

AI Assisted Coding Lab ASS-4.4

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1. Sentiment Classification for Customer Reviews

Scenario:

An e-commerce platform wants to analyze customer reviews and classify

Week2

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. The main file is `simple_sentiment_classifier.py`, which contains Python code for sentiment analysis. The code defines a classifier function that takes a review text and returns a sentiment label ('Positive', 'Negative', or 'Neutral'). It uses lists of positive, negative, and neutral words to determine the sentiment based on the presence of these words in the input text. The code also includes a section to print the accuracy of the classifier across all reviews.

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 code editor, there is a message bar indicating that a sentiment classification Python file has been created and a complete system has been built. A 'Features' section provides details about the dataset and classifier.

OUTPUT:

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:

The screenshot shows a Jupyter Notebook interface with several tabs at the top: File, Edit, Selection, View, ..., CP LAB ASS, and OUT. The main notebook area contains Python code for sentiment analysis, specifically for classifying customer messages into categories like 'Purchase Inquiry', 'Complaint', and 'Feedback'. The code includes functions for extracting intent keywords from messages and classifying them based on specific keywords. It also includes examples of how to use the classifier and some sample messages.

```
File Edit Selection View ... < > CP LAB ASS OUT  
CP LAB ASS sentiment_analysis.py sentiment_classification_with_validation.py simple_sentiment_classifier.py customer_intent_classifier.py  
  
# Customer Intent Classification  
#  
# Define intent keywords  
# Intent Keywords  
# Intent_Keywords = {  
#     "Purchase Inquiry": [  
#         "keyword": "price", "available", "stock", "buy", "purchase", "interested", "specifications", "features", "how much", "do you have",  
#         "complaint": "broken", "damaged", "defective", "refund", "return", "wrong item", "doesn't work", "not as described", "poor", "issue", "problem", "failed",  
#         "feedback": [  
#             "keyword": "great", "love", "excellent", "good", "suggestion", "improve", "thanks", "happy", "satisfied", "recommend", "opinion"],  
#             ]  
#     ]  
# }  
  
# Intent classification  
#  
# classify_intent(message: str) -> str  
#     "Classify customer message intent"  
#     intent_scores = {}  
#     message_lower = message.lower()  
#     for intent, data in intent_keywords.items():  
#         score = 0  
#         for keyword in data["keywords"]:  
#             if keyword in message_lower:  
#                 score += 1  
#         intent_scores[intent] = score  
#     return intent_scores  
#     # intent with highest score  
#     return max(intent_scores, key=intent_scores.get)  
  
# A text with the provided message  
# message = "The item arrived broken and I want a refund."  
# intent = classify_intent(message)  
# intent  
#  
# Output: PURCHASE INTENT CLASSIFICATION  
#  
# Examples:  
#  
# print("Purchase example")  
# print("PURCHASE INTENT CLASSIFICATION")  
#  
# print("Complaint example")  
# print("COMPLAINT INTENT CLASSIFICATION")  
#  
# print("Feedback example")  
# print("FEEDBACK INTENT CLASSIFICATION")  
#  
# Examples:  
#  
# print("I love this product, highly recommend.")  
# print("The product didn't work. I need a refund.")  
# print("Do you have this item in stock?")  
# print("Great service, but the packaging could be better.")  
#  
# For msg in examples:  
#     predicted_intent = classify_intent(msg)  
#     print(f"Message '{msg}'")  
#     print(f"Intent {predicted_intent}")  
  
# User Documentation and Examples  
#  
# USER DATA COLLECTION AND ANALYSIS IN PYTHON...  
# Created sentiment classifier Python file  
# User defined version with just the essentials:  
# 6 reviews with expected sentiments  
# 3 different intent types  
# One (classif) function  
# Quick comparison table showing ID, Expected, Predicted, Difference, Overall accuracy  
# Saved at: simple_sentiment_classifier.py  
  
# Classify the intent of the following customer message as Purchase Inquiry, Complaint, or Feedback  
# Message: "The item arrived broken and I want a refund."  
#  
# Created customer intent classifier file  
# Created a customer intent classifier  
# For your message:  
#     Message: "The item arrived broken and I want a refund."  
#     Intent: Complaint ✓  
# How it works:  
#     Key words for "Complaint" include broken, damaged, refund, return problem, issue, failed  
#     Key words for "Purchase" include broken, damaged, refund, return problem, issue, failed  
#     Key words for "Feedback" include great, love, excellent, good, suggestion, improve, thanks, happy, satisfied, recommend, opinion  
# Classification includes:  
# 1. Purchase Inquiry - Asking about price, availability, specifications  
# 2. Complaint - Reporting broken, damaged, refund, return problem, issue, failed  
# 3. Feedback - Praise, suggestions, recommendations  
# Includes examples showing all 3 intent types  
# Saved at: customer_intent_classifier.py  
# Claude Hallé 43 - 14
```

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:

The screenshot shows a Jupyter Notebook environment with several open files in the left sidebar. The main code cell contains Python code for intent classification, including imports, keyword mapping, intent definitions, and a test function. The sidebar on the right displays a classification interface with tabs for 'CHAT' and 'USE DATA COLLECTION AND ANONYMIZATION IN PYTHON...'. It includes sections for 'specifications', 'Complaint - Reporting issues, damaged items, refund requests', 'Feedback - Praise, suggestions, recommendations', and 'Purchase Inquiry - Asking about prices, availability, stock levels'. Below these are examples of messages and their predicted intents. A 'Classification Rules:' table lists rules for Purchase Inquiry, Complaint, and Feedback. At the bottom, there's a 'Describe what to build next' section and a 'Agent' dropdown.

```

File Edit Selection View ... ← → Q CP LAB ASS
EXPLORER
CP LAB ASS
  ecommerce_sentiment_analysis
    +-- intent_classification.py ...
  secure_logging.py
  sentiment_analysis_with_ml.py
  simple_intent_classification.py
  simple_recommendation.py
  simple_secure_logging.py
  simple_sentiment_analysis.py
  simple_sentiment_classification.py
  ultra_simple_recommendation.py
  user_data_collection.py
  user_data_protection.py
intent_classification.py
File Edit Selection View ... ← → Q CP LAB ASS
EXPLORER
CP LAB ASS
  ecommerce_sentiment_analysis
    +-- intent_classification.py ...
  intent_classification.py ...
  secure_logging.py
  sentiment_analysis_with_ml.py
  simple_intent_classification.py
  simple_recommendation.py
  simple_secure_logging.py
  simple_sentiment_analysis.py
  simple_sentiment_classification.py
  ultra_simple_recommendation.py
  user_data_collection.py
  user_data_protection.py
intent_classification.py
# Intent classification - Complete example
# Intent keywords mapping
# Intents =
#   "Purchase Inquiry": ["price", "available", "stock", "buy", "purchase", "how much", "specifications", "features", "interested"],
#   "Complaint": ["broken", "damaged", "refund", "return", "doesn't work", "poor", "issue", "problem", "unhappy", "disappointed"],
#   "Feedback": ["great", "like", "occasional", "good", "thanks", "happy", "satisfied", "recommend", "opinion", "suggestion"],
#   "Purchase Inquiry": ["what's the price", "what's available", "what's the stock level", "what's the buy price", "what's the purchase price", "what's the refund amount", "what's the return policy", "what's the issue with the product", "what's the problem with the product", "what's the unhappy experience with the product", "what's the disappointed experience with the product"],

# Intent: Complaint
def classify(message):
    """Classify message intent"""
    msg_lower = message.lower()
    scores = {}
    for intent, keywords in intents.items():
        score = sum(1 for keyword in keywords if keyword in msg_lower)
        scores[intent] = score
    return max(scores, key=scores.get)

# Test messages
test_messages = [
    ("I am unhappy with the product quality.", "Complaint"),
    ("The item arrived broken and I want a refund.", "Complaint"),
    ("What's the price of this laptop?", "Purchase Inquiry"),
    ("Do you have this item in stock?", "Purchase Inquiry"),
    ("I love this product! Highly recommend!", "Feedback"),
    ("Great service, thanks!", "Feedback"),
    ("Feedback", "Feedback")
]

print("+"*80)
print("CUSTOMER INTENT CLASSIFICATION")
print("+"*80)
for message in test_messages:
    predicted = classify(message)
    match = "✓" if predicted == expected else "✗"
    if predicted == expected:
        correct += 1
    print(f"\n{message[0]}: {predicted} ({expected}) {match}")
print("\n"+("+"*80))
print(f"Accuracy: {correct}/{len(test_messages)} ({correct/len(test_messages)*100:.2f}%)")
print("+"*80)

```

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 a code editor interface with the following details:

- File Menu:** File, Edit, Selection, View, ...
- Search Bar:** CP LAB ASS
- Explorer Bar:** Shows a tree view of files under "CP LAB ASS".
- Code Editor:** The main area displays the content of the file "intent_classification.py".

```
commerce_sentiment_analysis.py    sentiment_classification_with_validation.py    simple_sentiment_classifier.py    customer_intent_classifier.py    intent_classification.py

# Intent Classification - Complete Example
#
# Intent keywords mapping
intents = {
    "Purchase Inquiry": ["price", "available", "stock", "buy", "purchase", "how much", "specifications", "features", "interested"],
    "Complaint": ["broken", "damaged", "refund", "return", "doesn't work", "poor", "issue", "problem", "unhappy", "disappointed"],
    "Feedback": ["great", "love", "excellent", "good", "thanks", "happy", "satisfied", "recommend", "opinion", "suggestion"]
}

# Classify message intent
def classify(message):
    """Classify message intent"""
    msg_lower = message.lower()
    scores = {}

    for intent, keywords in intents.items():
        score = sum(1 for keyword in keywords if keyword in msg_lower)
        scores[intent] = score

    return max(scores, key=scores.get)

# Test messages
test_messages = [
    ("I am unhappy with the product quality.", "Complaint"),
    ("The item arrived broken and I want a refund.", "Complaint"),
    ("What's the price of this laptop?", "Purchase Inquiry"),
    ("Do you have this item in stock?", "Purchase Inquiry"),
    ("I love this product! Highly recommend!", "Feedback"),
    ("Great service, thanks!", "Feedback"),
]

print("*"*80)
print("CUSTOMER INTENT CLASSIFICATION")
print("*"*80)

correct = 0
for message, expected in test_messages:
    predicted = classify(message)
    match = "V" if predicted == expected else "X"
    if predicted == expected:
        correct += 1

    print(f"\nMessage: '{message}'")
    print(f"Expected: {expected}")
    print(f"Predicted: {predicted} ({match})")

print(f"\n{'='*80}")
print(f"Accuracy: {(correct/len(test_messages)) * ((correct/len(test_messages))*100:.0f)%}")
print(f"{'='*80}\n")
```

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.

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

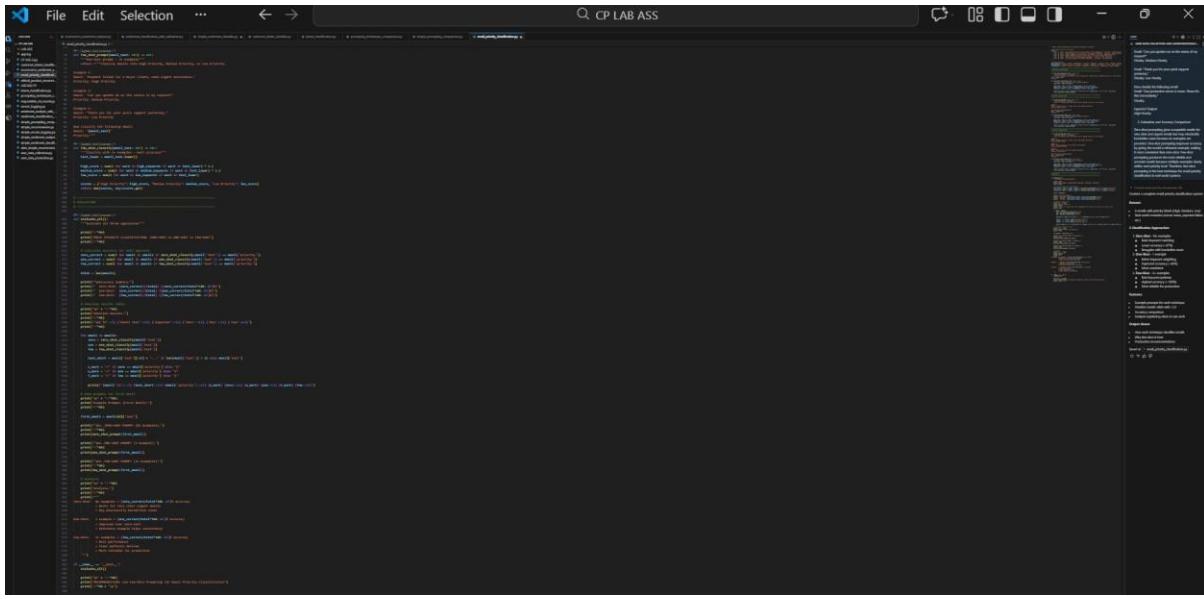
Now classify the following email:

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

A screenshot of a Jupyter Notebook interface. The left pane shows a code cell with Python code related to email priority classification. The right pane shows the output of the code, which includes several examples of emails and their corresponding priority classifications.

OUTPUT:

```
PS C:\Users\chunc_yhjtdd3\OneDrive\Documents\CP LAB ASS & C:\Users\chunc_yhjtdd3\.codeplex\envs\codeplex-agent\python.exe "c:/users/chunc_yhjtdd3/OneDrive/Documents/CP LAB ASS/email_priority_classification.py"
=====
Example Prompts (First Email):
=====
1. ZERO-SHOT PROMPT (No Examples):
-----
Email: "Our production server is down. Please fix this immediately."
Priority: High Priority

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

2. ONE-SHOT PROMPT (1 Example):
-----
Email: "Payment failed for a major client, need urgent assistance."
Priority: High Priority

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

3. FEW-SHOT PROMPT (> Examples):
-----
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:

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

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

Few-Shot: 3+ examples = 100% accuracy
  * Best performance
  * 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:

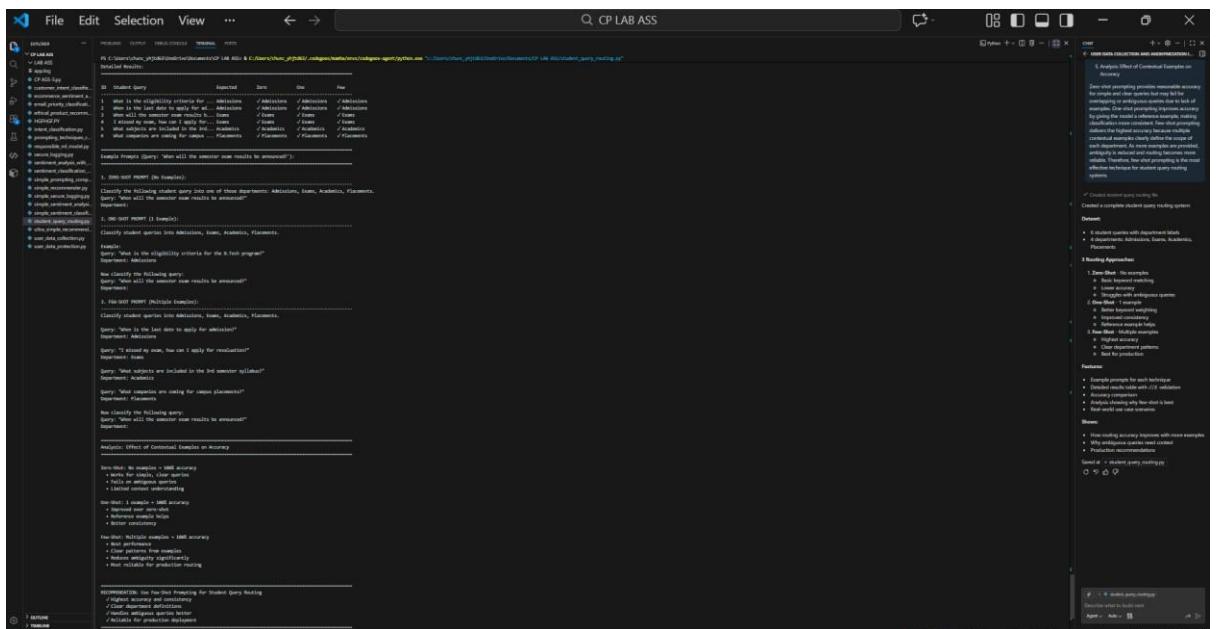
Query: "When will the semester exam results be announced?"

Department:

5 Analysis: Effect of Contextual Examples on Accuracy



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
Few-Shot	Transactional

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\duuc_yh\OneDrive\Documents\CP LAB ASS & C:\Users\duuc_yh\OneDrive\Documents\CP LAB ASS & C:\Users\duuc_yh\OneDrive\Documents\CP LAB ASS\chatbot_query_classification.py
=====
Example Inputs (Query: "I want to cancel my subscription."):
=====
1. ZERO-SHOT PROMPT (No Examples):
   Classify the following user 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. FINE-TUNED 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: 26% accuracy
✗ Handles ambiguous queries
✗ Limited context understanding
✓ Fast and flexible

One-Shot: 36% accuracy
✓ Improves correctness
✓ Better consistency
→ Moderate improvement over zero-shot

Few-Shot: 38% accuracy
✓ Best accuracy and consistency
✓ Handles ambiguity well
✓ Learns patterns from examples
✓ Most reliable for production

Observations
=====

1. Few-shot gives most accurate results (38%)
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 contexts

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.

The screenshot shows a code editor window with a Python script titled 'ambiguity_handling.py'. The code implements a function to handle ambiguous user queries by classifying them into four categories: Informational, Transactional, Complaint, or Feedback. It uses a few-shot prompting approach where it provides examples for each category and asks the user to choose one. The code also includes a section for handling specific requests related to account deletion and password resets.

```
def classify_query(query):
    # Few-shot prompting for classification
    examples = [
        ("What are your customer support working hours?", "Informational"),
        ("Please help me update my billing details.", "Transactional"),
        ("The app keeps crashing and I am very frustrated.", "Complaint"),
        ("Great service, I really like the new update.", "Feedback")
    ]
    print("Please choose the category for the following query: (Informational, Transactional, Complaint, Feedback)")
    for example in examples:
        print(f"> {example[0]} - {example[1]}")
    choice = input("Your choice: ")
    if choice == "Informational":
        return "Informational"
    elif choice == "Transactional":
        return "Transactional"
    elif choice == "Complaint":
        return "Complaint"
    elif choice == "Feedback":
        return "Feedback"
    else:
        print("Invalid choice. Please try again.")
        return classify_query(query)

def handle_request(query):
    # Ambiguity handling logic
    if "cancel subscription" in query:
        return "Complaint"
    elif "reset password" in query:
        return "Informational"
    elif "update billing" in query:
        return "Transactional"
    else:
        return classify_query(query)

# Example usage
query = "I want to cancel my subscription."
print(handle_request(query))
```

OUTPUT:

```
PS C:\Users\chris_jhj\OneDrive\Documents\OP_LM_ABs & C:\Users\chris_jhj\Downloads\codigos\hans\mnis\codigos-agent\python\mnis\mnis.py
```

Accuracy Summary:

Model Type	Zero-Shot	One-Shot	Few-Shot
Zero-Shot	367/38 (96%)	367/38 (96%)	367/38 (96%)
One-Shot	367/38 (96%)	367/38 (96%)	367/38 (96%)
Few-Shot	367/38 (96%)	367/38 (96%)	367/38 (96%)

RECOMMENDATION: Use Few-Shot Pretraining for Mental Health Chatbot Sentence Detection

- ✗ Best accuracy (96%)
- ✓ Fewer parameters
- ✓ Statistical significance better
- ✓ Critical for mental health support accuracy

PS C:\Users\chris_jhj\OneDrive\Documents\OP_LM_ABs & C:\Users\chris_jhj\Downloads\codigos\hans\mnis\codigos-agent\python\mnis\mnis.py

MENTION DETECTION: ZERO-SHOT vs ONE-SHOT vs FEW-SHOT

Accuracy Summary:

Model Type	Zero-Shot	One-Shot	Few-Shot
Zero-Shot	367/38 (96%)	367/38 (96%)	367/38 (96%)
One-Shot	367/38 (96%)	367/38 (96%)	367/38 (96%)
Few-Shot	367/38 (96%)	367/38 (96%)	367/38 (96%)