Next Gen Stats: Going Beyond Top Speed

By

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Abstract

Currently, much emphasis is placed on top speed as a measurement of performance for NFL wide receivers; however, many factors go into defining a successful route runner. These factors, such as change of direction, can be seen but have yet to be successfully quantified. As a method to better understand wide receiver performance in the NFL, new metrics were created and proved to be overall successful indicators of wide receiver performance.

Keywords: football, NFL, sports, wide receiver, performance metrics, Next Gen Stats, speed, acceleration, change of direction

Executive Summary

This research endeavor entailed developing the calculations to compute different relevant metrics describing wide receiver performance and applying a rigorous validation process to understand their viability and applicability.

Wide receiver metrics were computed using iterative calculations utilizing player tracking data from the 2018 NFL season. For each passing play, every wide receiver's route was classified, and route-specific computations were performed to calculate relevant metrics describing player performance. These metrics were then aggregated and validated to ensure they would be novel, stable, and differentiating metrics of performance.

Three families of metrics were created. First, change of direction metrics were calculated based on the radius, time, and angular velocity a player carried during a sharp change of direction movement. Second, speed metrics were created to describe top-end speed. Finally, burst metrics were created to capture acceleration, time to top speed, and other metrics related to how quickly a player can accelerate.

These metrics were validated by analyzing whether they were differentiating, stable, and correlated to traditional measures of wide receiver performance. It was determined that change of direction was a valid metric by these criteria for In, Out, and Slant routes. Burst metrics were relevant for all types of routes. Speed metrics were relevant for Post, Corner, Cross, and Go routes. These validations provide proof-of-concept that tracking data can be used to create viable metrics to describe on-field performance.

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Introduction

The National Football League (NFL) is the professional American football league in the United States. In 2020, the 32 NFL teams generated revenue of $12.2B (Gough, 2021). NFL player tracking, conducted by the NFL's Next Gen Stats team, captures real-time location data, speed, and acceleration for every player, every play, on every inch of the field. Radio-frequency identification (RFID) sensors throughout the stadium track tags placed on players' shoulder pads, charting individual movements within inches (NFL Next Gen Stats, n.d.). NFL Next Gen Stats leverages this tracking data in real time to create new stats, predict success rates of plays, and improve player health and safety, all while creating a better experience for fans, players, and teams. Using machine learning and data analytic services provided by Amazon Web Services, the Next Gen Stats team provides accurate insights on their platform to help clubs analyze trends and player performance.

The Next Gen Stats team has three primary stakeholders who utilize the outputs of this tracking data. First, the 32 NFL clubs use this data to evaluate players and make roster decisions. Second, the league itself, which focuses on using the data to enhance player safety and drive business-decisions made by the NFL Football Operations team. Lastly, media partners share insights from this data to enhance the experience for fans watching the game on TV. The media partners are the revenue generating stakeholders of Next Gen Stats.

Opportunity Statement

The NFL Next Gen Stats team wants to help their stakeholders better understand the complex physics and kinesthetics of the game. Currently, Next Gen Stats focuses primarily on top speed as a metric of measuring player performance and are interested in better understanding the physiological aspects of the game outside of this metric. There is an opportunity to develop aggregate statistical performance differentiators to help clubs to better understand wide receiver performance. The Next Gen Stats team believes the answers lie within their data.

The NFL Next Gen Stats team seeks to improve its understanding of wide receiver performance to assist clubs and further enhance television broadcasts and other opportunities for fan engagement. The clubs are interested in this information to further improve and optimize scouting of new wide receivers and performance of existing wide receivers. Media partners are interested in this data to further immerse fans in player performance analytics, creating more engagement and excitement around players and plays during the game.

Analysis Goals

The primary goal was to design new metrics to effectively describe key elements of wide receiver performance. These elements include burst off the line, change of direction time, change of direction radius, time to top speed, and high/low speed acceleration. Secondarily, a validation framework was created to help the NFL understand the usability of these new metrics as indicators of wide receiver performance. As the goals focused on the generation of new metrics, the approach taken did not require any machine learning models. Rather, in-depth data exploration, filtering, and rule-based logic was needed to achieve the goal.

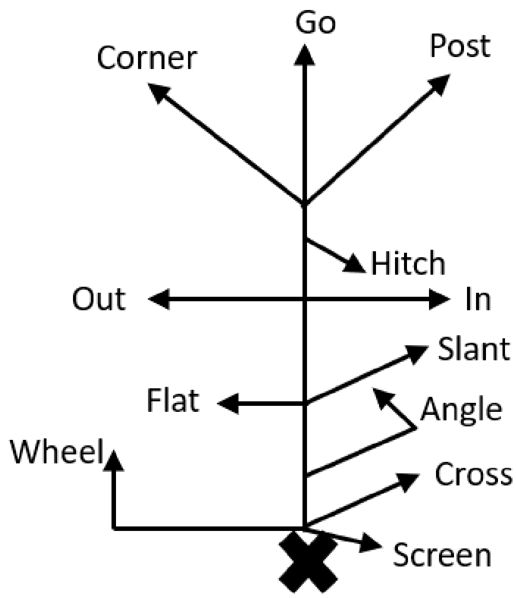
Scope

The scope was limited to wide receivers in the NFL from the 2018 season, though the method of calculating these metrics can be applied to offensive passing routes for various player positions from all seasons in which Next Gen Stats RFID tracking devices were utilized.

Background

In football, one primary way to advance the ball is passing downfield. This involves a quarterback throwing the ball to a receiver. The receivers run different types of “routes,” which are patterns designed to maneuver around or past a defender. These routes are intended to create space between a receiver and the defender, which allows the quarterback ample room to throw the football without the defense being able to obstruct the pass. The NFL Next Gen stats team has identified 12 primary types of routes that are run by receivers, illustrated in Figure 1.

Figure 1. *Common route types run by football wide receivers*



The success a player finds in creating space between him and his defender is largely a function of quality route running, which is commonly defined by speed, acceleration, and agility. However, traditional measurement of these traits can be difficult and/or arbitrary. Oftentimes, coaches can qualitatively determine how effective a receiver is at running a particular route by analyzing game film closely. While this is the predominant way for coaches to evaluate players, it often suffers from subjectivity and bias. Historically, quantitative solutions to this problem have not been readily available. Through a mathematical and quantitative analysis, there is an opportunity to create objective measures that quantify wide receiver performance on the field, and identify which features are most predictive of success on gameday.

Literature Review

Currently, players who wish to enter the NFL participate in the combine each spring before the draft. The combine consists of several strength and speed tests (40-yard dash, bench press, vertical jump, etc.) to assess performance. As players enter the draft from different colleges, the combine is an event that allows coaches to compare all players head-to-head based on the results of these tests. However, it has been found that there is no consistent statistical relationship between the combine tests and future performance in the NFL for wide receivers (Kuzmits & Adams, 2008). The measurement of raw speed (using the 40-yard dash) is likely not a good predictor of actual performance in the NFL, as there is no significant relationship between the time of this test and first year (rookie) performance (including number of games played) for wide receivers (Treme & Allen, 2009). In fact, when rookie contracts are re-structured based off performance, it was found that slower sprint times in the 40-yard dash are associated with larger third-year salaries (Kuzmits & Adams, 2008).

Just as speed alone may not be a good indicator of successful performance in the NFL, this has been found to be true of other team sports as well. To best optimize team rosters, many sports are turning to analytics to better understand how to define success of players. In elite female soccer it was found that, although there was a near perfect association between linear spring speed and curve sprint velocities, players who perform well on these speed metrics often exhibit greater deficits on change of direction speeds (Kobal, et al., 2021). Though linear speed is important for athletes who play field sports, it has been discovered that change in direction and acceleration speeds are also essential to athlete success (Lockie, et al., 2013). Research has found that traditional intensity-based thresholds for acceleration and deceleration exhibit poor reliability and are inappropriate for time-series data (Delaney, et al., 2017). Speed and acceleration can occur separately from each other, and thus should be treated as somewhat independent when assessing athlete performance.

Despite the growth of wearable technology in sports over the past decade (Luczak, et al., 2019), the analytics outputs associated with these are not always actionable to coaches who do not have a technical statistics background. Frustration among these stakeholders is common due to the lack of meaningful recommendations that come from the data outputs of this technology. When working with data produced by wearables, "what does the data mean" is a question these coaches are often not able to easily answer (Luczak, et al., 2019).

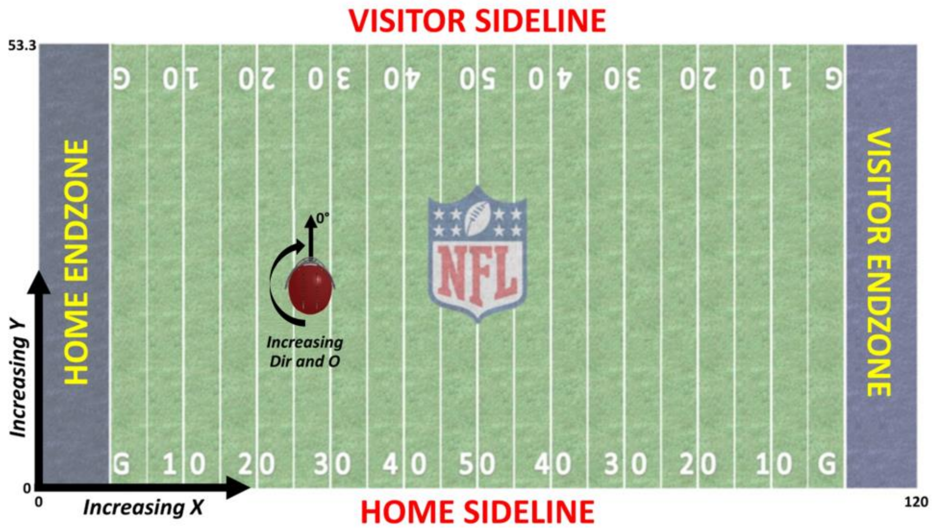
In addition to wearable technology, RFID and video technology are growing forms of data collection in sports. In basketball, high resolution shot capture systems are used to evaluate shooting ability of players (Marty, 2017). Conventional shot charts rely on shooting percentage alone to measure performance, which do not provide a lot of insight into the "why" surrounding the statistics. Using court maps allows coaches to have a better description of the weaknesses and strengths of players, which in turn are used to give actionable recommendations for roster building and player improvement. In golf, the PGA tour also uses video technology to assess player performance. ShotLink data records information taken on every stroke, which has allowed analytic professionals to create new metrics to assess skills, such as putting. Using ideas from spatial statistics, a map of each green is constructed, and difficulty is measured by combining both distance to the hole and direction (Yousefi & Swartz, 2013). While distance is traditionally used to predict putting success, the addition of orientation provides a more accurate estimation of the expected number of putts.

As analytics are increasingly relied on to assess performance in sports, it is important to ensure that new metrics are reliable indicators of player ability. Quantifying sources of variability is essential for understanding how sports metrics can be used (Franks, et al., 2016). New metrics should be evaluated on stability, discrimination, and independence. This ensures that new sports stats can accurately predict player performance year-over-year, in addition to quantitatively differentiating between players. Additionally, the independence criteria ensures that new metrics are providing new information that does not already exist in currently available sports stats. Though it is easy to evaluate metrics alone on correlation with standard measures of successful outcomes (such as team winning percentages or player salaries), it is important to also evaluate them on consistency over time in order to fully measure the potential repeat performance of players (Berri, 2012).

Data

The Next Gen Stats team has installed a tracking system in every NFL stadium which is composed of: 20–30 ultra-wide band receivers, 2–3 RFID tags installed into the players' shoulder pads, RFID tags on officials, pylons, sticks, chains, and in the ball. Altogether, an estimated 250 devices are in a stadium for any given game. The tracking system captures player data such as location, speed, distance traveled, and acceleration at a rate of 10 times per second, and charts individual movements within inches. More than 200 new data points are created on every play of every game (NFL, n.d.). The raw tracking data consists of X, Y coordinates of player location, which associates with the vertical and horizontal yard measurement on the football field (as seen in Figure 2).

Figure 2. *Coordinate plane representation of a football field*



Data Sources

Data from the 2018 NFL season was leveraged for analysis. In total, the 2018 season has approximately 17 million observations from the player tracking data. Game data, consisting of information for all 256 regular season games, was referenced to ensure consistency of the data. Variables such as teams, season-week, and time of game were cross-referenced with the other datasets. A player dataset, which consisted of the name, position, height, and weight of each player was used to filter the tracking data down to focus on the 228 wide receivers who ran at least one route in 2018. Play data, including information about each play, such as game, time, yard line, team of possession, type of play, and result of play, was used to filter the tracking data down to analyze only the 19,420 passing plays run in 2018. Tracking data, including the location of players on the field, speed, acceleration, orientation, and the type of route for each play, was measured every one-tenth of a second.

The input variables used to understand metrics of success for each route were the tracking data for the targeted wide receiver, such as: speed, acceleration, orientation, direction of travel.

The unit of analysis is each player per play. As the creation of these metrics was inherently unsupervised, there was no dependent variable used in the creation of the new metrics.

For validation, various traditional wide receiver performance statistics were gathered. This included salary, game metrics (number of receptions, total yards, yards per reception, catch percentage, touchdowns), fantasy football stats (total season points and average weekly points), draft data (round and number of pick), and combine stats (height, weight, 40-yard dash time, vertical jump, broad jump, 3 cone drill, shuttle run, bench press).

Descriptive Analysis

In total, the data contained 12 different types of passing routes. Screen and Flat routes were removed from the analysis, as these routes typically do not depend on the kinesthetic movements that would be measured by the new player metrics created. In addition, Wheel and Angle routes were removed due to a very low number of observations. Plays where the route was undefined were also removed. Table 1 shows the total number of plays, by route type, that were used in the analysis.

Table 1. *Number of plays, by route type*

Route Type	Number of Plays
Go	11,295
Hitch	7,965
Cross	4,831
Out	4,291
In	4,246
Post	3,922
Slant	3,216
Corner	1,876

With the wide range of route types included in the tracking data, extensive exploratory data analysis was conducted to understand the best rules to create to calculate the metrics by route type. Given that the primary goal of this work was to identify rules to generate new player performance metrics, the details of these analyses are described in the Methodology. Measurement of peak performance from a wide receiver is heavily dependent on identifying situations when a player exerts maximum effort. With 41,642 plays and 170 players, there was an average of 165 player-play combinations per game. 87% of routes run by wide receivers did not result in a caught pass, as there are up to 5 eligible receivers per pass play. Intensive filtering of the tracking data was conducted to isolate instances when wide receivers were playing at their peak performance.

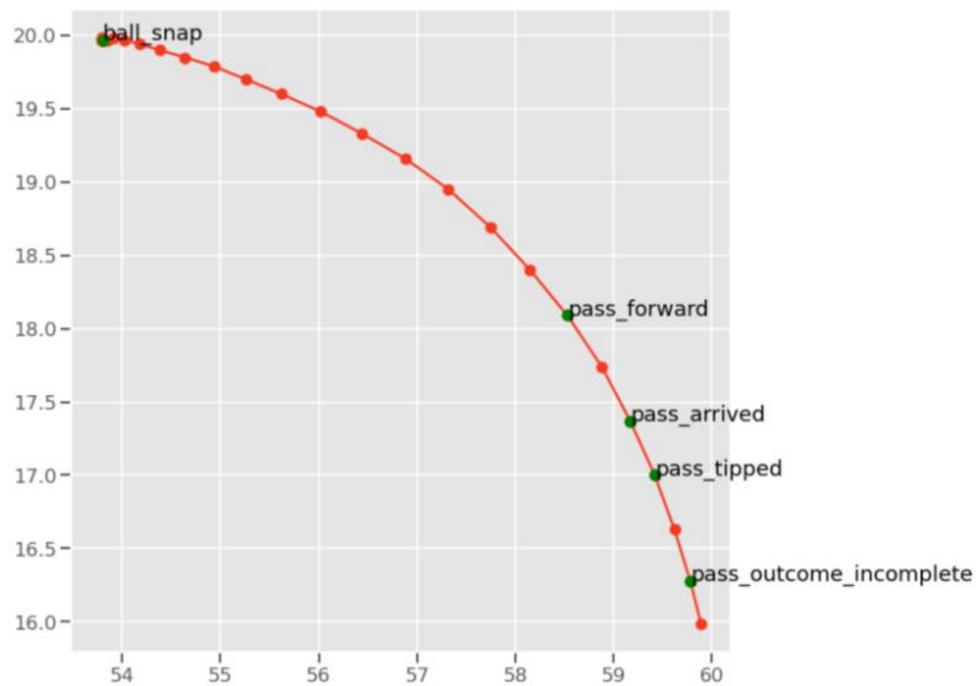
Methodology

Data Pre-Processing

Given the large number of observations, it was necessary to perform thorough pre-processing to standardize the tracking data. First, the data was extracted and filtered to only include wide receivers on passing plays for the 8 routes analyzed. Next, the data was normalized to a consistent direction the players were traveling on the field. Since the nature of player tracking data is dependent on the direction of travel on the field, the X/Y, direction, and orientation values had to be normalized to a consistent point of reference.

As the tracking data was measured to the one-tenth of a second, it was necessary to define the start and end of the play for the route calculations. The “event” column of the tracking data noted aspects of the play, such as when the ball was snapped to the quarterback and the pass was thrown, among others. To get a clean definition of the start of the play, all data up to 0.3 seconds post-snap was eliminated to allow each play to have a defined start time. This was necessary to remove as much noise as possible from the tracking data as players released from the line without removing meaningful data from the analysis. The play-level tracking data was truncated at the time of the pass arriving to the targeted receiver to remove any movement after the ball was caught and players were traveling downfield. Figure 3 displays an X/Y plot of a route ran by a receiver with the associated play events labeled.

Figure 3. *Example of events in a route*



For purposes of this research, it was imperative to sufficiently filter to only include plays where players were exerting maximum effort. Football games can last up to 4 hours and 70+ plays, thus it is not realistic to expect a player will be operating at peak performance and intensity throughout the entire duration. Filtering logic was applied for each player/play combination in order to isolate peak performance for our measurements and metrics and exclude plays where players did not exert maximum effort.

Metric Generation

A primary area of interest for the NFL was investigating physics-related metrics. Understanding performance related to change of direction was key to this analysis. In addition, other metrics related to speed and acceleration that would be more specific to the differences in routes were focused on. These were determined to be important, as the current top speed / top acceleration metrics used by the NFL do not encompass aspects such as burst, which is only applicable to a certain portion of a route. In total, 10 metrics were generated to describe wide receiver performance. Definitions of these metrics are included in Table 2.

Table 2. *Definition of Metrics*

Change of direction time	How long it takes for a player to complete his break
Change of direction radius	The radius of the break
Burst off the line: acceleration	Peak acceleration in pre-break segment
Burst off the line: speed	Peak speed in pre-break segment
Time to top speed off the line	Time to reach peak speed in pre-break segment
Top speed	Top speed during the play
Top acceleration	Top acceleration during the play
Time to top speed	Seconds to reach top speed metric
Low speed acceleration	Top acceleration during low-speed portion of route
High speed acceleration	Mean acceleration during high-speed portion of route

As the running path of the wide receiver is unique for each route type, different calculations were needed for each metric at a route-specific level. Additionally, not all metrics were relevant for all routes. Table 3 shows the list of metrics, by route, that were created.

Table 3. *Metrics created, by route type*

	In	Out	Cross	Go	Hitch	Slant	Post	Corner
Change of direction time	X	X				X	X	X
Change of direction radius	X	X				X		
Burst off the line: acceleration	X	X			X	X	X	X
Burst off the line: speed	X	X			X	X	X	X
Time to top speed off the line	X	X			X	X	X	X
Top speed			X	X			X	X
Top acceleration			X	X			X	X
Time to top speed			X	X				
Low speed acceleration			X	X				
High speed acceleration			X	X				
Top speed burst			X	X				
Change of direction combined (angular velocity)	X	X				X		

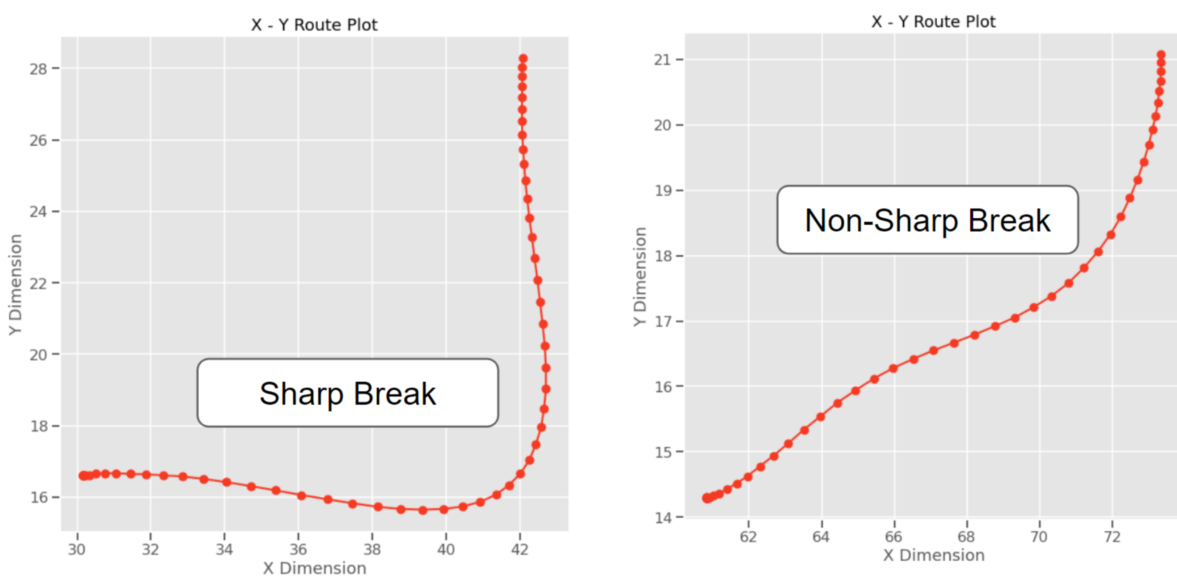
Based on the exploratory data analysis and trial and error, route-specific rules were created to ensure the nuances between route types were properly accounted for in the calculations. Breaking routes (In, Out, Slant, Post, Corner, Hitch) were segmented into pre-break and post-break segments. To identify the break (where the player was changing direction) first order differencing was used to create a rolling average of orientation and direction change. When this rolling average difference was greater than a designated threshold, a break was identified. In addition, the overall change in direction traveled during the break was important, as the goal was to identify and compare similar breaks. This step was necessary due to limitations in the route classification algorithm provided by the NFL. Due to this, each route had a specific threshold that the overall break orientation change had to fall between to be considered a valid break. The break orientation thresholds for each route can be found in Table 4.

Table 4. *Threshold break must fall between to qualify for change of direction metrics*

Route	Threshold (in degrees)
In	60-120
Out	60-120
Hitch	130-210
Slant	>= 30
Post	20-90
Corner	20-90

Thresholds for break orientation change were created to differentiate between shallow and sharp breaks, with the aim of including only sharp breaks for further analysis. Figure 4 illustrates examples of a sharp and shallow break on the X, Y plane of the field.

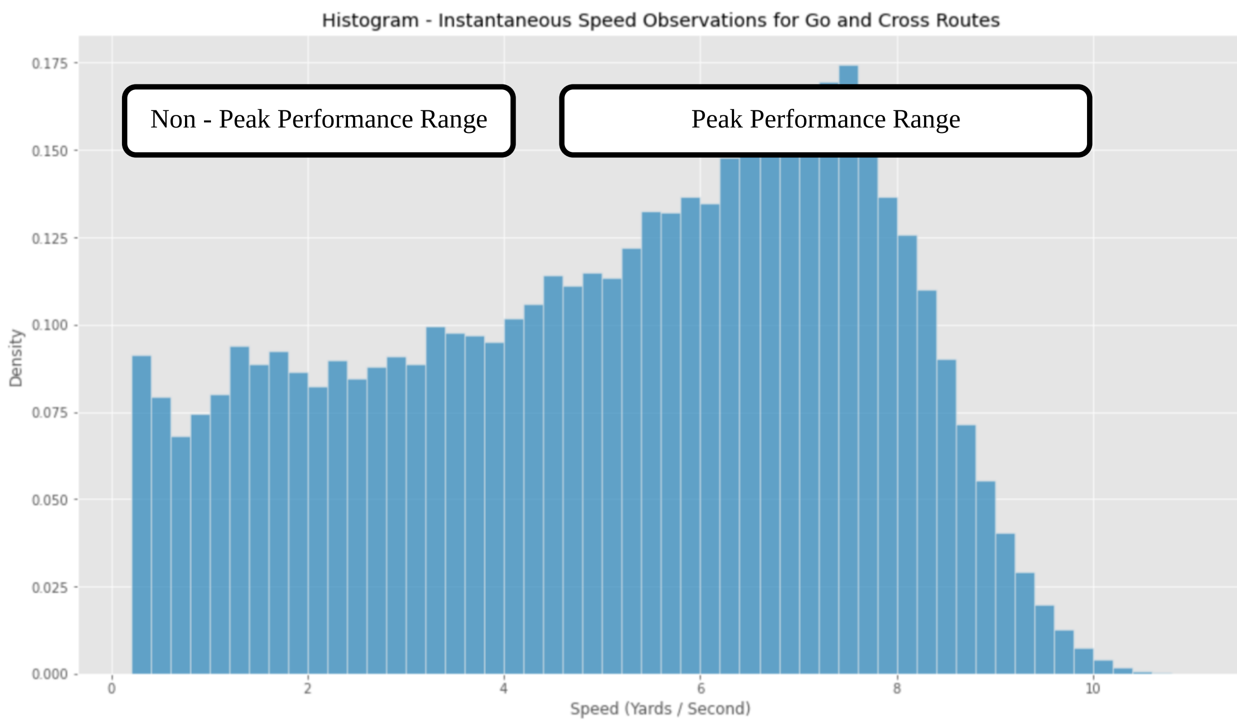
Figure 4. *Example of a sharp vs. non-sharp (shallow) break*



This filtering procedure was developed and executed for all breaking route types. Change of direction time was calculated by measuring how long it took a player to complete his break, and the radius was measured using an iterative trigonometric approximation. A change of direction combined metric was created using angular velocity, which accounted for both the speed and radius of the break. The burst off the line (speed and acceleration) metrics were calculated by the top acceleration and speed of the player in the pre-break section of the route (prior to changing direction). Similarly, time to top speed off the line was the amount of time (in seconds) it took the player to reach the burst off the line top speed.

One indicator of peak performance that was important to understand was speed. Figure 5 shows a distribution of instantaneous speed measurements for Go and Cross routes, which are two routes where players are expected to reach their true top speed. This analysis helped identify the range of speeds players were traveling on these types of routes. It also begins to illustrate the instances and speeds where players were reaching peak performance and where players were not at peak performance. In the chart below, it was interpreted that most players tend to reach peak performance around 6 – 10 yards per second (y/s). Top speed and top acceleration were calculated as the max speed and acceleration in the route, while time to top speed was the time (in seconds) it took a player to reach the top speed metric.

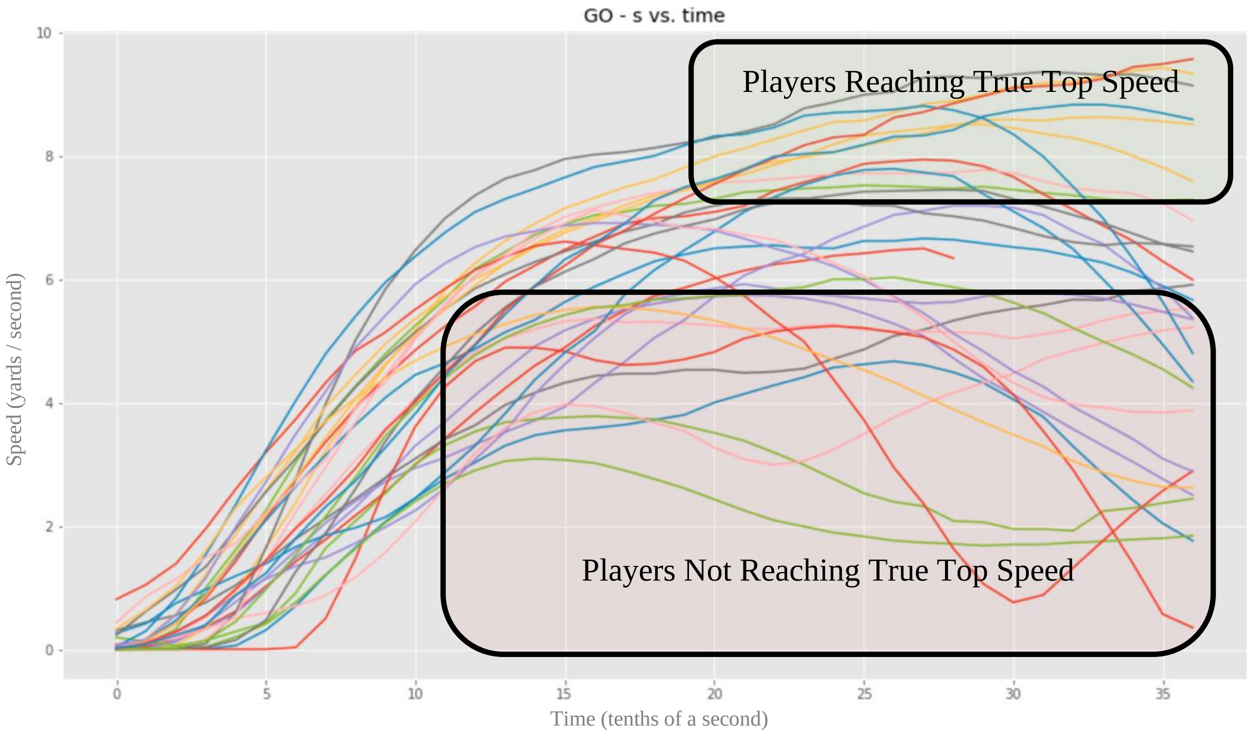
Figure 5. *Distribution of speed during go and crossing routes*



Another insight from this analysis was the unique distribution of these instantaneous speeds. As seen in Figure 5, there is a near uniform distribution from 0 – 4 y/s, and a normal distribution above 4 y/s. This indicates there are two segments to this route, a low speed, high acceleration portion and a high-speed portion of the route. The threshold to segment these two portions of the route was determined to be 4 y/s. For Cross and Go routes, low-speed acceleration and high-speed acceleration metrics were calculated. Low-speed acceleration was calculated by taking the top acceleration in the low-speed segment of the route, while the high-speed acceleration was calculated by taking the average of the player's acceleration during the high-speed portion of the route.

Figure 6 shows a subset of Go routes in the tracking dataset. Each line indicates an individual route, with the x-axis being time of the individual play from the snap onwards, and the y-axis indicating the speed. From this view, it is clear only a small fraction of Go routes result in a player reaching his top speed, and often players decelerate prematurely or are unable to reach their top speed for another reason (the play ended early, the player was not going to be the targeted receiver, the route-classification algorithm misclassified the route, etc.).

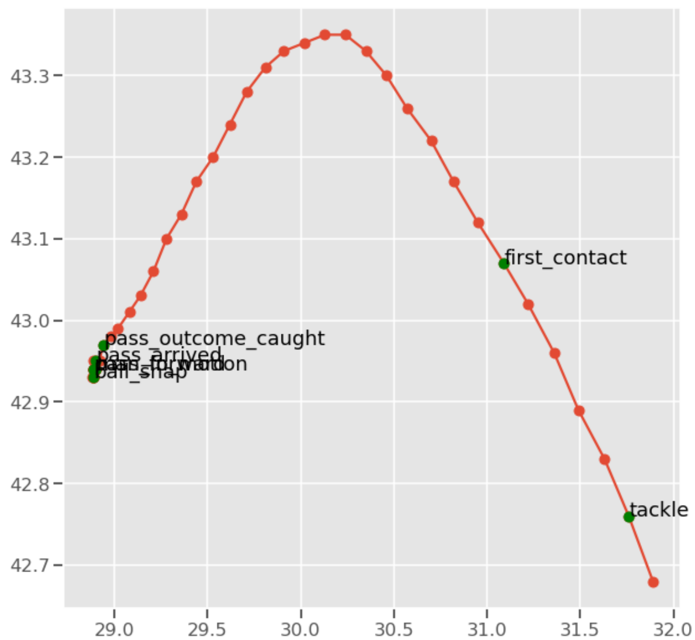
Figure 6. *Speed of players over the length of a play*



An analogous methodology was executed on every route type for multiple metrics to discern patterns and identify when players were exerting maximum effort, and these findings were translated into filtering rules to remove non-peak performance plays from subsequent calculations.

For Go routes, it was determined a player must have increased speed for at least the first 2.5 seconds of the play in order to compute top speed and acceleration metrics for this analysis. This ensured that any short plays or instances a where player did not have sufficient time to reach top speed would not influence measurements and skew the final metrics. Additionally, the total length of the player's movement must have been at least 1 yard to be included in the final calculations. This helped to eliminate any plays where players did not have a sufficient chance to release from the line and enter a route. Figure 7 shows an example of a route that was filtered out during the analysis, as the play was too short from the start of the play to the ball arriving to be considered an adequate representation of route running.

Figure 7. *Example of route not included due to short length of play*



Once the metrics were created, they were aggregated at the player and route level to determine a player's season-long performance at the route level for all key relevant metrics. To be included in a player/route level aggregation, a player must have run at least five plays of that route type. This was intended to ensure that players who only had a few instances of a specific route did not overly influence the results of the aggregation and indexing. Different quantiles were used for each metric during the aggregation. In addition, these quantiles were different based off whether the wide receiver was targeted on the play or not. The quantile-level aggregation was another effort to appropriately isolate and measure a player's peak performance. This further eliminated any plays where the wide receiver was not exerting maximum effort. The average of the targeted and non-targeted metrics was taken to create one final aggregated metric. Once aggregated, a min-max scaler was applied to each play-route metric on a scale of 50-100. This scale was used as it is consistent with the NFL's current practices to score players.

Table 5. *Quantiles used to calculate player-route aggregation*

Metric	Percentile: Non-Targeted	Percentile: Targeted
Change of direction time	10th	25th
Change of direction radius	10th	25th
Burst off the line: acceleration	90th	75th
Burst off the line: speed	90th	75th
Time to top speed off the line	10th	25th
Top speed	90th	75th
Top acceleration	90th	75th
Time to top speed	10th	25th
Low speed acceleration	90th	75th
High speed acceleration	90th	75th

Lastly, three final performance metrics were created to capture player performance across all route types. A "speed" composite metric was created by taking the average of all scaled top speed metrics across all route types. A "burst" composite metric was created by taking the average of top acceleration, low speed acceleration, high speed acceleration, acceleration burst off the line, and speed burst off the line scaled scores across all routes. A "change of direction" composite metric was calculated by taking an average of the change of direction combined (angular velocity) scaled score across all routes. Finally, a "total" composite was created by summing a player's values in composite speed, burst, and change of direction metrics.

Validation

The intention when developing these statistics was to be able to use them as an additional tool to evaluate wide receiver performance. These statistics were treated as performance indicators and were validated as such. The primary mode of validation used was divided into three categories: discrimination, stability, and independence.

Discrimination was used to understand the usefulness of the new metrics in assessing performance. This was done by performing a one-way ANOVA test on each metric, by route, to understand if there was significant difference among the players. For this ANOVA test, performed at a 0.05 significance level, the null hypothesis was that there is no significant difference among players.

Validation of stability was performed to provide confidence that one year's performance will be predictive of another. For this, the metrics were aggregated by player on a week-by-week basis. Then, the coefficient of variation (standard deviation divided by mean) was calculated for each player's route-metric combination. Finally, the average route-metric coefficient of variation was calculated based off all players, and this metric was multiplied by 100. For field studies, a coefficient of variation under 10 is considered very good, 10-20 is considered good, and 20-30 is acceptable. A coefficient of variation over 30 is deemed as not acceptable to prove stability.

Independence was assessed to ensure that the metrics would give us new information that was not already provided in traditional player performance stats, while still understanding that these new metrics were not wholly independent information. Correlation within metrics, as well as against current measurements of player performance, was performed. Statistical significance testing at the 90% level was then performed on the correlation coefficients. A 90% confidence level was chosen as there are many external variables in a football game that can impact a player's performance that are outside of their control.

Findings

The results of the one-way ANOVA test for validating discrimination can be found in Table 6. This analysis was conducted at the play level, prior to any aggregation and indexing. Route-metric combinations highlighted in green rejected the null hypothesis that there was no significant difference among players.

Table 6. *Results of one-way ANOVA test*

	In	Out	Cross	Go	Hitch	Slant	Post	Corner
Change of direction time	<.001	0.001				0.013	0.958	0.320
Change of direction radius	<.001	0.003				0.041		
Burst off the line: acceleration	0.083	0.438			0.002	0.709	0.612	0.134
Burst off the line: speed	<.001	<.001			<.001	0.142	0.065	0.085
Time to top speed off the line	<.001	<.001			<.001	0.412	0.350	0.207
Top speed			<.001	<.001			0.005	<.001
Top acceleration			<.001	<.001			0.087	0.010
Time to top speed			0.002	0.062				
Low speed acceleration			<.001	<.001				
High speed acceleration			<.001	<.001				
Top speed burst			<.001	<.001				
Change of direction combined (angular velocity)	0.009	<.001				0.095		
Indicates null hypothesis was rejected at 5% significance level								

Table 7 is the output of the coefficient of variation test for stability. Route-metric combinations highlighted in green or yellow are considered acceptable to prove stability over the season.

Table 7. *Average player coefficient of variation across all 16 games*

	In	Out	Cross	Go	Hitch	Slant	Post	Corner
Change of direction time	15.28	18.09				10.36	11.67	9.50
Change of direction radius	37.81	44.12				26.38		
Burst off the line: acceleration	21.17	23.64			17.75	21.83	18.17	19.53
Burst off the line: speed	17.87	21.51			14.45	18.68	11.72	14.97
Time to top speed off the line	19.81	20.94			17.49	15.69	21.41	20.06
Top speed			7.40	7.01			8.81	7.55
Top acceleration			19.08	18.01			15.77	16.06
Time to top speed			14.72	11.69				
Low speed acceleration			20.71	18.57				
High speed acceleration			19.14	17.41				
Top speed burst			11.29	9.66				
Change of direction combined (angular velocity)	23.78	28.52				13.93		
CV Scores Key:	0-10: Very Good		10-20: Good		20-30: Acceptable		30: Not Acceptable	

Table 8 shows metrics that successfully passed both the discrimination and stability validation tests, shown in Tables 6 and 7. If a metric within a route passed both tests, it is marked as a significant indicator of wide receiver performance in Table 8 below.

Table 8. *Metrics that are validated indicators of wide receiver performance*

	In	Out	Cross	Go	Hitch	Slant	Post	Corner
Change of direction time	X	X				X		
Change of direction radius						X		
Burst off the line: acceleration					X			
Burst off the line: speed	X	X			X		X	
Time to top speed off the line	X	X			X			
Top speed			X	X			X	X
Top acceleration			X	X				X
Time to top speed			X					
Low speed acceleration			X	X				
High speed acceleration			X	X				
Top speed burst			X	X				
Change of direction combined (angular velocity)	X	X						

Table 9 shows the correlation of the player-element metrics to commonly held indicators of wide receiver performance, including game/season statistics, salary, and combine data.

Table 9. *Correlation of player-element metrics with current performance indicators*

	Burst	COD	Speed	Total
Salary: Cash Spent	-0.17	-0.04	-0.06	-0.13
Receptions	-0.04	0.31	-0.12	0.08
Catch Percentage	-0.11	0.37	-0.25	0.00
Total Yards	0.02	0.22	-0.02	0.12
Yards per Reception	0.25	-0.20	0.27	0.16
Touchdowns	-0.02	0.15	0.08	0.14
40-yard Dash Time	-0.18	-0.01	-0.48	-0.40
3 Cone Drill Time	-0.37	-0.03	-0.03	-0.19
Indicates Statistically Significant Correlation at 10% Level				

Discussion

The developed metrics were intended to best describe elements of in-game performance, given the player tracking data. From this analysis, it is believed that the computations reflected the on-field reality closely. Change of direction is an exceptionally novel computation and concept for tracking data-derived calculations. The methodology to calculate this was tested and iterated on until a suitable version was developed. As expected, the results follow standard football intuition. Namely, the faster a player is running and the sharper the turn, the longer it takes to change direction. Conversely, if a player is not moving fast, like on Slant routes, a change of direction can occur more rapidly. This underscores the importance of measuring and comparing players on a route-specific level and utilizing a physics-based approach to measuring change of direction ability. The change of direction radius metric did not perform well with the validation testing. One issue with this was that the thresholds created to ensure the player was making a sharp break may have been too limiting. As the goal was to capture top performance, this was necessary to ensure consistency among what was classified as a break. Since only the 2018 season data was available, this strict rule often caused a small number of observations to be valid. If additional seasons' data were available, this metric could be continually iterated on to create better thresholds. Alternatively, the change of direction metrics could be split into sharp vs. shallow breaks, with different thresholds and calculations. This could allow for additional details and more plays falling within the requirements. The change of direction combined metric was successful in describing wide receiver performance. Using the angular velocity formula allowed for both speed and radius to be included in this calculation, which is a better descriptor of successful route running for breaking routes.

Wide receivers are often instructed to adjust their route running based on the type of defensive coverage they are facing. Often, wide receivers will adjust the angles, the sharpness of the route, and how fast they are running to manipulate and exploit the defensive coverage they are seeing. This is commonly witnessed when a defensive team is playing zone coverage. In zone coverage, a defender is not responsible for guarding a specific wide receiver, but instead responsible for covering a specific area on the field. Wide receivers are coached to recognize zone coverage and adjust the angle, speed, and other features of the route accordingly. This is evident in the player tracking data, as sometimes certain players will have a large spread within an individual metric, likely indicating they had to adjust their execution of the route based on the defensive coverage. With this in mind, it is not surprising that some metrics did not successfully pass the validation test(s). For example, time to top speed for Go routes did not prove to have discrimination among players. As Go routes are a play intended for the wide receiver to run far down the field, the player may not try to hit their top speed immediately after the snap, as they would be showing the defense they are running that route type. Instead, the player may start slower to deceive the defender, and then speed up to run further down the field.

There are nuances to the game and strategy that cannot be sufficiently gleaned from tracking data alone. Nonetheless, isolating 90^{th} and 75^{th} percentile performance in the aggregations was intended to identify peak performance and eliminate situations where outside factors influenced a player to perform below his peak ability. Additionally, this successfully captured the differences in efforts players exert when they know whether or not they will be targeted for the pass. There are other strategic and play-calling nuances that present noise into the metrics. Sometimes, a player is not intended to receive the ball on a given play, but rather be used as a decoy to attract the defense's attention, which allows a teammate to get open. In this situation, a player may not be running the route to his fullest potential.

Regarding discrimination, the metrics at a route level followed normal football intuition as to which metrics showed significance, as seen in Table 6. For example, a Go route involves a player running in a near-straight line to outrun his defender. However, given that defenders are also fast players, the offensive players rely on deception to outrun a defender. Often, an offensive player on a Go route will not immediately accelerate as fast as possible, but rather disguise the route as a breaking route or a shallow route, and then begin his acceleration. This is reflected in the time to top speed metric not being significant in the ANOVA model, since time to top speed is often artificially influenced by the offensive player and not a true measurement of how fast he can accelerate.

Another example of this is the Slant route. All metrics related to burst off the line are not significant in the ANOVA model. On a Slant route, a player often only takes a few steps forward and travels only a few yards before making a sharp turn. Before making the turn, players are often not accelerating at maximum effort because they will only be running for a short period of time before turning. Often, a Slant route is also intended to exploit cushion, or the space that a defender is playing off the offensive player at the snap, rather than a violent, high-speed turn to create separation from a defender who is closely guarding the receiver.

As seen in Table 7, change of direction metrics tended to show less week-over-week stability, especially with In and Out routes. Due to the extensive filtering needed to properly measure metrics within a route type, often players would only have fewer than three eligible routes of a given type per game. This becomes a small sample on a weekly basis and change of direction metrics are more susceptible to noise given that players are not always intending to make the sharpest break on every play. Otherwise, these metrics showed acceptable stability across the board.

The created metrics showed correlation with some traditional metrics, as shown in Table 9. Burst and Speed both had moderate and statistically significant correlation with yards per reception. This is notable because yards per reception controls for the quarterback's ability of delivering an accurate throw and the catching ability of a wide receiver, and simply measures how many yards a receiver gains when he does catch the ball. It is expected that faster players who can accelerate at a high level can gain a lot of yards when they catch the ball. Speed is also strongly and significantly correlated with 40-yard dash time, which is the predominant measure coaches and scouts currently use to assess the speed of a wide receiver.

Change of direction shows moderate, statistically significant correlation with catch percentage. In football, catching the ball is a product of the quarterback's throwing ability, a wide receiver's catching ability, and how open a player is. A player who is good at quickly changing directions is more likely to become open on breaking routes. When a player is open, it is much easier to catch the ball, and this is reflected in the correlation data.

Salary did not show a statistically significant correlation with any of the new performance metrics. This was not unexpected, due to the way NFL player contracts are structured. In general, new players sign on to smaller salaries when initially drafted, and restructure to larger contracts after a few years in the league, once they have proven their talent. Table 10 shows the correlation of salary with the new metrics for seasoned players, which are those who are in their 5th or later season in the NFL. Compared to the values for all players shown in Figure 9, there is a stronger correlation with speed and the total combined metric, which is in line with the idea that top players receive larger salaries after restructuring.

Table 10. *Correlation of player-element metrics with salary for seasoned players*

	Burst	COD	Speed	Total
Salary: Cash Spent	0.14	-0.08	0.67	0.43

Though seasoned players have had the opportunity to prove their skills, and therefore increase their salaries, the performance value of wide receivers decreases as years of experience increases. Figure 11 shows the correlation of years in the league with the new metrics. Despite being paid less in early years in the league, these young players perform better than their seasoned counterparts.

Table 11. *Correlation of player-element metrics with years in league*

	Burst	COD	Speed	Total
Years in League	-0.31	-0.01	-0.29	-0.32

One issue that was discovered throughout the process of creating the metrics was the current route-classification algorithm used by the NFL. In some instances, routes were inaccurately classified, which led to outliers in the outputs of the metrics, as the calculations were specific for the classified route type. Other times, a route may be classified as one of the standard routes but contain nuances that are not captured accurately by the tracking data. One example of this is something called a “Pivot” route. This is an Out route where a receiver fakes running an In route and “pivots” to the outside to surprise the defense. In this situation, the change of direction time would be measured artificially high, because the offensive player turned 270^{o} instead of 90^{o}, as part of intentional deception. These types of nuances are difficult to detect from tracking data alone.

Conclusion

Metrics related to change of direction are novel quantitative measurements in sports. Currently, teams must watch film to get this sort of insight, rather than have the ease of using aggregated metrics to analyze performance. This work is a solid base for the NFL Next Gen Stats team to continue iterating on these metrics. Further applying physics principles, such as those used for angular velocity, can help the Next Gen Stats team create more differentiating metrics that quantify the kinesthetic aspects of football. The framework created can be directly applied to other players running receiving routes, as well as used as a base to build new metrics for other position players (such as understanding similar movements defensive backs make when covering wide receivers).

Advanced technology and player tracking is the future of analytics in sports, and the NFL is well-positioned with Next Gen Stats to revolutionize the way teams scout new players and maximize the output of current players. Overall, the new metrics, particularly those related to change of direction and burst, are novel and successful indicators of wide receiver performance. As the initial attempts to create these metrics proved successful, the NFL should continue to investigate these metrics, using the calculations created through this work as a framework.

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