```python
# Import libraries
import pandas as pd
import numpy as np
from datetime import datetime

from pathlib import Path

current_dir = Path.cwd()
print("Current directory:", current_dir)


# Load all CSVs
claims = pd.read_csv('patient_claims_data.csv')
prescribers = pd.read_csv('prescriber_data.csv')
market = pd.read_csv('market_lookup_table.csv')
calendar = pd.read_csv('calendar_table.csv')
```

```
Current directory: D:\anusha_project
```

```python
claims.head(5)
```

```
  patient_id    ndc_code drug_name  start_date    end_date  
days_supply  \
0     P23104  51904-9849    Drug_B  2022-05-12  2022-07-11  
60
1     P80678  29769-4788    Drug_D  2022-05-08  2022-06-07  
30
2     P13617  45614-6502    Drug_A  2024-02-19  2024-04-19  
60
3     P23577  29769-4788    Drug_D  2024-05-08  2024-08-06  
90
4     P44718  20561-3267    Drug_C  2024-06-11  2024-08-10  
60

  provider_id specialty diagnosis_code region
0     HCP3414   General           D654   East
1     HCP1400   General           D654   West
2     HCP7311   General           D789   East
3     HCP5499   General           D321  South
4     HCP1727   General           D789   West
```

```python
prescribers.head(5)
```

```
    hcp_id      specialty brand_written region
0  HCP7311  Endocrinology        Drug_E  South
1  HCP4114        General        Drug_E  South
2  HCP5173      Neurology        Drug_E   East
```

```
3  HCP1727      Neurology        Drug_E   West
4  HCP8144     Cardiology        Drug_C  North
```

```python
market.head(5)
```

```
  brand_name    molecule therapeutic_class
0     Drug_A  Molecule_0           Class_A
1     Drug_B  Molecule_1           Class_B
2     Drug_C  Molecule_2           Class_C
3     Drug_D  Molecule_3           Class_A
4     Drug_E  Molecule_4           Class_B
```

```python
calendar.head(5)
```

```
         date  month  year  fiscal_quarter  fiscal_year
0  2022-01-01      1  2022               1         2022
1  2022-01-02      1  2022               1         2022
2  2022-01-03      1  2022               1         2022
3  2022-01-04      1  2022               1         2022
4  2022-01-05      1  2022               1         2022
```

```python
# Convert 'start_date' to datetime format for date calculations
claims['start_date'] = pd.to_datetime(claims['start_date'])

# Sort claims by patient and claim start date to maintain
chronological order
claims = claims.sort_values(['patient_id', 'start_date'])

# Get the previous claim's end date for each patient
claims['prev_end'] = claims.groupby('patient_id')['end_date'].shift(1)

# Calculate the gap in days between the current claim's start and the
previous claim's end
claims['gap'] = (claims['start_date'] -
pd.to_datetime(claims['prev_end'])).dt.days

# Flag claims that start after a gap of more than 180 days —
indicating a "new start"
claims['new_start'] = claims['gap'] > 180

# ----------------------------
# Discontinuation Detection
# ----------------------------

# Find the last fill (latest end_date) for each patient
last_fill = claims.groupby('patient_id')
['end_date'].max().reset_index()

# Flag patients as discontinued if it's been more than 60 days since
```

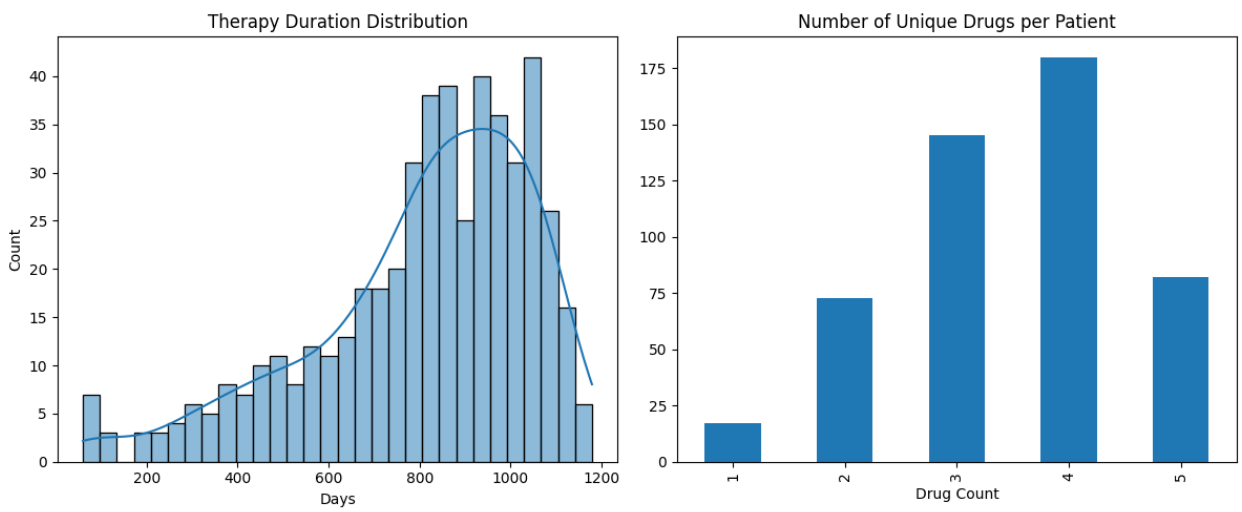
```
their last fill
last_fill['discontinued'] = (
    pd.to_datetime('today') - pd.to_datetime(last_fill['end_date'])
).dt.days > 60

# ----------------------------
# Molecule Switch Detection
# ----------------------------

# Merge claims with the 'market' dataset to associate each drug with
its molecule
claims = pd.merge(claims, market, left_on='drug_name',
right_on='brand_name', how='left')

# Detect if the molecule has changed from the previous claim — flag as
molecule switch
# Compares current molecule with the one from the previous claim per
patient
claims['molecule_switch'] = (
    claims.groupby('patient_id')['molecule'].shift(1) !=
claims['molecule']
)

# Show the first 5 rows of the modified DataFrame
claims.head(5)
```

```
  patient_id    ndc_code drug_name start_date    end_date  days_supply
\
0     P10074  20561-3267    Drug_C 2022-04-06  2022-07-05           90

1     P10074  29769-4788    Drug_D 2022-06-26  2022-09-24           90

2     P10074  51904-9849    Drug_B 2022-07-29  2022-08-28           30

3     P10074  60205-3503    Drug_E 2022-11-23  2023-02-21           90

4     P10074  20561-3267    Drug_C 2023-08-21  2023-11-19           90


  provider_id specialty diagnosis_code region    prev_end    gap
new_start  \
0     HCP8043   General           D654  South         NaN    NaN
False
1     HCP7790   General           D123  North  2022-07-05   -9.0
False
2     HCP6344   General           D456  South  2022-09-24  -57.0
False
3     HCP6067   General           D321  South  2022-08-28   87.0
False
4     HCP1090   General           D123   East  2023-02-21  181.0
```

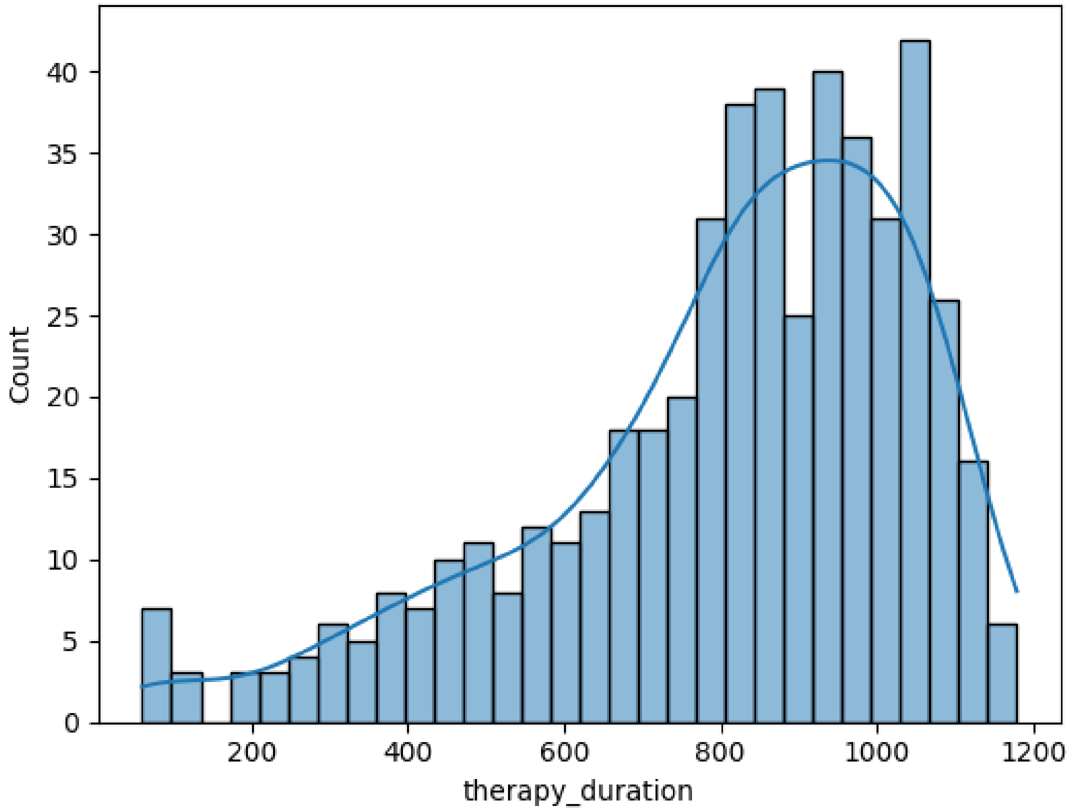
```
True

  brand_name    molecule therapeutic_class  molecule_switch
0     Drug_C  Molecule_2           Class_C             True
1     Drug_D  Molecule_3           Class_A             True
2     Drug_B  Molecule_1           Class_B             True
3     Drug_E  Molecule_4           Class_B             True
4     Drug_C  Molecule_2           Class_C             True
```

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

def create_patient_funnel(claims):
    # Ensure 'start_date' and 'end_date' columns are in datetime
format
    claims['start_date'] = pd.to_datetime(claims['start_date'])
    claims['end_date'] = pd.to_datetime(claims['end_date'])

    # Group by patient and calculate funnel metrics
    funnel = claims.groupby('patient_id').agg(
        initiated=('start_date', 'min'),       # First recorded claim
(start of therapy)
        last_fill=('end_date', 'max'),         # Last recorded claim
(end of therapy)
        unique_drugs=('drug_name', 'nunique'), # Number of distinct
drugs the patient was prescribed
        total_rx=('ndc_code', 'count')         # Total number of
prescriptions (NDC codes) filled
    ).reset_index()

    # Calculate duration of therapy in days
    funnel['therapy_duration'] = (funnel['last_fill'] -
funnel['initiated']).dt.days

    # Plotting two visualizations side by side
    plt.figure(figsize=(12, 5))

    # Histogram of therapy durations
    plt.subplot(1, 2, 1)
    sns.histplot(funnel['therapy_duration'], bins=30, kde=True)
    plt.title('Therapy Duration Distribution')
    plt.xlabel('Days')

    # Bar chart of number of unique drugs per patient
    plt.subplot(1, 2, 2)

funnel['unique_drugs'].value_counts().sort_index().plot(kind='bar')
    plt.title('Number of Unique Drugs per Patient')
    plt.xlabel('Drug Count')
```

```
    # Adjust layout and display the plots
    plt.tight_layout()
    plt.show()

    return funnel

# Run the funnel analysis and generate plots
funnel = create_patient_funnel(claims)

# (Redundant re-calculation below - could be removed)
# Recalculate patient funnel data again (already done above)
funnel = claims.groupby('patient_id').agg(
    initiated=('start_date', 'min'),
    last_fill=('end_date', 'max'),
    unique_drugs=('drug_name', 'nunique')
).reset_index()

# Recalculate therapy duration
funnel['therapy_duration'] = (funnel['last_fill'] -
funnel['initiated']).dt.days

# Plot therapy duration distribution again
import seaborn as sns
sns.histplot(funnel['therapy_duration'], bins=30, kde=True)
```



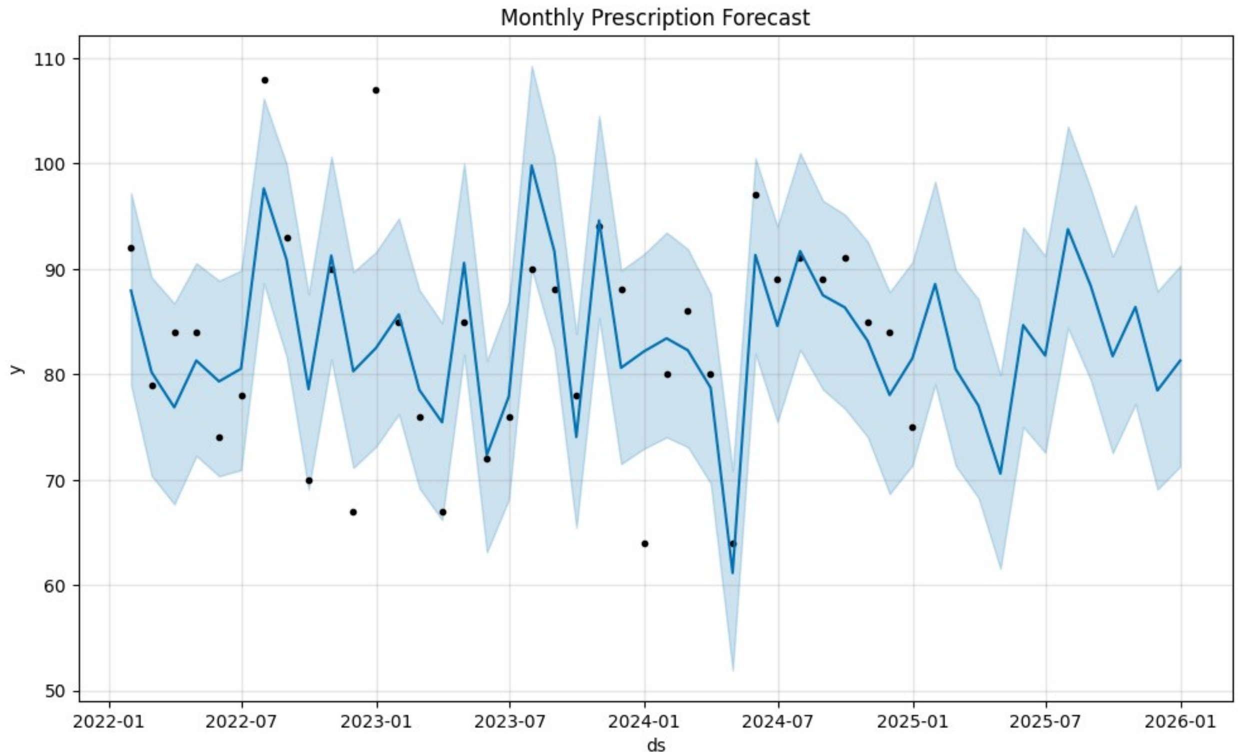

```
<Axes: xlabel='therapy_duration', ylabel='Count'>
```

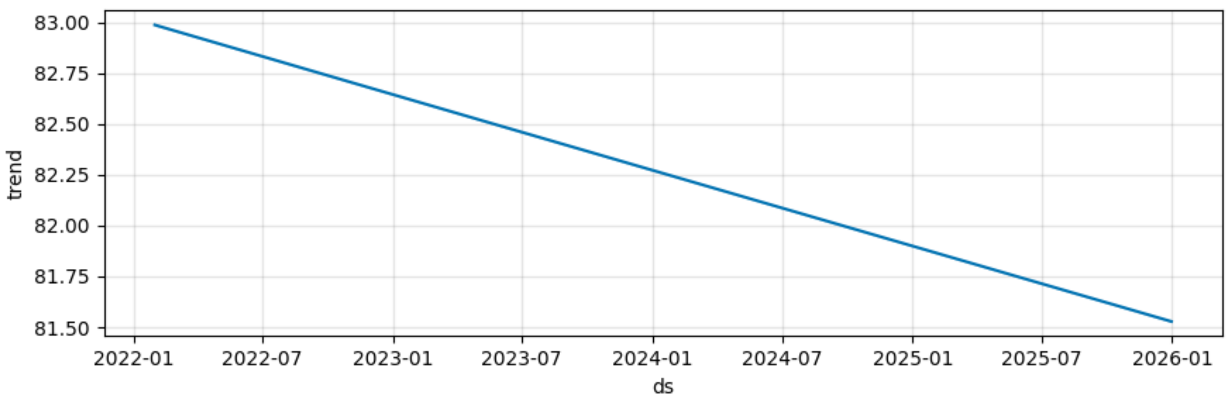


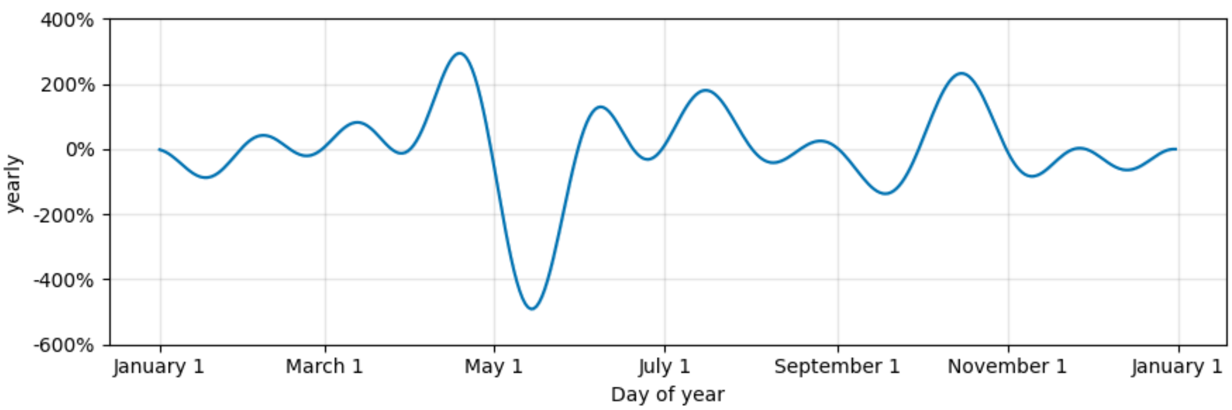

```
import pandas as pd
from prophet import Prophet
import matplotlib.pyplot as plt

# Merge claims with prescriber details using provider/hcp IDs
df = pd.merge(claims, prescribers, left_on='provider_id',
right_on='hcp_id', how='left')

# Ensure calendar date is in datetime format
calendar['date'] = pd.to_datetime(calendar['date'])

# Merge calendar data with the claims dataframe based on the start
date of prescription
df = pd.merge(df, calendar, left_on='start_date', right_on='date',
how='left')

# Create patient-level quarterly features
features = df.groupby(['patient_id', 'fiscal_quarter']).agg(
    fills=('ndc_code', 'count'),                            # Total
number of prescriptions in the quarter
    adherence=('days_supply', lambda x: x.sum() / 90),   # Proportion
of Days Covered (PDC) — rough adherence metric
    gap_days=('gap', 'mean'),                               # Average
days between prescriptions
    hcp_specialty=('specialty_y', 'first'),                 #
```

```
Prescriber's specialty (take first occurrence)
    region=('region_x', 'first')                         # Patient or
provider region
).reset_index()

# Group data by month and count total prescriptions
monthly_rx = (df.groupby(pd.to_datetime(df['start_date']))['ndc_code']
              .count()
              .resample('ME')       # 'ME' = month-end
              .sum()
              .reset_index())

# Rename columns for Prophet compatibility
monthly_rx.columns = ['ds', 'y']

# Initialize Prophet model with multiplicative seasonality (good for
percentage changes)
model = Prophet(seasonality_mode='multiplicative')
model.fit(monthly_rx)  # Fit the model to historical data

# Create a future dataframe with 12 months ahead
future = model.make_future_dataframe(periods=12, freq='ME')

# Generate predictions for future dates
forecast = model.predict(future)

# Plot forecast (actuals + predictions)
fig = model.plot(forecast)
plt.title('Monthly Prescription Forecast')
plt.show()

# Plot Prophet components (seasonality, trend, holidays)
fig2 = model.plot_components(forecast)
plt.show()
```

```
22:00:11 - cmdstanpy - INFO - Chain [1] start processing
22:00:11 - cmdstanpy - INFO - Chain [1] done processing
```


Monthly Prescription Forecast
y
ds
110
100
90
80
70
60
50
2022-01
2022-07
2023-01
2023-07
2024-01
2024-07
2025-01
2025-07
2026-01


trend
ds
83.00
82.75
82.50
82.25
82.00
81.75
81.50
2022-01
2022-07
2023-01
2023-07
2024-01
2024-07
2025-01
2025-07
2026-01


yearly
Day of year
400%
200%
0%
-200%
-400%
-600%
January 1
March 1
May 1
July 1
September 1
November 1
January 1

```python
from xgboost import XGBClassifier
from sklearn.model_selection import train_test_split
import pandas as pd

# Keep a copy of original features
features_original = features.copy()
features_processed = features.copy()

# Create binary target: whether the patient will have any fills next
quarter
features_processed['target'] =
features_processed.groupby('patient_id')['fills'].shift(-1) > 0

# Drop rows with NaNs (i.e., last quarter for each patient where
shift(-1) has no future data)
features_processed_2 = features_processed.dropna()

# One-hot encode categorical variables (hcp_specialty, region) for
model input
X = pd.get_dummies(features_processed_2.drop(['target', 'patient_id'],
axis=1),
                   columns=['hcp_specialty', 'region'])

# Target variable
y = features_processed_2['target']

# Split data into training and test sets (80/20)
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Train XGBoost classification model to predict if patient will
continue filling meds
model = XGBClassifier(enable_categorical=False)  # Turn off native
categorical encoding
model.fit(X_train, y_train)  # Fit model

print("Model trained successfully!")
```

```
Model trained successfully!
```

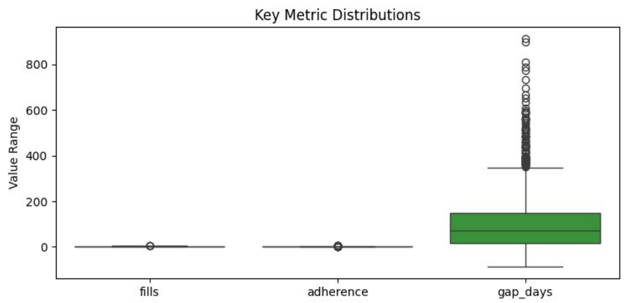
```python
features_processed_2.head(10)
X.head(5)
```

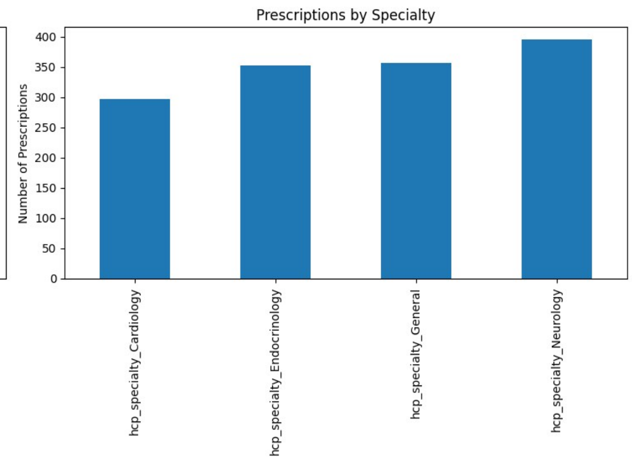
```
   fiscal_quarter  fills  adherence    gap_days
hcp_specialty_Cardiology  \
0               2      4   3.000000   59.333333
False
1               3      4   2.000000   32.750000
False
2               4      2   1.333333   20.500000
False
```

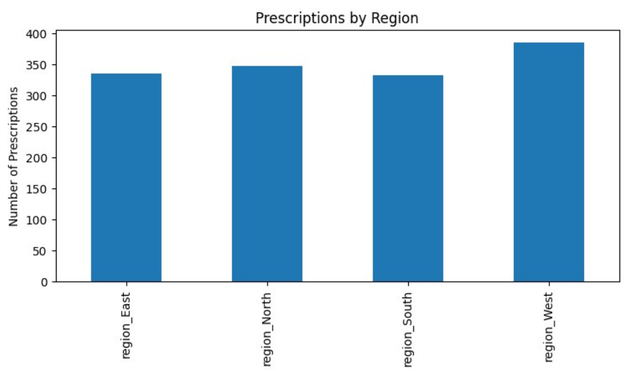
```
3                2      2   1.333333   61.500000
False
4                3      2   1.333333  150.000000
False

   hcp_specialty_Endocrinology  hcp_specialty_General  \
0                         True                  False
1                        False                   True
2                        False                   True
3                        False                  False
4                         True                  False

   hcp_specialty_Neurology  region_East  region_North  region_South  \
0                    False        False         False          True
1                    False        False         False          True
2                    False        False         False          True
3                     True        False         False         False
4                    False        False         False          True

   region_West
0        False
1        False
2        False
3         True
4        False

# Import visualization and math libraries
import matplotlib.pyplot as plt  # Base plotting library
import seaborn as sns            # Enhanced statistical visualizations
import numpy as np               # Numerical operations and math
functions

# ==================================================================
# DATA PREPARATION SECTION
# ==================================================================

# Merge actual prescription data with forecasted values
# - Filters monthly_rx to only include dates after Jan 2023
# - Joins with forecast predictions (yhat) on date column (ds)
pred_vs_actual = pd.merge(
    monthly_rx[monthly_rx['ds'] > '2023-01-01'],  # Actual values
post-Jan 2023
    forecast[['ds', 'yhat']],                     # Forecast
predictions
    on='ds'                                       # Join on date
column
)

# Calculate Mean Absolute Percentage Error (MAPE)
# - Measures forecast accuracy as percentage error
```

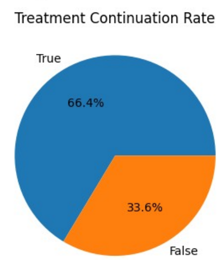
```python
# - Formula: average of (|actual - predicted| / actual)
mape = np.mean(np.abs(pred_vs_actual['y'] - pred_vs_actual['yhat']) /
pred_vs_actual['y'])

# Get indices that would sort feature importance scores
# - argsort() returns indices from least to most important
# - Will use later to plot top features
sorted_idx = model.feature_importances_.argsort()

# ==================================================================
# VISUALIZATION SECTION
# ==================================================================

# 1. FEATURE DISTRIBUTIONS PLOT (4-in-1 layout)
plt.figure(figsize=(15,10))  # Create 15x10 inch figure

# Subplot 1: Boxplots of numerical features
plt.subplot(2,2,1)  # 2x2 grid, position 1
sns.boxplot(data=X[['fills','adherence','gap_days']])  # Distribution
visualization
plt.title('Key Metric Distributions')  # Shows median, quartiles and
outliers
plt.ylabel('Value Range')  # Y-axis label

# Subplot 2: Specialty distribution
plt.subplot(2,2,2)  # Position 2
X.filter(like='hcp_specialty_').sum().plot(kind='bar')  # Sum one-hot
encoded columns
plt.title('Prescriptions by Specialty')  # Which specialties prescribe
most
plt.ylabel('Number of Prescriptions')

# Subplot 3: Regional distribution
plt.subplot(2,2,3)  # Position 3
X.filter(like='region_').sum().plot(kind='bar')  # Sum regional one-
hot columns
plt.title('Prescriptions by Region')  # Geographic distribution
plt.ylabel('Number of Prescriptions')

# Subplot 4: Target class balance
plt.subplot(2,2,4)  # Position 4
y.value_counts().plot(kind='pie', autopct='%1.1f%%')  # Show
percentage distribution
plt.title('Treatment Continuation Rate')  # % of patients continuing
treatment
plt.ylabel('')  # Remove default y-label

plt.tight_layout()  # Prevent label overlapping
plt.show()  # Display the figure
```

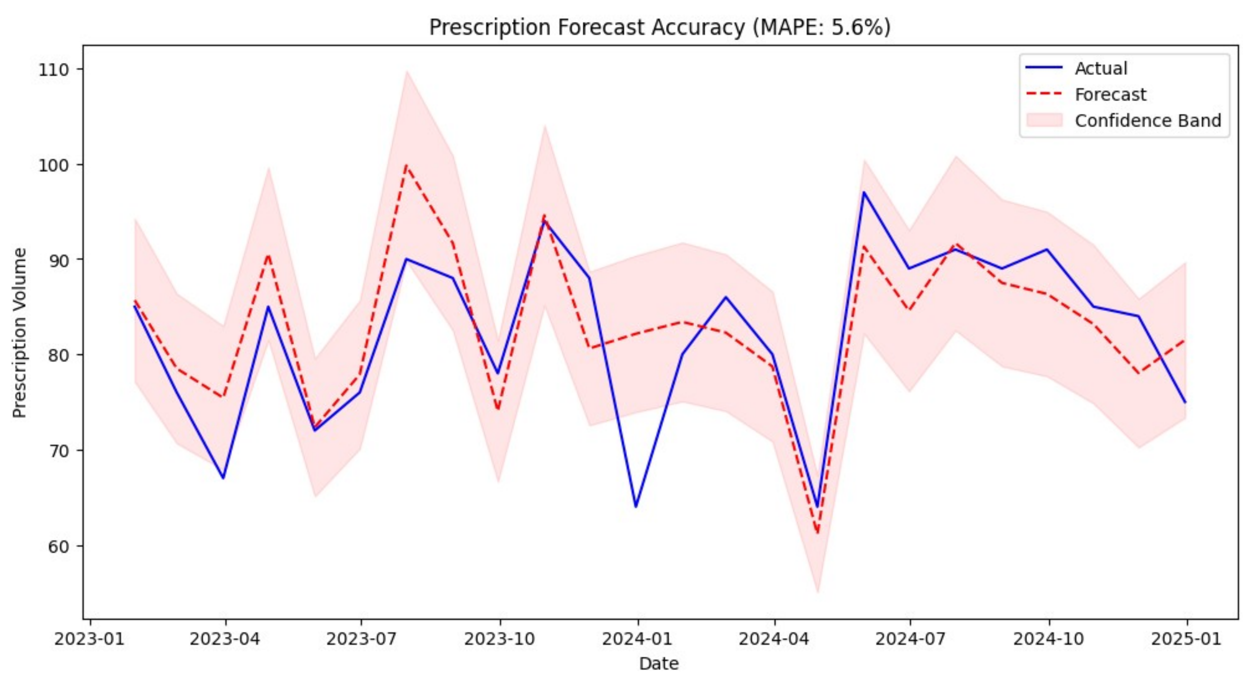
```
# 2. FORECAST ACCURACY PLOT
plt.figure(figsize=(12,6))  # New 12x6 inch figure

# Plot actual prescription values as blue line
plt.plot(pred_vs_actual['ds'], pred_vs_actual['y'], 'b-',
label='Actual')

# Plot forecasted values as red dashed line
plt.plot(pred_vs_actual['ds'], pred_vs_actual['yhat'], 'r--',
label='Forecast')

# Add confidence band (90-110% of forecast)
plt.fill_between(pred_vs_actual['ds'],
                pred_vs_actual['yhat']*0.9,  # Lower bound
                pred_vs_actual['yhat']*1.1,  # Upper bound
                color='r', alpha=0.1, label='Confidence Band')  #
Semi-transparent red

# Add title with MAPE score formatted as percentage
plt.title(f'Prescription Forecast Accuracy (MAPE: {mape:.1%})')
plt.xlabel('Date')  # X-axis label
plt.ylabel('Prescription Volume')  # Y-axis label
plt.legend()  # Show line labels
plt.show()  # Display plot

# 3. FEATURE IMPORTANCE PLOT
plt.figure(figsize=(10,6))  # New 10x6 inch figure

# Horizontal bar plot of top 10 important features
# [sorted_idx][-10:] gets indices of top 10 features
plt.barh(X.columns[sorted_idx][-10:],        # Feature names on Y-axis
        model.feature_importances_[sorted_idx][-10:],  # Importance
scores on X
        color='skyblue')  # Bar color

plt.title('Top 10 Predictive Features')  # Chart title
plt.xlabel('Importance Score')  # X-axis label
plt.ylabel('Feature Name')  # Y-axis label
plt.tight_layout()  # Adjust spacing
plt.show()  # Display plot
```

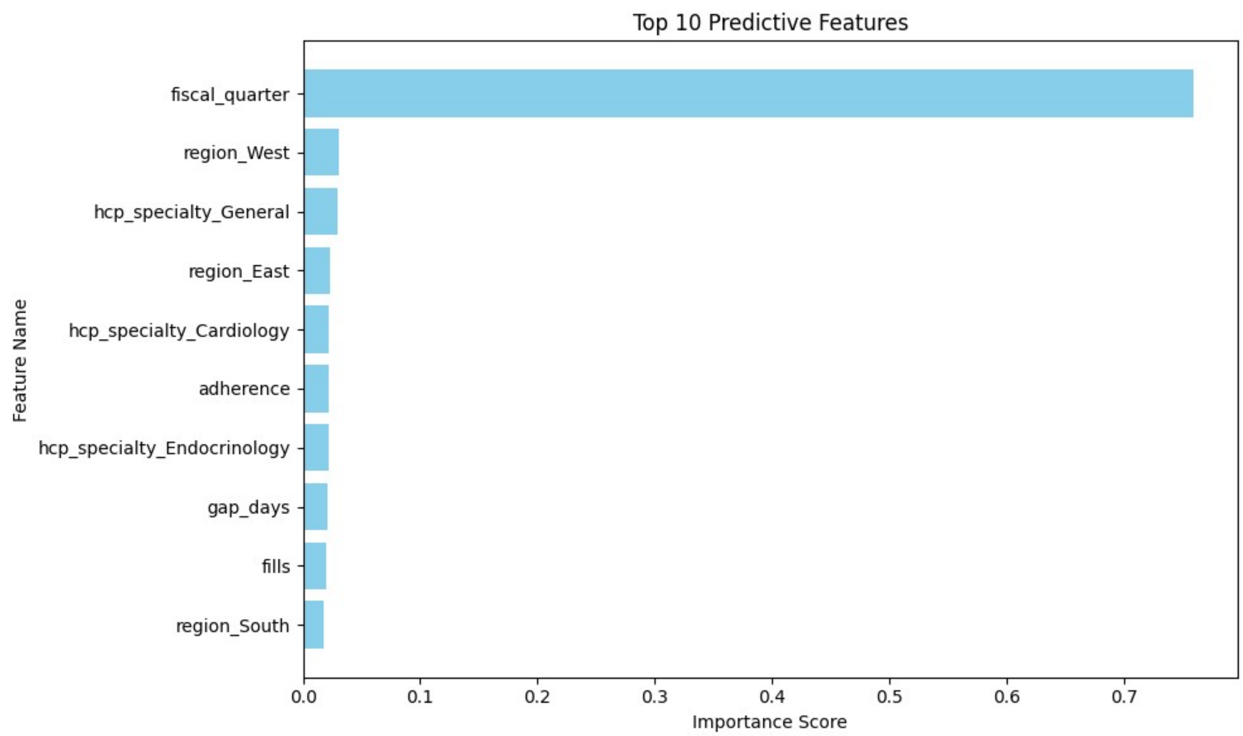

Key Metric Distributions
Value Range
800
600
400
200
0
fills
adherence
gap_days


Prescriptions by Specialty
Number of Prescriptions
400
350
300
250
200
150
100
50
0
hcp_specialty_Cardiology
hcp_specialty_Endocrinology
hcp_specialty_General
hcp_specialty_Neurology


Prescriptions by Region
Number of Prescriptions
400
350
300
250
200
150
100
50
0
region_East
region_North
region_South
region_West


Treatment Continuation Rate
True
66.4%
33.6%
False


Prescription Forecast Accuracy (MAPE: 5.6%)
Actual
Forecast
Confidence Band
Prescription Volume
110
100
90
80
70
60
2023-01
2023-04
2023-07
2023-10
2024-01
2024-04
2024-07
2024-10
2025-01
Date


Top 10 Predictive Features
Feature Name
fiscal_quarter
region_West
hcp_specialty_General
region_East
hcp_specialty_Cardiology
adherence
hcp_specialty_Endocrinology
gap_days
fills
region_South
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
Importance Score