount among at-risk players contacted by email
- Winning or losing during slot machine play appears to have significant consequences on the impact of a warning message
- 25% said messages helped them gain control, but only 8% actually reduced play
- Personalized feedback impacts positively - reduction in time and money spent.
But, machine learning is difficult to interpret

New Approach
Create a suite of machine learning techniques that produce more explainable models, while maintaining a high level of learning performance

Machine learning models look a bit like this.
Personalised, relevant, & changing communications are likely to have a more positive effect (1/2)
Personalised, relevant, & changing communications are likely to have a more positive effect (2/2)
Concluding thoughts

- Transparency and ethics in the use of data and AI are paramount to build trust and widespread adoption;
  - How we design and build algorithms
  - Their strengths and weaknesses
  - The results and effects.
THANK YOU