Evolving a Smarter Football Strategy

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Abstract

In this paper, I present a genetic algorithm (and an accompanying open source application, *Football-o-Genetics*) for discovering near-optimal offensive play calling strategies in American football. By "mating" individuals (representing various play calling strategies) with a frequency proportional to their relative fitness, near-optimal play calling strategies can be evolved. An individual's fitness corresponds to the percentage of Markov chain simulations of an offensive drive that result in a touchdown. I tested the algorithm on each of the 32 NFL teams from the 2012 season, and, in each case, the evolved play calling strategies outperformed the observed play calling strategies in touchdown production. The genetic algorithm also produces several metrics that can be used for assessing the quality of individual coaches and players. The results presented in this paper suggest genetic algorithms (and other machine learning techniques) can be useful tools for investigating sporting strategy.

1 Introduction

In American football, the offense scores points by either ***(A)*** advancing the ball (i.e., "driving") across the opposing team's goal line (i.e., "scoring a touchdown") or ***(B)*** kicking the ball through the opposing team's field goal posts. When a drive begins, the offense is given four opportunities (i.e., "downs") to advance the ball a distance of ten or more yards from its starting position. If the offense is successful in gaining ten or more yards, it is awarded a new set of downs, and the distance is reset to ten yards. On each down, the offense attempts to advance the ball by executing a "play", which is an orchestrated series of movements involving the 11 team members.

Due to the discrete down structure of football, a fair amount of strategy can go into choosing each play. To illustrate this point, imagine the following scenario: an offense has the ball at its own 38 yard line in the third quarter; it is second down with six yards to go and the score is 13-17. Pass plays generally have a greater payoff than rush plays (Alamar, 2006; Alamar, 2010), which suggests a pass might be the offense's best choice in this scenario; however, an incompletion would result in third down with six yards to go, which is fairly difficult to convert. Further, let us assume the offense has a running back who reliably gains two to four yards on each carry. In that case, a rush play might make the most sense, as it increases the likelihood of a more manageable third down and short situation (see McGough et al., 2010 for a discussion on the effects of personnel variability in football strategy). But now imagine that the opposing defensive coordinator has picked up on the offense's tendency to run on second down and, as a result, he has started calling blitzes with greater frequency (see Jordan et al., 2009 for a discussion on the effects of defensive strategy). In response to the defense's change in strategy, the offense might decide that a pass play is, in fact, its best option in this scenario.

As the previous thought experiment (hopefully) demonstrates, a fairly large number of factors can go into choosing each play, including: down, distance, field position, score, time remaining, personnel, and defensive strategy. In reality, play calling is even more nuanced than what has been presented here (the offensive playbooks of most NFL teams have hundreds of plays; not two), which can make choosing the best play for a given situation even more difficult. In fact, the best offenses in the National Football League (NFL) only score touchdowns on approximately 30% of their drives (Football Outsiders, 2013), which is a testament to the difficulty surrounding offensive strategy. Because a football team's chances of winning are at least partially dependent on its ability to produce points, a tool capable of predicting optimal play calls for various game situations could have a pronounced impact on that team's future success.

At its essence, football play calling strategy is analogous to a “state space search problem” (a common abstraction used in artificial intelligence research for addressing optimization tasks), with each state representing a unique combination of various game factors (down, distance, etc.). By analyzing past data, the “quality” of a particular play for a given game situation can be estimated. “Quality”, in this case, could be the expected number of yards gained on the play, or the expected number of points resulting from the drive. Once a quality metric has been defined, and the goal established (e.g., maximizing the expected number of yards gained, or maximizing the expected number of points scored), an appropriate search algorithm can be developed. Genetic algorithms, which explore multidimensional “fitness landscapes” by mimicking the process of evolution by natural selection, can take an arbitrary number of input parameters to model complex decision making processes. As a result, genetic algorithms represent ideal tools for investigating optimal play calling strategies in American football.

In this paper, I present a genetic algorithm for predicting near-optimal offensive play calling strategy in American football. The algorithm considers down, distance, and roster, but can be easily expanded to include an arbitrary number of parameters. In section 2, I briefly summarize the methods for data collection; in section 3, I describe the genetic algorithm and the fitness heuristic used to evolve near-optimal play calling strategies; in section 4, I discuss the accuracy of the fitness heuristic; in section 5, I discuss the results of the study in the context of real NFL situations; in section 6, I describe how the model could be adapted for defensive strategy; and in section 7, I discuss other potential applications of machine learning techniques in sporting strategy.

2 Data Collection

Play-by-play descriptions for all games from the 2012 NFL season were acquired from AdvancedNFLStats.com. The offensive team, defensive team, quarter, down, distance, field position, play (i.e., “Pass” or “Rush”), player who executed the play, and yards gained on the play were recorded from each play-by-play description. An individual player's turnover rate was calculated by dividing the player's number of turnovers (interceptions in the case of quarterbacks, fumbles in the case of running backs) by the player's number of play attempts (passes in the case of quarterbacks, rushes in the case of running backs).

3 Model

3.1 Genetic Algorithm

A population of N individuals, each with g randomly initialized genes (the number of genes used in the simulation depends on the number of *a priori* assumptions) was used to evolve a team's optimal offensive play calling strategy. Each gene represented either the probability of a rush in various down and distance situations, or the probability of a particular player executing the play, given the down, distance, and play (see Table 1 for a detailed description of the individual genes). Each individual's fitness was calculated by simulating D offensive drives while using the individual's genes as parameters (described in detail below). Individuals were then randomly selected to reproduce with a frequency proportional to their relative fitness (R_i):

$$R_i = \frac{F_i}{\sum_{j=1}^{N} F_j} \tag{1}$$

where F_i represents the fitness of individual i. Genetic material was exchanged between mating individuals at a single, randomly selected crossover point (Figure 1). Finally, a single gene was mutated with probability m in each offspring (Figure 1). The process was then repeated on the new population of N children for G generations.

3.2 Fitness

An individual's fitness (F_i) was defined as the percentage of simulated drives (D) that resulted in a touchdown.

$$F_i = \frac{T_i}{D} \times 100 \tag{2}$$

Each drive simulation began at the 27 yard line (the average starting field position for NFL teams in 2010; ESPN, 2012) and was conducted using a Markov chain model (see Goldner, 2012 and Cafarelli et al., 2012 for other examples of Markov chains modeling football). For second down and third down situations, a rush play was selected with probability

$$p\left(Rush \mid Down, Distance\right) \tag{3}$$

, while a pass play was selected with probability

$$1 - p\left(Rush \mid Down, Distance\right) \tag{4}$$

Although *Distance* can theoretically range anywhere from one to 99 yards, only three *Distance* categories were used in the fitness calculation: “Short”, “Medium”, and “Long”. “Short” represented situations with two or fewer yards to go, while “Medium” represented situations with three to six yards to go and “Long” represented situations with seven or more yards to go. Distance was ignored when choosing a play on first down because first downs are overwhelmingly associated with a distance of 10 yards.

Once a play was chosen, Player A was randomly selected to execute the play with probability

$$p\left(PlayerA \mid Down, Distance, Play\right) \tag{5}$$

while Player B was randomly selected to execute the play with probability

$$1 - p\left(PlayerA \mid Down, Distance, Play\right) \tag{6}$$

Following player selection, a turnover was randomly generated with probability

$$p\left(Interception \mid Player\right) \tag{7}$$

in the case of a pass or

$$p(Fumble|Player) \tag{8}$$

in the case of a rush. If the play resulted in a turnover, the drive was concluded and a new drive would begin. Otherwise, the yards gained on the play were selected with probability

$$p(Yards|Down, Distance, Play, Player) \tag{9}$$

The down, distance, and field position were updated according to the rules of football. If a team scored a touchdown or reached fourth down, the drive was concluded. A tally of drives resulting in touchdowns (T_i) was kept during each individual's fitness simulation.

3.3 Additional Terms

Predicted touchdown percentage (*PTP*) refers to the fitness (F_i) of a specific team's observed play calling strategy. Observed touchdown percentage (*OTP*) refers to the observed percentage of drives resulting in a touchdown for a specific team, while evolved touchdown percentage (*ETP*) refers to the percentage of drives resulting in a touchdown for a specific team when using an evolved play calling strategy. *ETP*, by representing the near maximal offensive production for a given roster, can be considered an approximate measure of a team's offensive talent. Therefore, a team's ability to maximize (*ATM*) its offensive talent can be defined as:

$$ATM = \frac{OTP}{ETP} \times 100 \quad . \tag{10}$$

4 Accuracy of the Fitness Heuristic

Genetic algorithms require an accurate fitness heuristic to evolve near-optimal solutions. To test the accuracy of my model's fitness heuristic, I compared the observed touchdown percentage (*OTP*) and the predicted touchdown percentage (*PTP*) of each NFL team (Table 2). The average absolute difference between *OTP* and *PTP* was 3.0 (σ = 2.2), which suggests the heuristic was reasonably accurate. The absolute difference between a team's *OTP* and its *PTP* was not correlated with the team's *OTP* (R^2 = 0.128; Table 2); that is to say, the quality of a team's offense did not affect the accuracy of the fitness heuristic.

5 Results and Discussion

5.1 Trends

There was surprisingly little variability in the offensive play calling strategies of NFL teams during the 2012 season. On average (Table 3), NFL teams (Appendix A) passed with a relative frequency of 0.481 on first down (σ = 0.0543), 0.338 on second down and short (σ = 0.136), 0.496 on second down and medium (σ = 0.0785), 0.657 on second down and long (σ = 0.0752), 0.454 on third down and short (σ = 0.111), 0.890 on third down and medium (σ = 0.0553), and 0.894 on third down and long (σ = 0.0575). In each team's case, the evolved touchdown percentage (*ETP*) was greater than the observed touchdown percentage (*OTP*; Table 4). On average (Table 3), the relative passing frequencies of the evolved play calling strategies (Appendix B) were significantly higher than the observed rates on first down ($p < 0.0001$; $\bar{x}$ = 0.852; σ = 0.298), second down and short (p = 0.0027; $\bar{x}$ = 0.517; σ = 0.331), and second down and long ($p < 0.0001$; $\bar{x}$ = 0.904; σ = 0.205), but were significantly lower than the observed relative passing frequencies on third down and short ($p < 0.0001$; $\bar{x}$ = 0.212; σ = 0.265) and third down and medium (p = 0.0008; $\bar{x}$ = 0.705; σ = 0.313).

Previous research has suggested NFL teams are overly risk-averse with regards to their passing strategy (Alamar, 2006; 2006; Alamar, 2010; see also Romer, 2006 for other risk-adverse tendencies of NFL teams); however, the evolved play calling strategies suggest this is only true for certain down and distance situations (e.g., first down). For other down and distance situations (e.g., third down and short or third down and medium), the evolved play calling strategies suggest NFL teams are unnecessarily risk-*prone* with regards to their passing strategy. This overemphasis on the pass in certain situations may indicate a tendency of NFL coaches to overestimate the defense's ability to stop the run in situations where the defense is expecting the run. Alternatively, NFL coaches may be overestimating the expected payoff from catching the defense off guard. That is to say, coaches may hold the false belief that a successful pass in a situation where the defense is expecting the run has a higher probability of resulting in a touchdown than is actually the case.

5.2 Assessing the Quality of Coaches and Players

In the NFL, poor coaching hires/fires and/or bad trades can end up costing a franchise millions of dollars and/or diminishing a team's ability to succeed on the field. As a result, the ability to accurately identify and address the cause of a team's shortcomings (whether they be coaching or roster related) is a valuable asset for NFL front office administrators. Ability to maximize (*ATM*) and evolved touchdown percentage (*ETP*) may provide some quantifiable justification for these types of personnel decisions (see section 3.3 for a detailed description of these terms). Both *ATM* and *ETP* are positively correlated (Figure 2 and Figure 3, respectively) with observed touchdown percentage (*OTP*), which (unsurprisingly) suggests both play calling strategy (as represented by *ATM*) and roster talent (as represented by *ETP*) are important factors for predicting a team's offensive success. Further, *ATM* and *ETP* are not correlated (Figure 4), which suggests a coach's ability to develop an effective play calling strategy is independent of the level of talent on his team's roster.

At the end of the 2012 NFL season, the Chicago Bears fired their head coach, Lovie Smith. Do the *ATM*, *ETP*, and *OTP* metrics justify the Bears' decision? In 2012, the Bears had an *OTP* of 17.0 (ranked 22nd out of the 32 NFL teams) and an *ATM* of 72.3 (ranked 7th out of the 32 NFL teams). The Bears' relatively high *ATM* suggests they were fairly effective at calling plays that maximized their team's offensive production; however, their relatively low *ETP* suggests they lacked the offensive talent necessary to be an offensive powerhouse. Based on this evidence, the Bears' decision to fire head coach Lovie Smith at the end of the 2012 season may have been ill-advised.

Throughout his career, Tony Romo (quarterback for the Dallas Cowboys during the 2012 season) has been the center of debates concerning his status as an “elite” quarterback (see Judge, 2012). Can *ATM*, *ETP*, and *OTP* contribute to the debate? The evolved play calling strategies for the 2012 Cowboys passed with a higher relative passing frequency than the observed value on first down and second down and long and passed with a lower relative passing frequency on third down and short (Table 5). Together, these data suggest the Cowboys would have benefited from relying more on their passing game in 2012. Additionally, the 2012 Cowboys had an *OTP* of 21.5 (11^{th} out of the 32 NFL teams) and an *ETP* of 37.2 (7^{th} out of the 32 NFL teams), which suggests the Cowboys' offensive roster was relatively high in talent. However, the Cowboys had one of the worst running attacks in the NFL in 2012 (ranking 29^{th} out of the 32 NFL teams in yards per rushing attempt), which suggests the majority of the Cowboys offensive talent was concentrated in players related to the passing game.

The quarterbacks for the six teams with a higher *ETP* than the Dallas Cowboys in 2012 were Peyton Manning (Denver Broncos), Colin Kaepernick (San Francisco 49ers), Tom Brady (New England Patriots), Robert Griffin III (Washington Redskins), Drew Brees (New Orleans Saints), and Matt Ryan (Atlanta Falcons). Manning, Brady, and Brees are likely future Hall of Famers and are generally agreed to be “elite” quarterbacks. Kaepernick and Griffin were both extremely productive in their first years as quarterbacks in the NFL, and they may very well end up being considered “elite” in time; however, the small sample size of their successes, combined with the tendency for mobile quarterbacks to suffer injuries (see Steve Young and Michael Vick), encourages restraint.

Intriguingly, Ryan, the last quarterback on the list ahead of Romo, has also been the subject of debates over his status as an “elite” quarterback (see Yasinskas, 2013). Unlike Kaepernick and Griffin, Ryan, like Romo, did not have talented running backs (such as Frank Gore of the 49ers or Alfred Morris of the Redskins) to aid him during the 2012 season (the Falcons ranked 30^{th} out of the 32 NFL teams in yards per rushing attempt). All together, the metrics derived from the genetic algorithm suggest that Romo, if not already an “elite” quarterback, is on the cusp of “elite-ness” and should be considered a highly valuable player at his position.

5.3 Depth Chart Adjustments

One of the primary responsibilities of NFL coaches is to identify players at each position who will maximize their teams' probability of success. The evolved play calling strategies presented in this paper may provide some quantifiable justification for such depth chart decisions. As an example, consider the 2012 San Francisco 49ers. The 49ers began their 2012 season with Alex Smith as their starting quarterback. During a game against the St. Louis Rams, Smith suffered a concussion and was unable to play for several weeks. While Smith was rehabilitating, second-year quarterback Colin Kaepernick assumed the starting role for the 49ers. Once Smith recovered from his injury, Jim Harbaugh (head coach of the 49ers in 2012) made the decision to continue with Kaepernick as the starting quarterback. At the time, Harbaugh's decision to start the youthful Kaepernick over the now-healthy Smith was considered fairly controversial by the media (see CBS News, 2012); however, the evolved play calling strategies for the 2012 San Francisco 49ers show a strong preference for Kaepernick at quarterback (Table 6), which provides some quantifiable justification for Harbaugh's decision.

5.4 Passing vs. Rushing

Previous research has suggested NFL teams could increase their offensive productivity by passing more (Alamar, 2006; Alamar, 2010), and several of the evolved play calling strategies presented in this paper support that claim; however, some NFL teams have considerably more talent at the running back position than they do at the quarterback position, which suggests passing with a higher frequency may not be a universally beneficial tactic. The Minnesota Vikings, who had one of the best rushing attacks in the NFL in 2012 (thanks to their MVP-winning running back, Adrian Peterson) and one of the worst passing attacks in the NFL (ranked 31st out of 32 teams in total passing yards), are an ideal candidate for determining whether a pass-heavy strategy is always the most effective strategy for NFL teams. In general, the evolved play calling strategies for the Vikings had a higher relative rush frequency than the observed value on first down, second down and short, second down and medium, third down and short, and third down and medium, but a lower relative rush frequency than the observed value on second down and long and third down and long (Table 7). The Vikings' preference for rushing over passing in the evolved play calling strategies suggests passing may not be the panacea for offensive production that has been previously suggested.

6 Defensive Strategy

While offensive plays can be classified as either “rushes” or “passes”, defensive plays lack a similar simple classification scheme. Both offensive and defensive plays consist of eleven individuals simultaneously carrying out eleven different (fairly complex) actions (e.g., at the snap, the right guard briefly fakes a pass block before pulling to the opposite side of the field to block the outside linebacker). In the case of offensive plays, the categorizations of “pass” and “rush” manage to retain much of the “information” contained within the original play while drastically reducing the complexity of the description (e.g., during a pass play, the linemen typically pass block, the receivers typically run routes, and the quarterback typically throws the ball). A similar classification system for defensive plays would likely need to incorporate both the coverage scheme (e.g., zone or man-to-man) and the number of rushers to accurately represent the dynamics of the play. Deducing the coverage scheme and the number of rushers from film (which is not publicly available, unlike offensive play-by-play descriptions) would likely be error-prone due to the defensive players reacting and adapting to the offense during the play; however, if a researcher had access to the defensive play calls for a particular team, the genetic algorithm could be easily adapted to discover near-optimal defensive play calling strategies. In the model, the defensive play would be selected with probability

$$p\left(DefensivePlay \mid Down, Distance\right) \tag{11}$$

, where *Defensive Play* incorporates both the coverage scheme and the number of rushers. The yards gained on the play by the offense would be selected with probability

$$p(Yards \mid Down, Distance, DefensivePlay) \tag{12}$$

Because the goal of a defense is to minimize the opposing offense's scoring, the fitness of an individual defensive strategy (F_d) would be calculated by taking the the reciprocal of the offense's fitness (F_i)

$$F_d = \frac{1}{F_i} \tag{13}$$

NFL teams are (understandably) hesitant to divulge their play calling strategies, so an alternative classification scheme for defensive strategy would be necessary to enable research on the topic. One possible solution is to classify defensive plays based on their formations (e.g., 4-3 or 3-4) as proposed by Jordan et al. (2009); however, the coverage scheme and the number of rushers on a defensive play cannot be deduced from defensive formation alone (e.g., a defense in the 4-3 formation could potentially blitz both outside linebackers or, alternatively, drop both outside linebackers and one defensive end into zone coverage, thereby resulting in two plays that are, strategically, quite different), which calls into question the usefulness of this method.

7 Machine Learning in Other Sports

Machine learning techniques have been used to predict the outcomes of sporting contests (Joseph et al., 2006) and to identify sports from audio-visual data (Zhong and Chang, 2004; Sadlier and O'Connor, 2005), but, before this paper, had not been applied to sporting strategy. To enable further research in the field, I have developed an open source application, *Football-o-Genetics* (Alcorn, 2013), which provides an easy-to-use interface for evolving football play calling strategies. By incorporating additional parameters into the model, such as opposing defenses' strategies, time remaining, and/or score differential (see Jordan et al., 2009), the model's accuracy will likely improve. Genetic algorithms (and other machine learning techniques) would likely be effective tools for identifying near-optimal strategies in other sports as well. For example, a coach in the National Basketball Association (NBA) might wish to determine the best lineup for defending the Miami Heat, or a Major League Baseball (MLB) manager might wish to identify the best batting lineup for competing against a curveball specialist. Additionally, machine learning techniques could be used to predict the future success of draft prospects, which would eliminate much of the uncertainty that is currently present in the draft process.

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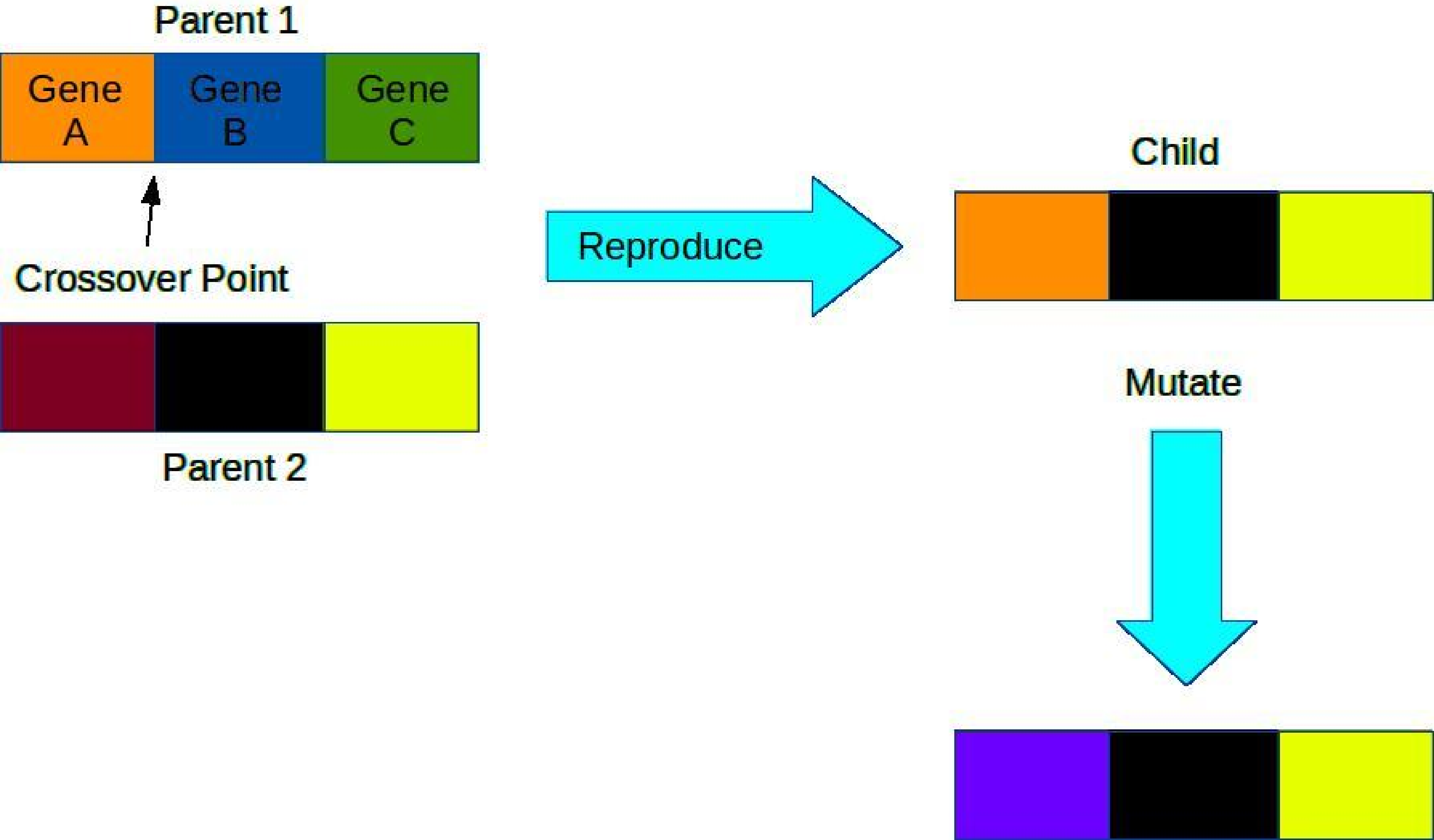
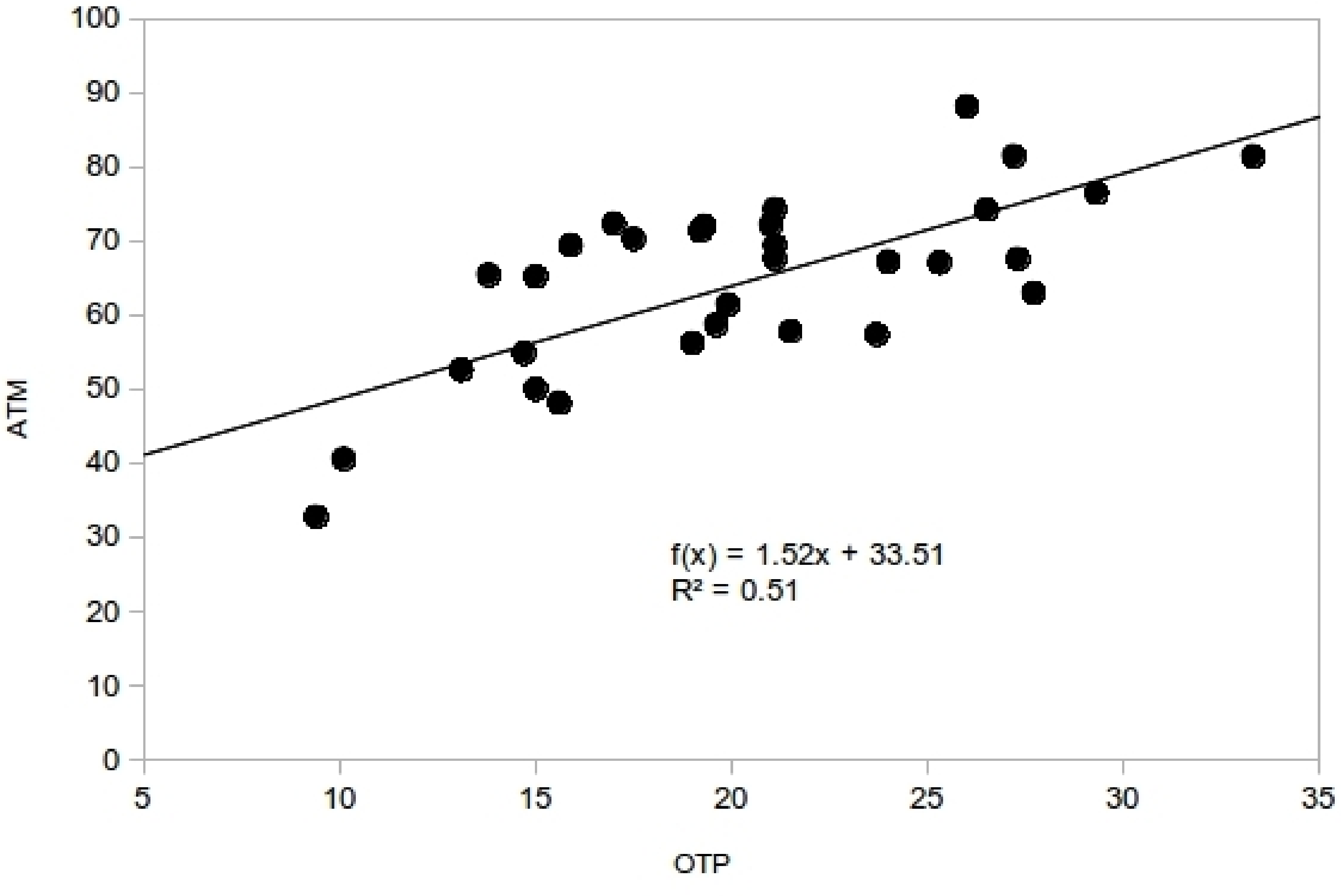
Figure 1: A pictorial representation of reproduction as it occurs within the genetic algorithm. Two individuals (Parent 1 and Parent 2) are randomly selected to mate with a frequency proportional to their relative fitness R_i. The two parents then exchange genetic material at a randomly selected crossover point, which results in a child. Finally, a single, randomly selected gene in the child is mutated with probability m.

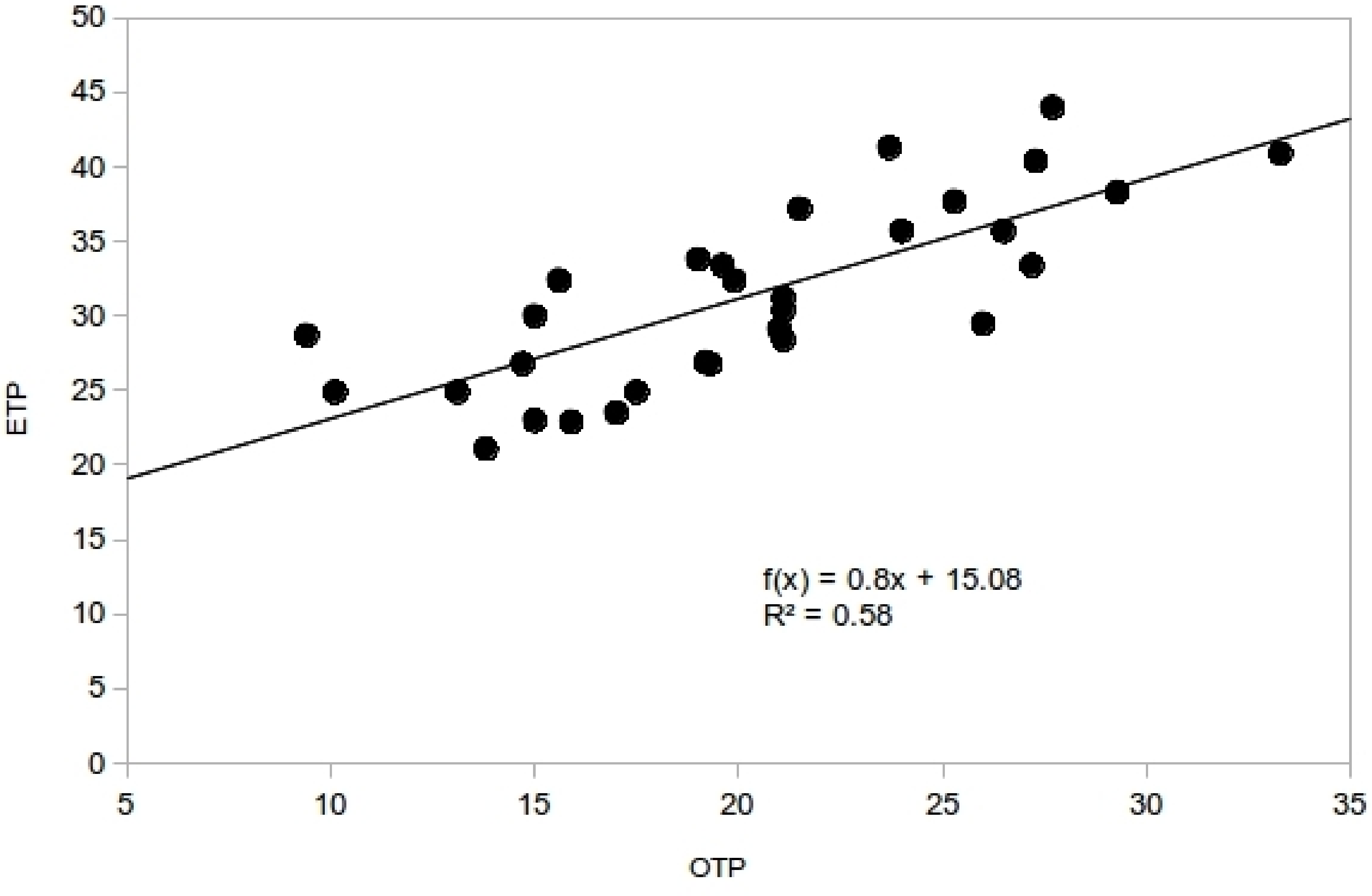
Figure 2: A scatter plot showing the relationship between a team's ability to maximize (*ATM*) and its observed touchdown percentage (*OTP*) (D = 1000; N = 1000; G = 100; m = 0.01).

Figure 3: A scatter plot showing the relationship between a team's evolved touchdown percentage (*ETP*) and its observed touchdown percentage (*OTP*) (D = 1000; N = 1000; G = 100; m = 0.01).

Figure 4: A scatter plot showing the relationship between a team's ability to maximize (*ATM*) and its evolved touchdown percentage (*ETP*) (D = 1000; N = 1000; G = 100; m = 0.01).


Parent 1
Gene A
Gene B
Gene C
Crossover Point
Parent 2
Reproduce
Child
Mutate


100
90
80
70
60
50
40
30
20
10
0
ATM
5
10
15
20
25
30
35
OTP
f(x) = 1.52x + 33.51
R² = 0.51



50
45
40
35
30
25
20
15
10
5
0
ETP
5
10
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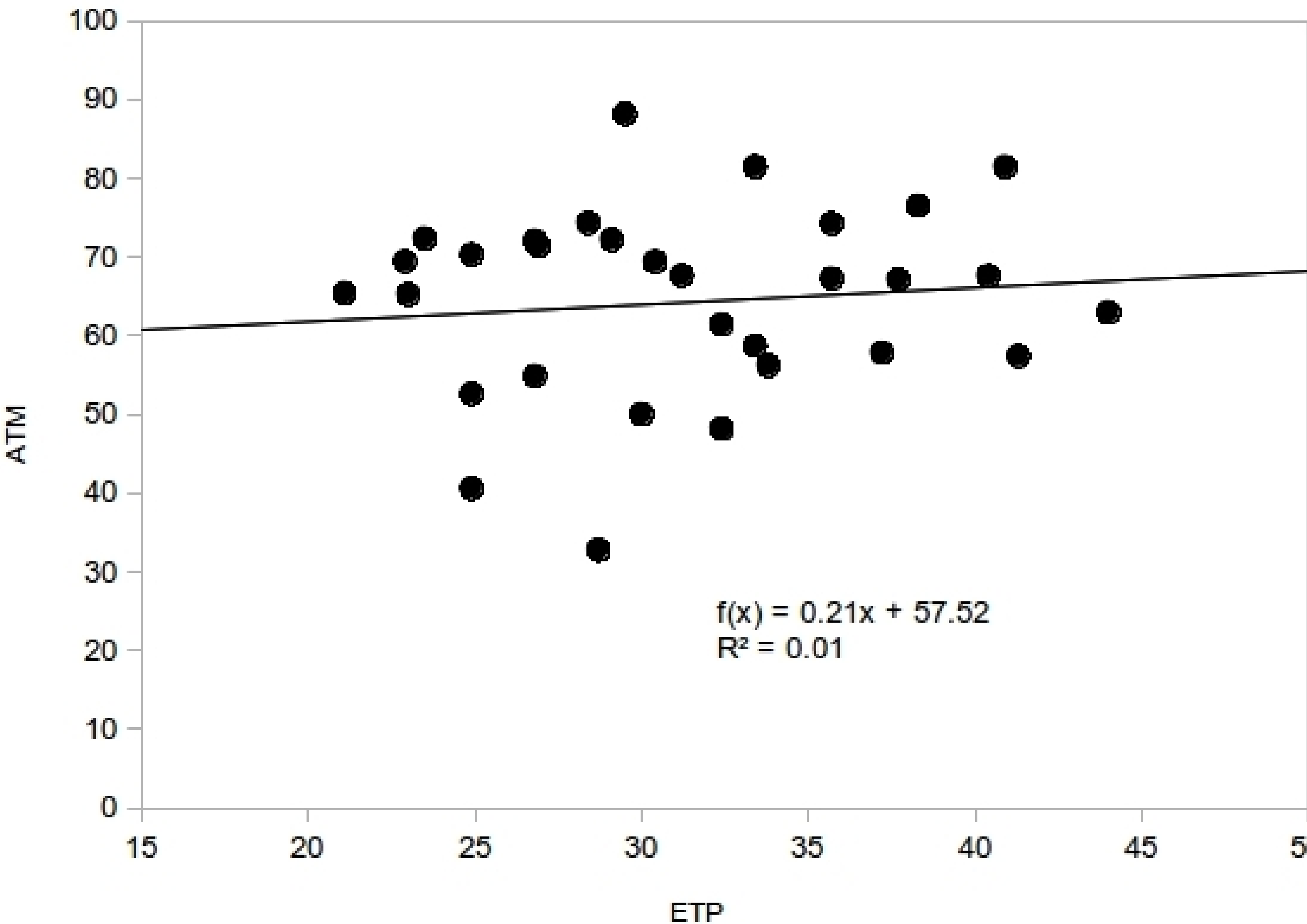
20
25
30
35
OTP
f(x) = 0.8x + 15.08
R² = 0.58



ATM
ETP
f(x) = 0.21x + 57.52
R² = 0.01
100
90
80
70
60
50
40
30
20
10
0
15
20
25
30
35
40
45
50

Table 1: The genes used to calculate each individual strategy's “fitness”. † denotes an optional gene, which was only included when a Player B was available.

Gene	Description
1	Probability of a rush on first down
2	Probability of a rush on second down and short
3	Probability of a rush on second down and medium
4	Probability of a rush on second down and long
5	Probability of a rush on third down and short
6	Probability of a rush on third down and medium
7	Probability of a rush on third down and long
8	Probability of Quarterback A executing a first down pass†
9	Probability of Quarterback A executing a second down and short pass†
10	Probability of Quarterback A executing a second down and medium pass†
11	Probability of Quarterback A executing a second down and long pass†
12	Probability of Quarterback A executing a third down and short pass†
13	Probability of Quarterback A executing a third down and medium pass†
14	Probability of Quarterback A executing a third down and long pass†
15	Probability of Running Back A executing a first down rush†
16	Probability of Running Back A executing a second down and short rush†
17	Probability of Running Back A executing a second down and medium rush†
18	Probability of Running Back A executing a second down and long rush†
19	Probability of Running Back A executing a third down and short rush†
20	Probability of Running Back A executing a third down and medium rush†
21	Probability of Running Back A executing a third down and medium rush†

Table 2: The observed touchdown percentages (*OTP*) and the predicted touchdown percentages (*PTP*) for each of the 32 NFL teams from the 2012 season (D = 1000).

Team	**OTP**	**PTP**	**Absolute Difference**
Arizona Cardinals	10.1	8.1	2.0
Atlanta Falcons	25.3	22.2	3.1
Baltimore Ravens	21.1	20.0	1.1
Buffalo Bills	19.6	18.9	0.7
Carolina Panthers	24.0	23.9	0.1
Chicago Bears	17.0	14.0	3.0
Cincinnati Bengals	21.0	14.4	6.6
Cleveland Browns	15.0	13.3	1.7
Dallas Cowboys	21.5	25.3	3.8
Denver Broncos	27.7	26.1	1.6
Detroit Lions	19.9	17.6	2.3
Green Bay Packers	27.2	20.7	6.5
Houston Texans	21.1	14.7	6.4
Indianapolis Colts	19.3	16.7	2.6
Jacksonville Jaguars	13.1	10.7	2.4
Kansas City Chiefs	9.4	15.4	6.0
Miami Dolphins	15.9	12.6	3.3
Minnesota Vikings	19.2	17.7	1.5
New England Patriots	33.3	28.6	4.7
New Orleans Saints	29.3	24.3	5.0
New York Giants	26.0	18.0	8.0
New York Jets	13.8	11.2	2.6
Oakland Raiders	15.0	15.4	0.4
Philadelphia Eagles	15.6	15.2	0.4
Pittsburgh Steelers	19.0	18.1	0.9
San Diego Chargers	17.5	14.2	3.3
San Francisco 49ers	23.7	23.7	0.0
Seattle Seahawks	26.5	23.0	3.5
St. Louis Rams	15.6	15.1	0.5

Tampa Bay Buccaneers	21.1	17.1	4.0
Tennessee Titans	14.7	14.8	0.1
Washington Redskins	27.3	21.0	6.3
Average	20.2	17.9	3.0

Table 3: The average relative rush frequencies of the observed play calling strategies and the evolved play calling strategies for each of the 32 NFL teams from the 2012 season (D = 1000; N = 1000; G = 100; m = 0.01). A bold p-value indicates a significant difference between the observed frequency and the evolved frequency in a Student's t-test (significance threshold = 0.01).

	1st Down (p < **0.0001**)		
	Observed	**Evolved**	**Difference**
Average rush frequency	0.519	0.148	0.371
Average pass frequency	0.481	0.852	-0.371
Standard deviation	0.054	0.298	
	2nd Down and Short (p = **0.0027**)		
	Observed	**Evolved**	**Difference**
Average rush frequency	0.662	0.483	0.179
Average pass frequency	0.338	0.517	-0.179
Standard deviation	0.136	0.331	
	2nd Down and Medium (p = 0.715)		
	Observed	**Evolved**	**Difference**
Average rush frequency	0.503	0.528	-0.025
Average pass frequency	0.497	0.472	0.025
Standard deviation	0.079	0.378	
	2nd Down and Long (p < **0.0001**)		
	Observed	**Evolved**	**Difference**
Average rush frequency	0.343	0.096	0.247
Average pass frequency	0.657	0.904	-0.247

Standard deviation	0.075	0.205	
3rd Down and Short (p < **0.0001**)			
	Observed	**Evolved**	**Difference**
Average rush frequency	0.546	0.788	-0.242
Average pass frequency	0.454	0.212	0.242
Standard deviation	0.111	0.265	
3rd Down and Medium (p = **0.0008**)			
	Observed	**Evolved**	**Difference**
Average rush frequency	0.110	0.295	-0.184
Average pass frequency	0.890	0.705	0.184
Standard deviation	0.055	0.313	
3rd Down and Long (p = 0.172)			
	Observed	**Evolved**	**Difference**
Average rush frequency	0.106	0.062	0.044
Average pass frequency	0.894	0.938	-0.044
Standard deviation	0.058	0.165	

Table 4: The observed touchdown percentages (*OTP*) and the evolved touchdown percentages (*ETP*) for each of the 32 NFL teams from the 2012 season (D = 1000; N = 1000; G = 100; m = 0.01).

Team	OTP	ETP
Arizona Cardinals	10.1	24.9
Atlanta Falcons	25.3	37.7
Baltimore Ravens	21.1	31.2
Buffalo Bills	19.6	33.4
Carolina Panthers	24.0	35.7
Chicago Bears	17.0	23.5
Cincinnati Bengals	21.0	29.1
Cleveland Browns	15.0	23.0
Dallas Cowboys	21.5	37.2
Denver Broncos	27.7	44.0
Detroit Lions	19.9	32.4
Green Bay Packers	27.2	33.4
Houston Texans	21.1	30.4
Indianapolis Colts	19.3	26.8
Jacksonville Jaguars	13.1	24.9
Kansas City Chiefs	9.4	28.7
Miami Dolphins	15.9	22.9
Minnesota Vikings	19.2	26.9
New England Patriots	33.3	40.9
New Orleans Saints	29.3	38.3
New York Giants	26.0	29.5
New York Jets	13.8	21.1
Oakland Raiders	15.0	30.0
Philadelphia Eagles	15.6	32.4
Pittsburgh Steelers	19.0	33.8
San Diego Chargers	17.5	24.9
San Francisco 49ers	23.7	41.3
Seattle Seahawks	26.5	35.7
St. Louis Rams	15.6	32.4
Tampa Bay Buccaneers	21.1	28.4
Tennessee Titans	14.7	26.8

Washington Redskins	27.3	40.4
Average	20.2	31.3

Table 5: The observed relative pass frequencies for the 2012 Dallas Cowboys (D = 1000; N = 1000; G = 100; m = 0.01).

Fitness	**1st Down**	**2nd Down and Short**	**2nd Down and Medium**	**2nd Down and Long**	**3rd Down and Short**	**3rd Down and Medium**	**3rd Down and Long**
			Observed				
25.3	0.586	0.425	0.578	0.754	0.488	0.943	0.921
			Evolved				
37.2	0.969	0.672	0.152	0.980	0.161	0.949	0.972
36.7	0.951	0.588	0.783	0.980	0.039	0.949	0.980
36.7	0.969	0.858	0.152	0.980	0.161	0.911	0.990
36.6	0.983	0.951	0.347	0.990	0.039	0.957	0.980
36.6	0.969	0.672	0.453	0.990	0.254	0.949	0.990
36.4	0.951	0.559	0.339	0.990	0.384	0.962	0.980
36.4	0.936	0.858	0.259	0.990	0.161	0.949	0.990
36.3	0.975	0.547	0.783	0.990	0.161	0.949	0.981
36.3	0.953	0.378	0.936	0.980	0.254	0.949	0.990
36.3	0.983	0.951	0.347	0.990	0.161	0.969	0.981

Table 6: The evolved relative frequencies with which Colin Kaepernick was used at quarterback on pass plays for the 2012 San Francisco 49ers (D = 1000; N = 1000; G = 100; m = 0.01).

ETP	**1st Down**	**2nd Down and Short**	**2nd Down and Medium**	**2nd Down and Long**	**3rd Down and Short**	**3rd Down and Medium**	**3rd Down and Long**
41.3	0.919	0.679	0.909	0.990	0.833	0.910	0.056
40.9	0.749	0.778	0.909	0.777	0.323	0.190	0.056
40.5	0.850	0.732	0.763	0.587	0.609	0.605	0.021
40.4	0.583	0.832	0.156	0.990	0.609	0.435	0.156
40.3	0.850	0.899	0.768	0.921	0.549	0.956	0.156
40.3	0.749	0.382	0.055	0.906	0.609	0.910	0.866
40.2	0.686	0.732	0.994	0.906	0.609	0.949	0.866
40.1	0.990	0.573	0.055	0.990	0.609	0.910	0.652
40.1	0.919	0.679	0.017	0.921	0.076	0.820	0.774
40.0	0.919	0.778	0.024	0.848	0.549	0.910	0.087

Table 7: The observed relative rush frequencies for the 2012 Minnesota Vikings (D = 1000; N = 1000; G = 100; m = 0.01).

Fitness	**1st Down**	**2nd Down and Short**	**2nd Down and Medium**	**2nd Down and Long**	**3rd Down and Short**	**3rd Down and Medium**	**3rd Down and Long**
				Observed			
17.7	0.567	0.483	0.478	0.478	0.372	0.197	0.103
				Evolved			
26.9	0.980	0.629	0.836	0.037	0.949	0.677	0.089
26.7	0.993	0.982	0.836	0.040	0.999	0.787	0.004
26.6	0.981	0.633	0.866	0.248	0.999	0.787	0.037
26.2	0.988	0.982	0.849	0.037	0.966	0.787	0.058
26.2	0.988	0.982	0.836	0.040	0.949	0.451	0.037
26.0	0.976	0.533	0.276	0.040	0.959	0.244	0.037
26.0	0.988	0.156	0.594	0.040	0.904	0.764	0.023
26.0	0.976	0.578	0.836	0.093	0.949	0.764	0.004
25.9	0.914	0.946	0.836	0.040	0.796	0.627	0.058
25.9	0.976	0.379	0.849	0.253	0.999	0.154	0.052

Appendix A: The observed relative rush frequencies for each of the 32 NFL teams from the 2012 season.

Team	1st Down	2nd Down and Short	2nd Down and Medium	2nd Down and Long	3rd Down and Short	3rd Down and Medium	3rd Down and Long
Arizona Cardinals	0.488	0.542	0.426	0.258	0.500	0.067	0.061
Atlanta Falcons	0.465	0.588	0.443	0.257	0.425	0.078	0.045
Baltimore Ravens	0.505	0.714	0.544	0.404	0.651	0.045	0.047
Buffalo Bills	0.532	0.719	0.612	0.321	0.500	0.145	0.120
Carolina Panthers	0.505	0.862	0.592	0.380	0.744	0.185	0.120
Chicago Bears	0.589	0.667	0.574	0.347	0.719	0.121	0.168
Cincinnati Bengals	0.550	0.636	0.459	0.227	0.677	0.172	0.094
Cleveland Browns	0.479	0.700	0.470	0.368	0.426	0.053	0.103
Dallas Cowboys	0.414	0.575	0.422	0.246	0.512	0.057	0.079
Denver Broncos	0.549	0.773	0.406	0.337	0.472	0.063	0.229
Detroit Lions	0.458	0.514	0.430	0.238	0.326	0.043	0.000
Green Bay Packers	0.534	0.500	0.451	0.320	0.532	0.088	0.108
Houston Texans	0.536	0.638	0.627	0.384	0.660	0.182	0.250
Indianapolis Colts	0.464	0.732	0.506	0.326	0.500	0.045	0.095
Jacksonville Jaguars	0.458	0.788	0.475	0.267	0.551	0.000	0.028
Kansas City Chiefs	0.601	0.724	0.659	0.409	0.725	0.108	0.114
Miami Dolphins	0.572	0.781	0.559	0.328	0.571	0.105	0.086
Minnesota Vikings	0.567	0.483	0.478	0.478	0.372	0.197	0.103
New England Patriots	0.498	0.732	0.614	0.351	0.672	0.164	0.112
New Orleans Saints	0.535	0.282	0.314	0.224	0.370	0.028	0.023
New York Giants	0.494	0.750	0.446	0.370	0.618	0.034	0.079
New York Jets	0.653	0.714	0.574	0.318	0.571	0.139	0.068

Oakland Raiders	0.435	0.700	0.468	0.358	0.556	0.097	0.027
Philadelphia Eagles	0.423	0.688	0.434	0.332	0.444	0.088	0.070
Pittsburgh Steelers	0.537	0.524	0.444	0.301	0.580	0.169	0.086
San Diego Chargers	0.516	0.897	0.524	0.327	0.605	0.149	0.153
San Francisco 49ers	0.604	0.816	0.610	0.505	0.587	0.113	0.227
Seattle Seahawks	0.511	0.615	0.495	0.533	0.656	0.215	0.202
St. Louis Rams	0.553	0.593	0.522	0.300	0.340	0.101	0.126
Tampa Bay Buccaneers	0.524	0.379	0.464	0.340	0.524	0.164	0.087
Tennessee Titans	0.487	0.696	0.458	0.364	0.475	0.032	0.063
Washington Redskins	0.567	0.857	0.598	0.453	0.605	0.176	0.098
Average	0.519	0.662	0.503	0.343	0.546	0.107	0.102
Standard deviation	0.054	0.136	0.079	0.075	0.111	0.058	0.060

Appendix B: The relative rush frequencies of the top ten evolved play calling strategies for each of the 32 NFL teams from the 2012 season (D = 1000; N = 1000; G = 100; m = 0.01).

Team	**1st Down**	**2nd Down and Short**	**2nd Down and Medium**	**2nd Down and Long**	**3rd Down and Short**	**3rd Down and Medium**	**3rd Down and Long**
Arizona Cardinals	0.032	0.900	0.040	0.096	0.545	0.122	0.009
Arizona Cardinals	0.018	0.907	0.162	0.078	0.623	0.122	0.009
Arizona Cardinals	0.029	0.805	0.125	0.096	0.623	0.122	0.009
Arizona Cardinals	0.022	0.014	0.040	0.096	0.840	0.404	0.009
Arizona Cardinals	0.029	0.907	0.040	0.096	0.296	0.122	0.009
Arizona Cardinals	0.022	0.724	0.262	0.219	0.280	0.122	0.020
Arizona Cardinals	0.018	0.503	0.116	0.096	0.623	0.325	0.075
Arizona Cardinals	0.018	0.286	0.162	0.078	0.623	0.122	0.009
Arizona Cardinals	0.020	0.968	0.262	0.219	0.545	0.127	0.009
Arizona Cardinals	0.022	0.623	0.262	0.087	0.135	0.127	0.009
Atlanta Falcons	0.015	0.841	0.071	0.020	0.835	0.100	0.041
Atlanta Falcons	0.007	0.890	0.041	0.006	0.751	0.010	0.020
Atlanta Falcons	0.024	0.275	0.030	0.053	0.886	0.010	0.022
Atlanta Falcons	0.038	0.729	0.034	0.014	0.800	0.047	0.041
Atlanta Falcons	0.024	0.207	0.111	0.123	0.886	0.010	0.025
Atlanta Falcons	0.015	0.420	0.111	0.206	0.901	0.010	0.041
Atlanta Falcons	0.017	0.069	0.071	0.050	0.886	0.010	0.025
Atlanta Falcons	0.006	0.831	0.030	0.050	0.835	0.010	0.007
Atlanta Falcons	0.006	0.474	0.034	0.050	0.886	0.010	0.007
Atlanta Falcons	0.015	0.474	0.174	0.053	0.957	0.010	0.020
Baltimore Ravens	0.026	0.994	0.668	0.001	0.920	0.629	0.004

Baltimore Ravens	0.017	0.954	0.946	0.012	0.952	0.811	0.004
Baltimore Ravens	0.135	0.922	0.779	0.001	0.952	0.969	0.004
Baltimore Ravens	0.172	0.427	0.946	0.001	0.952	0.859	0.054
Baltimore Ravens	0.017	0.787	0.946	0.065	0.952	0.811	0.002
Baltimore Ravens	0.356	0.894	0.946	0.001	0.952	0.951	0.004
Baltimore Ravens	0.160	0.590	0.946	0.001	0.996	0.992	0.004
Baltimore Ravens	0.017	0.787	0.668	0.001	0.952	0.773	0.018
Baltimore Ravens	0.172	0.894	0.946	0.001	0.945	0.090	0.007
Baltimore Ravens	0.037	0.787	0.918	0.001	0.996	0.588	0.006
Buffalo Bills	0.842	0.069	0.824	0.864	0.963	0.368	0.149
Buffalo Bills	0.844	0.803	0.874	0.864	0.939	0.045	0.061
Buffalo Bills	0.842	0.946	0.862	0.839	0.989	0.187	0.059
Buffalo Bills	0.889	0.467	0.934	0.839	0.993	0.507	0.059
Buffalo Bills	0.776	0.094	0.874	0.864	0.993	0.466	0.061
Buffalo Bills	0.811	0.969	0.945	0.864	0.989	0.466	0.005
Buffalo Bills	0.811	0.946	0.882	0.839	0.989	0.285	0.059
Buffalo Bills	0.714	0.351	0.823	0.839	0.963	0.285	0.061
Buffalo Bills	0.722	0.883	0.981	0.864	0.996	0.265	0.061
Buffalo Bills	0.844	0.883	0.981	0.839	0.996	0.187	0.061
Carolina Panthers	0.028	0.605	0.950	0.042	0.867	0.406	0.012
Carolina Panthers	0.032	0.580	0.986	0.080	0.849	0.045	0.032
Carolina Panthers	0.014	0.621	0.875	0.080	0.771	0.145	0.012
Carolina Panthers	0.081	0.785	0.981	0.016	0.986	0.045	0.032
Carolina Panthers	0.014	0.613	0.981	0.016	0.834	0.045	0.007
Carolina Panthers	0.032	0.686	0.950	0.018	0.940	0.258	0.027

Carolina Panthers	0.028	0.990	0.992	0.128	0.986	0.206	0.017
Carolina Panthers	0.126	0.613	0.981	0.052	0.940	0.054	0.032
Carolina Panthers	0.084	0.692	0.992	0.042	0.986	0.212	0.032
Carolina Panthers	0.028	0.692	0.998	0.016	0.980	0.045	0.012
Chicago Bears	0.151	0.122	0.869	0.067	0.945	0.057	0.013
Chicago Bears	0.087	0.676	0.917	0.114	0.991	0.523	0.005
Chicago Bears	0.121	0.676	0.950	0.114	0.985	0.057	0.016
Chicago Bears	0.010	0.173	0.992	0.156	0.991	0.056	0.013
Chicago Bears	0.073	0.286	0.397	0.011	0.991	0.156	0.013
Chicago Bears	0.010	0.616	0.921	0.195	0.991	0.014	0.016
Chicago Bears	0.010	0.767	0.950	0.011	0.985	0.106	0.003
Chicago Bears	0.087	0.198	0.921	0.114	0.985	0.057	0.003
Chicago Bears	0.010	0.767	0.917	0.195	0.991	0.066	0.003
Chicago Bears	0.010	0.746	0.935	0.083	0.953	0.014	0.003
Cincinnati Bengals	0.017	0.134	0.944	0.043	0.981	0.889	0.008
Cincinnati Bengals	0.017	0.134	0.994	0.030	0.926	0.571	0.013
Cincinnati Bengals	0.017	0.134	0.994	0.016	0.991	0.626	0.013
Cincinnati Bengals	0.017	0.123	0.980	0.068	0.991	0.889	0.015
Cincinnati Bengals	0.017	0.379	0.994	0.030	0.998	0.733	0.015
Cincinnati Bengals	0.017	0.047	0.994	0.030	0.977	0.130	0.008
Cincinnati Bengals	0.017	0.069	0.936	0.021	0.977	0.889	0.013
Cincinnati Bengals	0.017	0.849	0.936	0.021	0.977	0.626	0.008
Cincinnati Bengals	0.037	0.445	0.980	0.076	0.991	0.889	0.015
Cincinnati Bengals	0.001	0.081	0.994	0.021	0.981	0.394	0.008
Cleveland Browns	0.009	0.194	0.781	0.002	0.497	0.434	0.050

Cleveland Browns	0.027	0.013	0.995	0.002	0.552	0.198	0.003
Cleveland Browns	0.002	0.074	0.667	0.046	0.586	0.167	0.012
Cleveland Browns	0.037	0.570	0.667	0.000	0.752	0.151	0.003
Cleveland Browns	0.018	0.194	0.992	0.046	0.994	0.501	0.003
Cleveland Browns	0.037	0.032	0.597	0.002	0.924	0.501	0.047
Cleveland Browns	0.009	0.032	0.400	0.000	0.514	0.454	0.003
Cleveland Browns	0.071	0.091	0.740	0.046	0.807	0.215	0.003
Cleveland Browns	0.041	0.032	0.977	0.000	0.903	0.501	0.003
Cleveland Browns	0.009	0.091	0.388	0.042	0.854	0.307	0.012
Dallas Cowboys	0.025	0.453	0.217	0.010	0.839	0.051	0.019
Dallas Cowboys	0.049	0.441	0.661	0.010	0.616	0.038	0.020
Dallas Cowboys	0.047	0.622	0.064	0.020	0.746	0.051	0.010
Dallas Cowboys	0.049	0.412	0.217	0.020	0.961	0.051	0.020
Dallas Cowboys	0.031	0.328	0.848	0.020	0.839	0.051	0.028
Dallas Cowboys	0.031	0.142	0.848	0.020	0.839	0.089	0.010
Dallas Cowboys	0.017	0.049	0.653	0.010	0.839	0.031	0.019
Dallas Cowboys	0.064	0.142	0.741	0.010	0.839	0.051	0.010
Dallas Cowboys	0.017	0.049	0.653	0.010	0.961	0.043	0.020
Dallas Cowboys	0.031	0.328	0.547	0.010	0.746	0.051	0.010
Denver Broncos	0.018	0.158	0.242	0.162	0.952	0.021	0.165
Denver Broncos	0.008	0.003	0.281	0.094	0.838	0.016	0.057
Denver Broncos	0.008	0.066	0.390	0.121	0.711	0.002	0.006
Denver Broncos	0.021	0.012	0.963	0.069	0.838	0.058	0.018
Denver Broncos	0.008	0.065	0.291	0.069	0.624	0.068	0.018
Denver Broncos	0.008	0.226	0.390	0.094	0.838	0.020	0.006

Denver Broncos	0.008	0.179	0.527	0.132	0.711	0.020	0.006
Denver Broncos	0.008	0.066	0.629	0.059	0.741	0.002	0.018
Denver Broncos	0.007	0.012	0.390	0.119	0.711	0.002	0.006
Denver Broncos	0.024	0.012	0.417	0.069	0.444	0.002	0.018
Detroit Lions	0.940	0.310	0.121	0.082	0.694	0.871	0.041
Detroit Lions	0.974	0.830	0.083	0.038	0.023	0.355	0.045
Detroit Lions	0.940	0.658	0.203	0.027	0.442	0.032	0.045
Detroit Lions	0.940	0.948	0.020	0.038	0.694	0.358	0.075
Detroit Lions	0.974	0.948	0.213	0.005	0.073	0.184	0.045
Detroit Lions	0.940	0.948	0.213	0.005	0.466	0.165	0.041
Detroit Lions	0.969	0.948	0.152	0.027	0.694	0.081	0.041
Detroit Lions	0.974	0.948	0.020	0.038	0.694	0.105	0.045
Detroit Lions	0.969	0.948	0.152	0.020	0.694	0.032	0.075
Detroit Lions	0.969	0.799	0.083	0.009	0.694	0.659	0.051
Green Bay Packers	0.055	0.134	0.325	0.006	0.528	0.006	0.034
Green Bay Packers	0.097	0.868	0.117	0.006	0.903	0.043	0.013
Green Bay Packers	0.055	0.532	0.085	0.005	1.000	0.043	0.013
Green Bay Packers	0.037	0.134	0.032	0.038	0.903	0.043	0.057
Green Bay Packers	0.043	0.475	0.159	0.010	0.701	0.088	0.039
Green Bay Packers	0.015	0.132	0.032	0.038	0.903	0.088	0.038
Green Bay Packers	0.057	0.132	0.032	0.048	0.903	0.088	0.057
Green Bay Packers	0.055	0.532	0.434	0.010	0.952	0.031	0.039
Green Bay Packers	0.037	0.134	0.434	0.005	0.896	0.088	0.057
Green Bay Packers	0.043	0.586	0.040	0.038	0.896	0.043	0.035
Houston Texans	0.143	0.153	0.015	0.020	0.876	0.443	0.044

Houston Texans	0.016	0.153	0.017	0.020	0.781	0.188	0.047
Houston Texans	0.032	0.153	0.218	0.020	0.902	0.060	0.044
Houston Texans	0.025	0.083	0.142	0.020	0.456	0.378	0.031
Houston Texans	0.016	0.153	0.017	0.009	0.948	0.303	0.031
Houston Texans	0.016	0.232	0.015	0.003	0.902	0.091	0.047
Houston Texans	0.016	0.232	0.146	0.009	0.781	0.188	0.012
Houston Texans	0.077	0.023	0.146	0.003	0.884	0.188	0.044
Houston Texans	0.016	0.496	0.017	0.003	0.876	0.188	0.047
Houston Texans	0.016	0.153	0.017	0.020	0.876	0.058	0.047
Indianapolis Colts	0.076	0.812	0.022	0.019	0.955	0.135	0.095
Indianapolis Colts	0.056	0.812	0.152	0.019	0.800	0.052	0.053
Indianapolis Colts	0.046	0.901	0.022	0.171	0.800	0.108	0.004
Indianapolis Colts	0.071	0.951	0.022	0.079	0.778	0.097	0.076
Indianapolis Colts	0.023	0.951	0.063	0.250	0.955	0.231	0.007
Indianapolis Colts	0.023	0.960	0.022	0.013	0.923	0.108	0.012
Indianapolis Colts	0.023	0.951	0.009	0.457	0.995	0.021	0.001
Indianapolis Colts	0.081	0.458	0.152	0.051	0.995	0.021	0.004
Indianapolis Colts	0.023	0.961	0.022	0.171	0.822	0.097	0.012
Indianapolis Colts	0.001	0.854	0.009	0.072	0.955	0.135	0.004
Jacksonville Jaguars	0.092	0.468	0.941	0.020	0.990	0.736	0.046
Jacksonville Jaguars	0.068	0.723	1.000	0.040	0.919	0.693	0.054
Jacksonville Jaguars	0.036	0.035	0.937	0.003	0.992	0.545	0.046
Jacksonville Jaguars	0.036	0.056	1.000	0.017	0.990	0.886	0.031
Jacksonville Jaguars	0.011	0.036	0.941	0.060	0.990	0.470	0.046
Jacksonville Jaguars	0.068	0.403	1.000	0.003	0.869	0.438	0.031

Jacksonville Jaguars	0.028	0.588	0.943	0.022	0.990	0.886	0.031
Jacksonville Jaguars	0.011	0.996	0.937	0.022	0.990	0.545	0.031
Jacksonville Jaguars	0.068	0.903	1.000	0.022	0.990	0.886	0.031
Jacksonville Jaguars	0.065	0.468	1.000	0.017	0.992	0.828	0.054
Kansas City Chiefs	0.995	0.859	0.205	0.027	0.972	0.679	0.057
Kansas City Chiefs	0.919	0.871	0.071	0.050	0.923	0.817	0.292
Kansas City Chiefs	0.983	0.643	0.071	0.027	0.838	0.652	0.044
Kansas City Chiefs	0.995	0.859	0.013	0.093	0.838	0.529	0.032
Kansas City Chiefs	0.936	0.871	0.013	0.078	0.972	0.670	0.044
Kansas City Chiefs	0.919	0.905	0.041	0.027	0.843	0.817	0.044
Kansas City Chiefs	0.936	0.871	0.164	0.107	0.866	0.798	0.054
Kansas City Chiefs	0.995	0.871	0.013	0.013	0.789	0.817	0.051
Kansas City Chiefs	0.995	0.967	0.025	0.027	0.876	0.968	0.104
Kansas City Chiefs	0.995	0.871	0.232	0.001	0.843	0.810	0.054
Miami Dolphins	0.013	0.689	0.677	0.024	0.525	0.017	0.032
Miami Dolphins	0.008	0.689	0.677	0.024	0.863	0.890	0.023
Miami Dolphins	0.013	0.645	0.165	0.016	0.874	0.830	0.032
Miami Dolphins	0.087	0.074	0.768	0.072	0.313	0.753	0.032
Miami Dolphins	0.013	0.074	0.538	0.024	0.696	0.017	0.032
Miami Dolphins	0.013	0.198	0.294	0.024	0.874	0.985	0.028
Miami Dolphins	0.013	0.014	0.259	0.010	0.313	0.107	0.023
Miami Dolphins	0.013	0.097	0.134	0.010	0.313	0.985	0.023
Miami Dolphins	0.013	0.908	0.134	0.010	0.283	0.985	0.106
Miami Dolphins	0.013	0.475	0.694	0.003	0.183	0.402	0.032
Minnesota Vikings	0.976	0.533	0.276	0.040	0.959	0.244	0.037

Minnesota Vikings	0.988	0.982	0.849	0.037	0.966	0.787	0.058
Minnesota Vikings	0.988	0.982	0.836	0.040	0.949	0.451	0.037
Minnesota Vikings	0.980	0.629	0.836	0.037	0.949	0.677	0.089
Minnesota Vikings	0.988	0.156	0.594	0.040	0.904	0.764	0.023
Minnesota Vikings	0.993	0.982	0.836	0.040	0.999	0.787	0.004
Minnesota Vikings	0.914	0.946	0.836	0.040	0.796	0.627	0.058
Minnesota Vikings	0.981	0.633	0.866	0.248	0.999	0.787	0.037
Minnesota Vikings	0.976	0.379	0.849	0.253	0.999	0.154	0.052
Minnesota Vikings	0.976	0.578	0.836	0.093	0.949	0.764	0.004
New England Patriots	0.044	0.068	0.168	0.033	0.912	0.159	0.080
New England Patriots	0.016	0.146	0.687	0.042	0.982	0.013	0.031
New England Patriots	0.075	0.109	0.842	0.042	0.982	0.013	0.122
New England Patriots	0.037	0.174	0.572	0.100	0.994	0.042	0.023
New England Patriots	0.039	0.300	0.284	0.047	0.994	0.013	0.003
New England Patriots	0.017	0.161	0.168	0.046	0.994	0.042	0.003
New England Patriots	0.037	0.146	0.583	0.041	0.982	0.014	0.031
New England Patriots	0.037	0.068	0.327	0.041	0.982	0.014	0.031
New England Patriots	0.017	0.672	0.473	0.025	0.994	0.013	0.003
New England Patriots	0.017	0.606	0.933	0.047	0.854	0.063	0.003
New Orleans Saints	0.023	0.344	0.036	0.017	0.952	0.055	0.017
New Orleans Saints	0.023	0.475	0.213	0.075	0.940	0.019	0.044
New Orleans Saints	0.034	0.724	0.152	0.057	0.940	0.018	0.001
New Orleans Saints	0.035	0.607	0.152	0.030	0.943	0.156	0.017
New Orleans Saints	0.022	0.125	0.152	0.057	0.952	0.019	0.037
New Orleans Saints	0.035	0.328	0.036	0.057	0.987	0.055	0.001

New Orleans Saints	0.023	0.136	0.017	0.057	0.917	0.018	0.061
New Orleans Saints	0.034	0.552	0.055	0.075	0.952	0.018	0.001
New Orleans Saints	0.004	0.136	0.099	0.017	0.952	0.055	0.017
New Orleans Saints	0.033	0.087	0.055	0.017	0.940	0.018	0.001
New York Giants	0.050	0.076	0.852	0.048	0.002	0.896	0.027
New York Giants	0.017	0.076	0.227	0.034	0.537	0.204	0.010
New York Giants	0.107	0.564	0.890	0.035	0.007	0.280	0.234
New York Giants	0.006	0.001	0.738	0.035	0.007	0.262	0.131
New York Giants	0.006	0.001	0.977	0.048	0.308	0.204	0.010
New York Giants	0.006	0.053	0.977	0.034	0.524	0.637	0.131
New York Giants	0.049	0.076	0.764	0.127	0.152	0.012	0.085
New York Giants	0.053	0.076	0.977	0.127	0.100	0.262	0.131
New York Giants	0.006	0.113	0.895	0.020	0.152	0.280	0.088
New York Giants	0.006	0.053	0.895	0.036	0.524	0.896	0.010
New York Jets	0.011	0.222	0.591	0.062	0.994	0.137	0.005
New York Jets	0.030	0.697	0.991	0.013	0.951	0.710	0.019
New York Jets	0.030	0.448	0.991	0.013	0.951	0.419	0.028
New York Jets	0.030	0.374	0.855	0.013	0.951	0.440	0.022
New York Jets	0.030	0.208	0.991	0.009	0.994	0.172	0.005
New York Jets	0.036	0.697	0.853	0.013	0.972	0.440	0.013
New York Jets	0.014	0.793	0.991	0.009	0.972	0.419	0.084
New York Jets	0.016	0.276	0.658	0.013	0.949	0.440	0.069
New York Jets	0.132	0.095	0.991	0.013	0.951	0.091	0.005
New York Jets	0.030	0.473	0.991	0.013	0.958	0.419	0.019
Oakland Raiders	0.017	0.167	0.550	0.049	0.283	0.334	0.044

Oakland Raiders	0.007	0.871	0.928	0.012	0.456	0.105	0.020
Oakland Raiders	0.007	0.871	0.919	0.006	0.797	0.105	0.001
Oakland Raiders	0.004	0.366	0.624	0.010	0.760	0.110	0.036
Oakland Raiders	0.007	0.315	0.353	0.010	0.760	0.110	0.036
Oakland Raiders	0.007	0.172	0.928	0.049	0.760	0.105	0.092
Oakland Raiders	0.004	0.871	0.944	0.012	0.760	0.012	0.036
Oakland Raiders	0.004	0.523	0.944	0.012	0.483	0.012	0.036
Oakland Raiders	0.007	0.239	0.944	0.013	0.760	0.110	0.036
Oakland Raiders	0.007	0.523	0.944	0.049	0.797	0.105	0.020
Philadelphia Eagles	0.052	0.833	0.989	0.030	0.993	0.004	0.067
Philadelphia Eagles	0.052	0.833	0.989	0.030	0.993	0.004	0.067
Philadelphia Eagles	0.035	0.011	0.952	0.008	0.993	0.045	0.035
Philadelphia Eagles	0.042	0.192	0.999	0.008	0.944	0.063	0.013
Philadelphia Eagles	0.042	0.833	0.952	0.003	0.975	0.080	0.013
Philadelphia Eagles	0.035	0.011	0.926	0.008	0.993	0.071	0.013
Philadelphia Eagles	0.041	0.402	0.999	0.003	0.975	0.080	0.056
Philadelphia Eagles	0.052	0.192	0.999	0.008	0.987	0.004	0.027
Philadelphia Eagles	0.042	0.526	0.999	0.003	0.935	0.120	0.013
Philadelphia Eagles	0.035	0.192	0.999	0.008	0.944	0.004	0.013
Pittsburgh Steelers	0.018	0.098	0.497	0.018	0.891	0.074	0.010
Pittsburgh Steelers	0.008	0.375	0.061	0.084	0.893	0.057	0.005
Pittsburgh Steelers	0.018	0.689	0.023	0.004	0.722	0.126	0.002
Pittsburgh Steelers	0.086	0.689	0.023	0.004	0.722	0.026	0.005
Pittsburgh Steelers	0.048	0.765	0.004	0.004	0.053	0.057	0.002
Pittsburgh Steelers	0.018	0.782	0.070	0.004	0.982	0.022	0.005

Pittsburgh Steelers	0.018	0.689	0.023	0.036	0.931	0.057	0.002
Pittsburgh Steelers	0.042	0.798	0.023	0.007	0.722	0.026	0.002
Pittsburgh Steelers	0.008	0.168	0.351	0.036	0.722	0.057	0.002
Pittsburgh Steelers	0.018	0.892	0.023	0.036	0.722	0.022	0.005
San Diego Chargers	0.066	0.820	0.217	0.022	0.251	0.114	0.069
San Diego Chargers	0.023	0.578	0.523	0.044	0.827	0.008	0.052
San Diego Chargers	0.023	0.982	0.090	0.044	0.620	0.095	0.052
San Diego Chargers	0.023	0.578	0.090	0.022	0.083	0.076	0.052
San Diego Chargers	0.041	0.386	0.393	0.022	0.612	0.000	0.069
San Diego Chargers	0.041	0.805	0.015	0.044	0.612	0.357	0.027
San Diego Chargers	0.041	0.077	0.386	0.022	0.736	0.095	0.005
San Diego Chargers	0.023	0.999	0.217	0.050	0.599	0.017	0.027
San Diego Chargers	0.023	0.999	0.870	0.028	0.612	0.017	0.033
San Diego Chargers	0.023	0.820	0.232	0.044	0.736	0.008	0.108
San Francisco 49ers	0.037	0.952	0.899	0.123	0.978	0.968	0.058
San Francisco 49ers	0.007	0.009	0.899	0.089	0.892	0.802	0.023
San Francisco 49ers	0.045	0.474	0.913	0.041	0.967	0.587	0.058
San Francisco 49ers	0.016	0.083	0.805	0.012	0.978	0.971	0.020
San Francisco 49ers	0.017	0.474	0.805	0.012	0.967	0.657	0.020
San Francisco 49ers	0.007	0.474	0.899	0.012	0.967	0.646	0.044
San Francisco 49ers	0.067	0.946	0.899	0.012	0.967	0.968	0.058
San Francisco 49ers	0.026	0.428	0.805	0.012	0.967	0.802	0.020
San Francisco 49ers	0.016	0.384	0.899	0.012	0.978	0.521	0.023
San Francisco 49ers	0.037	0.384	0.899	0.064	0.978	0.495	0.003
Seattle Seahawks	0.036	0.065	0.944	0.098	0.956	0.039	0.060

Seattle Seahawks	0.015	0.115	0.583	0.075	0.999	0.163	0.084
Seattle Seahawks	0.025	0.043	0.890	0.033	0.812	0.382	0.027
Seattle Seahawks	0.003	0.037	0.930	0.197	0.970	0.049	0.028
Seattle Seahawks	0.036	0.104	0.922	0.018	0.970	0.428	0.028
Seattle Seahawks	0.015	0.082	0.944	0.009	0.947	0.049	0.027
Seattle Seahawks	0.031	0.037	0.833	0.018	0.947	0.216	0.005
Seattle Seahawks	0.003	0.074	0.780	0.009	0.843	0.049	0.060
Seattle Seahawks	0.036	0.115	0.833	0.107	0.887	0.200	0.058
Seattle Seahawks	0.036	0.068	0.833	0.009	0.970	0.002	0.005
St. Louis Rams	0.008	0.730	0.252	0.104	0.999	0.182	0.024
St. Louis Rams	0.068	0.029	0.005	0.071	0.999	0.176	0.015
St. Louis Rams	0.008	0.178	0.077	0.007	0.922	0.182	0.102
St. Louis Rams	0.172	0.367	0.005	0.012	0.999	0.173	0.001
St. Louis Rams	0.014	0.408	0.492	0.071	0.999	0.087	0.001
St. Louis Rams	0.014	0.183	0.077	0.071	0.944	0.087	0.001
St. Louis Rams	0.014	0.309	0.549	0.012	0.999	0.173	0.001
St. Louis Rams	0.014	0.205	0.077	0.071	0.999	0.176	0.001
St. Louis Rams	0.014	0.096	0.306	0.067	0.999	0.176	0.001
St. Louis Rams	0.068	0.096	0.005	0.068	0.944	0.182	0.001
Tampa Bay Buccaneers	0.008	0.994	0.852	0.000	0.421	0.217	0.059
Tampa Bay Buccaneers	0.084	0.675	0.634	0.140	0.148	0.467	0.004
Tampa Bay Buccaneers	0.008	0.945	0.863	0.045	0.038	0.569	0.004
Tampa Bay Buccaneers	0.001	0.652	0.401	0.000	0.358	0.655	0.004
Tampa Bay Buccaneers	0.012	0.911	0.401	0.000	0.038	0.655	0.004
Tampa Bay Buccaneers	0.065	0.846	0.852	0.045	0.038	0.086	0.069

Tampa Bay Buccaneers	0.089	0.994	0.863	0.045	0.038	0.426	0.061
Tampa Bay Buccaneers	0.008	0.803	0.049	0.126	0.038	0.191	0.004
Tampa Bay Buccaneers	0.065	0.605	0.652	0.000	0.421	0.962	0.032
Tampa Bay Buccaneers	0.008	0.846	0.718	0.126	0.909	0.351	0.004
Tennessee Titans	0.070	0.612	0.223	0.010	0.615	0.018	0.024
Tennessee Titans	0.042	0.692	0.078	0.024	0.918	0.015	0.184
Tennessee Titans	0.164	0.692	0.108	0.010	0.904	0.015	0.087
Tennessee Titans	0.147	0.681	0.223	0.010	0.997	0.018	0.033
Tennessee Titans	0.114	0.145	0.078	0.010	0.904	0.015	0.033
Tennessee Titans	0.070	0.980	0.121	0.003	0.997	0.015	0.033
Tennessee Titans	0.164	0.964	0.114	0.024	0.997	0.018	0.033
Tennessee Titans	0.070	0.964	0.078	0.005	0.615	0.011	0.024
Tennessee Titans	0.014	0.692	0.078	0.024	0.997	0.020	0.047
Tennessee Titans	0.070	0.964	0.108	0.074	0.918	0.018	0.047
Washington Redskins	0.061	0.415	0.756	0.896	0.169	0.984	0.963
Washington Redskins	0.001	0.931	0.295	0.896	0.150	0.925	0.963
Washington Redskins	0.001	0.415	0.021	0.391	0.180	0.934	0.963
Washington Redskins	0.010	0.532	0.547	0.948	0.470	0.933	0.963
Washington Redskins	0.061	0.277	0.961	0.896	0.188	0.934	0.963
Washington Redskins	0.040	0.581	0.578	0.896	0.307	0.934	0.963
Washington Redskins	0.006	0.277	0.817	0.974	0.188	0.934	0.963
Washington Redskins	0.040	0.788	0.510	0.896	0.307	0.419	0.963
Washington Redskins	0.010	0.931	0.374	0.896	0.188	0.925	0.947
Washington Redskins	0.040	0.532	0.358	0.896	0.257	0.934	0.963
Average	0.148	0.483	0.528	0.096	0.788	0.295	0.062

Standard Deviation	0.298	0.331	0.378	0.205	0.265	0.313	0.165