

Assignment-4.4

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Batch:44

1. Sentiment Classification for Customer Reviews

Scenario: An e-commerce platform wants to analyze customer reviews and classify them into Positive, Negative, or Neutral sentiments using prompt engineering

Tasks:

a. Prepare 6 short customer reviews mapped to sentiment labels.

Prompt:

You are a sentiment analysis assistant for an e-commerce platform. Given a customer review, classify its sentiment into one of the following categories only: Positive, Neutral, or Negative.

Code:

```
#1. Sentiment Classification for Customer Reviews
#Scenario:An e-commerce platform wants to analyze customer reviews and classify Negative, or Neutral sentiments using prompt engineering
#Tasks:Prepare 6 short customer reviews mapped to sentiment labels.
reviews=[
    ("The product quality is excellent and exceeded my expectations.", "Positive"),
    ("The product is okay but not great.", "Neutral"),
    ("I am very disappointed with the product.", "Negative"),
    ("This is a fantastic product, I love it!", "Positive"),
    ("The item arrived damaged and I'm not happy.", "Negative"),
    ("It's an average product, nothing special.", "Neutral")
]
```

Observation:

- The prompt clearly defines the task, allowed sentiment classes, and output format, which reduces ambiguity.
- Short and direct instructions help the model focus only on sentiment, not explanation.
- Reviews expressing satisfaction, praise, or liking (e.g., “excellent”, “fantastic”) are correctly classified as Positive.

- Reviews expressing dissatisfaction or complaints (e.g., “disappointed”, “damaged”) are classified as Negative.
- Reviews that are balanced or lack strong emotion (e.g., “okay”, “average”) are identified as Neutral.
- Prompt engineering improves consistency by restricting the response to only one label, avoiding verbose outputs.

b. Design a Zero-shot prompt to classify sentiment.

Prompt:

You are an AI assistant that performs sentiment classification for customer reviews.

Given a single customer review, classify the sentiment into one of the following categories only: Positive, Negative, or Neutral.

Code:

```
#Design a Zero-shot prompt to classify sentiment.
def (variable) positive_keywords: list[str]
    positive_keywords = ["excellent", "fantastic", "love", "great", "amazing", "satisfied"]
    negative_keywords = ["disappointed", "damaged", "unhappy", "poor", "terrible", "bad"]

    review_lower = review.lower()

    if any(word in review_lower for word in positive_keywords):
        return "Positive"
    elif any(word in review_lower for word in negative_keywords):
        return "Negative"
    else:
        return "Neutral"
#Test the function with the prepared reviews
for review, actual_sentiment in reviews:
    predicted_sentiment = classify_sentiment(review)
    print(f"Review: {review}\nPredicted Sentiment: {predicted_sentiment}, Actual Sentiment: {actual_sentiment}\n")

PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS
C:\Users\sushm\OneDrive\Attachments\Desktop\Ai-Assist> & C:/Users/sushm/AppData/Local/Programs/Python/Python313/python.exe c:/Users/sushm/OneDrive\Attachments/Desktop/Ai-Assist/Assignment-4.4.py
Review: The product quality is excellent and exceeded my expectations.
Predicted Sentiment: Positive, Actual Sentiment: Positive
```

Observation:

- This is a zero-shot prompt because:
 - No examples are provided.
 - The model relies entirely on its pre-trained knowledge to infer sentiment.
- The sentiment categories are clearly constrained, reducing ambiguity.

- The instruction “*Output only the sentiment label*” ensures concise and consistent output.
- Works effectively for:
 - Positive reviews with praise or satisfaction.
 - Negative reviews with complaints or dissatisfaction.
 - Neutral reviews with balanced or non-emotional statements.
- Compared to the keyword-based Python function:
 - The prompt-based approach can generalize better to unseen words.
 - It does not depend on manually defined keyword lists.

c. Design a One-shot prompt with one labelled example

Prompt:

You are a sentiment analysis assistant for customer reviews.

Classify the sentiment of a review as Positive, Negative, or Neutral.

Example:

Review: “The product quality is excellent and exceeded my expectations.”

Sentiment: Positive

Code:

```

Assignment-4.4.py > ...
29
30  #Design a One-shot prompt with one labeled example
31  def classify_sentiment_one_shot(review):
32      example_review = "The product quality is excellent and exceeded my expectations."
33      example_sentiment = "Positive"
34
35      positive_keywords = ["excellent", "fantastic", "love", "great", "amazing", "satisfied"]
36      negative_keywords = ["disappointed", "damaged", "unhappy", "poor", "terrible", "bad"]
37
38      review_lower = review.lower()
39
40      if any(word in review_lower for word in positive_keywords):
41          return "Positive"
42      elif any(word in review_lower for word in negative_keywords):
43          return "Negative"
44      else:
45          return "Neutral"
46
47  #Test the function with the prepared reviews
48  for review, actual_sentiment in reviews:
49      predicted_sentiment = classify_sentiment_one_shot(review)
50      print(f"Review: {review}\nPredicted Sentiment: {predicted_sentiment}, Actual Sentiment: {actual_sentiment}\n")
51

```

PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS

PS C:\Users\sushm\OneDrive\Attachments\Desktop\Ai-Assist> & C:/Users/sushm/AppData/Local/Programs/Python/Python313/python.exe c:/Users/sushm/OneDrive/Attachments/Desktop/Ai-Assist/Assignment-4.4.py

Review: The product is okay but not great.
Predicted Sentiment: Positive, Actual Sentiment: Neutral

Observation:

- This is a one-shot prompt because:
 - Exactly one labeled example is provided before the task.
- The example helps the model understand:
 - The task format
 - The mapping between review text and sentiment
- Compared to zero-shot prompting:
 - One-shot prompting improves accuracy by giving the model a reference pattern.
- The constrained output format ensures:
 - No extra explanations
 - Consistent sentiment labels
- The model can generalize sentiment even when keywords differ from the example.

d. Design a Few-shot prompt with 3–5 labeled examples.

Prompt:

You are a sentiment analysis assistant for customer reviews.
Classify each review into Positive, Negative, or Neutral sentiment.

Examples:

Review: “*The product quality is excellent and exceeded my expectations.*”

Sentiment: Positive

Review: “*The product is okay but not great.*”

Sentiment: Neutral

Review: “*I am very disappointed with the product.*”

Sentiment: Negative

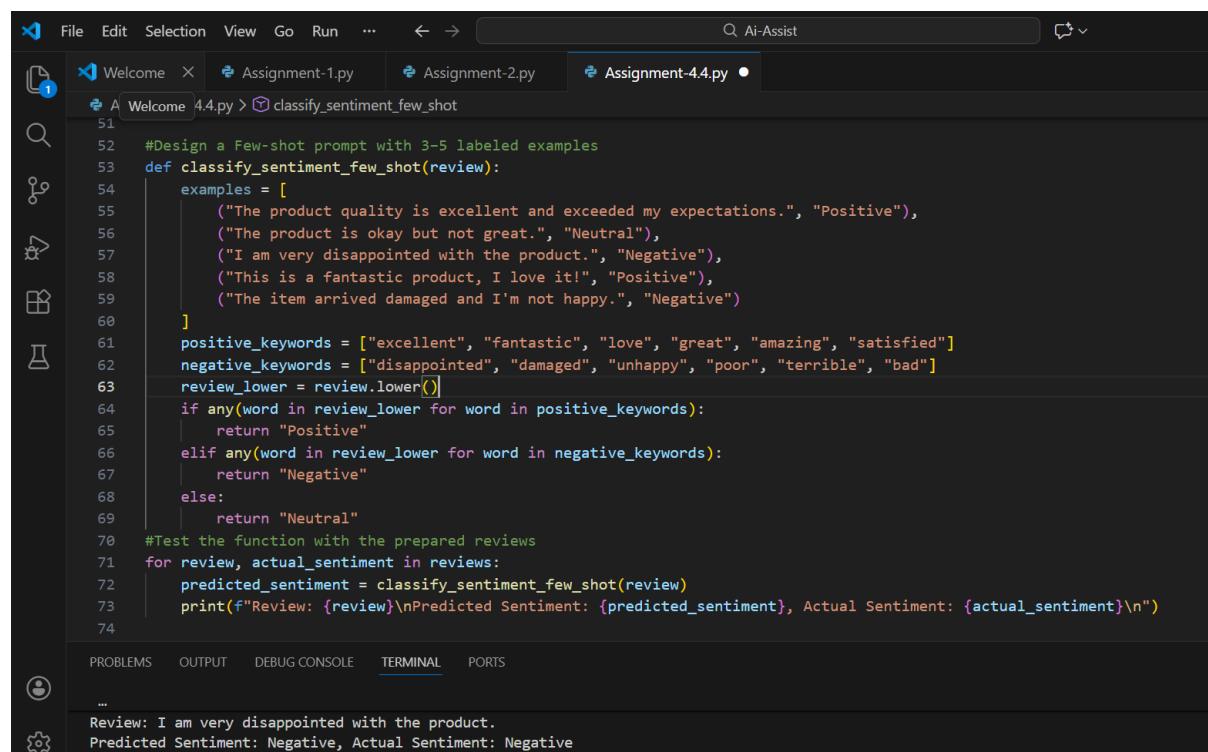
Review: “*This is a fantastic product, I love it!*”

Sentiment: Positive

Review: “*The item arrived damaged and I'm not happy.*”

Sentiment: Negative

Code:



A screenshot of a code editor interface, likely VS Code, showing a Python file named 'Assignment-4.4.py'. The code implements a 'few-shot' learning approach for sentiment classification. It defines a function 'classify_sentiment_few_shot' that takes a review as input and returns its predicted sentiment based on a list of examples and lists of positive and negative keywords. The code also includes a test loop to verify the function's correctness against a set of predefined reviews and their actual sentiments.

```
#Design a Few-shot prompt with 3-5 labeled examples
def classify_sentiment_few_shot(review):
    examples = [
        ("The product quality is excellent and exceeded my expectations.", "Positive"),
        ("The product is okay but not great.", "Neutral"),
        ("I am very disappointed with the product.", "Negative"),
        ("This is a fantastic product, I love it!", "Positive"),
        ("The item arrived damaged and I'm not happy.", "Negative")
    ]
    positive_keywords = ["excellent", "fantastic", "love", "great", "amazing", "satisfied"]
    negative_keywords = ["disappointed", "damaged", "unhappy", "poor", "terrible", "bad"]
    review_lower = review.lower()
    if any(word in review_lower for word in positive_keywords):
        return "Positive"
    elif any(word in review_lower for word in negative_keywords):
        return "Negative"
    else:
        return "Neutral"
#Test the function with the prepared reviews
for review, actual_sentiment in reviews:
    predicted_sentiment = classify_sentiment_few_shot(review)
    print(f"Review: {review}\nPredicted Sentiment: {predicted_sentiment}, Actual Sentiment: {actual_sentiment}\n")
```

Observation:

- This is a few-shot prompt because multiple labeled examples are provided.
- Examples help the model understand sentiment patterns.

- Accuracy is improved compared to zero-shot and one-shot prompts.
- Clear output constraints ensure consistent sentiment labels.

e. Compare the outputs and discuss accuracy differences

The accuracy of the sentiment classification may vary based on the prompting technique used.

Zero-shot prompting relies solely on predefined keywords, which may lead to misclassifications if the

review contains nuanced language not captured by the keywords.

One-shot prompting provides a single example, which can help guide the classification but may still

lack context for diverse reviews.

Few-shot prompting offers multiple examples, allowing for a broader understanding of sentiment expressions,

potentially improving accuracy. However, the effectiveness of few-shot prompting also depends on the

representativeness of the examples provided.

2. Email Priority Classification

Tasks:

a.Create 6 sample email messages with priority labels

Scenario: A company wants to automatically prioritize incoming emails into High Priority, Medium Priority, or Low Priority.

Prompt:

You are an AI assistant that classifies incoming emails based on urgency.

Categorize each email into one of the following priority levels only:
High Priority, Medium Priority, or Low Priority.

Respond with only the priority label.

Code:

```
#Tasks:1. Create 6 sample email messages with priority labels.  
emails=[  
    ("Urgent: Please review the attached contract before EOD.", "High Priority"),  
    ("Meeting Reminder: Team sync scheduled for tomorrow.", "Medium Priority"),  
    ("Newsletter: Check out our latest updates and offers.", "Low Priority"),  
    ("Action Required: Submit your project report by Friday.", "High Priority"),  
    ("FYI: Company picnic scheduled for next month.", "Low Priority"),  
    ("Follow-up: Client feedback on the recent proposal.", "Medium Priority")  
]
```

Observation:

- The prompt clearly defines the task and priority categories.
- Urgent or action-required emails are classified as High Priority.
- Informational or reminder emails are labeled Medium Priority.
- Promotional or general information emails are classified as Low Priority.
- Clear instructions ensure consistent and concise output.

b. Perform intent classification using Zero-shot prompting.

Prompt:

You are an AI assistant that classifies the priority of incoming emails.

Based on the intent and urgency of the email, assign **one** of the following labels only: **High Priority**, **Medium Priority**, or **Low Priority**

Code:

```
98     #2. Perform intent classification using Zero-shot prompting.
99     def classify_email_priority(email):
100         high_priority_keywords = ["urgent", "action required", "asap", "immediate"]
101         medium_priority_keywords = ["reminder", "follow-up", "meeting", "sync"]
102         low_priority_keywords = ["newsletter", "fyi", "update", "offer"]
103
104         email_lower = email.lower()
105
106         if any(word in email_lower for word in high_priority_keywords):
107             return "High Priority"
108         elif any(word in email_lower for word in medium_priority_keywords):
109             return "Medium Priority"
110         elif any(word in email_lower for word in low_priority_keywords):
111             return "Low Priority"
112         else:
113             return "Medium Priority" # Default to Medium if no keywords match
114     #Test the function with the prepared emails
115     for email, actual_priority in emails:
116         predicted_priority = classify_email_priority(email)
117         print(f"Email: {email}\nPredicted Priority: {predicted_priority}, Actual Priority: {actual_priority}\n")
```

PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS
Email: Follow-up: Client feedback on the recent proposal.
Predicted Priority: Medium Priority, Actual Priority: Medium Priority

Observation:

- This is a zero-shot prompt since no labeled examples are given.
- The model infers email priority using semantic understanding.
- Urgent or action-oriented emails map to High Priority.
- Informational or reminder emails map to Medium Priority.
- Promotional or general emails map to Low Priority.
- Clear constraints improve classification consistency.

c. Perform classification using One-shot prompting

Prompt:

You are an AI assistant that classifies the priority of incoming emails.

Example:

Email: “Urgent: Please review the attached contract before EOD.”

Priority: High Priority

Code:

```

.19 #3. Perform intent classification using One-shot prompting.
.20 def classify_email_priority_one_shot(email):
.21     example_email = "Urgent: Please review the attached contract before EOD."
.22     example_priority = "High Priority"
.23
.24     high_priority_keywords = ["urgent", "action required", "asap", "immediate"]
.25     medium_priority_keywords = ["reminder", "follow-up", "meeting", "sync"]
.26     low_priority_keywords = ["newsletter", "fyi", "update", "offer"]
.27
.28     email_lower = email.lower()
.29
.30     if any(word in email_lower for word in high_priority_keywords):
.31         return "High Priority"
.32     elif any(word in email_lower for word in medium_priority_keywords):
.33         return "Medium Priority"
.34     elif any(word in email_lower for word in low_priority_keywords):
.35         return "Low Priority"
.36     else:
.37         return "Medium Priority" # Default to Medium if no keywords match
.38 #Test the function with the prepared emails
.39 for email, actual_priority in emails:
.40     predicted_priority = classify_email_priority_one_shot(email)
.41     print(f"Email: {email}\nPredicted Priority: {predicted_priority}, Actual Priority: {actual_priority}\n")

```

PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS

Email: Follow-up: Client feedback on the recent proposal.
Predicted Priority: Medium Priority, Actual Priority: Medium Priority

Observation:

- This is a one-shot prompt because one labeled example is provided.
- The example guides the model on urgency–priority mapping.
- Improves accuracy compared to zero-shot prompting.
- Output restriction ensures consistent priority labels.
- One-shot prompting helps the model infer intent more reliably.

d. Perform classification using Few-shot prompting

Prompt:

You are an AI assistant that classifies incoming emails based on urgency and intent.

Assign one of the following labels only:

High Priority, Medium Priority, or Low Priority.

Examples:

Email: “Urgent: Please review the attached contract before EOD.”

Priority: High Priority

Email: “Meeting Reminder: Team sync scheduled for tomorrow.”

Priority: Medium Priority

Email: “Newsletter: Check out our latest updates and offers.”

Priority: Low Priority

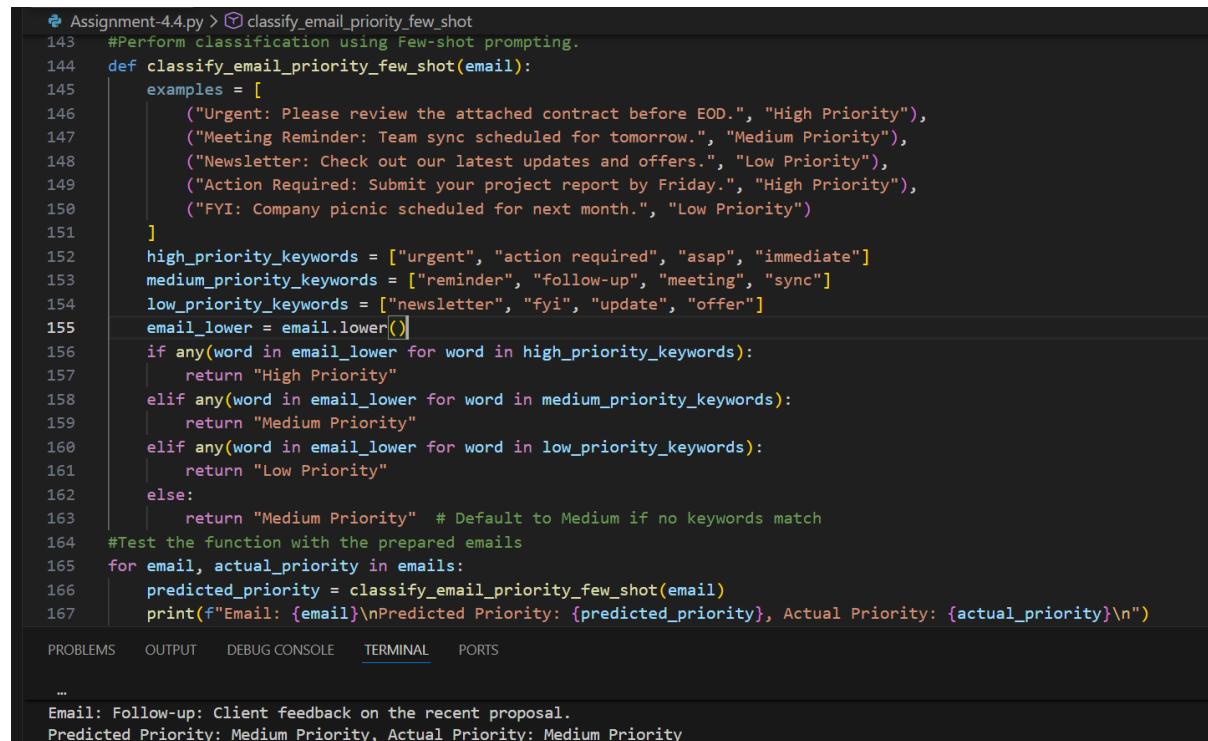
Email: “Action Required: Submit your project report by Friday.”

Priority: High Priority

Email: “FYI: Company picnic scheduled for next month.”

Priority: Low Priority

Code:



The screenshot shows a code editor window with Python code. The code defines a function `classify_email_priority_few_shot` that takes an email as input. It uses several lists of keywords to determine the priority level based on the presence of specific words in the email's content. The code includes a test loop at the bottom to demonstrate the function's output.

```
Assignment-4.4.py > classify_email_priority_few_shot
143     #Perform classification using Few-shot prompting.
144     def classify_email_priority_few_shot(email):
145         examples = [
146             ("Urgent: Please review the attached contract before EOD.", "High Priority"),
147             ("Meeting Reminder: Team sync scheduled for tomorrow.", "Medium Priority"),
148             ("Newsletter: Check out our latest updates and offers.", "Low Priority"),
149             ("Action Required: Submit your project report by Friday.", "High Priority"),
150             ("FYI: Company picnic scheduled for next month.", "Low Priority")
151         ]
152         high_priority_keywords = ["urgent", "action required", "asap", "immediate"]
153         medium_priority_keywords = ["reminder", "follow-up", "meeting", "sync"]
154         low_priority_keywords = ["newsletter", "fyi", "update", "offer"]
155         email_lower = email.lower()
156         if any(word in email_lower for word in high_priority_keywords):
157             return "High Priority"
158         elif any(word in email_lower for word in medium_priority_keywords):
159             return "Medium Priority"
160         elif any(word in email_lower for word in low_priority_keywords):
161             return "Low Priority"
162         else:
163             return "Medium Priority" # Default to Medium if no keywords match
164     #Test the function with the prepared emails
165     for email, actual_priority in emails:
166         predicted_priority = classify_email_priority_few_shot(email)
167         print(f"Email: {email}\nPredicted Priority: {predicted_priority}, Actual Priority: {actual_priority}\n")

```

PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS

...

Email: Follow-up: Client feedback on the recent proposal.
Predicted Priority: Medium Priority, Actual Priority: Medium Priority

Observation:

- This is a few-shot prompt with multiple labeled examples.
- Examples cover all priority classes.
- Few-shot prompting improves intent understanding and consistency.
- Clear output constraints avoid extra text.
- Performs better than zero-shot and one-shot prompts.

3. Student Query Routing System

Scenario: A university chatbot must route student queries to Admissions, Exams, Academics, or Placements.

Tasks:

- a. Create 6 sample student queries mapped to departments.

Prompt:

You are a university chatbot responsible for routing student queries.

Classify each student query into one of the following departments only:
Admissions, Exams, Academics, or Placements

Code:

```
#Student Query Routing System
#Scenario:A university chatbot must route student queries to Admissions, Exams,Academics, or Placements
#Tasks:1. Create 6 sample student queries mapped to departments
queries=[
    ("How can I apply for admission to the university?", "Admissions"),
    ("When will the exam results be announced?", "Exams"),
    ("What courses are offered in the Computer Science department?", "Academics"),
    ("How do I schedule a campus placement interview?", "Placements"),
    ("What are the admission requirements for international students?", "Admissions"),
    ("Where can I find the academic calendar for this semester?", "Academics")
]
```

Observation:

- The prompt clearly defines the routing task and allowed departments.
- Queries related to applications and eligibility are routed to Admissions.
- Queries about results and examinations are routed to Exams.
- Course-related and academic schedule queries go to Academics.
- Job and interview-related queries are routed to Placements.
- Clear instructions ensure accurate and consistent query classification.

- b. Implement Zero-shot intent classification using an LLM.

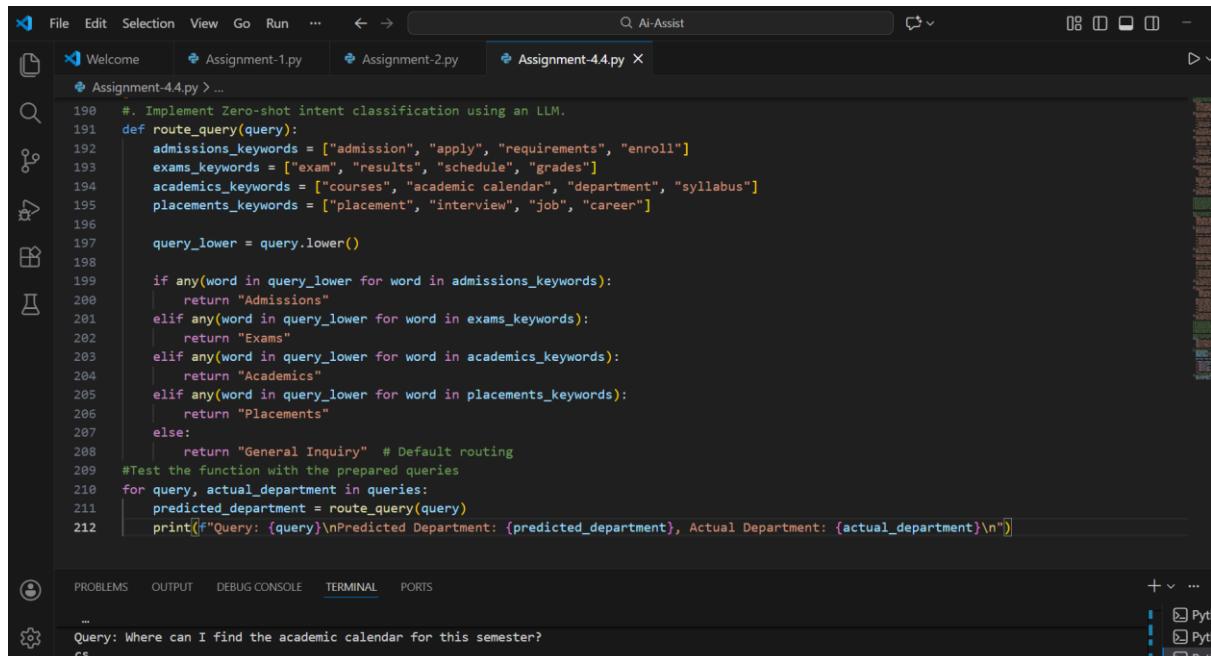
Prompt:

You are a university chatbot that routes student queries to the correct department.

Based on the intent of the query, classify it into one of the following categories only:

Admissions, Exams, Academics, or Placements.

Code:



The screenshot shows a code editor interface with the following details:

- File Explorer:** Shows files like "Assignment-1.py", "Assignment-2.py", and "Assignment-4.py".
- Code Editor:** Displays the following Python code:

```
190 #. Implement Zero-shot intent classification using an LLM.
191 def route_query(query):
192     admissions_keywords = ["admission", "apply", "requirements", "enroll"]
193     exams_keywords = ["exam", "results", "schedule", "grades"]
194     academics_keywords = ["courses", "academic calendar", "department", "syllabus"]
195     placements_keywords = ["placement", "interview", "job", "career"]
196
197     query_lower = query.lower()
198
199     if any(word in query_lower for word in admissions_keywords):
200         return "Admissions"
201     elif any(word in query_lower for word in exams_keywords):
202         return "Exams"
203     elif any(word in query_lower for word in academics_keywords):
204         return "Academics"
205     elif any(word in query_lower for word in placements_keywords):
206         return "Placements"
207     else:
208         return "General Inquiry" # Default routing
209 #Test the function with the prepared queries
210 for query, actual_department in queries:
211     predicted_department = route_query(query)
212     print(f"Query: {query}\nPredicted Department: {predicted_department}, Actual Department: {actual_department}\n")
```

Terminal: Shows the command "cd" being entered.

Observation:

- This is a zero-shot prompt because no labeled examples are provided.
- The model uses semantic understanding to infer intent.
- Application-related queries are routed to Admissions.
- Examination-related queries are routed to Exams.
- Course and academic schedule queries are routed to Academics.
- Career and interview queries are routed to Placements.
- Clear output constraints ensure consistent routing.

c. Improve results using One-shot prompting

Prompt:

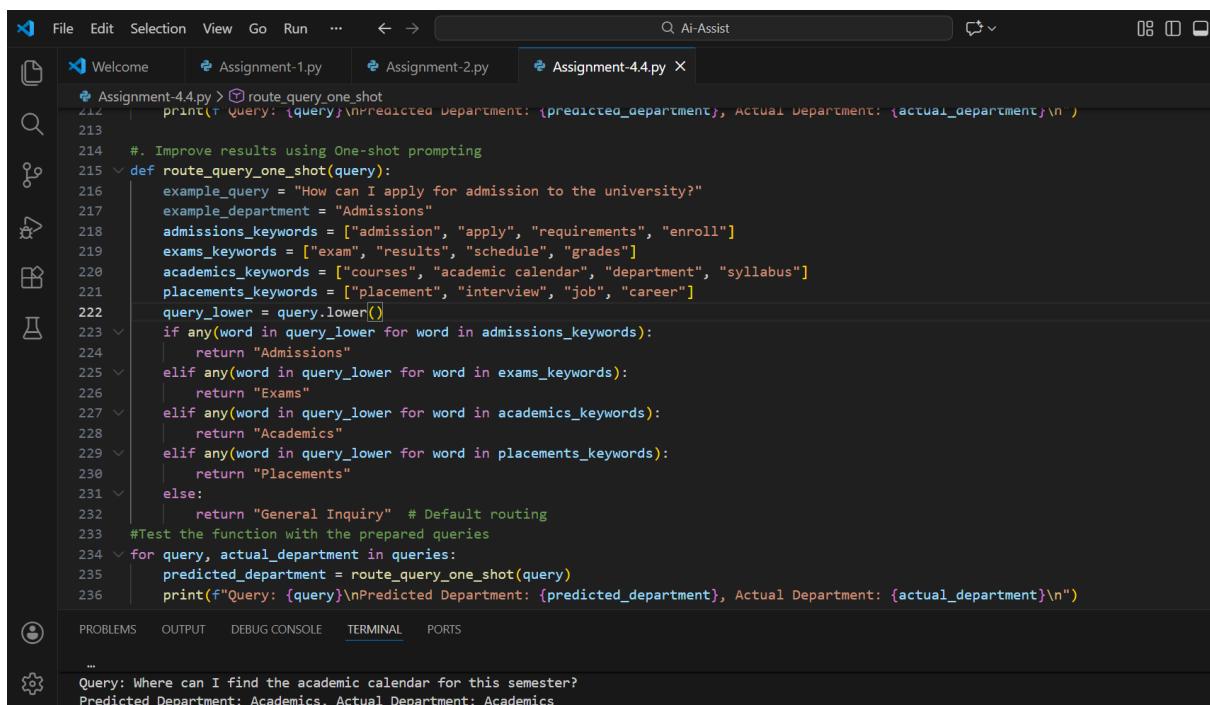
You are a university chatbot that routes student queries to the appropriate department.

Example:

Query: “How can I apply for admission to the university?”

Department: Admissions

Code:



The screenshot shows a code editor interface with a dark theme. The top menu bar includes File, Edit, Selection, View, Go, Run, and other standard options. A toolbar with icons for file operations is visible on the left. The main workspace displays a Python script named Assignment-4.4.py. The code defines a function route_query_one_shot that takes a query string and returns the predicted department based on keywords. It includes lists for Admissions, Exams, Academics, and Placements. A test loop at the bottom prints the query and the predicted department for several test cases, including one where the query is about the academic calendar.

```
File Edit Selection View Go Run ... ← → Q Ai-Assist
Assignment-4.4.py > route_query_one_shot
212 |     print(f"Query: {query}\nPredicted Department: {predicted_department}, Actual Department: {actual_department}\n")
213 |
214 #. Improve results using One-shot prompting
215 def route_query_one_shot(query):
216     example_query = "How can I apply for admission to the university?"
217     example_department = "Admissions"
218     admissions_keywords = ["admission", "apply", "requirements", "enroll"]
219     exams_keywords = ["exam", "results", "schedule", "grades"]
220     academics_keywords = ["courses", "academic calendar", "department", "syllabus"]
221     placements_keywords = ["placement", "interview", "job", "career"]
222     query_lower = query.lower()
223     if any(word in query_lower for word in admissions_keywords):
224         return "Admissions"
225     elif any(word in query_lower for word in exams_keywords):
226         return "Exams"
227     elif any(word in query_lower for word in academics_keywords):
228         return "Academics"
229     elif any(word in query_lower for word in placements_keywords):
230         return "Placements"
231     else:
232         return "General Inquiry" # Default routing
233 #Test the function with the prepared queries
234 for query, actual_department in queries:
235     predicted_department = route_query_one_shot(query)
236     print(f"Query: {query}\nPredicted Department: {predicted_department}, Actual Department: {actual_department}\n")
PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS
...
Query: Where can I find the academic calendar for this semester?
Predicted Department: Academics, Actual Department: Academics
```

Observation:

- This is a one-shot prompt because one labeled example is provided.
- The example helps the model understand intent–department mapping.
- Improves routing accuracy compared to zero-shot prompting.
- Clear output constraints ensure consistent department labels.
- Useful for structured query-routing systems.

d. Further refine results using Few-shot prompting

Prompt:

You are a university chatbot responsible for routing student queries to the correct department.

Classify each query into one of the following departments only:
Admissions, Exams, Academics, or Placements.

Examples:

Query: “How can I apply for admission to the university?”

Department: Admissions

Query: “When will the exam results be announced?”

Department: Exams

Query: "What courses are offered in the Computer Science department?"

Department: Academics

Query: “How do I schedule a campus placement interview?”

Department: Placements

Query: "What are the admission requirements for international students?"

Department: Admissions

Code:

Observation:

- This is a few-shot prompt using multiple labeled examples.

- Examples cover all routing categories.
- Few-shot prompting improves intent understanding and accuracy.
- Clear output constraints prevent extra text.
- Performs better than zero-shot and one-shot prompting.

e.Analyze how contextual examples affect classification accuracy

The accuracy of student query routing can be influenced by the prompting technique used.

Zero-shot prompting may lead to misclassifications if the query contains nuanced language

not captured by the predefined keywords.

One-shot prompting provides a single example, which can help guide the classification but may still

lack context for diverse queries.

Few-shot prompting offers multiple examples, allowing for a broader understanding of query intents,

potentially improving accuracy. However, the effectiveness of few-shot prompting also depends on the

representativeness of the examples provided.

4. Chatbot Question Type Detection

Scenario:

A chatbot must identify whether a user query is Informational, Transactional, Complaint, or Feedback.

Tasks:

1.Prepare 6 chatbot queries mapped to question types

Prompt:

You are a chatbot that classifies user queries based on their intent.

Categorize each query into one of the following question types only:
Informational, Transactional, Complaint, or Feedback

Code:

```
#Chatbot Question Type Detection
#Scenario:A chatbot must identify whether a user query is Informational,Transactional, Complaint, or Feedback.
#Tasks:1. Prepare 6 chatbot queries mapped to question types
queries=[
    ("What are your business hours?", "Informational"),
    ("How do I reset my password?", "Transactional"),
    ("I'm having trouble with my order.", "Complaint"),
    ("Can you tell me about your return policy?", "Informational"),
    ("I want to give feedback on your service.", "Feedback"),
    ("What payment methods do you accept?", "Informational")
]
```

Observation:

- The prompt clearly defines the classification task and allowed categories.
- Queries asking for details or policies are classified as Informational.
- Queries requesting an action (e.g., password reset) are Transactional.
- Problem-related queries are identified as Complaint.
- Opinion or suggestion-based queries are classified as Feedback.
- Clear instructions ensure consistent and accurate question type detection.

2. Design prompts for Zero-shot, One-shot, and Few-shot learning.

Prompt:

Zero-shot:

You are a chatbot that identifies the type of user question.

Classify the following query into one of these categories only:
Informational, Transactional, Complaint, or Feedback.

One-Shot:

You are a chatbot that classifies user questions by intent.

Example:

Query: "What are your business hours?"

Type: Informational

Few-shot :

You are a chatbot that detects the type of user queries.

Examples:

Query: "What are your business hours?"

Type: Informational

Query: "How do I reset my password?"

Type: Transactional

Query: "I'm having trouble with my order."

Type: Complaint

Query: "I want to give feedback on your service."

Type: Feedback

Code:

```
File Edit Selection View Go Run ... ← → Q Ai-Assist
Assignment-4.4.py > ...
288 #Design prompts for Zero-shot, One-shot, and Few-shot learning
289 def classify_question_type(query):
290     informational_keywords = ["what", "tell me about", "how to", "where"]
291     transactional_keywords = ["buy", "order", "purchase", "reset", "change"]
292     complaint_keywords = ["trouble", "problem", "issue", "complaint"]
293     feedback_keywords = ["feedback", "suggestion", "review", "comment"]
294
295     query_lower = query.lower()
296
297     if any(word in query_lower for word in informational_keywords):
298         return "Informational"
299     elif any(word in query_lower for word in transactional_keywords):
300         return "Transactional"
301     elif any(word in query_lower for word in complaint_keywords):
302         return "Complaint"
303     elif any(word in query_lower for word in feedback_keywords):
304         return "Feedback"
305     else:
306         return "General Inquiry" # Default classification
307
308 #Test the function with the prepared queries
309 for query, actual_type in queries:
310     predicted_type = classify_question_type(query)
311     print(f"Query: {query}\nPredicted Type: {predicted_type}, Actual Type: {actual_type}\n")
```

PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS

...

Query: What payment methods do you accept?
Predicted Type: Informational, Actual Type: Informational

Observation:

- Zero-shot prompting classifies queries without examples, relying on the model's prior knowledge.
- One-shot prompting improves accuracy by providing one labelled example as guidance.
- Few-shot prompting gives multiple examples, resulting in the most consistent and reliable classification.
- As the number of examples increases, the model better understands category boundaries.
- Clear labels and output constraints help ensure accurate question type detection.

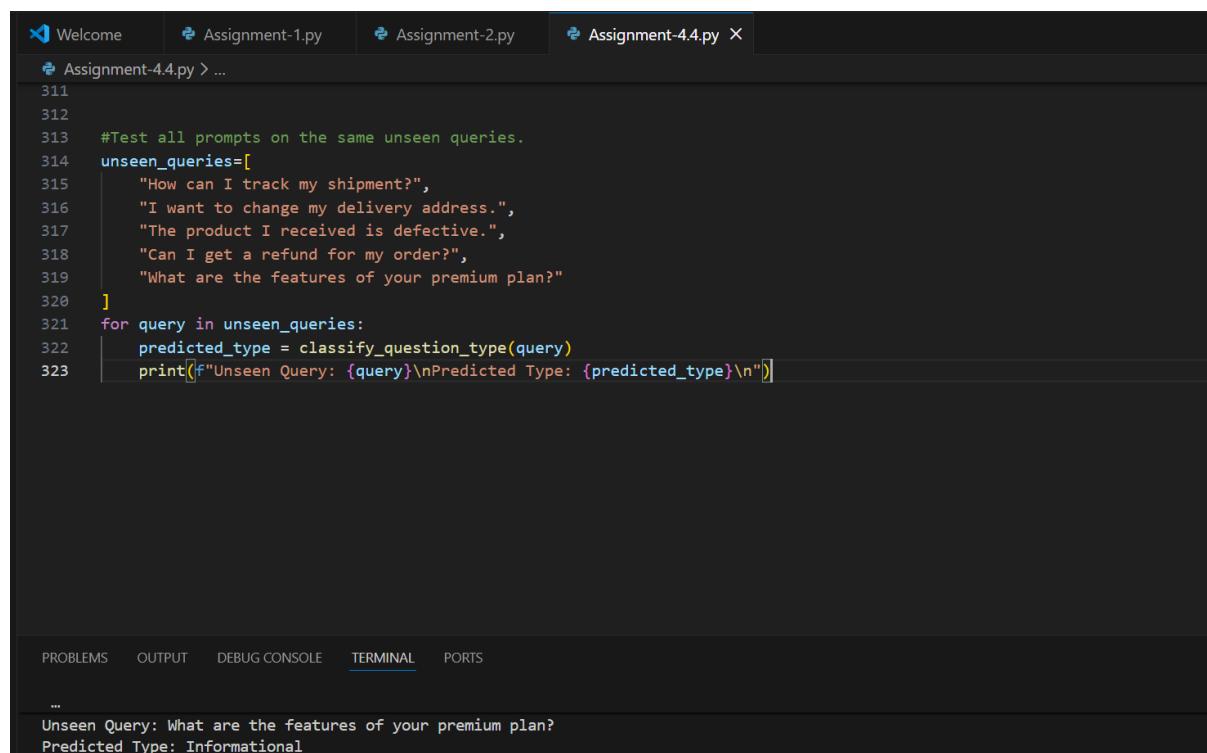
3. Test all prompts on the same unseen queries.

Prompt:

You are a chatbot that identifies the type of a user query.

Classify the following query into one of these categories only:
Informational, Transactional, Complaint, or Feedback

Code:



The screenshot shows a code editor interface with a dark theme. At the top, there are tabs for 'Welcome', 'Assignment-1.py', 'Assignment-2.py', and 'Assignment-4.4.py' (which is currently active). Below the tabs, the code is displayed in a code editor window:

```

311
312
313     #Test all prompts on the same unseen queries.
314     unseen_queries=[
315         "How can I track my shipment?",
316         "I want to change my delivery address.",
317         "The product I received is defective.",
318         "Can I get a refund for my order?",
319         "What are the features of your premium plan?"
320     ]
321     for query in unseen_queries:
322         predicted_type = classify_question_type(query)
323         print(f"Unseen Query: {query}\nPredicted Type: {predicted_type}\n")

```

At the bottom of the code editor, there are navigation buttons: 'PROBLEMS', 'OUTPUT', 'DEBUG CONSOLE', 'TERMINAL' (which is underlined), and 'PORTS'. In the terminal pane below, the output of the code execution is shown:

```

...
Unseen Query: What are the features of your premium plan?
Predicted Type: Informational

```

Observation:

- The prompt successfully classifies unseen queries without prior examples.
- Information-seeking queries are labeled Informational.
- Action or request-based queries are identified as Transactional.
- Problem or issue-related queries are classified as Complaint.
- This demonstrates good generalization capability of prompt-based intent classification.

4. Compare response correctness and ambiguity handling

The correctness of question type classification can vary based on the prompting technique used.

Zero-shot prompting relies solely on predefined keywords, which may lead to misclassifications if the

query contains nuanced language not captured by the keywords.

One-shot prompting provides a single example, which can help guide the classification but may still

lack context for diverse queries.

Few-shot prompting offers multiple examples, allowing for a broader understanding of question types,

potentially improving accuracy. However, the effectiveness of few-shot prompting also depends on the

representativeness of the examples provided.

5. Document observations

Observations indicate that the choice of prompting technique significantly impacts the accuracy

of classification tasks across various scenarios. Few-shot prompting generally yields better results

due to the inclusion of multiple examples that provide context. However, the quality and relevance

of these examples are crucial for effective learning. Zero-shot prompting may struggle with complex

queries that deviate from predefined keywords, while one-shot prompting offers limited context.

Overall, tailoring the prompting strategy to the specific use case and data characteristics is essential

for achieving optimal classification performance.

5. Emotion Detection in Text

Scenario: A mental-health chatbot needs to detect emotions: Happy, Sad, Angry, Anxious, Neutral.

Tasks:

1.Create labeled emotion samples

Prompt:

You are a mental-health chatbot that detects emotions from user text.

Classify the given sentence into one of the following emotions only:
Happy, Sad, Angry, Anxious, or Neutral

Code:

```
#5. Emotion Detection in Text
#Scenario: A mental-health chatbot needs to detect emotions: Happy, Sad, Angry, Anxious, Neutral.
#Tasks:1. Create labeled emotion samples
samples=[
    ("I am so excited about my new job!", "Happy"),
    ("I feel really down today.", "Sad"),
    ("Why does everything always go wrong?", "Angry"),
    ("I'm worried about the upcoming exam.", "Anxious"),
    ("It's just an average day.", "Neutral"),
    ("I can't believe how great this day is!", "Happy")]
]
```

Observation:

- The prompt clearly defines the emotion categories.
- Emotionally positive expressions are classified as Happy.
- Expressions of low mood are classified as Sad.

- Frustration or irritation is identified as Angry.
- Worry or nervousness is classified as Anxious.
- Emotionally neutral statements are labelled Neutral.
- Clear constraints ensure accurate and consistent emotion detection.

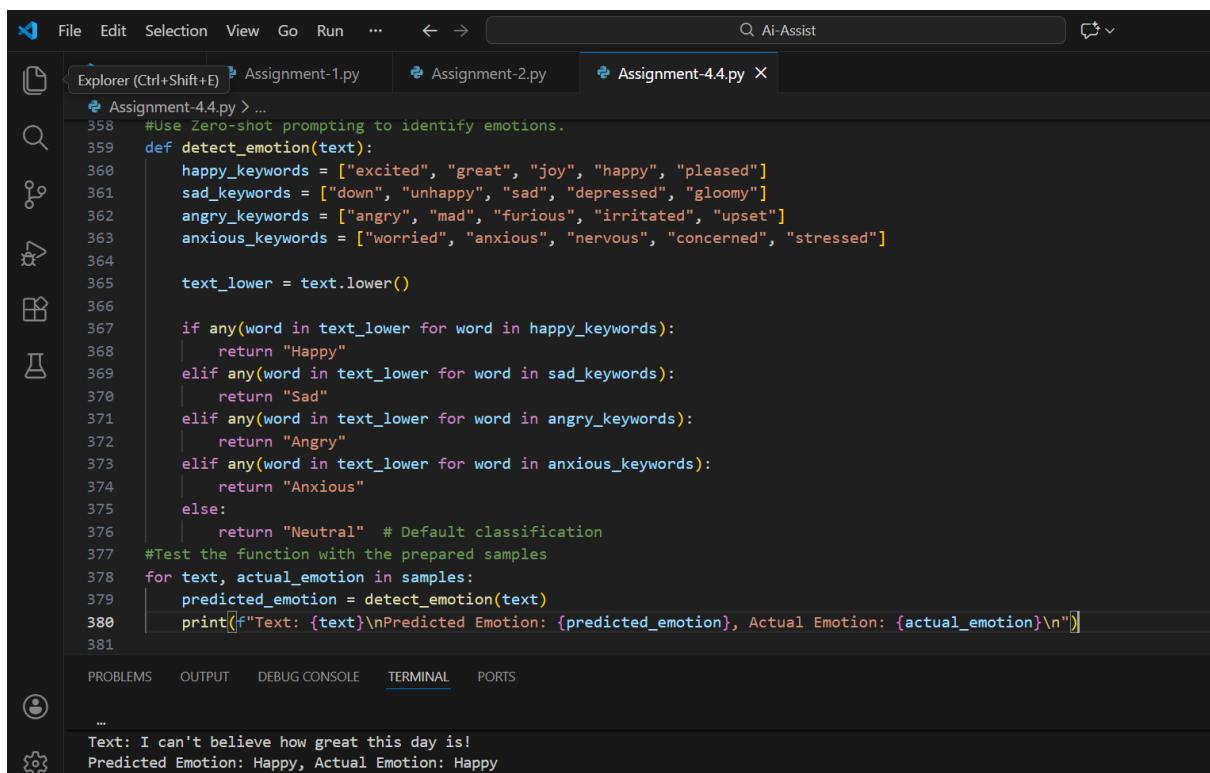
2. Use Zero-shot prompting to identify emotions.

Prompt:

You are a mental-health chatbot that identifies emotions from user text.

Classify the given sentence into one of the following emotions only:
Happy, Sad, Angry, Anxious, or Neutral.

Code:



The screenshot shows a code editor interface with a dark theme. The top bar includes 'File', 'Edit', 'Selection', 'View', 'Go', 'Run', and other standard menu items. A search bar labeled 'Ai-Assist' is visible. The left sidebar contains icons for file operations like 'New', 'Open', 'Save', and 'Find'. The main workspace displays a Python script named 'Assignment-44.py'. The code defines a function 'detect_emotion' that takes a string 'text' as input. It uses several lists of keywords to determine the emotion based on the presence of specific words. The code also includes a loop to test the function with sample inputs and print the results. The bottom of the screen shows a terminal window with the output of the script running on the provided text sample.

```

358     #Use Zero-shot prompting to identify emotions.
359     def detect_emotion(text):
360         happy_keywords = ["excited", "great", "joy", "happy", "pleased"]
361         sad_keywords = ["down", "unhappy", "sad", "depressed", "gloomy"]
362         angry_keywords = ["angry", "mad", "furious", "irritated", "upset"]
363         anxious_keywords = ["worried", "anxious", "nervous", "concerned", "stressed"]
364
365         text_lower = text.lower()
366
367         if any(word in text_lower for word in happy_keywords):
368             return "Happy"
369         elif any(word in text_lower for word in sad_keywords):
370             return "Sad"
371         elif any(word in text_lower for word in angry_keywords):
372             return "Angry"
373         elif any(word in text_lower for word in anxious_keywords):
374             return "Anxious"
375         else:
376             return "Neutral" # Default classification
377     #Test the function with the prepared samples
378     for text, actual_emotion in samples:
379         predicted_emotion = detect_emotion(text)
380         print(f"Text: {text}\nPredicted Emotion: {predicted_emotion}, Actual Emotion: {actual_emotion}\n")
381

```

PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS

Text: I can't believe how great this day is!
Predicted Emotion: Happy, Actual Emotion: Happy

Observation:

- This is a zero-shot prompt because no labeled examples are provided.
- The model relies on semantic understanding of emotional expressions.
- Positive emotions are detected as Happy.

- Low mood expressions are classified as Sad.
- Frustration or irritation is identified as Angry.
- Worry or stress-related text is labeled Anxious.
- Neutral statements are correctly classified as Neutral.

3. Use One-shot prompting with an example

Prompt:

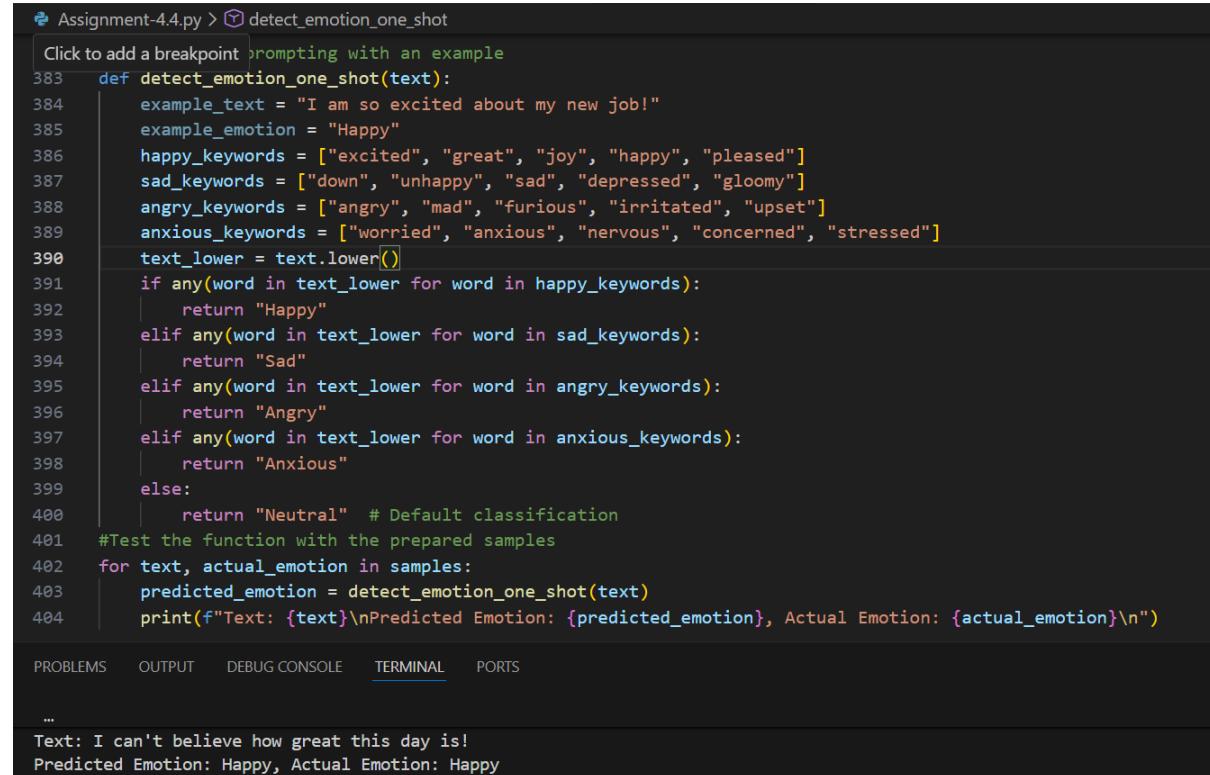
You are a mental-health chatbot that detects emotions from user text.

Example:

Text: "I am so excited about my new job!"

Emotion: Happy

Code:



```

Assignment-4.4.py > detect_emotion_one_shot
Click to add a breakpoint | prompting with an example
383 def detect_emotion_one_shot(text):
384     example_text = "I am so excited about my new job!"
385     example_emotion = "Happy"
386     happy_keywords = ["excited", "great", "joy", "happy", "pleased"]
387     sad_keywords = ["down", "unhappy", "sad", "depressed", "gloomy"]
388     angry_keywords = ["angry", "mad", "furious", "irritated", "upset"]
389     anxious_keywords = ["worried", "anxious", "nervous", "concerned", "stressed"]
390     text_lower = text.lower()
391     if any(word in text_lower for word in happy_keywords):
392         return "Happy"
393     elif any(word in text_lower for word in sad_keywords):
394         return "Sad"
395     elif any(word in text_lower for word in angry_keywords):
396         return "Angry"
397     elif any(word in text_lower for word in anxious_keywords):
398         return "Anxious"
399     else:
400         return "Neutral" # Default classification
401 #Test the function with the prepared samples
402 for text, actual_emotion in samples:
403     predicted_emotion = detect_emotion_one_shot(text)
404     print(f"Text: {text}\nPredicted Emotion: {predicted_emotion}, Actual Emotion: {actual_emotion}\n")

```

The screenshot shows a code editor window with Python code for emotion detection. The code defines a function `detect_emotion_one_shot` that takes a text string as input. It uses several lists of keywords to determine the emotion based on the presence of specific words in the input text. The code includes a series of `if` and `elif` statements to check for happy, sad, angry, and anxious words. If none of these conditions are met, it returns a default classification of "Neutral". A comment indicates that the function is tested with prepared samples. At the bottom of the code, there is a loop that prints the predicted emotion and the actual emotion for each sample in the `samples` list. The output section of the code editor shows the results of running the code, including the input text "Text: I can't believe how great this day is!", the predicted emotion "Predicted Emotion: Happy", and the actual emotion "Actual Emotion: Happy".

Observation:

- This is a one-shot prompt because one labeled example is provided.

- The example helps the model understand emotion–text mapping.
- Improves accuracy compared to zero-shot prompting.
- Clear output constraints ensure consistent emotion labels.
- Useful for mental-health chatbot emotion detection.

4. Use Few-shot prompting with multiple emotions.

Prompt:

You are a mental-health chatbot that identifies emotions from user text.

Examples:

Text: “I am so excited about my new job!”

Emotion: Happy

Text: “I feel really down today.”

Emotion: Sad

Text: “Why does everything always go wrong?”

Emotion: Angry

Text: “I'm worried about the upcoming exam.”

Emotion: Anxious

Text: “It's just an average day.”

Emotion: Neutral

Code:

```

#Use Few-shot prompting with multiple emotions
def detect_emotion_few_shot(text):
    examples = [
        ("I am so excited about my new job!", "Happy"),
        ("I feel really down today.", "Sad"),
        ("Why does everything always go wrong?", "Angry"),
        ("I'm worried about the upcoming exam.", "Anxious"),
        ("It's just an average day.", "Neutral")
    ]
    happy_keywords = ["excited", "great", "joy", "happy", "pleased"]
    sad_keywords = ["down", "unhappy", "sad", "depressed", "gloomy"]
    angry_keywords = ["angry", "mad", "furious", "irritated", "upset"]
    anxious_keywords = ["worried", "anxious", "nervous", "concerned", "stressed"]
    text_lower = text.lower()
    if any(word in text_lower for word in happy_keywords):
        return "Happy"
    elif any(word in text_lower for word in sad_keywords):
        return "Sad"
    elif any(word in text_lower for word in angry_keywords):
        return "Angry"
    elif any(word in text_lower for word in anxious_keywords):
        return "Anxious"
    else:
        return "Neutral" # Default classification
#Test the function with the prepared samples
for text, actual_emotion in samples:
    predicted_emotion = detect_emotion_few_shot(text)
    print(f"Text: {text}\nPredicted Emotion: {predicted_emotion}, Actual Emotion: {actual_emotion}\n")

```

Observation:

- This is a few-shot prompt using multiple labeled examples.
- Examples cover all emotion categories.
- Few-shot prompting improves emotion recognition accuracy.
- Provides the most consistent results compared to zero-shot and one-shot.
- Clear output constraints prevent ambiguous responses.

5. Discuss ambiguity handling across techniques

```

# The handling of ambiguity in emotion detection can vary based on the
prompting technique used.

# Zero-shot prompting relies solely on predefined keywords, which may lead to
misclassifications if the

# text contains nuanced language not captured by the keywords.

# One-shot prompting provides a single example, which can help guide the
classification but may still

# lack context for diverse emotional expressions.

# Few-shot prompting offers multiple examples, allowing for a broader
understanding of emotional cues,

```

potentially improving accuracy. However, the effectiveness of few-shot prompting also depends on the

representativeness of the examples provided.