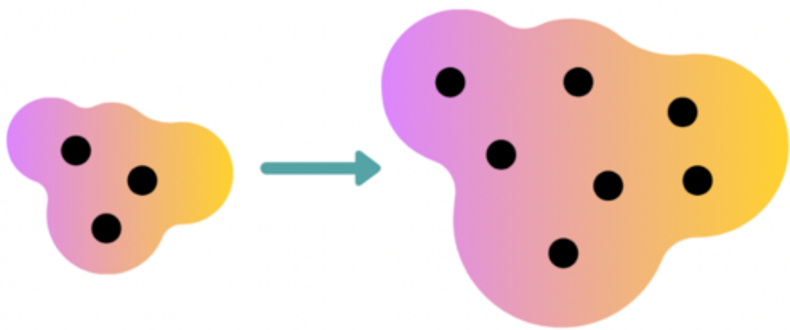
Brief Introduction of LLM (& medical applications)

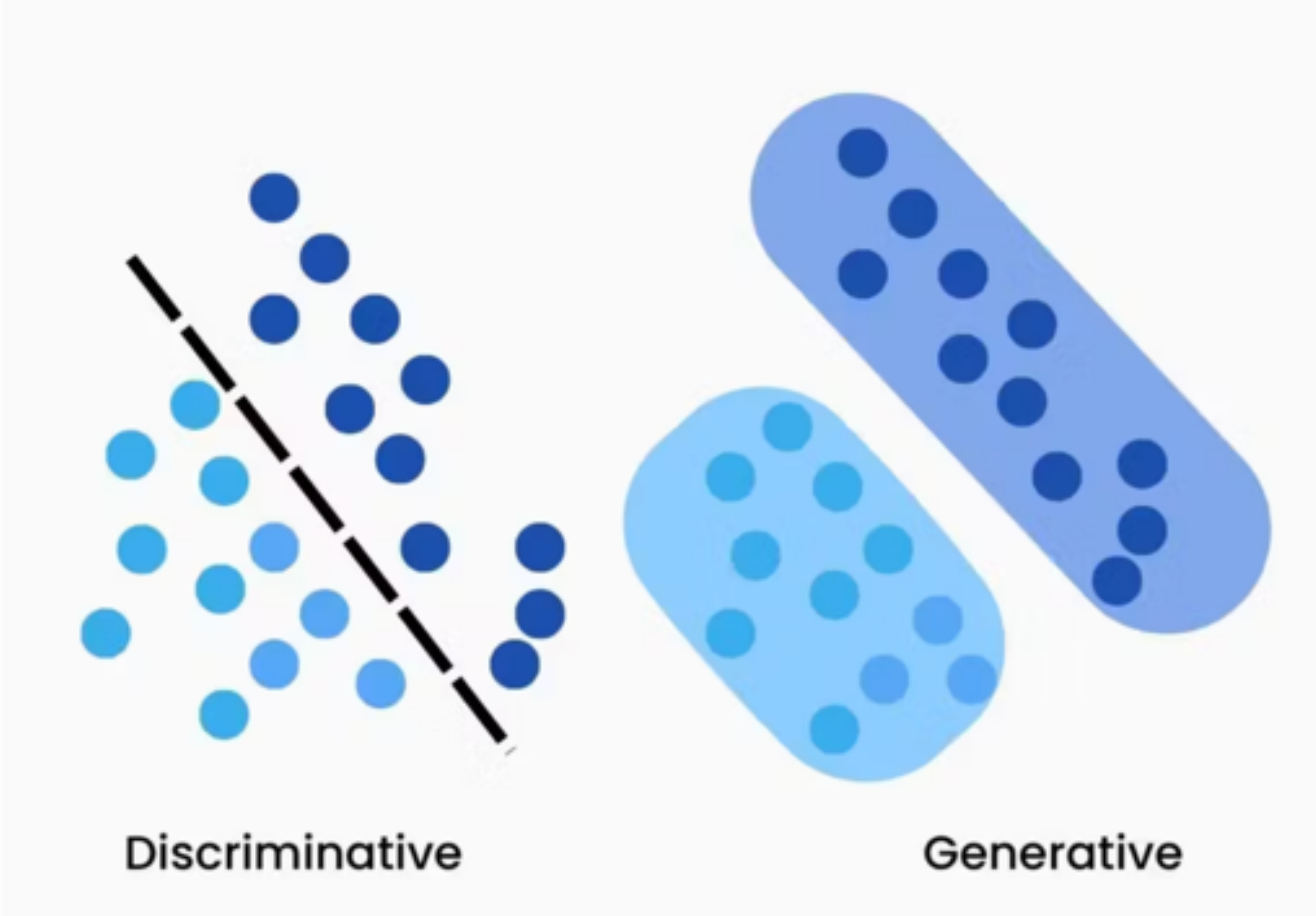


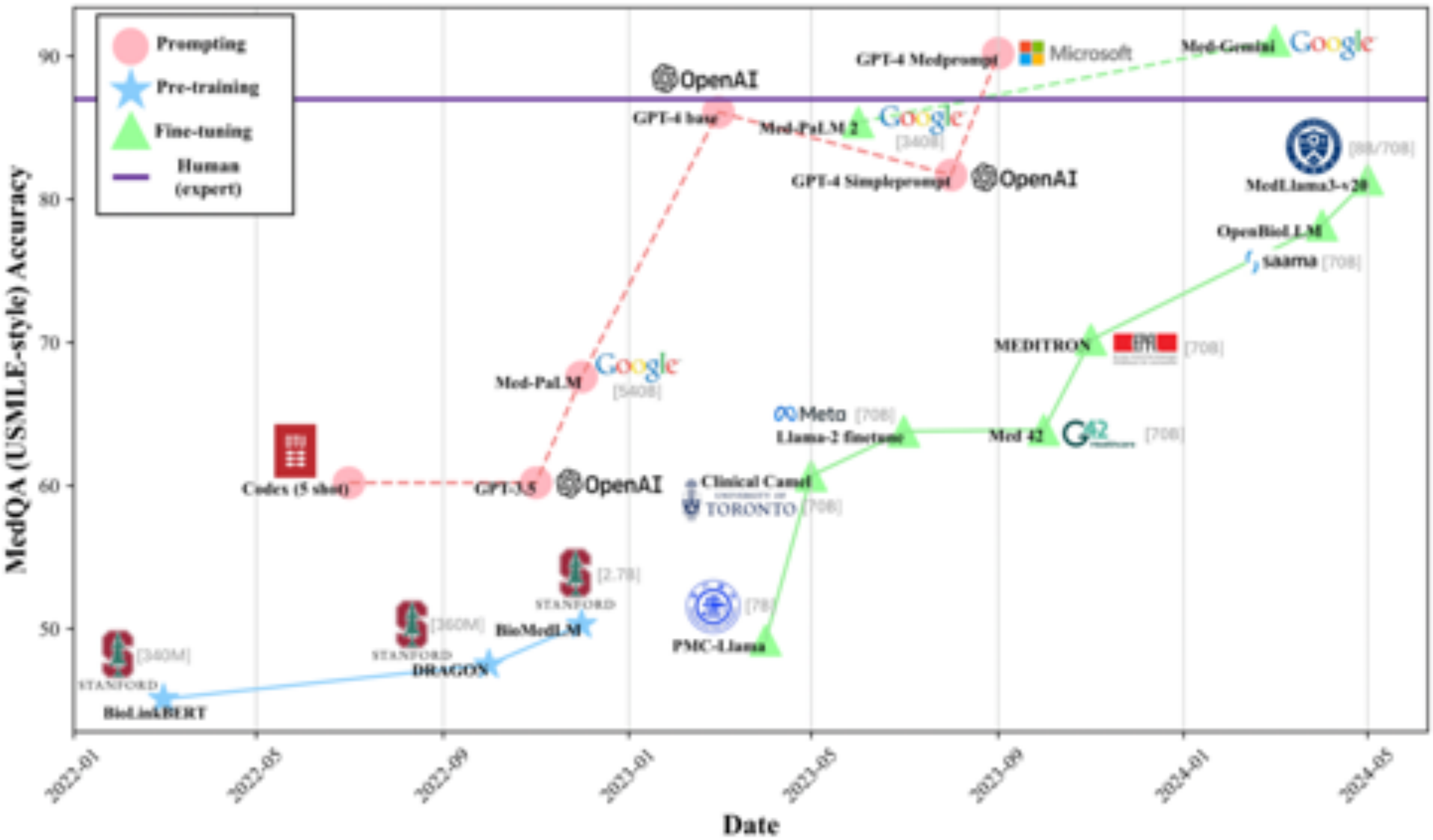
Generating new data using past data

Stable diffusion

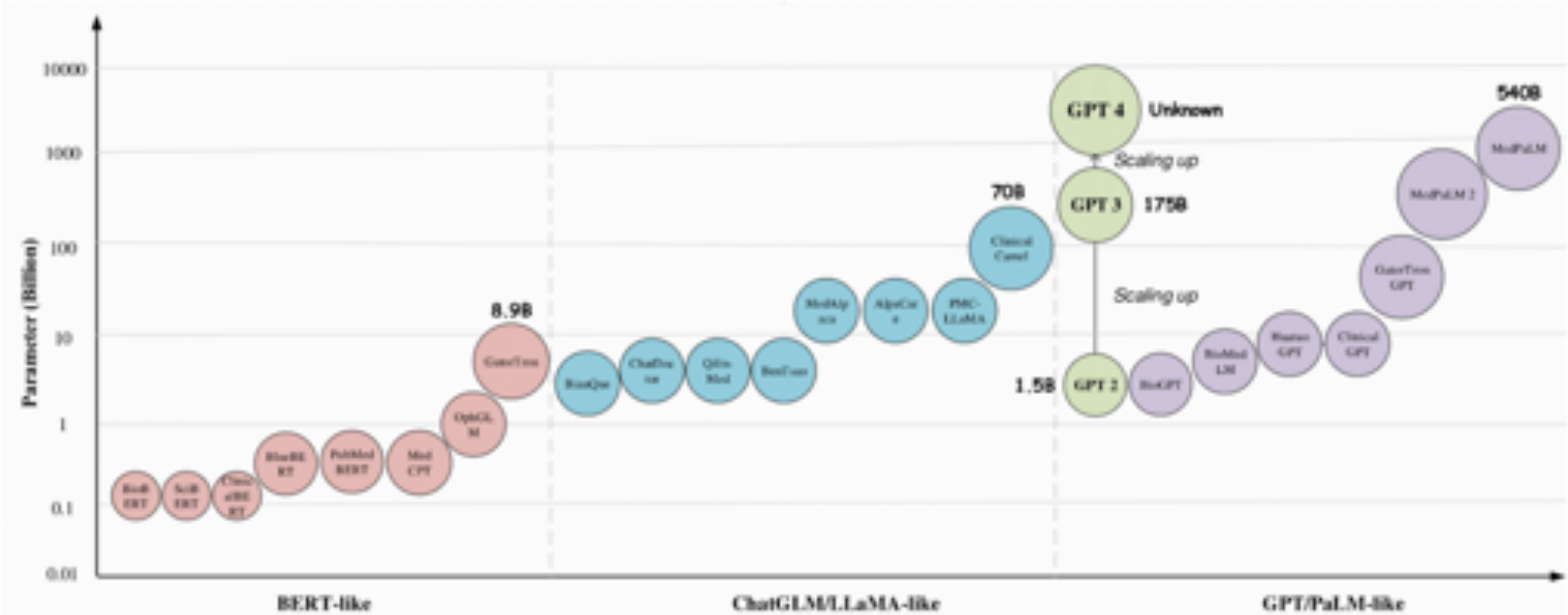
RESEMBLE.AI

LLaMA


Discriminative
Generative



Prompting
Pre-training
Fine-tuning
Human (expert)
MedQA (USMLE-style) Accuracy
Date
90
80
70
60
50
2022-01
2022-05
2022-09
2023-01
2023-05
2023-09
2024-01
2024-05
BioLinkBERT
[340M]
DRAGON
[360M]
BioMedLM
[2.7B]
Codex (5 shot)
GPT-3.5
Med-PaLM
[540B]
GPT-4 base
Med-PaLM 2
[340B]
GPT-4 Simpleprompt
GPT-4 Medprompt
Med-Gemini
PMC-Llama
[7B]
Clinical Camel
[70B]
Llama-2 finetune
[70B]
Med 42
[70B]
MEDITRON
[70B]
saama
[70B]
OpenBioLLM
MedLlama3-v20
[8B/70B]

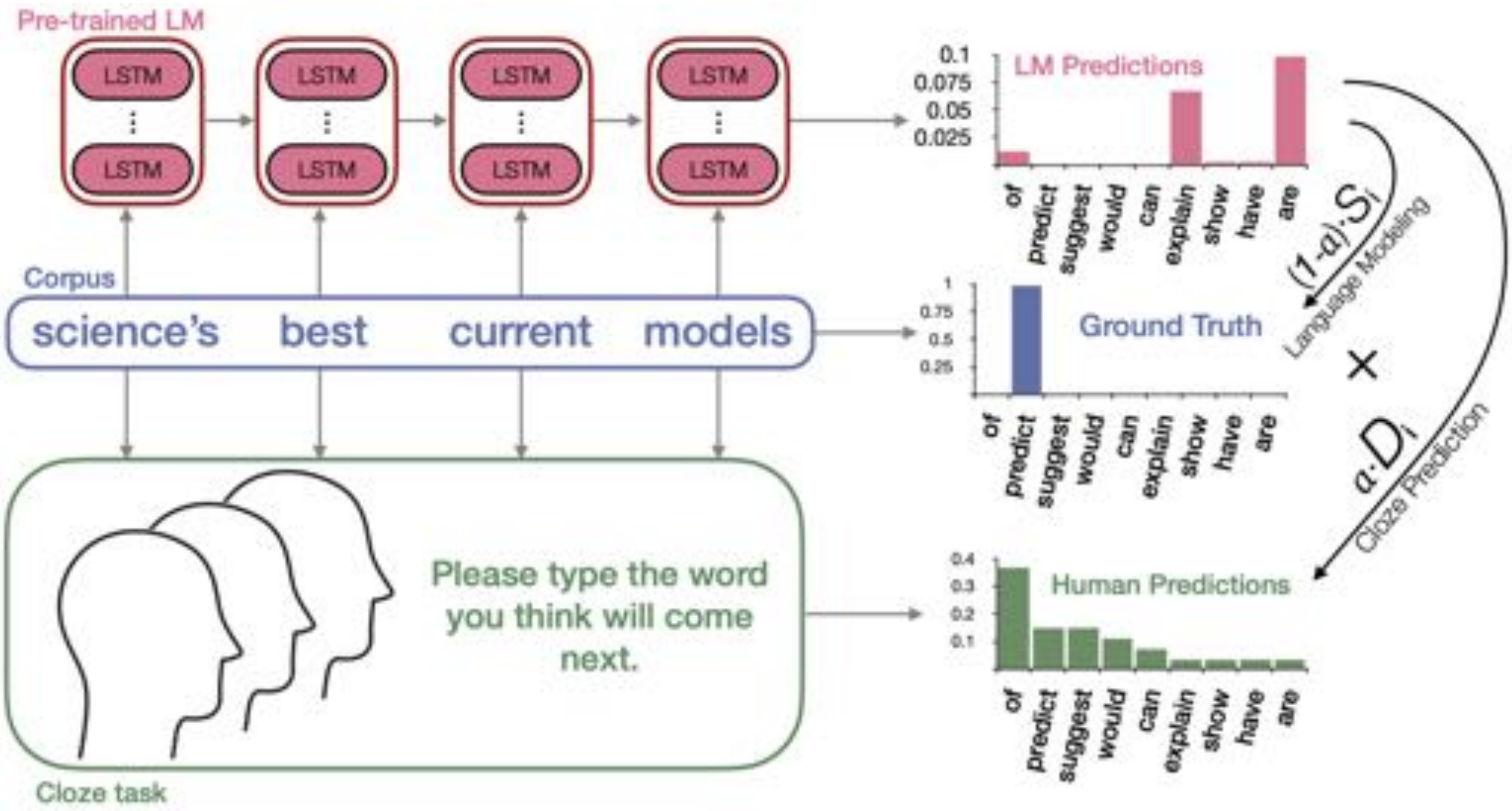


Parameter (Billion)
10000
1000
100
10
1
0.1
0.01
8.9B
70B
GPT 4
Unknown
Scaling up
GPT 3
175B
Scaling up
1.5B
GPT 2
540B
BERT-like
ChatGLM/LLaMA-like
GPT/PaLM-like

Text labeling is tedious and expensive…

The patient is a pleasant 17-year-old Age gentleman Gender who was playing basketball today RelativeDate in gym. Two hours prior RelativeTime to presentation, he Gender started to fall Disease_Syndrome_Disorder and someone stepped on his Gender ankle External_body_part_or_region and kind of twisted his Gender right ankle Symptom and he Gender cannot bear weight Symptom on it now. It hurts to move or bear weight Symptom. No other injuries Injury_or_Poisoning noted. He Gender does not think he Gender has had injuries Injury_or_Poisoning to his Gender ankle External_body_part_or_region in the past. He Gender was given adderall and accutane.

Basic LLM: next word prediction



Basic LLM: next word prediction

Enter text:

how are

how 4919 are 389

4919 389

Prediction

#	probs	next token ID	predicted next token
0	39.65%	345	you
1	16.25%	356	we
2	10.20%	484	they
3	6.42%	262	the
4	3.01%	777	these
5	1.65%	534	your
6	1.21%	661	people
7	1.02%	883	those
8	0.97%	477	all
9	0.90%	674	our

https://tinyurl.com/yaeexkb3

The patient is a pleasant 17-year-old gentleman who was playing basketball today in gym. Two hours prior to presentation, he started to fall and someone stepped on his right ankle and kind of twisted his right ankle and cannot bear weight on it now. It hurts to move or bear weight. No other injuries noted. He does not think he has had injuries to his ankle in the past. He was given ________ and _________.

The patient is a pleasant 17-year-old gentleman who was playing basketball today in gym. Two hours prior to presentation, he started to fall and someone stepped on his right ankle and kind of twisted his right ankle and cannot bear weight on it now. It hurts to move or bear weight. No other injuries noted. He does not think he has had injuries to his ankle in the past. He was given adderall and accutane.

THOSE ARE ALREADY IN THE RECORD SOMEWHERE!

You can get paired translation from bilingual text

Tomorrow we will run faster, stretch out our [I CAN GUESS A WORD] further. . .

And then one fine morning— So we beat on,

boats against the current,

borne back ceaselessly into the past.

You can get paired translation from bilingual text

Tomorrow we will run faster,
stretch out our arms farther. . .

And then one fine morning— So
we beat on,

boats against the current,

[I CAN GUSESS THE FOLLOWING SENTENCE]

You can get paired translation from bilingual text

Tomorrow we will run faster, stretch out our arms farther. . .

And then one fine morning— So we beat on,

[OR SOMETHING IN BETWEEN]

borne back ceaselessly into the past.

You can get paired translation from bilingual text

Tomorrow we will run faster, stretch out our arms farther. . .

明天我們會跑得更快，伸出的手臂會更遠。

And then one fine morning— So we beat on,

然後在某個美好的早晨——就這樣，

boats against the current,

我們奮力向前，如同逆流而上的船隻，

borne back ceaselessly into the past.

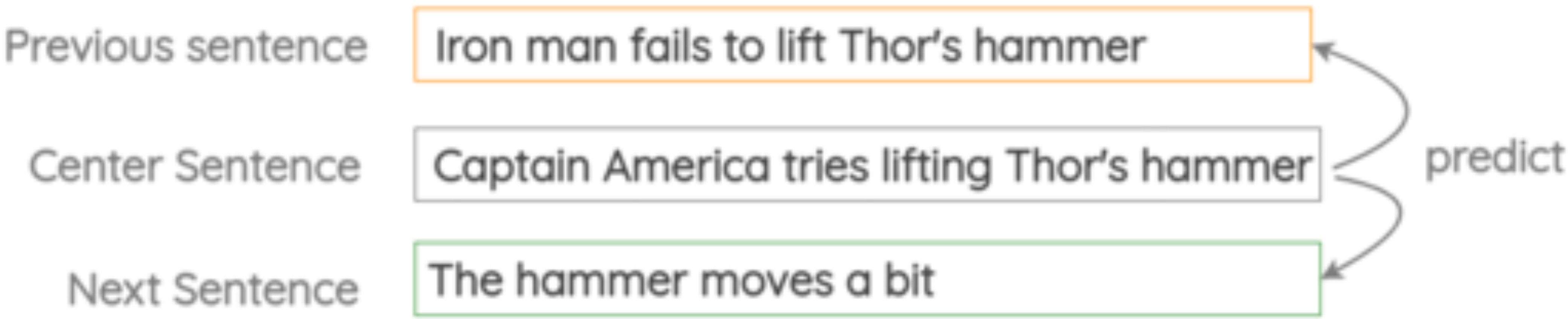
不停地被推回到過去。

"Tomorrow we will run faster, stretch out our [I CAN GUESS A WORD] further. . ."

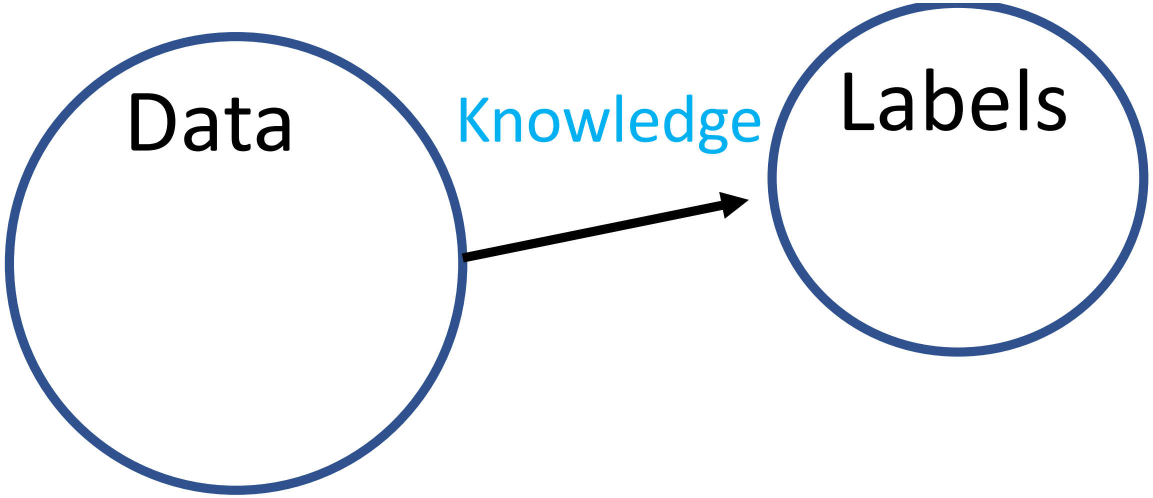
(a) Original images (b) Masked images (c) Inpainted images

Just like inpainting… you are using the context to guess the missing part

Self-supervised Methods

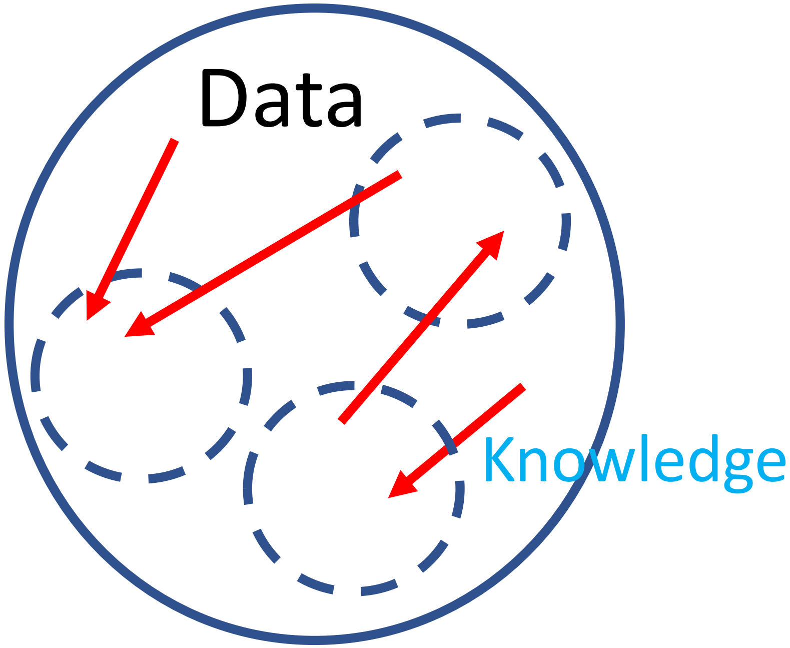


Supervised

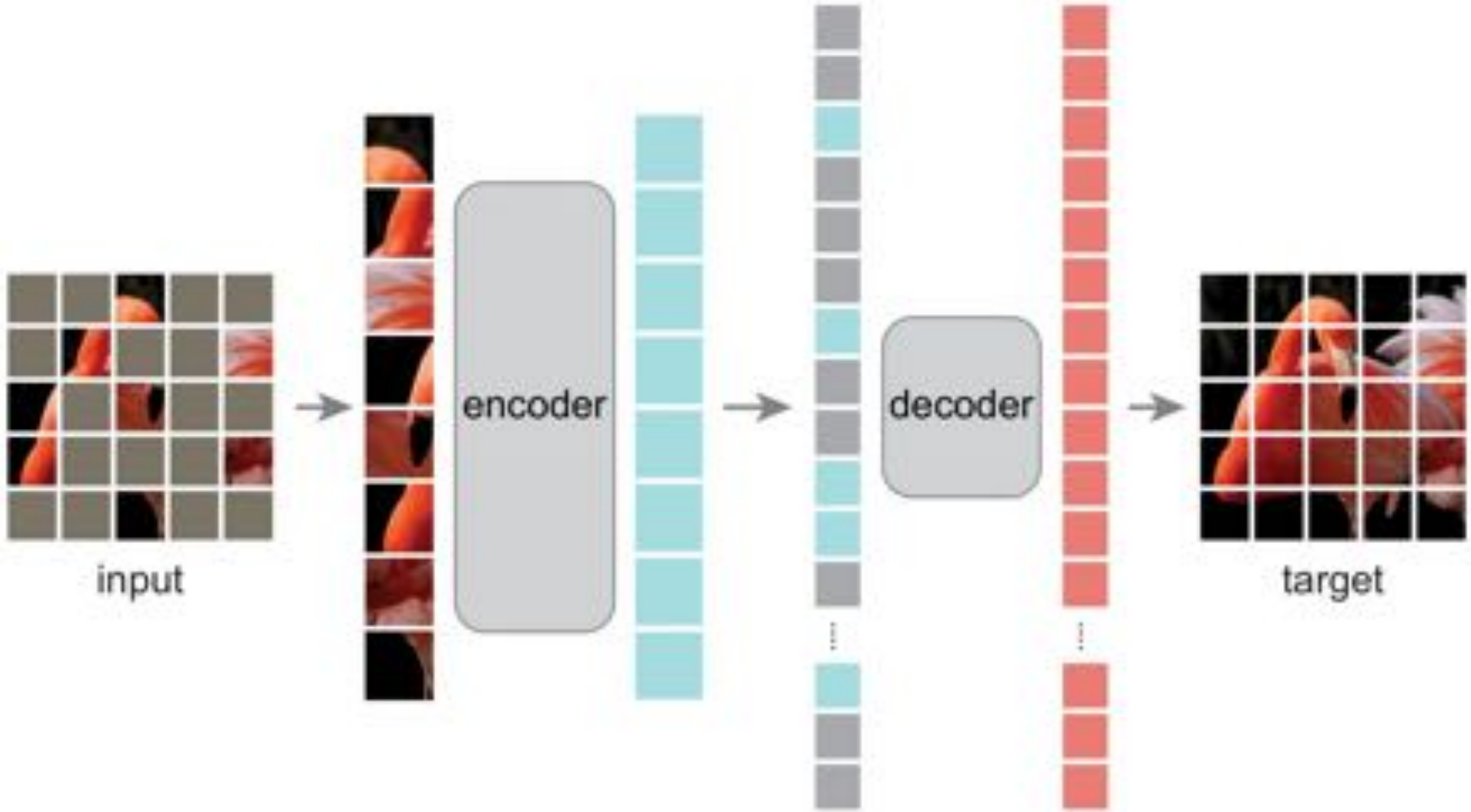


Self-supervised

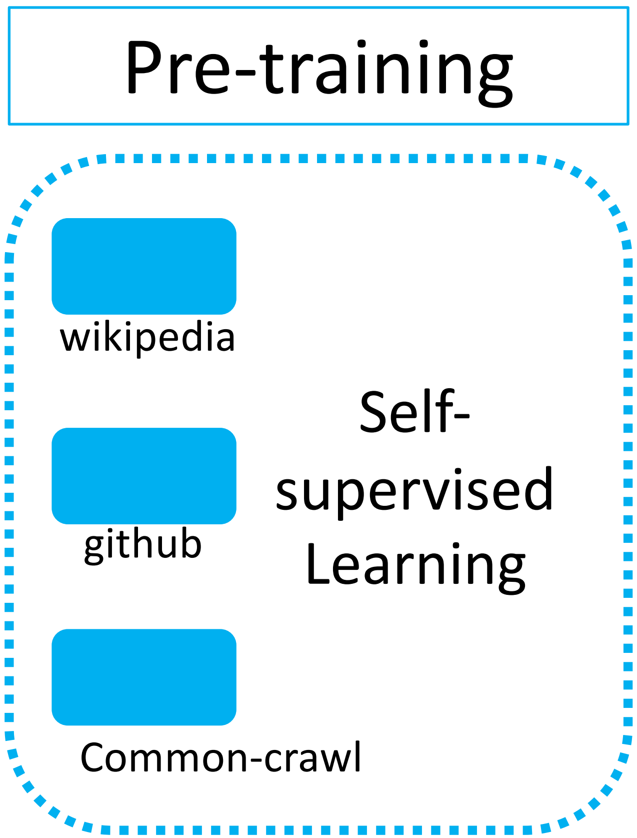
(or unsupervised..)



Self-supervised for Image Model



Not as useful. Why?

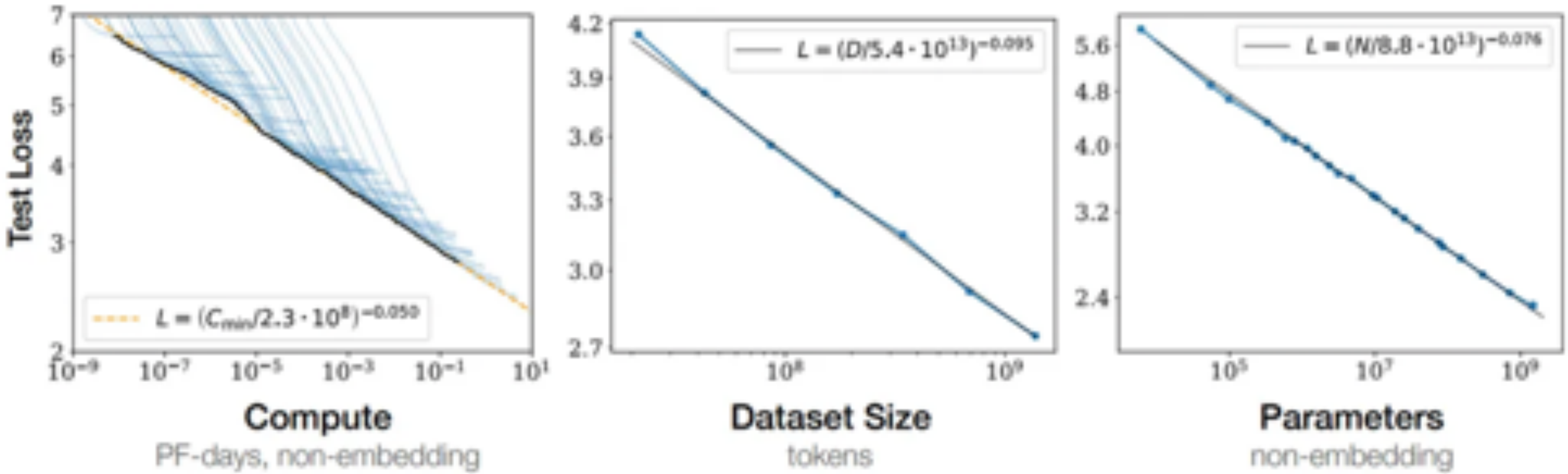


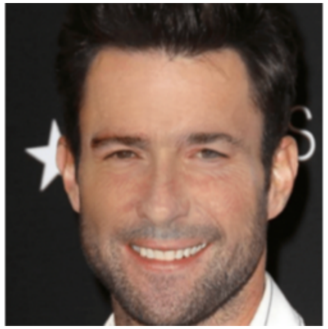
Pre-training:

Obtaining general knowledge

(like the ability to speak regardless of the context)

Scaling law in LLM





(r, g, b)

(231, 201, 83)

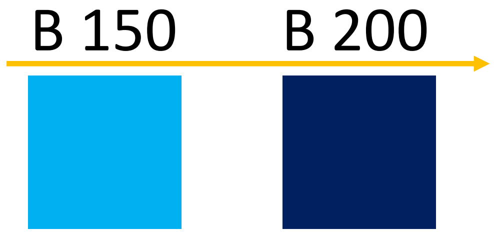


Image can be represented by intensities values of pixels

How about words?

Code by alphabetical order?

make: m(13) a(1) t(20) e(5)

Too loose

$26^4=456976$

of combinations

<5000 are commonly used

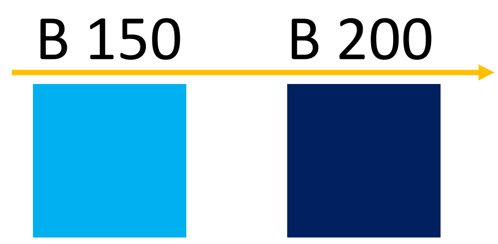
How about words?

mate: m(13) a(1) t(20) e(5)

meat: m(13) e(5) a(1) t (20)

Different order means very different things!

vs

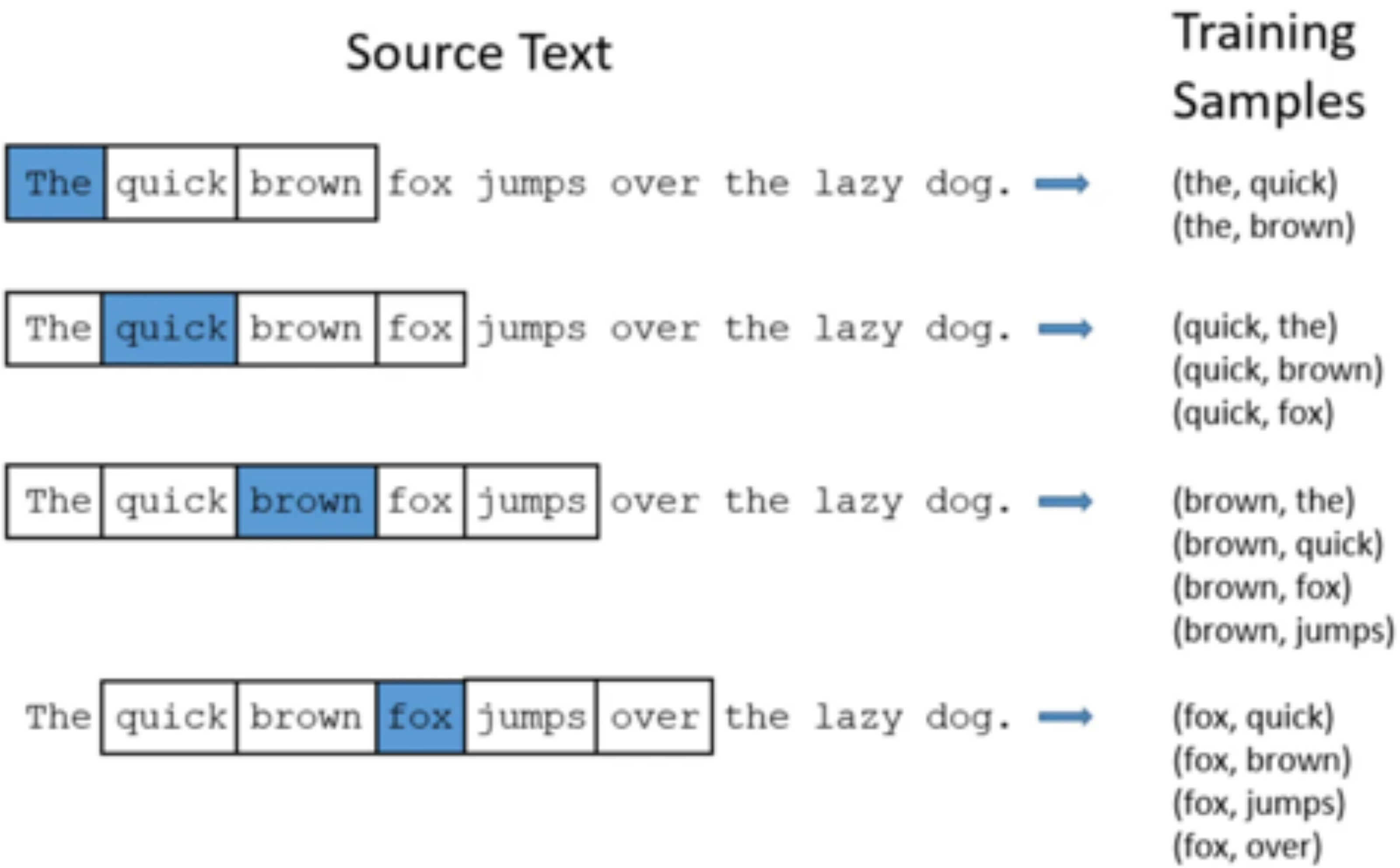


Contextual Learning:
Words are embedded by analyzing how they appear in context with other words.

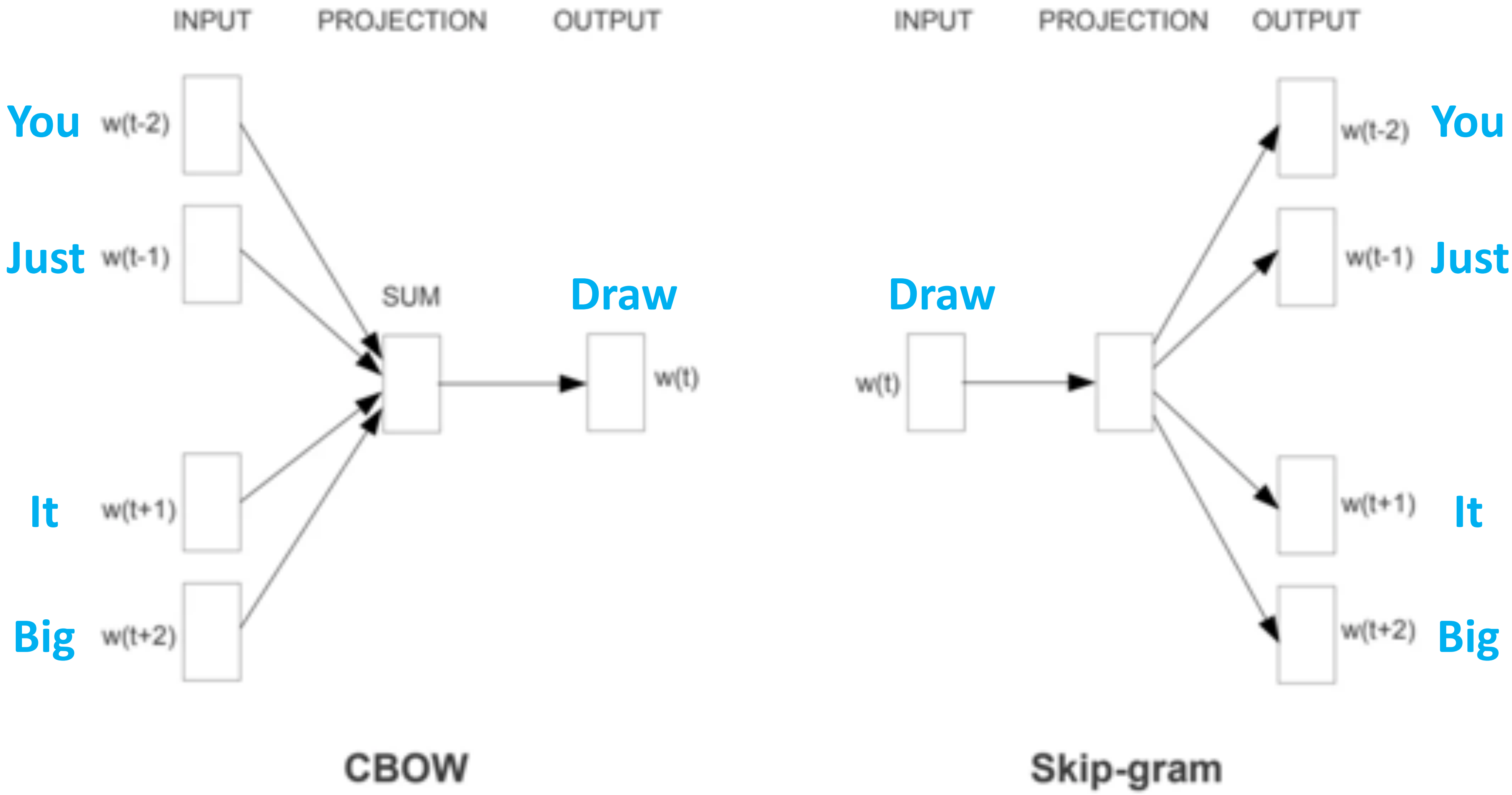
"The **dog** plays **fetch** in the backyard."

“My **cat** plays with the **yarn** on the floor."

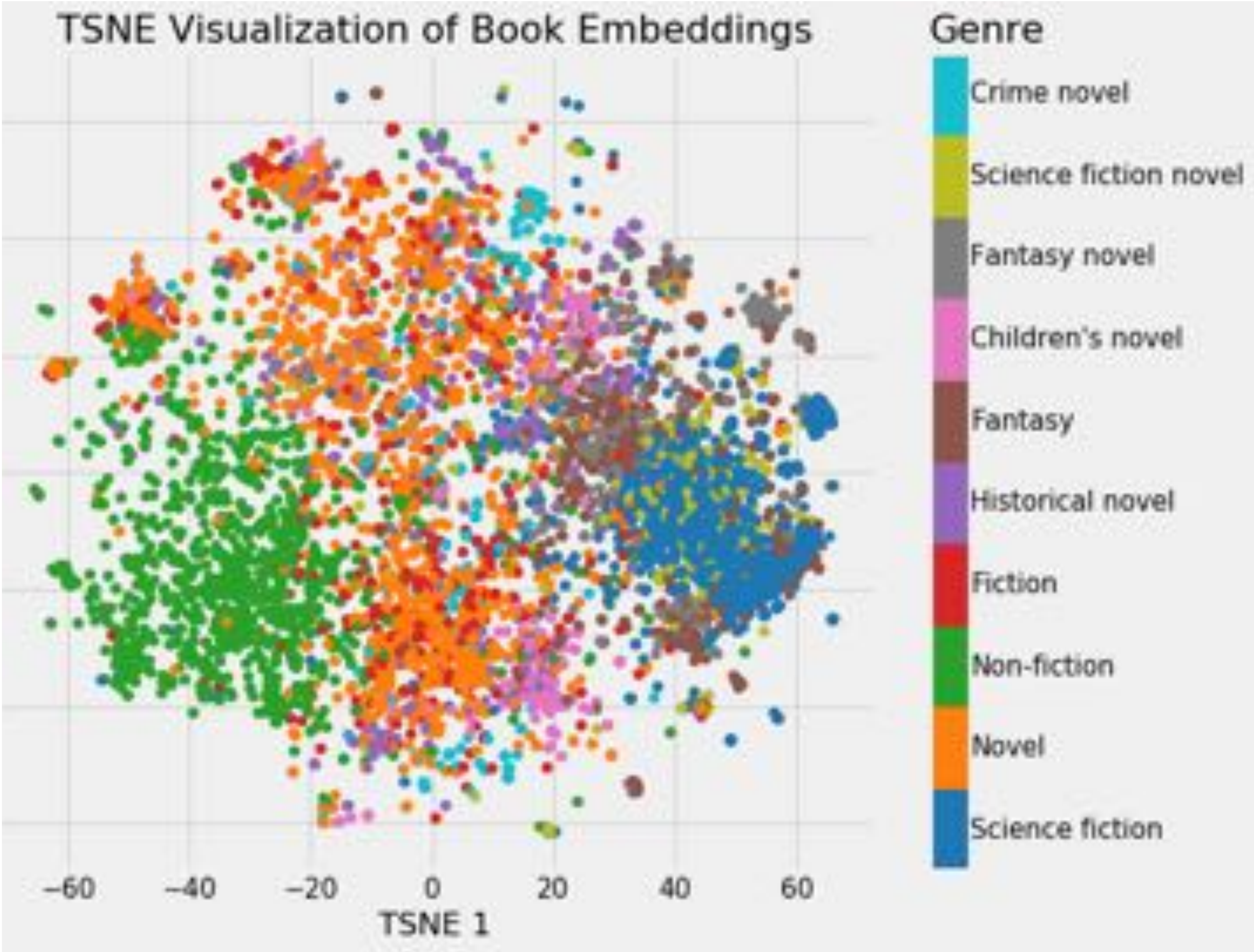
Word2vec: Find the neighboring words



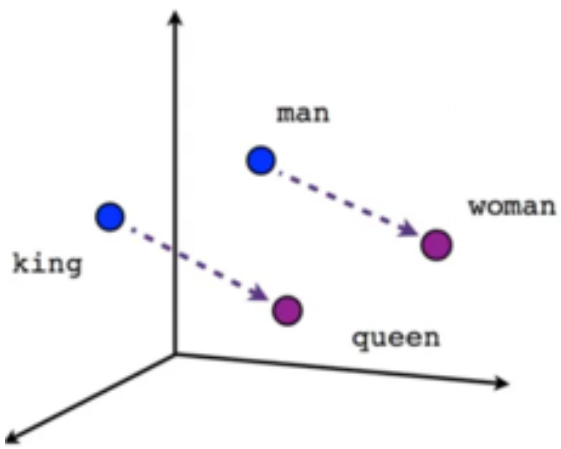
Word2vec: Find the neighboring words



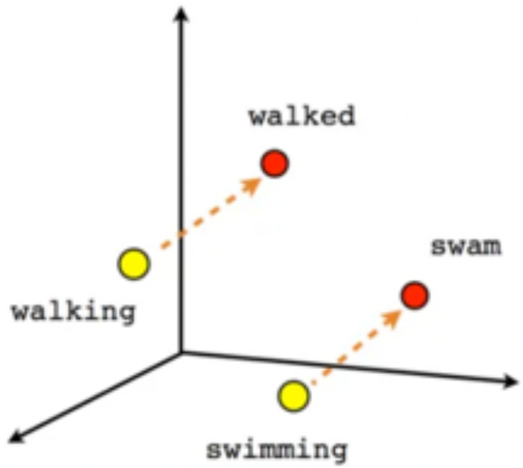
High-dimensional Embedding



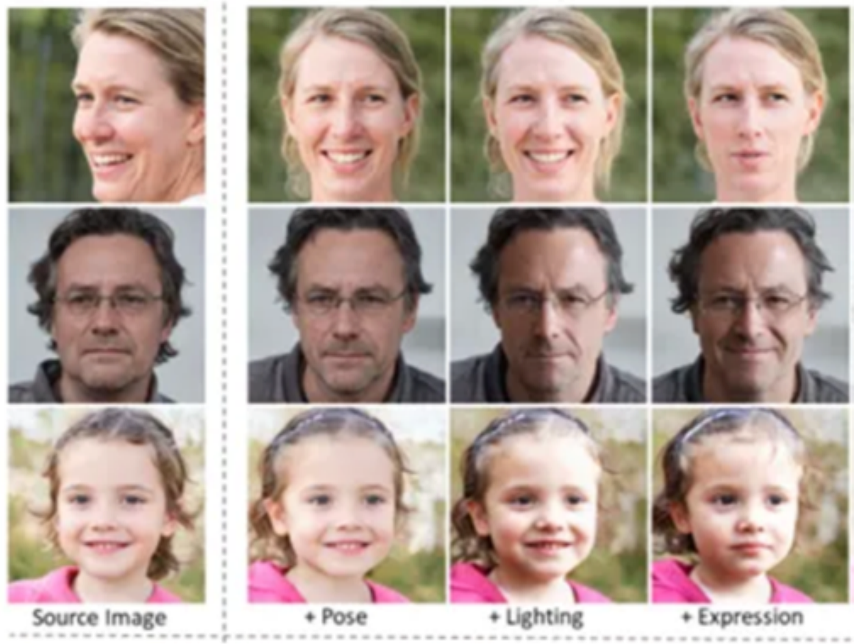
Latent Interpolation



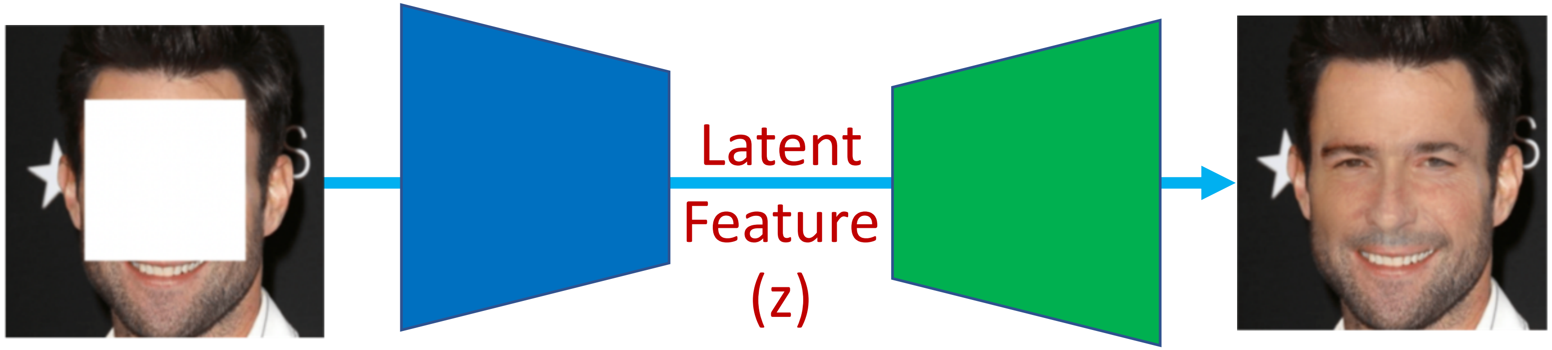
Male-Female



Verb tense



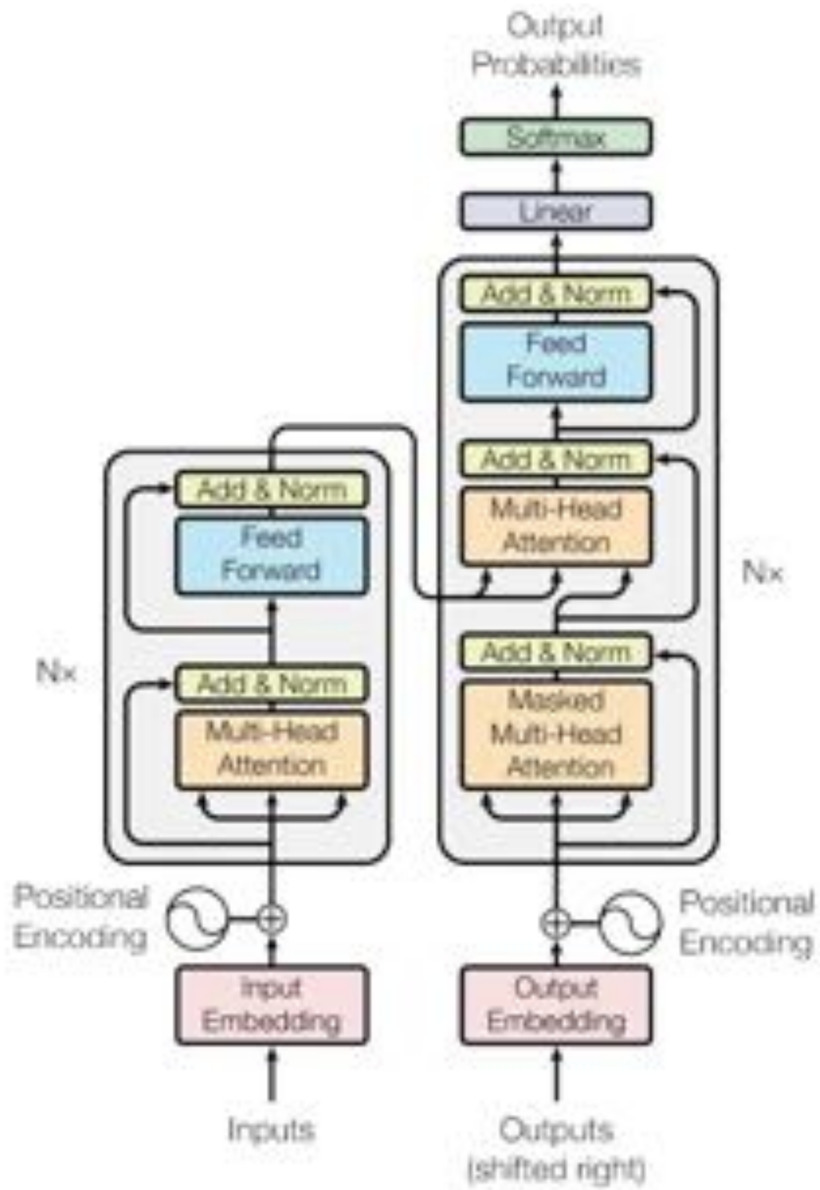
How to turn sentences into features?

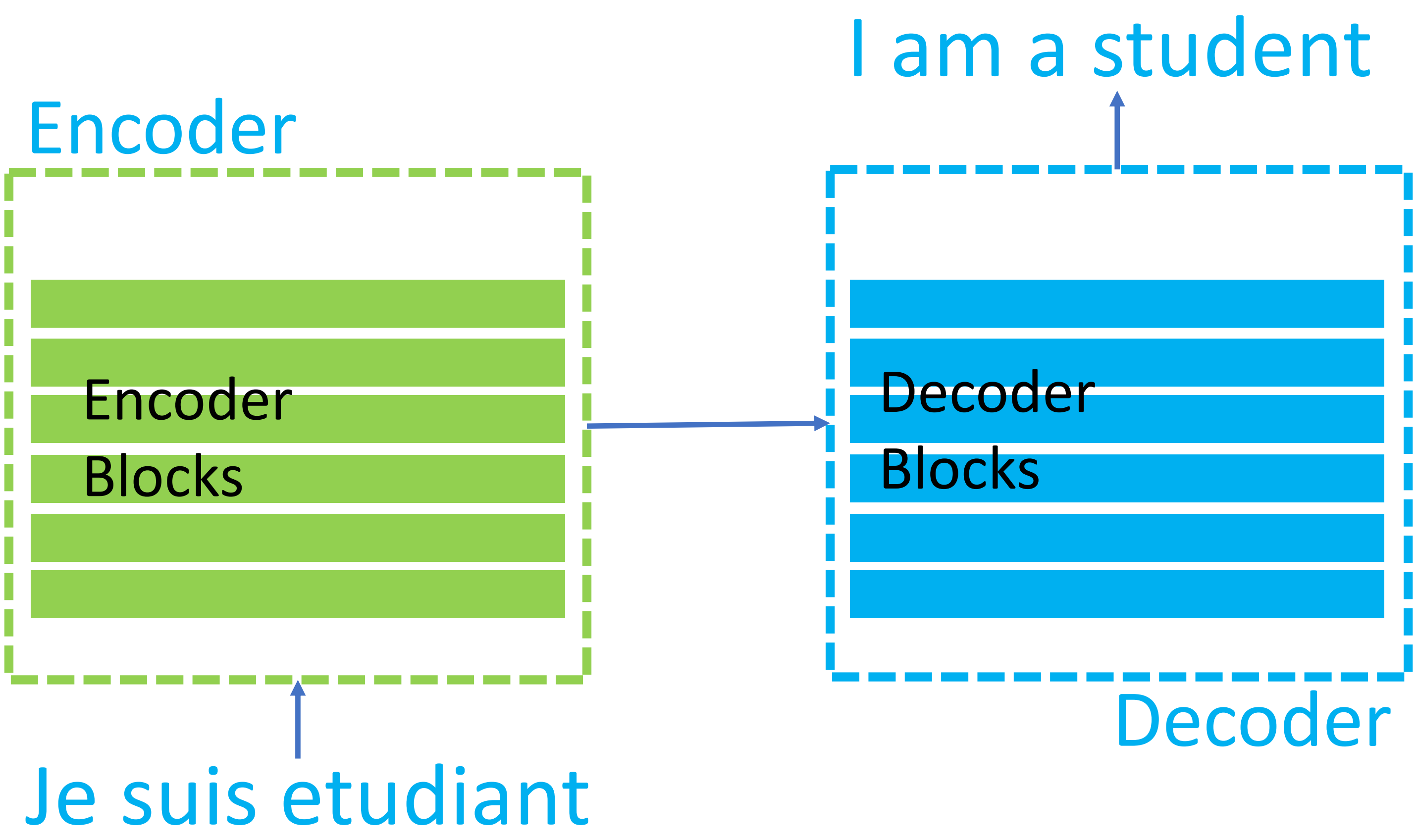


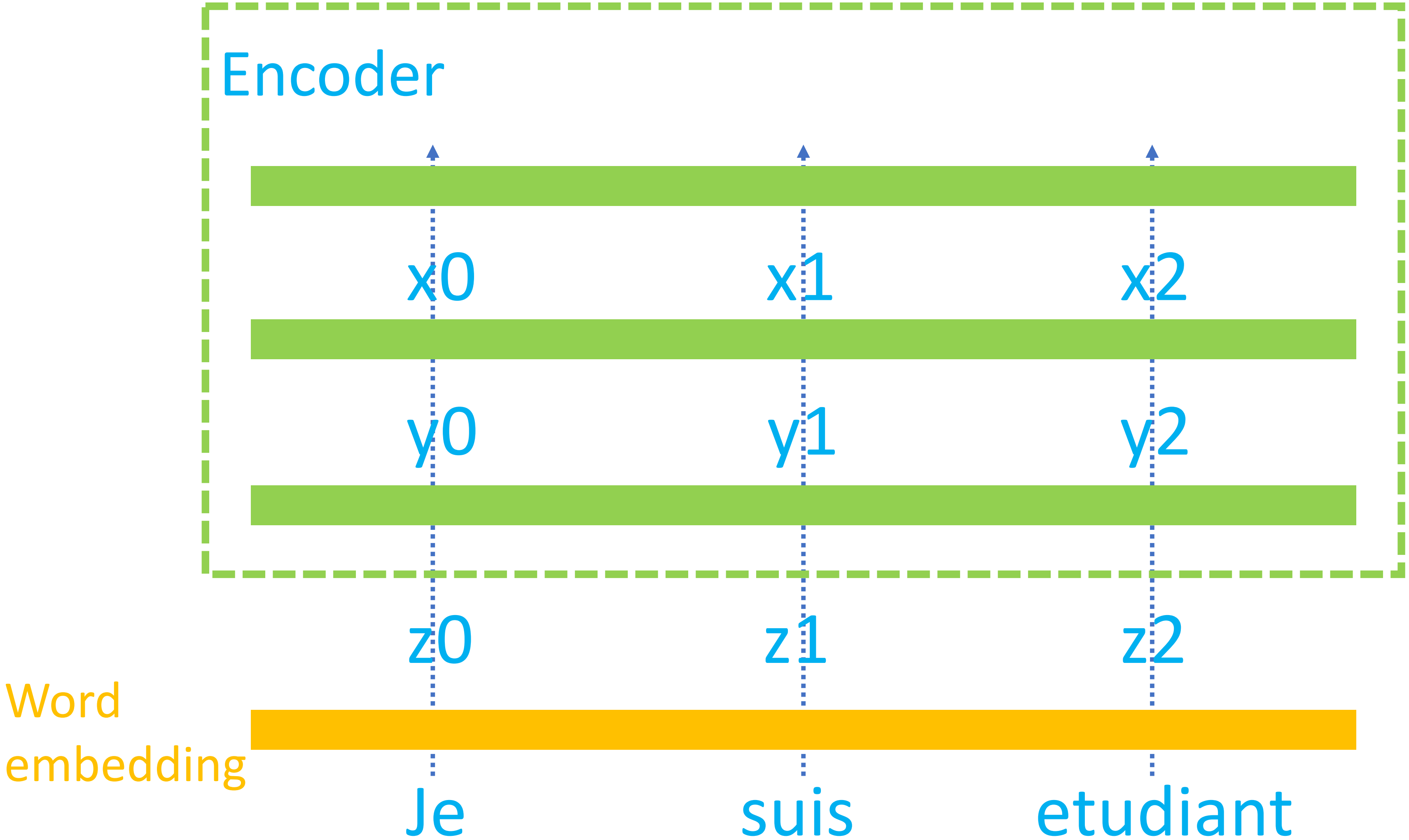
The patient is a pleasant 17-year-old gentleman who was playing basketball today in gym.

Latent
Feature
(z)

Transformer Architecture




I am a student
Encoder
Encoder
Blocks
Decoder
Blocks
Decoder
Je suis etudiant



Encoder
x0
x1
x2
y0
y1
y2
z0
z1
z2
Word embedding
Je
suis
etudiant

In Each Encoder Blocks:

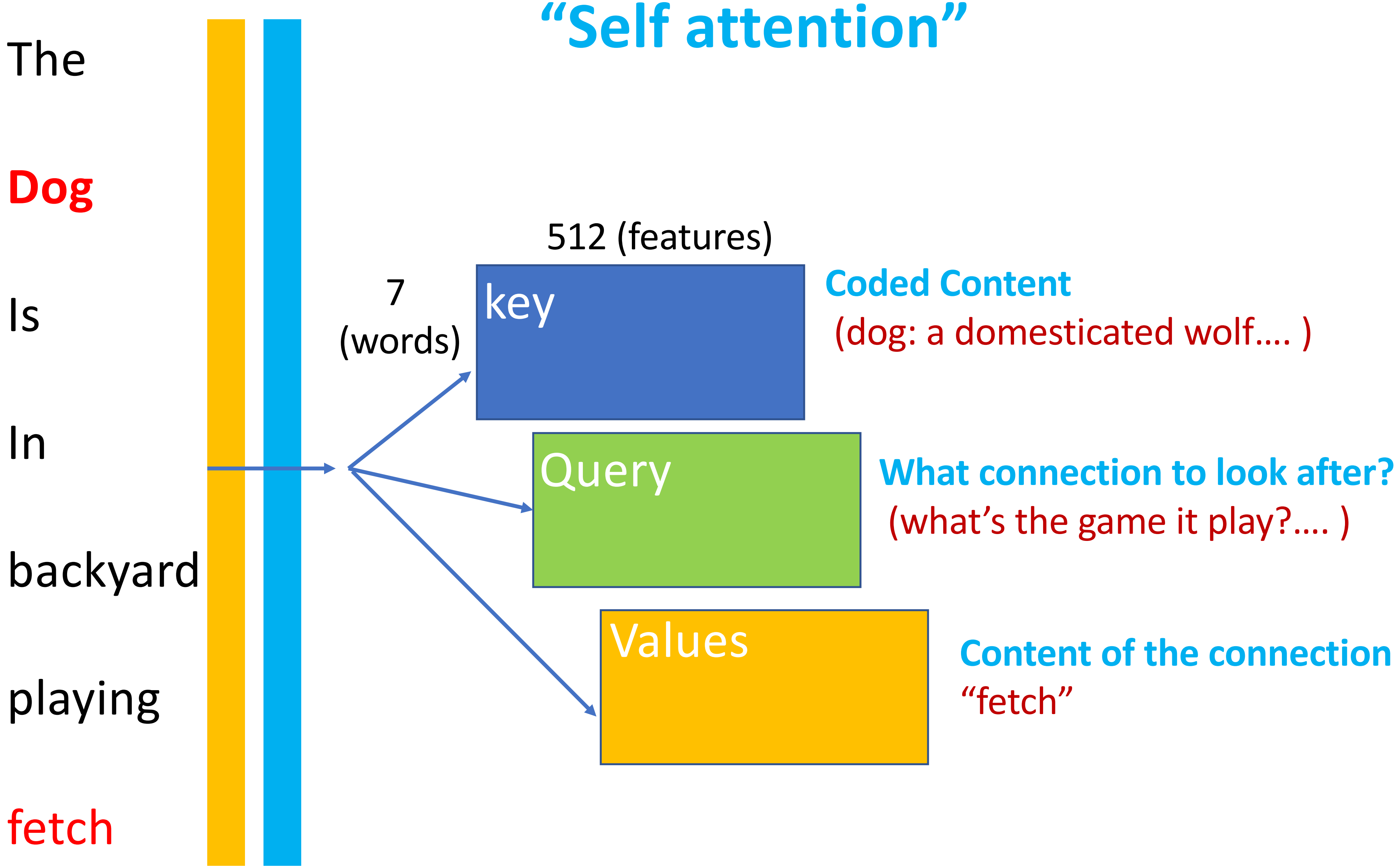
Self-attention Layer

Fully-connected (FC)

"The **dog** is in the backyard playing fetch"

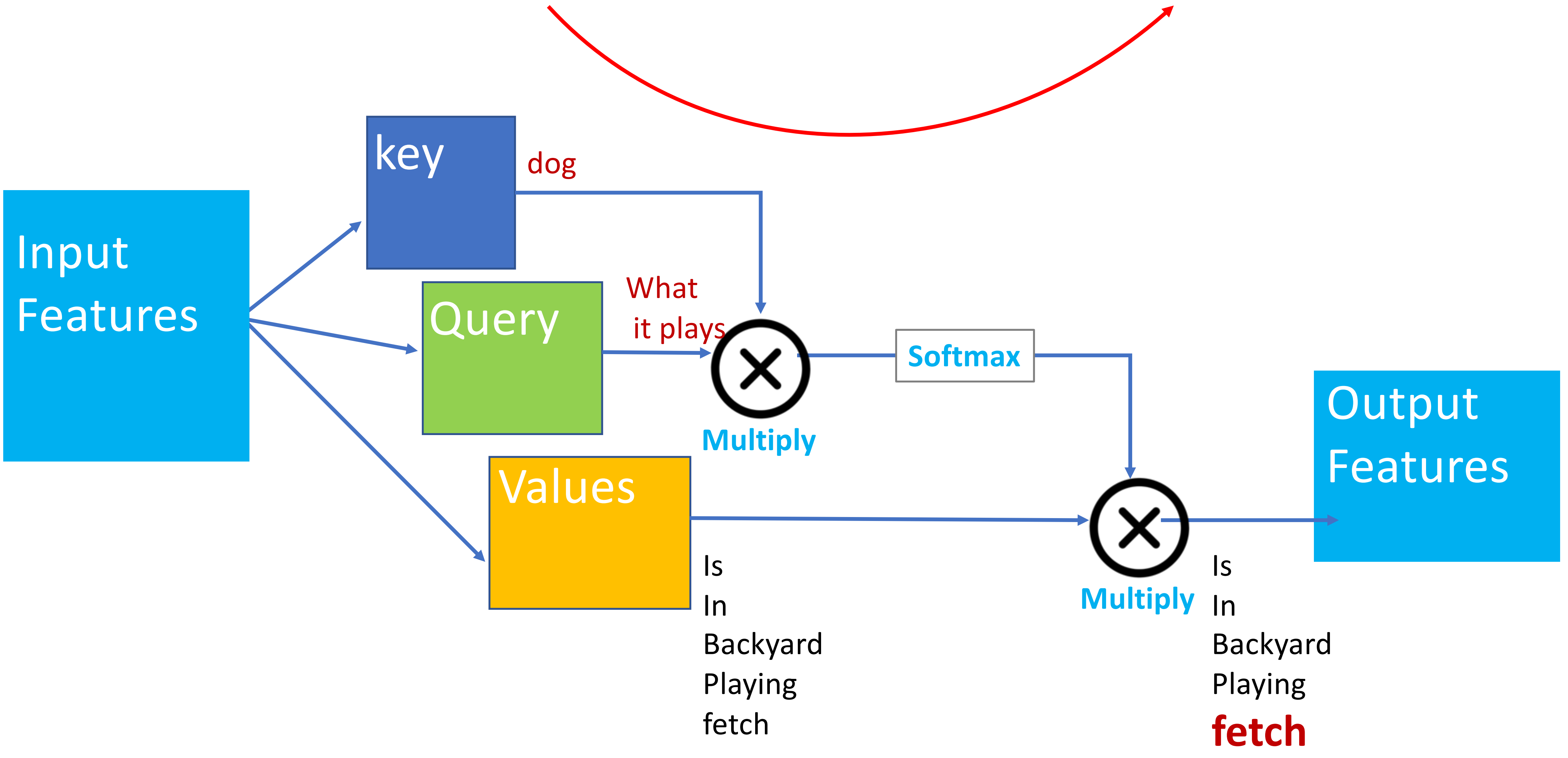
Need a way to connect distant information

“Self attention”

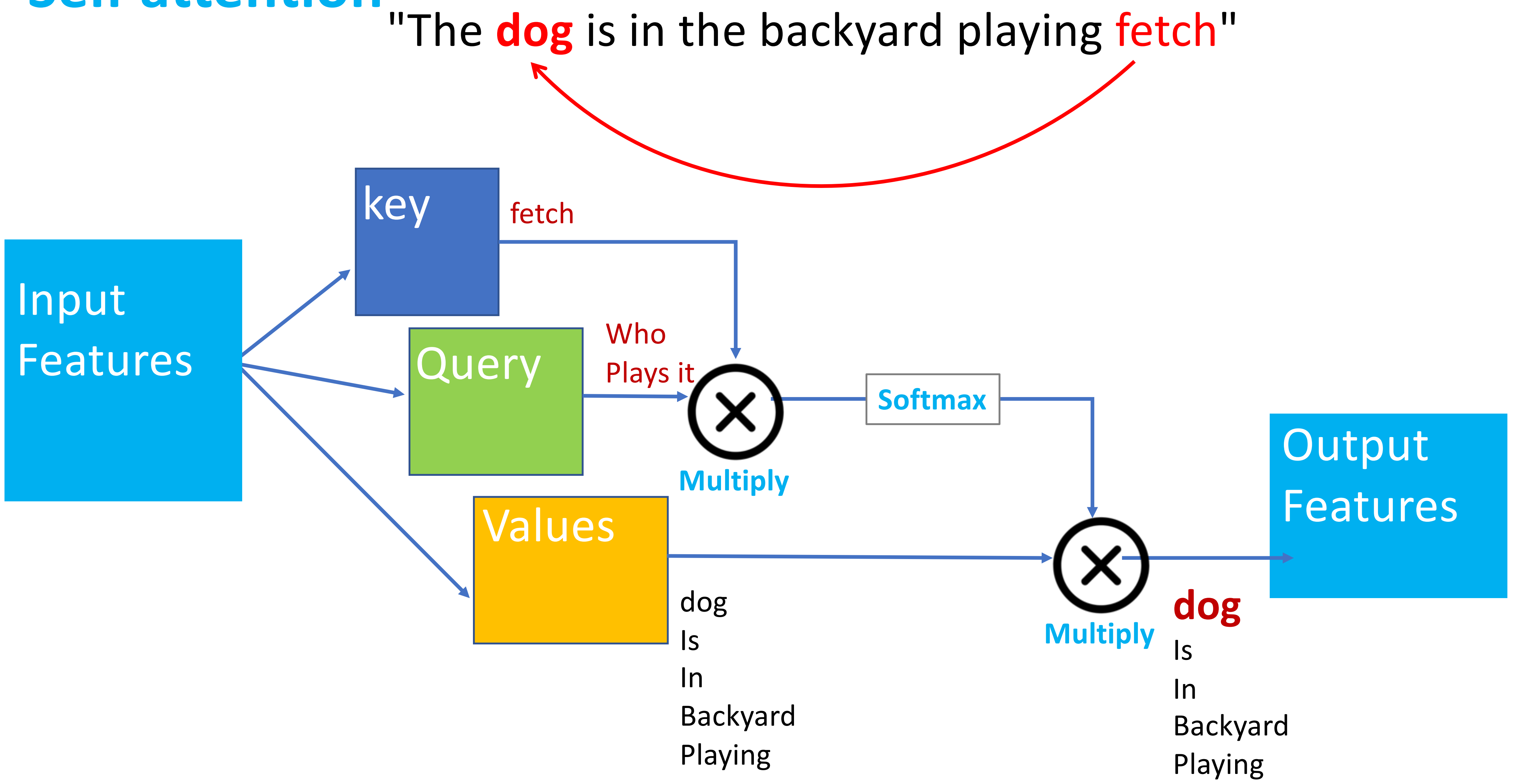


“Self attention”

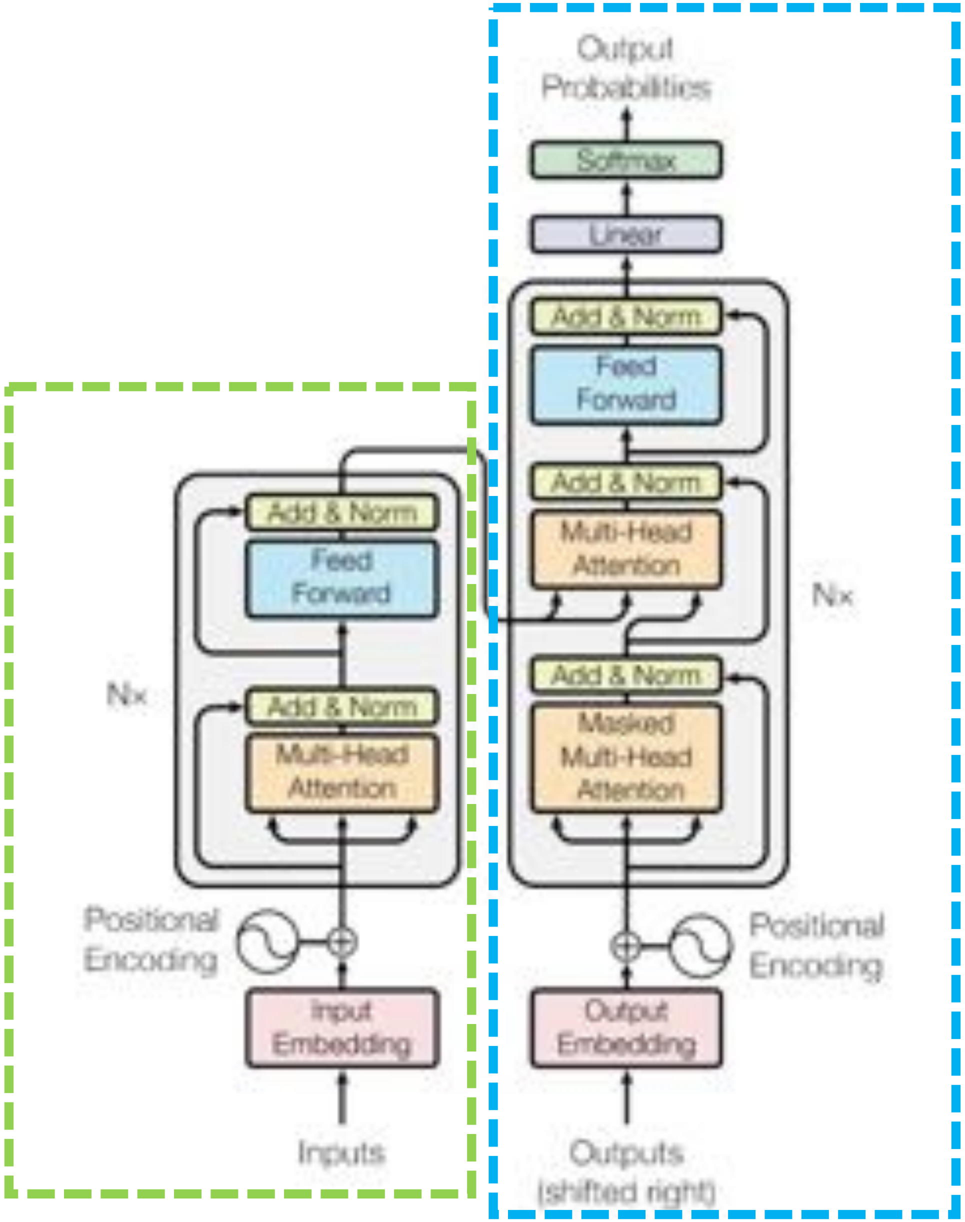
"The **dog** is in the backyard playing fetch"



“Self attention”

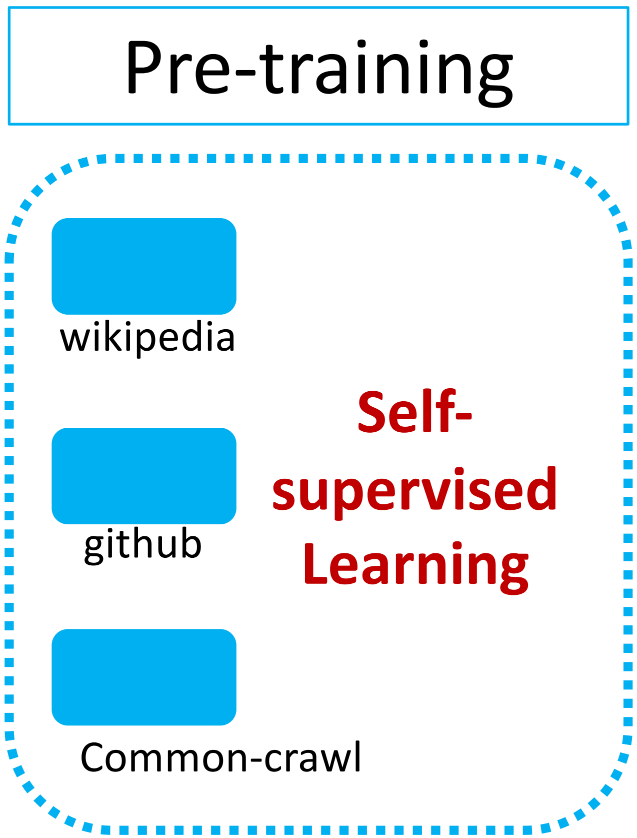


Transformer Architecture



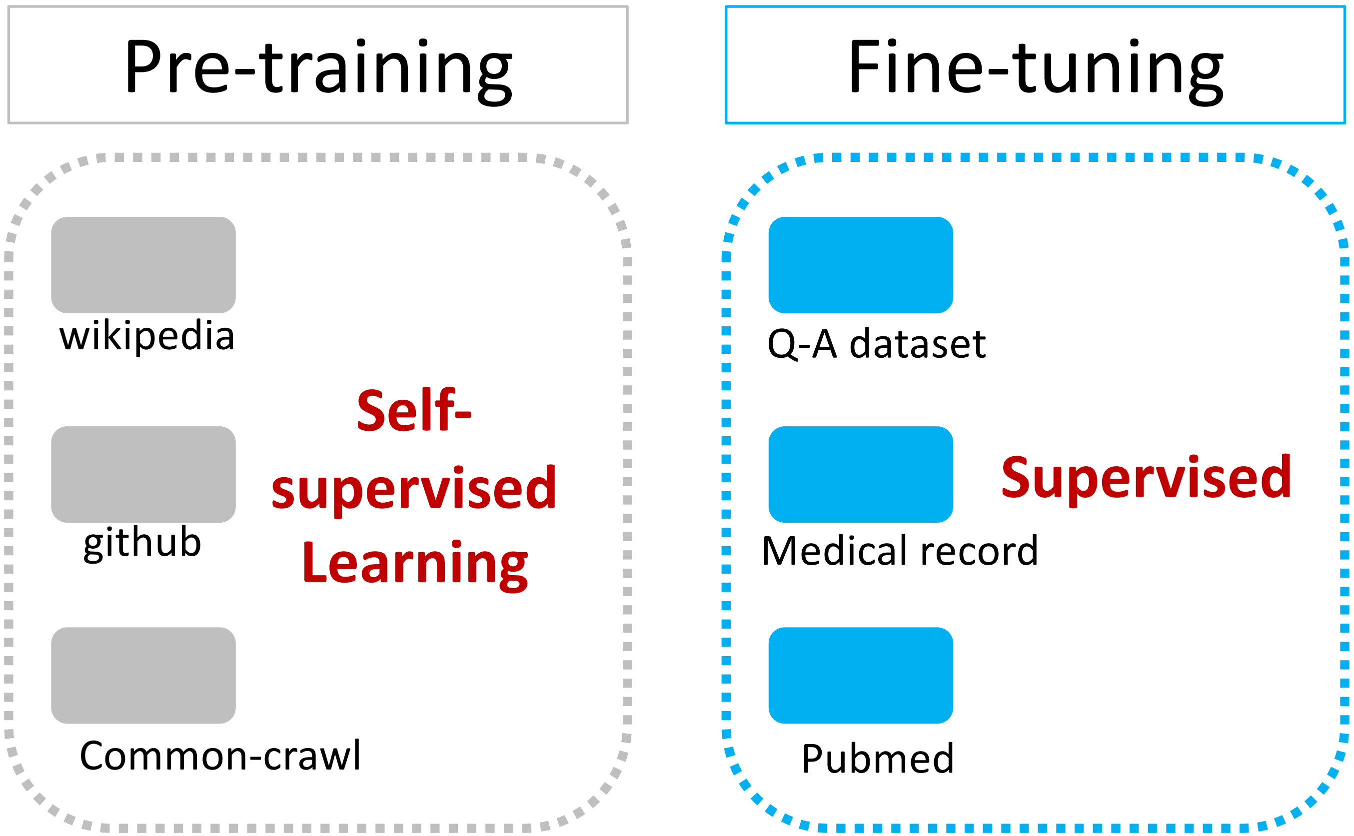
Encoder

Decoder



Pre-training:

The Model can speak,
but may not be useful for our purpose



Using smaller,
Specialized data
For our purpose

Supervised Medical Q & A Dataset

Question (medicine): A 13-year-old girl is operated on due to Hirschsprung illness at 3 months of age. Which of the following tumors is more likely to be present?
1. Abdominal neuroblastoma
2. Wilms tumor
3. Mesoblastic nephroma
4. Familial thyroid medullary carcinoma.

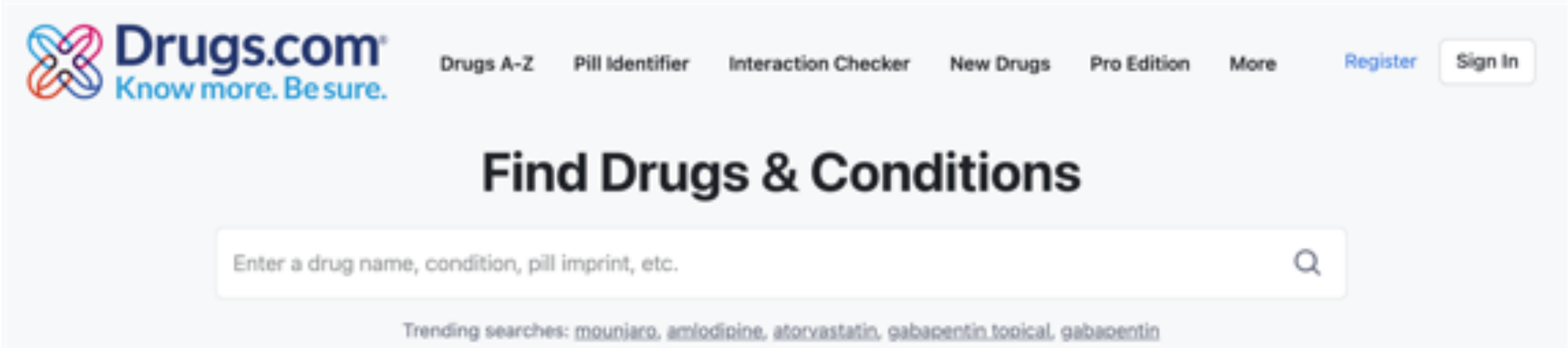
Question (pharmacology) The antibiotic treatment of choice for Meningitis caused by Haemophilus influenzae serogroup b is:
1. Gentamicin
2. Erythromycin
3. Ciprofloxacin
4. Cefotaxime

Question (psychology) According to research derived from the Eysenck model, there is evidence that extraverts, in comparison with introverts:
1. Perform better in surveillance tasks.
2. Have greater salivary secretion before the lemon juice test.
3. Have a greater need for stimulation.
4. Have less tolerance to pain.

MedQA

https://huggingface.co/datasets/GBaker/MedQA-USMLE-4-options/viewer/default/train?row=4

A 23-year-old pregnant woman at 22 weeks gestation presents with burning upon…	Nitrofurantoin	{ "A": "Ampicillin", "B": "Ceftriaxone", "C": "Doxycycline", "D": "Nitrofurantoin" }
A 3-month-old baby died suddenly at night while asleep. His mother noticed that he had…	Placing the infant in a supine position on a firm mattress while sleeping	{ "A": "Placing the infant in a supine position on a firm mattress while sleeping",…
A mother brings her 3-week-old infant to the pediatrician's office because she is…	Abnormal migration of ventral pancreatic bud	{ "A": "Abnormal migration of ventral pancreatic bud", "B": "Complete failure of…
A pulmonary autopsy specimen from a 58-year-old woman who died of acute hypoxic…	Thromboembolism	{ "A": "Thromboembolism", "B": "Pulmonary ischemia", "C": "Pulmonary hypertension", "D"…
A 20-year-old woman presents with menorrhagia for the past several years. She says that her menses "have always been heavy", and she has experienced easy bruising for as long as she can remember. Family history is significant for her mother, who had similar problems with bruising easily. The patient's vital signs include: heart rate 98/min, respiratory rate 14/min, temperature 36.1°C (96.9°F), and blood pressure 110/87 mm Hg. Physical examination is unremarkable. Laboratory tests show the following: platelet count 200,000/mm3, PT 12 seconds, and PTT 43 seconds. Which of the following is the most likely cause of this patient's symptoms?	Von Willebrand disease	{ "A": "Hemophilia A", "B": "Lupus anticoagulant", "C": "Protein C deficiency", "D": "Von Willebrand disease" }


Drugs.com
Know more. Be sure.
Drugs A-Z
Pill Identifier
Interaction Checker
New Drugs
Pro Edition
More
Register
Sign In
Find Drugs & Conditions
Enter a drug name, condition, pill imprint, etc.
Trending searches: mounjaro, amlodipine, atorvastatin, gabapentin topical, gabapentin


CDC
U.S. CENTERS FOR DISEASE
CONTROL AND PREVENTION


PubMed®


NHS
Health A-Z
Live Well
Mental health
Home
Medicines A to Z

Using unrelated but high-level QA also help

StackExchange

Q

Is it possible to solve $3f(x)^2 - 2f(x)^3 - c = 0$?

Asked yesterday Modified today Viewed 59 times

2

I am trying to solve for x, from

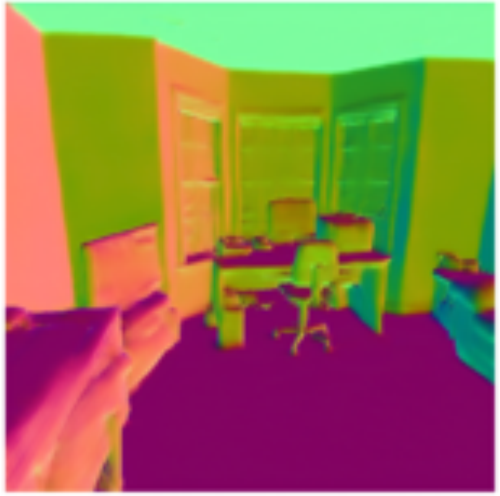
$$3f(x)^2 - 2f(x)^3 - c = 0$$

where $f(x) = 1 - (1-x)^b$, $c \in (0, 1)$ and $b > 0$. I don't remember very well how to resolve this type of thing, is it legal to resolve $3u^2 - 2u^3 - c = 0$? and then solve for x? The only thing I know is that there is a root in the interval $(0, 1)$, and I am interested in finding this root. Is it possible to solve for x without resorting to numerical methods? I appreciate any reference or suggestion. Greetings

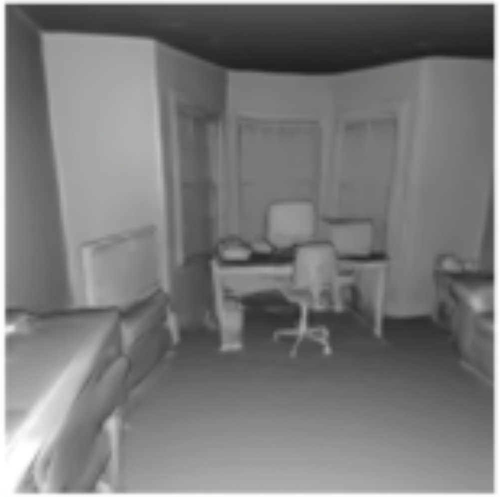
A

polynomials

Normals

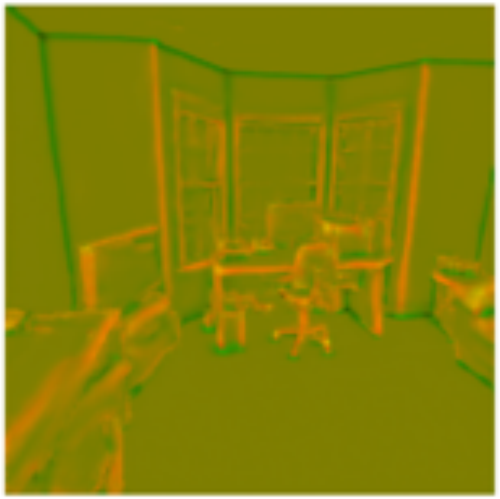


Reshading

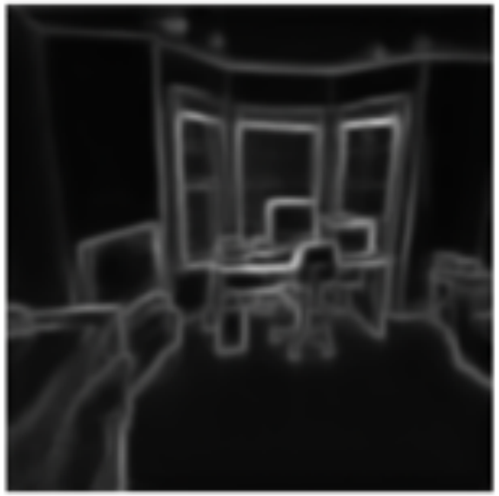


Depth

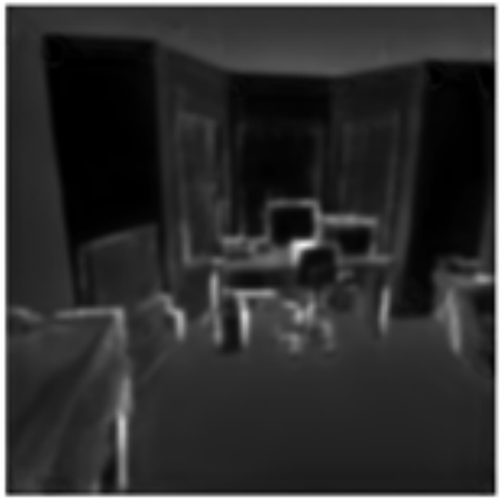
Curvature

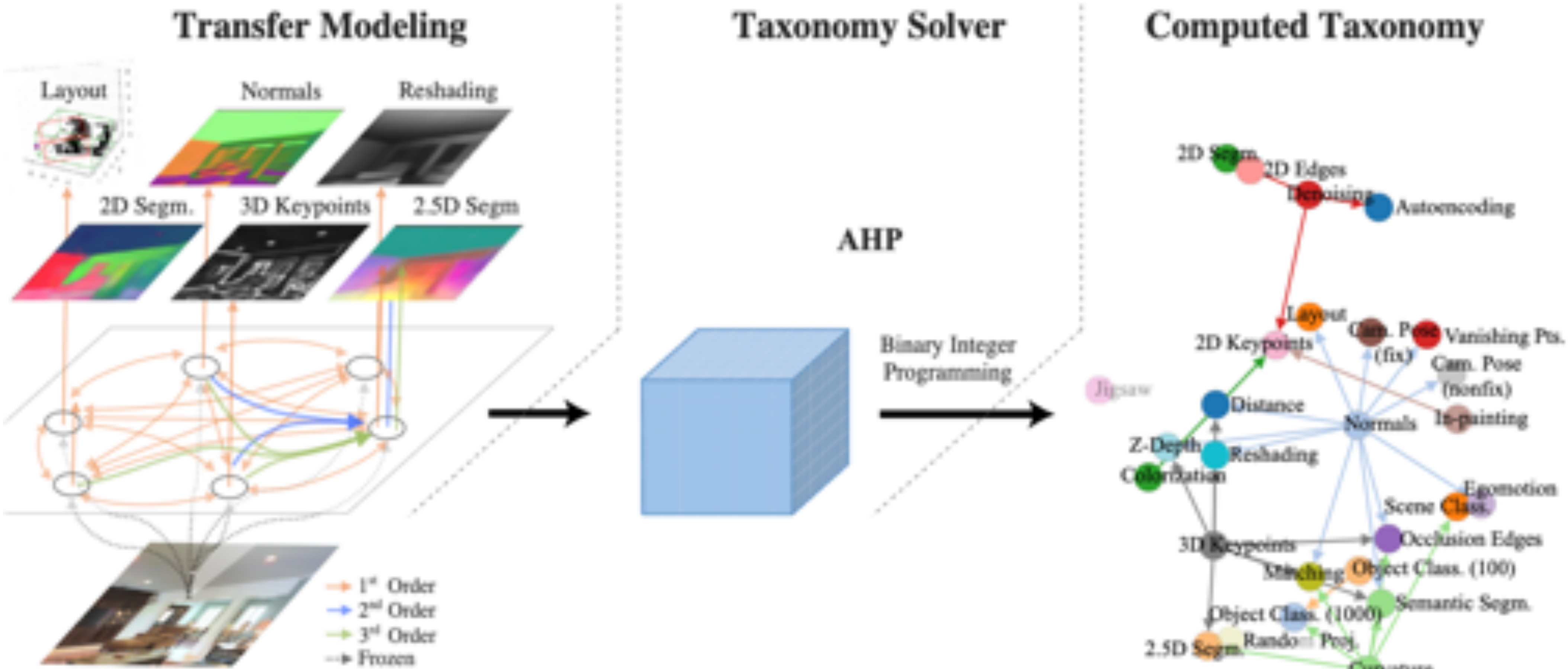


2D Edges



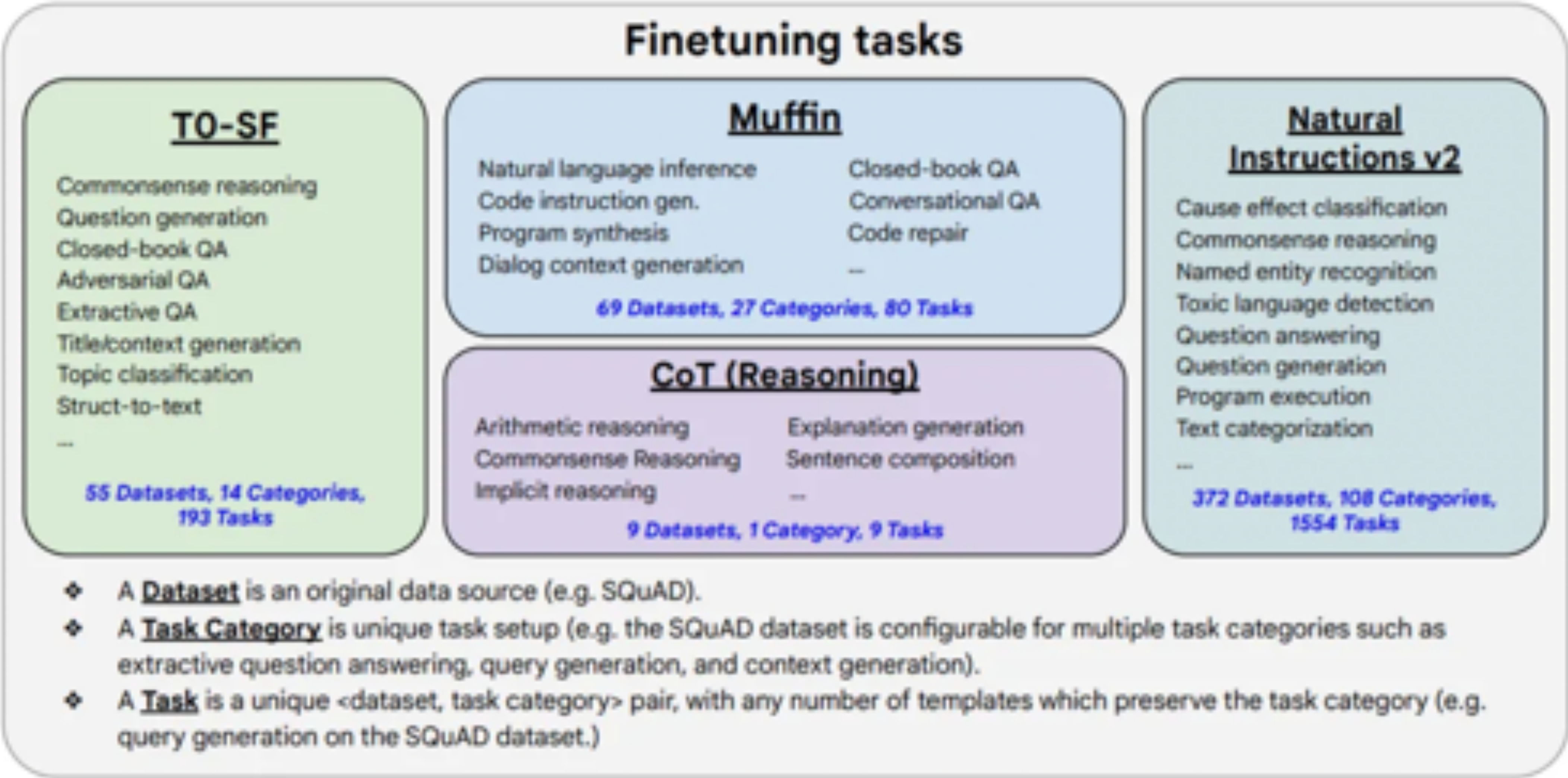
Occlusion Edges

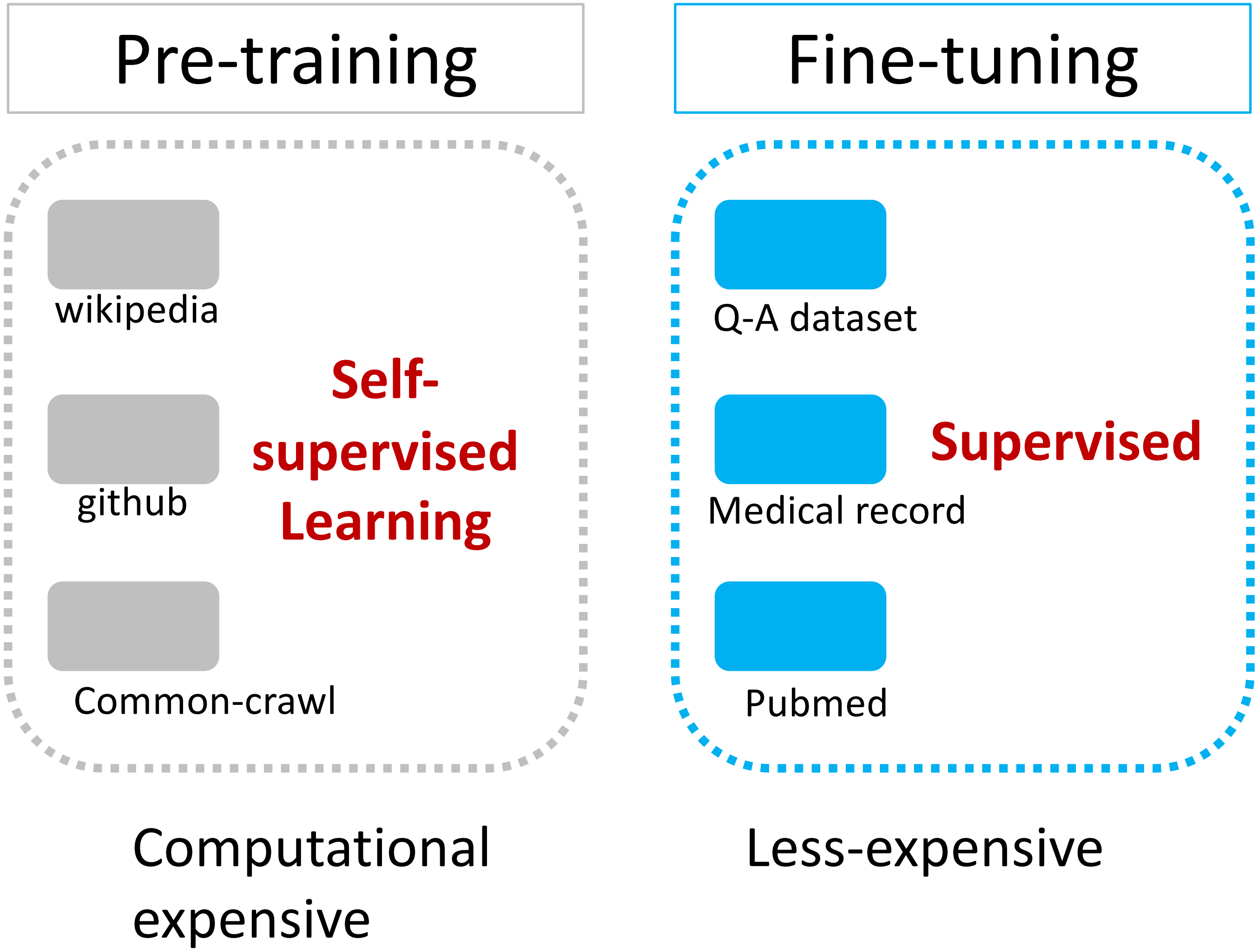




Transfer Modeling
Taxonomy Solver
Computed Taxonomy
Layout
Normals
Reshading
2D Segm.
3D Keypoints
2.5D Segm
1st Order
2nd Order
3rd Order
Frozen
AHP
Binary Integer Programming
2D Segm.
2D Edges
Denoising
Autoencoding
Layout
2D Keypoints
Cam. Pose (fix)
Vanishing Pts.
Cam. Pose (nonfix)
Jigsaw
Distance
Normals
In-painting
Z-Depth
Reshading
Colorization
Egomotion
Scene Class.
3D Keypoints
Occlusion Edges
Matching
Object Class. (100)
Object Class. (1000)
Semantic Segm.
2.5D Segm.
Random Proj.
Curvature

Supervised fine-tuning





But this still not guarantee the output fit our using scenario…

Textbook answering. It is not wrong, but…..

"When a patient presents with chest pain, medical professionals should conduct a thorough evaluation. The diagnostic process involves gathering patient history including onset and radiation of pain, cardiovascular risk factors, and previous cardiac events. Symptoms like associated shortness of breath, nausea, or sweating must be noted. Differential diagnosis for chest pain includes acute coronary syndrome, pulmonary embolism, aortic dissection, pneumothorax, and gastroesophageal reflux disease……….

Let’s reframe our question to make the answer more useful..

For patient with chest pain:

Presentation: [symptoms, onset, risk factors]
Vitals: [measurements]
Medications: [list]

Provide: 1. Top 2 diagnoses with reasoning
2. Immediate next steps
3. Critical red flags

Let’s reframe our question to make the answer more useful..

”Prompt”

For patient with chest pain:

Presentation: [symptoms, onset, risk factors]

Provide: 1. Top 2 diagnoses with reasoning

2. Immediate next steps….

”Output”

Presentation:

Sharp chest pain radiating left, 1hr onset Vitals: BP 160/90, HR 95, O2 97%

Medications: ASA, metformin

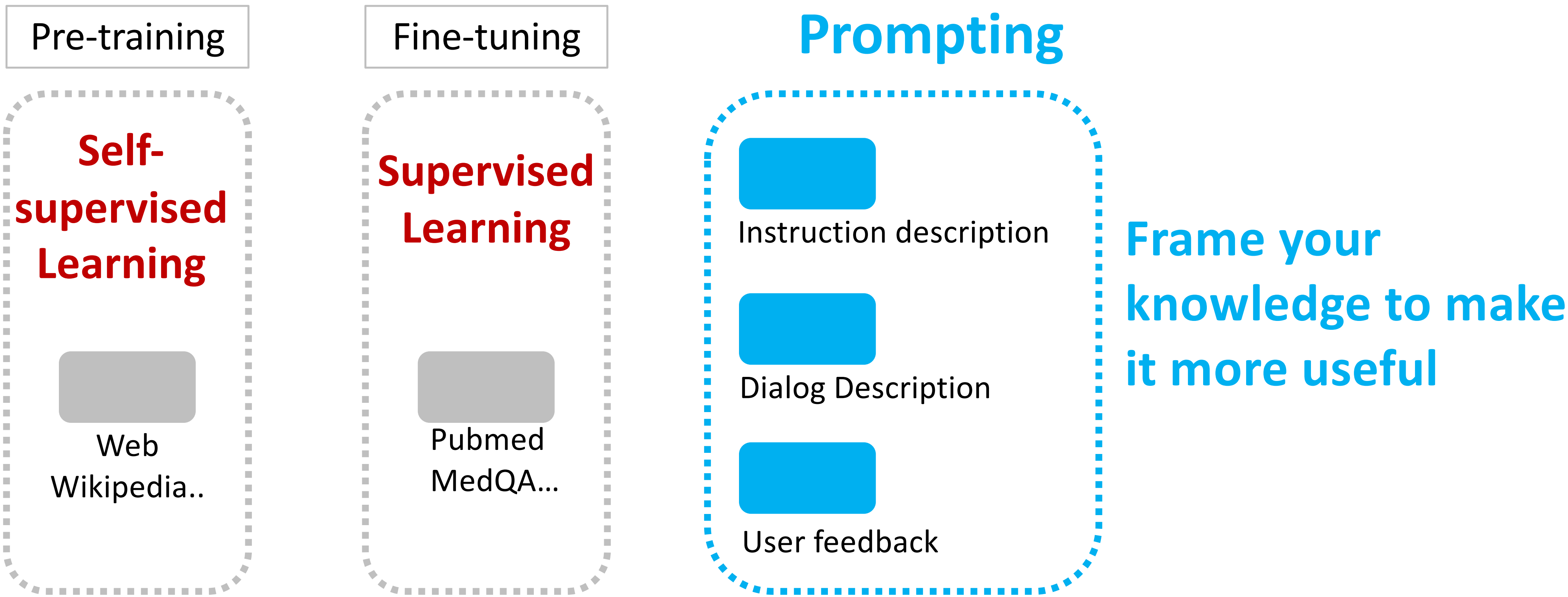
Top diagnoses:

Aortic dissection: sudden sharp pain + hypertension……

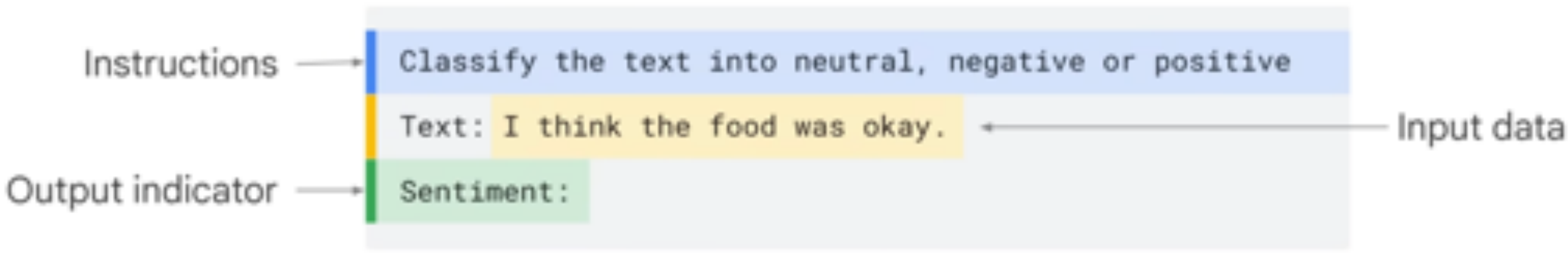
Immediate steps:

Stat ECG

Troponins…..


Pre-training
Self-supervised Learning
Web
Wikipedia..
Fine-tuning
Supervised Learning
Pubmed
MedQA…
Prompting
Instruction description
Dialog Description
User feedback
Frame your knowledge to make it more useful

Instruction Tuned LLM



Dialog Tuned LLM

Dialog-tuned models are a special case of instruction tuned where requests are typically framed as questions to a chat bot.

Dialog tuning is a further specialization of instruction tuning that is expected to be in the context of a longer back and forth conversation, and typically works better with natural question-like phrasings.

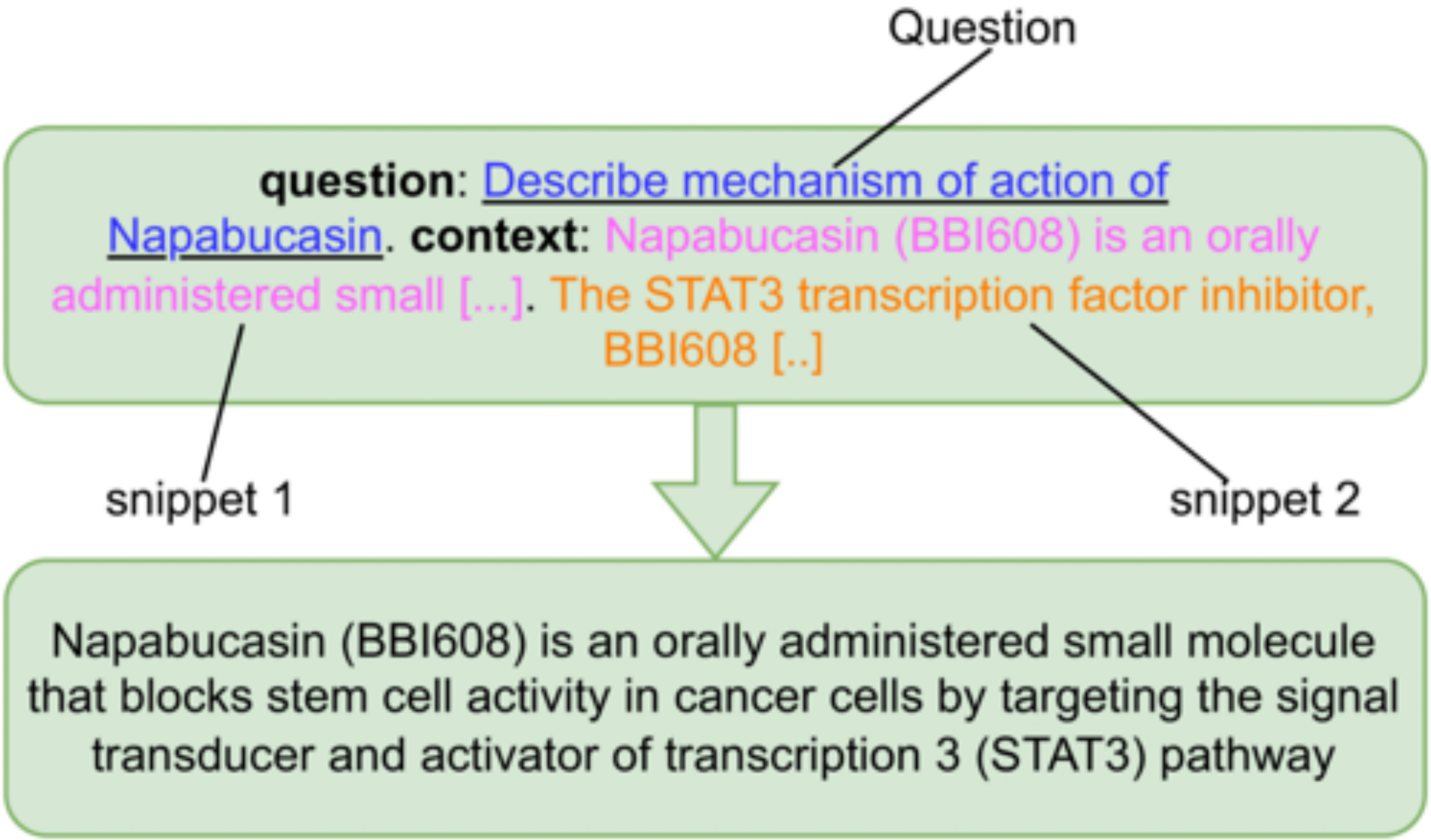
Prompt examples

```
[User] Is the comment "do you like the
weather?" ok or toxic?
[Bot] ok.
[User] can you briefly say why?
[Bot]
```

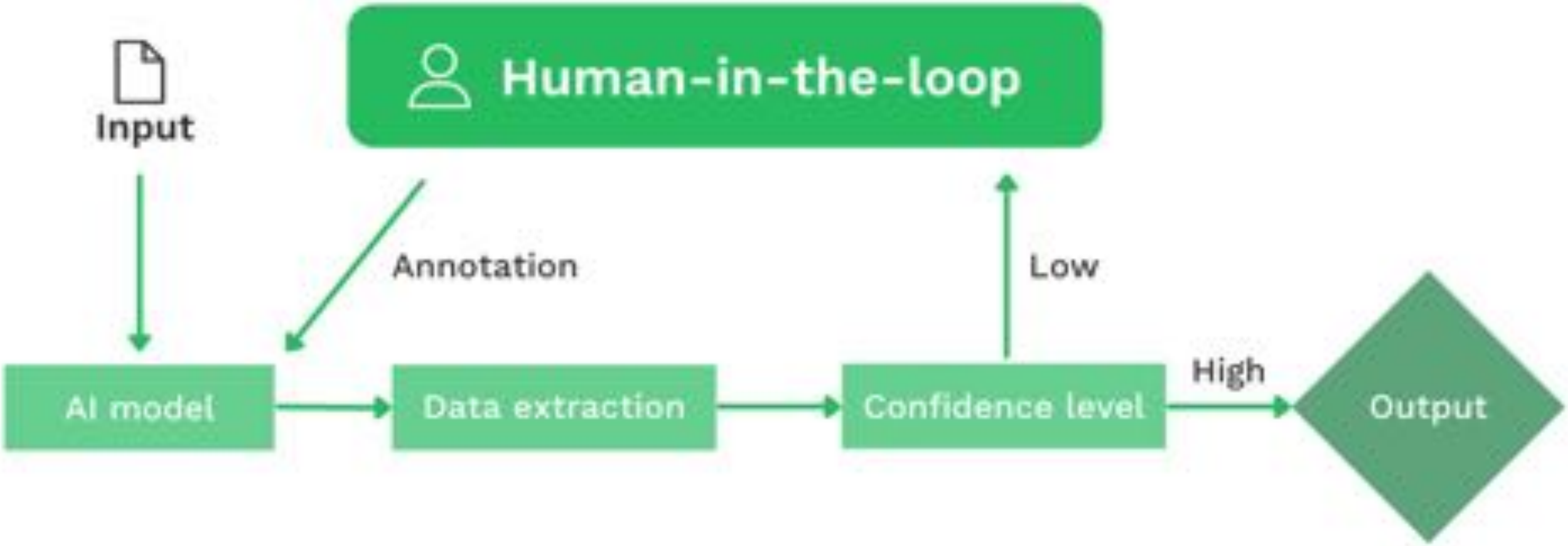
Model Output

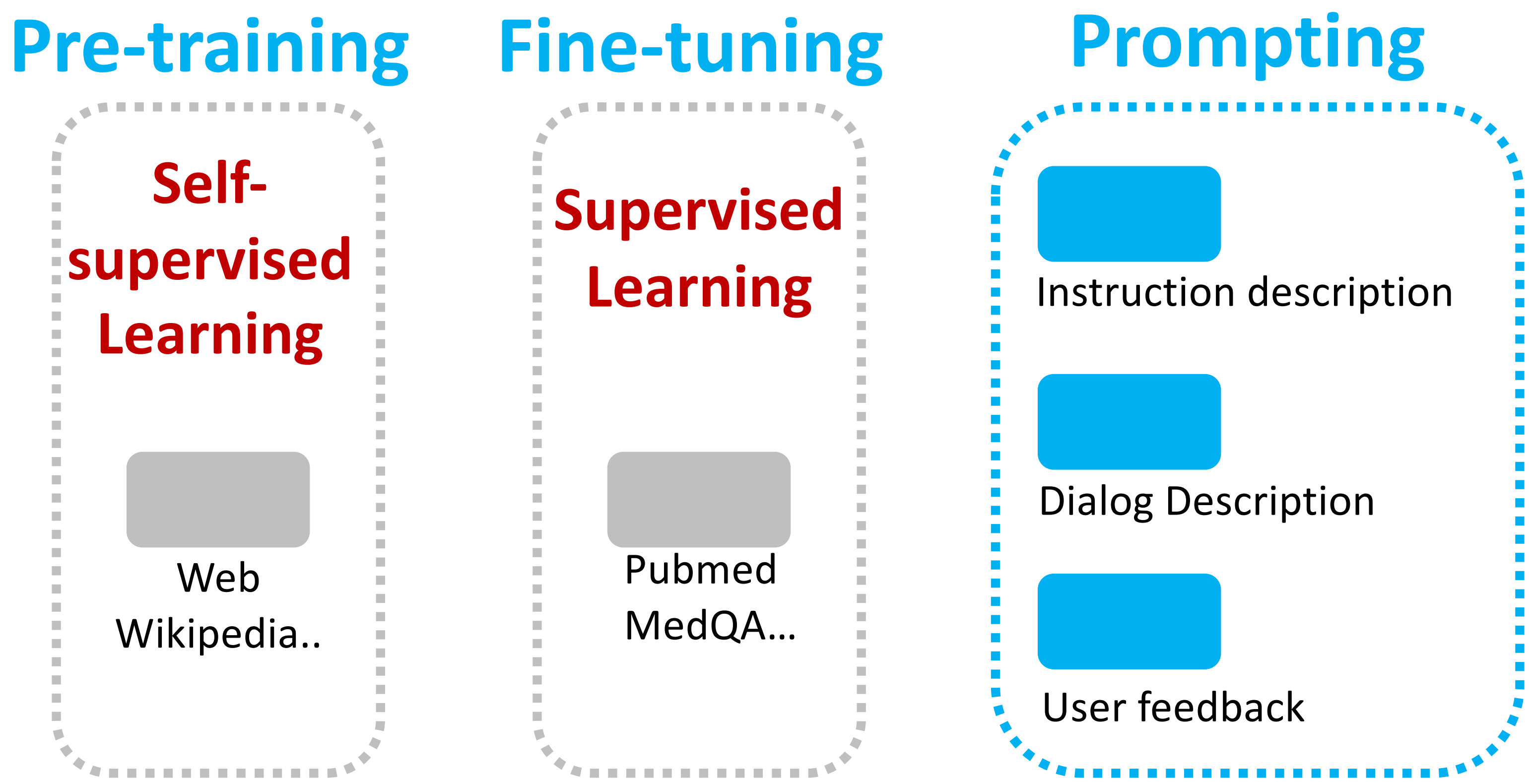
```
It's just a question about the weather, people
are not usually upset by that.
```

BioASQ Tasks



Human in the loop annotation

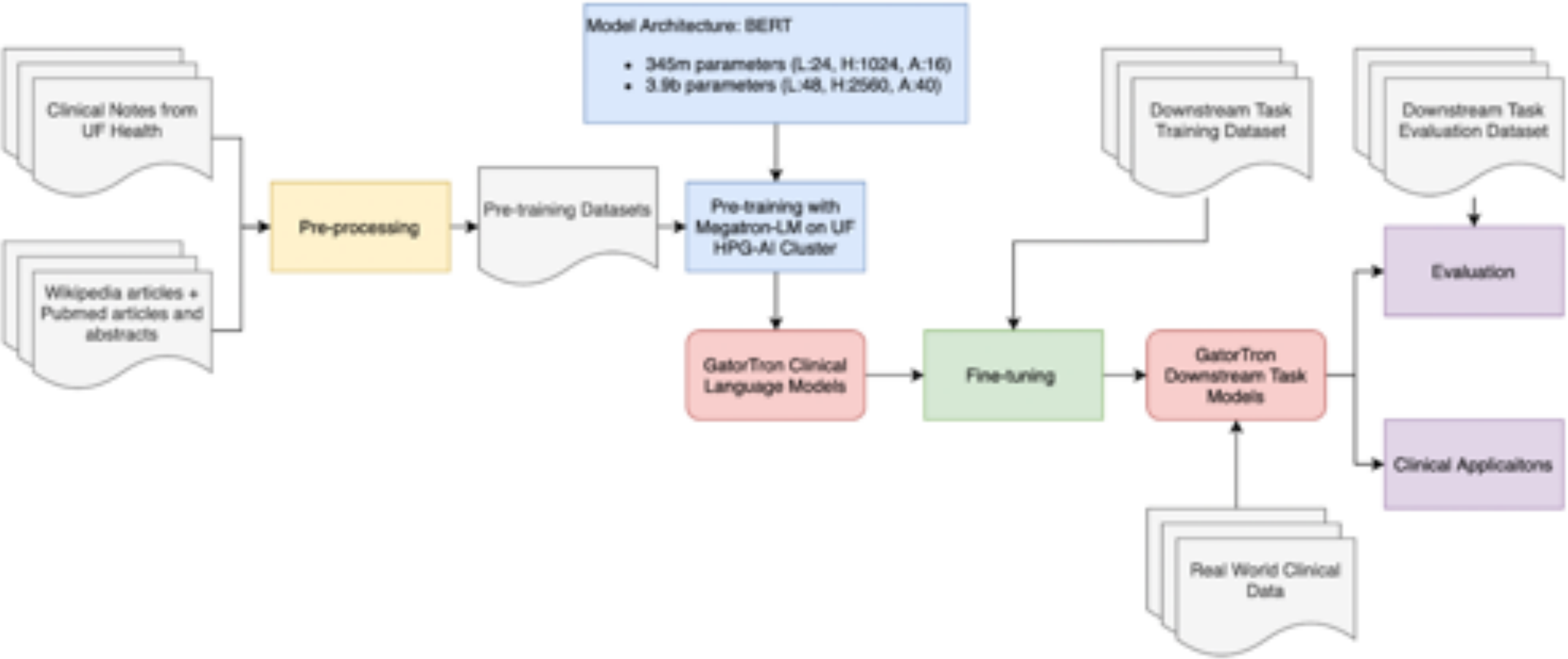




We probably can only do these two…

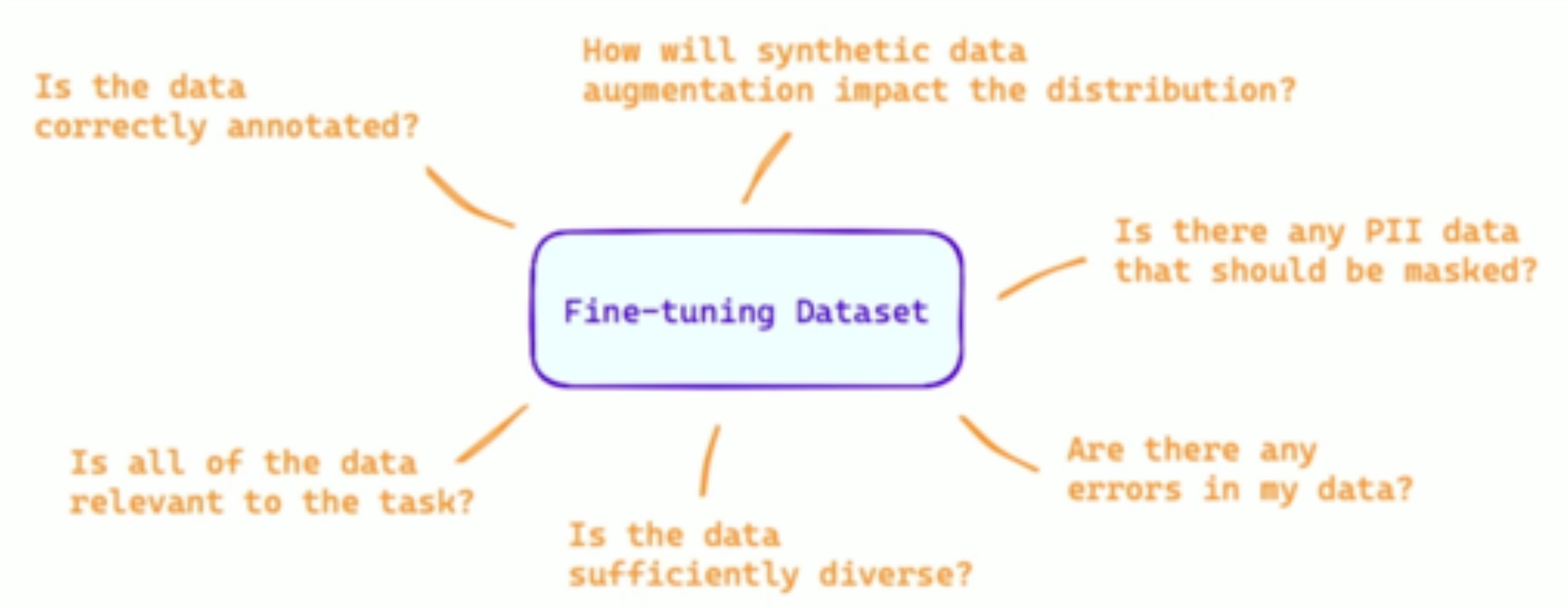
GatorTron

all scripts used in gatortron project



Data Preparation

Training Data Quality



Sample data from LIMA

Question: "Does vegetarianism affect life expectancy?\nIs an average vegetarian supposed to live longer just because of their diet?",

Answer: "Yes, according to a paper by the American Society for Clinical Nutrition.\n\n> Results: Our review of the 6 studies found the following trends: 1) a very low meat intake was associated with a significant decrease in risk of death in 4 studies, a nonsignificant decrease in risk of death in the fifth study, and virtually no association in the sixth study; 2) 2 of the studies in which a low meat intake significantly decreased mortality risk also indicated that a longer duration (≥ 2 decades) of adherence to this diet contributed to a significant decrease in mortality risk and a significant 3.6-y (95% CI: 1.4, 5.8 y) increase in life expectancy; and 3) the protective effect of a very low meat intake seems to attenuate after the ninth decade. Some of the variation in the survival advantage in vegetarians may have been due to marked differences between studies in adjustment for confounders, the definition of vegetarian, measurement error, age distribution, the healthy volunteer effect, and intake of specific plant foods by the vegetarians.\n\nTL;DR:\n\n* less meat = less risk of death,\n* less meat for a longer time = an average of a 3 year longer lifespan + less risk of death,\n* after 90 years of no meat it stops decreasing your risk of death.\n\n\n> Conclusion: Current prospective cohort data from adults in North America and Europe raise the possibility that a lifestyle pattern that includes a very low meat intake is associated with greater longevity.\n\nSo yes, scientific research says that vegetarianism could help you live longer, but it primarily decreases your risk of death. (i.e. you might not live to 105, but you probably won't die at 55)"

LIMA examples

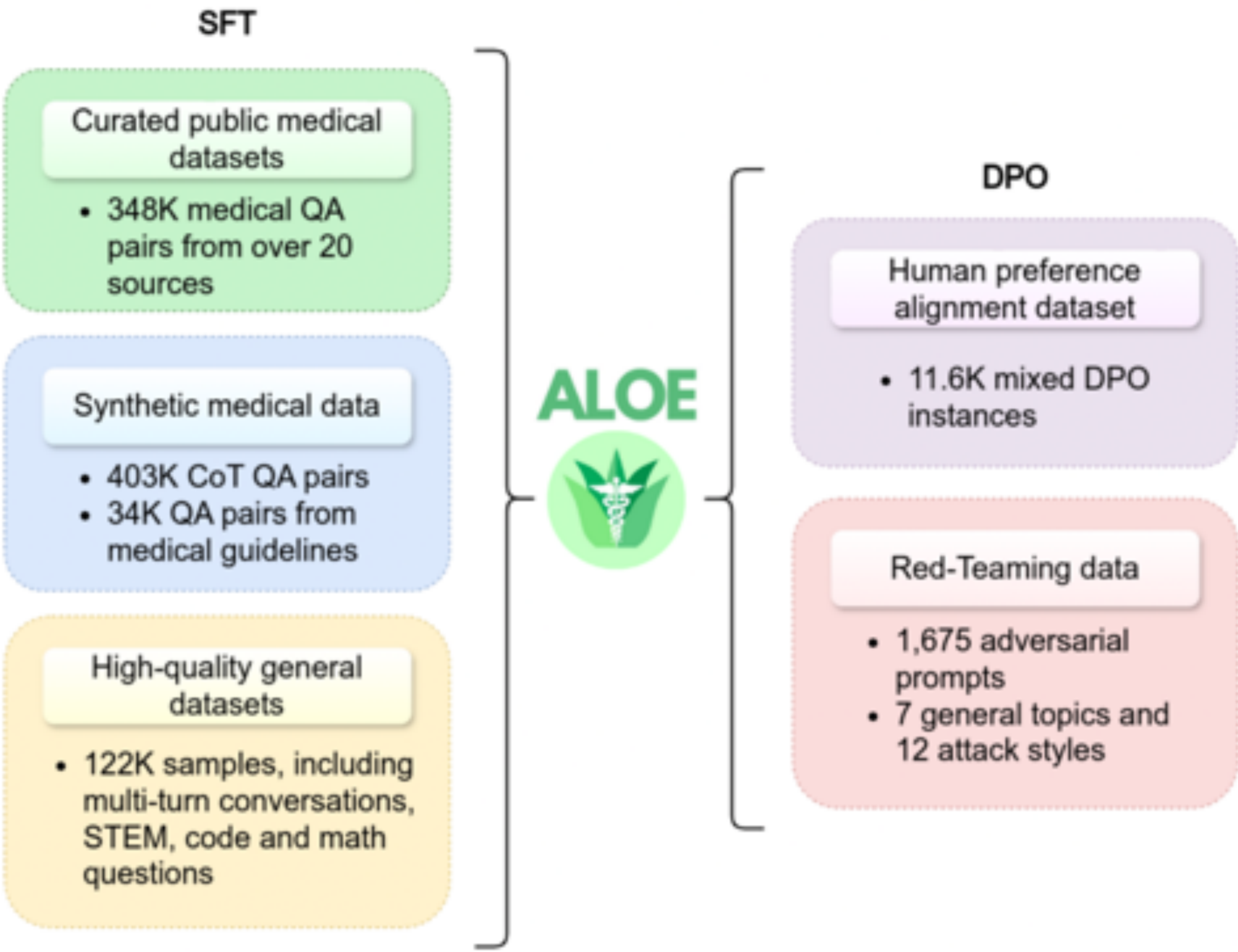
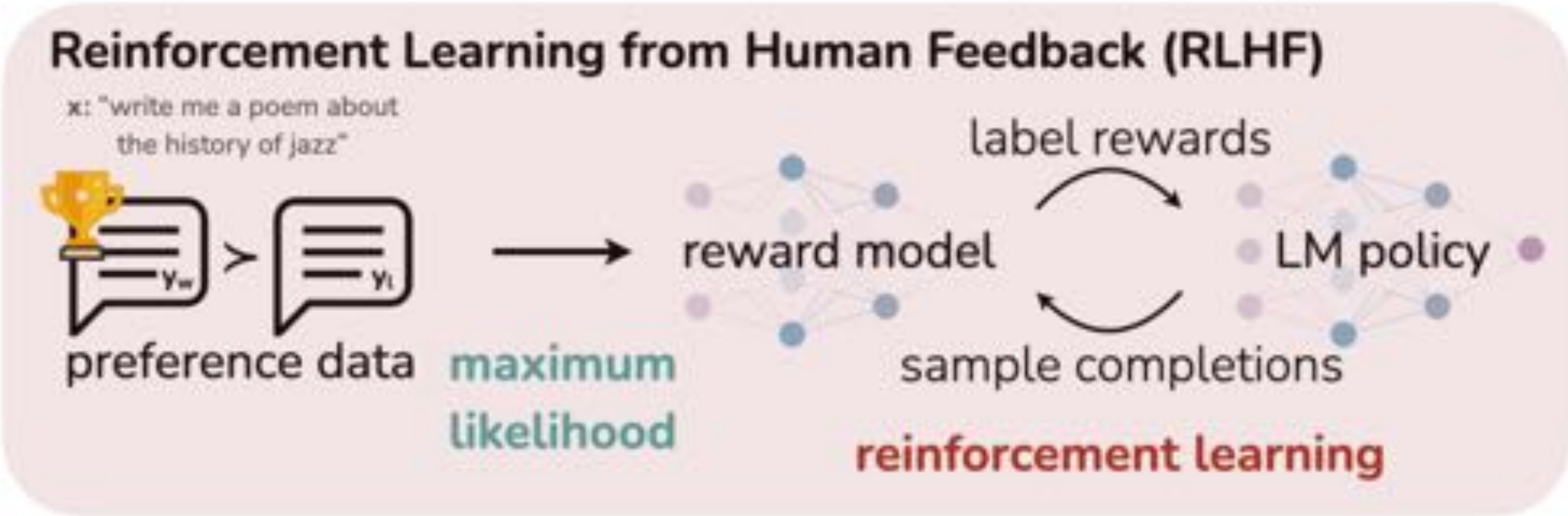


Figure 1: Summary of Aloe training stages and data sources.

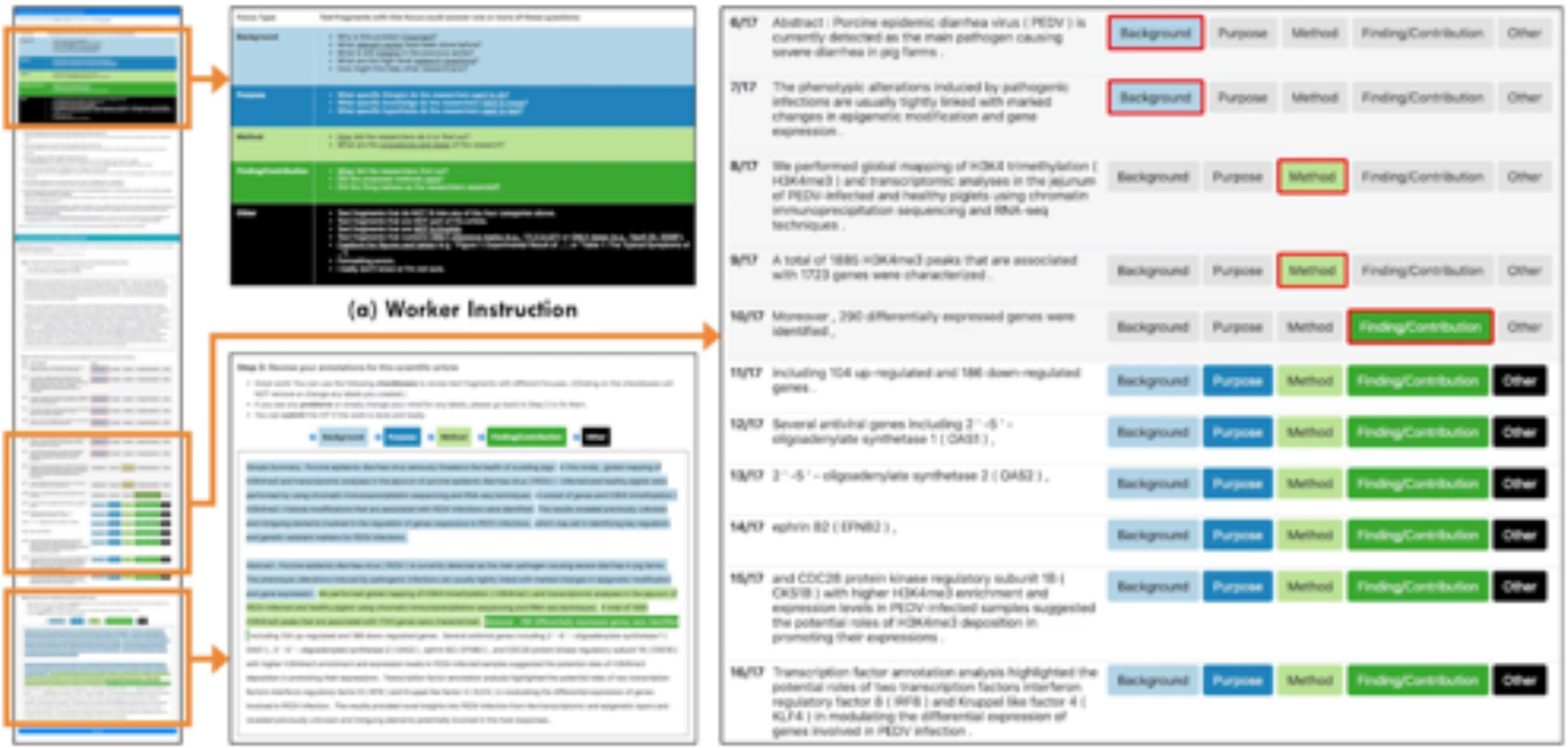
BioASQ Curations

During the annotation phase of the BioASQ, the experts compose biomedical questions. The participating systems provide answers in the challenge. Finally, in the assessment phase, the experts manually assess the system responses and refine and extend the dataset.



Question	Answer
What should you drink to avoid deep vein thrombosis (dvt)?	Wear loose clothes and drink lots of water when you travel. They'll dehydrate you, which makes your veins narrower and blood thicker, so you're more likely to get a clot.
All the following ATT are given in pregnancy except :Options:A. RifampicinB. EthambutolC. NHD. Streptomycin	Explanation: StreptomycinAnswer: D.
How is the generation of antibody specificity achieved?	The generation of antibody specificity is achieved via somatic hypermutation with affinity maturation.
Oxygenated blood from the placenta reaches the fetal heart in utero via:Options:A. Umbilical arteriesB. Umbilical veinC. Ductus venosusD. Ductus arteriosus	Answer: C.
In tandem bullet, number of bullet/ bullets coming out of the gun is/are:Options:A. 1B. 2C. 3D. 4	Explanation: 2Answer: B.

Crowdsource Annotation



Synthetic Data

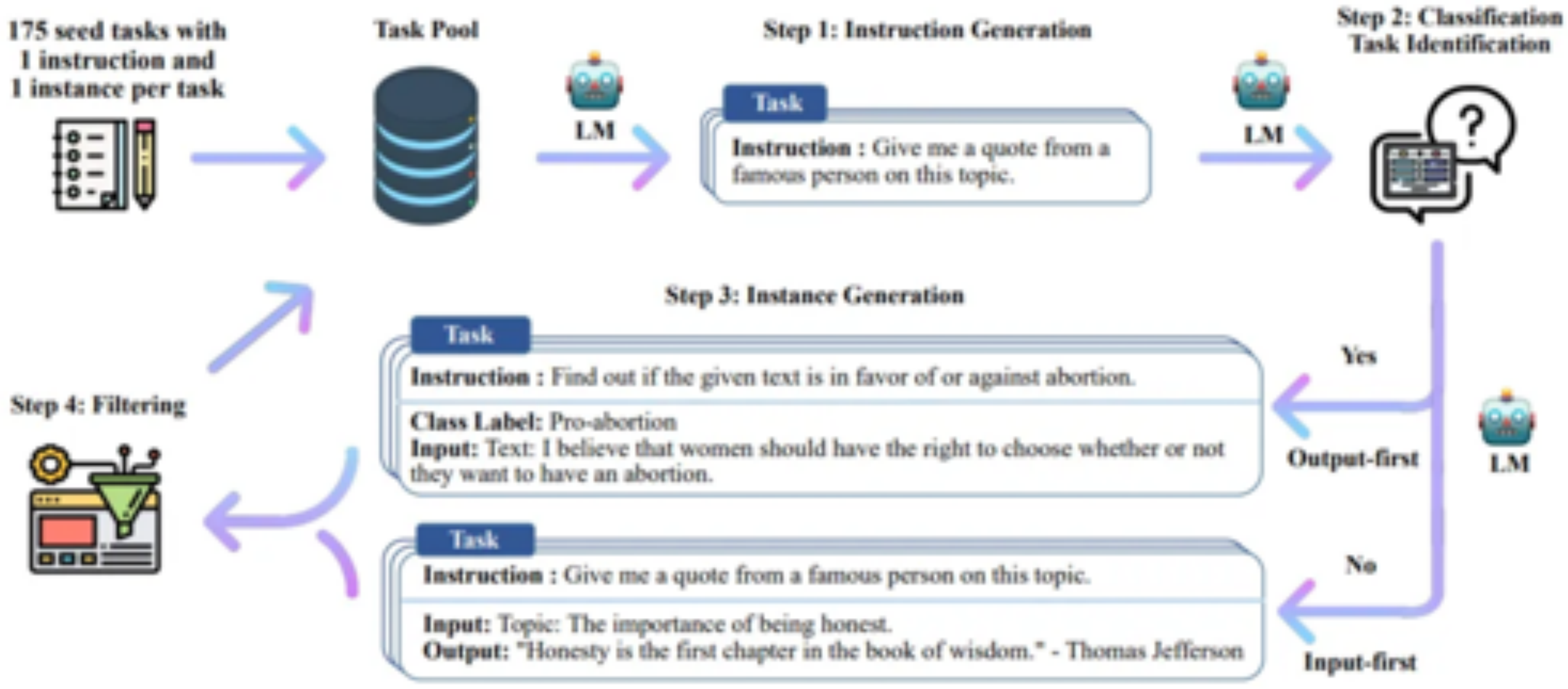
I want you to act as both a psychologist and dialogue rewriter. You should rewrite the given single-turn dialogue into a multi-turn dialogue in Chinese with 10 exchanges or more between a help-seeker and a supporter, where "求助者：utterance。\n支持者：utterance。" represents an exchange.

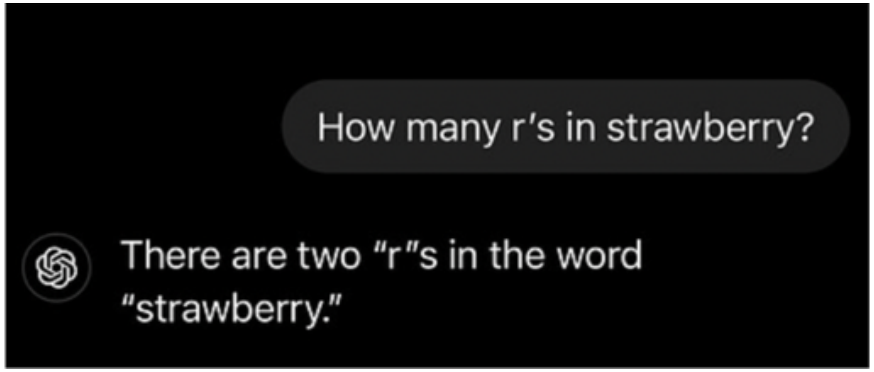
You should adhere to these requirements:
1. First, you should focus on the topic of the dialogue given.
2. Each sentence must start with "求助者：" or "支持者：".
3. The dialogue should begin with "求助者：".
4. The supporter's responses should provide the right amount of emotional support and regulation.
5. Separate each exchange with "\n".
6. Ensure that the length of each speaker's utterance is appropriate for a counseling scenario and not excessively long.

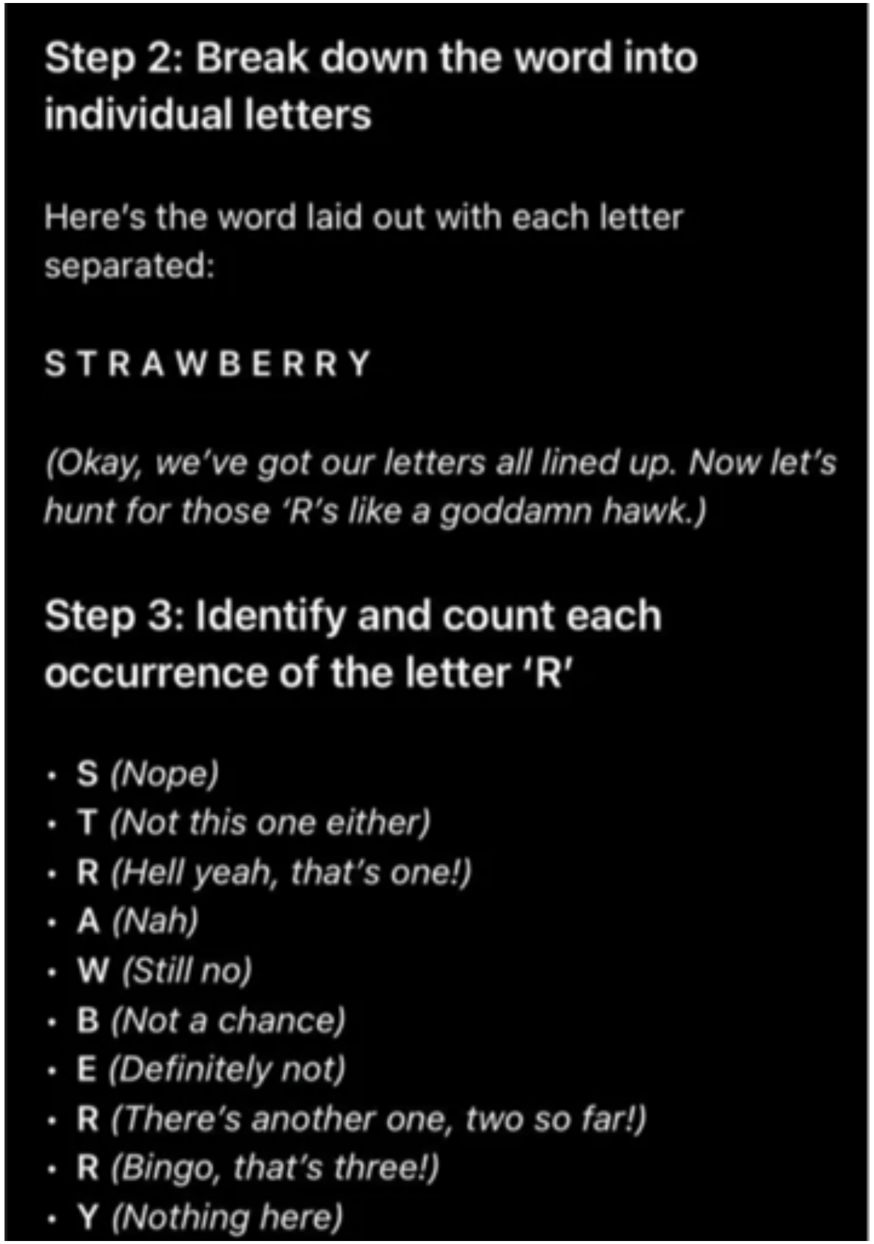
Single-turn dialogue: **{QA}**

Your rewritten multi-turn dialog is:

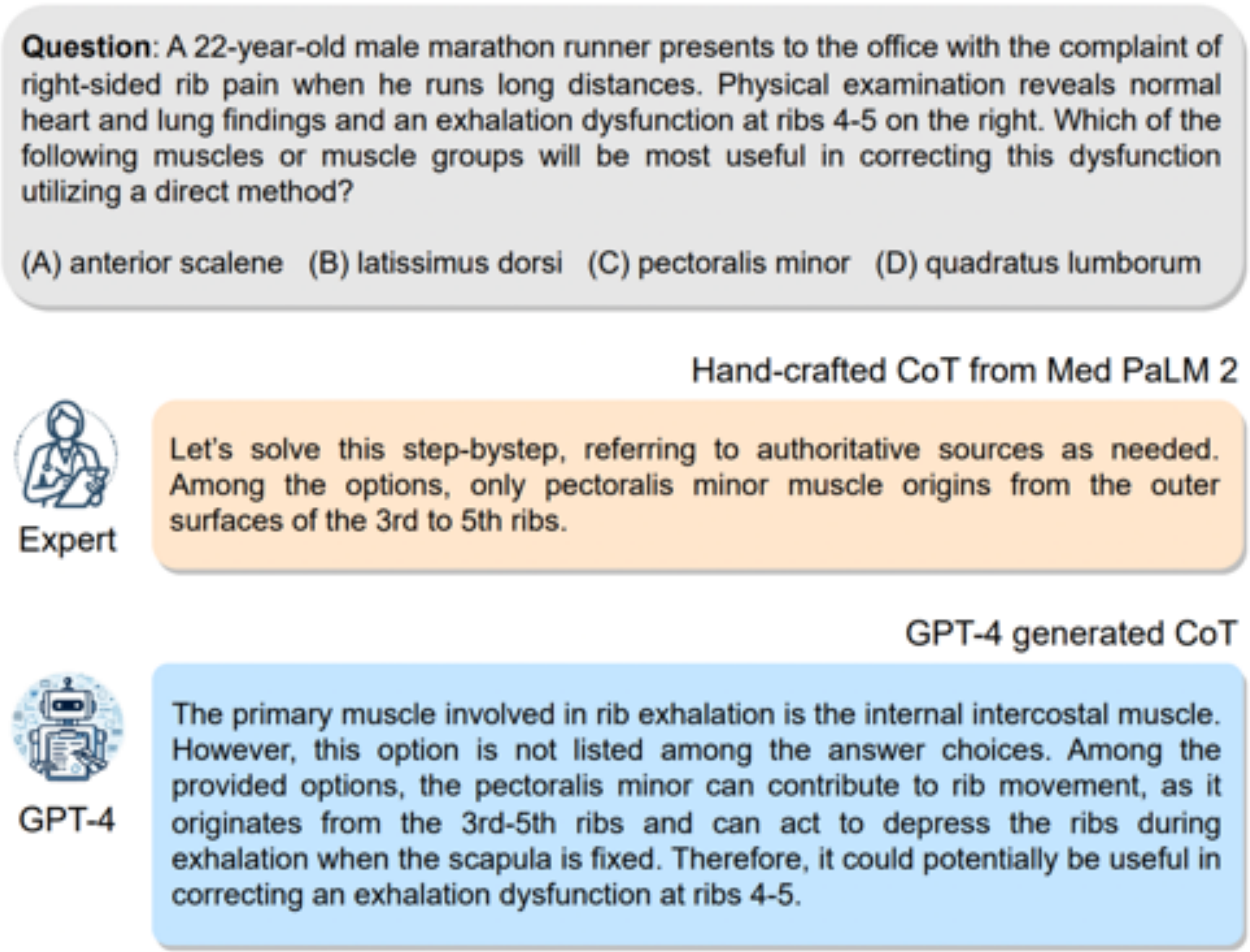
AI-assisted Annotation




How many r's in strawberry?
There are two "r"s in the word "strawberry."


Step 2: Break down the word into individual letters
Here's the word laid out with each letter separated:
S T R A W B E R R Y
(Okay, we've got our letters all lined up. Now let's hunt for those 'R's like a goddamn hawk.)
Step 3: Identify and count each occurrence of the letter 'R'
S (Nope)
T (Not this one either)
R (Hell yeah, that's one!)
A (Nah)
W (Still no)
B (Not a chance)
E (Definitely not)
R (There's another one, two so far!)
R (Bingo, that's three!)
Y (Nothing here)

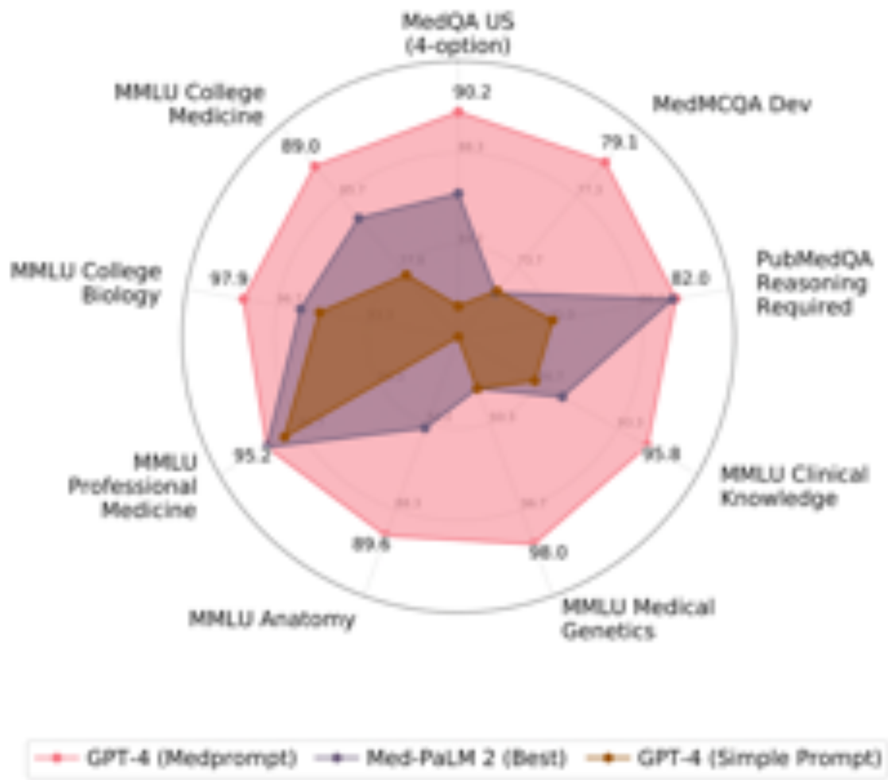
Chain-of-thought Prompt



Downstream Tasks of LLM

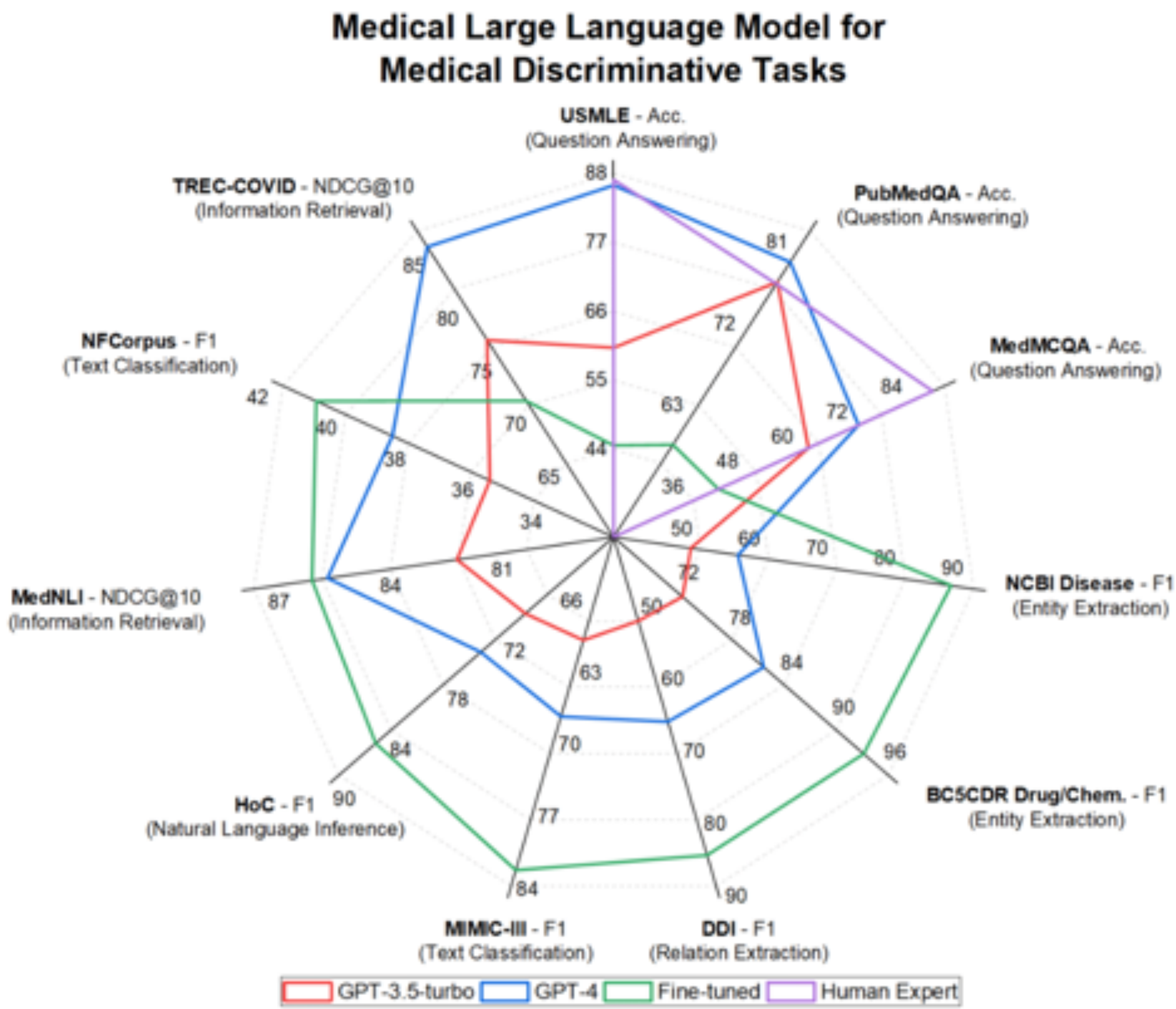
Med prompt from LLM

(a)

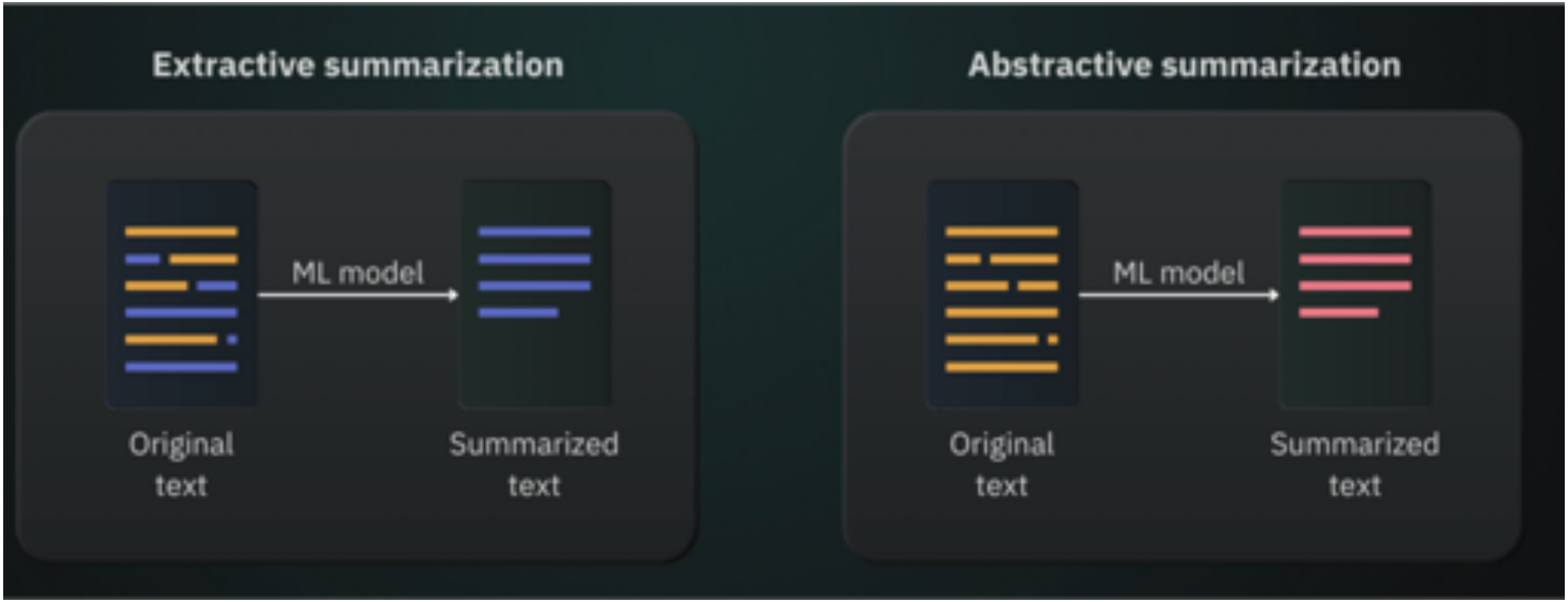


(b)

Figure 1: (a) Comparison of performance on MedQA. (b) GPT-4 with Medprompt achieves SoTA on a wide range of medical challenge questions.


Medical Large Language Model for
Medical Discriminative Tasks
USMLE - Acc.
(Question Answering)
PubMedQA - Acc.
(Question Answering)
MedMCQA - Acc.
(Question Answering)
NCBI Disease - F1
(Entity Extraction)
BC5CDR Drug/Chem. - F1
(Entity Extraction)
DDI - F1
(Relation Extraction)
MIMIC-III - F1
(Text Classification)
HoC - F1
(Natural Language Inference)
MedNLI - NDCG@10
(Information Retrieval)
NFCorpus - F1
(Text Classification)
TREC-COVID - NDCG@10
(Information Retrieval)
88
77
66
55
44
81
72
63
84
72
60
48
36
90
80
70
60
50
96
90
84
78
72
90
80
70
60
50
84
77
70
63
66
90
84
78
72
87
84
81
42
40
38
36
34
85
80
75
70
65
GPT-3.5-turbo
GPT-4
Fine-tuned
Human Expert

LLM text extraction



Entity Extraction

Input

45F with right knee pain onset 3 months ago. After slip and fall, developed progressive pain and swelling. Morning stiffness lasting 30min. Pain worse with walking and stairs. No relief with ibuprofen.

PE: BP 120/80, HR 72, Temp 98.6 Right knee: moderate effusion, limited ROM, positive McMurray No erythema or warmth

MRI knee: Grade II medial meniscus tear, joint effusion, BML in medial femoral condyle
Dx: Medial meniscus tear with early OA Rx: Meloxicam 15mg qd, PT 2x/week

Output

45F with **right knee pain** onset **3 months ago**. After **slip and fall**, developed **progressive pain** and **swelling**. **Morning stiffness** lasting **30min**. Pain worse with **walking** and **stairs**. No relief with **ibuprofen**.

PE: **BP 120/80**, **HR 72**, **Temp 98.6 Right knee**: **moderate effusion**, **limited ROM**, **positive McMurray** No **erythema** or **warmth**

MRI knee: **Grade II medial meniscus tear**, **joint effusion**, **BML in medial femoral condyle**
Dx: **Medial meniscus tear** with **early OA** Rx: **Meloxicam 15mg qd**, **PT 2x/week**

Entity Extraction (record summary)

Input

Patient ID: 287654
Date: Oct 15, 2024
CC: Right knee pain x3mo

HPI:
45F with worsening right knee pain after slip/fall. Pain worse with activity, morning stiffness 30min. Failed OTC NSAIDs. No fever.

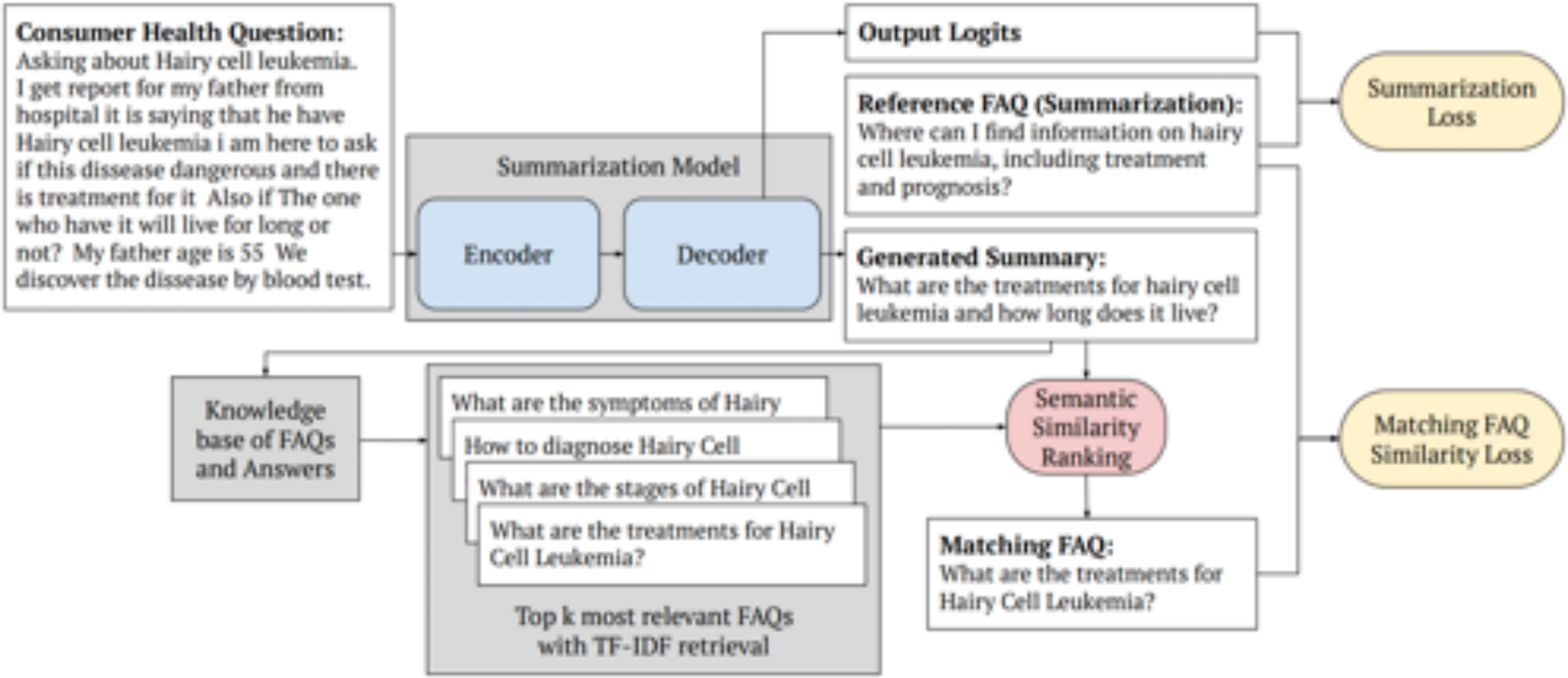
Exam:
VS stable
Right knee: effusion, limited ROM, (+) McMurray
No erythema

Plan:
- Meloxicam 15mg
- PT referral
- F/u 4wks
- May need scope if fails conservative tx

Output

45F
Right Knee Injury
Key Points:
- Post-fall injury x3mo
- Failed NSAIDs - MRI: meniscus tear + effusion + early OA
- McMurray positive Plan: Meloxicam + PT, f/u 4wk Consider scope if no improvement

Medical Question Answering System w/ summarization



BlueCross BlueShield of North Carolina

NOTICE: The following includes confidential personal health information that is subject to the Health Insurance Portability and Accountability Act, the Health Information Technology for Economic and Clinical Health Act, North Carolina Consumer and Customer Information Privacy Act and all other applicable laws.

Patient Care Summary

04/18/2012 10:58 AM

Last Name	First Name	DOB	Gender	Subscriber ID
PUBLIC	JOHN	01/01/1957	M	YPPW0123456701

Summary Refresh Date: 03/25/2012 - Information herein is based on BCBSNC Claims Data only and is refreshed monthly

Potential Gaps in Evidence Based Care: Identified as past due

Condition	Potential Gap	Months Overdue
Diabetes	Diab: Retinal Eye Exam	17
Diabetes	Diab:Medical Attention for nephropathy	17
Preventive	Colorectal Cancer Screen	16

Prescriptions: Ten most recent unique medications in the last 12 months. Rx used to treat substance abuse are omitted due to privacy regulations.

Latest Fill	Prescriber	Medication	Dose	Days Supply (#)
02/11/2012	Ralph P. Sample, M.D.	GEMFIBROZIL	600 MG	30 (60)
02/11/2012	Ralph P. Sample, M.D.	VITAMIN D	50000 UNIT	4 (4)
12/09/2011	Ralph P. Sample, M.D.	LIPITOR (generic available)	20 MG	30 (30)
12/05/2011	Ralph P. Sample, M.D.	APAP/HYDROCODONE BITARTRATE	7.5-500 MG	30 (90)
12/05/2011	Ralph P. Sample, M.D.	CEPHALEXIN (Rx not picked up)	500 MG	0 (0)
09/15/2011	Sarah T. Example, M.D.	TRAMADOL HYDROCHLORIDE	50 MG	10 (40)
09/02/2011	Ralph P. Sample, M.D.	PREDNISONE	10 MG	8 (20)
06/23/2011	Ralph P. Sample, M.D.	AZITHROMYCIN	250 MG	5 (6)

Medical care: Claims identified up to a maximum of 10 over the past 36 months - labs, substance abuse, abortion, DME, radiology, anesthesiology, and pathology claims omitted.

Date of Visit	Provider	Specialty	Place of Service	Diagnosis Codes
12/09/2011	Ralph P. Sample, M.D.	INTERNAL MEDICINE	OFFICE	250.00
12/05/2011	Ralph P. Sample, M.D.	INTERNAL MEDICINE	OFFICE	250.00
09/21/2011	Leanne K. Test, M.D.	NEUROLOGY	OUTPATIENT HOSPITAL	355.5
09/21/2011	FACILITY	GENERAL ACUTE CARE HOSPITAL	OUTPATIENT HOSPITAL	729.5 825.25
09/02/2011	Ralph P. Sample, M.D.	INTERNAL MEDICINE	OFFICE	724.3
06/23/2011	Ralph P. Sample, M.D.	INTERNAL MEDICINE	OFFICE	466.0
05/09/2011	Ralph P. Sample, M.D.	INTERNAL MEDICINE	OFFICE	250.00
01/17/2011	Ralph P. Sample, M.D.	INTERNAL MEDICINE	OFFICE	466.0
10/22/2010	Ralph P. Sample, M.D.	INTERNAL MEDICINE	OFFICE	250.0
08/13/2010	Lawrence A. Quiz, M.D.	UROLOGY	OFFICE	592.1

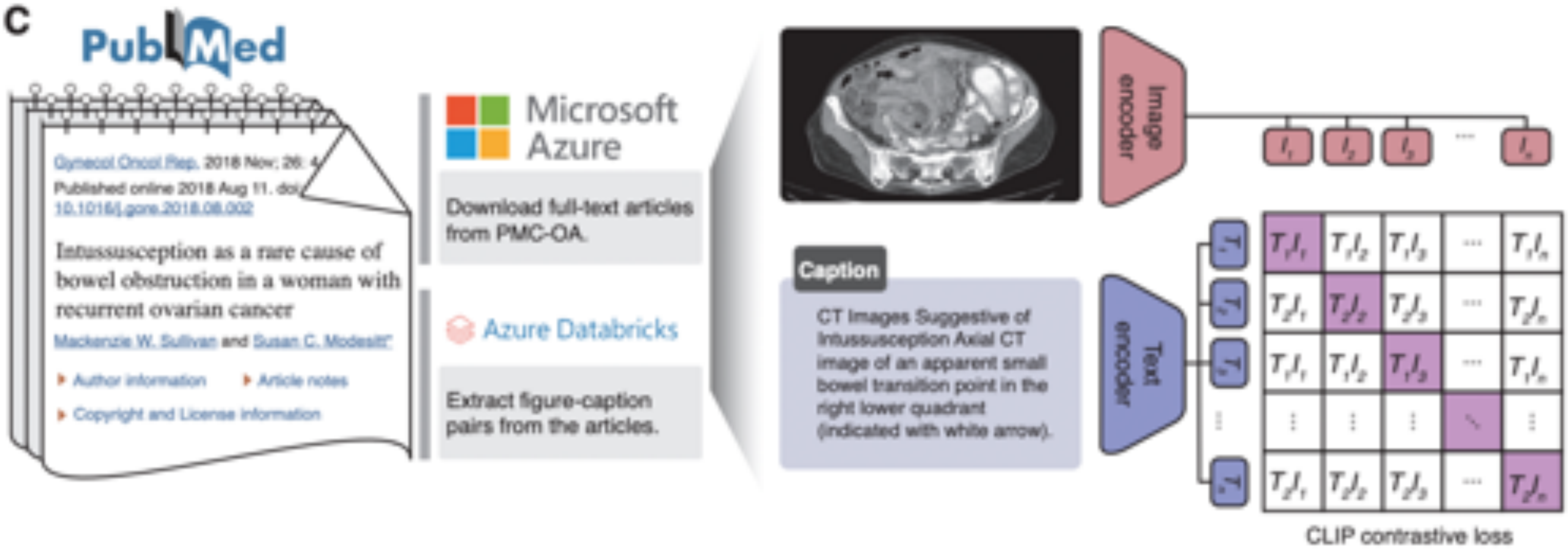
Provider Alerts

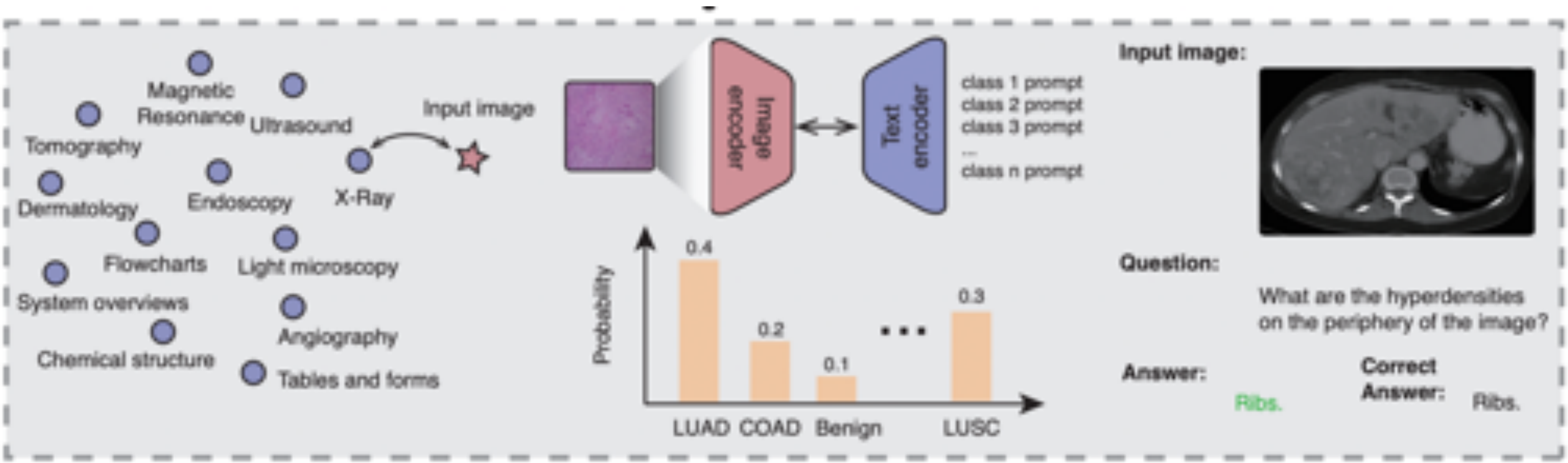
BCBSNC is actively trying to reach this patient for Care Management assistance. Please encourage this patient to contact us at 1-800-218-5295, option 3.

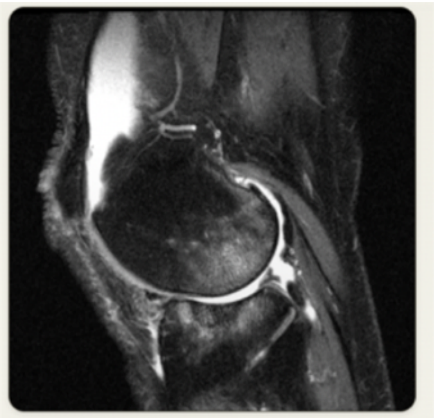
This patient may have the opportunity to save out-of-pocket costs by switching to a generic medication.

Date	Entry type	Person	Details	ICD Codes
02/11/2012	Medication	Ralph P. Sample, M.D.	GEMFIBROZIL	
02/11/2012	Medication	Ralph P. Sample, M.D.	VITAMIN D	
12/09/2011	Diagnosis	Ralph P. Sample, M.D.		250.00
12/09/2011	Medication	Ralph P. Sample, M.D.	LIPITOR (generic available)	
12/09/2011	Diagnosis	Ralph P. Sample, M.D.		250.00
12/05/2011	Medication	Ralph P. Sample, M.D.	APAP/HYDROCODONE BITARTRATE	
12/05/2011	Medication	Ralph P. Sample, M.D.	CEPHALEXIN (Rx not picked up)	
09/21/2011	Diagnosis	Leanne K. Test, M.D.		355.5
09/21/2011	Diagnosis	FACILITY		729.5 825.25
09/15/2011	Medication	Sarah T. Example, M.D.	TRAMADOL HYDROCHLORIDE	
09/02/2011	Diagnosis	Ralph P. Sample, M.D.		724.3
09/02/2011	Medication	Ralph P. Sample, M.D.	PREDNISONE	
06/23/2011	Diagnosis	Ralph P. Sample, M.D.		466.0
06/23/2011	Medication	Ralph P. Sample, M.D.	AZITHROMYCIN	
05/09/2011	Diagnosis	Ralph P. Sample, M.D.		250.00
01/17/2011	Diagnosis	Ralph P. Sample, M.D.		466.0
10/22/2010	Diagnosis	Ralph P. Sample, M.D.		250.0
08/13/2010	Diagnosis	Lawrence A. Quiz, M.D.		592.1

Text-image captioning







Speaking from a biomedical imaging research perspective, this appears to be a T2-weighted sagittal MRI scan of the knee joint showing notable signal characteristics:

1. There appears to be increased signal intensity in the anterior (front) portion of the lateral meniscus, which could suggest structural alterations or degeneration
2. The posterior cruciate ligament (PCL) appears to be visible with normal signal characteristics
3. The articular cartilage along the femoral condyle shows some irregular signal patterns
4. There is some evidence of increased signal in the suprapatellar region which could indicate fluid collection

Relation-retrieval (oncology)

Input

In patients with **metastatic melanoma**, the presence of **BRAF V600E mutation** significantly affects treatment choices. **Vemurafenib**, a **BRAF inhibitor**, has shown **improved survival rates** of **6-8 months** when combined with **MEK inhibitor Cobimetinib**. However, patients often develop **drug resistance** through **PI3K pathway activation**. Recent studies show that **immune checkpoint inhibitors** like **Pembrolizumab** are particularly effective in tumors with high **PD-L1 expression** and increased **tumor mutational burden**. **Side effects** include **fatigue**, **skin rash**, and **autoimmune reactions**. Regular monitoring of **liver function** and **thyroid levels** is recommended during treatment

Output

•Disease-Mutation Relations: Metastatic melanoma
  -> associated with BRAF V600E
•Drug resistance
  -> caused by PI3K pathway activation
•Disease-Treatment Relations: Metastatic melanoma
  -> treated by Vemurafenib
  -> treated by Cobimetinib
  -> treated by Pembrolizumab
•Drug-Target Relations: Vemurafenib
  -> inhibits BRAF

•Cobimetinib -> inhibits MEK
•Pembrolizumab -> targets PD-L1
•Treatment-Outcome Relations:
  Vemurafenib + Cobimetinib -> improves survival 6-8 months

•Drug treatment -> leads to resistance
•Treatment -> requires liver/thyroid monitoring

Some clinical LLM projects to follow….

README License

NYUTron: Health System Scale Language Models Are All-purpose Prediction Engine

CC BY NC SA | Maintained? yes | Built with 🤗Huggingface | Code style black

……30-day all-cause readmission prediction, in-hospital mortality prediction, comorbidity index prediction, length of stay prediction, and insurance denial prediction

Clinical Text Summarization by Adapting LLMs | Nature Medicine

Official implementation from Stanford University

- **Title:** Adapted Large Language Models Can Outperform Medical Experts in Clinical Text Summarization
- **Authors:** Dave Van Veen, Cara Van Uden, Louis Blankemeier, Jean-Benoit Delbrouck, Asad Aali, Christian Bluethgen, Anuj Pareek, Malgorzata Polacin, Eduardo Pontes Reis, Anna Seehofnerova Nidhi Rohatgi, Poonam Hosamani, William Collins, Neera Ahuja, Curtis P. Langlotz, Jason Hom, Sergios Gatidis, John Pauly, Akshay S. Chaudhari
- **Contact:** {vanveen} [at] stanford [dot] edu

medAlpaca: Finetuned Large Language Models for Medical Question Answering

Project Overview

MedAlpaca expands upon both Stanford Alpaca and AlpacaLoRA to offer an advanced suite of large language models specifically fine-tuned for medical question-answering and dialogue applications. Our primary objective is to deliver an array of open-source language models, paving the way for seamless development of medical chatbot solutions.

These models have been trained using a variety of medical texts, encompassing resources such as medical flashcards, wikis, and dialogue datasets. For more details on the data utilized, please consult the data section.

MEDIQA-Chat-2023

- **Website:** https://sites.google.com/view/mediqa2023/clinicalnlp-mediqa-chat-2023
- **Google group:** https://groups.google.com/g/mediqa-nlp

Tasks

- **Task A - Short Dialogue2Note Summarization**: generating a section summary (section header and content) associated with the short input conversation. Section header will be one of twenty normalized section labels provided with the training data.
- **Task B - Full Dialogue2Note Summarization**: generating a clinical note from the full input conversation. The note should include all relevant sections. Accepted first-level section headers are: "HISTORY OF PRESENT ILLNESS", "PHYSICAL EXAM", "RESULTS", "ASSESSMENT AND PLAN".
- **Task C - Note2Dialogue Generation**: generating a doctor-patient conversation from the full input note. This task addresses data augmentation through the generation of synthetic conversations from clinical notes. We encourage the participants to apply the models developed for this task to generate additional data for tasks A & B.