Quantifying Risk and Reward in Golf: A Probabilistic Framework for Shot Decisions

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1 Introduction

Can you predict where golf shots will land? Can those predictions be applied to optimize shot strategy and improve outcomes? Can this be achieved with limited sample data from golf simulators? With factors like lie, wind, elevation, and other course hazards to take into consideration, professional golf players have developed a finely-tuned intuition in their club choices and aim lines. However, this intuition can still be wrong and a single misjudgment can be the deciding factor in winning a tournament. By reframing golf as a problem of statistical inference, we introduce a method that quantifies risk and reward to recommend the mathematically optimal shot for a player.

2 Methods

Individual shot recommendations begin by obtaining a shot dispersion, with at least 10 shots per club from a golf simulator, which serve as the basis for a bivariate Gaussian $D(x, y|\,\vec{\mu}, \Sigma)$. The dispersion model is projected onto a real course, with respect to the players' position, and overlaps course elements such as the Green, Fairway, Bunkers, Rough, and Water. For the i-th element of course, C_i, we calculate the probability that a shot, represented by a random variable $X = (X, Y)$, will land within any of the course elements by computing $P_i\big((X, Y) \in C_i\big) = \iint_S D(x, y \mid \mu, \Sigma)\, dx\, dy$. Each club's dispersion model is rotated incrementally, relative to the player's aim line, and P_i is evaluated at every step to find the optimal club and aim line. The optimal club and aim line is then taken as the shot recommendation, an example is illustrated in Figure 1.

We evaluate two scenarios modeling the shot dispersions of four high-skill players. In Scenario 1, individualized recommendations are tested against player intuition to evaluate shot outcome differences in single shot decisions. Three players take curated tee and approach shots on a real course. Each player takes a shot with their own club and aim line choice and then repeats the shot using the club and aim line recommendation. Shot quality is assessed and compared with strokes gained (SG). In Scenario 2, the fourth player plays entire holes with and without recommendations to evaluate the end-to-end latent decision making process.

Figure 1: Example shot recommendation that suggests an aim line compensating for an expected hook. The blue ellipses represent the 1σ and 2σ bands of the dispersion. The blue dot is the shot outcome.

3 Results

The results are shown in Table 3. Scenario 1 showed that our decision-making heuristic benefits two out of three players. Player 1 performed slightly worse by losing 0.02 strokes on average with recommendations. Player 2 gained 0.2 strokes on average with recommendations. Player 3 had significant improvements on all shots with recommendations. For all players, the reduction in error suggests that the recommendation also produces more consistent shots. Player 4 demonstrated that the recommendations provided an improvement with a cumulative strokes gain difference of 0.3.

4 Conclusion

Our recommendation algorithm, from model calculation to hole playthrough, has shown to benefit player decision making. Without methods reliant on sizable statistics, we have presented a personalized decision making strategy that takes the guesswork out of golf and leads to performance gains in real-world settings.

Curated Shots						
	No Recommendation			Recommendation		
Tee Shots	N Shots	$\sum$ SG	$\overline{\text{SG}} \pm$ SE	$\sum$ SG	$\overline{\text{SG}} \pm$ SE	$\Delta\overline{SG}$
Player 1	5	-0.04	-0.01 ± 0.09	-0.1	-0.02 ± 0.06	-0.01
Player 2	5	-1.74	-0.4 ± 0.2	0.54	0.01 ± 0.05	0.41
Player 3	3	-1.56	-0.5 ± 0.2	0.34	0.11 ± 0.05	0.63
Approach Shots						
Player 1	6	-1.01	-0.2 ± 0.1	-1.24	-0.2 ± 0.1	0.0
Player 2	5	-0.21	-0.04 ± 0.1	-0.43	-0.09 ± 0.07	-0.05
Player 3	4	-0.71	-0.2 ± 0.2	0.47	-0.12 ± 0.07	0.08
Combined Shots						
Player 1	11	-1.05	-0.1 ± 0.1	-1.34	-0.12 ± 0.08	-0.02
Player 2	10	-1.95	-0.2 ± 0.1	0.11	0.01 ± 0.05	0.2
Player 3	7	-2.27	-0.3 ± 0.1	0.81	0.12 ± 0.04	0.42
Continuous Shots						
Player 4	-	-0.1	-0.01 ± 0.05	0.1	0.01 ± 0.04	0.03