

Alignment Learning Paradigms

Wisdom Ikezogwo

Supervised Learning

Problem:

- Data samples: X, Y
- Unknown target function: $f^*: X \rightarrow Y$
- Family of models (i.e hypothesis): $H = \{f \mid f: X \rightarrow Y\}$

Given:

- A training set of instances of the unknown target function
 - $(x^1, y^1), (x^2, y^2), \dots, (x^N, y^N)$

Goal:

- Output a function f in H that best approximates f^*

Supervised Learning

- When Y is discrete we term this a classification task
- When Y is continuous, it is a regression task
- And when it's more structured e.g. a sequence of discrete labels it can be made to various tasks e.g segmentation, or machine translation

Algorithm and Architecture Evolution:

Nearest Neighbor classifier

Support Vector Machines (SVM)

Linear classifiers

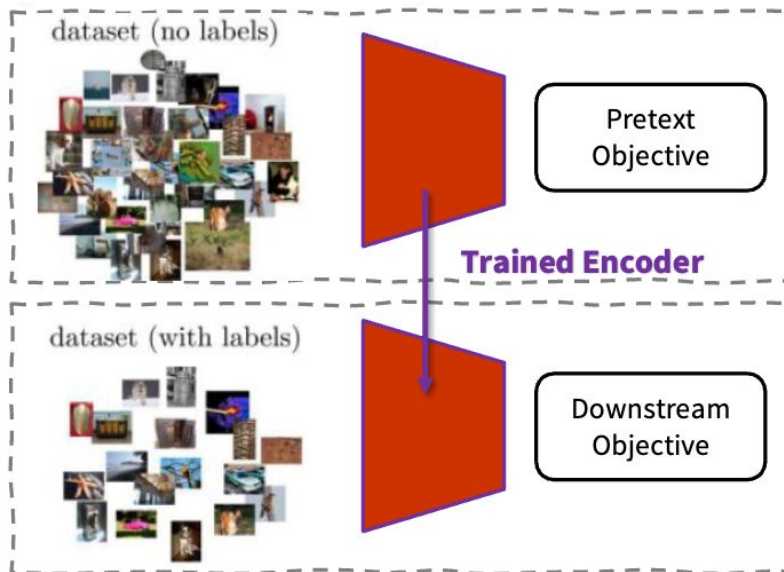
Neural networks

Convolution Neural networks

Transformers

Self-Supervised Learning

While Supervised learning learns good representations/functions for various tasks it requires collecting label data for each task (expensive) and it isn't how we learn as humans.



Pretext Task

- Define a task based on the data itself
- No manual annotation
- Could be considered an **unsupervised** task;
- but we learn with supervised learning objectives, e.g., classification or regression.

Downstream Task

- The application you care about
- You do not have large datasets
- The dataset is labeled

Self-Supervised Learning: Pretext Tasks

Generative: Predict part of the input signal

- Autoencoders (sparse, denoising, masked)
- Autoregressive
- GANs
- Colorization
- Inpainting

Discriminative: Predict something about the input signal

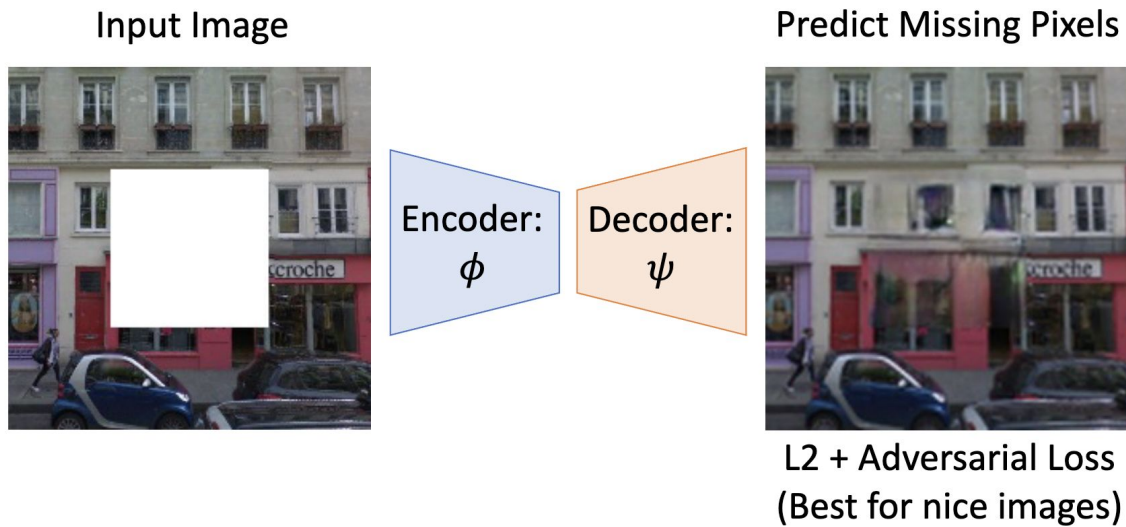
- Context prediction
- Rotation
- Clustering
- Contrastive

Multimodal: Use some additional signal in addition to RGB images

- Video
- 3D
- Sound
- Language

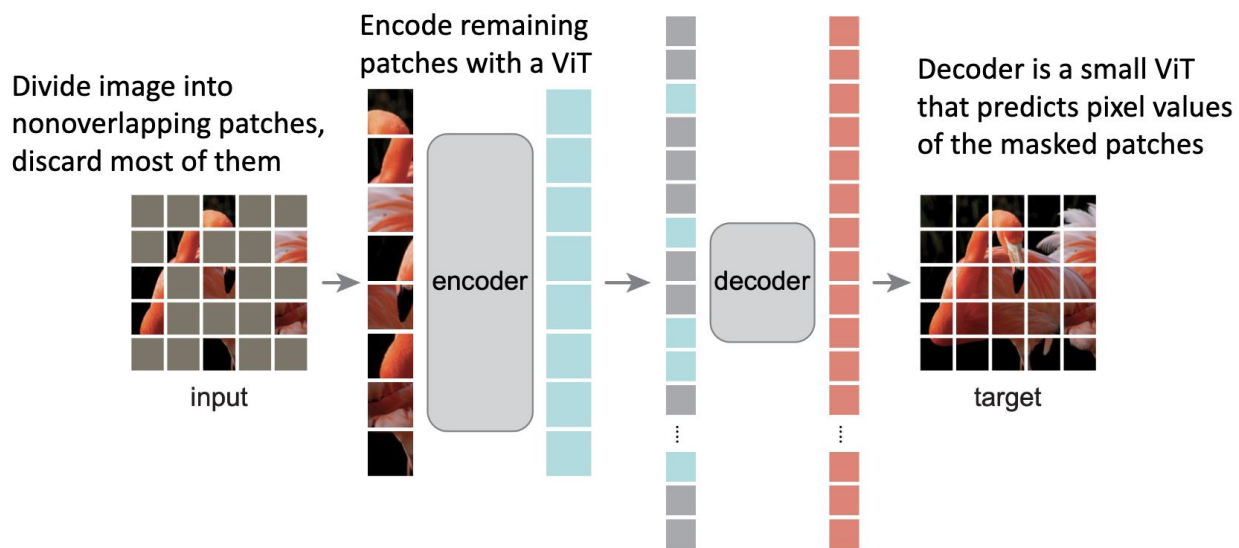
Self-Supervised Learning: Pretext Tasks

Learning by Inpainting



Self-Supervised Learning: Pretext Tasks

Learning by Masking

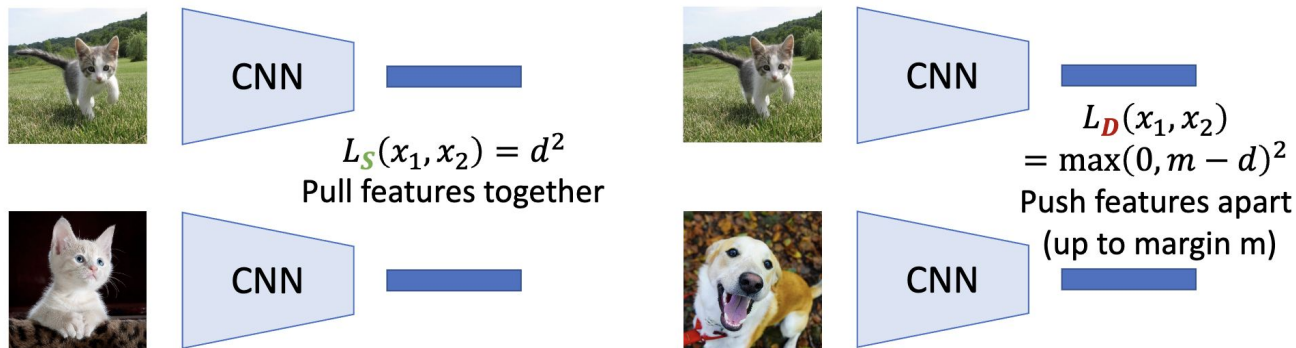


Self-Supervised Learning: Pretext Tasks

Learning contrastively

Let $d = \|\phi(x_1) - \phi(x_2)\|_2$ be the Euclidean distance between features for two images

Similar images should have similar features **Dissimilar** images should have dissimilar features



Self-Supervised Learning: Pretext Tasks

Learning contrastively

What we want:

$$\text{score}(f(x), f(x^+)) \gg \text{score}(f(x), f(x^-))$$

x : reference sample; x^+ positive sample; x^- negative sample

Given a chosen score function, we aim to learn an encoder function f that yields high score for positive pairs (x, x^+) and low scores for negative pairs (x, x^-) .

Self-Supervised Learning: Pretext Tasks

Learning contrastively

Loss function given 1 positive sample and $N - 1$ negative samples:

$$L = -\mathbb{E}_X \left[\log \frac{\exp(s(f(x), f(x^+)))}{\exp(s(f(x), f(x^+))) + \sum_{j=1}^{N-1} \exp(s(f(x), f(x_j^-)))} \right]$$

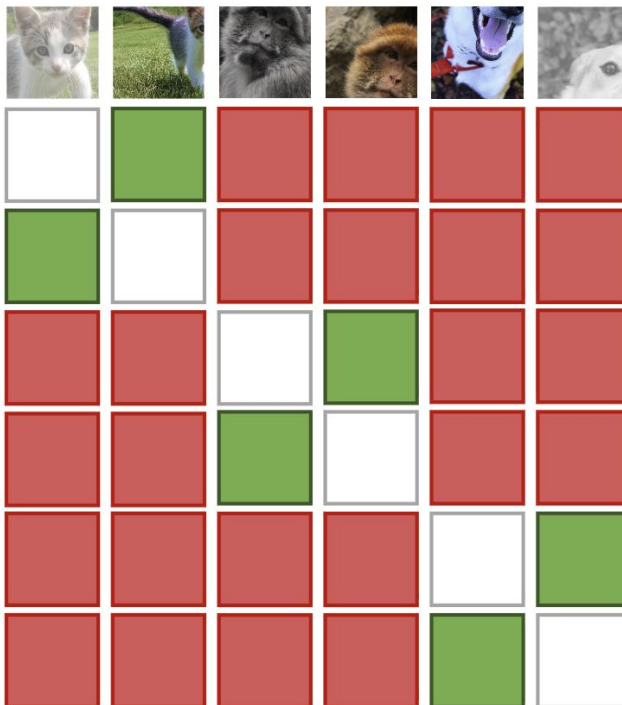
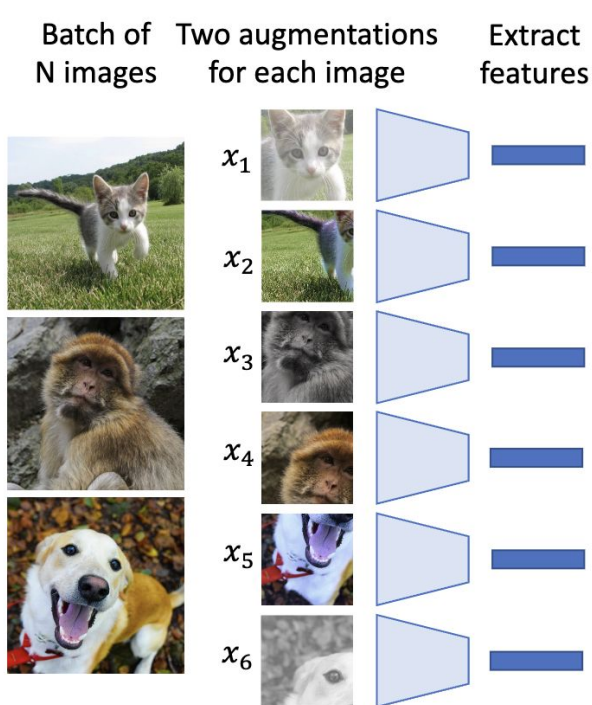
Commonly known as the InfoNCE loss ([van den Oord et al., 2018](#))

A lower bound on the mutual information between $f(x)$ and $f(x^+)$

$$MI[f(x), f(x^+)] - \log(N) \geq -L$$

The larger the negative sample size (N), the tighter the bound

Self-Supervised Learning: Contrastive methods



Each image tries to predict which of the *other* 2N-1 images came from the same original image

Similarity between x_i and x_j :

$$s_{i,j} = \frac{\phi(x_i)^T \phi(x_j)}{\|\phi(x_i)\| \cdot \|\phi(x_j)\|}$$

If (x_i, x_j) is a positive pair, then loss for x_i is:

$$L_i = -\log \frac{\exp(s_{i,j}/\tau)}{\sum_{\substack{k=1 \\ k \neq i}}^{2N} \exp(s_{i,k}/\tau)}$$

(τ is a *temperature*)

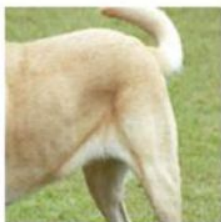
Interpretation: Cross-entropy loss over the other 2N-1 elements in the batch!

Self-Supervised Learning: Pretext Tasks

SimCLR: generating positive samples from data augmentation



(a) Original



(b) Crop and resize



(c) Crop, resize (and flip)



(d) Color distort. (drop)



(e) Color distort. (jitter)



(f) Rotate $\{90^\circ, 180^\circ, 270^\circ\}$



(g) Cutout



(h) Gaussian noise



(i) Gaussian blur

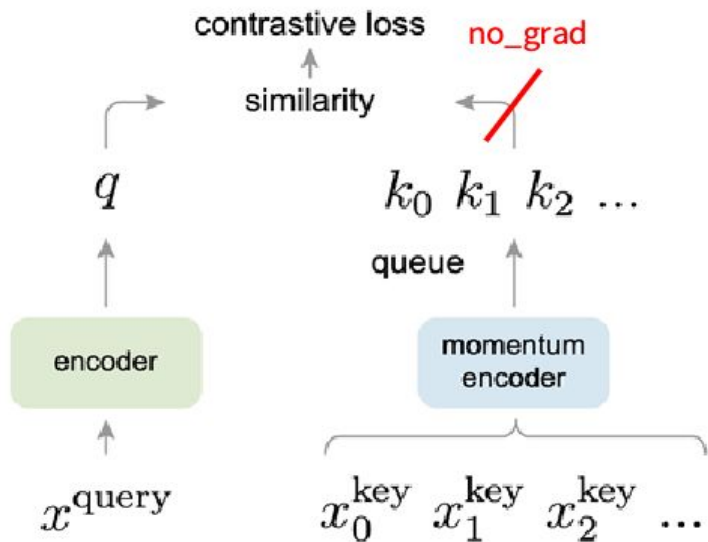


(j) Sobel filtering

Source: [Chen et al., 2020](#)

Self-Supervised Learning: Contrastive methods

Momentum Contrastive Learning (MoCo)



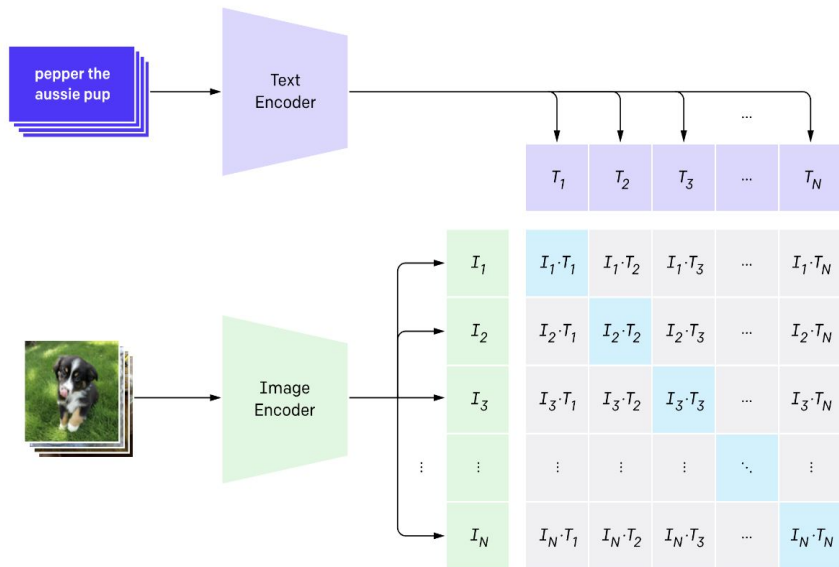
Key differences to SimCLR:

- Keep a running **queue** of keys (negative samples).
- Compute gradients and update the encoder **only through the queries**.
- Decouple min-batch size with the number of keys: can support **a large number of negative samples**.
- The key encoder is **slowly progressing** through the momentum update rules:
$$\theta_k \leftarrow m\theta_k + (1 - m)\theta_q$$

Source: [He et al., 2020](#)

Self-Supervised Learning: Pretext Tasks

Learning by Contrasting modalities



Contrastive loss: Each image predicts which caption matches

Large-scale training on 400M (image, text) pairs from the internet

1. **Semantic density:** Just a few words give rich information

2. **Universality:** Language can describe any concept

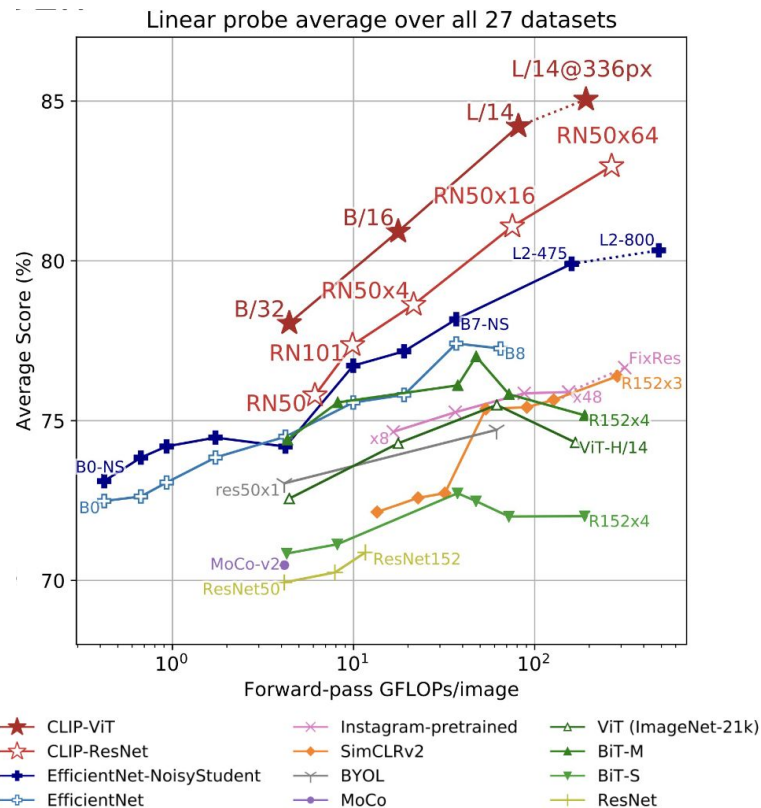
3. **Scalability:** Non-experts can easily caption images; data can also be collected from the web at scale

Self-Supervised Learning: Pretext Tasks

Learning by Contrasting modalities

Very strong performance on many downstream vision problems!

Performance continues to improve with larger models



Self-Supervised Learning: Histopathology representation learning

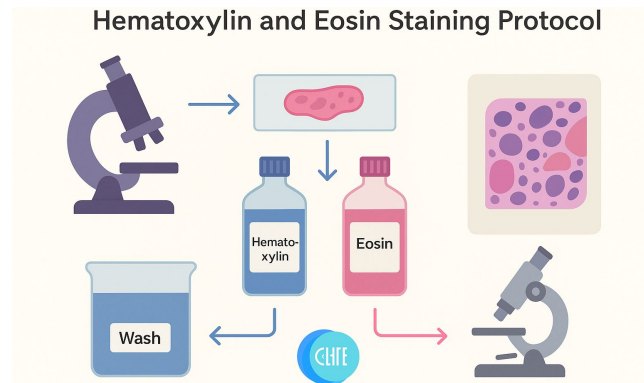
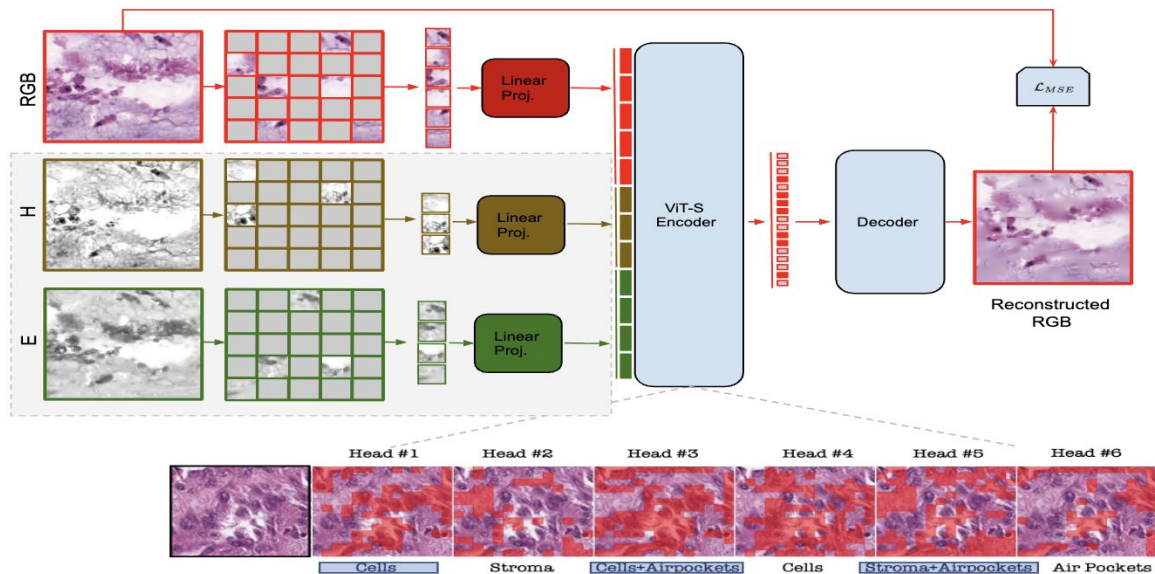
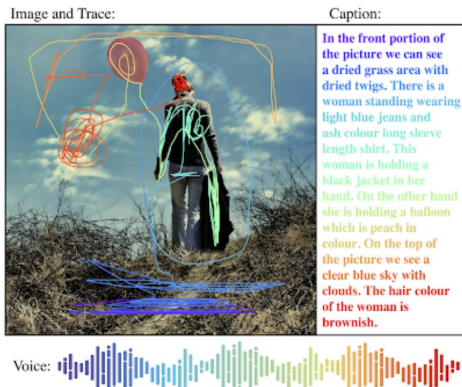


Table 1: Accuracy and PRAUC results (shown as Accuracy/PRAUC) obtained with 5-fold CV

Models	n = 100	n = 1000	n = all
DINO	89.6/91.1	92.6/95.2	84.9/93.3
MAE	92/94.6	93/95.6	88.1/94.5
MMAE	92.3/94.1	93.3/96	88.4/94.8

Histopathology image-text understanding

Normal scale



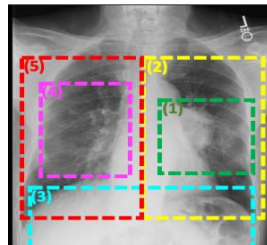
Dataset size:

10^{11} (e.g LAION)

Grounding and metadata:



Normal scale

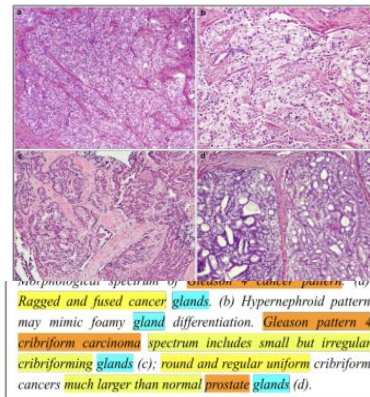


(1) A mass is present in the superior segment of the left lower lobe and therefore malignancy must be considered. (2) Elsewhere, the left lung appears clear. (3) There is no pleural effusion. (4) Calcified pleural plaque is present in the right mid zone. (5) The right lung appears clear.

10^6 (MIMIC)



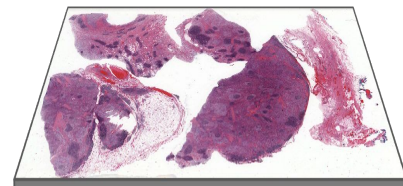
Normal scale



10^3 (ArCH)



Giga-Pixel (TCGA)



SURGICAL PATHOLOGY REPORT

FINAL DIAGNOSIS:

1. Left temporal parietal tumor: Anaplastic astrocytoma, grade III of IV (WHO scale), see microscopic description, SEE NOTE

Comment:

The proliferation index of 7.2% is within the expected range for an anaplastic astrocytoma, grade III.

This diagnostic report has been personally interpreted by the signatory of record.

Microscopic Description:

The tumor consists of a moderately pleomorphic and highly infiltrative proliferation of astrocytes. There are rare mitoses. There is no endothelial proliferation or necrosis. Immunohistochemistry for the proliferation antigen ki67 was performed as follows: Ten 250 x 250 micron fields were counted and the percentage of labeled nuclei determined. Over 1,000 cells were counted. The proliferation index ranged from 4.4% to 17.5% with an

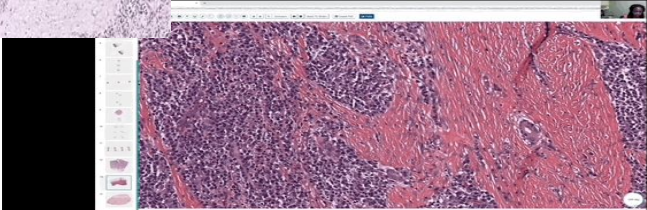
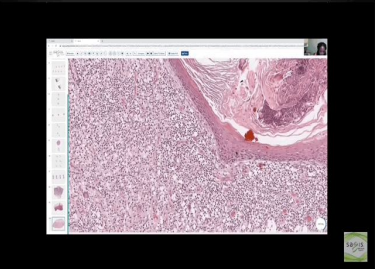
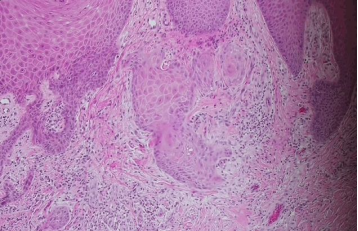
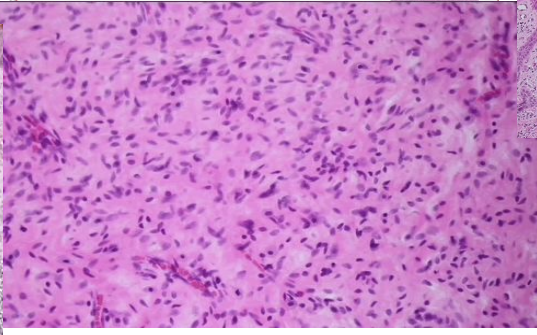
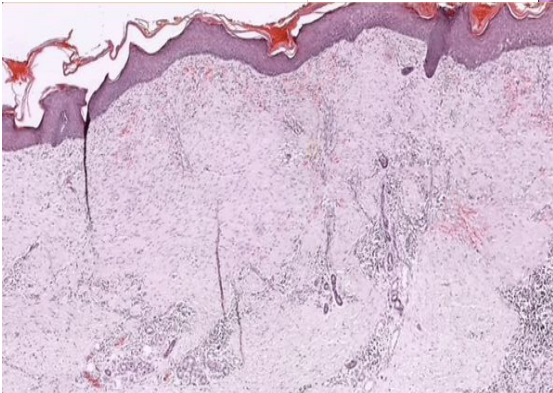
10^4 (TCGA)



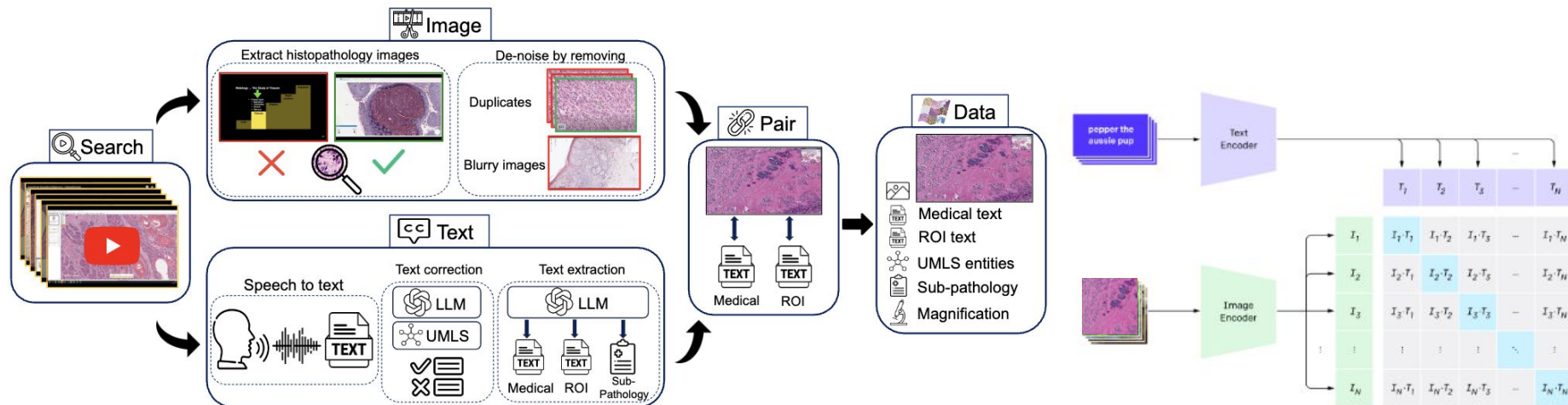
Free Lunch: Educational Histopathology Videos



Project	Image	Annotations	Hierarchy	Workflow
Name				
Background	255 255 255			
Pixel width	0.2525 µm			
Pixel height	0.2525 µm			
Width	131472 px (33196.68 µm)			
Pyramid	1 4 16 64			
Uncompressed size	33.6 GB			
Dimensions (CZT)	3 x 1 x 1			
Magnification	40.0			
Height	91388 px (23075.47 µm)			
Image type	Brightfield (H&E)			
Stain 2	Eosin 0.218 0.031 0.558			
URL	file:///C:/uhc/projects/paths/roba...			
Stain 1	Hematoxylin 0.651 0.701 0.29			
Metadata changed	No			
Server type	OpenSlide			
Stain 3	FastRed 0.370 0.308 0.737			
Pixel type	uint8 (rgb)			
Name	USFT-00-0003-012-00-DX1.SFT-Q...			
thumbnail				



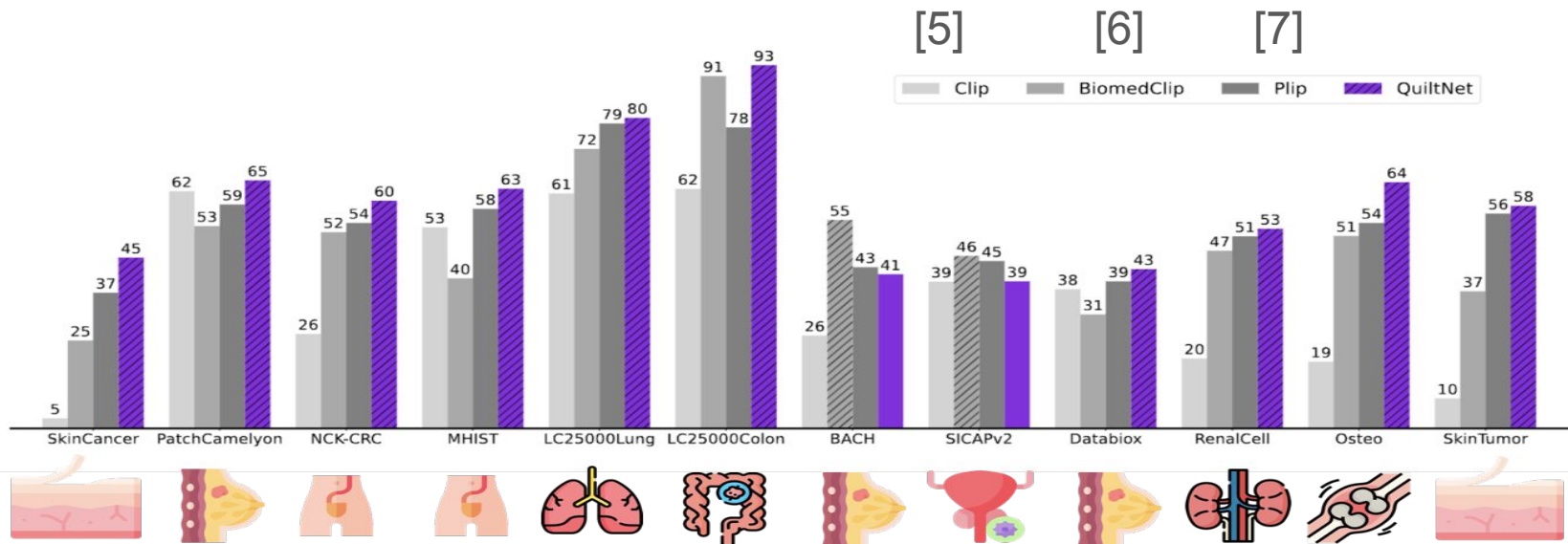
Self-Supervised Learning: Histopathology image understanding



How well does training on Quilt-1M work ?



- Zero-Shot Classification



[5] Radford, Alec, et al. "Learning transferable visual models from natural language supervision." *International conference on machine learning*. PMLR, 2021.

[6] Zhang, Sheng, et al. "Large-scale domain-specific pretraining for biomedical vision-language processing." *arXiv preprint arXiv:2303.00915* 2.3 (2023): 6.

[7] Huang, Zhi, et al. "A visual-language foundation model for pathology image analysis using medical twitter." *Nature medicine* 29.9 (2023): 2307-2316.

Results and Evaluation: Results

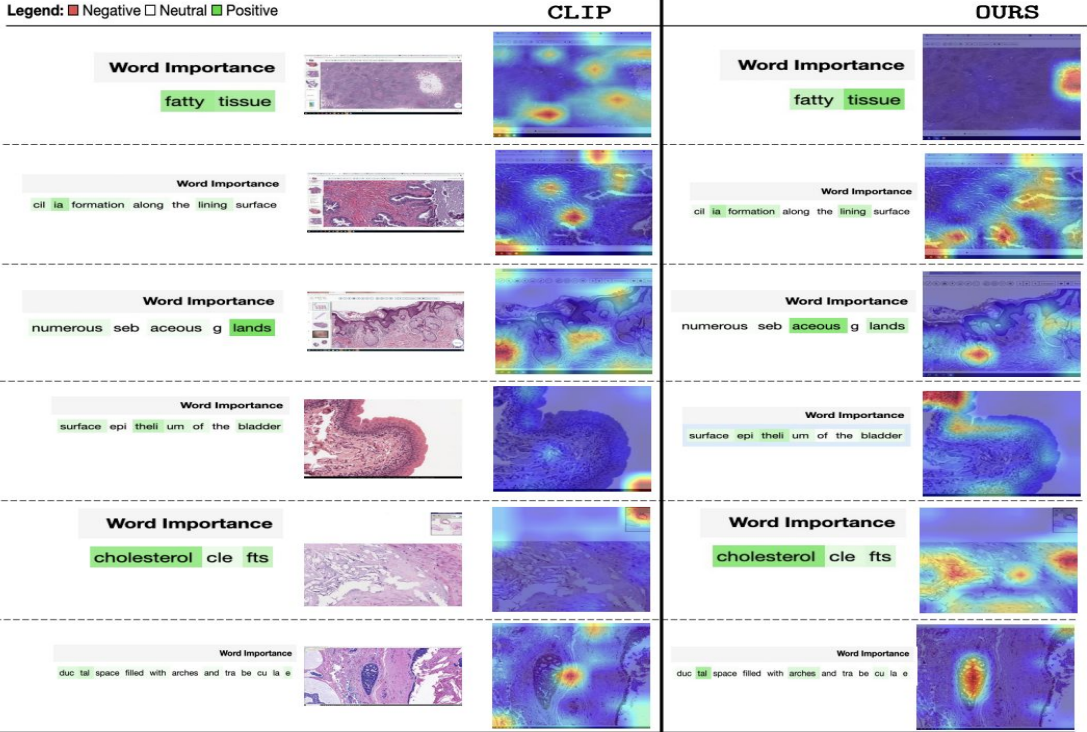


- Zero-Shot Retrieval

model	config	Text-to-Image (%)			Image-to-Text (%)		
		R@1	R@50	R@200	R@1	R@50	R@200
CLIP	ViT-B/32IGPT/77	0.49/0.07	4.73/2.42	10.15/7.21	0.39/0.05	3.99/2.52	8.80/7.22
PLIP	ViT-B/32IGPT/77	1.05/0.56	10.79/13.10	21.80/29.85	0.87/0.74	11.04/13.75	21.63/29.46
QUILTNET	ViT-B/32IGPT/77	1.17/1.41	16.31/19.87	31.99/39.13	1.24/1.35	14.89/19.20	28.97/38.57
CLIP	ViT-B/16IGPT/77	0.83/0.09	5.63/2.73	11.26/8.72	0.66/0.13	5.02/3.09	10.82/9.04
QUILTNET	ViT-B/16IGPT/77	2.42/1.29	22.38/20.30	41.05/40.89	2.00/1.01	21.66/16.18	39.29/34.15
BiomedCLIP	ViT-B/16(224)IPMB/256	4.34/ 8.89	14.99/53.24	25.62/71.43	3.88/ 9.97	13.93/52.13	23.53/68.47
QUILTNET	ViT-B/16(224)IPMB/256	6.20/8.77	30.28/55.14	50.60/77.64	6.27/9.85	31.06/53.06	50.86/73.43

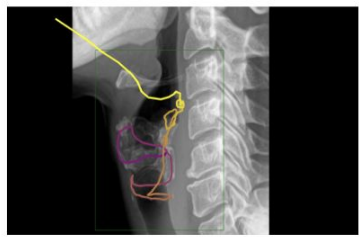
Table 2: Cross-modal retrieval results on QUILT and ARCH datasets (bold is best) In every cell the left value shows results obtained for QUILT-1M holdout set and the value on the right shows the results for ARCH dataset.

Results and Evaluation: Visualization



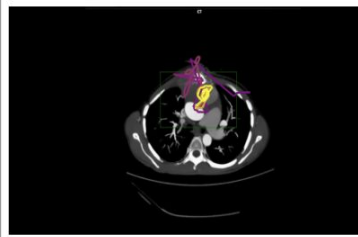
Enter, MedicalNarratives.

XRAY



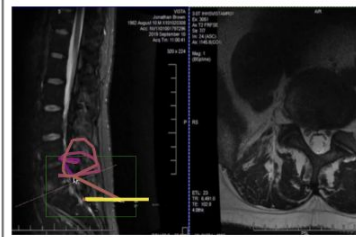
['Laryngeal and thyroid cartilage calcifications, cricoid cartilage, arytenoid cartilage, and corniculate cartilage are present.', 'Large density anterior to the neck is physiological calcification']

CT



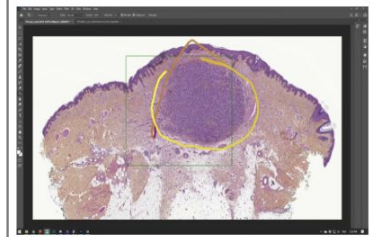
['Traumatic pseudoaneurysm in the mediastinum, not an aneurysm. Blood collecting within the mediastinum']

MRI



['The scan shows disc degeneration in the patients lower back, which may be related to the pain he is experiencing.', 'IDD therapy is being used to traction out the discs.']

HISTOPATHOLOGY



['Description of an intradermal nodule with large spindle and epithelial cells, nuclear cytoplasmic atypia, and multinucleated cells', 'Direct invasion of adjacent dermis without immune reaction.']



ULTRASOUND



['A large mass growing out of the left wall of the bladder is observed.', 'The mass has a polyploid appearance with frond-like margin']

DENTAL



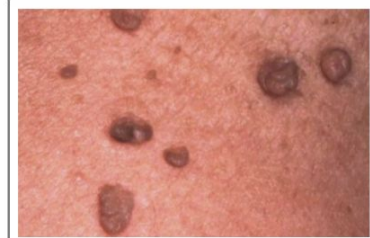
['The patient is a 14-year-old with four developing third molars and limited space. Wisdom teeth removal is recommended.']

OPHTHALMOLOGY



['Dense vitreous can make it difficult to see details inside the eye.', 'Posterior vitreous detachment can suddenly make dense vitreous noticeable.']

DERMATOLOGY



['Skin tags usually vary in size from about two to six millimeters', 'Multiple skin tags may be associated with diabetes.']

Medical Narratives Samples



Transcript

Here is the third ventricle, foramen of Monroe, coming down into the **fourth** ventricle over here. We have our normal basal cisterns, this star shape. These are our basal cisterns, and there's no blood in them, and they are patent. Lastly, we'll look at our vascular structures, a little difficult to evaluate on a non-contrast enhanced exam, but we can get a rough look at them. So here are your vertebral arteries, and they're going to join to become a basilar artery, which is

Medical Text

['Describing the anatomy of the brain including the third ventricle, foramen of Monroe, and fourth ventricle.', 'Normal basal cisterns are visible and patent.']

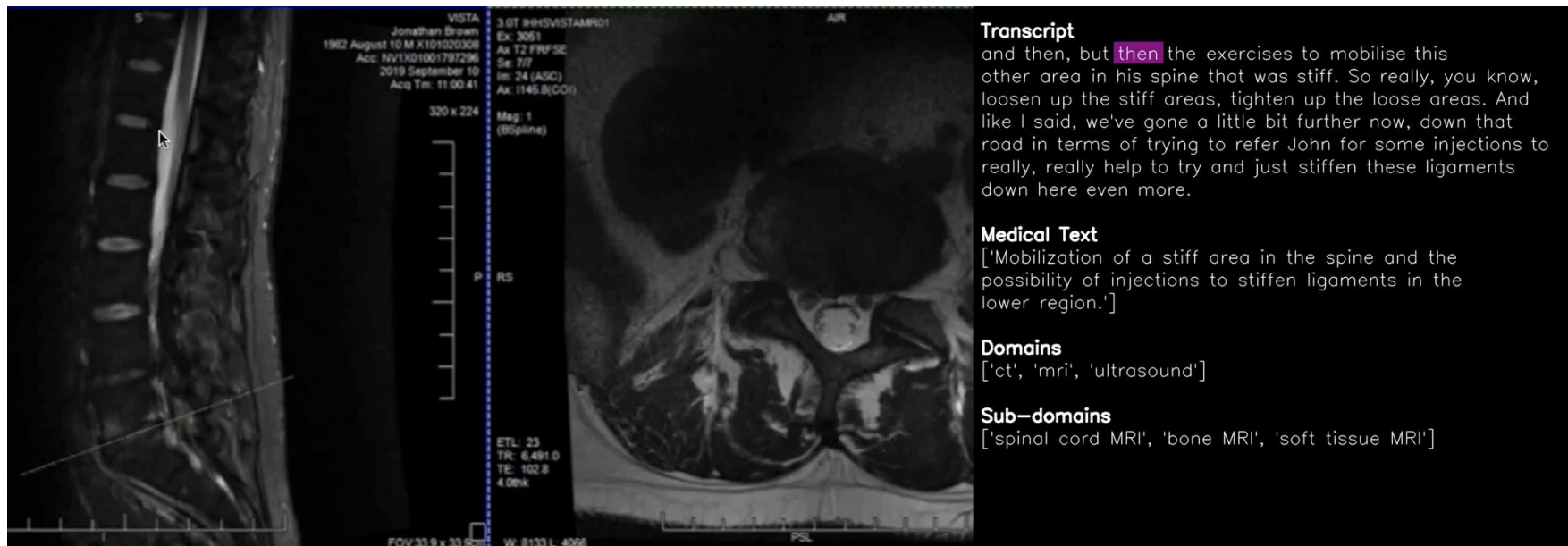
Domains

['ct']

Sub-domains

['head CT', 'sequential CT', 'spiral CT']

Medical Narratives Samples (paired views)



MedicalNarratives Samples



Medical Text
[Cricoid cartilage, the arytenoid cartilage, and the corniculate cartilage. On this example, we can see a large density anterior to the neck. And this is also normal physiologic calcification. On this patient, you can see very prominent, yet normal, thyroid cartilage, laryngeal cartilage calcification. Now,

Medical Text
[‘Laryngeal and thyroid cartilage calcifications, cricoid cartilage, arytenoid cartilage, and corniculate cartilage are present.’, ‘Large density anterior to the neck is physiological calcification.’, ‘Prominent yet normal thyroid cartilage and laryngeal cartilage are observed.’]

Domains
[‘xray’]

Sub-domains
[‘neck xray’, ‘spine xray’, ‘extremities xray’]

Data Driven Supervised Finetuning

Large scale pretraining of LMs produce really strong models but are not aligned with User Intent.

PROMPT *Explain the moon landing to a 6 year old in a few sentences.*

COMPLETION GPT-3

Explain the theory of gravity to a 6 year old.

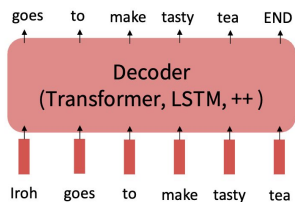
Explain the theory of relativity to a 6 year old in a few sentences.

Explain the big bang theory to a 6 year old.

Explain evolution to a 6 year old.

Step 1: Pretrain (on language modeling)

Lots of text; learn general things!



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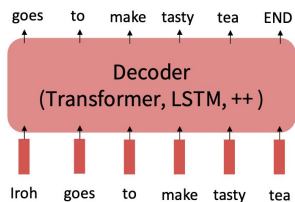
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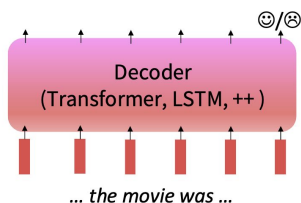
Step 1: Pretrain (on language modeling)

Lots of text; learn general things!



Step 2: Finetune (on your task)

Not many labels; adapt to the task!



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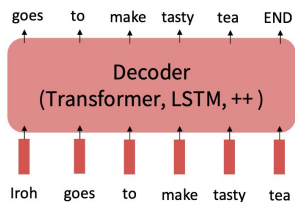
PROMPT *Explain the moon landing to a 6 year old in a few sentences.*

COMPLETION **Human**

A giant rocket ship blasted off from Earth carrying astronauts to the moon. The astronauts landed their spaceship on the moon and walked around exploring the lunar surface. Then they returned safely back to Earth, bringing home moon rocks to show everyone.

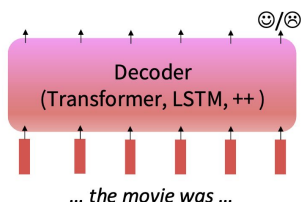
Step 1: Pretrain (on language modeling)

Lots of text; learn general things!



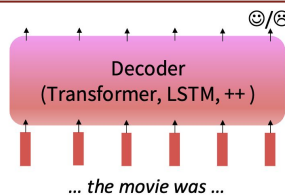
Step 2: Finetune (on your task)

Not many labels; adapt to the task!



Step 2: Finetune (on many tasks)

Not many labels; adapt to the tasks!



Data Driven Supervised Finetuning: Instruction Tuning

Model input (Disambiguation QA)

Q: In the following sentences, explain the antecedent of the pronoun (which thing the pronoun refers to), or state that it is ambiguous.

Sentence: The reporter and the chef will discuss their favorite dishes.

Options:

- (A) They will discuss the reporter's favorite dishes
- (B) They will discuss the chef's favorite dishes
- (C) Ambiguous

A: Let's think step by step.

Before instruction finetuning

The reporter and the chef will discuss their favorite dishes.

The reporter and the chef will discuss the reporter's favorite dishes.

The reporter and the chef will discuss the chef's favorite dishes.

The reporter and the chef will discuss the reporter's and the chef's favorite dishes.

✘ (doesn't answer question)

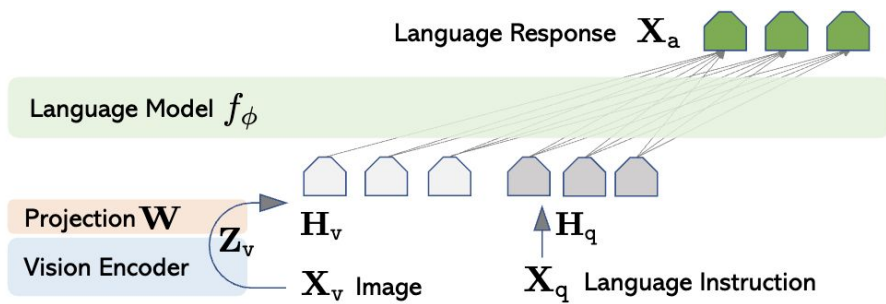
After instruction finetuning

The reporter and the chef will discuss their favorite dishes does not indicate whose favorite dishes they will discuss. So, the answer is (C). ✔

- You don't need many samples to instruction tune [[LIMA](#)]

Data Driven Supervised Finetuning

We can now combine a language model with a vision encoder (e.g clip vision tower)



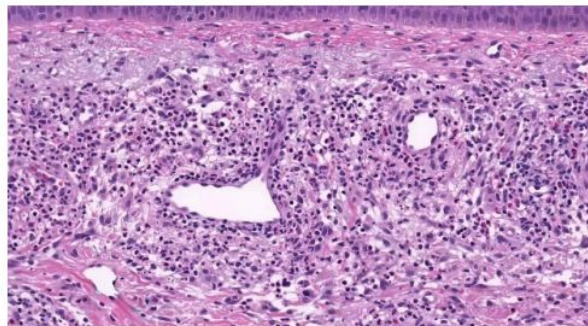


QUILT-LLaVA: Visual Instruction Tuning by Extracting **Localized Narratives** from Open-Source Histopathology Videos

Tackling generation and Localization

W UNIVERSITY *of* WASHINGTON

Can we enable reasoning toward diagnosis?



User: Can you provide a concise description of the histopathology image shown?



Quilt-LLaVA: Upon examination of the histopathology image, it is evident that there is a significant presence of lymphocytes. These cells are densely packed and exhibit a high degree of pleomorphism, indicating a possible pathological condition. The lymphocytes are irregular in shape and size, with some displaying enlarged nuclei and prominent nucleoli. In addition to the lymphocytes, there is also a noticeable presence of eosinophils. These cells are characterized by their bright pink cytoplasm and bilobed nuclei. The eosinophils are scattered throughout the tissue, suggesting an ongoing immune response. The overall cellular architecture appears disrupted, with the normal tissue architecture replaced by a dense infiltrate of lymphocytes and eosinophils. This could be indicative of an inflammatory or immune-mediated process. Further diagnostic tests may be required to confirm the exact nature of this pathological condition.

How do we extract localized narratives?

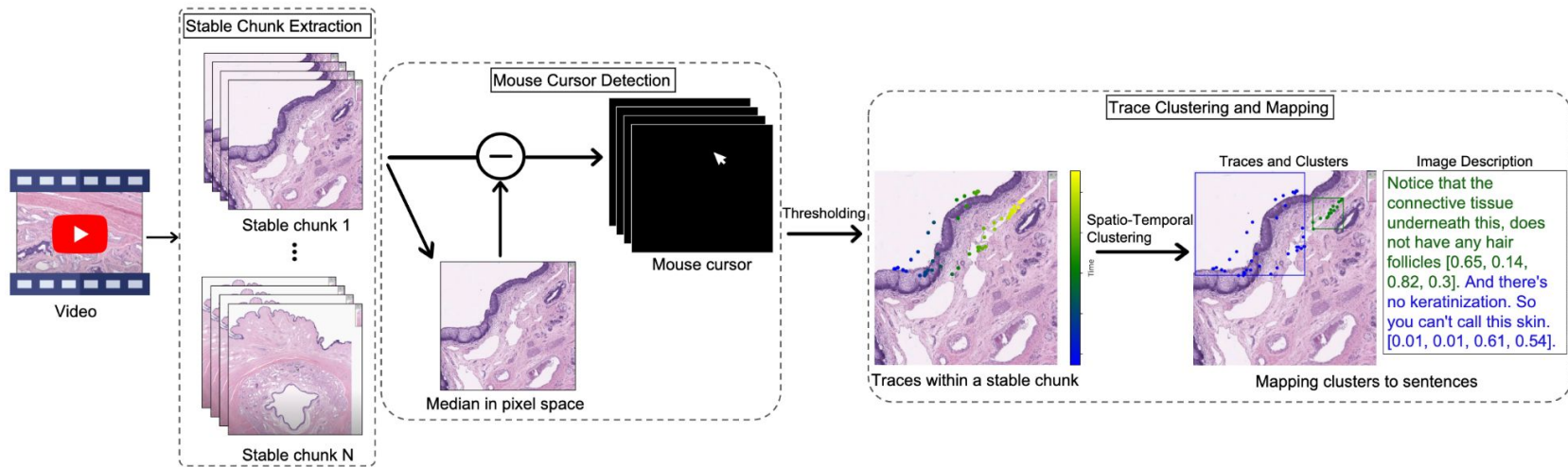
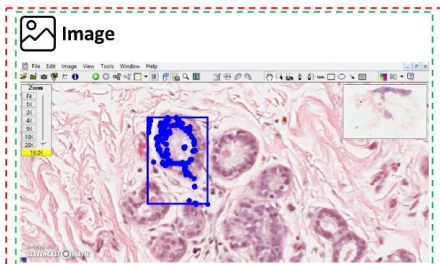


Figure 2. To create QUILT-INSTRUCT, we first identify stable chunks within the video. For each chunk, we compute a median frame in the pixel domain and subtract it from every frame within the chunk. We then apply a threshold to reduce noise and take the maximum value to capture the mouse cursor points. These cursor points are then clustered to localize medical content in image captions. Please note that color encodes time in the "Trace Clustering and Mapping" part of the figure.

Instruction Tuning



Description

look at the lobule, they're usually made up of small rounded glandular formations. And classically, the benign lobule has got two layers. There is an outer myoepithelial layer you can see here, one row of outer nuclei and then one inner row of nuclei. These are the luminal cells and of course that's the lumen. So this bilayered appearance is indicative of benign breast parenchyma and you can see this nice lobular architecture, [0.31, 0.27, 0.46, 0.71]

Diagnosis

Invasive Ductal Carcinoma

Supporting Facts

1. Irregular, infiltrative blue areas in the breast tissue.
2. Presence of irregular, angulated glands infiltrating into the fibrous and fatty stroma.
3. Comparison of benign lobule and malignant invasive breast gland showing irregularity and distortion in latter.
4. Nuclear pleomorphism with variation in size and shape
5. Presence of prominent nucleoli.
6. Frequent mitotic figures indicating rapid growth.
7. Increased nuclear cytoplasmic ratios.
8. Poorly formed, irregular glands on low power view.
9. Infiltrative growth pattern where the glands invade into the surrounding stroma.

Conversation

User: Can you describe the main features visible in this histopathology image?

Assistant: The image primarily showcases a lobule, which is a small rounded glandular formation typically found in breast tissue. This lobule exhibits a classic benign structure with two distinct layers. The outer layer is composed of myoepithelial cells, identifiable by a single row of outer nuclei. [...continues]

User: Where is this lobular architecture located within the image?

Assistant: The lobular architecture is prominently displayed in the central region of the image, extending towards the upper right quadrant. The bilayered structure of the lobule, with its myoepithelial and luminal cells, is clearly visible in this area.

User: What does this bilayered appearance indicate about the condition of the breast tissue?

Assistant: The bilayered appearance, with distinct myoepithelial and luminal cell layers, is indicative of benign breast parenchyma. This means that the breast tissue appears to be healthy and non-cancerous. [...continues]

Complex Medical Reasoning

User: Can we make a diagnosis based on this single patch of histopathology image?

Assistant: The patch under examination reveals a lobule with a typical bilayered structure. This structure consists of an outer myoepithelial layer and an inner luminal cell layer, surrounding a central lumen. The presence of these two distinct layers of cells and the well-preserved lobular architecture are characteristic features of benign breast parenchyma. The myoepithelial cells, represented by the outer row of nuclei, play a crucial role in maintaining the integrity of the breast tissue. They act as a natural barrier against potential invasion of cancer cells into the surrounding stroma. The luminal cells, represented by the inner row of nuclei, are the ones that usually undergo malignant transformation in most breast cancers. However, in this patch, the lobule appears to maintain its normal architecture without any signs of distortion or irregularity. There are no visible signs of nuclear pleomorphism, which would indicate variation in size and shape of the nuclei, a common feature in malignancies. Also, there are no evident mitotic figures, which would suggest rapid cell division and growth, another hallmark of cancer. Based on these observations, this patch seems to represent benign breast tissue. However, it's important to note that this conclusion is based solely on this single patch. Breast cancer, such as invasive ductal carcinoma, often presents as irregular, infiltrative areas in the breast tissue, with angulated glands infiltrating into the fibrous and fatty stroma. [...continues]

Detailed Description

User: In a few words, what does the histopathology image depict?

Assistant: In the central to lower right portion of the histopathology image, there is a clear depiction of a lobule, a characteristic structure in benign breast parenchyma. This lobule is composed of small, rounded glandular formations, demonstrating a classic bilayered appearance. The outer layer of the lobule is made up of myoepithelial cells, which can be identified by a single row of nuclei. Adjacent to this, there is an inner layer composed of luminal cells, also identifiable by a single row of nuclei. The space between these luminal cells forms the lumen. This bilayered structure, with its distinct outer myoepithelial layer and inner luminal cell layer surrounding the lumen, is a hallmark of benign breast tissue. The lobular architecture is well-preserved and clearly visible in this region of the image, further supporting the benign nature of the tissue.

Iterative Abductive Reasoning

User: I see a lobule with small rounded glandular formations, exhibiting a bilayered appearance with an outer myoepithelial layer and an inner luminal cell layer. Could this be indicative of benign breast parenchyma?

Assistant: Your observation of the bilayered appearance of the lobule is correct and it is indeed indicative of benign breast parenchyma. However, it's important to remember that the presence of benign structures doesn't rule out the possibility of malignancy elsewhere. **Hint:** While you've correctly identified benign structures, consider looking for signs of irregularity or distortion in the glandular formations. [...continues]

User: I notice some irregularity and distortion in the glandular formations. There also seems to be nuclear pleomorphism and prominent nucleoli. Could this suggest the presence of a malignant process, possibly breast carcinoma?

Assistant: Your observations are indeed suggestive of a malignant process. The presence of nuclear pleomorphism and prominent nucleoli are key features of malignancy. However, the specific type of breast carcinoma might still be unclear. **Hint:** Consider the growth pattern of the glands. Are they infiltrating into the surrounding stroma? [...continues]

User: I see the glands infiltrating into the surrounding stroma and frequent mitotic figures. Could this suggest an invasive ductal carcinoma of the breast?

Assistant: CORRECT!!! Your observations and deductions are spot on. The presence of glands infiltrating into the surrounding stroma and frequent mitotic figures are indeed indicative of an invasive process, specifically invasive ductal carcinoma of the breast. **Hint:** None needed.

Instruction Tuning

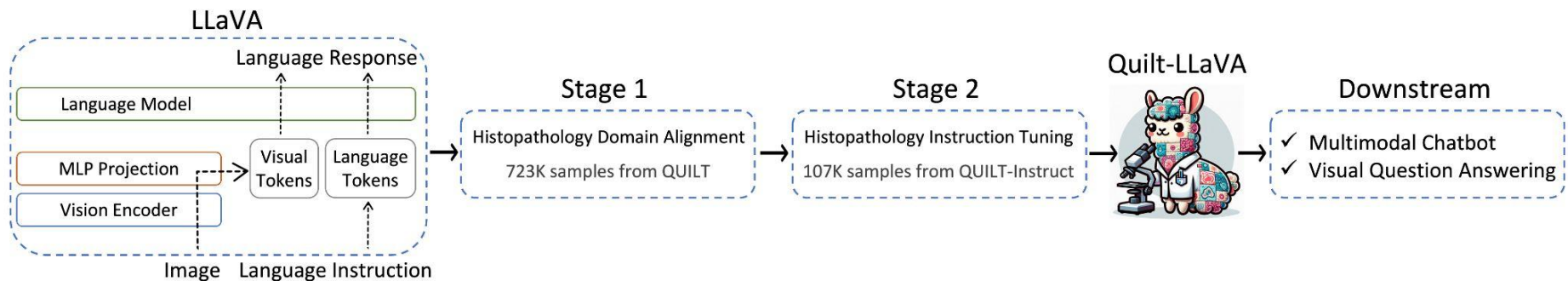
We extracted 162,566 image-caption pairs from QUILT.

Filtering out samples with fewer than 20 words and those with more than 150 words resulted in a dataset of 114,343 pairs, with an average caption length of 55 words.

From this, we created **QUILT-INSTRUCT**, comprising **107,131** question/answer pairs where, on average, we have questions with 16.5 words and answers with 101 words.

For reasoning-based prompts, we manually reviewed 4,149 videos and selected 2,066 that focused on a single WSI from a single patient.

Training



Tuning and VQA Evaluation Results



(Question Count)	Question Types		Sub-Domains														Overall (326)
	Conv (256)	Desc (70)	Bone (25)	Breast (23)	Cyto (23)	Derm (21)	Endo (23)	Gastro (23)	Bone (23)	Geni (22)	Gyne (24)	H&N (22)	Neuro (24)	Pulm (25)	Renal (23)	Soft (25)	
LLAVA [12]	61.4	36.5	54.5	62.0	49.2	48.0	60.1	49.5	62.5	62.2	61.9	49.7	59.7	44.8	53.9	62.7	55.7
LLaVA-MED [10]	70.1	46.9	62.1	69.3	54.1	64.0	61.0	60.7	71.2	68.1	70.3	66.9	66.0	58.9	62.7	73.4	64.8
QUILT-LLAVA @ 40K	76.3	58.7	83.4	73.3	69.2	66.7	71.7	67.2	84.5	81.1	78.4	63.2	68.9	55.2	63.5	87.7	72.3
QUILT-LLAVA @ 107K	78.4	66.0	82.5	84.4	75.0	79.0	76.2	72.8	75.3	82.1	79.1	69.1	68.7	58.1	67.8	89.0	75.6

(a) Performance comparison of multi-modal chat instruction-following abilities, measured by the relative score via language GPT-4 evaluation. Our best model QUILT-LLAVA with ViT-B-32 Vision Encoder [7], 7B Language Model (trained for Stage1: 3 epochs, Stage2:1 epoch) outperforms the baselines.

QUILT-LLAVA Model Variants			PathVQA		PMC-VQA-Subset	QUILT-VQA		QUILT-VQA ○				Average	
Instruct	Stage 1	Stage 2	Open	Closed	Closed	Open	Closed	Open (w/o ● w/)		Closed (w/o ● w/)		Open	Closed
<i>QUILTNET ViT-B-32 Vision Encoder [7], 7B Language Model</i>													
107K	1	1	14.24	58.42	19.63	59.82	64.43	58.81 ●	61.08	68.52 ●	70.37	44.29	56.27
107K	1	3	12.79	56.30	17.21	57.62	63.55	56.21 ●	58.32	65.74 ●	69.44	42.21	54.45
107K	3	1	15.30	54.93	16.01	60.97	60.64	59.24 ●	64.06	56.48 ●	59.26	45.03	49.46
<i>LLAVA [12] checkpoint, 7B Language Model</i>													
107K	1	1	15.06	58.68	28.56	55.39	68.81	54.24 ●	59.83	71.30 ●	75.00	41.56	60.47
<i>Baselines</i>													
LLaVA-Med [10] 7B	0	0	11.97	56.15	1.34	54.81	61.22	52.58 ●	53.97	69.44 ●	64.81	39.79	50.59
LLaVA [12] 7B	0	0	11.65	54.02	33.91	55.81	57.73	54.74 ●	59.96	51.85 ●	60.19	40.73	51.54

(b) Ablation studies with varying number of training epochs at different stages. 107K indicates the size of instruct data used in Stage-2.

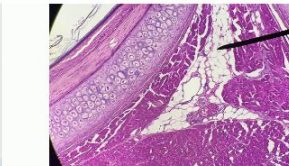
QUILT-LLAVA Instruction Data				PathVQA		PMC-VQA-Subset	QUILT-VQA		QUILT-VQA ○			
Conv	Detail	Complex	Abductive	Open	Closed	Closed	Open	Closed	Open (w/o ● w/)		Closed (w/o ● w/)	
10k	10k	0	0	12.56	50.99	12.04	57.52	64.14	55.81 ●	55.29	68.52 ●	59.26
0	0	10k	10k	17.53	44.50	30.46	73.95	39.65	74.37 ●	69.64	39.81 ●	41.67
5k	5k	5k	5k	14.04	57.12	22.13	61.75	65.60	60.15 ●	62.04	59.82 ●	67.59
10k	10k	10k	10k	14.10	57.33	22.17	61.42	65.60	59.67 ●	58.50	66.67 ●	67.59

(c) Finetuning Data Ablation Study: finetuning QUILT-LLAVA on the instruction-tuning data subsets with varying number of samples in each Q/A type.

Table 1. Quantitative results on histopathology VQA datasets. For open-set questions, we report recall for our free-form text generation method in column *Open*. For closed-set questions, we report the accuracy in column *Closed*. Red indicates the best-performing model.

Qualitative results

Visual input example, Histopathology image:



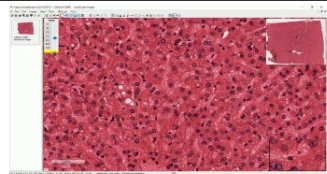
User	What is the connective tissue visible in the image?
QUILT-LLAVA	The connective tissue in the image is identified as the perichondrium. It's a layer of dense irregular connective tissue that surrounds the cartilage. The perichondrium is visible in the upper left quadrant of the image.
LLaVA-Med	The connective tissue visible in the image is lamellar keratinized epithelium. This type of tissue is composed of multiple layers of keratinized cells, which are cells that produce keratin, a tough, fibrous protein that provides protection and structural support.
LLaVA	The connective tissue visible in the image is a piece of human muscle tissue.
Answer	The connective tissue visible in the image is cartilage.

Visual input example, Histopathology image:



User	What is visible in the middle of the image?
QUILT-LLAVA	In the middle of the image, there is a significant presence of mucin. Mucin is a protein that forms mucus, and its presence in large amounts can be indicative of certain conditions.
LLaVA-Med	In the middle of the image, you can see a histopathological section of the human prostate. Histopathology refers to the microscopic examination of tissue to study the manifestations of disease.
LLaVA	In the middle of the image, there is a close-up view of a human organ, specifically the stomach.
Answer	Mucus is visible in the middle of the image.

Visual input example, Histopathology image:



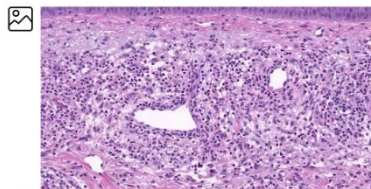
User	What type of cells are the majority in the liver as seen in the image?
QUILT-LLAVA	The image shows that the majority of cells in the liver are hepatocytes, which are the primary cell type in the liver. These cells are located in the central to the right middle region of the image.
LLaVA-Med	The majority of the cells in the liver as seen in the image are foamy macrophages.
LLaVA	The majority of cells in the liver as seen in the image are red blood cells.
Answer	The majority of the cells in the liver, as seen in the image, are hepatocytes.

Visual input example, Histopathology image:



User	What are the three criteria visible in the image that suggest eosinophilic esophagitis?
QUILT-LLAVA	The image shows three key features that are indicative of eosinophilic esophagitis. Firstly, there is a noticeable increase in the number of eosinophils, which are a type of white blood cell. Secondly, there is a significant amount of eosinophilic infiltration, which refers to the accumulation of these cells in the tissue. Lastly, there is evidence of basal cell hyperplasia, which is an increase in the number of cells in the basal layer of the tissue. These three features together strongly suggest a diagnosis of eosinophilic esophagitis.
LLaVA-Med	The three criteria visible in the image that suggest eosinophilic esophagitis are: 1. Increased intraepithelial eosinophils (H&E, x40) 2. Eosinophilic infiltrates in the lamina propria (H&E, x40) 3. Presence of eosinophils in the muscularis mucosa (H&E, x40) These criteria are based on the histological features of the tissue sample, which can help in the diagnosis of eosinophilic esophagitis.
LLaVA	In the image, there are three criteria visible that suggest eosinophilic esophagitis (EoE). First, the esophageal tissue is inflamed, as indicated by the red and pink coloration. Second, there are numerous eosinophils present in the tissue, which are white blood cells that are typically elevated in EoE cases. Finally, the tissue appears to be thickened, which is another characteristic of EoE. These three criteria together suggest that the image depicts a case of eosinophilic esophagitis.
Answer	The three criteria visible in the image that suggest eosinophilic esophagitis are the presence of eosinophils, basal cell hyperplasia, and spongiosis.

Qualitative multi-turn results



User: Can you provide a concise description of the histopathology image shown?

Quilt-LLaVA: Upon examination of the histopathology image, it is evident that there is a significant presence of lymphocytes. These cells are densely packed and exhibit a high degree of pleomorphism, indicating a possible pathological condition. The lymphocytes are irregular in shape and size, with some displaying enlarged nuclei and prominent nucleoli. In addition to the lymphocytes, there is also a noticeable presence of eosinophils. These cells are characterized by their bright pink cytoplasm and bilobed nuclei. The eosinophils are scattered throughout the tissue, suggesting an ongoing immune response. The overall cellular architecture appears disrupted, with the normal tissue architecture replaced by a dense infiltrate of lymphocytes and eosinophils. This could be indicative of an inflammatory or immune-mediated process. Further diagnostic tests may be required to confirm the exact nature of this pathological condition.

User: Given the presence of a mixture of lymphocytes and eosinophils, what can be deduced from this single image regarding a possible diagnosis?

Quilt-LLaVA: The presence of a mixture of lymphocytes and eosinophils in this patch suggests an inflammatory response. This could be seen in a variety of conditions, including infections, autoimmune diseases, and certain types of skin lesions. However, without additional context, it's challenging to make a definitive diagnosis based solely on this feature. It's important to note that the presence of these cells alone does not necessarily indicate a malignant condition. In fact, these cells can be seen in a variety of benign conditions as well. Therefore, a comprehensive evaluation of the whole slide image, including the overall architecture of the lesion, the presence of a junctional and dermal component, and the absence of atypia or mitotic activity, would be necessary to make a more accurate diagnosis.



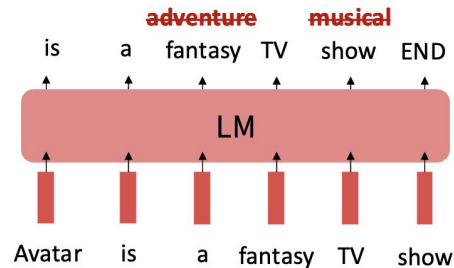
62k

Limitations of Instruction tuning

While Supervised instruction finetuning (including reasoning structured data tuning) helps use *align* models to users desires the still have some issues:

- It's still *expensive* to collect ground-truth data for various tasks
- There are several tasks that do not have one single right answer (*open-ended*)
 - E.g creative writing
- The autoregressive LM loss *penalizes all token-level errors equally*, lacking any nuance that some errors are worse than others.

So there's still a mismatch between the LM objective and the objective "satisfy human preferences".



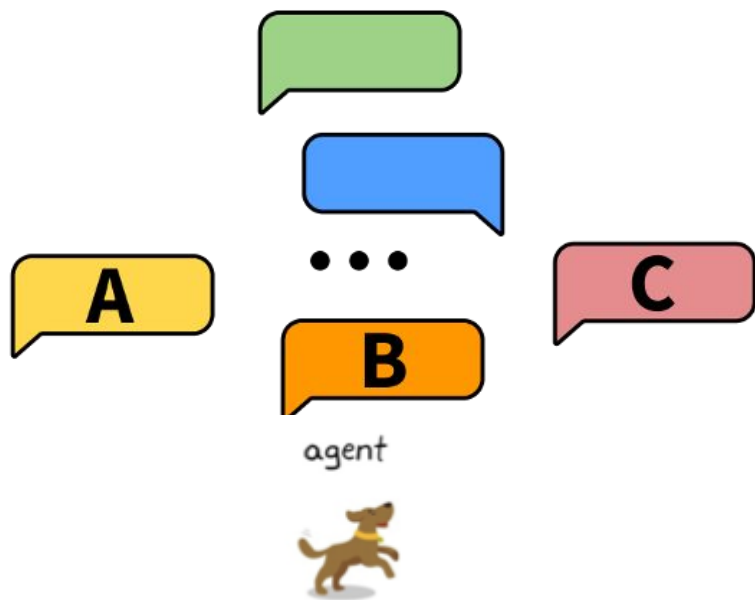
Reinforced objectives: Intuition

Action: generating responses/tokens



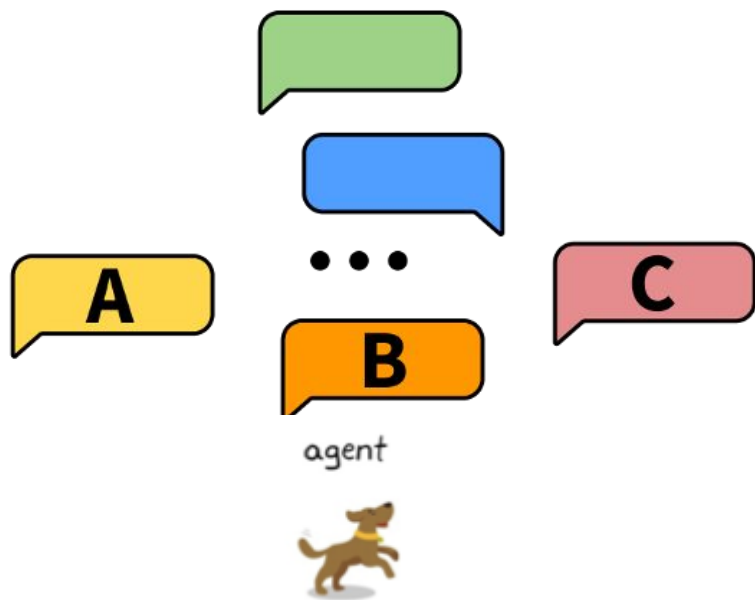
Reinforced objectives: Intuition

Action: generating responses/tokens



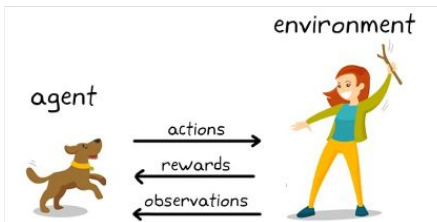
Reinforced objectives: Intuition

Action: generating responses/tokens



Reinforced objectives: Intuition

human rates better response



Human
I have to come up with a conversation with an AI assistant for the purposes of showing it off in a demo. What sorts of conversation topics would you recommend?

Assistant
I think the best topics for conversation are common themes and interests that everyone could have. Things like weather, sports, hobbies, current events, popular culture, and general life topics like relationships and work would all be good conversation topics. You could also have more advanced conversations discussing philosophy and morality if you want to demonstrate some higher level AI capabilities.

Human
I think I'm more interested in an advanced conversation. What's a good starter question if I wanted to discuss something philosophical, like epistemology or the nature of language?

Assistant
I think an excellent philosophical topic would be epistemology, which is the theory of knowledge, and specifically how we can know and understand the world around us. A really good starting question would be something like "How can we truly know and understand the world?", or "What is the nature of knowledge?". If you want to go even deeper, I think philosophy of language would also be fascinating - questions like "What is meaning?", "How do language and thought relate?", and "How can language mislead and deceive?" would be great discussion topics.

Human
How would you answer a question like: How do language and thought relate?

Choose the most helpful and honest response

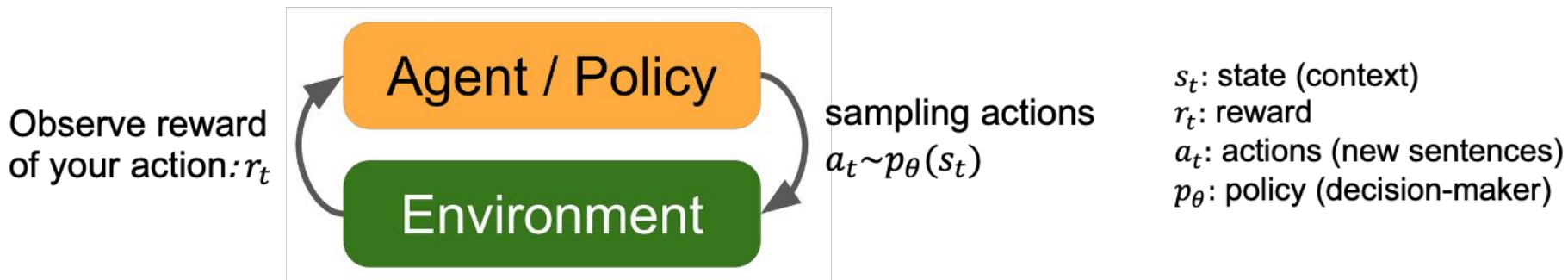
A
I think a good answer to that would be that language helps us to structure our thoughts and express what we are thinking. Language gives us a symbolic system of signs and meanings that we use to communicate our ideas and make sense of the world. It's critical for how we record and relate knowledge, and I think it's impossible to completely understand and express our thoughts without the use of language. Without language, our thoughts would just remain as instinctual impulses and basic desires, and we would have a much harder time comprehending and reflecting on the world around us.

B
I think the key relationship between language and thought is that language allows us to communicate and express our thoughts and ideas to others. Language is a system of symbols and signs that we use to organize and express our thoughts and mental concepts. So language is how we translate our inner thoughts and ideas into something shared and communicable with others. Without language, we wouldn't be able to express or understand the thoughts and ideas of others, and so language is essentially bridge between our inner minds and the shared external world.

A A A A B B B B
A is better B is better

Reinforcement Learning:

- An agent **interacts** with an environment by taking **actions**
- The environment returns a **reward** for the **action** and a **new state** (representation of the world at that moment).
- Agent uses a **policy function** to choose an action at a given **state**.
- We need to figure out: (1) reward function and (2) the policy function



Reinforcement Learning from Human Feedback

- Imagine a reward function: $R(s; \text{prompt}) \in \mathbb{R}$ for any output s to a prompt.
- The reward is higher when humans prefer the output.
- Good generation is equivalent to finding reward-maximizing outputs:

$$\mathbb{E}_{\hat{s} \sim p_{\theta}} [R(\hat{s}; \text{prompt})]$$

- What we need to do:
 - Estimate the reward function $R(s; \text{prompt})$.
 - Find the best generative model p_{θ} that maximizes the expected reward:

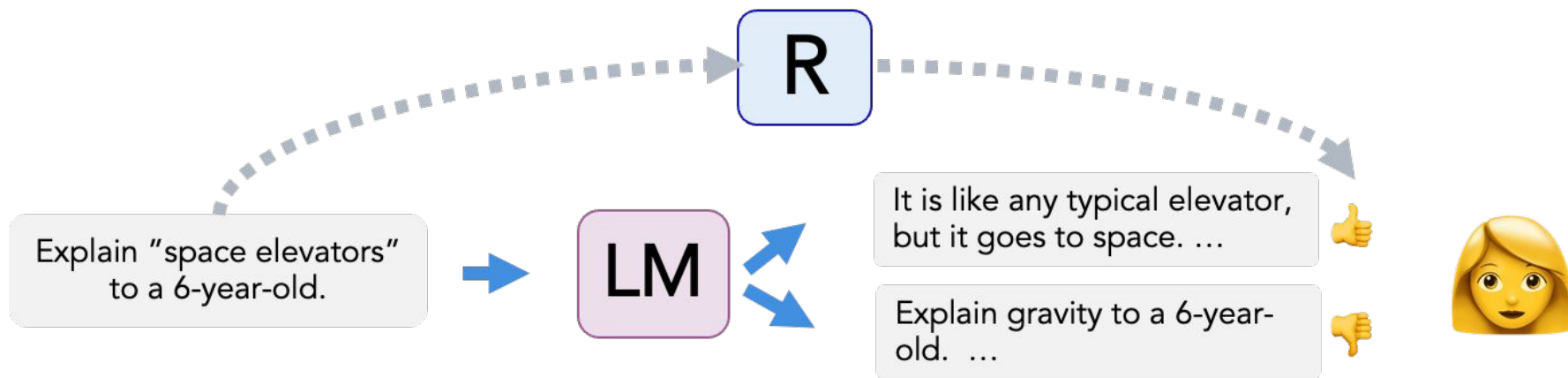
$$\hat{\theta} = \operatorname{argmax}_{\theta} \mathbb{E}_{\hat{s} \sim p_{\theta}} [R(\hat{s}; \text{prompt})]$$

Estimating the Reward R

$$J(\phi) = -\mathbb{E}_{(s^+, s^-)} [\log \sigma(R(s^+; \text{prompt}) - R(s^-; \text{prompt}))]$$

“winning”
sample

“losing”
sample

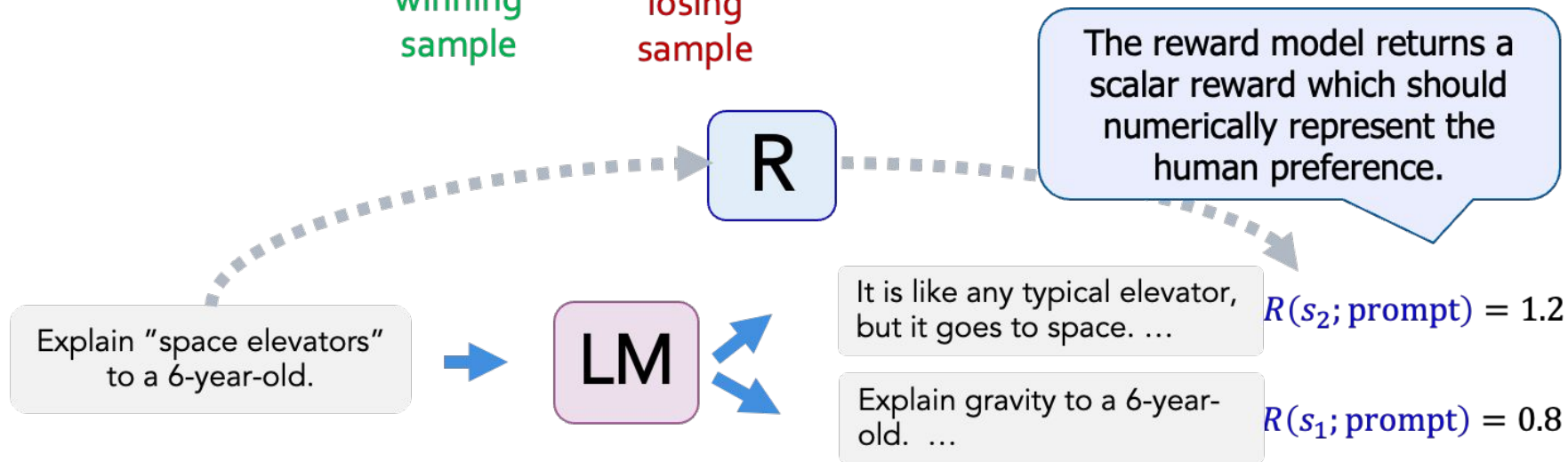


Estimating the Reward R

$$J(\phi) = -\mathbb{E}_{(s^+, s^-)} [\log \sigma(R(s^+; \text{prompt}) - R(s^-; \text{prompt}))]$$

"winning"
sample

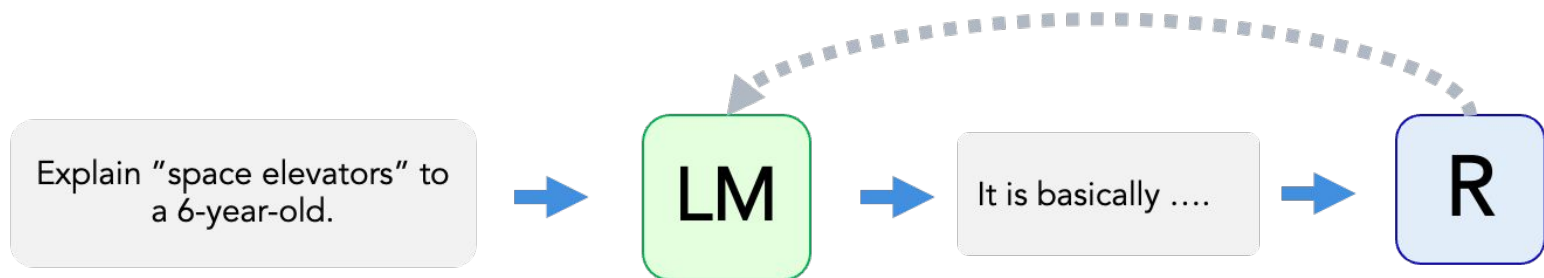
"losing"
sample



Optimizing the policy function

- Policy function := The model that makes decisions (here, generates responses)
- How do we change our LM parameters θ to maximize this?

$$\hat{\theta} = \operatorname{argmax}_{\theta} \mathbb{E}_{\hat{s} \sim p_{\theta}} [R(\hat{s}; \text{prompt})]$$



Optimizing the policy function

- Policy function := The model that makes decisions (here, generates responses)
- How do we change our LM parameters θ to maximize this?

$$\hat{\theta} = \operatorname{argmax}_{\theta} \mathbb{E}_{\hat{s} \sim p_{\theta}} [R(\hat{s}; \text{prompt})]$$

- Let's try doing gradient ascent!

$$\theta_{t+1} \leftarrow \theta_t + \alpha \nabla_{\theta_t} \mathbb{E}_{\hat{s} \sim p_{\theta}} [R(\hat{s}; \text{prompt})]$$

How do we estimate the gradient of this expectation?

Notice that R is not directly dependent on θ . (You can't compute its grad with respect to θ)

Policy Gradient [Williams, 1992]

- Policy function := The model that makes decisions (here, generates responses)
- How do we change our LM parameters θ to maximize this?

$$\hat{\theta} = \operatorname{argmax}_{\theta} \mathbb{E}_{\hat{s} \sim p_{\theta}} [R(\hat{s}; \text{prompt})]$$

- Let's try doing gradient ascent!

$$\theta_{t+1} \leftarrow \theta_t + \alpha \nabla_{\theta_t} \mathbb{E}_{\hat{s} \sim p_{\theta}} [R(\hat{s}; \text{prompt})]$$

- With a bit of math, this can be approximated as Monte Carlo samples from $p_{\theta}(s)$:

$$\nabla_{\theta} \mathbb{E}_{s \sim p_{\theta}} [R(s; \text{prompt})] \approx \frac{1}{n} \sum_{i=1}^n R(s_i; \text{prompt}) \nabla_{\theta} \log p_{\theta}(s_i; \text{prompt})$$

- This is “**policy gradient**”, an approach for estimating and optimizing this objective.

Policy Gradient [Williams, 1992]

Note, $R(s; \text{prompt})$ could be any arbitrary, non-differentiable reward function that we design.

- This gives us the following update rule:

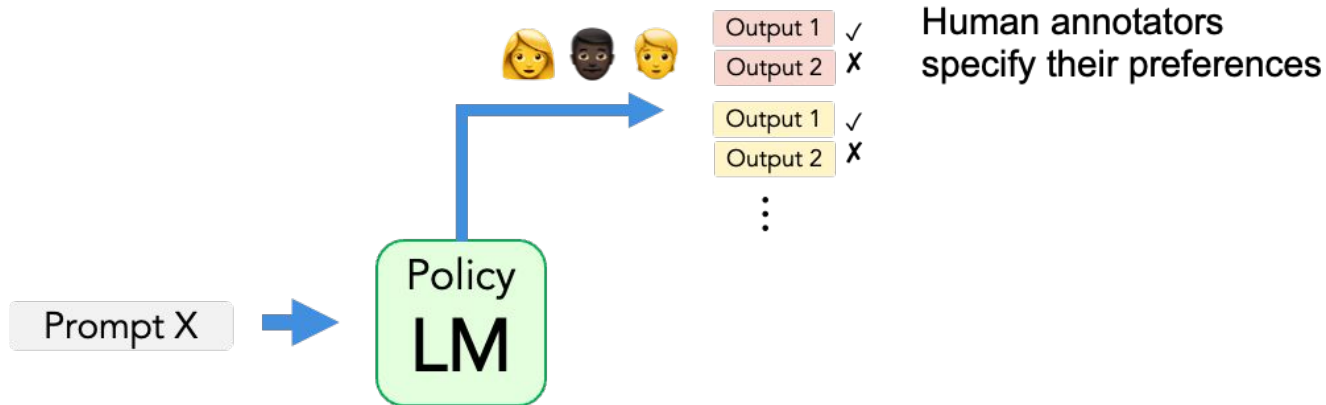
$$\theta_{t+1} \leftarrow \theta_t + \alpha \frac{1}{|\text{samples}| \times |\text{prompts}|} \sum_{p \in \text{prompts}} \sum_{s_i \sim p_\theta(p)} R(s_i; p) \nabla_\theta \log p_\theta(s_i; p)$$

- If $R(s; p)$ is **large**, we take proportionately **large** steps to maximize $p_\theta(s)$
- If $R(s; p)$ is **small**, we take proportionately **small** steps to maximize $p_\theta(s)$

This is why it's called "reinforcement learning":
we reinforce good actions, increasing the chance they happen again.

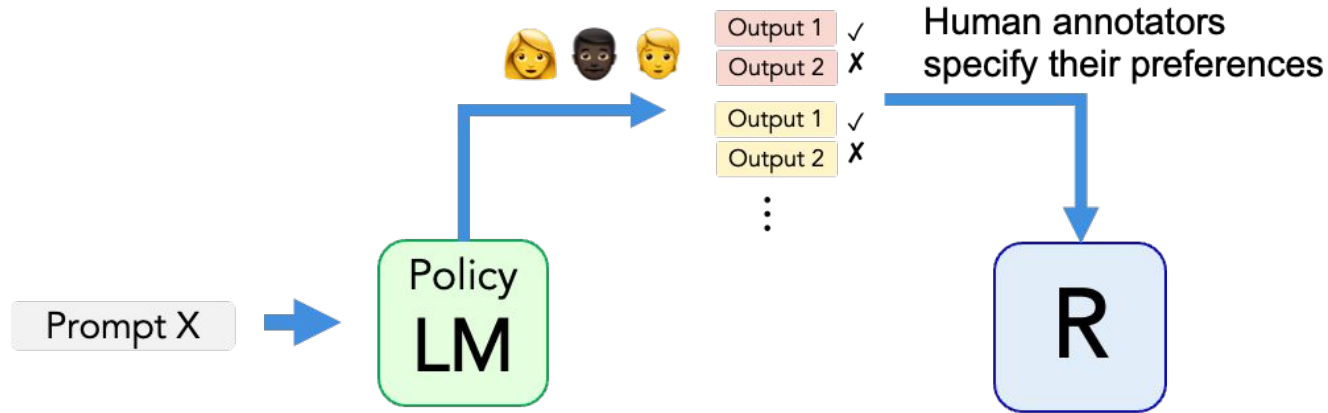
Putting it together, RLHF:

- First collect a dataset of human preferences
 - Present multiple outputs to human annotators and ask them to rank the output based on preferability



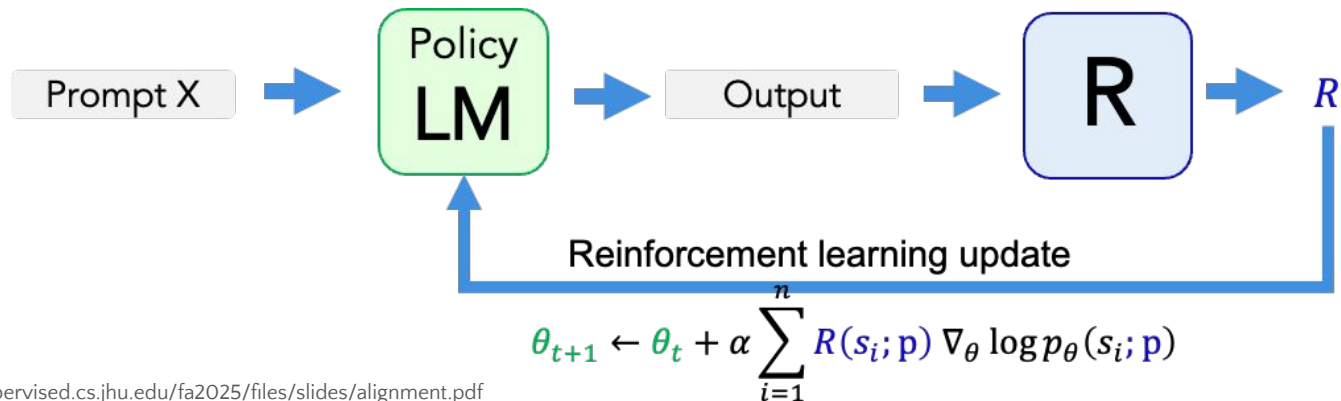
Putting it together, RLHF:

- Using this data, we can train a reward model
 - The reward model returns a scalar reward which should numerically represent the human preference



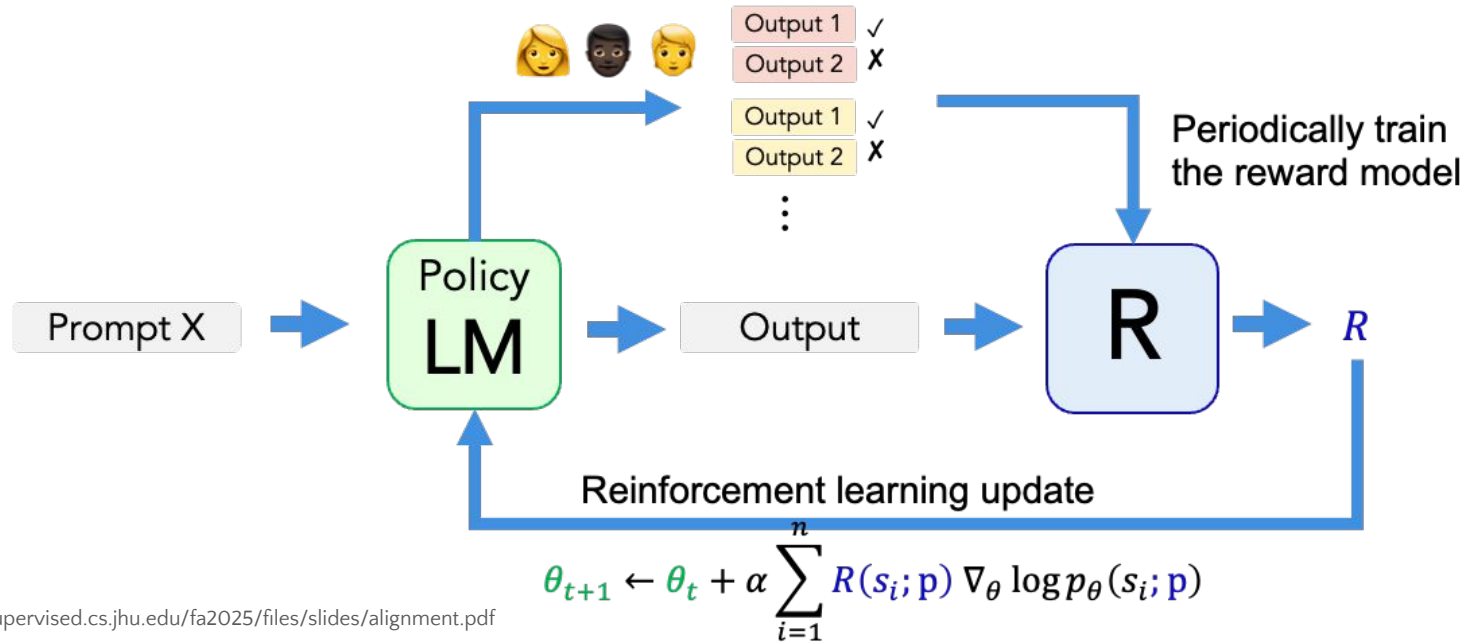
Putting it together, RLHF:

- We want to learn a policy (a Language Model) that optimizes against the reward model



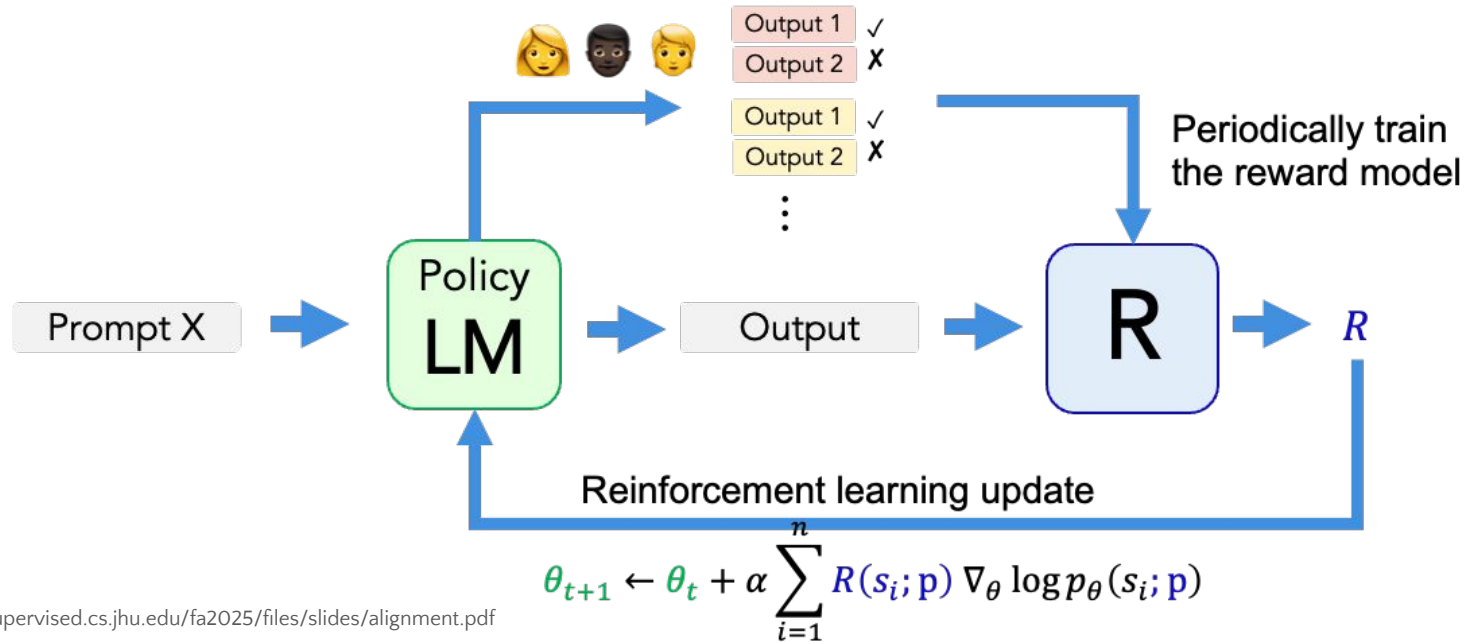
Putting it together, RLHF:

- Periodically train the reward model with more samples and human feedback



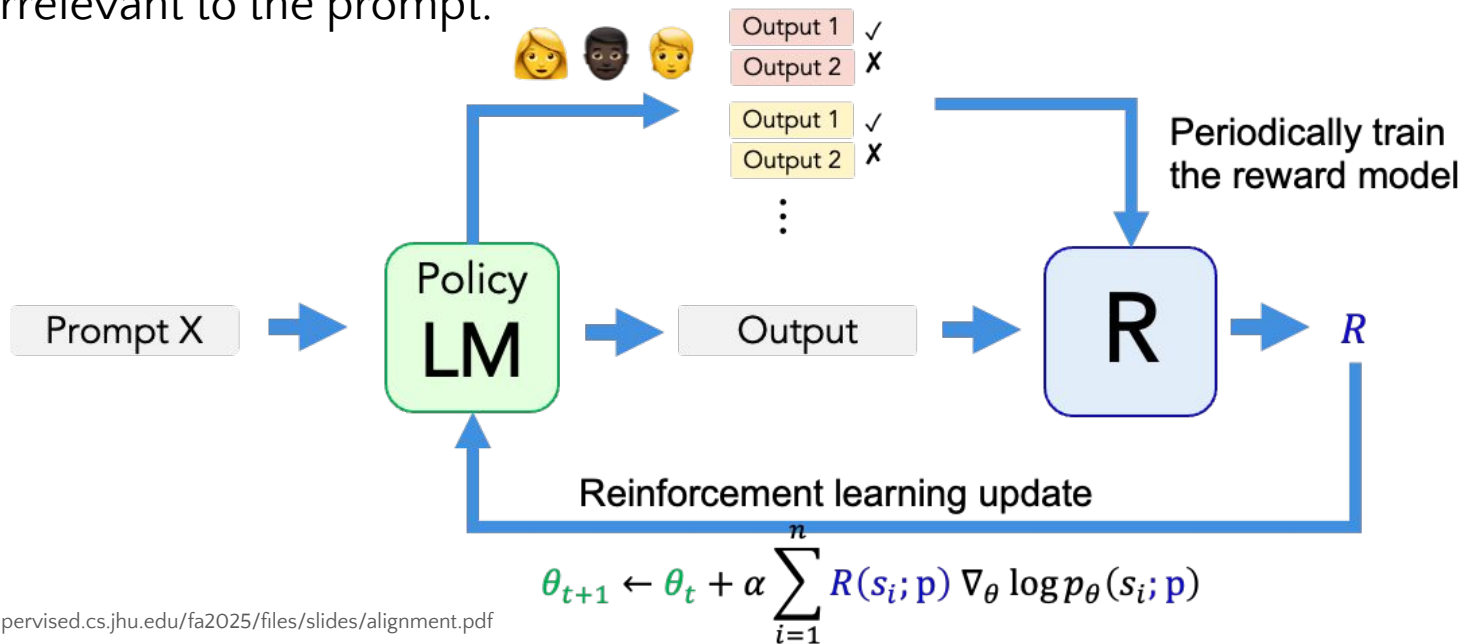
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- It turns out that this approach doesn't quite work. (Any guesses why?)



Putting it together, RLHF:

- Periodically train the reward model with more samples and human feedback
- It turns out that this approach doesn't quite work. (Any guesses why?)
- Will learn to produce an output that would get a high reward but is gibberish or irrelevant to the prompt.



Regularizing with Pre-trained Model

- Solution: add a penalty term that penalizes too much deviations from the distribution of the pre-trained LM.

$$\hat{R}(s; p) := R(s; p) - \beta \log \left(\frac{p_{\theta}^{RL}(s)}{p^{PT}(s)} \right)$$

- This prevents the policy model from diverging too far from the pretrained model.
 - $p_{\theta}^{RL}(s) \gg p^{PT}(s)$: Pay an explicit price
 - $p_{\theta}^{RL}(s) \ll p^{PT}(s)$: Sampling s becomes unlikely
- The above regularization is equivalent to adding a KL-divergence regularization term.

Putting it together, RLHF as basic Policy Gradient:

- Select a pre-trained generative model p^{RL}_{θ} as your base: p^{PT}_{θ}
- Build a reward model $R(s;p)$ that produces scalar rewards for outputs, trained on a dataset of human comparisons

- Regularize the reward function:
$$\hat{R}(s;p) := R(s;p) - \beta \log \left(\frac{p^{\text{RL}}(s)}{p^{\text{PT}}(s)} \right)$$

- Iterate:
 - Fine-tune the policy $p^{\text{RL}}_{\theta}(s)$ to maximize our reward model $R(s;p)$

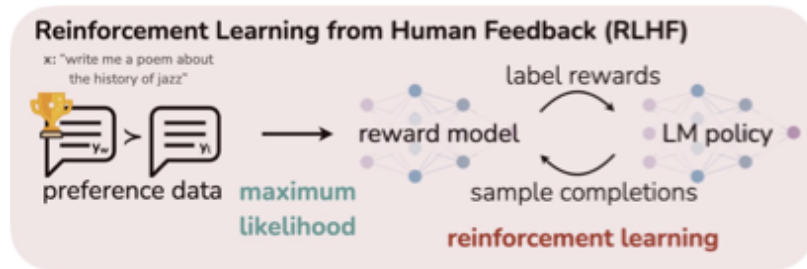
$$\theta_{t+1} \leftarrow \theta_t + \alpha \frac{1}{n} \sum_{i=1}^n \hat{R}(s;p) \nabla_{\theta} \log p^{\text{RL}}_{\theta}(s)$$

- Occasionally repeat repeat 2-3 to update the reward model.

Simplifying RLHF:

- The RLHF pipeline is considerably more complex than supervised learning
 - Involves training multiple LMs and sampling from the LM policy in the loop of training

Q: Is there a way to simplify this pipeline?



Simplifying RLHF, Direct Policy Optimization:

- DPO directly optimizes for human preferences
 - avoiding RL and fitting a separate reward model
- One can use mathematical derivations to simplify the RLHF objective to an equivalent objective that is simpler to optimize.

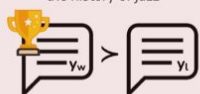
RLHF objective



DPO objective

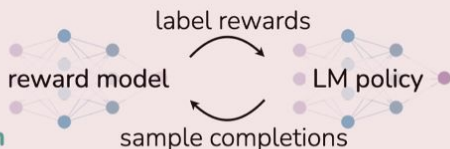
Reinforcement Learning from Human Feedback (RLHF)

x: "write me a poem about the history of jazz"



preference data

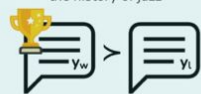
maximum likelihood



reinforcement learning

Direct Preference Optimization (DPO)

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preference data

maximum likelihood

Simplifying RLHF, Direct Policy Optimization:

RLHF objectives y_w : preferred response / y_l : dispreferred response

(i) Reward objective $\mathcal{L}_R(r_\phi, \mathcal{D}) = -\mathbb{E}_{(x, y_w, y_l) \sim \mathcal{D}} [\log \sigma(r_\phi(x, y_w) - r_\phi(x, y_l))]$

(ii) Policy objective $\max_{\pi_\theta} \mathbb{E}_{x \sim \mathcal{D}, y \sim \pi_\theta(y|x)} [r_\phi(x, y)] - \beta \mathbb{D}_{\text{KL}} [\pi_\theta(y | x) || \pi_{\text{ref}}(y | x)]$

Maximizing the reward of the generated prompts

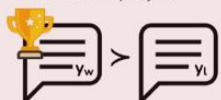
Minimizing the deviation from the base policy

DPO objective $\mathcal{L}_{\text{DPO}}(\pi_\theta; \pi_{\text{ref}}) = -\mathbb{E}_{(x, y_w, y_l) \sim \mathcal{D}} \left[\log \sigma \left(\beta \log \frac{\pi_\theta(y_w | x)}{\pi_{\text{ref}}(y_w | x)} - \beta \log \frac{\pi_\theta(y_l | x)}{\pi_{\text{ref}}(y_l | x)} \right) \right]$

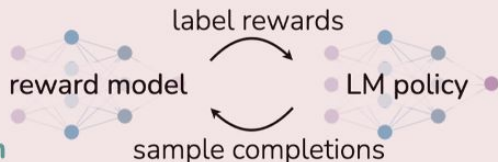
(1) Maximizing reward of the pref response vs that of dispref one; (2) Minimizing deviations from the base policy

Reinforcement Learning from Human Feedback (RLHF)

x: "write me a poem about the history of jazz"



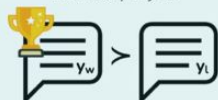
maximum likelihood



reinforcement learning

Direct Preference Optimization (DPO)

x: "write me a poem about the history of jazz"



maximum likelihood



Policy Gradient (Revisit)

- The algorithm that we saw earlier: gradients updates of policy weighted by reward:

$$\theta_{t+1} \leftarrow \theta_t + \alpha \nabla_{\theta_t} \mathbb{E}_{\hat{s} \sim p_{\theta}} [R(\hat{s}; \text{prompt})]$$

$$\nabla_{\theta} \mathbb{E}_{s \sim p_{\theta}} [R(s; \text{prompt})] \approx \frac{1}{n} \sum_{i=1}^n R(s_i; \text{prompt}) \nabla_{\theta} \log p_{\theta}(s_i; \text{prompt})$$

$$\theta_{t+1} \leftarrow \theta_t + \alpha g^{\text{PG}}$$

$$g^{\text{PG}} = \mathbb{E}_{a_t \sim \pi_{\theta}} [\nabla_{\theta} \log \pi_{\theta}(a_t | s_t) R_t]$$

- In the RL literature, this is typically referred to as **REINFORCE** algorithm.

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- In literature, is typically referred to as **REINFORCE** algorithm.

Policy Gradient (with Advantage Function)

Issues:

- Distribution drift: We added KL regularization to deal with this.
- High variance: The gradient estimates \hat{g}^{PG} suffer from high variance. This may lead to destructively large updates and sample inefficiency.

The baseline estimate

- To reduce the variance of g^{PG} we can subtract a **baseline estimate** $b_t(s_t)$:

$$g^{\text{VR}} = \mathbb{E}[\nabla_{\theta} \log \pi_{\theta}(a_t | s_t) (R_t - b_t)]$$

- Note, by design, the baseline depends on states s_t but not the action a_t and is an unbiased estimator of g^{PG}
- A good baseline is a function that can correct for variance (should correlate well with R).

Value Function as a Baseline

- One common choice is $b_t(s) = V^{\pi}(s)$ (the value function), i.e., expected reward from here on under policy π , assuming that we're at state s

$$V^{\pi}(s) = \mathbb{E}_{a \sim \pi}[R_t | S_t = s]$$

$$g^{\text{VR}} = \mathbb{E}_{a \sim \pi}[\nabla_{\theta} \log \pi_{\theta}(a_t | s_t) (R_t - V^{\pi}(s))]$$

Policy Gradient (with Advantage Function)

$$g^{\text{VR}} = \mathbb{E}_{a \sim \pi} [\nabla_{\theta} \log \pi_{\theta}(a_t | s_t) (R_t - V^{\pi}(s))]$$

- It's more common to replace R_t with Q^{π} and write it in this form:

$$Q^{\pi}(s) = \mathbb{E}_{a \sim \pi} [R_t | S_t = s, A_t = a]$$

$$R_t - V^{\pi}(s) \rightarrow A^{\pi}(s, a) := Q^{\pi}(s, a) - V^{\pi}(s)$$

- Basically, Q the Monte Carlo estimate of R_t upon doing multiple rollouts (seq of actions).
- Each rollout has some stochasticity; averaging reduces this per-rollout variance
- Remember: Q function is defined as the **expected reward** from here on under policy π , assuming we take action a at state s .

Policy Gradient (with Advantage Function)

- Advantage-based Policy Gradient updates:

$$g^{\text{APG}} = \mathbb{E}[\nabla_{\theta} \log \pi_{\theta}(a_t | s_t) A_t]$$
$$A^{\pi}(s, a) = Q^{\pi}(s, a) - V^{\pi}(s)$$

- We don't (always) need to compute the absolute benefit of an action, but only how much better it is relative to others (i.e., the **relative advantage** of that action.)
- The advantage function $A^{\pi}(s, a)$ of a policy π **quantifies how much better it is to take a specific action a in state s , over a randomly selecting an action according to $\pi(\cdot|s)$, assuming you act according to π forever after.**

From policy to surrogate objective

- Policy gradient gives us a gradient estimator:

$$g = \mathbb{E} \left[\nabla_{\theta} \log \pi_{\theta}(a_t | s_t) \hat{A}_t \right]$$

- This

$$L^{\text{surrogate}}(\theta) = \mathbb{E} \left[\frac{\pi_{\theta}(a_t | s_t)}{\pi_{\theta_{\text{old}}}(a_t | s_t)} \hat{A}_t \right]$$

- **Why this matters:** a gradient estimator gives you one step. An objective function lets you take **multiple optimization steps** on the same batch of data.

Sampling from target or ref policy?

- Idea: sample many rollouts from π_{ref} once and re-use.
- But wait:

$$\mathbb{E}_{a_t \sim \pi_\theta} [f] \neq \mathbb{E}_{a_t \sim \pi_{\text{ref}}} [f]$$

- We correct this mismatch by using importance weights:

$$\mathbb{E}_{a_t \sim \pi_\theta} [f] = \mathbb{E}_{a_t \sim \pi_{\text{ref}}} \left[\frac{\pi_\theta(\tilde{a}_t | s_t)}{\pi_{\text{ref}}(a_t | s_t)} f \right]$$

Proximal Policy Optimization (PPO)

- Provides several empirical advantages, such as increased stability and faster learning.
- PPO is an advantage actor-critic method:
 - **Actor-critic:** the learning objective includes an estimated value function to “critique” the policy (actor) actions.
 - **Advantage:** instead of optimizing directly using rewards like REINFORCE, updates rely on “advantage”.

Algorithm 1 PPO, Actor-Critic Style

```
for iteration=1, 2, ... do
  for actor=1, 2, ..., N do
    Run policy  $\pi_{\theta_{\text{old}}}$  in environment for  $T$  timesteps
    Compute advantage estimates  $\hat{A}_1, \dots, \hat{A}_T$ 
  end for
  Optimize surrogate  $L$  wrt  $\theta$ , with  $K$  epochs and minibatch size  $M \leq NT$ 
   $\theta_{\text{old}} \leftarrow \theta$ 
end for
```

$$\underset{\theta}{\text{maximize}} \hat{\mathbb{E}}_t \left[\frac{\pi_{\theta}(a_t | s_t)}{\pi_{\theta_{\text{old}}}(a_t | s_t)} \hat{A}_t - \beta \text{KL}[\pi_{\theta_{\text{old}}}(\cdot | s_t), \pi_{\theta}(\cdot | s_t)] \right]$$

Group Relative Policy Optimization (GRPO)

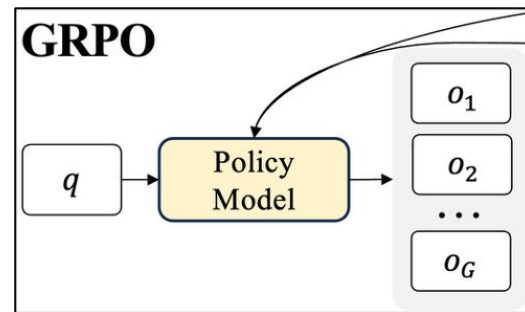
- PPO has 4 LLMs in the mix: reward, value, policy and reference policy.
 - Massive memory footprint.
- GRPO drops the value model. Significant reduction of memory usage.
- Remember the reason that we had value function in PPO is to estimate "advantage" values.
 - If we find alternative way of estimating advantage, we can drop value function.

GRPO: Key Idea

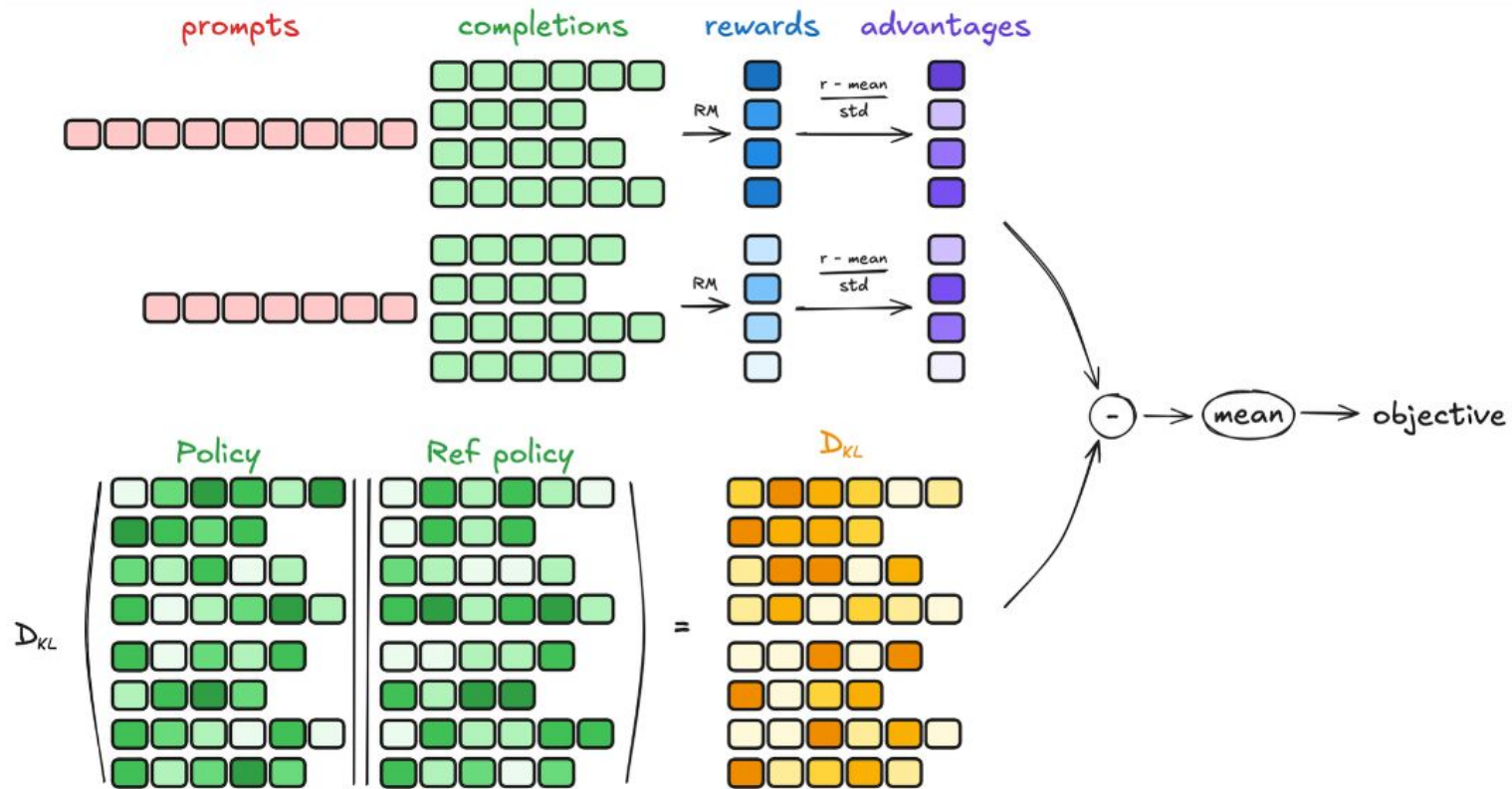
- Execute multiple rollouts from each.
- Given these rollouts, we can estimate the “advantage” function based on the **relative goodness of these responses**.

$$\hat{A}_{i,t} = \tilde{r}_i = \frac{r_i - \text{mean}(\mathbf{r})}{\text{std}(\mathbf{r})}$$

- Advantage of each rollout is simply the gap between its reward compared to the mean reward of other responses, normalized with std.



GRPO



GRPO

Algorithm 1 Iterative Group Relative Policy Optimization

Input initial policy model $\pi_{\theta_{\text{init}}}$; reward models r_{φ} ; task prompts \mathcal{D} ; hyperparameters ε, β, μ

- 1: policy model $\pi_{\theta} \leftarrow \pi_{\theta_{\text{init}}}$
- 2: **for** iteration = 1, ..., I **do**
- 3: reference model $\pi_{\text{ref}} \leftarrow \pi_{\theta}$
- 4: **for** step = 1, ..., M **do**
- 5: Sample a batch \mathcal{D}_b from \mathcal{D}
- 6: Update the old policy model $\pi_{\theta_{\text{old}}} \leftarrow \pi_{\theta}$
- 7: Sample G outputs $\{o_i\}_{i=1}^G \sim \pi_{\theta_{\text{old}}}(\cdot | q)$ for each question $q \in \mathcal{D}_b$
- 8: Compute rewards $\{r_i\}_{i=1}^G$ for each sampled output o_i by running r_{φ}
- 9: Compute $\hat{A}_{i,t}$ for the t -th token of o_i through group relative advantage estimation.
- 10: **for** GRPO iteration = 1, ..., μ **do**
- 11: Update the policy model π_{θ} by maximizing the GRPO objective (Equation 21)
- 12: Update r_{φ} through continuous training using a replay mechanism.

Output π_{θ}

RLVR: When Rewards Are Verifiable

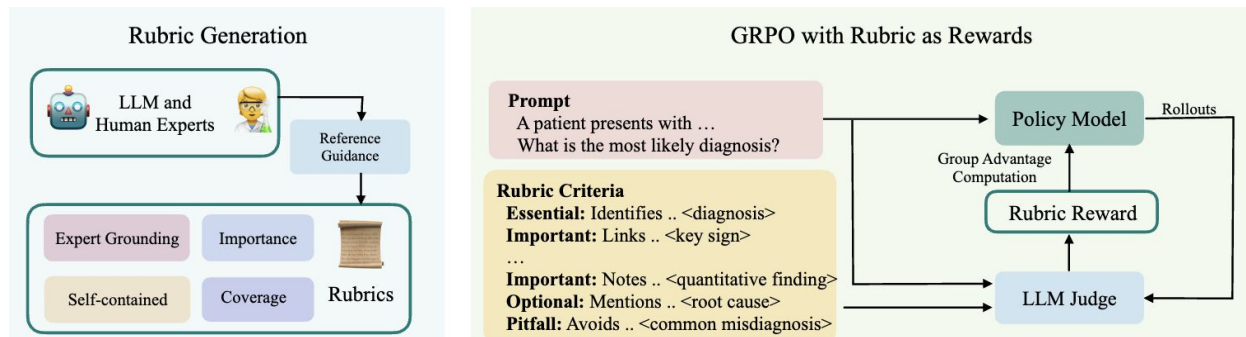
- GRPO with rule-based rewards (RL with Verifiable Feedback: RLVR) is applied mostly to task with environments with verifiable feedback e.g coding, math, gaming
- For other tasks and environments with non-verifiable rewards how can we train models with RL?

Rewards: Rubrics as Rewards (RaR)

$$r(x, \hat{y}) = \frac{\sum_{j=1}^k w_j \cdot c_j(x, \hat{y})}{\sum_{j=1}^k w_j}$$

Rubrics as Rewards subsumes RLVR: The RLVR setting is a special case of rubric-based rewards, where $k = 1$, $w_1 = 1$, and $c_1(x, \hat{y})$ reduces to a single verifiable correctness function that compares the model output \hat{y} against the known correct answer y . For example, this could involve exact match or test case execution. Formally:

$$r_{\text{RLVR}}(x, \hat{y}) = \text{match}(y, \hat{y})$$



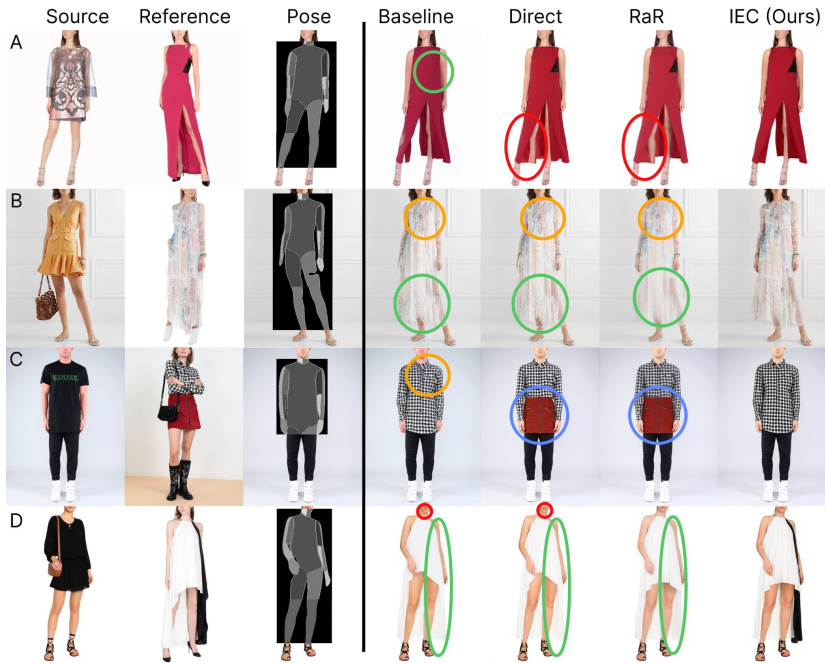
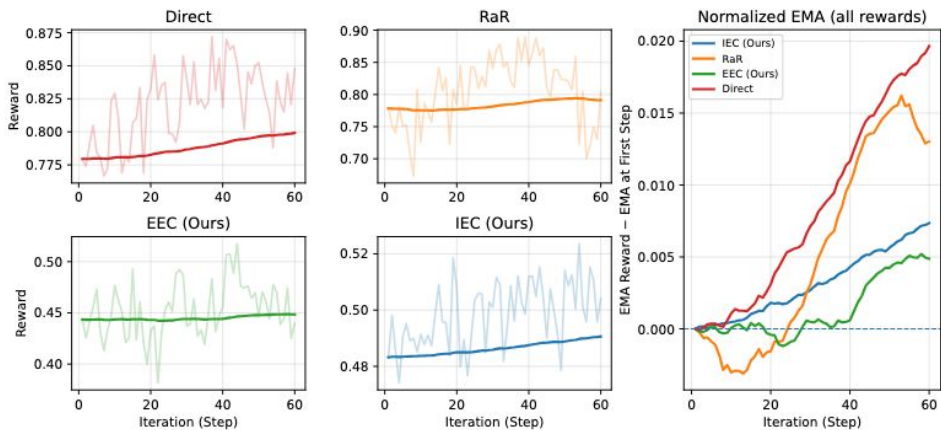
Rewards: Error Enumeration as reward

- **RaR** requires access to the ideal reference answer to create the rubrics
- In reference-free domains we show that error enumeration is a better reward function
- We apply this to a virtual try-on task where in there can be multiple valid outcomes, yet subtle errors break human preference

$$\mathcal{E}_a^{(i)} = \{(e_k, w_k)\}_{k=1}^{|\mathcal{E}_a^{(i)}|}, \quad w_k \in \{0, 1\}.$$

$$R_a^{(i)} = \frac{1}{|\mathcal{E}_a^{(i)}|} \sum_k w_k \quad \text{where} \quad R_i = 1 - \frac{1}{5} \sum_{a=1}^5 R_a^{(i)}$$

Rewards: Error Enumeration as reward

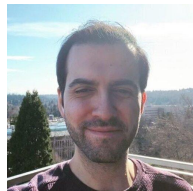


Method	CEC↓	RaR↑	Direct↑	Garm.Trans.↑	Attr.Pres.↑	Realism↑	Light.↑	Src.Int.↑
Baseline (SFT)	5.489 \pm 1.48	0.811 \pm 0.13	0.815 \pm 0.05	0.835 \pm 0.12	0.848 \pm 0.11	0.754 \pm 0.11	0.767 \pm 0.10	0.902 \pm 0.10
Direct	5.284 \pm 1.54	0.867 \pm 0.11	0.837 \pm 0.04	0.870 \pm 0.07	0.879 \pm 0.07	0.782 \pm 0.08	0.770 \pm 0.09	0.906 \pm 0.11
RaR (Gunjal et al., 2025)	5.533 \pm 1.65	0.850 \pm 0.14	0.829 \pm 0.05	0.862 \pm 0.08	0.863 \pm 0.09	0.769 \pm 0.09	0.770 \pm 0.10	0.905 \pm 0.13
IEC w/o GC	5.259 \pm 1.51	0.890\pm0.11	0.852 \pm 0.04	0.878 \pm 0.07	0.887 \pm 0.06	0.799 \pm 0.07	0.799\pm0.08	0.918\pm0.10
IEC (Ours)	5.203\pm1.48	0.883 \pm 0.10	0.852\pm0.04	0.882\pm0.07	0.893\pm0.06	0.803\pm0.07	0.796 \pm 0.08	0.910 \pm 0.11

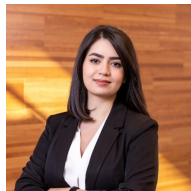
Thank You!



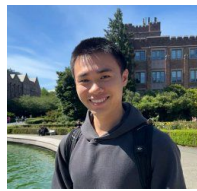
Wisdom Ikezogwo



Saygin Seyfioglu



Fatemeh Ghezloo



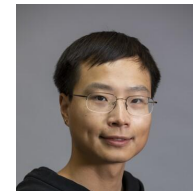
Kevin Zhang



Mahtab Bigverdi



Rustin Soraki



Beibin Li



Prof. Linda Shapiro



Prof. Ranjay Krishna



Dr. Joann Elmore

