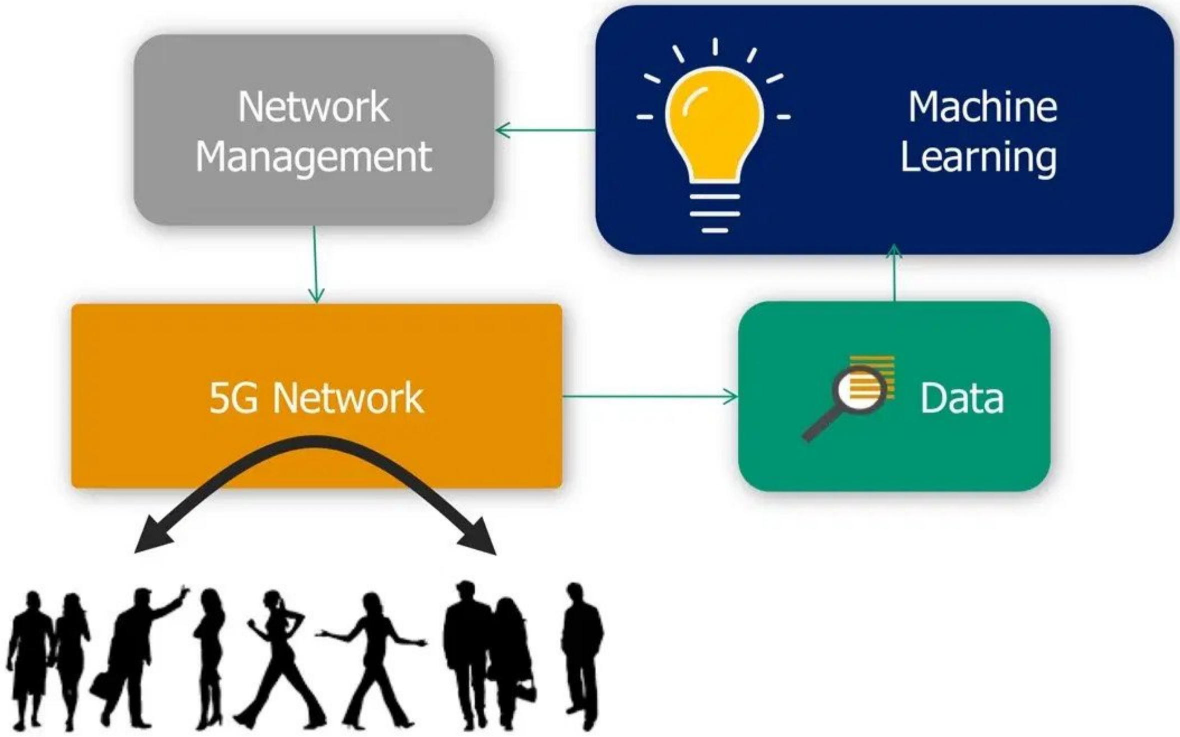
Resource Allocation Optimization in 5G Networks: A Machine Learning Approach



In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px # is a high-level interface for creating various types of in
import plotly.graph_objects as go # is a lower-level interface that offers more control
```

In [2]:

```
import warnings
warnings.filterwarnings('ignore')
```

In [3]:

```
df = pd.read_csv("5G_Service.csv")
```

In [4]:

```
df.head()
```

Out[4]:

	Timestamp	User_ID	Application_Type	Signal_Strength	Latency	Required_Bandwidth	A
0	09-03-2023 10:00	User_1	Video_Call	-75 dBm	30 ms	10 Mbps	
1	09-03-2023 10:00	User_2	Voice_Call	-80 dBm	20 ms	100 Kbps	
2	09-03-2023 10:00	User_3	Streaming	-85 dBm	40 ms	5 Mbps	
3	09-03-2023 10:00	User_4	Emergency_Service	-70 dBm	10 ms	1 Mbps	
4	09-03-2023 10:00	User_5	Online_Gaming	-78 dBm	25 ms	2 Mbps	

In [5]:

```
df.tail()
```

Out[5]:

	Timestamp	User_ID	Application_Type	Signal_Strength	Latency	Required_Bandwidth
395	09-03-2023 10:06	User_396	Streaming	-110 dBm	61 ms	1.3 Mbps
396	09-03-2023 10:06	User_397	Video_Call	-40 dBm	53 ms	14.5 Mbps
397	09-03-2023 10:06	User_398	Video_Streaming	-113 dBm	58 ms	1.0 Mbps
398	09-03-2023 10:06	User_399	Emergency_Service	-40 dBm	5 ms	0.4 Mbps
399	09-03-2023 10:06	User_400	Web_Browsing	-113 dBm	0 ms	0.1 Mbps

In [6]:

```
df.shape
```

Out[6]:

```
(400, 8)
```

In [7]:

```
df.columns
```

Out[7]:

```
Index(['Timestamp', 'User_ID', 'Application_Type', 'Signal_Strength',
       'Latency', 'Required_Bandwidth', 'Allocated_Bandwidth',
       'Resource_Allocation'],
      dtype='object')
```

In [8]:

```
df.duplicated().sum()
```

Out[8]:

```
0
```

In [9]:

```
df.isnull().sum()
```

Out[9]:

```
Timestamp              0
User_ID                0
Application_Type       0
Signal_Strength        0
Latency                0
Required_Bandwidth     0
Allocated_Bandwidth    0
Resource_Allocation    0
dtype: int64
```

In [10]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 8 columns):
 #   Column               Non-Null Count  Dtype 
---  ------               --------------  ----- 
 0   Timestamp            400 non-null    object
 1   User_ID              400 non-null    object
 2   Application_Type     400 non-null    object
 3   Signal_Strength      400 non-null    object
 4   Latency              400 non-null    object
 5   Required_Bandwidth   400 non-null    object
 6   Allocated_Bandwidth  400 non-null    object
 7   Resource_Allocation  400 non-null    object
dtypes: object(8)
memory usage: 25.1+ KB
```

In [11]:

```
df.nunique()
```

Out[11]:

```
Timestamp               7
User_ID               400
Application_Type       11
Signal_Strength        84
Latency                87
Required_Bandwidth    188
Allocated_Bandwidth   194
Resource_Allocation     9
dtype: int64
```

In [12]:

```
df['Timestamp'] = pd.to_datetime(df['Timestamp'])
```

In [13]:

```
df['Signal_Strength'] = df['Signal_Strength'].str.replace(' dBm', '').astype(float)
df['Latency'] = df['Latency'].str.replace(' ms', '').astype(float)
df['Required_Bandwidth'] = df['Required_Bandwidth'].str.replace(' Mbps', '').str.replace
df['Allocated_Bandwidth'] = df['Allocated_Bandwidth'].str.replace(' Mbps', '').str.repla
df['Resource_Allocation'] = df['Resource_Allocation'].str.rstrip('%').astype(float) / 10
```

In [14]:

```
missing_values = df.isnull().sum()
print("Missing Values:")
print(missing_values)
```

```
Missing Values:
Timestamp              0
User_ID                0
Application_Type       0
Signal_Strength        0
Latency                0
Required_Bandwidth     0
Allocated_Bandwidth    0
Resource_Allocation    0
dtype: int64
```

In [15]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 8 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   Timestamp            400 non-null    datetime64[ns]
 1   User_ID              400 non-null    object
 2   Application_Type     400 non-null    object
 3   Signal_Strength      400 non-null    float64
 4   Latency              400 non-null    float64
 5   Required_Bandwidth   400 non-null    float64
 6   Allocated_Bandwidth  400 non-null    float64
 7   Resource_Allocation  400 non-null    float64
dtypes: datetime64[ns](1), float64(5), object(2)
memory usage: 25.1+ KB
```

In [16]:

```
df.describe()
```

Out[16]:

	Signal_Strength	Latency	Required_Bandwidth	Allocated_Bandwidth	Resource_All
count	400.000000	400.000000	400.000000	400.000000	400.
mean	-80.495000	33.825000	3.135512	3.502380	0.
std	20.701119	21.122139	3.984097	4.460801	0.
min	-123.000000	0.000000	0.000000	0.000000	0.
25%	-98.000000	21.750000	0.417500	0.417500	0.
50%	-83.000000	31.000000	1.200000	1.350000	0.
75%	-64.000000	45.000000	4.100000	4.425000	0.
max	-40.000000	110.000000	14.500000	15.800000	0.

In [17]:

```
object_columns = df.select_dtypes(include='object').columns.tolist()
numerical_columns = df.select_dtypes(include=['int', 'float']).columns.tolist()

print("Object columns:", object_columns)
print("Numerical columns:", numerical_columns)
```

```
Object columns: ['User_ID', 'Application_Type']
Numerical columns: ['Signal_Strength', 'Latency', 'Required_Bandwidth', 'A
llocated_Bandwidth', 'Resource_Allocation']
```

In [18]:

```
df['Application_Type'].unique()
```

Out[18]:

```
array(['Video_Call', 'Voice_Call', 'Streaming', 'Emergency_Service',
       'Online_Gaming', 'Background_Download', 'Web_Browsing',
       'IoT_Temperature', 'Video_Streaming', 'File_Download', 'VoIP_Cal
l'],
      dtype=object)
```

In [19]:

```
df['Application_Type'].value_counts()
```

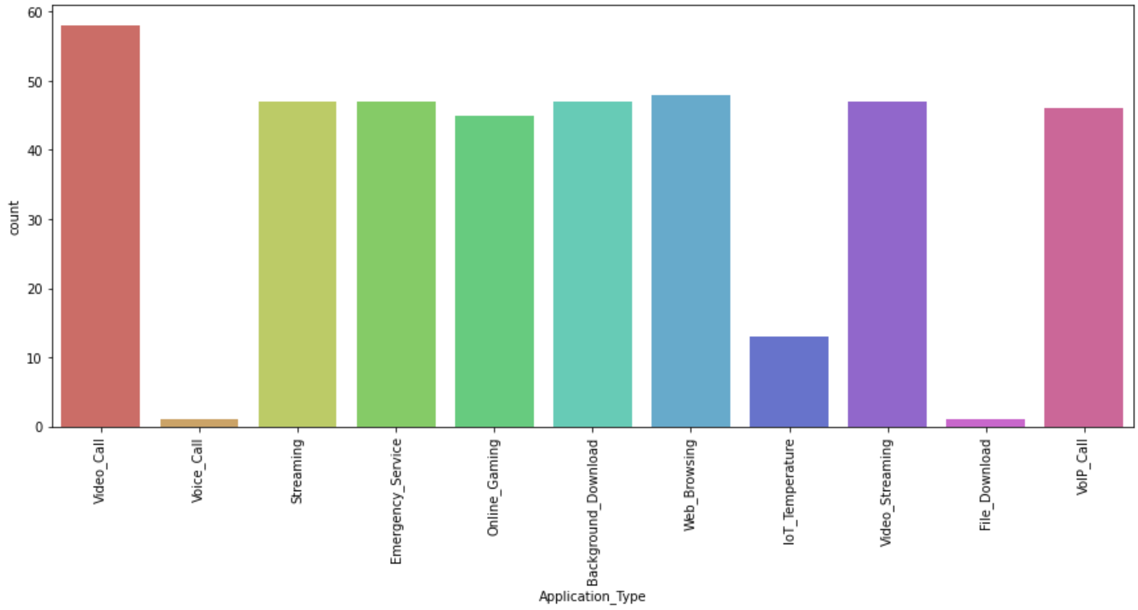
Out[19]:

```
Video_Call             58
Web_Browsing           48
Streaming              47
Emergency_Service      47
Background_Download    47
Video_Streaming        47
VoIP_Call              46
Online_Gaming          45
IoT_Temperature        13
Voice_Call              1
File_Download           1
Name: Application_Type, dtype: int64
```

In [20]:

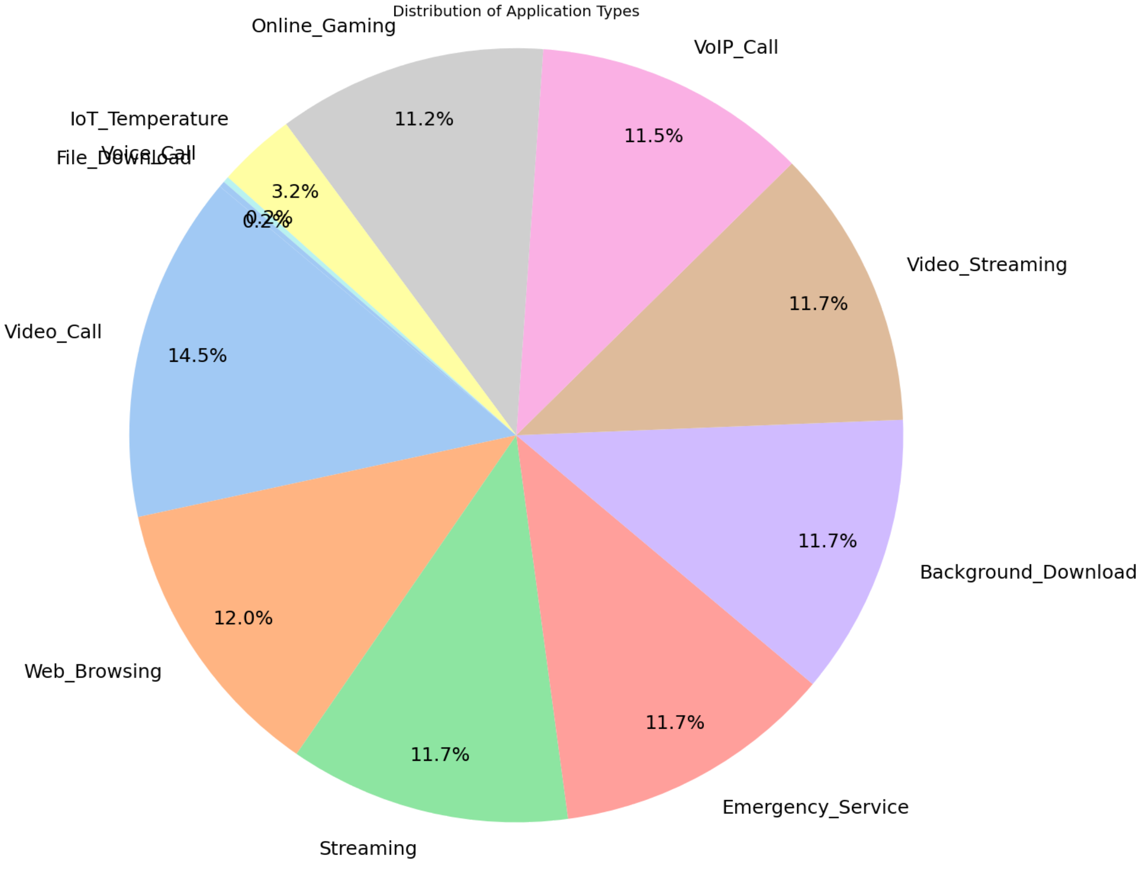
```
print('Countplot for:', 'Application Type')
plt.figure(figsize=(15,6))
sns.countplot(df['Application_Type'], data = df, palette = 'hls')
plt.xticks(rotation = 90)
plt.show()
print('\n')
```

Countplot for: Application Type



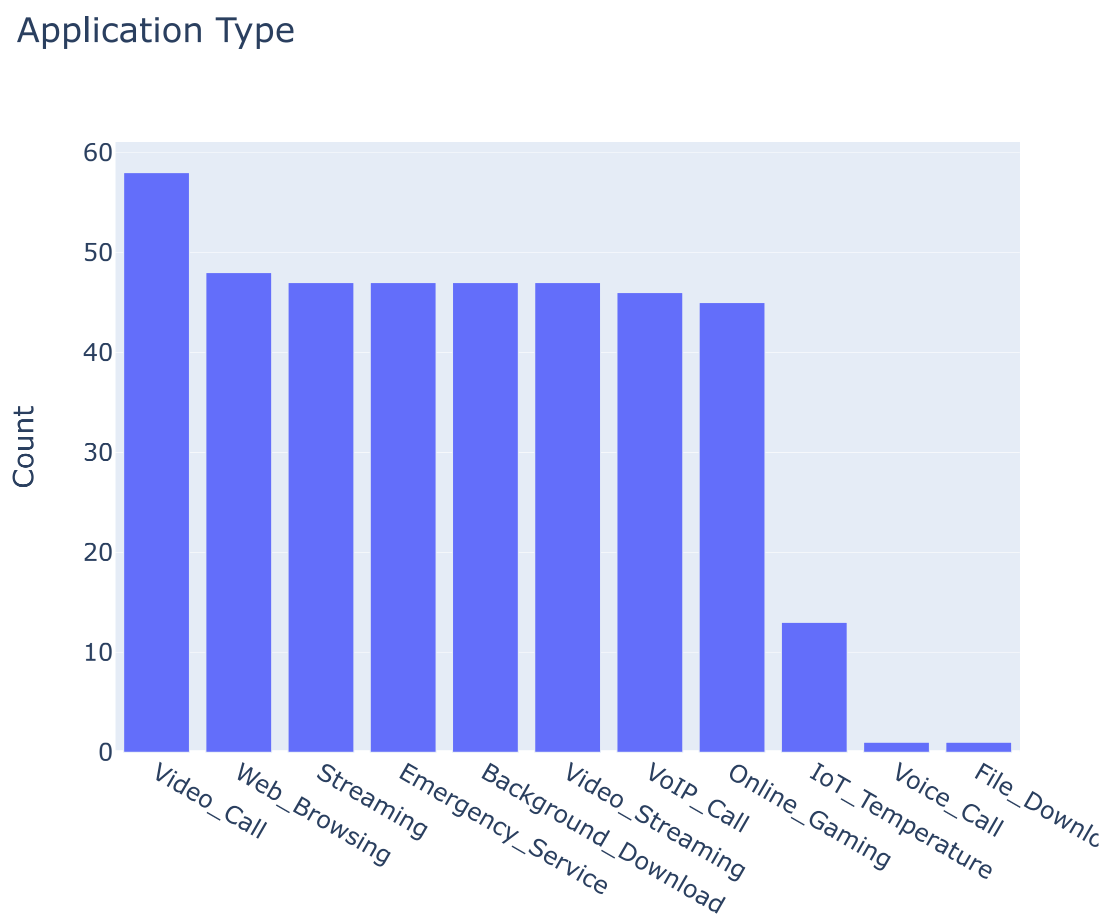
In [21]:

```
plt.figure(figsize=(20, 20))
application_type_counts = df['Application_Type'].value_counts()
colors = sns.color_palette('pastel')[0:len(application_type_counts)]
plt.pie(application_type_counts, labels=application_type_counts.index, colors=colors, au
plt.title("Distribution of Application Types", fontsize=20)
plt.axis('equal')
plt.show()
```



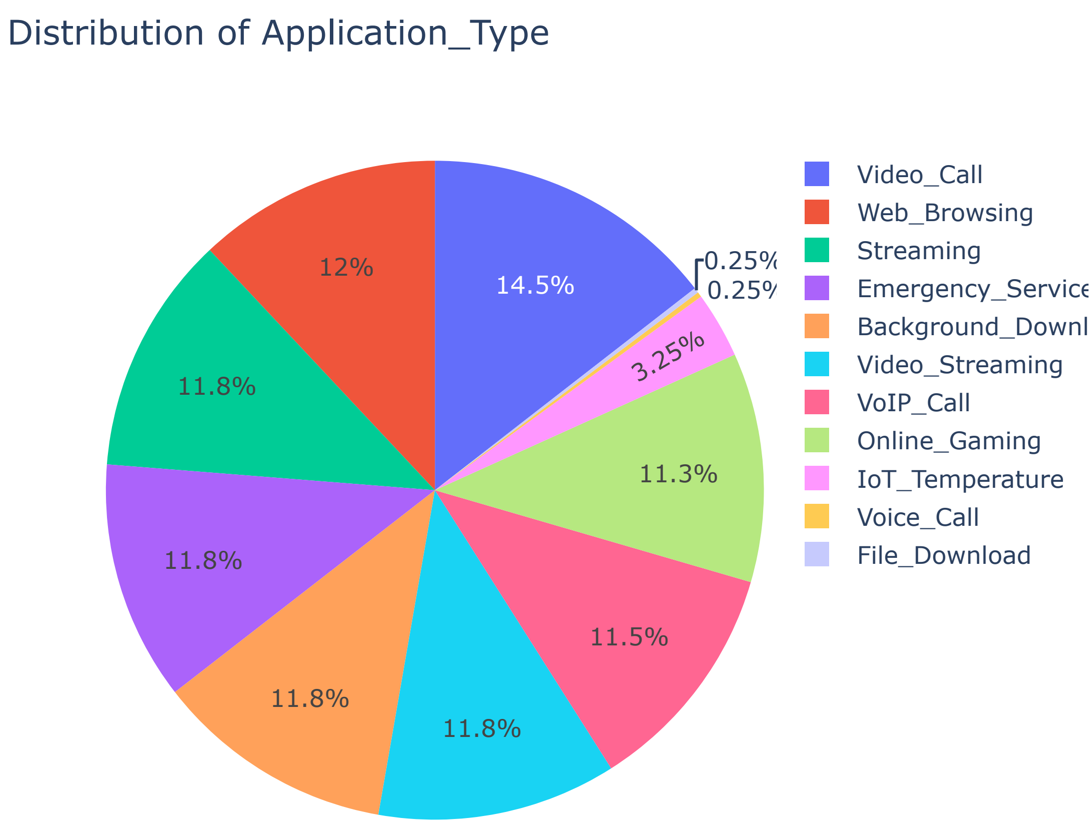
In [22]:

```
fig = go.Figure(data=[go.Bar(x=df['Application_Type'].value_counts().index, y=df['Applic
fig.update_layout(title='Application Type', xaxis_title='Application Type',
                  yaxis_title="Count")
fig.show()
```



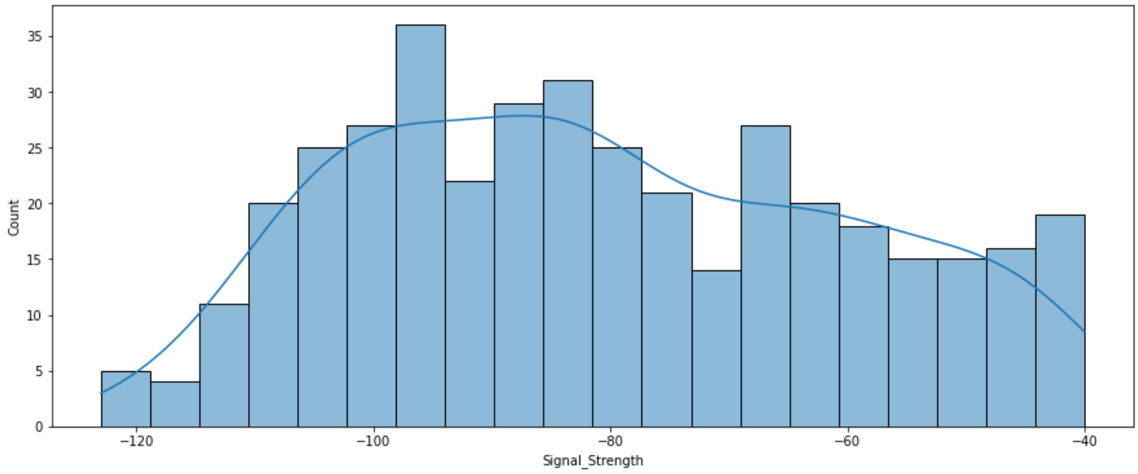
In [23]:

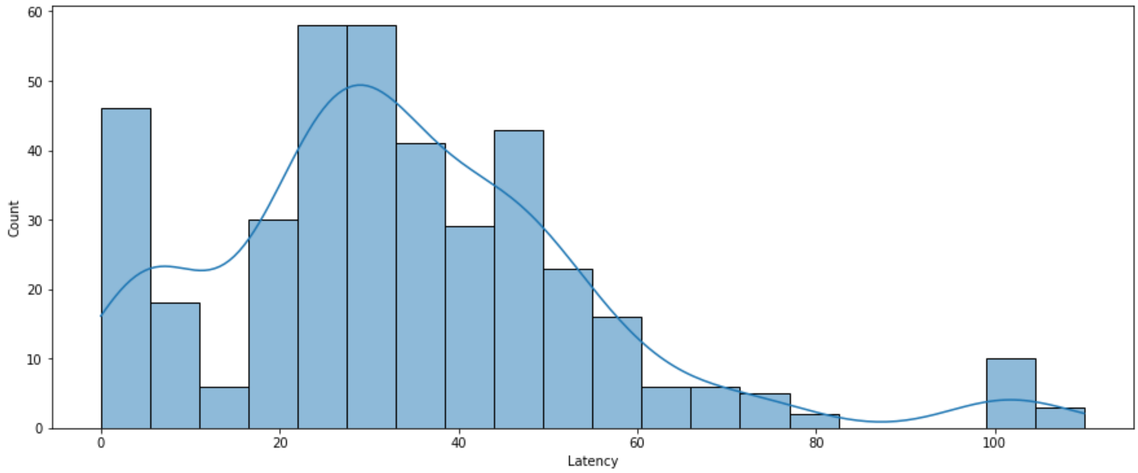
```
fig = px.pie(df, names= 'Application_Type', title='Distribution of ' + 'Application_Type
fig.show()
```

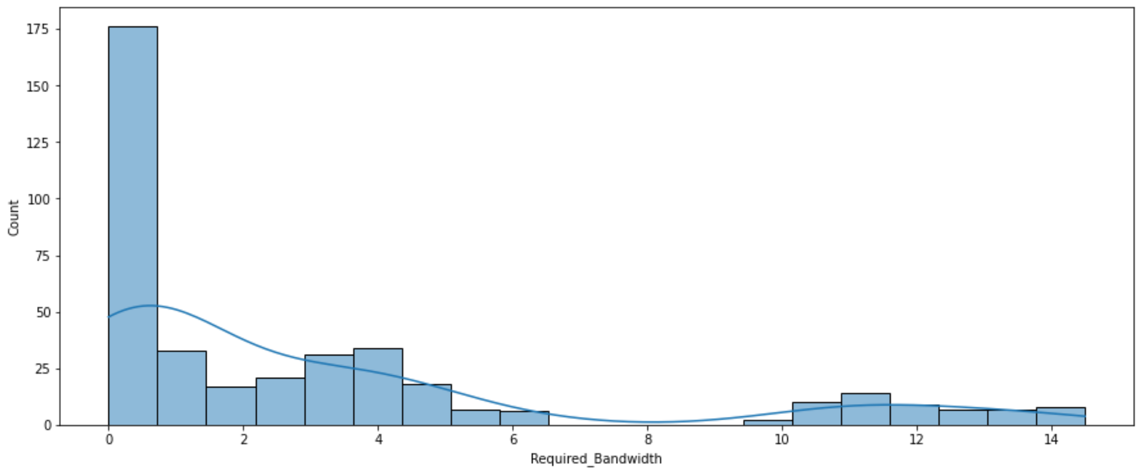


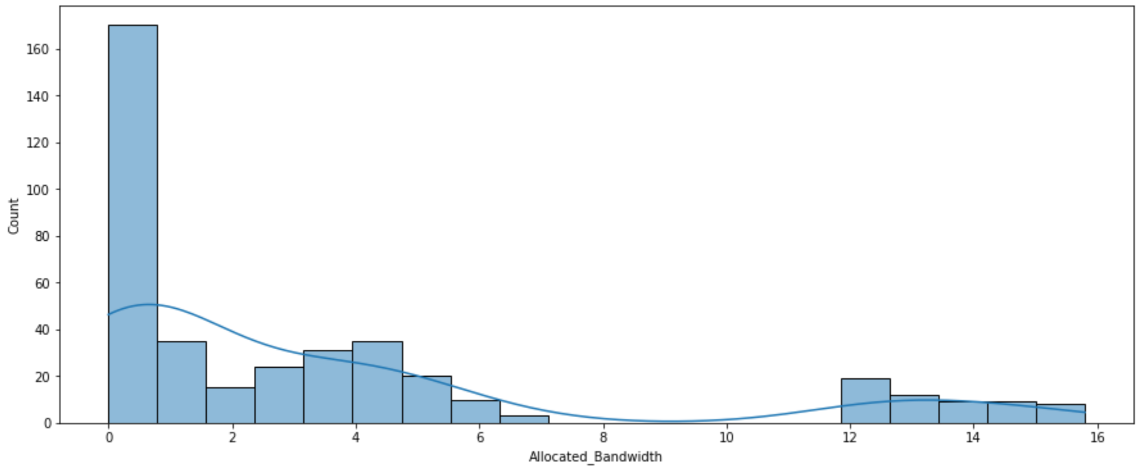
In [24]:

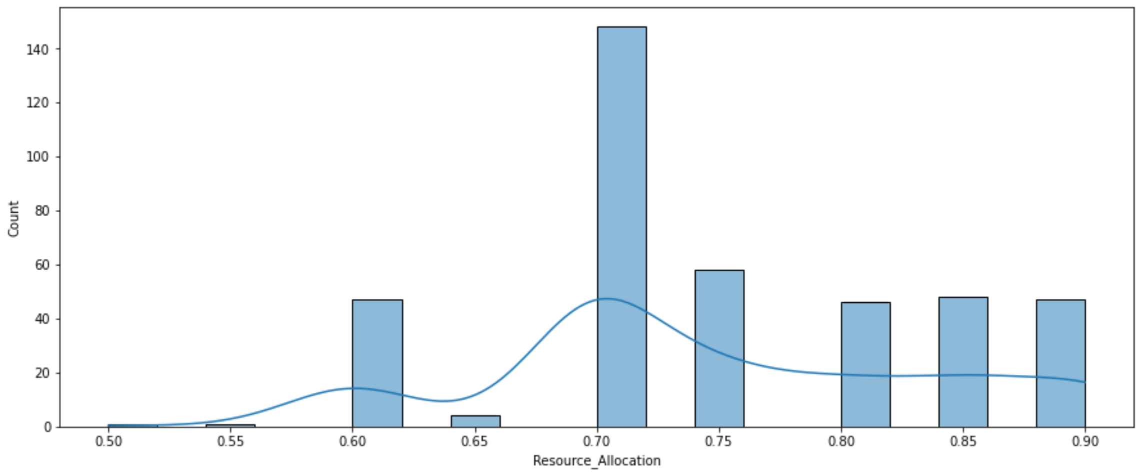
```
for i in numerical_columns:
    plt.figure(figsize=(15,6))
    sns.histplot(df[i], kde = True, bins = 20, palette = 'hls')
    plt.xticks(rotation = 0)
    plt.show()
```





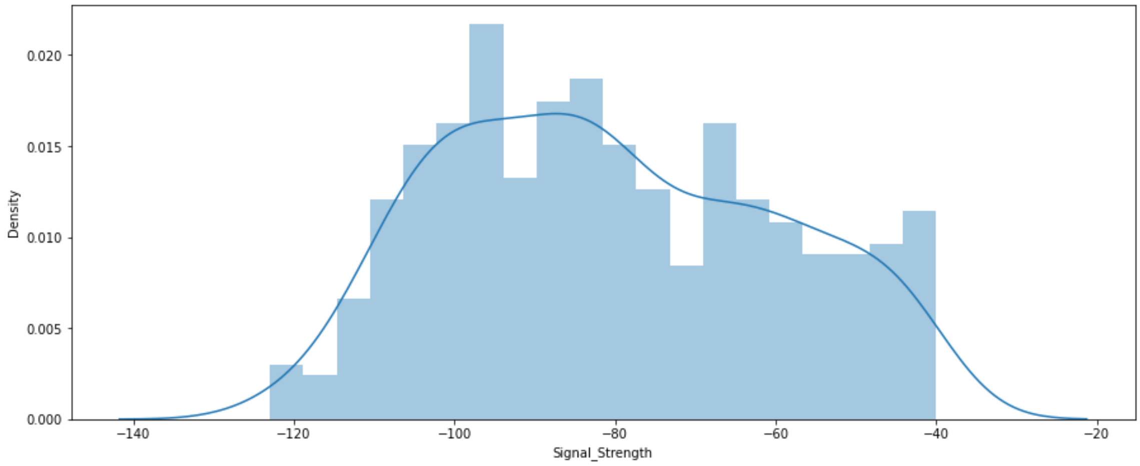


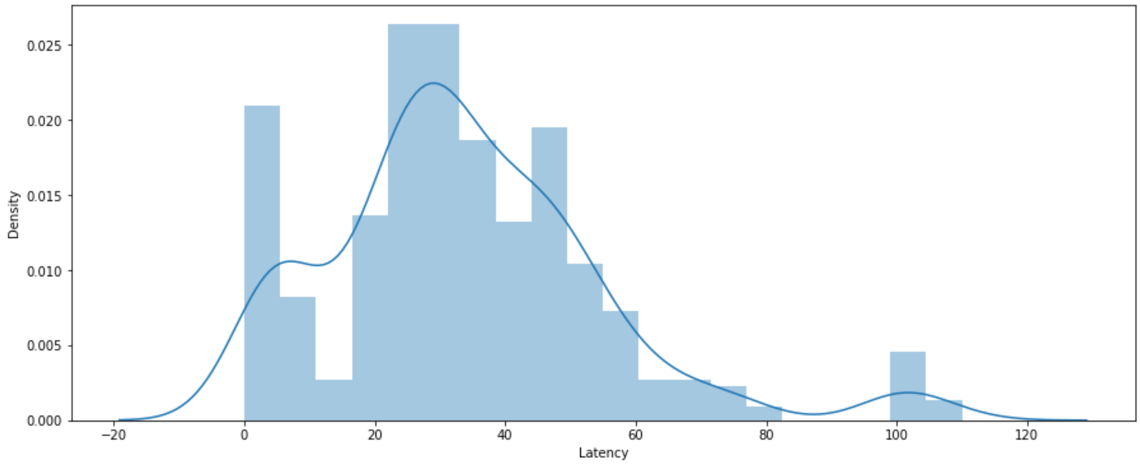

Count
Allocated_Bandwidth
0
2
4
6
8
10
12
14
16
0
20
40
60
80
100
120
140
160

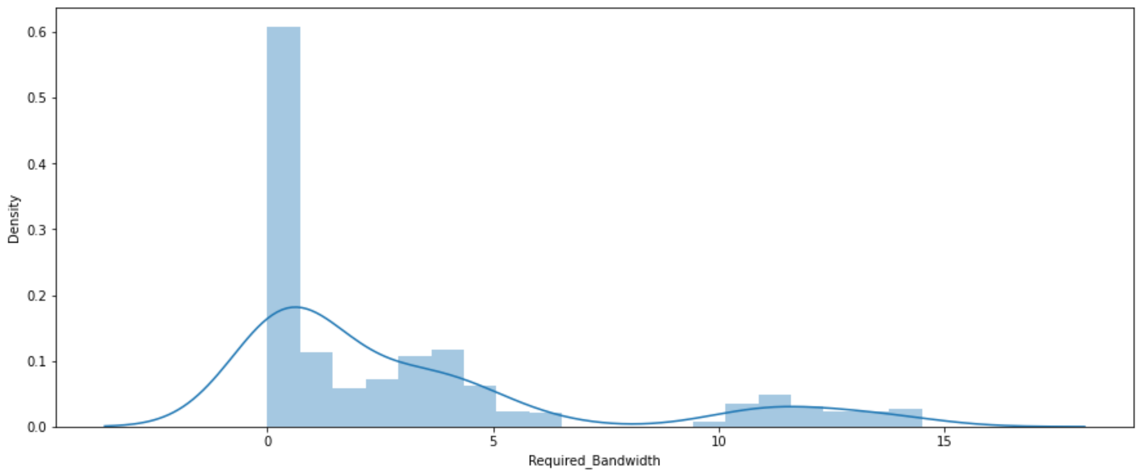

Count
Resource_Allocation
0.50
0.55
0.60
0.65
0.70
0.75
0.80
0.85
0.90
0
20
40
60
80
100
120
140

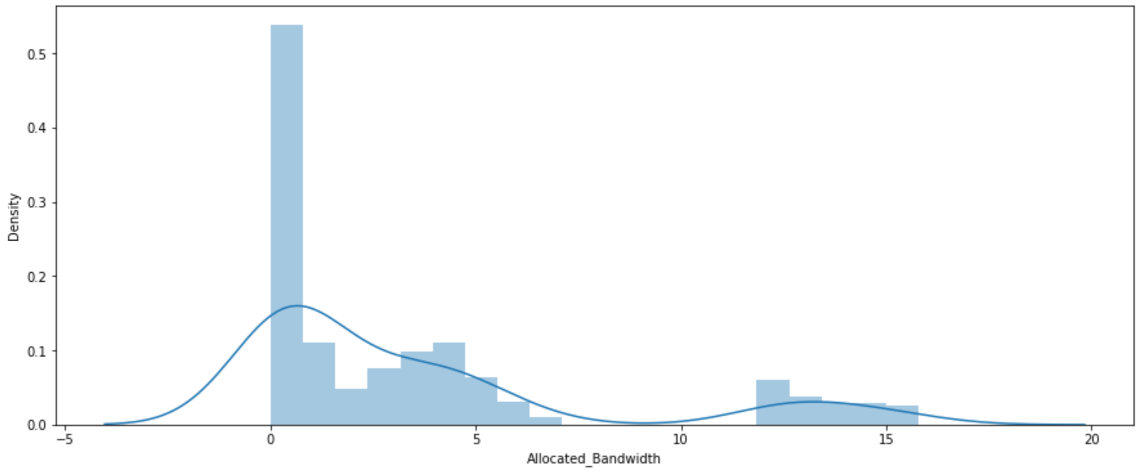
In [25]:

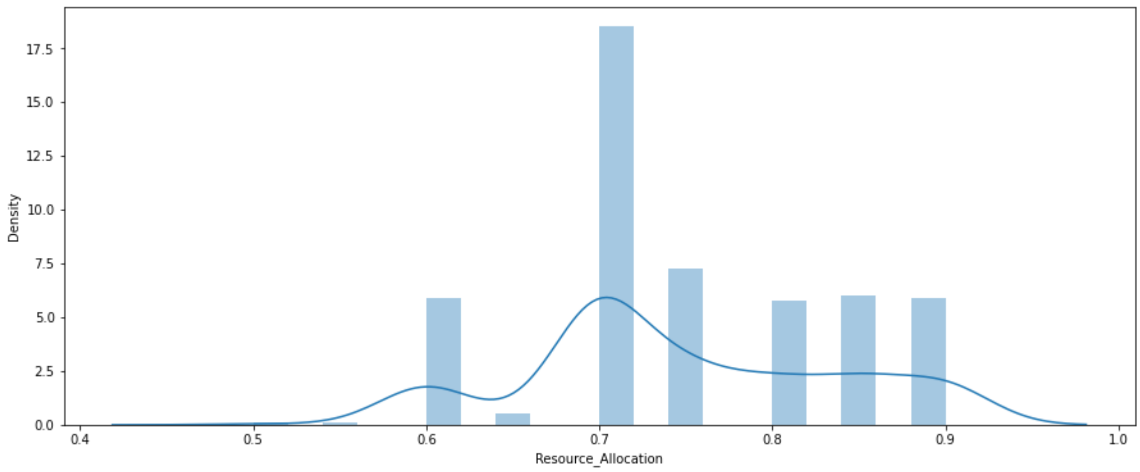
```
for i in numerical_columns:
    plt.figure(figsize=(15,6))
    sns.distplot(df[i], kde = True, bins = 20)
    plt.xticks(rotation = 0)
    plt.show()
```





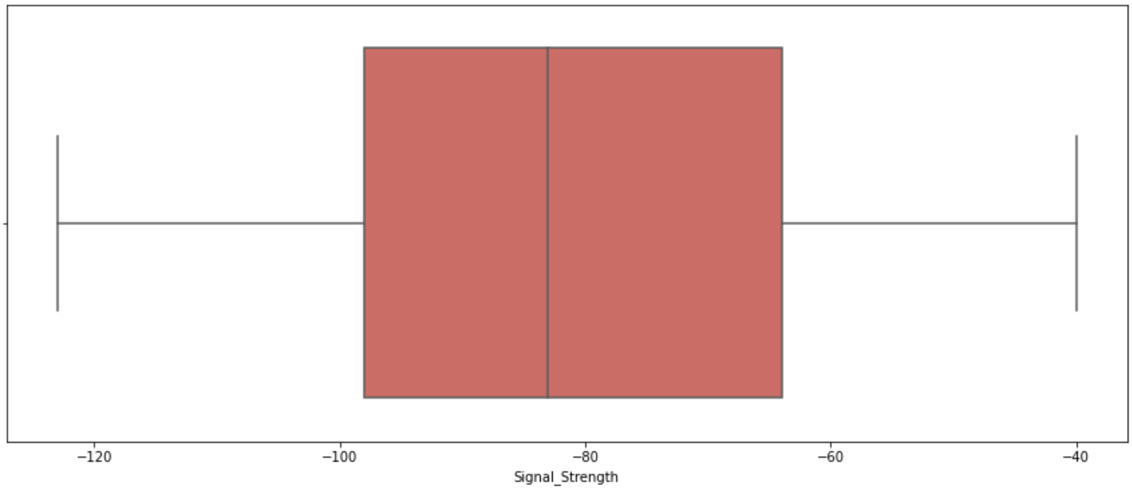


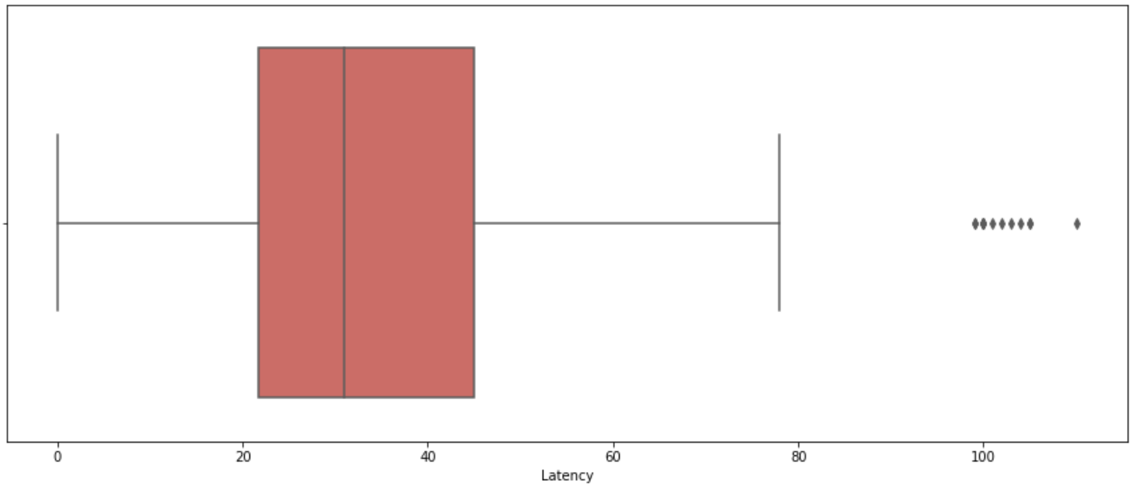

Density
Allocated_Bandwidth
0.0
0.1
0.2
0.3
0.4
0.5
−5
0
5
10
15
20

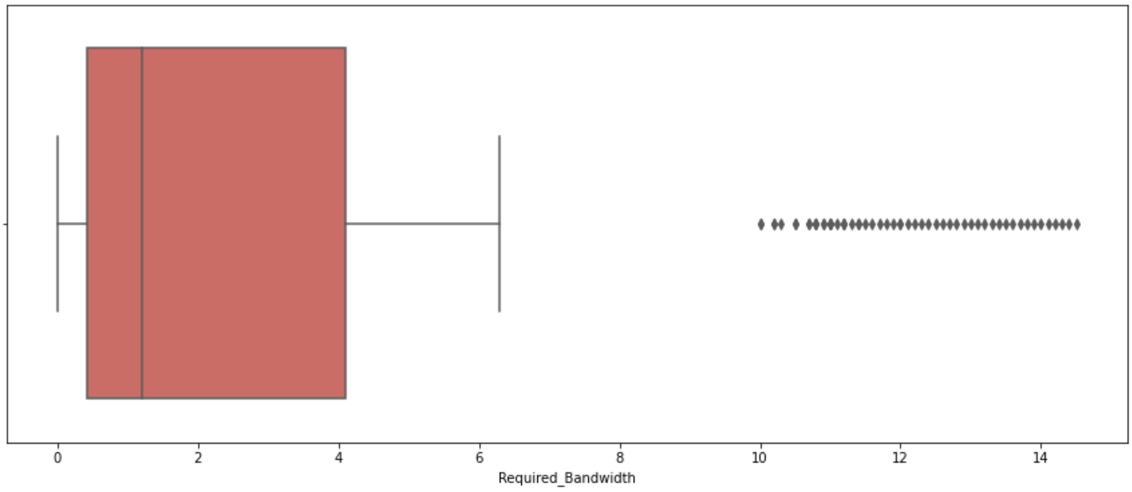

Density
Resource_Allocation
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
0.4
0.5
0.6
0.7
0.8
0.9
1.0

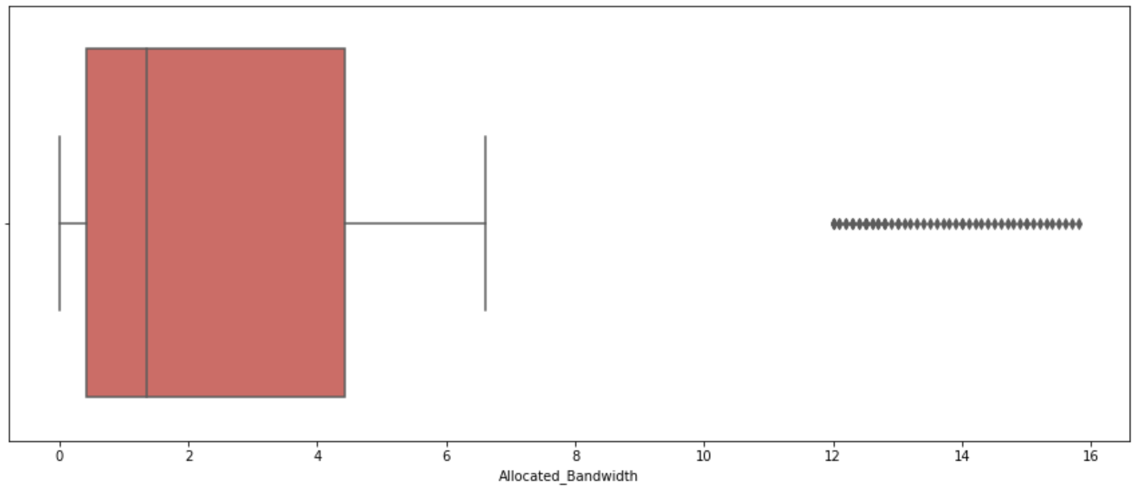
In [26]:

```
for i in numerical_columns:
    plt.figure(figsize=(15,6))
    sns.boxplot(df[i], data=df, palette='hls')
    plt.xticks(rotation = 0)
    plt.show()
```

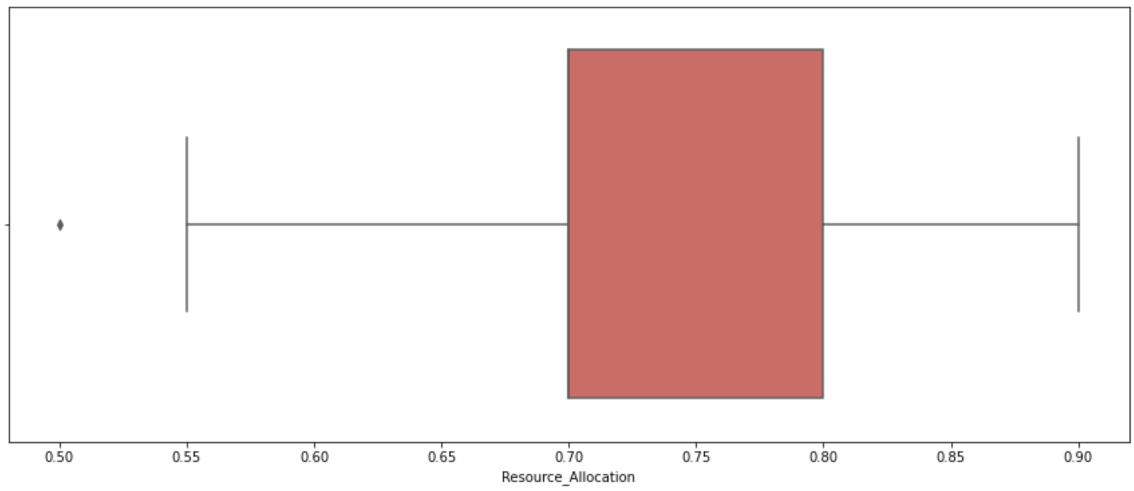








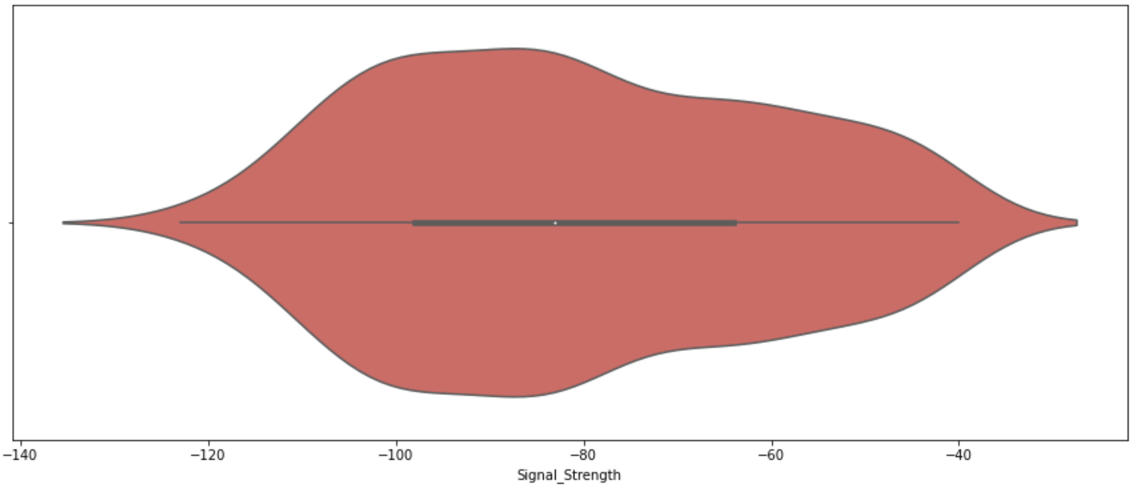
0
2
4
6
8
10
12
14
16
Allocated_Bandwidth

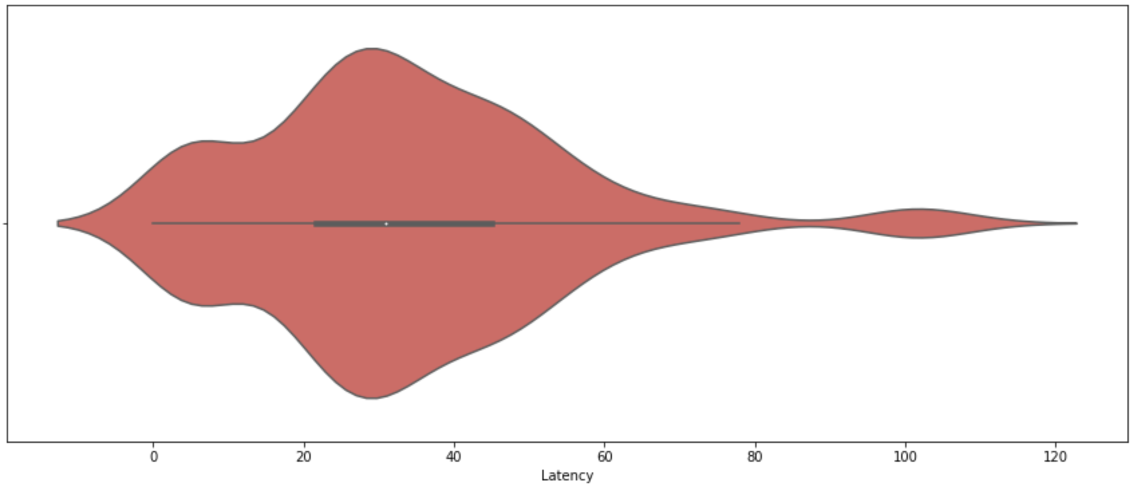


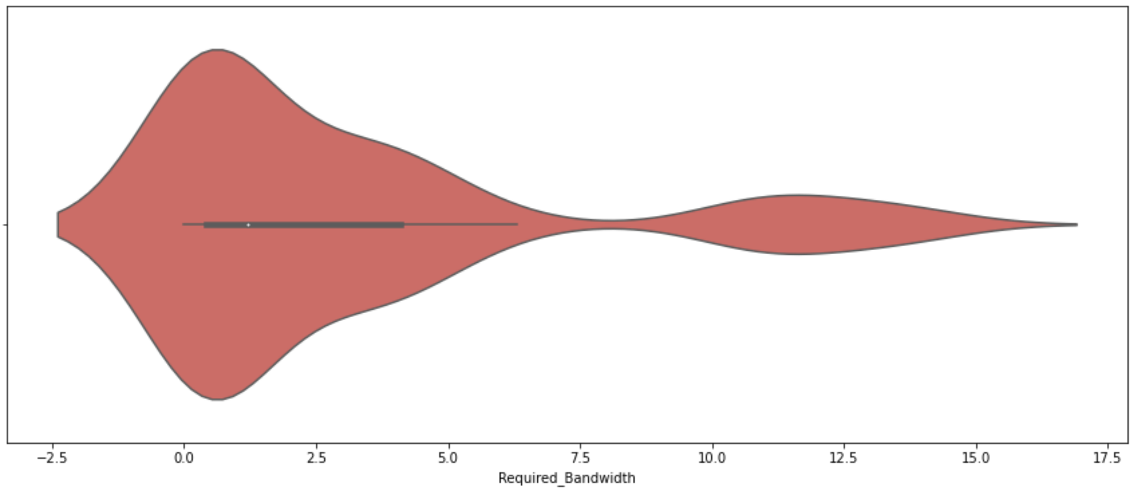
0.50
0.55
0.60
0.65
0.70
0.75
0.80
0.85
0.90
Resource_Allocation

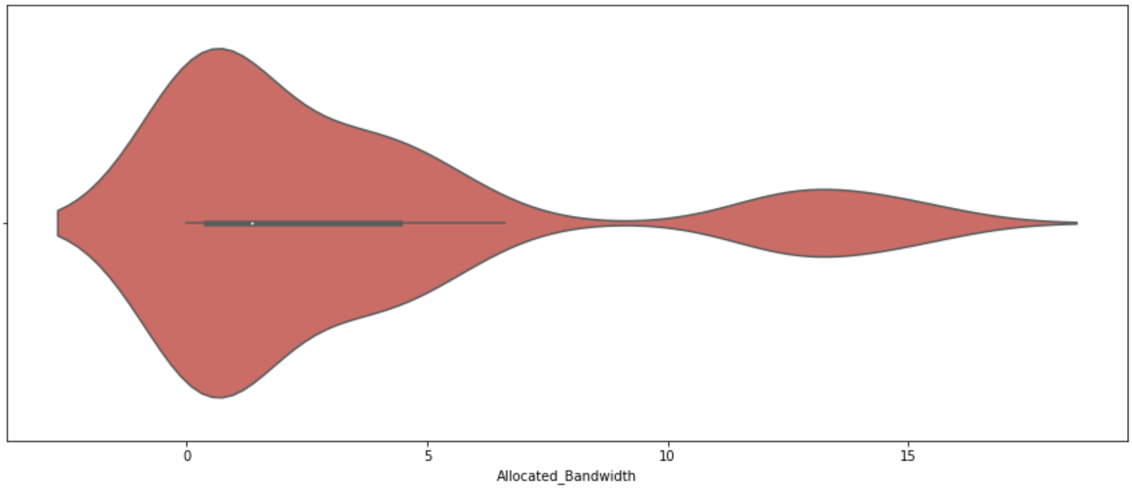
In [27]:

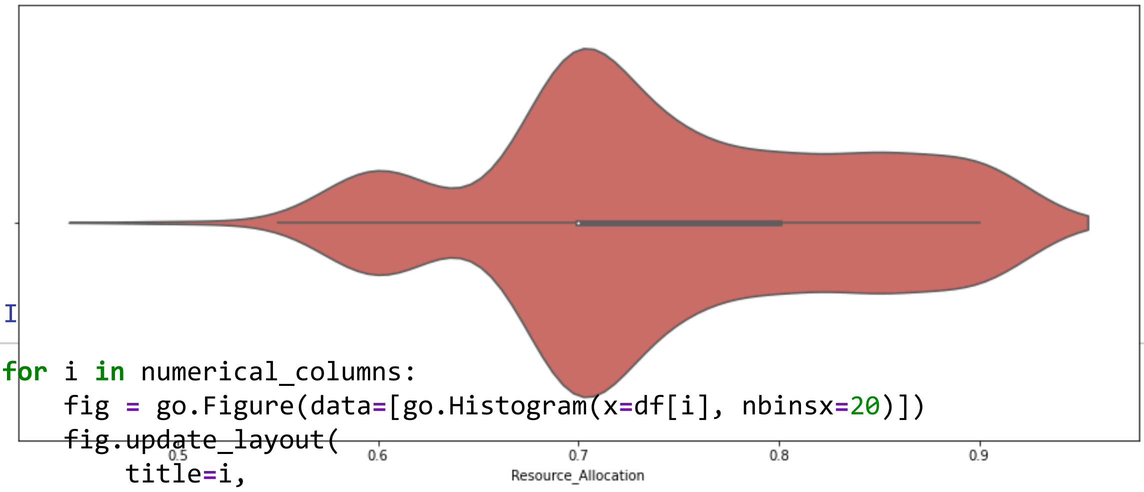
```
for i in numerical_columns:
    plt.figure(figsize=(15,6))
    sns.violinplot(df[i], data=df, palette='hls')
    plt.xticks(rotation = 0)
    plt.show()
```



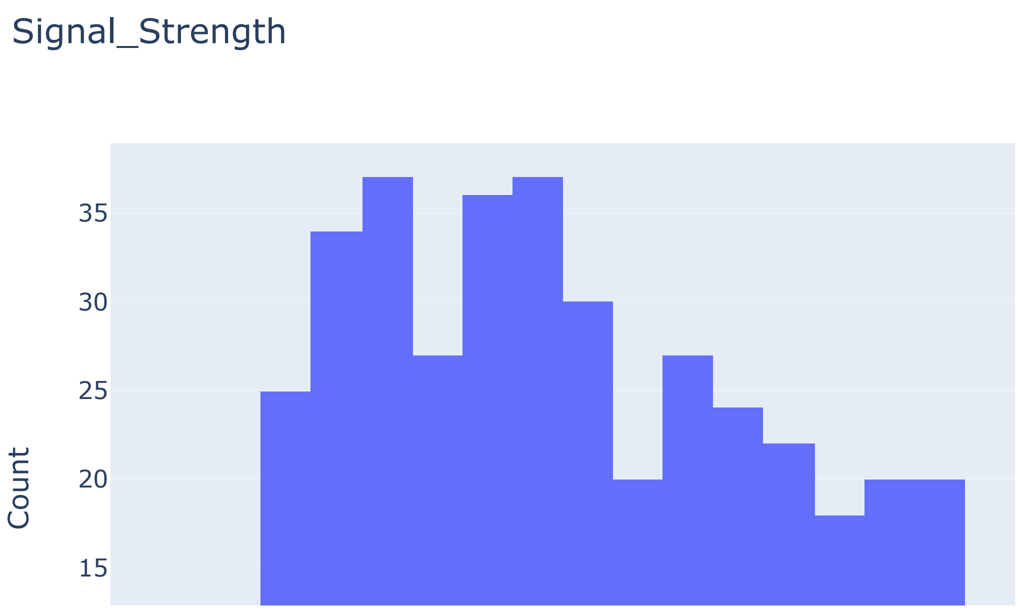






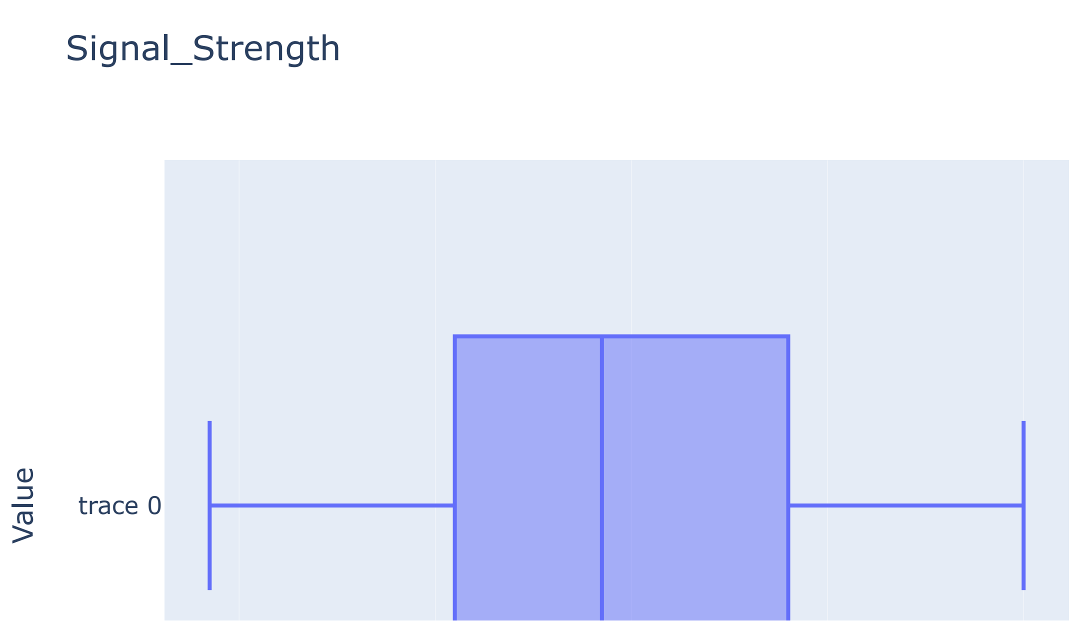



```
for i in numerical_columns:
    fig = go.Figure(data=[go.Histogram(x=df[i], nbinsx=20)])
    fig.update_layout(
        title=i,
        xaxis_title=i,
        yaxis_title="Count")
    fig.show()
```



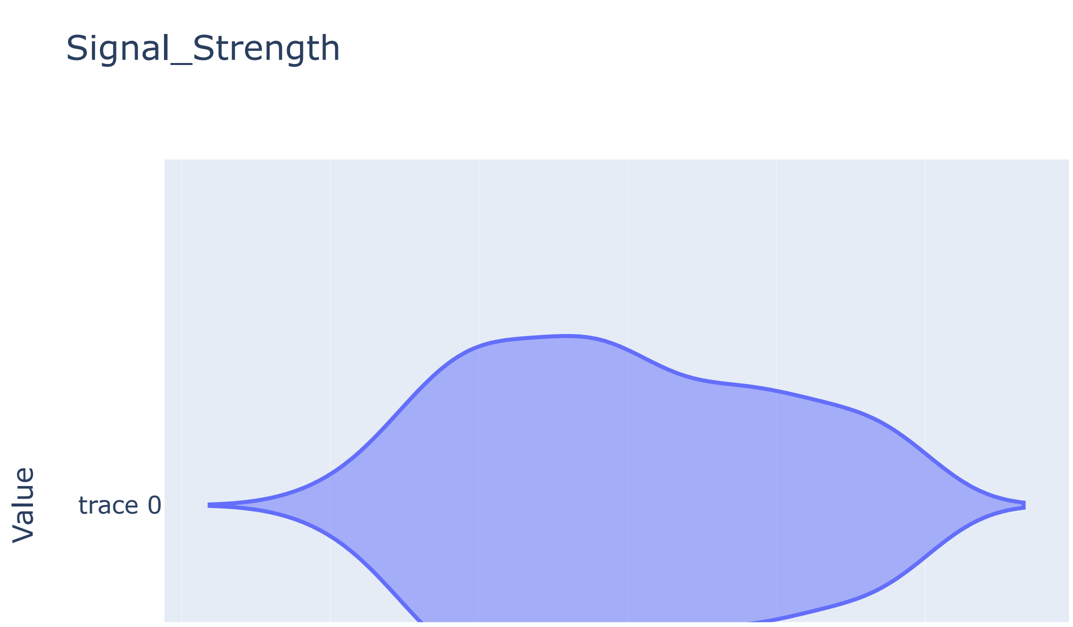
In [29]:

```
for i in numerical_columns:
    fig = go.Figure(data=[go.Box(x=df[i])])
    fig.update_layout(
        title=i,
        xaxis_title=i,
        yaxis_title="Value")
    fig.show()
```



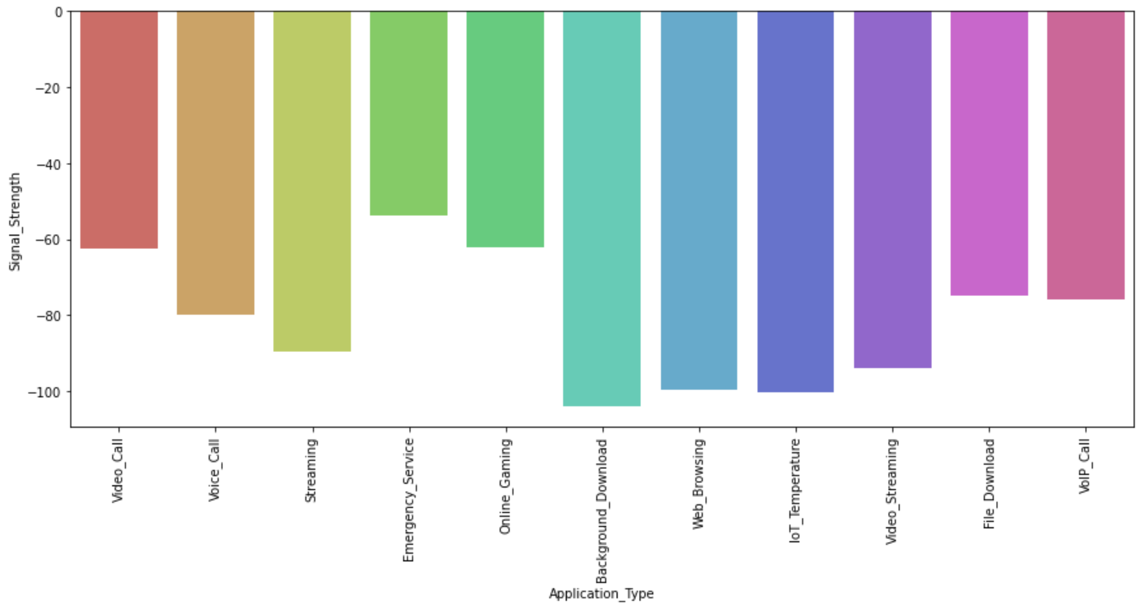
In [30]:

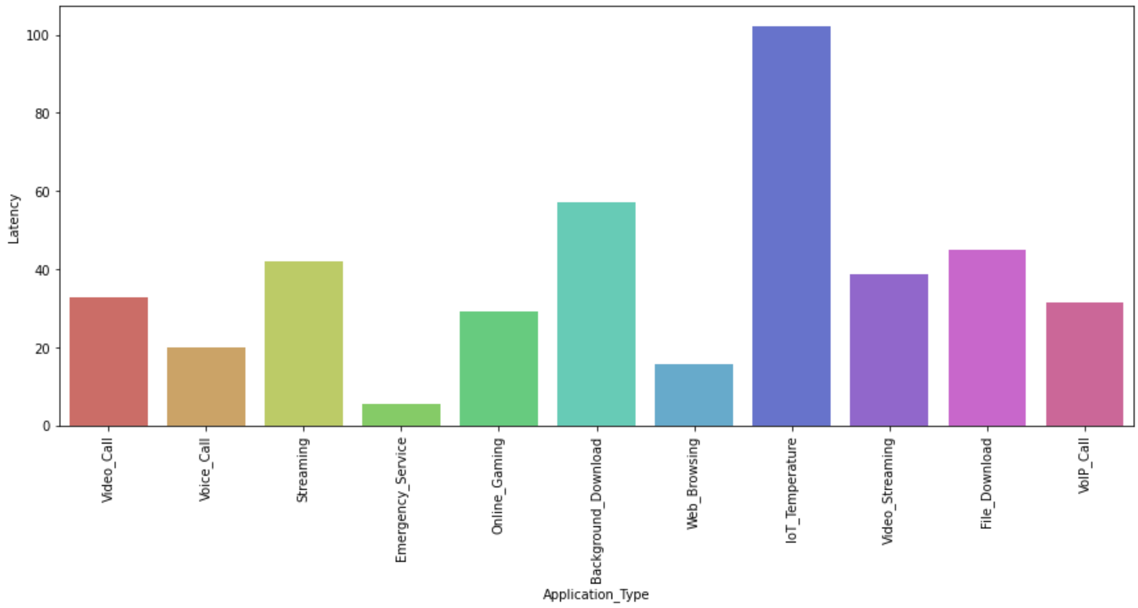
```
for i in numerical_columns:
    fig = go.Figure(data=[go.Violin(x=df[i])])
    fig.update_layout(
        title=i,
        xaxis_title=i,
        yaxis_title="Value")
    fig.show()
```

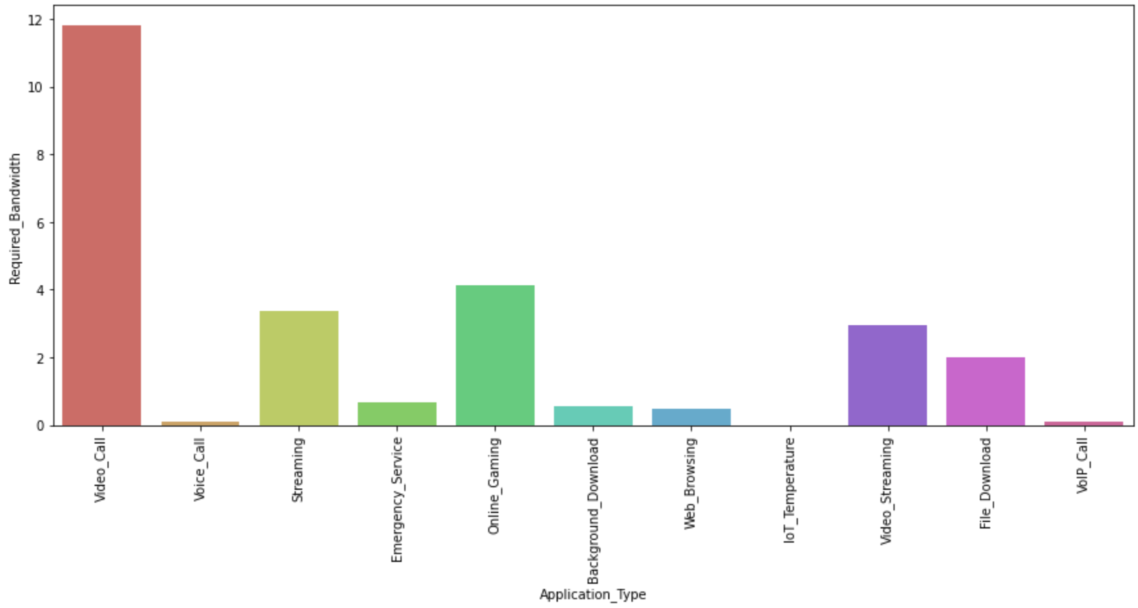


In [31]:

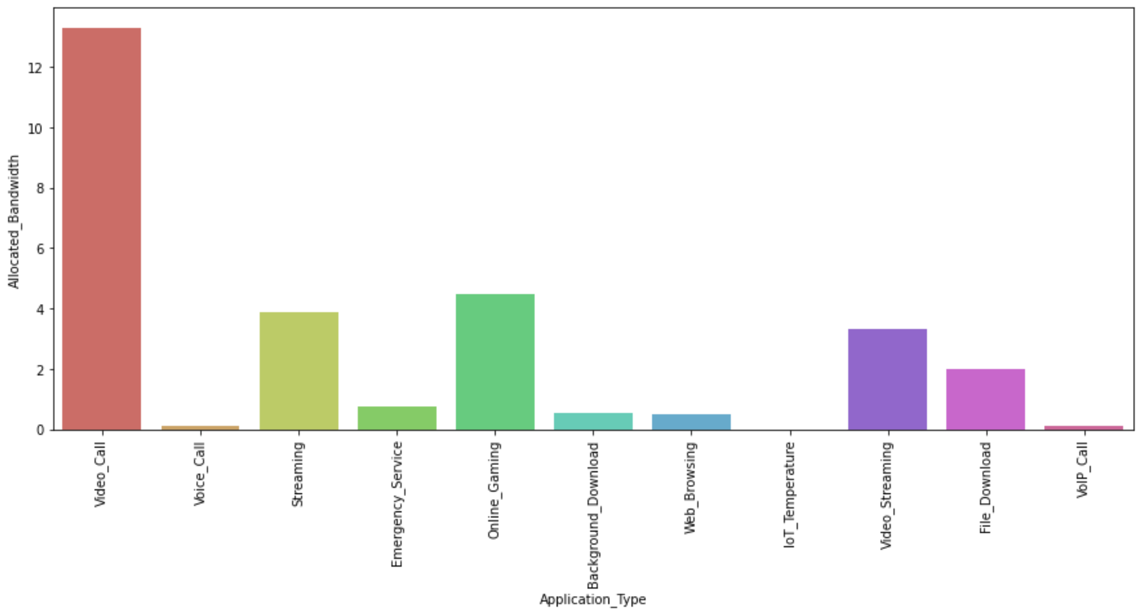
```
for i in numerical_columns:
    plt.figure(figsize=(15,6))
    sns.barplot(x = df['Application_Type'], y = df[i], data = df, ci = None, palette = '
    plt.xticks(rotation = 90)
    plt.show()
```



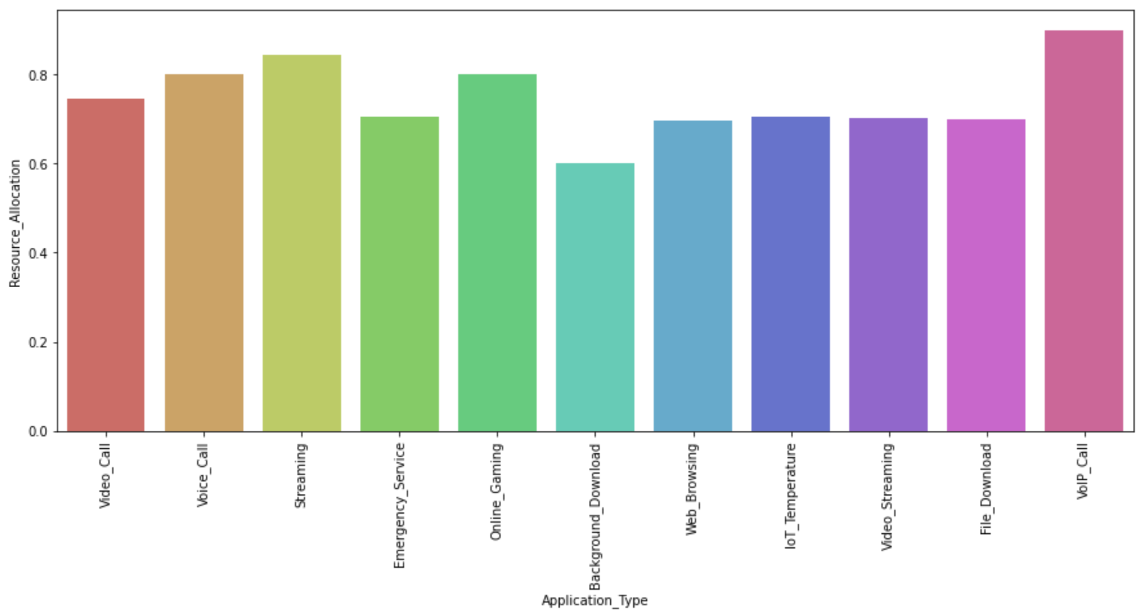




Required_Bandwidth
12
10
8
6
4
2
0
Video_Call
Voice_Call
Streaming
Emergency_Service
Online_Gaming
Background_Download
Web_Browsing
IoT_Temperature
Video_Streaming
File_Download
VoIP_Call
Application_Type



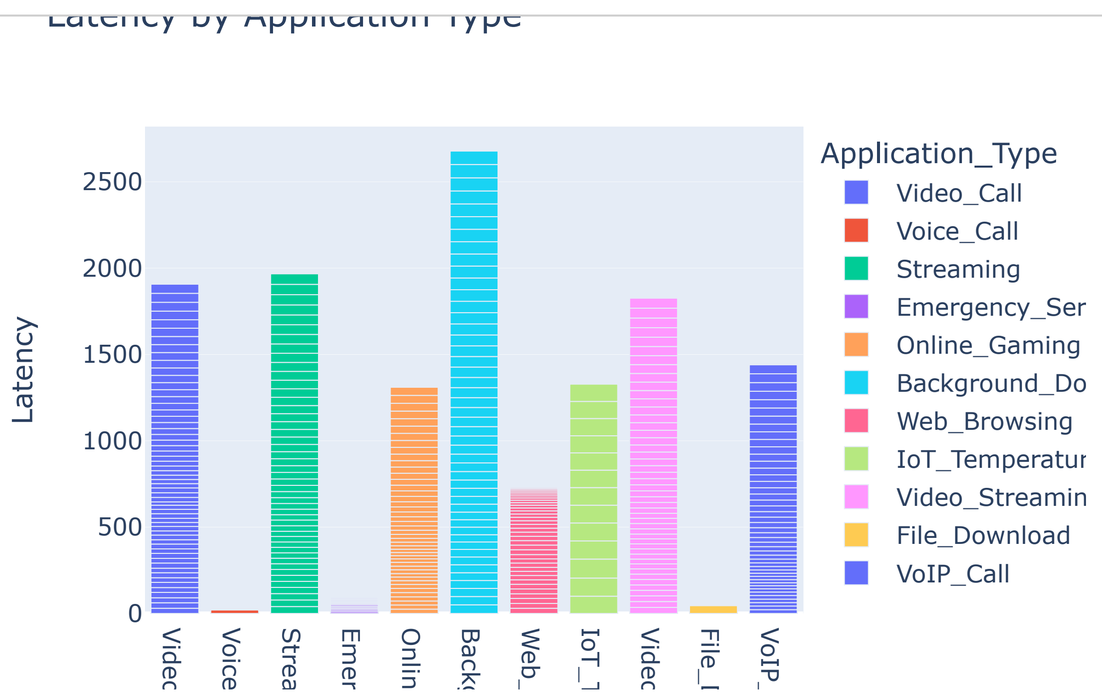
Allocated_Bandwidth
12
10
8
6
4
2
0
Video_Call
Voice_Call
Streaming
Emergency_Service
Online_Gaming
Background_Download
Web_Browsing
IoT_Temperature
Video_Streaming
File_Download
VoIP_Call
Application_Type



Resource_Allocation
0.8
0.6
0.4
0.2
0.0
Video_Call
Voice_Call
Streaming
Emergency_Service
Online_Gaming
Background_Download
Web_Browsing
IoT_Temperature
Video_Streaming
File_Download
VoIP_Call
Application_Type

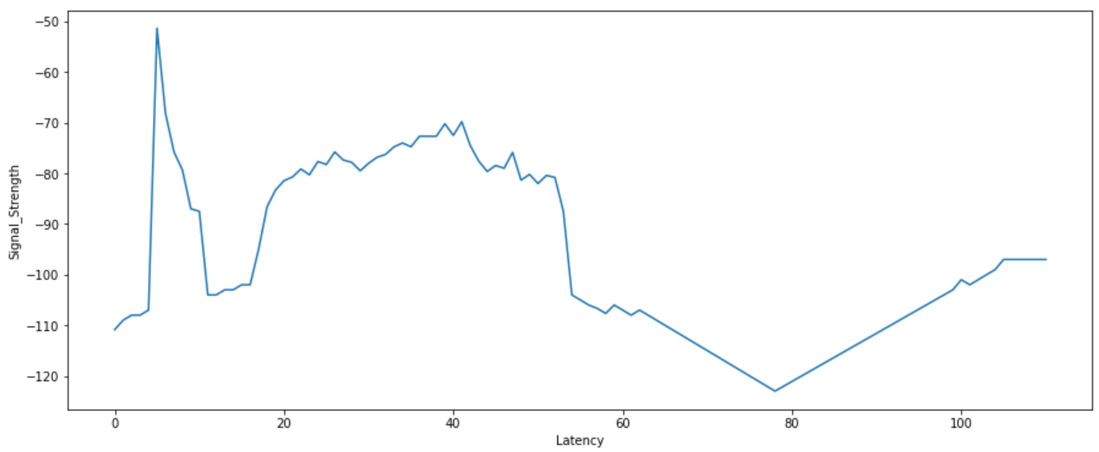
In [32]:

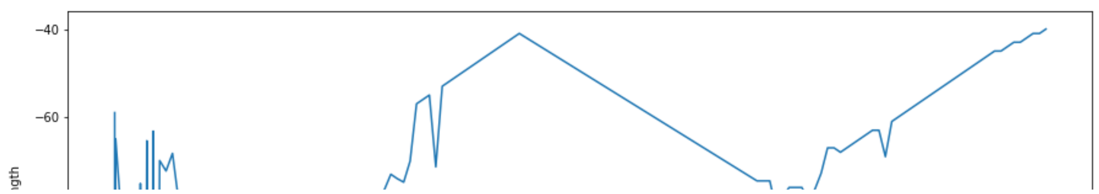
```python
for i in numerical_columns:
    fig = px.bar(df, x='Application_Type', y=i, color='Application_Type',
                 title=f'{i} by Application Type')
    fig.update_layout(xaxis_title='Application Type', yaxis_title=i)
    fig.show()
```



In [33]:

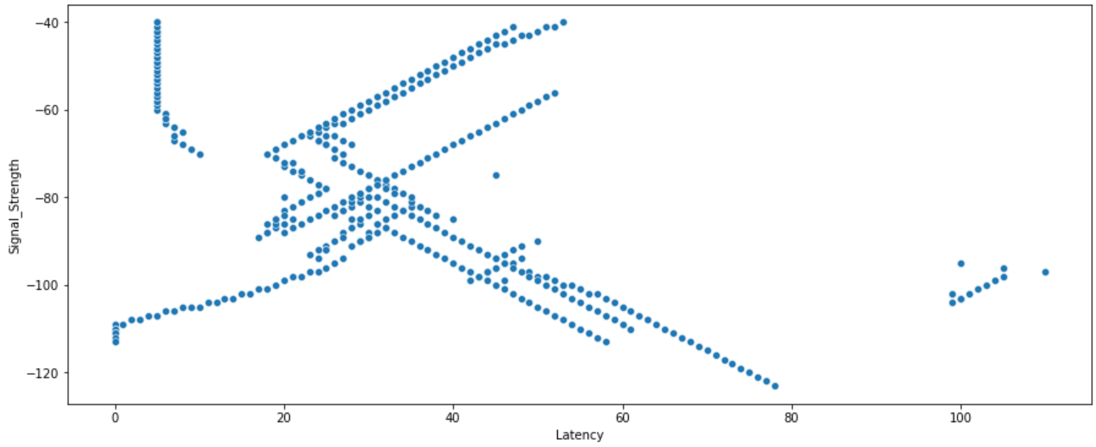
```python
for i in numerical_columns:
    for j in numerical_columns:
        if i != j:
            plt.figure(figsize=(15,6))
            sns.lineplot(x = df[j], y = df[i], data = df, ci = None, palette = 'hls')
            plt.show()
```

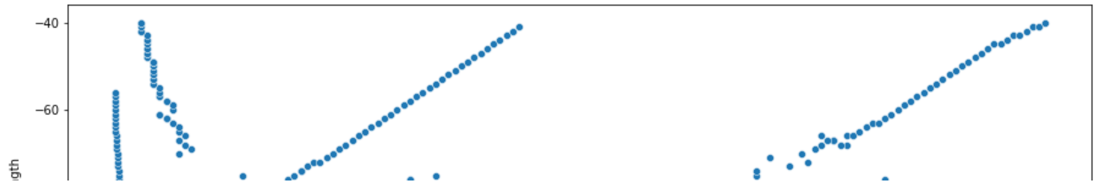




In [34]:

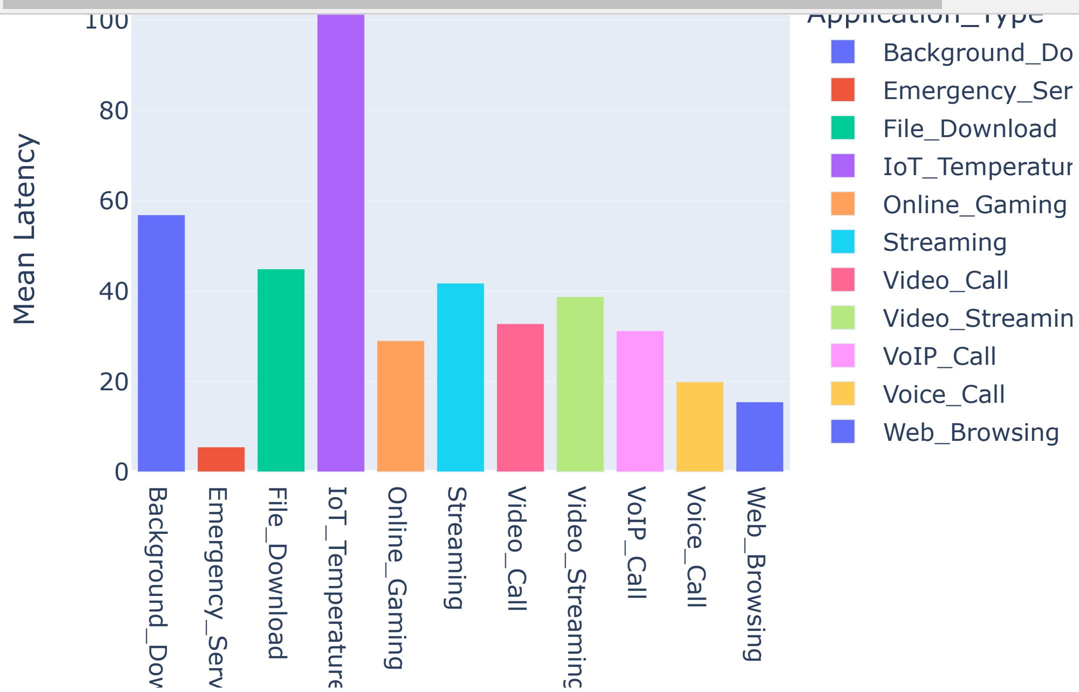
```
for i in numerical_columns:
    for j in numerical_columns:
        if i != j:
            plt.figure(figsize=(15,6))
            sns.scatterplot(x = df[j], y = df[i], data = df, ci = None, palette = 'hls')
            plt.show()
```





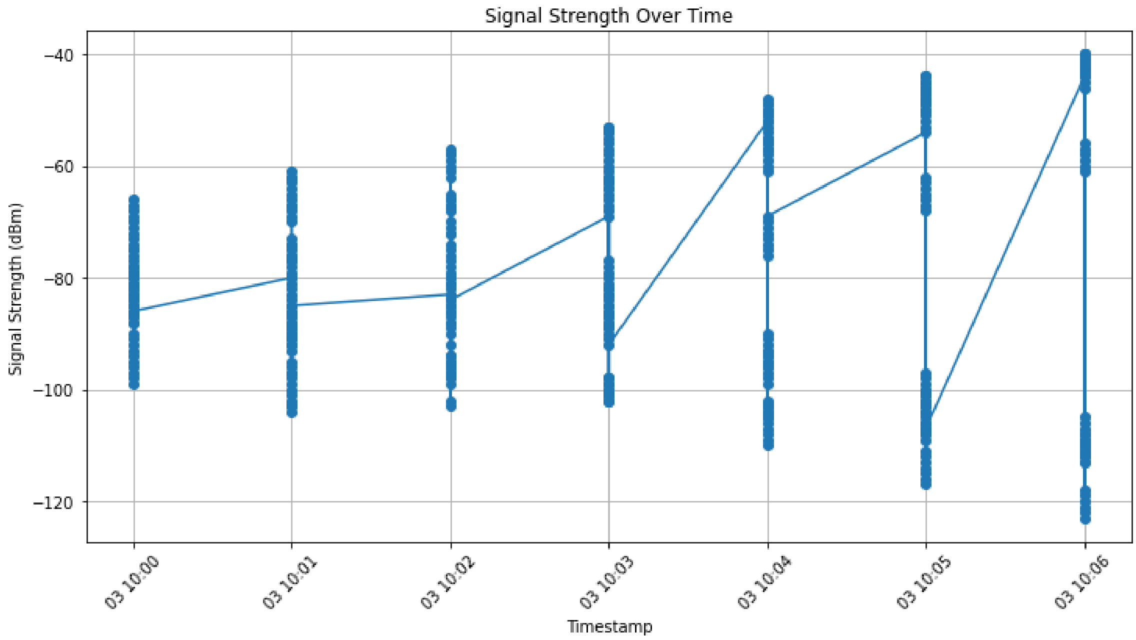
In [35]:

```
for i in numerical_columns:
    grouped_df = df.groupby('Application_Type')[i].mean().reset_index()
    fig = px.bar(grouped_df, x='Application_Type', y=i, color='Application_Type', title=
    fig.update_layout(xaxis_title='Application Type', yaxis_title=f'Mean {i}')
    fig.show()
```



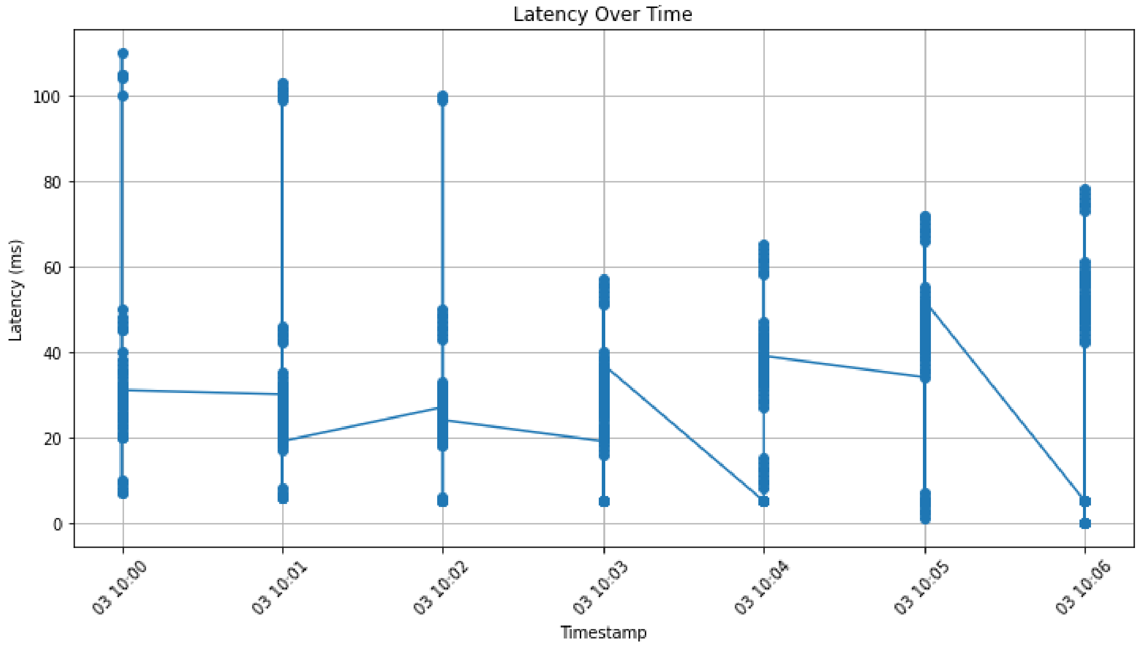
In [36]:

```
plt.figure(figsize=(12, 6))
plt.plot(df['Timestamp'], df['Signal_Strength'], marker='o', linestyle='-')
plt.xlabel('Timestamp')
plt.ylabel('Signal Strength (dBm)')
plt.title('Signal Strength Over Time')
plt.grid(True)
plt.xticks(rotation=45)
plt.show()
```



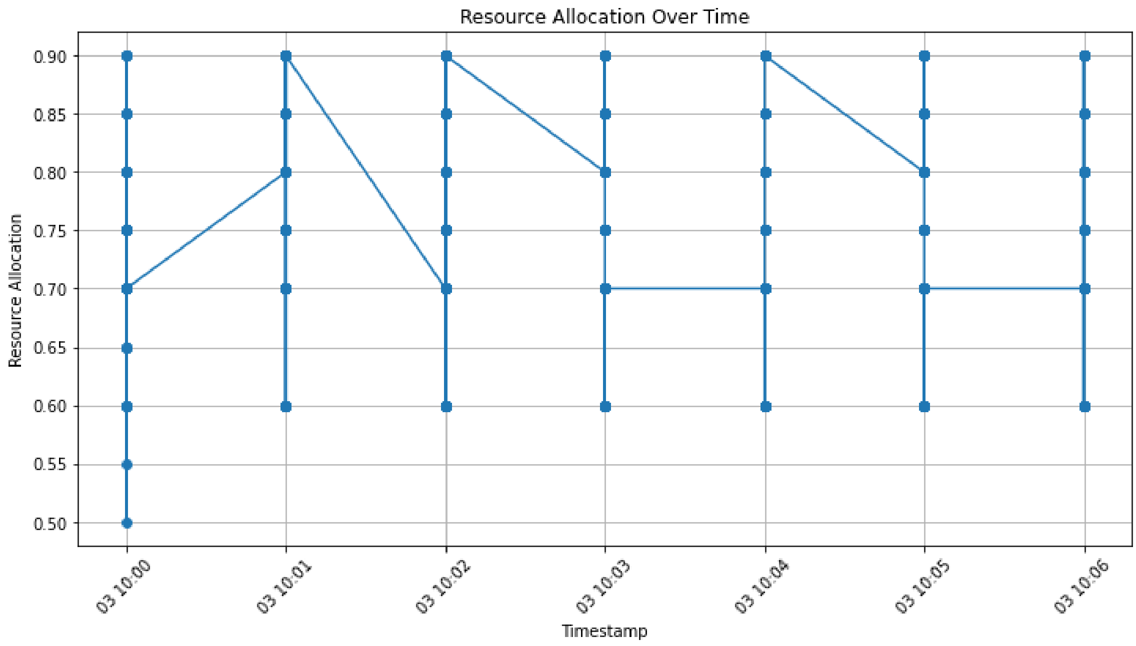
In [37]:

```
plt.figure(figsize=(12, 6))
plt.plot(df['Timestamp'], df['Latency'], marker='o', linestyle='-')
plt.xlabel('Timestamp')
plt.ylabel('Latency (ms)')
plt.title('Latency Over Time')
plt.grid(True)
plt.xticks(rotation=45)
plt.show()
```



In [38]:

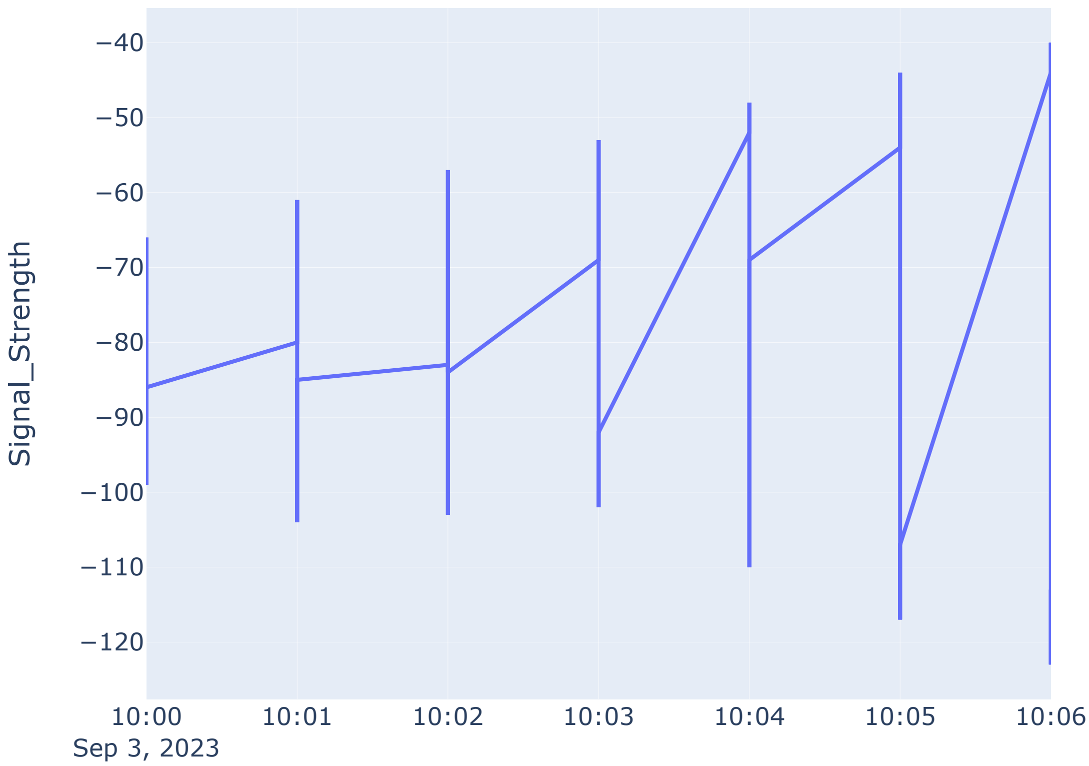
```
plt.figure(figsize=(12, 6))
plt.plot(df['Timestamp'], df['Resource_Allocation'], marker='o', linestyle='-')
plt.xlabel('Timestamp')
plt.ylabel('Resource Allocation')
plt.title('Resource Allocation Over Time')
plt.grid(True)
plt.xticks(rotation=45)
plt.show()
```



In [39]:

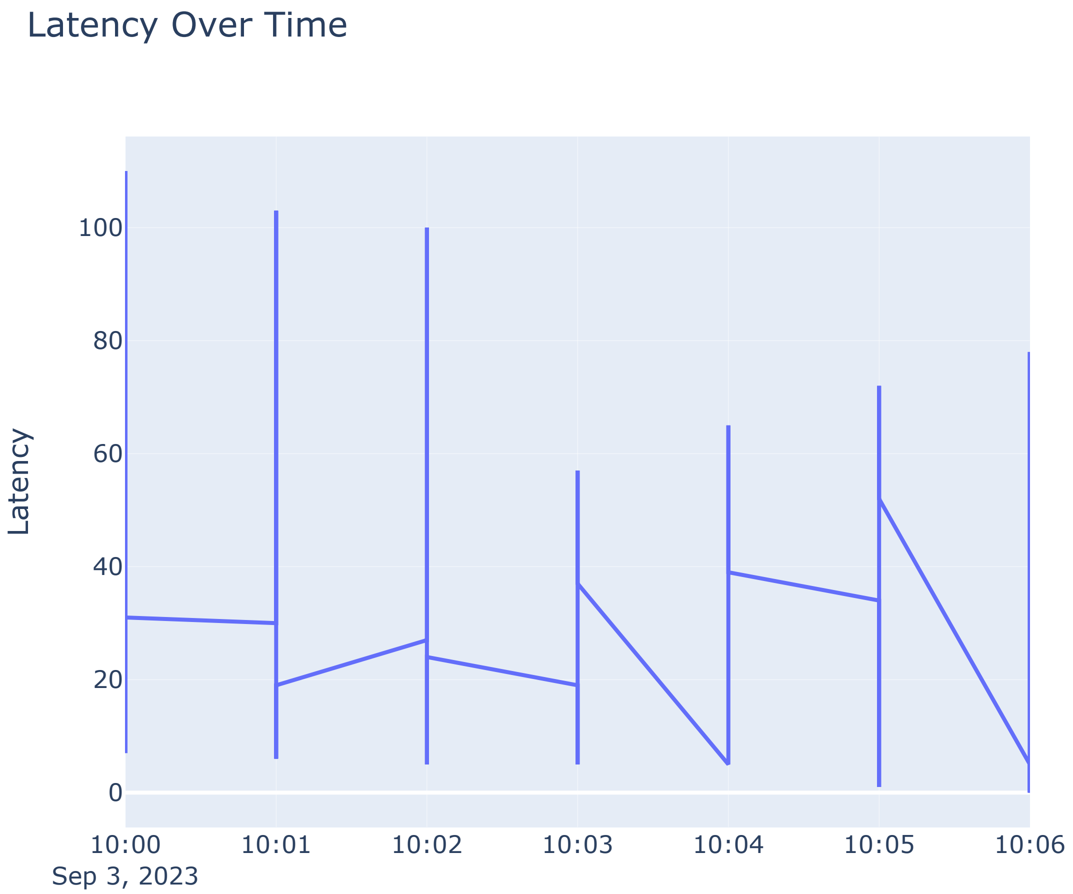
```
fig_latency = px.line(df, x='Timestamp', y='Signal_Strength', title='Signal Strength Ove
fig_latency.show()
```

Signal Strength Over Time



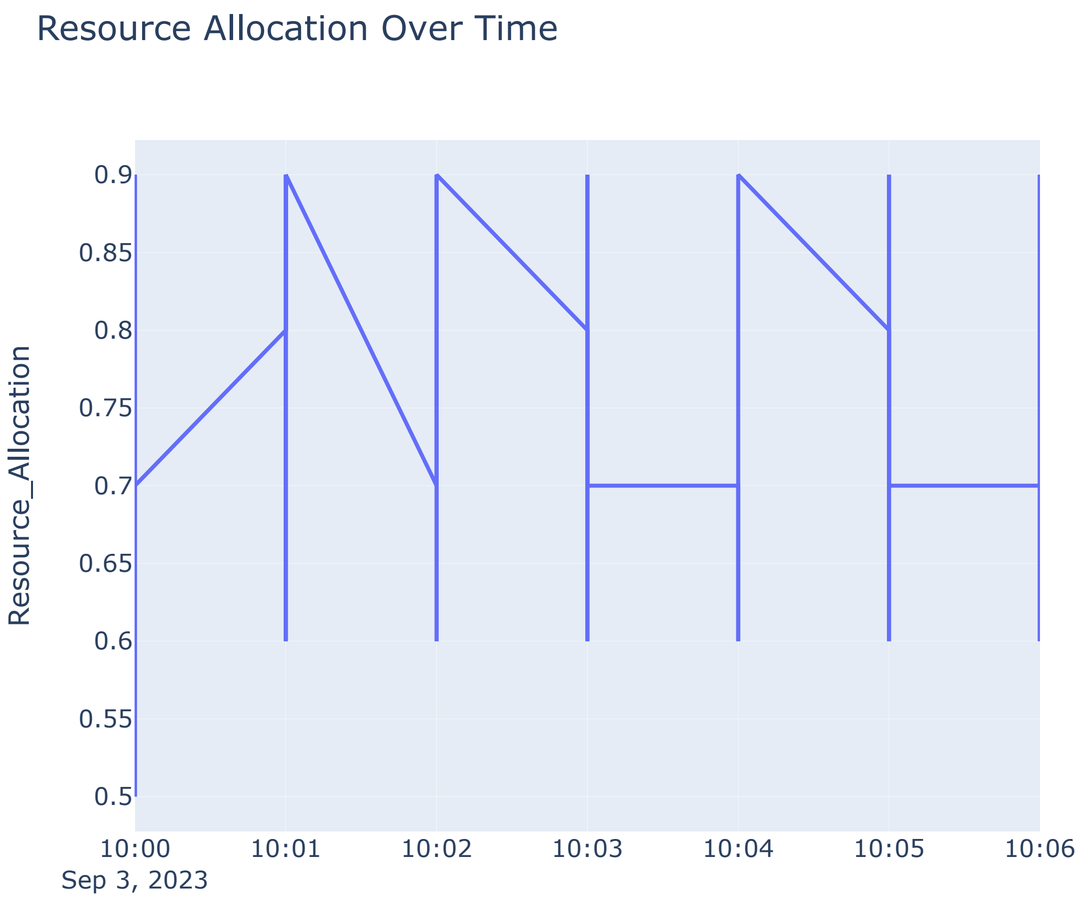
In [40]:

```
fig_latency = px.line(df, x='Timestamp', y='Latency', title='Latency Over Time')
fig_latency.show()
```



In [41]:

```
fig_allocation = px.line(df, x='Timestamp', y='Resource_Allocation', title='Resource All
fig_allocation.show()
```

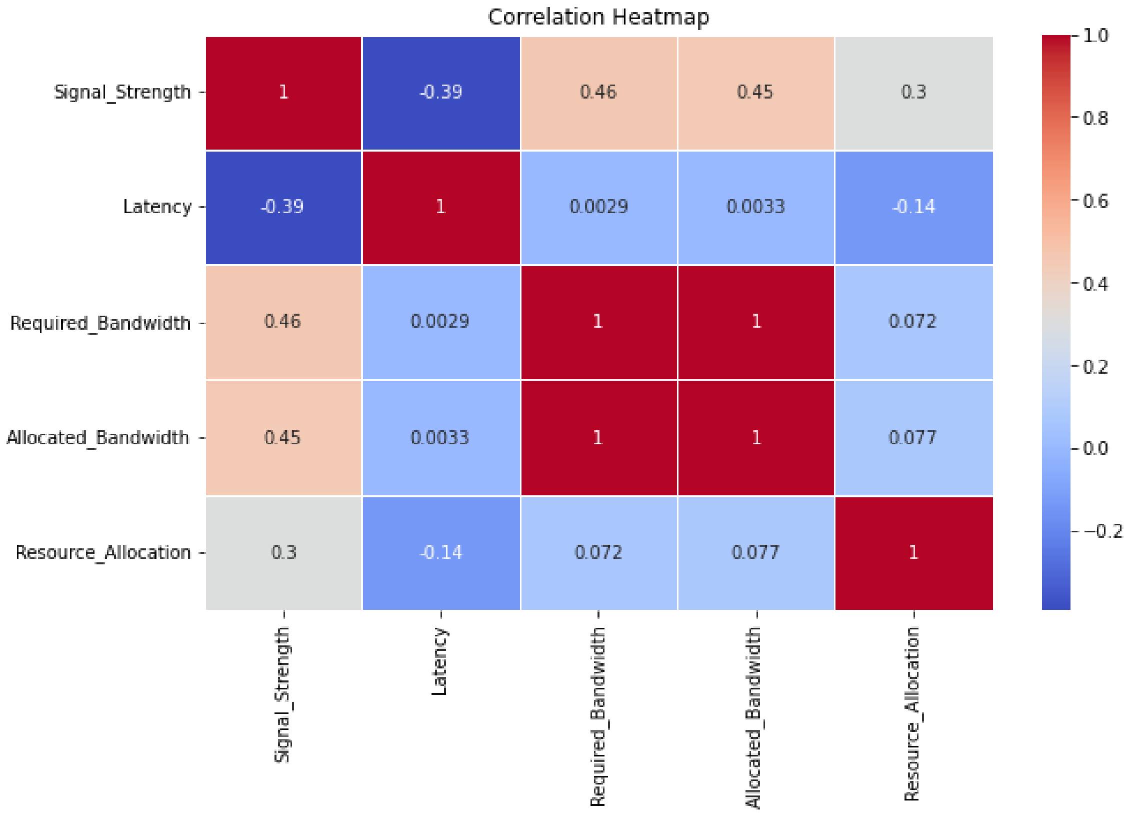


In [42]:

```
correlation_matrix = df.corr()
```

In [43]:

```
plt.figure(figsize=(10, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=0.5)
plt.title('Correlation Heatmap')
plt.show()
```



In [44]:

```
df['Efficiency_Ratio_Latency'] = df['Allocated_Bandwidth'] / df['Latency']
df['Resource_Performance'] = df['Resource_Allocation'] * df['Signal_Strength']
```

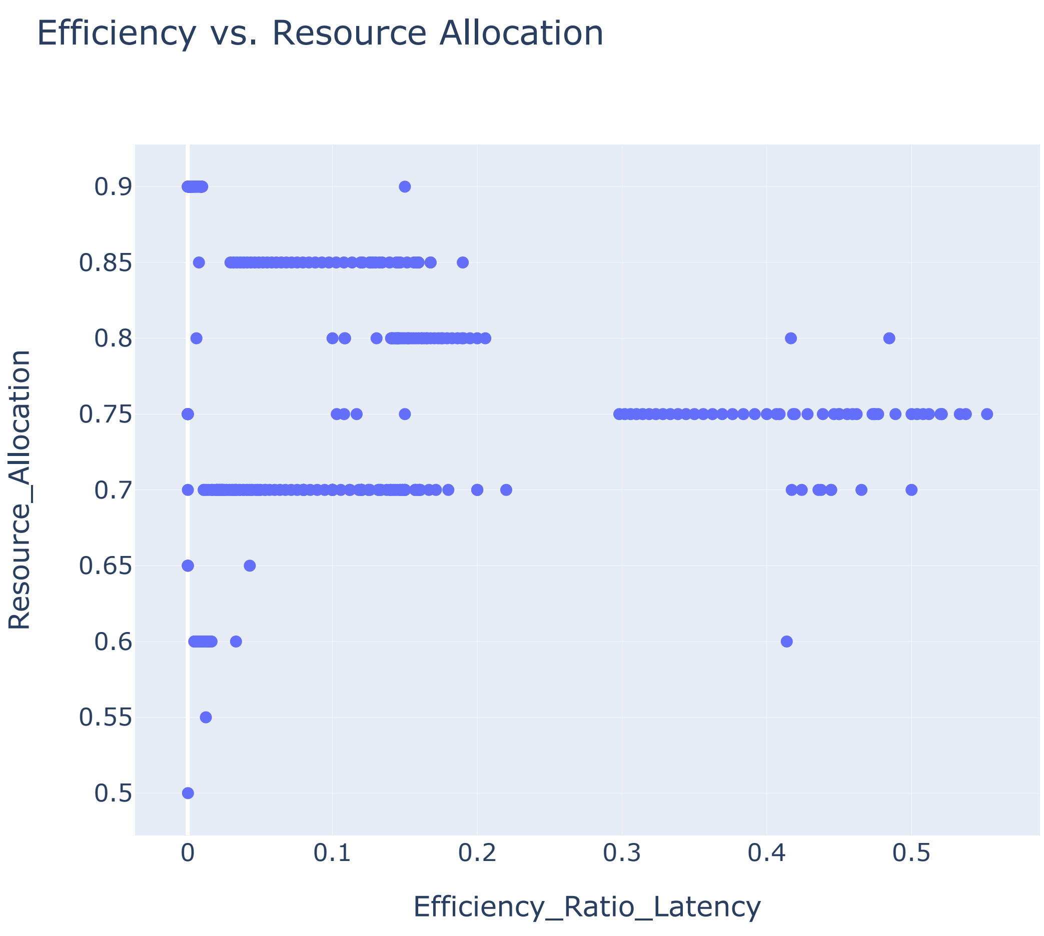
In [45]:

```
print(df[['Efficiency_Ratio_Latency', 'Resource_Performance']].head())
```

```
   Efficiency_Ratio_Latency  Resource_Performance
0                     0.500                -52.50
1                     0.006                -64.00
2                     0.150                -63.75
3                     0.150                -63.00
4                     0.120                -66.30
```

In [46]:

```
fig_efficiency = px.scatter(df, x='Efficiency_Ratio_Latency', y='Resource_Allocation', t
fig_efficiency.show()
```



In [47]:

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

In [48]:

```
X = df[['Signal_Strength', 'Required_Bandwidth']]
y = df['Resource_Allocation']
```

In [49]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42
```

In [50]:

```
model = LinearRegression()
model.fit(X_train, y_train)
```

Out[50]:

```
▾ LinearRegression
LinearRegression()
```

In [51]:

```
y_pred = model.predict(X_test)
```

In [52]:

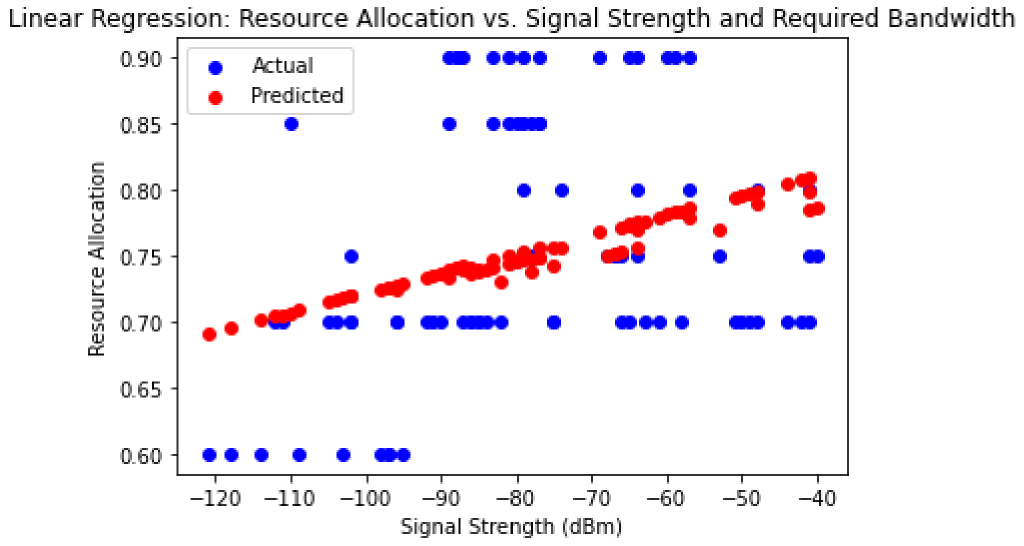
```
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f'Mean Squared Error: {mse}')
print(f'R-squared: {r2}')
```

```
Mean Squared Error: 0.007977063585505356
R-squared: 0.08959552499247914
```

In [53]:

```
plt.scatter(X_test['Signal_Strength'], y_test, color='blue', label='Actual')
plt.scatter(X_test['Signal_Strength'], y_pred, color='red', label='Predicted')
plt.xlabel('Signal Strength (dBm)')
plt.ylabel('Resource Allocation')
plt.legend()
plt.title('Linear Regression: Resource Allocation vs. Signal Strength and Required Bandw
plt.show()
```



In [54]:

```
from sklearn.preprocessing import PolynomialFeatures
from sklearn.pipeline import make_pipeline
```

In [55]:

```
degree = 5
polyreg = make_pipeline(PolynomialFeatures(degree), LinearRegression())
polyreg.fit(X_train, y_train)
```

Out[55]:

```
▸ Pipeline
▸ PolynomialFeatures
▸ LinearRegression
```

In [56]:

```
y_pred_poly = polyreg.predict(X_test)
```

In [57]:

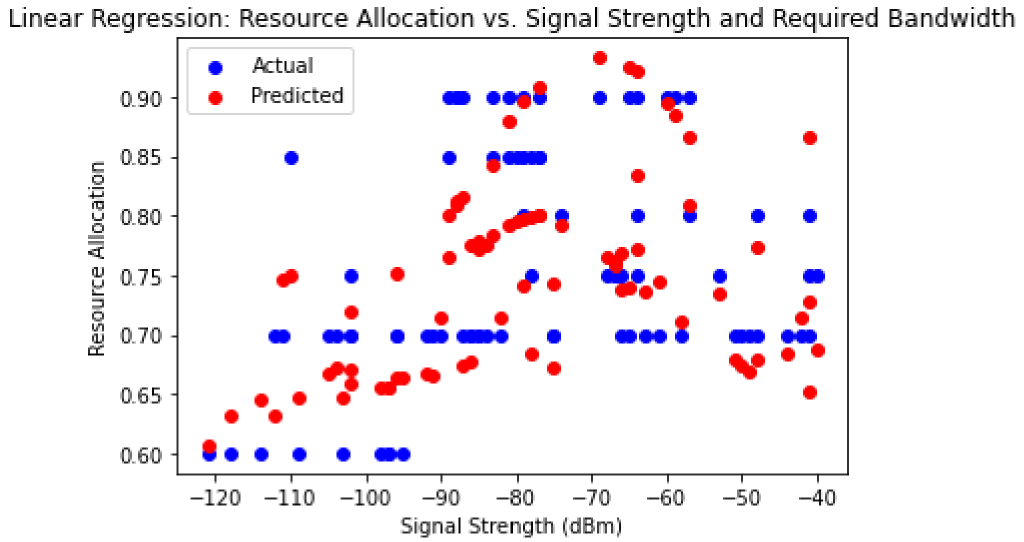
```
mse_poly = mean_squared_error(y_test, y_pred_poly)
r2_poly = r2_score(y_test, y_pred_poly)

print(f'Polynomial Regression - Mean Squared Error: {mse_poly}')
print(f'Polynomial Regression - R-squared: {r2_poly}')
```

```
Polynomial Regression - Mean Squared Error: 0.002299303304758281
Polynomial Regression - R-squared: 0.7375856421835318
```

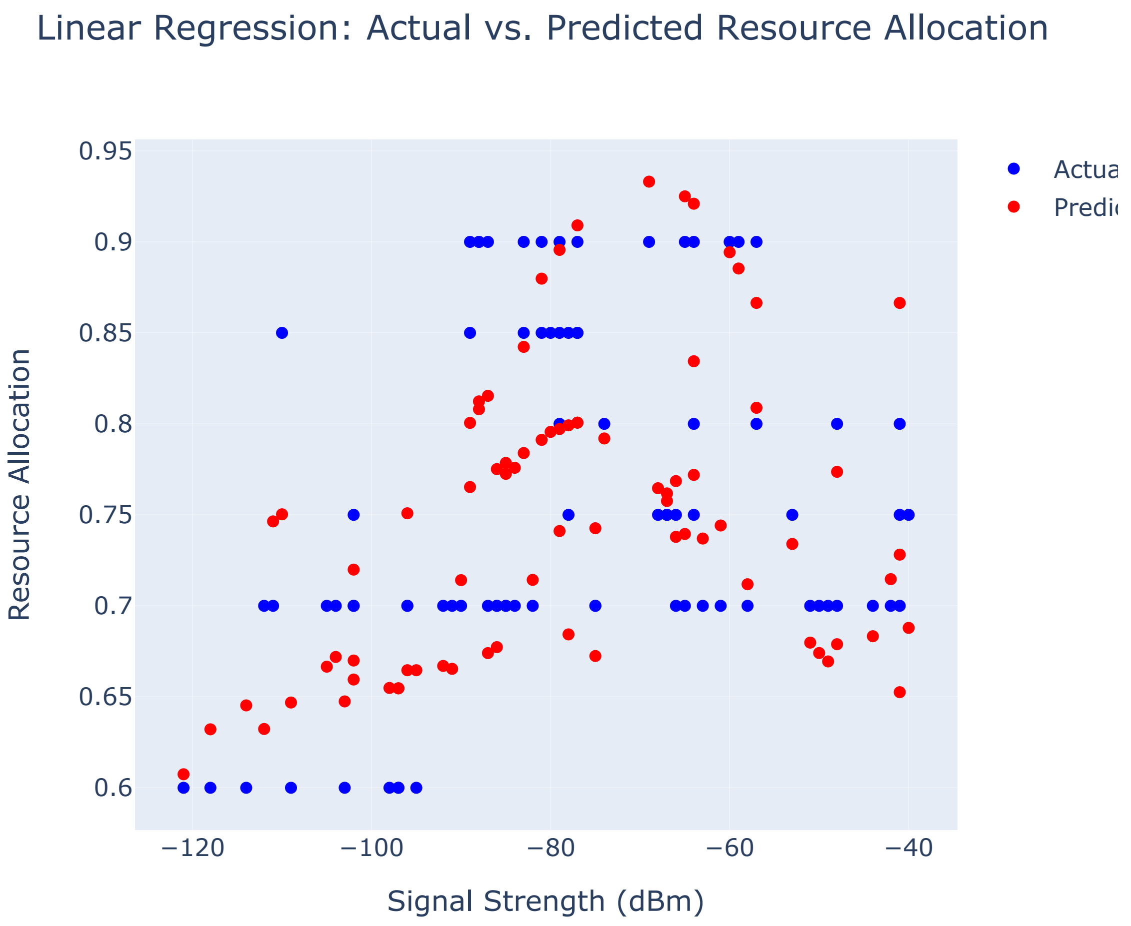
In [58]:

```
plt.scatter(X_test['Signal_Strength'], y_test, color='blue', label='Actual')
plt.scatter(X_test['Signal_Strength'], y_pred_poly, color='red', label='Predicted')
plt.xlabel('Signal Strength (dBm)')
plt.ylabel('Resource Allocation')
plt.legend()
plt.title('Linear Regression: Resource Allocation vs. Signal Strength and Required Bandw
plt.show()
```



In [60]:

```
fig = go.Figure()
fig.add_trace(go.Scatter(x=X_test['Signal_Strength'], y=y_test, mode='markers', name='Ac
fig.add_trace(go.Scatter(x=X_test['Signal_Strength'], y=y_pred_poly, mode='markers', nam
fig.update_layout(xaxis_title='Signal Strength (dBm)', yaxis_title='Resource Allocation'
fig.show()
```



In [61]:

```
df['Latency_Signal_Interaction'] = df['Latency'] * df['Signal_Strength']
```

In [62]:

```
X = df[['Latency', 'Latency_Signal_Interaction']]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42
```

In [63]:

```
model = LinearRegression()
model.fit(X_train, y_train)
```

Out[63]:

```
▾ LinearRegression
LinearRegression()
```

In [64]:

```
y_pred = model.predict(X_test)
```

In [65]:

```
mse_new_feature = mean_squared_error(y_test, y_pred)
r2_new_feature = r2_score(y_test, y_pred)

print(f'Mean Squared Error with New Feature: {mse_new_feature}')
print(f'R-squared with New Feature: {r2_new_feature}')
```

```
Mean Squared Error with New Feature: 0.006822902316122303
R-squared with New Feature: 0.22131737643114047
```

In [66]:

```
degree = 4
polyreg = PolynomialFeatures(degree)
X_poly_train = polyreg.fit_transform(X_train)
X_poly_test = polyreg.transform(X_test)
```

In [67]:

```
model = LinearRegression()
model.fit(X_poly_train, y_train)
```

Out[67]:

```
▾ LinearRegression
LinearRegression()
```

In [68]:

```
y_pred_poly = model.predict(X_poly_test)
```

In [69]:

```
mse_poly = mean_squared_error(y_test, y_pred_poly)
r2_poly = r2_score(y_test, y_pred_poly)

print(f'Mean Squared Error with Polynomial Feature: {mse_poly}')
print(f'R-squared with Polynomial Feature: {r2_poly}')
```

```
Mean Squared Error with Polynomial Feature: 0.004833682728885595
R-squared with Polynomial Feature: 0.4483425711761795
```

Thanks !!!