

Foundation Models for Healthcare

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BIODS 271: Foundation Models for Healthcare

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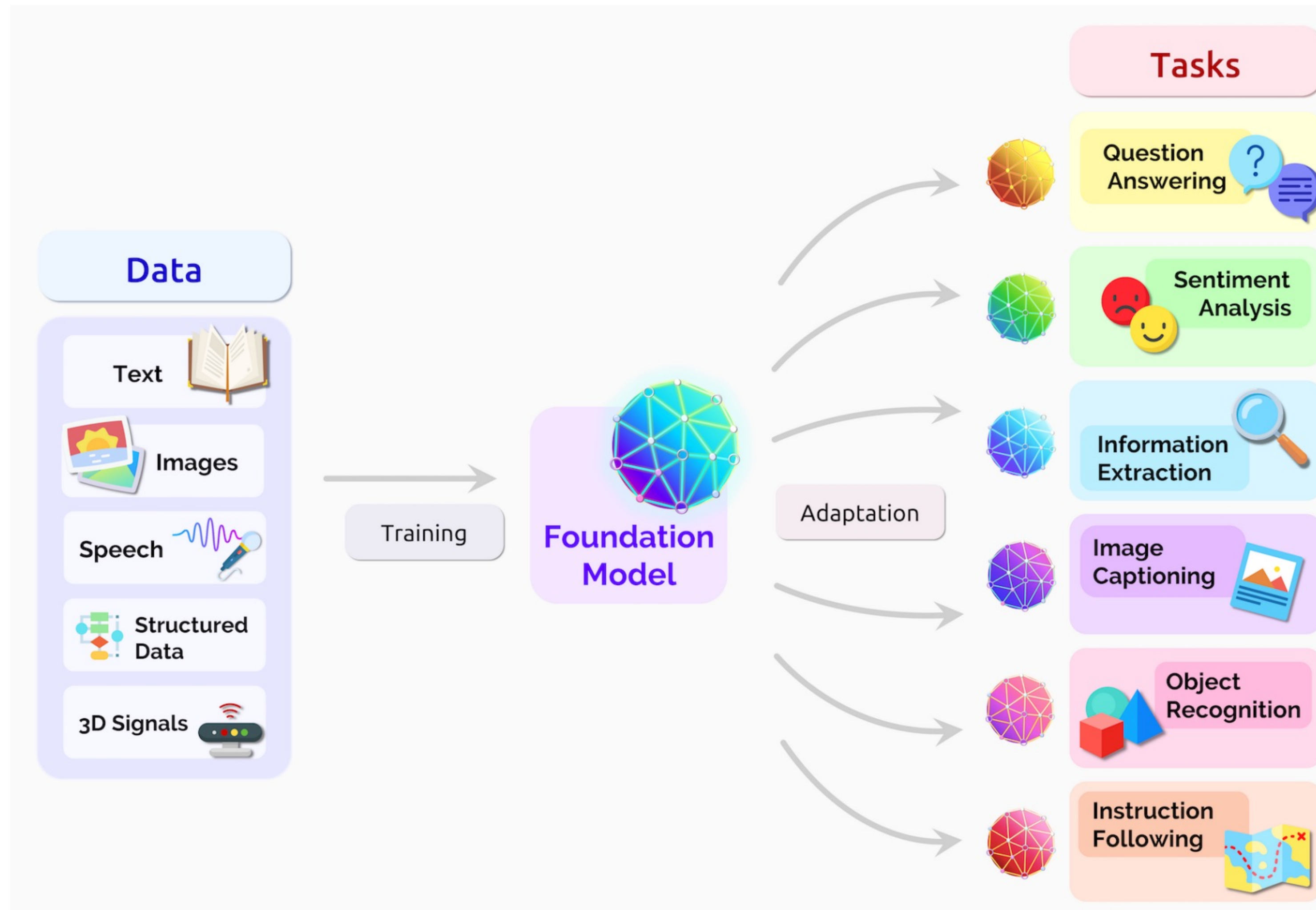
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<https://web.stanford.edu/class/biods271/>

Foundation Models



What to Expect from Course

- Provide background and discussion of (some) of the latest large-scale foundation models
- Discuss applications, exciting opportunities, and challenges for adaptation to healthcare
- Educate in this rapidly moving area and help enable high-quality research and applications

What to Expect from Students

- Active participation in course content - discussions, readings, and assignment
- Working towards a high-quality final project
- Flexibility to adapt to a fast-changing field!!

To What Extent Do You Use FMs?

- A. I have used FMs occasionally
- B. I use FMs during my day-to-day activities
- C. I am a power-user of FMs
- D. I exclusively vibe code

What are Your Common FM Uses?

- A. Coding
- B. General writing
- C. Image generation/manipulation
- D. Agentic workflows
- E. Other

(Rough) Course Outline – Part 1

Week 1

Mar 31: **BACKGROUND** Course Overview & Introduction to Foundation Models

Apr 02: **BACKGROUND** Introduction to LLMs

Week 2

Apr 07: **APPLICATIONS** AI Scientist Agents

Apr 09: **OPPORTUNITIES** Current Advances in LLMs and Agents

Week 3

Apr 14: **BACKGROUND** Evaluations of LLMs and agents

Apr 16: **APPLICATIONS** Generative AI for Drug Discovery

(Rough) Course Outline – Part 2

Week 4

Apr 21: **BACKGROUND** Self-Supervised Learning for Vision

HOMEWORK #1 DUE

Apr 23: **BACKGROUND** Self-Supervised Vision-Language Models

Week 5

Apr 28: **APPLICATIONS** Generative VLMs in Health

Apr 30: **APPLICATIONS** Foundation Models for Imaging

Week 6

May 05: **BACKGROUND** Foundation Model Adaptation and Evaluation

HOMEWORK #2 DUE

(Rough) Course Outline – Part 3

May 07: **BACKGROUND** Improving LLM Performance

Week 7

May 12: **OPPORTUNITIES** Training and Deployment Considerations

May 14: **BACKGROUND** Mixture of Expert Models

Week 8

May 19: **OPPORTUNITIES** Deployment Considerations

HOMEWORK #3 DUE

May 21: **OPPORTUNITIES** Inference Scaling and Reasoning

(Rough) Course Outline – Part 4

Week 9

May 28: **APPLICATIONS** EMR Foundation Models

Week 10

Jun 2: **OPPORTUNITIES** Bias and Health Equity

Jun 4: **PROJECT PRESENTATIONS DUE** Final Presentations

Week 11

Jun 11: **PROJECT REPORTS DUE**

Course Grading

- 10% Class participation
- 45% Homework (3 assignments)
- 45% Final Project

Classic ML Models



Input	Output	Function	Tasks	Application
<ul style="list-style-type: none">• Structured• Time series• Text• Image• Audio• Video• Table• Domain-specific• Multi-D• Multimodal	<ul style="list-style-type: none">• Label• Regression• Text• Image• Audio• Video• Table• Domain-specific	<ul style="list-style-type: none">• Clustering• Classification• Prediction• Regression• Synthesis	<ul style="list-style-type: none">• Recognition• Detection• Segmentation• Captioning• Image/text/synthesis• Audio/Video/multimodal synthesis• Question answering• Text generation• Autocompletion• Translation• Summarization• Sentiment analysis• Navigation• Search/IR• Recommendation• ...	<ul style="list-style-type: none">• Customer service• Social Media• Marketing• Code generation• Automated reporting• Domain-specific

Foundation Models

Input



Foundation Model

Output



Input

Output

Function

Tasks

Application

- Trained on a variety of data input

- Different types of output based on downstream use

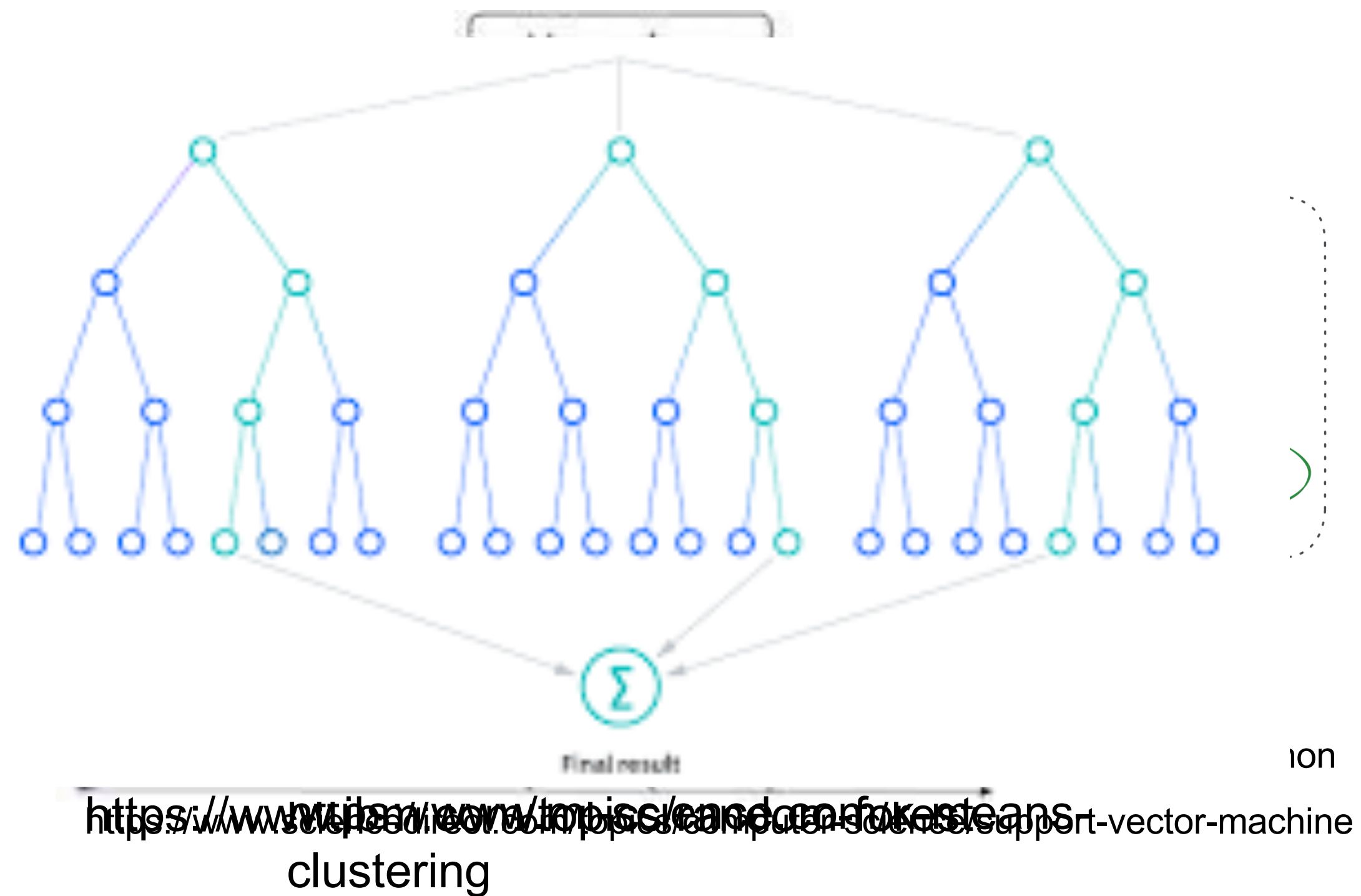
- Defined based on the scope of ability, range of uses, breadth of tasks or types of output and input
- Encoder
- Decoder
- Encoder-Decoder

- A single model can accomplish multiple tasks:
- Sentence completion
- Sentiment classification
- Summarization
-
- Works for arbitrary input
- Can be fine-tuned

- Same model can serve multiple applications
 - Customer service
 - Code generation
 - ...

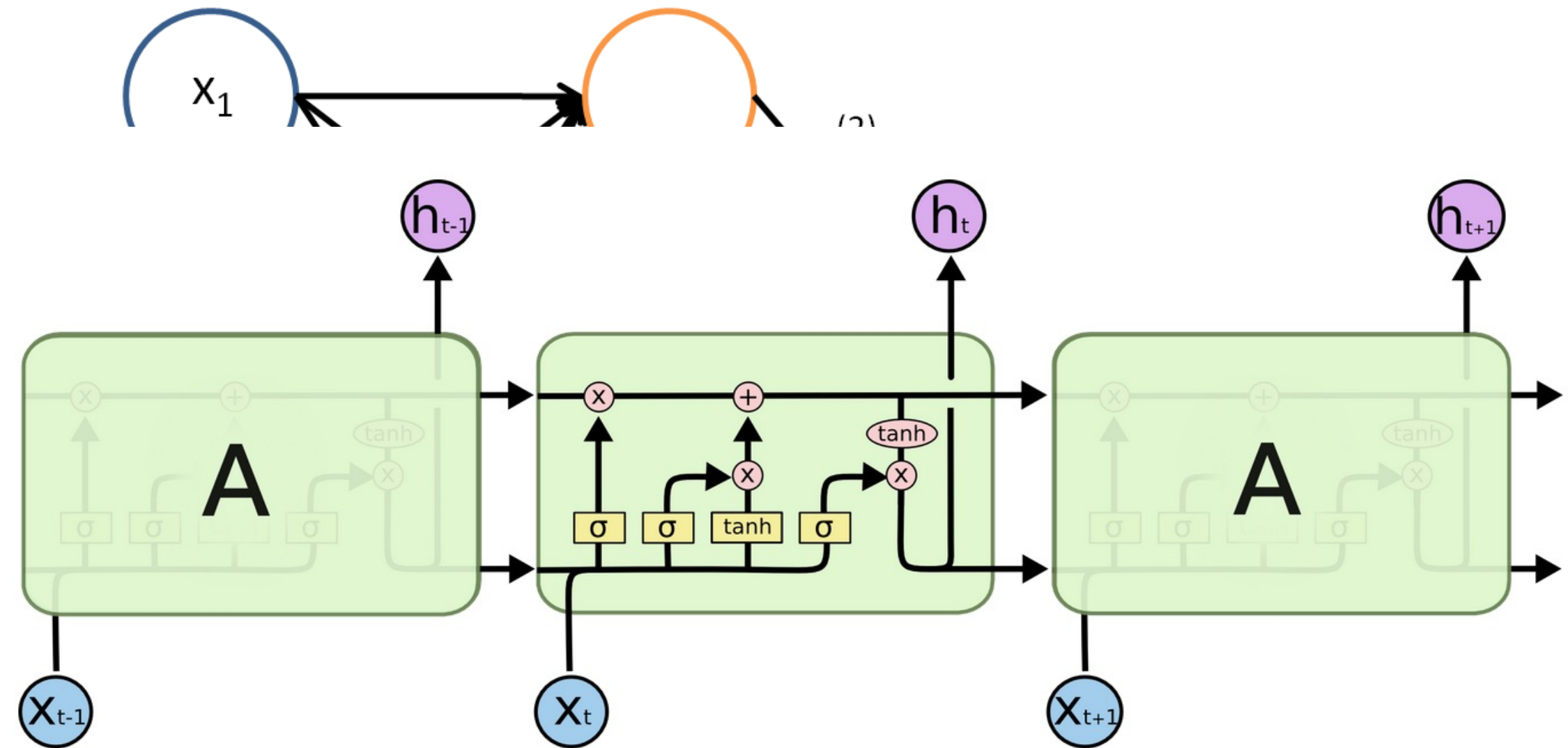
Are these Foundation Models?

- Decision Trees
- Clustering
- Support Vector Machines
- Random Forests



Are these Foundation Models?

- Multi-layer perceptron
- RNN
- LSTM

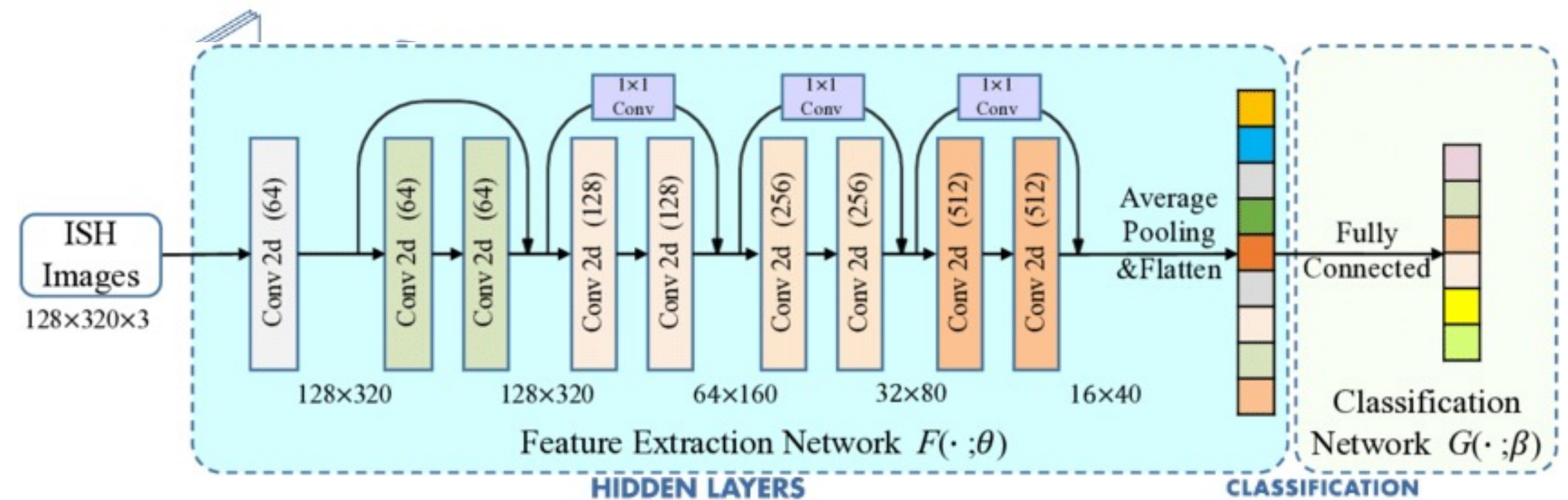


The repeating module in an LSTM contains four interacting layers.

<https://colah.github.io/posts/2015-08-Understanding-LSTMs/>
<http://deeplearning.stanford.edu/tutorial/supervised/MultiLayerNeuralNetworks/>

Are these Foundation Models?

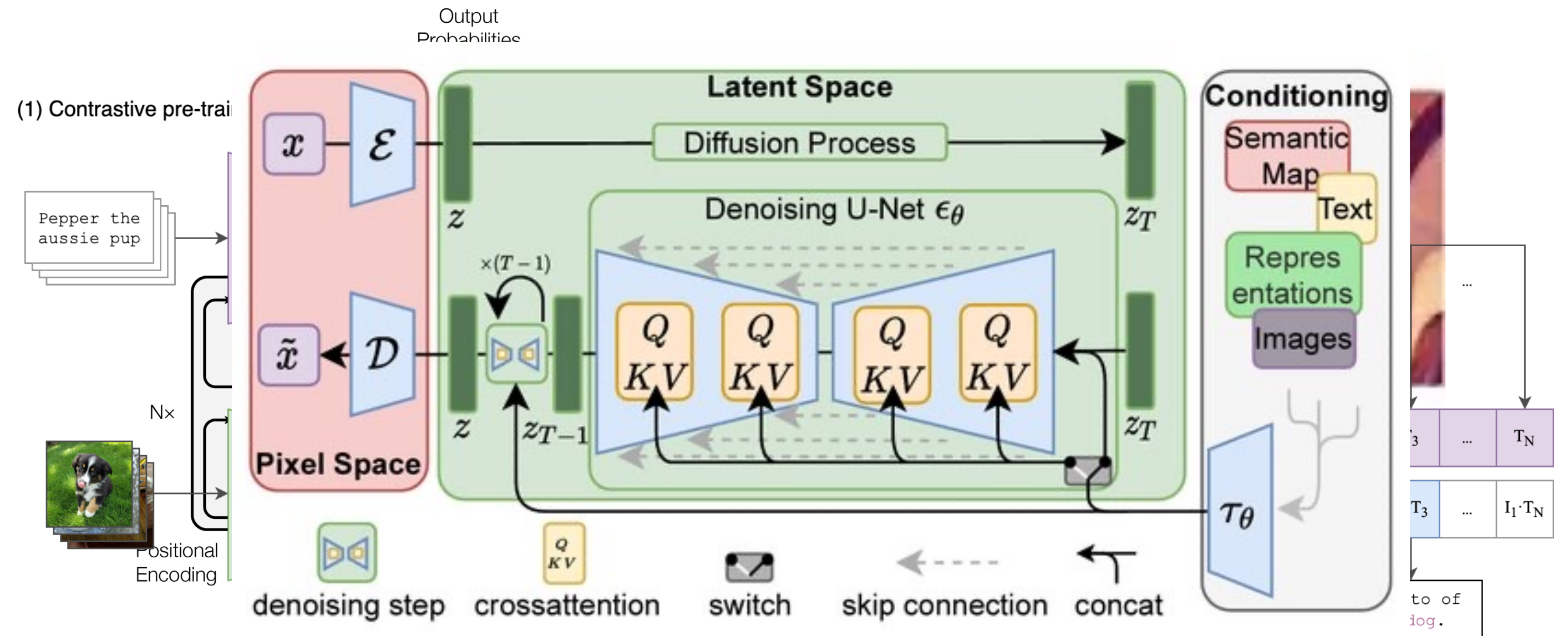
- Convolutional neural networks
- ResNet
- DNN



<https://www.linkedin.com/pulse/deep-residual-networks-resnet-ayoub-krouane>
<https://towardsdatascience.com/convolutional-neural-networks-explained-9cc5188c4939>

Are these Foundation Models?

- Auto-encoders
- GANs
- Transformers
- GPT
- CLIP
- Diffusion models



https://openaccess.thecvf.com/content/CVPR2022/papers/Rombach_High-Resolution_Image_Synthesis_using_Latent_Diffusion_Models_CVPR_2022_paper.pdf

<https://arxiv.org/abs/1706.03762>

Foundation vs Traditional ML models

Foundation	Traditional ML
<ul style="list-style-type: none">• Trained on broad unlabeled data for a variety of tasks• Very large number of parameters• Fine-tuning for adaptation• Self-supervision for labeling• Reduced development time, less ongoing maintenance• Dataset bias• lack of domain specificity, potential for misuse	<ul style="list-style-type: none">• Trained on specific datasets and designed for particular tasks• Fewer parameters compared to foundation models.• Label supervision• Easy to implement, interpret, and computationally efficient.• Risk of overfitting or underfitting• Limited generalization

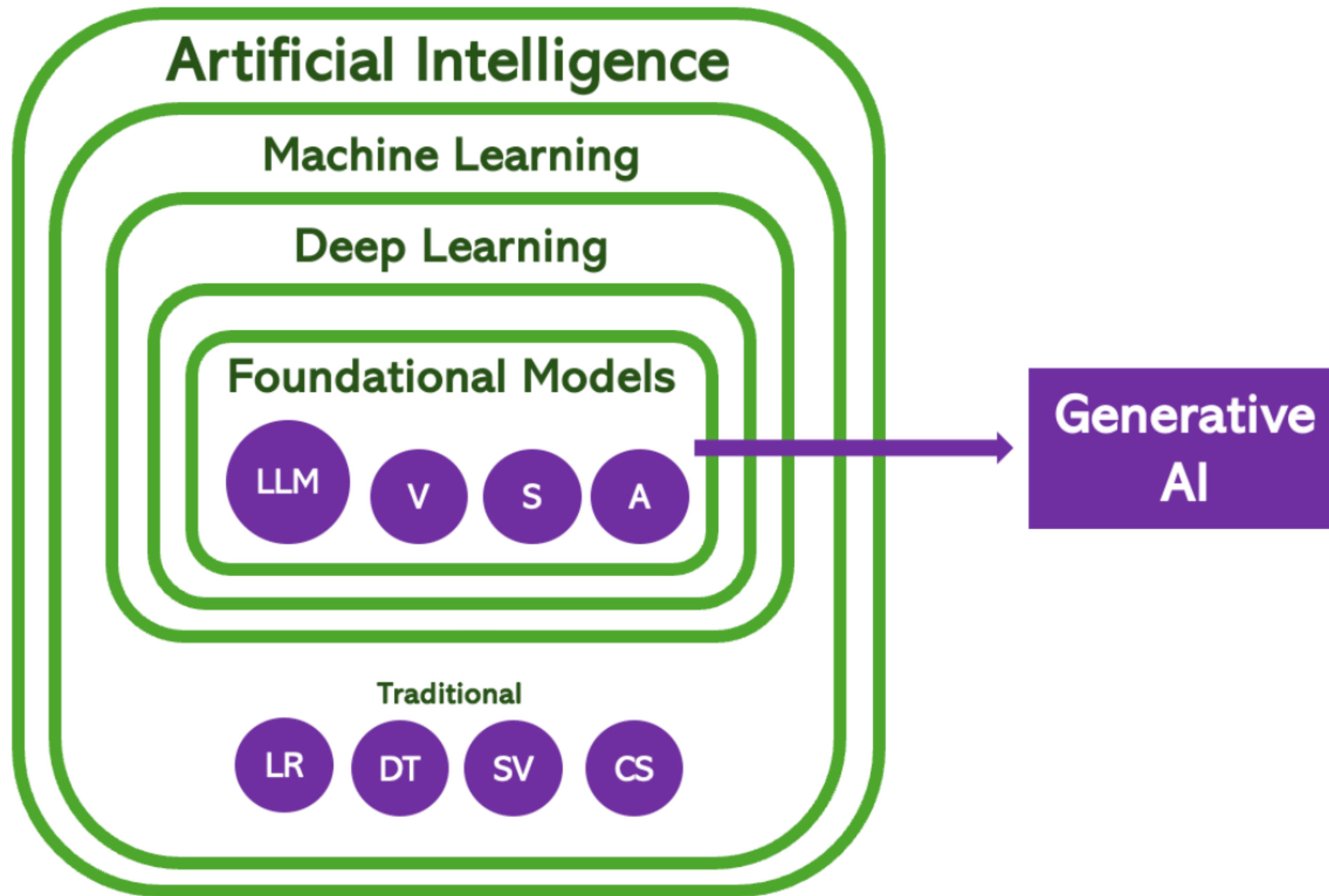
Which model is more suitable?

- Recognition
 - Detection
 - Segmentation
 - Synthesis
 - Summarization
 - Search
 - Sentiment analysis
- Traditional ML
 - Deep Learning
 - Foundational model
 - LLM
 - Generative AI

Case study

- In a large hospital system, the new CIO has been tasked to improve revenue cycle management by identifying cases of additional billing:
 - Which ML model to use?
 - Is a model alone sufficient?

Evolution of ML models

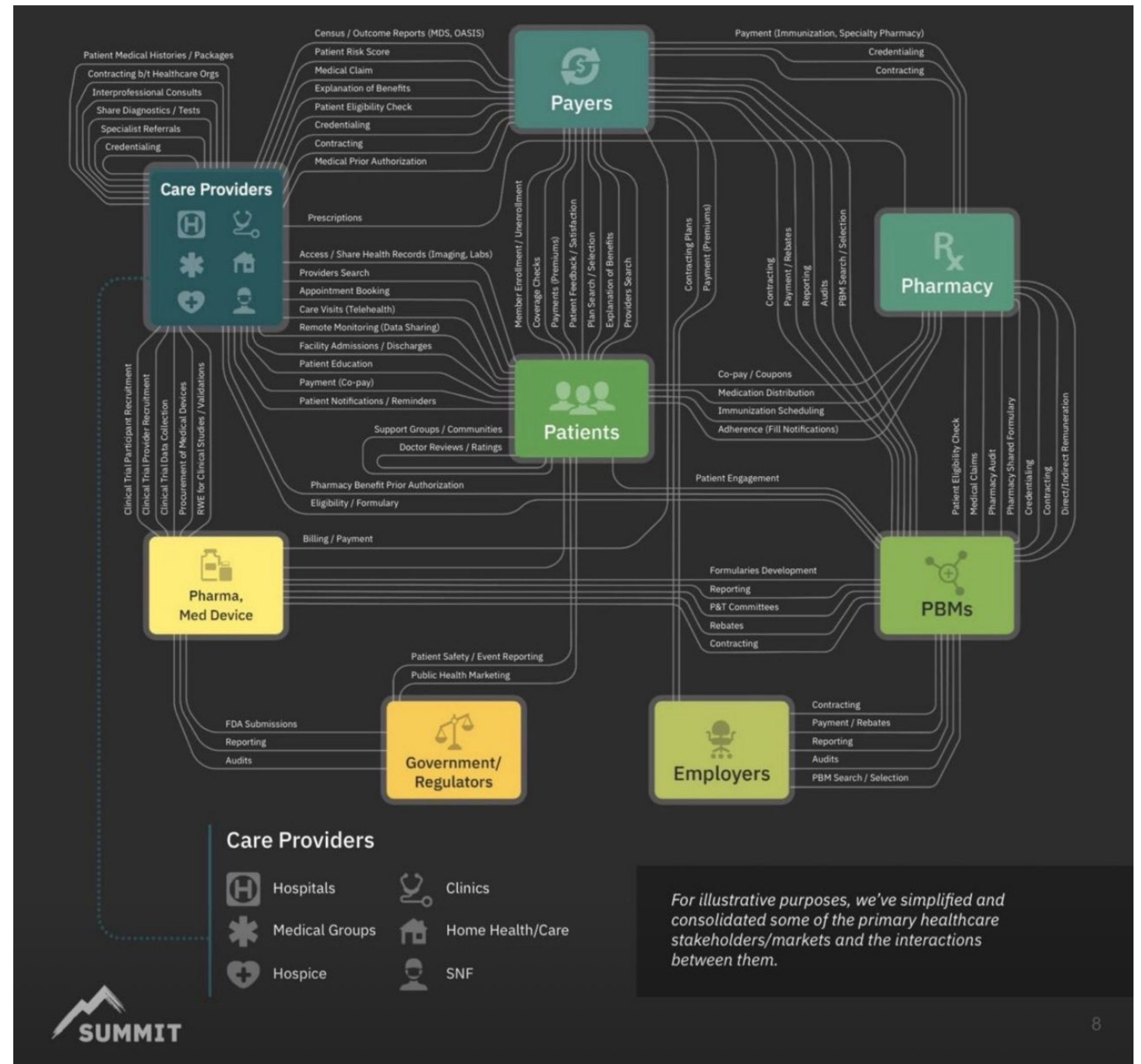


Benefits of Modern Day FMs

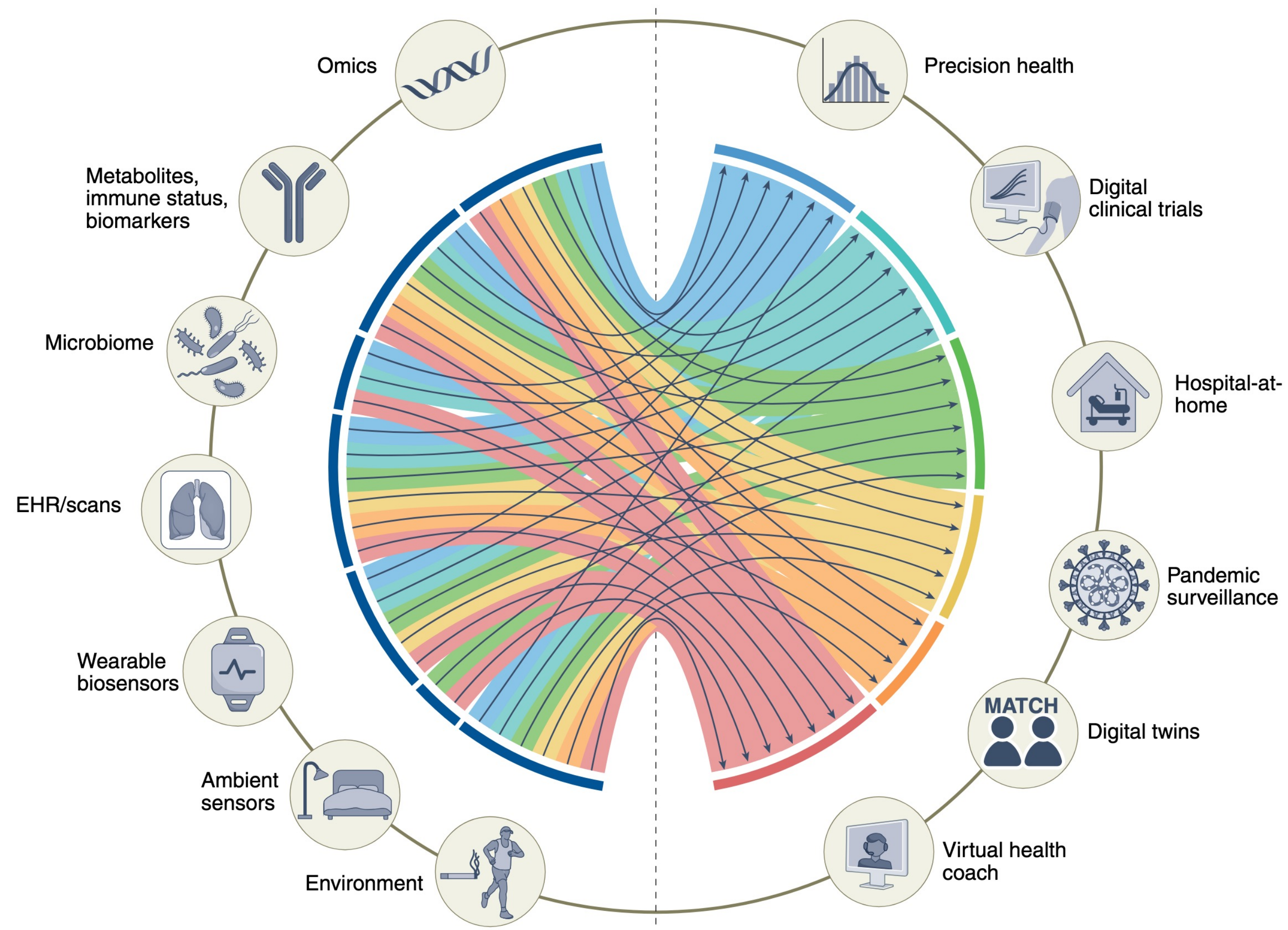
- Can perform generative and discriminative tasks
- Can be conditioned in a variety of ways
- Can be aligned with human preferences
- Can be (easily) adapted

Opportunities in Healthcare

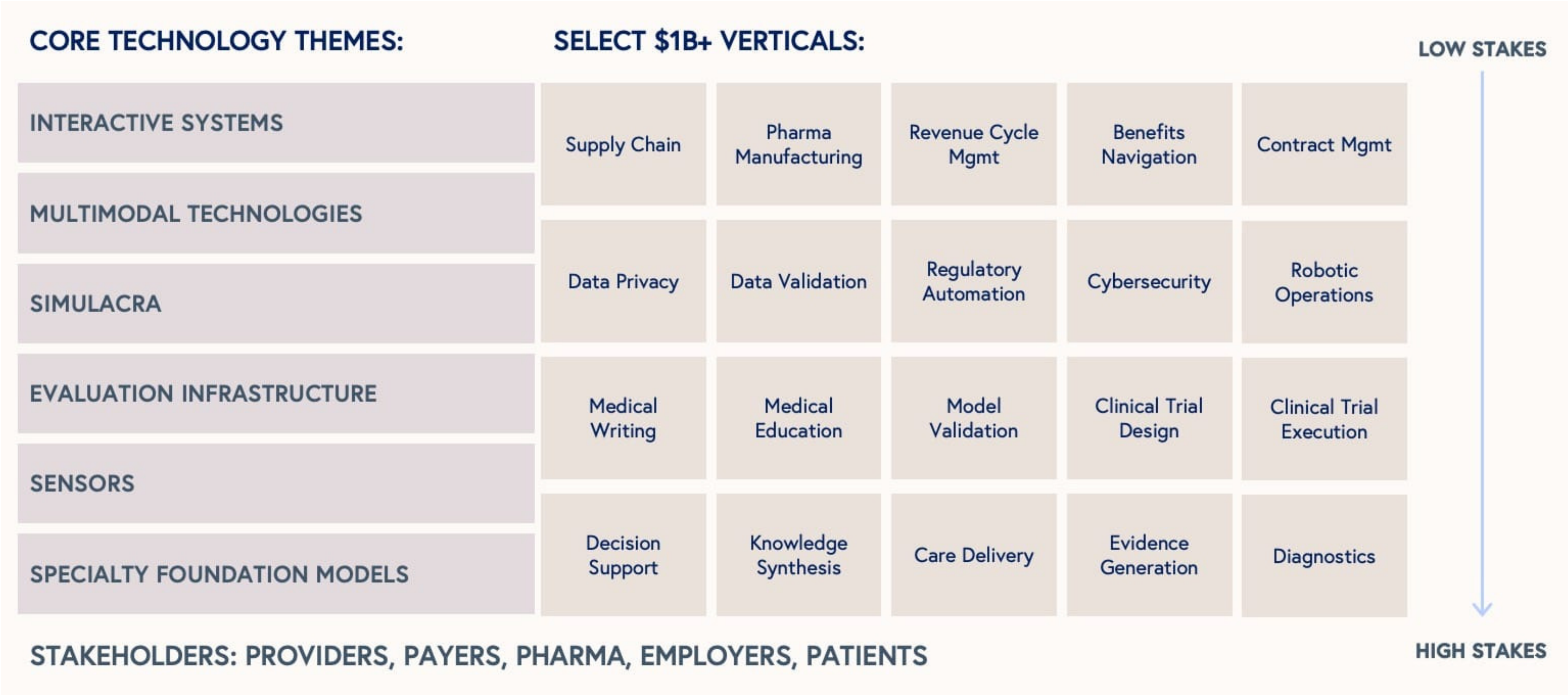
- Vast interconnected set of stakeholders
- Disparate but complementary needs/challenges



Opportunities in Healthcare



Opportunities in Healthcare



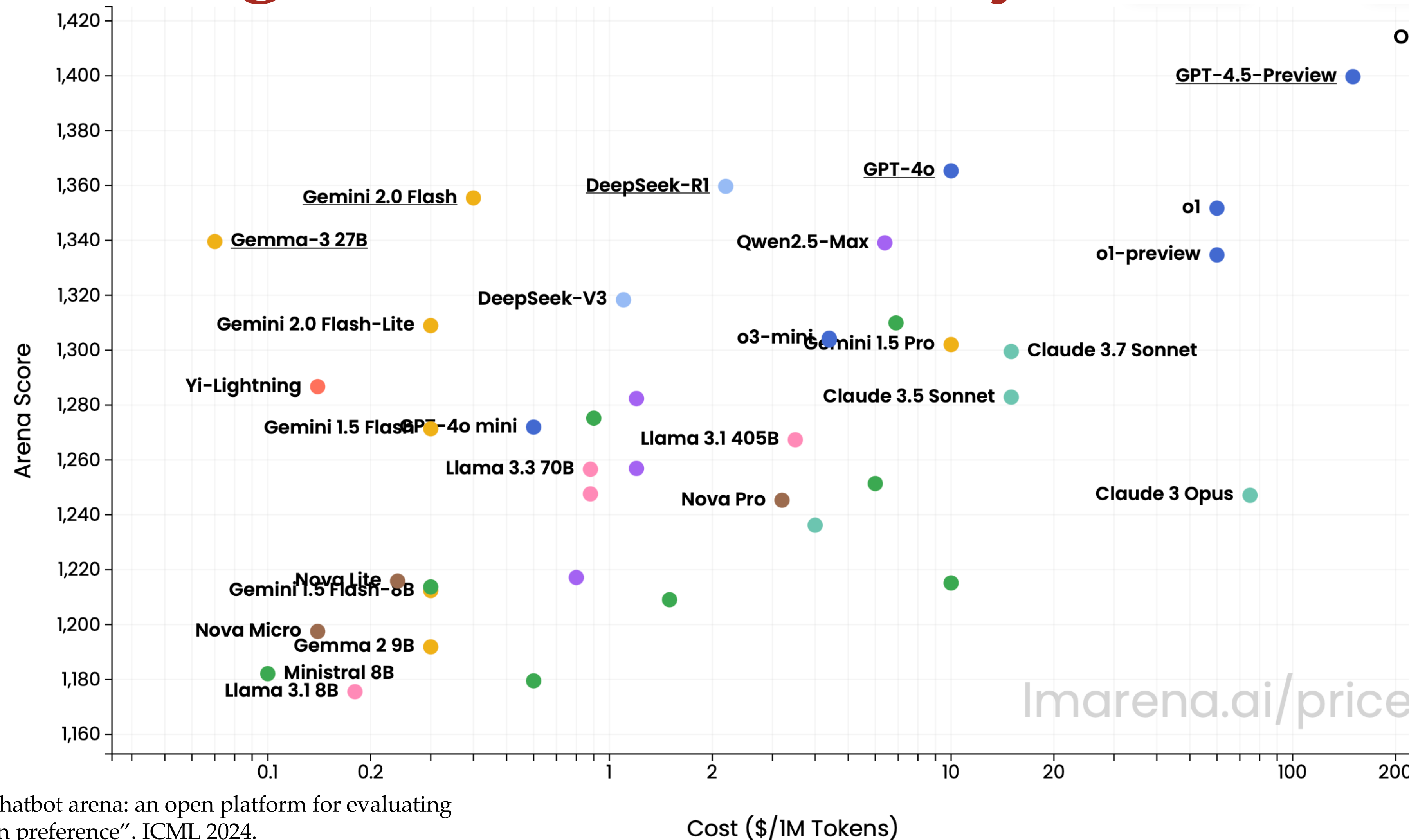
Challenges of Modern Day FMs

- Data requirements (pre- and post-training)
- Computational demands
- Inference efficiency/costs
- Adequate evaluation

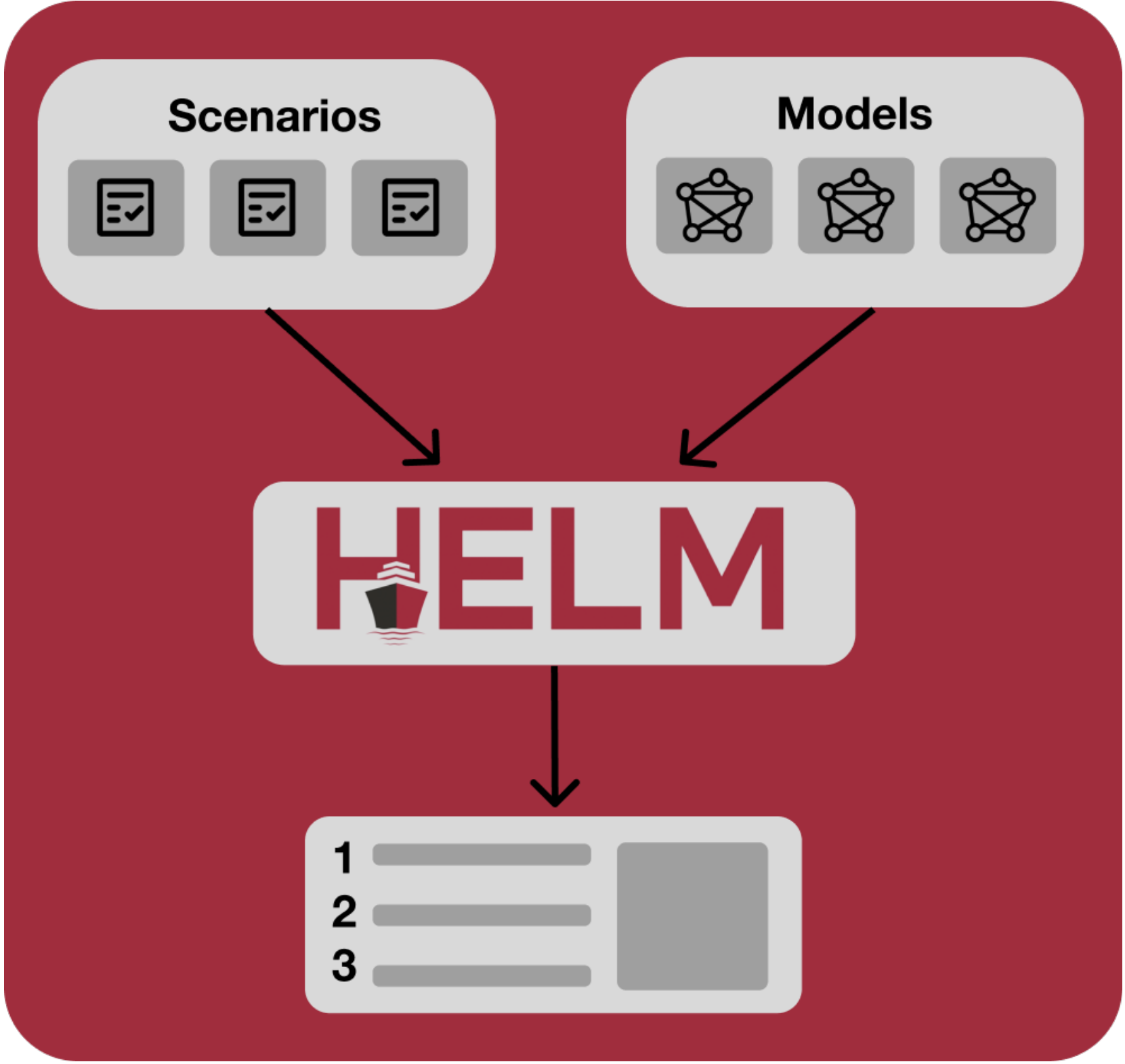
Challenges of Modern Day FMs

🏆 Chatbot Arena LLM Leaderboard: Community-driven Evaluation for Best LLM and AI chatbots							
🗨️ Language	🖥️ Overview	📢 Price Analysis	🕸️ WebDev Arena	👁️ Vision	🎨 Text-to-Image	💻 Copilot Arena	Arena-Hard-Auto
Total #models: 220. Total #votes: 2,816,680. Last updated: 2025-03-25.							
Code to recreate leaderboard tables and plots in this notebook . You can contribute your vote at lmarena.ai !							
Category		Apply filter		Overall Questions			
Overall		<input type="checkbox"/> Style Control <input type="checkbox"/> Show Deprecate		#models: 220 (100%) #votes: 2,816,680 (100%)			
Rank* (UB) ▲	Rank (StyleCtrl) ▲	Model ▲	Arena Score ▲	95% CI ▲	Votes ▲	Organization	License ▲
1	1	Gemini-2.5-Pro-Exp-03-25	1443	+11/-8	3474	Google	Proprietary
2	2	ChatGPT-4o-latest (2025-03-26)	1408	+11/-12	2676	OpenAI	Proprietary
2	4	Grok-3-Preview-02-24	1404	+6/-6	10397	xAI	Proprietary
2	2	GPT-4.5-Preview	1398	+6/-7	10907	OpenAI	Proprietary
5	7	Gemini-2.0-Flash-Thinking-Exp-01-21	1381	+4/-5	22987	Google	Proprietary

Challenges of Modern Day FMs



Challenges of Modern Day FMs



Categories	Subcategories	Datasets	Metric	Model-1
Clinical Decision Support	Supporting Diagnostic Decisions	MedCalc-Bench	Exact Match	
	Planning Treatments	MTSamples	BertScore-F1	
⋮		⋮	⋮	
Clinical Note Generation	Documenting Patient Visits	DischargeMe	BertScore-F1	
	Documenting Care Plans	Note Extract	BertScore-F1	
⋮		⋮	⋮	
Patient Communication and Education	Providing Patient Education Resources	Medication QA	BertScore-F1	
	Patient-Provider Messaging	MedDialog	BertScore-F1	
⋮		⋮	⋮	
Medical Research Assistance	Conducting Literature Research	PubMed	Exact Match	
	Analyzing Clinical Research Data	EHR-SQL	EHRSQLReAns	
⋮		⋮	⋮	

MedHELM