Decision impact in MOBA games

**Problem**
- Many factors in determining game outcomes
- How to quantify impact of the strategic choices?

**Data**
- 12,000 silver-league (mid-level) online matches
- For each match, 10 players, pick 1 randomly
- Game features:
  - Allied / Enemy Champions: 1-hot encoded
  - Player Item purchases: 1-hot
  - Player Gold, XP at 5 and 10 min: cumulative
  - Meant to capture “game state”
- Data format:

<table>
<thead>
<tr>
<th>champion 1 is ally</th>
<th>champion 1 is opponent</th>
<th>item 2 purchased</th>
<th>gold @ 5 min</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>1</td>
<td>863</td>
</tr>
</tbody>
</table>

**Results**
- Item choice as a whole has subtle effects
  - Logistic, SVM w/ Kernels, Decision trees overfit and do not benefit from decision data once game state data is included
  - Game is “well-balanced” by designers
- When we narrow the focus to specific items and control for correlations we begin to see modest causal effects.

**Decision Impact in MOBA games**

**Causal Modeling**
- Correlation ≠ Causation:
  - Winning teams buy expensive items
  - Expensive items may not help much in general
- OLS assumes: X (item choice) orthogonal to e
- Game state Z affects both X and Y
  - e is correlated with X (choice of items is endogenous)
  - Biased estimates for effect X has on Y

**Early Game Decision Making**
- Increase in information => Increase in accuracy
- Item Impact = (Model 3 Acc.) - (Model 2 Acc.)

**Early Game Decision Making**

**Causal Modeling**
- Propensity Score Matching:
  - Propensity score: p(x=X|Z)
  - Each sample is paired with counterfactual with similar propensity
  - In paired data, Z is no longer correlated with X
  - Distribution of propensities are similar across treatment groups {x=1, x=0} after PSM:

**Linear Classifiers**
- Logistic Regression: L2 regularization
- SVM: Linear, Poly-Deg2, RBF kernels. Linear wins

**Propensity Score Matching**
- In paired data, Z is no longer correlated with X
  - Distribution of propensities are similar across treatment groups {x=1, x=0} after PSM:

**Decision Trees**
- Hypothesis: Interdependence between features
  - Some items context-specific
  - Game is “well-balanced” by designers
- When we narrow the focus to specific items and control for correlations we begin to see modest causal effects.

**Results**
- Item choice as a whole has subtle effects
  - Logistic, SVM w/ Kernels, Decision trees overfit and do not benefit from decision data once game state data is included
  - Game is “well-balanced” by designers
- When we narrow the focus to specific items and control for correlations we begin to see modest causal effects.

**Early Gold + XP (GS)**

**Early Item Purchases (IP)**

**Model 1:**
Win ~ C

**Model 2:**
Win ~ C + GS

**Model 3:**
Win ~ C + GS + IP

**Item Impact:**
- Not noticeable, even with kernel
  - Predictive Delta = -.003

**Random Forest Overfit:**
- Best at Depth 1

**Depth 1 AdaBoost Trees:**
- No better than Logistic

**Logistic Regression:**
- L2 regularization

**SVM:**
- Linear, Poly-Deg2, RBF kernels. Linear wins

**Propensity Score:**
- p(x=X|Z)
- Each sample is paired with counterfactual with similar propensity
- In paired data, Z is no longer correlated with X
- Distribution of propensities are similar across treatment groups {x=1, x=0} after PSM:

**Hypothesis:**
- Interdependence between features
  - Some items context-specific
- Game is “well-balanced” by designers
- When we narrow the focus to specific items and control for correlations we begin to see modest causal effects.

**Results**
- Item choice as a whole has subtle effects
  - Logistic, SVM w/ Kernels, Decision trees overfit and do not benefit from decision data once game state data is included
  - Game is “well-balanced” by designers
- When we narrow the focus to specific items and control for correlations we begin to see modest causal effects.

**Early Game Decision Making**
- Increase in information => Increase in accuracy
- Item Impact = (Model 3 Acc.) - (Model 2 Acc.)

**Early Gold + XP (GS)**

**Early Item Purchases (IP)**

**Model 1:**
Win ~ C

**Model 2:**
Win ~ C + GS

**Model 3:**
Win ~ C + GS + IP

**Item Impact:**
- Not noticeable, even with kernel
  - Predictive Delta = -.003

**Random Forest Overfit:**
- Best at Depth 1

**Depth 1 AdaBoost Trees:**
- No better than Logistic

**Logistic Regression:**
- L2 regularization

**SVM:**
- Linear, Poly-Deg2, RBF kernels. Linear wins

**Propensity Score:**
- p(x=X|Z)
- Each sample is paired with counterfactual with similar propensity
- In paired data, Z is no longer correlated with X
- Distribution of propensities are similar across treatment groups {x=1, x=0} after PSM: