Databases Final Project: Exploratory Analysis using Tennis Data Set

This notebook outlines our queries of the tennis players, matches, and rankings databases. We perform large scale analysis on statistics and display them!

We take a look at the following statistics:

- **General Data Analysis**
- **World Number 1 Ranking**
- **Performance by Age**
- **Performance by Country**
- **Performance by Handedness**
- **Player Analysis**

In [1]:

```
import pandas as pd
import os
```

In [2]:

```
%load_ext sql
```

In [3]:

```
project_folder = %pwd
database_path = os.path.join(project_folder, 'archive', 'database.sqlite')
%sql sqlite:///{database_path}
```

General Data Analysis

In our data tables, we have this many rows for each:

- **matches : 932504**
- **players : 64675**
- **rankings: 3190379**

In our data tables, we have this many columns for each:

- **matches : 81**
- **players : 8**
- **rankings: 4**

For more details on what is included in the data, please visit the Kaggle link: https://www.kaggle.com/datasets/guillemservera/tennis/data

Let's look at the number of players per ranking year and include info on the maximum points and average points per year.

In [4]:

```
%%sql result_set <<
SELECT
    SUBSTR(CAST(ranking_date AS STRING), 1, 4) AS ranking_year,
    COUNT(DISTINCT player) AS number_of_players,
    SUM(points) AS maxPoints,
    AVG(points) AS avgPoints
FROM
    rankings
GROUP BY
    ranking_year
HAVING
    maxPoints IS NOT NULL AND avgPoints IS NOT NULL
ORDER BY
    ranking_year
```

```
 * sqlite:////Users/thomasyu/Desktop/Project/archive/database.sqlite
Done.
Returning data to local variable result_set
```

We will display the data.

In [5]:

```
df = result_set.DataFrame()
display(df)
```

	ranking_year	number_of_players	maxPoints	avgPoints
0	1990	1602	4801538.0	85.677492
1	1991	1603	5595642.0	101.342787
2	1992	1697	6209566.0	107.059637
3	1993	1693	6877411.0	114.935759
4	1994	1729	7448389.0	118.955346
5	1995	1831	7598822.0	117.289302
6	1996	1901	8562352.0	125.422628
7	1997	1990	9370894.0	131.017477
8	1998	2062	9810755.0	127.164679
9	1999	2042	9779934.0	118.730306
10	2000	2033	8140186.0	100.298004
11	2001	2091	8877007.0	103.307502
12	2002	2135	8609010.0	101.934854
13	2003	2188	8474126.0	95.945812
14	2004	2296	8711505.0	95.771869
15	2005	2395	9057824.0	98.472805
16	2006	2528	9106359.0	89.155659
17	2007	2447	9400359.0	94.021454
18	2008	2435	9382620.0	95.754700
19	2009	2365	15430313.0	158.301834
20	2010	2270	12234914.0	132.078006
21	2011	[illegible]	[illegible]	[illegible]

	ranking_year	number_of_players	maxPoints	avgPoints
21	2011	2362	11046623.0	129.275869
22	2012	2489	11342055.0	124.357581
23	2013	2691	11194707.0	117.879969
24	2014	2766	11456451.0	113.330343
25	2015	2843	11538550.0	112.982365
26	2016	2762	11857813.0	119.760163
27	2017	2536	11769285.0	120.540005
28	2018	2523	11701155.0	126.852789
29	2019	2265	10624400.0	180.028806
30	2020	2034	7103103.0	133.624979
31	2021	2384	14240954.0	147.086904
32	2022	2776	11853431.0	123.966523
33	2023	2488	9743748.0	126.348557

Now let's analyze using heatmaps for each column individually.

In [6]:

```
# Separate the DataFrame into three DataFrames based on columns
df_number_of_players = df[['ranking_year', 'number_of_players']].copy()
df_maxPoints = df[['ranking_year', 'maxPoints']].copy()
df_avgPoints = df[['ranking_year', 'avgPoints']].copy()
```

Let's see number of players over the years.

In [7]:

```
# Apply background gradient styling on number of players.
styled_df_gradient = (
    df_number_of_players
    .style
    .background_gradient(cmap='viridis', axis=None)
)
# Display the styled DataFrame with background gradient
display(styled_df_gradient)
```

	ranking_year	number_of_players
0	1990	1602
1	1991	1603
2	1992	1697
3	1993	1693
4	1994	1729
5	1995	1831
6	1996	1901
7	1997	1990
8	1998	2062
9	1999	2042
10	2000	2033
11	2001	2091
12	2002	2135
13	2003	2188
14	2004	2296
15	2005	2395
16	2006	2528
17	2007	2447
18	2008	2435
19	2009	2365
20	2010	2270
21	2011	2362
22	2012	2489
23	2013	2691
24	2014	2766
25	2015	2843
26	2016	2762
27	2017	2536
28	2018	2523
29	2019	2265
30	2020	2034
31	2021	2384
32	2022	2776
33	2023	2488

As we can see, there are more professional tennis players as the years go on.

In [8]:

```
# Apply background gradient styling on maximum points in a year.
styled_df_gradient = (
    df_maxPoints
    .style
    .background_gradient(cmap='viridis', axis=None)
)
# Display the styled DataFrame with background gradient
display(styled_df_gradient)
```

	ranking_year	maxPoints
0	1990	4801538.000000

	ranking_year	maxPoints
1	1991	5595642.000000
2	1992	6209566.000000
3	1993	6877411.000000
4	1994	7448389.000000
5	1995	7598822.000000
6	1996	8562352.000000
7	1997	9370894.000000
8	1998	9810755.000000
9	1999	9779934.000000
10	2000	8140186.000000
11	2001	8877007.000000
12	2002	8609010.000000
13	2003	8474126.000000
14	2004	8711505.000000
15	2005	9057824.000000
16	2006	9106359.000000
17	2007	9400359.000000
18	2008	9382620.000000
19	2009	15430313.000000
20	2010	12234914.000000
21	2011	11046623.000000
22	2012	11342655.000000
23	2013	11194707.000000
24	2014	11456451.000000
25	2015	11538550.000000
26	2016	11857813.000000
27	2017	11769285.000000
28	2018	11701155.000000
29	2019	10624400.000000
30	2020	7103103.000000
31	2021	14240954.000000
32	2022	11853431.000000
33	2023	9743748.000000

In [9]:

```python
# Apply background gradient styling on average points per player.
styled_df_gradient = (
    df_avgPoints
    .style
    .background_gradient(cmap='viridis', axis=None)
)
# Display the styled DataFrame with background gradient
display(styled_df_gradient)
```

	ranking_year	avgPoints
0	1990	85.677492
1	1991	101.342787
2	1992	107.059637
3	1993	114.935759
4	1994	118.955346
5	1995	117.289302
6	1996	125.422628
7	1997	131.017477
8	1998	127.164679
9	1999	118.730306
10	2000	100.298004
11	2001	103.307502
12	2002	101.934854
13	2003	95.945812
14	2004	95.771869
15	2005	98.472805
16	2006	89.155659
17	2007	94.021454
18	2008	95.754700
19	2009	158.301834
20	2010	132.078006
21	2011	129.275869
22	2012	124.357581
23	2013	117.879969
24	2014	113.330343
25	2015	112.982365
26	2016	119.760163
27	2017	120.540005
28	2018	126.852789
29	2019	180.028806
30	2020	133.624979

	ranking_year	avgPoints
31	2021	147.086904
32	2022	123.966523
33	2023	126.348557

The number of players each year increases, which is entirely expected! We know that tennis is still a growing sport despite its long history. We can see the increasing popularity and competition as the maximum points and average points are generally increasing each year. This means that there are tournaments and more players are participating in the tournaments.

We will be using the year a lot. In the data, the dates are represented as a single number, so we will need to extract the year from that date number. Here, we create a temporary table for the ranking year. Additionally, the rankings table does not include player names, so we will add that as well.

In [10]:

```
%%sql
CREATE TEMP TABLE player_rankings AS
SELECT
    r.*,
    p.*,
    p.name_first || ' ' || p.name_last AS player_name,
    SUBSTR(CAST(r.ranking_date AS STRING), 1, 4) AS year
FROM
    rankings AS r
LEFT JOIN
    players AS p ON p.player_id = r.player
```

```
 * sqlite:////Users/thomasyu/Desktop/Project/archive/database.sqlite
Done.
```

Out[10]:

```
[]
```

World Number 1 Ranking

Since we have data about player rankings, it will be interesting to see which players have consistently been ranked number 1 over time. This can give us insight on who we might consider to be the GOAT (Greatest of All Time).

In [11]:

```
%%sql
SELECT
    player_name, COUNT(*) as ranked_first, count(DISTINCT year) as years_being_first
FROM
    player_rankings
WHERE
    rank = 1
GROUP BY
    player_name
ORDER BY
    ranked_first desc
LIMIT
    25
```

```
 * sqlite:////Users/thomasyu/Desktop/Project/archive/database.sqlite
Done.
```

Out[11]:

player_name	ranked_first	years_being_first
Novak Djokovic	355	12
Roger Federer	307	9
Pete Sampras	285	8
Ivan Lendl	228	8
Rafael Nadal	193	10
John McEnroe	136	6
Jimmy Connors	104	8
Andre Agassi	100	5
Bjorn Borg	94	4
Lleyton Hewitt	80	3
Stefan Edberg	71	3
Jim Courier	58	2
Gustavo Kuerten	43	2
Andy Murray	37	2
Carlos Alcaraz	31	2
Mats Wilander	16	2
Daniil Medvedev	13	1
Andy Roddick	13	2
Boris Becker	12	1
Ilie Nastase	10	2
Marat Safin	9	2
Juan Carlos Ferrero	8	1
Yevgeny Kafelnikov	6	1
Thomas Muster	6	1
Marcelo Rios	6	1

Just as suspected, we can see that the big three (Djokovic, Nadal, and Federer) are quite dominant even among the best in history. We can also see some other big names and how they compare.

Performance by Age

We can look at the players table a bit more. THe table also has dob (date of birth) for the player so we can use it to identify how old they are.

Age Analysis

In [12]:

```
%%sql result_set <<
SELECT
    year,
```

```
    AVG(year - CAST(SUBSTR(dob, 1, 4) AS INT)) AS average_age
FROM
    player_rankings
WHERE
    rank = 1
GROUP BY
    year
ORDER BY
    year asc
```

```
 * sqlite:////Users/thomasyu/Desktop/Project/archive/database.sqlite
Done.
Returning data to local variable result_set
```

In [13]:

```
df = result_set.DataFrame()
display(df)
```

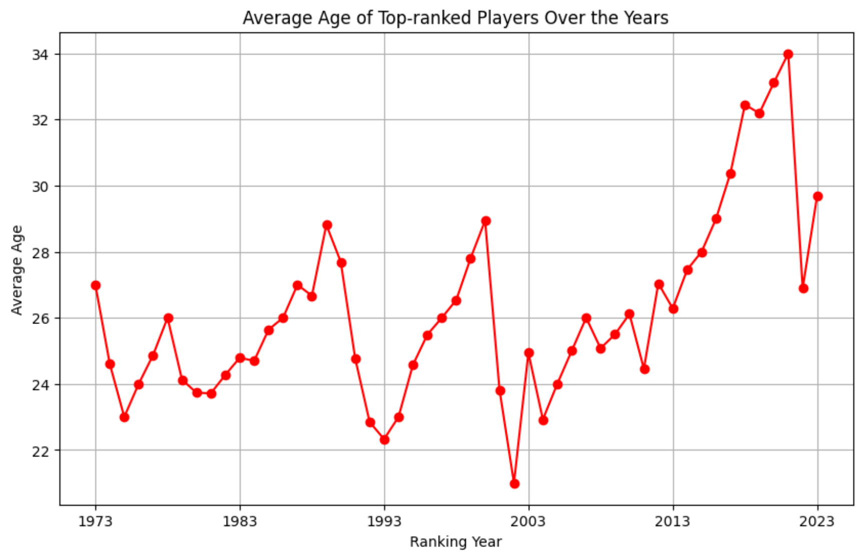
	year	average_age
0	1973	27.000000
1	1974	24.600000
2	1975	23.000000
3	1976	24.000000
4	1977	24.875000
5	1978	26.000000
6	1979	24.128205
7	1980	23.733333
8	1981	23.714286
9	1982	24.272727
10	1983	24.790698
11	1984	24.697674
12	1985	25.642857
13	1986	26.000000
14	1987	27.000000
15	1988	26.666667
16	1989	28.813953
17	1990	27.692308
18	1991	24.769231
19	1992	22.846154
20	1993	22.326923
21	1994	23.000000
22	1995	24.576923
23	1996	25.490566
24	1997	26.000000
25	1998	26.538462
26	1999	27.807692
27	2000	28.941176
28	2001	23.811321
29	2002	21.000000
30	2003	24.942308
31	2004	22.923077
32	2005	24.000000
33	2006	25.000000
34	2007	26.000000
35	2008	25.076923
36	2009	25.500000
37	2010	26.115385
38	2011	24.456522
39	2012	27.042553
40	2013	26.282609
41	2014	27.456522
42	2015	28.000000
43	2016	29.000000
44	2017	30.382979
45	2018	32.446809
46	2019	32.191489
47	2020	33.111111
48	2021	34.000000
49	2022	26.891304
50	2023	29.684211

Let's plot this on a graph to make it easier to interpret.

In [14]:

```
import matplotlib.pyplot as plt

# Plot the data
plt.figure(figsize=(10, 6))
plt.plot(df['year'], df['average_age'], marker='o', linestyle='-', color='r')
plt.title('Average Age of Top-ranked Players Over the Years')
plt.xlabel('Ranking Year')
plt.ylabel('Average Age')
plt.xticks(df['year'][::10])
plt.grid(True)
```

```
plt.show()
```



The age of the number 1 ranked player seems to iterate through eras. It creeps up for a number of years and then sinks down again as a new champion takes over the reigns. From the year 2000 to 2020 we can see that this is the era of the big 3 as they dominate and age.

We can also take a look at different ranking positions other than world number 1.

In [15]:

```
%%sql result_set <<
SELECT
    year,
    ROUND(MAX(CASE WHEN rank = 1 THEN average_age ELSE NULL END), 2) AS rank_1,
    ROUND(MAX(CASE WHEN rank < 5 THEN average_age ELSE NULL END), 2) AS top_5,
    ROUND(MAX(CASE WHEN rank < 10 THEN average_age ELSE NULL END), 2) AS top_10,
    ROUND(MAX(CASE WHEN rank < 20 THEN average_age ELSE NULL END), 2) AS top_20,
    ROUND(MAX(CASE WHEN rank < 50 THEN average_age ELSE NULL END), 2) AS top_50,
    ROUND(MAX(CASE WHEN rank < 100 THEN average_age ELSE NULL END), 2) AS top_100
FROM (
    SELECT
        year,
        rank,
        AVG(year - CAST(SUBSTR(dob, 1, 4) AS INT)) AS average_age
    FROM
        player_rankings
    GROUP BY
        year, rank
) subquery
GROUP BY
    year
ORDER BY
    year ASC
```

```
 * sqlite:////Users/thomasyu/Desktop/Project/archive/database.sqlite
Done.
Returning data to local variable result_set
```

In [16]:

```
df = result_set.DataFrame()
display(df)
```

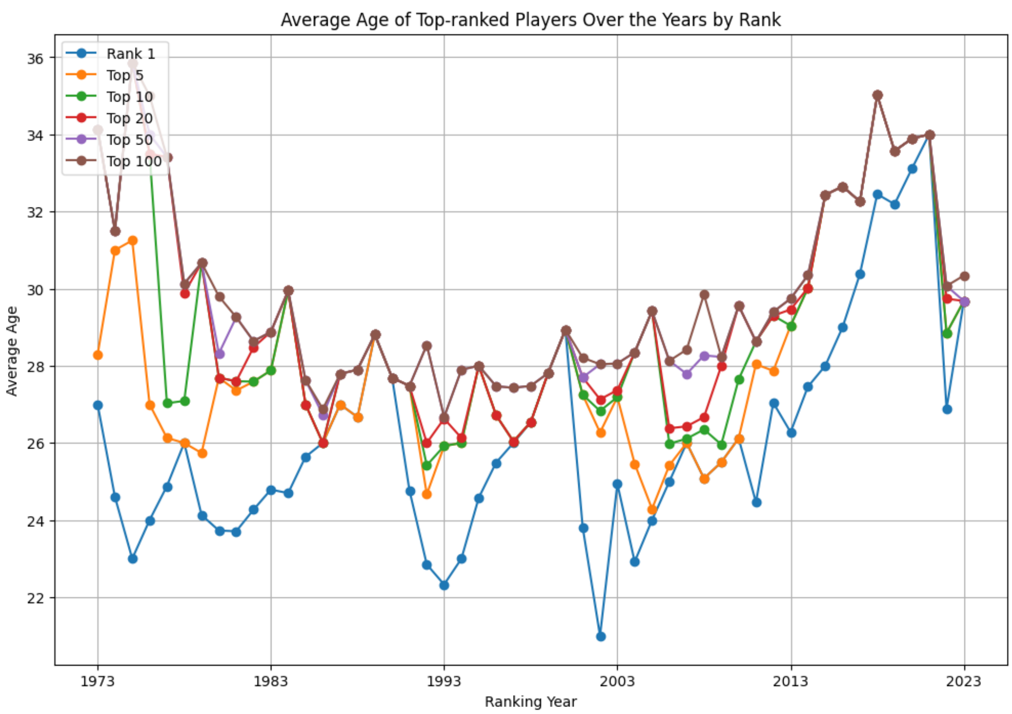
	year	rank_1	top_5	top_10	top_20	top_50	top_100
0	1973	27.00	28.29	34.14	34.14	34.14	34.14
1	1974	24.60	31.00	31.50	31.50	31.50	31.50
2	1975	23.00	31.25	35.86	35.86	35.86	35.86
3	1976	24.00	27.00	33.50	33.50	34.00	35.00
4	1977	24.88	26.13	27.03	33.41	33.41	33.41
5	1978	26.00	26.00	27.09	29.88	30.13	30.13
6	1979	24.13	25.74	30.67	30.67	30.67	30.67
7	1980	23.73	27.69	27.69	27.69	28.32	29.80
8	1981	23.71	27.36	27.60	27.60	29.26	29.26
9	1982	24.27	27.59	27.59	28.48	28.64	28.64
10	1983	24.79	27.88	27.88	28.88	28.88	28.88
11	1984	24.70	29.95	29.95	29.95	29.95	29.95
12	1985	25.64	27.00	27.00	27.00	27.63	27.63
13	1986	26.00	26.00	26.00	26.00	26.73	26.88
14	1987	27.00	27.00	27.79	27.79	27.79	27.79
15	1988	26.67	26.67	27.90	27.90	27.90	27.90
16	1989	28.81	28.81	28.81	28.81	28.81	28.81
17	1990	27.69	27.69	27.69	27.69	27.69	27.69
18	1991	24.77	27.48	27.48	27.48	27.48	27.48
19	1992	22.85	24.67	25.42	26.00	28.54	28.54
20	1993	22.33	25.92	25.92	26.63	26.67	26.67
21	1994	23.00	26.00	26.00	26.13	27.90	27.90
22	1995	24.58	28.00	28.00	28.00	28.00	28.00
23	1996	25.49	26.72	26.72	26.72	27.47	27.47
24	1997	26.00	26.04	26.04	26.04	27.43	27.43
25	1998	26.54	26.54	26.54	26.54	27.48	27.48

	year	rank_1	top_5	top_10	top_20	top_50	top_100
26	1999	27.81	27.81	27.81	27.81	27.81	27.81
27	2000	28.94	28.94	28.94	28.94	28.94	28.94
28	2001	23.81	27.25	27.25	27.70	27.70	28.21
29	2002	21.00	26.27	26.83	27.13	28.04	28.04
30	2003	24.94	27.19	27.19	27.37	28.06	28.06
31	2004	22.92	25.46	28.35	28.35	28.35	28.35
32	2005	24.00	24.29	29.42	29.42	29.42	29.42
33	2006	25.00	25.42	25.98	26.38	28.13	28.13
34	2007	26.00	26.00	26.11	26.43	27.79	28.42
35	2008	25.08	25.08	26.35	26.67	28.27	29.85
36	2009	25.50	25.50	25.96	28.00	28.23	28.23
37	2010	26.12	26.12	27.65	29.56	29.56	29.56
38	2011	24.46	28.04	28.63	28.63	28.63	28.63
39	2012	27.04	27.87	29.30	29.30	29.40	29.40
40	2013	26.28	29.04	29.04	29.46	29.74	29.74
41	2014	27.46	30.02	30.02	30.02	30.35	30.35
42	2015	28.00	32.43	32.43	32.43	32.43	32.43
43	2016	29.00	32.65	32.65	32.65	32.65	32.65
44	2017	30.38	32.26	32.26	32.26	32.26	32.26
45	2018	32.45	35.02	35.02	35.02	35.02	35.02
46	2019	32.19	33.57	33.57	33.57	33.57	33.57
47	2020	33.11	33.89	33.89	33.89	33.89	33.89
48	2021	34.00	34.00	34.00	34.00	34.00	34.00
49	2022	26.89	28.85	28.85	29.74	30.07	30.07
50	2023	29.68	29.68	29.68	29.68	29.68	30.34

Let's also graph this to make it more interpretable.

In [17]:

```python
# Plot the data
plt.figure(figsize=(12, 8))

plt.plot(df['year'], df['rank_1'], marker='o', linestyle='-', label='Rank 1')
plt.plot(df['year'], df['top_5'], marker='o', linestyle='-', label='Top 5')
plt.plot(df['year'], df['top_10'], marker='o', linestyle='-', label='Top 10')
plt.plot(df['year'], df['top_20'], marker='o', linestyle='-', label='Top 20')
plt.plot(df['year'], df['top_50'], marker='o', linestyle='-', label='Top 50')
plt.plot(df['year'], df['top_100'], marker='o', linestyle='-', label='Top 100')

plt.title('Average Age of Top-ranked Players Over the Years by Rank')
plt.xlabel('Ranking Year')
plt.ylabel('Average Age')
plt.xticks(df['year'][::10])
plt.legend(loc='upper left')
plt.grid(True)
plt.show()
```



There are some interesting patterns here. Seems that the average age moves together and varies a lot throughout the years. This indicates that the overall players on tour are varying in a age a lot through the years. Seems that professional players come in waves and generations. Very interesting.

In the graph, it appears that the number ranking seems to be a bit younger than the rest of the pack. I wonder if this is because youth has an advantage. Let's look at the youngest number 1 players.

In [18]:

```sql
%%sql
WITH RankedPlayers AS (
    SELECT
        year,
        player_name,
        year - CAST(SUBSTR(dob, 1, 4) AS INT) AS age,
```

```
        ROW_NUMBER() OVER(PARTITION BY year, player_name ORDER BY year ASC) AS row
    FROM
        player_rankings
    WHERE rank = 1
)

SELECT
    year,
    player_name,
    age
FROM
    RankedPlayers
WHERE
    row = 1
ORDER BY
    age ASC
LIMIT
    25
```

```
 * sqlite:////Users/thomasyu/Desktop/Project/archive/database.sqlite
Done.
```

Out[18]:

year	player_name	age
2022	Carlos Alcaraz	19
2000	Marat Safin	20
2001	Lleyton Hewitt	20
2023	Carlos Alcaraz	20
1977	Bjorn Borg	21
1980	John McEnroe	21
2001	Marat Safin	21
2002	Lleyton Hewitt	21
2003	Andy Roddick	21
1974	Jimmy Connors	22
1981	John McEnroe	22
1992	Jim Courier	22
1993	Pete Sampras	22
2003	Lleyton Hewitt	22
2004	Andy Roddick	22
2008	Rafael Nadal	22
1975	Jimmy Connors	23
1979	Bjorn Borg	23
1982	John McEnroe	23
1983	Ivan Lendl	23
1993	Jim Courier	23
1994	Pete Sampras	23
1998	Marcelo Rios	23
1999	Carlos Moya	23
2003	Juan Carlos Ferrero	23

We can see some of the greats, and how successful they were at such young ages. We can also see a more recent young guy doing well (Carlos Alcaraz). Great for the future of tennis!

Performance by Handedness

As a left-handed tennis player myself, I have heard many times that it is an advantage. I wonder if this is true in professional tennis as well. Let's find out!

In [19]:

```
%%sql
SELECT
    hand,
    COUNT(*) AS cases,
    AVG(rank) AS ranking_by_hand
FROM
    player_rankings
WHERE
    hand IN ('L', 'R')
GROUP BY
    hand
LIMIT
    10
```

```
 * sqlite:////Users/thomasyu/Desktop/Project/archive/database.sqlite
Done.
```

Out[19]:

hand	cases	ranking_by_hand
L	278010	674.2971439876263
R	2234345	731.5845811636073

There seems to be a clear correlation between handedness and ranking. Lefties are ranked higher (lower number is better) than righties on average.

Let's see what percentage of high rankings are lefties. Let's start with the top 10.

In [20]:

```
%%sql
SELECT
    rank,
    (sum(CASE WHEN hand = 'L' THEN 1 ELSE 0 END) / CAST(count(*) AS REAL)) * 100 AS lefties_percentage
FROM
    player_rankings
WHERE
    rank <= 10
GROUP BY
    rank
LIMIT
    10
```

```
 * sqlite:////Users/thomasyu/Desktop/Project/archive/database.sqlite
Done.
```

Out[20]:

rank	lefties_percentage
1	20.0
2	31.41831238779174
3	19.53195319531953
4	15.01123595505618
5	15.985630893578806
6	15.92442645074224
7	12.398921832884097
8	9.712230215827338
9	13.689407540394974
10	12.455035971223023

As we can see, it is a small percentage, but there are a lot of lefties ranked high in the top 10 all the time. Especially in the top 3 players. These guys are much more frequently left-handed. This is likely skewed due to super star players such as Rafael Nadal and John McEnroe, who were/are lefties.

Let's see what percentage of the top 100 players are lefties.

In [21]:

```
%%sql
SELECT
    (SUM(CASE WHEN hand = 'L' THEN 1 ELSE 0 END) / CAST(COUNT(*) AS REAL)) * 100 AS lefties_percentage
FROM
    player_rankings
WHERE
    rank <= 100
```

```
 * sqlite:////Users/thomasyu/Desktop/Project/archive/database.sqlite
Done.
```

Out[21]:

lefties_percentage
14.816479737474994

So just under 15% of top 100 players in the world are lefty usually. That doesn't seem like a lot. Let's compare this with how many players are lefty in the first place.

In [22]:

```
%%sql
SELECT
    hand,
    COUNT(*) AS total_cases,
    AVG(rank) AS ranking_by_hand,
    COUNT(*) * 100.0 / SUM(COUNT(*)) OVER () AS percentage_of_total
FROM
    player_rankings
WHERE
    hand IN ('L', 'R')
GROUP BY
    hand
LIMIT
    10
```

```
 * sqlite:////Users/thomasyu/Desktop/Project/archive/database.sqlite
Done.
```

Out[22]:

hand	total_cases	ranking_by_hand	percentage_of_total
L	278010	674.2971439876263	11.065713245142506
R	2234345	731.5845811636073	88.9342867548575

So only 11% of the players were lefty in the first place. Yet, all the top ranking positions have a higher percentage of lefties occupying. This makes it pretty evident that being left-handed is an advantage in tennis!

It is also worth noting that some players on tour don't have known handedness. That data was omitted from our analysis.

Performance by Country

Now we will look at players performance based on what country they are from. We will look at how many points countries have in total from their players. Total points will indicate both how strong players are from a country as well as how many players reside from said country. A country with many strong players will have more points.

In [23]:

```
%%sql
SELECT
    ioc, sum(points) as country_points
FROM
    player_rankings
GROUP BY
    ioc
ORDER BY
    country_points desc
LIMIT
    25
```

```
 * sqlite:////Users/thomasyu/Desktop/Project/archive/database.sqlite
Done.
```

Out[23]:

ioc	country_points
ESP	36384117.0
USA	32983420.0
FRA	26052278.0
GER	19536655.0
ARG	18709291.0
ITA	14498405.0
RUS	13312107.0
AUS	13006544.0
SUI	11621000.0
SRB	11267457.0

ioc	country_points
CZE	10570540.0
GBR	9477252.0
SWE	9420275.0
CRO	7190220.0
AUT	6691896.0
BRA	6433650.0
NED	6137481.0
BEL	5259736.0
JPN	4887741.0
CAN	4629628.0
SVK	4113360.0
CHI	3853831.0
RSA	3844179.0
ROU	2788844.0
UKR	2487952.0

As we can see, Spain holds the most overall points. This likely indicates they have a lot of professional tennis players, and their players are strong!

We can also see whether countries are able to top the rankings over the years. We expect countries that had a high number of total points to do well here (Spain, USA, Franace). This will show which countries are able to produce champions. Let's only take a look at the top 10 countries with the most points.

In [24]:

```
%%sql result_set <<
SELECT
    year,
    MAX(CASE WHEN ioc = 'ESP' THEN highest_ranked_player END) AS ESP,
    MAX(CASE WHEN ioc = 'USA' THEN highest_ranked_player END) AS USA,
    MAX(CASE WHEN ioc = 'FRA' THEN highest_ranked_player END) AS FRA,
    MAX(CASE WHEN ioc = 'GER' THEN highest_ranked_player END) AS GER,
    MAX(CASE WHEN ioc = 'ARG' THEN highest_ranked_player END) AS ARG,
    MAX(CASE WHEN ioc = 'ITA' THEN highest_ranked_player END) AS ITA,
    MAX(CASE WHEN ioc = 'RUS' THEN highest_ranked_player END) AS RUS,
    MAX(CASE WHEN ioc = 'AUS' THEN highest_ranked_player END) AS AUS,
    MAX(CASE WHEN ioc = 'SUI' THEN highest_ranked_player END) AS SUI,
    MAX(CASE WHEN ioc = 'SRB' THEN highest_ranked_player END) AS SRB
FROM (
    SELECT
        ioc,
        year,
        MIN(rank) AS highest_ranked_player
    FROM
        player_rankings
    WHERE ioc IN ('ESP', 'USA','FRA','GER','ARG','ITA','RUS','AUS','SUI','SRB')
    GROUP BY
        ioc, year
) subquery
GROUP BY
    year
ORDER BY
    year
```

```
 * sqlite:////Users/thomasyu/Desktop/Project/archive/database.sqlite
Done.
Returning data to local variable result_set
```

In [25]:

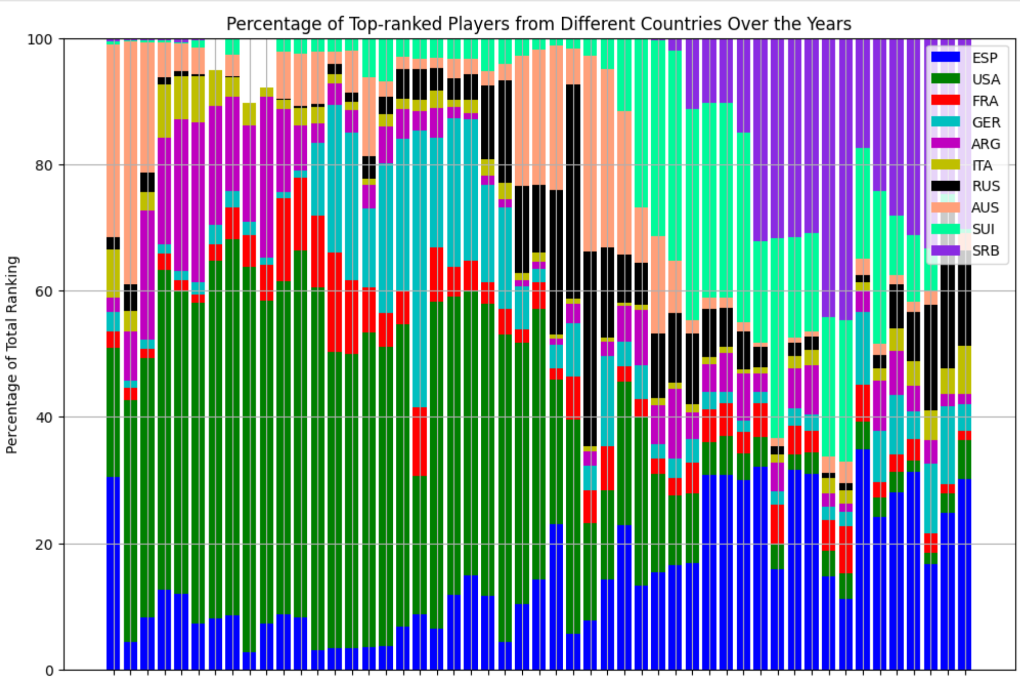
```
df = result_set.DataFrame()
display(df)
```

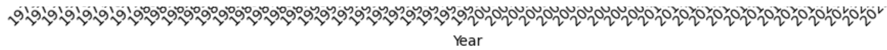
	year	ESP	USA	FRA	GER	ARG	ITA	RUS	AUS	SUI	SRB
0	1973	2	3	23	20	27	8	32.0	2	126	111.0
1	1974	9	1	20	33	5	12	9.0	1	148	121.0
2	1975	5	1	26	31	2	14	13.0	2	156	92.0
3	1976	4	1	19	36	3	6	47.0	9	190	134.0
4	1977	4	1	27	34	2	7	60.0	11	234	68.0
5	1978	7	1	38	28	2	7	144.0	12	48	122.0
6	1979	7	1	22	19	3	10	NaN	15	51	312.0
7	1980	7	1	12	23	4	19	249.0	18	24	309.0
8	1981	23	1	12	30	4	17	NaN	8	23	NaN
9	1982	7	1	9	41	2	39	NaN	8	36	450.0
10	1983	6	1	4	58	4	35	616.0	7	25	NaN
11	1984	7	1	5	55	8	22	180.0	7	23	NaN
12	1985	19	1	5	5	19	21	131.0	7	26	NaN
13	1986	14	1	3	2	14	31	30.0	24	22	NaN
14	1987	14	1	4	2	13	37	32.0	7	23	NaN
15	1988	14	1	7	4	13	53	14.0	4	8	NaN
16	1989	13	1	9	2	8	26	17.0	19	7	1103.0
17	1990	7	1	9	2	10	31	10.0	24	17	684.0
18	1991	5	2	4	1	14	24	9.0	26	14	413.0
19	1992	8	1	6	3	11	18	15.0	32	17	383.0
20	1993	4	1	10	2	27	42	14.0	15	15	317.0
21	1994	3	1	9	2	48	21	11.0	19	14	474.0
22	1995	4	1	14	3	30	18	4.0	20	9	473.0
23	1996	11	1	12	3	37	19	3.0	19	12	394.0
24	1997	4	1	20	6	43	39	3.0	2	16	218.0
25	1998	3	1	10	21	35	31	4.0	2	26	176.0
26	1999	1	1	13	6	23	41	1.0	1	23	176.0
27	2000	6	1	5	4	11	42	1.0	6	24	157.0
28	2001	4	2	6	8	14	40	1.0	1	12	200.0

	year	ESP	USA	FRA	GER	ARG	ITA	RUS	AUS	SUI	SRB
29	2002	2	2	4	2	12	42	2.0	1	6	183.0
30	2003	1	1	9	6	4	44	3.0	1	2	134.0
31	2004	2	1	9	5	3	35	4.0	3	1	106.0
32	2005	2	2	12	14	5	28	3.0	2	1	75.0
33	2006	2	3	12	11	3	31	3.0	4	1	16.0
34	2007	2	3	7	9	8	25	3.0	16	1	3.0
35	2008	1	6	6	11	7	27	4.0	18	1	3.0
36	2009	1	5	6	17	5	33	5.0	20	1	3.0
37	2010	1	7	9	17	4	45	5.0	19	1	2.0
38	2011	1	7	6	18	11	32	10.0	41	2	1.0
39	2012	2	8	5	16	7	22	25.0	27	1	1.0
40	2013	1	13	7	11	5	16	15.0	39	2	1.0
41	2014	1	9	9	12	4	13	14.0	38	2	1.0
42	2015	3	11	9	22	21	18	47.0	18	2	1.0
43	2016	4	11	6	20	33	21	39.0	13	2	1.0
44	2017	1	8	6	3	11	25	29.0	13	2	2.0
45	2018	1	8	10	3	3	13	11.0	14	1	1.0
46	2019	1	9	10	3	4	8	4.0	18	3	1.0
47	2020	1	18	9	7	8	8	4.0	18	3	1.0
48	2021	2	19	11	3	9	7	2.0	15	5	1.0
49	2022	1	8	16	2	13	6	1.0	20	16	1.0
50	2023	1	5	20	7	19	4	2.0	11	40	1.0

In [26]:

```python
import matplotlib.pyplot as plt
import pandas as pd

# Assuming result_set is your result set from the SQL query
# Convert the result_set to a Pandas DataFrame
df = result_set.DataFrame()

# Extract countries and their respective columns
countries = ['ESP', 'USA', 'FRA', 'GER', 'ARG', 'ITA', 'RUS', 'AUS', 'SUI', 'SRB']

colors = ['b', 'g', 'r', 'c', 'm', 'y', 'k', '#FFA07A', '#00FA9A', '#8A2BE2']

# Invert the ranking values
df[countries] = 1 / df[countries]

# Calculate the total ranking for each year
df['total_ranking'] = df[countries].sum(axis=1)

# Calculate the percentage of ranking for each country
for country in countries:
    df[country + '_percentage'] = (df[country] / df['total_ranking']) * 100.0

# Plot the data as a stacked bar chart
plt.figure(figsize=(12, 8))

bottom = None
for i, country in enumerate(countries):
    plt.bar(df['year'], df[country + '_percentage'], label=country, color=colors[i], bottom=bottom)
    if bottom is None:
        bottom = df[country + '_percentage']
    else:
        bottom += df[country + '_percentage']

plt.title('Percentage of Top-ranked Players from Different Countries Over the Years')
plt.xlabel('Year')
plt.ylabel('Percentage of Total Ranking')
plt.legend(loc='upper right')

# Rotate x-axis labels for better visibility
plt.xticks(rotation=45, ha='right')

plt.grid(True)
plt.show()
```





This is some interesting data to look at. As we can see, Spain has always had a player ranked high throughout the years. They must invest a lot into their professional athletes! We can see that the US dominated up until the 2000s and we can also see the contributions made by the big three to their respective countries (SRB, ESP, and SUI).

Let's take a look at how our home country (USA) has done over the years.

In [27]:

```
%%sql
WITH RankedPlayers AS (
    SELECT
        year,
        player_name,
        ROW_NUMBER() OVER(PARTITION BY year, player_name ORDER BY rank ASC) AS rn
    FROM
        player_rankings
    WHERE ioc = 'USA'
)

SELECT DISTINCT
    RP.player_name,
    R.rank,
    R.ioc,
    R.year
FROM
    RankedPlayers RP
JOIN
    player_rankings R ON RP.year = R.year AND RP.player_name = R.player_name
WHERE
    RP.rn = 1
ORDER BY
    R.rank, R.year
LIMIT
    25
```

```
 * sqlite:////Users/thomasyu/Desktop/Project/archive/database.sqlite
Done.
```

Out[27]:

player_name	rank	ioc	year
Jimmy Connors	1	USA	1974
Jimmy Connors	1	USA	1975
Jimmy Connors	1	USA	1976
Jimmy Connors	1	USA	1977
Jimmy Connors	1	USA	1978
Jimmy Connors	1	USA	1979
John McEnroe	1	USA	1980
John McEnroe	1	USA	1981
John McEnroe	1	USA	1982
Jimmy Connors	1	USA	1982
John McEnroe	1	USA	1983
Jimmy Connors	1	USA	1983
Ivan Lendl	1	USA	1983
John McEnroe	1	USA	1984
Ivan Lendl	1	USA	1984
John McEnroe	1	USA	1985
Ivan Lendl	1	USA	1985
Ivan Lendl	1	USA	1986
Ivan Lendl	1	USA	1987
Ivan Lendl	1	USA	1988
Ivan Lendl	1	USA	1989
Ivan Lendl	1	USA	1990
Jim Courier	1	USA	1992
Jim Courier	1	USA	1993
Pete Sampras	1	USA	1993

As you can see, a lot of Americans have reached the number 1 ranking. So let's take a look at rankings in recent years, specifically 2023.

In [28]:

```
%%sql
WITH RankedPlayers AS (
    SELECT
        year,
        player_name,
        ROW_NUMBER() OVER(PARTITION BY year, player_name ORDER BY rank ASC) AS rn
    FROM
        player_rankings
    WHERE ioc = 'USA'
)

SELECT DISTINCT
    RP.player_name,
    R.rank,
    R.ioc,
    R.year
FROM
    RankedPlayers RP
JOIN
    player_rankings R ON RP.year = R.year AND RP.player_name = R.player_name
WHERE
    RP.rn = 1
ORDER BY
    R.year DESC, R.rank
LIMIT
    25
```

```
 * sqlite:////Users/thomasyu/Desktop/Project/archive/database.sqlite
Done.
```

Out[28]:

player_name	rank	ioc	year
Taylor Fritz	5	USA	2023
Taylor Fritz	7	USA	2023
Taylor Fritz	8	USA	2023
Taylor Fritz	9	USA	2023
Taylor Fritz	10	USA	2023
Frances Tiafoe	10	USA	2023
Frances Tiafoe	11	USA	2023
Frances Tiafoe	12	USA	2023
Tommy Paul	12	USA	2023
Tommy Paul	13	USA	2023
Frances Tiafoe	13	USA	2023
Frances Tiafoe	14	USA	2023
Tommy Paul	14	USA	2023
Frances Tiafoe	15	USA	2023
Tommy Paul	15	USA	2023
Ben Shelton	15	USA	2023
Frances Tiafoe	16	USA	2023
Tommy Paul	16	USA	2023
Ben Shelton	16	USA	2023
Frances Tiafoe	17	USA	2023
Tommy Paul	17	USA	2023
Ben Shelton	17	USA	2023
Tommy Paul	18	USA	2023
Frances Tiafoe	19	USA	2023
Tommy Paul	19	USA	2023

Pretty cool! We see our top Americans in recent years. Taylor Fritz seems to be our top guy this year. We could do this for any country that we want!

We can do the same for any country that appears in the database. Enter a country! Note that we need country abbreviation.

In [29]:

```
# Define the SQL query template
sql_query = "SELECT COUNT(*) FROM player_rankings WHERE ioc = :country_input"

while True:
    # Take user input for the country
    country_input = input("Enter a country abbreviation in caps (or 'exit' to stop): ")

    # Check if the user wants to exit
    if country_input.lower() == 'exit':
        print("Exiting...")
        break

    # Execute SQL query to check if the country exists
    result = %sql $sql_query

    # Extract the count from the result
    count = result[0][0]

    # Check if the country exists
    if count > 0:
        print(f"The country '{country_input}' is in the database.")
        break
    else:
        print(f"The country '{country_input}' is not in the database. Please try again.")
```

```
 * sqlite:////Users/thomasyu/Desktop/Project/archive/database.sqlite
Done.
The country 'ESP' is in the database.
```

Run the next cell for information for this specific country!

In [30]:

```
%%sql
WITH RankedPlayers AS (
    SELECT
        year,
        player_name,
        ROW_NUMBER() OVER(PARTITION BY year, player_name ORDER BY rank ASC) AS rn
    FROM
        player_rankings
    WHERE ioc = '{country_input}'
)

SELECT
    RP.player_name,
    R.rank,
    R.points,
    R.ioc,
    R.year
FROM
    RankedPlayers RP
JOIN
    player_rankings R ON RP.year = R.year AND RP.player_name = R.player_name
WHERE
    RP.rn = 1
ORDER BY
    R.year DESC, R.rank
LIMIT
    25
```

```
 * sqlite:////Users/thomasyu/Desktop/Project/archive/database.sqlite
Done.
```

Out[30]:

player_name	rank	points	ioc	year
Carlos Alcaraz	1	6820.0	ESP	2023
Carlos Alcaraz	1	6820.0	ESP	2023
Carlos Alcaraz	1	6820.0	ESP	2023
Carlos Alcaraz	1	7420.0	ESP	2023

player_name	rank	points	ioc	year
Carlos Alcaraz	1	6815.0	ESP	2023
Carlos Alcaraz	1	7675.0	ESP	2023
Carlos Alcaraz	1	7675.0	ESP	2023
Carlos Alcaraz	1	9675.0	ESP	2023
Carlos Alcaraz	1	9375.0	ESP	2023
Carlos Alcaraz	1	9225.0	ESP	2023
Carlos Alcaraz	1	9225.0	ESP	2023
Carlos Alcaraz	1	9395.0	ESP	2023
Carlos Alcaraz	1	9815.0	ESP	2023
Carlos Alcaraz	1	9815.0	ESP	2023
Rafael Nadal	2	6020.0	ESP	2023
Rafael Nadal	2	5770.0	ESP	2023
Rafael Nadal	2	5770.0	ESP	2023
Carlos Alcaraz	2	6730.0	ESP	2023
Carlos Alcaraz	2	6730.0	ESP	2023
Carlos Alcaraz	2	6730.0	ESP	2023
Carlos Alcaraz	2	6480.0	ESP	2023
Carlos Alcaraz	2	6780.0	ESP	2023
Carlos Alcaraz	2	6780.0	ESP	2023
Carlos Alcaraz	2	6780.0	ESP	2023

Player Analysis

Let's see an example of the matches data.

In [31]:

```
%%sql
SELECT
    *
FROM
    matches
LIMIT
    1
```

```
 * sqlite:////Users/thomasyu/Desktop/Project/archive/database.sqlite
Done.
```

Out[31]:

tourney_id	tourney_name	surface	draw_size	tourney_level	tourney_date	match_num	winner_id	winner_seed	winner_entry	winner_name	winner_hand	winner_ht	winner_ioc	winner_age	loser_id	loser_seed	loser_entry	loser_name	loser_I
2003-1536	Madrid Masters	Hard	48	M	20031013.0	1	101965.0	None	None	Wayne Ferreira	R	185.0	RSA	32.0	103344.0	None	None	Ivan Ljubicic	

Alright, we can make an analysis of specific players. Enter a professional tennis player!

In [32]:

```
# Define the SQL query template
sql_query = "SELECT COUNT(*) FROM player_rankings WHERE player_name = :player_name_input"

while True:
    # Take user input for the player name
    player_name_input = input("Enter a player name (or 'exit' to stop): ")

    # Check if the user wants to exit
    if player_name_input.lower() == 'exit':
        print("Exiting...")
        break

    # Execute SQL query to check if the player name exists
    result = %sql $sql_query

    # Extract the count from the result
    count = result[0][0]

    # Check if the player name exists
    if count > 0:
        print(f"The player name '{player_name_input}' is in the database.")
        break
    else:
        print(f"The player name '{player_name_input}' is not in the database. Please try again.")
```

```
 * sqlite:////Users/thomasyu/Desktop/Project/archive/database.sqlite
Done.
The player name 'Novak Djokovic' is in the database.
```

Lets show the matches that this player most recently played.

In [33]:

```
%%sql
SELECT
    *
FROM
    matches
WHERE
    winner_name = :player_name_input OR loser_name = :player_name_input
ORDER BY
    tourney_date DESC
LIMIT
    10
```

```
 * sqlite:////Users/thomasyu/Desktop/Project/archive/database.sqlite
Done.
```

Out[33]:

tourney_id	tourney_name	surface	draw_size	tourney_level	tourney_date	match_num	winner_id	winner_seed	winner_entry	winner_name	winner_hand	winner_ht	winner_ioc	winner_age	loser_id	loser_seed	loser_entry	loser_name	loser_I
2023-0605	Tour Finals	Hard	8	A	20231113.0	300	104925.0	1.0	None	Novak Djokovic	R	188.0	SRB	36.4	206173.0	4.0	None	Jannik Sinner	
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	Novak	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	Carlos	

tourney_id	tourney_name	surface	draw_size	tourney_level	tourney_date	match_num	winner_id	winner_seed	winner_entry	winner_name	winner_hand	winner_ht	winner_ioc	winner_age	loser_id	loser_seed	loser_entry	loser_name
2023-0605	Tour Finals	Hard	8	A	20231113.0	298	104925.0	1.0	None	Djokovic	R	188.0	SRB	36.4	207989.0	2.0	None	Alcaraz
2023-0605	Tour Finals	Hard	8	A	20231113.0	297	206173.0	4.0	None	Jannik Sinner	R	188.0	ITA	22.2	104925.0	1.0	None	Novak Djokovic
2023-0605	Tour Finals	Hard	8	A	20231113.0	296	104925.0	1.0	None	Novak Djokovic	R	188.0	SRB	36.4	128034.0	9.0	None	Hubert Hurkacz
2023-0605	Tour Finals	Hard	8	A	20231113.0	295	104925.0	1.0	None	Novak Djokovic	R	188.0	SRB	36.4	208029.0	8.0	None	Holger Rune
2023-0352	Paris Masters	Hard	64	M	20231030.0	300	104925.0	1.0	None	Novak Djokovic	R	188.0	SRB	36.4	105777.0	None	None	Grigor Dimitrov
2023-0352	Paris Masters	Hard	64	M	20231030.0	299	104925.0	1.0	None	Novak Djokovic	R	188.0	SRB	36.4	126094.0	5.0	None	Andrey Rublev
2023-0352	Paris Masters	Hard	64	M	20231030.0	297	104925.0	1.0	None	Novak Djokovic	R	188.0	SRB	36.4	208029.0	6.0	None	Holger Rune
2023-0352	Paris Masters	Hard	64	M	20231030.0	293	104925.0	1.0	None	Novak Djokovic	R	188.0	SRB	36.4	134868.0	None	None	Tallon Griekspoor
2023-0352	Paris Masters	Hard	64	M	20231030.0	285	104925.0	1.0	None	Novak Djokovic	R	188.0	SRB	36.4	144869.0	None	None	Tomas Martin Etcheverry

We can see all the results from this year.

In [34]:

```
%%sql result_set <<
WITH MatchResults AS (
    SELECT
        CASE WHEN winner_name = :player_name_input THEN loser_name ELSE winner_name END AS opponent,
        CASE WHEN winner_name = :player_name_input THEN 'Win' ELSE 'Loss' END AS result,
        CASE WHEN winner_name = :player_name_input THEN loser_rank ELSE winner_rank END AS opponent_rank,
        tourney_date,
        score
    FROM
        matches
    WHERE
        (winner_name = :player_name_input OR loser_name = :player_name_input)
        AND SUBSTR(tourney_date, 1, 4) = '2023'
)
SELECT
    opponent,
    result,
    opponent_rank,
    tourney_date,
    score
FROM
    MatchResults
UNION ALL
SELECT
    'Total',
    '',
    '',
    '',
    COUNT(*) || ' Matches'
FROM
    MatchResults
```

```
 * sqlite:////Users/thomasyu/Desktop/Project/archive/database.sqlite
Done.
Returning data to local variable result_set
```

In [35]:

```
df = result_set.DataFrame()
pd.set_option('display.max_rows', 1000)
display(df)
```

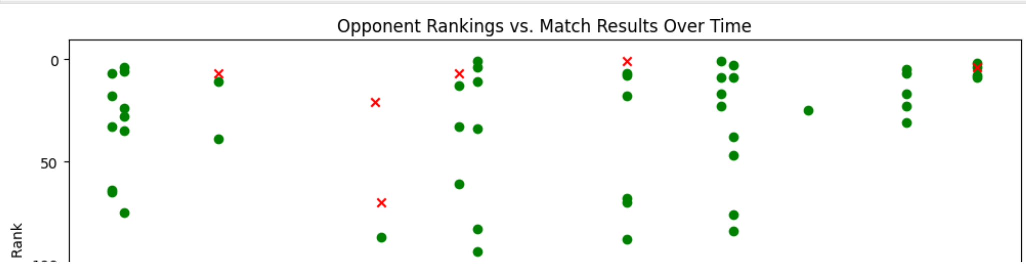
	opponent	result	opponent_rank	tourney_date	score
0	Sebastian Korda	Win	33.0	20230102.0	6-7(8) 7-6(3) 6-4
1	Daniil Medvedev	Win	7.0	20230102.0	6-3 6-4
2	Denis Shapovalov	Win	18.0	20230102.0	6-3 6-4
3	Quentin Halys	Win	64.0	20230102.0	7-6(3) 7-6(5)
4	Constant Lestienne	Win	65.0	20230102.0	6-3 6-2
5	Roberto Carballes Baena	Win	75.0	20230116.0	6-3 6-4 6-0
6	Enzo Couacaud	Win	191.0	20230116.0	6-1 6-7(5) 6-2 6-0
7	Grigor Dimitrov	Win	28.0	20230116.0	7-6(7) 6-3 6-4
8	Alex De Minaur	Win	24.0	20230116.0	6-2 6-1 6-2
9	Andrey Rublev	Win	6.0	20230116.0	6-1 6-2 6-4
10	Tommy Paul	Win	35.0	20230116.0	7-5 6-1 6-2
11	Stefanos Tsitsipas	Win	4.0	20230116.0	6-3 7-6(4) 7-6(5)
12	Daniil Medvedev	Loss	7.0	20230227.0	6-4 6-4
13	Hubert Hurkacz	Win	11.0	20230227.0	6-3 7-5
14	Tallon Griekspoor	Win	39.0	20230227.0	6-2 6-3
15	Tomas Machac	Win	130.0	20230227.0	6-3 3-6 7-6(1)
16	Lorenzo Musetti	Loss	21.0	20230410.0	4-6 7-5 6-4
17	Ivan Gakhov	Win	198.0	20230410.0	7-6(5) 6-2
18	Dusan Lajovic	Loss	70.0	20230417.0	6-4 7-6(6)
19	Luca Van Assche	Win	87.0	20230417.0	6-7(4) 6-3 6-2
20	Holger Rune	Loss	7.0	20230508.0	6-2 4-6 6-2
21	Cameron Norrie	Win	13.0	20230508.0	6-3 6-4
22	Grigor Dimitrov	Win	33.0	20230508.0	6-3 4-6 6-1
23	Tomas Martin Etcheverry	Win	61.0	20230508.0	7-6(5) 6-2
24	Aleksandar Kovacevic	Win	114.0	20230529.0	6-3 6-2 7-6(1)
25	Marton Fucsovics	Win	[illegible]	[illegible]	[illegible]

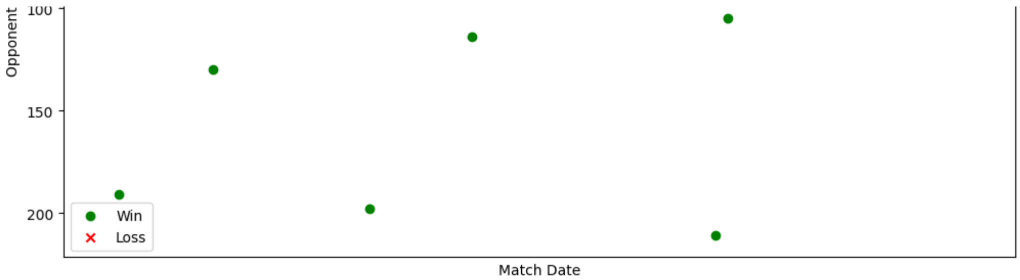
	opponent	result	opponent_rank	tourney_date	score
25	Marton Fucsovics	Win	83.0	20230529.0	7-6(2) 6-0 6-3
26	~~Alejandro Davidovich Fokina~~	~~Win~~	~~34.0~~	~~20230529.0~~	~~7-6(4) 7-6(5) 6-2~~
27	Juan Pablo Varillas	Win	94.0	20230529.0	6-3 6-2 6-2
28	Karen Khachanov	Win	11.0	20230529.0	4-6 7-6(0) 6-2 6-4
29	Carlos Alcaraz	Win	1.0	20230529.0	6-3 5-7 6-1 6-1
30	Casper Ruud	Win	4.0	20230529.0	7-6(1) 6-3 7-5
31	Pedro Cachin	Win	68.0	20230703.0	6-3 6-3 7-6(4)
32	Jordan Thompson	Win	70.0	20230703.0	6-3 7-6(4) 7-5
33	Stan Wawrinka	Win	88.0	20230703.0	6-3 6-1 7-6(5)
34	Hubert Hurkacz	Win	18.0	20230703.0	7-6(6) 7-6(6) 5-7 6-4
35	Andrey Rublev	Win	7.0	20230703.0	4-6 6-1 6-4 6-3
36	Jannik Sinner	Win	8.0	20230703.0	6-3 6-4 7-6(4)
37	Carlos Alcaraz	Loss	1.0	20230703.0	1-6 7-6(6) 6-1 3-6 6-4
38	Carlos Alcaraz	Win	1.0	20230814.0	5-7 7-6(7) 7-6(4)
39	Alexander Zverev	Win	17.0	20230814.0	7-6(5) 7-5
40	Taylor Fritz	Win	9.0	20230814.0	6-0 6-4
41	Gael Monfils	Win	211.0	20230814.0	6-3 6-2
42	Alejandro Davidovich Fokina	Win	23.0	20230814.0	6-4 0-0 RET
43	Alexandre Muller	Win	84.0	20230828.0	6-0 6-2 6-3
44	Bernabe Zapata Miralles	Win	76.0	20230828.0	6-4 6-1 6-1
45	Laslo Djere	Win	38.0	20230828.0	4-6 4-6 6-1 6-1 6-3
46	Borna Gojo	Win	105.0	20230828.0	6-2 7-5 6-4
47	Taylor Fritz	Win	9.0	20230828.0	6-1 6-4 6-4
48	Ben Shelton	Win	47.0	20230828.0	6-3 6-2 7-6(4)
49	Daniil Medvedev	Win	3.0	20230828.0	6-3 7-6(5) 6-3
50	Grigor Dimitrov	Win	17.0	20231030.0	6-4 6-3
51	Andrey Rublev	Win	5.0	20231030.0	5-7 7-6(3) 7-5
52	Holger Rune	Win	7.0	20231030.0	7-5 6-7(3) 6-4
53	Tallon Griekspoor	Win	23.0	20231030.0	4-6 7-6(2) 6-4
54	Tomas Martin Etcheverry	Win	31.0	20231030.0	6-3 6-2
55	Jannik Sinner	Win	4.0	20231113.0	6-3 6-3
56	Carlos Alcaraz	Win	2.0	20231113.0	6-3 6-2
57	Jannik Sinner	Loss	4.0	20231113.0	7-5 6-7(5) 7-6(2)
58	Hubert Hurkacz	Win	9.0	20231113.0	7-6(1) 4-6 6-1
59	Holger Rune	Win	8.0	20231113.0	7-6(4) 6-7(1) 6-3
60	Alejandro Davidovich Fokina	Win	25.0	20230915.0	6-3 6-4
61	Total				61 Matches

We will graphically represent the players wins and losses. You can notice interesting patterns in their performance against players of different ranks.

In [36]:

```
import matplotlib.pyplot as plt

# Assuming 'df' is your DataFrame
# Filter out the 'Total' row if it exists
df_plot = df[df['result'].isin(['Win', 'Loss'])]

# Create a scatter plot
plt.figure(figsize=(12, 6))

# Plot wins (green circles)
plt.scatter(
    pd.to_datetime(df_plot[df_plot['result'] == 'Win']['tourney_date']),
    df_plot[df_plot['result'] == 'Win']['opponent_rank'],
    color='green',
    marker='o',
    label='Win'
)

# Plot losses (red "x" markers)
plt.scatter(
    pd.to_datetime(df_plot[df_plot['result'] == 'Loss']['tourney_date']),
    df_plot[df_plot['result'] == 'Loss']['opponent_rank'],
    color='red',
    marker='x',
    label='Loss'
)

# Set plot labels and title
plt.xlabel('Match Date')
plt.ylabel('Opponent Rank')
plt.title('Opponent Rankings vs. Match Results Over Time')
plt.legend()

# Remove x-axis ticks (labels)
plt.xticks([])

# Flip the y-axis
plt.gca().invert_yaxis()

# Show the plot
plt.show()
```





Opponent
100
150
200
Win
Loss
Match Date