Hiroshi Nakahara, Kazuya Takeda, and Keisuke Fujii*

Pitching strategy evaluation via stratified analysis using propensity score

Abstract: Recent measurement technologies enable us to analyze baseball at higher levels. There are, however, still many unclear points around the pitching strategy. The two elements make it difficult to measure the effect of pitching strategy. First, most public datasets do not include location data where the catcher demands a ball, which is essential information to obtain the battery’s intent. Second, there are many confounders associated with pitching/batting results when evaluating pitching strategy. We here clarify the effect of pitching attempts to a specific location, e.g., inside or outside. We employ a causal inference framework called stratified analysis using a propensity score to evaluate the effects while removing the effect of disturbing factors. We used a pitch-by-pitch dataset of Japanese professional baseball games held in 2014-2019, which includes location data where the catcher demands a ball. The results reveal that an outside pitching attempt is more effective than an inside one to minimize allowed run on average. Besides, the stratified analysis shows that the outside pitching attempt was always effective despite the magnitude of the estimated batter’s ability, and the ratio of pitched inside for pitcher/batter. Our analysis would provide practical insights into selecting a pitching strategy to minimize allowed runs.

Keywords: baseball; pitching strategy; causal inference; propensity score

1 Introduction

Baseball is a good friend of statistics due to its features. Each scene of baseball is discrete, making it easy to allocate responsibilities of each play to players. Many
formulas and statistics (stats) were developed and employed to evaluate players’ performance from a long time ago (James, 2010; Lewis, 2004; Click and Keri, 2006; Tango et al., 2007; Beneventano et al., 2012; Costa et al., 2012). Most stats are computed using batting, pitching, and fielding results (for detail, see Section 2). Currently, measurement technologies and data platforms are getting developed, and all sensing data measured in Major League Baseball (MLB) games are provided and accessible. It enables us to develop stats to evaluate player’s performance using speed and angle of batted balls, such as expected weighted On Base Average (xwOBA) and expected Earned Run Average (xERA) (MLB.com, 2015b,a), which can acquire more important information and findings to win. “Fly ball revolution”, which specifies the effective speed and angle of batted balls to hit a long hit, is a symbol of that.

While a lot of stats are widely used to evaluate a player’s performance, there are many unclear points around the pitching strategy. The pitching strategy here means a strategy of battery (pitcher and catcher) to defeat the opponent batter. Battery combines various pitch types, courses, and pitch combinations (e.g., inside fastball after outside breaking ball). During a game, a catcher often suggests where/which to pitch the next ball to a pitcher (especially in Japanese Professional Baseball (NPB)). The catcher then sends a signal to the pitcher with their mitt and finger. The pitcher receives information about the next pitch type/course and accepts or rejects it. Sometimes, their coach in their dugout sends the signal to the catcher in advance.

It is unknown whether the ability for selecting an appropriate pitching strategy exists. Woolner (2002) concluded the ability might exist, but cannot detect from batting results due to noise. In other words, the ability does not include noises or lucks and an unmeasured variable. There are some quantitative studies on the effects of pitching sequences. Gray (2002) revealed that “fastball after a series of late balls is effective” by virtual experiments. However, there are no statistics to evaluate the overall effect to select a pitching strategy. We consider that two elements make it difficult to measure the effect of pitching strategy: 1) most public datasets do not include location data where the catcher demands a ball, 2) there are a lot of confounders associated with pitching/batting results.

First, we explain why we need the location data where the catcher demands. It is known that a pitcher cannot always pitch to the location of the catcher’s demand perfectly. For example, Shinya et al. (2017) revealed that pitched location follows a two-dimensional normal distribution. Figure 1 shows the pitch distribution where the catcher demands a lower 1st-base/3rd-base side (unless otherwise noted, figures are from the pitcher’s perspective). There is a gap between demanded location and the actually pitched one. Thus, a catcher needs to suggest the next pitch location considering the gap between the required course and the pitched one. For the above
Fig. 1: All-pitched location of four-seam where the catcher demands lower 1st-base/3rd-base side (regardless of batter’s hand) from pitcher’s perspective pitched by Taisuke Yamakoa, right-handed pitcher belongs to Orix Buffaloes in 2019 ($N = 935$ in total). Units are centimeters.

reason, in the fielding team’s position, we should measure the effects of pitching “attempts” to a specific course, not pitched.

In addition to the difficulty of observing the catcher’s demand, many confounders associated with pitching/batting results make it difficult to evaluate pitching strategy. For example, it is known that a good batter is more frequently pitched inside (especially in NPB). The correlation between weighted On Base Average (wOBA; high wOBA means good batter), and the ratio of inside pitching attempts was $r = 0.31$ in our computation\(^1\). If simply comparing the results where demanding inside with the outside, the effect of outside pitching attempts can be overestimated since poor hitters are attempted outside more frequently than hard hitters. Thus, we cannot compare them directly.

For the above reason, we propose a method of estimating the effect of demanding inside/outside with causal inference called stratified analysis using propensity score (e.g., Rubin (1997); Damluji et al. (2019)), which can statistically reduce confounders and estimate the effects. We define the effect of each demand as a variation of run expectancy, computed by pitching/batting results. Thus, we develop the model to compute the propensity score (i.e., the probability of demanding inside) with confounding variables (e.g., the ratio of pitched inside for the batter, the pitcher in the season), and make up for unobserved data with it. We then estimate the

\(^1\) We computed the correlation (Pearson’s $r$-value) for the batters which have more than 300 plate appearances in a season from 2014 to 2019 in NPB games. Please refer to Section 3.2 for the definition of inside pitching attempts, and the detail.
expected effect of demanding inside and outside. Furthermore, we investigate specific questions about unknown problems in baseball. We group the data into some groups based on the estimated batter’s batting ability, and the ratio of pitched inside for pitcher/batter, and estimated the effect for each group (i.e., stratified analysis). For the estimated batter’s batting ability, we examine the effectiveness of the inside pitch attempt against a good batter, because it is considered that a good batter is more frequently pitched inside (especially in NPB). In the same way, we investigate the effect of the ratio of pitched inside for pitcher/batter because the pitcher would think their inside pitch attempts are effective and pitch more frequently.

In summary, the main contributions of the study are as follows: (1) We analyzed the effects of pitching attempts to a specific location (inside/outside) for the first time; (2) We used the stratified analysis using the propensity score to estimate the effect by removing confounders in complicated scenes of baseball; (3) We revealed the effect of pitching attempts on a specific course exists. The remainder of the paper is organized as follows. We review the related work in Section 2. In Section 3 we describe the proposed method. Section 4 presents the experimental results. Finally, we discuss the results and present the conclusions in Sections 5 and 6, respectively.

2 Related work

A lot of formulas and stats were developed, and employed to evaluate past or predict future player’s performance from a long time ago (Silver 2003; James 2010; Lewis 2004; Click and Keri 2006; Tango et al. 2007; Beneventano et al. 2012; Costa et al. 2012). These stats are computed by batting results. One of the most essential perspectives when evaluating the player’s performance is to consider uncertainty. Even if two players have the same ability, the two results can be different due to uncertainty. To deal with the problem, some stats focus on the “true ability”: strikeout, home run, walk (Davies and Basco 2010). These stats are considered to be stable for each player for evaluating the player’s performance.

Recently, measurement technology and data platform have been developed, and all sensing data measured in MLB games are provided and accessible. It enables us to develop stats to evaluate player’s performance using speed and angle of batted balls, such as expected weighted On Base Average (xwOBA) and expected Earned Run Average (xERA) (MLB.com 2015b). The speed and angle of batted balls are relatively stable stats for an individual player (i.e., the value does not fluctuate significantly across seasons.). These new stats can extract a player’s potential
more validly. Comparing with evaluating batting/pitching performance, evaluating pitching strategy is a challenging field. Some researches predicted the next pitch type using various machine learning methods (Hoang et al., 2015; Bock, 2015). Besides, the methods for predicting the batting result are suggested (Martin, 2019; Harrison and Salmon, 2019; Healey, 2015). When estimating the ability to select a pitching strategy for the catcher, the simplest idea is computing ERA where the catcher is in the games, called catcher’s ERA (Herrlin, 2015). Woolner (2002) showed that the catcher’s ERA computed using batting results cannot detect the difference in abilities. It seems difficult to estimate the catcher’s ability to select a pitching strategy with batting results. Besides, there is no study with the data of catcher’s demanding as far as we know.

In team sports, propensity score matching was used to investigate the causal effect of some plays or timeouts in many sports such as going for the touchdown in American football (Yam and Lopez, 2019), clearing the puck in ice hockey (Toumi and Lopez, 2019), the effectiveness of timeouts in basketball (Gibbs et al., 2020), and crossing the ball in soccer (Wu et al., 2021). In the dynamic setting, Vock and Vock (2018) applied a g-computation method to examine the effect of taking a pitch during a 3-0 count in MLB and Fujii et al. (2022) proposed a framework for estimating individual treatment effect (ITE) in basketball motions. Among approaches without causal inference methods, in baseball, counterfactual predictions could be performed such as using simulation and supervised learning in team hitting strategies (Nakahara et al., 2022a) and using game theory and semi-supervised learning in a third base coach’s decision making (Nakahara et al., 2022b). Compared with these approaches, since the outcome prediction in our task was very difficult (in a more general pitching case than the study of Vock and Vock 2018), we used stratified analysis (not to predict outcomes) rather than regression analysis to predict outcomes.

3 Methods

In this section, we describe the proposed method to clarify the effect of pitching attempts to specific locations. First, we describe the stratified analysis using the propensity score to estimate the effect of demanding inside/outside pitch. Second, we introduce the new dataset, including the location where the catcher demands. Finally, we describe the processing method to compute the propensity score.
3.1 Stratified analysis using propensity score

Our motivation is to reveal the effect of demanding inside/outside, and we need to reduce confounders for valid estimations. To deal with confounding, we employed methods introduced by Rosenbaum and Rubin (1985), defined as follows. $X$ is a confounding variable. $Z \in (0, 1)$ is a treatment allocation. $Z = 0$ corresponds to nontreatment, and $Z = 1$ corresponds to given treatment. In this study, $Z = 0$ ($Z = 1$) means catcher demands outside (inside) pitch. $Y$ is a potential outcome. $Y^{(1)}$ ($Y^{(0)}$) denotes the outcome if (not) treatments are applied, in this case, the outcome if a catcher demands inside (outside). The outcome is defined as the variation of run expectancy before and after the event (i.e., pitch result or batting result) ($\Delta RE$). For details, see Section 3.3. For simplicity, denote $X$ in the $i$-th unit (sample or pitch) as $X_i$. The same is true for the other variables. $\tau$ denotes the average treatment effect (ATE), and is described as follows:

$$\tau = E[Y^{(1)}] - E[Y^{(0)}].$$  \hspace{1cm} (1)

The main problem in causal inference is that we cannot observe $Y_{i1}$ and $Y_{i0}$ simultaneously, known as “the fundamental problem of causal inference” (Holland 1986). To overcome the problem, various methods are proposed, and one of the popular fundamental ideas is comparing groups (i.e., sets of units), which have similar confounding variables. It should be noted that we used the stratified analysis (not to predict outcomes) rather than regression analysis to predict outcomes. This is because the outcome prediction in our task was very difficult in our preliminary experiment. The propensity score is considered as the criteria for measuring the similarity between each unit. The propensity score (here denoted by $P(X)$) is the probability of being assigned treatment computed using confounding variables. We can consider the distributions of confounding variables are the same between treatment and nontreatment groups when comparing data with a similar propensity score, according to Rosenbaum and Rubin (1985). That is, comparing data with similar propensity scores reduces confounding. Note that here we assume three popular assumptions in causal inference: consistency, exchangeability, and positivity (Cole and Hernán 2008, Austin and Stuart 2015). Exchangeability (or ignorable treatment assignment) is the assumption of no unmeasured confounders that affect treatment selection and outcomes. However in the actual baseball data, we cannot say that there is no possibility of that. We also discuss the limitation of this study from this viewpoint in Section 5. Consistency means that a pitch’s potential outcome under the treatment actually received is equal to the pitch’s observed outcome. Positivity is the assumption that all pitches have a non-zero probability of receiving each treatment.
We use the Inverse Probability Weighting (IPW), one of the practical causal inference methods using propensity scores (Robins et al., 2000). In IPW, the propensity score is used to make up for unobserved outcomes. It is the same with comparing units which have similar propensity scores, mathematically. IPW estimates the treatment effect ($\tau$) as follows.

$$\hat{\tau} = E[\hat{Y}(1)] - E[\hat{Y}(0)],$$

$$E[\hat{Y}(1)] = \frac{\sum_{i=1}^{N} \frac{Y_i(1)Z_i}{P(X_i)}}{\sum_{i=1}^{N} Z_i P(X_i)},$$

$$E[\hat{Y}(0)] = \frac{\sum_{i=1}^{N} \frac{Y_i(0)(1-Z_i)}{1-P(X_i)}}{\sum_{i=1}^{N} \frac{1-Z_i}{1-P(X_i)}},$$

where $\hat{\tau}$, $\hat{Y}(0)$, and $\hat{Y}(1)$ are expected values of $\tau$, $Y(0)$, and $Y(1)$, respectively. As an example, we consider the units that satisfy $X = x$, $Z = 1$, $P(Z = 1|X = x) = 0.3$. Then, $P(Z = 0|X = x) = 0.7$, and 70% of units with $X = x$ do not be assigned treatment. We cannot observe these outcomes with treatment. To obtain the unobserved outcomes counterfactually, each observed outcome is multiplied by $1/P(Z = 1|X = x)$ (i.e., $1/0.3$). Since we cannot observe the true propensity score, we need to develop a prediction model for its estimation. Using random forest, propensity scores were estimated by modeling the associations of covariates with treatment (i.e., the random forest classifies whether the treatment exists or not). The number of trees was 130, and the maximum depth of the tree was 9.

We compute the expected effect and confidence interval to examine the treatment effect to be statistically significant. We compute this on average for ATE, and this on each interested group (e.g., the estimated batter’s batting ability and the ratio of pitched inside for pitcher/batter) as a stratified analysis. We employed the bootstrap method, which is one of the Monte Carlo methods, resampling data randomly to estimate the confidence interval (such as used in Bock et al. (2012)). The bootstrap method repeats the following operation multiple times: extracting the same number of data as the original from the original dataset randomly with replacement, and estimating the effect using IPW. Among various methods to estimate confidence interval of the treatment effect (e.g., Haukoos and Lewis (2005)), we used the normal approximation method in this paper. It approximates the resampling distribution as the normal distribution. Then, the confidence interval is calculated using the sample average and its standard deviation.
3.2 Dataset

We used the dataset of NPB games held in 2014-2019 provided by Delta Inc. since it contains location data where the catcher demands. Although most baseball studies used MLB data (Koseler and Stephan, 2017), no MLB dataset includes the demanding location in public. We used the pitch-by-pitch data (e.g., game situation, the location of a pitch, the location of catcher’s demanding by catcher just before pitching, pitch type, pitch speed, and pitching/batting result) of 1,591,586 pitches. We assume that demanding location indicates the catcher’s intent since the pitch distribution of inside and outside are different and scattered around the edge of the inside and outside, respectively (Figure 1). Note that the location data is inputted manually (most teams collect sensing data themselves, but not in public in Japanese professional baseball). We show the detail of features in Section 3.3.

Figure 2 shows the coordinate system of pitching location and the definition of inside/outside pitch. Demanding and pitched locations are plotted on 160 × 200 px (100 × 125 cm) campus. The coordinate system has the X-axis horizontal and the Y-axis vertical with the origin (0, 0) at the lower 1st-base side corner. Note that we use a case when a pitcher faces a right-handed batter for a simple explanation (in the case of left-handed batter, reverse right-handed case). We define “the catcher demands inside (outside)” where the plot is located in 1) more right (left) than one-third of a home base’s right side (left side), and 2) lower than the top-third of the strike zone. The data with the high demanded ball was excluded due to the small sample size, and the data where the balls touched the ground was included. We group into “the catcher demands inside” where $D_x \geq 96$ and $D_y \leq 80$, “the
catcher demands outside” where \( D_x \leq 64 \) and \( D_y \leq 80 \). Here, \( D_x, D_y \) denotes the coordinates of the location of demand.

### 3.3 Data processing

In this study, we used the data that games were held from March to June each season to compute feature values (e.g., batter’s batting stats, the ratio of pitching inside for the pitcher, and so on). Thus, we predicted them for the games held from July to September in each season. We used only data pitched four-seam fastball since the location of each breaking ball’s demanding is fixed (e.g., most right-handed pitchers try pitching their slider into the left side of the home base from the pitcher’s perspective). The data on the batter’s plate appearance or the pitcher’s total faced batters less than 100 through a season were excluded due to the small samples. In addition, the data grouped into neither inside nor outside were also excluded. We used 286,430 pitches to execute causal inference. The number of inside pitches was 91,186, while that of outside pitches was 195,224.

Here we describe the computation of the input feature for propensity score and the difference in run expectancy as the outcome. The original dataset in baseball includes pitch results (called strike, swinging strike, foul, ball) and batting results (e.g., hit, strikeout, and walk). To evaluate pitch results and batting results with unified criteria, we converted pitching/batting results into the run scale. It is because there is a strong correlation between a win and earned runs, and the pitching strategy should be evaluated using runs. The linear weights (LWTS) is one of the most popular ideas for converting each event (pitching/batting results) into run scale and ideas for evaluating each result in sabermetrics (Thorn et al., 2015). In LWTS, the run expectancy is computed for each game situation, considering out count, and runners on base regularly (e.g., the run expectancy of 0 out without runner is 0.44). With the run expectancy for each game situation, we can compute the variation of run expectancy as follows.

\[
\Delta RE = RE_{after} - RE_{before},
\]

where \( RE_{after} \) and \( RE_{before} \) are the run expectancy of after/before event. In other words, the value of each event is regarded as the variation of run expectancy. To compute the variation of run expectancy, we compute the expected variation of run expectancy for each event as follows:

\[
\Delta RE(event) = \frac{1}{N} \sum_{i \in event} \Delta RE_i,
\]
Tab. 1: Variation of run expectancy ($\Delta RE$) for each event.

| Result              | $\Delta RE$ | Result                | $\Delta RE$ |
|---------------------|-------------|-----------------------|-------------|
| strike              | -0.038      | hit by pitch          | 0.311       |
| ball                | 0.032       | intended walk         | 0.155       |
| single              | 0.437       | bunt                  | -0.133      |
| double              | 0.786       | bunt and error        | 0.720       |
| triple              | 1.117       | bunt strike out       | -0.249      |
| home run            | 1.408       | bunt and fielder’s choice | 0.700 |
| field out           | -0.235      | sacrifice fly         | 0.007       |
| double play         | -0.746      | sacrifice fly and error | 0.713 |
| foul fly            | -0.266      | error                 | 0.664       |
| swinging strike out | -0.255      | fielding interference | -0.337      |
| called strike out   | -0.238      | batting interference  | 0.516       |
| uncaught third strike | 0.294     | foul liner            | -0.426      |
| walk                | 0.292       |                       |             |

where $\Delta RE(event)$ is the expected variation of run expectancy for the specific event, observed $N$ times. Table 1 shows the specific $\Delta RE$ of each event.

For valid computation of the propensity score, we propose another feature value called pitch confidence $C(n)$. It indicates how pitcher and catcher are confident about inside/four-seam pitch in $n$-th pitch. We only illustrate the inside confidence model. The four-seam confidence function is the same as the inside one. The formula is computed as follows:

$$C_{in}(n) = \begin{cases} \alpha \Delta RE(n-1) + (1-\alpha)C_{in}(n-2) & \text{if ($n-1$)th pitch was inside} \\
C_{in}(n-1) & \text{otherwise,} \end{cases}$$

(5)

$$C_{out}(n) = \begin{cases} \alpha \Delta RE(n-1) + (1-\alpha)C_{out}(n-2) & \text{if ($n-1$)th pitch was outside} \\
C_{out}(n-1) & \text{otherwise,} \end{cases}$$

(6)

$$C(n) = C_{in}(n) - C_{out}(n),$$

(7)

where $\alpha$ denotes a constant value ($0 < \alpha < 1$). It expresses how much “confidence” remembers recent results. The larger, the more “confidence” forgets old pitch results and weights recent pitch results. The smaller, the more “confidence” remembers old results well and does not weight recent results relatively. In this study, we added
two confidence models. One is $\alpha = 0.6$ and the other is $\alpha = 0.001$, determined empirically.

Finally, we used 18 feature values for prediction, as follows: game condition (ball count, out count, runner on base, run difference, whether the batter’s hand is the same as the pitcher’s hand or not), pitcher (total pitch in the game, pitch result one pitch ago, pitch result two-pitch ago, pitch speed one pitch ago, pitch speed two-pitch ago, the confidence of pitching into the inside ($\alpha = 0.6, 0.01$), the confidence of pitching four-seam ($\alpha = 0.6, 0.01$), previous batting result, the ratio of pitched into inside in the season), batter (the ratio of pitched into inside in the season, wOBA).

4 Results

In this section, we first verified the propensity scores, which is the basis of the causal inference method. Second, we show the contribution of each variable to propensity score computation. Third, we show the estimated total treatment effect (i.e., the effect of demanding inside/outside). Finally, we show the treatment effect within the groups based on a) the magnitude of the estimated batter’s batting ability (wOBA in this case), b) that of the ratio of the inside pitch for the batter, c) that of the ratio of the inside pitch for the pitcher (i.e., stratified analysis).

4.1 Verification of propensity scores

As a verification of the causal inference, propensity score distributions must be similar between treatment and nontreatment groups. Figure 3 shows the plots of the density of the propensity scores in (left) raw data and (right) weighted data via IPW. We confirmed that the distribution was adjusted by the IPW method using the propensity score adequately (for details, see Figure 3 and the caption).

Next, each covariate must be balanced between the treatment and nontreatment groups. We employed Average Standardized Absolute Mean distance (ASAM) to balance them, and it is computed as follows.

$$ASAM = \frac{|x_{in} - x_{out}|}{s}$$

$$s = \sqrt\frac{n_in s_{in}^2 + n_out s_{out}^2}{n_in + n_out}$$

where $x_{in}$ and $x_{out}$ are the confounders with pitched inside and outside, respectively. $\bar{x}_{in}$ and $\bar{x}_{out}$ are the arithmetical means of $x_{in}$ and $x_{out}$. $n_{in}$ and $n_{out}$ are the
number of data with pitched inside and outside, respectively. $s_{in}$ and $s_{out}$ are the standard deviation of $x_{in}$ and $x_{out}$, respectively. According to the previous work (Cannas and Arpino, 2019), researchers should aim at obtaining an ASAM lower than 0.1 for as many variables as possible. Figure 4 shows the adjusted and nonadjusted ASAM. Although there was only one covariate (i.e., the ratio of pitched inside for pitcher) over 0.1, the value 0.116 was close to 0.1. We consider each covariate was adjusted adequately using a propensity score since almost all of ASAM of confounding variables were lower than 0.1. These results show that control for confounding would be possible across the entire range of the propensity score.

4.2 Contribution of each variable

The contribution of the input variables to the propensity score model prediction was computed by SHAP (SHapley Additive exPlanations) (Lundberg and Lee, 2017), which utilizes an interpretable approximate model of the original nonlinear prediction model and also used for sports analysis (Toda et al., 2021). Figure 5 shows the contribution of the input variables (SHAP). Note that variables including “result” are converted into run scale, and a negative value means a pitcher is in advantage. The ratios of pitched inside in the season for pitcher/batter were important for prediction. Following them, previous pitch result, runner, whether pitcher’s hand is the same as the batter’s one were also important.
Fig. 4: Absolute Standardized Absolute Mean distance (ASAM). Red and blue markers indicate before/after adjusted ASAM, respectively. Each ASAM should be lower than 0.1.

4.3 Total ATE

We then analyzed the total ATE computed in Equation (2). The positive effect means the outside pitching attempt is effective, in contrast, the negative effect means the inside pitching attempt is effective. The ATE was $6.29 \times 10^{-3}$, and the confidence interval (99%) was $6.21 \times 10^{-3} \leq ATE \leq 6.36 \times 10^{-3}$. It means that demanding an outside pitch is more effective than demanding an inside pitch. Since the effect of getting a strike is about $-3.8 \times 10^{-2}$, it did not seem a large effect.

Next, for comparison, we just compared the variation of run expectancy between inside attempts and outside ones (without IPW). Results show that that of an outside pitching attempt was $7.71 \times 10^{-3}$ runs/pitch smaller than that of an inside one. The results suggest that the outside pitching attempt was more effective than the inside pitching attempt compared with the analysis with IPW, which overestimated the value of outside pitching attempts.
Fig. 5: Contribution of the input variables to the propensity score model prediction. The variables related to the prediction are shown in the order of their contribution. Each dot (but merged) represents each event. The color represents the value of the feature (blue and red indicate low and high, respectively). The horizontal axis shows the impact on the prediction (strongly positive and negative impacts are plotted to the right and left, respectively).

4.4 Stratified analysis

Next, we show the treatment effect within the groups based on a) the magnitude of the estimated batter’s batting ability (wOBA in this case), b) that of the ratio of the inside pitch for the batter, c) that of the ratio of the inside pitch for the pitcher (Figure 6). Each data was divided into some groups based on the magnitude of each confounding variable. We eliminated the data with the confounding variable greater than the 10,000 samples. Each point represents a mean value, and the extended line represents a (99%) confidence interval computed using the bootstrap method. The result indicates that the pitching attempt to the outside is effective, regardless of the magnitude of each confounding variable.

For the wOBA levels in Fig. 6(a), comparing groups with wOBA less than 0.3 and 0.3 or more, the effectiveness of pitching to the outside decreased when wOBA was large. For the ratio of the inside pitch for the batter in Fig. 6(b), an outside pitch attempt was effective even against batters frequently pitched inside (0.4 or more), but these effects were smaller than the rest of the groups. For the ratio of the inside pitch for the pitcher in Fig. 6(c), an outside pitch attempt was also
Discussed the results of ATE, stratified analysis, propensity scores, and limitations and future perspectives of this study. As shown in Section 4.3, the pitching attempt to the outside was found to be more effective than to the inside when pitching the four-seam fastball. In NPB, the pitching strategy is based on pitching to the outside with an occasional mix of pitching to the inside, generally. An inside pitching attempt is considered risky and requires more courage to pitch compared to an outside one. This common belief is consistent with the results.
The results revealed that the total ATE of selecting outside pitch was about $6.29 \times 10^{-3}$ runs. We assume that every straight pitch has a right pitching strategy and the effect is about $6.29 \times 10^{-3}$ (i.e., a right pitching strategy reduces $6.29 \times 10^{-3}$ runs/pitch than the wrong one). Then, we also assume that 150 pitches are thrown in a game and 50% of that are four-seam fastball (75 four-seam fastballs are thrown in a game). Under these assumptions, the maximum contribution of saving runs by selecting an appropriate pitching course was estimated at 0.47 runs/game. Although the difference of pitching strategy among catchers needs to be considered, this implies that we can measure the effect of selecting pitch course to save runs (and type) may exist.

As shown in Section 4.4, the outside pitching attempt was found to be always more effective in each situation. For the estimated batting ability, it is known that a hard hitter is more frequently pitched inside (especially in NPB), which means they think an inside pitch attempt is effective against a good batter. For the wOBA levels in Fig. 6(a), the effectiveness of pitching to the outside decreased when wOBA was large. For the ratio of the inside pitch for the batter/pitcher in Figs. 6(b) and (c), an outside pitch attempt was effective even against batters and for pitchers frequently pitched inside, but these effects were smaller than the rest of the groups. Although the pitch attempt to the inside was less effective than the pitch attempt to the outside from the perspective of the outside pitch attempt, overall, the pitch to the outside was more effective than those to the inside. Considering the difficulty of controlling the location of the pitch, an inside pitching attempt might be overrated. The scene where an inside pitching attempt was effective might be limited than expected.

We also computed the contribution of each variable to the propensity score model prediction (whether the catcher demands an inside pitch or not). We clarified that the ratios of pitched inside for pitcher/batter were important, which seems to be obvious. On the other hand, we also clarified that some variables contributed to predicting the propensity score model unexpectedly. Previous pitch results one/two pitch ago were the third and fifth most important variables, respectively. For both of them, the high SHAP value was associated with a low value, which means they tend to try to pitch inside more frequently where they are in advantage. It might be also an important insight since there is no study about predicting the course of catcher’s demand ever.

If you are a baseball fan, you can easily understand that it is inappropriate to conclude that the pitcher should try to always pitch to the outside from these results. It is because the ratio of pitching inside and outside needs to be balanced to keep their effects. If all pitches were thrown to the outside, the batter could prepare for hitting the outside pitch (e.g., standing closer to home base and stepping outside). The batter only needs to focus on hitting the same course, improving the
reproducibility of the accurate swing to hit a ball. Thus, the effect of the scattering pitching course should be considered to obtain a more practical result.

From the perspective of causal inference, this study has mainly two limitations. First, there might be unmeasured confounders because we can measure and use a limited number of variables in baseball games. For example, batter’s intentions and pitcher/batter’s condition are possible unobserved confounders. Second, datasets of baseball games are longitudinal in each game and in all games for each team. Although we added the history of performances for batters and pitchers to the input features, we need to consider the models including time-varying confounders and treatment for future work.

In this study, we employed the IPW method that estimates ATE, adjusting the distribution, and comparing by groups. Estimating the effect by comparing groups, such as IPW, is a common and traditional idea in causal inference. On the other hand, various causal inference methods have been proposed, which can estimate Individual Treatment Effect (ITE) (e.g., Künzel et al. (2019)). These methods estimate the potential outcome, which is not observed in real, counterfactually. While the IPW method reduces a causal problem to predict the probability of allocated treatment for each data, the method estimating ITE reduces it to predict counterfactual pitching/batting results. It is equivalent to predicting results with game information. Predicting pitching/batting result is more difficult compared to predicting treatment probability. Although we did not employ a method for estimating ITE due to the difficulty in the prediction, we are sure that estimating ITE will extend or improve this study.

6 Conclusions

In this study, a causal inference method using the location of the catcher mitt right before pitching revealed that an outside pitching attempt is more effective than an inside pitching attempt. We also found that the outside pitching attempt was always effective despite the magnitude of the ratio of pitched inside for pitcher/batter. Besides, we revealed that the previous pitch result is also important to predict if the catcher demands an inside pitch.

For future perspectives, the application of this study is 1) evaluating the catcher’s selection of pitching strategy and 2) seeking a better pitching strategy. First, our approach can reveal where courses and which types to pitch is effective in each game situation. This enables us to evaluate each pitching strategy. If we can compute ITE in our problem, we can evaluate each catcher's selections of pitching strategy.
Second, estimating the effect of each pitch makes it possible to seek a better pitching strategy, if we can develop a pitching strategy model. Some Japanese companies are developing an automatic selecting pitching strategy system called “AI catcher”. Systems for predicting better strategy can entertain enthusiastic baseball fans as well as support decision-making.

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