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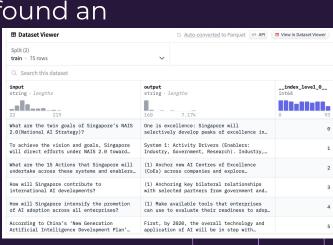
# Al PolicyChat 94812 - Team#5 Report

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### **Data Collection**

- We started by collecting 20 Al policy documents from various trusted sources listed on our course's Canvas page;
- Made Questions: We came up with around 100 questions that cover a broad range of AI policy topics;
- Found Answers: For each question, we found an answer in our collected documents.
- Pushed to Hugging Face hub.







# **Policy Chat**

Question: Why is international cooperation on AI important?

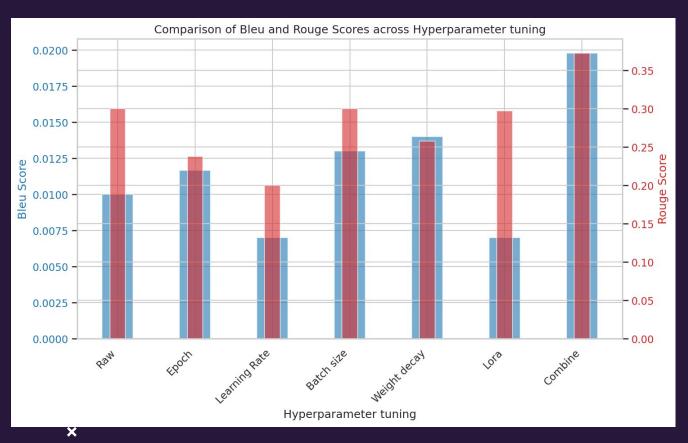
### Raw Llama:

- </s><s> nobody knows
- International cooperation on AI is important for several reasons:
- 1. \*\*Sharing knowledge and resources\*\*: By working together, countries can share their expertise and resources in AI, leading to faster progress and more innovative solutions.
- 2. \*\*Addressing ethical and social implications\*\*: Al raises complex ethical and social implications, such as privacy, bias, and job displacement. International cooperation can help address

### After Fine tuning:

International cooperation on AI is important because it can help address global challenges, such as climate change, pandemics, and economic inequality, more effectively than any one country could alone. It can also help ensure that AI is developed and used in ways that are ethical, transparent, and respectful of human rights.

# Hyperparameter Tuning



## **Baseline Model**

	BLEU_Score	ROUGE-1	ROUGE-2	ROUGE-I
Raw_llama2	0.012922	0.307788	0.077700	0.256869
Fine_tuned_llama2_batch	0.005380	0.309104	0.067997	0.264924

```
# Quantization Config
quant_config = BitsAndBytesConfig(
    load_in_4bit=True,
    bnb_4bit_quant_type="nf4",
    bnb_4bit_compute_dtype=torch.float16,
    bnb_4bit_use_double_quant=False
)
```

```
# LoRA Config
peft_parameters = LoraConfig(
    lora alpha=16,
    lora dropout=0.1.
    r=8,#rank
    bias="none".
    task type="CAUSAL LM"
# Training Params
train params = TrainingArguments(
    output_dir="./results_modified",
    evaluation_strategy = "epoch",
    num train epochs=30,
    per_device_train_batch_size=4,
    gradient_accumulation_steps=1,
   optim="paged adamw 32bit",
    save steps=100,
    logging_steps=20
    learning_rate=2e-4,
    weight decay=1e-3,
    fp16=False,
    bf16=False,
    max grad norm=0.3,
   max steps=-1,
    warmup ratio=0.03,
    group_by_length=True,
    lr scheduler type="constant",
    report to="tensorboard"
```

# Learning Řate

#### **Critical role of learning rate in Fine-Tuning**

- Determines how effectively the model adapts to new data
- Balances knowledge retention with new information assimilation
- Prevents overfitting to maintain generalization

#### Experimentation with different learning rates (1e-4 & 2e-4)

	BLEU_Score	ROUGE-1	ROUGE-2	ROUGE-1
Raw_llama2	0.006988	0.287063	0.056603	0.235454
Fine_tuned_llama2_lr_1e_4_metrics	0.007629	0.205463	0.037827	0.183335
Fine_tuned_llama2_lr_2e_4_metrics	0.005543	0.229239	0.032119	0.204028



## **Lora Hyper-parameter**

### What Lora is & What We Chose

- lora\_alpha: This parameter controls the scaling factor applied to the low-rank matrices in LoRA. It is used to adjust the magnitude of the updates to the original model parameters.
- lora\_dropout: This parameter specifies the dropout rate applied to the low-rank matrices in LoRA. Dropout
  is a regularization technique used to prevent overfitting by randomly setting a fraction of the input units to 0
  during training.
- r: This parameter defines the rank of the low-rank matrices in LoRA. The rank determines the number of columns in the low-rank matrices, which in turn controls the amount of parameter reduction.
- bias: This is a boolean parameter that indicates whether to include bias terms in the low-rank adaptation.

lora_alpha	lora_dropout	r	bias
32	0.2	8	none

#### **How Lora Performs**

	BLEU_Score	ROUGE-1	ROUGE-2	ROUGE-1
Raw_llama2	0.012922	0.307788	0.077700	0.256869
Fine_tuned_llama2_Lora	0.007254	0.297749	0.066084	0.252001

# Number of Epochs

### Base model:

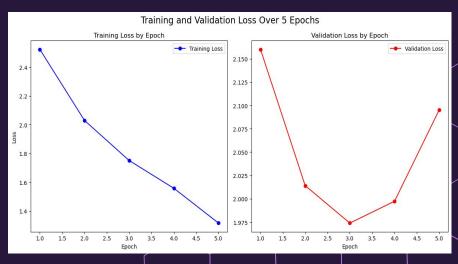
NousResearch/Llama-2-7b-chat-hf

	BLEU_Score	ROUGE-1	ROUGE-2	ROUGE-l
Raw_llama2	0.006171	0.298435	0.062240	0.256231
Fine_tuned_llama2_3_epoches	0.007181	0.331065	0.088585	0.261162

#### Base model:

meta-llama/Llama-2-7b-chat-hf

	BLEU_Score	ROUGE-1	ROUGE-2	ROUGE-l
Raw_llama2	0.002833	0.243284	0.046212	0.213330
Fine_tuned_llama2_3_epoches	0.011653	0.238402	0.047726	0.192272



num\_train\_epochs=3 is the best.

## **Batch Size**

### Gradient accumulation = 2

	BLEU_Score	ROUGE-1	ROUGE-2	ROUGE-l
Raw_llama2	0.012922	0.307788	0.077700	0.256869
Fine_tuned_llama2_batch	0.013182	0.312330	0.271695	0.237278

Larger batch size usually makes gradient approximation more accurate and stabilize training. Our baseline batch size is 4. Because T4 **GPU RAM** is limited to 14 GB, large batch like 8 cannot fit into the GPU.

Gradient accumulation is a technique used to train models with large mini-batches that cannot fit entirely into the GPU memory at once.

We can backward the gradient after two gradients of two small batches are calculated and add them to get a large batch gradient, and update the model.

# **Weight Decay**

How does weight decay affect the model? L2 Regularization.

The weight decay parameter is a regularization technique used during the training of neural networks, and it serves multiple purposes:

- Preventing Overfitting
- Improving Generalization
- Stabilizing Training

	BLEU_Score	ROUGE-1	ROUGE-2	ROUGE-1
Raw_Ilama2	0.007532	0.227682	0.043049	0.197577
Fine_tuned_llama2_control_codes_prompting	0.014546	0.258092	0.059738	0.219957

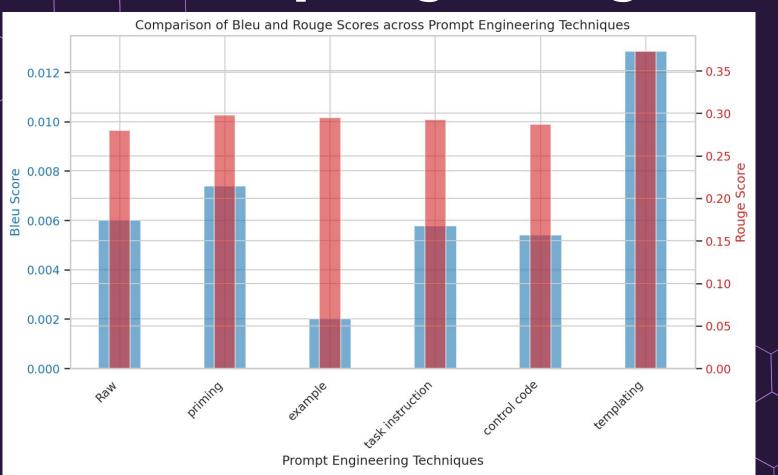
Our experiments with varying weight decay values from 0.0001 to 0.1 during the training of the LLaMA model demonstrated that this parameter had little effect on the training loss, indicating a low influence on the model's learning across the dataset used.

# Combine hyperparams tuning

```
Lora_rank=16,
Gradient Accumulation=2,
Learning_rate=1e-5,
Weight_decay=2e-3,
Max_grad_norm=0.1,
Epoch=10
```

	BLEU_Score	ROUGE-1	ROUGE-2	ROUGE-1
Raw_llama2	0.012922	0.307788	0.077700	0.256869
Fine_tuned_llama2_combineHyp	0.019834	0.299497	0.080271	0.257430

# **Prompt Engineering**



## **Examples**

### Adopting fixed example method for Examples prompting technique

- Mitigates risks of biased guidance in model responses
- Provides a consistent template for quality and format
- Ensures stylistic uniformity without content influence

### **How it performs:**

	BLEU_Score	ROUGE-1	ROUGE-2	ROUGE-1
Raw_llama2	0.006988	0.287063	0.056603	0.235454
Ilama2_examples_prompting	0.002679	0.295252	0.057654	0.233252

# **Priming**

	BLEU_Score	ROUGE-1	ROUGE-2	ROUGE-l
generations_without_priming	0.006171	0.298435	0.062240	0.256231
generations_with_global_priming	0.007318	0.364842	0.085737	0.293611

```
from tqdm.notebook import tqdm
import gc
priming_text = """
The following responses should reflect a deep understanding of AI Policy, including ethical considerations,
regulatory frameworks, and the societal impact of AI technologies.
Answers should be informed, nuanced, and precise, demonstrating a comprehensive grasp of the subject matter.
generations primed =[]
for i in tqdm(range(len(df_test_all)), "generating..."):
  prompt = f"{priming_text}### Question: {df_test_all['input'][i]}\n Briefly, in 100 words answer the question. ### Answer: </s>"
  # Generate predictions
  inputs = llama_tokenizer(prompt, return_tensors='pt')
  inputs = inputs.to("cuda")
  output = raw_model.generate(**inputs, max_new_tokens=200,temperature=0.2)
  response = llama_tokenizer.decode(output[0].tolist())
  # print(response)
  # break
  generations_primed.append(response)
  del inputs, output
  gc.collect()
  torch.cuda.empty_cache()
```

# Task Instruction

### What Task Instruction Is:

Task Instruction: **Providing specific task instructions** showed a balanced improvement across all metrics, suggesting that task instruction might be a more effective approach than individual priming in certain contexts.

In the experiment, before the question, we add "Based on your knowledge, please answer the question:"

### **How it performs:**

	Experiment	BLEU Score	ROUGE-1	ROUGE-2	ROUGE-L
0	Baseline	0.006728	0.213823	0.035865	0.176707
1	Task Instruction	0.005774	0.292351	0.051474	0.255964

# **Control Codes Prompting**

### What Control Codes Prompting Is:

Control Codes: **Special instructions or tokens** we prepend or append to our input prompt to guide the model's generation towards a desired format, tone, or content type.

For the Llama-2 7b model, this involves specifying the type of response needed (e.g., factual, analytical, policy recommendation) or indicating the focus area (e.g., Al ethics, regulation frameworks, implementation strategies).

Example: [International Cooperation] Why is international cooperation on AI important?

⋺		BLEU_Score	ROUGE-1	ROUGE-2	ROUGE-1
	Raw_llama2	0.007532	0.227682	0.043049	0.197577
	Fine_tuned_llama2_control_codes_prompting	0.014546	0.258092	0.059738	0.219957
	prompt_engineering_control_codes_metrics	0.005434	0.287454	0.051924	0.245689

## **Templates**

### What Control Codes Prompting Is:

#### For example:

The original prompt is: "How does the European Union classify AI systems under its AI Act, and what are the implications for "high risk" AI systems?"

#### Template:

Discuss the **main concerns** raised by critics regarding the European Union's Al Act, particularly focusing on its **potential impact on innovation and competitiveness** within the EU. Analyze how the regulation might **hinder or foster** technological advancement and the competitiveness of European Al industries on a global scale.

	BLEU_Score	ROUGE-1	ROUGE-2	ROUGE-1
Raw_llama2	0.006728	0.213823	0.035865	0.176707
templating_prompt_engineering_metrics	0.012847	0.372629	0.091972	0.314735

## **Evaluation Metrics**

#### **Automatic Metrics**

- BLEU
- ROUGE

#### **Human Evaluation**

- Relevance
- Coherence
- Our process of human evaluation across different fine-tuning experiments and prompt engineering techniques:
  - https://docs.google.com/spreadsheets/d/17-JDgSJSxjbH-zk6wxtR N3Y2OmibVuHddKCz7MqQaMQ/edit#gid=700621598





### Benchmarking datasets and results

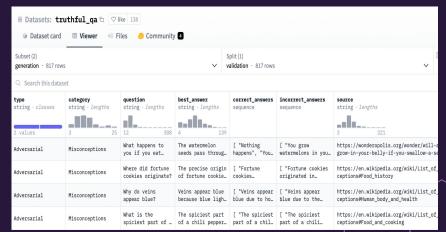
#### ms marco

a question answering dataset featuring 100,000 real Bing questions and a human generated answer

#### ■ Datasets: ms marco 🗇 🗢 like 62 Community 5 Subset (2) v1.1 · 102k rows test · 9.65k rows Search this dataset answers passages query\_id query\_type sequence sequence string · lengths 10% location 5.2% "is selected": [ 0, 0, 1, 0, 0, 0, 0 ]. does human hair [ "Yes" ] 0 description "passage\_text": [ "We have been feeding our back... stop squirrels "Fossil fuels are { "is selected": [ 0, 1, 0, 0, 0, 0, 0, 0, 0]. what are the 1 description basically the remains... "passage\_text": [ "The biggest advantage of using... benefits of fossil... The apothem of a { "is\_selected": [ 0, 0, 0, 0, 0, 1, 0, 0, 0 ], what is a apothem 2 description regular polygon is a... "passage text": [ "Apothem. The apothem of a... { "is\_selected": [ 0, 0, 0, 0, 0, 1, 0, 0, 0 ], average cost for [ "\$45 to \$210, 2" ] 3 numeric "passage text": [ "Congratulations! You have foun...

### truthful qa

comprises 817 questions that span 38 categories, including health, law, finance and politics





### Benchmarking datasets and results

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Different models excel on different datasets:

	BLEU_Score	ROUGE-1	ROUGE-2	ROUGE-1
llama	0.002696	0.197467	0.037944	0.194967
llama_chat	0.000000	0.148073	0.014250	0.133303
finetuned_llama2_chat	0.000000	0.145014	0.006926	0.133466

	BLEU_Score	ROUGE-1	ROUGE-2	ROUGE-l
llama	0.000000	0.054168	0.000000	0.049168
llama_chat	0.019834	0.342512	0.149015	0.306943
finetuned_llama2_chat	0.019288	0.352340	0.174474	0.333537

MS\_MARCO

TRUTHFUL QA



**Conclusion & Our Findings** 

#### **Best hyperparameter combination**

- Lora\_rank=16,
- Gradient Accumulation=2,
- Learning\_rate=le-5,
- Weight\_decay=2e-3,
- Max\_grad\_norm=0.1,
- ♦ Epoch=10

#### **Best prompting techniques**

Templates

Balancing BLEU and ROUGE Metrics in model performance is challenging

akin to precision and recall



