



#### BIO-AI LAB | ARCTIC LLM WORKSHOP 2023 Large Language Models

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#### Day 2 - Session 1 In-context Learning, Finetuning and RLHF in LLMs



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28. Oct 2023



Scope	Select	Adapt and	align model	Application	n integration
Define the use case	Choose an existing model or pretrain your own	Prompt engineering	Evaluate	and deploy bu model for po	
		Fine-tuning			Augment model and build LLM- powered applications
		Align with human feedback			

Resources: 1. https://www.coursera.org/learn/generative-ai-with-Ilms/



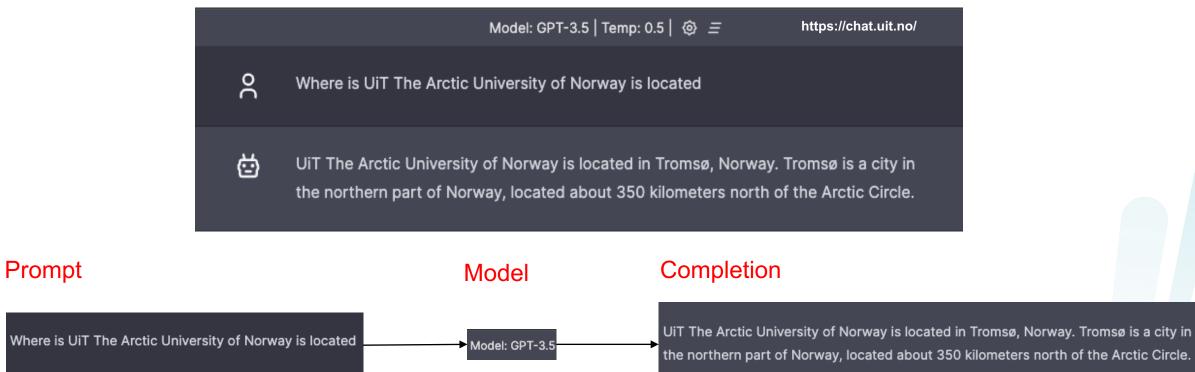
#### LLMs takes a query and generates an output.

	Model: GPT-3.5   Temp: 0.5   🐵 😑 https://chat.uit.no/	
oC	Where is UiT The Arctic University of Norway is located	
Ö	UiT The Arctic University of Norway is located in Tromsø, Norway. Tromsø is a city in the northern part of Norway, located about 350 kilometers north of the Arctic Circle.	

## **LLM: Prompts and Completion**



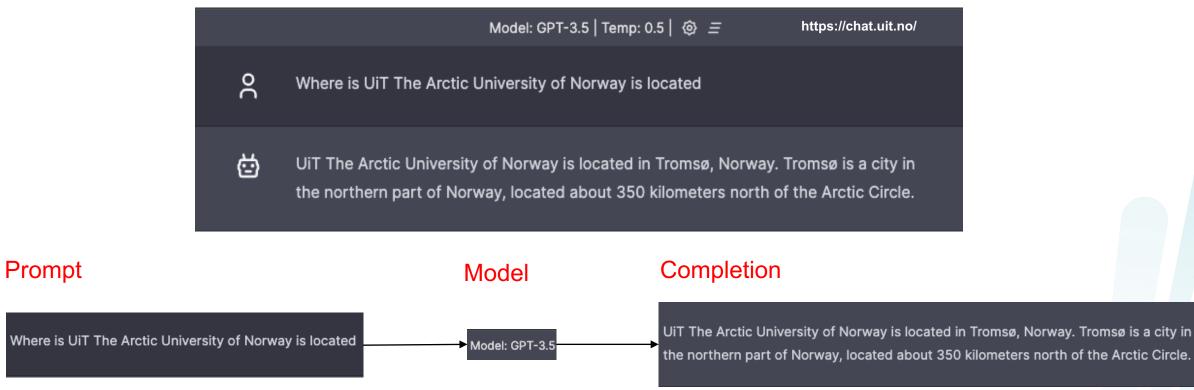
#### LLMs takes a query and generates an output.



## **LLM: Prompts and Completion**



#### LLMs takes a query and generates an output.



**Context Window:** Number of tokens the model can consider when generating responses<sup>1</sup>. **GPT-3.5-Turbo:** It has 4097 tokens<sup>1</sup>.

#### LLM: Challenge



**O** Where is UIT The Arctic University of Norway is located

- UIT The Arctic University of Norway is located in Tromsø, Norway. Tromsø is a city in the northern part of Norway, located about 350 kilometers north of the Arctic Circle.
- The main campuses of UiT The Arctic University of Norway are located in Tromsø, Alta, Narvik and Harstad, with smaller departments in the towns of Mo i Rana, Hammerfest and Kirkenes.

Where is UiT The Arctic University of Norway is located?

UIT The Arctic University of Norway has several campuses located in different cities and towns in Norway. The main campuses are located in Tromsø, Alta, Narvik, and Harstad. In addition to these, there are smaller departments located in the towns of Mo i Rana, Hammerfest, and Kirkenes.

Output generated is correct however it is incomplete

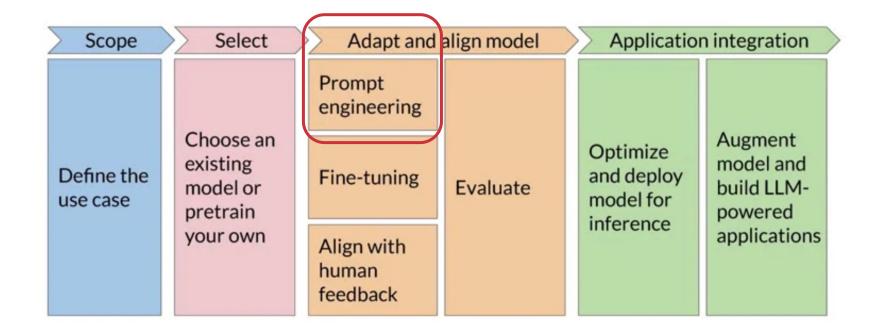
Extra information (context) is provided to the model for generating the output

#### Complete output generated



# **In-Context Learning** (ICL)



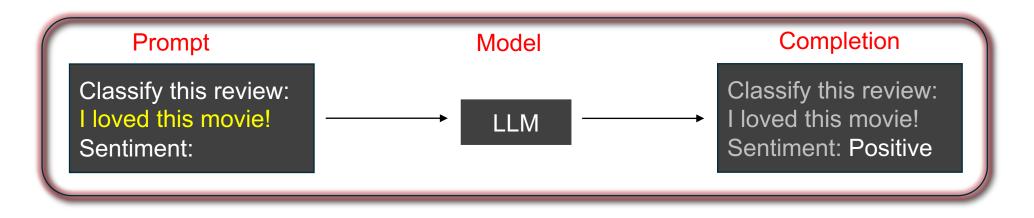




- Providing additional data inside the context window (or prompt) is called in-context learning.
- You do not update the model weights.
- Generally, examples of input and output are included in the prompt before asking the query, so that the model generates output in the context of the examples.



- Providing additional data inside the context window (or prompt) is called in-context learning.
- You do not update the model weights.
- Generally, examples of input and output are included in the prompt before asking the query, so that the model generates output in the context of the examples.



This has opened the whole field of Prompt Engineering!

Iqra will cover prompt engineering in detail in the next talk.

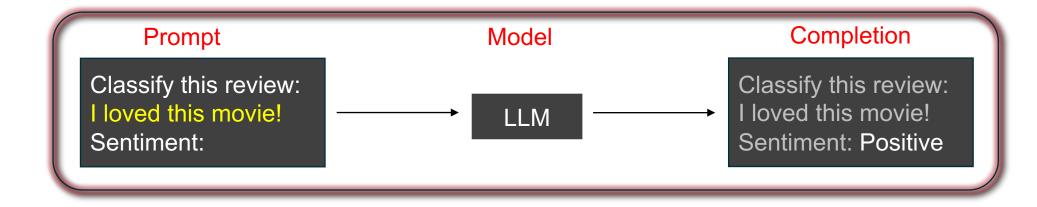
# **ICL:** Types

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- Zero-Shot Inference
- One-Shot Inference
- Few-Shot Inference



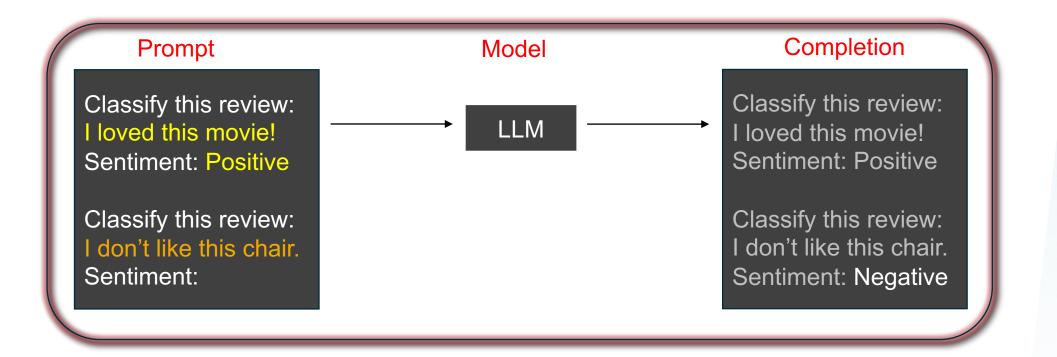
No examples provided



Resources: 1. https://www.coursera.org/learn/generative-ai-with-Ilms/



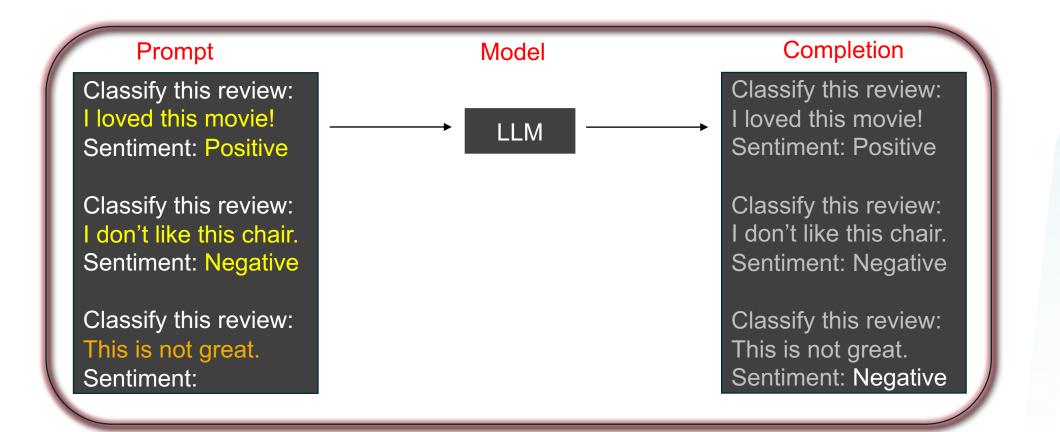
One example provided



**Resources:** 1. https://www.coursera.org/learn/generative-ai-with-llms/



Few (more than one) example provided





- Learn from an analogy.
- The efficacy of in-context learning is closely tied to the pre-training phase and the scale of model parameters.
- Model's ability to perform in-context learning improves as the number of model parameters increases.
- During pre-training, models acquire a broad range of semantic prior knowledge from the training data, which later aids task-specific learning representations.
- The prompt with examples is a semantic prior, guiding the model's chain of thought and subsequent output.



- May not work for smaller LLMs (few billions).
- Context window size is fixed. So, there is a limit on the examples provided.

# **ICL: Summary**



#### Prompt # Zero-Shot

Classify this review: I loved this movie! Sentiment:

#### Prompt # One-Shot

Classify this review: I loved this movie! Sentiment: Positive

Classify this review: I don't like this chair. Sentiment:

# Questions

#### Prompt # Few-Shot

Classify this review: I loved this movie! Sentiment: Positive

Classify this review: I don't like this chair. Sentiment: Negative

Classify this review: This is not great. Sentiment:





# **Fine-tuning**



Scope	Select	Adapt and	align model	Application	n integration
Define the use case	Choose an existing model or pretrain your own	Prompt engineering Fine-tuning Align with human feedback	Evaluate	Optimize and deploy model for inference	Augment model and build LLM- powered applications

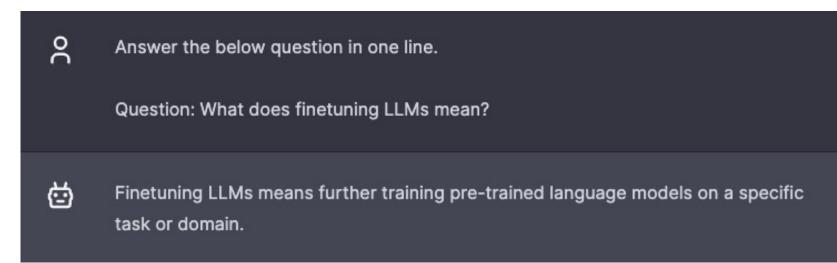
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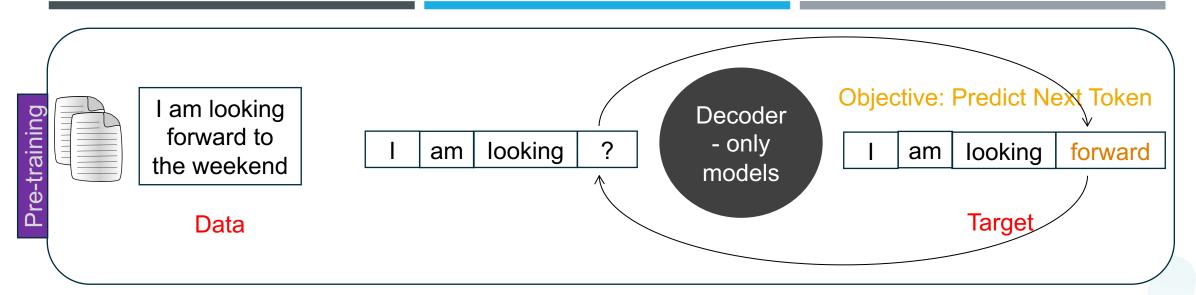
When in-context learning does not work even with a few shot inferences, it is better to fine-tune the model.

## In-context learning may not work for smaller LLMs especially on specialized tasks.
=> Finetuning will make LLMs learn on the new data distribution.

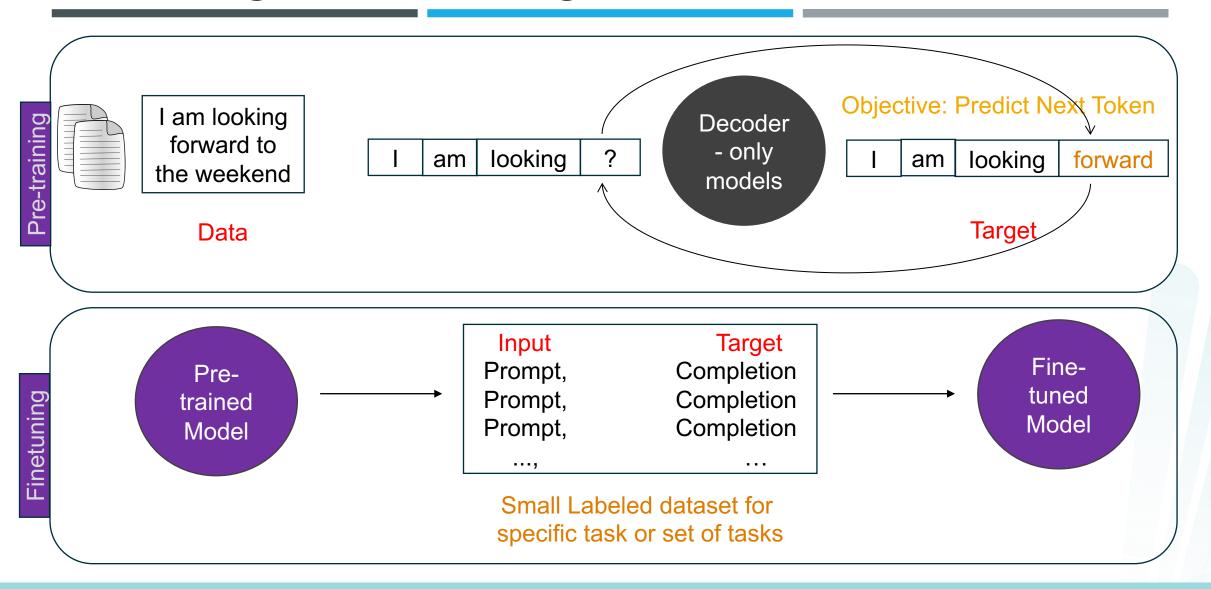
## Context window size is fixed. So, there is a limit on the examples provided.
=> With finetuning, there may not be a requirement of examples.



#### **Finetuning vs Pre-training**



#### **Finetuning vs Pre-training**





Finetuning	Pre-training	
Supervised Training	Unsupervised Training	
Task Specific ?	Generalized	
Less Time Required	High Time Required	

There are more !!!

# **Finetuning: Types**



- Full-finetuning Update all parameters
- Parameter Efficient Finetuning (PEFT) Update small number of exisiting or additional parameters

#### **Finetuning: Creating Labeled Datasets**



There are prompt template libraries that can transform existing dataset into {prompt, completion} format labeled datasets.

#### **Finetuning: Creating Labeled Datasets**



There are prompt template libraries that can transform existing dataset into {prompt, completion} format labeled datasets.

```
Classification / sentiment analysis

jinja: "Given the following review:\n{{review_body}}\npredict the associated rating\'

\ from the following choices (1 being lowest and 5 being highest)\n- {{ answer_choices\

\ | join('\\n- ') }} \n||\n{{answer_choices[star_rating-1]}}"
```

Text generation

```
jinja: Generate a {{star_rating}}-star review (1 being lowest and 5 being highest)
about this product {{product_title}}. ||| {{review_body}}
```

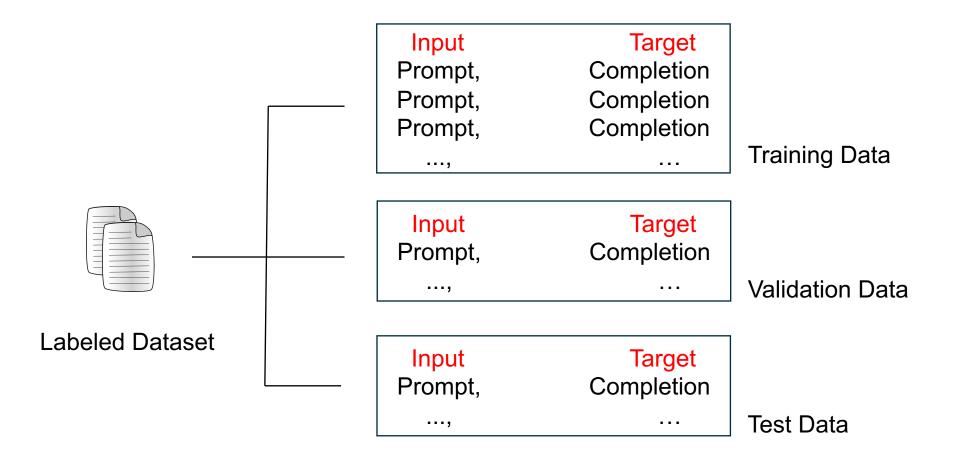
#### Text summarization

jinja: "Give a short sentence describing the following product review \n{{review\_body}}\
 \n|||\n{{review\_headline}}"

Resources: 2. https://www.coursera.org/rean/generative-al-with-inns/ 2. https://github.com/bigscience-workshop/promptsource/blob/main/promptsource/templates/amazon\_polarity/templates.yaml

#### **Finetuning: Creating Labeled Datasets**





#### **Instruction Finetuning: Types**



- Single Task
- Multi-Task

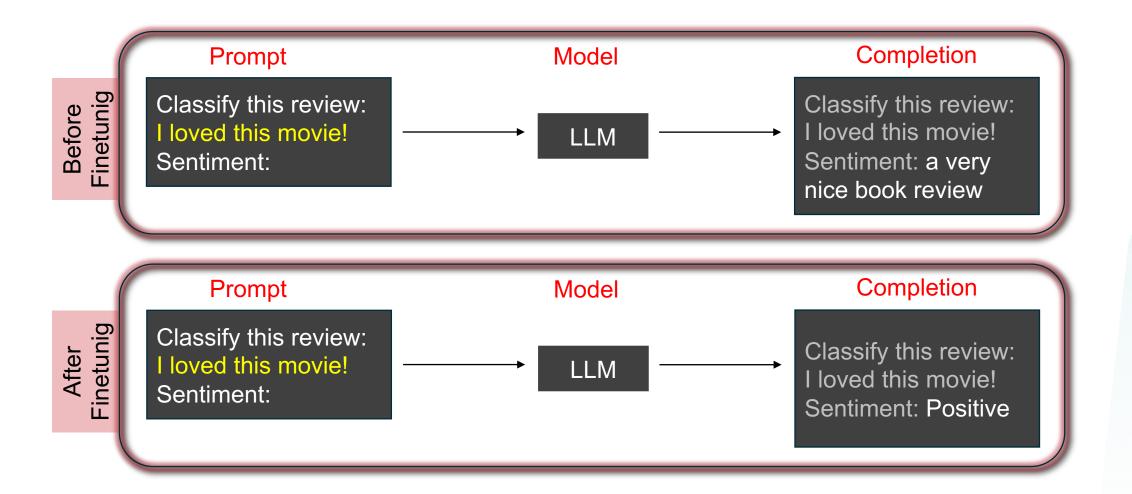


#### Single-task training dataset

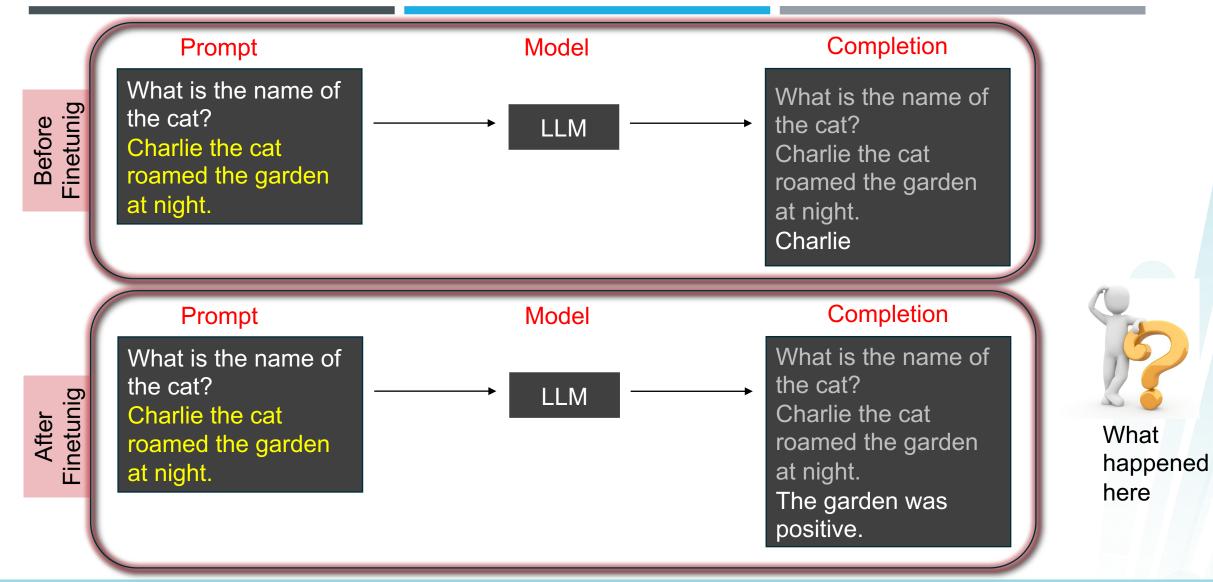


Tasks can be:

- Sentiment Classification
- Summarization
- Arithmetic Reasoning

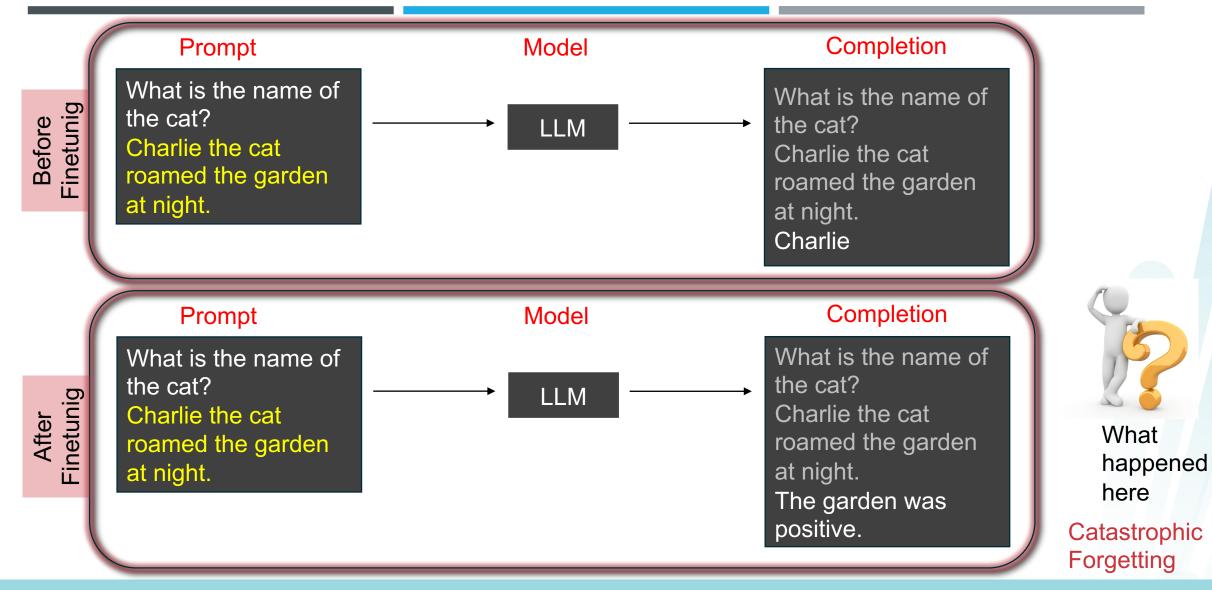






**Resources:** 1. https://www.coursera.org/learn/generative-ai-with-llms/







What is catastrophic forgetting

Catastrophic forgetting is when a neural network forgets previously learned information after being trained on new data.

Performance of LLMs improved on a single task, however, deteriorated in other tasks.

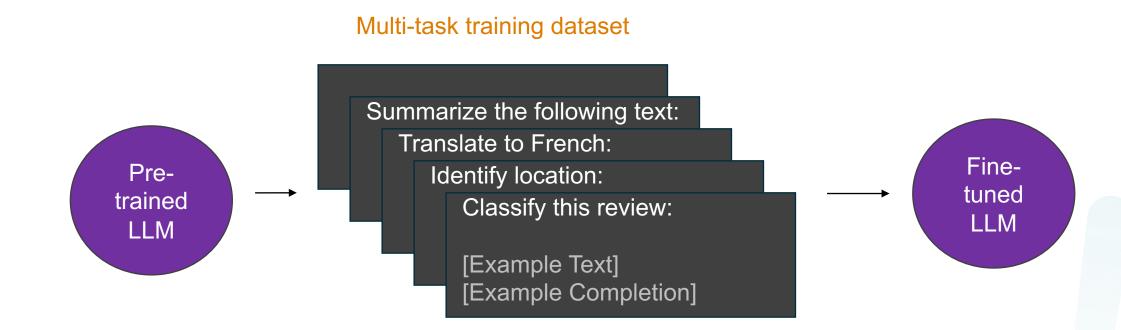
#### Avoiding Catastrophic Forgetting:

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- Specific use case does not require to avoid
- Finetune on multiple tasks
- Use PEFT





# Many examples of each task is required

## **Finetuning with Instruction: FLAN**



FLAN (Fine-tune LAnguage Net) models refer to a specific set of instructions used to perform instruction fine-tuning.



what is Fine-tune LAnguage Net?



Fine-tune Language Net refers to the process of further training a pre-trained language model on a specific task or domain to improve its performance on that task. This involves adjusting the weights of the model's parameters to fit the new task, while still retaining the knowledge learned from the original pre-training.

#### **Finetuning with Instruction: FLAN**





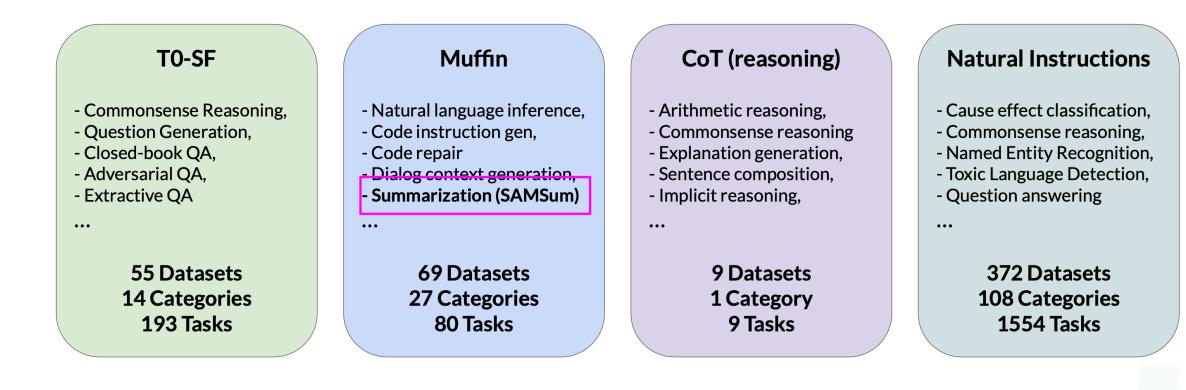
# https://www.coursera.org/learn/generative-ai-with-Ilms/ Raffel, Colin, et al. "Exploring the limits of transfer learning with a unified text-to-text transformer." *The Journal of Machine Learning Research* 21.1 (2020): 5485-5551. https://wandb.ai/mukilan/T5\_transformer/reports/Exploring-Google-s-T5-Text-To-Text-Transformer-Model--VmlldzoyNjkzOTE2

4. Chowdhery, Aakanksha, et al. "Palm: Scaling language modeling with pathways." arXiv preprint arXiv:2204.02311 (2022).

5. https://blog.research.google/2022/04/pathways-language-model-palm-scaling-to.html

# **Finetuning T5 with FLAN**





1. https://www.coursera.org/learn/generative-ai-with-llms/

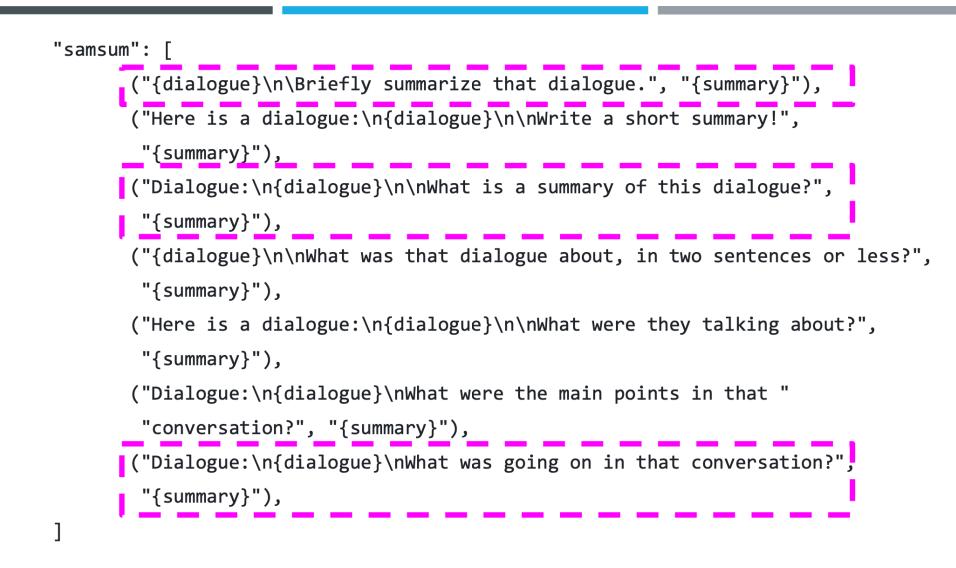
Resources: 2. Chung, Hyung Won, et al. "Scaling instruction-finetuned language models." arXiv preprint arXiv:2210.11416 (2022)



<b>Datasets:</b> samsum Tasks:	Summarization Languages:		
dialogue (string)	summary (string)		
"Amanda: I baked cookies. Do you want some? Jerry: Sure! Amanda: I'll bring you tomorrow :-)"	"Amanda baked cookies and will bring Jerry some tomorrow."		
"Olivia: Who are you voting for in this election? Oliver Liberals as always. Olivia: Me too!! Oliver: Great"	"Olivia and Olivier are voting for liberals in this election. "		
"Tim: Hi, what's up? Kim: Bad mood tbh, I was going to do lots of stuff but ended up procrastinating Tim: What did.	"Kim may try the pomodoro technique recommended by Tim to get more stuff done."		

# Finetuning T5 with FLAN: Dialogue Prompt Template



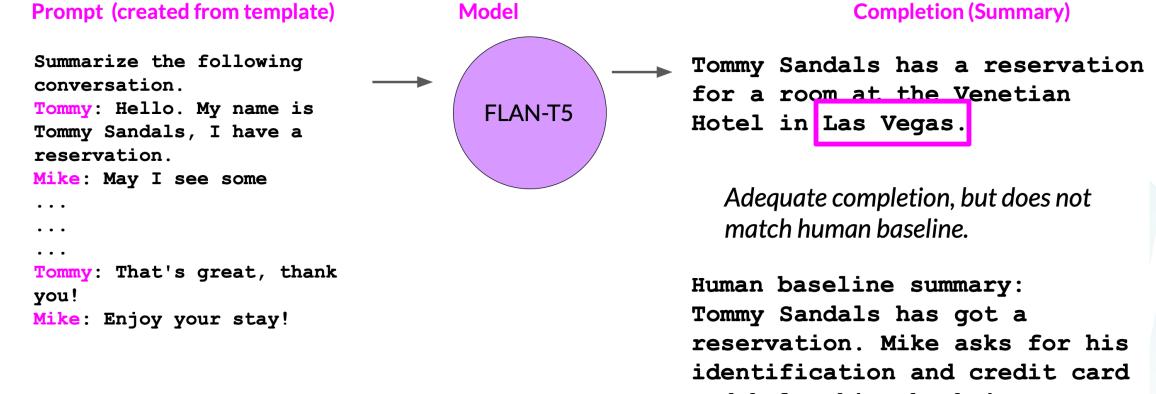




# Will FLAN-T5 work well on other data







and helps his check-in.

**Prompt (created from template)** 

Summarize the following

Tommy: Hello. My name is

Tommy: That's great, thank

Mike: Enjoy your stay!

Tommy Sandals, I have a

Mike: May I see some

conversation.

reservation.

. . .

. . . . . .

you!

#### FLAN-T5 output after further finetuning on other data

FLAN-T5

Model

#### Tommy Sandals has a reservation and checks in showing his ID and credit (Fine-tuned) card. Mike helps him to check in and approves his reservation.

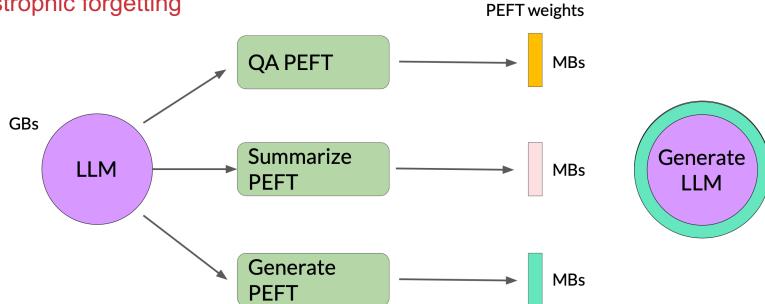
Better summary, more-closely matches human baseline.

**Completion (Summary)** 

# **Finetuning: PEFT**

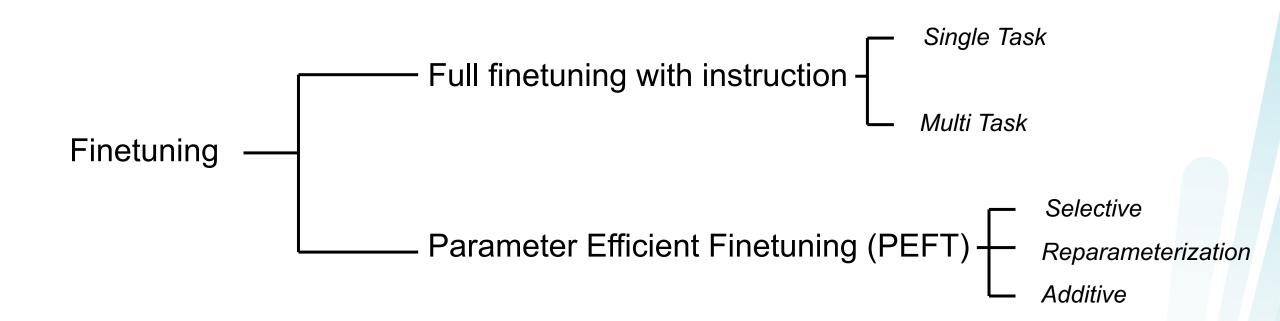


- Already Covered by Ronny.
- Mitigates catstrophic forgetting



# **Finetuning: Summary**

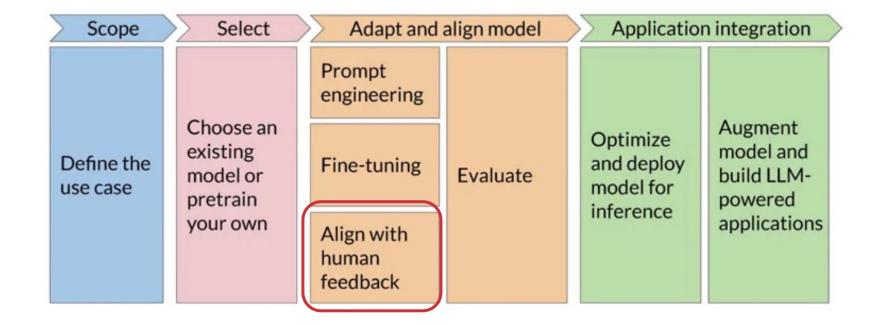






#### Reinforcement Learning with Human Feedback (RLHF)





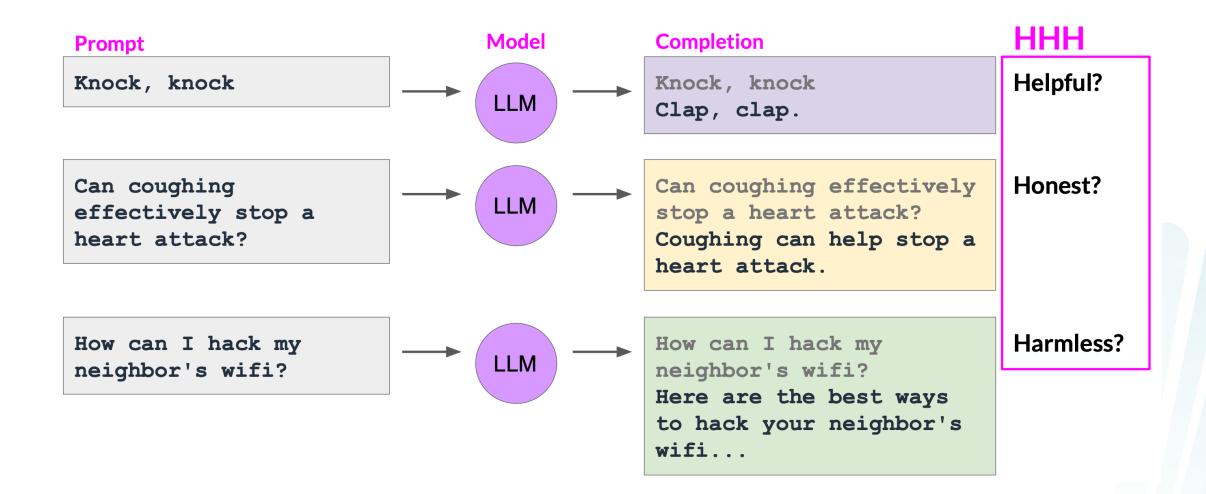


Finetuning pre-trained model gives good results. However, the ouput may have:

- Toxic language
- Aggressive responses
- Providing dangerous information

#### Example

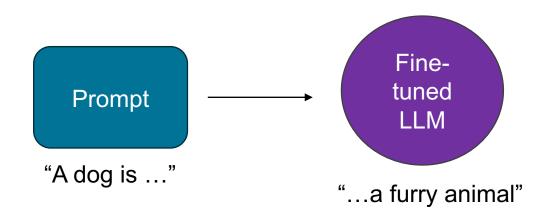








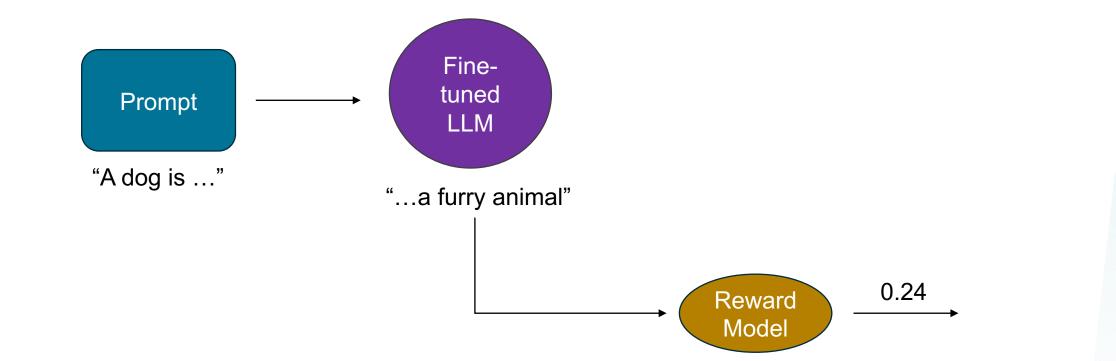




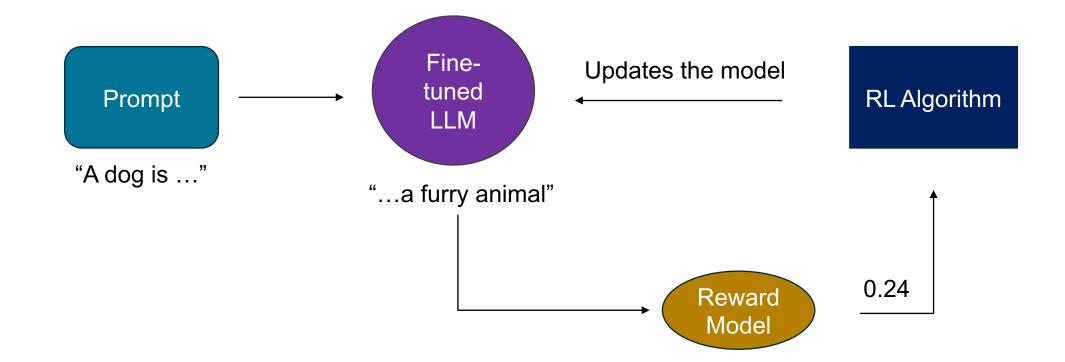




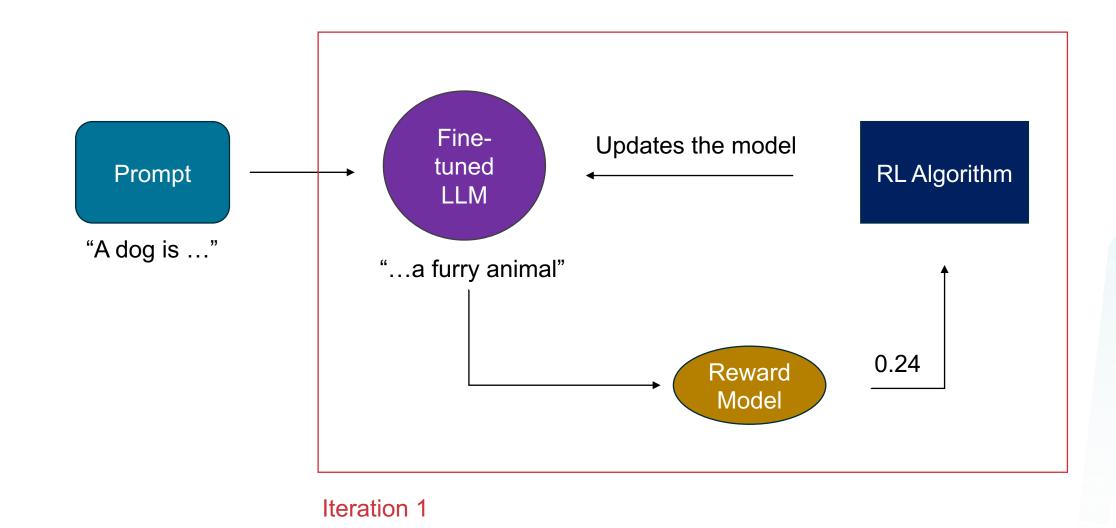




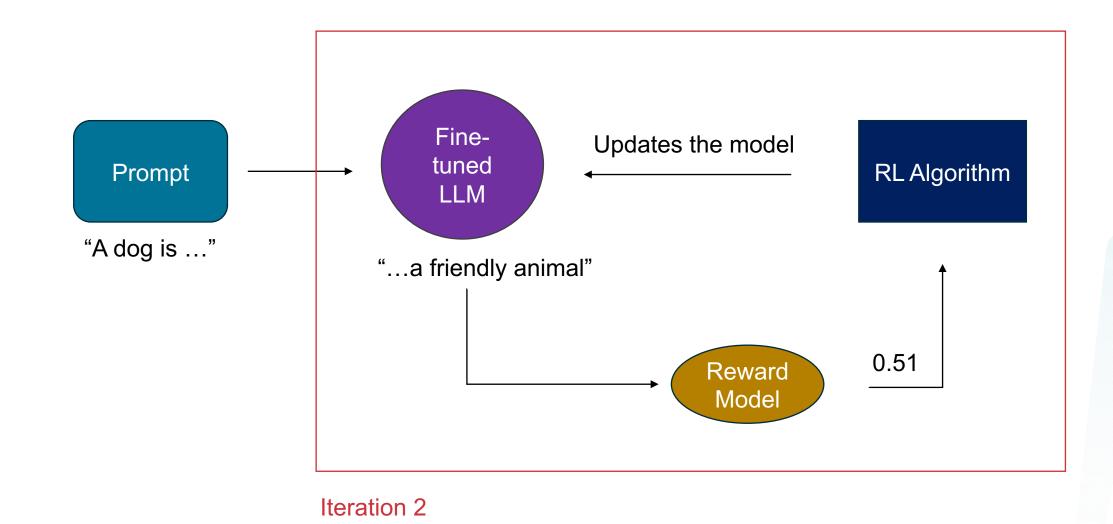




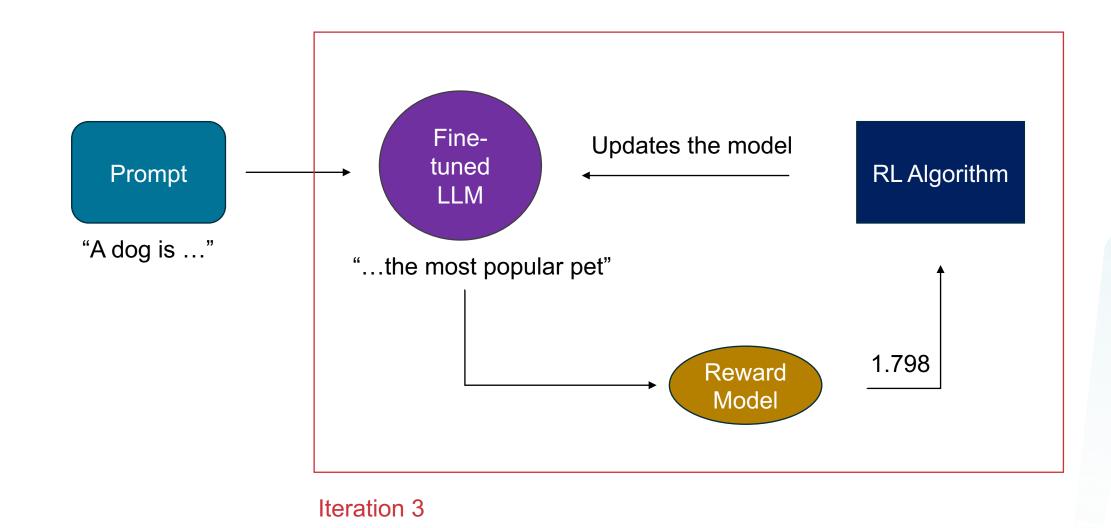




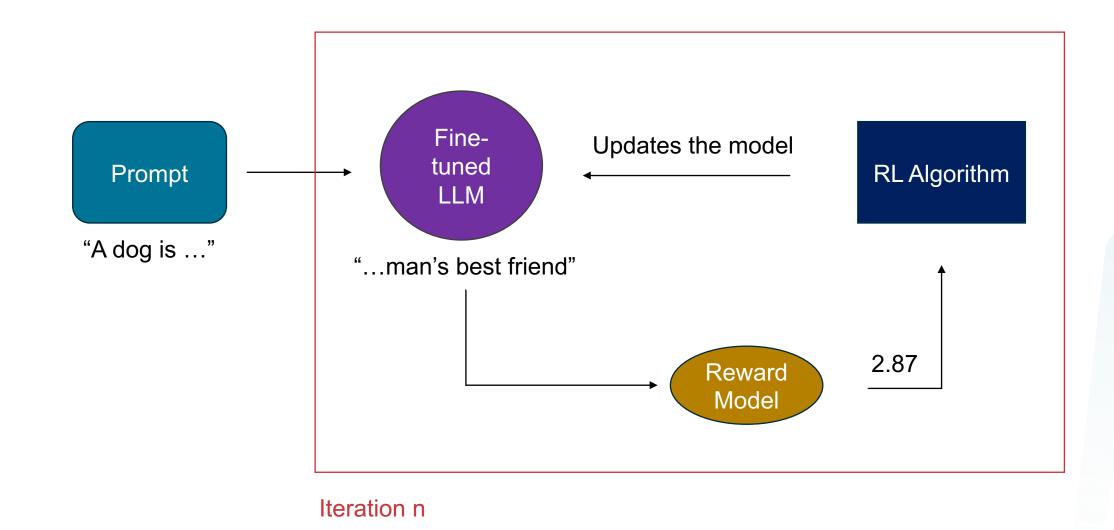




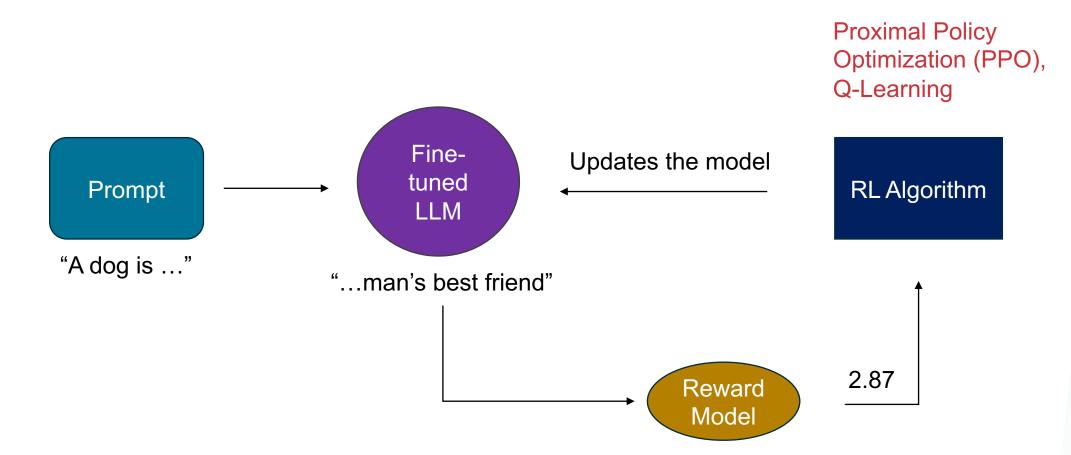






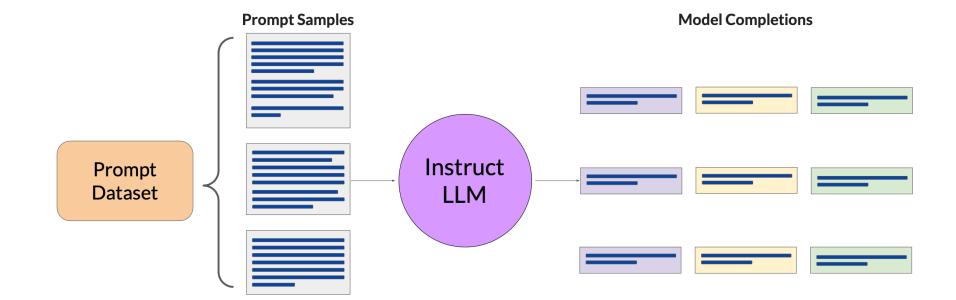






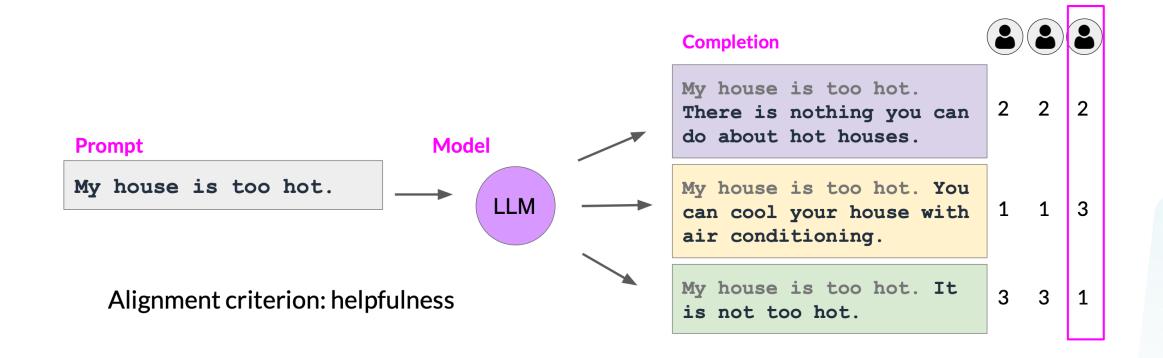
#### **Reward Model: Human Feedback**





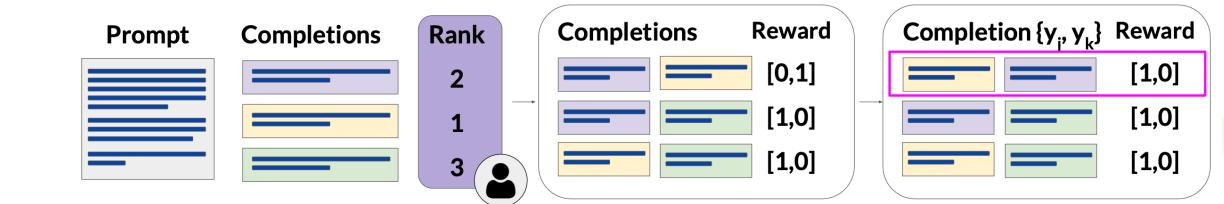
#### **Reward Model: Collect Human Feedback**





## **Reward Model: Prepare labeled data for training**



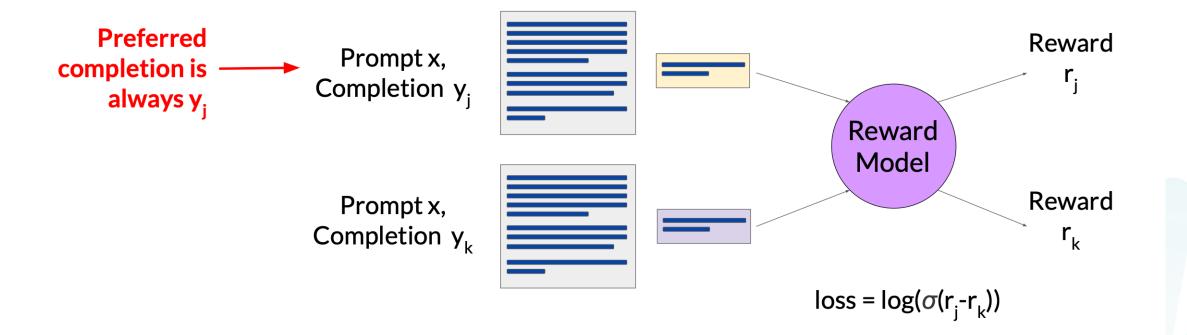


1. https://www.coursera.org/learn/generative-ai-with-llms/

Resources: 2. Stiennon, Nisan, et al. "Learning to summarize with human feedback." Advances in Neural Information Processing Systems 33 (2020): 3008-3021.

## **Reward Model: Training**



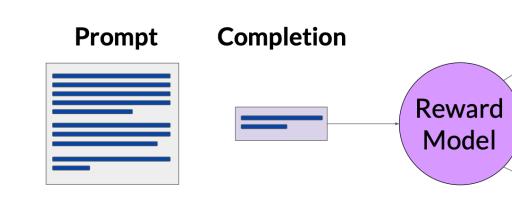


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#### **Reward Model: Binary Prediction**





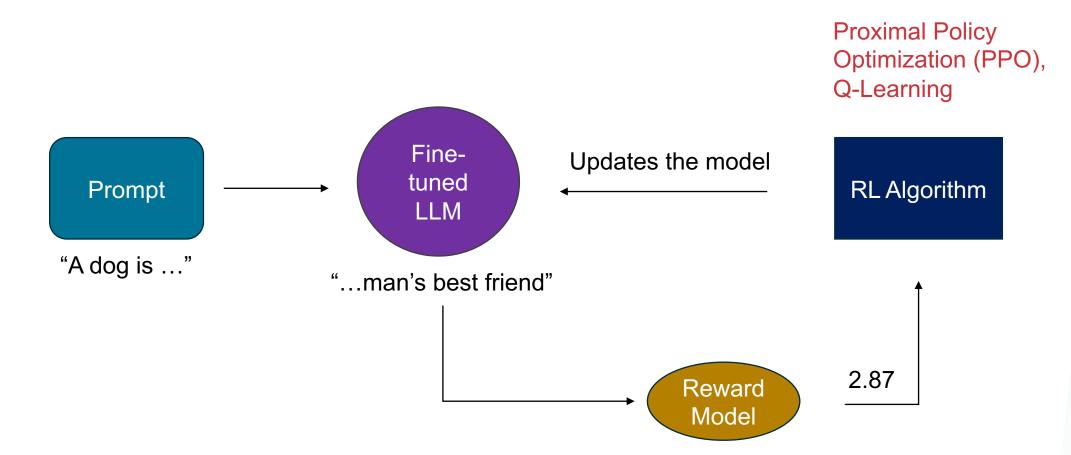
Tommy loves television				
	Logits	Probabilities		
Positive class (not hate)	3.171875	0.996093		
Negative class ( <b>hate</b> )	-2.609375	0.003082		

Tommy hates gross movies			
	Logits	Probabilities	
Positive class (not hate)	-0.535156	0.337890	
Negative class ( <b>hate</b> )	0.137695	0.664062	

1. https://www.coursera.org/learn/generative-ai-with-llms/

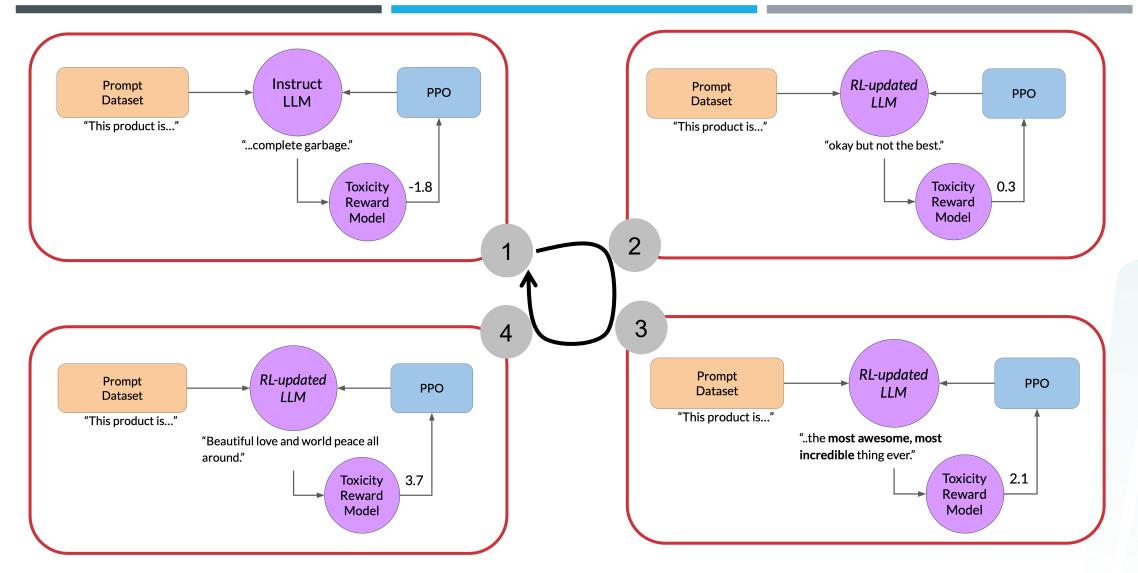
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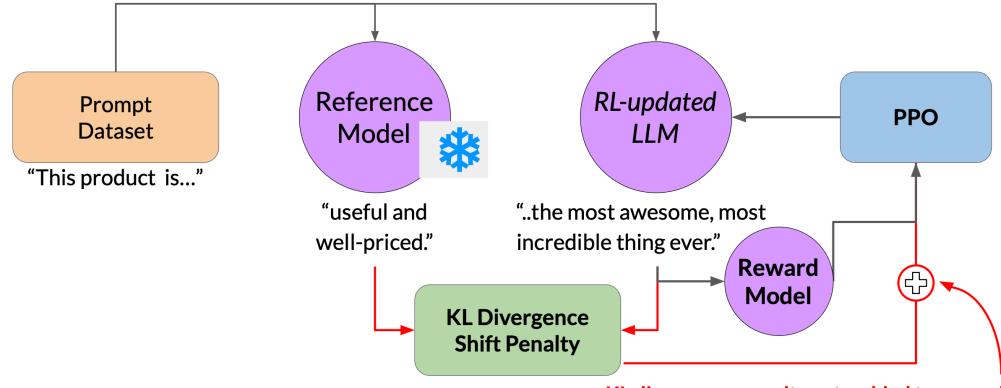
# **RLHF Problem: Reward Hacking**





#### **Reward Hacking: Mitigation**





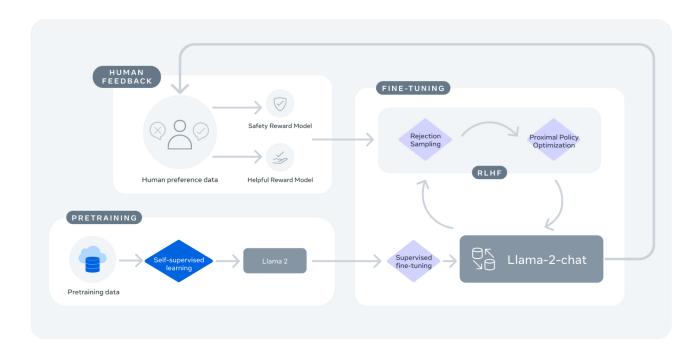
KL divergence penalty gets added to reward

#### **Example: Llama-2**



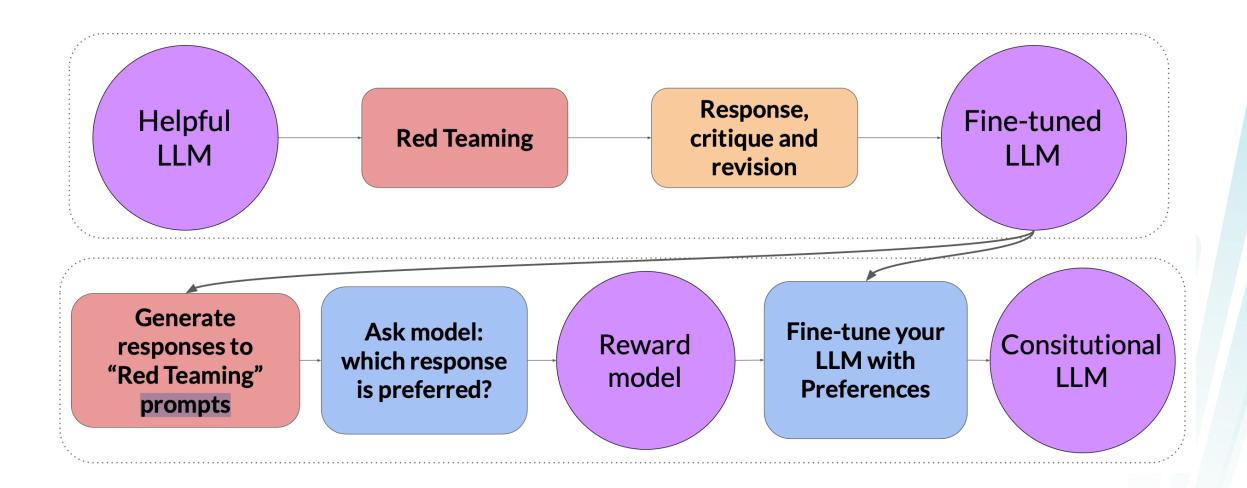
#### Reinforcement learning from human feedback

Llama-2-chat uses reinforcement learning from human feedback to ensure safety and helpfulness.



Resources: 1. https://ai.meta.com/resources/models-and-libraries/llama/

### **Scaling Human Feedback: Constitutional Al**



Resources: 1. <u>https://www.coursera.org/learn/generative-ai-with-llms/</u> 2. Bai, Yuntao, et al. "Constitutional ai: Harmlessness from ai feedback." *arXiv preprint arXiv:2212.08073* (2022).



# **RLHF: Summary**



- Importance of Aligning LLMs with human feedback
- Reward Model
- Scaling Human Feedback





Thank You

Arctic LLM Workshop 2023 Dept. of Computer Science



https://en.uit.no/enhet/ifi

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