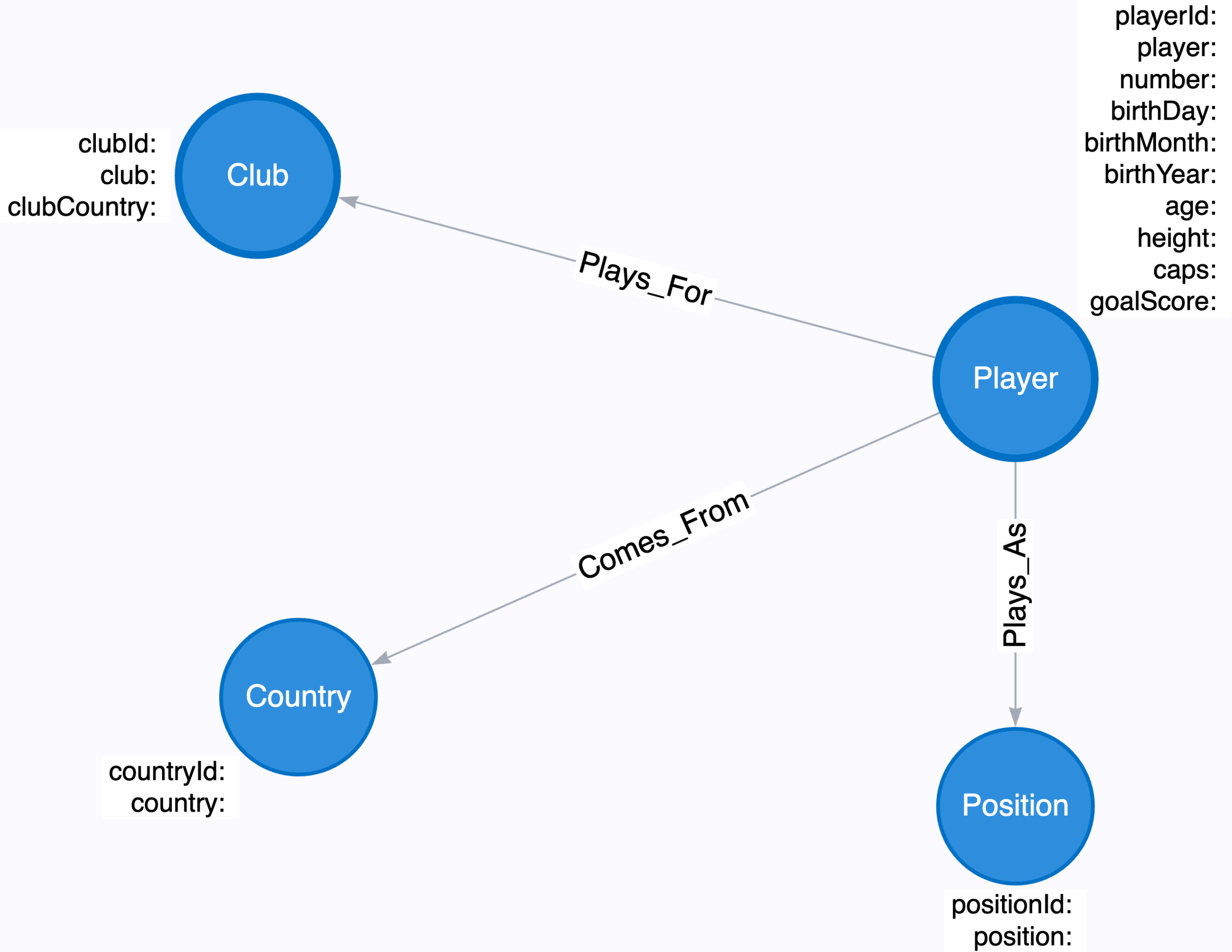


CITS5504 - Group project

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Graph Database Design and Implementation Process

Property graph:



• Explanation and description of the property graph design:

There are 4 types of nodes (node labels) and 3 relationships in this property graph.

- **Player node:** Each row in "player" table is a unique player node in this graph database. It represents every unique player with attributes "player's id", "player's name", "player's number", "player's birth day", "player's birth month", "player's birth year", "player's age", "player's height", "player's caps number", and "player's international goals number". For example, a player named ALAN PULIDO with ID 336722, number 11, date of birth 08 March 1991, age 23, height 176 cm, five international caps for the national team, and four goals for the national team, would be a player node in this graph database.
- **Club node:** Each row in "club" table is a unique club node in this graph database. It represents every unique club with attributes "club's id", "club's name", and "club's country". For example, a club named TIGERS UANL with ID 1, and located in Mexico, would be a club node in this graph database.
- **Position node:** Each row in "position" table is a unique position node in this graph database. It represents every unique position played by the player with attributes "position's id" and "position". For example, Forward with ID 1, would be a position node in this graph database.
- **Country node:** Each row in "country" table is a unique country node in this graph database. It represents every unique player's national country with attributes "country's id" and "country name". For example, Mexico with ID 1, would be a country node in this graph database.

• Rationale behind the design of the property graph:

Justin Rasband states that "Should it be a Node, a Relationship, or a Property is depends on the kinds of queries you want to run against your model". "Any data element that isn't frequently used to access the graph directly, has no internal object complexity/multiplicity, and/or needs to always return with the rest of the data in the node is a good candidate for a Property" (Rasband 2022).

Based on these concepts, and after considering the dataset and the queries required to be answered in the project sheet, we made the following design decisions:

- **Player node:** This contains many attributes that are descriptive information about the player, such as "player's age", "player's height", and "player's caps". Each of these attributes only returns with another single attribute within player node in the required queries, having low internal object complexity. Therefore, I designed them as attributes rather than nodes.
- **Position node:** There are only two attributes in it, "position id" and "position name". The reason I chose to make position a node rather than an attribute in the player node is that the queries involving player positions are relatively complex. For example, "Identify pairs of players from the same national team who play in different positions but have the closest number of caps. Return these pairs along with their positions and the difference in caps." Therefore, making position a separate node rather than an attribute can improve query efficiency.
- **Club node:** This node includes attributes "club id", "club name", "club's country", and so on. Similarly, making club a node is because some queries involving the club are relatively complex. For example, "Find all players who play at (a specific club), returning in ascending order of age." For this query, if the club were an attribute within the player node, the query would need to use three attributes within player node. In contrast, making the club a separate node rather than an attribute is more efficient. The "club's country" is an attribute because it is descriptive information about the club.
- **Country node:** There are only two attributes in it, "country id" and "country name". Similarly, making country a node is because queries involving the player's country are relatively complex. For example, "Identify pairs of players from the same national team who play in different positions but have the closest number of caps. Return these pairs along with their positions and the difference in caps." Therefore, making the player's country a separate node rather than an attribute can improve query efficiency.

ETL Process

1. Extract Data

Extract 'FIFA2014 - all players.csv' and transform it into dataframe:

```
In [28]: import pandas as pd
df_FIFA2014_all_players = pd.read_csv("FIFA2014 - all players.csv")
```

2. Transform Data

a. Data quality check and Data cleaning

For data quality purpose, we performed data quality checks, cleaning, reordering, renaming, and other operations on the dataset.

a(1). Check for duplicate rows

```
In [29]: # Count the number of duplicate rows
duplicates = df_FIFA2014_all_players.duplicated()
num_duplicates = duplicates.sum()
print("It can be seen that there is " + str(num_duplicates) + " duplicate row in the dataset.")

It can be seen that there is 0 duplicate row in the dataset.
```

a(2). Check for missing values

```
In [30]: # calculates the missing value for each column, then add to the last as a supplementary for easy to view.
df_FIFA2014_all_players_check = df_FIFA2014_all_players.copy()
null_counts_df = df_FIFA2014_all_players_check.isnull().sum()
df_FIFA2014_all_players_check.loc['null_counts'] = null_counts_df
df_FIFA2014_all_players_check
```

Out [30]:

	Player id	Player	Position	Number	Club	Club (country)	D.O.B	Age	Height (cm)	Country	Caps	International goals	Plays in home country?	
	0	336722	Alan PULIDO	Forward	11	Tigres UANL	Mexico	08.03.1991	23	176	Mexico	5	4	1
	1	368902	Adam TAGGART	Forward	9	Newcastle United Jets FC	Australia	02.06.1993	21	172	Australia	4	3	1
	2	362641	Reza GHOOCHANNEJAD	Forward	16	Charlton Athletic FC	England	20.09.1987	26	181	Iran	13	9	0
	3	314197	NEYMAR	Forward	10	FC Barcelona	Spain	05.02.1992	22	175	Brazil	48	31	0
	4	212306	Didier DROGBA	Forward	11	Galatasaray SK	Turkey	11.03.1978	36	180	Ivory Coast	100	61	0

	732	369050	Ivan MOCINIC	Midfielder	15	HNK Rijeka	Croatia	30.04.1993	21	180	Croatia	0	0	1
	733	380000	Marcelo BROZOVIC	Midfielder	14	GNK Dinamo Zagreb	Croatia	16.11.1992	21	180	Croatia	0	0	1
	734	380009	Luis LOPEZ	Goalkeeper	1	Real Espana	Honduras	13.09.1993	20	182	Honduras	0	0	1
	735	379910	Adnan JANUZAJ	Midfielder	20	Manchester United FC	England	05.02.1995	19	180	Belgium	0	0	0
	null_counts	0	0	0	0	0	0	0	0	0	0	0	0	0

737 rows x 13 columns

According to the output, it can be seen that there is no missing values in the dataset.

a(3). Check for invalid values

Check the data type for all column that in case there are invalid values, especially column "Number", "Age", "Height(cm)", "Caps", "International goals" which should be numerical.

```
In [31]: # Use 'dtypes' to check the type of each field and print them
print(df_FIFA2014_all_players.dtypes)

Player id          int64
Player            object
Position          object
Number            int64
Club              object
Club (country)    object
D.O.B             object
Age               int64
Height (cm)       int64
Country           object
Caps              int64
International goals int64
Plays in home country? bool
dtype: object

It can be seen that there is no invalid value in the dataset.
```

a(4). Check for outlier values

Check if there is any outlier values for numerical column (except "Player id" and "Plays in home country?" column) in the data set.

```
In [32]: # Use describe function to check outlier values
print(df_FIFA2014_all_players["Number"].describe(),df_FIFA2014_all_players["Age"].describe(),
      df_FIFA2014_all_players["Height (cm)"].describe(),df_FIFA2014_all_players["Caps"].describe(),
      df_FIFA2014_all_players["International goals"].describe())
```

```
count      736.00000
mean       12.00000
std        6.63776
min        1.00000
25%        6.00000
50%       12.00000
75%       18.00000
max       23.00000
Name: Number, dtype: float64 count      736.000000
mean       26.895380
std        3.818491
min       18.000000
25%       24.000000
50%       27.000000
75%       29.000000
max       43.000000
Name: Age, dtype: float64 count      736.000000
mean       181.388587
std        7.048217
min      156.000000
25%      177.000000
50%      182.000000
75%      186.000000
max     201.000000
Name: Height (cm), dtype: float64 count      736.000000
mean       33.216033
std       30.440723
min        0.000000
25%        9.000000
50%       24.000000
75%       49.000000
max      153.000000
Name: Caps, dtype: float64 count      736.000000
mean        4.460598
std        8.542081
min        0.000000
25%        0.000000
50%        1.000000
75%        5.000000
max       68.000000
Name: International goals, dtype: float64
```

According to standard deviation method and quartile deviation method , all values are in a reasonable data range.

a(5). Remove redundant column

We decide to remove this column not due to performance issue, but because we think it is redundant. By comparing the “club(country)” column with the “country” column, we can know whether players play for their home country or not. Therefore, we remove “plays in home country” column to reduce data redundancy:

```
In [7]: del df_FIFA2014_all_players["Plays in home country?"]
```

a(6). Rename columns

Rename the columns to make them easier to use and understand

```
In [8]: # Rename columns name for easy reading:
df_FIFA2014_all_players.rename(columns={"Player id":"playerId", "Player":"player", "Position":"position", "Number":"number", "Club":"club",
                                         "Club (country)": "clubCountry", "D.O.B":"birthdayDate", "Age":"age", "Height (cm)": "height",
                                         "Country":"country", "Caps":"caps", "International goals":"goalScore"}, inplace=True)
```

a(7). Unify Name Rules

The player's name and club's name contain uppercase and lowercase letters, which is not easy to read. Hence, we should uniform the name rules.

```
In [9]: # Change the letter of all player's name and club's name to uppercase.
df_FIFA2014_all_players["player"] = df_FIFA2014_all_players["player"].str.upper()
df_FIFA2014_all_players["club"] = df_FIFA2014_all_players["club"].str.upper()
```

a(8). Deal with Date Time

To make data processing more convenient, we separate the player’s birthday column into three columns (the day of birth, the month of birth, and the year of birth).

```
In [10]: # use str.split() to separate it:
df_FIFA2014_all_players[["birthDay", "birthMonth", "birthYear"]] = df_FIFA2014_all_players["birthdayDate"].str.split(".", expand=True)
```

a(9). Reorder the columns

Reorder the columns to make the dataset clearer and more logical.

```
In [11]: new_order = ["playerId", "player", "position", "number", "club", "clubCountry", "birthdayDate", "birthDay", "birthMonth",
                    "birthYear", "age", "height", "country", "caps", "goalScore"]
df_FIFA2014_all_players = df_FIFA2014_all_players[new_order]
```

```
In [12]: df_FIFA2014_all_players_cleaned = df_FIFA2014_all_players.copy()
df_FIFA2014_all_players_cleaned
```

Out[12]:

	playerId	player	position	number	club	clubCountry	birthdayDate	birthDay	birthMonth	birthYear	age	height	country	caps	goalScore	
	0	336722	ALAN PULIDO	Forward	11	TIGRES UANL	Mexico	08.03.1991	08	03	1991	23	176	Mexico	5	4
	1	368902	ADAM TAGGART	Forward	9	NEWCASTLE UNITED JETS FC	Australia	02.06.1993	02	06	1993	21	172	Australia	4	3
	2	362641	REZA GHOOCHANNEJAD	Forward	16	CHARLTON ATHLETIC FC	England	20.09.1987	20	09	1987	26	181	Iran	13	9
	3	314197	NEYMAR	Forward	10	FC BARCELONA	Spain	05.02.1992	05	02	1992	22	175	Brazil	48	31
	4	212306	DIDIER DROGBA	Forward	11	GALATASARAY SK	Turkey	11.03.1978	11	03	1978	36	180	Ivory Coast	100	61

	731	379165	BAILEY WRIGHT	Defender	8	PRESTON NORTH END FC	England	28.07.1992	28	07	1992	21	184	Australia	0	0
	732	369050	IVAN MOCINIC	Midfielder	15	HNK RIJEKA	Croatia	30.04.1993	30	04	1993	21	180	Croatia	0	0
	733	380000	MARCELO BROZOVIC	Midfielder	14	GNK DINAMO ZAGREB	Croatia	16.11.1992	16	11	1992	21	180	Croatia	0	0
	734	380009	LUIS LOPEZ	Goalkeeper	1	REAL ESPANA	Honduras	13.09.1993	13	09	1993	20	182	Honduras	0	0
	735	379910	ADNAN JANUZAJ	Midfielder	20	MANCHESTER UNITED FC	England	05.02.1995	05	02	1995	19	180	Belgium	0	0

736 rows × 15 columns

```
In [13]: # Transform the df_players dataframe to a csv file:
df_FIFA2014_all_players_cleaned.to_csv("FIFA2014 - all players - after cleaned.csv", index = False)
```

b. Create node tables

Next, we are going to create four node tables that we need

b(1). Create player table:

```
In [14]: # copy the necessary columns from the df_FIFA2014_all_players dataframe:
df_players = df_FIFA2014_all_players[["playerId", "player", "number", "birthDay", "birthMonth", "birthYear", "age", "height", "caps", "goalScore"]].copy()

# drop duplicates to get unique players:
df_players = df_players.drop_duplicates()
```

df_players

Out[14]:		playerId	player	number	birthDay	birthMonth	birthYear	age	height	caps	goalScore
	0	336722	ALAN PULIDO	11	08	03	1991	23	176	5	4
	1	368902	ADAM TAGGART	9	02	06	1993	21	172	4	3
	2	362641	REZA GHOOCHANNEJAD	16	20	09	1987	26	181	13	9
	3	314197	NEYMAR	10	05	02	1992	22	175	48	31
	4	212306	DIDIER DROGBA	11	11	03	1978	36	180	100	61

	731	379165	BAILEY WRIGHT	8	28	07	1992	21	184	0	0
	732	369050	IVAN MOCINIC	15	30	04	1993	21	180	0	0
	733	380000	MARCELO BROZOVIC	14	16	11	1992	21	180	0	0
	734	380009	LUIS LOPEZ	1	13	09	1993	20	182	0	0
	735	379910	ADNAN JANUZAJ	20	05	02	1995	19	180	0	0

736 rows x 10 columns

```
In [15]: # Transform the df_players dataframe to a csv file:
df_players.to_csv("player_node.csv", index = False)
```

b(2). Create club table:

```
In [16]: # copy the necessary columns from the df_FIFA2014_all_players dataframe:
df_clubs = df_FIFA2014_all_players[["club", "clubCountry"]].copy()

# drop duplicates to get unique club and country combinations:
df_clubs = df_clubs.drop_duplicates()

# generate unique club id starting from 1 for each unique club and country combination:
df_clubs["clubId"] = range(1, len(df_clubs) + 1)

# set clubID as the index of the DataFrame:
df_clubs.set_index("clubId", inplace=True)

df_clubs
```

Out[16]:		club	clubCountry
	clubId		
	1	TIGRES UANL	Mexico
	2	NEWCASTLE UNITED JETS FC	Australia
	3	CHARLTON ATHLETIC FC	England
	4	FC BARCELONA	Spain
	5	GALATASARAY SK	Turkey

	293	VFR AALEN	Germany
	294	BUSAN IPARK FC	South Korea
	295	NK LOKOMOTIVA ZAGREB	Croatia
	296	PRESTON NORTH END FC	England
	297	HNK RIJEKA	Croatia

297 rows x 2 columns

```
In [17]: # Transform the df_clubs dataframe to a csv file:
df_clubs.to_csv("club_node.csv")
```

b(3). Create position table:

```
In [18]: # copy the necessary columns from the df_FIFA2014_all_players dataframe:
position_name = df_FIFA2014_all_players["position"].copy()

# get the unique game years:
unique_position_name = position_name.unique()

# generate unique position id starting from 1 for each unique position:
position_id = range(1, len(unique_position_name) + 1)

# create a DataFrame containing the game year and the corresponding unique ID
df_positions = pd.DataFrame({"positionId": position_id, "position": unique_position_name})

df_positions
```

Out[18]:		positionId	position
	0	1	Forward
	1	2	Defender
	2	3	Midfielder
	3	4	Goalkeeper

```
In [19]: # Transform the df_positions dataframe to a csv file:
df_positions.to_csv("position_node.csv", index=False)
```

b(4). create country table:

```
In [20]: country_name = df_FIFA2014_all_players["country"].copy()

unique_country_name = country_name.unique()

country_id = range(1, len(unique_country_name) + 1)

df_countries = pd.DataFrame({"countryId": country_id, "country": unique_country_name})

df_countries
```


Out [20]:

	countryId	country
0	1	Mexico
1	2	Australia
2	3	Iran
3	4	Brazil
4	5	Ivory Coast
5	6	Spain
6	7	Uruguay
7	8	Bosnia & Herzegovina
8	9	Netherlands
9	10	Argentina
10	11	Algeria
11	12	Germany
12	13	Japan
13	14	Cameroon
14	15	Switzerland
15	16	Nigeria
16	17	England
17	18	Chile
18	19	Ghana
19	20	USA
20	21	Croatia
21	22	Honduras
22	23	Portugal
23	24	Columbia
24	25	Italy
25	26	South Korea
26	27	Greece
27	28	Ecuador
28	29	Russia
29	30	France
30	31	Belgium
31	32	Costa Rica

In [21]:

```
# Transform the df_countries dataframe to a csv file:
df_countries.to_csv("country_node.csv", index=False)
```

c. Create a table to combine the data and four unique ids together (This table is created for subsequent relationship table creation):

In [22]:

```
# Copy the df_FIFA2014_all_players dataframe to a new dataframe called df_FIFA2014_all_players_add_id_columns:
df_FIFA2014_all_players_add_id_columns = df_FIFA2014_all_players.copy()

# Generate unique IDs for the combination of "Club's name" and "Club's country" columns starting from 1 for each unique club and country combination:
df_FIFA2014_all_players_add_id_columns["clubId"] = pd.factorize(df_FIFA2014_all_players_add_id_columns["club"].astype(str) + "_" +
                                                                df_FIFA2014_all_players_add_id_columns["clubCountry"].astype(str))[0] + 1

# Generate unique IDs for "Position name" column starting from 1 for each unique position:
df_FIFA2014_all_players_add_id_columns["positionId"] = pd.factorize(df_FIFA2014_all_players_add_id_columns["position"])[0] + 1

# Generate unique IDs for "Country name" column starting from 1 for each unique country:
df_FIFA2014_all_players_add_id_columns["countryId"] = pd.factorize(df_FIFA2014_all_players_add_id_columns["country"])[0] + 1

# Reorder the columns in the df_FIFA2014_all_players_add_id_columns dataframe:
new_order = ["playerId", "player", "number", "birthDay", "birthMonth", "birthYear", "age", "height", "caps", "goalScore",
             "clubId", "club", "clubCountry", "positionId", "position", "countryId", "country"]
df_FIFA2014_all_players_add_id_columns = df_FIFA2014_all_players_add_id_columns[new_order]

df_FIFA2014_all_players_add_id_columns
```

Out [22]:

	playerId	player	number	birthDay	birthMonth	birthYear	age	height	caps	goalScore	clubId	club	clubCountry	positionId	position	countryId	country
0	336722	ALAN PULIDO	11	08	03	1991	23	176	5	4	1	TIGRES UANL	Mexico	1	Forward	1	Mexico
1	368902	ADAM TAGGART	9	02	06	1993	21	172	4	3	2	NEWCASTLE UNITED JETS FC	Australia	1	Forward	2	Australia
2	362641	REZA GHOOCHANNEJAD	16	20	09	1987	26	181	13	9	3	CHARLTON ATHLETIC FC	England	1	Forward	3	Iran
3	314197	NEYMAR	10	05	02	1992	22	175	48	31	4	FC BARCELONA	Spain	1	Forward	4	Brazil
4	212306	DIDIER DROGBA	11	11	03	1978	36	180	100	61	5	GALATASARAY SK	Turkey	1	Forward	5	Ivory Coast
...
731	379165	BAILEY WRIGHT	8	28	07	1992	21	184	0	0	296	PRESTON NORTH END FC	England	2	Defender	2	Australia
732	369050	IVAN MOCINIC	15	30	04	1993	21	180	0	0	297	HNK RIJEKA	Croatia	3	Midfielder	21	Croatia
733	380000	MARCELO BROZOVIC	14	16	11	1992	21	180	0	0	23	GNK DINAMO ZAGREB	Croatia	3	Midfielder	21	Croatia
734	380009	LUIS LOPEZ	1	13	09	1993	20	182	0	0	28	REAL ESPANA	Honduras	4	Goalkeeper	22	Honduras
735	379910	ADNAN JANUZAJ	20	05	02	1995	19	180	0	0	8	MANCHESTER UNITED FC	England	3	Midfielder	31	Belgium

736 rows x 17 columns

d. Create relationship tables

Then, we are going to create three relationship tables that we need

d(1). Create relationship "Plays_For" from "player" and "club":

In [23]:

```
# The relationship between "Player" and "Club" can obtain from "df_FIFA2014_all_players_add_id_columns"
df_plays_for_table = df_FIFA2014_all_players_add_id_columns.loc[:, ["playerId", "clubId"]]

# Transform the df_plays_for_table dataframe to a csv file:
df_plays_for_table.to_csv("rel_plays_for.csv", index=False)

df_plays_for_table
```

```
Out [23]:
```

	playerId	clubId
0	336722	1
1	368902	2
2	362641	3
3	314197	4
4	212306	5
...
731	379165	296
732	369050	297
733	380000	23
734	380009	28
735	379910	8

736 rows x 2 columns

d(2). Create relationship "Comes_From" from "player" and "Country":

```
In [24]: # The relationship between "Player" and "Country" can obtain from "df_FIFA2014_all_players_add_id_columns"
df_comes_from_table = df_FIFA2014_all_players_add_id_columns.loc[:, ['playerId', 'countryId']]

# Transform the df_comes_from_table dataframe to a csv file:
df_comes_from_table.to_csv('rel_comes_from.csv', index=False)

df_comes_from_table
```

```
Out [24]:
```

	playerId	countryId
0	336722	1
1	368902	2
2	362641	3
3	314197	4
4	212306	5
...
731	379165	2
732	369050	21
733	380000	21
734	380009	22
735	379910	31

736 rows x 2 columns

d(3). Create relationship "Plays_As" from "player" and "position":

```
In [25]: # as you can see, the relationship between "Player" and "Position" can obtain from "df_FIFA2014_all_players_add_id_columns"
df_plays_as_table = df_FIFA2014_all_players_add_id_columns.loc[:, ['playerId', 'positionId']]

# Transform the df_plays_as_table dataframe to a csv file:
df_plays_as_table.to_csv('rel_plays_as.csv', index=False)

df_plays_as_table
```

```
Out [25]:
```

	playerId	positionId
0	336722	1
1	368902	1
2	362641	1
3	314197	1
4	212306	1
...
731	379165	2
732	369050	3
733	380000	3
734	380009	4
735	379910	3

736 rows x 2 columns

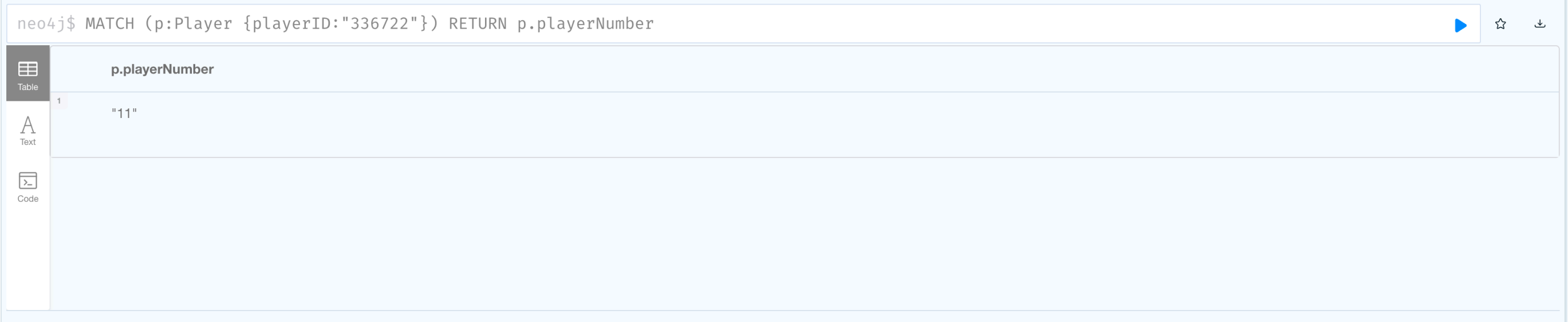
3. Load Data

After we get all the required csv files from the previous steps, we need to load them into Neo4j, so that we can do queries in next steps (This part's code is in "cypher_scripts.txt").

Queries and The Corresponding Resultls

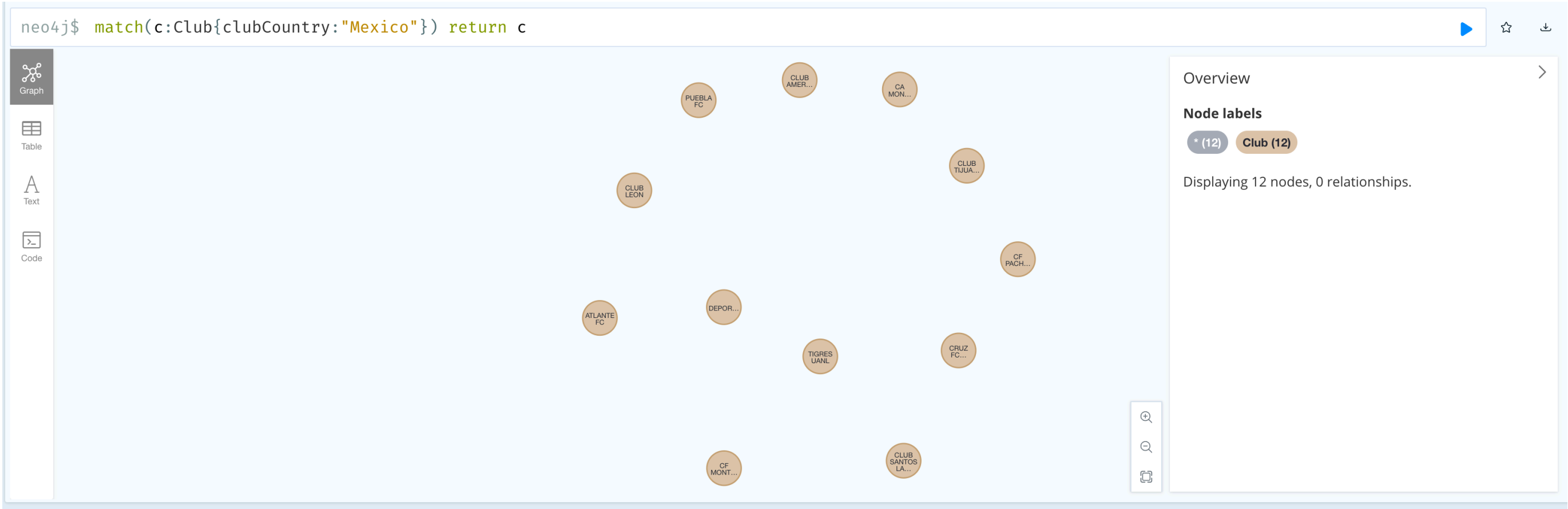
a. What is the jersey number of the player with '336722'?

MATCH (p:Player {playerID:"336722"}) RETURN p



b. Question: Which clubs are based in Mexico ?

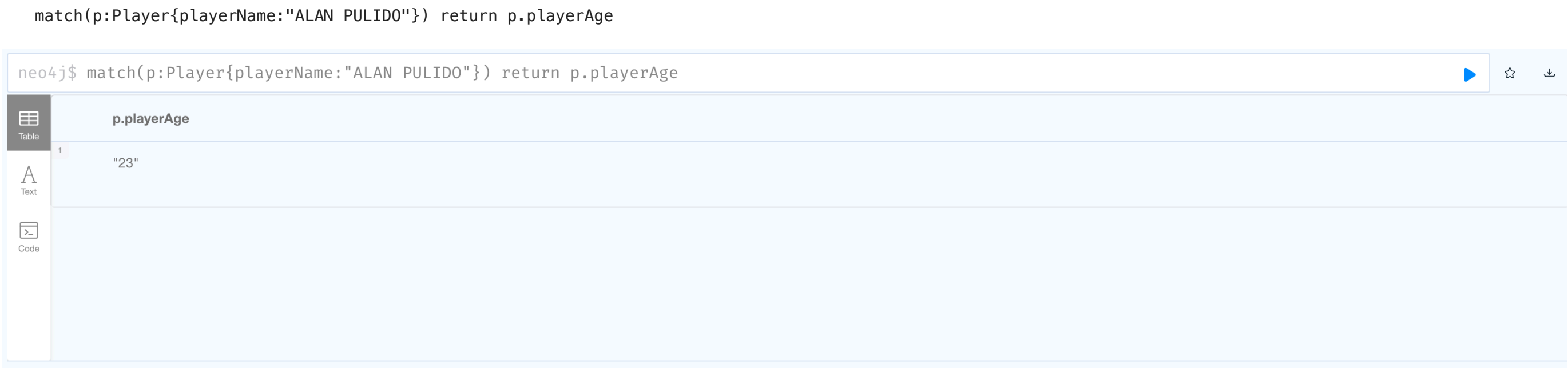
MATCH (c:Club{clubCountry:"Mexico"}) RETURN c



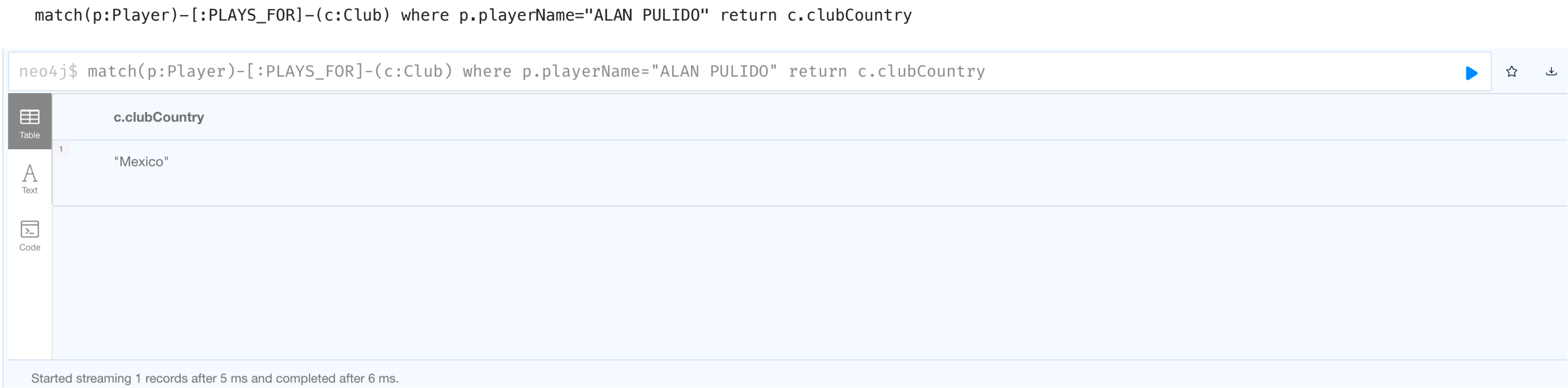
c. Which club does Alan Pulido play for?



d. How old is Alan Pulido?

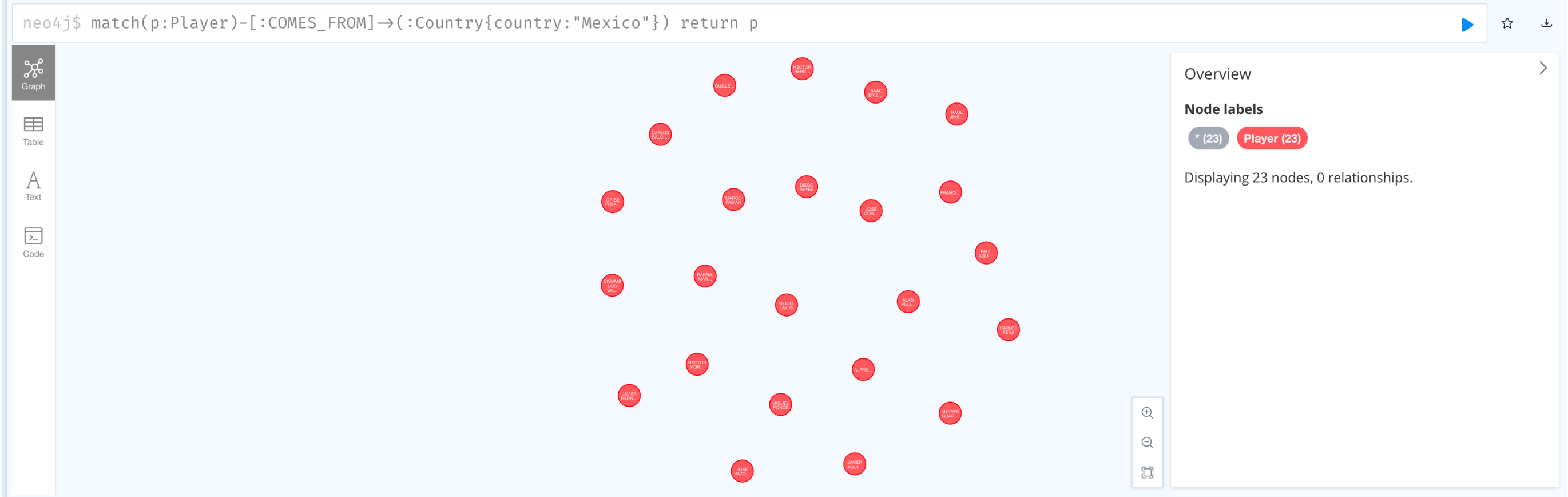


e. In which country is the club that Alan Pulido plays for?



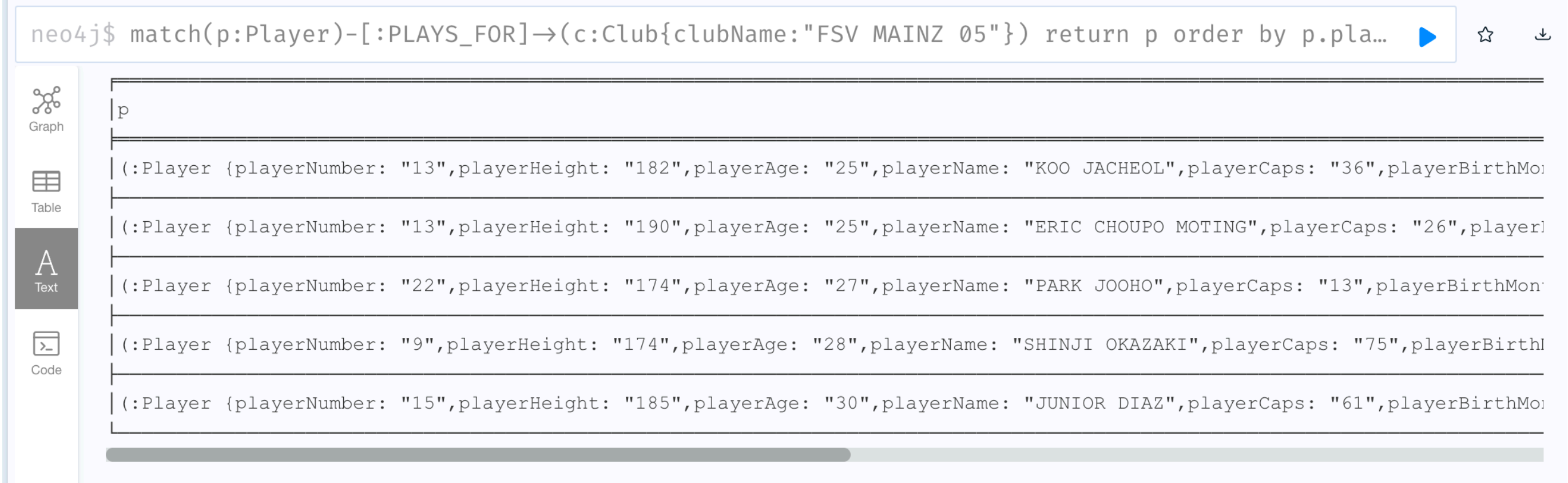
f. Find a club that has players from Mexico.

`match(p:Player)-[:COMES_FROM]->(Country{country:"Mexico"}) return p`



g. Find all players play at FSV Mainz 05, returning in ascending orders of age.

```
match(p:Player)-[:PLAYS_FOR]->(c:Club{clubName:"FSV MAINZ 05"}) return p order by p.playerAge
```



h. Find all Forward players in national team of USA, returning in descending order of caps.

```
match (po:Position{positionName:"Forward"})<-[:PLAYS_AS]-(p:Player)-[:COMES_FROM]->(c:Country{country:"USA"}) return p order by p.playerCaps
```



i. Find all players born in 1990 and in national team of Japan, returning in descending order of caps.

```
MATCH (p:Player{playerBirthYear:"1990"})-[:COMES_FROM]->(:Country{country:"Japan"}) return p order by toInteger(p.playerCaps) DESC
```



j. Find the players that belongs to the same club in national team of USA, returning in descending order of international goals.

```
MATCH (:Country{country:"USA"})<-[:COMES_FROM]-(p:Player)-[:PLAYS_FOR]->(c:Club)
WITH c, COUNT(p) AS playerCount, COLLECT(p) AS players
WHERE playerCount > 1
UNWIND players as player
RETURN c.clubName as club, player ORDER BY club ASC, toInteger(player.playerInternationalGoals) DESC
```


1 MATCH (:Country{country:"USA"})←[:COMES_FROM]-(p:Player)-[:PLAYS_FOR]→(c:Club)

2 WITH c, COUNT(p) AS playerCount, COLLECT(p) AS players

3 WHERE playerCount > 1

4 UNWIND players as player

5 RETURN c.clubName as club, player ORDER BY club ASC, toInteger(player.playerInternationalGoals) DESC

Graph

Table

Text

Code

club	player
"REAL SALT LAKE"	(:Player {playerNumber: "15",playerHeight: "181",playerAge: "32",playerName: "KYLE BECKERMAN",playerCaps: "36",playerBirthMonth: "04",playerBirthYear: "1982",playerInternationalGoals: "1",playerBirthDay: "23",playerID: "175512"})
"REAL SALT LAKE"	(:Player {playerNumber: "22",playerHeight: "182",playerAge: "35",playerName: "NICK RIMANDO",playerCaps: "14",playerBirthMonth: "06",playerBirthYear: "1979",playerInternationalGoals: "0",playerBirthDay: "17",playerID: "184982"})
"SEATTLE SOUNDERS FC"	(:Player {playerNumber: "8",playerHeight: "185",playerAge: "31",playerName: "CLINT DEMPSEY",playerCaps: "103",playerBirthMonth: "03",playerBirthYear: "1983",playerInternationalGoals: "36",playerBirthDay: "09",playerID: "207851"})
"SEATTLE SOUNDERS FC"	(:Player {playerNumber: "2",playerHeight: "175",playerAge: "20",playerName: "DEANDRE YEDLIN",playerCaps: "4",playerBirthMonth: "07",playerBirthYear: "1993",playerInternationalGoals: "0",playerBirthDay: "09",playerID: "368973"})
"SPORTING KANSAS CITY"	(:Player {playerNumber: "19",playerHeight: "177",playerAge: "27",playerName: "GRAHAM ZUSI",playerCaps: "22",playerBirthMonth: "08",playerBirthYear: "1986",playerInternationalGoals: "3",playerBirthDay: "18",playerID: "360728"})
"SPORTING KANSAS CITY"	(:Player {playerNumber: "5",playerHeight: "182",playerAge: "27",playerName: "MATT BESLER",playerCaps: "16",playerBirthMonth: "02",playerBirthYear: "1987",playerInternationalGoals: "0",playerBirthDay: "11",playerID: "367433"})

k. Count how many players are born in 1990.

MATCH (p:Player{playerBirthYear:"1990"}) RETURN COUNT(p) AS count

neo4j\$ MATCH (p:Player{playerBirthYear:"1990"}) RETURN COUNT(p) AS count

Table

Text

Code

count
63

l. Which age has the highest participation in the 2014 FIFA World Cup?

MATCH (p:Player)
WITH p.playerAge AS age, COUNT(p) AS count
ORDER BY count DESC
LIMIT 1
RETURN age, count

neo4j\$ MATCH (p:Player) WITH p.playerAge AS age, COUNT(p) AS count ORDER BY count DESC LIMIT 1 RETURN age, count

Table

Text

Code

age	count
"27"	77

m. Find the path with a length of 2 or 3 between Tigres UANL and Newcastle United Jets FC.

MATCH p=(c1:Club {clubName:"TIGRES UANL"})-[:PLAYS_FOR|COMES_FROM|PLAYS_AS*2..3]-(c2:Club {clubName:"MANCHESTER UNITED FC"})
RETURN p

1 MATCH p=(c1:Club {clubName:"TIGRES UANL"})-[:PLAYS_FOR|COMES_FROM|PLAYS_AS*2..3

2]-(c2:Club {clubName:"MANCHESTER UNITED FC"})

3 RETURN p

Table

(no changes, no records)

Code

Completed after 4 ms.

It returns none. So we change the maximum length and try again. We can see that there at least 4 length of the two clubs.

1 MATCH p=(c1:Club {clubName:"TIGRES UANL"})-[:PLAYS_FOR|COMES_FROM|PLAYS_AS*2..4

2]-(c2:Club {clubName:"MANCHESTER UNITED FC"})

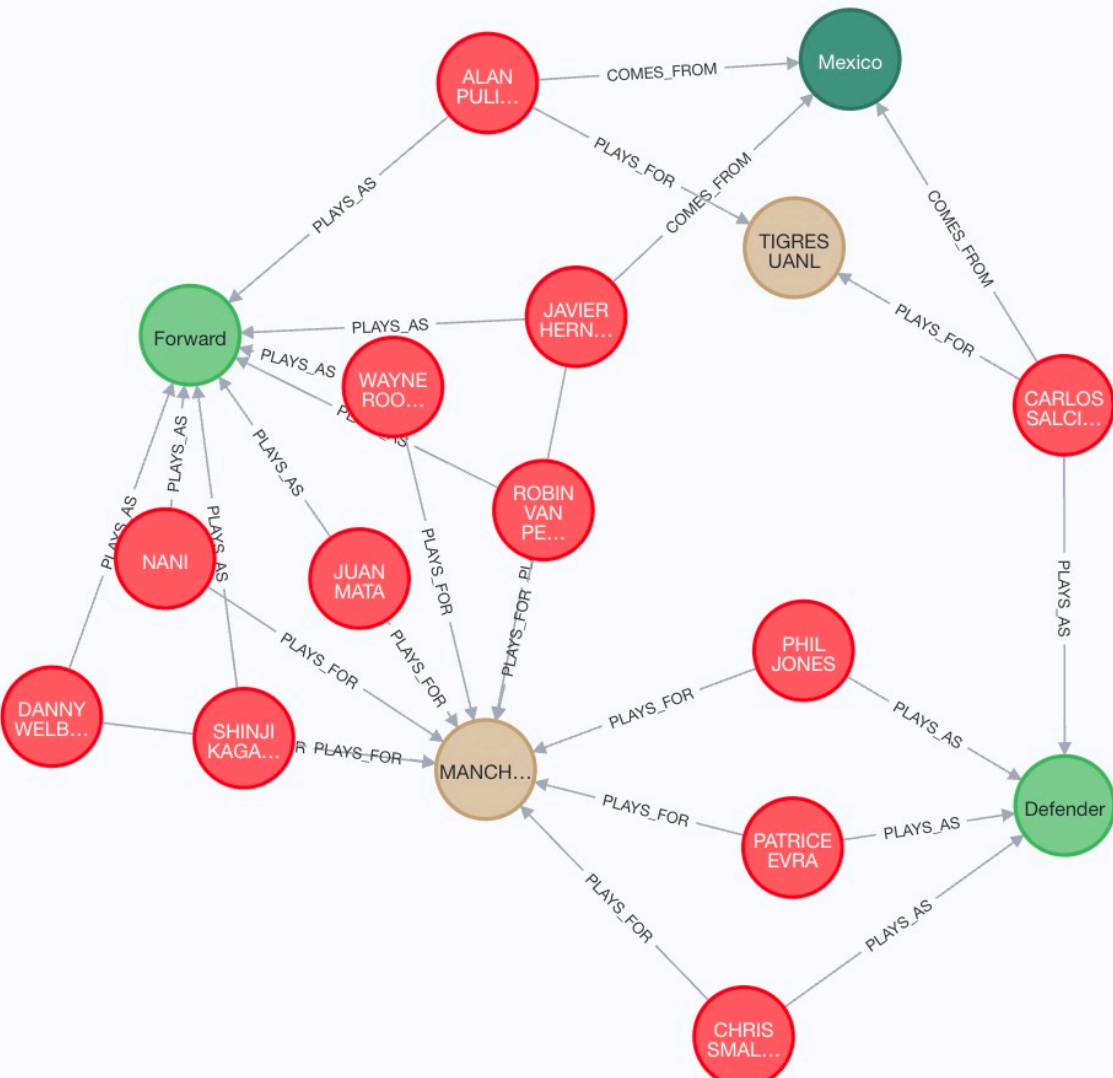
3 RETURN p

Graph

Table

Text

Code



Overview

Node labels

* (17)

Club (2)

Player (12)

Position (2)

Country (1)

Relationship types

* (27)

PLAYS_FOR (12)

PLAYS_AS (12)

COMES_FROM (3)

Displaying 17 nodes, 48 relationships.

n. Find the top 5 countries with players who have the highest average number of international goals. Return the countries and their average international goals in descending order.

```
MATCH (p:Player)-[:COMES_FROM]->(c:Country)
WITH c, avg(toInteger(p.playerInternationalGoals)) AS avgGoal
RETURN c.country AS country, round(avgGoal * 100)/100 AS averageGoal
ORDER BY averageGoal DESC
LIMIT 5
```

1 MATCH (p:Player)-[:COMES_FROM]->(c:Country)

2 WITH c, avg(toInteger(p.playerInternationalGoals)) AS avgGoal

3 RETURN c.country AS country, round(avgGoal * 100)/100 AS averageGoal

4 ORDER BY averageGoal DESC

5 LIMIT 5

Table

Text

Code

	country	averageGoal
1	"Germany"	9.52
2	"Spain"	9.43
3	"Netherlands"	7.0
4	"Uruguay"	6.22
5	"Ivory Coast"	6.13

o. Identify pairs of players from the same national team who play in different positions but have the closest number of caps. Return these pairs along with their positions and the difference in caps.

```
MATCH (pos1:Position)-[:PLAYS_AS]-(p1:Player)-[:COMES_FROM]->(country:Country)-[:COMES_FROM]-(p2:Player)-[:PLAYS_AS]->(pos2:Position)
WHERE pos1 <> pos2 AND p1 <> p2
WITH p1, p2, pos1, pos2, country, abs(toInteger(p1.playerCaps) - toInteger(p2.playerCaps)) AS capDifference
```



```
ORDER BY country, capDifference ASC
WITH country, collect({player1: p1, position1: pos1, player1Caps: p1.playerCaps, player2: p2, position2: pos2, player2Caps: p2.playerCaps, capDifference:
capDifference}) AS pairs
RETURN country.country AS country, pairs[0].player1.playerName AS player1, pairs[0].position1.positionName AS position1, pairs[0].player1Caps AS
player1Caps,
        pairs[0].player2.playerName AS player2, pairs[0].position2.positionName AS position2, pairs[0].player2Caps AS player2Caps, pairs[0].capDifference AS
capDifference
```

```
1 MATCH (pos1:Position)←[:PLAYS_AS]-(p1:Player)-[:COMES_FROM]→(country:Country)←
[:COMES_FROM]-(p2:Player)-[:PLAYS_AS]→(pos2:Position)
2 WHERE pos1 < pos2 AND p1 < p2
3 WITH p1, p2, pos1, pos2, country, abs(toInteger(p1.playerCaps) -
toInteger(p2.playerCaps)) AS capDifference
4 ORDER BY country, capDifference ASC
5 WITH country, collect({player1: p1, position1: pos1, player1Caps: p1.playerCaps, player2:
p2, position2: pos2, player2Caps: p2.playerCaps, capDifference: capDifference}) AS pairs
6 RETURN country.country AS country, pairs[0].player1.playerName AS player1,
pairs[0].position1.positionName AS position1, pairs[0].player1Caps AS player1Caps,
7 | | pairs[0].player2.playerName AS player2, pairs[0].position2.positionName AS
position2, pairs[0].player2Caps AS player2Caps, pairs[0].capDifference AS capDifference
```

Table

Text

Code

country	player1	position1	player1Caps	player2	position2	player2Caps	cap
"Mexico"	"ISAAC BRIZUELA"	"Midfielder"	"7"	"MIGUEL PONCE"	"Defender"	"7"	0
"Australia"	"BEN HALLORAN"	"Forward"	"1"	"MASSIMO LUONGO"	"Midfielder"	"1"	0
"Iran"	"AMIRHOSSEIN SADEGHI"	"Defender"	"14"	"REZA GHOOCHANNEJAD"	"Forward"	"13"	1
"Brazil"	"FERNANDINHO"	"Midfielder"	"6"	"VICTOR"	"Goalkeeper"	"6"	0
"Ivory Coast"	"SOULEYMANE BAMBA"	"Defender"	"42"	"ISMAEL TIOTE"	"Midfielder"	"42"	0
"Spain"	"JUANFRAN"	"Defender"	"7"	"KOKE"	"Midfielder"	"7"	0
"Uruguay"	"MAXIMILIANO PEREIRA"	"Defender"	"89"	"DIEGO PEREZ"	"Midfielder"	"89"	0
"Bosnia & Herzegovina"	"AVDIJA VRSAJEVIC"	"Midfielder"	"13"	"OGNJEN VRANJES"	"Defender"	"13"	0
"Netherlands"	"LEROY FER"	"Midfielder"	"5"	"TIM KRUL"	"Goalkeeper"	"5"	0
"Argentina"	"ANGEL DI MARIA"	"Midfielder"	"45"	"SERGIO ROMERO"	"Goalkeeper"	"45"	0

p. What number is the most in forward players?

```
MATCH (p:Player)-[:PLAYS_AS]→(po:Position{positionName:"Forward"})
WITH p.playerNumber AS jerseyNumber, COUNT(p) AS count
RETURN jerseyNumber, count
ORDER BY count DESC
LIMIT 1
```

neo4j\$ MATCH (p:Player)-[:PLAYS_AS]→(po:Position{positionName:"Forward"}) WITH p.playerNumber AS jerseyNumber, COUNT(p) AS count RETURN jerseyNumber, count ORDER BY coun...

Table

Text

Code

jerseyNumber	count
"9"	29

Started streaming 1 records after 8 ms and completed after 13 ms.

q. All players have Jersey number 11, in descending order by their age.

```
MATCH(p:Player{playerNumber:"11"}) RETURN p ORDER BY p.playerAge DESC
```

neo4j\$ MATCH(p:Player{playerNumber:"11"}) RETURN p ORDER BY p.playerAge DESC

Graph

Table

Text

Code

(:Player {playerNumber: "11",playerHeight: "180",playerAge: "36",playerName: "DIDIER DROGBA",playerCaps: "100",playerBirthMonth: "03",playerBirthYear: "1978",playerInternationalGoals: "61",playerBirthDay: "11",pl
(:Player {playerNumber: "11",playerHeight: "182",playerAge: "36",playerName: "MIROSLAV KLOSE",playerCaps: "131",playerBirthMonth: "06",playerBirthYear: "1978",playerInternationalGoals: "68",playerBirthDay: "09",f
(:Player {playerNumber: "11",playerHeight: "180",playerAge: "33",playerName: "MAXI RODRIGUEZ",playerCaps: "53",playerBirthMonth: "01",playerBirthYear: "1981",playerInternationalGoals: "15",playerBirthDay: "02",pl
(:Player {playerNumber: "11",playerHeight: "184",playerAge: "33",playerName: "LOUKAS VYNTRA",playerCaps: "49",playerBirthMonth: "02",playerBirthYear: "1981",playerInternationalGoals: "0",playerBirthDay: "05",play
(:Player {playerNumber: "11",playerHeight: "182",playerAge: "32",playerName: "DARIJO SRNA",playerCaps: "111",playerBirthMonth: "05",playerBirthYear: "1982",playerInternationalGoals: "21",playerBirthDay: "01",play
(:Player {playerNumber: "11",playerHeight: "175",playerAge: "31",playerName: "ALEKSANDR KERZHAKOV",playerCaps: "80",playerBirthMonth: "11",playerBirthYear: "1982",playerInternationalGoals: "25",playerBirthDay: "2
(:Player {playerNumber: "11",playerHeight: "170",playerAge: "31",playerName: "JEAN MAKOUN",playerCaps: "67",playerBirthMonth: "05",playerBirthYear: "1983",playerInternationalGoals: "5",playerBirthDay: "29",player
(:Player {playerNumber: "11",playerHeight: "180",playerAge: "30",playerName: "ARJEN ROBBEN",playerCaps: "74",playerBirthMonth: "01",playerBirthYear: "1984",playerInternationalGoals: "22",playerBirthDay: "23",play
(:Player {playerNumber: "11",playerHeight: "177",playerAge: "30",playerName: "MICHAEL BARRANTES",playerCaps: "50",playerBirthMonth: "10",playerBirthYear: "1983",playerInternationalGoals: "4",playerBirthDay: "04",
(:Player {playerNumber: "11",playerHeight: "178",playerAge: "30",playerName: "GHASEM HADADIFAR",playerCaps: "16",playerBirthMonth: "07",playerBirthYear: "1983",playerInternationalGoals: "0",playerBirthDay: "12",f
(:Player {playerNumber: "11",playerHeight: "177",playerAge: "29",playerName: "LEE KEUNHO",playerCaps: "63",playerBirthMonth: "04",playerBirthYear: "1985",playerInternationalGoals: "18",playerBirthDay: "11",player

MAX COLUMN WIDTH: 100%

The Capabilities of Graph Databases Compared to Relational Databases

The fundamental differences between graph databases and relational databases are how to store data and handle relationships between each entity. Relational databases, like MySQL, organize data into tables consisting of rows and columns and connect through relationships defined by foreign keys, which establish links between rows in different tables. While graph databases, such as Neo4j, store data in graph structures consisting of nodes, edges, and properties. Nodes represent entities, edges represent the relationships between entities, and properties are attributes of nodes and edges ("Transition from Relational to Graph Database - Getting Started," n.d.).

Following are key differences that achievable in graph databases but not feasible in relational databases:

a. Graph databases are easier to scale

Relational databases scaling may need to upgrade the hardware to increase the workload that the server can handle, which increasing the operation cost. While the graph database uses the data structure of nodes and edges which means that the data does not need to be structured in advance and can be modified and extended anytime as needed.

b. Graph database are more efficient to query

The main calculation model of relational database is based on select, join, filter, etc. When processing complex data, it is necessary to conduct multiple associated queries, which will lead to the decline of query efficiency. However, the calculation model of graph database starts from a series of initial points, and finds data by traversing nodes and edges, which can reduce the number of queries and improve the efficiency of queries. In particular, with the rapid development of social networking, Internet of things, finance, e-commerce and other fields, the resulting data shows exponential growth. In this context, the traditional relational database perform poor in dealing with complex data, but the graph database only has a millisecond query delay even when processing hundreds of millions of levels of data.

c. Graph database more more flexible present

Compared with relational databases, graph databases can represent not only simple relationships between entities, but also more complex relationships such as hierarchies, networks, and many-to-many relationships. This makes graph databases better suited for dealing with unstructured and complex data. In our daily lives, a lot of data is semi-structured data and unstructured data, for example, text data, image data, video data, and so on. Traditional relational databases are not good at dealing with them. But the graph database can store these semi-structured data and unstructured data through the graph model to achieve more flexible and efficient data management.

d. Graph databases are easier to understand

Graph databases are perfect for visual presentation because they are graphical structures. Therefore, a variety of visualization tools can be used to present and analyze data. Today, it is also widely used, such as knowledge graph, intelligent search, intelligent recommendation, intelligent question and answer. Graph databases can be use with AI tools to make people's lives more convenient ("Graph vs Relational Databases - Difference between Databases - AWS," n.d.).

Practical Application using Graph Data Science

a. Finance:

Banking can use graph database to create knowledge graph to capture relationships and insights in retail banking. Analyzing the flow of funds within financial systems. Also, it the graph can easily capture financial fraud in personal loan applications and detect money laundering activities ("Financial Services," n.d.).

b. Manufacturing :

By using a graph for a bill of materials analysis, user can create a model for analyzing the product information and dependencies to create a variety of models. This enables you to explore component trust, vendor reliability, supplier options, and more. ("7 Use Cases for Graph Databases and Graph Analytics," n.d.)

c. Social:

Social networking platforms like Facebook, Twitter, and LinkedIn use graph databases to store and query the relationships between users, their connections, and their interactions. This allows them to easily retrieve information such as a user's friends, followers, and likes, as well as to recommend new connections based on shared interests or connections (Yousry 2024). What's more, systems can recommending users based on shared interests.

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