

Project Deliverable I | Use Case, Data Model, and Projections

Section I: Business Context

In the competitive environment of college admissions, universities can attract more applicants through sports. Successful football programs in recent years, like Appalachian State, saw an increase of 25% in applications following their 2007 gridiron success, improving the quality of their students (Eggers, A. F., Groothuis, P. A., & Redding, P. T., 2021).

The key to football success is player talent, proving to be immensely consequential in the world of college football. For larger college football programs in the SEC, Big Ten, and Big Twelve, recruiting success accounts for 63% to 80% of a team's on-field outcomes (Caro, 2012). Although large football operations possess enormous budgets to scout, engage, and select potential athletes, smaller programs must be more selective in employing resources to find and bring in the right talent. For example, the University of Georgia's 2018 Recruiting budget was \$4,346,403, a figure nearly eight times that of University of North Carolina at Charlotte's 2018 Recruiting budget of \$548,707 (McLaughlin, 2021; US Department, 2021).

Additionally, player recruit ratings, as assigned by recruiting services, massively influences on-field results; explaining up to 36% of the variability in final Sagarin team ratings, a sufficient proxy of team success (Mankin et al. 2019). As recruit ratings routinely dictates team success, modest football programs walk a tightrope; attempting to assemble the most talented roster possible while running a lean operation, expending fractions of the resources dispensed by college football juggernauts (US Department, 2021).

Section II: Business Use Case

As a smaller football program with a restricted budget, UNC Charlotte must align their recruiting scope to fit their allocated budget. Utilizing methods to target talent hotbeds by region, position, and rating, the UNC Charlotte football program can more efficiently and effectively administer resources to these areas. Analyzing annual and multi-year trends will help the program develop a more agile, purposeful, and prosperous recruiting strategy, which translates to on-field achievement.

Another vital consideration is the stature of UNC Charlotte's football team and its relative position in the college football ecosystem, which often determines the quality of prospect a program has the capacity to attract to the university. UNC Charlotte must pursue recruits appropriately and correctly attune expectations that correspond to the caliber of player that could realistically commit to play football. Likewise, a coherent and holistic recruiting process should emphasize different facets and advantages of the football program and university most likely to entice prospects according to their respective ratings (Mirabile and Witte, 2017).

Geographic data like city, longitude, latitude, and FIPS codes are instrumental tools to prepare an efficient recruiting strategy, aiding to identify clusters of players as potential recruits. Beyond fixating on local talent, travel expenses can be reduced through concentrating on clusters of players in an area simultaneously. Cultivating connections with local coaches and maintaining a presence in specific talent rich communities are beneficial activities that can pay dividends in later recruiting cycles.

Section III: Data Description

A yearly player recruit database hosted by Bill Radjewski ([College Football Data website](#)) compiles players' names, school, hometown, college commitment (if any), position, rank (by class), rating, height, weight, and more. This dataset provides player evaluation data through class rankings and a composite rating derived from various recruiting services that assess a player's skill and ability. A crucial aspect in

shaping the recruiting strategy, the composite ratings component will establish a range of player quality that UNC Charlotte can feasibly draw to the football program.

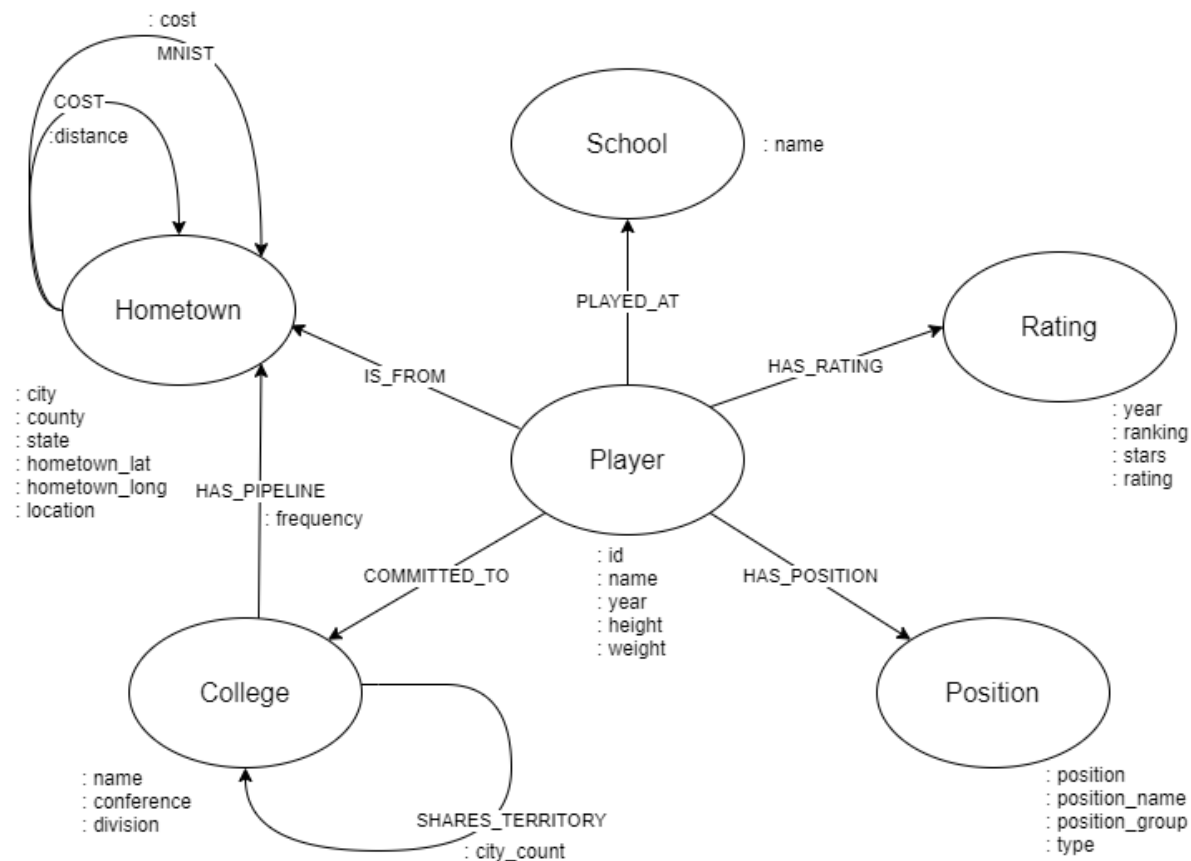
Several records have missing data, most notably the “committedTo” column, denoting the recruit’s college commitment, with 5,326 blank fields representing uncommitted players, data which will be retained for their geographic elements. After removing 1,021 rows of missing geographic data, this analysis will examine player recruits across six years of recruiting classes, from 2015 to 2021, comprising of 24,442 observations.

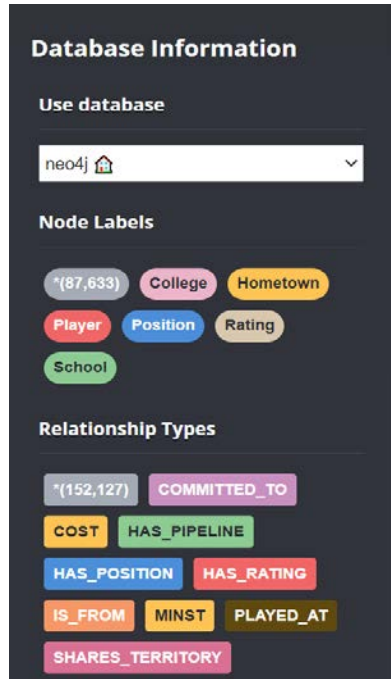
In the data’s nineteen total variables, five are continuous variables including height, weight, rating, hometown longitude, and hometown latitude. While the “star” variable values range from one to five, it represents five categories of player classes corresponding to different ratings threshold. However, the “star” class is unevenly distributed: 87% of players falling into the two and three star categories, 11% designated four star status, and slightly more than one percent of all players are labeled as five star recruits.

After applying graph analytics techniques and algorithms to this dataset, new relationships can be illustrated between player ability, position, region, time, and other attributes, providing valuable insights to maximize recruiting results.

Project Deliverable II | Graph Database Setup and Application of Algorithms

Section IV: Graph Data Model (Updated)





A number of updates to the data model was required to process queries and execute graph algorithms. First, the key variables were separated into node labels and assigned the appropriate properties. A location property was added to define points which could be referenced to calculate distance. The “ncPageRank” property on the “College” node is the score output of the PageRank algorithm of colleges recruiting at least one player from North Carolina

In addition, the relationships required maintenance and redundancies were removed from the model. New relationships include a ‘HAS_PIPELINE’ between the “College” node and “Hometown” node with a property called “frequency”, representing the number of players recruited from a city. The ‘SHARES_TERRITORY’ relationship describes the number of cities where both universities recruited a player to find common player sources. The ‘COST’ relationship depicts the distance between two cities that are less than 35 kilometers away from one another, with “distance” as the relationship property name. Utilizing the distance attribute, the Minimum Spanning Tree algorithm was calculated and its results written into the model, signifying the ‘MINST’ relationship.

Section V: Graph Projections (Updated)

See Section VII: Graph Algorithms

Section VI: Cypher Queries

Which high schools had multiple players commit to Charlotte? Identifying which high schools have existing relationships with the Charlotte football program supports future recruiting efforts of potential athletes.

Figure 6.1. Frequent High School commits query

```
1 MATCH (n:Player)←[:COMMITTED_TO]-(c:College {name: 'Charlotte'})
2 WITH n, c
3 MATCH (h:Hometown)-[:IS_FROM]→(n)←[:PLAYED_AT]-(s:School)
4 WITH h.state AS state, h.city AS city, s.name AS high_school, count(c) AS charlotte_recruits
5 WHERE charlotte_recruits > 1
6 RETURN state, city, high_school, charlotte_recruits ORDER BY charlotte_recruits DESC
```

Table 6.1. Frequent High School commits results

State	City	High School	Number of Recruits
NC	Charlotte	Mallard Creek	3
FL	Orlando	Bishop Moore Catholic	2
GA	Buford	Buford	2
FL	Tallahassee	Tallahassee Leon	2
NC	Mooresville	Mooresville Senior	2
TN	Murfreesboro	Blackman	2
NC	Jamestown	Lucy Ragsdale	2
SC	Mount Pleasant	Wando	2
NC	Charlotte	Zebulon B. Vance	2
SC	Blythewood	Blythewood	2
NC	Matthews	Butler	2

Four local high schools had multiple players commit to Charlotte with Mallard Creek topping all secondary schools. Surprisingly, this list contains two Florida schools, more than any bordering state other than South Carolina. The Charlotte football program can leverage their connections to high schools to attract future athletes.

What are the average rankings and ratings of Charlotte commits? Determining the range of a typical Charlotte recruit's rating narrows the focus on realistic candidates, preventing the program from wasting effort and resources on unfeasible expectations.

For the seven years of recruiting classes dating 2015 and 2021, Charlotte's average player rated about 0.8 out of one. However, Charlotte's football program is still in its infancy, joining the top collegiate division in 2015. This likely posed a detrimental effect on recruiting top players; adjusting for more recent data would reflect a more accurate situation.

Figure 6.2. Charlotte recruiting statistics query

```

1 MATCH (n:Player)←[:COMMITTED_TO]-(c:College {name: "Charlotte"})
2 WITH n
3 MATCH (n)-[:HAS_RATING]→(t:Rating)
4 RETURN percentileDisc(toFloat(t.rating), 0.25) AS lower_quartile_rating, AVG(toFloat(t.rating)) AS avg_rating,
   percentileDisc(toFloat(t.rating), 0.75) AS upper_quartile_rating, percentileDisc(toFloat(t.ranking), 0.75) AS
   lower_quartile_rank, AVG(toFloat(t.ranking)) AS avg_rank, percentileDisc(toFloat(t.ranking), 0.25) AS upper_quartile_rank

```

Table 6.2. Charlotte recruiting statistics results

Lower Quartile Rating	Average Rating	Upper Quartile Rating	Lower Quartile Rank	Average Rank	Upper Quartile Rank
0.7731	0.7949	0.8178	3,090	2,510	1,954

Evaluating the last three years from 2019 to 2021, the 49ers recruited much better than the aggregate performance of the past seven years back to 2015. Concentrating their efforts on a specific range of players, staff can be more efficient in utilizing and distributing their available resources.

Figure 6.3. Charlotte recruiting statistics from 2019 to 2021 query

```

1 MATCH (n:Player)←[:COMMITTED_TO]-(c:College {name: "Charlotte"})
2 WITH n
3 MATCH (n)-[:HAS_RATING]→(t:Rating)
4 WHERE t.year > '2018'
5 RETURN percentileDisc(toFloat(t.rating), 0.25) AS lower_quartile_rating, AVG(toFloat(t.rating)) AS avg_rating,
   percentileDisc(toFloat(t.rating), 0.75) AS upper_quartile_rating, percentileDisc(toFloat(t.ranking), 0.75) AS
   lower_quartile_rank, AVG(toFloat(t.ranking)) AS avg_rank, percentileDisc(toFloat(t.ranking), 0.25) AS upper_quartile_rank

```

Table 6.3. Charlotte recruiting statistics from 2019 to 2021 results

Lower Quartile Rating	Average Rating	Upper Quartile Rating	Lower Quartile Rank	Average Rank	Upper Quartile Rank
0.7831	0.8072	0.8301	3,096	2,387	1,689

Where are recruits in North and South Carolina that could realistically commit to Charlotte?

Recognizing and prioritizing talent rich areas reinforces an efficient recruitment plan, an important task in

effective resource utilization. Local recruits are not only likely to be interested in staying close to home, but they also reduce budget strain with low traveling expenses.

Figure 6.4. Charlotte target areas query

```
1 MATCH (n:Player)←[:IS_FROM]-(h:Hometown)
2 WHERE h.state = 'NC' OR h.state = 'SC'
3 WITH n, h
4 MATCH (n)-[:HAS_RATING]→(t:Rating)
5 WHERE t.rating > '0.78' AND t.rating < '0.84'
6 RETURN h.state AS state, h.city AS city, count(n) AS num_players
7 ORDER BY num_players DESC
8 LIMIT 10
```

Besides Charlotte, the most populous cities in the Carolinas are not always producing the most recruiting targets! Raleigh totaled ten recruits falling into the range of 0.78 to 0.84 rating since 2015, which is the same amount as the significantly smaller South Carolina towns of Blythewood, Anderson, and Sumter.

Table 6.3. Charlotte target areas results

State	City	Number of Target Players
NC	Charlotte	63
SC	Columbia	21
NC	Greensboro	20
NC	Cornelius	12
NC	High Point	10
NC	Fayetteville	10
NC	Raleigh	10
SC	Sumter	10
SC	Blythewood	10
SC	Anderson	10

Section VII: Graph Algorithms

Pathfinding: Minimum Weight Spanning Tree

Creating an efficient itinerary to visit or scout players can be challenging, especially when recruits are located in a similar, but not close, proximity. Ideal for this scenario, a Minimum Weight Spanning Tree algorithm optimizes a connected route, ensuring that staff will travel in an efficient course.

For example, if a coach was heading from campus to High Point to see a recruit and they also wanted to visit every target player in cities on the way, this algorithm provides an optimal path to their destination through nine towns that contain players in our target rating range.

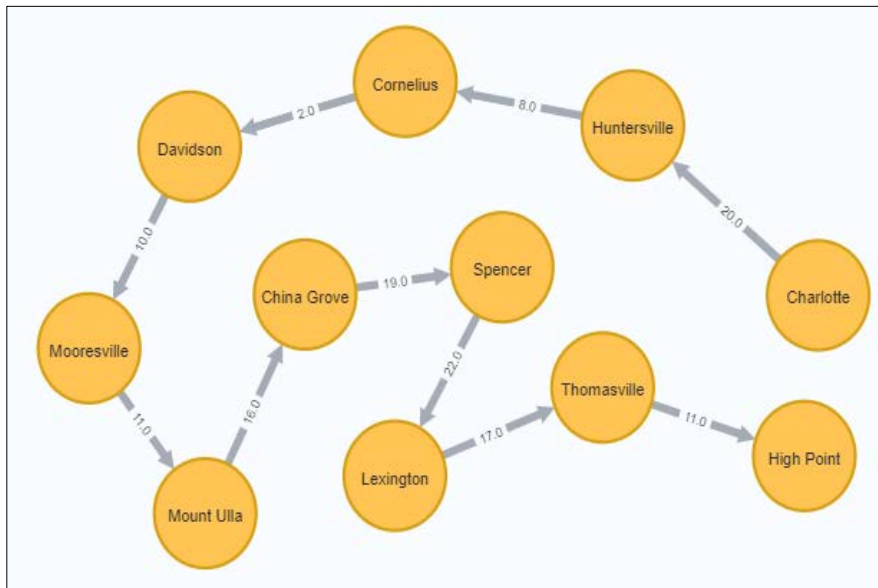
Figure 7.1. Code to call MSP algorithm

```
1 MATCH (n:Hometown{city:'Charlotte'})
2 \CALL gds.alpha.spanningTree.minimum.write({
3   startNodeId: id(n),
4   nodeProjection: 'Hometown',
5   relationshipProjection: {
6     COST: {
7       type: 'COST',
8       properties: 'distance',
9       orientation: 'UNDIRECTED'
10    }
11  },
12  relationshipWeightProperty: 'distance',
13  writeProperty: 'MINST',
14  weightWriteProperty: 'cost'
15 })
16 YIELD createMillis, computeMillis, writeMillis, effectiveNodeCount
17 RETURN createMillis, computeMillis, writeMillis, effectiveNodeCount;
```

Table 7.1. MSP algorithm output

Source	Destination	Cost (km)
Charlotte	Huntersville	20
Huntersville	Cornelius	8
Cornelius	Davidson	2
Davidson	Mooresville	10
Mooresville	Mount Ulla	11
Mount Ulla	China Grove	16
China Grove	Spencer	19
Spencer	Lexington	22
Thomasville	High Point	11

Figure 7.2. A minimum weight spanning tree from Charlotte to High Point



Similarity: Jaccard

Since players often weigh several scholarship offers, Charlotte isn't the only team contending for a player's commitment. Recognizing the competition is an important step in order to differentiate Charlotte from other programs. The Jaccard Similarity algorithm will show which colleges received commitments from high schools that Charlotte players also attended.

Figure 7.3 Code to call MSP algorithm

```

1 MATCH (c1:College {name: 'Charlotte'})-[:COMMITTED_TO]-(n)-[:PLAYED_AT]-(school1)
2 WITH c1, collect(id(school1)) AS c1School
3 MATCH (c2:College)-[:COMMITTED_TO]-(n)-[:PLAYED_AT]-(school2) WHERE c1 <> c2
4 WITH c1, c1School, c2, collect(id(school2)) AS c2School
5 RETURN c1.name AS charlotte, c2.name AS other_college,
6 gds.alpha.similarity.jaccard(c1School, c2School) AS similarity ORDER BY similarity DESC

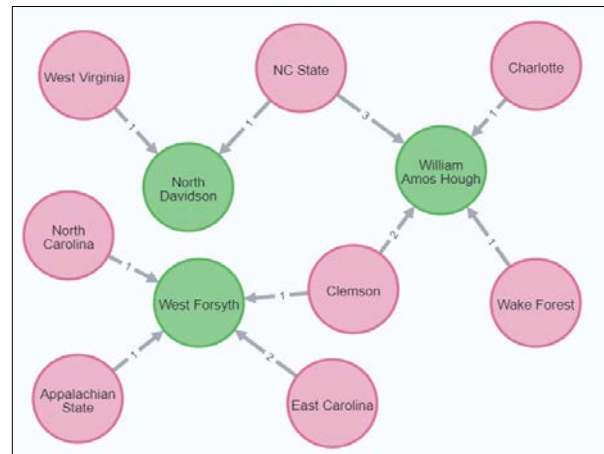
```

Larger universities possess a significant presence in the high schools where Charlotte attempts to procure talent. To counter powerhouse programs, staff should promote unique selling points to attract players; like early playing time, proximity to a world class city, and post-football career opportunities. Also, staff can even emphasize negative aspects of other colleges, such as a program instability, rural location, or a poor fit into a team's coaching scheme.

Table 7.2. Jaccard Similarity algorithm output

College	Other College	Similarity
Charlotte	South Carolina	0.072
Charlotte	North Carolina	0.070
Charlotte	NC State	0.067
Charlotte	Wake Forest	0.065
Charlotte	Tennessee	0.056
Charlotte	Georgia State	0.051
Charlotte	East Carolina	0.051
Charlotte	Appalachian State	0.051
Charlotte	Coastal Carolina	0.050
Charlotte	Liberty	0.049

Figure 7.4. Sample projected similarity graph



Centrality: PageRank

Since only few programs can recruit nationally, a football program must ensure its locking down players from its own state. The PageRank algorithm will determine which colleges battling for players in the same cities hold the most influence over the state's geography.

Figure 7.5. Code to call and write PageRank algorithm

```

1 CALL gds.pageRank.write({
2   nodeQuery: 'MATCH (n:College)-[r:HAS_PIPELINES]-(h:Hometown)'
3   WHERE h.state = $state RETURN DISTINCT id(n) AS id',
4   relationshipQuery: 'MATCH (h:Hometown)-[:HAS_PIPELINES]-(n)-[r:SHARES_TERRITORY]-(m)'
5   WHERE h.state = $state
6   RETURN id(n) AS source, id(m) AS target, r.city_count AS weight, type(r) AS type',
7   writeProperty: "ncPageRank",
8   validateRelationships: false,
9   parameters: { state: 'NC' }})
10 YIELD nodePropertiesWritten, createMillis, computeMillis, writeMillis, ranIterations
11 RETURN nodePropertiesWritten, createMillis, computeMillis, writeMillis, ranIterations;
```

Figure 7.6. Query to view top PageRank results and statistics

```

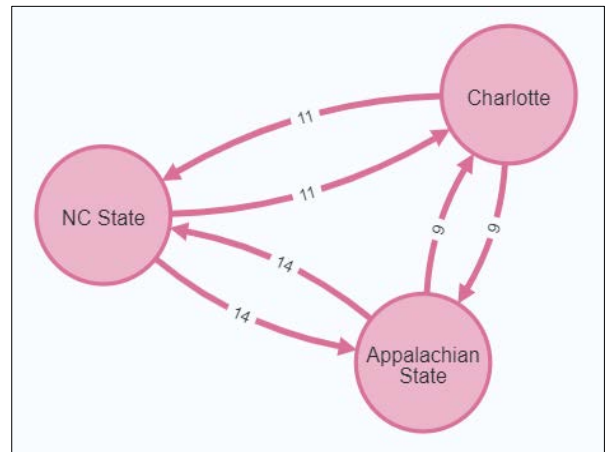
1 MATCH (c1:College)-[:HAS_PIPELINES]-(h:Hometown {state: 'NC'})
2 WITH c1, count(DISTINCT h.city) AS num_cities
3 MATCH (c1:College)-[r:SHARES_TERRITORY]-(c2:College)
4 RETURN c1.name, c1.ncPageRank, count(r) AS share_cnt, num_cities
5 ORDER BY c1.ncPageRank DESC LIMIT 10
```

North Carolina's flagship university possesses the most sway over the state's numerous cities of the 100 colleges that recruited a player in the state; however, smaller programs are outpacing more prominent schools like Wake Forest and Duke, which could be related to academic standards. All service academy players are on scholarship so Navy's inclusion isn't reflective of a typical college football program's scholarship constraints. While this does not account for the density of players by city, PageRank reveals that Charlotte is scouring the state for talent well in competitive areas.

Table 7.3. PageRank algorithm results and statistics

College	NC pageRank	Colleges Sharing City	City Count
North Carolina	2.076	88	35
Appalachian State	1.986	87	27
NC State	1.935	86	40
Charlotte	1.858	81	23
East Carolina	1.771	75	33
Wake Forest	1.664	79	25
Duke	1.587	74	19
Coastal Carolina	1.563	74	18
Old Dominion	1.535	71	15
Navy	1.507	70	12

Figure 7.7. Sample PageRank graph projection



Project Deliverable III / Graph Visualizations

Section VIII: Cypher Actions

Action I: Uncommitted Player Ratings by Position

The Charlotte football team may lack depth at certain positions for a number of reasons including unforeseen injuries, transfers to other universities, or graduation attrition. The football staff will need to identify potential recruits that play that position and determine each player's ability.

Search phrase *

Uncommitted Player ratings by position \$position_name

Description

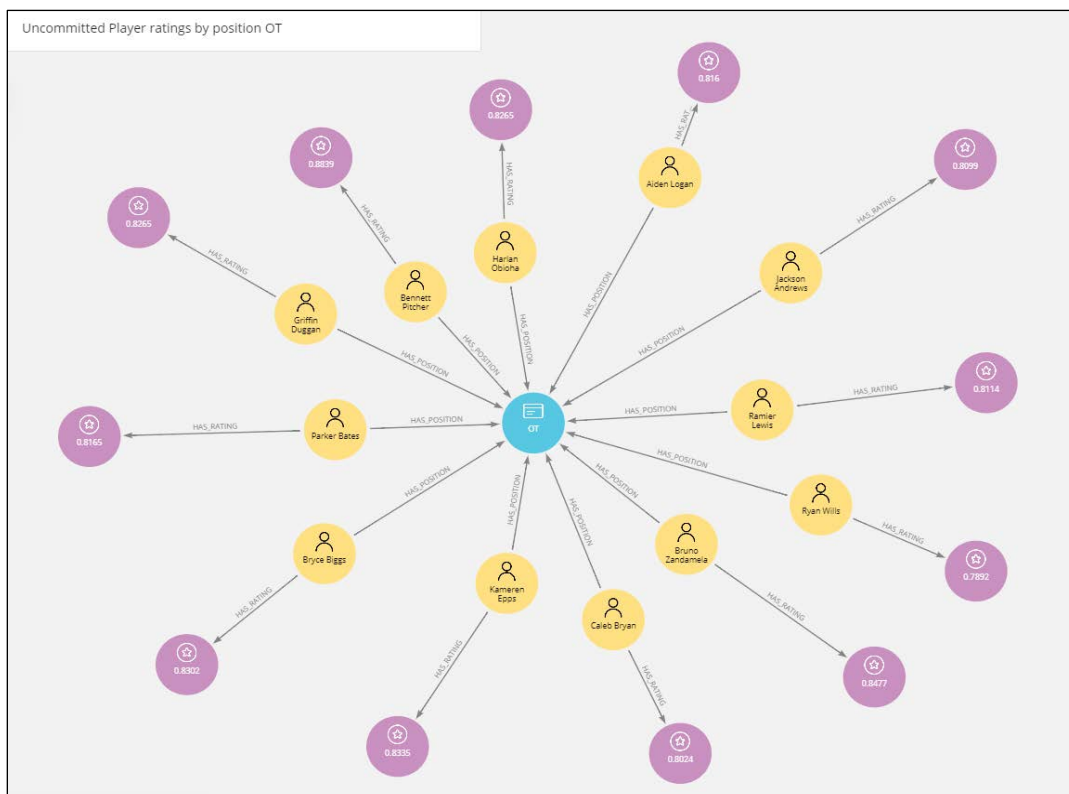
Search for uncommitted players by a specific position

Cypher query *

```
MATCH (p:Position {name: $position_name})<-
[r1:HAS_POSITION]-(n:Player)<-[r2:COMMITTED_TO]-
(c:College {name: "Uncommitted"})
WHERE n.year = '2021'
WITH n, p, c, r1
MATCH (p)<-[r1:HAS_POSITION]-(n)-[r3:HAS_RATING]->
(t:Rating)
WITH p, n, t, r1, r3
RETURN *
```

The search phrase called “Uncommitted Player Ratings by Position” allows staff members to find by position which recruits have not yet committed to play for a university.

For example, Charlotte only has only recruited four offensive tackles (OT) since 2018, a meager amount considering two offensive tackles are customary for every offensive snap. Using the search phrase, a coach or assistant can quickly pull up the names and ratings of available offensive tackles. In the visualization below, searching for “OT” yields 12 players who have not yet committed to a college football program.



Action 2: College Recruiting by High School

Before visiting a recruit, staff should examine previous links the football program has maintained with the player's high school, in addition to any potential ties rival colleges have established over time.

A search phrase titled "Colleges by High School" detects which universities have recruited players from a particular high school and also indicates the class year of a recruit. Recently graduated athletes will most likely have existing relationships with younger players and that familiarity can help sway recruits into a potential commitment. Football staff can easily execute this action by typing the phrase and entering in the name of the high school, a simple task performed before every visit that could pay dividends in the future.

Search phrase *

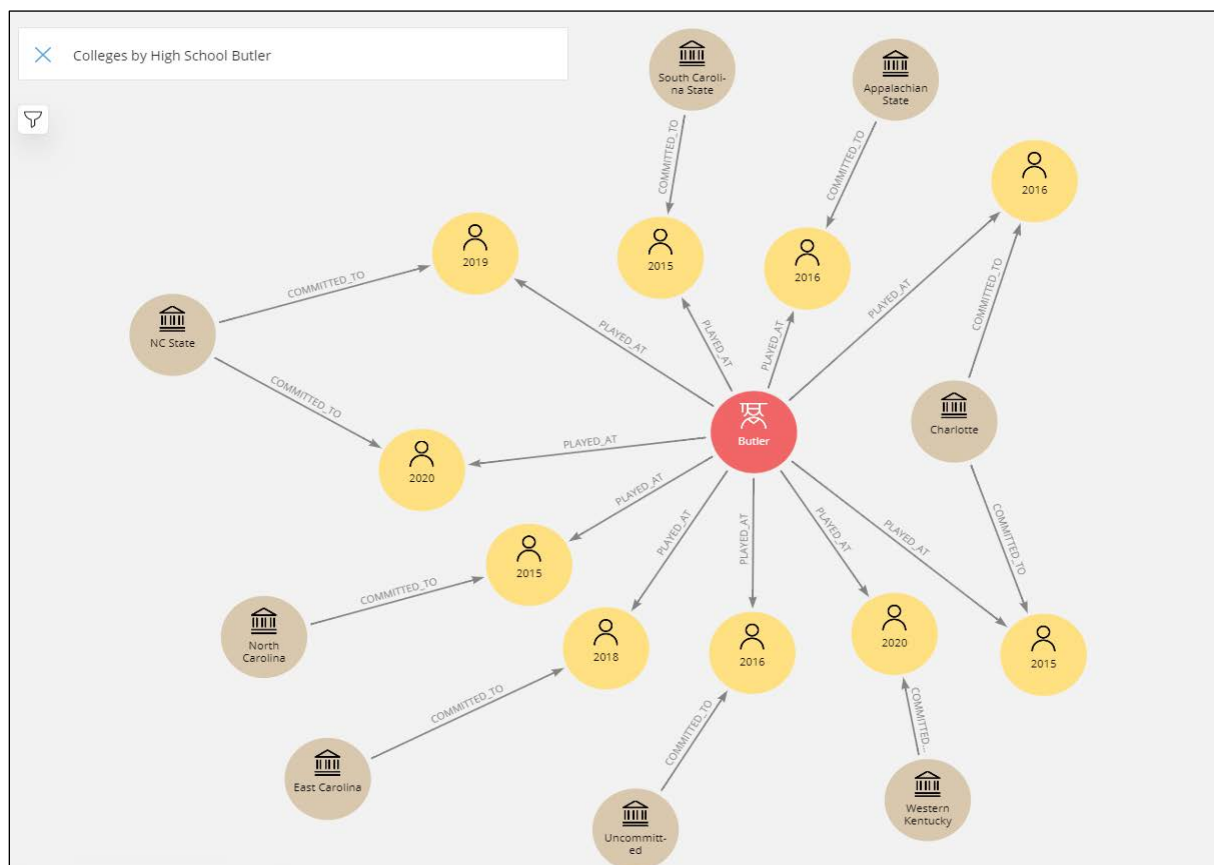
Colleges by High School \$school_name

Description

Search for a specific high school's previous college commitments

Cypher query *

```
MATCH (s:School {name: $school_name})-[r1:PLAYED_AT]->
(n:Player)
WITH s, n, r1
MATCH (s)-[r1:PLAYED_AT]->(n)->[r2:COMMITTED_TO]-
(c:College)
RETURN *
```

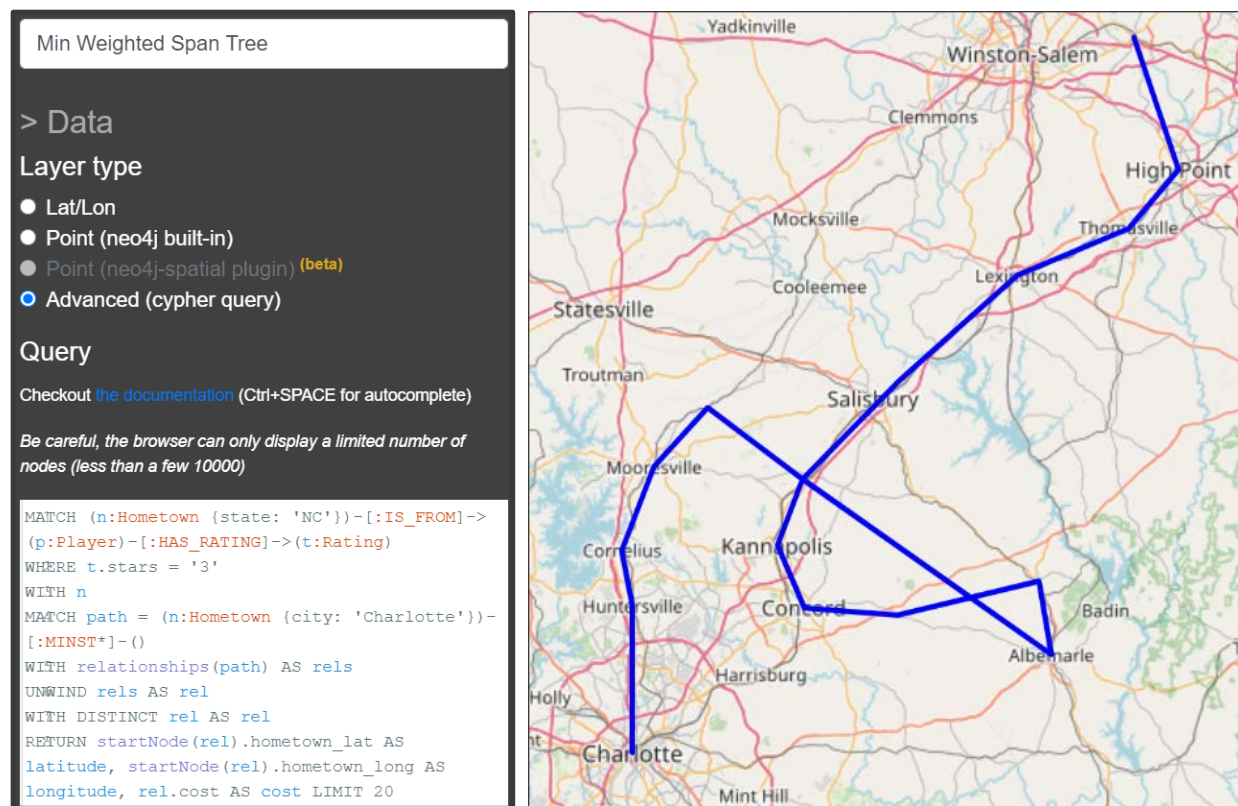


Section IX: Graph Visualizations

Pathfinding: Minimum Weight Spanning Tree

Employing NeoMap, a Neo4j Desktop application for spatial data, the Minimum Weight Spanning Tree algorithm from Section VII can illustrate its function in a practical and intuitive manner. While the location nodes and their relationships convey critical information, this visualization demonstrates the performance of the algorithm on a map where most are accustomed to viewing pathfinding data.

Maximizing the time a coach can spend visiting players is a vital part of any football program's strategy and features one of the highest returns of investment. This makes a coach's time extremely valuable and this visualization demonstrates utilizing their time as efficiently as possible, delivering a tremendous advantage to a staff's approach.

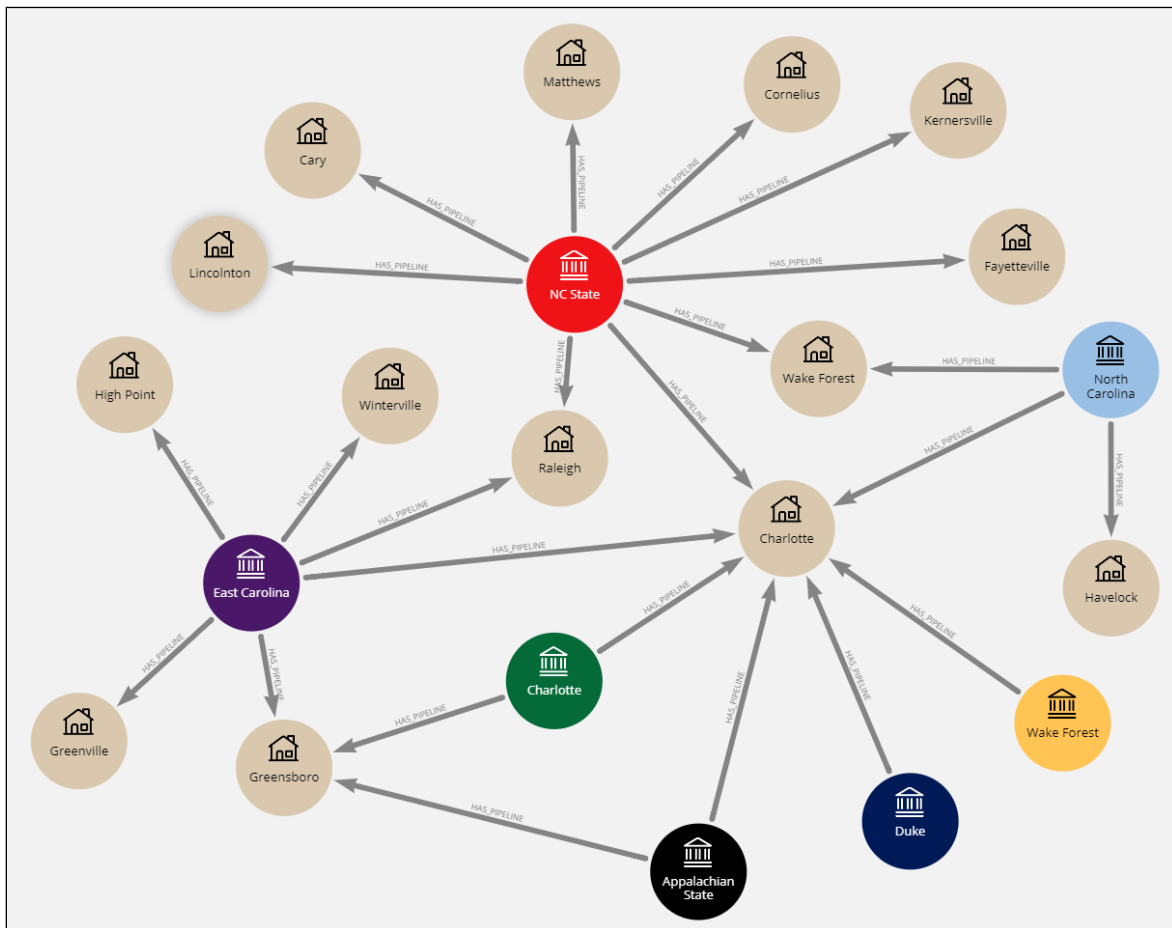


Centrality: PageRank

While the PageRank algorithm output in Section VII proved North Carolina to be the most influential university in the state, the resulting statistics did not conclusively affirm their case. Ranked third in PageRank score, North Carolina State's player network covered more cities than any other team with nearly as many colleges sharing recruiting territory so why didn't PageRank rate them more favorably?

As political junkies often say "land doesn't vote, people do"; the visualization below helps illuminate why geography is not analogous to density by locating the cities where the top ten PageRank scoring colleges have received three or more recruits in the past seven years. North Carolina State has locked down certain rural parts of the state; however, most gifted athletes reside in metropolitan areas as North Carolina's average recruit rating within the state has been over three points higher than North Carolina State's average rating during the same time period.

An intelligent recruiting plan must first be devised in order to implement an effective recruiting strategy and Charlotte is on the right track, focusing on competitive, talent rich regions.



Final Project Deliverable / Summary

Section X:

Using these tools, UNC Charlotte can identify, target, and locate recruits that will better their football program; thus, becoming more attractive to prospective students, increasing applicants, and improving the quality of the incoming student population.

References

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