XGBoost

In [1]:
```
# Import necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import LabelEncoder
import xgboost as xgb
```

In [2]:
```
# Import dataset
private_data = "../datasets/cleaned/cleaned_private.csv"

df = pd.read_csv(private_data, quotechar='"', escapechar='\\', thousands=',')
df
```

Out[2]:

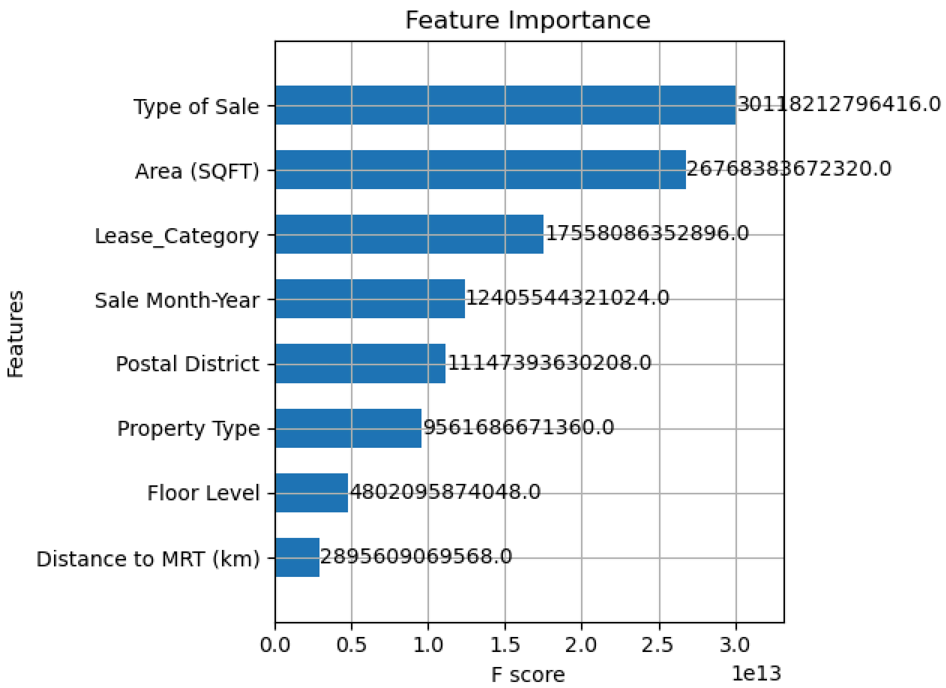
	Project Name	Transacted Price ($)	Area (SQFT)	Unit Price ($ PSF)	Sale Date	Street Name	Type of Sale	Type of Area	Property Type	Number of Units	...	longitude	latitude
0	ONE BERNAM	2088000	807.30	2586	1/12/2022	BERNAM STREET	New Sale	Strata	Apartment	1	...	103.843685	1.273874
1	RIVIERE	3390000	1140.98	2971	1/12/2022	JIAK KIM STREET	New Sale	Strata	Apartment	1	...	103.831584	1.284899
2	RIVIERE	3780000	1216.33	3108	1/12/2022	JIAK KIM STREET	New Sale	Strata	Apartment	1	...	103.831584	1.284899
3	LEEDON GREEN	1923000	710.42	2707	1/12/2022	LEEDON HEIGHTS	New Sale	Strata	Condominium	1	...	103.803546	1.313033
4	LEEDON GREEN	1590000	538.20	2954	1/12/2022	LEEDON HEIGHTS	New Sale	Strata	Condominium	1	...	103.803546	1.313033
...	...	...	...	...	...	...	...	...	...	...	...	...	...
128344	THE WHITLEY RESIDENCES	4998000	7190.35	695	1/3/2020	WHITLEY ROAD	Resale	Strata	Semi-Detached House	1	...	103.837373	1.325460
128345	WEST SHORE RESIDENCES	2850000	3982.68	716	1/3/2020	PASIR PANJANG ROAD	Resale	Strata	Terrace House	1	...	103.784856	1.281301
128346	ESTRIVILLAS	3180000	4703.87	676	1/3/2020	JALAN LIM TAI SEE	Resale	Strata	Semi-Detached House	1	...	103.793074	1.321131
128347	KEW RESIDENCIA	1570000	2142.04	733	1/3/2020	KEW CRESCENT	Resale	Strata	Terrace House	1	...	103.948504	1.317953
128348	THE SHAUGHNESSY	1600000	3993.44	401	1/3/2020	MILTONIA CLOSE	Resale	Strata	Terrace House	1	...	103.846917	1.417699

128349 rows × 26 columns

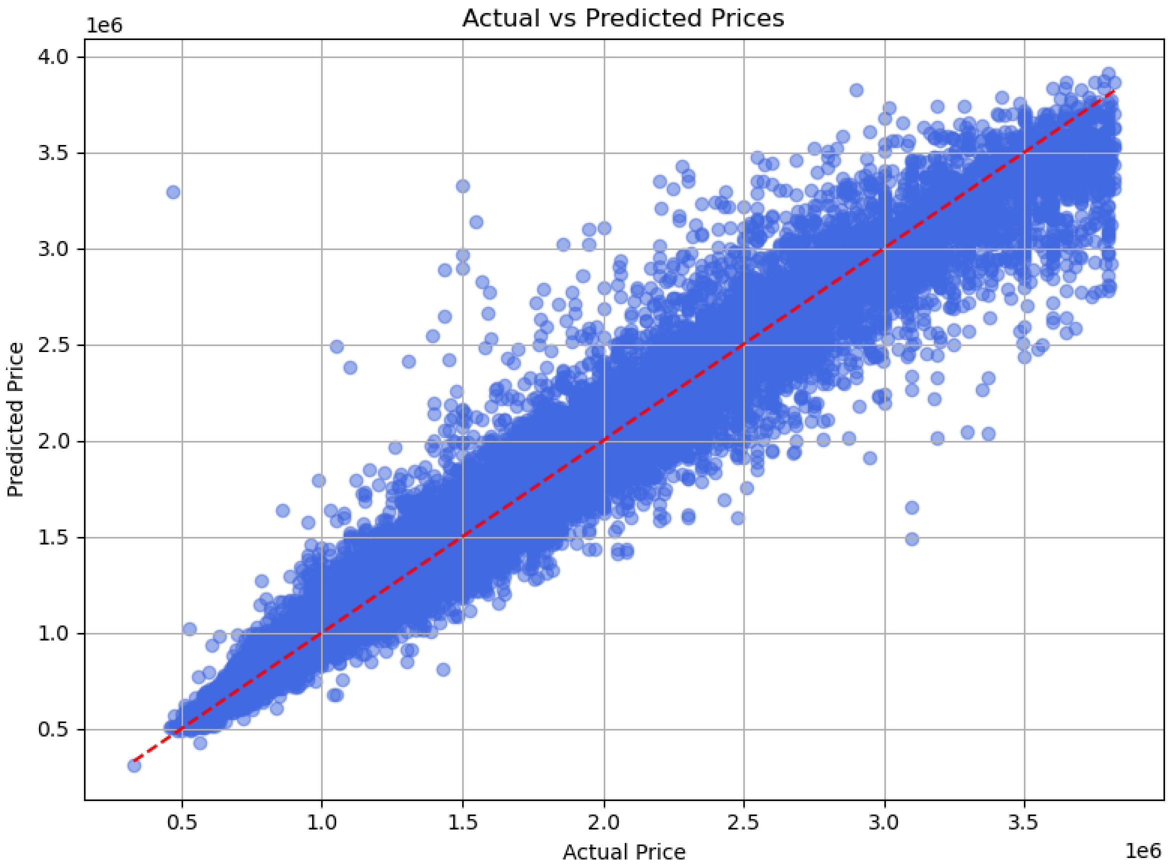
In [4]:
```
# Preprocess data: Extract 'Sale Month-Year' from 'Sale Date'
df['Sale Month-Year'] = pd.to_datetime(df['Sale Date']).dt.to_period('M').astype(str)

# Remove price outliers using IQR method
Q1 = df['Price'].quantile(0.25)
Q3 = df['Price'].quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
df = df[(df['Price'] >= lower_bound) & (df['Price'] <= upper_bound)]

# Reset index (optional if not filtering)
df.reset_index(drop=True, inplace=True)

# Select relevant columns
features = ['Area (SQFT)', 'Lease_Category', 'Property Type', 'Postal District',
            'Type of Sale', 'Floor Level', 'Sale Month-Year', 'Distance to MRT (km)']
target = 'Price'

# Encode categorical features
```

```
df_encoded = df[features + [target]].copy()
categorical_cols = ['Lease_Category', 'Property Type', 'Postal District',
                    'Type of Sale', 'Floor Level', 'Sale Month-Year']
label_encoders = {}

for col in categorical_cols:
    le = LabelEncoder()
    df_encoded[col] = le.fit_transform(df_encoded[col])
    label_encoders[col] = le  # Save if needed later

# Split into features and target
X = df_encoded[features]
y = df_encoded[target]

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=40)

# Train XGBoost Regressor
model = xgb.XGBRegressor(objective='reg:squarederror', random_state=40)
model.fit(X_train, y_train)

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

In [5]:
```
# Feature Importance Plot (which features XGBoost found most useful during training)
xgb.plot_importance(model, importance_type='gain', height=0.6)
plt.title('Feature Importance')
plt.tight_layout()
plt.show()
```



In [6]:
```
# Scatter Plot of Actual vs Predicted Prices (how close predictions are to the actual values)
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred, alpha=0.5, color='royalblue')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--')  # perfect prediction line
plt.xlabel('Actual Price')
plt.ylabel('Predicted Price')
plt.title('Actual vs Predicted Prices')
plt.grid(True)
plt.tight_layout()
plt.show()
```



In [7]:
```
# Evaluate XGBoost model
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f"Mean Squared Error (MSE): {mse:.2f}")
print(f"Mean Absolute Error (MAE): {mae:.2f}")
print(f"R^2 Score: {r2:.4f}")
```

```
Mean Squared Error (MSE): 24470016620.15
Mean Absolute Error (MAE): 98851.68
R^2 Score: 0.9504
```