Defending the Edge: Evaluating OT Performance through Euclidean Measurements

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Abstract:

NFL data used in the Kaggle competition NFL Databowl[1] is based in x,y coordinates, this allows for the measuring of player positions in relation to each other to be easily measured using Euclidean Distance (d). The problem of automated analysis of Offensive Lines remains a problem in NFL analytics. I develop a series of metrics to automate analysis using Euclidean Distances. I develop a proof of concept by focusing on the edge rush from Defensive Ends that are mitigated through the blocking by the Offensive Tackle (OT) position.

Like GIS applications the NFL tracks each game using visual recognition systems to locate the players on the playing field and marking their x.y locations 10 times per second. This data can be used to track player actions for each play. This typical graph representation allows for easy computational paradigms to be used to automate the interpretation of plays on the field. I develop a metric system based on six aspects of evaluating each play.

Euclidean Distance in Metrics

First, a basic understanding of Euclidean Distance is presented. If we look at equation 1 below, we see that it is a straight forward line-of-sight measurement or 'as the crow flies' between two vectors, say $P^1_{x,y}$ and $P^2_{x,y}$ giving a value for the distance between the two vectors.

$$d = |\mathbf{x} - \mathbf{y}| = \sqrt{\sum_{i=1}^{n} |x_i - y_i|^2} \,. \tag{1}$$

I use Euclidean Distance for several different measurements, measuring the distance (d) between the Defensive Rusher (DE) and the OT used for analyzing the style of block which is stored in the 'frame_metrics' table. The d between the DE and the Quarterback (QB), for comparison of starting d and ending d for measuring momentum. Another place that I use d is for measuring the d of straight line positions of the DE from one frame to the next and how effective the OT is in deterring the DE from proceeding in a straight line toward the QB, the shortest path to the goal. The straight line d is expressed as:

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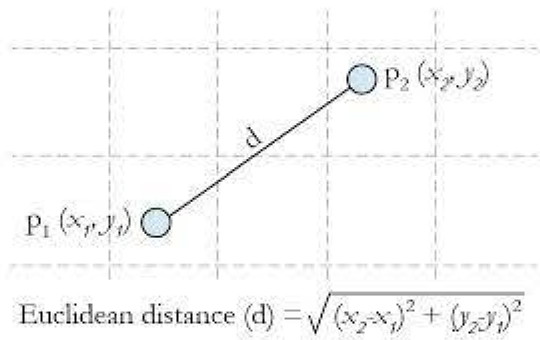
[1] Addison Howard, Ally Blake, Andrew Patton, Michael Lopez, Thompson Bliss, Will Cukierski , NFL Big Databowl 2023, ,(2023) https://kaggle.com/competitions/nfl-big-data-bowl-2023}

$$P^{1}{}_{x^{i-1},y^{i-1}} \text{ and } P^{2}{}_{x^{i},y^{i}}$$



Where P1 is the predicted straight line next position. P2 is the next x,y coordinate of the actual path of the DE. That is a predicted path is made from the current position of the DE to the QB, then the next step in that predicted path is measured as d to the actual next step taken. The larger the d the greater the OT deterred the DE from proceeding in the shortest path to the goal.

Time Length of Plays in Evaluation Metrics

It should be noted that there is a limit on the evaluation of plays, I do not evaluate past 4 seconds of a play, this affects a minority of the plays (n=2078) as the large majority of plays are less than 4 seconds (n=8379). 100ms equals 1 frame (10fps) in the NFL data. Also, one can see a distinction in the length of plays, one could query the database based on frames (i.e. where total_frames = 25, etc) to see results for a given time range in the plays and compare the scores for different time lengths. Plays become more chaotic the longer the play. I use 4s as a baseline since it provides enough of a sample size to provide variety in scoring without encountering too much noise in the data due to the chaos of long plays.

QBI Avg by Length of Play (n is # of plays)*

Play Length	QBI Avg
QBI < 2s[2]	2.98405172413793 (n=580)
QBI >= 2.0s < 2.5s[3]	2.97064531780689 (n=2061)
QBI i >= 2.5s < 3.0s	2.93430656934307 (n=2603)
QBI >= 3.0s < 3.5s	2.88750641354541 (n=1949)
QBI >= 3.5s <= 4.0s	2.69439338235294 (n=3264)

[2] select AVG(qbi_rating) from play_results WHERE total_frames < 20

[3] select AVG(qbi_rating) from play_results WHERE total_frames >= 20 AND total_frames < 25

* there is a decrease in success with an increase in length of time. Decremental: .0134, .0366, .047, .193. With the difference between 3.0 to 3.5 to 3.5 to 4.0s a four fold decremental decrease in success.

Also related to the time length is that of the concept of ‘interface length’ which I define as when a Defender and Blocker and/or QB are within 1.5yds of each other. Several metrics are only calculated during this ‘interface length’ as a limiting factor on data analysis. This is important for measuring momentum, straight lines, block efficiency, and QB-DE metrics, It is viewed as the length that an OT can reasonably affect the DE.

Frame Metrics Aggregation

As mentioned above d is measured between the Blocker, Defender and QB, these measurements are stored in the ‘frame_metrics table in the db. Frame metrics gathers relevant x,y coordinates of QB, OT, and DE or other rusher, measures the required euclideans and writes these values to the 'frame_metrics' table in the db[4] giving 3 different sets of euclideans to do data analysis on to formulate the basis of the evaluation metrics. The code that drives this aggregation is in the OT_Defending_The_Edge_Metric_Aggregation.ipynb notebook file.

Six Aspects of Evaluation

There are six different metrics generated by me to use in evaluating each block. I view 1 as quantitative and 5 as related to individual style. The QBI is quantitative and I use it in comparison to other systems for evaluating blocks such as those by PFF (pff.com). The other 5 are more subjective in understanding and do not directly relate to success or failure as some blockers are less prone to close proximity blocking and use their arms but generate as good results as those that focus on body blocks.

- Quality of Block Index (QBI)
- Block Efficiency
- Block Momentum
- QB-DE Rating
- QB-DE Euclidean
- Straight Lines Euclideans

The above metrics are presented in more detail below.

-QBI: Quality Block Index is a rating system that penalizes based on the OT either being beaten or allowing himself or the rusher to enter three zones around the QB: buffer (1.5yds), danger (1.0yds) or sack (<.7yds). It is based on a scale of 0-3 and comprises the primary metric for overall evaluation akin to PFF ranking of OT, also I only rate players with at least 100 plays in the dataset. If a blocker or defender is in the buffer zone a .5pt penalty is applied, if in the danger zone a further .5pt penalty, if in the sack area they are zeroed out, score=0, note that sack area is not equal to a sack, but

[4] The db, 40_databowl.db is available at https://www.kaggle.com/autonomous019/defending-the-edge-game-results/ in the data directory, /inputs/4-seconds/

means that a sack should have been made irregardless of an actual tackle or not, a catastrophic failure in blocking is failed block not dependent on defenders ability to finish the play.The buffer and danger zones are theorized as the area that impedes the QB from maximum performance, the danger zone is the arm length of a defender, who may either grab the QB or impede his throwing arm or motion. If they are beaten, the DE is closer to the QB than the blocker, a .5pt penalty, if they regain control, the beaten penalty is .25pts. These are strictly speaking position based or coordinate based ratings relative to the QB. Qualitative metrics are noted below. I use two scales: the QBI and the QBI+Style (QBI+) Metrics for evaluation. QBI data is held in the qbi_metrics table in the db. QBI is what I use to rank players although other more quantitative measures from the styles metrics such as block momentum and QB-DE Euclidean could be combined to augment the results. According to QBI alone rankings the top 10 results were:

QBI Rank	Name	nflId in db	AVG(QBI) all plays
1	Andrew Whitworth	30869	2.934584
2	Tristan Wirfs	52421	2.934543
3	Andrew Thomas	52412	2.926037
4	Charles Leno	41475	2.921698
5	Trent Williams	35443	2.920399
6	Rob Havenstein	42400	2.919004
7	Riley Reiff	38553	2.915470
8	Justin Herron	52603	2.907897
9	Donovan Smith	42377	2.902957
10	Brian O'Neill	46131	2.893011

As is seen some of these players are usually included in most top 10 lists of OTs, such as PFF's. It should be noted that these rankings are based on partial game plays not a full game, which gives different results depending on the plays included in the partial sample of the game. If by random chance there is a negative or positive bias in the plays dramatically affects overall rankings, such as the results of Riley Reiff and Brian O'Neill. See discussion below regarding rectifying results with other evaluation systems, whereas the majority of the top 10 are also in many lists of top 10 OTs here.

-Block Efficiency: Is a measure based on d that gives a score for the percentage of blocks that are close to the body (<.8yds Euclidean distance between OT and DE), viz arm blocks (>1.667yds <.8yds Euclidean distance between OT and DE) , with arm close to fully extended. A positive score is given if the close body block is above 25% of the overall interaction length. I assumed that the typical reach of a OT and DE is around .7-.8yds). Typically DE momentum slows with close proximity blocking. An interesting statistic to look at is when the efficiency rate is < or >= .25 (25%). On efficiency => .25 (n=5077 plays), the momentum avg is 0.5639, QBI 2.8339, the d between QB-DE[5] is 4.9894. When the efficiency is < .25 (25%) momentum (n=5380) goes down to 0.5310, but QBI goes up 2.8858, the d b/w QB-DE is 5.5366. A knowledge domain experts review of the Straight Line plots may provide more insights into the relationship between the QB-DE d and close proximity blocking, to the unprofessional eye, such as my own, I see that as the DE gets closer to the QB the OT closes their d to the DE as they put up more resistance as the play gets closer to the QB. So we may see a direct correlation between low QBI score, high efficiency (close proximity) and low QB-DE d resulting in lower QBI but higher efficiency scores. This may be one thing that needs to be tuned in future iterations of this evaluation model, how to score efficiency more accurately.

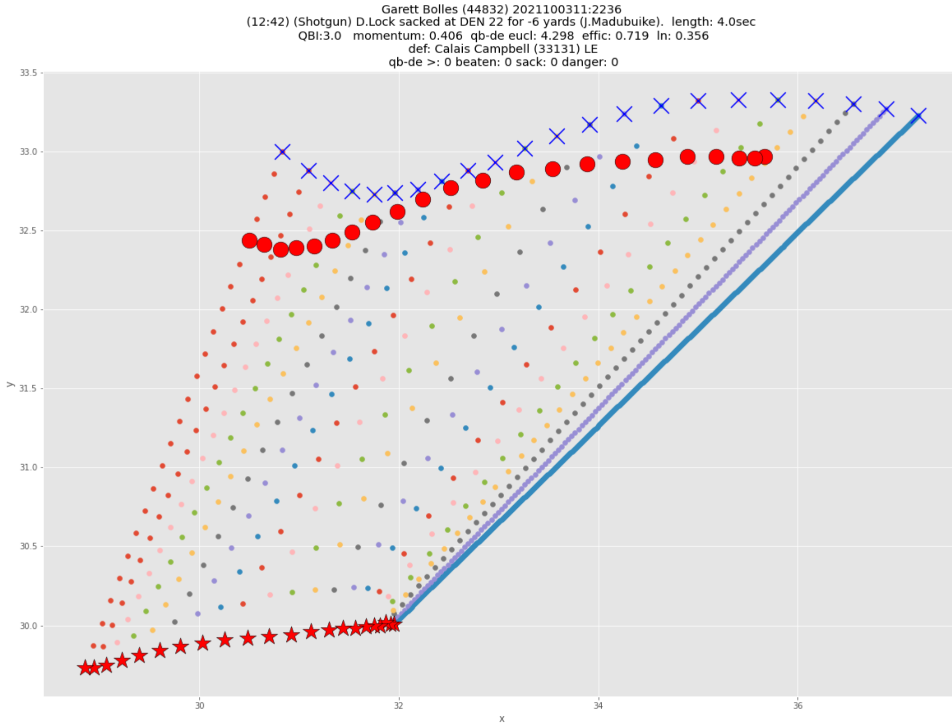
-Block Momentum: Is a measure based on whether the blocker is able to slow the momentum from the start of the interface length to the end of the interface length, if a blocker is able to slow the momentum in more frames then not slowing the defender (>=50%) a positive score is given. Momentum is a measure of whether the blocker slows the rate of closure on the QB, measured on a frame by frame basis; score reflects the total percentage of frames where momentum decreased during the interface.

-QB-DE Rating and Euclidean: Is a measure that looks at the d between the DE and the QB. If the d of the DE increases, between the QB and DE, from the start of the interaction to the end of the interface length a positive score is given and the QB-DE Rating is given as 1, otherwise it is scored as 0 (0,1). If the euclidean average value is above 4yds then a positive score is given. It is important to note that this value usually increases on edge rushes when the arc is affected by the OT to push the rusher away or outward from the QB, arc increases. This can be seen in the plots provided at the link below. A source of noise for this measurement is a scrambling QB that either scrambles toward the DE or away, future versions will need to detect this anomaly.

-Straight Lines Divergence: Is an evaluation based on the concept of divergence of the defender from taking a straight line toward the quarterback, the ability of the blocker to deter the rusher from the shortest path toward his target, the QB, it is also based in measuring the euclidean. This euclidean is a measurement from the defender's position compared to his predicted position on a straight line to the QB from his previous position. The higher the euclidean distance the better the result, the higher one is off the straight line to the QB. Straight Lines is held in the 'lines_metrics' table in the db. If the line_rating avg for the play is above .3yds (1ft) a positive score is given. There is a divergence in all metrics between completed and incompleted passes. It is interesting to look at the straight line averages in all the data as an example of this, see below.

Metrics such as Momentum, the euclidean relative to start and end of play during interface between

[5] select AVG(qb_de_eucl_avg) from play_results where efficiency >= .25



Plot showing Metrics and Straight Lines to QB from Defender[6]

blocker and defender, the QB-DE rating and euclidean scores are aggregated in the 'block_metrics' table. So that 4 metrics are created through the block metrics algo: qb-de rating (0,1), qb-de euclidean (float), momentum (0-100) and efficiency (0-100). The code for the aggregation algorithm for the block metrics table is in the QBI and Block Metric Algorithm Notebook[7]

-Play and Game Results: As mentioned the QBI Rating, used for a more objective evaluation and the QBI+Style (QBI+) evaluation which includes measures that are a question of blocking styles and more subjective but informative on an individual level of blocking style. The final QBI+ is on a scale of 0-5.5 with QBI 3pts and QB-DE Rating (.5pts), QB-DE Euclidean (.5pts), Lines Rating (.5pts), Momentum (.5pts) and Efficiency (.5pts). Scores are 0 or .5 based on a threshold value. Completed Passes v. Incompleted Passes is one interesting comparison to look at as far as the total results go based on averages for all play results in all games for all blockers. Though caution is given not to

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[6] Straight Line plots are coded in the notebook at https://colab.research.google.com/drive/1C6aM5tLTj6luCqj951OdMvQhbH_IHBQE?usp=sharing. A collection of SL plots is at https://drive.google.com/drive/folders/1J-aUNbdA4JR2sLAj_nBjyn6IsjmnwznF?usp=sharing
5-on-5 plots are set in the '5 on 5 Plots of Each Relevant Play' section of OT_Defending_The_Edge_Metric_Aggregation.ipynb notebook in the Github repo.

[7] https://colab.research.google.com/drive/1sGJMSsW4gVAAPmYzmH0JQ_VeP-vQbQOp?usp=sharing

make too broad of conclusions as we are only analyzing one person's contributions to a completed pass which involves the synchronicity of 11 players in all, even in terms of pass blocking we are only dealing with 1 out of 5 players involved in blocking, thus more often than not the individual player is successful in their assignment but someone else may not be thus giving a incompletion. However, as a broad measure it is an interesting comparison nonetheless.

Metric	**Completed (n=5687)**	**Incompleted (n=4770)**
QBI	2.91670564508992	2.79130113132339
QBI+Styles	4.30825119043233	4.20102202731276
Straight Lines	0.302775380602603	0.29456476156998
Efficiency	0.257506123423736	0.282060508846367
Momentum	0.534847609731337	0.558647465270838
QB-DE Euclidean Distance	5.35071634105951	5.21878901320947
QB-DE Rating	0.223161053178863	0.247030742322318

These comparisons suggest that some measures are more objective than others, since they match with the outcomes such as QBI, Straight Lines, and QB-DE Euclidean. Due to computation time lengths the next version will include all 5 blockers in the data rather than just one player per play, which may shed more light on what metrics are more informative in building a model of evaluating OL performance. To go over play and game results in more detail see the notebook https://www.kaggle.com/autonomous019/defending-the-edge-game-results

Rectifying Differences Between this Evaluation Model and Other Systems of Evaluation

As mentioned above, depending on the bias in the random sample of the plays involved, being an incomplete set, most evaluations use a full game or every play rather than a subset, and this has given a couple surprising results both positively and negatively. In contrast to such consistent results between this evaluation and PFF[8] where Andrew Whitworth finishes in the top spot in both, and

[8] PFF data is at https://premium.pff.com/nfl/positions/2021/REGPO/offense-pass-blocking?position=T, file is behind a pay-wall subscription service. (Accessed 12/19/22)

players like Charles Leno, Dion Dawkins finishing almost in identical positions in both, others move up or down depending on the type of data in the partial data set used in this evaluation. A deeper look at the data used to model these results explains this divergence. Looking at Jordan Mailata, who is rated by PFF as the no. 7 Pass Blocker but here finished 49 of 50. Inversely we look at Riley Reiff who finished in the top 10 in QBI but is rated by PFF as the 99th Pass Blocker. As well as look at Tyron Smith who slides down from no. 3 on PFF PB ratings to 16 in QBI score here.

First, for Jordan Mailata it is important to note that in the 6 games rated he actually participated in 243 plays, but this dataset only has 161 of those plays. If you consider PFF sacks, hits, hurries and pressures you get a negativity rate of .1069. In this dataset used to measure QBI when considering negative plays such as sack area, danger area, buffer area, beaten we have a negativity rate of .260 which is 160% divergence. In both systems the sack is weighted heavier but in PFF dataset there are 2 sacks, in this dataset there are 5. So we see the different results are explained by the different sample size and the negative bias of that sample set.

On the opposite side of things is the rapid rise of Reilly Reif in these results compared to PFF's up from PFF's 99th PB OT to 7 out of 50 here. Again, looking at the sample size we see that he participated in 7 games in weeks 1-8 for a total of 287 plays, in this dataset 245 are rated, the negativity rate in the PFF rated plays is .1045, but in this dataset it is only marginally greater .1306, in this evaluation there are more negative chances then in PFF data. Most error rates double between PFF and this QBI evaluation, so this error rate of Reif is very low. Notably in the PFF ratings there are 4 sacks, but in this evaluation dataset there are 0 in the sack area, so we see how this divergence is explained.

Finally, there is the large slide of Tyron Smith PFF No.3, QBI 16 of 50, again this can be explained in the sample versus actual datasets. There are 264 plays in PFF data, in this dataset there are 188 plays. The PFF negativity rate is .0378, the QBI negativity rate is .1329, so 3 fold greater. in QBI data has 6 plays with a score <= 2.0, 2 in sack area, in PFF data only 1 sack and very low numbers for other negative plays.

This gives us a clearer picture for interpreting the results. To truly test the results of this evaluation we would need to be able to directly compare them to all the plays for all the blockers. It does suggest that QBI is a good way to measure automatically whether a blocker is doing a credible job or not when we consider bias in the partial data set samples and the fact that there are many consistent results between QBI and PFF rankings with less biased partial data samples such as Andrew Whitworth.

All Code is available at the Github repo:
https://github.com/autonomous019/NFL_Big_Data_Bowl_23

Aggregation and Plotting algorithms were made to run on Google Colab. Results algorithms were made to run on Kaggle.