## A Modern Love Story:

Machine Learning Engines \&
The Global Sports Betting Industry

## Lloyd Danzig





## U.S. Legalization Map



| Green | Live, Legal Sports Betting (13 States) |
| :--- | :--- |
| Light Green | Legal Sports Betting, Not Yet Operational (6 States + DC) |
| Blue | Active 2019 Sports Betting Legislation (5 States) |
| Light Blue | Dead Sports Betting Legislation in 2019 (19 States) |
| Gray | No Sports Betting Bills in 2019 (8 States) |

Source: AGA
As of: November 7, 2019


AMERICAN
GAMING GAMING
Association

## Future Trends Betting on Esports

- Fans are projected to wager \$30 billion on Esports in 2020
- Sportsbook operators would generate over \$2 billion in GGR
- Challenges: lack of reliable data, pricing difficulties, and cheating

Esportsbook betting volume by game

```
League of Legends \(\quad \mathrm{CS}: \mathrm{GO} \quad\) Dota \(2 \square\) Starcraft \(2 \square\) Other
```



## Future Trends Sports Betting Bots

- Sophisticated forecasting models
- Convert event probabilities into prices
- Look for differences in model price and market price
- Seek out arbitrage opportunities


## Future Trends Blockchain Sportsbooks

- "Provably Fair" gaming
- Guaranteed, instantaneous payouts via smart contracts
- Streamlined, real-time financial auditing




## Revenue Model: Sportsbook

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Bob thinks New York will lose
Alice risks $\$ 100$ to win $\$ 190$ Bob risks \$225 to win \$100


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## Sportsbook operators

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New York wins. Sportsbook returns Alice's $\$ 100$ plus $\$ 190$ winnings Profit = \$325-\$290 = \$35


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Alice risks \$100 to win \$190 Bob risks \$225 to win \$100


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New York loses. Sportsbook returns Bob’s \$225 plus \$100 winnings Profit $=\$ 325-\$ 325=\$ 0$


Sportsbook Odds:

## Revenue Model: Betting Exchange

Alice thinks New York has a 33\% chance of winning, represented in fair odds as +203 .


NEW YORK KNICKS
DETROIT PISTONS

Exchanges offer a number of dramatic advantages over sportsbooks, most notably in the form of drastically improved odds.

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## Revenue Model: Betting Exchange

| NEW YORK KNICKS | +190 | ${ }_{\text {+ }}^{+5.5}(-10)$ |
| :---: | :---: | :---: |
| DETROIT PISTONS | -225 | $-5.5$ |

Alice thinks New York has a $33 \%$ chance of winning, represented in fair odds as +203 .

She offers to accept a wager from anyone interested in Detroit -203 (to win \$100). The best sportsbook is offering 'Detroit -225 , so Bob accepts the other side of Alice's wager.


New York wins. Bob pays Alice $\$ 203$, a small percentage of which goes to the exchange. Operator Profit $=\$ 10.15$


New York loses. Alice pays Bob $\$ 100$, a small percentage of which goes to the exchange. Operator Profit = \$5.00


Exchanges offer a number of dramatic advantages over sportsbooks, most notably in the form of drastically improved odds.

## Revenue Model: Customer Perspective

| veats of | Sportsbook | Exchange |
| :---: | :---: | :---: |
| O | \$190.00 |  |
| $\underset{\substack{8 \\ 8}}{\substack{200}}$ | \$44.44 |  |

## Revenue Model: Customer Perspective

|  | Sportsbook | Exchange |
| :---: | :---: | :---: |
| Q | \$190.00 | \$193.00 |
| $\underset{\text { boo }}{8}$ | \$44.44 |  |

Ultimately, all

Revenue Model: Customer Perspective

|  | Sportsbook | Exchange |
| :---: | :---: | :---: |
| O | \$190.00 | \$193.00 |
| $e_{\text {boc }}^{2 l e}$ | \$44.44 | \$46.80 |

having used the exchange.

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## Revenue Model: Customer Perspective

| , | Sportsbook | Exchange |
| :---: | :---: | :---: |
| 8 | \$190.00 | \$193.00 |
| $8$ | \$44.44 | \$46.80 |


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| :---: | :---: | :---: |
| Q | \$52.63 |  |
| $\theta$ | \$225.00 |  |

Ultimately, all

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| 8 | \$190.00 | \$193.00 |
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| , masit | Sportsbook | Exchange |
| :---: | :---: | :---: |
| $\underbrace{}_{\text {alce }}$ | \$52.63 | \$51.85 |
| $8$ | \$225.00 |  |

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| , | Sportsbook | Exchange |
| :---: | :---: | :---: |
| 8 | \$190.00 | \$193.00 |
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|  | Sportsbook | Exchange |
| :---: | :---: | :---: |
| 0 | \$52.63 | \$51.85 |
| $8$ | \$225.00 | \$213.68 |

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## Industry Standard <br> Monte Carlo Simulation

Monte Carlo simulation is a method for iteratively evaluating a deterministic model using sets of nondeterministic (i.e. random) numbers as inputs.
E.g. "What is the probability of rolling a 1 during a single throw of a six-sided die?"

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| Die |  |
| :---: | :---: |
|  | $\square$ |
|  | 0 |
|  | [0] |
|  | [8] |
|  | (\%) |
|  | [8] |

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| Die | \# of Outcomes |
| :---: | :---: |
| $\square$ | 16648 |
| 0 | 16521 |
| [0] | 16910 |
| (0) | 16539 |
| (\%) | 16843 |
| (8) | 16540 |

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| :---: | :---: |
| New York Yankees | 5.588 |
| Boston Red Sox | 5.390 |

## Industry Standard <br> Monte Carlo Simulation

| Team | Avg. Runs Scored | Avg. Runs Against |
| :---: | :---: | :---: |
| New York Yankees | 5.588 | 4.375 |
| Boston Red Sox | 5.390 | 4.732 |



## Industry Standard <br> Monte Carlo Simulation

| Team | Avg. Runs Scored | Avg. Runs Against | Adj. Runs Scored | StDev (Runs Scored) |
| :---: | :---: | :---: | :---: | :---: |
| New York Yankees | 5.588 | 4.375 | 5.142 | 3.001 |
| Boston Red Sox | 5.390 | 4.732 | 4.856 | 3.358 |

## Industry Standard $=N O R M \cdot I N V\left(R A N D(), \mu_{\text {Yankees }}, \sigma_{\text {Yankees }}\right)$ Monte Carlo Simulation

| Team | Avg. Runs Scored | Avg. Runs Against | Adj. Runs Scored | StDev (Runs Scored) | Norm.Inv_Runs |
| :---: | :---: | :---: | :---: | :---: | :---: |
| New York Yankees | 5.588 | 4.375 | 5.142 | 3.001 | 3.358 |
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| New York Yankees | 5.588 | 4.375 | 5.142 | 3.001 | 10.147 |
| Boston Red Sox | 5.390 | 4.732 | 4.856 | 3.358 | 7.945 |


| Simulation \# | New York Yankees | Boston Red Sox | Winner |
| :---: | :---: | :---: | :---: |
| 1 | 10.147 | 7.945 | New York Yankees |
| 2 | 0.643 | 5.715 | Boston Red Sox |
| 3 | 3.123 | 5.009 | Boston Red Sox |
| 4 | 9.203 | 4.555 | New York Yankees |
| 5 | 4.150 | 7.523 | Boston Red Sox |
| 6 | 1.737 | 4.017 | Boston Red Sox |
| 7 | 2.147 | 3.671 | Boston Red Sox |
| . | . | . | . |
| . | . | . | . |
| . | . | . | . |
| . | . | . | . |
| . | . | . | . |
| . | . | . | . |
| 9997 | 4.040 | 3.188 | New York Yankees |
| 9998 | 4.667 | 5.493 | Boston Red Sox |
| 9999 | 7.927 | 4.856 | New York Yankees |
| 10000 | 4.934 | 0.000 | New York Yankees |

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| . | . | . | . |
| . | . | . | . |
| . | . | . | . |
| . | . | . | . |
| . | . | . | . |
| . | . | . | . |
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| 9999 | 4.934 | 4.856 | New York Yankees |
| 10000 |  | 0.000 | New York Yankees |




## Computer Vision

## Explanatory Augmented Reality

## Competitor Overlays

Viewpoint Synthesis

Performance Analysis

## Computer Vision



INCS, IT CAN BE HARD TO EXPLAIN THE DIFFERENCE BETWEEN THE EASY AND THE VIRTUALUY IMPOSSIBLE.
i
$=\sqrt{7}$.

## Wearables




## Use Case Summary

## $\frac{+1=}{x \mid=}$ Handicapping

Risk Management


Responsible Gaming
(10n

## Causes for Concern


$\left[\begin{array}{l}\circ{ }^{\circ} \mathrm{F} \\ 0 \\ 0\end{array}\right]$ Black Box Problem


Flash Crash Potential

Odds Manipulation

Fraud Masking

## Causes for Concern



## Handicapping (Pre-match)

Machine Learning offers dramatic improvements over industry standards in setting pre-match odds.

These benefits should all be viewed in the context of reducing human error while freeing up intellectual capital to be deployed elsewhere within an organization.

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Pre-trained models combined with maximally efficient algorithms allow can be leveraged into competitive advantages.

Not only does Machine Learning increase short-term operator profitability, but it vastly improves the user experience, boosting customer retention.

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## Risk Management

## (A) Real-Time Book Balancing

## Efficient Suspension Implementation

## Increased Turnover

 Capacity*Turnover: Total dollar amount of wagers accepted

## Bet Recommendations



## Bet Recommendations

| F) FANDUEL | Home Lve | Promolions | Casino |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| popliar |  | caswo Ne | Sucn |  |  |  |
| (3) iv | Pbetfair | Black | ck, Roulette, S | \& more! |  |  |
| (13) NBA |  |  |  | $\underline{4}$ |  |  |
|  | Today's Pick: |  |  |  |  |  |
| (6) val ( $)$ odes Boost |  |  | Cete |  |  |  |

Promotion Type
Preference

## Bet Recommendations



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## Responsible Gaming

Enhanced pattern recognition will revolutionize an operator's ability to detect deviations from responsible gaming

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| Avg. Wager | $\$ 10.01$ |
| :---: | :---: |
|  | Wager StDev |
|  | Bets/Week |
|  | U Player Props |
|  | Max. Bet |


|  | Avg. Wager |
| :---: | :---: |
|  | Wager StDev |
|  | Bets/Week |
|  | \% Player Props |
|  | Max. Bet |

## Sustainable Gaming

Enhanced pattern recognition will revolutionize an operator's ability to detect deviations from responsible gaming

| Avg. Wager | $\$ 10.01$ |  |
| :---: | :---: | :---: |
|  | Wager StDev | $\$ 0.41$ |
|  | Bets/Week | $4.3(85 \%$ Baseball) |
|  | \% Player Props | $17 \%$ |
|  | Max. Bet | $\$ 35.00$ |


|  | Avg. Wager |
| :---: | :---: |
|  | Wager StDev |
|  | Bets/Week |
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## Fraud Detection



## Use Case Summary

## $\frac{+1=}{x \mid=}$ Handicapping

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(10n


## Thank You

Office Hours: 1:15pm-2:00pm

## Lloyd Danzig



SHARP RLPHA ROVISDRS



## Economics: Sportsbook

Customers view odds set by sportsbook

NEW YORK KNICKS

## Economics: Sportsbook

Customers view odds set by sportsbook
l

| Team | Odds | Impl. Prob. |
| :---: | :---: | :---: |
| NYK | +190 | $34.48 \%$ |
| DET | -225 | $69.23 \%$ |

## Economics: Sportsbook



Customers view odds set by sportsbook
$+5.5$ (-110)

| Team | Odds | Impl. Prob. | Fair Prob. | Sportsbook Profit |
| :---: | :---: | :---: | :---: | :---: |
| NYK | +190 | $34.48 \%$ | $33.25 \%$ | $\$ 35.00$ |
| DET | -225 | $69.23 \%$ | $66.75 \%$ | $\$ 0.00$ |
|  |  | $103.71 \%$ |  |  |

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| Team | Odds | Impl. Prob. | Fair Prob. | Sportsbook Profit | Expected Profit |
| :---: | :---: | :---: | :---: | :---: | :---: |
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|  |  | $\mathbf{1 0 3 . 7 1 \%}$ |  |  | $\$ 11.64$ |

## Overround:

$103.71 \%-100.00 \%=3.71 \%$
Bookmaker will pay out
\$100.00 for every \$103.71
it collects

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Customers view odds set by sportsbook

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|  |  | $\mathbf{1 0 3 . 7 1 \%}$ |  |  | $\$ 11.64$ |

## Overround:

103.71\% - 100.00\% = 3.71\%

Bookmaker will pay out
\$100.00 for every \$103.71 it collects

Profit Margin:
$\frac{\$ 3.71}{\$ 103.71}=3.58 \%$

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Customers view odds set by sportsbook

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| :---: | :---: | :---: | :---: | :---: | :---: |
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| Overround: | Profit Margin: | Expected Profit: |
| :--- | :---: | :---: |
| $103.71 \%-100.00 \%=3.71 \%$ | $\$ 3.71$ |  |
| Bookmaker will pay out <br> $\$ 100.00$ for every $\$ 103.71$ <br> it collects | $\frac{\$ 103.71}{}=3.58 \%$ | $\frac{\$ 11.64}{\$ 325.00}=3.58 \%$ |

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| Team | Fair Prob. | Winnings | Commission | Sportsbook Profit | Expected Profit |
| :---: | :---: | :---: | :---: | :---: | :---: |
| NYK | $33.25 \%$ | $\$ 203$ | $5.00 \%$ | $\$ 10.15$ | $\$ 3.37$ |
| DET | $66.75 \%$ | $\$ 100$ | $5.00 \%$ | $\$ 5.00$ | $\$ 3.34$ |
|  |  |  |  |  | $\$ 6.71$ |

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| DET | $66.75 \%$ | $\$ 100$ | $5.00 \%$ | $\$ 5.00$ | $\$ 3.34$ |
|  |  |  |  |  | $\$ 6.71$ |

Simulation:


Exchanges offer the benefit of being riskless to operate, since payouts to winners come from deposits by losers.
Favorable Odds
Operator Risk
Potential Market Variety
Reward/Bonus Programs
Bet to Lose
Bet Matching
Predictive Capacity
Max Profit (Operator)

## Sportsbook Betting Exchange

|  | Sportsbook | Betting Exchange |
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| Operator Risk |  |  |
| Potential Market Variety |  |  |
| Reward/Bonus Programs |  |  |
| Bet to Lose |  |  |
| Bet Matching |  |  |
| Predictive Capacity |  |  |
| Max Profit (Operator) |  |  |

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