In [1]:
```python
# Imports

# Primary Imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import plotly.express as px
import seaborn as sns
import warnings
import datetime

# Dependency Imports
from mpl_toolkits import mplot3d
from mpl_toolkits.mplot3d import Axes3D
from collections import Counter

# Script Imports
%matplotlib inline
warnings.filterwarnings('ignore')
pd.options.display.max_columns = 100
pd.options.display.max_colwidth = 100
```

R4 Data Science Exercise

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Scope

Data Columns:

1. ID (user ID) 2. First_Play_Date (date user first used service) 3. Play_Date (date of play/stream) 4. Genre (genre of portal being played)

Questions

Question A:

What are some of the first things you notice about this data set? What is in it?

- Rows contain user IDs containing the first initial play date, as well as each subsequent client access of the service. We can see that there are 2798 unique user IDs using the service.
- 6 unique genres of:
  - Bullseye (1183 appearances, 435 unique IDs)
  - Discovery (105489 appearences, 2519 unique IDs)
  - Fingerprint (21802 appearences, 1959 unique IDs)
  - Mashboard (2339 appearences, 592 unique IDs)
  - Product (2711 appearences, 451 unique IDs)
  - Spider (1426 appearences, 609 unique IDs)
- User ID (WMT-eb43dc75-8c60-487c-9615-4e750042a0e3-26930-7f412b5358c1bbab7a1b8356f2794c7ee30fc26) has the highest number of games, having played Discovery 1077 times.

Question B:

Using this data, please answer the question- does genre usage shift week-to-week (relative to when a user first used the service)? For example, are users more likely to play Fingerprint during week one of their subscription, but then Mashboard during week 2 and 3?

- Users are most likely to start off with Discovery, then in week 2 move on to Fingerprint in leading up to and during week 2. After week 2, Discovery plays drop off sharply, while Fingerprint playthroughs taper off slightly. Other game genres mostly hold steady throughout the subsequent weeks.

Question C:

How would you improve the service by improving customer engagement?

- Provide incentives for playthoughs of each genre, specific to the game. For example: create leaderboards, viewable stat data of their closest peers, discord servers for game genres where a community can grow; including developer interaction, and in-game challenges that reap trophies or awards specific to gameplay tasks.
- Run A/B testing on the above implementations subsetting a control group of players who have access to the aforementioned gameplay incentives, and those who do not.
- Run timeseries models using Arima, Sarimax, etc. to view the predictive weekly engagement of the following weeks past the border data of 2/9/2015.

Data Import & Cleaning

In [2]:
```python
# Read in Dataframe
r4 = pd.read_csv('data/r4_data_exercise.csv')
```

In [3]:
```python
r4.head(10)
```

Out[3]:

	ID	First_Play_Date	Play_Date	Genre	Unnamed: 4	Unnamed: 5	Unnamed: 6	Unnamed: 7	Unnamed: 8
0	ASP-122a358d-be37-49bf-98ea-402ccfe33898-26768-6d9d2b9c3e3cdc8e7a57d5f851e7faf44163f8d	08Jan2015	08Jan2015	Discovery	NaN	NaN	NaN	NaN	NaN
1	ASP-122a358d-be37-49bf-98ea-402ccfe33898-26768-6d9d2b9c3e3cdc8e7a57d5f851e7faf44163f8d	08Jan2015	08Jan2015	Discovery	NaN	NaN	NaN	NaN	NaN
2	ASP-122a358d-be37-49bf-98ea-402ccfe33898-26768-6d9d2b9c3e3cdc8e7a57d5f851e7faf44163f8d	08Jan2015	08Jan2015	Discovery	NaN	NaN	NaN	NaN	NaN
3	ASP-122a358d-be37-49bf-98ea-402ccfe33898-26768-6d9d2b9c3e3cdc8e7a57d5f851e7faf44163f8d	08Jan2015	08Jan2015	Discovery	NaN	NaN	NaN	NaN	NaN
4	ASP-122a358d-be37-49bf-98ea-402ccfe33898-26768-6d9d2b9c3e3cdc8e7a57d5f851e7faf44163f8d	08Jan2015	08Jan2015	Discovery	NaN	NaN	NaN	NaN	NaN
5	ASP-122a358d-be37-49bf-98ea-402ccfe33898-26768-6d9d2b9c3e3cdc8e7a57d5f851e7faf44163f8d	08Jan2015	08Jan2015	Discovery	NaN	NaN	NaN	NaN	NaN
6	ASP-122a358d-be37-49bf-98ea-402ccfe33898-26768-6d9d2b9c3e3cdc8e7a57d5f851e7faf44163f8d	08Jan2015	08Jan2015	Discovery	NaN	NaN	NaN	NaN	NaN
7	ASP-122a358d-be37-49bf-98ea-402ccfe33898-26768-6d9d2b9c3e3cdc8e7a57d5f851e7faf44163f8d	08Jan2015	08Jan2015	Discovery	NaN	NaN	NaN	NaN	NaN
8	ASP-122a358d-be37-49bf-98ea-402ccfe33898-26768-6d9d2b9c3e3cdc8e7a57d5f851e7faf44163f8d	08Jan2015	08Jan2015	Discovery	NaN	NaN	NaN	NaN	NaN
9	ASP-122a358d-be37-49bf-98ea-402ccfe33898-26768-6d9d2b9c3e3cdc8e7a57d5f851e7faf44163f8d	08Jan2015	08Jan2015	Discovery	NaN	NaN	NaN	NaN	NaN

In [4]:
```python
# Checking data types of the dataframe
r4.dtypes
```

Out[4]:
```
ID                  object
First_Play_Date     object
Play_Date           object
Genre               object
Unnamed: 4         float64
Unnamed: 5         float64
Unnamed: 6         float64
Unnamed: 7         float64
Unnamed: 8         float64
dtype: object
```

In [3]:
```python
# Dropping unused columns and NaN values
r4.drop(['Unnamed: 4', 'Unnamed: 5', 'Unnamed: 6', 'Unnamed: 7', 'Unnamed: 8'], axis = 1, inplace = True)
r4.dropna(inplace = True)
```

In [4]:
```python
# Confirming the shape of our dataframe and that there are no more NaN values
r4.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 134950 entries, 0 to 134949
Data columns (total 4 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   ID               134950 non-null  object
 1   First_Play_Date  134950 non-null  object
 2   Play_Date        134950 non-null  object
 3   Genre            134950 non-null  object
dtypes: object(4)
memory usage: 5.1+ MB
```

In [5]:
```python
# Converting date to datetime objects for time manipulation and EDA
r4['First_Play_Date'] = pd.to_datetime(r4['First_Play_Date'])
r4['Play_Date'] = pd.to_datetime(r4['Play_Date'])
r4.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 134950 entries, 0 to 134949
Data columns (total 4 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   ID               134950 non-null  object
 1   First_Play_Date  134950 non-null  datetime64[ns]
 2   Play_Date        134950 non-null  datetime64[ns]
 3   Genre            134950 non-null  object
dtypes: datetime64[ns](2), object(2)
memory usage: 5.1+ MB
```

In [6]:
```python
# Confirming final dataframe shape and attributes
r4.head()
```

Out[6]:

	ID	First_Play_Date	Play_Date	Genre
0	ASP-122a358d-be37-49bf-98ea-402ccfe33898-26768-6d9d2b9c3e3cdc8e7a57d5f851e7faf44163f8d	2015-01-08	2015-01-08	Discovery
1	ASP-122a358d-be37-49bf-98ea-402ccfe33898-26768-6d9d2b9c3e3cdc8e7a57d5f851e7faf44163f8d	2015-01-08	2015-01-08	Discovery
2	ASP-122a358d-be37-49bf-98ea-402ccfe33898-26768-6d9d2b9c3e3cdc8e7a57d5f851e7faf44163f8d	2015-01-08	2015-01-08	Discovery
3	ASP-122a358d-be37-49bf-98ea-402ccfe33898-26768-6d9d2b9c3e3cdc8e7a57d5f851e7faf44163f8d	2015-01-08	2015-01-08	Discovery
4	ASP-122a358d-be37-49bf-98ea-402ccfe33898-26768-6d9d2b9c3e3cdc8e7a57d5f851e7faf44163f8d	2015-01-08	2015-01-08	Discovery

Feature Engineering

In [7]:
```python
# Creating new columns to track numerical data of games played by genre, by play date
r4['bullseye_plays'] = np.where((r4['Genre'] == 'Bullseye'), 1, 0)
r4['discovery_plays'] = np.where((r4['Genre'] == 'Discovery'), 1, 0)
r4['fingerprint_plays'] = np.where((r4['Genre'] == 'Fingerprint'), 1, 0)
r4['mashboard_plays'] = np.where((r4['Genre'] == 'Mashboard'), 1, 0)
r4['product_plays'] = np.where((r4['Genre'] == 'Product'), 1, 0)
r4['spider_plays'] = np.where((r4['Genre'] == 'Spider'), 1, 0)
```

In [8]:
```python
r4.head()
```

Out[8]:

	ID	First_Play_Date	Play_Date	Genre	bullseye_plays	discovery_plays	fingerprint_plays	mashboard_
0	ASP-122a358d-be37-49bf-98ea-402ccfe33898-26768-6d9d2b9c3e3cdc8e7a57d5f851e7faf44163f8d	2015-01-08	2015-01-08	Discovery	0	1	0	
1	ASP-122a358d-be37-49bf-98ea-402ccfe33898-26768-6d9d2b9c3e3cdc8e7a57d5f851e7faf44163f8d	2015-01-08	2015-01-08	Discovery	0	1	0	
2	ASP-122a358d-be37-49bf-98ea-402ccfe33898-26768-6d9d2b9c3e3cdc8e7a57d5f851e7faf44163f8d	2015-01-08	2015-01-08	Discovery	0	1	0	
3	ASP-122a358d-be37-49bf-98ea-402ccfe33898-26768-6d9d2b9c3e3cdc8e7a57d5f851e7faf44163f8d	2015-01-08	2015-01-08	Discovery	0	1	0	
4	ASP-122a358d-be37-49bf-98ea-402ccfe33898-26768-6d9d2b9c3e3cdc8e7a57d5f851e7faf44163f8d	2015-01-08	2015-01-08	Discovery	0	1	0	

EDA

In [9]:
```python
# Checking the unique number of IDs, thus the count of client-side access
unique_users = len(pd.unique(r4['ID']))
print(f'Number of unique users is: {unique_users}')

# Checking the unique number of Genres
unique_genres = len(pd.unique(r4['Genre']))
print(f'Number of unique genres is: {unique_genres}')
```

```
Number of unique users is: 2798
Number of unique genres is: 6
```

In [10]:
```python
# Checking the First Play Date values in the dataframe
np.sort(r4['First_Play_Date'].unique())
```

Out[10]:
```
array(['2015-01-07T00:00:00.000000000', '2015-01-08T00:00:00.000000000',
       '2015-01-09T00:00:00.000000000', '2015-01-10T00:00:00.000000000',
       '2015-01-11T00:00:00.000000000', '2015-01-12T00:00:00.000000000',
       '2015-01-13T00:00:00.000000000'], dtype='datetime64[ns]')
```

In [11]:
```python
# Checking the Subsequent Play Date values in the dataframe
np.sort(r4['Play_Date'].unique())
```

Out[11]:
```
array(['2015-01-07T00:00:00.000000000', '2015-01-08T00:00:00.000000000',
       '2015-01-09T00:00:00.000000000', '2015-01-10T00:00:00.000000000',
       '2015-01-11T00:00:00.000000000', '2015-01-12T00:00:00.000000000',
       '2015-01-13T00:00:00.000000000', '2015-01-14T00:00:00.000000000',
       '2015-01-15T00:00:00.000000000', '2015-01-16T00:00:00.000000000',
       '2015-01-17T00:00:00.000000000', '2015-01-18T00:00:00.000000000',
       '2015-01-19T00:00:00.000000000', '2015-01-20T00:00:00.000000000',
       '2015-01-21T00:00:00.000000000', '2015-01-22T00:00:00.000000000',
       '2015-01-23T00:00:00.000000000', '2015-01-24T00:00:00.000000000',
       '2015-01-25T00:00:00.000000000', '2015-01-26T00:00:00.000000000',
       '2015-01-27T00:00:00.000000000', '2015-01-28T00:00:00.000000000',
       '2015-01-29T00:00:00.000000000', '2015-01-30T00:00:00.000000000',
       '2015-01-31T00:00:00.000000000', '2015-02-01T00:00:00.000000000',
       '2015-02-02T00:00:00.000000000', '2015-02-03T00:00:00.000000000',
       '2015-02-04T00:00:00.000000000', '2015-02-05T00:00:00.000000000',
       '2015-02-06T00:00:00.000000000', '2015-02-07T00:00:00.000000000',
       '2015-02-08T00:00:00.000000000', '2015-02-09T00:00:00.000000000'],
      dtype='datetime64[ns]')
```

In [12]:
```python
# Exploring the spread of genres across users
r4.groupby('Genre')['ID'].describe()
```

Out[12]:

Genre	count	unique	top	freq
Bullseye	1183	435	SBD-405445b7-d087-463f-9d84-3ec48774cbc2-1110-a06646e4f44358aa17a4903ae565f833ef679e5	36
Discovery	105489	2519	WMT-eb43dc75-8c60-487c-9615-4e750042a0e3-26930-7f412b5358c1bbab7a1b8356f2794c7ee30fc26	1077
Fingerprint	21802	1959	ONG-47ee5eef-b687-4707-bf58-2c7bc094041f-29682-93665e4dc033e944a854d5755e29d4a4262f3d1	174
Mashboard	2339	592	P158-4a478455-dcaf-4c4f-b325-fecb7a161b20-25-a70dee78befeec153f04b80b6b9088f45577856	48
Product	2711	451	P158-9fc39447-ef30-4e95-8f3c-73aa5e991169-421-b556d2b8b3e195395eb5ab1a17c907165e85da4	78
Spider	1426	609	P158-81ee652f-623a-4a49-8abb-b907933b1916-3158-9a9b530229916d9e2a491eaa16f171d22ddd6c7	39

In [13]:
```python
# Viewing grouping of genre play counts by ID
r4.groupby('Genre')['ID'].count()
```

Out[13]:
```
Genre
Bullseye         1183
Discovery      105489
Fingerprint     21802
Mashboard        2339
Product          2711
Spider           1426
Name: ID, dtype: int64
```

In [14]:
```python
# View first initial play dates by daily breakdown
daily_first_play = r4.groupby('Genre')['First_Play_Date'].describe()
daily_first_play.head()
```

Out[14]:

Genre	count	unique	top	freq	first	last
Bullseye	1183	7	2015-01-13	208	2015-01-07	2015-01-13
Discovery	105489	7	2015-01-07	20247	2015-01-07	2015-01-13
Fingerprint	21802	7	2015-01-07	3639	2015-01-07	2015-01-13
Mashboard	2339	7	2015-01-07	451	2015-01-07	2015-01-13
Product	2711	7	2015-01-09	440	2015-01-07	2015-01-13

In [15]:
```python
# View daily breakdown of first and last play dates
daily_plays = r4.groupby('Genre')['Play_Date'].describe()
daily_plays.head()
```

Out[15]:

Genre	count	unique	top	freq	first	last
Bullseye	1183	34	2015-01-15	83	2015-01-07	2015-02-09
Discovery	105489	34	2015-01-14	6325	2015-01-07	2015-02-09
Fingerprint	21802	34	2015-01-13	1392	2015-01-07	2015-02-09
Mashboard	2339	34	2015-01-13	178	2015-01-07	2015-02-09
Product	2711	34	2015-01-10	212	2015-01-07	2015-02-09

In [16]:
```python
# View first play dates by genre breakdown
daily_genre = r4.groupby('First_Play_Date')['bullseye_plays','discovery_plays','fingerprint_plays','mashboard_p
    'product_plays','spider_plays'].sum().reset_index()

# daily_genre.to_csv('data/daily_genre.csv', index = False)
daily_genre.head()
```

Out[16]:

	First_Play_Date	bullseye_plays	discovery_plays	fingerprint_plays	mashboard_plays	product_plays	spider_plays
0	2015-01-07	176	20247	3639	451	353	268
1	2015-01-08	174	15027	3221	362	396	209
2	2015-01-09	110	12309	3042	260	440	160
3	2015-01-10	151	12282	2895	389	407	168
4	2015-01-11	172	11711	2333	267	402	132

In [17]:
```python
# View first play dates by genre breakdown
# Index is kept in order to reset for the timeseries object later
sub_daily_genre = r4.groupby('Play_Date')['bullseye_plays','discovery_plays','fingerprint_plays','mashboard_pla
    'product_plays','spider_plays'].sum()

# sub_daily_genre.to_csv('data/sub_daily_genre.csv', index = False)
sub_daily_genre.head()
```

Out[17]:

Play_Date	bullseye_plays	discovery_plays	fingerprint_plays	mashboard_plays	product_plays	spider_plays
2015-01-07	10	1069	198	17	27	14
2015-01-08	34	2524	547	104	110	32
2015-01-09	38	3148	769	147	119	39
2015-01-10	45	3769	1087	129	212	27
2015-01-11	43	4133	931	100	159	27

In [18]:
```python
# View total play frequency accounting for first and subsequent plays
play_freq = r4.groupby(['First_Play_Date', 'Play_Date'])['bullseye_plays','discovery_plays','fingerprint_plays'
    'product_plays','spider_plays'].sum()

play_freq.head(10)
```

Out[18]:

First_Play_Date	Play_Date	bullseye_plays	discovery_plays	fingerprint_plays	mashboard_plays	product_plays	spider_plays
2015-01-07	2015-01-07	10	1069	198	17	27	14
	2015-01-08	27	1798	366	78	60	22
	2015-01-09	14	1238	222	45	24	8
	2015-01-10	12	1084	200	24	3	5
	2015-01-11	6	900	143	19	18	4
	2015-01-12	23	752	139	9	14	0
	2015-01-13	8	767	190	7	19	0
	2015-01-14	3	802	157	20	10	7
	2015-01-15	4	721	124	11	13	9
	2015-01-16	4	659	114	10	9	10

In [19]:
```python
# View first play dates by genre breakdown
genre_weekly = sub_daily_genre.resample('W').sum().reset_index()

# genre_weekly.to_csv('data/genre_weekly.csv', index = False)
genre_weekly.head()
```

Out[19]:

	Play_Date	bullseye_plays	discovery_plays	fingerprint_plays	mashboard_plays	product_plays	spider_plays
0	2015-01-11	170	14643	3532	497	627	139
1	2015-01-18	388	35775	6681	742	866	313
2	2015-01-25	280	24200	4442	433	531	400
3	2015-02-01	189	19350	4058	336	352	408
4	2015-02-08	154	11173	3006	317	323	157

Visualizations

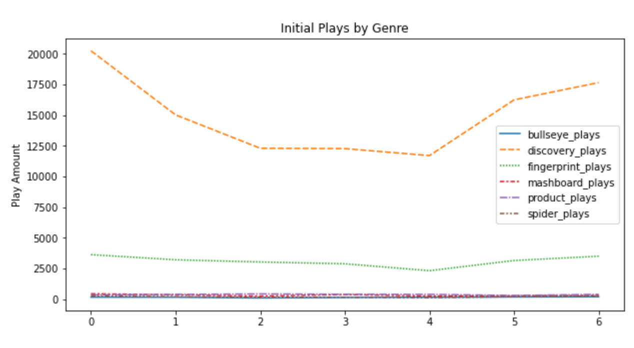
Initial Play Rates

In [20]:
```python
# Visualizing rate of initial plays for each genre

fig, ax = plt.subplots(figsize = (10, 5))

sns.lineplot(data = daily_genre)
ax.set_ylabel('Play Amount')
ax.set_title('Initial Plays by Genre')
# plt.savefig('img/initial_plays_genre.png');
;
```

Out[20]: ''



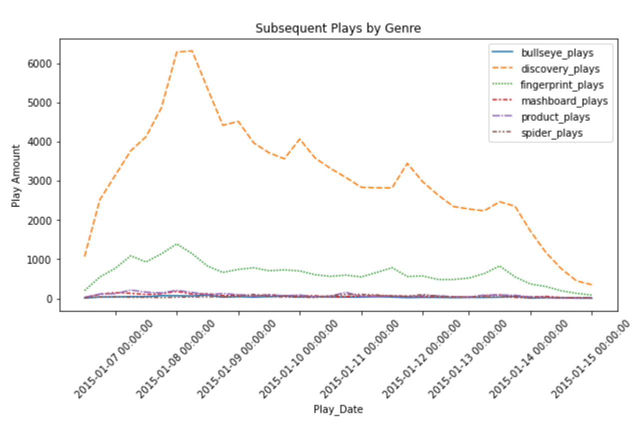
Subsequent Play Rates

Daily Subsequent Play Rates

In [21]:
```python
# Visualizing rate of secondary plays for each genre
# Reset the index here under a new variable to avoid issues later with the timeseries object
sub_index = sub_daily_genre.reset_index()
labels = sub_index['Play_Date']
fig, ax = plt.subplots(figsize = (10, 5))

sns.lineplot(data = sub_daily_genre)
ax.set_ylabel('Play Amount')
ax.set_xticklabels(labels, rotation = 45)
ax.set_title('Subsequent Plays by Genre')
# plt.savefig('img/sub_plays_genre.png');
;
```

Out[21]: ''



Takeaways:

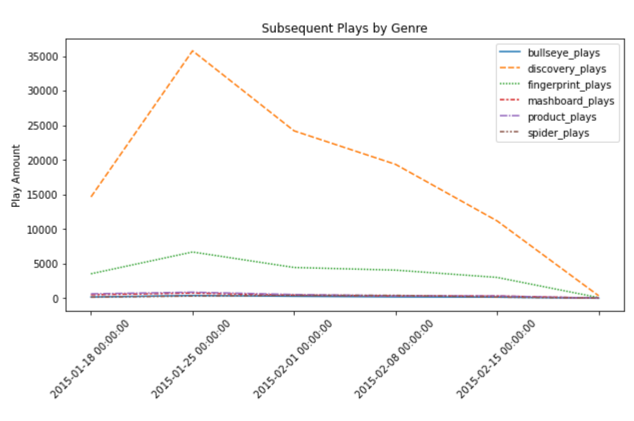
Discovery plays increase steadily for the first 2 1/2 weeks, then tapers off steadily while experiencing some seasonality. Players are likely to move on and dabble in Fingerprint, but the rate of change is more static compared to Discovery.

Weekly Subsequent Play Rates

In [22]:
```python
# Visualizing weekly change rate of initial and secondary plays for each genre
labels = genre_weekly['Play_Date']
fig, ax = plt.subplots(figsize = (10, 5))

sns.lineplot(data = genre_weekly)
ax.set_ylabel('Play Amount')
ax.set_xticklabels(labels, rotation = 45)
ax.set_title('Subsequent Plays by Genre')
# plt.savefig('img/weekly_plays_genre.png');
;
```

Out[22]: ''



Takeaways:

Weekly view of the play data smoothes out the seasonality of the data, but at the same time enhances the view of dominance that Discovery has over the other game genres. Examination of the intricacies of the other genres could provide some insight into why user engagement with them is so low.

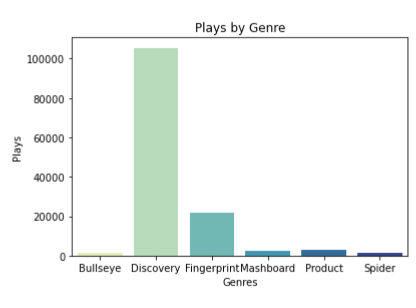
Users by Genre

In [23]:
```python
# Visualization of Users by Genre
genre_vals = r4.groupby('Genre')['ID'].count().values
genre_vis = ['Bullseye', 'Discovery', 'Fingerprint', 'Mashboard', 'Product', 'Spider']

fig, ax = plt.subplots()
sns.barplot(x = genre_vis, y = genre_vals, palette = 'YlGnBu')

ax.set_xlabel('Genres')
ax.set_ylabel('Plays')
ax.set_title('Plays by Genre')
# plt.savefig('img/plays_by_genre.png');
;
```

Out[23]: ''



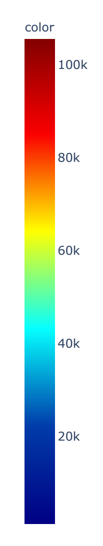
Takeaways:

Discovery has by far the most initial playthroughs. This is exacerbated by its continual play rate in the subsequent weeks, solidifying its popularity over the other game modes. Fingerprint comes in a distant second but is still in its own tier as compared to the other 4 game modes.

3D Plot of Genre Play Dates

In [24]:
```python
# Visualizing Genres by First and subsequent play dates
date_genre_group = r4.groupby('Genre')['Play_Date'].count()
id_first_play_date = r4.groupby('Genre')['First_Play_Date'].count()

fig = px.scatter_3d(r4, x = genre_vis, y = genre_vals, z = id_first_play_date, color = date_genre_group, size_m
                    color_continuous_scale='jet')
fig.update_layout(margin=dict(l=0, r=0, b=0, t=0))
```



Next Steps

1. Explore other game genres and differences to pinpoint why one genre has such dominance over the other five.
2. Implement the analysis and modeling outlined in Question C.
3. Work with longer/larger data to view more user engagement across months or years