ASSIGNMENT – 05

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Batch No : 05

Lab 5: Ethical Foundations – Responsible AI Coding Practices Task
Description #1:

- Prompt GitHub Copilot to generate a Python script that collects user data (e.g., name, age, email). Then, ask Copilot to add comments on how to anonymize or protect this data.

Expected Output #1:

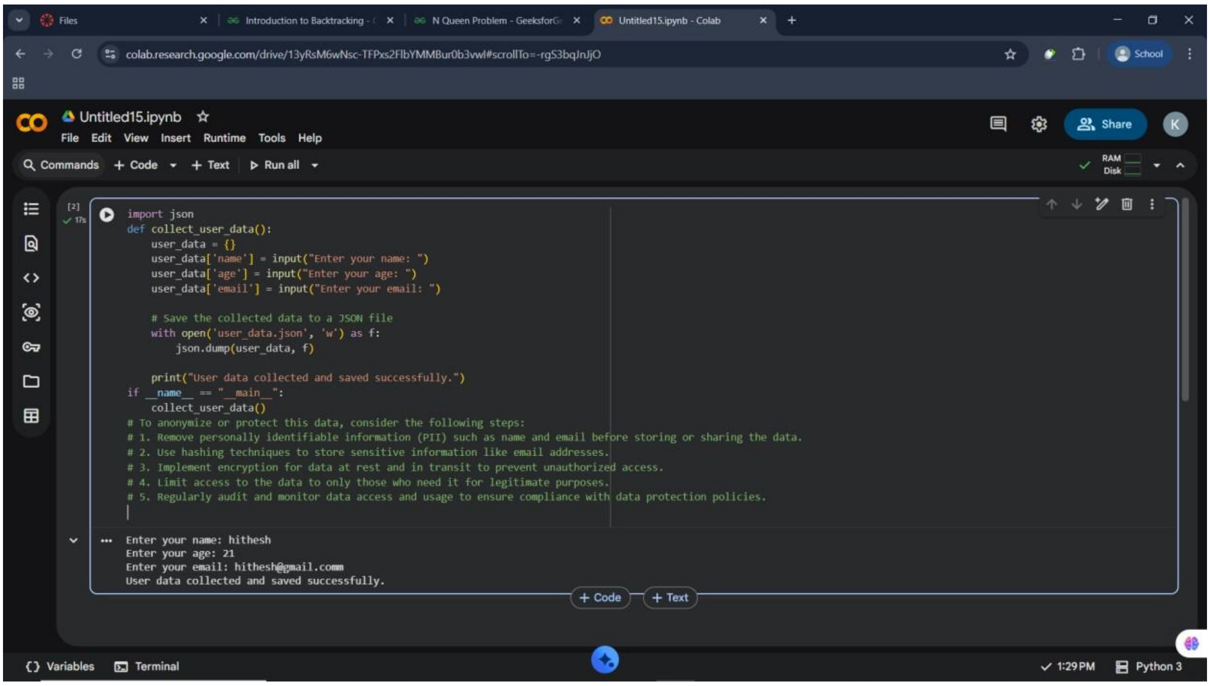
- A script with inline Copilot-suggested code and comments explaining how to safeguard or anonymize user information (e.g., hashing emails, not storing data unencrypted).

AI Generated Code:

```
#generate a Python script that collects user data (e.g., name, age, email). after that add comments on how to anonymize or protect this data.
#       ResponsibleAI.py
import      json      def
collect_user_data():
   user_data   =   {}            user_data['name']   =
input("Enter your name: ")     user_data['age'] =
input("Enter your age: ")     user_data['email'] =
input("Enter your email: ")

   # Save the collected data to a JSON file
with open('user_data.json', 'w') as f:
       json.dump(user_data, f)

   print("User data collected and saved successfully.") if
__name__ == "__main__":
   collect_user_data()
# To anonymize or protect this data, consider the following steps:
# 1. Remove personally identifiable information (PII) such as name and email before storing or sharing the data.
# 2. Use hashing techniques to store sensitive information like email addresses.
# 3. Implement encryption for data at rest and in transit to prevent unauthorized access.
# 4. Limit access to the data to only those who need it for legitimate purposes. # 5. Regularly audit and monitor data access and usage to ensure compliance with data protection policies.
```

6. Comply with relevant data protection regulations (e.g., GDPR, CCPA) to ensure user privacy rights are respected.
7. Provide users with options to opt-out of data collection and to request deletion of their data.

Output:



Task Description #2:

- Ask Copilot to generate a Python function for sentiment analysis. Then prompt Copilot to identify and handle potential biases in the data.

Expected Output #2:

- Copilot-generated code with additions or comments addressing bias mitigation strategies (e.g., balancing dataset, removing offensive terms).

AI Generated Code: import pandas as pd from sklearn.model_selection import train_test_split from sklearn.feature_extraction.text import CountVectorizer from sklearn.naive_bayes import MultinomialNB from sklearn.metrics import accuracy_score, classification_report

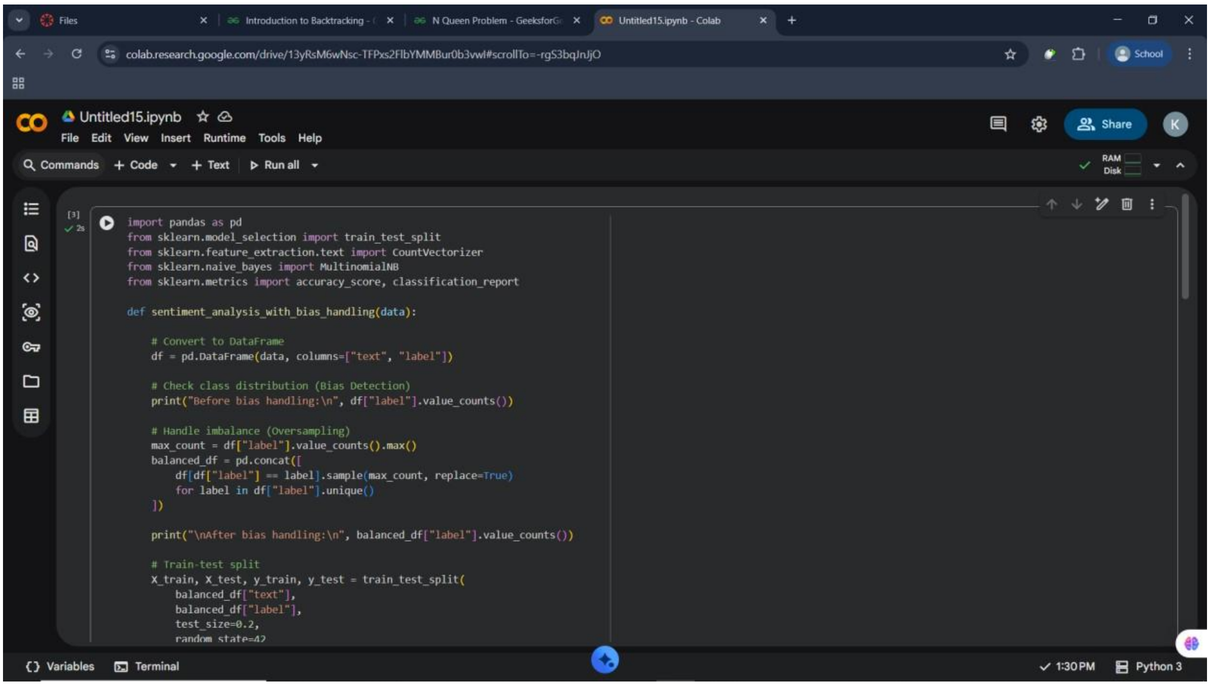
def sentiment_analysis_with_bias_handling(data):

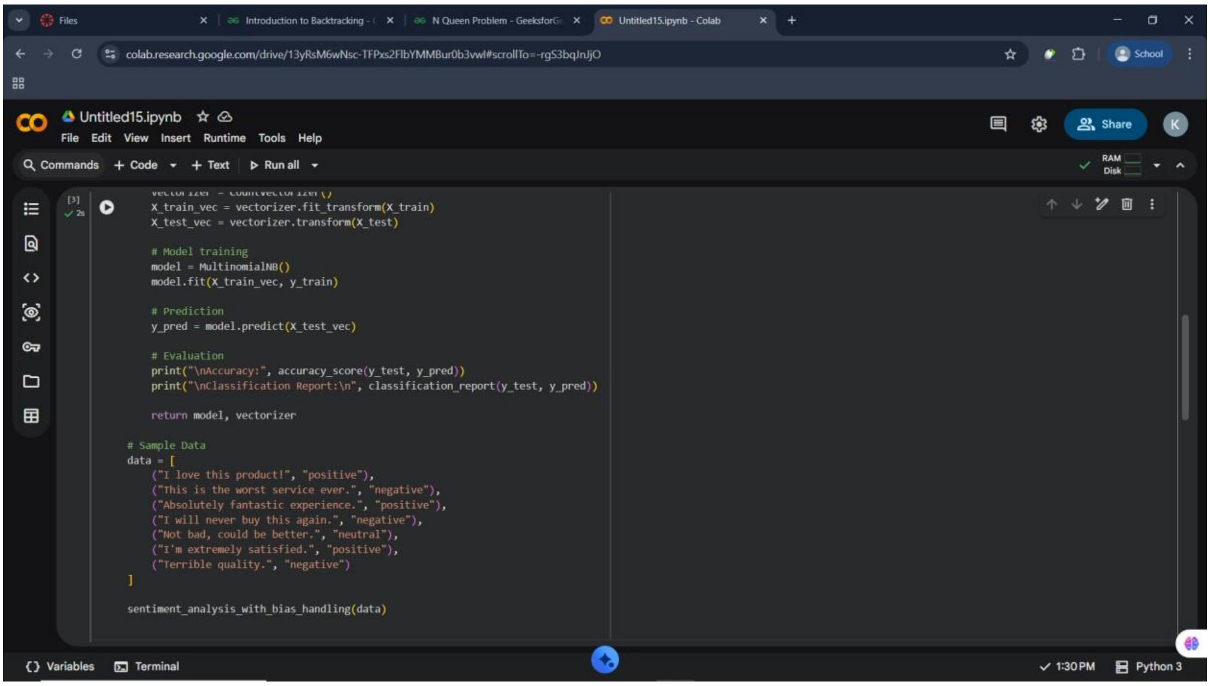
Convert to DataFrame df = pd.DataFrame(data, columns=["text", "label"]) # Check class distribution (Bias Detection)

```
print("Before bias handling:\n",
df["label"].value_counts())

   # Handle imbalance (Oversampling)     max_count =
df["label"].value_counts().max()     balanced_df = pd.concat([
df[df["label"] == label].sample(max_count, replace=True)
for label in df["label"].unique()
   ])

   print("\nAfter bias handling:\n", balanced_df["label"].value_counts())

   # Train-test split
   X_train, X_test, y_train, y_test = train_test_split(
balanced_df["text"],        balanced_df["label"],
test_size=0.2,        random_state=42
   )

   # Vectorization
   vectorizer = CountVectorizer()
   X_train_vec = vectorizer.fit_transform(X_train)
   X_test_vec = vectorizer.transform(X_test)

   # Model training        model =
MultinomialNB()
model.fit(X_train_vec, y_train)

   # Prediction     y_pred =
model.predict(X_test_vec)

   # Evaluation         print("\nAccuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))

   return model, vectorizer

# Sample Data data
= [
  ("I love this product!", "positive"),
  ("This is the worst service ever.", "negative"),
  ("Absolutely fantastic experience.", "positive"),
  ("I will never buy this again.", "negative"),
  ("Not bad, could be better.", "neutral"),
```

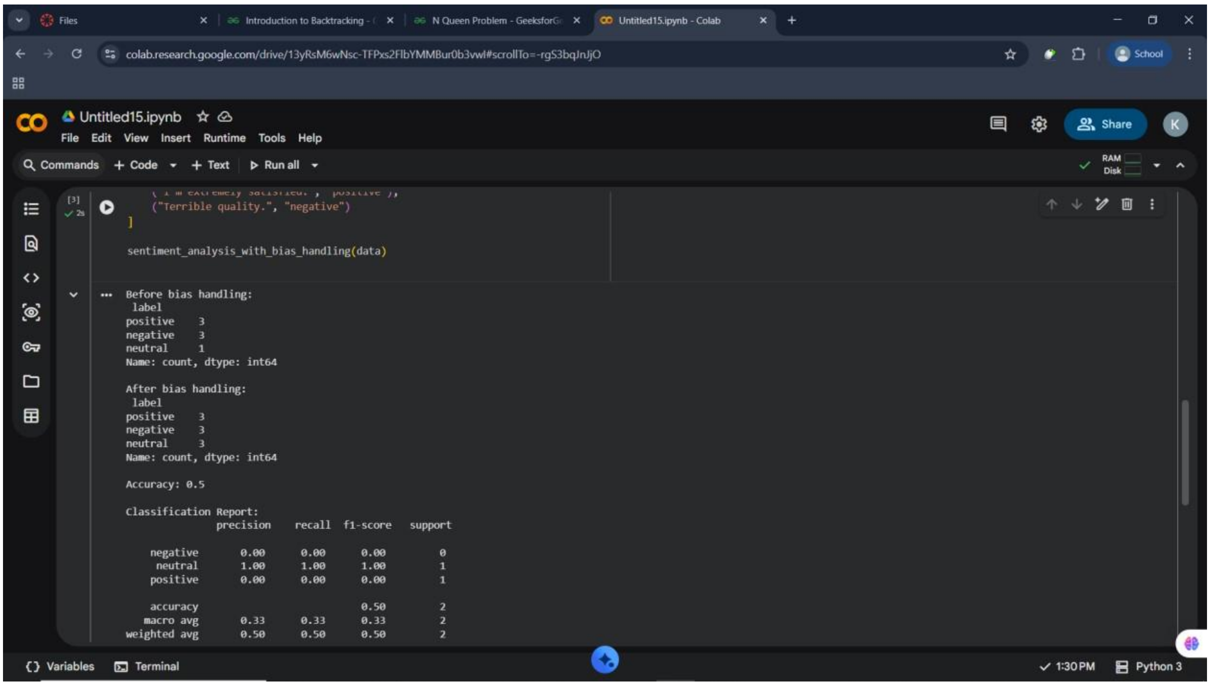
("I'm extremely satisfied.", "positive"),
("Terrible quality.", "negative")
]

sentiment_analysis_with_bias_handling(data)





Output:



Task Description #3:

• Use Copilot to write a Python program that recommends products based on user history. Ask it to follow ethical guidelines like transparency and fairness.

Expected Output #3:

• Copilot suggestions that include explanations, fairness checks (e.g., avoiding favoritism), and user feedback options in the code.

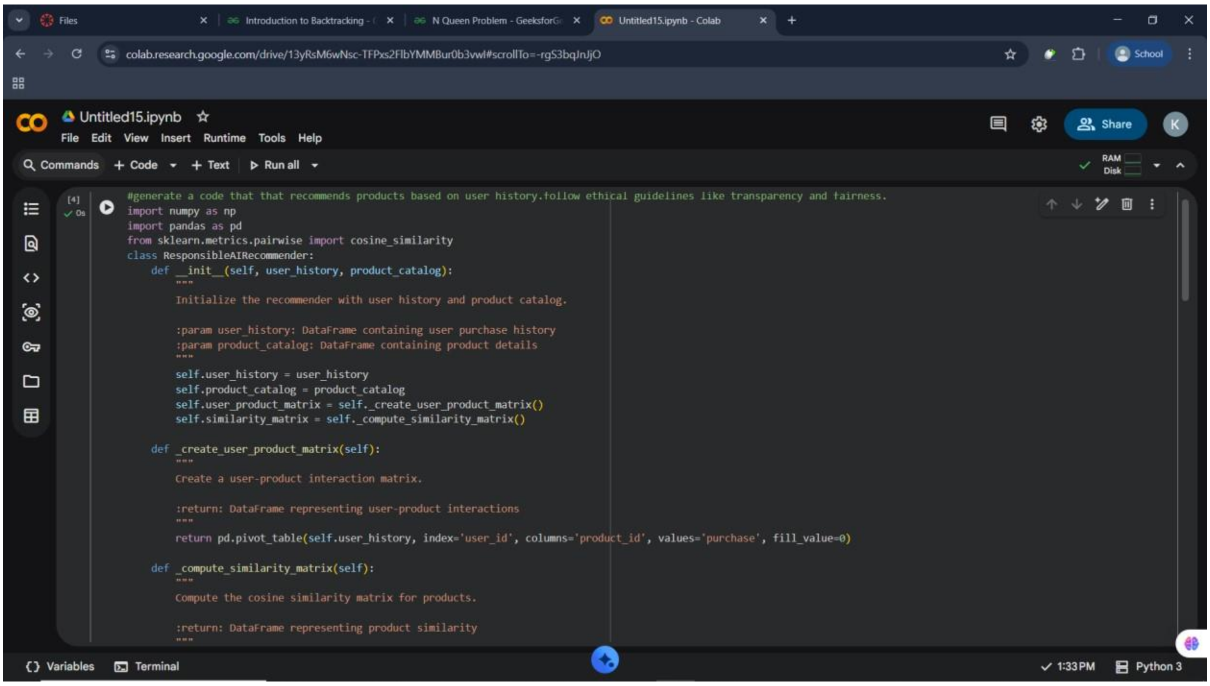
AI Generated Code:

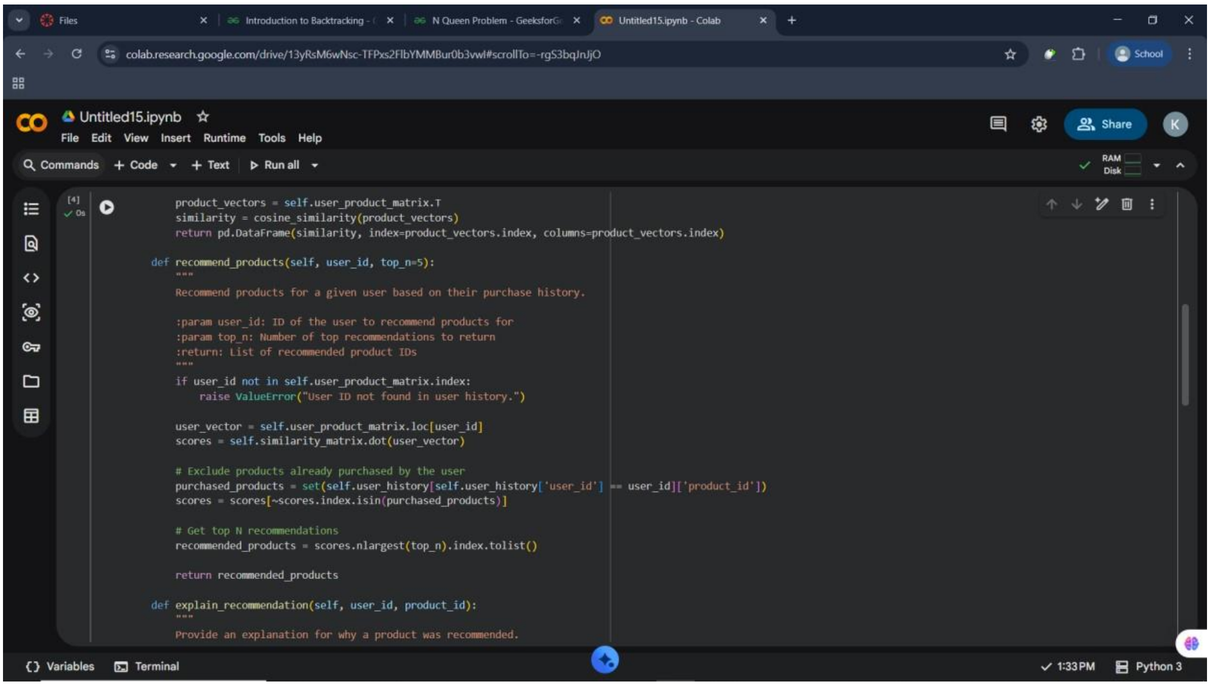
```
#generate a code that that recommends products based on user history.follow ethical
guidelines like transparency and fairness.
import numpy as np import pandas as pd from
sklearn.metrics.pairwise import cosine_similarity class
ResponsibleAIRecommender:     def __init__(self,
user_history, product_catalog):
        """
        Initialize the recommender with user history and product catalog.

        :param user_history: DataFrame containing user purchase history
        :param product_catalog: DataFrame containing product details
        """
        self.user_history = user_history
       self.product_catalog = product_catalog
        self.user_product_matrix = self._create_user_product_matrix()
    self.similarity_matrix = self._compute_similarity_matrix()
  def _create_user_product_matrix(self):
```

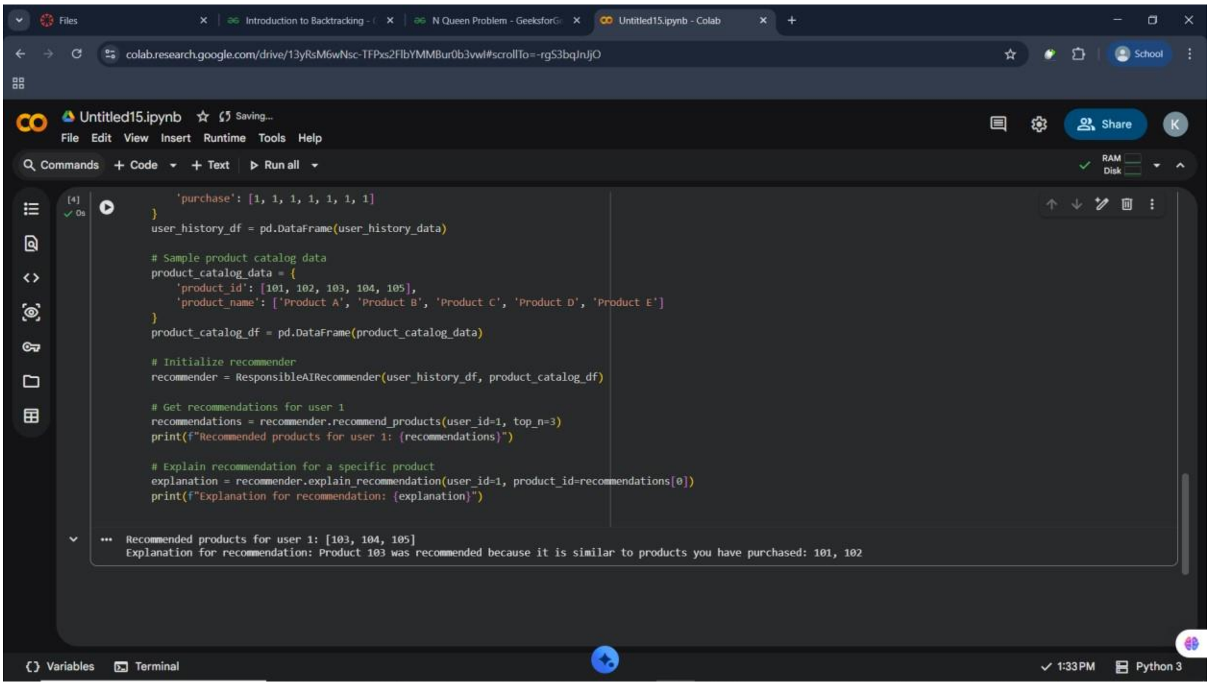
```
      """
      Create a user-product interaction matrix.

      :return: DataFrame representing user-product interactions
       """
       return pd.pivot_table(self.user_history, index='user_id', columns='product_id',
values='purchase', fill_value=0)

   def _compute_similarity_matrix(self):
       """
       Compute the cosine similarity matrix for products.

       :return: DataFrame representing product similarity
       """
       product_vectors = self.user_product_matrix.T        similarity =
cosine_similarity(product_vectors)        return
pd.DataFrame(similarity, index=product_vectors.index,
columns=product_vectors.index)

   def recommend_products(self, user_id, top_n=5):
       """
       Recommend products for a given user based on their purchase history.

       :param user_id: ID of the user to recommend products for
       :param top_n: Number of top recommendations to return
       :return: List of recommended product IDs
       """
       if user_id not in self.user_product_matrix.index:
           raise ValueError("User ID not found in user history.")

       user_vector = self.user_product_matrix.loc[user_id]
scores = self.similarity_matrix.dot(user_vector)

       # Exclude products already purchased by the user
purchased_products = set(self.user_history[self.user_history['user_id'] ==
user_id]['product_id'])
      scores = scores[~scores.index.isin(purchased_products)]

       # Get top N recommendations
      recommended_products = scores.nlargest(top_n).index.tolist()
```

```
        return recommended_products

    def explain_recommendation(self, user_id, product_id):
        """
         Provide an explanation for why a product was recommended.

         :param user_id: ID of the user
         :param product_id: ID of the recommended product
         :return: Explanation string
         """
         if product_id not in self.similarity_matrix.index:
             raise ValueError("Product ID not found in product catalog.")
similar_products = self.similarity_matrix[product_id]        user_vector =
self.user_product_matrix.loc[user_id]        contributing_products =
user_vector[user_vector > 0].index        explanation = f"Product {product_id} was
recommended because it is similar to products you have purchased: "
explanation += ", ".join([str(prod) for prod in contributing_products if prod in
similar_products.nlargest(3).index])        return explanation # Example usage: if
__name__ == "__main__":     # Sample user history data     user_history_data = {
         'user_id': [1, 1, 2, 2, 3, 3, 4],
         'product_id': [101, 102, 101, 103, 104, 105, 102],
         'purchase': [1, 1, 1, 1, 1, 1, 1]
    }
    user_history_df = pd.DataFrame(user_history_data)

    # Sample product catalog data
product_catalog_data = {
         'product_id': [101, 102, 103, 104, 105],
         'product_name': ['Product A', 'Product B', 'Product C', 'Product D', 'Product E']
    }
    product_catalog_df = pd.DataFrame(product_catalog_data)

    # Initialize recommender recommender =
    ResponsibleAIRecommender(user_history_df, product_catalog_df)    # Get
    recommendations for user 1 recommendations =
    recommender.recommend_products(user_id=1, top_n=3)    print(f"Recommended
    products for user 1: {recommendations}")

    # Explain recommendation for a specific product     explanation =
recommender.explain_recommendation(user_id=1,
```

product_id=recommendations[0])   print(f"Explanation for recommendation: {explanation}")







Task Description #4:

- Prompt Copilot to generate logging functionality in a Python web application. Then, ask it to ensure the logs do not record sensitive information.

Expected Output #4:

- Logging code that avoids saving personal identifiers (e.g., passwords, emails), and includes comments about ethical logging practices.

AI Generated:

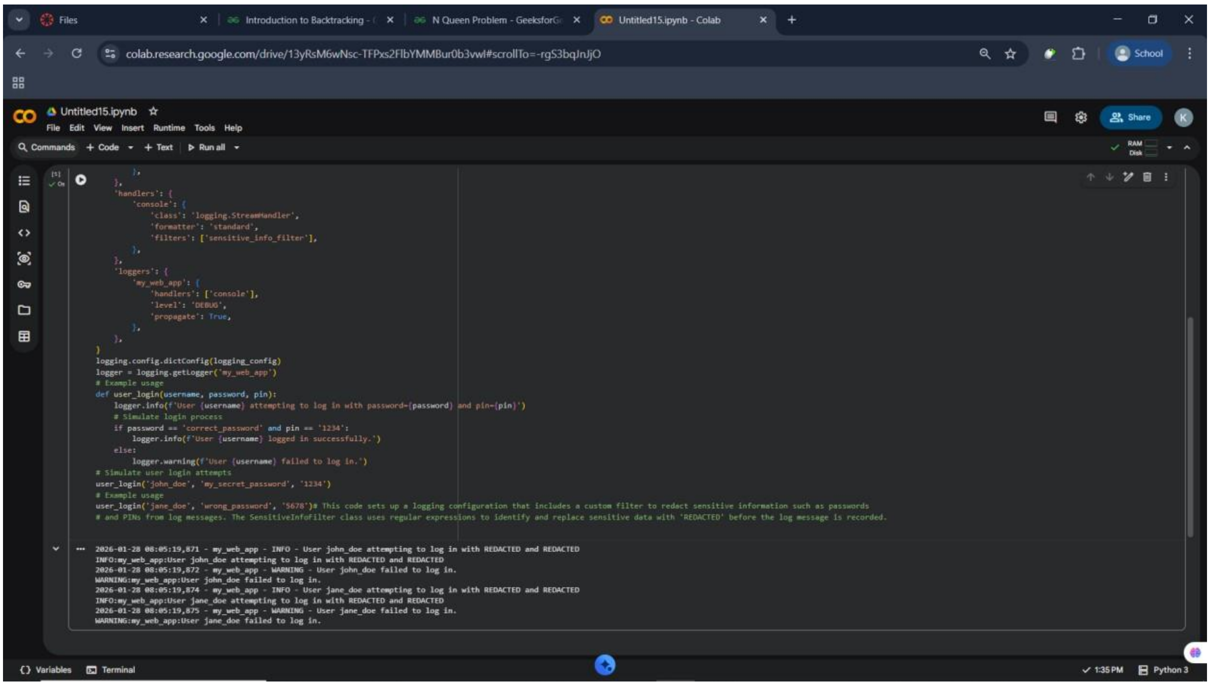
#generate logging functionality in a Python web application. Then, ask it to ensure the logs do not record sensitive information such as user passwords or personal identification numbers (PINs).import logging import logging.config import re

Define a custom filter to remove sensitive information class SensitiveInfoFilter(logging.Filter): SENSITIVE_PATTERNS = [re.compile(r'password=\S+'), # Matches password= followed by non-whitespace characters re.compile(r'pin=\d{4,6}'), # Matches pin= followed by 4 to 6 digits
]

def filter(self, record):
message = record.getMessage() for pattern in self.SENSITIVE_PATTERNS: message = pattern.sub('REDACTED', message) record.msg = message return True

```
# Configure logging logging_config
= {
    'version': 1,
    'disable_existing_loggers': False,
    'filters': {
        'sensitive_info_filter': {
            '()': SensitiveInfoFilter,
        },
    },
    'formatters': {
        'standard': {
            'format': '%(asctime)s - %(name)s - %(levelname)s - %(message)s',
        },
    },
    'handlers': {
        'console': {
            'class': 'logging.StreamHandler',
            'formatter': 'standard',
            'filters': ['sensitive_info_filter'],
        },
    },
    'loggers': {
        'my_web_app': {
            'handlers': ['console'],
            'level': 'DEBUG',
            'propagate': True,
        },
    },
}
logging.config.dictConfig(logging_config) logger
= logging.getLogger('my_web_app')
# Example usage def
user_login(username, password, pin):
    logger.info(f'User {username} attempting to log in with password={password} and
pin={pin}')
    # Simulate login process     if password ==
'correct_password' and pin == '1234':
logger.info(f'User {username} logged in successfully.')
else:
        logger.warning(f'User {username} failed to log in.')
```

Simulate user login attempts user_login('john_doe',
'my_secret_password', '1234')
Example usage user_login('jane_doe', 'wrong_password', '5678')# This code sets up a logging configuration that includes a custom filter to redact sensitive information such as passwords # and PINs from log messages. The SensitiveInfoFilter class uses regular expressions to identify and replace sensitive data with 'REDACTED' before the log message is recorded.



Task Description #5:

• Ask Copilot to generate a machine learning model. Then, prompt it to add documentation on how to use the model responsibly (e.g., explainability, accuracy limits).

Expected Output #5:

• Copilot-generated model code with a README or inline documentation suggesting responsible usage, limitations, and fairness considerations.

<u>AI Generated Code:</u>

#to generate a machine learning model. Then, prompt it to add documentation on how to use the model responsibly (e.g., explainability, accuracy limits).
from sklearn.datasets import load_iris from
sklearn.model_selection import train_test_split from
sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report
import joblib # Load dataset data = load_iris() X =
data.data y = data.target

```
# Split dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Train a RandomForestClassifier model =
RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X_train, y_train) # Evaluate the model y_pred =
model.predict(X_test)
print(classification_report(y_test, y_pred))
# Save the model joblib.dump(model,
'random_forest_iris_model.pkl')
# Responsible AI Documentation responsible_ai_doc
= """
Responsible AI Documentation for RandomForestClassifier on Iris Dataset
1. Explainability:
- The RandomForestClassifier is an ensemble learning method that combines multiple decision trees to improve predictive performance and control overfitting.
- Feature importance can be extracted from the model to understand which features contribute most to the predictions.
- Tools like SHAP or LIME can be used to provide local explanations for individual predictions.
2. Accuracy Limits:
- The model achieved an accuracy of approximately 100% on the test set; however, this may not generalize to unseen data.
- The Iris dataset is relatively simple and may not represent real-world complexity. Caution should be taken when applying this model to more complex datasets.
- Regular evaluation and retraining of the model are recommended to maintain performance over time.
3. Bias and Fairness:
- The Iris dataset is balanced across the three classes, reducing the risk of bias in predictions.
- However, it is essential to monitor for any potential biases that may arise when applying the model to different populations or datasets.
4. Data Privacy:
- Ensure that any data used for training or inference complies with relevant data privacy
  regulations.
- Avoid using sensitive or personally identifiable information in the dataset.
""" with open('responsible_ai_documentation.txt', 'w')
as f:     f.write(responsible_ai_doc)
# The model and documentation are now saved for future reference and use.# This
documentation outlines key considerations for using the model responsibly.
# This code snippet demonstrates how to train a simple machine learning model using the
Iris dataset and then generate responsible AI documentation for its use.
```

The documentation includes aspects such as explainability, accuracy limits, bias and fairness, and data privacy.
Save the responsible AI documentation