CAP 6315 - Social Networks and Big Data Analytics

Project Part #1

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Colab Project Link

GitHub Project Link

This project with be using the *Twitch Social Network* datasets, and be examining the Brazilian Portuguese language stream for our network.

In [67]:

```
# Setup and Imports
import random
import os
import zipfile

import matplotlib.pyplot as plt
import networkx as nx
import numpy as np
from pyspark.sql import (
    SparkSession,
    Window,
)
import pyspark.sql.functions as F
import pyspark.sql.types as T
import seaborn as sns


SEED = 1234
LANG = "PTBR"
PATH = os.getcwd()
DATA_PATH = os.path.join(
    PATH,
    "twitch",
    LANG,
)


random.seed(SEED)
np.random.seed(SEED)
```

Importing the data and creating PySpark session

Unzipping archive file

In [2]:

```
arhive_file = "twitch.zip"
with zipfile.ZipFile(os.path.join(PATH, arhive_file), "r") as archive_obj:
  archive_obj.extractall(PATH)
```

Creating the Spark Session and Loading the Dataset

In [3]:
```
spark = SparkSession.builder \
    .appName("ProjectPart-1") \
    .getOrCreate()
```

In [4]:
```
df = spark.read.csv(
    path=os.path.join(DATA_PATH, f"musae_{LANG}_edges.csv"),
    header=True,
    inferSchema=True
)
df.head(5)
```

Out[4]:
```
[Row(from=0, to=92),
 Row(from=0, to=428),
 Row(from=1, to=689),
 Row(from=1, to=1147),
 Row(from=1, to=1666)]
```

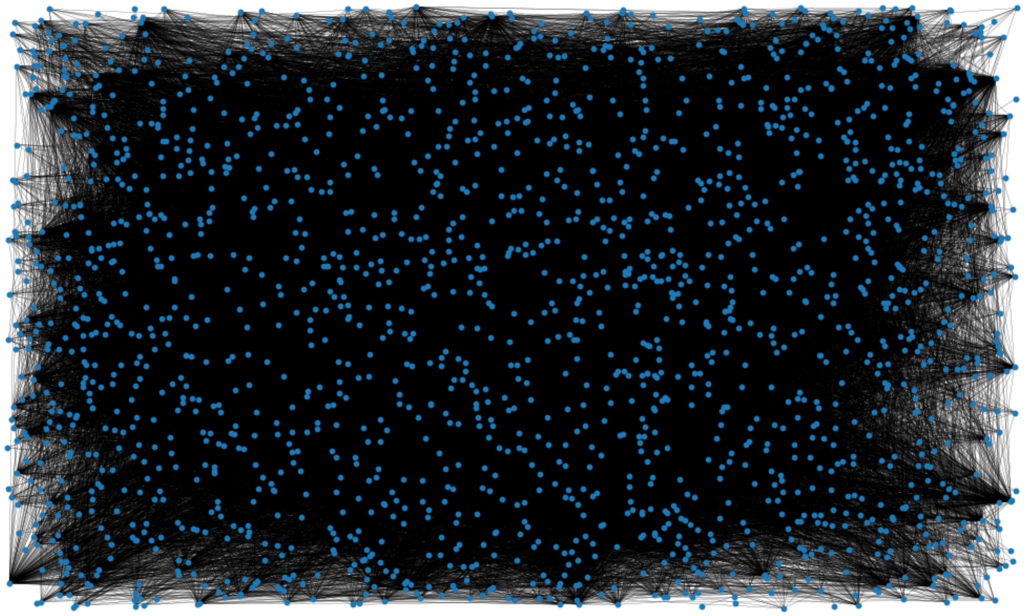
Creating Graph with NetworkX

In [5]:
```
G = nx.Graph()

edges = df.collect()
G.add_edges_from([
    (row["from"], row["to"])
    for row in edges
])
```

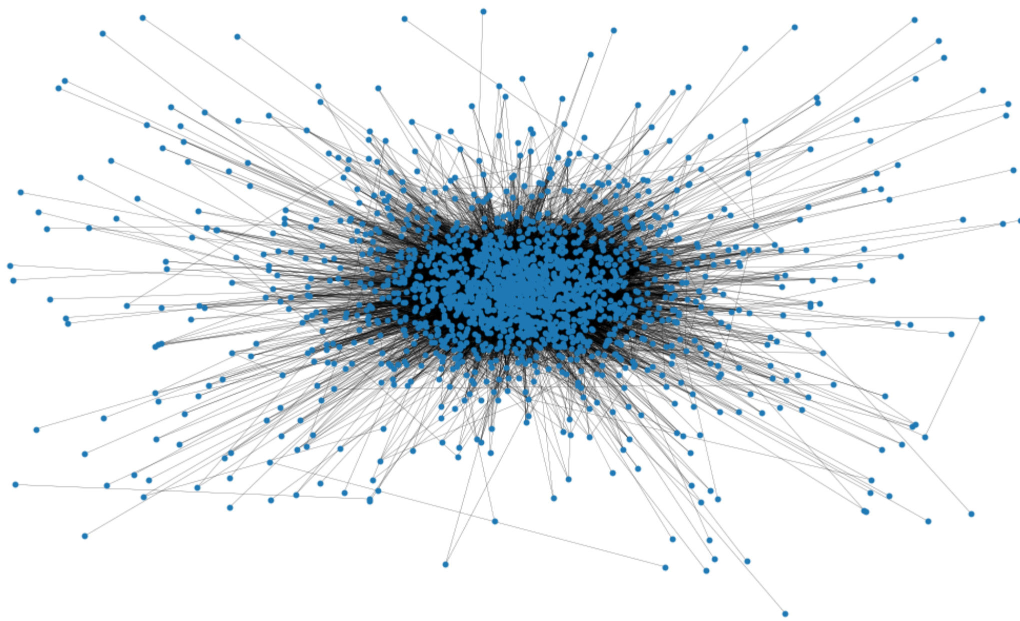
Graph Visualization

In [6]:
```
plot_options = {
    "node_size": 10,
    "with_labels": False,
    "width": 0.15,
}
```

In [7]:
```
fig, ax = plt.subplots(figsize=(15, 9))
ax.axis("off")
nx.draw_networkx(
    G,
    pos=nx.random_layout(G),
    ax=ax,
    **plot_options)
```



In [8]:
```
pos = nx.spring_layout(
    G,
    iterations=15,
    seed=SEED,
)
fig, ax = plt.subplots(figsize=(15, 9))
ax.axis("off")
nx.draw_networkx(
    G,
    pos=pos,
    ax=ax,
    **plot_options)
```



Calculate the Number of Nodes in the Graph

In [9]:
```
nn = G.number_of_nodes()
print(f"The Number of Nodes: {nn}")
```

```
The Number of Nodes: 1912
```

Calculate the Number of Edges in the Graph

In [10]:
```
ne = G.number_of_edges()
print(f"The Number of Edges: {ne}")
```

```
The Number of Edges: 31299
```

Calculate the Network Diameter

> Both methods are displayed

In [11]:
```
min_path_len = dict(nx.all_pairs_shortest_path_length(G))
diameter = max(nx.eccentricity(G, sp=min_path_len).values())

print(f"Diameter with Eccentrictiy Method: {diameter}")
print(f"Diameter with NetworkX: {nx.diameter(G)}")
```

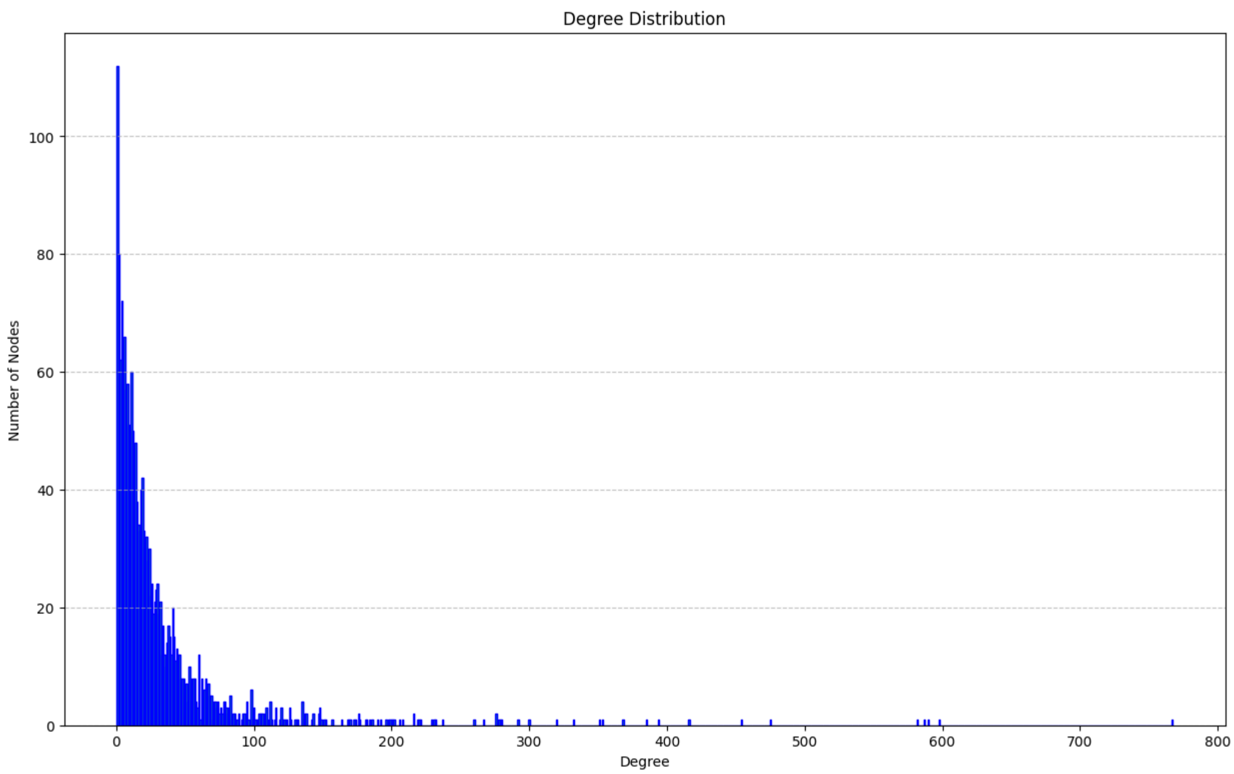
```
Diameter with Eccentrictiy Method: 7
Diameter with NetworkX: 7
```

Network Diameter Interpretation

> The diameter of the network is **7**, which means that at most any user is **7** connections or friendships away from any other user in the network.

Histogram of Degree Distribution

In [12]:
```
deg = [d for _, d in G.degree()]

plt.figure(figsize=(15, 9))
plt.hist(
    x=deg,
    bins=range(min(deg), max(deg) + 2),
    edgecolor="blue",
    align="left",
)
plt.title("Degree Distribution")
plt.xlabel("Degree")
plt.ylabel("Number of Nodes")
plt.grid(
    axis="y",
    linestyle="dashed",
    alpha=0.7,
)
plt.show()
```



Histogram Observations

> The distribution is very skewed which would follow a power-law distribution. So, a lot of users have a small amount of friends and towards the right side of the graph a few users have a large amount of friends.

Average Degree of a Node

In [13]:
```
avg_deg = np.mean([d for _, d in G.degree()])
print(f"Average Degree of a Node: {avg_deg}")
```

```
Average Degree of a Node: 32.73953974895397
```

Average Degree in Dataset Context

> On average, a user has almost **33** friends in the network.

Calculate the Average Shortest Path Length Between Any Two Nodes

In [14]:
```
avg_path_len = [
    np.mean(list(mpl.values()))
    for mpl in min_path_len.values()
]
print(f"Average Shortest Path Length: {np.mean(avg_path_len)}")
```

```
Average Shortest Path Length: 2.5310546909192766
```

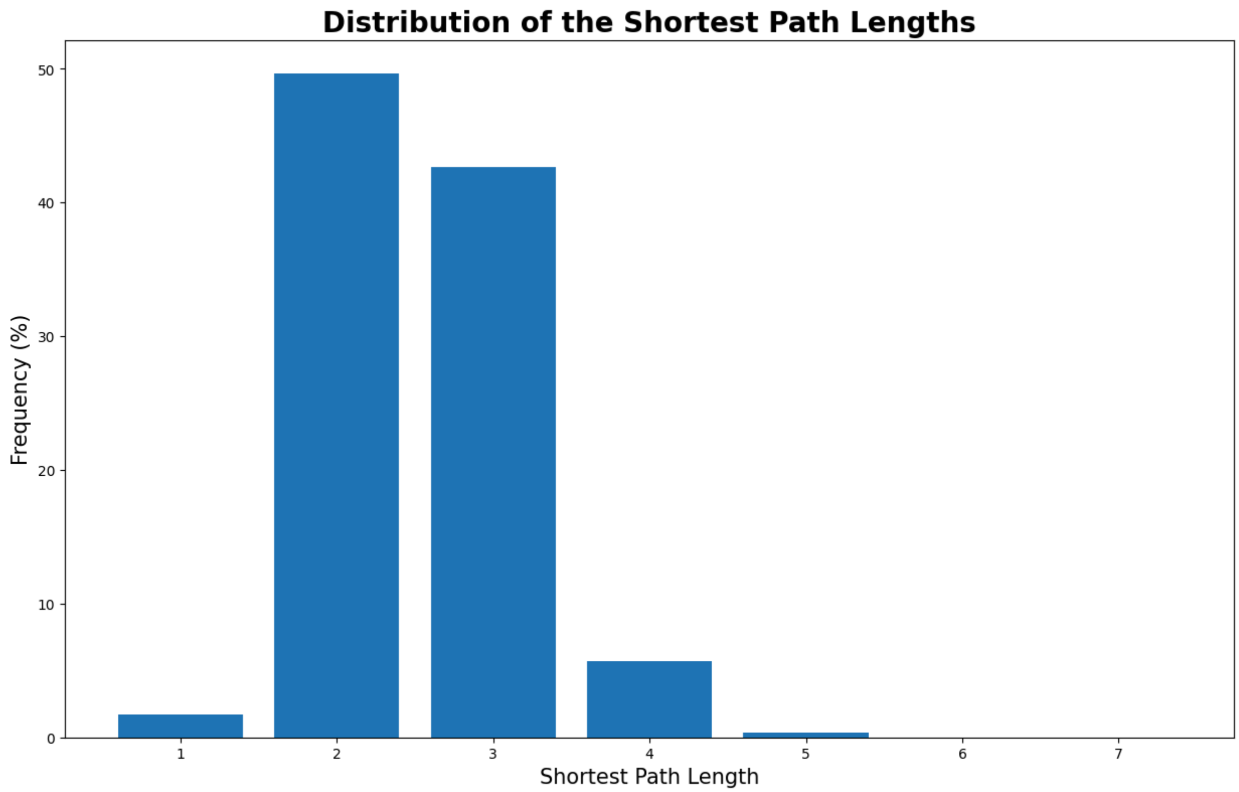
Average Shortest Path Dataset Context

> On average, a user is **3** friendships away from another user in the network.

Plot the Distribution of the Shortest Path Lengths

In [15]:
```
path_len = np.zeros(diameter + 1, dtype=int)

for pls in min_path_len.values():
    pl, cnt = np.unique(list(pls.values()), return_counts=True)
    path_len[pl] += cnt

freq_percent = 100 * path_len[1:] / np.sum(path_len[1:])

fig, ax = plt.subplots(figsize=(15, 9))
ax.bar(np.arange(1, diameter + 1), height=freq_percent)
ax.set_title(
    label="Distribution of the Shortest Path Lengths",
    fontdict={
        "fontsize": 20,
        "fontweight": "bold",
    },
    loc="center",
)
ax.set_xlabel(
    xlabel="Shortest Path Length",
    fontdict={
        "fontsize": 15,
    },
)
ax.set_ylabel(
    ylabel="Frequency (%)",
    fontdict={
        "fontsize": 15,
    },
)
```

Out[15]:
```
Text(0, 0.5, 'Frequency (%)')
```



Shortest Path Histogram Observations

> The majority of the users are from 2 to 3 friends apart. These two shortest paths account for around 90% of how far a user is away from another user. So, the chance that any pair of users are 5, 6, or 7 *(7 being the network diameter)* friends apart is rare.

Calculate the Edge Density of this Graph

In [16]:
```
print(f"Edge Density: {nx.density(G)}")
```

```
Edge Density: 0.017132150575067492
```

Conclusion on Histogram with Edge Density

> We can conclude that the network is relatively sparse since only around 17% of the possible edges are present in the network.

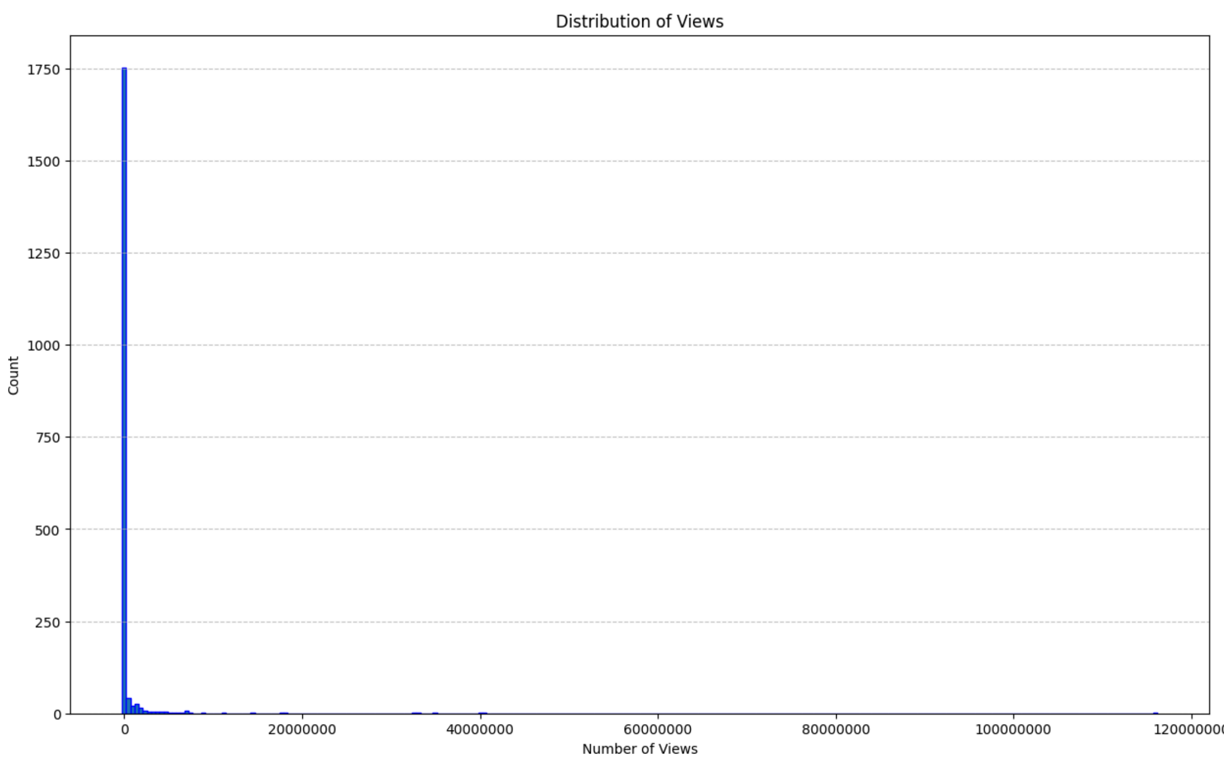
Load the Node Attribute File and Display the First Few Rows of the Dataset

In [17]:
```
att_df = spark.read.csv(
    path=os.path.join(DATA_PATH, f"musae_{LANG}_target.csv"),
    header=True,
    inferSchema=True
)

att_df.show(5)
```

```
+---------+----+------+------+-------+------+
|       id|days|mature| views|partner|new_id|
+---------+----+------+------+-------+------+
| 44891403|1943| false|929459|   true|  1706|
| 61180621|1633| false| 11194|  false|  1273|
|145109685| 632| false|  2850|  false|   313|
|122121521| 906|  true|  3422|  false|  1570|
|189445819| 267| false|    71|  false|   800|
+---------+----+------+------+-------+------+
only showing top 5 rows
```

Plot a Histogram of the Views

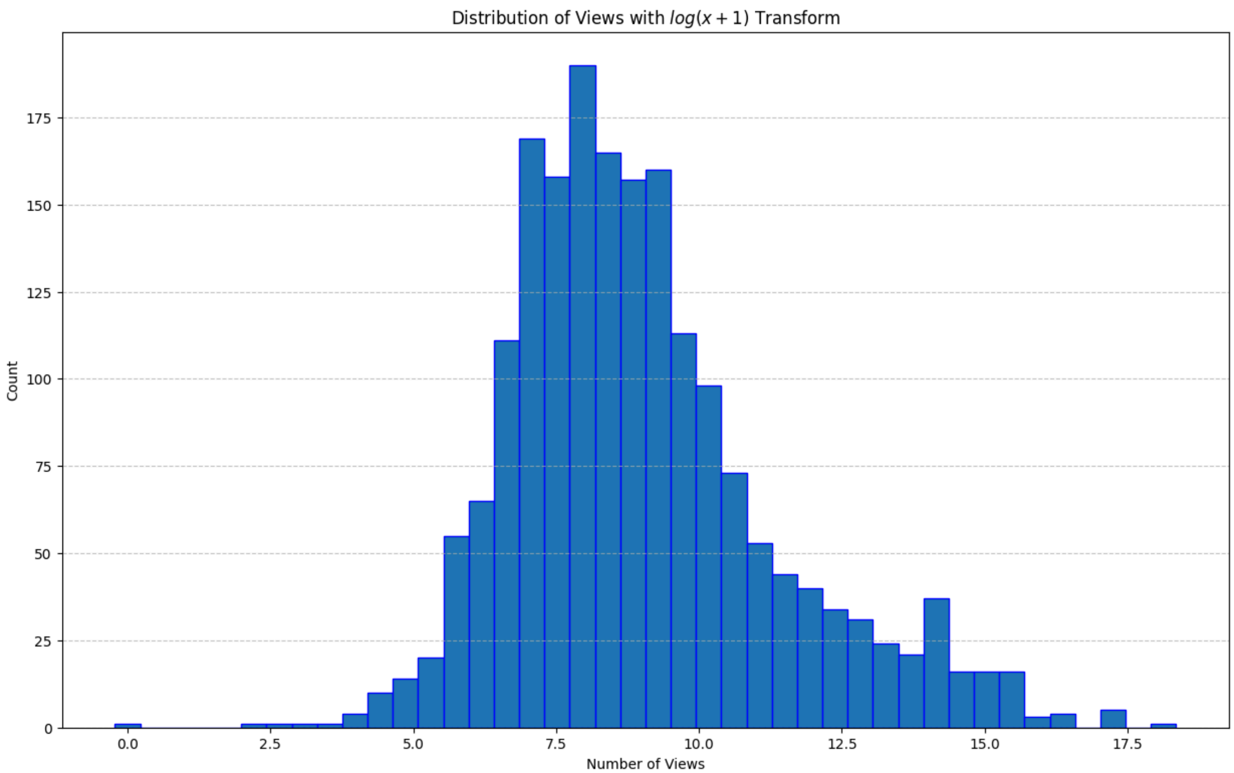
In [18]:
```python
views = att_df.select("Views").rdd.map(lambda x: x[0]).collect()

plt.figure(figsize=(15, 9))
plt.hist(
    x=views,
    bins=250,
    edgecolor="blue",
    align="left",
)
plt.title("Distribution of Views")
plt.xlabel("Number of Views")
plt.ticklabel_format(style="plain")
plt.ylabel("Count")
plt.grid(
    axis="y",
    linestyle="dashed",
    alpha=0.7,
)
plt.show()
```



Since there is a large skewness in the number of views; A Log Transformation $log(x+1)$ was preformed to normalize the data.

In [19]:

```
log_views = np.log([v + 1 for v in views])

plt.figure(figsize=(15, 9))
plt.hist(
    x=log_views,
    bins="auto",
    edgecolor="blue",
    align="left",
)
plt.title("Distribution of Views with $log(x+1)$ Transform")
plt.xlabel("Number of Views")
plt.ticklabel_format(style="plain")
plt.ylabel("Count")
plt.grid(
    axis="y",
    linestyle="dashed",
    alpha=0.7,
)
plt.show()
```



Viewer Distribution Observations

> There is a skewness to the distribution, and after the data was normalized with a log transformation we are able to see that there are also outliers in the dataset.

Create a Bar Plot

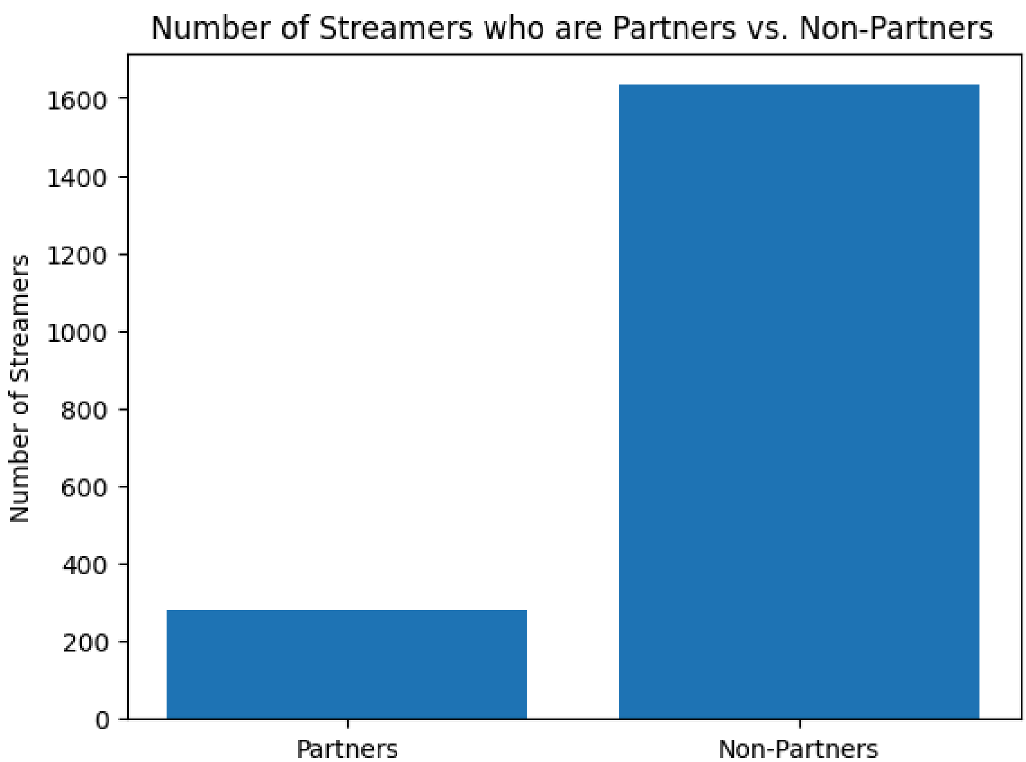
> Showing the Number of Streamers who are Partners vs. Non-Partners

In [20]:

```
att_df.groupBy("partner").count().show()

plt.bar(
    x = ["Partners", "Non-Partners"],
```

```
    height =att_df.groupBy("partner").count().rdd.map(lambda x: x[1]).collect(),
)
plt.title("Number of Streamers who are Partners vs. Non-Partners")
plt.ylabel("Number of Streamers")

plt.show()
```

```
+-------+-----+
|partner|count|
+-------+-----+
|   true|  279|
|  false| 1633|
+-------+-----+
```



Partnership Bar Chart Observations

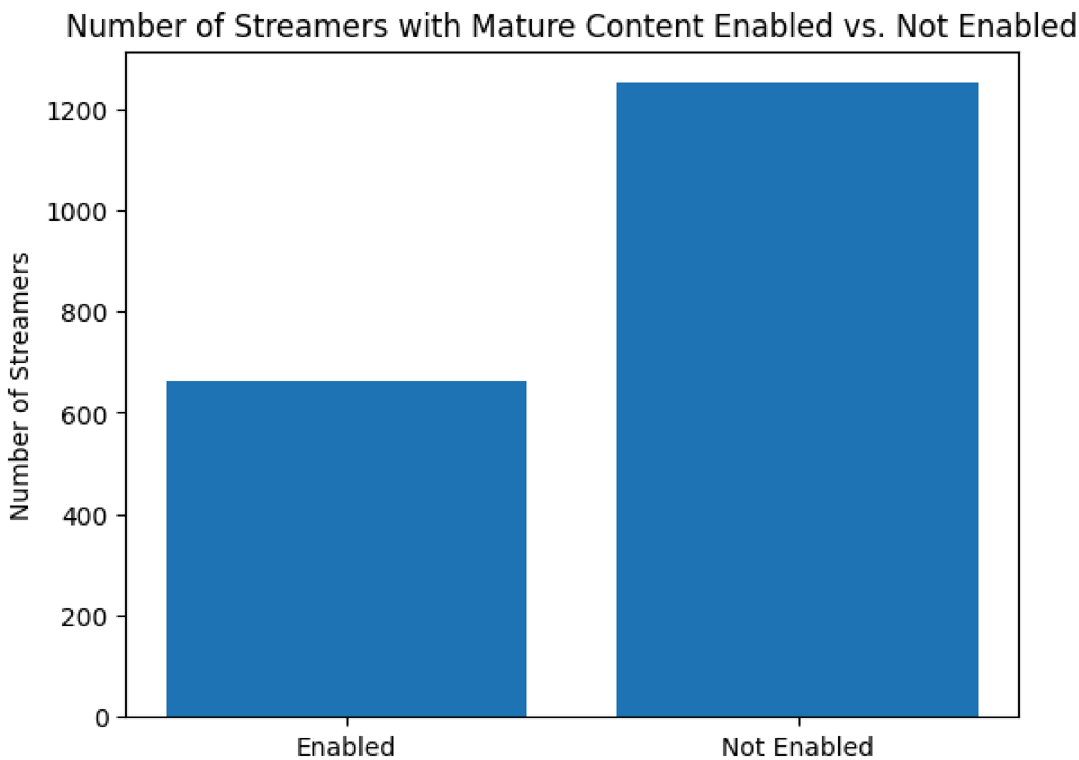
> The proportion of streamers that are partnered make up around 85.4% of the dataset.

Create a Bar Plot

> Showing the Number of Streamers with Mature Content Enabled vs. Not Enabled

In [21]:
```
att_df.groupBy("mature").count().show()

plt.bar(
    x=["Enabled", "Not Enabled"],
    height=att_df.groupBy("mature").count().rdd.map(lambda x: x[1]).collect(),
)
plt.title("Number of Streamers with Mature Content Enabled vs. Not Enabled")
plt.ylabel("Number of Streamers")
plt.show()
```

```
+------+-----+
|mature|count|
+------+-----+
|  true|  661|
| false| 1251|
+------+-----+
```

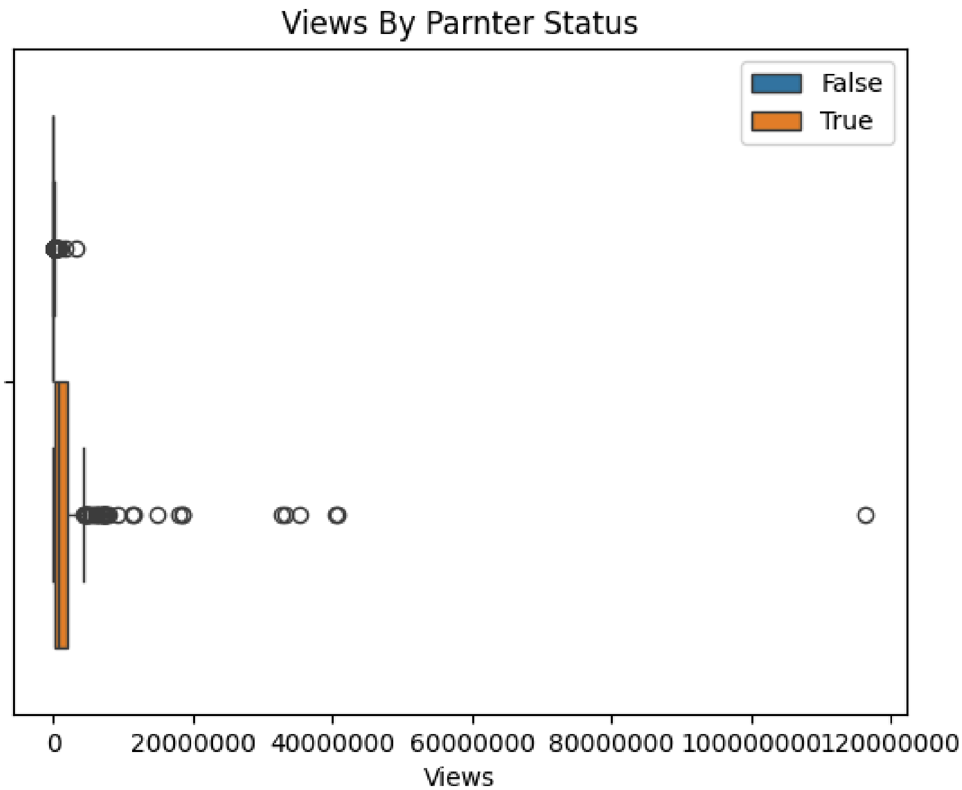


Mature Content Bar Chart Observations

> The majority of streamers do not have mature content enable with a little more 65.43% of streamers not enabling mature content.

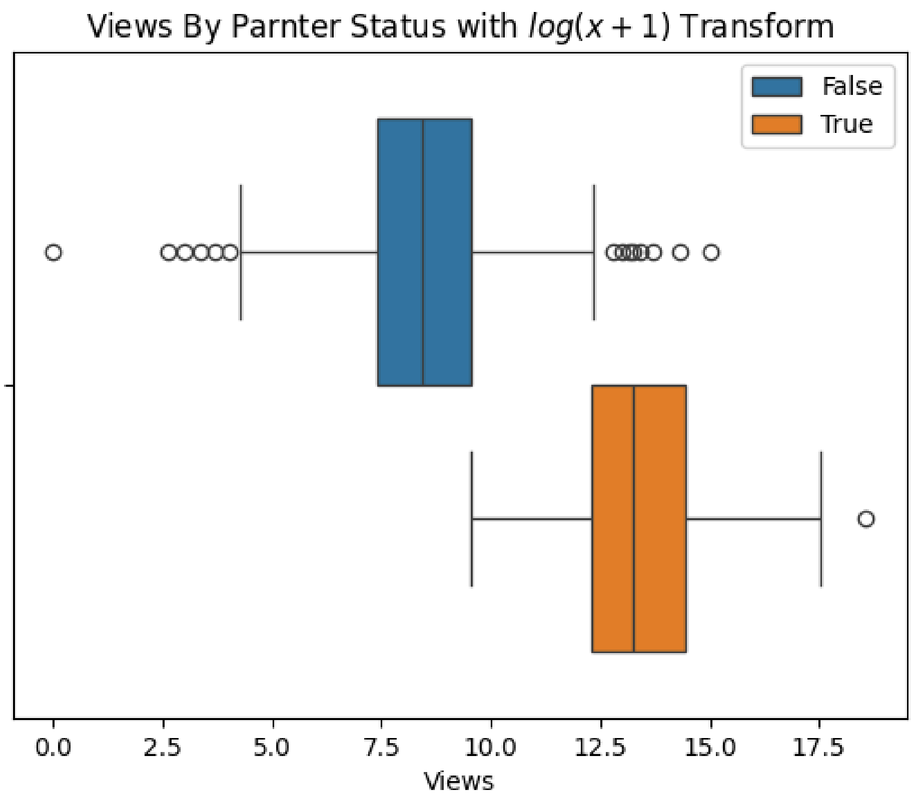
Create a Boxplot Comparing Views by Partner Status

In [22]:
```
sns.boxplot(
    x=att_df.select("Views").rdd.map(lambda x: x[0]).collect(),
    hue=att_df.select("Partner").rdd.map(lambda x: x[0]).collect(),
)
plt.title("Views By Parnter Status")
plt.xlabel("Views")
plt.ticklabel_format(axis="x", style="plain")
plt.show()
```



As before we applied the Log Transformation $log(x+1)$ on the number views to normalized the data.

In [23]:
```
sns.boxplot(
    x=log_views,
    hue=att_df.select("Partner").rdd.map(lambda x: x[0]).collect(),
)
plt.title("Views By Parnter Status with $log(x+1)$ Transform")
plt.xlabel("Views")
plt.show()
```



Views by Partnership Status Boxplot Observations

> The initial boxplot shows that Partners do have higher views than Non-Partners by a large margin, this is reforced with boxplot that examines the log transformed data.

Compute for All Nodes

- Degree Centrality
- Betweenness Centrality
- Closeness Centrality
- Eigenvector Centrality
- PageRank

In [24]:
```
degree = nx.degree_centrality(G)
betweenness = nx.betweenness_centrality(G)
closeness = nx.closeness_centrality(G)
eigenvector = nx.eigenvector_centrality(G)
pagerank = nx.pagerank(G)
```

In [25]:
```
centrality_list = [
    {"degree centrality": degree},
    {"betweenness centrality": betweenness},
    {"closeness centrality": closeness},
    {"eigenvector centrality": eigenvector},
    {"pagerank": pagerank},
]

for centrality in centrality_list:
    print(f"Top 10 {list(centrality)[0].title()}")
    centrality_dict = centrality[list(centrality)[0]]
```

```
    nodes = sorted(
        centrality_dict.items(),
        key=lambda x: x[1],
        reverse=True
    )[:10]

    for node in nodes:
        print(f"{node[0]}: {node[1]}")
    print()
```

```
Top 10 Degree Centrality
127: 0.4013605442176871
1476: 0.3129251700680272
290: 0.3087388801674516
1297: 0.30716902145473574
467: 0.304552590266876
1660: 0.24856096284667714
67: 0.23757195185766616
1320: 0.217687074829932
1758: 0.20617477760334904
1259: 0.20146520146520147

Top 10 Betweenness Centrality
127: 0.0992613670254655
1476: 0.054894872658417665
1297: 0.05042095543765276
290: 0.05011201385679391
467: 0.04382473622801392
67: 0.034425706705748176
1660: 0.02624664025473586
1259: 0.023294665516722747
287: 0.022120764244835684
428: 0.021980008718637752

Top 10 Closeness Centrality
127: 0.6009433962264151
1297: 0.5684116597263533
467: 0.565050266114725
290: 0.5595900439238654
1476: 0.5594262295081968
67: 0.5435153583617748
1660: 0.5416666666666666
1593: 0.5295095594347464
1259: 0.5237051246916964
287: 0.5227024070021882

Top 10 Eigenvector Centrality
127: 0.17877831012617343
1297: 0.15866803272155214
467: 0.1572393891554249
290: 0.15150156437553064
1476: 0.1457607576802339
1660: 0.13375702630371897
67: 0.1311805297345441
1593: 0.12589762048531492
1320: 0.11858724919571517
1758: 0.11540890407339242

Top 10 Pagerank
127: 0.011868965496806964
1476: 0.008978180166428392
290: 0.008649101005769455
1297: 0.008500930100419827
467: 0.00842343460623767
1660: 0.00674011506372157
67: 0.006323889093141329
1320: 0.005883878568697245
1758: 0.005648521214050491
1259: 0.00561101915085292
```

Observations on Centrality Measures and PageRank

> Looking across the measures node 127 is at the top of each measure.

> Nodes $67, 290, 467, 1297, 1476$ and 1660 appearing in the top 7 of each measure.

> Nodes 1320 and 1758 appears in *Degree* and *Eigenvector* centralities and *PageRank*, where node 1259 appears across all measures except for *Eigenvector* cetrality.

> Node 1593 is in the top 10 for only *Closeness* and *Eigenvector* centralities. Node 287 is only in the top 10 for *Betweeness* and *Closeness* centralities.

> Finally, node 428 is only in the top 10 *Betweenness* centrality across all the centralities and PageRank.

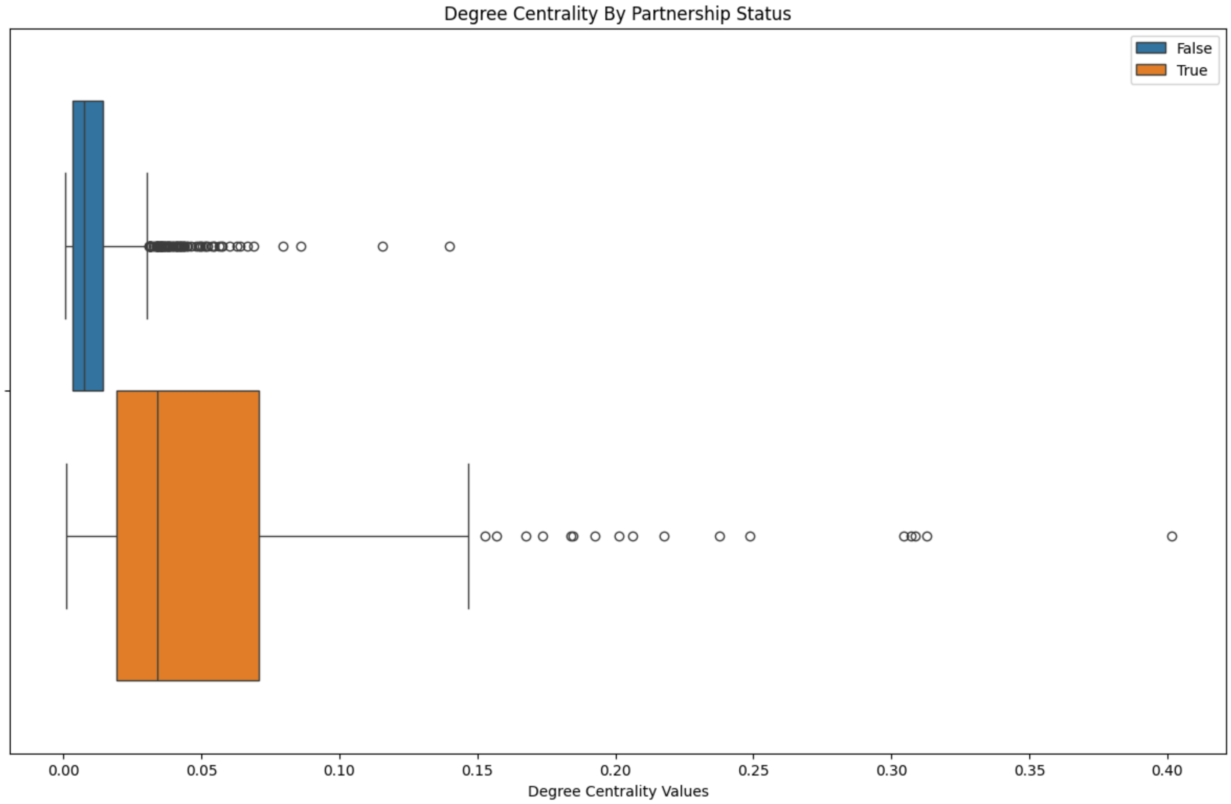
Create Boxplots Comparing Centralities and PageRang Values Between Partner Streamers and Non-Partner Streamers

Create the dataframe by joining the attributes data with centrality dictionary.

- Create PySpark dataframe from the centrality dictionary
- Join the dataframe to the attributes data to established partnership
- Visualize the boxplot for each centrality

In [26]:

```
cent_df = spark.createDataFrame(
    degree.items(), ["node", "centrality"])
cent_df = cent_df.join(
    other=att_df.select("new_id", "Partner"),
    on=[cent_df.node == att_df.new_id],
    how="inner",
)
plt.figure(figsize=(15, 9))
sns.boxplot(
    x=cent_df.select("centrality").rdd.map(lambda x: x[0]).collect(),
    hue=cent_df.select("partner").rdd.map(lambda x: x[0]).collect(),
)
plt.title("Degree Centrality By Partnership Status")
plt.xlabel("Degree Centrality Values")
plt.show()
```

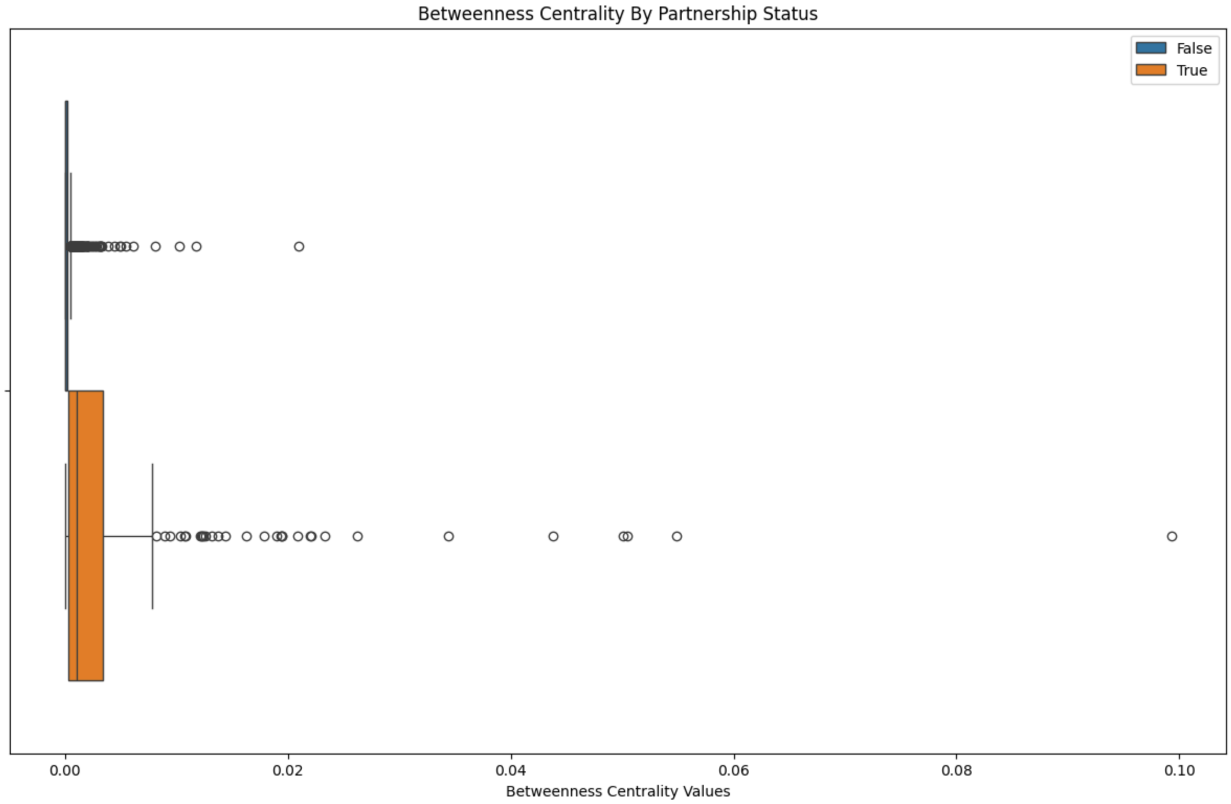


Degree Centrality Boxplot

> The partnered streamers have a lot more direct friendships than the non-partnered streamers. From the boxplot for *degree centrality* the largest > outlier in the non-partnered streamers would not be an outlier among the partnered streamers, and a majority of the non-partnered outliers would fall below the third quartile $Q3$ of the partnered streamer group.

In [27]:

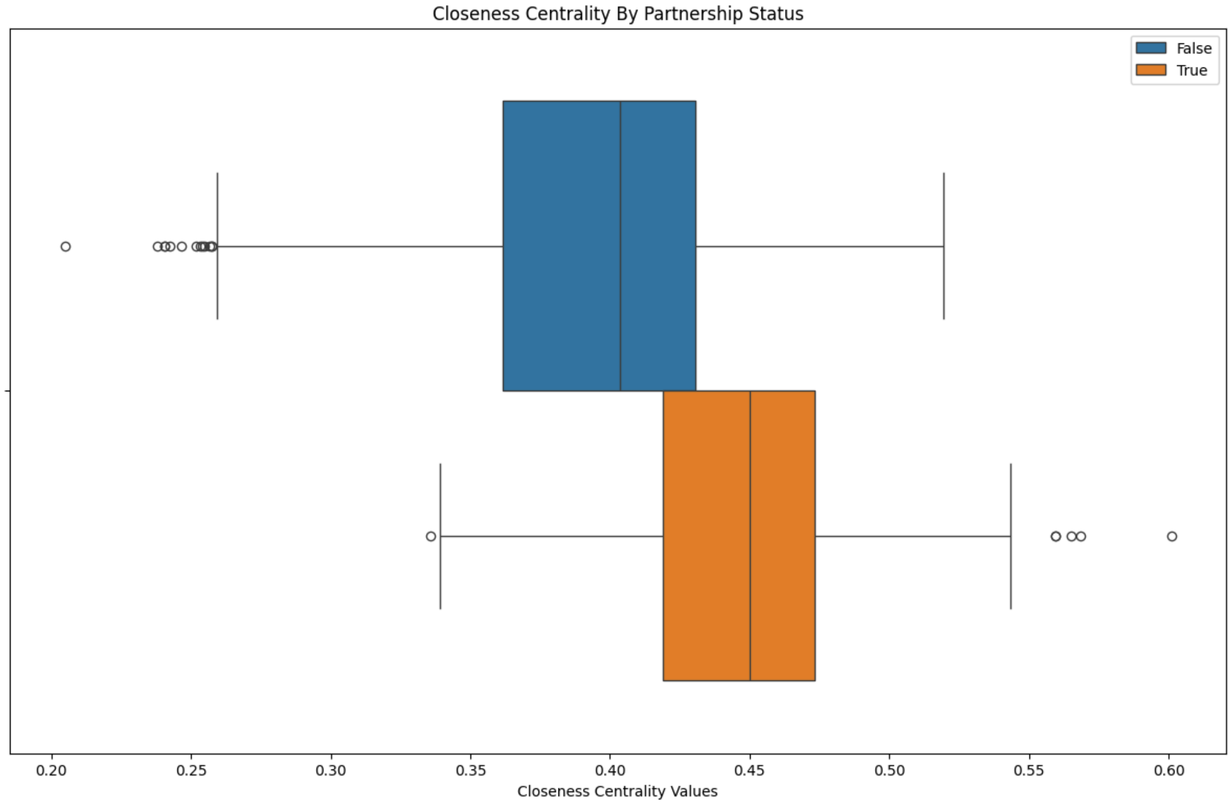
```
cent_df = spark.createDataFrame(
    betweenness.items(), ["node", "centrality"])
cent_df = cent_df.join(
    other=att_df.select("new_id", "Partner"),
    on=[cent_df.node == att_df.new_id],
    how="inner",
)
plt.figure(figsize=(15, 9))
sns.boxplot(
    x=cent_df.select("centrality").rdd.map(lambda x: x[0]).collect(),
    hue=cent_df.select("partner").rdd.map(lambda x: x[0]).collect(),
)
plt.title("Betweenness Centrality By Partnership Status")
plt.xlabel("Betweenness Centrality Values")
plt.show()
```



Betweenness Centrality Boxplot

> From the boxplot for *betweenness centrality* the partnered streamers are more important connecting to other user than the non-partnered streamers even though the betweenness in either group is not large.

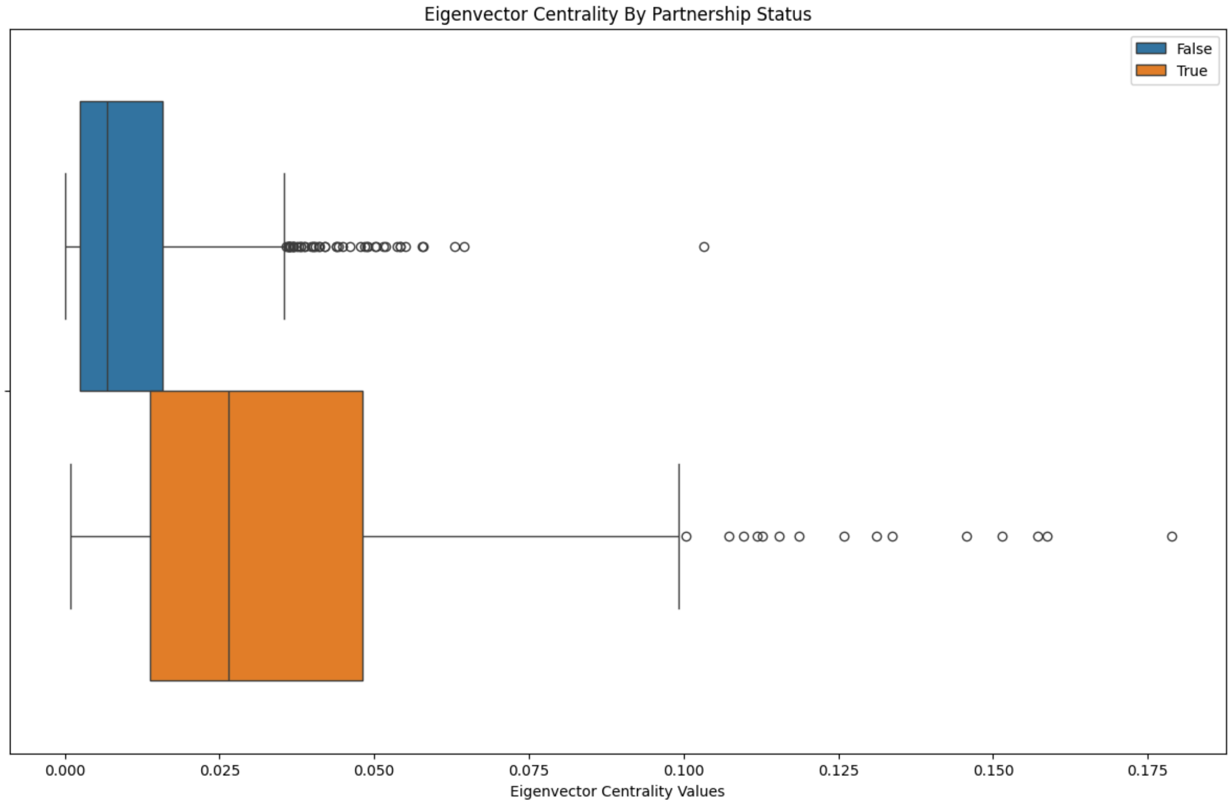
In [28]:
```
cent_df = spark.createDataFrame(
    closeness.items(), ["node", "centrality"])
cent_df = cent_df.join(
    other=att_df.select("new_id", "Partner"),
    on=[cent_df.node == att_df.new_id],
    how="inner",
)
plt.figure(figsize=(15, 9))
sns.boxplot(
    x=cent_df.select("centrality").rdd.map(lambda x: x[0]).collect(),
    hue=cent_df.select("partner").rdd.map(lambda x: x[0]).collect(),
)
plt.title("Closeness Centrality By Partnership Status")
plt.xlabel("Closeness Centrality Values")
plt.show()
```



Closeness Centrality Boxplot

> The *closeness centrality* boxplot shows that partnered streamers have a greater ability to reach other users than the non-partnered streamers.

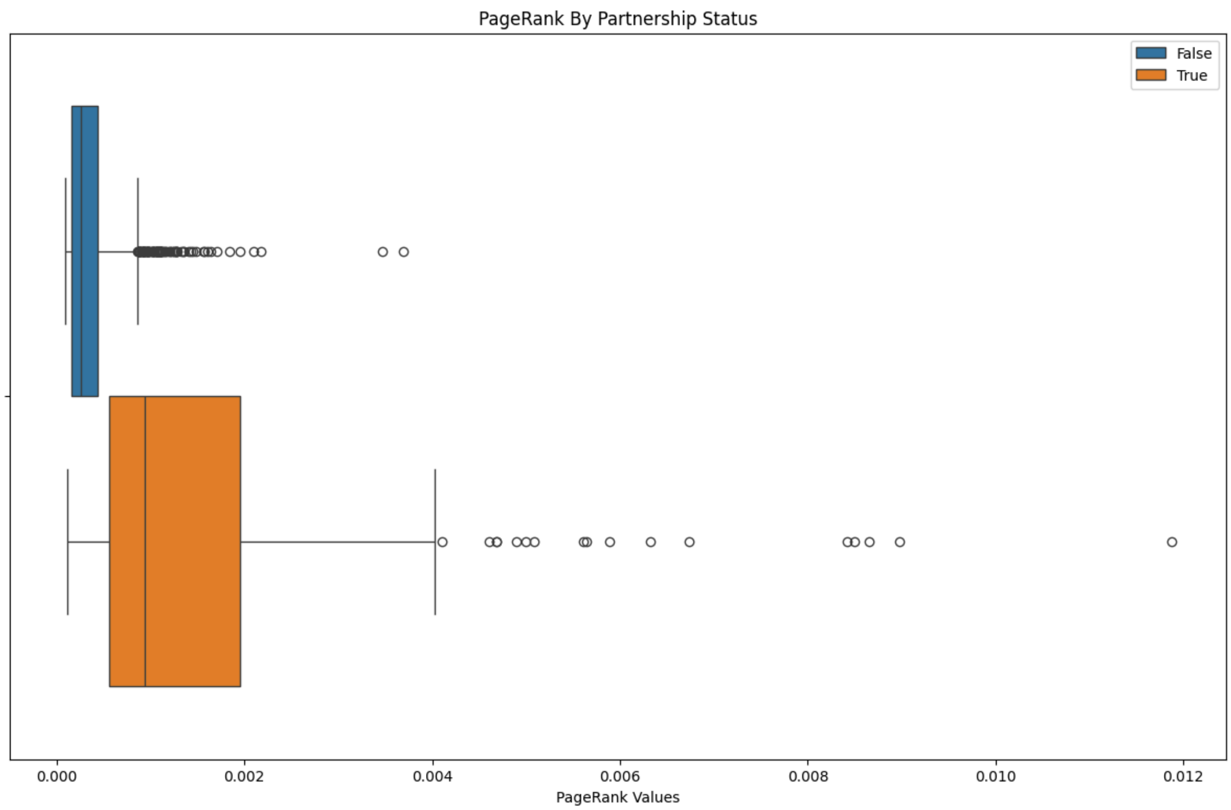
In [29]:
```
cent_df = spark.createDataFrame(
    eigenvector.items(), ["node", "centrality"])
cent_df = cent_df.join(
    other=att_df.select("new_id", "Partner"),
    on=[cent_df.node == att_df.new_id],
    how="inner",
)
plt.figure(figsize=(15, 9))
sns.boxplot(
    x=cent_df.select("centrality").rdd.map(lambda x: x[0]).collect(),
    hue=cent_df.select("partner").rdd.map(lambda x: x[0]).collect(),
)
plt.title("Eigenvector Centrality By Partnership Status")
plt.xlabel("Eigenvector Centrality Values")
plt.show()
```



Eigenvector Centrality Boxplot

> The *Eigenvector centrality* boxplot shows that partnered streamers are more influential than non-partnered streamers. The maximum and a majority of the non-partnered streamers outliers still fall below the third quartile $Q3$ of the partnered streamers showing us that partnered streamers are influenctial.

In [30]:
```
cent_df = spark.createDataFrame(
    pagerank.items(), ["node", "centrality"])
cent_df = cent_df.join(
    other=att_df.select("new_id", "Partner"),
    on=[cent_df.node == att_df.new_id],
    how="inner",
)
plt.figure(figsize=(15, 9))
sns.boxplot(
    x=cent_df.select("centrality").rdd.map(lambda x: x[0]).collect(),
    hue=cent_df.select("partner").rdd.map(lambda x: x[0]).collect(),
)
plt.title("PageRank By Partnership Status")
plt.xlabel("PageRank Values")
plt.show()
```



PageRank Boxplot

> The *PageRank* boxplot shows us that partnered streamers are more important to the friendships in the network than non-partnered streamers. Again, this is very heavily favored towards partnered streamers against non-partnered streamers.

Apply the Louvain Community Detection Algorithm Report the Number of Communities

> After reading the documentation on NetworkX Louvain Community Algorithms:
>
> - louvain_communities: returns the last iteration of the algorithms
> - louvain_partitions: yields all iterations
>   - Converting to a list results the same as louvain_communities

Note: A seed was set for both of the algorithms

In [31]:
```
communities = nx.community.louvain_communities(G, seed=SEED)
print(f"Number of Communities: {len(communities)}")
```

```
Number of Communities: 6
```

In [32]:
```
partitions = list(nx.community.louvain_partitions(G, seed=SEED))
print(f"Number of Partitions: {len(partitions)}")
print(f"Number of Partitions: {len(partitions[-1])}")
```

```
Number of Partitions: 3
Number of Partitions: 6
```

There are 6 communities from the Louvian community detection algorithm.

In [33]:

```
print("Nodes Per Community")
for p, c in zip(partitions[-1], communities):
    print(f"Partition Algorithm:{len(p)}")
    print(f"Community Algorithm:{len(c)}")
    print()
```

```
Nodes Per Community
Partition Algorithm:96
Community Algorithm:96

Partition Algorithm:374
Community Algorithm:374

Partition Algorithm:485
Community Algorithm:485

Partition Algorithm:304
Community Algorithm:304

Partition Algorithm:437
Community Algorithm:437

Partition Algorithm:216
Community Algorithm:216
```

Compute the Average Views and Days per Community

Converting the list of sets to a dictionary with a community value.

In [34]:

```
comm_dict = {}
for c in range(len(communities)):
    print(f"Current Node Count in Dictionary: {len(comm_dict)}")
    print(f"Adding Comminuity {c + 1} Nodes: {len(communities[c])}")
    comm_dict.update(
        {(node, c + 1) for node in list(communities[c])}
    )
    print(f"New Node Count in Dictionary: {len(comm_dict)}\n")
```

```
Current Node Count in Dictionary: 0
Adding Comminuity 1 Nodes: 96
New Node Count in Dictionary: 96

Current Node Count in Dictionary: 96
Adding Comminuity 2 Nodes: 374
New Node Count in Dictionary: 470

Current Node Count in Dictionary: 470
Adding Comminuity 3 Nodes: 485
New Node Count in Dictionary: 955

Current Node Count in Dictionary: 955
Adding Comminuity 4 Nodes: 304
New Node Count in Dictionary: 1259

Current Node Count in Dictionary: 1259
Adding Comminuity 5 Nodes: 437
New Node Count in Dictionary: 1696

Current Node Count in Dictionary: 1696
Adding Comminuity 6 Nodes: 216
New Node Count in Dictionary: 1912
```

Creating a dataframe with communities and combining to attribute data

In [35]:
```
comm_df = spark.createDataFrame(
    comm_dict.items(), ["node", "community"])

comm_df = comm_df.join(
    other=att_df.select("new_id", "Views", "Days"),
    on=[comm_df.node == att_df.new_id],
    how="inner",
)
comm_df.show(5)
```

```
+----+---------+------+------+----+
|node|community|new_id| Views|Days|
+----+---------+------+------+----+
|  80|        1|    80|  9889|2284|
|  34|        1|    34|  6126| 719|
| 507|        1|   507|187209| 809|
| 586|        1|   586|  3470|2332|
|1343|        1|  1343|   294|1753|
+----+---------+------+------+----+
only showing top 5 rows
```

Create the dataframe with communities, average views, and average per day usage.

In [88]:
```
window = Window.partitionBy()

comm_avg_df = comm_df.groupBy("community") \
    .agg(
        F.count("community").alias("community_count"),
        F.round(F.avg("Views"), 6).alias("avg_views"),
        F.sum("Days").alias("per_day"),
        F.round(F.avg("Days"), 6).alias("avg_per_days"),
    ) \
    .withColumn(
        "percent_avg_views",
        F.round(
```

```
            F.col("avg_views")
            / F.sum("avg_views").over(window), 4).cast(T.DoubleType())
            * 100
    ) \
    .withColumn(
        "percent_per_day",
        F.round(
            F.col("per_day")
            / F.sum("per_day").over(window), 4).cast(T.DoubleType())
            * 100
    ) \
    .withColumn(
        "percent_avg_days",
        F.round(
            F.col("avg_per_days")
            / F.sum("avg_per_days").over(window), 4).cast(T.DoubleType())
            * 100
    ) \
    .orderBy("community")

comm_avg_df.show()
```

```
+---------+---------------+-------------+-------+------------+-----------------+------
------------+------------------+
|community|community_count|    avg_views|per_day|avg_per_days|percent_avg_views|   per
cent_per_day|  percent_avg_days|
+---------+---------------+-------------+-------+------------+-----------------+------
------------+------------------+
|        1|             96| 293829.479167| 166889| 1738.427083|            12.02|
6.58|20.669999999999998|
|        2|            374| 212264.254011| 457668|  1223.71123|             8.68|18.029
999999999998|14.549999999999999|
|        3|            485| 272537.934021| 675075| 1391.907216|            11.15|
26.6|             16.55|
|        4|            304|1291529.848684| 402944| 1325.473684|            52.82|15.879
999999999999|             15.76|
|        5|            437| 308141.036613| 485237| 1110.382151|             12.6|
19.12|13.200000000000001|
|        6|            216|  66690.791667| 350209| 1621.337963|             2.73|
13.8|             19.28|
+---------+---------------+-------------+-------+------------+-----------------+------
------------+------------------+
```

Average Views and Per Day Usage Per Community Observations

> Community 1 with 96 user accounts is the smallest community with 12.02% of average views, but has the highest average per day with around 20.67%. This group accounts for 6.58% of days.

> Community 2 with 374 users has one of the lowest average views with a third largest community at 8.68%, and has the second lowest per day with 14.56%. This group accounts for 18.03% of days.

> Community 3 with 485 users is the largest community. The views and per day averages are in the middle of the pack with 11.15% and 16.55% respectively. This group accounts for 26.60% of days.

> Community 4 with 304 users leads average views by a massive margin with 52.82% of all views, but has less average per day than communities $1, 3$ and 6 with only around

> 15.88%. This group accounts for 18.03% of days.

> Community 5 with 437 users is the second largest community with an average 12.60% of all views, but has the lowest average per day with only 13.20%. This group accounts for 19.12% of days.

> Community 6 with 216 users is the second smallest community, and has the lowest average views with only 2.73% of all views, but has the second highest average per day with around 19.28%. This group accounts for 13.80% of days.

> So from the table and information above, it would appear that communities 1 and 6 have the highest per day average in their community. Community 4 leads with the most views from a smaller user pool, and community 3 with the largest user group lead for per day usage, but only the third highest average per day usage.

End of Project