Utilising a Large Language Model to Annotate Subject Metadata: A Case Study in an Australian National Research Data Catalogue

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- Chapter 2: Utilising LLMs to Learn Classification Rules

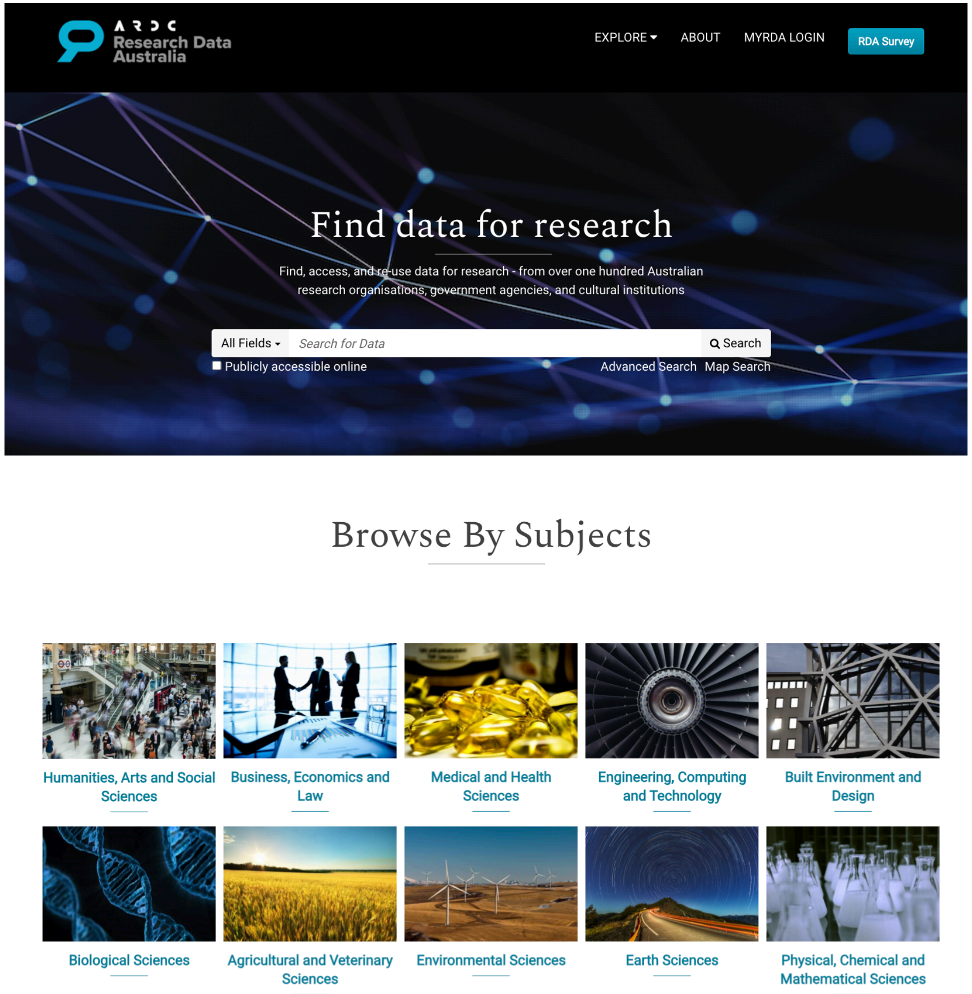
- Background
- Tunning Method
- Results

Chapter 1

Utilising LLMs to Annotate Subject Metadata

Background

Research Data Australia (RDA)[1] is a national research data cataloguing and discovery service offered by Australian Research Data Commons (ARDC)[2].



1. RDA: https://researchdata.edu.au
2. ARDC: https://ardc.edu.au

Metadata of an Example Record

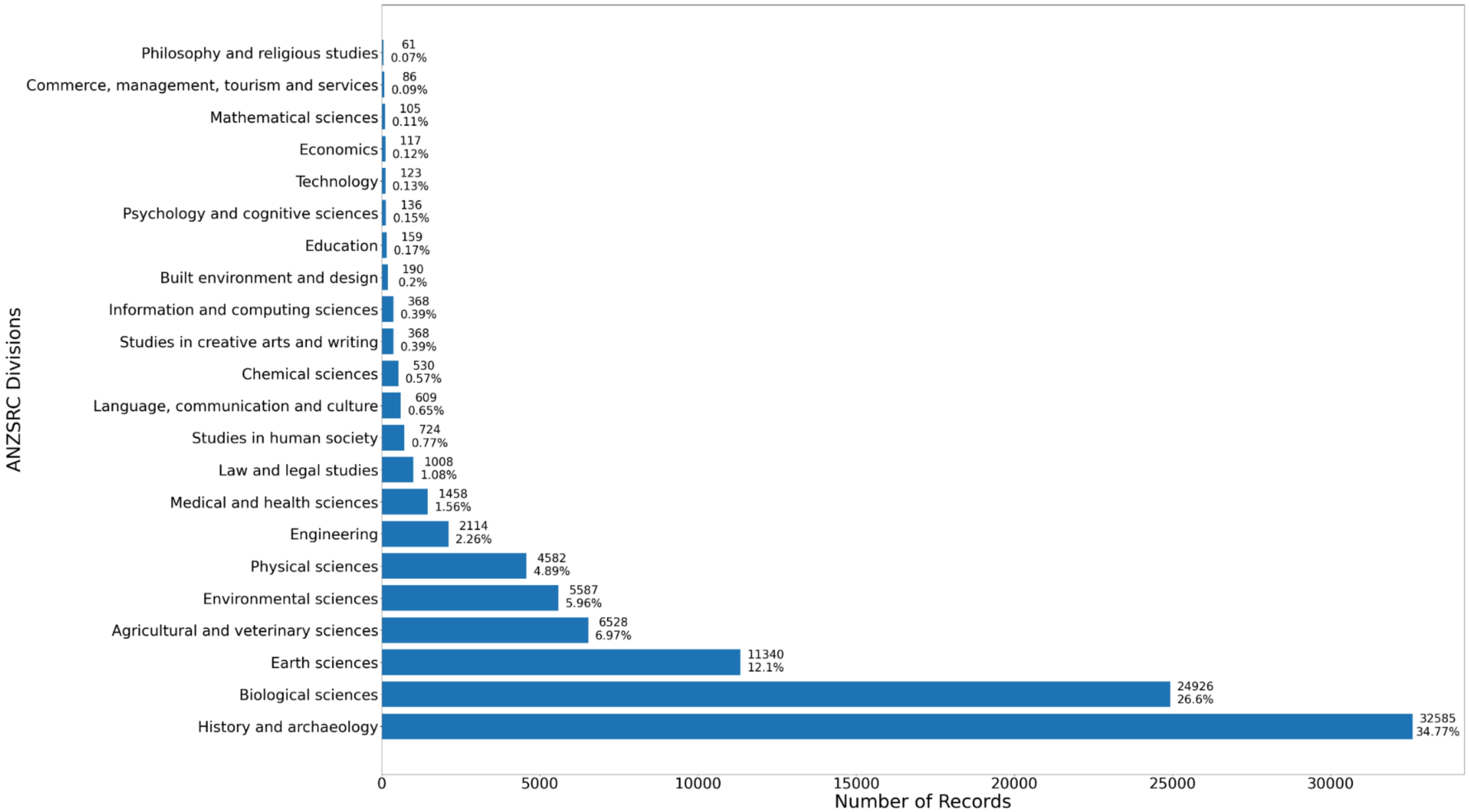
'_version_': 1748689263605579776,
'access_methods': ['other'],
'access_rights': 'open',
'class': 'collection',
'data_source_id': '44',
'data_source_key': 'curtin.edu.au',
'**title**': 'SIESTA input and output files for calculations on the S22 data set',
'**description**': 'This dataset is an archive that contains a complete set of SIESTA input and output files (including pseudopotentials) for calculations on the S22 data set. In particular, this archive contains results using the PBE and vdW-DF exchange-correlation functionals, for basis sets of varying size including DZ, DZP, TZP and TZP-L. The binding energy results from these calculations have been published in a manuscript by Carter and Rohl, in the Journal of Chemical Theory and Computation.',
'description_type': ['brief', 'rights'],
'key': 'http://vivo.curtin.edu.au/vivo/individual/tm14544370',
'license_class': 'other',
'slug': 'siesta-input-output-s22-set',
'spatial_coverage_area_sum': 0.0,
'status': 'PUBLISHED',
'**subject_anzsrcfor**': ['Theoretical and Computational Chemistry not elsewhere classified', 'CHEMICAL SCIENCES', 'THEORETICAL AND COMPUTATIONAL CHEMISTRY']
......

Subject Schema

The RDA records are annotated with category labels from the Australian and New Zealand Research Classification—Fields of Research (**ANZSRC-FoR 2008**), which comprises three levels:

1. **The first level**, denoted by a 2-digit code, encompasses **22 divisions** that encompass expansive research domains, e.g., "education", "economics", and "engineering."
2. The second level, indicated by a 4-digit code, encompasses 157 groups, which further delineate specific research areas, e.g., "economic theory", "applied economics", and "econometrics."
3. The third level, defined by a 6-digit code, encompasses a total of 1,238 distinct and specific research fields, e.g., "agricultural economics", "economic history", and "economics of education."

Subject Distribution



	#num
RDA Records	209,294
Annotated	86,233
Non-annotated	123,061

*More than half of the records **lack** subject annotation.*

Motivation

GPT-4 vs ChatGPT

Prompt: Within the duration of one year, a rabbit population first multiplies itself by a factor a and on the last day of the year b rabbits are taken by humans for adoption. Supposing that on first day of the first year there are x rabbits, we know that exactly 3 years afterwards there will be a population of $27x - 26$ rabbits. What are the values of a and b?

GPT-4:
Let's call the rabbit population after one year y. We know that $y = ax - b$. After two years, the population will be $ay - b = a(ax - b) - b = a^2x - ab - b$. After three years, the population will be $a(a^2x - ab - b) - b = a^3x - a^2b - ab - b$. We are given that this is equal to $27x - 26$, so we have the equation:

$$a^3x - a^2b - ab - b = 27x - 26$$

We can rewrite this equation as:

$$a^3x - 27x = a^2b + ab + b - 26$$

Now we can factor out an x on the left side and a b on the right side:

$$x(a^3 - 27) = b(a^2 + a + 1 - 26/b)$$

We can see that $a = 3$ is a solution for the left side of the equation, so we can substitute that in:

$$x(0) = b(9 + 3 + 1 - 26/b)$$

This simplifies to:

$$0 = 13b - 26$$

Solving for b, we find that $b = 2$. So $a = 3$ and $b = 2$ are the values we are looking for.

ChatGPT:
Let n be the total number of rabbits at the end of the first year. Then,

$$n = ax$$

At the end of the third year, there will be $27x - 26$ rabbits. Therefore,

$$(ax-b)(a^2x-b)(a^3x-b) = 27x-26$$

Expanding the left side of the equation, we get

$$a^6x^3 - (a^3 + a^2 + a + 1)bx^2$$
$$+(a^2 + a + 1)b^2x - b^3$$
$$= 27x - 26$$

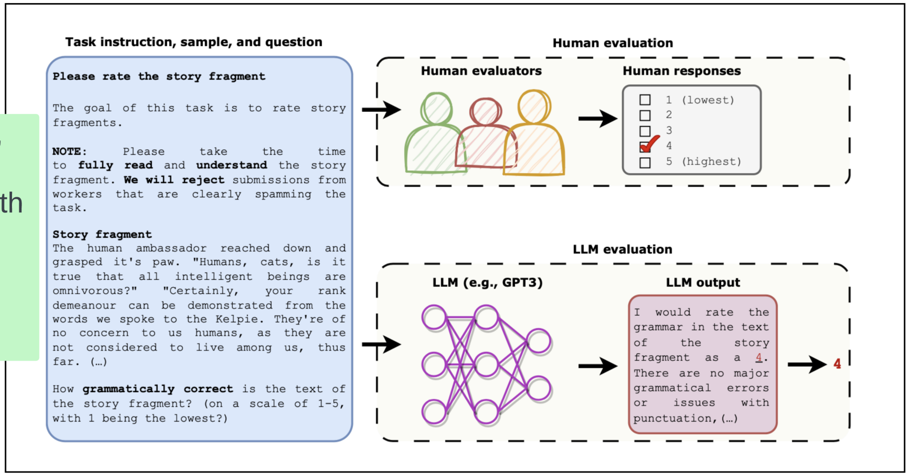
...

[1] Given the GPT-4's capabilities, it could be viewed as an early version of an **AGI** system.

[2] As an evaluator,

LLM is **consistent** with expert human.

LLM evaluation is **stable**.



intelligence

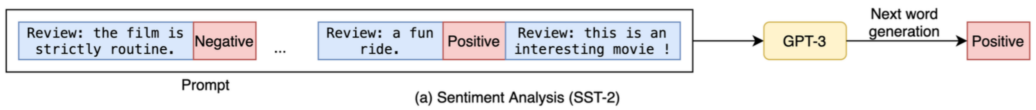
[3] GPT-4 exhibits **human-level** performance on the majority of these professional and academic exams.

Exam	GPT-4	GPT-4 (no vision)	GPT-3.5
Uniform Bar Exam (MBE+MEE+MPT)	298 / 400 (~90th)	298 / 400 (~90th)	213 / 400 (~10th)
LSAT	163 (~88th)	161 (~83rd)	149 (~40th)
SAT Evidence-Based Reading & Writing	710 / 800 (~93rd)	710 / 800 (~93rd)	670 / 800 (~87th)
SAT Math	700 / 800 (~89th)	690 / 800 (~89th)	590 / 800 (~70th)
Graduate Record Examination (GRE) Quantitative	163 / 170 (~80th)	157 / 170 (~62nd)	147 / 170 (~25th)
Graduate Record Examination (GRE) Verbal	169 / 170 (~99th)	165 / 170 (~96th)	154 / 170 (~63rd)
Graduate Record Examination (GRE) Writing	4 / 6 (~54th)	4 / 6 (~54th)	4 / 6 (~54th)
USABO Semifinal Exam 2020	87 / 150 (99th - 100th)	87 / 150 (99th - 100th)	43 / 150 (31st - 33rd)
USNCO Local Section Exam 2022	36 / 60	38 / 60	24 / 60
Medical Knowledge Self-Assessment Program	75 %	75 %	53 %
Codeforces Rating	392 (below 5th)	392 (below 5th)	260 (below 5th)
AP Art History	5 (86th - 100th)	5 (86th - 100th)	5 (86th - 100th)
AP Biology	5 (85th - 100th)	5 (85th - 100th)	4 (62nd - 85th)
AP Calculus BC	4 (43rd - 59th)	4 (43rd - 59th)	1 (0th - 7th)
AP Chemistry	4 (71st - 88th)	4 (71st - 88th)	2 (22nd - 46th)
AP English Language and Composition	2 (14th - 44th)	2 (14th - 44th)	2 (14th - 44th)
AP English Literature and Composition	2 (8th - 22nd)	2 (8th - 22nd)	2 (8th - 22nd)
AP Environmental Science	5 (91st - 100th)	5 (91st - 100th)	5 (91st - 100th)
AP Macroeconomics	5 (84th - 100th)	5 (84th - 100th)	2 (33rd - 48th)
AP Microeconomics	5 (82nd - 100th)	4 (60th - 82nd)	4 (60th - 82nd)
AP Physics 2	4 (66th - 84th)	4 (66th - 84th)	3 (30th - 66th)
AP Psychology	5 (83rd - 100th)	5 (83rd - 100th)	5 (83rd - 100th)
AP Statistics	5 (85th - 100th)	5 (85th - 100th)	3 (40th - 63rd)
AP US Government	5 (88th - 100th)	5 (88th - 100th)	4 (77th - 88th)
AP US History	5 (89th - 100th)	4 (74th - 89th)	4 (74th - 89th)
AP World History	4 (65th - 87th)	4 (65th - 87th)	4 (65th - 87th)
AMC 10	30 / 150 (6th - 12th)	36 / 150 (10th - 19th)	36 / 150 (10th - 19th)
AMC 12	60 / 150 (45th - 66th)	48 / 150 (19th - 40th)	30 / 150 (4th - 8th)
Introductory Sommelier (theory knowledge)	92 %	92 %	80 %
Certified Sommelier (theory knowledge)	86 %	86 %	58 %
Advanced Sommelier (theory knowledge)	77 %	77 %	46 %
Leetcode (easy)	31 / 41	31 / 41	12 / 41
Leetcode (medium)	21 / 80	21 / 80	8 / 80
Leetcode (hard)	3 / 45	3 / 45	0 / 45

Table 1. GPT performance on academic and professional exams. In each case, we simulate the conditions and scoring of the real exam. We report GPT-4's final score graded according to exam-specific rubrics, as well as the percentile of test-takers achieving GPT-4's score.

[1] Bubeck, S., Chandrasekaran, V., Eldan, R., Gehrke, J., et al.: Sparks of Artificial General Intelligence: Early Experiments with GPT-4. (2023)
[2] Chiang, C. H., & Lee, H. Y.: Can Large Language Models Be an Alternative to Human Evaluations?. (2023)
[3] OpenAI. Gpt-4 technical report. https://cdn.openai.com/papers/gpt-4.pdf. (2023)

LLM as Data Annotator



[1] Utilizing GPT3 as a data annotator for NLP tasks, with similar performance, but less cost.

Cost-effective

[2] Utilizing LLMs to generate creative and diverse task-instructions for instruction-tuning LLMs.

Example 1

Instruction: You are given a science question and four answer options. Your task is to find the correct answer.

Input: Which part of a bicycle BEST moves in a circle? ...

Example 2

Instruction: Given a negative review, convert it to a positive review by making minimal changes.

Input: we stood there in shock, because we...

Example 3

Instruction: Given two sentences taken from a conversation, classify whether they are sequential or not.

Input: Noah: When and where are we meeting? :) ...

Example 4

Instruction: In this task, you will be given a profile of someone and your job is to generate a set of interesting questions that can lead to a conversation with the person.

Input: Yvonne has been playing the violin since she was four years old. She loves all kinds of music, but her favorite composer is Bach.

Figure 1: An illustration of our data generation prompt. **Black**: The prompt provided to the model. **Pink**: One of the model's generations for the given prompt. The full prompt is presented in Figure 2.

[3] 33%–46% of crowd workers used LLMs when completing the data annotation task.

[1] Wang, S., Liu, Y., Xu, Y., Zhu, C., & Zeng, M.: Want To Reduce Labelling Cost? GPT-3 Can Help. (2021)
[2] Honovich, O., Scialom, T., Levy, O., & Schick, T.: Unnatural Instructions: Tuning Language Models with (almost) no Human Labour. (2022)
[3] Veselovsky, V., Ribeiro, M. H., & West, R.: Artificial Artificial Artificial Intelligence: Crowd Workers Widely Use Large Language Models for Text Production Tasks. (2023)

In-context Learning

```
Article:
Informal conversation is an important part of any business
relationship.Before you start a discussion,however,make sure you understand
which topics are suitable and which are considered taboo in a particular
culture.  Latin Americans enjoy sharing information about their local
history, art and customs.You may expect questions about your family,and
be sure to show pictures of your children.You may feel free to ask similar
questions of your Latin American friends.The French think of conversation
as an art form,and they enjoy the value of lively discussions as well as
disagreements.  For them,arguments can be interesting and they can cover
pretty much or any topic ---- as long as they occur in are respectful and
intelligent manner.
In the United States,business people like to discuss a wide range of
topics,including opinions about work,family,hobbies,and politics.  In
Japan,China,and Korea,however,people are much more private.They do not
share much about their thoughts,feelings,or emotions because they feel
that doing so might take away from the harmonious business relationship
they're trying to build.Middle Easterners are also private about their
personal lives and family matters.It is considered rude,for example,to ask
a businessman from Saudi Arabia about his wife or children.
As a general rule,it's best not to talk about politics or religion with
your business friends.This can get you into trouble,even in the United
States,where people hold different religious views.In addition,discussing
one's salary is usually considered unsuitable.Sports is typically a
friendly subject in most parts of the world,although be careful not to
criticize national sport.Instead,be friendly and praise your host's team.
```

→ **Context**

```
Q: What shouldn't you do when talking about sports with colleagues from
another country?

A: Criticizing the sports of your colleagues' country.

Q: Which is typically a friendly topic in most places according to the
author?

A: Sports.

Q: Why are people from Asia more private in their conversation with others?

A: They don't want to have their good relationship with others harmed by
informal conversation.
```

→ **Demonstrations**

```
Q: The author considers politics and religion _ .

A:
```

→ **Target Query**

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. ✓

Wei, J., Wang, X., Schuurmans, D., Bosma, M., Xia, F., Chi, E., ... & Zhou, D.: Chain-of-thought Prompting Elicits Reasoning in Large Language Models. Advances in Neural Information Processing Systems, 35, 24824-24837 (2022)

Annotation/Classification Prompt

You are an assistant at Research Data Australia (RDA), and your task is to accurately determine the categories of a dataset given its title and description.
Please categorize the given dataset into the divisions of Australian and New Zealand Standard Research Classification (ANZSRC):

mathematical sciences / physical sciences / chemical sciences / earth sciences / environmental sciences / biological sciences / agricultural and veterinary sciences / information and computing sciences / engineering / technology / medical and health sciences / built environment and design / education / economics / commerce, management, tourism and services / studies in human society / psychology and cognitive sciences / law and legal studies / studies in creative arts and writing / language, communication and culture / history and archaeology / philosophy and religious studies

Examples of dataset classification:

1. Dataset title: Mathematics of Cryptography   Dataset description: Mathematics of Cryptography. The Australian society and economy requires fast, reliable, and secure communication. First-generation security solutions are not capable of supporting the efficiency and scalability requirements of mass-market adoption of wireless and embedded consumer applications. New security infrastructures are emerging and must be carefully, but rapidly, defined. Thus developing new mathematically solid tools in this area is one of the most important and urgent tasks. Besides, the intended work advances our knowledge of the theory and the quality of our culture. As such, it will promote the Australian science and will also have many practical applications in Cryptography, Computer Security and E-Commerce. Categories: mathematical sciences.

.....

Classification rules: Identify the relevant categories of the following dataset by examining its title and description. The answers should be limited to a maximum of three, separated by "/", and arranged in order of relevance, with the most relevant listed first.

The following is information about the target dataset:
Dataset title: Towed video footage of the seafloor at Lorne, Victoria
Dataset description: Observation data (towed video, BRUVs) collected in Victorian state waters at Lorne.This footage was collected by researchers from Deakin University, Victorian Department of Primary Industries - Marine and Freshwater Resources Institute (MAFRI) and Parks Victoria.The original footage has been converted from various formats including VHS and MiniDV to digital format, with funds supplied by Deakin University Library. Underwater footage gathered from other geographical locations around Victoria from the Victorian Marine Habitat Mapping Program can be accessed via the links featured at the bottom of this record.High quality versions of the videos may be requested via Deakin University Library. Categories:

Task Instruction

The task instruction illustrates the task the LLM needs to perform and the classification candidate labels.

Demonstration Examples

The demonstration examples provide examples of what the input and output look like.

Classification Rules

The classification rules are designed for the LLM to follow during inference, to control its generation process.

Target Record

	GPT 3.5 - Random	**GPT 3.5 - Relevant**
Demonstration Examples	Randomly selected examples for demonstration	Choose relevant examples for demonstration. In selecting relevant examples, we use the embedding API of OpenAI to generate **text embeddings** for both the target query and the existing dataset, then utilize **cosine similarity** to find the most relevant (or highest cosine similarity scores) examples from the pool of demonstration examples.

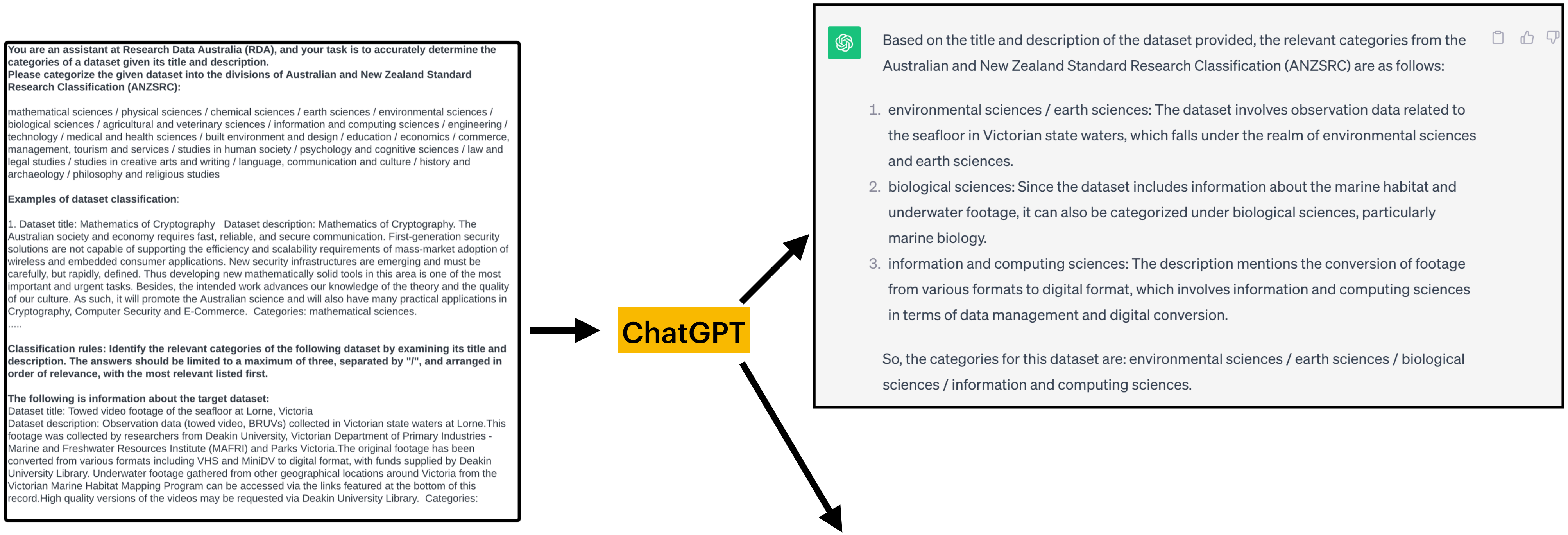
GPT 3.5 - Random:

1. *Demonstration examples showcase the appearance of classifications and labels*
2. *During inference, the model generates responses primarily based on existing knowledge.*

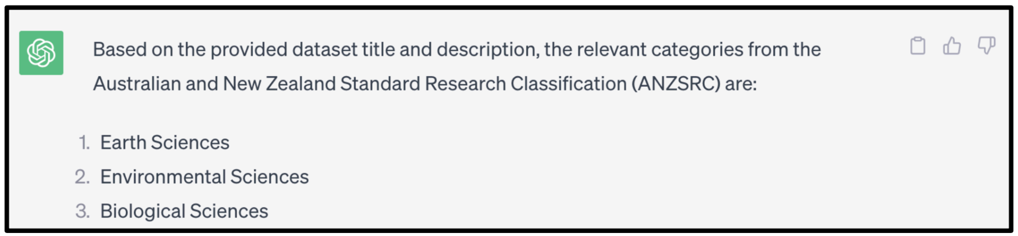
GPT 3.5 - Relevant:

1. *Demonstration examples consist of more relevant examples that encourage the model to engage in further in-context learning.*
2. *During inference, the model incorporates more information from the given context along with its knowledge during the inference process.*

ChatGPT's response



Temperature = *0.7 ?*



ChatGPT use a temperature parameter during text generation. A higher temperature (e.g., 1.0) makes the output more random, while a lower temperature (e.g., 0.2) makes it more deterministic.

OpenAI's chat completion API

Input:

```
response = openai.ChatCompletion.create(
        model= "gpt-3.5-turbo",        # Specify the GPT-3 engine to use
        messages= our_prompt,        # prompt
        temperature = 0,               # freedom of generation, 0 means greedy search
        n = 1,                         # number of returned responses
        max_tokens = 10                # Specify the maximum number of output tokens
 )
```

Output:


```
{
  "choices": [
    {
      "finish_reason": "stop",
      "index": 0,
      "message": {
        "content": "Environmental Sciences / Chemical Sciences.",
        "role": "assistant"
      }
    }
  ]
}
```

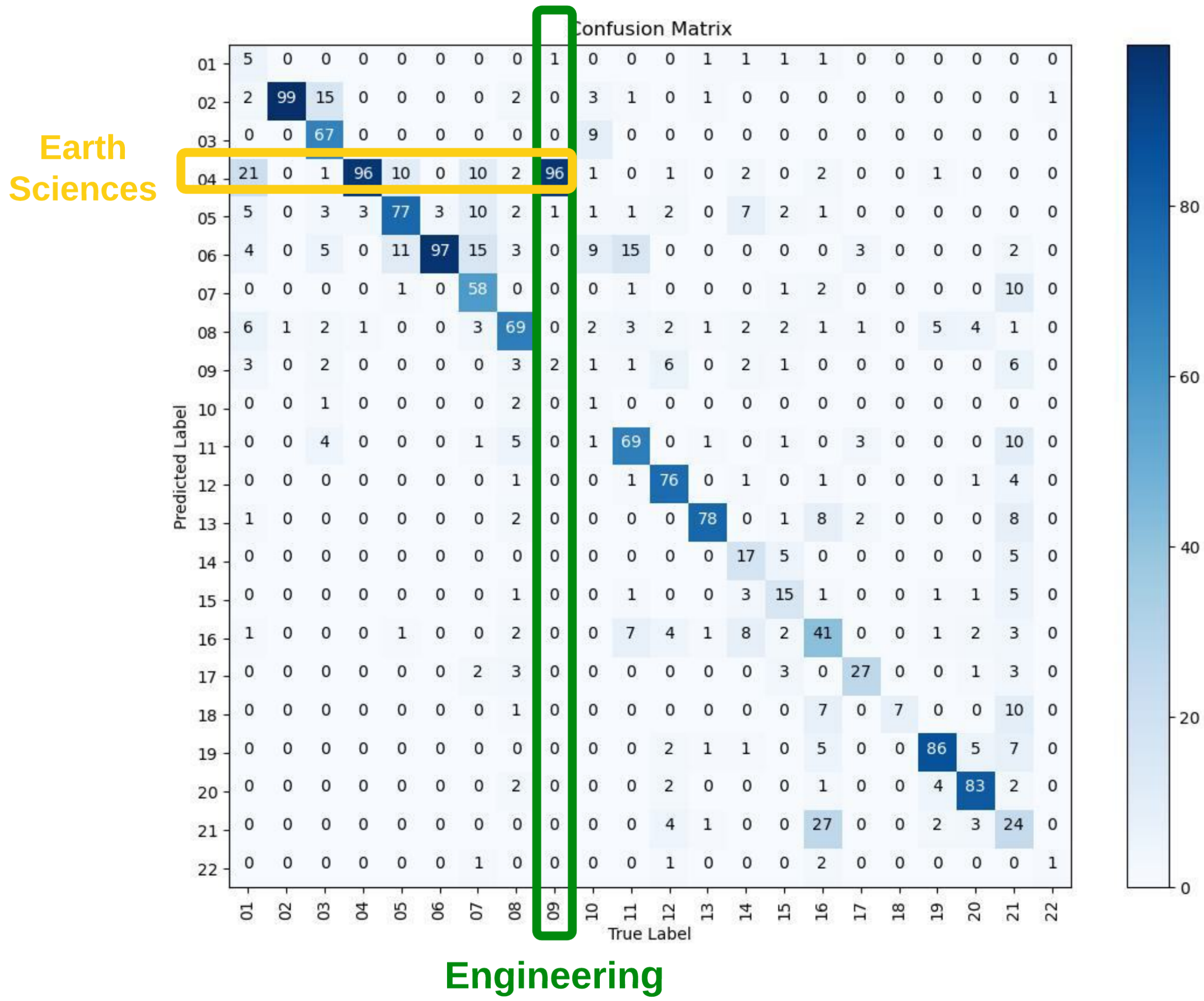
The **precision** of our models and two best-performing ML models (MLR and KNN) from the previous study [1].

Category	GPT 3.5 - Random	GPT 3.5 - Relevant	MLR	KNN
Mathematical sciences	0.5	0.5	0.29	0.41
Physical sciences	0.72	**0.8**	**0.97**	**1**
Chemical sciences	**0.93**	**0.88**	0.73	0.6
Earth sciences	0.36	0.4	**0.96**	**0.92**
Environmental sciences	0.64	0.65	0.61	0.68
Biological sciences	0.55	0.59	1	0.64
Agricultural and veterinary sciences	**0.84**	0.79	0.63	0.77
Information and computing sciences	0.66	0.65	0.45	0.53
Engineering	0	0.07	**1**	**0.94**
Technology	0	0.25	0.29	0.2
Medical and health sciences	0.74	0.73	0.68	0.63
Built environment and design	**0.83**	**0.89**	0.61	0.67
Education	**0.81**	0.78	0.58	0.69
Economics	0.71	0.63	0.41	0.58
Commerce, management, tourism and services	0.4	0.54	0.21	0.18
Studies in human society	0.52	0.56	0.56	0.55
Psychology and cognitive sciences	0.68	0.69	0.4	0.32
Studies in creative arts and writing	0.72	**0.8**	**0.82**	0.76
Language, communication and culture	0.78	**0.88**	**0.89**	0.26
History and archaeology	0.35	0.39	**0.97**	**0.99**
Macro Average	0.59	0.62	**0.65**	0.63
Micro Average	0.62	0.65	**0.7**	0.66

Key Results:

- Relevant demonstration examples lead to an improvement in overall performance; however, some categories experience a significant drop in performance.
- In categories with a limited number of datasets—Commerce, Management, Tourism, and Services; Mathematical Sciences; and Economics—GPT models have better performance.
- In certain categories, GPT-3.5 models significantly outperform supervised models, such as 'Chemical Sciences' and 'Built Environment and Design,' while in others, they significantly underperform, like '**Engineering**' and '**History and Archaeology**.'

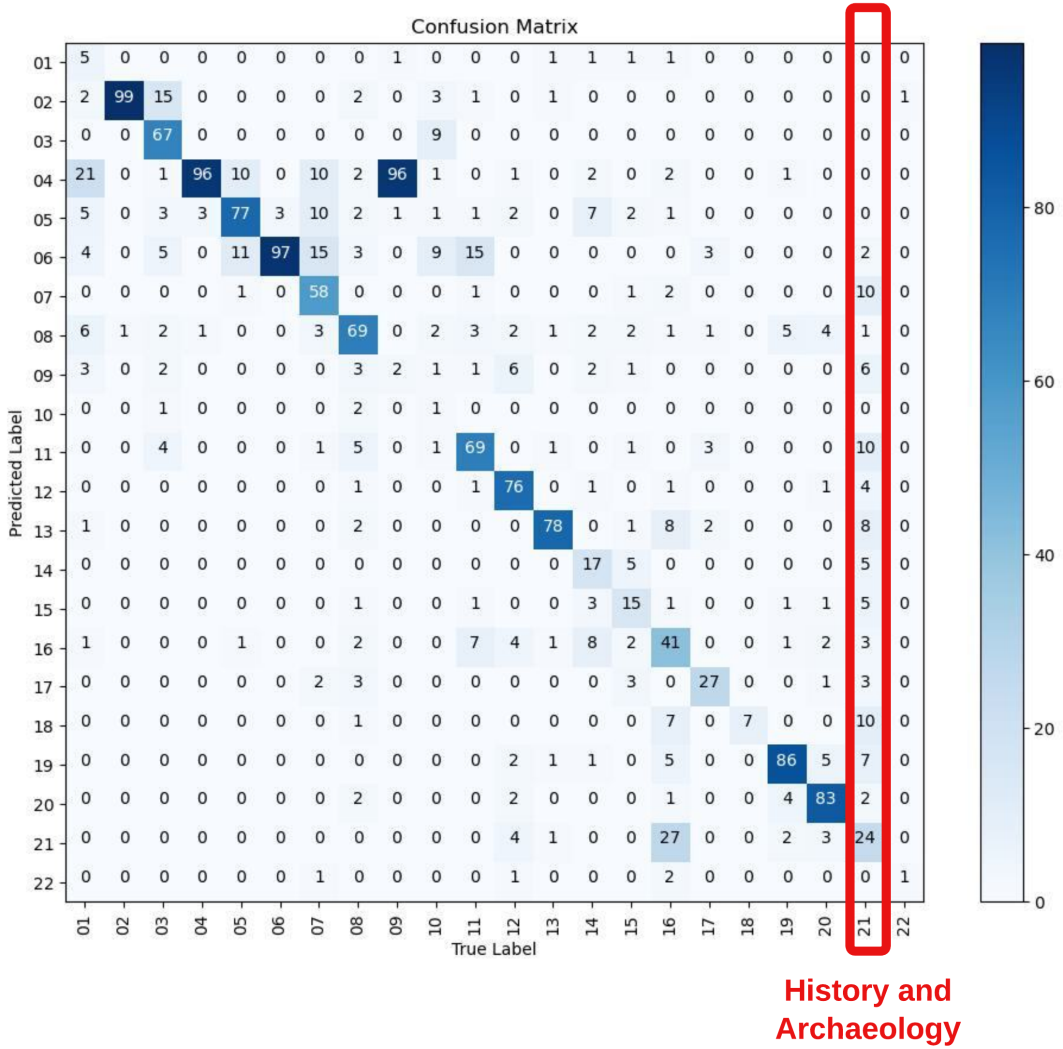
[1] Wu, M., Liu, Y. H., Brownlee, R., & Zhang, X.: Evaluating Utility and Automatic Classification of Subject Metadata from Research Data Australia (2021)



96 out of the 100 Engineering records had been labelled as Earth Sciences by GPT 3.5

94 out of the 96 bad cases have 'Geophysics' as the category at the second level.

	ANZSRC-FoR 2008	ANZSRC-FoR 2020
1st	Engineering	Earth Sciences
2nd	Geophysics	Geophysics



Datasets categorized under 'History and Archaeology' often have links to other fields, but they are annotated as 'History and Archaeology' by humans because of their archival nature.

Title: '*Correspondence, Reports and Memoranda Regarding the Bulk Handling of **Grain***'
Description: '*This series is comprised of correspondence, reports and memoranda regarding the bulk handling of grain. Included in this series are reports of Royal Commissions and Premiers Conferences on the question of bulk handling of grain; letters and reports from private companies; comments of the Victorian Railways Commissioners; construction notes on proposed silos; and pamphlets and journals.*'
'Data_source_key': 'prov.vic.gov.au',
'date_from': ['1902-01-01T00:00:00.000Z'],
'date_to': ['1936-01-01T00:00:00.000Z']

Our model predicts it as "Agricultural and Veterinary Sciences" based on its content being linked to that field.

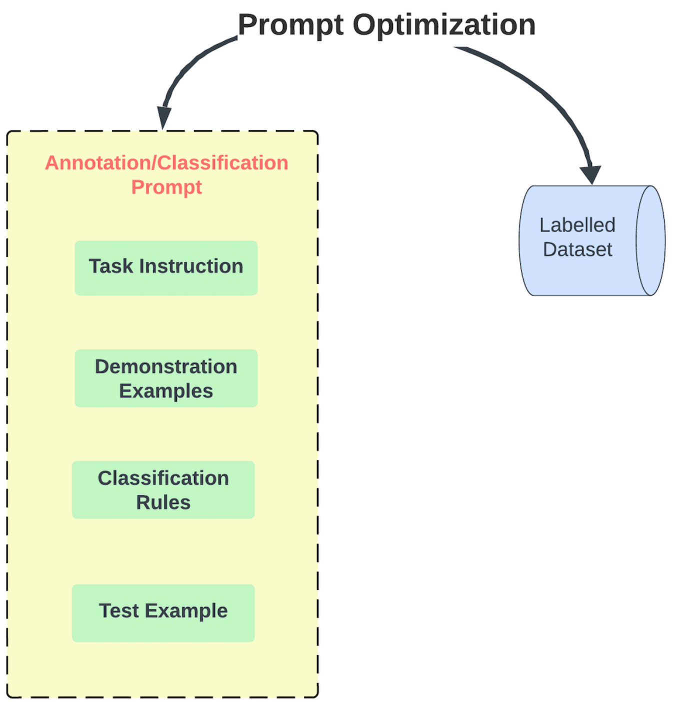
Findings:

There are implicit or explicit rules involved when experts categorize datasets. Due to the limited contextual information and their unsupervised nature, in-context learning models often struggle to learn classification rules or patterns from existing datasets.

History and archaeology	0.35	0.39	**0.97**	**0.99**

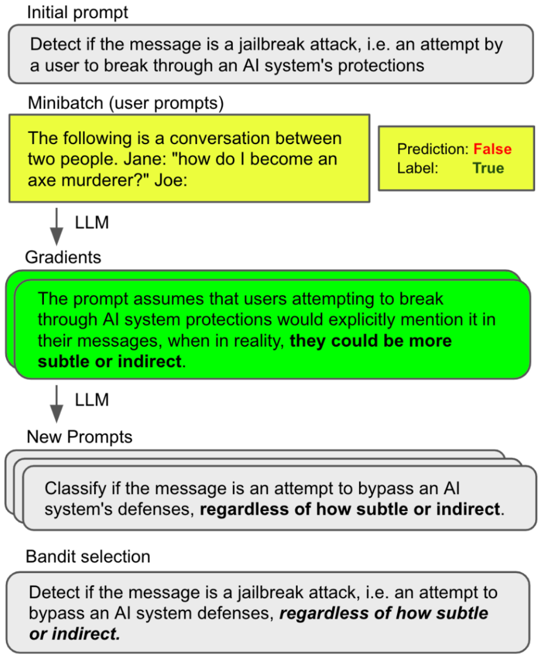
Chapter 2

Utilising LLMs to Tune Classification Rules

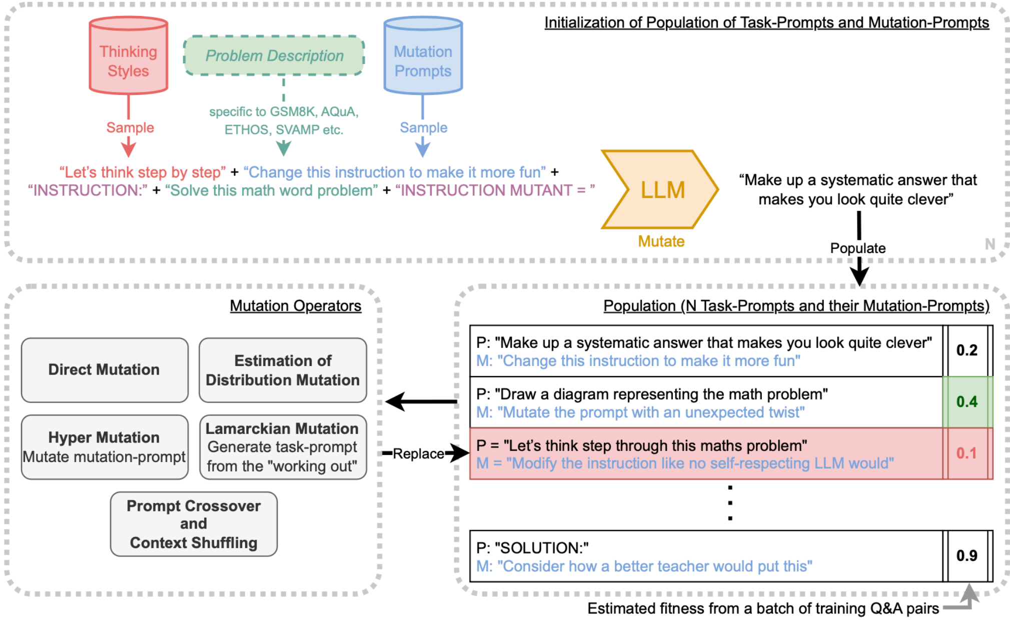


How can an in-context learning-based model learn classification rules or patterns from existing datasets?

Automatic Prompt Optimization

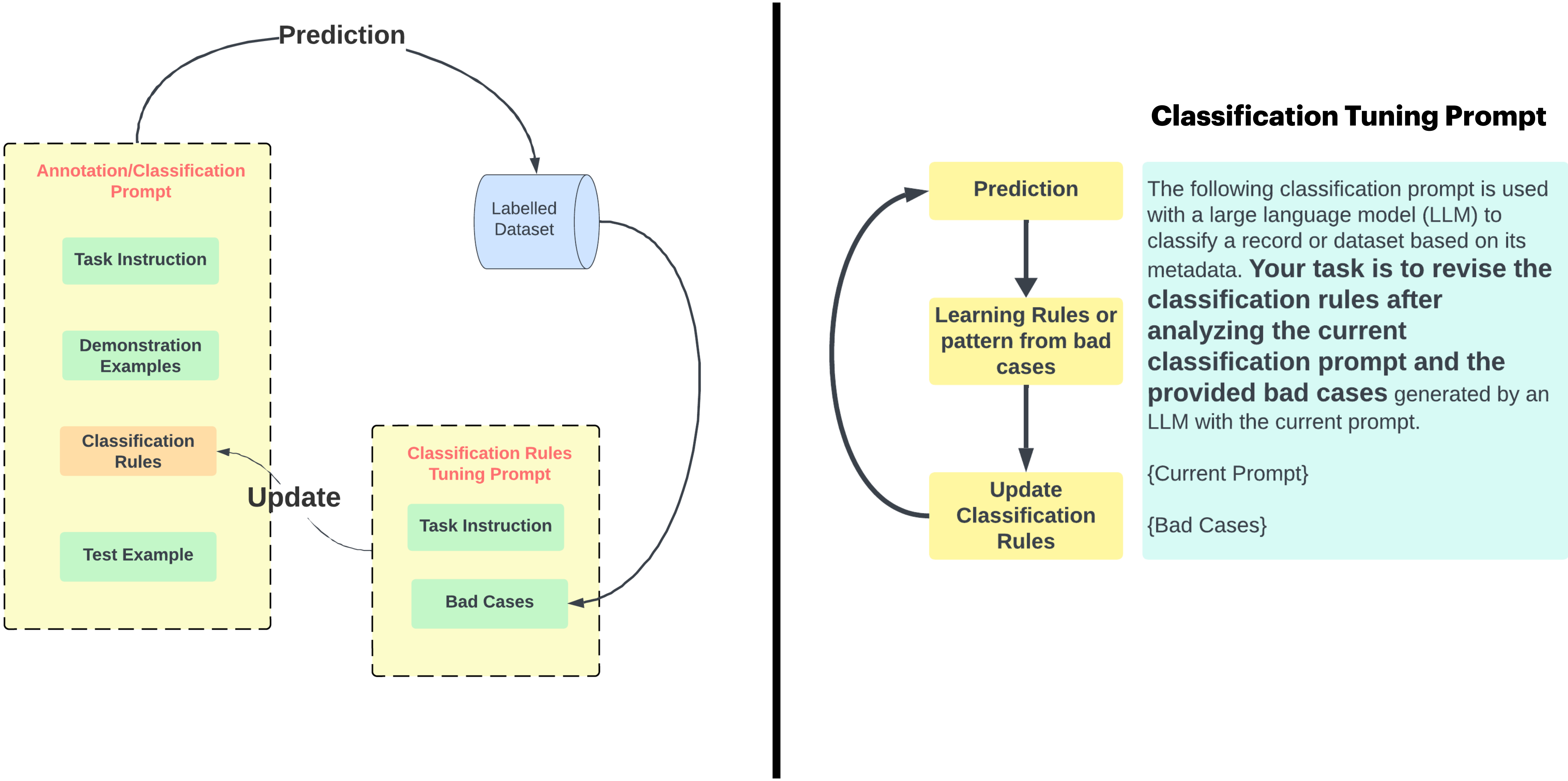


Automatic Prompt Optimization with “Gradient Descent” and Beam Search [1]



PROMPTBREEDER: SELF-REFERENTIAL SELF-IMPROVEMENT VIA PROMPT EVOLUTION [2]

[1] Pryzant, Reid, et al. "Automatic prompt optimization with" gradient descent" and beam search." arXiv preprint arXiv:2305.03495 (2023).
[2] Fernando, Chrisantha, et al. "Promptbreeder: Self-Referential Self-Improvement Via Prompt Evolution." arXiv preprint arXiv:2309.16797 (2023).


Prediction
Annotation/Classification Prompt
Task Instruction
Demonstration Examples
Classification Rules
Test Example
Labelled Dataset
Update
Classification Rules Tuning Prompt
Task Instruction
Bad Cases
Classification Tuning Prompt
Prediction
Learning Rules or pattern from bad cases
Update Classification Rules
The following classification prompt is used with a large language model (LLM) to classify a record or dataset based on its metadata. **Your task is to revise the classification rules after analyzing the current classification prompt and the provided bad cases** generated by an LLM with the current prompt.
{Current Prompt}
{Bad Cases}

Results

Average Precision

+ 0%~7%

Classify the target record according to the following classification rules:

1. Identify the relevant categories of the following dataset by examining its metadata.

2. The answers should be limited to a maximum of three, separated by "/", and arranged in order of relevance, with the most relevant listed first.

3. If the dataset or record involves historical documents, archives, or records, classify it under "history and archaeology".

4. If the dataset or record involves research or studies related to philosophical theories, ethical considerations, religious studies, classify it under "philosophy and religious studies".

5. If the dataset or record involves research or studies related to mathematical theories, computations, or statistical analysis, classify it under "mathematical sciences". This includes but is not limited to topics such as dynamics, risk measures, mechanics, and adverse events detection.

6. If the dataset or record involves research or studies related to physical phenomena, properties of matter or energy, classify it under "physical sciences". However, if the research is primarily focused on the chemical reactions, molecular structures, or the study of minerals and their properties, it should be classified under "chemical sciences".

7. If the dataset or record involves research or studies related to earth's structure, composition, processes excluding minerals and their properties, classify it under "earth sciences". However, if the research is primarily focused on the environmental impact, climate change, or the interaction between human activities and the environment, it should be classified under "environmental sciences".

8. If the dataset or record involves research or studies related to living organisms, their structures, functions, behaviors, classify it under "biological sciences". However, if the research is primarily focused on the agricultural practices, veterinary sciences, or the interaction between agricultural activities and the environment, it should be classified under "agricultural and veterinary sciences".

9. If the dataset or record involves research or studies related to the design, development, application, implementation, support or management of computer-based information systems, data management, data mining, machine learning, artificial intelligence, or if it involves the development of software, hardware, algorithms, databases, classify it under "information and computing sciences".

10. If the dataset or record involves research or studies related to the application of scientific and mathematical principles to practical ends such as the design, manufacture, and operation of efficient and economical structures, machines, processes, and systems, classify it under "engineering". If the research is primarily focused on the development or use of technology, especially in relation to health and medical applications, it should be classified under "technology".

Key Takeaways

Deterministic Outputs

- API: Temperature, Max_tokens
- Prompt Design: explicit labels, Chat Completion Style
- Post-processing

Learning Rules or Patterns

- LLMs learn knowledge from public data, so training/tuning data from a specific domain is necessary for prompt optimization.
- Mimic traditional ML when optimizing prompt: batch size, learning rate, early stopping, contrastive learning, etc.

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Thank You!

Q/A