In [1]:
```
import pandas as pd
import numpy as np
```

In [2]:
```
df=pd.read_csv('/content/Global Crude Petroleum Trade 1995-2021.csv')
df.head()
```

Out[2]:

	Continent	Country	Trade Value	Year	Action
0	Africa	Angola	2.767000e+10	2021	Export
1	Africa	Botswana	2.055000e+03	2021	Export
2	Africa	Cote d'Ivoire	4.447282e+08	2021	Export
3	Africa	Cameroon	1.865465e+09	2021	Export
4	Africa	Democratic Republic of the Congo	5.815086e+08	2021	Export

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7925 entries, 0 to 7924
Data columns (total 5 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   Continent    7925 non-null   object 
 1   Country      7925 non-null   object 
 2   Trade Value  7925 non-null   float64
 3   Year         7925 non-null   int64  
 4   Action       7925 non-null   object 
dtypes: float64(1), int64(1), object(3)
memory usage: 309.7+ KB
```

In [4]:
```
df.describe()
```

Out[4]:

	Trade Value	Year
count	7.925000e+03	7925.000000
mean	5.365169e+09	2008.589148
std	1.940226e+10	7.569435
min	1.000000e+00	1995.000000
25%	1.416080e+05	2002.000000
50%	8.549274e+07	2009.000000
75%	1.828030e+09	2015.000000
max	3.283380e+11	2021.000000

In [5]:
```
df.isnull().sum()
```

Out[5]:

	0
Continent	0
Country	0
Trade Value	0
Year	0
Action	0

dtype: int64

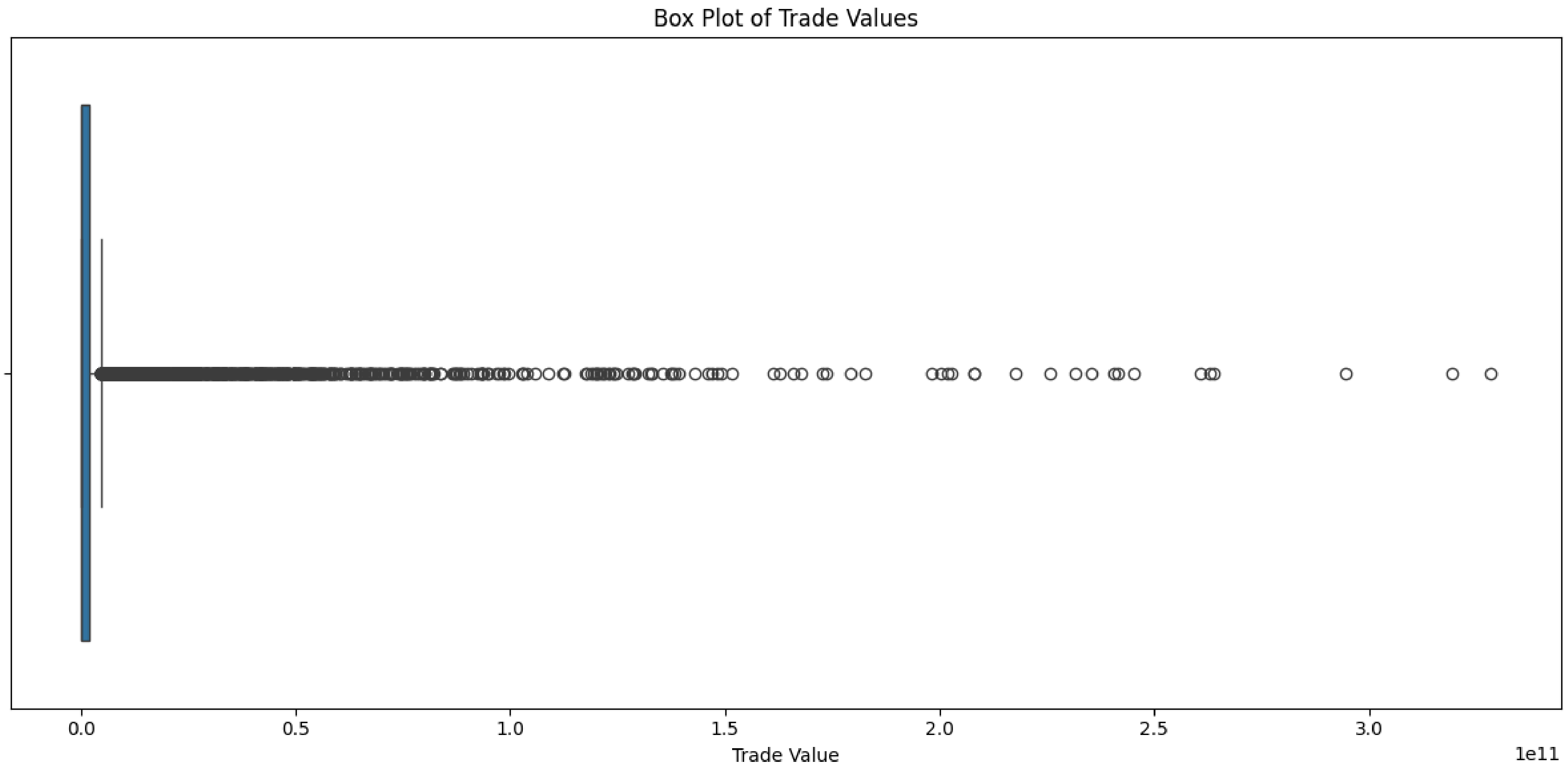
In [6]:
```
df.shape
```

Out[6]:
```
(7925, 5)
```

Detect outliers

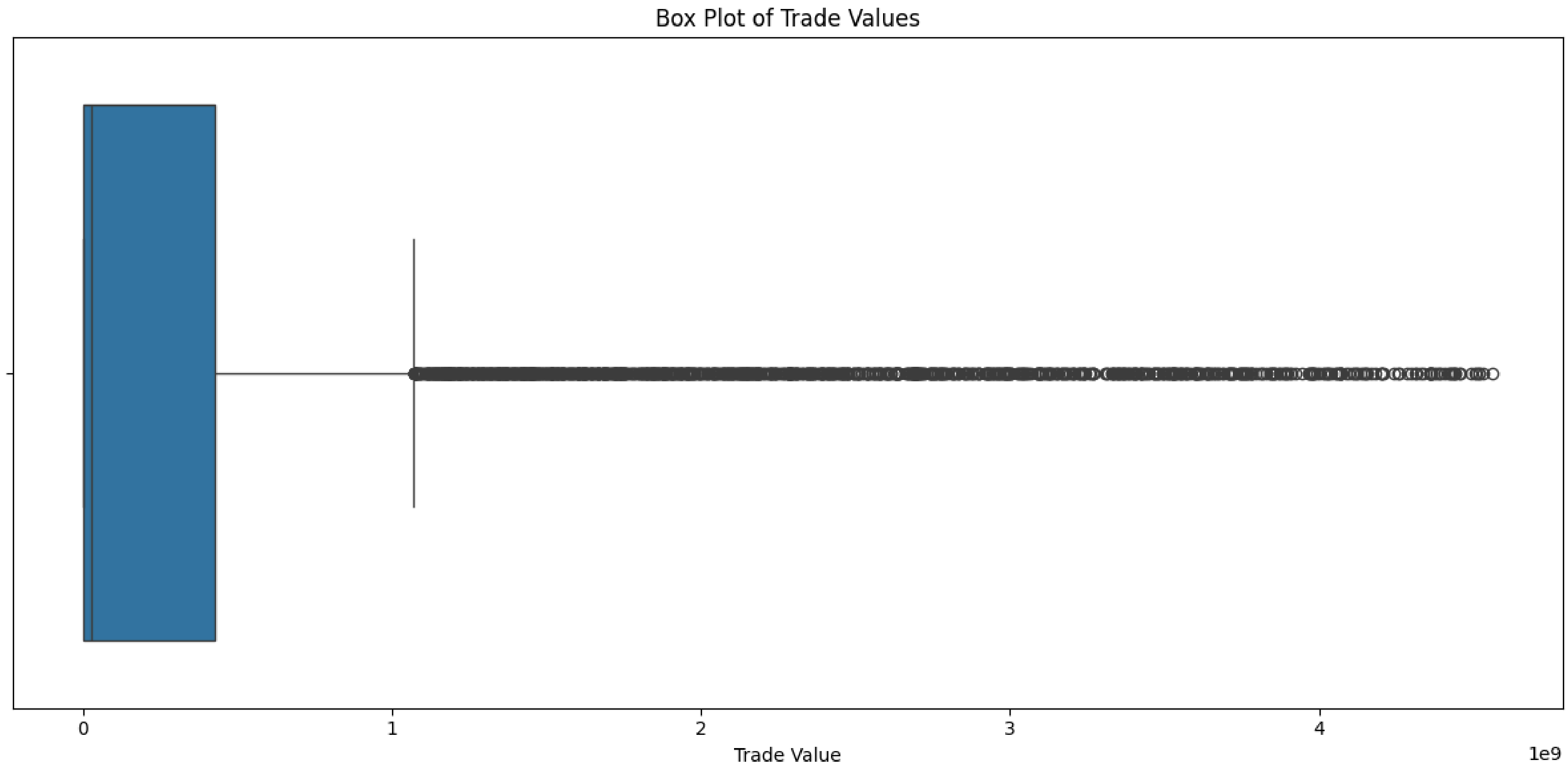
In [7]:
```
import pandas as pd
import matplotlib.pyplot as plt
```

```
import seaborn as sns


# Create box plots for each numeric column to detect outliers
plt.figure(figsize=(12, 6))

# Plot box plot for Trade Value column
plt.subplot(1, 1, 1)
sns.boxplot(x=df['Trade Value'])
plt.title('Box Plot of Trade Values')
plt.xlabel('Trade Value')

plt.tight_layout()
plt.show()
```



In [8]:
```
import numpy as np

# Detect outliers using the IQR method
Q1 = df['Trade Value'].quantile(0.25)
Q3 = df['Trade Value'].quantile(0.75)
IQR = Q3 - Q1

# Define the outlier range
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Filter out outliers
df = df[(df['Trade Value'] >= lower_bound) & (df['Trade Value'] <= upper_bound)]
```

In [9]:
```
# Create box plots for each numeric column to detect outliers
plt.figure(figsize=(12, 6))

# Plot box plot for Trade Value column
plt.subplot(1, 1, 1)
sns.boxplot(x=df['Trade Value'])
plt.title('Box Plot of Trade Values')
plt.xlabel('Trade Value')

plt.tight_layout()
plt.show()
```



In [10]:
```
import pandas as pd
import networkx as nx
import matplotlib.pyplot as plt

# Load the dataset
df = pd.read_csv('/content/Global Crude Petroleum Trade 1995-2021.csv')

# Print a sample of the data to verify
print(df.head())

# Adjust column names based on the dataset
continent_column = 'Continent'
trade_value_column = 'Trade Value'
action_column = 'Action'
```

```
# Create a directed graph
G = nx.DiGraph()

# Define colors for export and import edges
export_color = 'blue'
import_color = 'red'

# Iterate through each unique action
for action in df[action_column].unique():
    for source_continent in df[continent_column].unique():
        # Filter the data for this source continent and action
        filtered_df = df[(df[continent_column] == source_continent) & (df[action_column] == action)]
        if filtered_df.empty:
            continue
        for target_continent in df[continent_column].unique():
            if source_continent != target_continent:
                # Sum the trade value for this pair of continents
                trade_value = filtered_df[trade_value_column].sum()
                if trade_value > 0:
                    color = export_color if action == 'Export' else import_color
                    G.add_edge(source_continent, target_continent, weight=trade_value, color=color)
                    print(f"Edge added: {source_continent} -> {target_continent} with weight {trade_value} (Action: {action})")

# Check if the graph has nodes and edges
print(f"Nodes: {G.nodes()}")
print(f"Edges: {G.edges(data=True)}")

# Draw the graph if there are any edges
if len(G.edges) > 0:
    pos = nx.circular_layout(G)  # Change layout for better visual representation
    plt.figure(figsize=(12, 8))

    # Draw nodes
    nx.draw_networkx_nodes(G, pos, node_size=6000, node_color='lightblue')

    # Draw edges with colors based on action type
    edges = G.edges()
    colors = [G[u][v]['color'] for u, v in edges]
    nx.draw_networkx_edges(G, pos, edgelist=edges, width=2, edge_color=colors, arrows=True, arrowstyle='->')

    # Draw labels for continents (nodes)
    nx.draw_networkx_labels(G, pos, font_size=12, font_family="sans-serif")
```

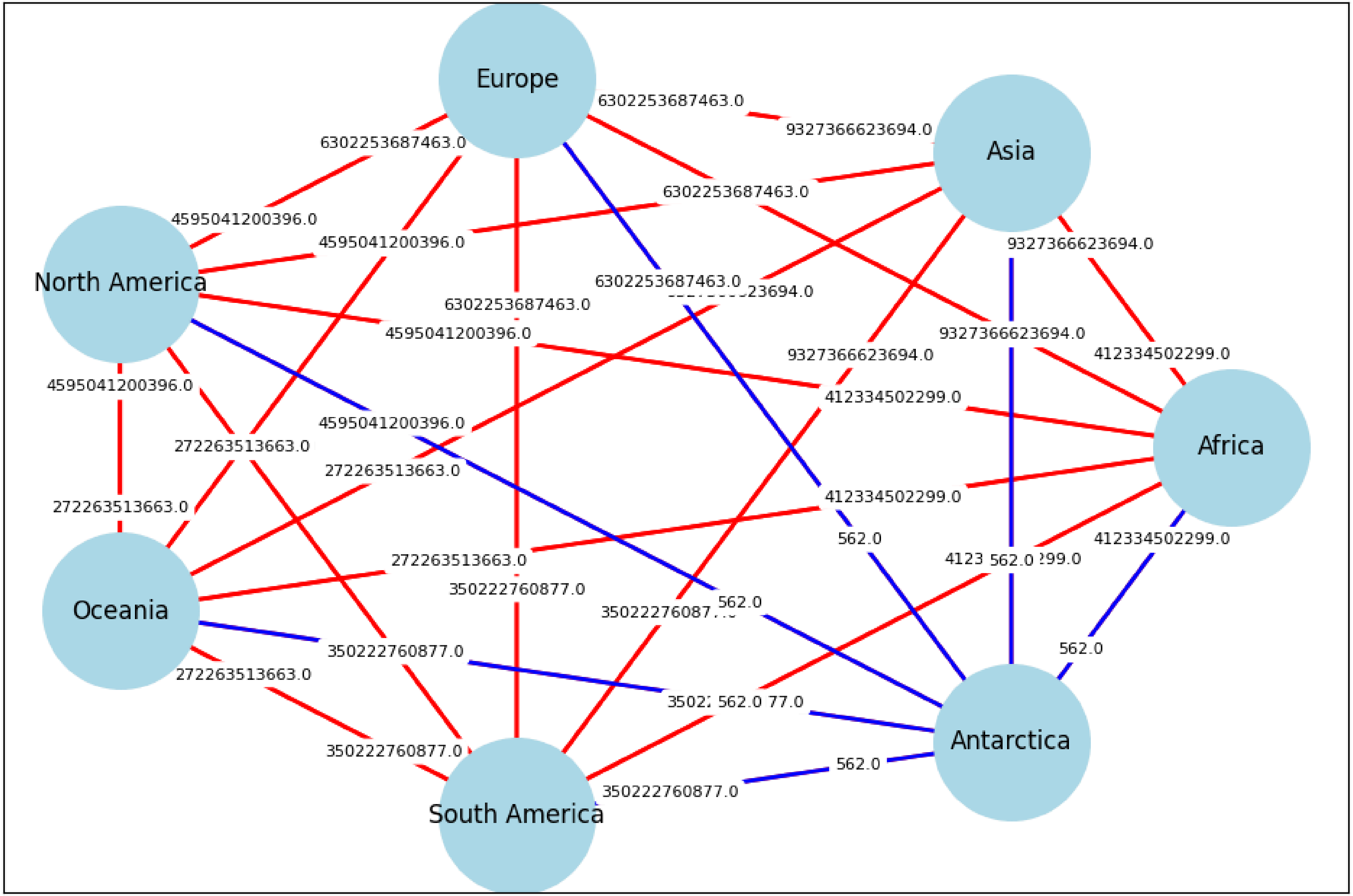
```
    # Draw edge labels (trade values) with horizontal alignment
    edge_labels = nx.get_edge_attributes(G, 'weight')
    nx.draw_networkx_edge_labels(G, pos, edge_labels=edge_labels, label_pos=0.3, font_size=8, rotate=False)

    plt.title('Global Crude Oil Trade Network (1995-2021)')
    plt.show()
else:
    print("No edges to display in the graph.")
```

```
  Continent                           Country   Trade Value  Year  Action
0    Africa                            Angola  2.767000e+10  2021  Export
1    Africa                          Botswana  2.055000e+03  2021  Export
2    Africa                     Cote d'Ivoire  4.447282e+08  2021  Export
3    Africa                          Cameroon  1.865465e+09  2021  Export
4    Africa  Democratic Republic of the Congo  5.815086e+08  2021  Export
Edge added: Africa -> Asia with weight 3517983260038.0 (Action: Export)
Edge added: Africa -> Europe with weight 3517983260038.0 (Action: Export)
Edge added: Africa -> North America with weight 3517983260038.0 (Action: Export)
Edge added: Africa -> Oceania with weight 3517983260038.0 (Action: Export)
Edge added: Africa -> South America with weight 3517983260038.0 (Action: Export)
Edge added: Africa -> Antarctica with weight 3517983260038.0 (Action: Export)
Edge added: Asia -> Africa with weight 9840708390207.0 (Action: Export)
Edge added: Asia -> Europe with weight 9840708390207.0 (Action: Export)
Edge added: Asia -> North America with weight 9840708390207.0 (Action: Export)
Edge added: Asia -> Oceania with weight 9840708390207.0 (Action: Export)
Edge added: Asia -> South America with weight 9840708390207.0 (Action: Export)
Edge added: Asia -> Antarctica with weight 9840708390207.0 (Action: Export)
Edge added: Europe -> Africa with weight 4106635101131.0 (Action: Export)
Edge added: Europe -> Asia with weight 4106635101131.0 (Action: Export)
Edge added: Europe -> North America with weight 4106635101131.0 (Action: Export)
Edge added: Europe -> Oceania with weight 4106635101131.0 (Action: Export)
Edge added: Europe -> South America with weight 4106635101131.0 (Action: Export)
Edge added: Europe -> Antarctica with weight 4106635101131.0 (Action: Export)
Edge added: North America -> Africa with weight 2087439622701.0 (Action: Export)
Edge added: North America -> Asia with weight 2087439622701.0 (Action: Export)
Edge added: North America -> Europe with weight 2087439622701.0 (Action: Export)
Edge added: North America -> Oceania with weight 2087439622701.0 (Action: Export)
Edge added: North America -> South America with weight 2087439622701.0 (Action: Export)
Edge added: North America -> Antarctica with weight 2087439622701.0 (Action: Export)
Edge added: Oceania -> Africa with weight 170210736861.0 (Action: Export)
Edge added: Oceania -> Asia with weight 170210736861.0 (Action: Export)
Edge added: Oceania -> Europe with weight 170210736861.0 (Action: Export)
Edge added: Oceania -> North America with weight 170210736861.0 (Action: Export)
Edge added: Oceania -> South America with weight 170210736861.0 (Action: Export)
Edge added: Oceania -> Antarctica with weight 170210736861.0 (Action: Export)
Edge added: South America -> Africa with weight 1536503497418.0 (Action: Export)
Edge added: South America -> Asia with weight 1536503497418.0 (Action: Export)
Edge added: South America -> Europe with weight 1536503497418.0 (Action: Export)
Edge added: South America -> North America with weight 1536503497418.0 (Action: Export)
Edge added: South America -> Oceania with weight 1536503497418.0 (Action: Export)
Edge added: South America -> Antarctica with weight 1536503497418.0 (Action: Export)
Edge added: Antarctica -> Africa with weight 562.0 (Action: Export)
Edge added: Antarctica -> Asia with weight 562.0 (Action: Export)
```

```
Edge added: Antarctica -> Europe with weight 562.0 (Action: Export)
Edge added: Antarctica -> North America with weight 562.0 (Action: Export)
Edge added: Antarctica -> Oceania with weight 562.0 (Action: Export)
Edge added: Antarctica -> South America with weight 562.0 (Action: Export)
Edge added: Africa -> Asia with weight 412334502299.0 (Action: Import)
Edge added: Africa -> Europe with weight 412334502299.0 (Action: Import)
Edge added: Africa -> North America with weight 412334502299.0 (Action: Import)
Edge added: Africa -> Oceania with weight 412334502299.0 (Action: Import)
Edge added: Africa -> South America with weight 412334502299.0 (Action: Import)
Edge added: Africa -> Antarctica with weight 412334502299.0 (Action: Import)
Edge added: Asia -> Africa with weight 9327366623694.0 (Action: Import)
Edge added: Asia -> Europe with weight 9327366623694.0 (Action: Import)
Edge added: Asia -> North America with weight 9327366623694.0 (Action: Import)
Edge added: Asia -> Oceania with weight 9327366623694.0 (Action: Import)
Edge added: Asia -> South America with weight 9327366623694.0 (Action: Import)
Edge added: Asia -> Antarctica with weight 9327366623694.0 (Action: Import)
Edge added: Europe -> Africa with weight 6302253687463.0 (Action: Import)
Edge added: Europe -> Asia with weight 6302253687463.0 (Action: Import)
Edge added: Europe -> North America with weight 6302253687463.0 (Action: Import)
Edge added: Europe -> Oceania with weight 6302253687463.0 (Action: Import)
Edge added: Europe -> South America with weight 6302253687463.0 (Action: Import)
Edge added: Europe -> Antarctica with weight 6302253687463.0 (Action: Import)
Edge added: North America -> Africa with weight 4595041200396.0 (Action: Import)
Edge added: North America -> Asia with weight 4595041200396.0 (Action: Import)
Edge added: North America -> Europe with weight 4595041200396.0 (Action: Import)
Edge added: North America -> Oceania with weight 4595041200396.0 (Action: Import)
Edge added: North America -> South America with weight 4595041200396.0 (Action: Import)
Edge added: North America -> Antarctica with weight 4595041200396.0 (Action: Import)
Edge added: Oceania -> Africa with weight 272263513663.0 (Action: Import)
Edge added: Oceania -> Asia with weight 272263513663.0 (Action: Import)
Edge added: Oceania -> Europe with weight 272263513663.0 (Action: Import)
Edge added: Oceania -> North America with weight 272263513663.0 (Action: Import)
Edge added: Oceania -> South America with weight 272263513663.0 (Action: Import)
Edge added: Oceania -> Antarctica with weight 272263513663.0 (Action: Import)
Edge added: South America -> Africa with weight 350222760877.0 (Action: Import)
Edge added: South America -> Asia with weight 350222760877.0 (Action: Import)
Edge added: South America -> Europe with weight 350222760877.0 (Action: Import)
Edge added: South America -> North America with weight 350222760877.0 (Action: Import)
Edge added: South America -> Oceania with weight 350222760877.0 (Action: Import)
Edge added: South America -> Antarctica with weight 350222760877.0 (Action: Import)
Nodes: ['Africa', 'Asia', 'Europe', 'North America', 'Oceania', 'South America', 'Antarctica']
Edges: [('Africa', 'Asia', {'weight': 412334502299.0, 'color': 'red'}), ('Africa', 'Europe', {'weight': 412334502299.0, 'color':
'red'}), ('Africa', 'North America', {'weight': 412334502299.0, 'color': 'red'}), ('Africa', 'Oceania', {'weight': 412334502299.
0, 'color': 'red'}), ('Africa', 'South America', {'weight': 412334502299.0, 'color': 'red'}), ('Africa', 'Antarctica', {'weigh
```

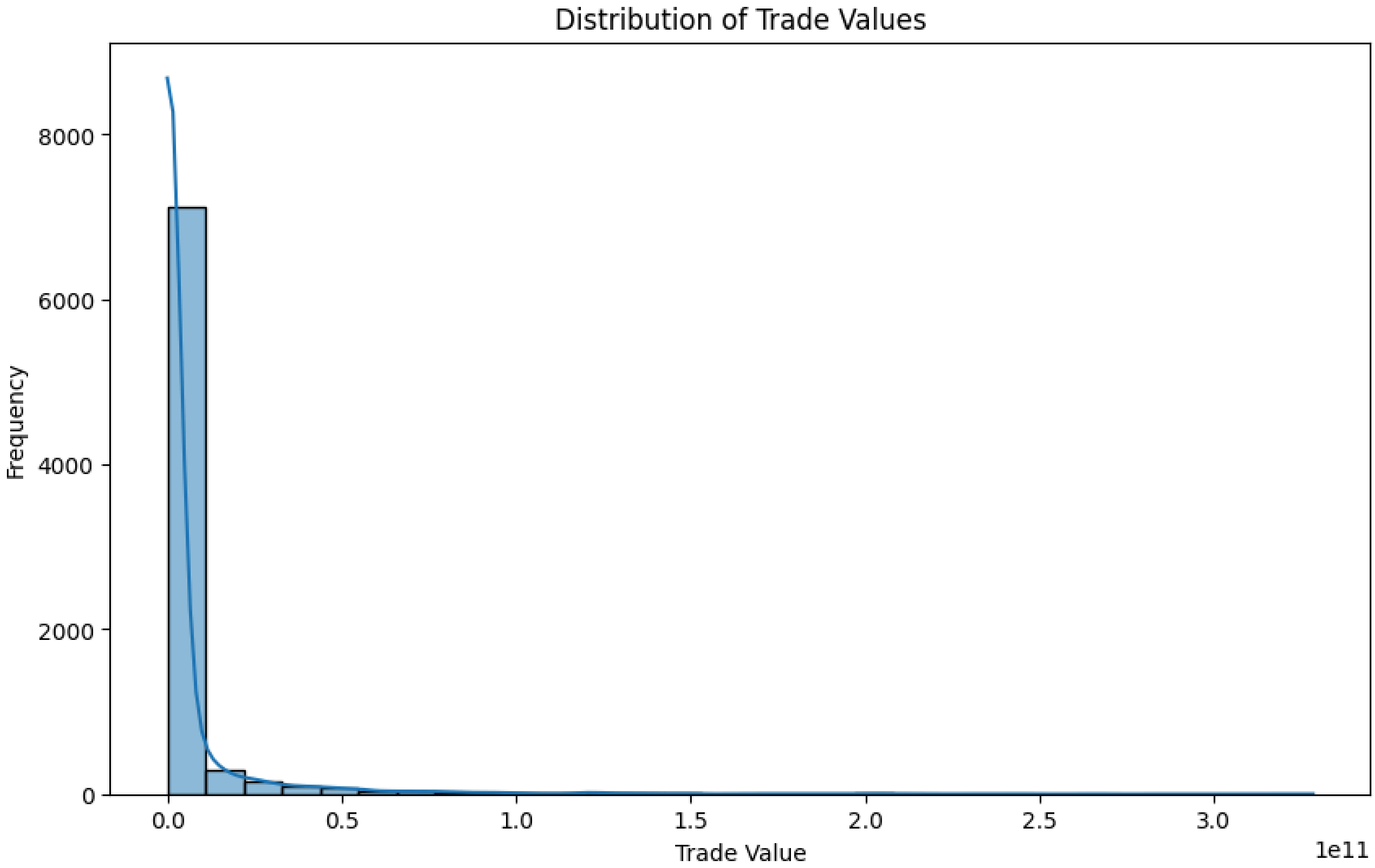
t': 412334502299.0, 'color': 'red'}), ('Asia', 'Africa', {'weight': 9327366623694.0, 'color': 'red'}), ('Asia', 'Europe', {'weight': 9327366623694.0, 'color': 'red'}), ('Asia', 'North America', {'weight': 9327366623694.0, 'color': 'red'}), ('Asia', 'Oceania', {'weight': 9327366623694.0, 'color': 'red'}), ('Asia', 'South America', {'weight': 9327366623694.0, 'color': 'red'}), ('Asia', 'Antarctica', {'weight': 9327366623694.0, 'color': 'red'}), ('Europe', 'Africa', {'weight': 6302253687463.0, 'color': 'red'}), ('Europe', 'Asia', {'weight': 6302253687463.0, 'color': 'red'}), ('Europe', 'North America', {'weight': 6302253687463.0, 'color': 'red'}), ('Europe', 'Oceania', {'weight': 6302253687463.0, 'color': 'red'}), ('Europe', 'South America', {'weight': 6302253687463.0, 'color': 'red'}), ('Europe', 'Antarctica', {'weight': 6302253687463.0, 'color': 'red'}), ('North America', 'Africa', {'weight': 4595041200396.0, 'color': 'red'}), ('North America', 'Asia', {'weight': 4595041200396.0, 'color': 'red'}), ('North America', 'Europe', {'weight': 4595041200396.0, 'color': 'red'}), ('North America', 'Oceania', {'weight': 4595041200396.0, 'color': 'red'}), ('North America', 'South America', {'weight': 4595041200396.0, 'color': 'red'}), ('North America', 'Antarctica', {'weight': 4595041200396.0, 'color': 'red'}), ('Oceania', 'Africa', {'weight': 272263513663.0, 'color': 'red'}), ('Oceania', 'Asia', {'weight': 272263513663.0, 'color': 'red'}), ('Oceania', 'Europe', {'weight': 272263513663.0, 'color': 'red'}), ('Oceania', 'North America', {'weight': 272263513663.0, 'color': 'red'}), ('Oceania', 'South America', {'weight': 272263513663.0, 'color': 'red'}), ('Oceania', 'Antarctica', {'weight': 272263513663.0, 'color': 'red'}), ('South America', 'Africa', {'weight': 350222760877.0, 'color': 'red'}), ('South America', 'Asia', {'weight': 350222760877.0, 'color': 'red'}), ('South America', 'Europe', {'weight': 350222760877.0, 'color': 'red'}), ('South America', 'North America', {'weight': 350222760877.0, 'color': 'red'}), ('South America', 'Oceania', {'weight': 350222760877.0, 'color': 'red'}), ('South America', 'Antarctica', {'weight': 350222760877.0, 'color': 'red'}), ('Antarctica', 'Africa', {'weight': 562.0, 'color': 'blue'}), ('Antarctica', 'Asia', {'weight': 562.0, 'color': 'blue'}), ('Antarctica', 'Europe', {'weight': 562.0, 'color': 'blue'}), ('Antarctica', 'North America', {'weight': 562.0, 'color': 'blue'}), ('Antarctica', 'Oceania', {'weight': 562.0, 'color': 'blue'}), ('Antarctica', 'South America', {'weight': 562.0, 'color': 'blue'})]

Global Crude Oil Trade Network (1995-2021)

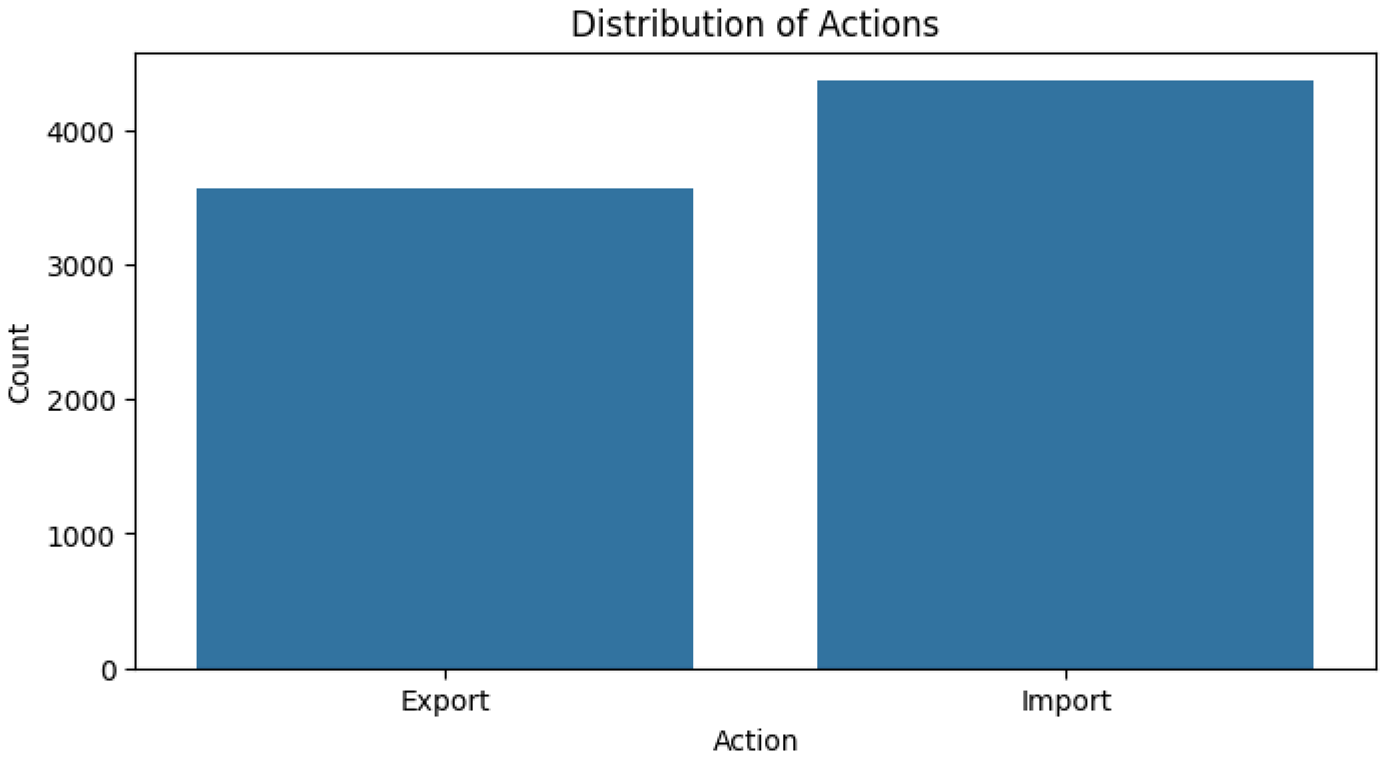


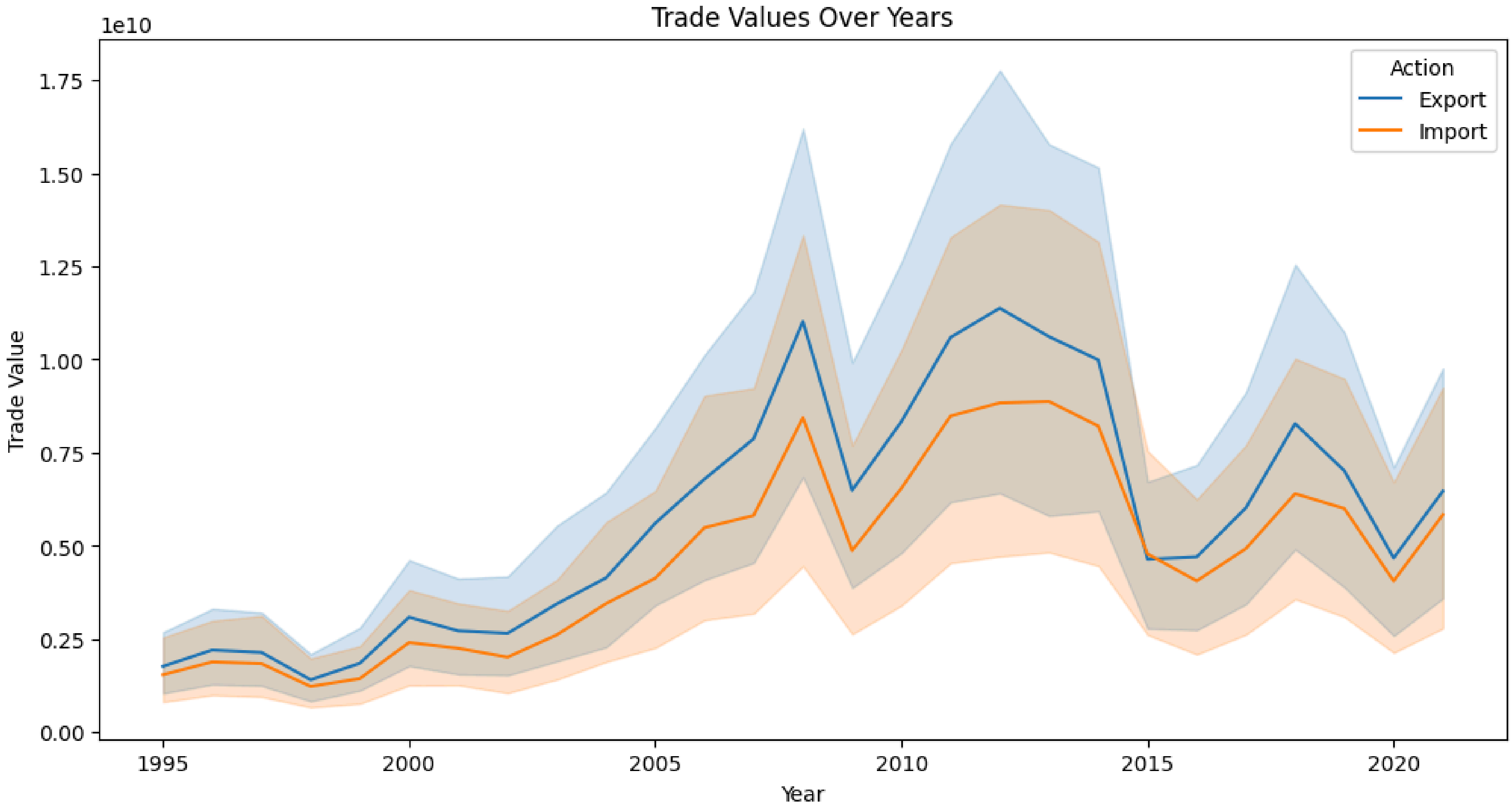
In [11]:
```
import matplotlib.pyplot as plt
import seaborn as sns
```

```
# Plot distribution of trade values
plt.figure(figsize=(10, 6))
sns.histplot(df[trade_value_column], bins=30, kde=True)
plt.title('Distribution of Trade Values')
plt.xlabel('Trade Value')
plt.ylabel('Frequency')
plt.show()

# Plot distribution of actions
plt.figure(figsize=(8, 4))
sns.countplot(data=df, x=action_column)
plt.title('Distribution of Actions')
plt.xlabel('Action')
plt.ylabel('Count')
plt.show()

# Plot year-wise trade values
plt.figure(figsize=(12, 6))
sns.lineplot(data=df, x='Year', y=trade_value_column, hue=action_column)
plt.title('Trade Values Over Years')
plt.xlabel('Year')
plt.ylabel('Trade Value')
plt.show()
```



Distribution of Trade Values
Frequency
8000
6000
4000
2000
0
0.0
0.5
1.0
1.5
2.0
2.5
3.0
1e11
Trade Value


Distribution of Actions
Count
4000
3000
2000
1000
0
Export
Import
Action



Dijkstra

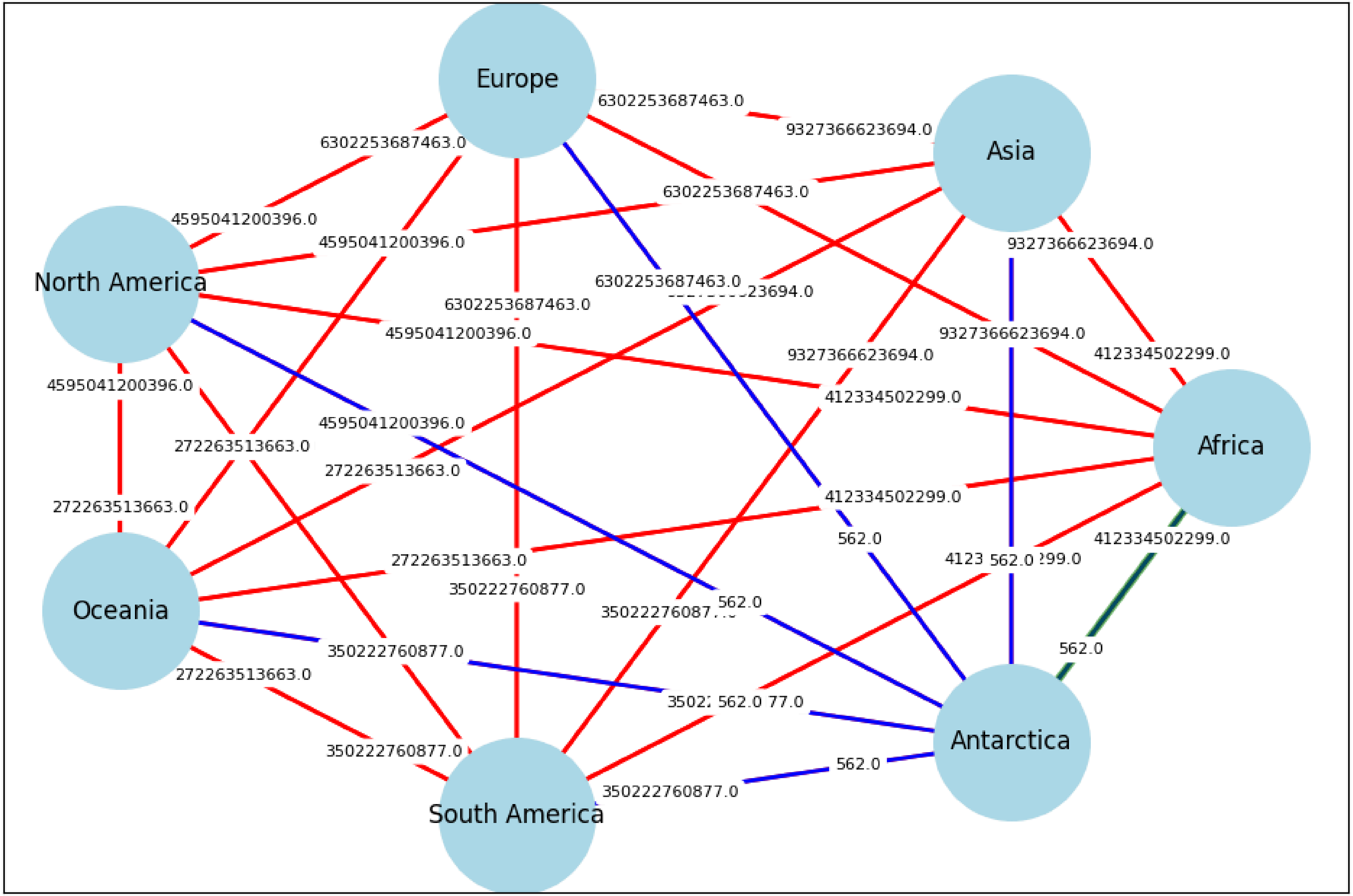
In [12]:
```
import networkx as nx
import matplotlib.pyplot as plt

# Assuming G is your graph with edge weights

# Function to get user input for source and destination nodes
def get_user_input():
    source_node = input("Enter the source continent: ")
    target_node = input("Enter the destination continent: ")
```

```
    return source_node, target_node

 plt.figure(figsize=(12, 8))

    # Draw nodes
    nx.draw_networkx_nodes(G, pos, node_size=6000, node_color='lightblue')

    # Draw edges
    edges = G.edges()
    edge_colors = [G[u][v].get('color', 'gray') for u, v in edges]
    nx.draw_networkx_edges(G, pos, edgelist=edges, width=2, edge_color=edge_colors, arrows=True, arrowstyle='->')

    # Highlight the shortest path edges
    if path_edges:
        nx.draw_networkx_edges(G, pos, edgelist=path_edges, edge_color='green', width=4, alpha=0.6, arrows=True, arrowstyle='->')

    # Draw labels
    nx.draw_networkx_labels(G, pos, font_size=12, font_family="sans-serif")

    # Draw edge labels (trade values)
    edge_labels = nx.get_edge_attributes(G, 'weight')
    nx.draw_networkx_edge_labels(G, pos, edge_labels=edge_labels, label_pos=0.3, font_size=8, rotate=False)

    plt.title(f'Global Crude Oil Trade Network with Highlighted Shortest Path ({layout} Layout)')
    plt.show()

# Main script
def main():
    # Get user input
    source_node, target_node = get_user_input()

    # Check if nodes exist
    if source_node in G.nodes and target_node in G.nodes:
        try:
            # Compute shortest path using Dijkstra's algorithm
            shortest_path = nx.shortest_path(G, source=source_node, target=target_node, weight='weight')
            print(f"Shortest path from {source_node} to {target_node}: {shortest_path}")

            # Convert the shortest path to edges for highlighting
            path_edges = list(zip(shortest_path, shortest_path[1:]))

            # Plot the graph with the shortest path highlighted
            plot_graph_with_highlight(G, path_edges=path_edges)
        except nx.NetworkXNoPath:
```

```
            print(f"No path found between {source_node} and {target_node}.")
    else:
        print("Invalid source or destination node.")

if __name__ == "__main__":
    main()
```

```
Enter the source continent: Africa
Enter the destination continent: Antarctica
Shortest path from Africa to Antarctica: ['Africa', 'Antarctica']
```

Global Crude Oil Trade Network with Highlighted Shortest Path (circular Layout)



Louvain Method

In [13]:
```
!pip install cdlib
from cdlib import algorithms, viz

# Compute the best partition for the graph using Louvain algorithm
partition = algorithms.louvain(G.to_undirected(), weight='weight')

# Draw the graph with communities
plt.figure(figsize=(12, 8))
pos = nx.circular_layout(G)  # Position nodes using circular layout
viz.plot_network_clusters(G, partition, pos, figsize=(12, 8))
plt.title('Graph with Community Detection (Louvain)')
plt.show()
```

```
Collecting cdlib
  Downloading cdlib-0.4.0-py3-none-any.whl.metadata (8.8 kB)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from cdlib) (1.26.4)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.10/dist-packages (from cdlib) (1.3.2)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from cdlib) (4.66.5)
Requirement already satisfied: networkx>=3.0 in /usr/local/lib/python3.10/dist-packages (from cdlib) (3.3)
Collecting demon (from cdlib)
  Downloading demon-2.0.6-py3-none-any.whl.metadata (5.1 kB)
Requirement already satisfied: python-louvain>=0.16 in /usr/local/lib/python3.10/dist-packages (from cdlib) (0.16)
Requirement already satisfied: scipy>=1.10 in /usr/local/lib/python3.10/dist-packages (from cdlib) (1.13.1)
Collecting pulp (from cdlib)
  Downloading PuLP-2.9.0-py3-none-any.whl.metadata (5.4 kB)
Requirement already satisfied: seaborn in /usr/local/lib/python3.10/dist-packages (from cdlib) (0.13.1)
Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages (from cdlib) (2.1.4)
Collecting eva-lcd (from cdlib)
  Downloading eva_lcd-0.1.1-py3-none-any.whl.metadata (731 bytes)
Collecting bimlpa (from cdlib)
  Downloading bimlpa-0.1.2-py3-none-any.whl.metadata (725 bytes)
Collecting python-igraph>=0.10 (from cdlib)
  Downloading python_igraph-0.11.6-py3-none-any.whl.metadata (2.8 kB)
Collecting angelcommunity (from cdlib)
  Downloading angelcommunity-2.0.0-py3-none-any.whl.metadata (4.0 kB)
Requirement already satisfied: pooch in /usr/local/lib/python3.10/dist-packages (from cdlib) (1.8.2)
Collecting dynetx (from cdlib)
  Downloading dynetx-0.3.2-py3-none-any.whl.metadata (2.9 kB)
Collecting thresholdclustering (from cdlib)
  Downloading thresholdclustering-1.1-py3-none-any.whl.metadata (4.2 kB)
Collecting python-Levenshtein (from cdlib)
  Downloading python_Levenshtein-0.25.1-py3-none-any.whl.metadata (3.7 kB)
Requirement already satisfied: plotly in /usr/local/lib/python3.10/dist-packages (from cdlib) (5.15.0)
Collecting igraph==0.11.6 (from python-igraph>=0.10->cdlib)
  Downloading igraph-0.11.6-cp39-abi3-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (3.9 kB)
Collecting texttable>=1.6.2 (from igraph==0.11.6->python-igraph>=0.10->cdlib)
  Downloading texttable-1.7.0-py2.py3-none-any.whl.metadata (9.8 kB)
Requirement already satisfied: future in /usr/local/lib/python3.10/dist-packages (from angelcommunity->cdlib) (1.0.0)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (from bimlpa->cdlib) (3.7.1)
Requirement already satisfied: decorator in /usr/local/lib/python3.10/dist-packages (from dynetx->cdlib) (4.4.2)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/dist-packages (from pandas->cdlib) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas->cdlib) (2024.1)
Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-packages (from pandas->cdlib) (2024.1)
Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from plotly->cdlib) (9.0.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from plotly->cdlib) (24.1)
Requirement already satisfied: platformdirs>=2.5.0 in /usr/local/lib/python3.10/dist-packages (from pooch->cdlib) (4.2.2)
Requirement already satisfied: requests>=2.19.0 in /usr/local/lib/python3.10/dist-packages (from pooch->cdlib) (2.32.3)
```

```
Collecting Levenshtein==0.25.1 (from python-Levenshtein->cdlib)
  Downloading Levenshtein-0.25.1-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (3.3 kB)
Collecting rapidfuzz<4.0.0,>=3.8.0 (from Levenshtein==0.25.1->python-Levenshtein->cdlib)
  Downloading rapidfuzz-3.9.6-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (12 kB)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-learn->cdlib) (1.4.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn->cdlib) (3.5.
0)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->bimlpa->cdlib) (1.
2.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib->bimlpa->cdlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->bimlpa->cdlib) (4.
53.1)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->bimlpa->cdlib) (1.
4.5)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->bimlpa->cdlib) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->bimlpa->cdlib) (3.
1.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.2->pandas->cdlib)
(1.16.0)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests>=2.19.0->pooch
->cdlib) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests>=2.19.0->pooch->cdlib) (3.
7)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests>=2.19.0->pooch->cdli
b) (2.0.7)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests>=2.19.0->pooch->cdli
b) (2024.7.4)
Downloading cdlib-0.4.0-py3-none-any.whl (263 kB)
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Downloading python_igraph-0.11.6-py3-none-any.whl (9.1 kB)
Downloading igraph-0.11.6-cp39-abi3-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (3.1 MB)
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Downloading angelcommunity-2.0.0-py3-none-any.whl (10 kB)
Downloading bimlpa-0.1.2-py3-none-any.whl (7.0 kB)
Downloading demon-2.0.6-py3-none-any.whl (7.3 kB)
Downloading dynetx-0.3.2-py3-none-any.whl (39 kB)
Downloading eva_lcd-0.1.1-py3-none-any.whl (9.2 kB)
Downloading PuLP-2.9.0-py3-none-any.whl (17.7 MB)
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Downloading python_Levenshtein-0.25.1-py3-none-any.whl (9.4 kB)
Downloading Levenshtein-0.25.1-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (177 kB)
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Downloading thresholdclustering-1.1-py3-none-any.whl (5.3 kB)
Downloading rapidfuzz-3.9.6-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (3.4 MB)
```
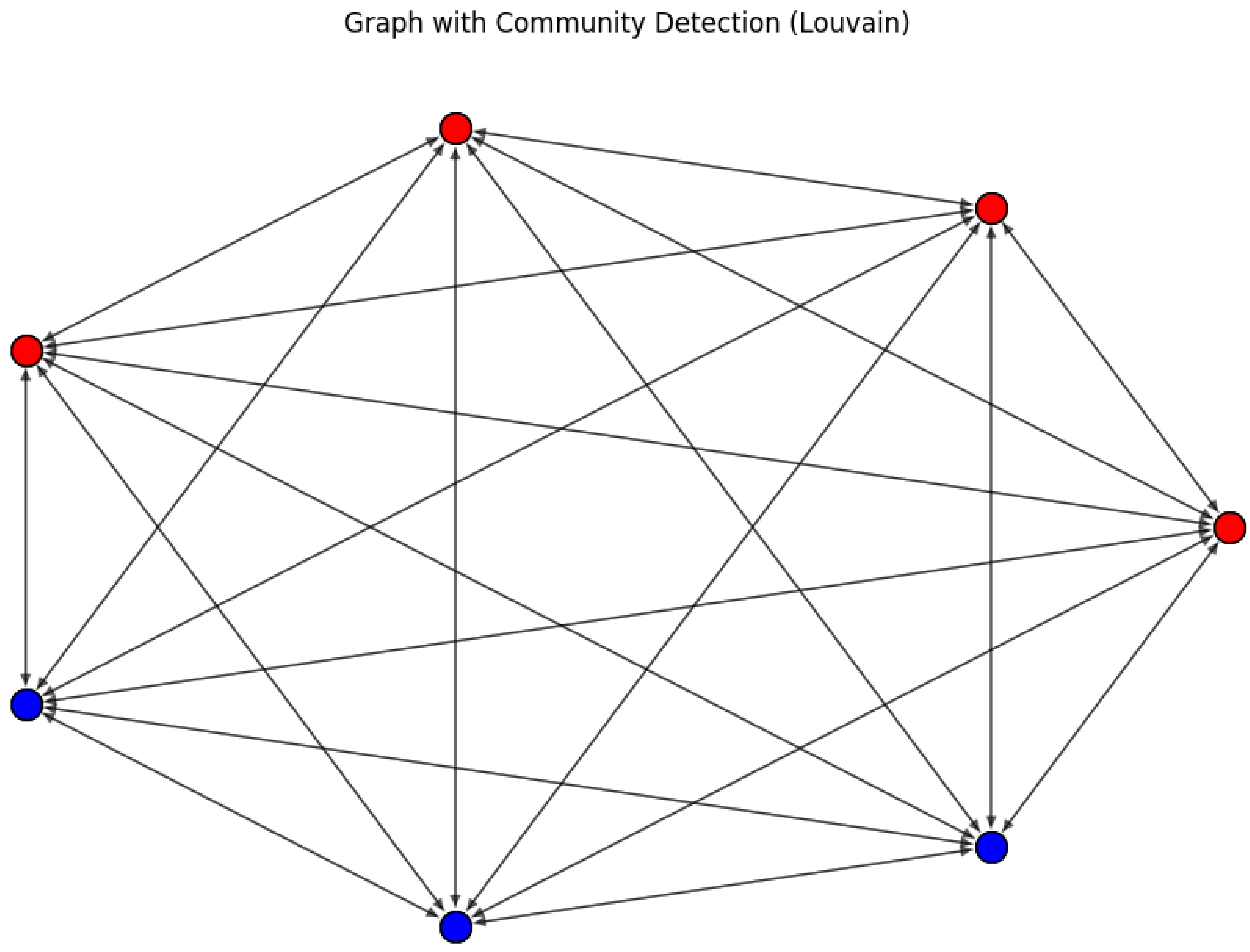

```
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 3.4/3.4 MB 84.1 MB/s eta 0:00:00
Downloading texttable-1.7.0-py2.py3-none-any.whl (10 kB)
Installing collected packages: texttable, thresholdclustering, rapidfuzz, pulp, igraph, eva-lcd, dynetx, demon, python-igraph, L
evenshtein, python-Levenshtein, bimlpa, angelcommunity, cdlib
Successfully installed Levenshtein-0.25.1 angelcommunity-2.0.0 bimlpa-0.1.2 cdlib-0.4.0 demon-2.0.6 dynetx-0.3.2 eva-lcd-0.1.1 i
graph-0.11.6 pulp-2.9.0 python-Levenshtein-0.25.1 python-igraph-0.11.6 rapidfuzz-3.9.6 texttable-1.7.0 thresholdclustering-1.1
Note: to be able to use all crisp methods, you need to install some additional packages:  {'bayanpy', 'leidenalg', 'graph_tool',
'wurlitzer', 'infomap'}
Note: to be able to use all crisp methods, you need to install some additional packages:  {'ASLPAw', 'pyclustering'}
Note: to be able to use all crisp methods, you need to install some additional packages:  {'wurlitzer', 'infomap', 'leidenalg'}
<Figure size 1200x800 with 0 Axes>
```



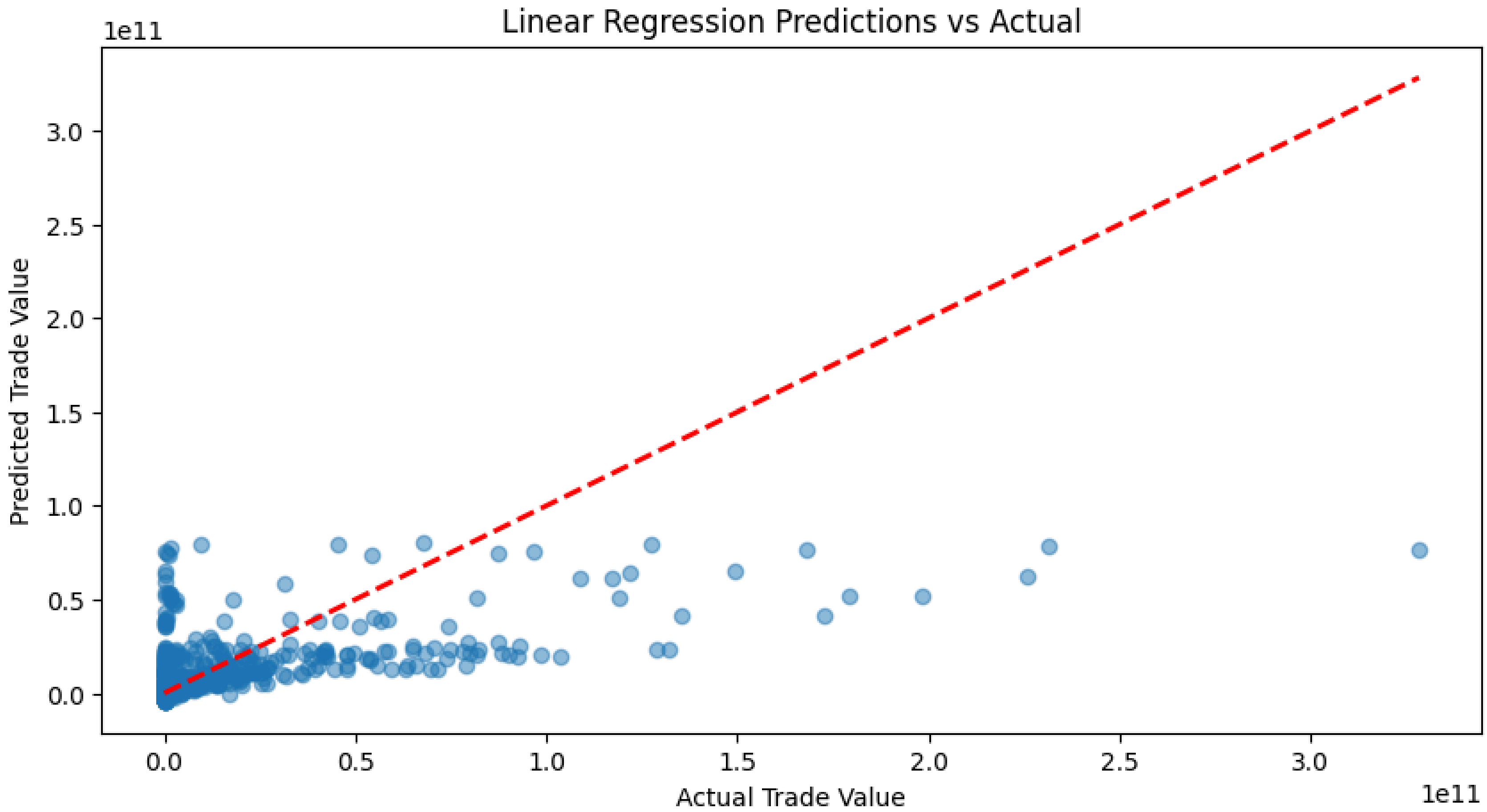
In [63]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import StandardScaler

# Load the dataset
df = pd.read_csv('/content/Global Crude Petroleum Trade 1995-2021.csv')

# Print the first few rows and columns info to check data types
print(df.head())
print(df.info())

# Preprocess the dataset
# Convert 'Year' to a numeric format
df['Year'] = pd.to_datetime(df['Year'], format='%Y').dt.year

# Convert categorical variables to numeric using one-hot encoding
df = pd.get_dummies(df, columns=['Continent', 'Country', 'Action'], drop_first=True)

# Ensure 'Trade Value' is numeric
df['Trade Value'] = pd.to_numeric(df['Trade Value'], errors='coerce')

# Handle missing values if any
df = df.dropna()

# Define features and target
features = df.drop(['Trade Value'], axis=1)
target = df['Trade Value']

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(features, target, test_size=0.2, random_state=42)

# Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Initialize models
models = {
    'Linear Regression': LinearRegression(),
    'Decision Tree': DecisionTreeRegressor(),
    'Random Forest': RandomForestRegressor()
```

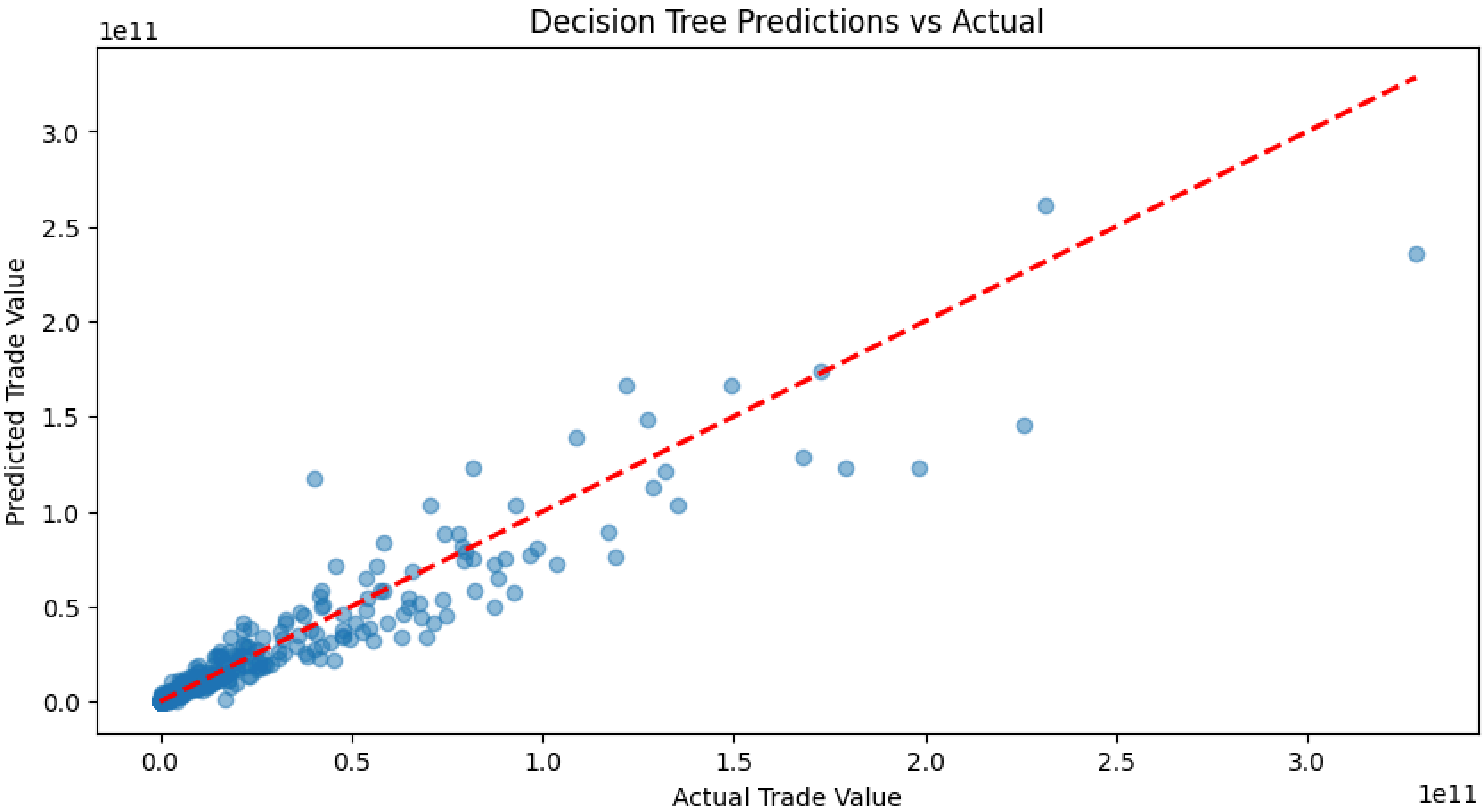
```
}

# Train and evaluate models
for model_name, model in models.items():
    model.fit(X_train_scaled, y_train)
    y_pred = model.predict(X_test_scaled)

    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)

    print(f"{model_name}:")
    print(f"  Mean Squared Error: {mse:.2f}")
    print(f"  R2 Score: {r2:.2f}")

    # Plot predictions vs actual values
    plt.figure(figsize=(10, 5))
    plt.scatter(y_test, y_pred, alpha=0.5)
    plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--', lw=2)
    plt.xlabel('Actual Trade Value')
    plt.ylabel('Predicted Trade Value')
    plt.title(f'{model_name} Predictions vs Actual')
    plt.show()

# User input for prediction
def predict_trade_value(model, scaler, feature_names):
    # Get user input
    print("Enter the details for prediction:")
    year = int(input("Year (e.g., 2021): "))
    continent = input("Continent (e.g., Africa, Asia): ")
    country = input("Country (e.g., Nigeria, China): ")
    action = input("Action (Export or Import): ")

    # Prepare input data
    user_data = {
        'Year': [year],
        **{f'Continent_{continent}': [1] if f'Continent_{continent}' in feature_names else [0] for f in feature_names if f.starts
        **{f'Country_{country}': [1] if f'Country_{country}' in feature_names else [0] for f in feature_names if f.startswith('Co
        **{f'Action_{action}': [1] if f'Action_{action}' in feature_names else [0] for f in feature_names if f.startswith('Action
    }

    # Ensure all possible columns are in user_data
    for col in feature_names:
        if col not in user_data:
            user_data[col] = [0]
```

```
    user_df = pd.DataFrame(user_data)

    # Ensure the feature columns match
    user_df = user_df.reindex(columns=feature_names, fill_value=0)

    # Standardize the user input data
    user_df_scaled = scaler.transform(user_df)

    # Predict using the best model
    model_name = 'Random Forest'  # or any other model you prefer
    model = models[model_name]
    prediction = model.predict(user_df_scaled)

    print(f"Predicted Trade Value: ${prediction[0]:,.2f}")

    # Plot the prediction
    plt.figure(figsize=(10, 5))
    plt.plot(['User Prediction'], prediction, marker='o', markersize=10, color='b', label='User Prediction')
    plt.ylabel('Trade Value')
    plt.title('Trade Value Prediction')
    plt.legend()
    plt.grid(True)
    plt.show()

# Get the feature names used for training
feature_names = X_train.columns

# Call the function to get user input and predict
predict_trade_value(RandomForestRegressor(), scaler, feature_names)
```

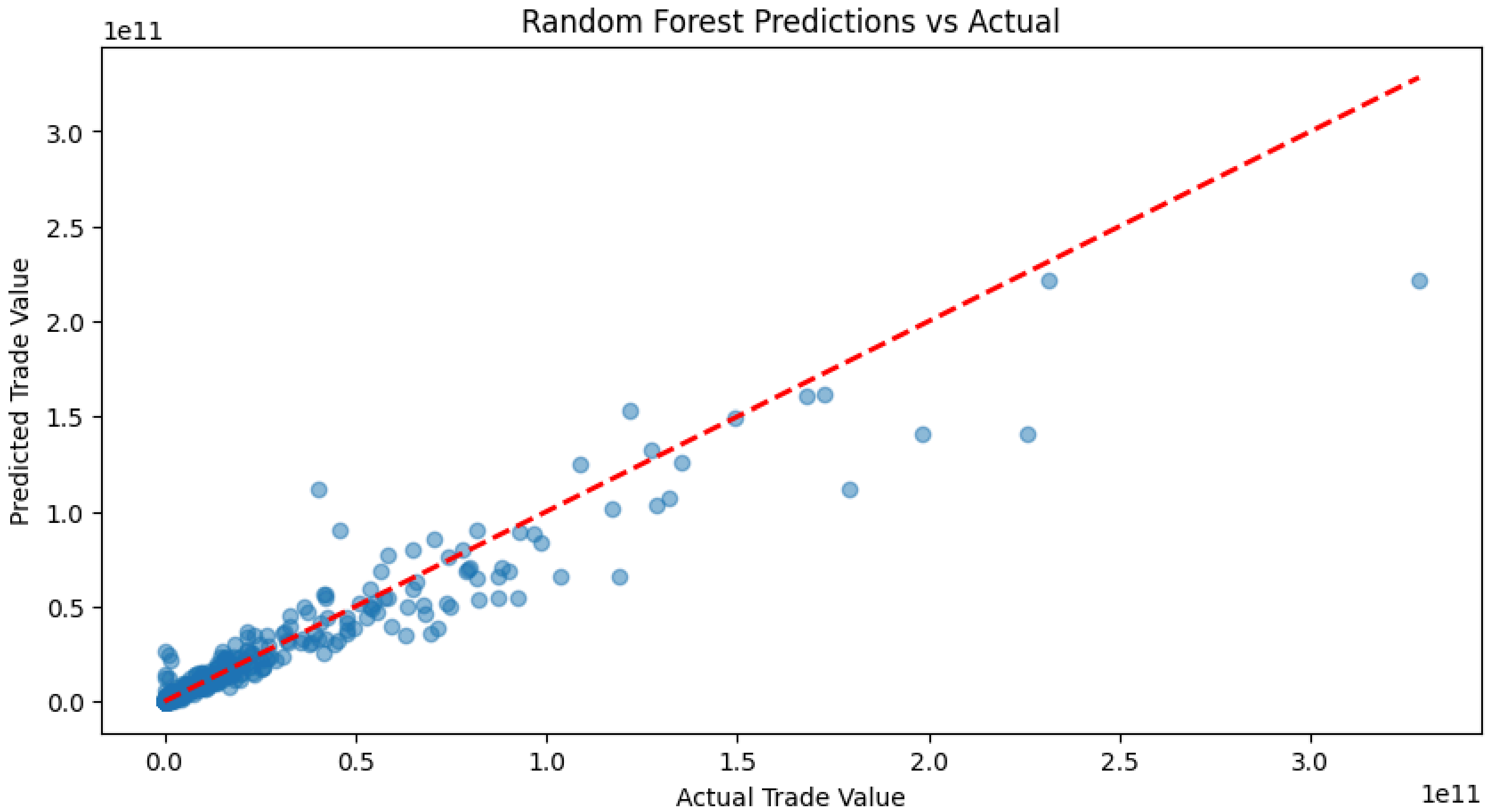
```
  Continent                           Country   Trade Value  Year  Action
0    Africa                            Angola  2.767000e+10  2021  Export
1    Africa                          Botswana  2.055000e+03  2021  Export
2    Africa                     Cote d'Ivoire  4.447282e+08  2021  Export
3    Africa                          Cameroon  1.865465e+09  2021  Export
4    Africa  Democratic Republic of the Congo  5.815086e+08  2021  Export
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7925 entries, 0 to 7924
Data columns (total 5 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   Continent    7925 non-null   object 
 1   Country      7925 non-null   object 
 2   Trade Value  7925 non-null   float64
 3   Year         7925 non-null   int64  
 4   Action       7925 non-null   object 
dtypes: float64(1), int64(1), object(3)
memory usage: 309.7+ KB
None
Linear Regression:
  Mean Squared Error: 296496647125145026560.00
  R2 Score: 0.36
```



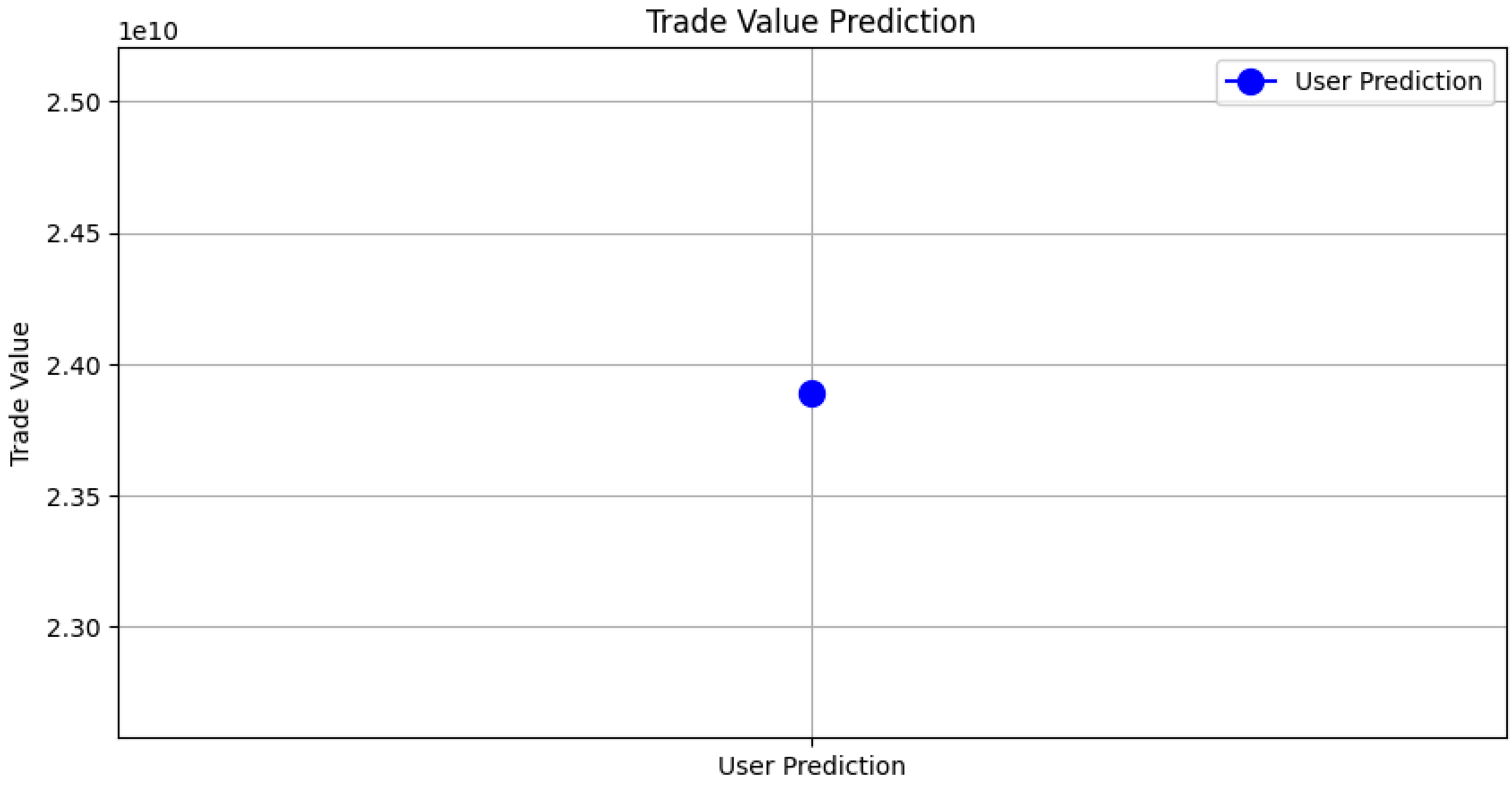

```
Decision Tree:
  Mean Squared Error: 4188932422585252249 6.00
  R2 Score: 0.91
```




```
Random Forest:
  Mean Squared Error: 38375081547744796672.00
  R2 Score: 0.92
```




```
Enter the details for prediction:
Year (e.g., 2021): 2021
Continent (e.g., Africa, Asia): Africa
Country (e.g., Nigeria, China): Angola
Action (Export or Import): Export
Predicted Trade Value: $23,892,164,642.24
```


Trade Value Prediction
1e10
User Prediction
2.50
2.45
2.40
2.35
2.30
Trade Value
User Prediction