



7-25-2023

Here Comes the STRAIN: Analyzing Defensive Pass Rush in American Football with Player Tracking Data

Quang Nguyen
Carnegie Mellon University, nmquang@cmu.edu

Ronald Yurko
Carnegie Mellon University

Gregory J. Matthews
Loyola University Chicago, gmatthews1@luc.edu

Follow this and additional works at: https://ecommons.luc.edu/math_facpubs



Part of the [Mathematics Commons](#)

Author Manuscript

This is a pre-publication author manuscript of the final, published article.

Recommended Citation

Nguyen, Quang; Yurko, Ronald; and Matthews, Gregory J.. Here Comes the STRAIN: Analyzing Defensive Pass Rush in American Football with Player Tracking Data. *The American Statistician*, , , 2023. Retrieved from Loyola eCommons, Mathematics and Statistics: Faculty Publications and Other Works, <http://dx.doi.org/10.1080/00031305.2023.2242442>

This Article is brought to you for free and open access by the Faculty Publications and Other Works by Department at Loyola eCommons. It has been accepted for inclusion in Mathematics and Statistics: Faculty Publications and Other Works by an authorized administrator of Loyola eCommons. For more information, please contact ecommons@luc.edu.



This work is licensed under a [Creative Commons Attribution-NonCommercial-No Derivative Works 4.0 International License](#).

© Taylor & Francis, 2023.

Here Comes the STRAIN: Analyzing Defensive Pass Rush in American Football with Player Tracking Data

Quang Nguyen

Department of Statistics & Data Science

Carnegie Mellon University

and

Ronald Yurko

Department of Statistics & Data Science

Carnegie Mellon University

and

Gregory J. Matthews

Department of Mathematics and Statistics

Center for Data Science and Consulting

Loyola University Chicago

July 31, 2023

Abstract

In American football, a pass rush is an attempt by the defensive team to disrupt the offense and prevent the quarterback (QB) from completing a pass. Existing metrics for assessing pass rush performance are either discrete-time quantities or based on subjective judgment. Using player tracking data, we propose STRAIN, a novel metric for evaluating pass rushers in the National Football League (NFL) at the continuous-time within-play level. Inspired by the concept of strain rate in materials science, STRAIN is a simple and interpretable means for measuring defensive pressure in football. It is a directly-observed statistic as a function of two features: the distance between the pass rusher and QB, and the rate at which this distance is being reduced. Our metric possesses great predictability of pressure and stability over time. We also fit a multilevel model for STRAIN to understand the defensive pressure contribution of every pass rusher at the play-level. We apply our approach to NFL data and present results for the first eight weeks of the 2021 regular season. In particular, we provide comparisons of STRAIN for different defensive positions and play outcomes, and rankings of the NFL's best pass rushers according to our metric.

Keywords: American football, defensive linemen, multilevel model, player tracking data

1 Introduction

In recent years, tracking data have replaced traditional box-score statistics and play-by-play data as the state of the art in sports analytics. Numerous sports are collecting and releasing data on player and ball locations on the playing surface over the course of a game. This multiresolution spatiotemporal source of data has provided exceptional opportunities for researchers to perform advanced studies at a more granular level to deepen our understanding of different sports. For complete surveys on how tracking data have transformed sports analytics, see Macdonald (2020), Baumer et al. (2023), and Kovalchik (2023).

In an attempt to foster analytics and innovate the game, the National Football League (NFL) introduced their player tracking system known as Next Gen Stats in 2016 (NFL Football Operations, 2023b). Next Gen Stats uses radio frequency identification (RFID) chips placed in players' shoulder pads (and in the ball) to collect data at a rate of 10 frames per second. The data capture real-time on-field information such as locations, speeds, and accelerations of all 22 players (and the football). While these data were initially only available for teams, media, and vendors, in December 2018 the NFL launched the inaugural edition of their annual Big Data Bowl competition (NFL Football Operations, 2023a).

The first Big Data Bowl led to several contributions largely focused on offensive performance evaluation. For example, one group of finalists introduced an approach for modeling the hypothetical completion probability of a pass aiding in the evaluation of quarterback (QB) decision making (Deshpande and Evans, 2020). The winners of the inaugural Big Data Bowl focused on identifying receiver routes via clustering techniques (Chu et al., 2020) and convolutional neural networks (Sterken, 2019). Along with the competition entries, the public release of NGS data allowed researchers to tackle a variety of other problems such as revisiting fourth down decision making (Lopez, 2020), annotating pass coverage with Gaussian mixture models (Dutta et al., 2020), and introducing a continuous-time framework to estimate within-play value (Yurko et al., 2020). Since its inception, the Big Data Bowl has chosen a different theme each year leading to new insight about evaluating different positions such as running backs, defensive backs, and special teams. The 2023 edition of the NFL Big Data Bowl asked participants to evaluate linemen on passing plays (Howard et al., 2022).

Our focus of this manuscript is specifically on measuring the performance of defensive

linemen in the NFL. There are two main types of defensive linemen in American football: defensive tackles and defensive ends. Typically, these positions are located within the interior of the line and along the edges, respectively; see Figure 1 (top) for example formation with defensive tackles and defensive ends. The primary purpose of both positions is to rush the QB on passing plays, with defensive ends displaying superiority in observed pass rushing ability (Eager and Chahrouri, 2018). Additionally, within defensive tackles there are nose tackles who directly line up across from the ball at the line of scrimmage; see Figure 1 (bottom) for example defensive scheme with a nose tackle. NFL teams often employ either one nose tackle or two defensive tackles on the interior with defensive ends along either side of the defensive line. Besides defensive lineman, other positions may attempt to rush the QB on blitzing plays such as outside linebackers, interior linebackers, and potentially members of the secondary (cornerbacks, free safeties, and strong safeties) whose primary role is pass coverage. Note that apart from the formations shown in Figure 1, defensive linemen can have the flexibility to line up differently. For example, a defensive end, depending on the opposing matchup, may not necessarily be positioned toward the outside of the line of scrimmage.

In this work, using data made available in the Big Data Bowl 2023, we present a novel approach to measure the performance of pass rushers. Relative to other aspects of American football, such as quarterback evaluation (Burke, 2019; Reyers and Swartz, 2021), the literature on evaluating pass rushers is scarce. Below, we provide a brief overview of existing pass rush metrics.

1.1 Previous Pass Rush Metrics

Table 1 gives a summary of existing football metrics for pass rush. We now highlight what these quantities describe as well as their limitations.

Perhaps the most commonly-known statistics for evaluating defensive linemen on pass rush plays are sacks, hits, and hurries, which are discretely observed at the play-level. Officially tracked by the NFL since 1982, a sack is recorded when a defender tackles the QB behind the line of scrimmage before the QB releases a pass. Other traditional box score statistics such as hits and hurries are collected by various outlets. A hit is a collision between a defender and the opposing team’s quarterback after the quarterback makes a throw. A hurry represents an instance when a defender successfully disrupts without

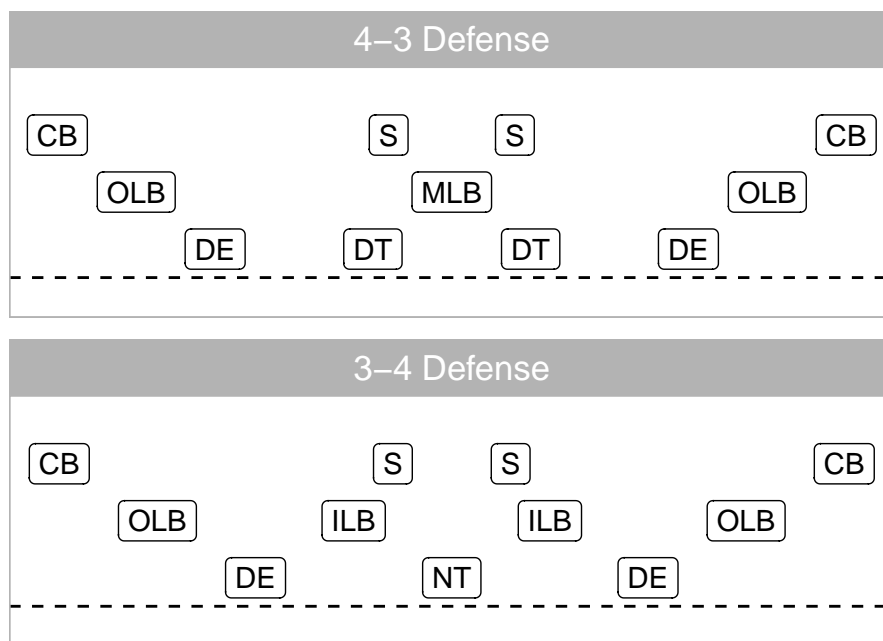


Figure 1: Two common defensive alignments in football: 4-3 defense (top) and 3-4 defense (bottom). The dashed line represents the line of scrimmage separating the defense and offense. Defensive tackles (DT), defensive ends (DE), and nose tackles (NT) primarily rush the QB on passing plays and attempt to stop the ball carrier as quickly as possible on running plays. Outside linebackers (OLB) and inside linebackers (ILB) usually play directly behind the defensive line and are involved in defending against passing and rushing plays. Cornerbacks (CB) and safeties (S) generally involve in defending against passing plays.

necessarily making direct contact with the QB and forces the QB to throw the football earlier than expected. These are all simple binary measures of pass rush outcome for any given play. However, for plays that do not result in the aforementioned outcomes (in particular, sack), there are still many intermediate defensive actions on the field within the play that are valuable and can be considered positive achievements.

In addition, the sum of sacks, hits, and hurries is often defined as pressures. This is better than the individual counts to some extent, but suffers from problems of subjectivity (e.g., whether there is an actual hurry or not). Pro Football Focus (PFF) defines a metric called pass-rush productivity, which is a minor modification from the aforementioned pressures metric (see Table 1). In particular, pass-rush productivity gives twice as much weight to a sack relative to hurries and hits, which is a small upgrade to pressures. However, the choice of weights is ad-hoc and still only considers binary outcomes, similar to

Table 1: A summary of previously-existing pass rush metrics.

Metric	Description
Sacks	A defender tackles the QB behind the line of scrimmage before a QB throw
Hits	A defender tackles the QB behind the line of scrimmage after a QB throw
Hurries	A defender pressures the QB behind the line of scrimmage forcing the QB to throw the ball sooner than intended
Pressures	Hurries + Hits + Sacks
Pass-Rush Productivity	$\frac{(\text{Hurries} + \text{Hits})/2 + \text{Sacks}}{\text{Pass Rush Snaps}}$
Time In Pocket	Time (in seconds) between ball snap and throw or pocket collapse for a QB
NGS Get Off	Average time (in seconds) required for a defender to cross the line of scrimmage after the ball snap
Pass Rush Win Rate	Rate at which pass rusher beats pass block within 2.5 seconds after ball snap

the shortcomings of previous metrics.

More recently proposed metrics such as time in pocket, NGS get off (Hermsmeyer, 2021), and pass rush win rate (Burke, 2018) are substantial improvements over the less sophisticated counting statistics, but nevertheless are still imperfect. Time in pocket refers to how long a QB can operate within the protected space behind the offensive line, known as the pocket. However, this measure is highly context-dependent, as it can be influenced by a number of factors such as the defensive scheme or type of passing route. NGS get off is an aggregated statistic, illustrating how quickly a defender can get past the line of scrimmage after the snap on average. Pass rush win rate is created using player tracking data, which is at a more granular level than previous measures. It demonstrates whether a pass rusher is able to beat their blocking matchup before a fixed time from the snap (2.5 seconds as chosen by ESPN). However, this depends on the rather arbitrary time threshold used to define a pass rush win. Besides, once a cutoff is chosen, pass rush win rate converts continuous data to a win-loss indicator, becoming dichotomous like most of the metrics discussed above.

1.2 Previous Research on Football Linemen

The peer-reviewed literature on measuring the performance of football linemen (either offensive or defensive) is scant. Alamar and Weinstein-Gould (2008) find an association between pass completion rate and successful pass blocking by offensive linemen. The data for this study are collected for the first three weeks of the 2007 NFL season, manually recording whether a lineman holds a block and the time it took for the quarterback to throw the football. Alamar and Goldner (2011) later follow up by using manually-tracked data for the 2010 season to estimate lineman performance for different team-positions instead of individual defenders (e.g., Chicago Bears’ left tackle, Pittsburgh Steelers’ center, etc.). This work uses survival analysis to model time in pocket and completion percentage for quarterbacks before proposing a measure for linemen’s contribution to their team’s passing in terms of yards gained.

Wolfson et al. (2017) comment on the two aforementioned articles that “[a]lthough these are exciting preliminary steps, there is still a long way to go before we can provide a comprehensive appraisal of the achievements of an individual lineman.” The challenge here is fundamental, since there were not enough public data at the time to develop any meaningful metric for linemen in football, as also noted by Alamar and Weinstein-Gould (2008). However, with the granularity of player tracking data, we have access to data not only for the linemen but also for every player on the field. This provides us with a great opportunity to study and gain better insights into linemen performance in football.

1.3 Our Contribution

In this paper, we focus on the evaluation of defensive linemen in football. We propose STRAIN, a metric for measuring pass rush effectiveness, inspired by the concept of strain rate in materials science. Our statistic gives a continuous measure of pressure for every pass rusher on the football field over the course of an entire play. This allows for the assessment of pass rush success even on plays that do not result in an observed outcome like a sack, hit, or hurry. We view this as a major step forward for accurately evaluating defensive linemen performance. We also demonstrate that STRAIN is a stable quantity over time and predictive of defensive pressure. Additionally, we consider a multilevel model to estimate every pass rusher’s contribution to the average STRAIN in a play while controlling

for player positions, team, and various play-level information. We note that although our focus in this paper is on pass rushers, our approach can be extended to the evaluation of pass blockers in American football.

The remainder of this manuscript is outlined as follows. We first describe the player tracking data provided by the Big Data Bowl 2023 in Section 2. We then introduce the mathematical motivation and definition of our measure STRAIN, followed by our modeling approach in Section 3. Next, we present applications of STRAIN and study different statistical properties of the metric in Section 4. We close with our discussion of future directions related to this work in Section 5.

2 Data

In the forthcoming analysis, we rely on the data from the NFL Big Data Bowl 2023 provided by the NFL Next Gen Stats tracking system. The data corresponds to 8,557 passing plays across 122 games in the first eight weeks of the 2021 NFL regular season. For each play, we have information on the on-field location, speed, angle, direction, and orientation of each player on the field and the football at a rate of 10 Hz (i.e., 10 measurements per second), along with event annotations for each frame such as ball snap, pass forward, and quarterback sack, to name a few.

For our investigation, we consider only the frames between the ball snap and when a pass forward or quarterback sack is recorded for each play. We also remove all plays with multiple quarterbacks on the field, since we need a uniquely defined quarterback to compute our metric. After preprocessing, there are 251,060 unique frames corresponding to moments of time from the start of the play at snap until the moment the quarterback either throws the pass or is sacked.

Table 2 displays a tracking data example for a play from the 2021 NFL regular season week six matchup between the Las Vegas Raiders and Denver Broncos, which ends with Broncos quarterback Teddy Bridgewater getting sacked by Raiders defensive end Maxx Crosby. In addition, Figure 2 presents the locations of every Las Vegas (in black) and Denver (in orange) player on the field from this play at 1, 2, 3 and 4 seconds after the ball snap, with Maxx Crosby highlighted in blue.

Along with the tracking information, the Big Data Bowl 2023 includes scouting data

Table 2: Example of tracking data for a play during the Las Vegas Raiders versus Denver Broncos NFL game on October 17, 2021. The data shown here are for Raiders defensive end Maxx Crosby, and the frames included are between the ball snap and when the sack by Crosby is recorded.

frameId	x	y	s	a	dis	o	dir	event
7	67.68	29.89	0.34	1.57	0.04	124.86	88.21	ball_snap
8	67.76	29.89	0.69	2.13	0.08	124.07	89.59	None
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
50	73.67	25.06	4.19	2.62	0.42	134.21	125.26	qb_sack

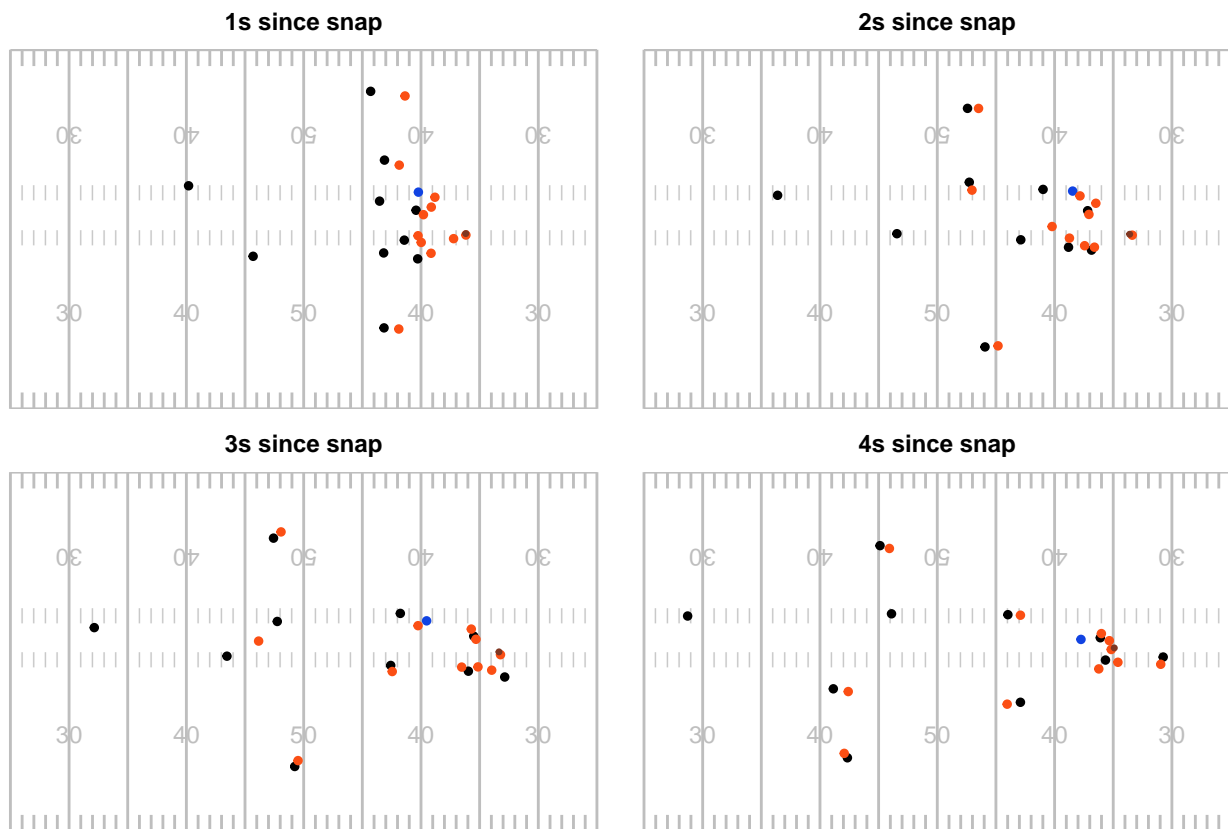


Figure 2: A display of the player tracking data for a play during the Las Vegas Raiders (defense, in black) versus Denver Broncos (offense, in orange) NFL game on October 17, 2021. Raiders defensive end Maxx Crosby is highlighted in blue. Snapshots are captured at 1, 2, 3, and 4 seconds after the ball snap.

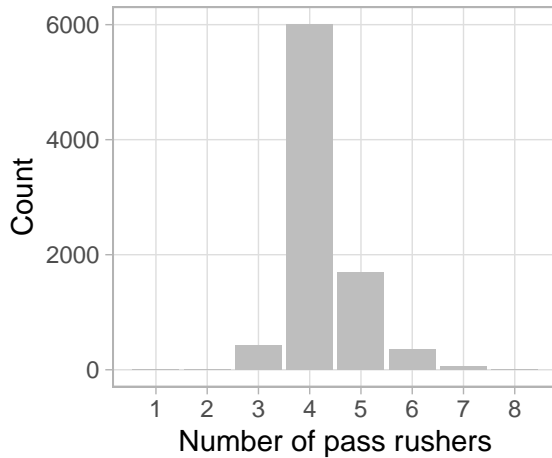


Figure 3: Distribution of the number of pass rushers on passing plays.

provided by Pro Football Focus (PFF). This contains manually-collected player-level information, such as the player’s role (e.g., whether they are a pass rusher and pass blocker) and credited events (e.g., player is credited with hitting the QB on the play). In this manuscript, we use the PFF data to identify 36,362 unique pass rush attempts by players designated in the “pass rush” role across all plays. For context, Figure 3 displays the distribution of the number of observed pass rushers involved in a play, ranging from 1 to 8 with 4 pass rushers (i.e., 4-man rush formation) as the most common value. We also leverage this scouting data to count how many hits, hurries, and sacks each pass rusher is credited with across the span of observed data. Additionally, we use the PFF player roles to identify the blocking matchup for each pass rusher in order to adjust for opponent strength, as discussed in Section 3.

3 Methods

3.1 Motivation and Definition of STRAIN

In materials science, strain (Callister and Rethwisch, 2018) is the deformation of a material from stress, showing the change in a material’s length relative to its original length. Formally, let $L(t)$ be the distance between any given two points of interest within a material at time t , and L_0 be the initial distance between those two points. The strain for a material at time t is defined as

$$\varepsilon(t) = \frac{L(t) - L_0}{L_0}.$$

Notice that this measure is unitless due to being a ratio of two quantities having the same unit.

Accordingly, the strain rate of a material measures the change in its deformation with respect to time. Mathematically, the strain rate of a material can be expressed as the derivative of its strain. That is,

$$\varepsilon'(t) = \frac{d\varepsilon}{dt} = \frac{v(t)}{L_0},$$

where $v(t)$ is the velocity at which the two points of interest within the material are moving away from or toward each other. Whereas strain has no units, the strain rate is measured in inverse of time, usually inverse second.

Motivated by its scientific definition, we draw a delightful analogy between strain rate and pass rushing in football. Just as strain rate is a measure of deformation in materials science, a pass rusher's efforts involve the application of deformation against the offensive line, with the ultimate goal of breaking through the protection to reach the quarterback. The players can be viewed as "particles" in some material and the defensive "particles" are attempting to exert pressure on the pocket with the aim of compressing and collapsing this pocket around the quarterback.

In order to apply strain rate to measure NFL pass rusher effectiveness, we make modifications to how this concept is traditionally defined. Let (x_{ijt}, y_{ijt}) be the (x, y) location on the field of pass rusher $j = 1, \dots, J$ at frame $t = 1, \dots, T_i$ for play $i = 1, \dots, n$; and $(x_{it}^{QB}, y_{it}^{QB})$ be the (x, y) location of the quarterback at frame t during play i .

- The distance between pass rusher j and the quarterback at frame t during play i is

$$s_{ij}(t) = \sqrt{(x_{ijt} - x_{it}^{QB})^2 + (y_{ijt} - y_{it}^{QB})^2}.$$

- The velocity at which pass rusher j is moving toward the quarterback at frame t during play i is

$$v_{ij}(t) = s'_{ij}(t) = \frac{ds_{ij}(t)}{dt}.$$

- The STRAIN for pass rusher j at frame t during play i is

$$\text{STRAIN}_{ij}(t) = \frac{-v_{ij}(t)}{s_{ij}(t)}.$$

Note that to distinguish our metric from strain and strain rate in materials science, we write it in capital letters (STRAIN) for the remainder of this manuscript.

Recall that based on its materials science property, an increase in strain rate is associated with an increase in the distance between two points. In the American football setting, the two points of interest are the pass rusher and the quarterback, and we expect our metric to increase as the distance between the pass rusher and the quarterback decreases. Thus, the negative sign in the numerator of our formula effectively accounts for this. Additionally, rather than keeping the initial distance (L_0 as previously denoted) between two points constant over time, we update the initial position to be the player locations at the beginning of each frame. This gives us the STRAIN for each frame throughout a play.

Since we only observe the distance and velocity quantities discretely in increments of 10 frames/second, a point estimate for our proposed metric STRAIN for pass rusher j at frame t during play i is

$$\widehat{\text{STRAIN}}_{ij}(t) = \frac{-\frac{s_{ij}(t) - s_{ij}(t-1)}{0.1}}{s_{ij}(t)}.$$

Notice that this quantity increases in two ways: 1) the rate at which the rusher is moving toward the quarterback increases, and 2) the distance between the rusher and the quarterback decreases. Both of these are indications of an effective pass rush attempt. Finally, our statistic STRAIN is measured in inverse second, similar to strain rate. Note that the reciprocal of our metric ($1/\text{STRAIN}$) has an interesting and straightforward interpretation: the amount of time required for the rusher to get to the quarterback at the current location and rate at any given time t .

Moreover, since we observe STRAIN at every tenth of a second within each play, we can then compute the average STRAIN across all frames played for every pass rusher. Formally, the average STRAIN, denoted by $\overline{\text{STRAIN}}$, for pass rusher j involved in n_j total plays across $\sum_{i \in Z_j} T_i$ total frames, where Z_j is the set of all plays with pass rusher j 's involvement, is

$$\overline{\text{STRAIN}}_j = \frac{1}{\sum_{i \in Z_j} T_i} \sum_{i \in Z_j} \sum_{t=1}^{T_i} \widehat{\text{STRAIN}}_{ij}(t).$$

This can be helpful for player evaluation, as we determine the most effective pass rushers based on their average STRAIN values in Section 4.3. We also use average STRAIN to assess different statistical properties of our metric in Section 4.4.

3.2 Multilevel Model for Play-Level STRAIN

In addition to the average STRAIN over all frames played, we can also calculate pass rusher j 's observed average STRAIN on a single play i consisting of T_i total frames,

$$\overline{\text{STRAIN}}_{ij} = \frac{1}{T_i} \sum_{t=1}^{T_i} \widehat{\text{STRAIN}}_{ij}(t).$$

While this aggregated measure is a simple first step for pass rush evaluation, the observed average STRAIN on a single play is likely due to numerous factors. Besides the pass rusher's ability, there is variability in the opposing strength of pass blockers across plays a pass rusher is involved, both at the individual and team levels. Thus, we need to appropriately divide the credit of an observed average STRAIN across the different players and team involved, amongst other factors.

To this end, we fit a multilevel model to evaluate pass rushers' impact on the average STRAIN observed in a play, while accounting for their team on defense, the opposing team on offense, and their assigned pass blocker. We identify the pass blocker linked with the pass rusher of interest using the scouting data provided by PFF as mentioned in Section 2. Since there can be multiple blockers matching up with a rusher, for simplicity, we consider the nearest blocker positioned to the pass rusher at the start of the play. We use random intercepts for the two player groups: pass rushers as R and nearest pass blockers as B , as well as for the two team groups: defense D and offense O . We also account for attributes about pass rusher j in play i through the covariate vector \mathbf{x}_{ij} , and estimate their respective coefficients $\boldsymbol{\beta}$ as fixed effects. Our model for the average STRAIN by pass rusher j on play i is as follows.

$$\begin{aligned} \overline{\text{STRAIN}}_{ij} &\sim N(R_{j[i]} + B_{b[ij]} + D_{d[i]} + O_{o[i]} + \mathbf{x}_{ij}\boldsymbol{\beta}, \sigma^2), \text{ for } i = 1, \dots, n \text{ plays} \\ R_j &\sim N(\mu_R, \sigma_R^2), \text{ for } j = 1, \dots, \# \text{ of pass rushers,} \\ B_b &\sim N(\mu_B, \sigma_B^2), \text{ for } b = 1, \dots, \# \text{ of pass blockers,} \\ D_d &\sim N(\mu_D, \sigma_D^2), \text{ for } d = 1, \dots, \# \text{ of defensive teams,} \\ O_o &\sim N(\mu_O, \sigma_O^2), \text{ for } o = 1, \dots, \# \text{ of offensive teams.} \end{aligned}$$

In detail, we consider a normal distribution to shrink the random intercepts for each player and team toward their respective group means. This is a useful property since we do not observe the same number of plays for each player. For the team effects, this provides

us with the average defense and offense team-level effects on a pass rusher’s STRAIN. Due to the nested nature of players on teams, the individual pass rusher and blocker random intercepts reflect the respective player’s effect relative to their team effects. We implement the model using penalized likelihood via the `lme4` package in R (Bates et al., 2015; R Core Team, 2023).

In order to provide a measure of uncertainty for our random effects, we use a bootstrapping strategy similar to the approach in Yurko et al. (2019). Specifically, we resample team drives within games, which preserves the fact that team schedules are fixed but allows for random variation in player usage since this is dependent on team decision making. By resampling plays within the same drive together, this allows us to generate realistic simulated data in comparison to sampling individual plays. For each bootstrapped dataset, we fit the aforementioned multilevel model to obtain a distribution of estimates for the considered player and team effects.

As for the fixed effects about pass rusher j in play i , we include a variety of features that likely contribute to variation in STRAIN. First, we adjust for the position of both the pass rusher and nearest blocker to account for any positional effects. Table 3 shows our positional categorization for the pass rush and pass block roles. These are encoded as indicator variables with defensive ends and tackles as the reference levels for the pass rushers and blockers, respectively. We also account for the number of pass blockers on the play, since teams may decide to employ a more protective scheme that could lower the observed STRAIN. Finally, we control for play-context covariates with respect to the offensive team. These include the current down (first, second, third, fourth, or two-point conversion), yards to go for a first down, and current yardline (i.e., distance from the possession team’s goal line). We consider play-context information since these variables impact a team’s designed play, which may result in a play with low or high STRAIN regardless of the pass rusher’s role. For instance, a team may call a short pass that is intended to be thrown early which could limit the amount of STRAIN on a play. Or a team may need to throw a deep pass which would require more time and potentially create more STRAIN. We do not account for time directly in the model due to the concern that the time it takes for a quarterback to throw the ball is itself a function of both the play call and pressure from pass rushers. Thus, since we do not know the designed play call, we condition on the play context to adjust for play-level differences attributing to a pass rusher’s STRAIN.

Table 3: Position groupings for pass rushers and blockers.

Role	Position
Pass rush	Defensive end
Pass rush	Defensive tackle
Pass rush	Nose tackle
Pass rush	Outside linebacker
Pass rush	Interior linebacker (middle linebacker, inside linebacker)
Pass rush	Secondary (cornerback, free safety, strong safety)
Pass block	Center
Pass block	Guard
Pass block	Tackle
Pass block	Other (tight end, running back, fullback, wide receiver)

4 Results

4.1 Real-Game Illustration of STRAIN

To illustrate our proposed metric STRAIN for pass rush evaluation, we use the same play from the Las Vegas Raiders and Denver Broncos game as mentioned in Section 2. Figure 4 shows an updated version of Figure 2, with the point size for each Las Vegas defender corresponding to the estimated STRAIN in the selected frames as the play progresses. This is accompanied by Figure 5, which is a line graph showing how Crosby’s distance from the quarterback, velocity, and STRAIN change continuously throughout the play.

We observe that for the first two seconds, Crosby is being blocked by a Denver offensive lineman and unable to get close to the quarterback, hence the corresponding STRAIN values are virtually zero. Suddenly at around three seconds after the snap, the STRAIN for Crosby starts to increase after the Raiders defensive end is freed up and charges toward Bridgewater. At 4 seconds after the snap, Crosby’s STRAIN is 2.30, which means at his current moving rate, it will take Crosby about 0.43 ($1/2.30$) seconds to make the distance between him and the quarterback 0 (i.e. essentially sack the quarterback). This matches well with the final outcome of the play, as the sack takes place at the very last frame (4.4 seconds) where the estimated STRAIN for Crosby reaches its peak at 3.96.

Moreover, Figure 5 clearly demonstrates the interactions between the features for Maxx

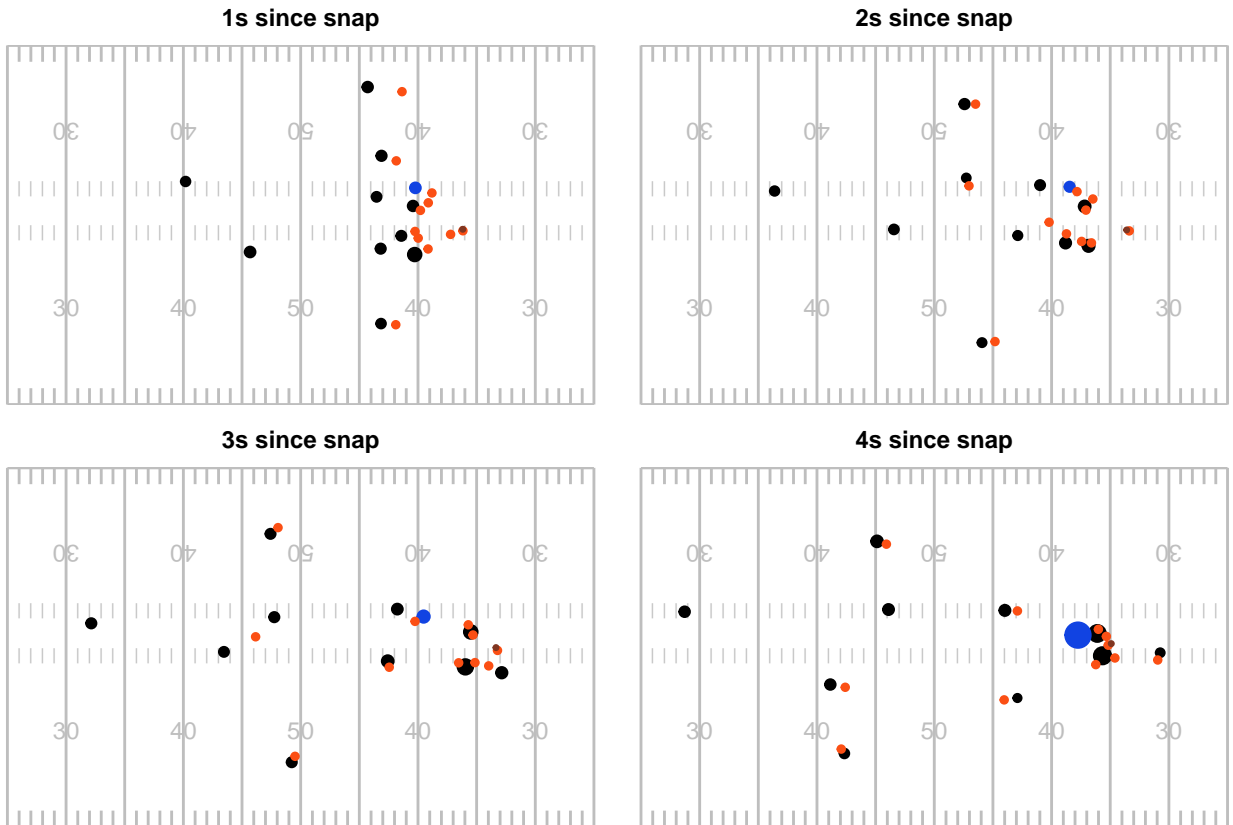


Figure 4: A display of the player tracking data for a play during the Las Vegas Raiders (defense, in black) versus Denver Broncos (offense, in orange) NFL game on October 17, 2021. Raiders DE Maxx Crosby is highlighted in blue. For each Raiders defender, the point size indicates their individual STRAIN value, with larger points suggesting larger STRAIN. Snapshots are captured at 1, 2, 3, and 4 seconds after the ball snap.

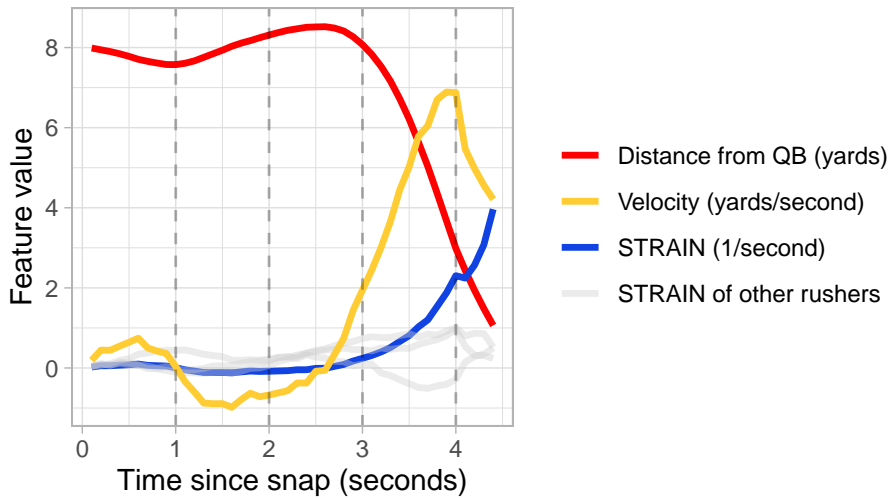


Figure 5: Changes in STRAIN, velocity, and distance from the quarterback for Maxx Crosby over the course of a successful pass rush play that results in a sack. The STRAIN for other pass rushers throughout this play is also displayed.

Crosby. Here, a higher STRAIN generally corresponds to faster moving rate toward the quarterback. STRAIN also increases as the distance between the pass rusher and quarterback is being reduced. Both of these relationships suggest an overall successful pass rush by Maxx Crosby. It is also notable that Crosby, who is credited with a sack, generates more STRAIN than other pass rushers during this play.

In contrast, Figure 6 shows the feature curves for an unsuccessful pass rush attempt by the Raiders defense from the same game. In this play, Broncos QB Teddy Bridgewater is well-protected by the offensive line and is able to release a long pass to a receiver. We see that the STRAIN generated by Crosby is relatively small over the course of this play, compared to the previous play (as shown in Figure 5) which results in a sack.

4.2 Positional STRAIN Curves

Figure 7 displays the average STRAIN by position for the first 40 frames (4 seconds) after the snap. For each position, the curve is based on the average of the observed STRAIN at each frame across all plays and players within the position. We observe a clear difference in STRAIN between edge rushers (outside linebackers and defensive ends) and interior linemen (defensive tackles and nose tackles). Specifically, edge rushers have higher STRAIN than interior linemen on average, as they are more easily able to approach the quarterback on

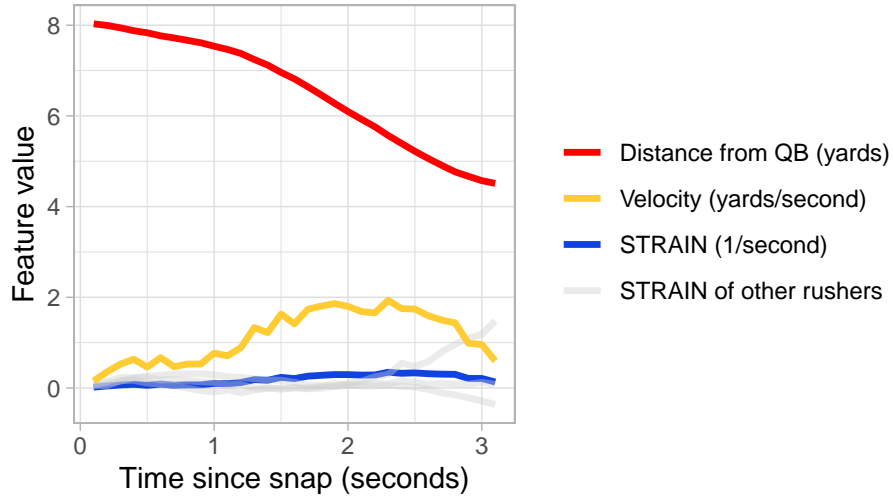


Figure 6: Changes in STRAIN, velocity, and distance from the quarterback for Maxx Crosby over the course of an unsuccessful pass rush play. The STRAIN for other pass rushers throughout this play is also displayed.

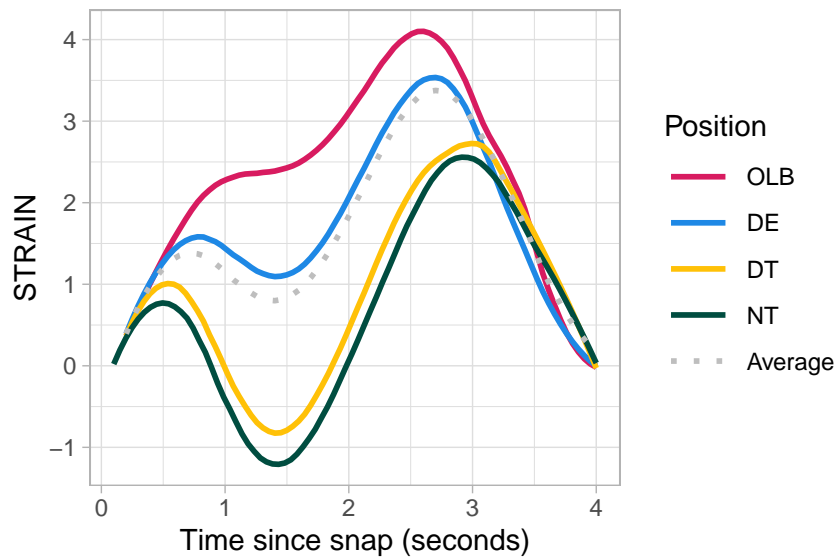


Figure 7: STRAIN curves for different positions. Edge rushers (outside linebackers and defensive ends) tend to generate more STRAIN than interior rushers (defensive tackles and nose tackles). The dotted gray line represents the average STRAIN curve for all players without accounting for position.

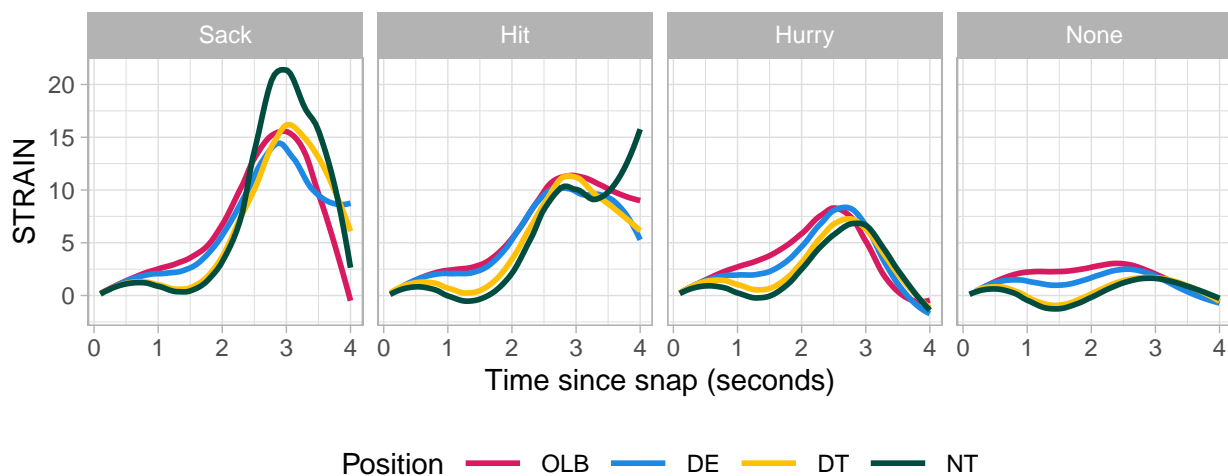


Figure 8: Positional STRAIN curves by play outcome (sack, hit, hurry, and none).

the edge of the pocket versus, for instance, a nose tackle attacking the line head on.

On average, STRAIN appears to increase for the first 0.5 seconds of a play, followed by a decline in the next second. STRAIN then increases again until around 2.5–3 seconds after the snap before trending down toward the end of the play. In context, this reflects the actions that a pass rusher initially moves toward the quarterback, but is then stopped by the offensive line while the quarterback drops back. When the quarterback stops dropping, the rusher closes the gap and increases STRAIN, before slowing down later on.

Further, Figure 8 shows the positional STRAIN curves by whether a play’s outcome is a hit, sack, hurry, or none of those. We clearly see that players tend to generate more STRAIN when a play ends in a hit, sack, or hurry, compared to no outcome. Within the three pressure metrics, it is not surprised that a sack corresponds to the highest amount of STRAIN, followed by a hit and hurry.

4.3 Ranking the Best Pass Rushers

Since STRAIN is observed continuously for every play in our data, this allows us to aggregate across all frames played and compute the average STRAIN for NFL pass rushers over the course of the eight-week sample size, as discussed in Section 3.1. Based on the clearly distinct patterns for different positions as previously observed, we evaluate interior pass rushers (nose tackles and defensive tackles) separately from edge rushers (outside linebackers and defensive ends). Tables 4 and 5 are leaderboards for the NFL’s best edge and interior rushers (with at least 100 plays) rated by the average STRAIN across all frames

Table 4: Top 15 edge rushers (with at least 100 snaps played) according to the average STRAIN across all frames played.

Rank	Player	Team	Position	Snaps	Hits	Hurries	Sacks	$\overline{\text{STRAIN}}$
1	Rashan Gary	GB	OLB	176	10	25	5	2.82
2	Leonard Floyd	LA	OLB	185	2	25	8	2.80
3	Justin Houston	BAL	OLB	132	8	8	4	2.78
4	Myles Garrett	CLE	DE	197	9	29	12	2.75
5	Von Miller	DEN	OLB	145	4	21	5	2.75
6	T.J. Watt	PIT	OLB	147	6	9	8	2.71
7	Yannick Ngakoue	LV	DE	175	6	20	4	2.70
8	Alex Highsmith	PIT	OLB	129	4	7	2	2.65
9	Preston Smith	GB	OLB	124	4	8	2	2.61
10	Randy Gregory	DAL	DE	134	7	19	5	2.58
11	Joey Bosa	LAC	OLB	160	5	21	4	2.58
12	Darrell Taylor	SEA	DE	107	5	9	3	2.57
13	Josh Sweat	PHI	DE	159	4	14	5	2.57
14	Maxx Crosby	LV	DE	198	12	30	7	2.56
15	Markus Golden	ARI	OLB	164	5	14	5	2.50

for the first eight weeks of the 2021 regular season. The tables also consist of the total number of hits, hurries, and sacks (determined from PFF scouting data) for each defender.

Our results are mostly consistent with conventional rankings of rushers. Notably, Myles Garrett and TJ Watt are widely recognized as top-tier edge rushers and both show up in our top edge rusher list; whereas Aaron Donald, who is undoubtedly the best interior defender in football, appears at the top of our interior rusher rankings. Moreover, our leaderboards largely match the rankings of experts in the field. For instance, there is considerable overlap between our lists and PFF’s edge (Monson, 2022) and interior (Linsey, 2022) rusher rankings released after the 2021 season. This ultimately lends credibility to our proposed metric STRAIN as a measure of pass rushing effectiveness.

Table 5: Top 15 interior rushers (with at least 100 snaps played) according to the average STRAIN across all frames played.

Rank	Player	Team	Position	Snaps	Hits	Hurries	Sacks	$\overline{\text{STRAIN}}$
1	Aaron Donald	LA	DT	239	8	24	6	1.67
2	Solomon Thomas	LV	DT	115	7	11	3	1.51
3	Quinton Jefferson	LV	DT	144	6	8	3	1.46
4	Chris Jones	KC	DT	139	3	18	3	1.42
5	DeForest Buckner	IND	DT	198	4	18	4	1.26
6	Cameron Heyward	PIT	DT	188	2	22	3	1.25
7	Javon Hargrave	PHI	DT	156	6	15	5	1.24
8	Jerry Tillery	LAC	DT	171	4	7	3	1.16
9	Ed Oliver	BUF	DT	133	4	12	1	1.15
10	Osa Odighizuwa	DAL	DT	162	3	18	3	1.13
11	Greg Gaines	LA	NT	111	2	13	2	1.11
12	Leonard Williams	NYG	DT	226	4	14	6	1.03
13	Christian Barmore	NE	DT	166	5	17	1	1.02
14	Vita Vea	TB	NT	184	6	12	1	1.01
15	B.J. Hill	CIN	DT	123	3	4	3	0.96

4.4 Statistical Properties of STRAIN

Next, we examine different statistical properties of our proposed metric STRAIN. Our focus here is to understand the stability and predictability of STRAIN, and we pose the following question: How much does our metric vary from week to week? In other words, is previous performance predictive of future performance based on our metric? Below, we attempt the answer these questions, and the following results are for pass rushers with at least 100 snaps played during the first eight weeks of the 2021 NFL regular season.

We first investigate the predictability of STRAIN as a measure of pressure. In particular, we look at how well our metric correlates with a simple measure of pressure rate, defined as the total hits, sacks and hurries per snap. Figure 9 is a scatterplot of average STRAIN and pressure rate over the course the provided eight-game sample, which reveals a fairly strong correlation ($r = 0.6255$) between the quantities. Hence, defenders with high STRAIN values also tend to generate more pressure toward the quarterback. Furthermore, the average STRAIN for the first four weeks of the 2021 season is more predictive of the last four weeks' pressure rate ($r = 0.3217$) than the first four weeks' pressure rate ($r = 0.0965$), as illustrated in Figure 10.

We also analyze the stability of STRAIN over time by comparing the average STRAIN across all frames played for the first and last four weeks of the 2021 NFL regular season. It is apparent from Figure 11 that there is a strong positive correlation ($r = 0.8545$) for this relationship. This means that STRAIN is a highly stable football metric over the provided eight-week time window, and pass rushers appear to carry their STRAIN values with them from week to week. Overall, STRAIN performs well in both explaining defensive pressure on the field and predicting future performance of pass rushers.

4.5 Multilevel Model Results

The results of fitting the multilevel model described in Section 3.2 is displayed in Table 6. First, we investigate the fixed effects terms of this model. It appears that that the average STRAIN decreases by 0.7366 (95% CI [-0.7875, -0.6858]) for every additional blocker in the offensive unit, after accounting for other covariates. In other words, NFL pass rushers tend to generate more pressure when facing fewer number of blockers, which makes intuitive sense.

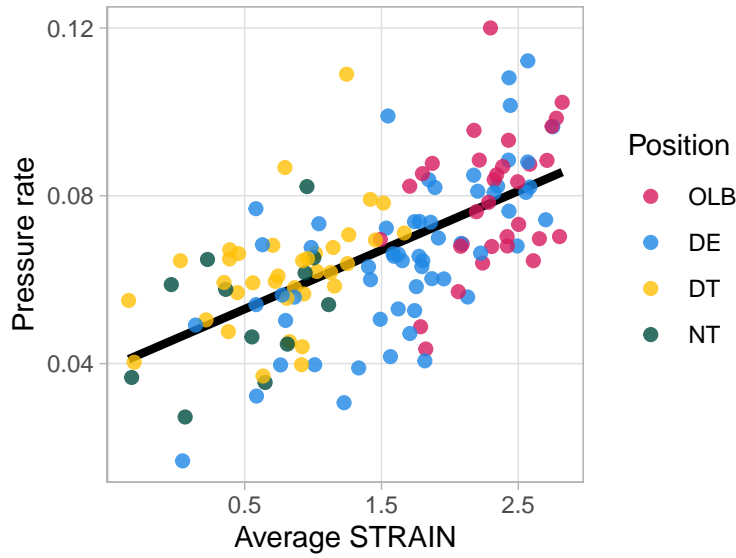


Figure 9: Relationship between average STRAIN and pressure rate (total hits, sacks, and hurries per snap) over the first eight weeks of the 2021 NFL season. There is a moderately strong association between average STRAIN and pressure rate ($r = 0.6255$). Results shown here are for pass rushers with at least 100 snaps played over the eight-week data.

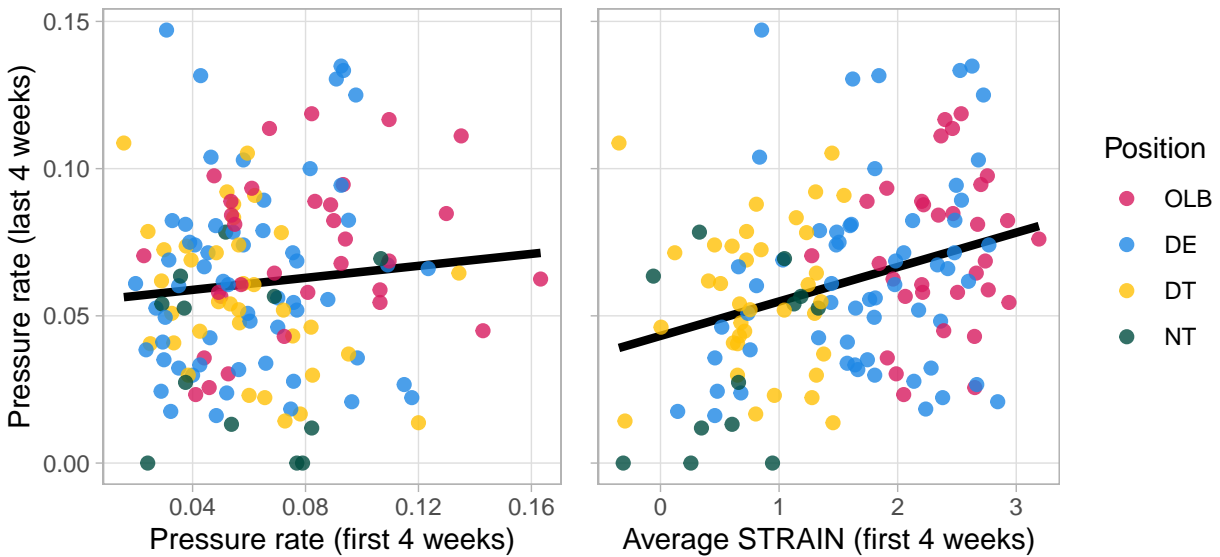


Figure 10: Relationships between pressure rate for the last 4 weeks of the 2021 NFL season and first four weeks' pressure rate (left) and average STRAIN (right). STRAIN is more predictive ($r = 0.3217$) of future pressure rate than previous pressure rate itself ($r = 0.0965$). Results shown here are for pass rushers with at least 100 snaps played over the eight-week data.

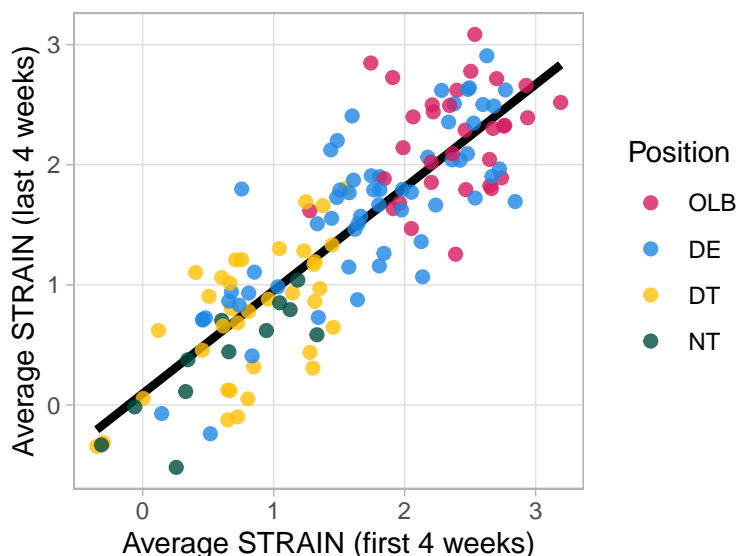


Figure 11: Relationship between average STRAIN for the last and first four weeks of the 2021 NFL season. A strong linear correlation ($r = 0.8545$) demonstrates that STRAIN is a highly stable metric over time. Results shown here are for pass rushers with at least 100 snaps played over the eight-week data.

As for play context, defensive pressure appears to increase when more yardage is required for the offense to reach a first down and for later plays within a set of down, when all other predictors are held constant. In particular, every extra yard in the distance needed for a first down is associated with a 0.0491 increase (95% CI [0.0426, 0.0555]) in the average STRAIN. Relative to first down situations, higher amount of pressure seem to happen in plays that come after (second, third, and fourth downs). In addition, we have insufficient evidence for a relationship between average STRAIN and the current yardline on the field for the offensive team.

Moreover, we observe statistically significant differences among the pass rush and pass block positions in most cases, while controlling for other variables. The coefficient estimates for the pass rush position terms reveal that players with positions closer to the line of scrimmage (defensive tackles and nose tackles) tend to generate less STRAIN (relative to defensive ends) than those lining up further back, which is consistent with our results in Section 4.2. For blockers, centers are those that absorb the most pressure on average, more than guards and other offensive positions (compared to the baseline level, tackles).

Next, Table 7 displays the intraclass correlation coefficients (ICC) for the four different

Table 6: Fixed effects coefficient estimates for the multilevel model for average STRAIN. Note that the reference down level is first down, the reference pass rusher level is defensive end (DE), denoted R:DE; the reference pass blocker level is tackle (T), denoted B:T.

	estimate	se	<i>t</i> -statistic	<i>p</i> -value
Intercept	1.8004	0.0991	18.1723	0.0000
Number of blockers	-0.7366	0.0259	-28.4153	0.0000
Yards to go	0.0491	0.0033	14.9013	0.0000
Current yardline	0.0001	0.0005	0.1844	0.8537
$I_{\{2\text{nd down}\}}$	0.5143	0.0290	17.7439	0.0000
$I_{\{3\text{rd down}\}}$	0.9176	0.0324	28.3613	0.0000
$I_{\{4\text{th down}\}}$	0.4649	0.0767	6.0637	0.0000
$I_{\{2\text{pt conversion}\}}$	-0.1384	0.1797	-0.7699	0.4413
$I_{\{R:DT\}}$	-0.7166	0.0678	-10.5658	0.0000
$I_{\{R:interior\}}$	0.5611	0.0999	5.6143	0.0000
$I_{\{R:NT\}}$	-0.9426	0.1021	-9.2344	0.0000
$I_{\{R:OLB\}}$	0.5574	0.0726	7.6742	0.0000
$I_{\{R:secondary\}}$	1.4252	0.1114	12.7899	0.0000
$I_{\{B:C\}}$	-0.2983	0.0594	-5.0237	0.0000
$I_{\{B:G\}}$	-0.1546	0.0471	-3.2847	0.0000
$I_{\{B:other\}}$	-0.1260	0.0646	-1.9508	0.0514

groupings, describing the proportion variance explained between the group terms in comparison to the residual variance. While the residual variance is unsurprisingly the largest value, between the player and team factors, we observe the largest ICC for pass rushers, followed by the offensive and defensive teams, and the blocker. This emphasizes how STRAIN is mostly attributable to pass rushers, but is necessary to adjust for opposition and other factors.

Aside from adjusting for opposition, our multilevel model allows us to provide some notion of uncertainty about the pass rusher’s effect on the play level STRAIN. Figure 12 displays the varying intercept distributions for the top ten pass rushers for each position. We obtain similar rankings based on the random intercepts in comparison to the average STRAIN results in Tables 4 and 5, with Myles Garrett (defensive end), T.J. Watt (outside

Table 7: Intraclass correlation coefficients for the multilevel model for average STRAIN.

	Pass rusher	Pass blocker	Defensive team	Offensive team	Residual
ICC	0.0365	0.0098	0.0134	0.0143	0.9260

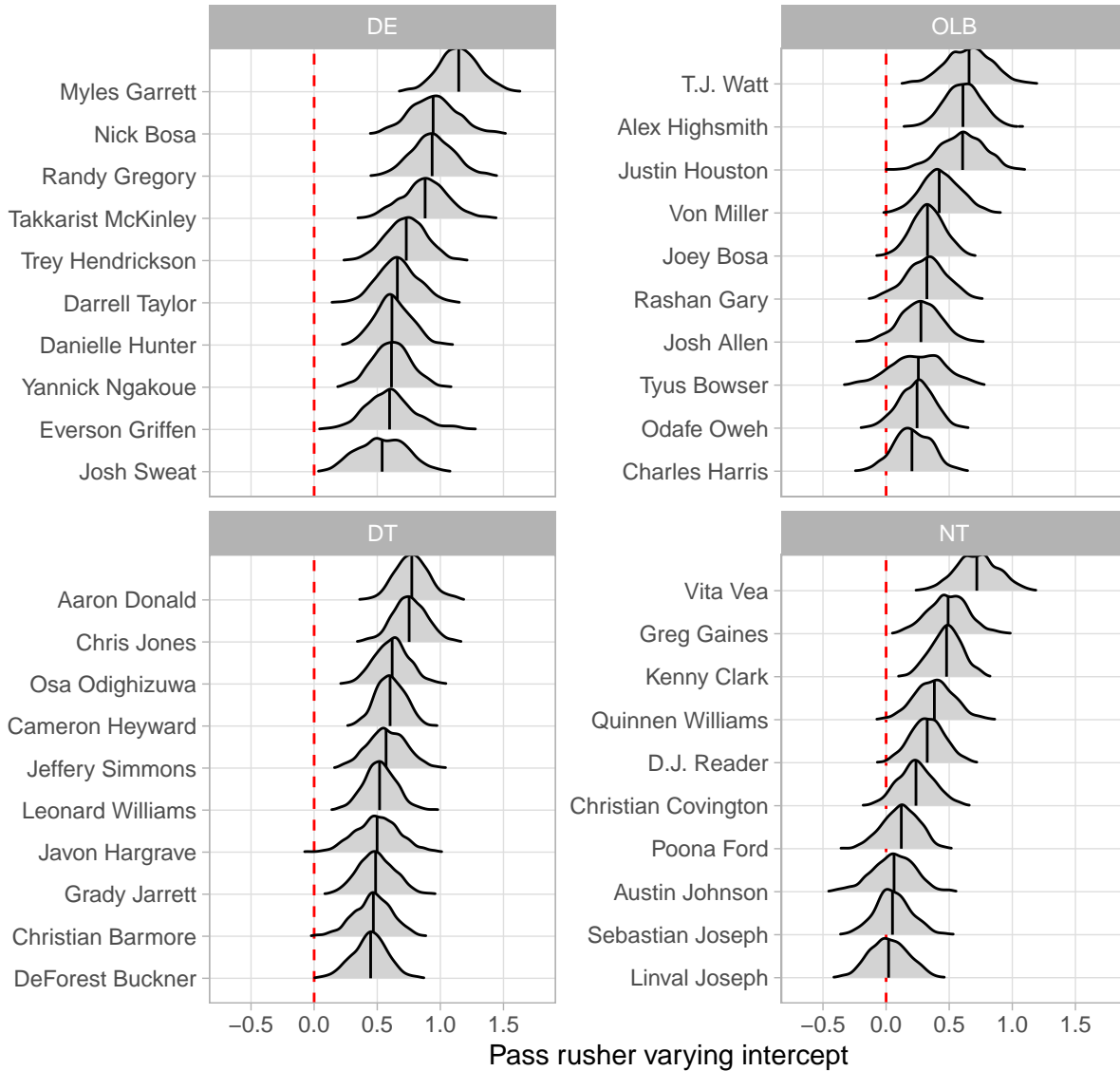


Figure 12: Distributions of player effects (obtained from 1,000 bootstrap samples) for top 10 pass rushers in each position (defensive end, outside linebacker, defensive tackle, nose tackle) by median varying intercept.

linebacker), Aaron Donald (defensive tackle), and Vita Vea (nose tackle) as the first-ranked pass rusher for their respective position. Additionally, we observe different levels of variability across these top defenders, with only a subset of players having intercept distributions strictly above zero. This is not necessarily surprising given the limited sample of data.

5 Discussion

In this work, we have proposed STRAIN—a simple and interpretable statistic for evaluating pass rushers—with higher values corresponding to greater pass rushing ability. STRAIN is a model-free metric which can easily be integrated into any data pipeline without much computational cost. Visualizations of STRAIN can be useful and intuitive for coaches and broadcasters in various aspects ranging from gameplan preparation to in-game real-time play analysis. We demonstrate that a pass rusher’s average STRAIN is both stable and more predictive of future pressure events than using the player’s previously observed pressure events. This is analogous to the use of exit velocity in baseball, a predictive measurement that avoids the noisy nature of observed outcomes, emphasizing how the opportunity of working with player tracking data can lead to the development of insightful metrics in American football. Through multilevel modeling, we observe that the pass rusher explains more variation in their play-level STRAIN, followed by the possession team and pass rushing team, and finally the pass rusher’s assigned blocker. This is an intuitive result, consistent with previous literature on pass rushing and defensive pressure.

Our multilevel model, however, is subject to several limitations. We only account for players directly involved as the pass rusher or nearest blocker, on top of team-level effects. The nested structure of our model enforces positive dependence between pass rushers on the same team, which may not be true. For instance, if one defender is known to be an elite pass rusher then the opposing team may focus their blocking efforts on this player. This could leave the path open for another player to rush the quarterback with ease, resulting in higher STRAIN values. As shown in Figure 12, the first- and fourth-ranked defensive ends Myles Garrett and Takkarist McKinley were teammates on the Cleveland Browns during the first eight weeks of the 2021 NFL season. McKinley is a surprising name on our list and we suspect that his high rank is mostly due to playing on the same defensive unit with Garrett, who is highly-regarded as a great pass rusher. In order to capture this

type of behavior, we could consider modeling an aggregate STRAIN across pass rushers with a regularized adjusted plus-minus (RAPM) regression approach. The use of RAPM techniques has been successfully demonstrated in American football by Sabin (2021), which accounts for all players on the field with Bayesian hierarchical models. We leave this type of analysis for future work, which will require careful consideration of available informative priors (Matano et al., 2023).

In addition, we believe there are other concepts in materials science that could be applied to evaluating pass rushing and pass blocking in American football. One potential idea is to consider a quantity called stress, which measures force over an area. By definition, force is the product of mass and acceleration, meaning this quantity would take into account the physical size of a pass rusher in the computation of force. We could then divide this force over the “area” of the pocket formed by pass blockers to compute stress.

Moreover, although we focus solely on pass rushers in this paper, STRAIN can also be applied to the assessment of pass blockers as a unit. This can be accomplished through the aforementioned RAPM regression or by simply looking at quantities such as the total STRAIN or the maximum STRAIN per frame aggregated across the entire play. It is also possible to apply STRAIN to assess individual offensive pass blockers, provided that a method of matching blockers to rushers is developed. Furthermore, compared to existing metrics, STRAIN measures pass rush effectiveness for every play continuously over time, which is at a much more granular level than considering whether the play resulted in a binary outcome such as a sack. Indeed, visualizations of STRAIN curves across moments of time within plays reveal variability that simple averaging may obscure. There is ample opportunity for working with the complete STRAIN trajectories via temporal modeling and functional data analysis techniques to better understand the impact of STRAIN on offensive production in American football.

Acknowledgements

We thank the organizers of the NFL Big Data Bowl 2023 for hosting the competition and providing access to the data.

SUPPLEMENTARY MATERIAL

All code related to this paper is available at <https://github.com/getstrained/intro-strain>. The data provided by the NFL Big Data Bowl 2023 is available at <https://www.kaggle.com/competitions/nfl-big-data-bowl-2023/data>.

References

- Alamar, B. and K. Goldner (2011). The blindside project: Measuring the impact of individual offensive linemen. *Chance* 24, 25–29.
- Alamar, B. C. and J. Weinstein-Gould (2008). Isolating the effect of individual linemen on the passing game in the national football league. *Journal of Quantitative Analysis in Sports* 4(2).
- Bates, D., M. Mächler, B. Bolker, and S. Walker (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software* 67(1), 1–48.
- Baumer, B. S., G. J. Matthews, and Q. Nguyen (2023). Big ideas in sports analytics and statistical tools for their investigation. *WIREs Computational Statistics*, e1612.
- Burke, B. (2018). We created better pass-rusher and pass-blocker stats: How they work. ESPN.com. [Accessed 16-May-2023].
- Burke, B. (2019). Deepqb: deep learning with player tracking to quantify quarterback decision-making & performance. In *Proceedings of the 2019 MIT Sloan Sports Analytics Conference*.
- Callister, W. D. and D. G. Rethwisch (2018). *Materials science and engineering: an introduction* (10 ed.). Hoboken, NJ: John Wiley & Sons, Inc.
- Chu, D., M. Reyers, J. Thomson, and L. Y. Wu (2020). Route identification in the national football league. *Journal of Quantitative Analysis in Sports* 16(2), 121–132.
- Deshpande, S. K. and K. Evans (2020). Expected hypothetical completion probability. *Journal of Quantitative Analysis in Sports* 16(2), 85–94.

- Dutta, R., R. Yurko, and S. L. Ventura (2020). Unsupervised methods for identifying pass coverage among defensive backs with nfl player tracking data. *Journal of Quantitative Analysis in Sports* 16(2), 143–161.
- Eager, E. and G. Chahrouri (2018). Edge vs Interior: Which pass-rusher reigns supreme. PFF.com. [Accessed 16-May-2023].
- Hermsmeyer, J. (2021). The NFL Has A New Way To Measure The Explosiveness Of Pass Rushers. FiveThirtyEight.com. [Accessed 16-May-2023].
- Howard, A., A. Blake, A. Patton, M. Lopez, T. Bliss, and W. Cukierski (2022). NFL Big Data Bowl 2023.
- Kovalchik, S. A. (2023). Player tracking data in sports. *Annual Review of Statistics and Its Application* 10(1), 677–697.
- Linsey, B. (2022). 2022 NFL interior defender rankings and tiers. PFF.com. [Accessed 16-May-2023].
- Lopez, M. J. (2020). Bigger data, better questions, and a return to fourth down behavior: an introduction to a special issue on tracking data in the national football league. *Journal of Quantitative Analysis in Sports* 16(2), 73–79.
- Macdonald, B. (2020). Recreating the Game: Using Player Tracking Data to Analyze Dynamics in Basketball and Football. *Harvard Data Science Review* 2(4).
- Matano, F., L. Richardson, T. Pospisil, C. A. Politsch, and J. Qin (2023). Augmenting adjusted plus-minus in soccer with fifa ratings. *Journal of Quantitative Analysis in Sports* 19(1), 43–49.
- Monson, S. (2022). 2022 NFL Edge Rusher Rankings and Tiers. PFF.com. [Accessed 16-May-2023].
- NFL Football Operations (2023a). Big Data Bowl. NFL.com. [Accessed 16-May-2023].
- NFL Football Operations (2023b). NFL Next Gen Stats. NFL.com. [Accessed 16-May-2023].

- R Core Team (2023). *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing.
- Reyers, M. and T. B. Swartz (2021). Quarterback evaluation in the national football league using tracking data. *AStA Advances in Statistical Analysis*, 1–16.
- Sabin, R. P. (2021). Estimating player value in american football using plus–minus models. *Journal of Quantitative Analysis in Sports* 17(4), 313–364.
- Sterken, N. (2019). Routenet: a convolutional neuralnetwork for classifying routes. *NFL Big Data Bowl*.
- Wolfson, J., V. Addona, and R. Schmicker (2017). Forecasting the performance of college prospects selected in the national football league draft. In *Handbook of Statistical Methods and Analyses in Sports*, pp. 137–163. Boca Raton, FL: CRC Press.
- Yurko, R., F. Matano, L. F. Richardson, N. Granered, T. Pospisil, K. Pelechrinis, and S. L. Ventura (2020). Going deep: models for continuous-time within-play valuation of game outcomes in american football with tracking data. *Journal of Quantitative Analysis in Sports* 16(2), 163–182.
- Yurko, R., S. Ventura, and M. Horowitz (2019). nflWAR: a reproducible method for offensive player evaluation in football. *Journal of Quantitative Analysis in Sports* 15(3), 163–183.