# LAB ASSIGNMENT – 5.4

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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.

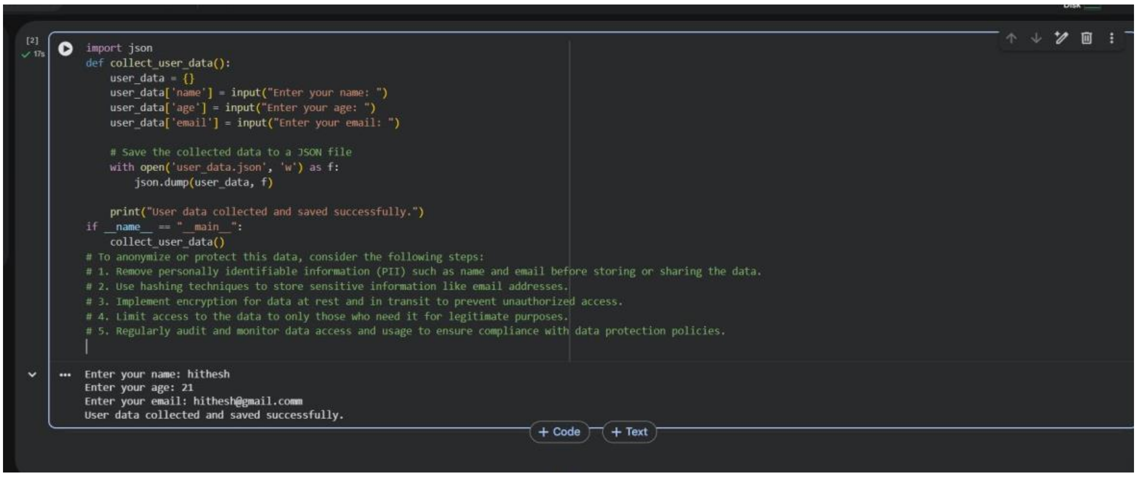
**Expected Output #1:**

- 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:**



```
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.
```

```
Enter your name: hithesh
Enter your age: 21
Enter your email: hithesh@gmail.comm
User data collected and saved successfully.
```

**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.

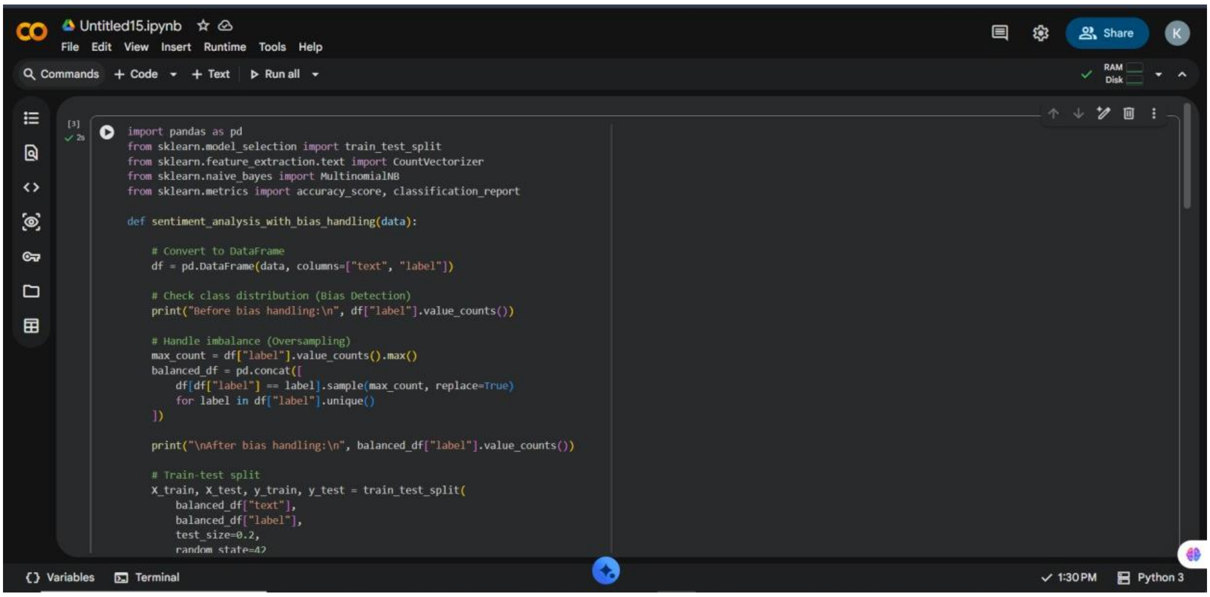
**Expected Output #2:**

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

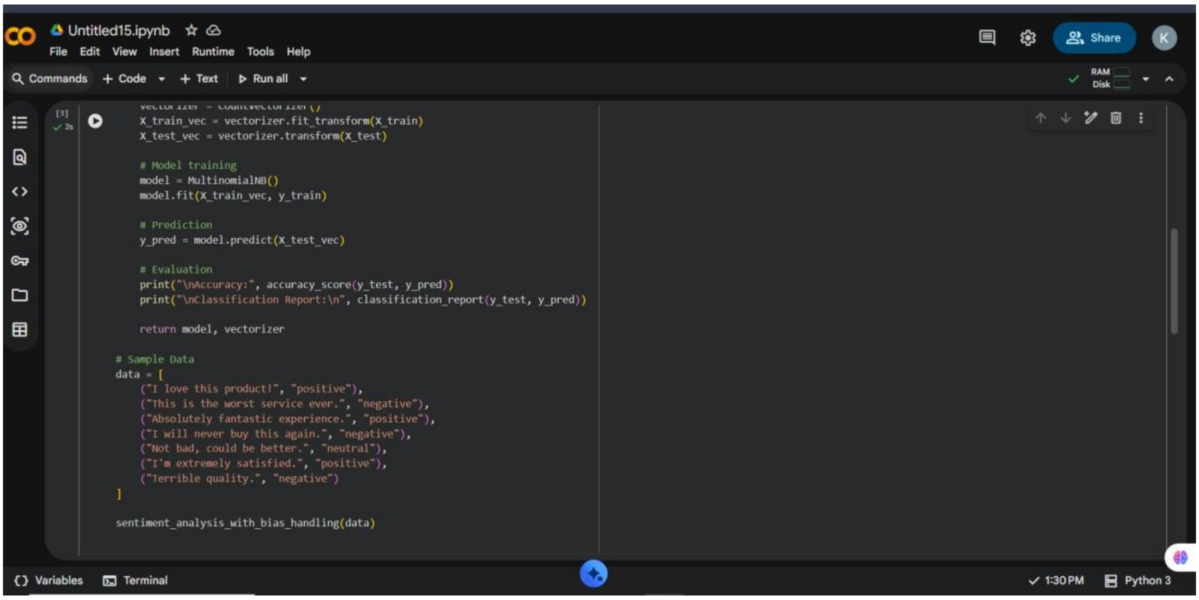
**AI Generated Code:**

```
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)
```

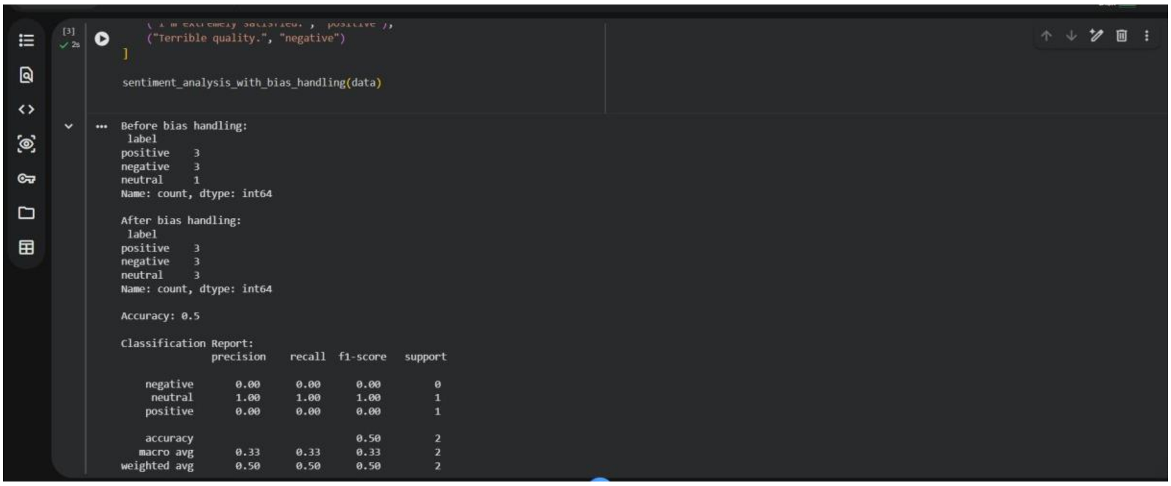
**Output:**


Untitled15.ipynb
File Edit View Insert Runtime Tools Help
Commands + Code + Text Run all
Share
RAM
Disk
[3]
2s
Variables
Terminal
1:30 PM
Python 3

```
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
```


Untitled15.ipynb
File Edit View Insert Runtime Tools Help
Commands + Code + Text Run all
Share
RAM
Disk
[3]
2s
Variables
Terminal
1:30 PM
Python 3

```
    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)
```



```
    ("Terrible quality.", "negative")
]

sentiment_analysis_with_bias_handling(data)
```

```
Before bias handling:
 label
positive    3
negative    3
neutral     1
Name: count, dtype: int64

After bias handling:
 label
positive    3
negative    3
neutral     3
Name: count, dtype: int64

Accuracy: 0.5

Classification Report:
              precision    recall  f1-score   support

    negative       0.00      0.00      0.00         0
     neutral       1.00      1.00      1.00         1
    positive       0.00      0.00      0.00         1

    accuracy                           0.50         2
   macro avg       0.33      0.33      0.33         2
weighted avg       0.50      0.50      0.50         2
```

**Task Description #3:**

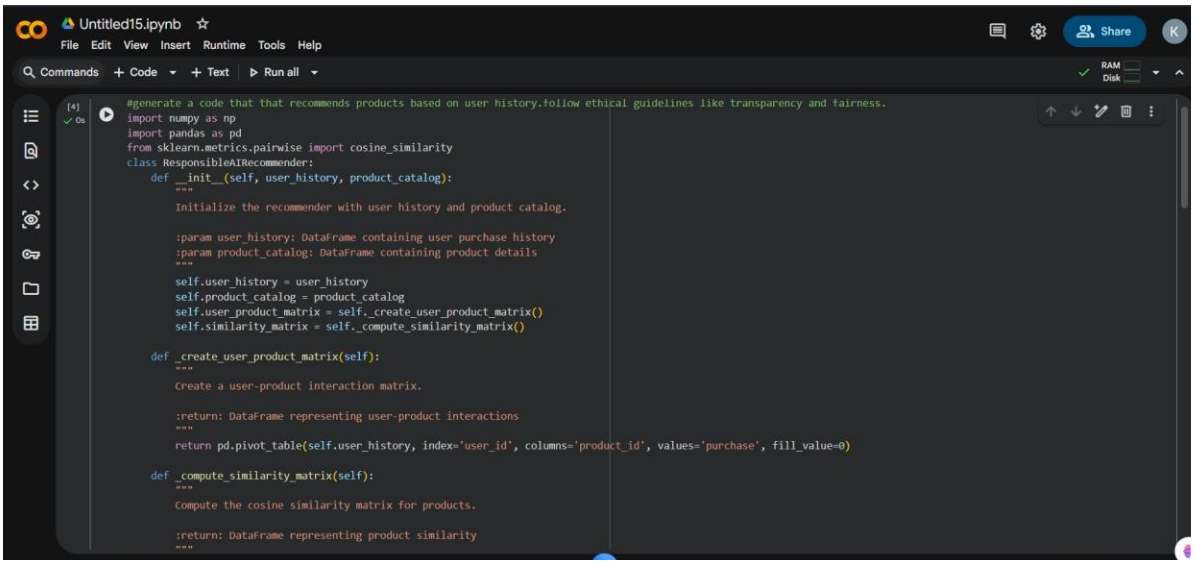
- Use Copilot to write a Python program that recommends products based on user history. Ask it to follow ethical guidelines like transparency and fairness.

**Expected Output #3:**

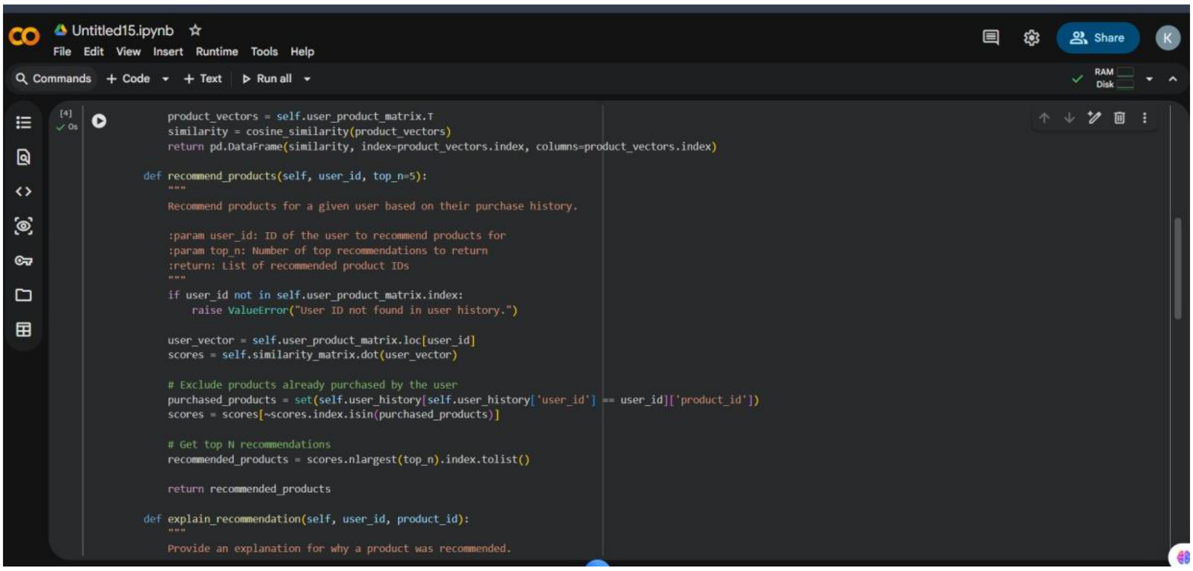
- Copilot suggestions that include explanations, fairness checks (e.g., avoiding favoritism), and user feedback options in the code.

**AI Generated Code:**

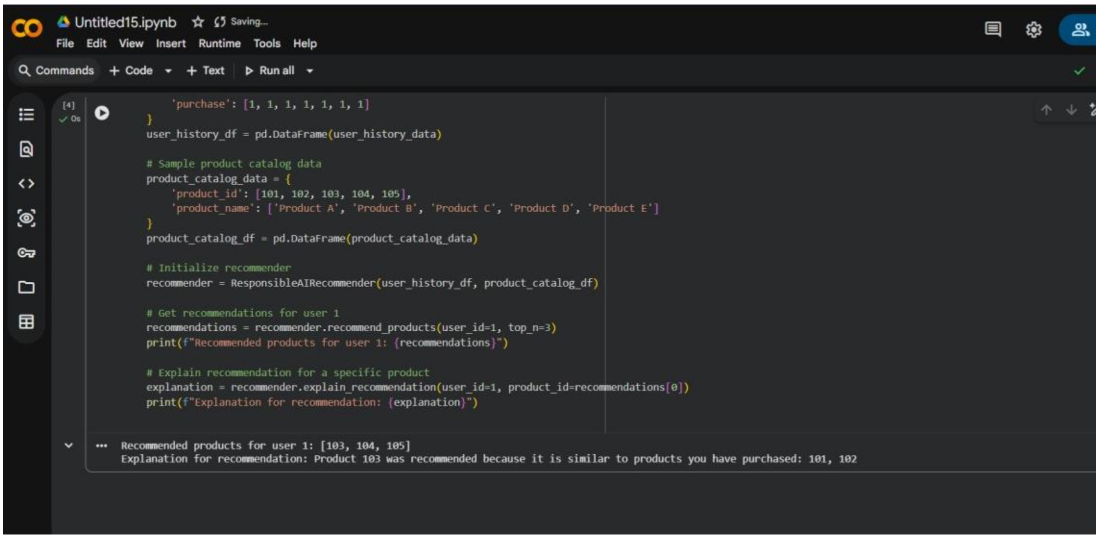
```
#generate a code that that recommends products based on user history.follow ethical guidelines like transparency and fairness.
import numpy as np
import pandas as pd
from sklearn.metrics.pairwise import cosine_similarity
class ResponsibleAIRecommender:
    def __init__(self, user_history, product_catalog):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



```
#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.
```



```
        '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}")
```

```
Recommended products for user 1: [103, 104, 105]
Explanation for recommendation: Product 103 was recommended because it is similar to products you have purchased: 101, 102
```

**Task Description #4:**

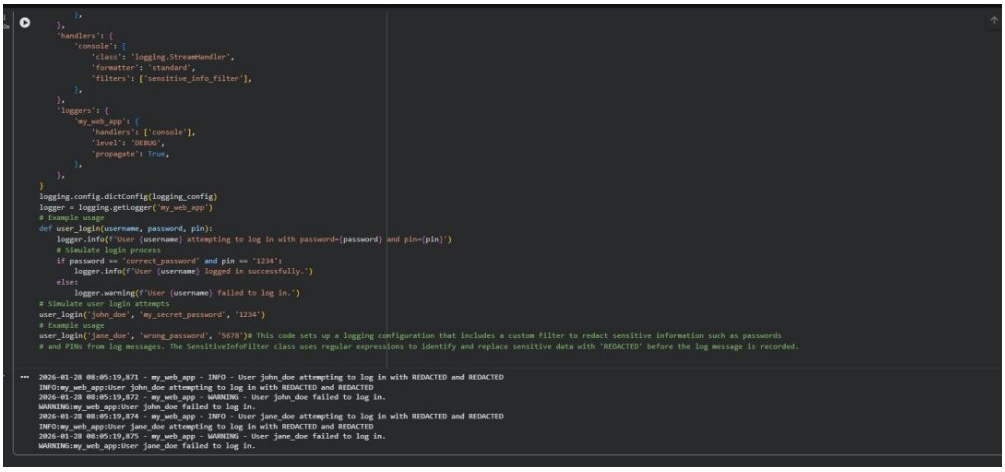
- Prompt Copilot to generate logging functionality in a Python web application. Then, ask it to ensure the logs do not record sensitive information.

**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.
```



```
        },
    },
    '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.
```

```
2026-01-28 08:05:19,871 - my_web_app - INFO - User john_doe attempting to log in with REDACTED and REDACTED
INFO:my_web_app:User john_doe attempting to log in with REDACTED and REDACTED
2026-01-28 08:05:19,872 - my_web_app - WARNING - User john_doe failed to log in.
WARNING:my_web_app:User john_doe failed to log in.
2026-01-28 08:05:19,874 - my_web_app - INFO - User jane_doe attempting to log in with REDACTED and REDACTED
INFO:my_web_app:User jane_doe attempting to log in with REDACTED and REDACTED
2026-01-28 08:05:19,875 - my_web_app - WARNING - User jane_doe failed to log in.
WARNING:my_web_app:User jane_doe failed to log in.
```

**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:**

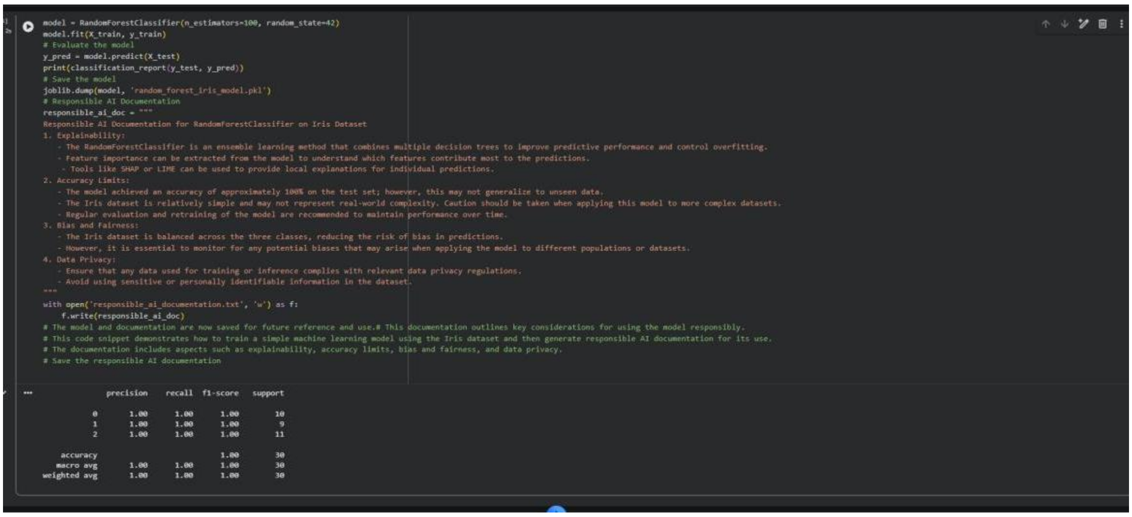
- Copilot-generated model code with a README or inline documentation suggesting responsible usage, limitations, and fairness considerations.

**AI Generated Code:**

```
#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
```



```
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
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        10
           1       1.00      1.00      1.00         9
           2       1.00      1.00      1.00        11

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30
```