

## *Use Case and Data Model*

### **Section I: Business Context**

Today's most effective college admissions advertising campaigns are not polished commercials or well-known faculty, rather, it's the weekly product showcased on football fields. Recent research reveals a university achieving sporting success attracts a higher quantity and quality of applicants, known as the "Flutie Effect." Name for football quarterback Doug Flutie, his performances elevated Boston College's national profile, which later enabled Boston College to undergo a 30% surge in applicants in subsequent years (Chung 2013). Likewise, small programs are not exempt from experiencing the "Flutie Effect"; for example, Appalachian State University boasted a 15% growth in applications in years following their historic upset of the University of Michigan in 2007 (Eggers et al. 2021). A successful football program's impact reverberates far beyond the stadium, enhancing an institution's academic quality and reputation.

An integral component to a successful football team, player talent is 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, and latitude 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 rewarding activities that pay dividends in future 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.

This analysis examines 27,180 records of player recruit data across seven years of recruiting classes from 2015 to 2021, beginning with the year UNC Charlotte joined the top level of college football. Several attributes have missing data, most notably the "committedTo" column, denoting a recruit's college commitment, containing 5,326 blanks, replaced by the string "Uncommitted" to signal athletes who did not enroll to play for a university's football program. Uncommitted players merit inclusion to reach further insights from other descriptive features like ability and origin. However, geographical information remains an essential part of this exercise and players lacking any of the hometown fields are omitted from the dataset, plus athletes hailing from outside the United States. After detecting and removing 1,021 tuples storing insufficient location data or duplicate players, the clean dataset comprises a total of 26,159 observations.

In the data's nineteen total features, five are continuous variables including height, weight, rating, hometown longitude, and hometown latitude. The rating attribute ranges from 0.7 to 1.0, which correspond to a star variable class between one, the minimum, and five, the top grade of recruits. Besides stars, the data's other ordinal categorical features displayed are year and ranking, which reveals a player's relative standing among all athletes in their recruiting year.

Five features describe a player's hometown: city, state, latitude, longitude, and the FIPS code associated with the hometown city. Using the FIPS codes to match against text from the census website ([Census County Codes Website](#)), county names are merged onto the dataset.

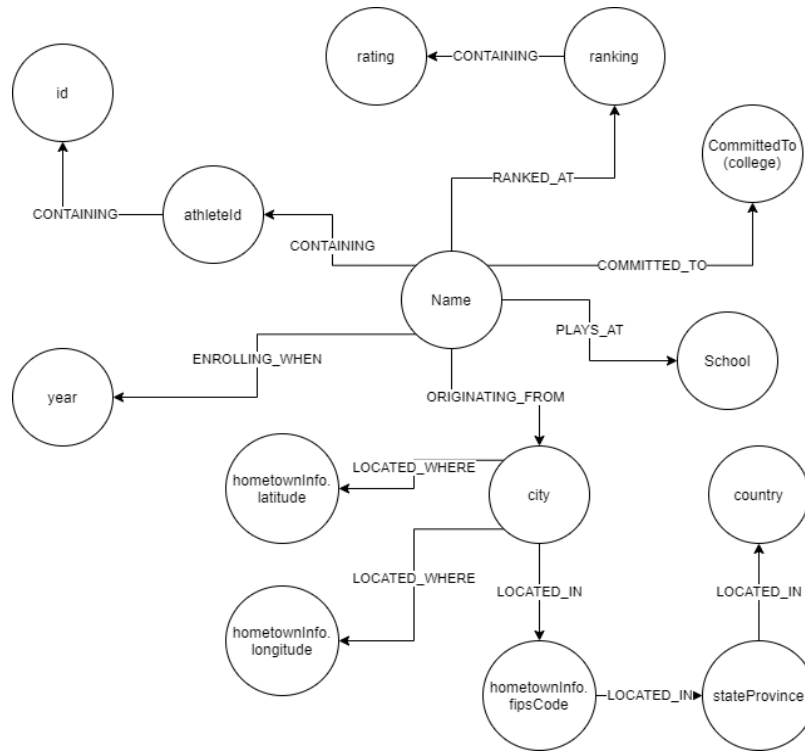
Difficult to interpret in its current state, the position attribute consists of twenty different types of acronyms. For instance, three abbreviations "PRO", "DUAL", and "QB" all represent the same position, quarterback. To alleviate ambiguity, a table detailing each position name, grouping, and unit on college football recruiting services website ([247 Sports Football Position Table](#)) is scraped, extracted, and joined to the existing dataset.

Following renaming the features to more accurately reflect its attributes, the cleaned data is ready to be separated, exported, and modeled into the Neo4j platform.

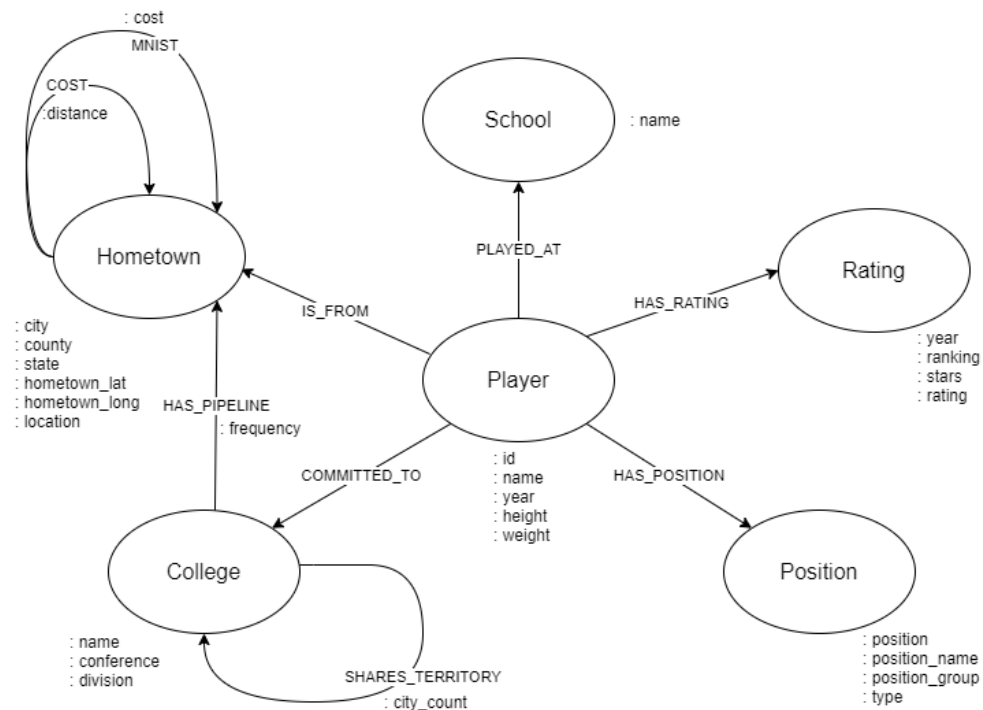
## Graph Database Setup and Application of Algorithms

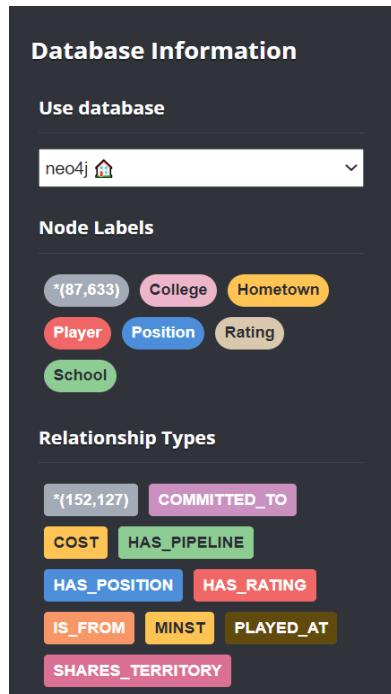
### Section IV: Graph Data Model

Original Data Model (Deliverable I)



Updated Data Model





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. The original data model's overly complicated structure was inefficient for analysis in Neo4j. Though a hierarchical tree is a logical choice to arrange the geographical hometown data, the model structure proved difficult to construct and operate cypher queries and actions.

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.

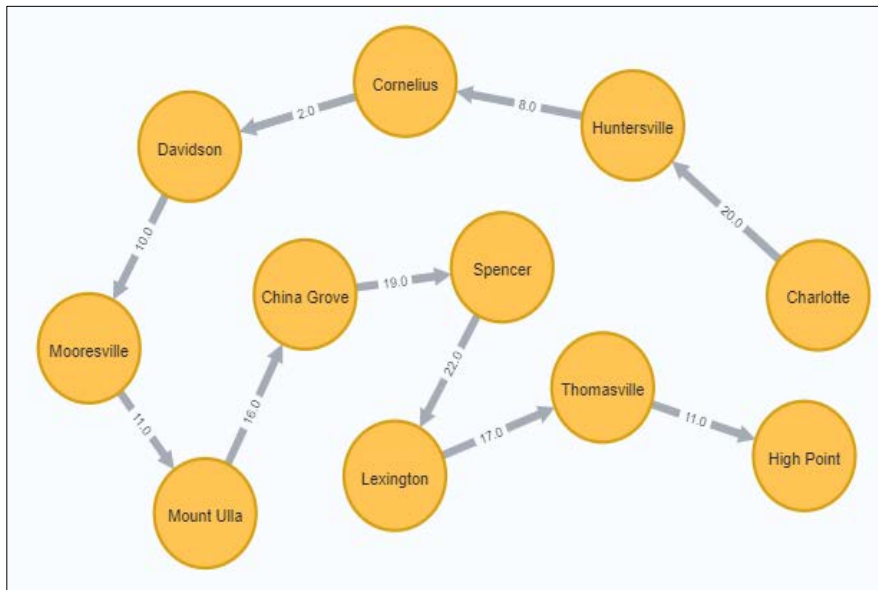
Figure 7.1. Code to call MSP algorithm

```
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

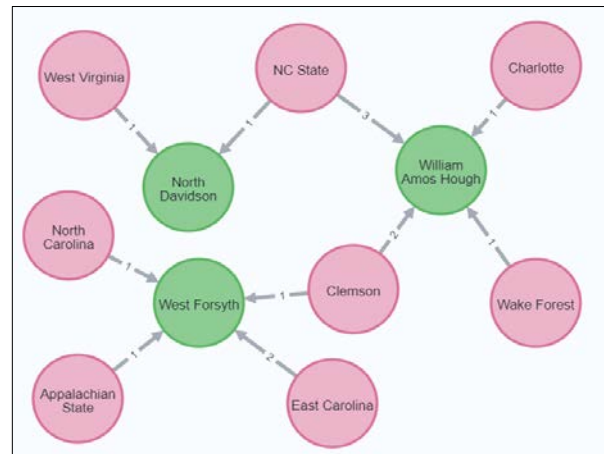
```

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

```

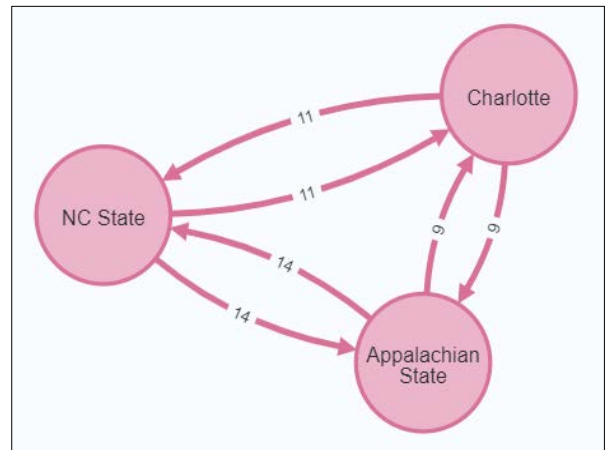
North Carolina's flagship university possesses the most sway over the state's numerous cities of the 100 colleges that recruited a player in the state; however, smaller programs are outpacing more prominent schools like Wake Forest and Duke, which could be related to academic standards. All service academy 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



## 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

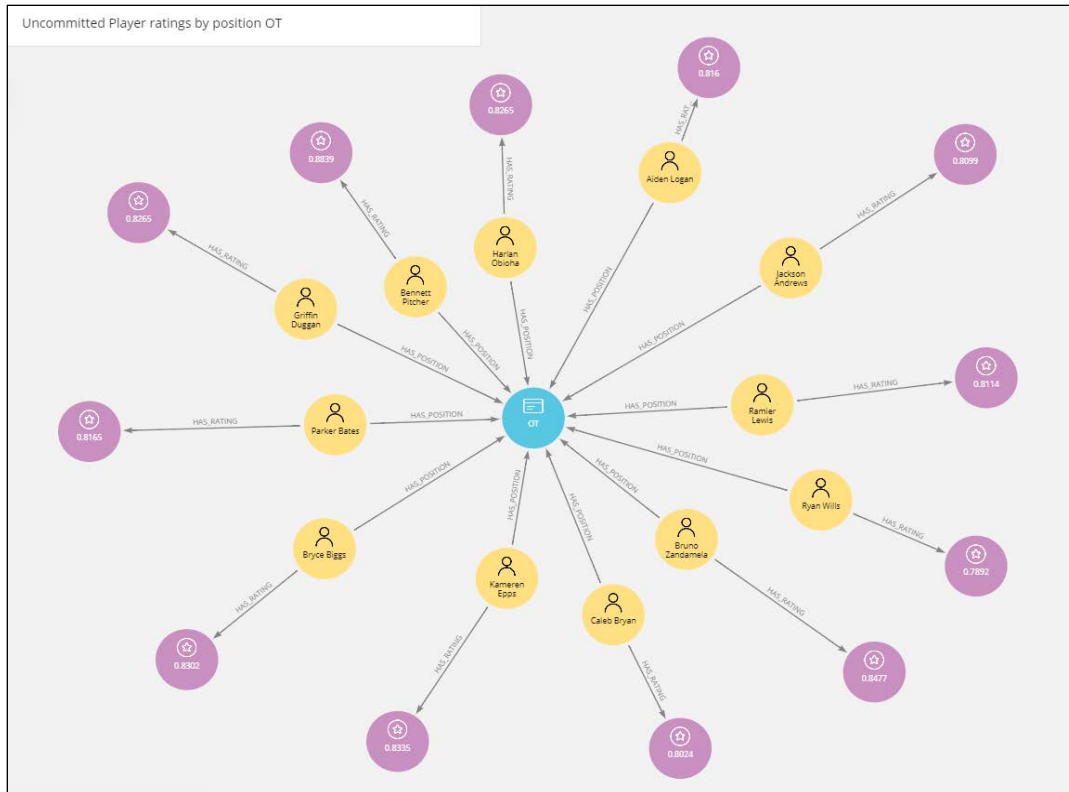
Cypher query \*

```

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

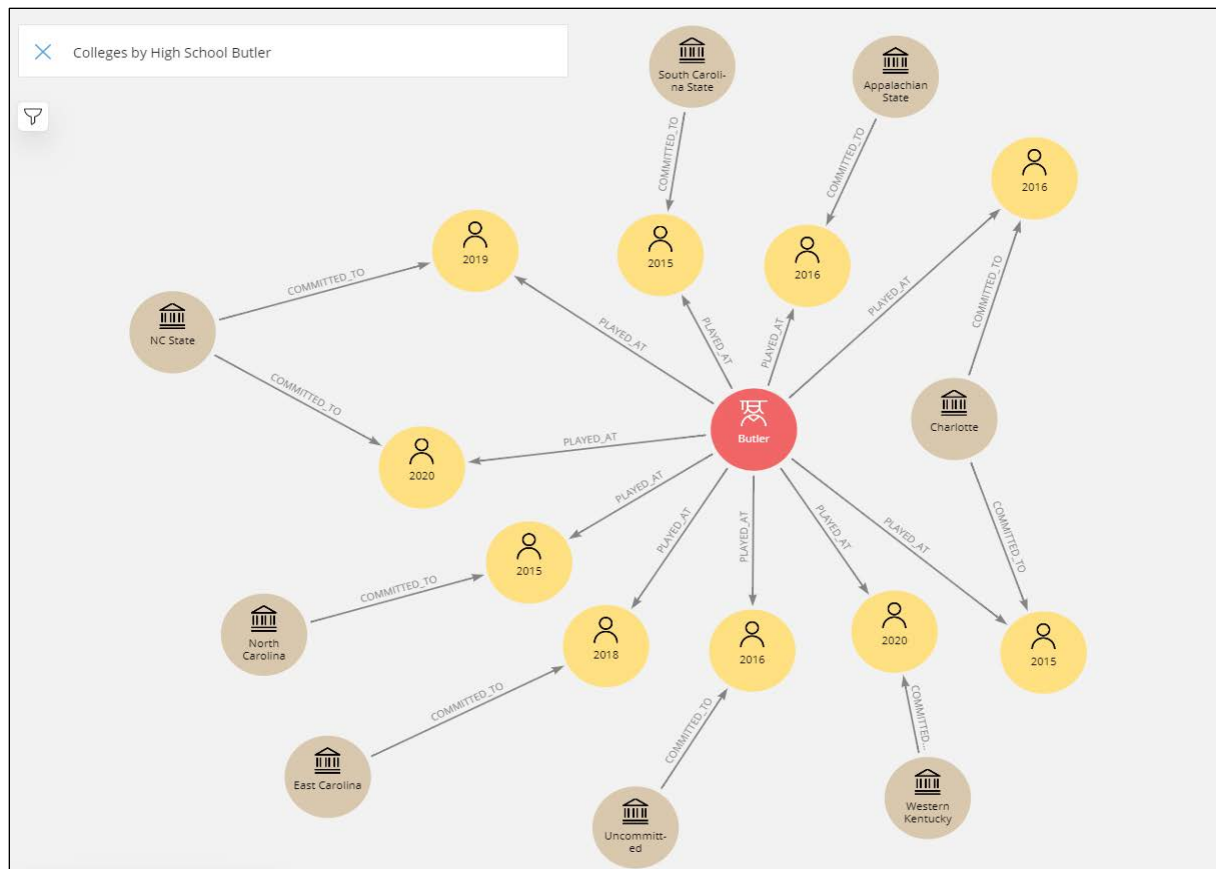
Description

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 *
  
```

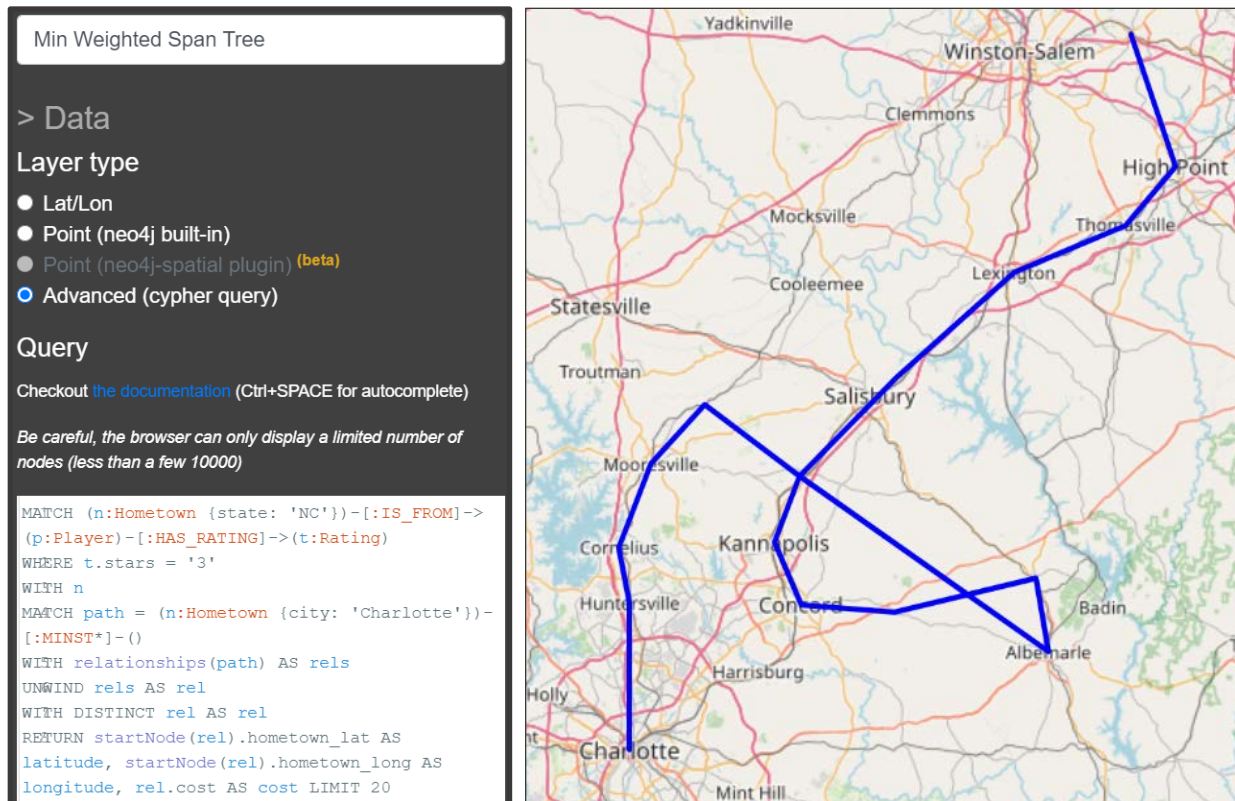


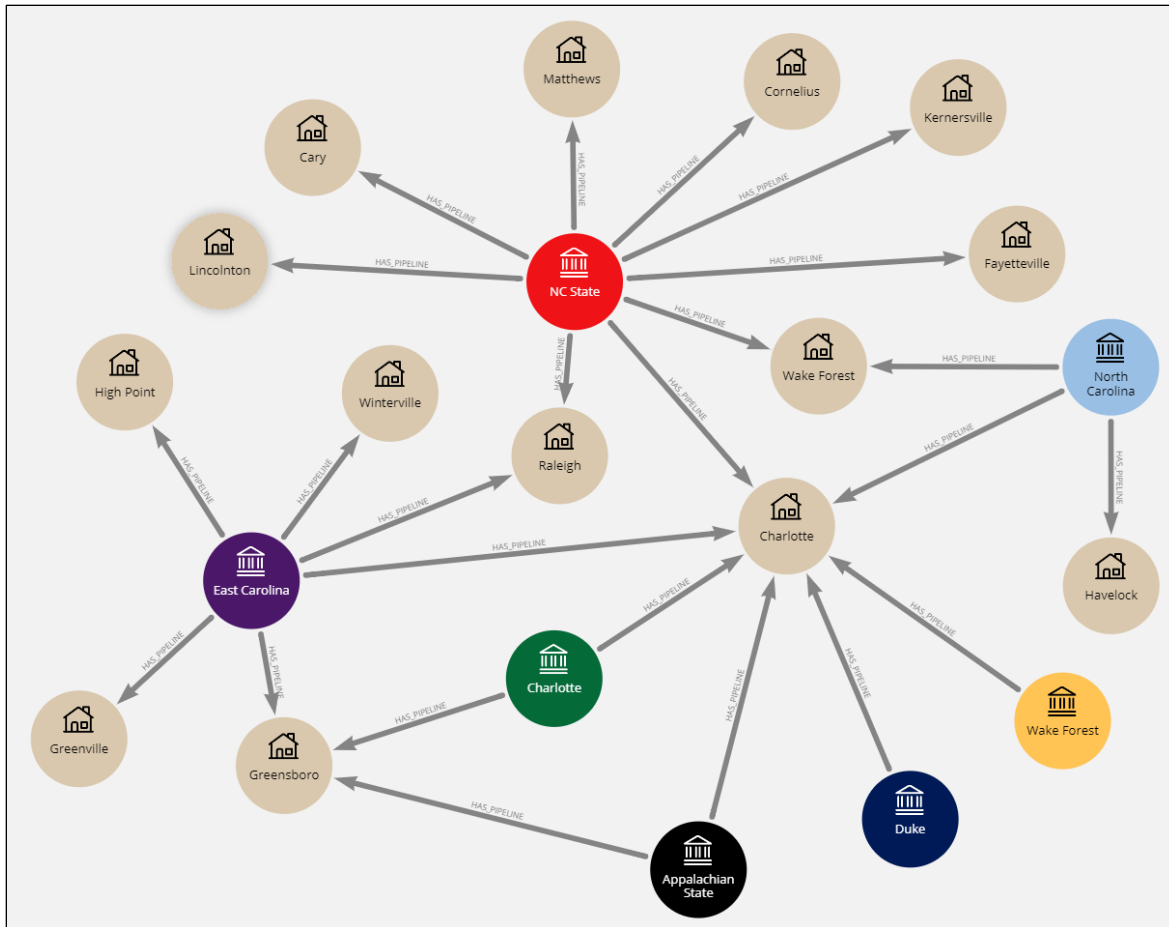
## Section IX: Graph Visualizations

### 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.





## Summary

### Section X: Solutions Value & Conclusions

Building a recruiting strategy from scratch is a daunting challenge, between the innumerable facets in consideration and the various tasks required to execute a thoughtful plan. Using the tools in previous sections, four key themes emerge in the analysis:

- I. **Realistic Expectations:** Narrow staff focus by determining player attributes more likely to result in a commitment

While the 49ers should not ignore four and five star recruits near campus, expending significant energy to chase top talent wastes precious time and resources, as well as opportunity costs of pursuing players. In

```

1 MATCH (n:Player)←[:COMMITTED_TO]-(c:College {name: "Charlotte"})
2 WITH n
3 MATCH (p:Position)←[:HAS_POSITION]-(n)-[:HAS_RATING]→(t:Rating)
4 WHERE t.year > '2018'
5 WITH p AS pos, n, t
6 RETURN pos.position_group, percentileDisc(toFloat(t.rating), 0.1)
   AS lower_10_rating, AVG(toFloat(t.rating)) AS
   rating_avg, percentileDisc(toFloat(t.rating), 0.9) AS
   upper_90_rating, count(n) AS cnt
7 ORDER By pos.position_group
  
```

the past three years, not a single four star recruit committed to play football for colleges in UNC Charlotte's conference. However, the 49ers have experienced more success in certain positions than others and should push for highly rated running backs, linebackers, and receivers especially.

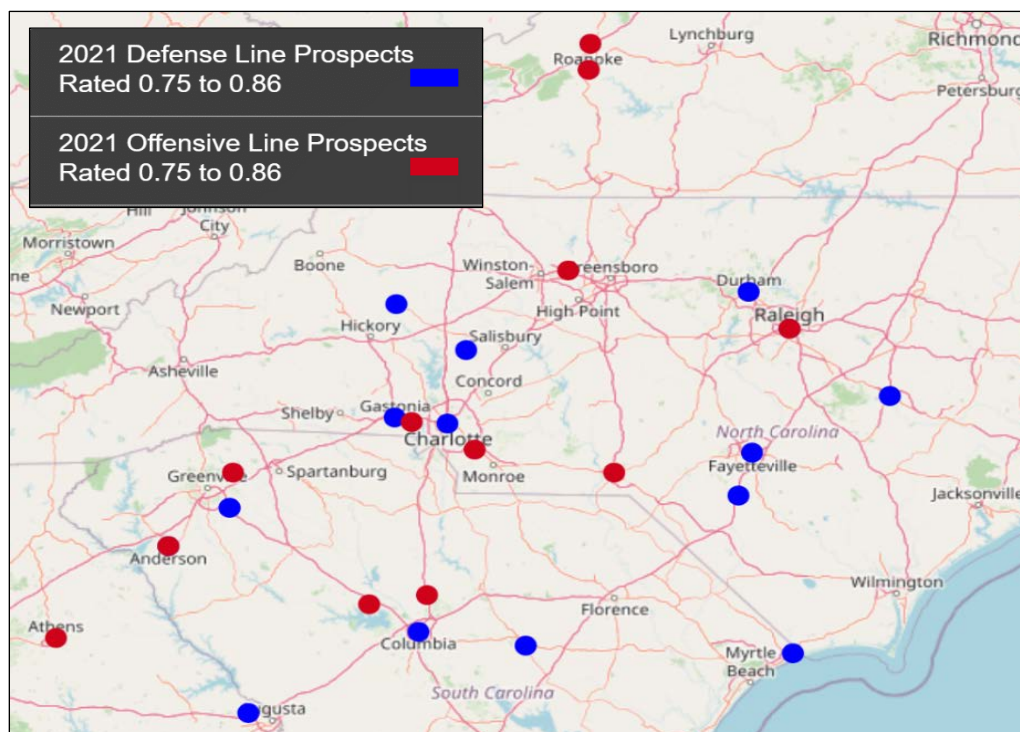


Position Group	10th Percentile Rating	Average Rating	90th Percentile Rating	Count of Players
Defensive Back	0.767	0.807	0.834	10
Defensive Line	0.768	0.801	0.831	7
Linebacker	0.767	0.810	0.843	6
Offensive Line	0.760	0.803	0.841	8
Quarterback	0.790	0.803	0.815	2
Receiver	0.778	0.815	0.842	12
Running Back	0.760	0.807	0.856	5
Special Teams	0.783	0.783	0.783	1

II. **Think Local:** Not only to reduce expenses, athletes are more likely to play for a school close to home

In the past three years, more than half of UNC Charlotte's recruits are from North or South Carolina and nearly 53% of North Carolina commit to a university located in North Carolina. Since 2019, about 40% of players from the Charlotte selected to play for an in state college, which has been trending upward over the past several years. Players clearly desire to attend programs that are close to their hometown, especially in recent years, and the 49ers should be increasing the amount of area targets to account for this development.

Evident from the table above, UNC Charlotte should look for future reinforcements on offensive and defensive lines, as those players take the longest to develop and adjust to the stronger college game. The visualization below displays the locations of players in the 2021 class considered worthwhile targets according to an attainable range of ability, formulating a road map for coaches to diagnose a plan of attack.



III. **Leverage Connections:** Pinpoint frequent sources of recruits and exploit existing relationships with high schools and area coaches

High School	Charlotte Recruit Count	Total Recruit Count
Buford	2	58
Mallard Creek	3	39
Bishop Moore Catholic	2	16
Zebulon B. Vance	2	16
Blackman	2	14
Blythewood	2	12
Tallahassee Leon	2	11
Butler	2	10
Mooreville Senior	2	6
Wando	2	5
Lucy Ragsdale	2	3

Similar to examining North Carolina State's peculiar PageRank score, it's useful to determine UNC Charlotte's share of players at high schools where UNC Charlotte received multiple players. Expanding on Table 6.1, the table on the next page looks at the potential to recruit more players from a high school where the 49ers have existing relationships.

Buford and Mallard Creek have the most opportunity as both schools are reliably producing players at an impressive rate. Charlotte locks down players coming out of Wando and Lucy Ragsdale so players are likely to already hold a favorable view of the 49er football program.

IV. **Customizing Campaigns:** Identify common competitors to curate a recruiting pitch that differentiates UNC Charlotte from rival schools

In section VII, the Jaccard similarity algorithm determined that the University of South Carolina frequents the most similar high schools for players as UNC Charlotte, a notable outcome due to South Carolina's low PageRank in the state of North Carolina. It's important to know which other universities are visiting high schools where Charlotte is attempting to recruit athletes, as rival schools will portray competitors in a negative light. Equipping coaches with prior knowledge of other football program's activities can prepare to combat any potential rumors and pitch attractive aspects of UNC Charlotte that other universities do not possess.

Search phrase \*

Shared High Schools by College \$college\_name

Description

Search universities recruiting the same high schools as Charlotte

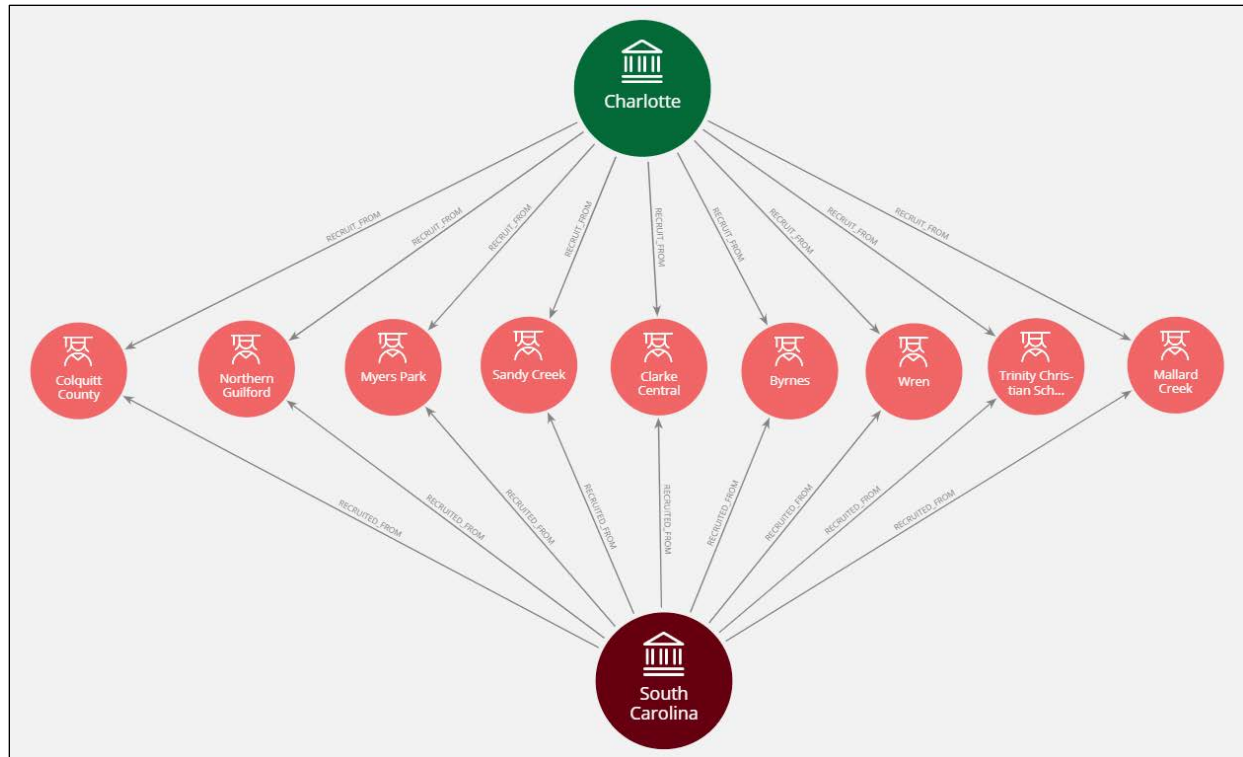
Cypher query \*

```

MATCH (c1:College {name: 'Charlotte'})-[:COMMITTED_TO]->
(n:Player)-[:PLAYED_AT]-(school1)
WHERE n.year > '2018'
WITH c1, school1, count(n) as cnt
MATCH (c2:College)-[:COMMITTED_TO]->(m:Player)-[:PLAYED_AT]-(school2)
WHERE c2.name = $college_name AND school1 = school2
WITH c1, school1, c2, school2, cnt, count(m) as cnt2
CALL apoc.create.vRelationship(c1, 'RECRUIT_FROM',
{weight: cnt}, school2) YIELD rel AS rel1
CALL apoc.create.vRelationship(c2, 'RECRUITED_FROM',
{weight: cnt2}, school2) YIELD rel AS rel2
RETURN *

```

Although the algorithm used all seven years of the dataset, older data is not pertinent to this use case so only the last three years of recruiting high school recruiting activity is utilized in this Cypher action. Mallard Creek and Myers Park, local sources of talent, are frequented by many large programs so those high schools would not surprise coaches; however, it would be important to alert visiting staff of Trinity Christian School, located in Texas, where they may not have expected to compete against South Carolina's recruiters.





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