Finding the causal effect of picking Slark in the game of Dota 2 on the final match outcome based on in-match events using the front-door adjustment

Hendy Liang
Supervisor(s): Jesse Krijthe, Rickard Karlsson
EEMCS, Delft University of Technology, The Netherlands
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Abstract

The front-door adjustment is a causal inference method with which it is possible to determine the causal effect of applying a treatment given a setting which satisfies the front-door criterion. This involves having a mediator through which all the causal effect flows from treatment to outcome. The front-door adjustment adjusts for confounders and tries to only measure the causal effect from treatment to outcome. The goal is to test the applicability of the front-door adjustment using the game of Dota 2 as a testing ground. The front-door adjustment has been applied to find the effect of picking 'Slark' on the outcome of the game. The mediator in this case is the enemy team buying an item called 'Hurricane Pike'. Two different approaches have been used, both giving varying results. These varying results lead to different possible interpretations. This variety of interpretations therefore suggest that the front-door adjustment is not a valid method for this specific scenario, likely due to the complexity of the game and perhaps the simplified representation of the game in the data-set.

1 Introduction

Dota 2 is a Multiplayer Online Battle Arena (MOBA) game in which players play in a team of five against another team of five. The main objective of a team is to destroy the enemy's team base. Each player has to choose a hero that they want to play and each hero fulfills a different role in the team. Currently, the game has 123 heroes which means that for 10 players, there are around 10^{14} different possible combinations of heroes. Adding the plethora of items that each player can buy into the mix, gives us a complex game that is interesting to analyze. MOBAs in general are a relatively new, wide and interesting field of study for a variety of reasons [11]. The main reason for this research being the availability of APIs that provide data.

Causal inference methods try to look at one specific, controllable variable and try to determine what happens if this variable is changed. This is often referred to as applying a treatment [9]. This research will use a causal inference method called the front-door adjustment [12] to analyze the causal effect of picking a specific hero on the final match outcome. The front-door adjustment is a method that determines the causal effect of a treatment using a mediator to quantify this causal effect. It is useful because it nullifies the effect of confounders by letting all the causal effects flow through the mediator.

At first, it might seem odd to analyze the causal effects of decisions in a video game, but it is possible to test the methodology used for creating this analysis. Dota 2 matches are readily available in the Open Dota API which allows users to retrieve data from past casual and professional matches [6]. This abundance of data is not always available since it might sometimes be too expensive or unethical to gather enough data to perform a robust investigation. This 'free' data serves as a nice testing ground and can be used to test the effectiveness of the methodology. It also tells us a bit about how the method deals with more complex environment such as the game of Dota 2. There are many elements at play which are hard to quantify. This methodology can then be used for other problems such as medicine testing and vaccine testing with more confidence. Next to this, it is also helpful to Dota 2 players that want to improve their chances of winning since the hero selection is a very important decision to make in the game.

1.1 Research Question

The research will be focused on the hero 'Slark' and the enemy's response to a player picking 'Slark'. This response will be the enemy buying a specific item called 'Hurricane Pike'. Picking the hero 'Slark' is analogous to applying the treatment. The sub-questions will focus on the separate causal effects that are in play, which is in line with the front-door adjustment. The causal effect of picking the hero on the enemy buying the item will be measured. Then, the causal effect of the enemy buying the item on the final match outcome will be measured. Combining these two together, finding the causal effect of picking the hero on the final match outcome can be found.

1.2 Related Work

Research into using causal inference methods on (MOBA) games has been done before and some of the most notable ones are highlighted here. Research involving the front-door adjustment in a different scenario is also mentioned.

Causal analysis using the front-door adjustment has been done before on another hero with another item [2]. The main shortcomings of this research was that it only focused on one player with a relatively small sample size (123 games), but it did show that the front-door adjustment is usable for this type of analysis.

Research focusing on other different causal inference methods used instrumental variables (IV) and a control function (CF) approach to determine the causal effects of the in-game metrics such as the tower damage dealt per minute and the kills per minute, to name a few examples [5]. It was found that these unbiased estimators provide higher accuracy when compared to naive estimators which were biased. It was found that the naive estimators were overvaluing the effects of some variables while undervaluing the effects of others. The unbiased IV and CF approaches were more accurate in measuring these effects.

Research into causal effects has also been performed through the creation of an in-game application that calculates the probability of winning as the game progresses using events in the game [4]. They built upon the research mentioned previously, using the same in-game metrics to guide players to increase their chances of winning.

Patches (game updates that alter the balance of the game) can also be seen as a treatment, and subsequently the causal effects of applying a patch can be measured as done in [8]. They used another causal inference method called causal trees to find the heterogeneous treatment effects of the patches. Their findings were interesting because they found that the patches provided were more beneficial to high-performing players than low-performing players. This is surprising because the patches are supposed to make the playing ground more even for all players.

The front-door adjustment is also applicable for other scenarios. Bellemare and Bloem used data from previous researches to perform the front-door adjustment for two real-world scenarios [1]. One about rice production and fertilizer usage in Mali and one about price risk and production of risk-averse products. It showed that the results obtained from the front-door adjustment were statistically indistinguishable from the benchmark results and thus viable for those specific settings.

1.3 Structure

The rest of this paper is structured in the following manner. Section 2 will go over the methodology that is going to be applied to find the answer to the research question. Section 3 will explain the findings using the results acquired from applying the methodology on the data. Section 4 will look at the results and origins of the data from an ethical point of view. Section 5 will discuss the findings in more detail and look at it from multiple perspectives. Section 6 will conclude this paper and give areas for potential future research.

2 Methodology

This section will cover the methodology employed to answer the research question. It will explain the steps from data gathering all the way to the computation of the estimate. All code used can be found on the GitHub repository [10].

2.1 Data Collection

Collecting data can be done through the OpenDota API. The OpenDota API provides matches that one can query and these matches contain all the required information that we want: ‘Slark picked’, ‘Enemy bought a Hurricane Pike’ and ‘Game won’. Each match provides two data points, one from the perspective of each team. After labelling the data with these attributes, the determining of the causal effect can begin. The API’s main endpoint naturally filters on game modes that are ‘balanced’. More specifications on the data-set can be found in Section 3.1.

Two endpoints were used, one to gather recent matches containing their match ids and one to gather more detailed information using those match ids. The first endpoint only provided the heroes picked and which team won the game. The second endpoint provided more detailed data including the items bought by the players, which is of interest to this specific case.

2.2 Front-Door Adjustment

The causal inference method that will be used is the front-door adjustment. This method was introduced by Pearl [12]. It essentially determines a causal effect through the use of a mediator.

It is easier to visualize causal effects and thus creating a causal directed acyclic graph (DAG) is helpful. The DAG for this case is described in Figure 1. The causal effect of ‘Slark’ on ‘Win’ is the relation that is the most important and the one for which the causal effect has to be determined.

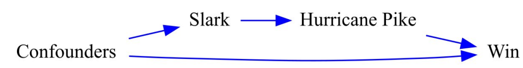

Figure 1: The causal DAG

Conceptually, the front-door adjustment looks at the causal effect from the treatment to the mediator. It then looks at the causal effect from the mediator to the outcome. Finally it combines the two to get the causal effect from the treatment to the outcome. In this specific case, it gives the following effects:

- The causal effect of ‘Slark’ on ‘Win’
  - The causal effect of ‘Slark’ on ‘Hurricane Pike’
  - The causal effect of ‘Hurricane Pike’ on ‘Win’

The front-door adjustment has to adhere to a set of rules called the front-door criterion. Fitted to this specific Dota 2 scenario, these would be:

1. ’Hurricane Pike’ intercepts all paths from ‘Slark’ to ‘Win’
2. There is no backdoor path from the ‘Slark’ to ‘Hurricane Pike’
3. All backdoor paths from ‘Hurricane Pike’ to ‘Win’ are blocked by ‘Slark’

Condition 1 states that the mediator is the only way for the treatment to affect the outcome. Condition 2 states that there is no confounding happening between the treatment and the mediator. Condition 3 states that all the confounding happening between the mediator and the outcome can be prevented by intervening on the treatment.

For the front-door adjustment to work, it is assumed that the path through ‘Hurricane Pike’ is the only way for ‘Slark’ to influence the outcome of ‘Win’ (Condition 1). This assumption has its caveats which are discussed in the Discussion section. However, for the purpose of the front-door adjustment, the shortcomings are ignored.

Do-operator

The do-operator will be a recurring operator in the following subsection so a quick explanation of the do-operator will be given here [12]. The do-operator looks like $do(X = x)$, but sometimes also just as $do(x)$ for brevity, where it means that there was a (hypothetical) intervention on X. For example, $P(Y|do(x))$ would mean the probability of Y after intervening on X and forcing it to be some value x.

In the next section, $do(T)$ and $do(\overline{T})$ would mean intervening for T to be true and not true respectively.

Front-Door Formula

Using the variables defined in Figure 1, it is possible to quantify the effect of ‘Slark’ on ‘Hurricane Pike’, ‘Hurricane Pike’ on ‘Win’ and ‘Slark’ on ‘Win’. Following the methods described in [9] and [12], the causal effects can be found.

For brevity, the variable names will be assigned to symbols to improve the readability of the formulas. The variable assignment will be as described in Table 1.

Variable name	Symbol
Slark	T
Hurricane Pike	M
Win	Y
Confounders	U

Table 1: Variable assignment

The first causal effect that needs to be calculated is the effect of T on M.

$$P(M|do(T)) \tag{1}$$
$$P(M|T) \tag{2}$$

There are no backdoor paths from T to M because the only other path from T to M is through U and Y but Y acts as a collider because the causal effects flow from M and U to Y as can be seen in Figure 1. Since there are no backdoor paths from T to M, the causal effect can be rewritten.

The causal effect of M on Y can be written as:

$$P(Y|do(M)) \tag{3}$$
$$\sum_T P(Y|M,T)P(T) \tag{4}$$

Since there is a backdoor path from M to Y, namely through T and then through U, this path needs to blocked by conditioning on T. This leads to the rewritten formula.

The causal effect of T on Y can be obtained by combining the two aforementioned causal effects. Combining the two gives:

$$P(Y|do(T)) \tag{5}$$
$$P(M|do(T))P(Y|do(M)) \tag{6}$$
$$\sum_M P(M|do(T))P(Y|do(M)) \tag{7}$$
$$\sum_M P(M|T)\sum_{T'} P(Y|M,T')P(T') \tag{8}$$

The summations are required because all possible values of M and T' have to be considered. Working out the do-operators in Equation 7 gives the formula in Equation 8 which is the front-door formula. The prime on the second T is to distinguish it from the T in the first probability which matches the initial T in the do-operator. This final equation is essentially the way of determining the causal effect of T on Y.

The average treatment effect (ATE) can be calculated by using the following formula:

$$P(Y|do(T)) - P(Y|do(\overline{T})) \tag{9}$$

3 Experimental Setup and Results

3.1 Data-set

The data is gathered using a Python script that calls the Open Dota API and queries it for match data. This code can be found alongside the other code used for the experiment in the GitHub repository [10]. The data-set that was retrieved from the API can also be found on the repository. The data-set is filtered on the attributes important to determining the causal effect. These are:

- Win
- Slark picked
- Enemy bought a Hurricane Pike

Slark can only be picked by one person but multiple people on the enemy team can buy a Hurricane Pike. In this case, it is considered a Boolean that is *false* for no Hurricane Pikes bought, and *true* for one or more Hurricane Pikes bought.

Specifications

The data-set contains games from the 6th of May 2022 up until the 10th of May 2022. The endpoints queried only contain games that are considered 'balanced' by the creators of the API [6]. This means that no team had an unfair advantage when starting the game. The most commonly played game modes fall under this category so the data is rather accurate regarding the actual player experience. The games were played in all regions that Dota 2 is available in. This ensures that there was no regional bias in the data.

The amount of occurrences is described in Table 2. Note that each game is two data points so the amount of actual games used is actually half of what is said in the table.

	Win	Hurricane Pike	Total
Slark Picked	3946	1682	8213
Slark Not Picked	117017	42728	233713
Total	120963	44410	241926

Table 2: Occurrences of attributes in the data-set

This already shows a negative win-rate (below 50%) for Slark, namely

$$3946/8213 * 100\% = 48.0\%$$

3.2 Front-Door Adjustment Applied

Two ways of applying the front-door adjustment have being utilised. The first is using a package called Ananke [3]. The second way is using a manual implementation [10]. These give contradictory results but both will be highlighted here. The results of a group-mate using a different causal inference method have also been included here as a comparison.

Manual implementation

The manual implementation uses the formula defined in Section 2.2. A 95% confidence interval was achieved using 1000 bootstraps. The probabilities used in the formula are the frequencies of the observed value given some condition over the total frequencies given that same condition:

$$\frac{Occurrences|Condition}{TotalOccurrences|Condition}$$

Using the win-rate as the example, this would be:

$$\frac{\#Wins|Slark}{\#TotalGames|Slark}$$

	Probability
$P(HurricanePike \mid do(Slark))$	0.2048
$P(Win \mid do(HurricanePike))$	0.4087
$P(Win \mid do(Slark))$	0.4976
$P(HurricanePike \mid do(\overline{Slark}))$	0.1828
$P(Win \mid do(\overline{HurricanePike}))$	0.5205
$P(Win \mid do(\overline{Slark}))$	0.5001

Table 3: The probabilities of the steps in the front-door criterion

Method	ATE	95% CI
Manual implementation	-0.00246	[-0.00346, -0.00148]
Ananke (Primal-IPW)	0.0098	[0.0060, 0.0139]
Ananke (Dual-IPW)	0.1961	[0.1170, 0.2740]
Ananke (APIPW)	0.1961	[0.1153, 0.2694]
Ananke (Eff-APIPW)	0.1961	[0.1137, 0.2745]
Stelios' results	-0.01119	NA

Table 4: The average treatment effect (ATE)

Table 3 shows the separate steps in the front-door criterion. These are the steps needed to calculate: $P(Win|do(Slark))$ and also $P(Win|do(\overline{Slark}))$. Recall that to calculate the ATE, it is needed to subtract the probability of $P(Win|do(\overline{Slark}))$ from $P(Win|do(Slark))$. This calculation and the Ananke results can be found in Table 4. The separate steps are also interesting to look at, it seems that picking Slark only leads to the enemy actively countering it in a fifth of the games and it also seems that buying a Hurricane Pike is a good decision since the enemy is less likely to win after you buy a Hurricane Pike. As a reminder, 'Hurricane Pike' means that the enemy team bought a Hurricane Pike and not the allied team.

It also shows that a win is more likely if the enemy does not buy a Hurricane Pike, suggesting that the item is a good item to buy in general if the players are aiming to win the game.

Ananke

Ananke requires a causal DAG and will then recommend an algorithm to use. In this case, it suggested Efficient Augmented Primal Inverse Probability Weighting (Eff-APIPW). Next to this, it said that Primal IPW, Dual IPW and APIPW were usable for this specific scenario. All four have being used to obtain an ATE.

Primal IPW refers to a more generalized version of IPW [9] that is applicable if a variable is primal-fixable (p-fixable). In Figure 1, this would mean that the confounder does not affect 'Slark' and its children ('Hurricane Pike') at the same time. Another easier way to check for primal fixability is that if the DAG satisfies the front-door criterion, the treatment is also p-fixable. So in this case, the treatment (picking Slark) is p-fixable and therefore this more generalized version of IPW is applicable.

The Dual IPW is essentially a more advanced version of the Primal IPW. The APIPW and the Eff-APIPW are versions that use the centered versions of the Primal and Dual IPW estimators together with another estimator called the plug-in estimator. More details can be found in [3].

Randomization

Lastly, the results from a group-mate (Stelios Avgousti), that is also using causal inference to determine the causal effect, have been considered. He used random data to determine the ATE. This randomization is utilized to filter out confounders such as skill level. To some extent, this can be seen as the 'true' causal effect since it filters out the confounders and only looks at the effect of Slark on winning.

Average Treatment Effects

As can be seen in Table 4, the ATEs found by Ananke are vastly different than the ATE found by the manual implementation except for the Primal IPW. The manual implementation and the Primal IPW results both show statistically insignificant results, one positive and one negative. This has multiple interpretations with the most likely one being that picking Slark does not have an effect on outcome of the game on its own.

The other Ananke results tell a different story. The causal effects are larger and statistically significant, suggesting that picking Slark increases your chances of winning even when the enemy buys an item that is supposed to counter Slark.

The first interpretation seems more likely because of the sheer complexity of the game. The causal effect in this specific scenario is probably too small to accurately measure. This is also in line with the results from Stelios, showing a relatively small causal effect. The second interpretation seems improbable. There are a total of 123 heroes and for one hero to have such a big effect is rather unlikely. This would be reflected in the win rate, making it much higher.

If it is assumed that the negative win-rate of Slark is not confounded by anything and reflects the effectiveness of the picking Slark, combined with Stelios' results, the negative ATE might be plausible as the 'true' result. This would then indicate a small decrease in chance of winning when picking Slark. However, the negative win-rate might be a confounded result and does not necessarily reflect the causal effect of picking Slark. The same holds for Stelios' results.

4 Responsible Research

This section will briefly go over the ethical sides of this research. This will be mainly about the way the data is gathered and the applications of the research.

The data for this research was gathered from an API that is accessible by anyone [6]. According to the developers of the project, the data in the API comes from public sources [7]. If wanted, it is possible for players to opt out of their matches being seen but this does not delete past data and only sets the player to anonymous in future data. In a way, this means the data is still gathered from the player even if they specifically said they do not want their data to be gathered, but it is anonymous so there is no real way of relating the data back to the specific player.

Since Dota 2 is published by Valve on Steam, the Steam regulations apply since Steam is owned by Valve. The Steam privacy policy [13] states that the "game statistics" are tracked by Steam. This therefore includes match data. When playing the game, the player has agreed to these terms so the data is being collected in a legal and informed way.

The data used does not contain any sensitive information such as medical or personal information. It only contains information about matches that were played in an online video game.

The contributions in this research can help in medicine and vaccine testing which is seen as a positive thing. The findings from those tests can then potentially be used to help people in medical need.

5 Discussion

This section will discuss the findings found and look at them from a different perspective. Assumptions made during the process will also be reviewed.

5.1 Assumptions

Arguably one of the biggest assumptions made during the research is that the enemy buying a Hurricane Pike is the only way that Slark influences the outcome of the match. The front-door criterion states that the mediator has to be the only way for the treatment to influence the outcome. This assumption is not entirely met. It can be argued that there are more variables influencing the game than just the enemy building one specific item in response to your hero pick. Just to give a few examples, the game can be influenced through the amount of kills Slark gets, the amount of map-objectives Slark takes or the amount of minion kills Slark gets. These are all ways for the treatment (picking Slark) to influence the outcome. However, these are all confounded by the (Slark) player skill level, so they were not viable mediators for the front-door adjustment but are still mediators.

A stronger counter-argument for the enemy buying a Hurricane Pike being the only mediator is the enemy buying other items to counter Slark. There are a big amount of items to choose from, some of which are also meant as counters to Slark's playstyle.

There is also the direct effect Slark has on the outcome of the game, which is what Stelios Avgousti's results are (to some extent). If it is possible to retrieve the true total effect that Slark has on the outcome of game, it would be interesting to compare it to the findings found in this research. The findings in this research should also reflect the total effect but as mentioned before, the assumptions aren't fully met, so it is only a partial effect.

This relatively weak assumption is due to the fact that the mediator has to be unaffected by any confounders. The plan at first was to use global objectives such as turrets taken or neutral monsters killed. However, these are highly dependent on the player skill level since in the higher skill brackets, these are generally more prioritised than in the lower skill brackets. When looking for a mediator that is unaffected by confounders, the option of enemy countering heroes with their item build was seen as the only viable option. This was seen as not confounded by any other variables because even in the lower skill brackets, specific items to counter a hero are a known thing. The opponent skill level could be seen as a potential confounder but this is not the case because this only affects the enemy buying Hurricane Pike and does not influence Slark being picked, since that is related to the skill level of the player picking Slark.

5.2 Validity

The main way of validating the results are by comparing them to win-rate of the hero in the data. The win-rate in the data-set used was 48,0%. This negative win-rate implies a negative effect on the outcome of the match when picking Slark. However, this might be influenced by other biases such as a selection bias, e.g. lower-rated players might pick Slark more often, but also lose more often because of their relatively worse skill level.

Other results to compare to are the results from Stelios Avgousti. His results were relatively close to the Primal IPW and manual implementation results. His results filter away the effects of most confounders but some stronger confounders might still have an influence on the causal effect. This is hard to measure but if we assume the results to be the 'true' results, then the Primal IPW and manual implementation are not that far off from what they should be, with the manual implementation being closer to the 'true' value.

The results might also be slightly inaccurate because the amount of Hurricane Pikes is not taken into consideration. The effect might be quantified more accurately if the amount of Hurricane Pikes is represented in the data. There is a notable difference between one player on the enemy team having a Hurricane Pike as opposed to all five of them having a Hurricane Pike to counter Slark. This representation was not done in this case for the sake of simplicity.

As already mentioned in Section 3, the results of the Ananke package (except Primal IPW) differ significantly from the results in the manual implementation and the Primal IPW. The ATEs calculated are significantly higher, suggesting a larger causal effect of picking Slark on the outcome of the game, which as already mentioned is unlikely. This might be caused by the underlying complexity of the methods used in the Ananke package. They might not be suited for the simplified representation of the game that was used as the data-set. This might cause over-fitting on the data. Another explanation is that the methods are not suitable for this specific scenario and thus give greatly differing results.

6 Conclusions and Future Work

This section will summarize the main findings of this research and derive conclusions from them.

The main goal of this research was to test the methodology, the front-door adjustment, using matches in Dota 2. Dota 2's complexity and easy access to data means that it is a suitable venue for experimentation. The two approaches used are both applications of the front-door criterion but they give vastly different results. The ATEs found using the manual implementation and the Primal IPW from the Ananke package both showed statistically insignificant results, which were similar to Stelios Avgousti's results. As opposed to the other Ananke methods, which used more advanced and complex algorithms. These gave an ATE of 0.1961.

There are multiple interpretations to the results, especially considering the results vary a lot. The interpretations vary from Slark having a big positive impact on the outcome of the game, to Slark having a slightly negative impact on the outcome of the game, to Slark not having any significant impact on the outcome of the game.

These inconsistent results and differing interpretations seem to suggest that the front-door adjustment is unusable for consistently determining causal effects in this specific Dota 2 scenario. This is likely due to the complexity of the game. The results might have been more consistent if the data-set used was also more complex and included more variables to properly represent this complexity. Sadly, this is not very plausible since things like player skill level are basically impossible to measure correctly.

Further investigation can be done into using other heroes and items to test the front-door adjustment. Research can also be performed into applying the front-door adjustment on simpler scenario's. Dota 2 is a complex game and the front-door adjustment might not be able to handle such a complex setting correctly. One of the assumptions is that the mediator is the only way for the treatment to affect the outcome, however this is virtually impossible in the case of Dota 2 because of its complexity. This means that some accuracy has to be sacrificed for the front-door adjustment to work. It is worthwhile to investigate other scenarios with differing levels of complexity to find the best fit for the front-door adjustment. Preferably scenarios where the mediator is a strong mediator and the confounders are weak, such as measuring the effect of discounting unpopular products in supermarkets on the sales of those products.

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