Task

In this task, you will work with dummy sales data of a well-known brand on Amazon. Your objective is to build a time series forecasting model that predicts the number of units sold for each item ID.

Load the datasets

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Load the datasets
data = pd.read_csv("/content/train.csv")
```

Exploratory Data Analysis (EDA)

```
# EDA for Training Dataset
print("Training Dataset")
print(data.head())
print(data.info())
print(data.describe())
print("Missing Values:\n", data.isnull().sum())

# Drop rows with missing values
data.dropna(inplace=True)

# Convert the 'date' column to datetime format
data['date'] = pd.to_datetime(data['date'])

# Extract additional features from the date
data['year'] = data['date'].dt.year
data['month'] = data['date'].dt.month
data['day'] = data['date'].dt.day
data['dayofweek'] = data['date'].dt.dayofweek
data['weekofyear'] = data['date'].dt.isocalendar().week
```

```
 2   Item Id     58763 non-null  object
 3   Item Name   58763 non-null  object
 4   ad_spend    58763 non-null  float64
 5   anarix_id   58763 non-null  object
 6   units       58763 non-null  float64
 7   unit_price  58763 non-null  float64
 8   year        58763 non-null  int32
 9   month       58763 non-null  int32
 10  day         58763 non-null  int32
```

```
min          1.0
25%         11.0
50%         24.0
75%         38.0
max         52.0
std     15.387658
Missing Values:
 ID           0
date         0
Item Id      0
Item Name    0
ad_spend     0
anarix_id    0
units        0
unit_price   0
year         0
month        0
day          0
dayofweek    0
weekofyear   0
dtype: int64
```

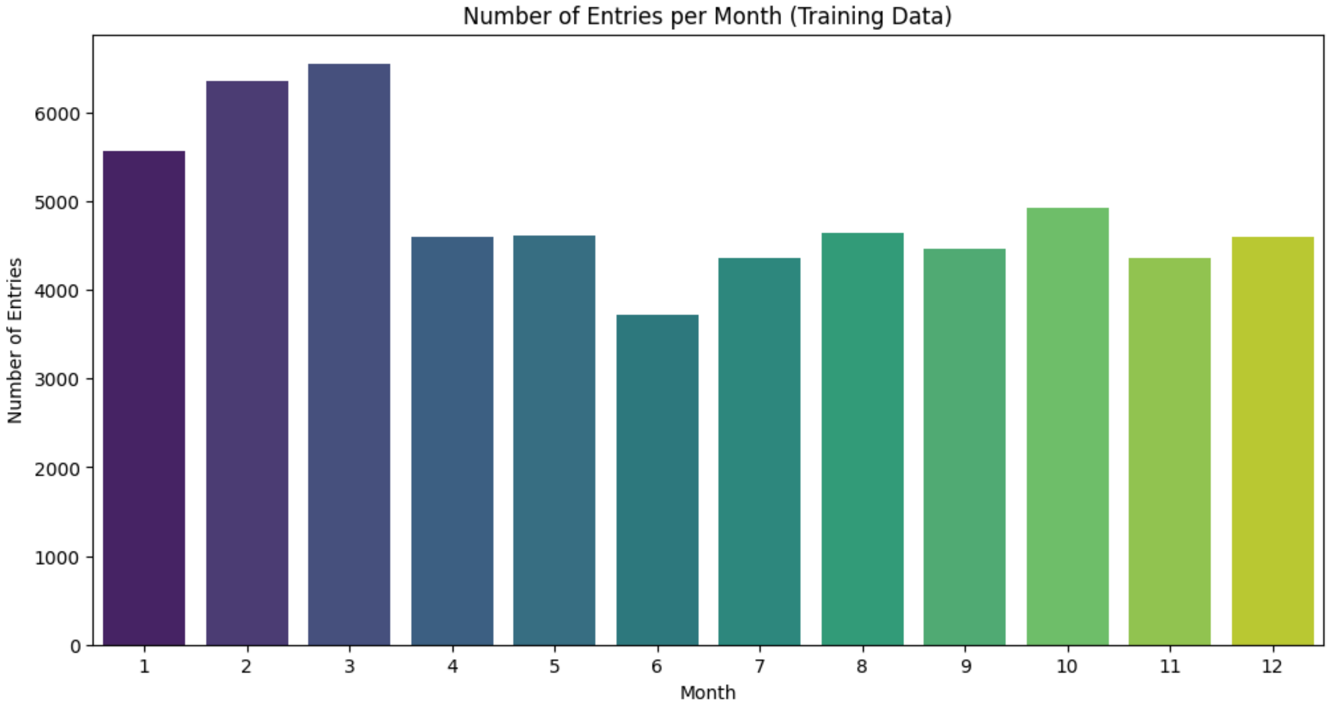
Start coding or generate with AI.

```
# Plot number of entries per month
plt.figure(figsize=(12, 6))
sns.countplot(data=data, x='month', palette='viridis')
plt.title('Number of Entries per Month (Training Data)')
plt.xlabel('Month')
plt.ylabel('Number of Entries')
plt.show()
```

```
<ipython-input-4-f7b90c5ed20f>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `l

  sns.countplot(data=data, x='month', palette='viridis')
```

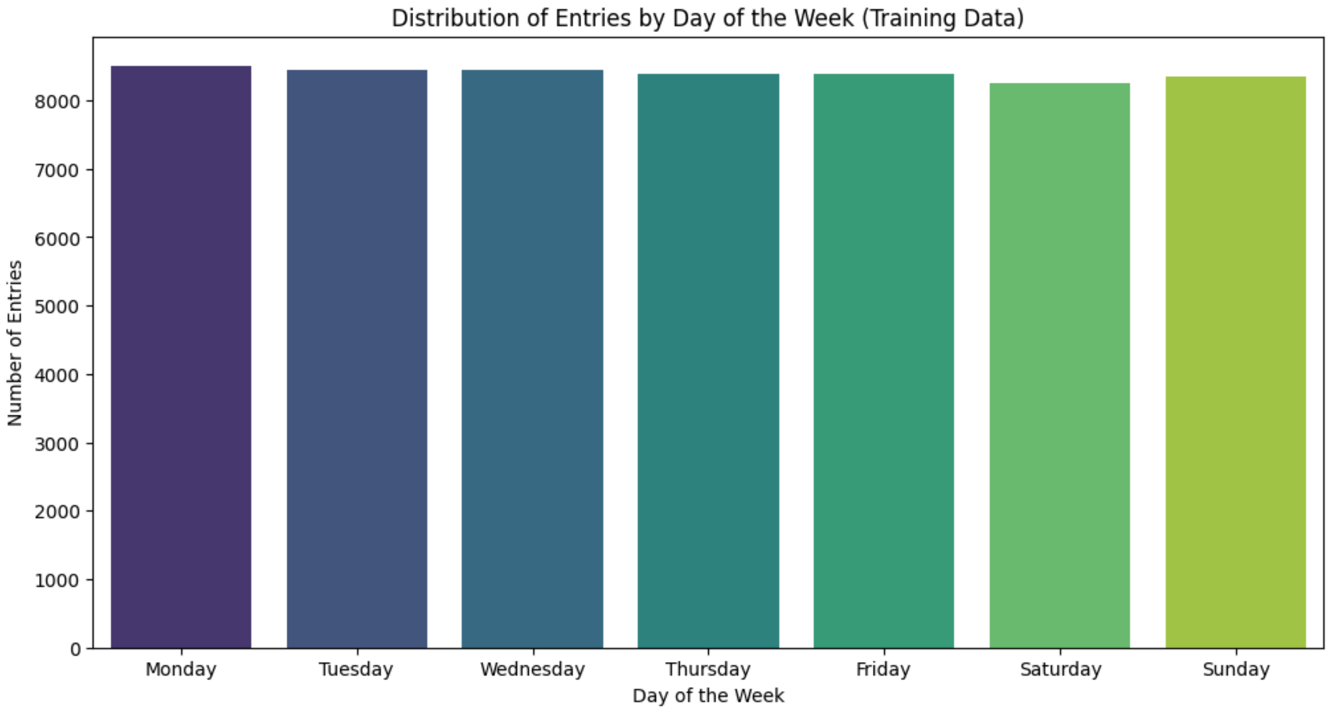



```
# Plot distribution of entries by day of the week
plt.figure(figsize=(12, 6))
sns.countplot(data=data, x='dayofweek', palette='viridis')
plt.title('Distribution of Entries by Day of the Week (Training Data)')
plt.xlabel('Day of the Week')
plt.ylabel('Number of Entries')
plt.xticks(ticks=range(7), labels=['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday'])
plt.show()
```

```
<ipython-input-5-fffc1a6101d0>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `l

  sns.countplot(data=data, x='dayofweek', palette='viridis')
```



Feature Engineering

```
# Create lag features and rolling mean features
data['units_lag_1'] = data.groupby('Item Id')['units'].shift(1)
data['units_lag_7'] = data.groupby('Item Id')['units'].shift(7)
data['units_roll_mean_7'] = data.groupby('Item Id')['units'].transform(lambda x: x.rolling(7).mean())
data['units_lag_30'] = data.groupby('Item Id')['units'].shift(30)
data['units_roll_mean_30'] = data.groupby('Item Id')['units'].transform(lambda x: x.rolling(30).mean())

# Drop rows with any missing values created by lag and rolling window operations
data.dropna(inplace=True)

# Define feature matrix X and target vector y
X = data.drop(['units', 'date', 'Item Id', 'Item Name'], axis=1)
y = data['units']
```

Model Selection

```python
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.metrics import mean_squared_error

# Split the data into training and validation sets
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42)

# Define categorical and numerical features
categorical_features = ['ID', 'anarix_id']
numerical_features = X_train.select_dtypes(include=[np.number]).columns.tolist()

# Create a column transformer for preprocessing
preprocessor = ColumnTransformer(
    transformers=[
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_features),
        ('num', Pipeline(steps=[
            ('imputer', SimpleImputer(strategy='mean')),
            ('scaler', StandardScaler())
        ]), numerical_features)
    ],
    remainder='passthrough'
)

# Define and train models
models = {
    'Linear Regression': Pipeline(steps=[
        ('preprocessor', preprocessor),
        ('model', LinearRegression())
    ]),
    'Ridge Regression': Pipeline(steps=[
        ('preprocessor', preprocessor),
        ('model', Ridge(alpha=1.0))
    ]),
    'Lasso Regression': Pipeline(steps=[
        ('preprocessor', preprocessor),
        ('model', Lasso(alpha=0.1))
    ]),
    'Gradient Boosting Machines': Pipeline(steps=[
        ('preprocessor', preprocessor),
        ('model', GradientBoostingRegressor(n_estimators=100, random_state=42))
    ])
}

# Train and evaluate models
mse_scores = {}
for model_name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_val)
    mse = mean_squared_error(y_val, y_pred)
    mse_scores[model_name] = mse
    print(f"{model_name} MSE: {mse}")

# Find the best model
best_model_name = min(mse_scores, key=mse_scores.get)
print(f"\nThe best model based on MSE is: {best_model_name} with MSE: {mse_scores[best_model_name]}")
```

```
Linear Regression MSE: 967.195947851786
Ridge Regression MSE: 967.1533279634668
Lasso Regression MSE: 942.9285037322292
Gradient Boosting Machines MSE: 516.6289504200828

The best model based on MSE is: Gradient Boosting Machines with MSE: 516.6289504200828
```

Hyperparameter Tuning

```python
from sklearn.model_selection import GridSearchCV

# Define the parameter grid for hyperparameter tuning
param_grid = {
    'model__n_estimators': [100, 200],
    'model__learning_rate': [0.01, 0.1],
    'model__max_depth': [3, 5]
}
```

```
# Initialize the Gradient Boosting Regressor within a Pipeline
gb_model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('model', GradientBoostingRegressor(random_state=42))
])

# Set up GridSearchCV for hyperparameter tuning
grid_search = GridSearchCV(gb_model, param_grid, cv=3, n_jobs=-1, scoring='neg_mean_squared_error')

# Fit GridSearchCV on the training data
grid_search.fit(X_train, y_train)

# Print best hyperparameters
print("Best parameters for Gradient Boosting Machines:", grid_search.best_params_)
```

```
Best parameters for Gradient Boosting Machines: {'model__learning_rate': 0.1, 'model__max_depth': 3, 'model__n_estimators': 200}
```

Predicting on Test Data

```
import numpy as np
import pandas as pd
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.impute import SimpleImputer

# Load the test dataset
test = pd.read_csv('/content/test.csv')

# Convert 'date' column to datetime
test['date'] = pd.to_datetime(test['date'])

# Extract additional features from the date
test['year'] = test['date'].dt.year
test['month'] = test['date'].dt.month
test['day'] = test['date'].dt.day
test['dayofweek'] = test['date'].dt.dayofweek
test['weekofyear'] = test['date'].dt.isocalendar().week

# Sort test data by 'Item Id' and 'date' to ensure proper time series operations
test = test.sort_values(by=['Item Id', 'date'])

# Create lag features and rolling mean features for the test dataset
test['units_lag_1'] = test.groupby('Item Id')['unit_price'].shift(1)
test['units_lag_7'] = test.groupby('Item Id')['unit_price'].shift(7)
test['units_lag_30'] = test.groupby('Item Id')['unit_price'].shift(30)
test['units_roll_mean_7'] = test.groupby('Item Id')['unit_price'].transform(lambda x: x.rolling(7).mean())
test['units_roll_mean_30'] = test.groupby('Item Id')['unit_price'].transform(lambda x: x.rolling(30).mean())

# Handle missing values in the test dataset created by lag and rolling window operations
test.fillna(0, inplace=True)

# Define the feature matrix for the test data
X_test = test.drop(['date', 'Item Id', 'Item Name'], axis=1)

# Define categorical and numerical features
categorical_features = ['ID', 'anarix_id']
numerical_features = X_test.select_dtypes(include=[np.number]).columns.tolist()

# Create a column transformer for preprocessing
preprocessor = ColumnTransformer(
    transformers=[
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_features),
        ('num', Pipeline(steps=[
            ('imputer', SimpleImputer(strategy='mean')),
            ('scaler', StandardScaler())
        ]), numerical_features)
    ],
    remainder='passthrough'
)

# Initialize the Gradient Boosting Regressor with best hyperparameters
best_gb_model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('model', GradientBoostingRegressor(n_estimators=200, learning_rate=0.1, max_depth=3, random_state=42))
])

# Fit the model on the training data again
```

```
best_gb_model.fit(X_train, y_train)

# Predict the target variable for the test dataset
test['TARGET'] = best_gb_model.predict(X_test)

# Create a submission file
submission = test[['date', 'Item Id', 'TARGET']]
submission.to_csv('sample_submission.csv', index=False)

print("Submission file created successfully.")
```

```
Submission file created successfully.
```