GWP 2 Submission

In [2]:

```
!pip install hmmlearn
```

```
Collecting hmmlearn
  Downloading hmmlearn-0.3.0-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (
160 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 160.4/160.4 kB 3.2 MB/s eta 0:00:00
Requirement already satisfied: numpy>=1.10 in /usr/local/lib/python3.10/dist-packages (fr
om hmmlearn) (1.23.5)
Requirement already satisfied: scikit-learn!=0.22.0,>=0.16 in /usr/local/lib/python3.10/d
ist-packages (from hmmlearn) (1.2.2)
Requirement already satisfied: scipy>=0.19 in /usr/local/lib/python3.10/dist-packages (fr
om hmmlearn) (1.11.2)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (
from scikit-learn!=0.22.0,>=0.16->hmmlearn) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-pac
kages (from scikit-learn!=0.22.0,>=0.16->hmmlearn) (3.2.0)
Installing collected packages: hmmlearn
Successfully installed hmmlearn-0.3.0
```

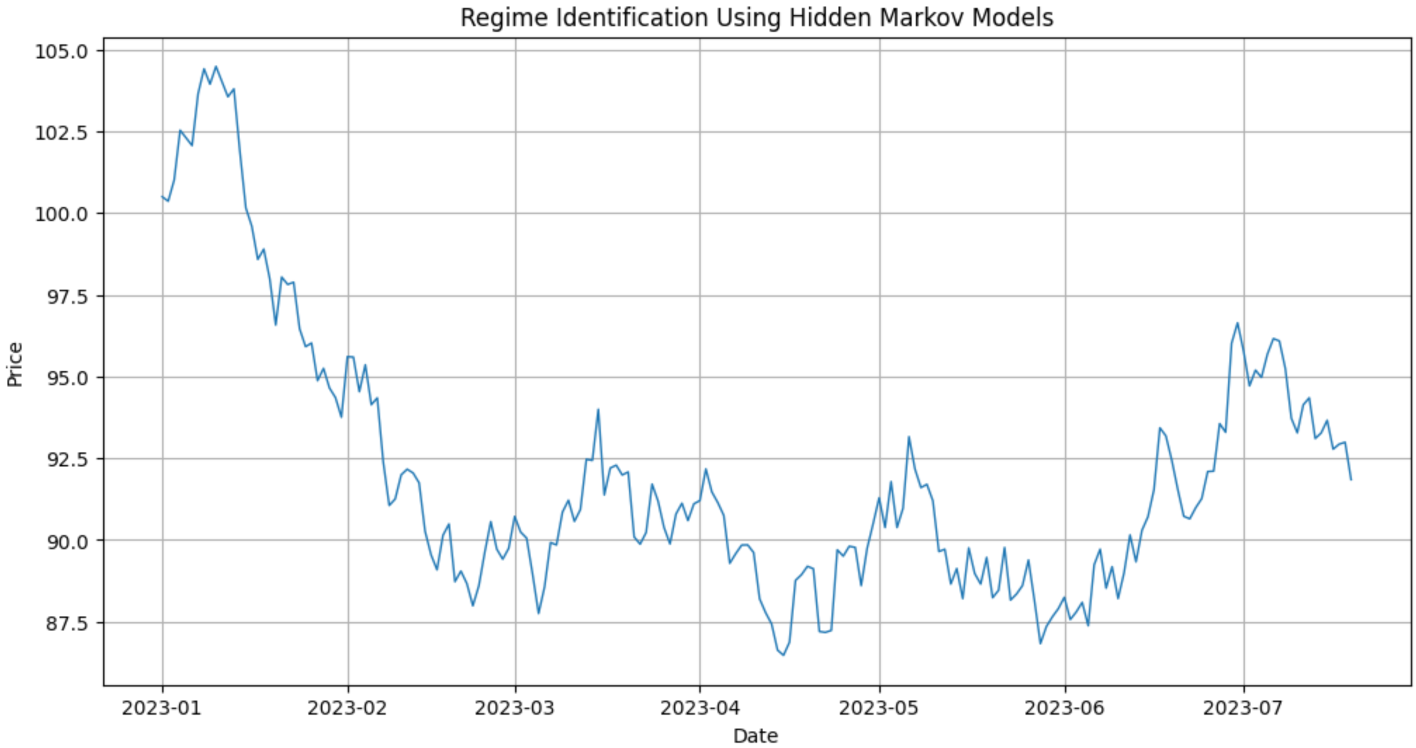
Regime Change detection

In [3]:

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from hmmlearn import hmm

# Generate sample time series data (you can replace this with your own data)
np.random.seed(42)
n = 200
dates = pd.date_range(start='2023-01-01', periods=n, freq='D')
price_data = np.cumsum(np.random.randn(n)) + 100

# Create a DataFrame with date and price columns
df = pd.DataFrame({'Date': dates, 'Price': price_data})

# Define the number of hidden states (regimes)
n_states = 3  # You can adjust this based on your problem and data

# Prepare the observation data (Price) for HMM
X = df['Price'].values.reshape(-1, 1)

# Create an HMM model
model = hmm.GaussianHMM(n_components=n_states, covariance_type="full", n_iter=100)

# Fit the model to the data
model.fit(X)

# Predict the most likely sequence of hidden states (regimes)
hidden_states = model.predict(X)

# Plot the price data and regime changes
plt.figure(figsize=(12, 6))
plt.plot(df['Date'], df['Price'], label='Price', linewidth=1)
plt.title('Regime Identification Using Hidden Markov Models')
plt.xlabel('Date')
plt.ylabel('Price')
plt.grid(True)

# Identify and print regime change points
regime_changes = np.where(np.diff(hidden_states) != 0)[0] + 1
for change_point in regime_changes:
```

```
    date = df['Date'][change_point]
    regime = hidden_states[change_point]
    print(f'Regime Change: Date={date}, Regime={regime}')

plt.show()
```

```
Regime Change: Date=2023-01-24 00:00:00, Regime=2
Regime Change: Date=2023-02-07 00:00:00, Regime=0
Regime Change: Date=2023-06-27 00:00:00, Regime=2
```



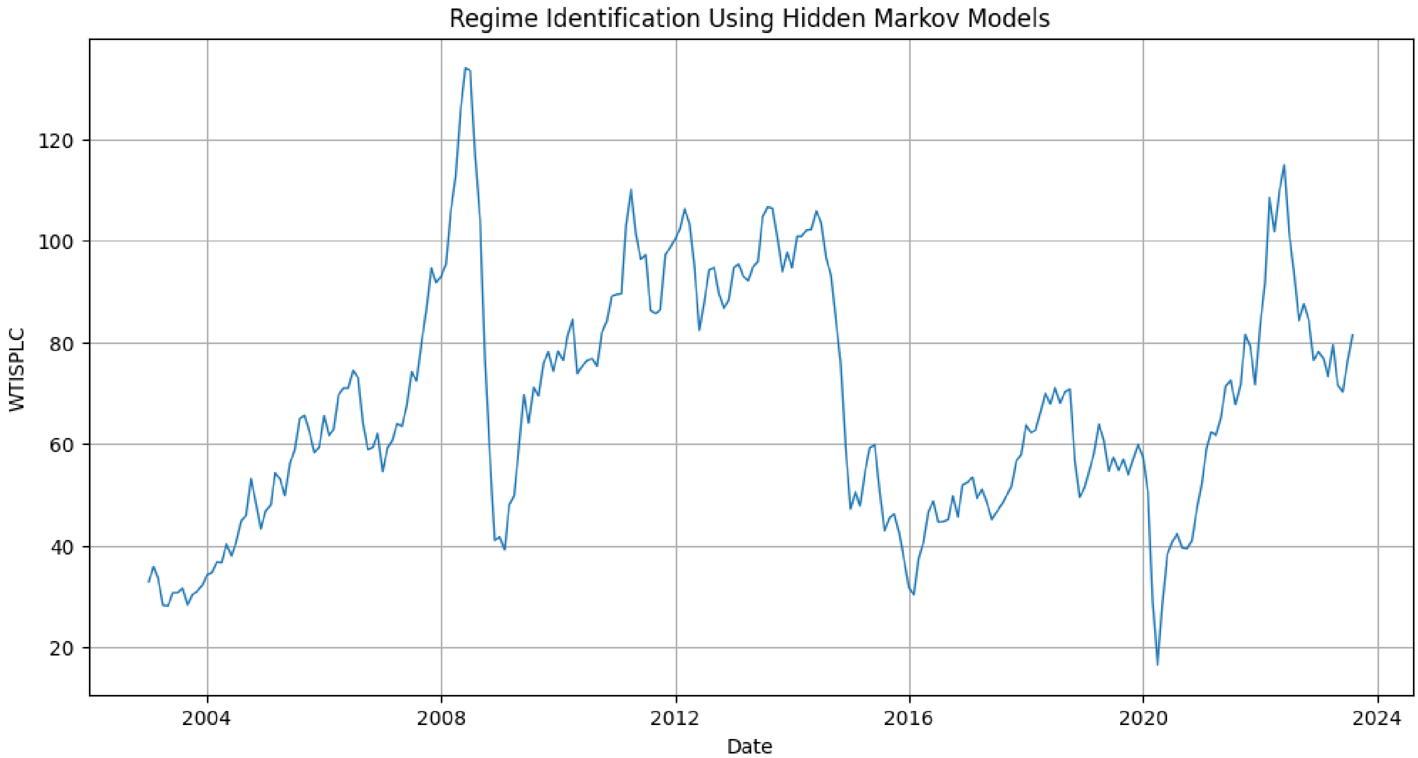
With Crude oil data

In [29]:

```
# Import necessary libraries
from fredapi import Fred

# Get oil price data from the Federal Reserve Economic Data (FRED) API
# Create data frames for current and forecasted spot crude oil prices
fred = Fred(api_key='87769799aa7b2dc41a0590ed8a688283')
current = pd.DataFrame(fred.get_series('WTISPLC'), columns=['WTISPLC'])
current.index.names = ['Date']
forecast = pd.DataFrame(fred.get_series('WTISPLC').shift(-1), columns=['Forecast'])
forecast.index.names = ['Date']

# Filter the data to a specific date range
current = current.drop((current[(current.index < '2003-01-01') | (current.index > '2023-
12-01')]).index, axis=0)

# Compute the difference (returns) and create a binary sequence
price = current['WTISPLC']
df=price
df=df.reset_index()

# Define the number of hidden states (regimes)
n_states = 3  # You can adjust this based on your problem and data

# Prepare the observation data (Price) for HMM
X = df['WTISPLC'].values.reshape(-1, 1)

# Create an HMM model
model = hmm.GaussianHMM(n_components=n_states, covariance_type="full", n_iter=100)

# Fit the model to the data
model.fit(X)
```

```python
# Predict the most likely sequence of hidden states (regimes)
hidden_states = model.predict(X)

# Plot the price data and regime changes
plt.figure(figsize=(12, 6))
plt.plot(df['Date'], df['WTISPLC'], label='WTISPLC', linewidth=1)
plt.title('Regime Identification Using Hidden Markov Models')
plt.xlabel('Date')
plt.ylabel('WTISPLC')
plt.grid(True)

# Identify and print regime change points
regime_changes = np.where(np.diff(hidden_states) != 0)[0] + 1
for change_point in regime_changes:
    date = df['Date'][change_point]
    regime = hidden_states[change_point]
    print(f'Regime Change: Date={date}, Regime={regime}')

plt.show()
```

```
Regime Change: Date=2005-06-01 00:00:00, Regime=2
Regime Change: Date=2007-09-01 00:00:00, Regime=1
Regime Change: Date=2008-11-01 00:00:00, Regime=0
Regime Change: Date=2009-05-01 00:00:00, Regime=2
Regime Change: Date=2009-10-01 00:00:00, Regime=1
Regime Change: Date=2014-12-01 00:00:00, Regime=0
Regime Change: Date=2017-11-01 00:00:00, Regime=2
Regime Change: Date=2020-02-01 00:00:00, Regime=0
Regime Change: Date=2021-02-01 00:00:00, Regime=2
Regime Change: Date=2021-10-01 00:00:00, Regime=1
```

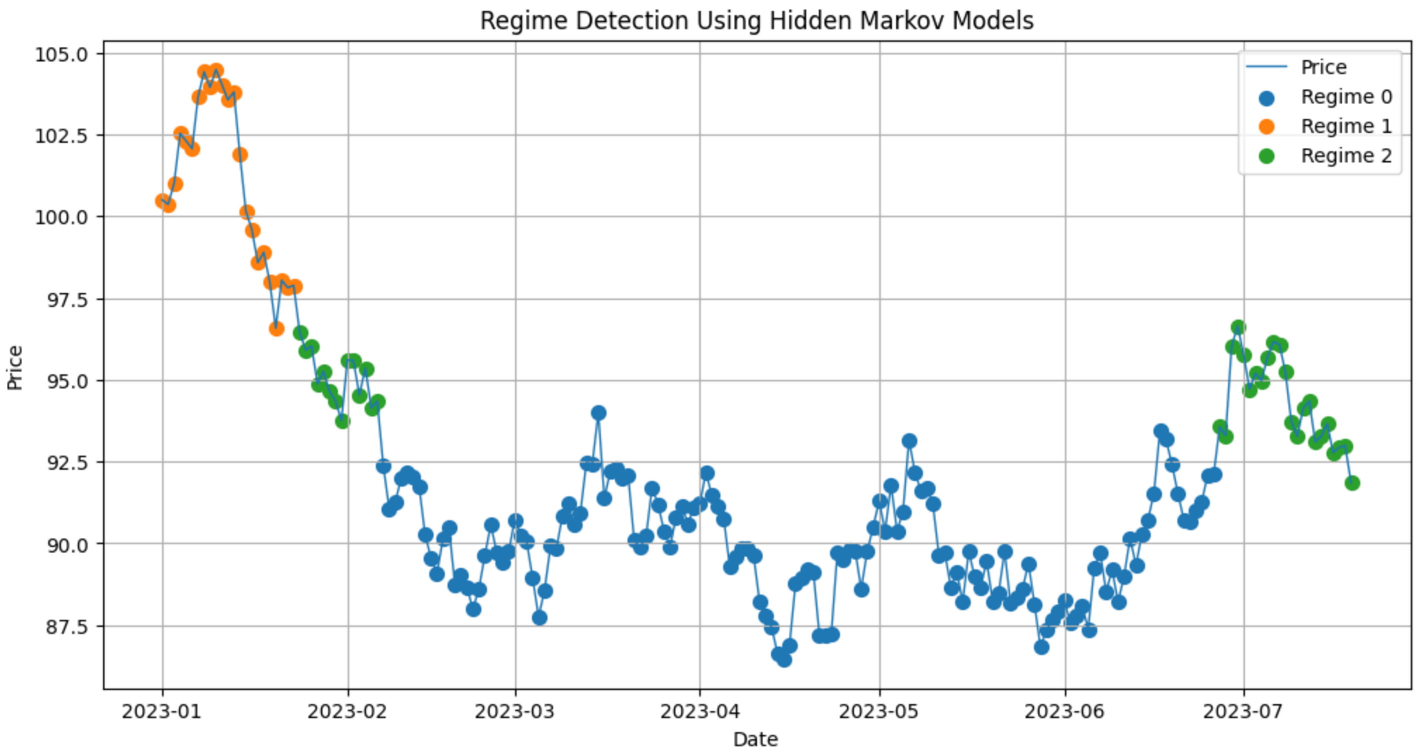


Regime Detection

In [13]:

```python
# Generate sample time series data (you can replace this with your own data)
np.random.seed(42)
n = 200
dates = pd.date_range(start='2023-01-01', periods=n, freq='D')
price_data = np.cumsum(np.random.randn(n)) + 100

# Create a DataFrame with date and price columns
df = pd.DataFrame({'Date': dates, 'Price': price_data})
```

```python
# Define the number of hidden states (regimes)
n_states = 3  # You can adjust this based on your problem and data

# Prepare the observation data (Price) for HMM
X = df['Price'].values.reshape(-1, 1)

# Create an HMM model
model = hmm.GaussianHMM(n_components=n_states, covariance_type="full", n_iter=100)

# Fit the model to the data
model.fit(X)

# Predict the most likely sequence of hidden states (regimes)
hidden_states = model.predict(X)

# Plot the price data and regime changes
plt.figure(figsize=(12, 6))
plt.plot(df['Date'], df['Price'], label='Price', linewidth=1)

# Plot regime changes
for i in range(n_states):
    mask = hidden_states == i
    plt.scatter(df['Date'][mask], df['Price'][mask], label=f'Regime {i}', s=50)

plt.title('Regime Detection Using Hidden Markov Models')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend()
plt.grid(True)

plt.show()
```



In [14]:

```python
df
```

Out[14]:

	Date	Price
0	2023-01-01	100.496714
1	2023-01-02	100.358450
2	2023-01-03	101.006138
3	2023-01-04	102.529168

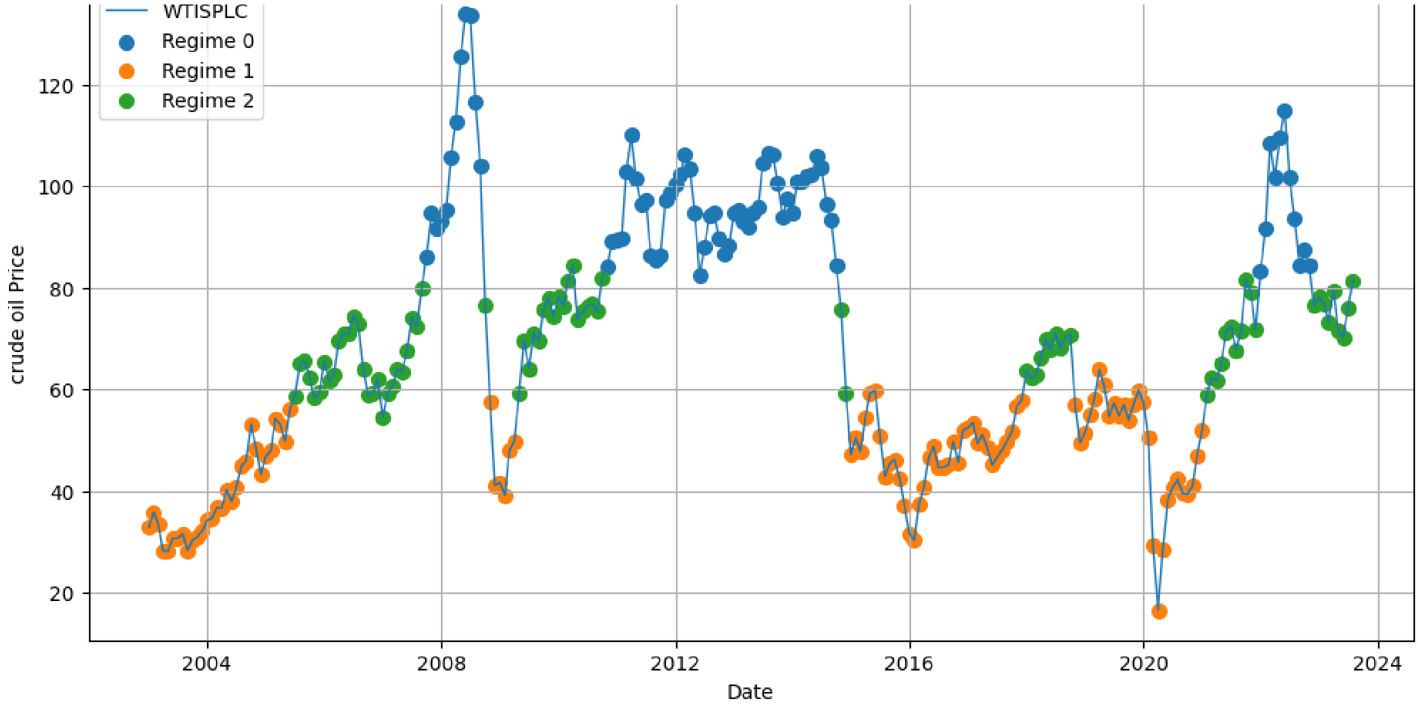
	Date	Price
4	2023-01-05	102.29[illegible]15
...	...	...
195	2023-07-15	93.660701
196	2023-07-16	92.776843
197	2023-07-17	92.930569
198	2023-07-18	92.988777
199	2023-07-19	91.845807

200 rows × 2 columns

Regime detection on Crude oil data

In [27]:

```
# Import necessary libraries
from fredapi import Fred

# Get oil price data from the Federal Reserve Economic Data (FRED) API
# Create data frames for current and forecasted spot crude oil prices
fred = Fred(api_key='87769799aa7b2dc41a0590ed8a688283')
current = pd.DataFrame(fred.get_series('WTISPLC'), columns=['WTISPLC'])
current.index.names = ['Date']
forecast = pd.DataFrame(fred.get_series('WTISPLC').shift(-1), columns=['Forecast'])
forecast.index.names = ['Date']

# Filter the data to a specific date range
current = current.drop((current[(current.index < '2003-01-01') | (current.index > '2023-12-01')]).index, axis=0)

# Compute the difference (returns) and create a binary sequence
price = current['WTISPLC']
df=price
df=df.reset_index()
# Define the number of hidden states (regimes)
n_states = 3  # You can adjust this based on your problem and data

# Prepare the observation data (Price) for HMM
X = df['WTISPLC'].values.reshape(-1, 1)

# Create an HMM model
model = hmm.GaussianHMM(n_components=n_states, covariance_type="full", n_iter=100)

# Fit the model to the data
model.fit(X)

# Predict the most likely sequence of hidden states (regimes)
hidden_states = model.predict(X)

# Plot the price data and regime changes
plt.figure(figsize=(12, 6))
plt.plot(df['Date'], df['WTISPLC'], label='WTISPLC', linewidth=1)

# Plot regime changes
for i in range(n_states):
    mask = hidden_states == i
    plt.scatter(df['Date'][mask], df['WTISPLC'][mask], label=f'Regime {i}', s=50)

plt.title('Regime Detection Using Hidden Markov Models')
plt.xlabel('Date')
plt.ylabel('crude oil Price')
plt.legend()
plt.grid(True)

plt.show()
```



In [22]:

In [23]:

```
df
```

Out[23]:

	Date	WTISPLC
0	2003-01-01	32.94
1	2003-02-01	35.87
2	2003-03-01	33.55
3	2003-04-01	28.25
4	2003-05-01	28.14
...	...	...
243	2023-04-01	79.45
244	2023-05-01	71.58
245	2023-06-01	70.25
246	2023-07-01	76.07
247	2023-08-01	81.39

248 rows × 2 columns

In [ ]: