## **ASSIGNMENT-4.5**

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#### SAMPLE DATA:

Reasoning: Create a dic onary with email categories as keys and lists of email samples as values, ensuring a total of 10 samples distributed across categories, and store it in the email samples variable.

#### output:

```
# Verify the number of samples
total_samples = sum(len(samples) for samples in email_samples.values())
print(f"Total number of email samples: {total_samples}")
Total number of email samples: 10
```

Zero-shot promp ng:

Subtask:

Design a prompt for zero-shot classifica on and test it on 5 emails.

```
## Similar classification and store results

## Placombian function for Lenguage model classification (replace with actual APT call)

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## For demonstration, we'll similar a classification (replace with actual APT call)

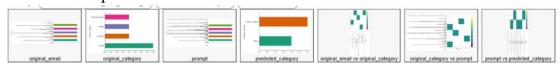
## For demonstration, we'll similar a classification does not report, lower() or "member" in prompt.lower() or "member" or "member" classify and companies of the recombination of "member" classify and companies of the recombination of "member" or "member" in prompt.lower() or "member" classify and companies of the recombination of "member" or "member" in prompt.lower() or "member" classify and recombination or "member" classify "prompt.lower() or "member" classify "great service" in prompt.lower() or "member" classify.email_prompt.compt() or "member" classify.email_prompt.compt() or "member" classification prompt.lower() or "member" classify.email_prompt.compt() or "member" classification prompt.compt() or "
```

Reasoning: Select 5 email samples for tes ng, design a zero-shot prompt, and then iterate through the selected samples to construct the full prompts and simulate the classifica on using a placeholder func on. Store the results.

### Output:



### recommended plots:



## One-shot promp ng

#### Subtask:

Design a prompt for one-shot classifica on with one example and test it on the same 5 emails.

```
Of facts on small imple as an accept for the one-but prout

ora_but_nampi_cmal; and all_unpin(one_but_nampi_category)[0] # using the first billing mail as an emergic

ora_but_nampi_cmal; and all_unpin(one_but_nampi_category)[0] # using the first billing mail as an emergic

ora_but_nampi_cmal; and all_unpin(one_but_nampi_category)[0] # using the first billing actegories "Billing", "Trabmical Support", "feminat", or "Others".

More is an emergical_content)

consult_nampi_cmal_content)

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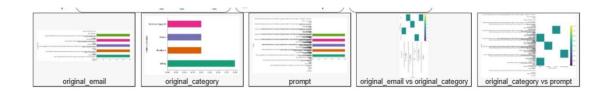
fo
```

Reasoning: Select one email as an example for the one-shot prompt, design the prompt template, iterate through the 5 test emails, construct the prompts, simulate classifica on, and store the results in a DataFrame.

#### **OUTPUT:**



## recommended plots:



# Few-shot promp ng

#### Subtask:

Design a prompt for few-shot classifica on with 3-5 examples and test it on the same 5 emails.

```
| Company | Comp
```

Reasoning: Select representa ve examples for the few-shot prompt, design the prompt template, construct the full prompts for the test emails, simulate the classifica on, and store and display the results in a DataFrame.



#### **RECOMMENDED PATHS:**



## Evalua on

#### Subtask:

Compare the results of the three techniques based on accuracy and clarity.

```
Calculate accuracy for Zero-shot
zero_shot_accuracy = (zero_shot_results_off['predicted_category'] == zero_shot_results_off['original_category']).mean()

# Calculate accuracy = (zero_shot_results_off['predicted_category'] == zero_shot_results_off['original_category']).mean()

# Calculate accuracy = (zero_shot_results_off['predicted_category'] == zero_shot_results_off['original_category']).mean()

# Calculate accuracy = (few_shot_results_off['predicted_category'] == few_shot_results_off['original_category']).mean()

# Salculate accuracy = (few_shot_results_off['predicted_category'] == few_shot_results_off['original_category']).mean()

# Summarize clarity = (few_shot_accuracy: 22)*)

# Summarize clarity (based on observing the prompts and predictions)
clarity_summary ===
clarity_observations:

# Zero-shot: The prompt includes an example, which clarifies the desired output format and potentially guides the model towards the correct categories. The predicted categories are simple.

# Pow-shot: The prompt includes an example, which clarifies the desired output format and demonstrating the classification for various categories. The predicted categories are simple.

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```

#### **OUTPUT:**

The Zero-shot Accuracy: 0.60
One-shot Accuracy: 0.60
One-shot Accuracy: 0.40
Few-shot Accuracy: 0.40
Clarity Observations:
- Zero-shot: The prompt is straightforward and asks directly for classification. The predicted categories are simple and follow the requested format.
- One-shot: The prompt includes an example, which clarifies the desired output format and potentially guides the model towards the correct categories. The predicted categories are simple.
- Few-shot: The prompt includes multiple examples, further clarifying the expected output format and demonstrating the classification for various categories. The predicted categories are simple.

## Document results

#### Subtask:

Create a .txt or .md file with prompts, responses, and a comparison table. Write a short reflec on on the findings.

Reasoning: Create the content for the documenta on file including headings, accuracy results, prompts, predic ons, a comparison table, and a reflec on, then save it to a markdown file.

# Summary:

#### Data Analysis Key Findings

- The zero-shot promp ng technique achieved an accuracy of 60% based on the simulated classifica on.
- Both the one-shot and few-shot promp ng techniques achieved an accuracy of 40% based on the simulated classifica on.
- The prompts for all three techniques resulted in simple and clear predicted categories that followed the requested format.
- The one-shot and few-shot prompts, by including examples, offered addi onal clarity regarding the desired output format and the classifica on process compared to the zero-shot prompt.
- A documenta on file (promp ng comparison.md) was successfully created, containing the prompts, simulated responses, a comparison table of accuracies, and a reflec on. Insights or Next Steps
- The simula on used for classifica on was keyword-based and did not accurately reflect how a real language model would leverage examples in one-shot and few-shot promp ng. A next step would be to test these prompts with an actual language model to get a more realis c evalua on of the techniques.
- While zero-shot performed best in this limited simula on, one-shot and few-shot promp ng are generally expected to improve performance on real LLMs by providing context and format examples. Future tes ng should focus on evalua ng the performance gain from examples using a true LLM.