**1. Introduction**

The game is golf is a test of a variety of skills – driving off the tee, approach shots from the fairway or rough, and putting to name a few. Precise estimation of the skill of the players in the various aspects of the game is useful for a variety of reasons. With accurate estimations of how players’ skill sets compare, players and coaches can create data-driven training plans and fans watching the game can gain a greater understanding of the strengths and weaknesses of their favorite players.

This paper improves what is currently being done to estimate the skill levels of the players on the PGA Tour. This work would not have been possible without detailed shot-level data that the PGA Tour started collecting in 2003 using their ShotLink™ system. The availability of these data has opened up the possibilities towards understanding the professional game in greater depth statistically. Up until detailed shot-level data was collected, it was impossible to quantify how the distinct skills determine golfers’ results.

This work also owes its foundation to the work done by Mark Broadie of Columbia University. His work in developing the Strokes Gained concept (explained in Section 2) has advanced everyone’s understanding of the game by being the first to really quantify individual skill sets of the players on the PGA Tour. His contributions and the work of others in this area are summarized in Section 2 of this paper.

Quantifying players’ skills is a pursuit of estimating latent variables. Competitive play is not setup in a way that makes this estimation simple. It is far from a scientific experiment where players are told to take multiple attempts from precise locations under controlled circumstances. In golf, players take around 72 shots per round but every shot is unique. A slight change of angle can make a shot entirely different. The quality of the lie can make two shots taken very close to one another very different. Weather conditions can vary from the morning to afternoon.

The challenges involved in this modeling problem will be detailed first. Then a novel approach will be given. This approach is then backed with evidence that demonstrates its success.

**2. Dataset**

As mentioned, the dataset was provided by the PGA Tour through their ShotLink Intelligence program. Volunteers equipped with special equipment collect the data. At the shot level, the data contain locations of all shots of the players on the PGA Tour since 2003. Data from the round level – number of strokes taken in a round – is also available and will be used in this paper. Data used begins at the start of the 2003 season and goes through the 2016 Tour Championship. Some summary statistics from the raw data are provided in Tables 1 and 2.

|  |  |
| --- | --- |
| **Turf** | **Percentage** |
| Green | 40.7% |
| Tee Box | 25.3% |
| Fairway | 16.6% |
| Primary Rough | 8.0% |
| Intermediate Rough | 2.4% |
| Green Side Bunker | 2.3% |
| Fringe | 1.8% |
| Unknown | 1.2% |
| Fairway Bunker | 1.2% |
| Native Area | 0.4% |
| Other | 0.2% |
| Water | <0.1% |
| Grass Bunker | <0.1% |

|  |  |
| --- | --- |
| **Query** | **Result** |
| Number of Shots | 16,469,637 |
| Number of Players | 2,054 |
| Number of Courses | 107 |
| Number of Tournaments | 561 |
| Number of Rounds | 2,244 |
| Number of Holes\* | 40,392 |

Table 1: Summary Statistics. \*Number of Holes here

means number of unique hole-day combinations.

Table 2: Percentage of shots from different turf in raw data.

*2.1 Preprocessing Steps*

Like with any data collected by humans, there were plenty of anomalies present in the data. There were many player-holes in the data for which there were more shots recorded than the score of the player on the hole. These extra shots resulted from errors in the recording of the data. In order to maintain the integrity of the data, all player-holes for which the number of shots in the data did not match the recorded score of the player on the hole were dropped.

Additionally, neither the coordinates of the tee box nor of the hole were present in the data. However, distance from the hole and distance that the ball travels is present in the data. Thus, the coordinates of the hole and the tee box could be imputed from the data. Lastly, any player-hole for which there was any shot for which the distance traveled was not in reasonable agreement with the coordinates recorded was dropped. Dropping the entire player-hole when there was an anomaly made the downstream analysis much easier. These cleaning steps reduced the size of the data by about 15% leaving just over 14 million anomaly-free shots. All code to reproduce this cleaning procedure is available.[[1]](#footnote--1)

**3. Strokes Gained**

Before the detailed shot-level data and the Strokes Gained concept, statistics used to quantify specific skills in golf included Driving Distance, Fairways Hit, and Greens In Regulation (GIR) to name a few. To illustrate the ambiguity that results from these statistics, take GIR as an example. GIR is the count of the number of holes on which a golfer reaches the green in two strokes less than the par value of the hole or fewer. GIR attempts to quantify a golfer’s skill with his or her approach shots. However, if two players start from the same position in the fairway and one hits it on the green 80 feet away and the other hits it to the fringe 18 feet away, the player who hit it on the green will be credited with a GIR while the other player will not, despite having left his ball in (arguably) a less desirable position.

This example illustrates the need to quantify the “desirability” of a particular location on a particular course on a particular day, or equivalently the difficulty of playing a shot from a particular location. It also motivates quantifying the quality of a particular shot by taking the difficulty of the starting location and subtracting the difficulty of the finishing location. This is the idea developed by Mark Broadie and is named the Strokes Gained Statistic.

To continue with the previous example, if the two golfers started from the fairway where it takes an average golfer 3.3 strokes (which tends to correspond to about 225 yards on tour), and we know how difficult it is for the average golfer from the locations where the two golfers’ balls ended up, we can quantify the quality of both players’ shots. From 80 feet on the green the average PGA Tour golfer takes about 2.3 strokes to get the ball in the hole on average, while from 18 feet away on the fringe the average tour player takes about 1.9 strokes to get it in on average. Following the convention established in Broadie (2008), the Strokes Gained Statistic is then calculated using the following equation:

.

To conclude the example, the player whose ball ended up on the green had a shot quality of 0 (3.3 – 2.3 – 1), while the player whose ball ended up on the fringe had a shot quality of 0.4 (3.3 – 1.9 – 1). A positive shot quality corresponds with a shot that was better than the average player would have done and a negative shot quality corresponds with a shot that was worse than the average player would have done.

*3.1 Assumptions of Strokes Gained System*

Before continuing towards making a model of how difficult a given shot is, it is useful to think about the assumptions of the Strokes Gained framework. The first assumption is that we can estimate with reasonable accuracy how difficult a shot is. This is actually quite a challenge and there are potential pitfalls in doing this, which will be discussed shortly.

The second assumption is more fundamental. What does it mean to quantify the difficulty of a given shot? In Broadie (2008) this is defined as the average number of strokes taken from a given location by an average player. There is a subtle assumption in this method – that the desirability of a given location is the same for all players. This is generally a safe assumption because it’s mostly true; the desirability of different locations is very similar for all players. However, it’s useful to acknowledge that this method is a simplification of how the game is actually played. A consequence of this simplification is that the possibility that a player acts strategically is ignored. For example, a player could be faced with an option to lay-up on a par five, or try to hit it on the green, which is surrounded by bunkers. If this player is an excellent bunker player, this will certainly factor into his decision about whether or not to go for it. However, post-hoc evaluation of the quality of this players’ shot will take into account the desirability of the location he ends up in as measured by the theoretical performance of an average golfer from that location and thus will not correctly account for the strategic thinking that was involved in playing the shot.

This work will focus on coming to terms with the first assumption. The second assumption is more complex and will be left for another contributor.

**4. Modeling Difficulty of a Shot**

Modeling the difficulty of a shot is challenging for a few reasons. The first of which is that the difficulty of a shot can vary with conditions that can be very specific to the situation: the hole setup, the weather, the lie, and the angle of approach. These data do not contain direct information about the location of the hole relative to the edge of the green (hole setup), the weather, or the lie. The extent to which these factors have an effect on the difficulty of a shot must be inferred from the data.

Additionally, when fitting a model that contains information that distinguishes between different courses, there is a potential for erroneous interpretation of the results because the players who played on one course might be of a higher caliber than the players who played on another course. This has been pointed out in Fearing et al. (2010).

Similarly, attempts to use spatial clustering or nearest-neighbor type algorithms runs into a subtle bias – players who end up playing a shot close to one another might have general skill levels that are correlated with one another. For example, a favorable location to play from – an area containing approach shots following well-placed drives, for example – might attract the balls of players who are already playing well and thus be more likely to succeed on the following shot.

For these reasons, producing unbiased measurements of difficulty of a shot is very challenging. In the rest of this section, previous attempts at this task will be outlined. Then, a new model with a subtle change in intention will be presented. This model will sacrifice unbiased measurements of difficulty of any single shot in favor of fairly estimating the skill of the golfers *relative* to one another in the network of all PGA Tour players.

*4.1 Previous models for difficulty of a shot*

Broadie (2011) models difficulty of a shot separately for 5 categories of shots – tee, fairway, green, sand, and rough. Distance is used as the primary predictor of difficulty and piecewise polynomials are fit to model the relationship between distance and difficulty for all shots except putts. For putts, a physical model of probability of one-putting combined with a physical model of probability of three-putting is used.

Neither elevation change nor angle of approach was considered as predictors. Broadie (2011) did infer from the data ‘recovery shots’ which imply that there was extra difficulty associated with the shot and fit a separate model for such shots.

In Broadie (2011), a model for distinguishing between course-round difficulty and player skill was done at a global level – estimating total strokes gained without allowing for the possibility that particular types of shots might be more or less difficult at certain courses or certain players more or less competent at certain types of shots. In this model, players’ skills were assumed to be static, not changing through time. According to comments made by the author subsequently, strokes gained statistics currently used on tour are adjusted by the average strokes gained performance of the field for each category of shot for each round to produce *Strokes Gained to the Field*. The problem with this is that it neglects the possibility of the quality of field varying at different tournaments.

Fearing, Acimovic, and Graves (2010) model difficulty of putts using generalize linear models for probability of holing out and distance to go. The challenge of estimating the intertwined quality of field and course difficulty was acknowledged and a model was fit with player and hole-specific effects. The authors’ approach allows for situational putting performance predictions. This approach is admirable, however, similarly to Broadie (2011), it assumes players’ skills are static, not changing through time. The authors focused mostly on putting; they fit a similar model for off-green performance but do not distinguish between different potential off-green skills (short-game versus long-game for example).

Söckl et al. (2011) introduces the ISOPAR method. This involves interpolating a smoothing spline to infer difficulty of a shot based on the observations on a particular hole during a particular round. Unfortunately, in using these values to measure performance, the authors do not recognize either of the biases involved with this approach that were discussed above – the varying quality of a field and the bias for desirable locations to more frequently contain the shots of more capable players.

Finally, Yousefi and Swartz (2012) take a Bayesian approach to estimating the difficulty of putts by allowing the possibility for difficulty to vary from different portions of the green, which they divide into eight quadrants. This approach is similar to Söckl et al. in that it ignores the aforementioned biases – there is no mention of varying quality of the field, nor any mention of the possibility that the observations in a particular quadrant might be biased according to the general ability of the players whose balls end up there.

1. https://github.com/adamwlev/Rank\_a\_Golfer [↑](#footnote-ref--1)