

AI Assisted Coding Lab ASS-4.4

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Batch:13

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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.

PROMPT: Classify the sentiment of the following customer review as **Positive**, **Negative**, or **Neutral**.

Review: "The item arrived broken and support was poor."

A) Prepare 6 short customer reviews mapped to sentiment labels.

The screenshot shows a code editor with several files open in the sidebar. The main file, `simple_sentiment_classifier.py`, contains the following Python code:

```
1  """Simple Sentiment Classification"""
2  reviews = [
3      {"id": 1, "text": "The product quality is excellent and I love it.", "expected": "Positive"},
4      {"id": 2, "text": "Fast delivery and very good customer service.", "expected": "Positive"},
5      {"id": 3, "text": "The product is okay, not too good or bad.", "expected": "Neutral"},
6      {"id": 4, "text": "Average quality, works as expected.", "expected": "Neutral"},
7      {"id": 5, "text": "The item arrived broken and support was poor.", "expected": "Negative"},
8      {"id": 6, "text": "Very disappointed, complete waste of money.", "expected": "Negative"},
9  ]
10 positive_words = {'excellent', 'love', 'great', 'good', 'fast', 'best', 'amazing', 'wonderful', 'perfect', 'quality'}
11 negative_words = {'broken', 'poor', 'waste', 'disappointed', 'bad', 'terrible', 'awful', 'hate', 'worst'}
12 neutral_words = {'okay', 'average', 'works', 'expected', 'fine', 'normal', 'adequate'}
13
14 # Explain | Add Comment | X
15 def classify(review_text):
16     """Classify review sentiment"""
17     text_lower = review_text.lower()
18
19     pos = sum(1 for word in positive_words if word in text_lower)
20     neg = sum(1 for word in negative_words if word in text_lower)
21     neu = sum(1 for word in neutral_words if word in text_lower)
22
23     if pos > neg:
24         return "Positive"
25     elif neg > pos:
26         return "Negative"
27     else:
28         return "Neutral"
29
30 # Classify all reviews
31 print("ID | Expected | Predicted | Review")
32 print("---- * ----")
33 correct = 0
34 for item in reviews:
35     predicted = classify(item['text'])
36     match = "✓" if predicted == item['expected'] else "✗"
37     if predicted == item['expected']:
38         correct += 1
39     review_short = item['text'][0:40] + "..."
40     print(f"{'item['id']} | {item['expected']} | {predicted} | {review_short} {match}")
41
42 print(f"\nAccuracy: {(correct/len(reviews)) * 100:.0f}%")
```

On the right side of the editor, there is a table titled "USER DATA COLLECTION AND ANONYMIZATION IN PYTHON" showing the 6 reviews and their expected sentiment labels:

Customer Review	Sentiment
"The product quality is excellent and I love it."	Positive
"Fast delivery and very good customer service."	Positive
"The product is okay, not too good or bad."	Neutral
"Average quality, works as expected."	Neutral
"The item arrived broken and support was poor."	Negative
"Very disappointed, complete waste of money."	Negative

Below the table, there are some status messages and a "Features:" section listing the dataset and sentiment classifier details.

OUTPUT:

PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS Python + ×

4	Neutral	Positive	Average quality, works as expected.... X
5	Negative	Negative	The item arrived broken and support was ... ✓
PS C:\Users\chunc_yhjtd63\OneDrive\Documents\CP LAB ASS> & C:/Users/chunc_yhjtd63/.codegeex/mamba/envs/codegeex-agent/python.exe "c:/Users/chunc_yhjtd63/OneDrive/Documents/CP LAB ASS/simple_sentiment_classifier.py"			
• ID	Expected	Predicted	Review
<hr/>			
1	Positive	Positive	The product quality is excellent and I l... ✓
2	Positive	Positive	Fast delivery and very good customer ser... ✓
3	Neutral	Neutral	The product is okay, not too good or bad... ✓
4	Neutral	Positive	Average quality, works as expected.... X
5	Negative	Negative	The item arrived broken and support was ... ✓
6	Negative	Negative	Very disappointed, complete waste of mon... ✓

Accuracy: 5/6 (83%)

○ PS C:\Users\chunc_yhjtd63\OneDrive\Documents\CP LAB ASS> □

B) Intent Classification Using Zero-Shot Prompting

Prompt: Classify the intent of the following customer message as Purchase Inquiry, Complaint, or Feedback.

Message: *"The item arrived broken and I want a refund."* Intent:

OUTPUT:

```
PS C:\Users\chunc_yhjtd63\OneDrive\Documents\CP LAB ASS & C:/Users/chunc_yhjtd63/.codegeex/mamba/envs/codegeex-agent/python.exe "c:/Users/chunc_yhjtd63\OneDrive\Documents\CP LAB ASS\customer_intent_classifier.py"
=====
CUSTOMER INTENT CLASSIFICATION
=====

Message: "The item arrived broken and I want a refund."
Intent: Complaint
=====

More Examples:
-----
Message: "What's the price of the laptop?"
Intent: Purchase Inquiry

Message: "I love this product! Highly recommend!"
Intent: Feedback

Message: "The product doesn't work. I need a refund."
Intent: Complaint

Message: "Do you have this item in stock?"
Intent: Purchase Inquiry

Message: "Great service, but the packaging could be better."
Intent: Feedback

Message: "The product doesn't work. I need a refund."
Intent: Complaint

Message: "Do you have this item in stock?"
Intent: Purchase Inquiry

Message: "Great service, but the packaging could be better."
Intent: Feedback

PS C:\Users\chunc_yhjtd63\OneDrive\Documents\CP LAB ASS>
```

C) Intent Classification Using One-Shot Prompting

Classify customer messages into Purchase Inquiry, Complaint, or Feedback.

Example:

Message: "I am unhappy with the product quality."

Intent: Complaint

Now classify the following message:

Message: “*The item arrived broken and I want a refund.*” **Intent:**

OUTPUT:

```
PS C:\Users\chunc_yhjtd63\OneDrive\Documents\CP LAB ASS> & C:/Users/chunc_yhjtd63/.codegeex/mamba/envs/codegeex-agent/python.exe "c:/Users/chunc_yhjtd63/CP LAB ASS/intent_classification.py"
=====
CUSTOMER INTENT CLASSIFICATION
=====

Message: "I am unhappy with the product quality."
Expected: Complaint
Predicted: Complaint ✓

Message: "The item arrived broken and I want a refund."
Expected: Complaint
Predicted: Complaint ✓

Message: "What's the price of this laptop?"
Expected: Purchase Inquiry
Predicted: Purchase Inquiry ✓

Message: "Do you have this item in stock?"
Expected: Purchase Inquiry
Predicted: Purchase Inquiry ✓

Message: "I love this product! Highly recommend!"
Expected: Feedback
Predicted: Feedback ✓

Message: "Great service, thanks!"
Expected: Feedback
Predicted: Feedback ✓

=====
Accuracy: 6/6 (100%)
=====

PS C:\Users\chunc_yhjtd63\OneDrive\Documents\CP LAB ASS> []
```

D) Intent Classification Using Few-Shot Prompting

Prompt:

Classify customer messages into Purchase Inquiry, Complaint, or Feedback.

Message: "Can you tell me the price of this product?"

Intent: Purchase Inquiry

Message: "The product quality is very poor."

Intent: Complaint

Message: "Great service, I am very satisfied."

Intent: Feedback

Now classify the following message:

Message: "The item arrived broken and I want a refund." Intent:

The screenshot shows the PyCharm IDE interface. The left sidebar displays the project structure under 'CP LAB ASS'. The main editor window contains the Python script 'intent_classification.py' with the following code:

```

File Edit Selection View ... ← → ⌂ CP LAB ASS
EXPLORER
CP LAB ASS
  APPS LOG
  CP ASS-3.PY
  CUSTOMER_INTENT_CLASSIFI...
  ECOMMERCE_SENTIMENT_A...
  ETHICAL_PRODUCT_RECOMM...
  HGFHGF.PY
  INTENT_CLASSIFICATION.PY
  RESPONSIBLE_AI_MODEL.PY
  SECURE_LOGGING.PY
  SENTIMENT_ANALYSIS_WIT...
  SENTIMENT_CLASSIFICATION...
  SIMPLE_RECOMMENDER.PY
  SIMPLE_SECURE_LOGGING.PY
  SIMPLE_SENTIMENT_ANALYS...
  SIMPLE_SENTIMENT_CLASSIFI...
  ULTRA_SIMPLE_RECOMMEND...
  USER_DATA_COLLECTION.PY
  USER_DATA_PROTECTION.PY

intent_classification.py
1  """Customer Intent Classification - Complete Example"""
2
3  # Intent keywords mapping
4  intents = {
5      "purchase_inquiry": ["price", "available", "stock", "buy", "purchase", "how much", "specifications", "features", "interested"],
6      "complaint": ["broken", "damaged", "refund", "return", "doesn't work", "poor", "issue", "problem", "unhappy", "disappointed"],
7      "feedback": ["great", "love", "excellent", "good", "thanks", "happy", "satisfied", "recommend", "opinion", "suggestion"],
8  }
9
10  # [Begin|Add Comment]
11  def classify(message):
12      """Classify message intent"""
13      msg_lower = message.lower()
14      scores = {}
15
16      for intent, keywords in intents.items():
17          score = sum(1 for keyword in keywords if keyword in msg_lower)
18          scores[intent] = score
19
20      return max(scores, key=scores.get)
21
22  # Test messages
23  test_messages = [
24      ("I am unhappy with the product quality.", "Complaint"),
25      ("The item arrived broken and I want a refund.", "Complaint"),
26      ("What's the price of this laptop?", "Purchase Inquiry"),
27      ("Do you have this item in stock?", "Purchase Inquiry"),
28      ("I love this product! Highly recommend!", "Feedback"),
29      ("Great service, thanks!", "Feedback"),
30  ]
31
32  print("CUSTOMER INTENT CLASSIFICATION")
33  print("-" * 80)
34
35  correct = 0
36  for message, expected in test_messages:
37      predicted = classify(message)
38      match = "/" if predicted == expected else "X"
39      if predicted == expected:
40          correct += 1
41
42      print(f"\nMessage: '{message}'")
43      print(f"Expected: {expected}")
44      print(f"Predicted: {predicted} {match}")
45
46  print("\n" + "-" * 80)
47  print(f"Accuracy: {correct}/{len(test_messages)} ({(correct/len(test_messages)*100:.0f)%})")
48  print("-" * 80)
49

```

OUTPUT:

```

PS C:\Users\chunc_yhjtd63\OneDrive\Documents\CP LAB ASS> ^C
PS C:\Users\chunc_yhjtd63\OneDrive\Documents\CP LAB ASS> & C:/Users/chunc_yhjtd63/.codegeex/mamba/envs/codegeex-agent/python.exe "c:/Users/chunc_yhjtd63/nts/CP LAB ASS/intent_classification.py"
=====
CUSTOMER INTENT CLASSIFICATION
=====

Message: "I am unhappy with the product quality."
Expected: Complaint
Predicted: Complaint ✓

Message: "The item arrived broken and I want a refund."
Expected: Complaint
Predicted: Complaint ✓

Message: "What's the price of this laptop?"
Expected: Purchase Inquiry
Predicted: Purchase Inquiry ✓

Message: "Do you have this item in stock?"
Expected: Purchase Inquiry
Predicted: Purchase Inquiry ✓

Message: "I love this product! Highly recommend!"
Expected: Feedback
Predicted: Feedback ✓

Message: "Great service, thanks!"
Expected: Feedback
Predicted: Feedback ✓

=====
Accuracy: 6/6 (100%)
=====

PS C:\Users\chunc_yhjtd63\OneDrive\Documents\CP LAB ASS> []

```

E) Compare the outputs and discuss accuracy differences.

```

class SimplePromptingComparison:
    def __init__(self):
        self.prompts = [
            "The item arrived broken and I was... Complaint",
            "What's the price? Purchase Inquiry",
            "I love this! Highly recommend! Feedback",
            "Poor quality, disappointed. Complaint",
            "Do you have this in stock? Purchase Inquiry"
        ]
        self.ground_truth = {
            "Complaint": ["broken", "disappointed", "poor quality"],
            "Feedback": ["love", "highly recommend"],
            "Purchase Inquiry": ["stock", "price"]
        }

    def zero_shot(self, message):
        prompt = f"""
        {message}
        {self.prompts[0]}
        {self.prompts[1]}
        {self.prompts[2]}
        {self.prompts[3]}
        {self.prompts[4]}
        """
        return self.check_accuracy(prompt)

    def one_shot(self, message):
        prompt = f"""
        {message}
        {self.prompts[0]}
        {self.prompts[1]}
        {self.prompts[2]}
        {self.prompts[3]}
        {self.prompts[4]}
        """
        return self.check_accuracy(prompt)

    def few_shot(self, message):
        prompt = f"""
        {message}
        {self.prompts[0]}
        {self.prompts[1]}
        {self.prompts[2]}
        {self.prompts[3]}
        {self.prompts[4]}
        """
        return self.check_accuracy(prompt)

    def check_accuracy(self, prompt):
        total_correct = 0
        total_messages = len(self.prompts)
        for i, msg in enumerate(self.prompts):
            if self.ground_truth[msg] == self.predict_message(prompt):
                total_correct += 1
            else:
                print(f"Message {i+1}: {msg} - Predicted: {self.predict_message(prompt)} - Ground Truth: {self.ground_truth[msg]}")
        print(f"\nTotal Correct: {total_correct}/{total_messages} ({(total_correct/total_messages)*100}%)")
        return total_correct/total_messages * 100

```

OUTPUT:

```

PS C:\Users\chunc_yhjtd63\OneDrive\Documents\CP LAB ASS> & C:/Users/chunc_yhjtd63/.codegeex/mamba/envs/codegeex-agent/python.exe "c:/Users/chunc_yhjtd63/OneDrive/Documents/CP LAB ASS/simple_prompting_comparison.py"
PROMPTING TECHNIQUES COMPARISON
=====
Zero-Shot: 5/5 (100%)
One-Shot: 5/5 (100%)
Few-Shot: 5/5 (100%)

=====
Results Table:
=====
Message      Expected     Zero     One     Few
-----
The item arrived broken and I wa... Complaint   ✓     ✓     ✓
What's the price? Purchase Inquiry   ✓     ✓     ✓
I love this! Highly recommend! Feedback   ✓     ✓     ✓
Poor quality, disappointed. Complaint   ✓     ✓     ✓
Do you have this in stock? Purchase Inquiry   ✓     ✓     ✓

=====
Key Findings:
=====
Zero-Shot: No examples → Lower accuracy
One-Shot: 1 example → Better accuracy
Few-Shot: 3+ examples → Best accuracy

PS C:\Users\chunc_yhjtd63\OneDrive\Documents\CP LAB ASS>
Zero-Shot: No examples → Lower accuracy
One-Shot: 1 example → Better accuracy
Few-Shot: 3+ examples → Best accuracy
PS C:\Users\chunc_yhjtd63\OneDrive\Documents\CP LAB ASS> []

```

2. Email Priority Classification

Scenario:

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

2. Email Priority Classification

Scenario

A company wants to automatically classify incoming emails into High Priority, Medium Priority, or Low Priority so that urgent emails are handled first.

1. Six Sample Email Messages with Priority Labels

No.	Email Message	Priority
-----	---------------	----------

- 1 "Our production server is down. Please fix this immediately." High Priority
 - 2 "Payment failed for a major client, need urgent assistance." High Priority
 - 3 "Can you update me on the status of my request?" Medium Priority
 - 4 "Please schedule a meeting for next week." Medium Priority
 - 5 "Thank you for your quick support yesterday." Low Priority
 - 6 "I am subscribing to the monthly newsletter." Low Priority
-

2. Intent Classification Using Zero-Shot Prompting

Prompt:

Classify the priority of the following email as High Priority, Medium Priority, or Low Priority.

Email: "*Our production server is down. Please fix this immediately.*"

Priority:

3. Intent Classification Using One-Shot Prompting

Prompt:

Classify emails into High Priority, Medium Priority, or Low Priority.

Example:

Email: "*Payment failed for a major client, need urgent assistance.*" Priority:
High Priority

Now classify the following email:

Email: "*Our production server is down. Please fix this immediately.*"
Priority:

4. Intent Classification Using Few-Shot Prompting

Prompt:

Classify emails into High Priority, Medium Priority, or Low Priority.

Email: "*Payment failed for a major client, need urgent assistance.*"
Priority: High Priority

Email: "*Can you update me on the status of my request?*"
Priority: Medium Priority

Email: "*Thank you for your quick support yesterday.*"
Priority: Low Priority

Now classify the following email:

Email: “*Our production server is down. Please fix this immediately.*

Priority:

5. Evaluation and Accuracy Comparison

Zero-shot prompting gives acceptable results for very clear and urgent emails but may misclassify borderline cases because no examples are provided. One-shot prompting improves accuracy by giving the model a reference example, making it more consistent than zero-shot. Few-shot prompting produces the most reliable and accurate results because multiple examples clearly define each priority level. Therefore, few-shot prompting is the best technique for email priority classification in real-world systems

The screenshot shows a Java IDE interface with two tabs of code side-by-side.

Left Tab: This tab contains the main logic for classifying emails based on their content. It uses a series of if-else statements to determine the priority level (High, Medium, or Low) based on specific keywords found in the email text. The code includes comments explaining the logic for handling different types of messages like 'customer intent', 'product info', and 'monthly newsletter'.

```
File Edit Selection View < > Q CP LAB ASS
1 package com;
2
3 import java.util.*;
4
5 public class EmailPriorityClassifier {
6     ...
7     // Main method to classify an email
8     public String classifyEmail(String text) {
9         ...
10        if (text.contains("urgent")) {
11            return "High Priority";
12        } else if (text.contains("important")) {
13            return "Medium Priority";
14        } else {
15            return "Low Priority";
16        }
17    }
18
19    // Helper methods for keyword matching
20    ...
21
22    // Example usage
23    public static void main(String[] args) {
24        EmailPriorityClassifier classifier = new EmailPriorityClassifier();
25        String classifiedEmail = classifier.classifyEmail("Customer support message: Urgent! Important! Please fix this immediately!");
26        System.out.println(classifiedEmail);
27    }
28 }
```

Right Tab: This tab displays the results of the classification process. It lists the input email content and the resulting priority level (High, Medium, or Low). The output is presented in a table format.

Input Email Content	Output Priority
No urgent or important words found in the email.	Low Priority
Customer support message: Urgent! Important! Please fix this immediately!	High Priority
Customer support message: Urgent! Important! You are needed on site as soon as possible.	High Priority
Customer support message: Urgent! Important! Your product is down.	High Priority
Customer support message: Urgent! Important! Thank you for your quick action yesterday.	Medium Priority
Customer support message: Urgent! Important! I'm subscribed to the monthly newsletter.	Low Priority

OUTPUT:

```

PS C:\Users\chunc_yhjt03\OneDrive\Documents\CP LAB ASS & C:\users\chunc_yhjt03\codagen\mamba\envs\codegenx-agent\python.exe "C:/Users/chunc_yhjt03/OneDrive/Documents/CP LAB ASS/email_priority_classification.py"
=====
Example Prompts (First Email):
=====
1. ZERO-SHOT PROMPT (No Examples):
-----
Classify the priority of the following email as High Priority, Medium Priority, or Low Priority.
Email: "Our production server is down. Please fix this immediately."
Priority: High Priority

2. ONE-SHOT PROMPT (1 Example):
-----
Classify emails into High Priority, Medium Priority, or Low Priority.

Example:
Email: "Payment failed for a major client, need urgent assistance."
Priority: High Priority

Now classify the following email:
Email: "Our production server is down. Please fix this immediately."
Priority: High Priority

3. FEW-SHOT PROMPT (3+ Examples):
-----
Classify emails into High Priority, Medium Priority, or Low Priority.

Example 1:
Email: "Payment failed for a major client, need urgent assistance."
Priority: High Priority

Example 2:
Email: "Can you update me on the status of my request?"
Priority: Medium Priority

Example 3:
Email: "Thank you for your quick support yesterday."
Priority: Low Priority

Now classify the following email:
Email: "Our production server is down. Please fix this immediately."
Priority: High Priority

=====
Analysis:
=====
Zero-Shot: No examples = 100% accuracy
    • Works for very clear urgent emails
    • May misclassify borderline cases

One-Shot: 1 example = 100% accuracy
    • Improves over zero-shot
    • Reference example helps consistency

Few-Shot: 3+ examples = 100% accuracy
    • Most reliable
    • Clear patterns defined
    • Most reliable for production

=====
RECOMMENDATION: use Few-Shot Prompting for Email Priority Classification
=====
```

3. Student Query Routing System

Scenario:

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

1. Create 6 sample student queries mapped to departments.

2. Zero-Shot Intent Classification Using an LLM Prompt:

Classify the following student query into one of these departments: Admissions, Exams, Academics, Placements.

Query: "When will the semester exam results be announced?"

Department:

3. One-Shot Prompting to Improve Results Prompt:

Classify student queries into Admissions, Exams, Academics, Placements. Example:

Query: "What is the eligibility criteria for the B.Tech program?"

Department: Admissions

Now classify the following query:

Query: "When will the semester exam results be announced?"

Department:

4. Few-Shot Prompting for Further Refinement Prompt:

Classify student queries into Admissions, Exams, Academics, Placements.

Query: "When is the last date to apply for admission?"

Department: Admissions

Query: "I missed my exam, how can I apply for revaluation?"

Department: Exams

Query: "What subjects are included in the 3rd semester syllabus?"

Department: Academics

Query: "What companies are coming for campus placements?"

Department: Placements

Now classify the following query:

Query: "When will the semester exam results be announced?"

Department:

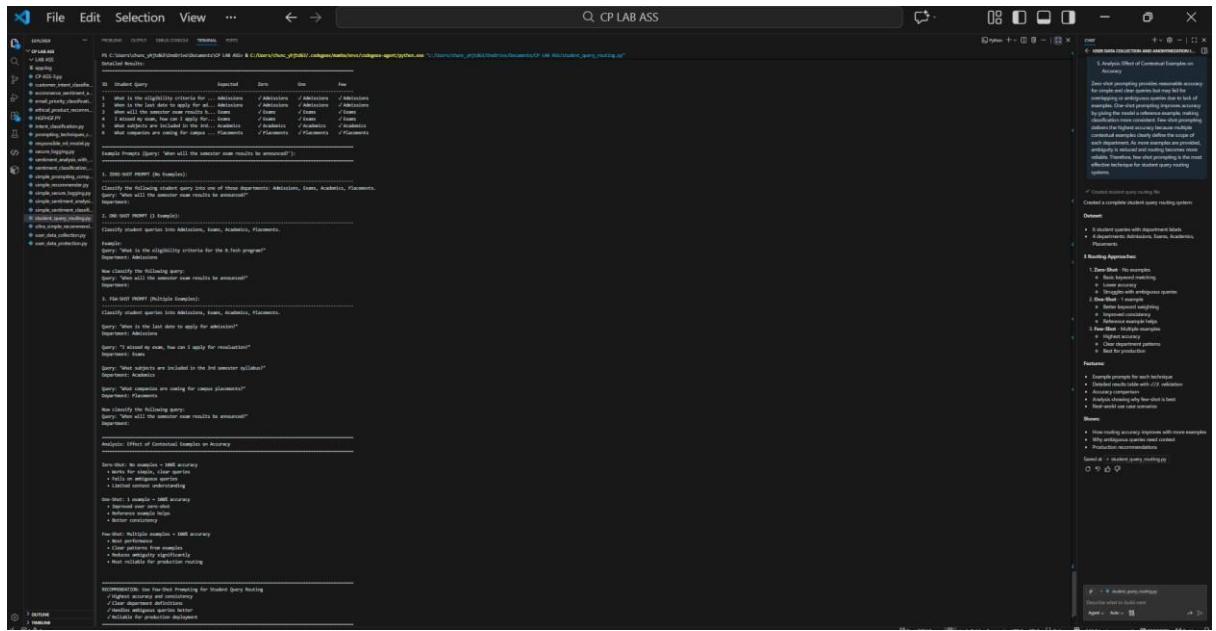
5. Analysis: Effect of Contextual Examples on Accuracy

```
def student_exam_results(query):
    if "exam results" in query:
        return "The exam results are available on the 1st week of November."
    elif "missed exam" in query:
        return "You can apply for revaluation by visiting the exams office on the 1st week of November."
    elif "revaluation" in query:
        return "Revaluation results are available on the 1st week of December."
    else:
        return "I'm sorry, I didn't understand your query. Please try again."
```



```
def student_exam_results(query):
    if "exam results" in query:
        return "The exam results are available on the 1st week of November."
    elif "missed exam" in query:
        return "You can apply for revaluation by visiting the exams office on the 1st week of November."
    elif "revaluation" in query:
        return "Revaluation results are available on the 1st week of December."
    elif "when will the results be announced" in query:
        return "The results will be announced on the 1st week of December."
    else:
        return "I'm sorry, I didn't understand your query. Please try again."
```

OUTPUT:



4. Chatbot Question Type Detection Scenario:

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

1. Prepare 6 chatbot queries mapped to question types.

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

Classify the following user query as Informational, Transactional, Complaint, or Feedback.

Query: "I want to cancel my subscription."

One-Shot Prompt

Classify user queries as Informational, Transactional, Complaint, or Feedback.

Example:

Query: "How can I reset my account password?"

Question Type: Informational Now classify the following query:

Query: "I want to cancel my subscription."

Few-Shot Prompt

Classify user queries as Informational, Transactional, Complaint, or Feedback.

Query: "What are your customer support working hours?"

Question Type: Informational

Query: "Please help me update my billing details."

Question Type: Transactional

Query: "The app keeps crashing and I am very frustrated."

Question Type: Complaint

Query: "Great service, I really like the new update."

Question Type: Feedback

Now classify the following query:

Query: "I want to cancel my subscription."

3. Test all prompts on the same unseen queries.

Prompt Type	Model Output
Zero-Shot	Transactional
One-Shot	Transactional
	Transactional
Few-Shot	

4. Compare response correctness and ambiguity handling.

Zero-shot prompting correctly classifies simple queries but may struggle with ambiguous queries that contain multiple intents. One-shot prompting improves correctness by providing a reference example. Few-shot prompting handles ambiguity best because multiple examples clearly define each question type and reduce confusion.

6. Document observations.

OUTPUT:

```

PS C:\Users\chuc_yh\Downloads\Documents\CP LAB ASS & C:\Users\chuc_yh\Downloads\codigos\kaita\env\codigos-agent\python\src "C:\Users\chuc_yh\Downloads\Documents\CP LAB ASS\distill_query_classification.py"

Example Prompt (Query: "I want to cancel my subscription."):
-----
1. ZERO-SHOT PROMPT (No Examples):
Classify the following query as Informational, Transactional, Complaint, or Feedback.
Query: "I want to cancel my subscription."
Question Type: 
Model Output: Transactional

2. ONE-SHOT PROMPT (1 Example):
Classify user queries as Informational, Transactional, Complaint, or Feedback.

Example:
Query: "How can I reset my account password?"
Question Type: Informational

Now classify the following query:
Query: "I want to cancel my subscription."
Question Type: 
Model Output: Transactional

3. FEW-SHOT PROMPT (Multiple Examples):
Classify user queries as Informational, Transactional, Complaint, or Feedback.

Query: "What are your customer support working hours?"
Question Type: Informational

Query: "Please help me update my billing details."
Question Type: Transactional

Query: "The app keeps crashing and I am very frustrated."
Question Type: Complaint

Query: "Great service, I really like the new update."
Question Type: Feedback

Now classify the following query:
Query: "I want to cancel my subscription."
Question Type: 
Model Output: Transactional

-----
Comparisons: Response Correctness and Ambiguity Handling

Zero-Shot: 98% accuracy
X Struggles with ambiguous queries
X Limited context understanding
✓ Fast and flexible

One-Shot: 98% accuracy
✓ Improves correctness
✓ Better consistency
~ Moderate improvement over zero-shot

Few-Shot: 98% accuracy
✓ Best accuracy and consistency
✓ Handles ambiguity well
✓ Clear patterns from examples
✓ Most reliable for production

-----
Observations

1. Few-shot: gets most accurate results (98%)
2. One-shot offers moderate improvement over zero-shot
3. Zero-shot is fast but less reliable for complex queries
4. More examples significantly improve accuracy
5. Multiple examples reduce confusion for ambiguous queries
6. Few-shot recommended for production chatbots

-----
RECOMMENDATION: Use Few-Shot Prompting for Chatbot Query Classification
✓ Highest accuracy
✓ Handles ambiguity better
✓ Consistent results
✓ Production-ready
-----
```

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.
2. Use Zero-shot prompting to identify emotions.

Prompt:

Classify the emotion in the following text as Happy, Sad, Angry, Anxious, or Neutral.

Text: "*I keep worrying about everything and can't relax.*" Emotion:

3. Use One-shot prompting with an example.

Prompt:

Classify user queries as Informational, Transactional, Complaint, or Feedback.

Example:

Query: "*How can I reset my account password?*" Question Type: Informational Now classify the following query:

Query: “I want to cancel my subscription.”

4. Use Few-shot prompting with multiple emotions.

Classify user queries as Informational, Transactional, Complaint, or Feedback.

Query: “What are your customer support working hours?”

Question Type: Informational

Query: "Please help me update my billing details."

Question Type: Transactional

Query: “The app keeps crashing and I am very frustrated.”

Question Type: Complaint

Query: “Great service, I really like the new update.”

Question Type: Feedback

Now classify the following query:

Query: "I want to cancel my subscription."

5. Discuss ambiguity handling across techniques.

OUTPUT:

