IOWA STATE UNIVERSITY
Apparel, Events, and Hospitality Management

Generative AI:
Application to Research

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AESHM Data Analytics Lab

AESHM Analytics Lab

- Launched in 2020

- Offers two programs
  - ➢ Social data collection for graduate research
    - o 2 projects per semester (supported 5 projects)
  - ➢ Research methods seminar (started in Fall 2024)

- Publications
  - ➢ 13 journal articles (8 published; 5 under review)
    - o Proposed new research methods: 1) Bayesian growth curve model, 2) fractional imputation-based causal inference method
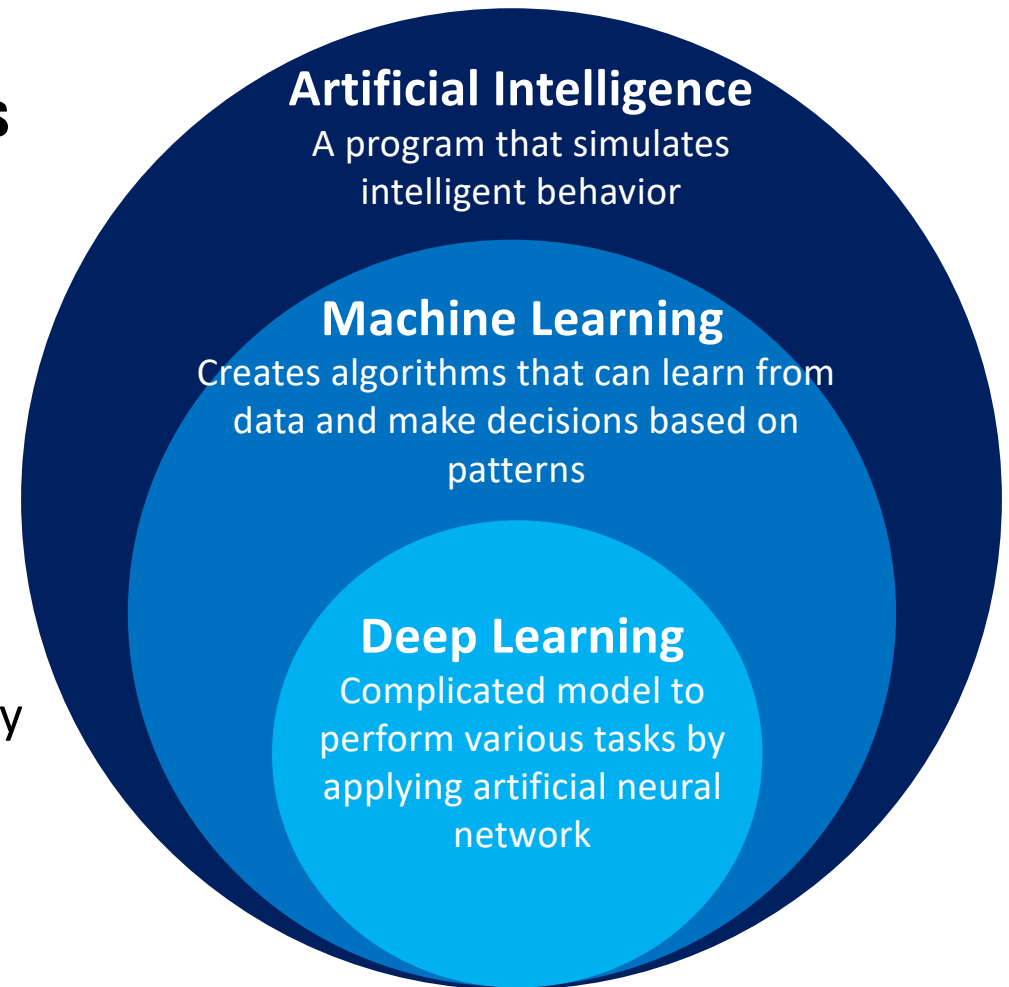 - ➢ 10 conference proceedings + 2 manuscripts accepted

Machine Learning (ML) Techniques

- Linear regression
- Logistic regression
- Clustering analysis

Deep Learning (DL) Techniques

- Convolution neural networks (CNNs)
- Recurrent neural networks (RNNs)
- Deep learning techniques are commonly used in Generative AI (GenAI) models (e.g., GPT, Claude).

Artificial Intelligence
A program that simulates intelligent behavior

Machine Learning
Creates algorithms that can learn from data and make decisions based on patterns

Deep Learning
Complicated model to perform various tasks by applying artificial neural network

What is GenAI?

- Deep-learning models that can generate new, original content such as text, images, audio or video.

- Foundation models are trained to learn patterns from existing data and mimic the patterns to produce creative outputs.
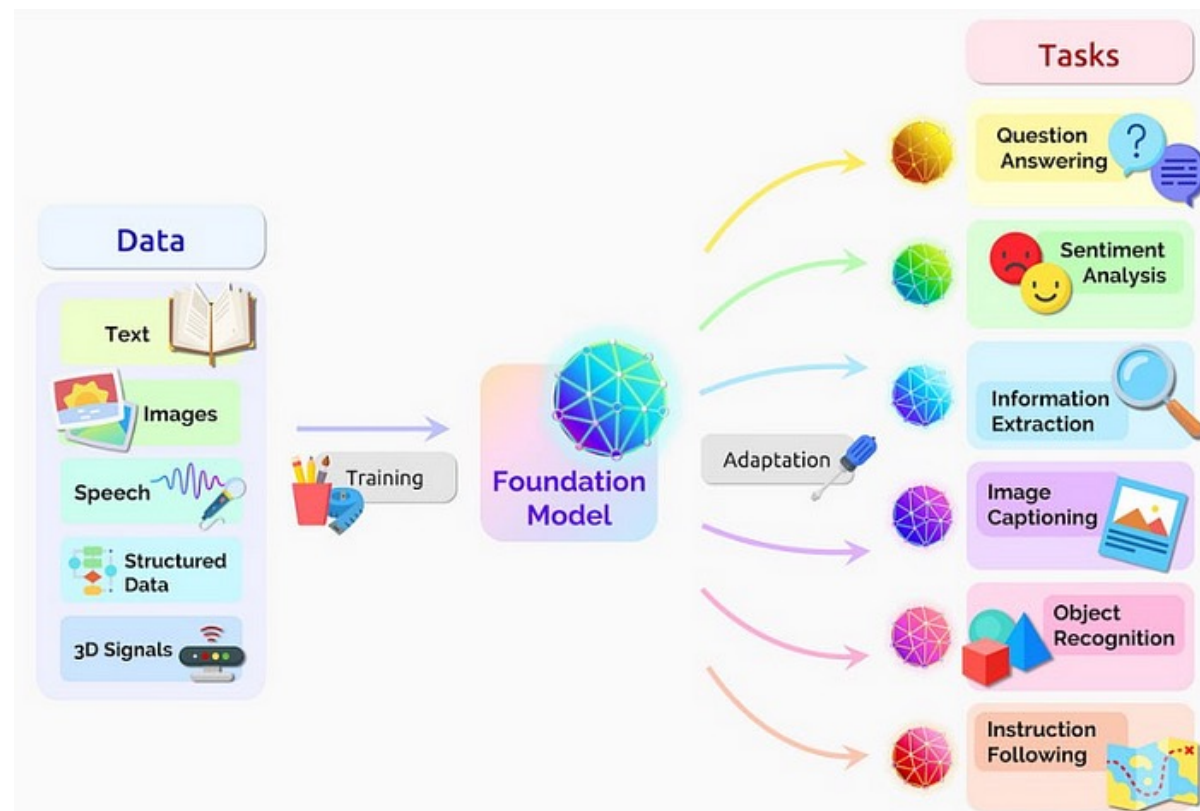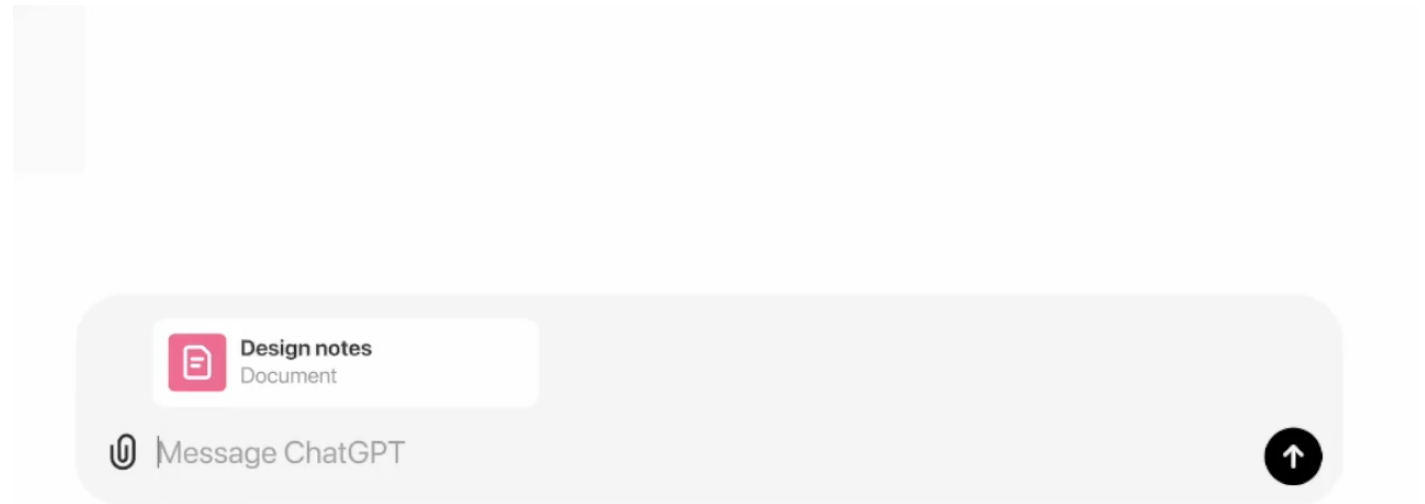
Current Capabilities of GenAI

- Open AI Sora

Current Capabilities of GenAI

- GPT with Canvas

Design notes
Document

Message ChatGPT

Current Capabilities of GenAI

- Computer Use from Claude

GPT (Generative Pre-trained Transformer)

- Transformer-based LLM
  - ➤ Foundation models for GPT from OpenAI, Claude from Anthropic, and Gemini from Google
  - ➤ LLMs are a specific type of GenAI models designed to understand and generate human language in a coherent and contextually relevant manner.
    - Responses: Answering questions; machine translation; text summarization; programing code generation; language generation
  - ➤ Transformer architecture is one type of the deep learning algorithms for GenAI.

GPT (Generative Pre-trained Transformer)

- Pre-training
  - ➢ GPT models (e.g., GPT-3.5, GPT-4.0) are pre-trained on large text datasets to learn grammar, semantics, and the general structure of language.

- ChatGPT
  - ➢ A conversational AI chatbot developed based on GPT models.

GPT API

- API (Application Programming Interface)
  - Allow different software applications to communicate with each other

GPT API

- Provide access to GPT models such as GPT-4o and GPT 4o mini.
- Allow to integrate GPT models into the applications to perform natural language processing tasks such as text generation, translation, summarization, etc.
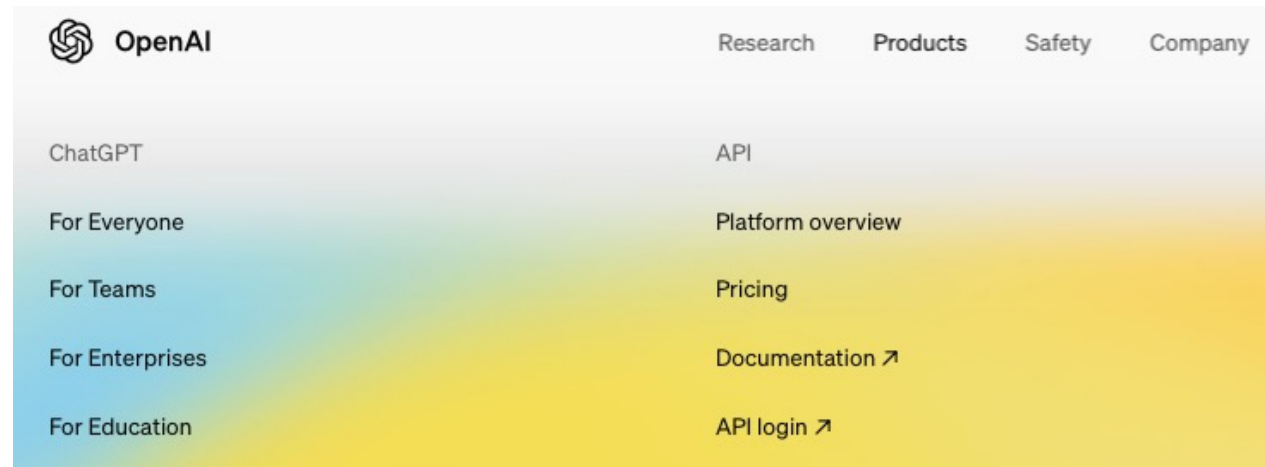
Advantages of GPT API over ChatGPT

- Integrate the capabilities of ChatGPT into your own applications.
- Scalability: Request large volumes of requests
  ➢ ChatGPT GPT4 allows 80 messages every 3 hours (as of 5/13/24).
- Consistent Performance:
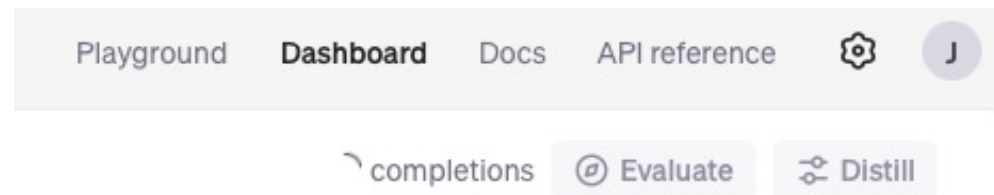 ➢ e.g., set parameter of temperature=0

Get GPT API Access
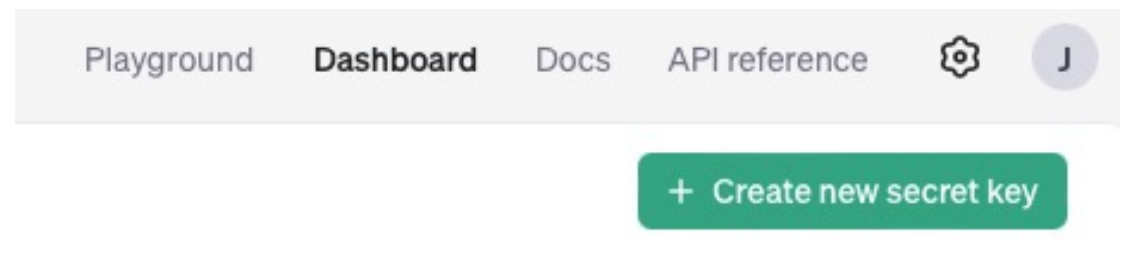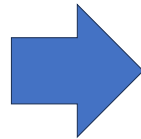
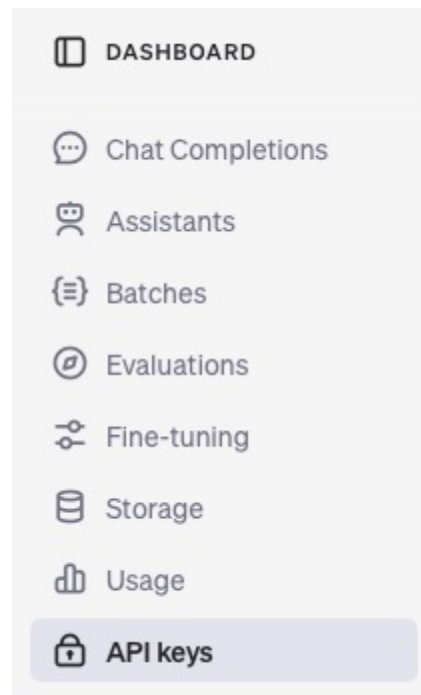- Go to the OpenAI website and sign up for an API account.

- Go to Dashboard on the top right corner.

Get GPT API Access

- Click "API keys" on the left column => Click "Create new secret key"

Get GPT API Access

- Create an API key in a pop-up window for secret key.

Create new secret key

Owned by

| You | Service account |

This API key is tied to your user and can make requests against the selected project. If you are removed from the organization or project, this key will be disabled.

Name Optional

Seminar

Project

Default project

Permissions

| All | Restricted | Read Only |

Cancel   Create secret key

Save your key

Please save this secret key somewhere safe and accessible. For security reasons, **you won't be able to view it again** through your OpenAI account. If you lose this secret key, you'll need to generate a new one.

sk-proj-qTL4aP5RciKIyRgKmuyaO9ibYgZuDEI58TDo4_trA   📋 Copy

Permissions

Read and write API resources

Done

Create a GPT function in Python

- Step 1: Install packages.
  - ➢ Open a Python script through Jupyter Notebook or Google Colab
  - ➢ Install packages for GPT API: 'openai', 'pandas'

```
!pip install openai==1.51.0
!pip install pandas
```

Create a GPT function in Python

- Step 2: Import the packages.

```python
import pandas as pd
import openai
import os
import time
```

- Step 3: Retrieve the GPT API key.

```python
# Retrieve a GPT API key
openai.api_key = 'Your API Key'
```

Create a GPT function in Python

- Step 4: Define a GPT function.

```python
# GPT 4o mini
def get_completion(prompt, model="gpt-4o-mini"):
    messages = [{"role": "user", "content": prompt}]
    response = openai.chat.completions.create(
        model=model,
        messages=messages,
        temperature=0, # this is the degree of randomness of the model's output
    )
    return response.choices[0].message.content
```

Create a GPT function in Python

- Step 5: Test a prompt.
  - ➤ Create a product review.

```python
# product review
prod_review = """
Got this panda plush toy for my daughter's birthday,\
who loves it and takes it everywhere. It's soft and\
super cute, and its face has a friendly look. It's\
a bit small for what I paid though. I think there\
might be other options that are bigger for the\
same price. It arrived a day earlier than expected,\
so I got to play with it myself before I gave it\
to her.
"""
```

Create a GPT function in Python

- Step 5: Test a prompt.
  - ➢ Create a prompt for text summarization.

  - ➢ Print the response from the GPT model.

```python
# Create a prompt for summarization
prompt = f"""
Your task is to generate a short summary of a product \
review from an ecommerce site to give feedback to the \
Shipping deparmtment.

Summarize the review below, delimited by triple
backticks, in at most 30 words, and focusing on any aspects \
that mention shipping and delivery of the product.

Review: ```{prod_review}```
"""

# Print the outputs
response = get_completion(prompt)
print(response)
```

Text Analytics with GenAI Models

1) Sentiment analysis
- Positive vs. Negative

2) Identification of emotions
- "Joy", "Sadness", "Anger", "Fear", "Trust", "Disgust", "Anticipation", "Surprise"

3) Classification of crowdfunding projects
- Foodservice vs. Non-foodservice

Text Analytics with GenAI Models

1) Sentiment analysis
- Positive vs. Negative

How can sentiment analysis be applied in research?
- Identify consumer sentiment from social media platforms (Twitter (X), Facebook)
- Qualitative research:
    - Extract themes from positive and negative review categories
- Quantitative research:
    - Investigate the impact of investor's sentiment on firm's stock returns (Chebbi et al., 2024)

Text Analytics with GenAI Models

1) Sentiment analysis
- Positive vs. Negative

Demonstration using Python Jupyter Notebook

Text Analytics with GenAI Models

2) Identification of emotions
- Theoretical Framework
  - Plutchik's Emotion Wheel
    - "Joy", "Sadness", "Anger", "Fear", "Trust", "Disgust", "Anticipation", "Surprise"

How can identification of emotions be applied in research?
- Identify consumer emotions from social media platforms (Twitter (X), Facebook, Yelp, TripAdvisor)
- Qualitative research:
  - Extract themes from reviews of each emotion category
- Quantitative research:
  - Investigate the impact of emotions on review helpfulness (Wang et al., 2019)

Text Analytics with GenAI Models

2) Identification of emotions

- Theoretical Framework
  - Plutchik's Emotion Wheel
    - "Joy", "Sadness", "Anger", "Fear", "Trust", "Disgust", "Anticipation", "Surprise"

Demonstration using Python Jupyter Notebook

Text Analytics with GenAI Models

3) Classification of crowdfunding projects
- Foodservice vs. Non-foodservice
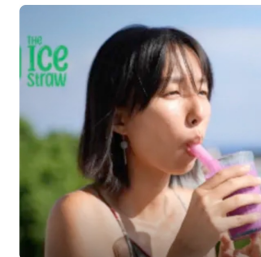
What is the challenge in my research?
- Research focuses on foodservice industry.
- However, crowdfunding platforms often contains irrelevant samples.
- *Filter out irrelevant samples!*
- But too time consuming!

INDIEGOGO

CATEGORY

All Categories

Tech & Innovation ⌃

Audio

Camera Gear

Education

Energy & Green Tech

Fashion & Wearables

Food & Beverages

Health & Fitness

Home

Phones & Accessories

Productivity

Transportation

Travel & Outdoors

KUKU Maker: Take Control Of Your Coffee Taste

Avensi Wave Flavor Enhancing Espresso & Coffee Cup

The Ice Straw

Model Evaluation

- Confusion Matrix
  - ➢ A table used describe the performance of a classification model

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

Model Evaluation

- Confusion Matrix

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + FP + TN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall or Sensitivity} = \frac{TP}{TP + FN}$$

$$\textbf{F1} = 2\,\frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

Model Evaluation

- Confusion Matrix

	Yes	No
Yes	5	1
No	0	4

$$Accuracy = \frac{correctly\ predicted\ instances}{total\ number\ of\ instances} = \frac{9}{10} = 90\%$$

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall\ or\ Sensitivity = \frac{TP}{TP + FN}$$

$$F1 = 2\ \frac{Precision * Recall}{Precision + Recall}$$

Model Evaluation

- Ground truth
  - ➤ True classification values which are compared with GPT classification results for model comparison.
- In the example, our true sentiment values are the star ratings by reviewers.
  - ➤ 1 & 2 stars => negative
 - ➤ 3 to 5 stars => positive

Model Evaluation

- Draw a Confusion Matrix

```python
# Create a confusion matrix
conf_matrix = confusion_matrix(df_50['manual'], df_50['GPT_label'] )      #(y, y_pred)
plt.figure(figsize=(10, 7))
sns.heatmap(conf_matrix, annot=True, fmt='g', cmap='Blues')
# plt.title('Confusion Matrix', fontsize=18)
plt.xlabel('GPT Labels', fontsize=14)
plt.ylabel('Human Labels', fontsize=14)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
# plt.savefig("/Users/sheng/Downloads/GPT_CM.png")
plt.show()
```

Model Evaluation

- Draw a Confusion Matrix
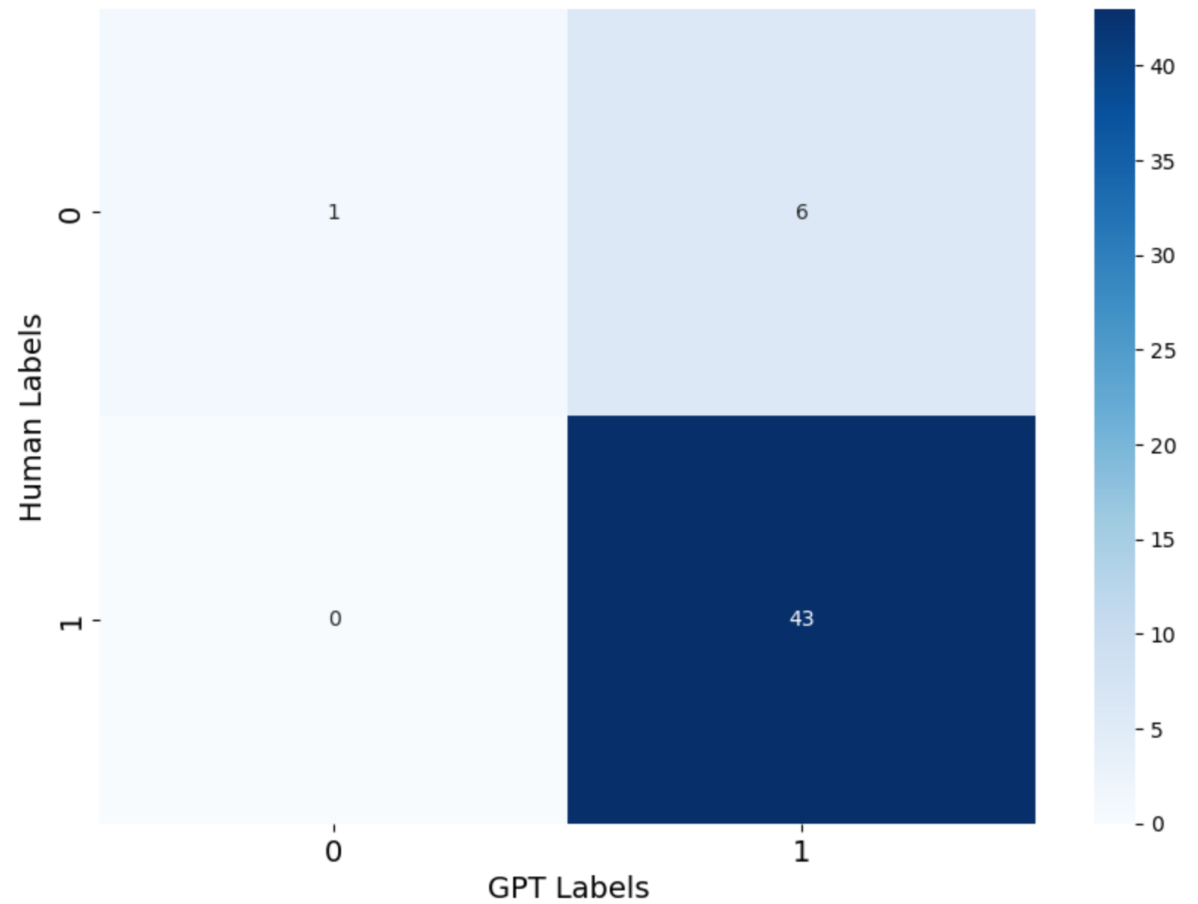
Model Evaluation

- Report four performance metrics.

```python
# Report the metrics
report = classification_report(df_50['manual'], df_50['GPT_label'], digits=4)
print(report)
```

	precision	recall	f1-score	support
0	1.0000	0.1429	0.2500	7
1	0.8776	1.0000	0.9348	43
accuracy			0.8800	50
macro avg	0.9388	0.5714	0.5924	50
weighted avg	0.8947	0.8800	0.8389	50

Improving GenAI Performance

Prompt engineering techniques
- Chain of Thought (CoT)
- Self-Reflection (SR)

Improving GenAI Performance

Sentiment analysis using standard prompt

```
prompt = f"""
What is the sentiment of the following hotel review, which is delimited with triple backticks?

Give your answer as a single word, either "positive" or "negative".

Review text: ```{review}```
"""
```

Table 1. Sentiment Analysis: Comparison of model performance

Iteration	Models	Prompts	Precision	Recall	F1	Accuracy
1	GPT-3.5	Simple	0.8783	0.9471	0.9034	0.9221
	GPT-4.0o	Simple	0.8263	0.9149	0.8487	0.8717
2	GPT-3.5	Simple	0.8781	0.9470	0.9032	0.9220
	GPT-4.0o	Simple	0.8253	0.9142	0.8475	0.8706
3	GPT-3.5	Simple	0.8787	0.9476	0.9038	0.9225
	GPT-4.0o	Simple	0.8269	0.9154	0.8495	0.8724

Improving GenAI Performance

Sentiment analysis using standard prompt

```
prompt = f"""
What is the sentiment of the following hotel review, which is delimited with triple backticks?

Give your answer as a single word, either "positive" or "negative".

Review text: ```{review}```
"""
```

Table 2. Sentiment analysis: Fleiss' Kappa for reliability test

Models	Prompts	Fleiss' Kappa	p-value
GPT-3.5	Simple	0.990	0.000
GPT-4.0o	Simple	0.965	0.000

Improving GenAI Performance

Chain of Thought (CoT)

- Involve a sequence of intermediate reasoning steps to guide a model toward the final output

Standard Prompting

Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The answer is 27. ❌

Chain-of-Thought Prompting

Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11. The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The cafeteria had 23 apples originally. They used 20 to make lunch. So they had 23 - 20 = 3. They bought 6 more apples, so they have 3 + 6 = 9. The answer is 9. ✔
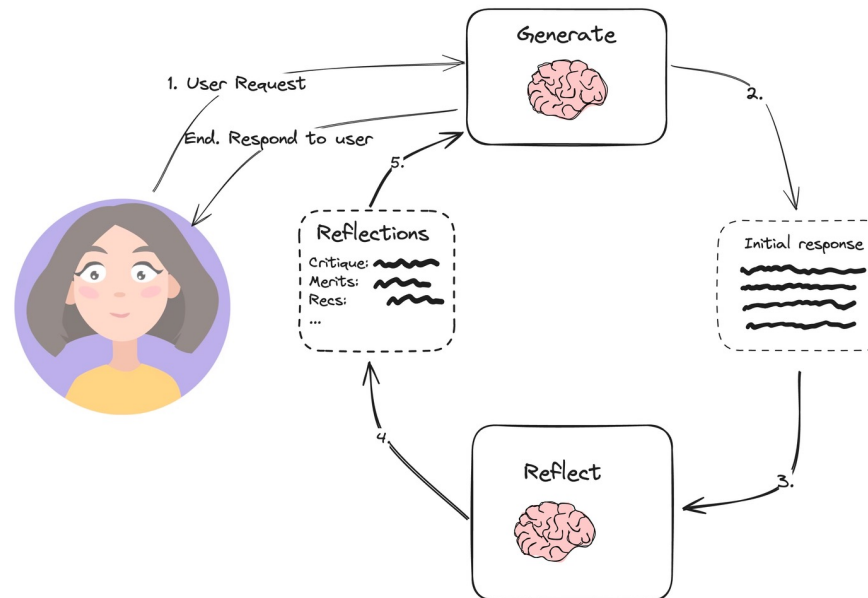
Adding reasoning step

"Let's think step by step"

Improving GenAI Performance

Self-Reflection (SR)
- Involves an LLM reflecting or evaluating its output to understand its reasoning process
- E.g., ask the model "are you sure?" about the generated output

Improving GenAI Performance

Sentiment analysis using CoT+SR prompt

Models	Prompts	Precision	Recall	F1	Accuracy
GPT-4.0o	CoT+SR	0.9317	0.9714	0.9491	0.9610

Conclusion

- Introduction to GenAI
- Application in research
- Model evaluation
- Model improvement

Python code and example datasets

https://github.com/chunshengj/-Users-sheng-Jupyter-AI_Workshop_AESHM

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