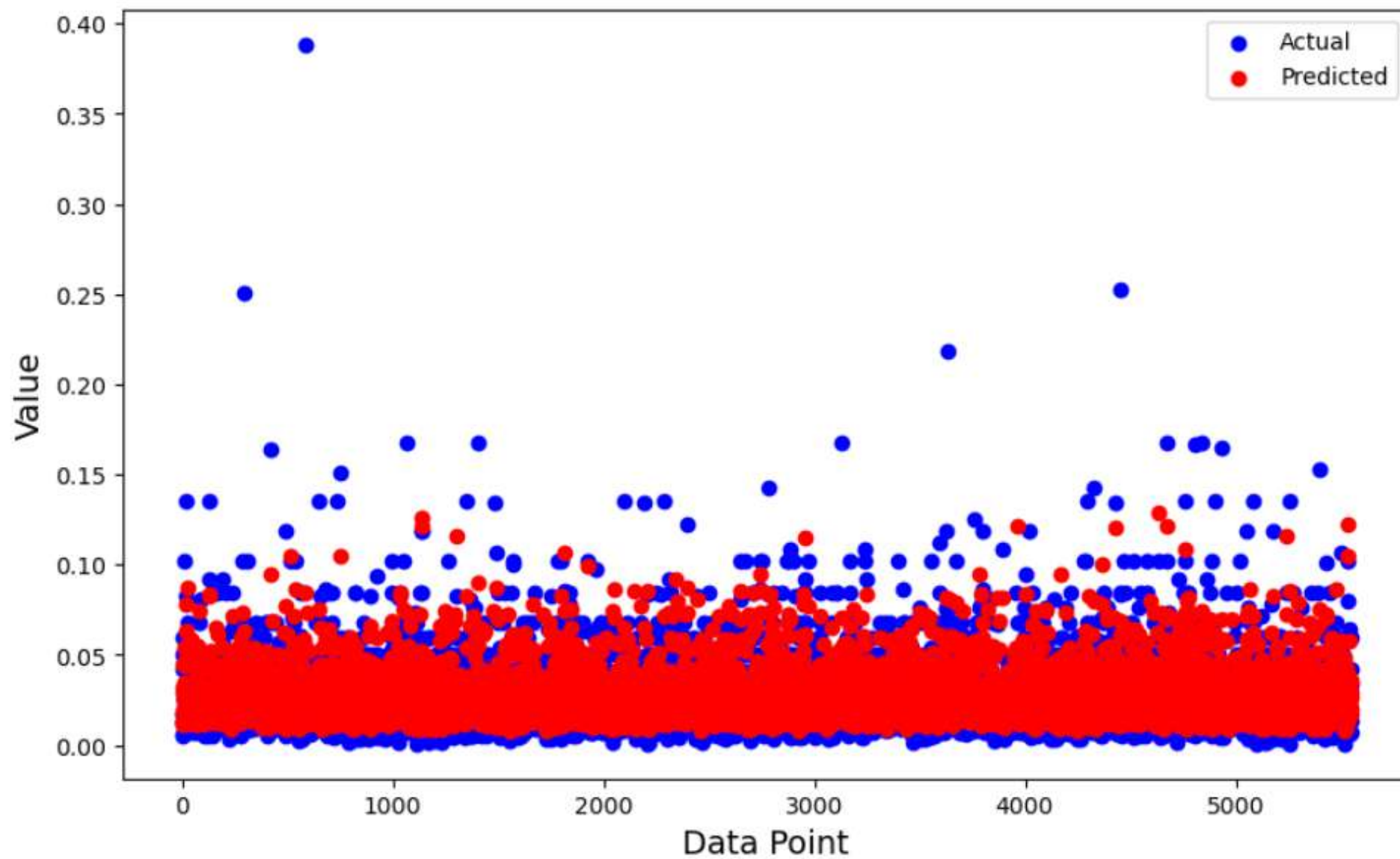
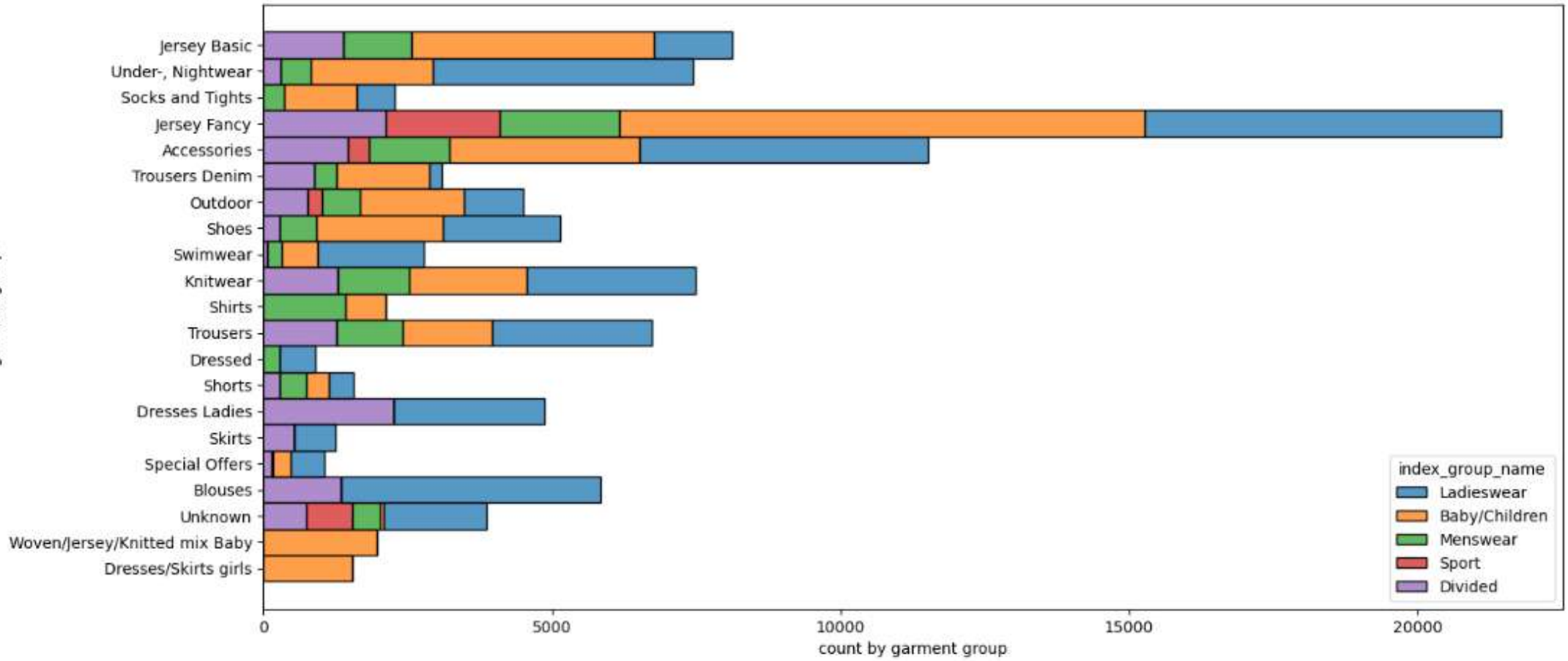


Actual vs. Predicted Values





```

# Convert categorical columns to numeric using one-hot encoding
categorical_cols = ['product_code', 'product_type_name', 'colour_group_name', 'department_name', 'FN']
X_encoded = pd.get_dummies(X_encoded, columns=categorical_cols)

# Drop remaining columns with object data type
X_encoded = X_encoded.select_dtypes(exclude=['object'])

train_ratio = 0.8 # 80% for training, 20% for testing
train_size = int(train_ratio * len(merged_df))
X_train, X_test = X_encoded[:train_size], X_encoded[train_size:]
y_train, y_test = y[:train_size].values, y[train_size:].values # Convert to NumPy arrays

# Define the LightGBM dataset
train_data = lgb.Dataset(X_train, label=y_train)

# Set the hyperparameters for LightGBM
params = {
    'objective': 'regression',
    'metric': 'rmse',
    'boosting_type': 'gbdt',
    'num_leaves': 31,
    'learning_rate': 0.05,
    'feature_fraction': 0.9,
    'bagging_fraction': 0.8,
    'bagging_freq': 5,
    'verbose': 0
}

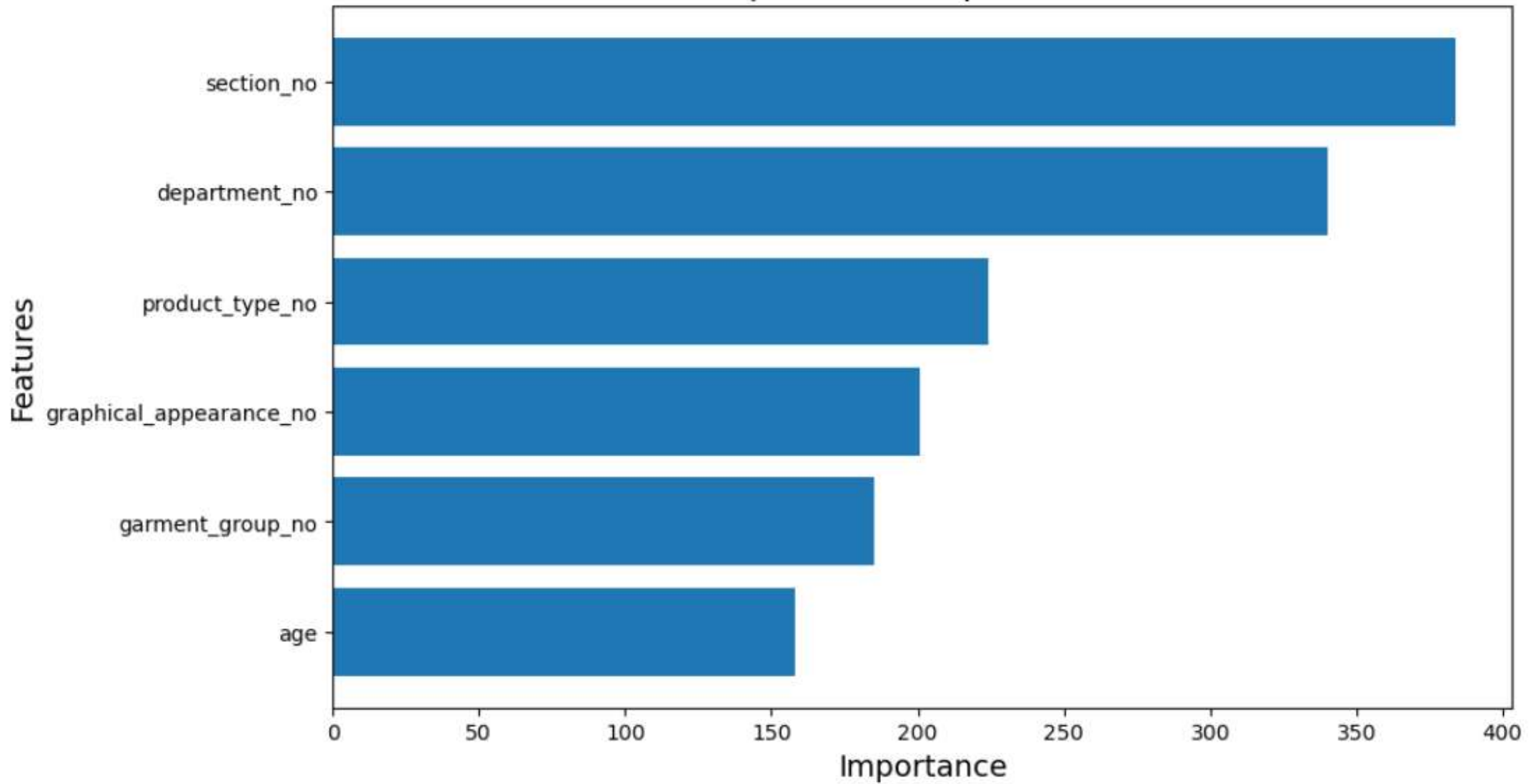
# Train the LightGBM model
model = lgb.train(params, train_data, num_boost_round=100)

# Predict on the test set
y_pred = model.predict(X_test)

# Access valuable information from the trained model
feature importances = model.feature_importance()

```

Top Feature Importances



Monthly sales

