Prediction based on Future Dates

Feature engineering

In [1]:

```
# Import libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

In [2]:

```
# Read data
df = pd.read_excel('sales_data.xlsx')
df.head()
```

Out[2]:

	Transaction ID	Date	Customer ID	Gender	Age	Product Category	Quantity	Price per Unit	Total Amount
0	1	2023-11-24	CUST001	Male	34	Beauty	3	50	150
1	2	2023-02-27	CUST002	Female	26	Clothing	2	500	1000
2	3	2023-01-13	CUST003	Male	50	Electronics	1	30	30
3	4	2023-05-21	CUST004	Male	37	Clothing	1	500	500
4	5	2023-05-06	CUST005	Male	30	Beauty	2	50	100

Quick analysis

In [3]:

```
# Total number of records
print(f"Total records: {len(df)}")
```

```
Total records: 1000
```

In [4]:

```
df.nunique()
```

Out[4]:

```
Transaction ID      1000
Date                 345
Customer ID         1000
Gender                 2
Age                   47
Product Category       3
Quantity               4
Price per Unit         5
Total Amount          18
dtype: int64
```

Observation:

This shows that all the Transaction IDs and Customer IDs are unique. Thus, can't be used as features.

In [5]:
```
# Group by date and sum if needed
daily_sales = df.groupby('Date')['Total Amount'].sum().reset_index()

# Add Weekday and Weekend info
daily_sales['Weekday'] = daily_sales['Date'].dt.weekday
daily_sales['IsWeekend'] = daily_sales['Weekday'].isin([5, 6])

# Compute average sales
avg_weekday_sales = daily_sales.loc[~daily_sales['IsWeekend'], 'Total Amount'].mean(
avg_weekend_sales = daily_sales.loc[daily_sales['IsWeekend'], 'Total Amount'].mean()

print(f"Average Weekday Sales: {avg_weekday_sales:.2f}")
print(f"Average Weekend Sales: {avg_weekend_sales:.2f}")
```

```
Average Weekday Sales: 1305.68
Average Weekend Sales: 1360.54
```

Observation:

The average of sales during weekend(2 days) is almost same as weekday(5 days). This defines that weekend the customer shops more. Thus, a strong feature to include.

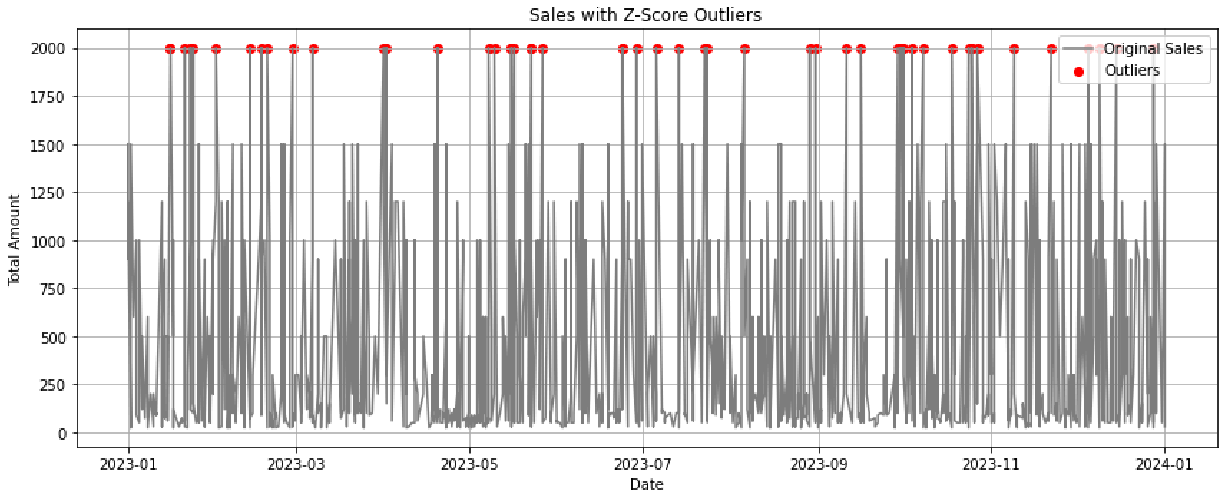
Detect Outlier and clip to max or min

In [6]:
```
import pandas as pd
import matplotlib.pyplot as plt

# Load or use existing df
df['Date'] = pd.to_datetime(df['Date'])

# Sort the DataFrame by date
df = df.sort_values('Date')

# Make sure 'Total Amount' is numeric
df['Total Amount'] = pd.to_numeric(df['Total Amount'], errors='coerce')

# Calculate Z-scores
mean = df['Total Amount'].mean()
std = df['Total Amount'].std()
df['Z_Score'] = (df['Total Amount'] - mean) / std

# Define outliers
z_threshold = 2
df['IsOutlierZ'] = df['Z_Score'].abs() > z_threshold

# Print how many outliers detected
num_outliers = df['IsOutlierZ'].sum()
print(f"Number of outliers detected using Z-score (|z| > {z_threshold}): {num_outlie
```

```
Number of outliers detected using Z-score (|z| > 2): 49
```

In [7]:
```
# Plot
plt.figure(figsize=(12, 5))
plt.plot(df['Date'], df['Total Amount'], label="Original Sales", color='gray')
plt.scatter(df['Date'][df['IsOutlierZ']], df['Total Amount'][df['IsOutlierZ']], colo
plt.title("Sales with Z-Score Outliers")
plt.xlabel("Date")
plt.ylabel("Total Amount")
plt.legend()
plt.grid(True)
```

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

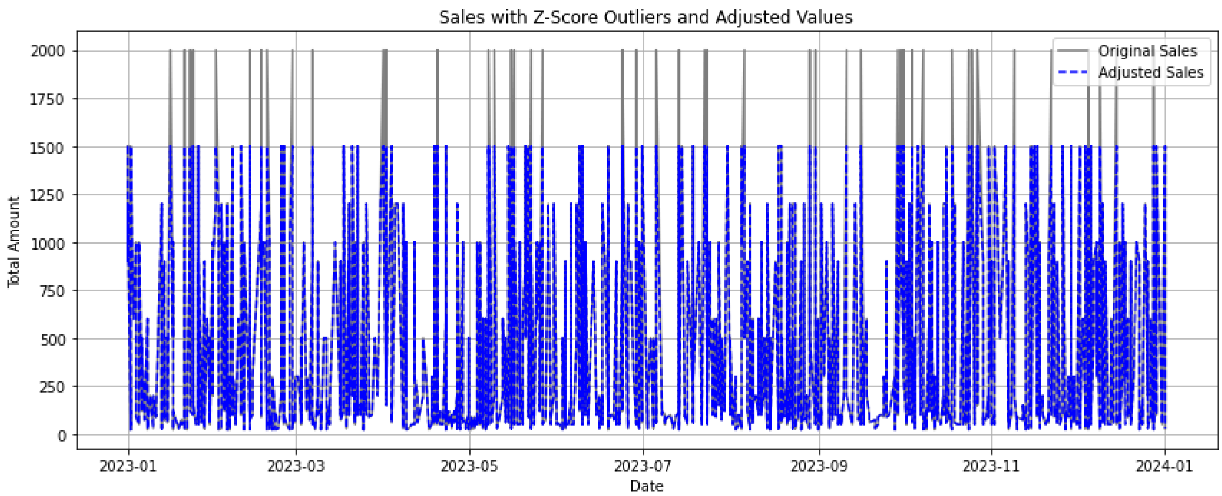


In [8]:

```
# Find bounds from non-outliers
non_outliers = df[~df['IsOutlierZ']]['Total Amount']
min_valid = non_outliers.min()
max_valid = non_outliers.max()

# Replace outliers
df['AdjustedTotalAmount'] = df.apply(
    lambda row: max_valid if row['Z_Score'] > z_threshold
    else min_valid if row['Z_Score'] < -z_threshold
    else row['Total Amount'],
    axis=1
)
```

In [9]:

```
# Plot
plt.figure(figsize=(12, 5))
plt.plot(df['Date'], df['Total Amount'], label="Original Sales", color='gray')
plt.plot(df['Date'], df['AdjustedTotalAmount'], label="Adjusted Sales", color='blue'
plt.title("Sales with Z-Score Outliers and Adjusted Values")
plt.xlabel("Date")
plt.ylabel("Total Amount")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



In [10]:
```
# Drop 'Z_Score' and 'Is_Outlier_Z' columns
df.drop(columns=['Z_Score', 'IsOutlierZ'], inplace=True)
```

In [11]:
```
df
```

Out[11]:

	Transaction ID	Date	Customer ID	Gender	Age	Product Category	Quantity	Price per Unit	Total Amount	AdjustedTota
521	522	2023-01-01	CUST522	Male	46	Beauty	3	500	1500	
179	180	2023-01-01	CUST180	Male	41	Clothing	3	300	900	
558	559	2023-01-01	CUST559	Female	40	Clothing	4	300	1200	
302	303	2023-01-02	CUST303	Male	19	Electronics	3	30	90	
978	979	2023-01-02	CUST979	Female	19	Beauty	1	25	25	
...	...	...	...	...	...	...	...	...	...	
232	233	2023-12-29	CUST233	Female	51	Beauty	2	300	600	
804	805	2023-12-29	CUST805	Female	30	Beauty	3	500	1500	
856	857	2023-12-31	CUST857	Male	60	Electronics	2	25	50	
210	211	2024-01-01	CUST211	Male	42	Beauty	3	500	1500	
649	650	2024-01-01	CUST650	Male	55	Electronics	1	30	30	

1000 rows × 10 columns

Modelling

Model 1 - Sales prediction based on product category

This modelling is done to predict the total sales for any future date provided based on the product category. Three algorithms RandomForest, GradientBoost and XGBoost are trained and compared.

In [12]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from xgboost import XGBRegressor
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import OneHotEncoder, StandardScaler
```

```python
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.metrics import mean_absolute_error, mean_squared_error

import joblib

# Ensure Date is datetime
df['Date'] = pd.to_datetime(df['Date'])

# Create new DataFrame with selected and engineered features
processed_df = pd.DataFrame({
    'Product Category': df['Product Category'],
    'Day': df['Date'].dt.day,
    'Month': df['Date'].dt.month,
    'Weekday': df['Date'].dt.weekday,
    'isWeekend': df['Date'].dt.weekday.isin([5, 6]).astype(int),
    'isAfter25': (df['Date'].dt.day > 25).astype(int),
    'LogTotalAmount': np.log1p(df['AdjustedTotalAmount'])
})

# Define Features and target
X = processed_df[['Product Category', 'Day', 'Month', 'Weekday', 'isWeekend', 'isAft
y = processed_df['LogTotalAmount']

# Train test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_stat
```

In [13]:

```python
processed_df.head()
```

Out[13]:

	Product Category	Day	Month	Weekday	isWeekend	isAfter25	LogTotalAmount
521	Beauty	1	1	6	1	0	7.313887
179	Clothing	1	1	6	1	0	6.803505
558	Clothing	1	1	6	1	0	7.090910
302	Electronics	2	1	0	0	0	4.510860
978	Beauty	2	1	0	0	0	3.258097

In [14]:

```python
# Define categorical and numerical features
cat_features = ['Product Category']
num_features = ['Day', 'Month', 'Weekday', 'isWeekend', 'isAfter25']

cat_transformer = Pipeline([
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

num_transformer = Pipeline([
    ('imputer', SimpleImputer(strategy='mean')),
    ('scaler', StandardScaler())
])

preprocessor = ColumnTransformer([
    ('cat', cat_transformer, cat_features),
    ('num', num_transformer, num_features)
])
```

In [15]:
```
# Define models with hypertune parameters
models = {
    'RandomForest': (RandomForestRegressor(random_state=42), {
        'regressor__n_estimators': [2000, 3000, 4000],
        'regressor__max_depth': [7, 9, 11]
    }),
    'XGBoost': (XGBRegressor(random_state=42, verbosity=0), {
        'regressor__n_estimators': [2000, 3000, 4000],
        'regressor__max_depth': [7, 9, 11],
        'regressor__learning_rate': [0.001, 0.01, 0.05, 0.1]
    }),
    'GradientBoosting': (GradientBoostingRegressor(random_state=42), {
        'regressor__n_estimators': [2000, 3000, 4000],
        'regressor__max_depth': [7, 9, 11],
        'regressor__learning_rate': [0.001, 0.01, 0.05, 0.1]
    })
}
```

Train Models

In [16]:
```
# Train
print("Training.........")
results = {}
best_model = None
best_mae = float('inf')

for name, (model, param_grid) in models.items():
    pipeline = Pipeline([
        ('preprocessor', preprocessor),
        ('regressor', model)
    ])
    grid = GridSearchCV(pipeline, param_grid, cv=3, scoring='neg_mean_squared_error'
    grid.fit(X_train, y_train)
    best_est = grid.best_estimator_
    y_pred_log = best_est.predict(X_test)
    y_pred = np.expm1(y_pred_log)
    y_true = np.expm1(y_test)
    mae = mean_absolute_error(y_true, y_pred)
    rmse = np.sqrt(mean_squared_error(y_true, y_pred))
    results[name] = (y_pred, mae, rmse)
    if mae < best_mae:
        best_model = name
        best_mae = mae
        best_rmse = rmse
        best_grid_est = grid.best_estimator_

        # Save best model
        joblib.dump(grid, "./models/category_sales_model.pkl")
```

```
Training.........
```

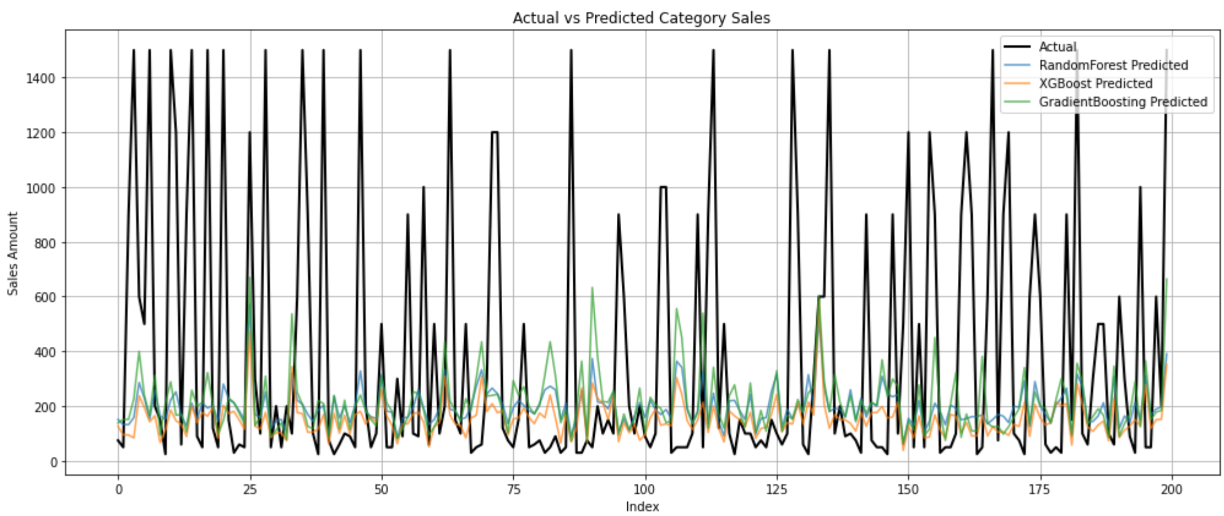
In [17]:
```
# Print best model
print(f"\nBest Model: {best_model}\nMAE: {best_mae:.2f}, RMSE: {best_rmse:.2f}")
```

```
Best Model: XGBoost
MAE: 336.53, RMSE: 535.24
```

In [18]:
```
best_grid_est
```

Out[18]:
```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('cat',
                                                  Pipeline(steps=[('imputer',
                                                                   SimpleImputer(stra
tegy='most_frequent')),
                                                                  ('onehot',
                                                                   OneHotEncoder(hand
le_unknown='ignore'))]),
                                                  ['Product Category']),
                                                 ('num',
                                                  Pipeline(steps=[('imputer',
                                                                   SimpleImputer()),
                                                                  ('scaler',
                                                                   StandardScaler
())]),
                                                  ['Day', 'Month', 'Weekday',
                                                   'isWeekend',
                                                   'isAfter25'])])),
                ('r...
                              feature_types=None, gamma=0, gpu_id=-1,
                              grow_policy='depthwise', importance_type=None,
                              interaction_constraints='', learning_rate=0.001,
                              max_bin=256, max_cat_threshold=64,
                              max_cat_to_onehot=4, max_delta_step=0,
                              max_depth=7, max_leaves=0, min_child_weight=1,
                              missing=nan, monotone_constraints='()',
                              n_estimators=3000, n_jobs=0, num_parallel_tree=1,
                              predictor='auto', random_state=42, ...))])
```

In [19]:
```python
# Plotting
plt.figure(figsize=(14, 6))
plt.plot(y_true.reset_index(drop=True), label='Actual', color='black', linewidth=2)

for name, (preds, _, _) in results.items():
    plt.plot(pd.Series(preds).reset_index(drop=True), label=f'{name} Predicted', alp

plt.legend()
plt.title("Actual vs Predicted Category Sales")
plt.xlabel("Index")
plt.ylabel("Sales Amount")
plt.grid(True)
plt.tight_layout()
plt.show()
```



Inference with best model

In [20]:
```
# Example prediction input
sample_input = pd.DataFrame([{
    'Product Category': 'Clothing',
    'Day': 10,
    'Month': 5,
    'Weekday': pd.Timestamp('2025-05-10').weekday(),
    'isWeekend': int(pd.Timestamp('2025-05-10').weekday() in [5, 6]),
    'isAfter25': int(3 > 25)
}])

# Load model and predict
model = joblib.load('./models/category_sales_model.pkl')
predicted_log = model.predict(sample_input)
predicted_sales = np.expm1(predicted_log[0])
print("Forecasted Sales:", round(predicted_sales, 2))
```

```
Forecasted Sales: 192.27
```

Conclusion:

Three multivariate models(RandomForest, GradientBoost, XGBoost) were fit and compared. The model doesn't seems to fit so well. All these models are hypertuned with grid search and the best model is saved. However, the models appear to be underfitting. It is also to under that the limited data sample of only a year is also a reason for models to find hard learning patterns.

We proceed with the best fit, which is XGBoost in our case with least MAE.

Possible Enhancements:

- Hyperune more with hihger estimators and higher learning rates
- Try wider architectures like MLP
- Experiment with Prophet model by Meta
- Combine with LSTM

Model 2 - Sales prediction based on all transaction data

This modelling is done to predict the total sales for any future date provided all transactional data gender, age, product category and date. Three algorithms RandomForest, GradientBoost and XGBoost are trained and compared.

In [21]:
```
# Import Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from xgboost import XGBRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error

import joblib

# Ensure Date is datetime
df['Date'] = pd.to_datetime(df['Date'])

# Create new DataFrame with selected and engineered features
```

```
processed_df = pd.DataFrame({
    'Gender': df['Gender'],
    'Age': df['Age'],
    'Product Category': df['Product Category'],
    'Day': df['Date'].dt.day,
    'Month': df['Date'].dt.month,
    'Weekday': df['Date'].dt.weekday,
    'isWeekend': df['Date'].dt.weekday.isin([5, 6]).astype(int),
    'isAfter25': (df['Date'].dt.day > 25).astype(int),
    'LogTotalAmount': np.log1p(df['AdjustedTotalAmount'])
})

# Define Features and target
X = processed_df[['Age', 'Gender', 'Product Category', 'Day', 'Month', 'Weekday', 'i
y = processed_df['LogTotalAmount']

# Train test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_stat
```

In [22]:

```
processed_df.head()
```

Out[22]:

	Gender	Age	Product Category	Day	Month	Weekday	isWeekend	isAfter25	LogTotalAmount
521	Male	46	Beauty	1	1	6	1	0	7.313887
179	Male	41	Clothing	1	1	6	1	0	6.803505
558	Female	40	Clothing	1	1	6	1	0	7.090910
302	Male	19	Electronics	2	1	0	0	0	4.510860
978	Female	19	Beauty	2	1	0	0	0	3.258097

In [23]:

```
# Define categorical and numerical features
cat_features = ['Gender', 'Product Category']
num_features = ['Age', 'Day', 'Month', 'Weekday', 'isWeekend', 'isAfter25']

cat_transformer = Pipeline([
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

num_transformer = Pipeline([
    ('imputer', SimpleImputer(strategy='mean')),
    ('scaler', StandardScaler())
])

preprocessor = ColumnTransformer([
    ('cat', cat_transformer, cat_features),
    ('num', num_transformer, num_features)
])
```

In [24]:

```
# Define models with hypertune parameters
models = {
    'RandomForest': (RandomForestRegressor(random_state=42), {
        'regressor__n_estimators': [2000, 3000, 4000],
        'regressor__max_depth': [7, 9, 11]
    }),
    'XGBoost': (XGBRegressor(random_state=42, verbosity=0), {
        'regressor__n_estimators': [2000, 3000, 4000],
```

```
        'regressor__max_depth': [7, 9, 11],
        'regressor__learning_rate': [0.001, 0.01, 0.05, 0.1]
    }),
    'GradientBoosting': (GradientBoostingRegressor(random_state=42), {
        'regressor__n_estimators': [2000, 3000, 4000],
        'regressor__max_depth': [7, 9, 11],
        'regressor__learning_rate': [0.001, 0.01, 0.05, 0.1]
    })
}
```

Train Models

In [25]:

```
# Train
print("Training.........")
results = {}
best_model = None
best_mae = float('inf')

for name, (model, param_grid) in models.items():
    pipeline = Pipeline([
        ('preprocessor', preprocessor),
        ('regressor', model)
    ])
    grid = GridSearchCV(pipeline, param_grid, cv=3, scoring='neg_mean_squared_error'
    grid.fit(X_train, y_train)
    best_est = grid.best_estimator_
    y_pred_log = best_est.predict(X_test)
    y_pred = np.expm1(y_pred_log)
    y_true = np.expm1(y_test)
    mae = mean_absolute_error(y_true, y_pred)
    rmse = np.sqrt(mean_squared_error(y_true, y_pred))
    results[name] = (y_pred, mae, rmse)
    if mae < best_mae:
        best_model = name
        best_mae = mae
        best_rmse = rmse
        best_grid_est = grid.best_estimator_

        # Save best model
        joblib.dump(grid, "./models/full_transaction_model.pkl")
```

```
Training.........
```

In [26]:

```
# Print best model
print(f"\nBest Model: {best_model}\nMAE: {best_mae:.2f}, RMSE: {best_rmse:.2f}")
```

```
Best Model: GradientBoosting
MAE: 342.34, RMSE: 514.68
```

In [27]:

```
best_grid_est
```

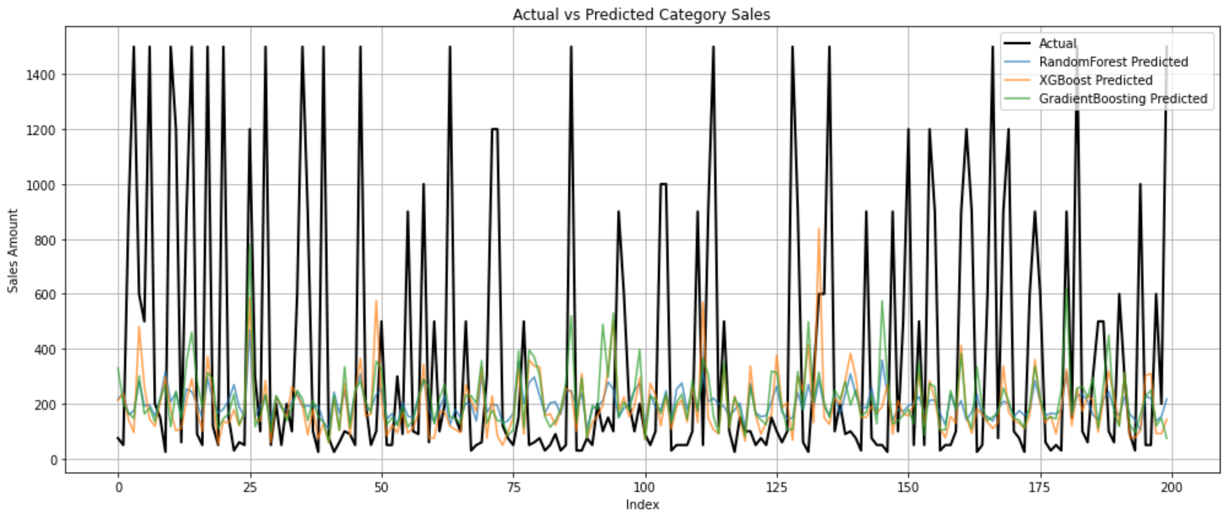
Out[27]:

```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('cat',
                                                  Pipeline(steps=[('imputer',
                                                                   SimpleImputer(stra
tegy='most_frequent')),
                                                                  ('onehot',
                                                                   OneHotEncoder(hand
le_unknown='ignore'))]),
                                                  ['Gender',
                                                   'Product Category']),
```

```
                                                  ('num',
                                                   Pipeline(steps=[('imputer',
                                                                    SimpleImputer()),
                                                                   ('scaler',
                                                                    StandardScaler
())]),
                                                   ['Age', 'Day', 'Month',
                                                    'Weekday', 'isWeekend',
                                                    'isAfter25'])])),
                ('regressor',
                 GradientBoostingRegressor(learning_rate=0.001, max_depth=7,
                                           n_estimators=2000,
                                           random_state=42))])
```

In [28]:

```python
# Plotting
plt.figure(figsize=(14, 6))
plt.plot(y_true.reset_index(drop=True), label='Actual', color='black', linewidth=2)

for name, (preds, _, _) in results.items():
    plt.plot(pd.Series(preds).reset_index(drop=True), label=f'{name} Predicted', alp

plt.legend()
plt.title("Actual vs Predicted Category Sales")
plt.xlabel("Index")
plt.ylabel("Sales Amount")
plt.grid(True)
plt.tight_layout()
plt.show()
```



Inference with best model

In [29]:

```python
# Example prediction input
sample_input = pd.DataFrame([{
    'Age': 30,
    'Gender': 'Male',
    'Product Category': 'Clothing',
    'Day': 10,
    'Month': 5,
    'Weekday': pd.Timestamp('2025-05-10').weekday(),
    'isWeekend': int(pd.Timestamp('2025-05-10').weekday() in [5, 6]),
    'isAfter25': int(3 > 25)
}])

# Load model and predict
model = joblib.load('./models/full_transaction_model.pkl')
```

```
predicted_log = model.predict(sample_input)
predicted_sales = np.expm1(predicted_log[0])
print("Forecasted Sales:", round(predicted_sales, 2))
```

```
Forecasted Sales: 221.83
```

Conclusion:

Three multivariate models(RandomForest, GradientBoost, XGBoost) were fit and compared. The model doesn't seems to fit so well. All these models are hypertuned with grid search and the best model is saved. However, the models appear to be underfitting. It is also to under that the limited data sample of only a year is also a reason for models to find hard learning patterns.

We proceed with the best fit, which is GradientBoost in our case with least MAE.

Possible Enhancements:

- Hypertune more with hihger estimators and higher learning rates
- Try wider architectures like MLP
- Experiment with Prophet model by Meta
- Combine with LSTM