Causal inference in DotA 2 when estimated through randomized data

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1.Background

- **Causal Inference**
  - Science of determining cause and effect between phenomena[1]
- **Dota 2**
  - Multiplayer online game with complex data structure
  - Randomized game mode
- **Role of randomization**
  - physical randomization of treatment value assignment

2.Research Questions

How and If,
matches with instances of randomization can be useful for predicting events using causal inference in DotA 2

1.How does the **selection of a hero** influence **the causal effect** on a team **winning** when estimated through **randomized data**?
2.How do the causal effects **compare** over **time**?

FOR A TOTAL OF 122 HEROES

3.Methodology

Average Causal Effect (ACE)

1) Treatment : The Hero 'Example' being picked
2) Causal Effect : Does the team with 'Example' win
3) Retrieve data that conform to randomization
4) Data will include games with and without 'Example'
5) Neyman's Average Causal Effect
6) Determine the causal effect

Pearsons Chi-square Test for Independence [2]

1) Statistical Independence between Hero selection and game outcome
2) Statistical Independence between update intervals and game outcome

4 .Experiments

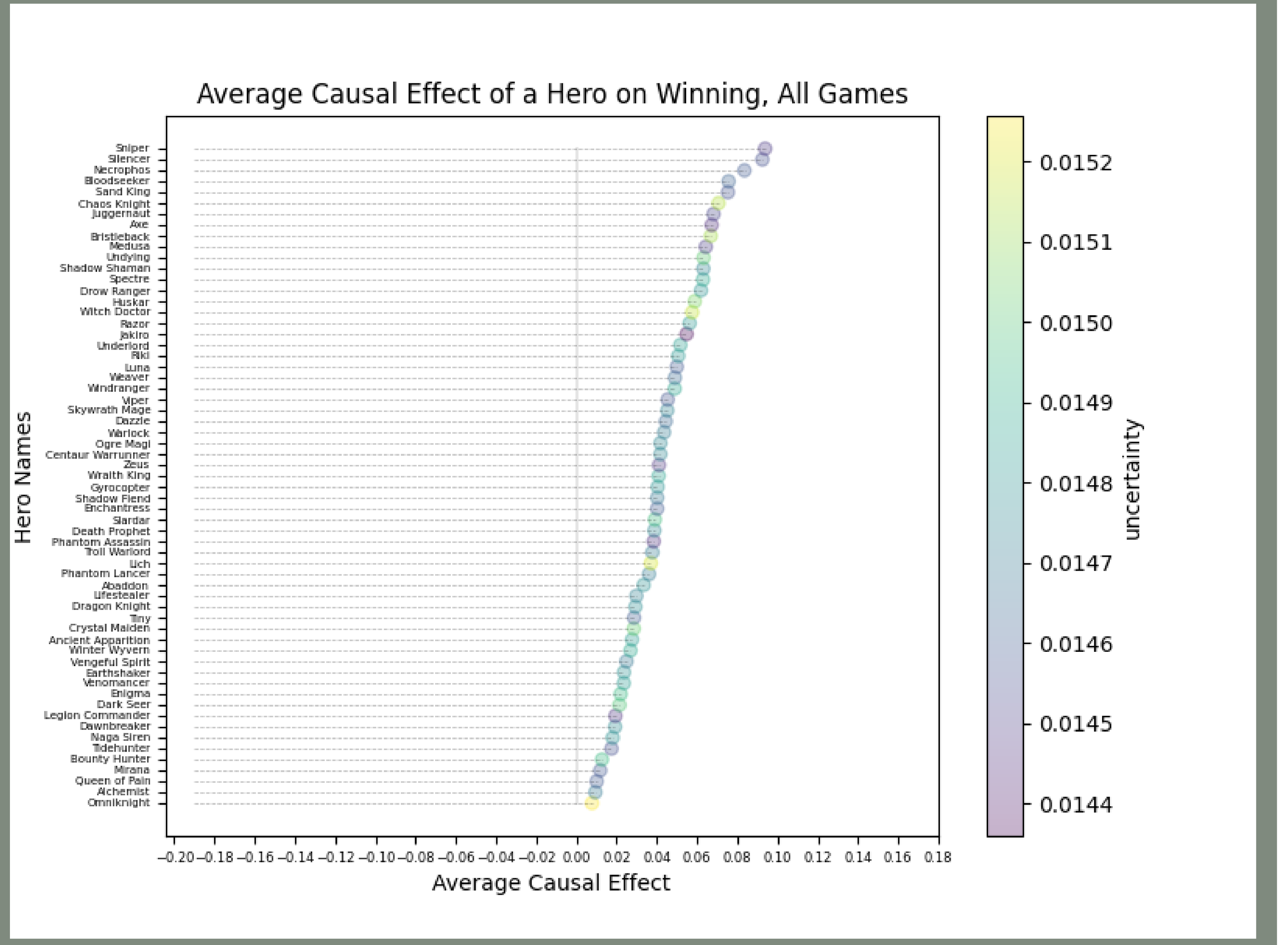
The experiment is done for all Heroes over 3 time dependent update intervals

1) 2 significant updates with 6.729 games
2) No significant updates with 5.134 games
3) 1 significant update with 4.770 games

Total of 16633 games

Average Causal Effect (ACE)

- **Binary treatment variable**
  - T_i ={0,1}, 0: Hero not in team, 1 : Hero in team
- Potential **outcomes** for each **unit**
  - $Y_i(1)$ and $Y_i(0)$ (win or loss)
- **Unit** causal effect $t_i = Y_t(1)- Y_t(0)$
  - we only know **one of the two** quantities
- Using additional assumptions
  - **All test statistics are equivalent to the difference-in-means estimator for binary outcomes [3]**



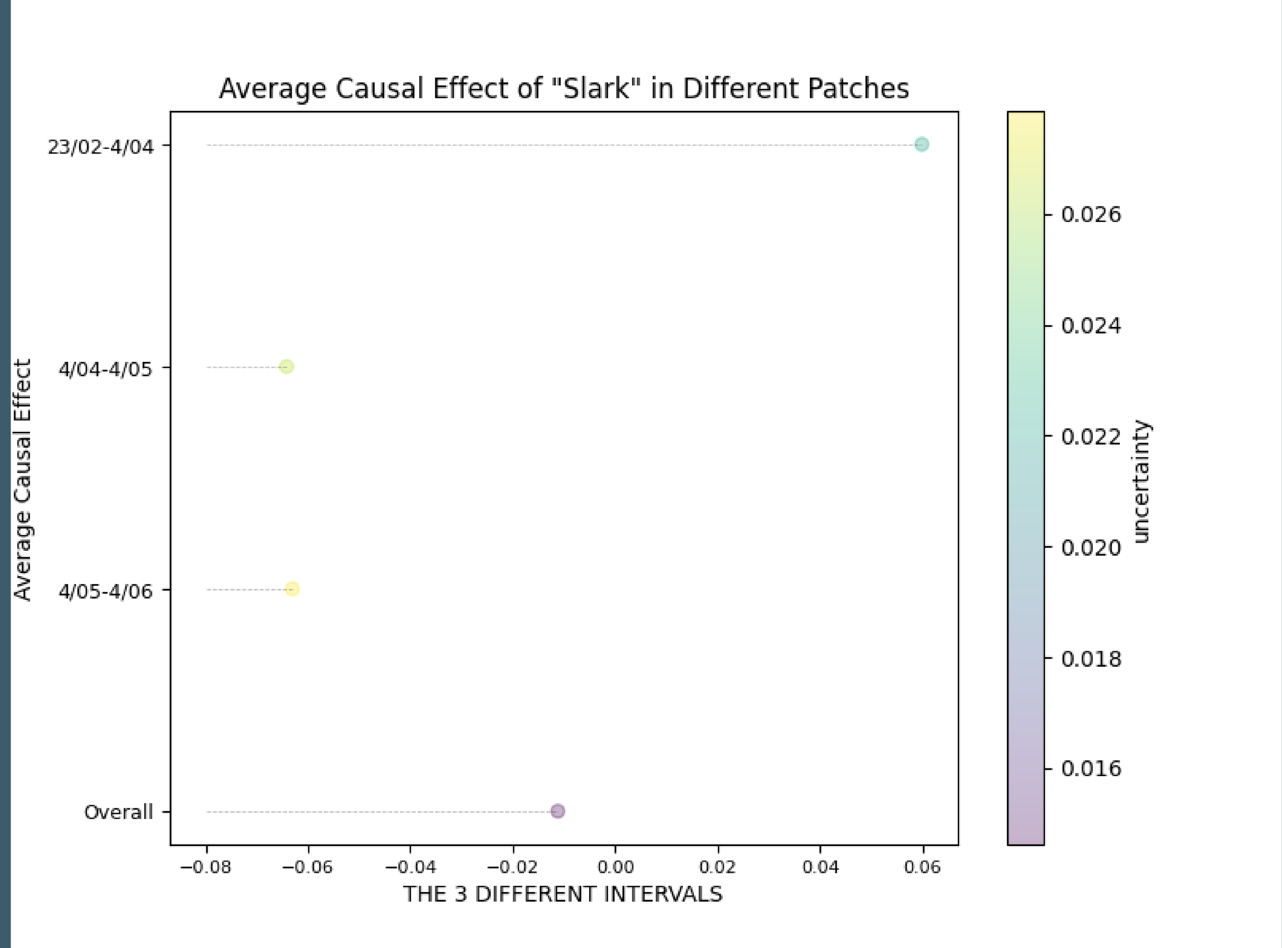
Independence test

- Game outcome vs Hero selection
  - Expected dependance (used as a validation test)
- Game outcome vs Update interval per Hero
  - See how game outcome is affected by patches and in relation to the causal effect

Hero Name	Dependance	P-value
Shadow Fiend	Independent	0.5826
Bane	Independent	0.4660
Slark	Dependent	0.0002
Sand King	Independent	0.8943
Storm Spirit	Independent	0.6243

5. Results

3 Update Intervals and Overall Game State **for 122 Heroes**
That means a lot of results!



123 Independence tests

Game outcome is Dependent on Hero selection (validation).
Independence tests could recognize patch dependance in some cases where the Hero's ACE would fluctuate in a significant manner between intervals

6.Conclusions

1. Amount of data really matters in randomization
2. The buffs or nerfs done to each Hero depending on the interval can be seen on the ACE
   1. **More accurate for simple Heroes**
   2. **Deceiving for Heroes that have big confounding factors (Meepo)**
3. The changes done to a hero are better represented by the Independence tests and ACE when the hero is simple and easy to play. For more complex heroes the results are not accurate

[1] R. J. Hernan MA, Causal Inference: What If. Boca Raton: Chapman & Hall/CRC,2020, vol. Chapter 3.a.
[2]Pearson's chi-squared test," Apr 2022. [Online]. Available: https://en.wikipedia.org/wiki/Pearson27s_chi-squared_test
[3]Ding, "Exploring the role of randomization in causal inference," 2015.

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