Revolutionizing Earth Science with Generalized AI Models

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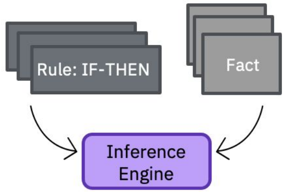
Inflection Point in AI

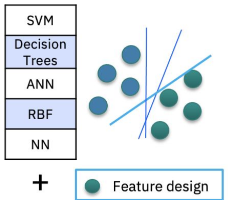
poised to dramatically accelerate enterprise AI adoption

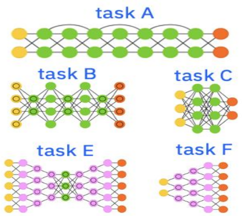
1980s Big data

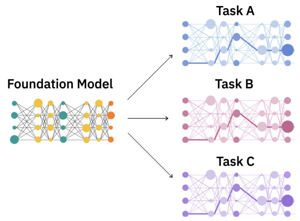
1980s to ~2010 Massive labeled data + Compute

2017+ **Self-supervision at scale** + Massive unlabeled data + Compute









Expert Systems
- Manually-crafted symbolic representations and rules
- No use of data and brittle

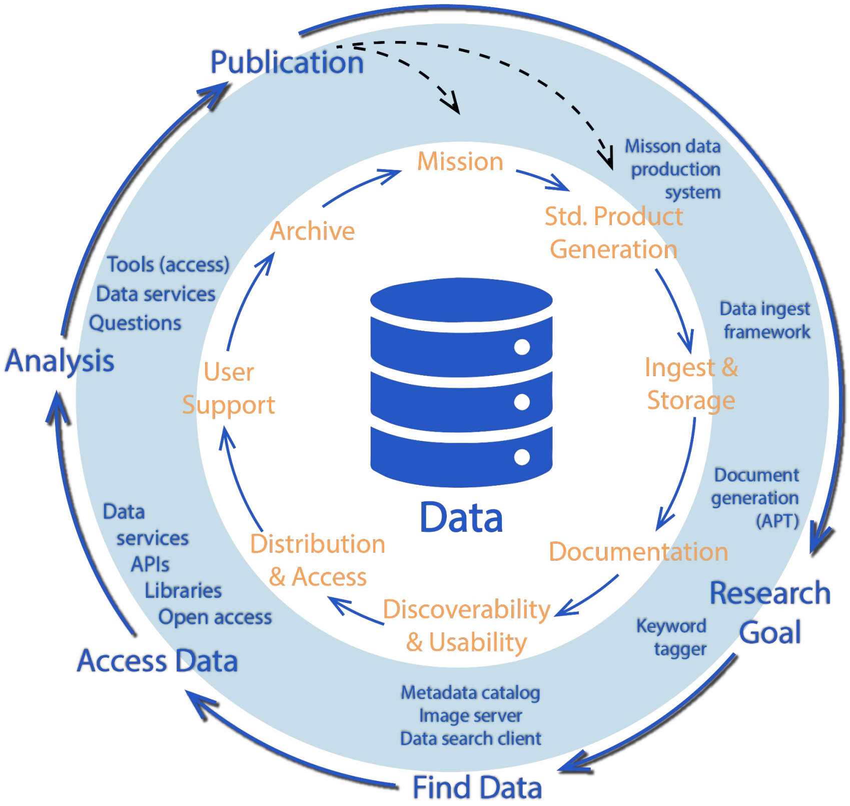
Machine Learning
- Less brittle but labor intensive
- Demanding data prep and feature engineering

Deep Learning
- Automatically learn if you have enough labeled data
- Enterprise adoption limited by availability of labeled data

Foundation Models
- Learn from lots of data *without requiring labels*
- Quickly adopt to enterprise tasks using limited labels

Slide source: Raghu Ganti/IBM Research

Building Blocks



Data + Tools/Infrastructure -> Enable Research Lifecycle

What Are Foundation Models?

- Foundation models (FM) are AI models that are ***designed to replace task-specific models and be applied to many different downstream applications***.
- FM are trained using ***self-supervised techniques*** and can be built on any type of ***sequence data***.
    - Self supervised learning removes t**he existing roadblock for developing a large annotated dataset for training.**
- FM can be applied to downstream tasks by ***using few shot learning and fine tuning***

- Some have to be ***trained at scales*** that limits the ability to a handful organizations

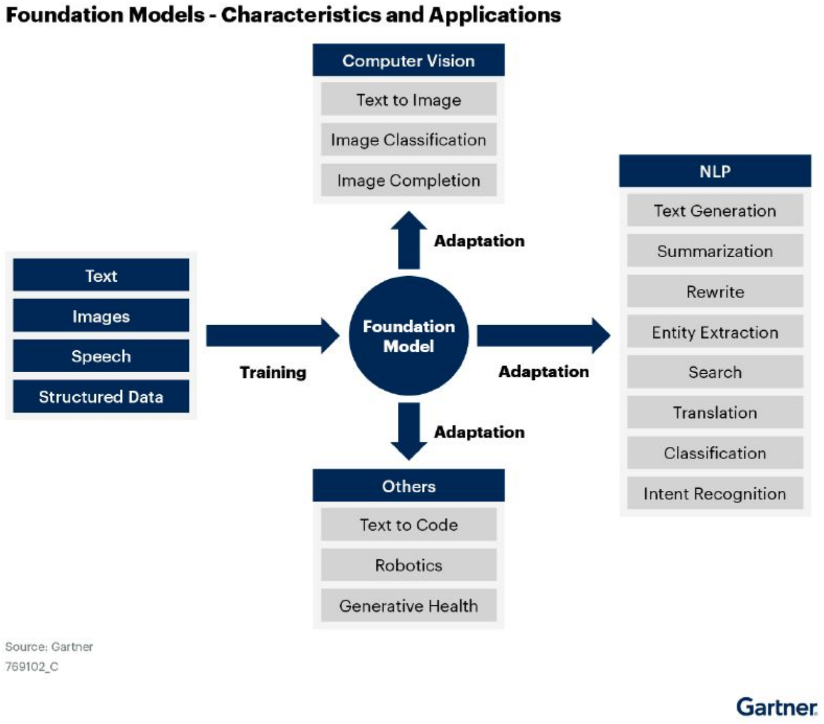
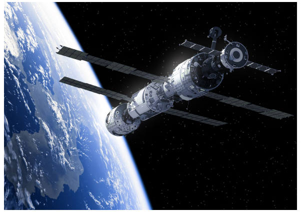


Image source: Gartner Report - Innovation Insight for Artificial Intelligence Foundation Models, Published 27 Oct 2022

Language Model for Earth Science

Train a new domain specific foundation model on Earth science literature that improves downstream tasks and enables information retrieval

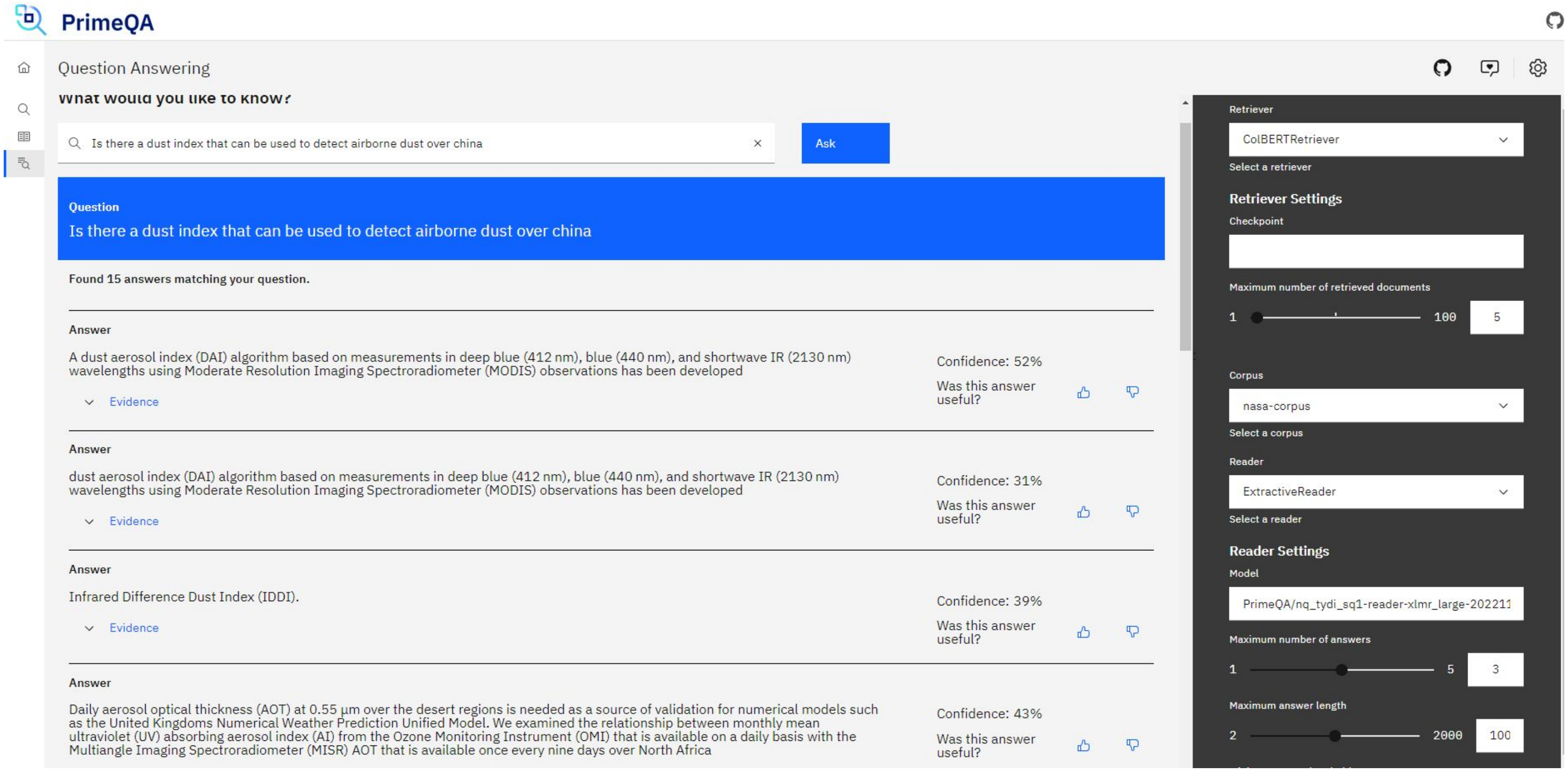


- Models built using FM stack
- Standard RoBERTa base architecture (125M)
- 120k papers (after data preprocessing and duplicate removals, reduced from 275k papers)
- 64 NVIDIA A100 GPUs
- 10 hrs of training
- 67k words/GPU/sec throughput

NASA RoBERTa model	Standard English RoBERTa
CAPE increase due to [*anthropogenic greenhouse warming*].	CAPE increase due to [*weather*].
The second most abundant element in the atmosphere is [*oxygen*].	The second most abundant element in the atmosphere is [*water*].
[*Oxygen*] atoms combine to form dioxygen.	[*The hydrogen*] atoms combine to form dioxygen.
An igneous rock is a rock that crystallizes from [*magma*].	An igneous rock is a rock that crystallizes from [*ashes*].
An igneous rock is a rock that crystallizes from [*igneous melt*].	An igneous rock is a rock that crystallizes from [*the ground*].

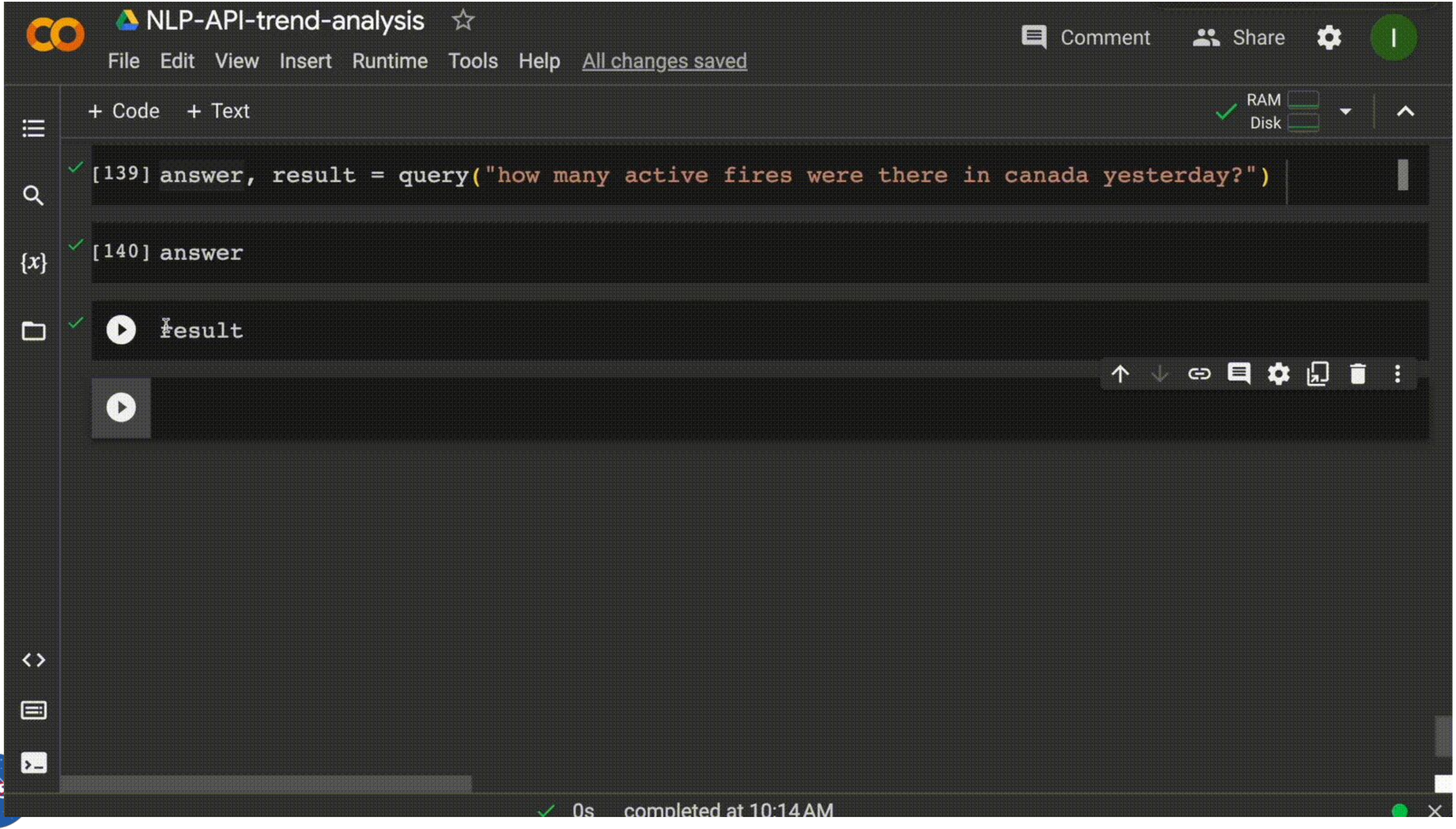
Slide source: Raghu Ganti/IBM Research

Using the Language Model for Question Answering

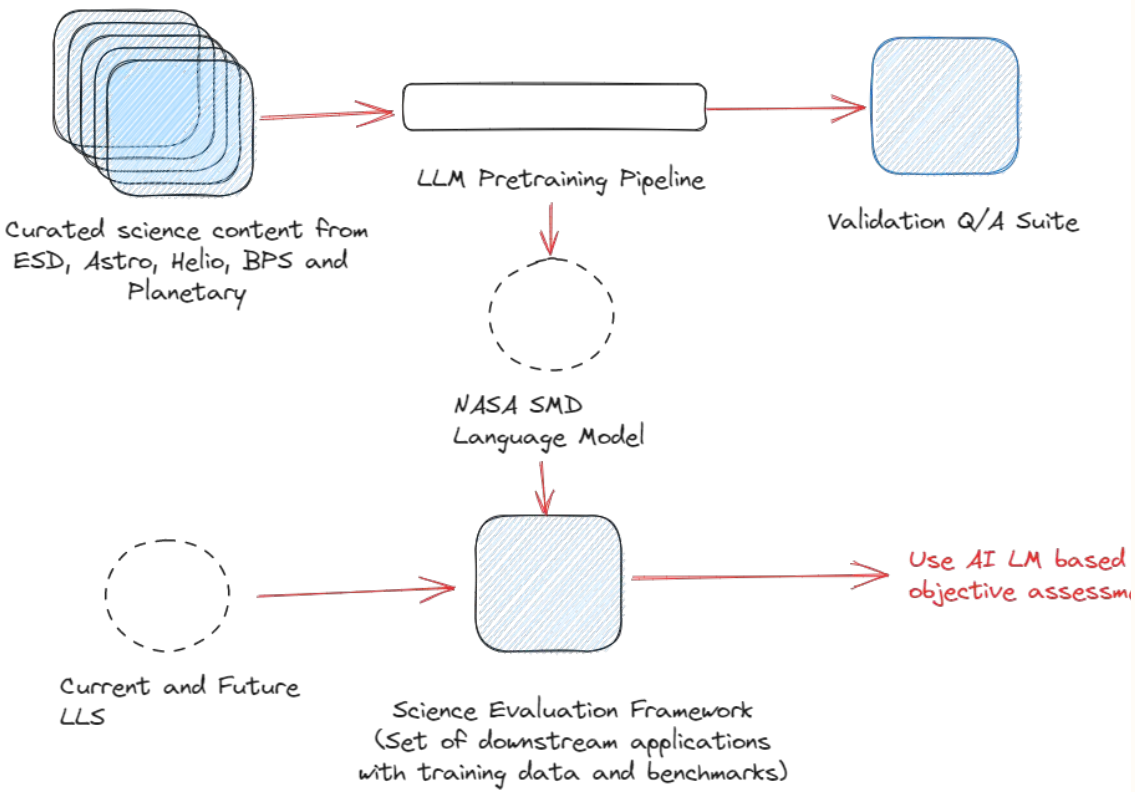


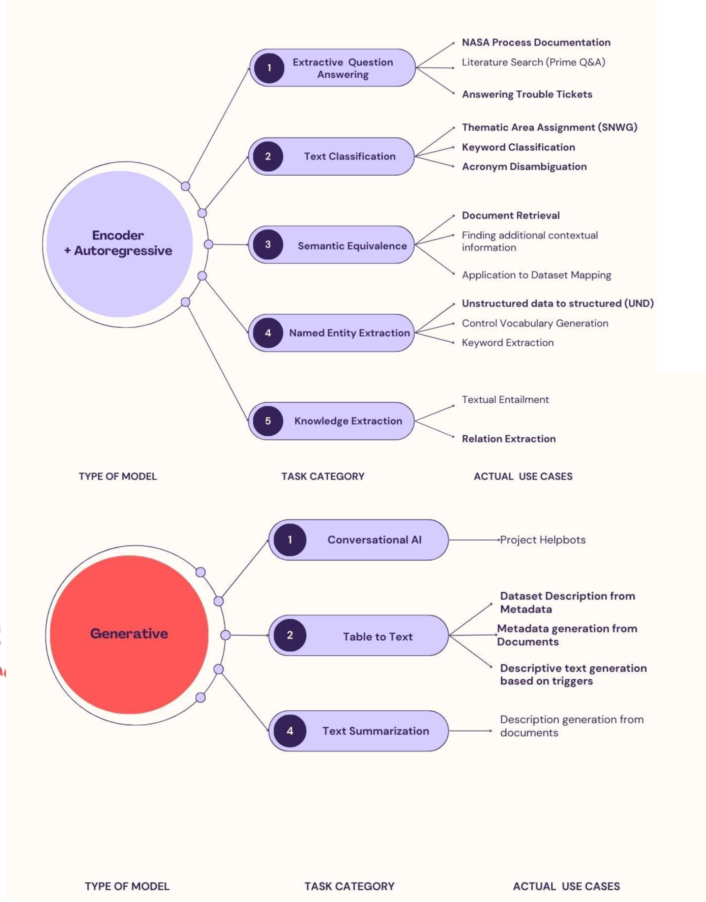
Proof of concept demo (IBM Research collaboration)

Enhancing Scientific Efficiency through AI (FIRMS Q&A)

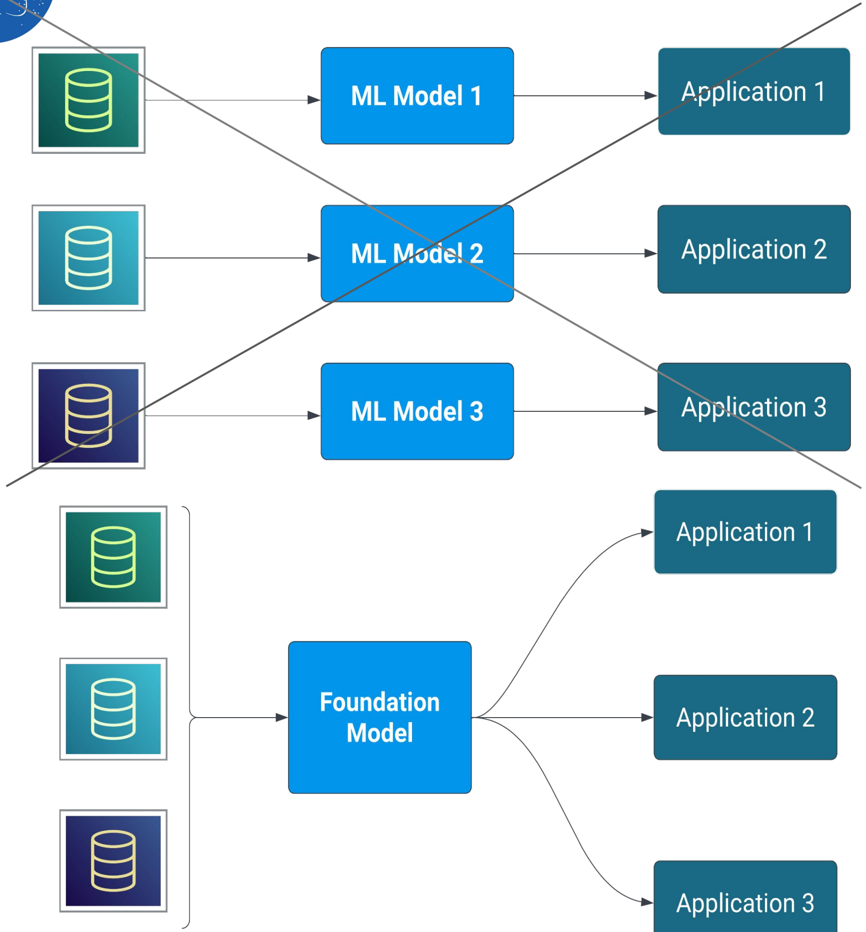


Foundation Language Model for Science





Foundation AI Models for Earth Science Data

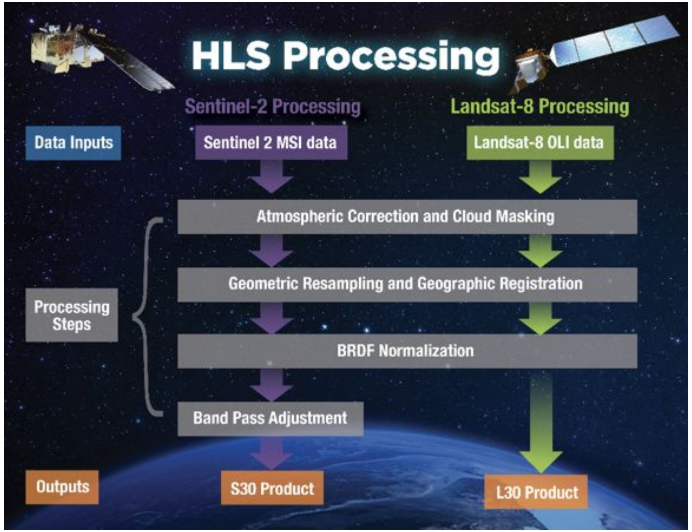


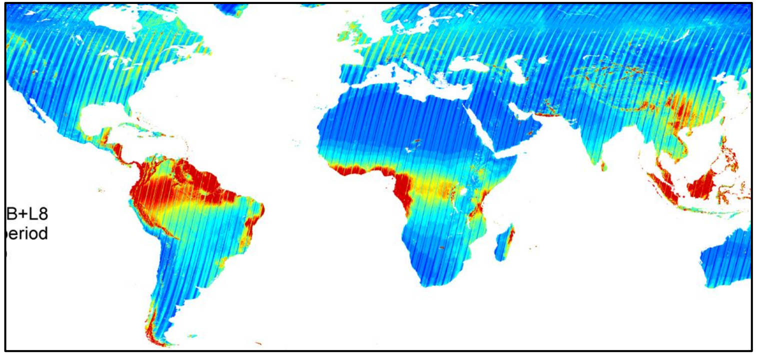
- Can we build foundation AI models for domains or representative types of data?
  - Optical remote sensing data, SAR, climate simulations
- Can these models capture underlying physical processes?

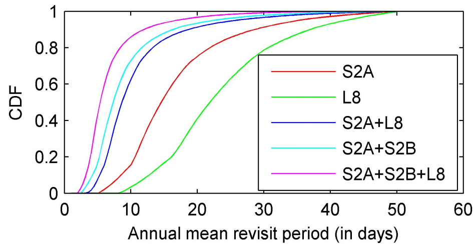
Foundation AI Model for Optical Remote Sensing Data

Harmonized Landsat Sentinel (HLS)

- “Seamless” near-daily 30m surface reflectance record including atmospheric corrections, spectral and BRDF adjustments, regridding
- Merges Sentinel-2 and Landsat data streams and can provide **2-4 day global coverage**







HLS FM Training Pipeline

DATALOADING

For multiple GPUS

IBM Cloud
Object Storage

HLS2 DATA SOURCE

DATA ACCESS
- *Downloading*
- *Streaming*
- *Sharding*

PREPROCESSING
- *cloudy/cloud adjacent pixels*
- *Filter based on % of NULL values*
- *Normalization*

TRAINING

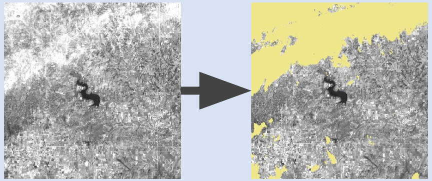
MASKING → *Masked image* → MODEL → *Inpainted image* → LOSS

MASKING Considering:
- *Random*
- *Square*
- *Pixelated, etc*

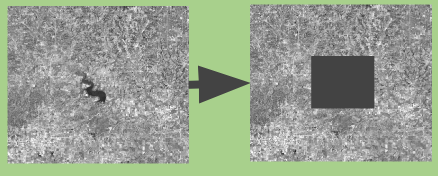
FOUNDATION MODEL Considering:
- *ViT (vision transformer)*
- *Spatio-temporal transformer*

LOSS Considering:
- *MAE,*
- *MSE*
- *etc*

PREPROCESSING
converts cloudy/cloud adjacent pixels to null values

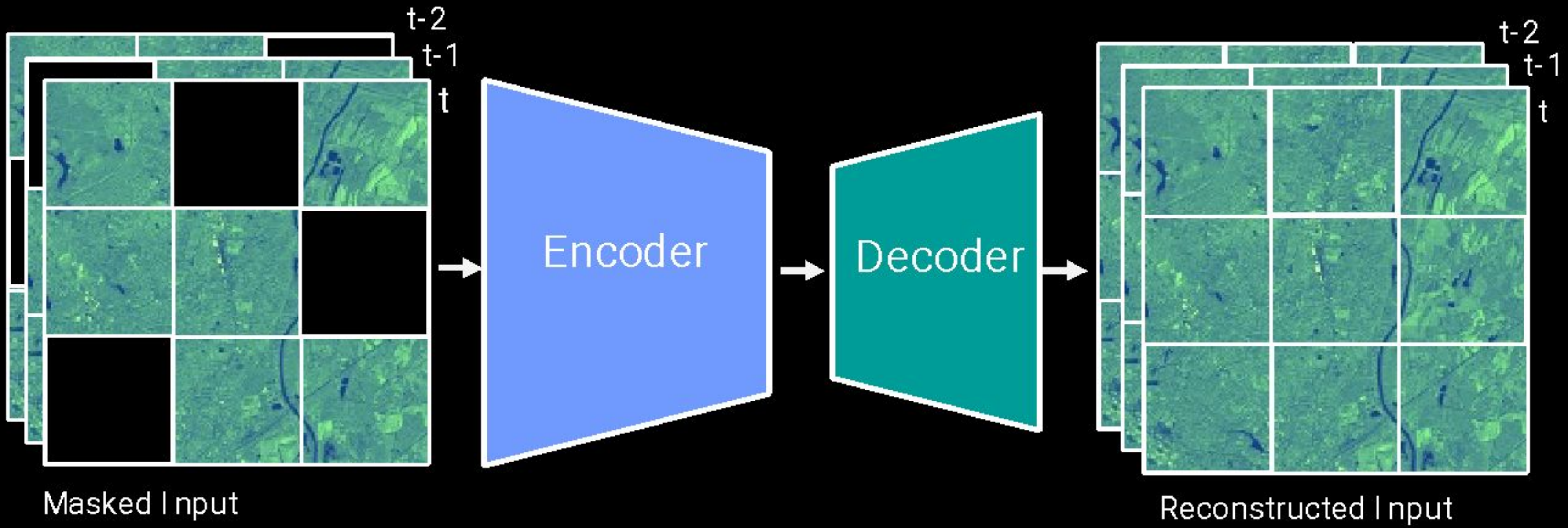


MASKING
Removing portion of image which will be inpainted by foundation model



Slide source: Raghu Ganti/IBM Research

HLS Model – Pretraining (Masked Modeling)

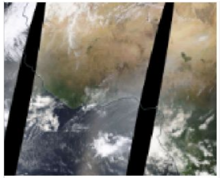


Slide source: Raghu Ganti/IBM Research

HLS FM Downstream Adaptation

Harmonized Landsat Sentinel-2

Surface reflectance data products



Training

HLS Foundation Model

Adaptation

Segmentation
Tornado tracks, Burn scars, Flooding

Similarity Search
Given an image, find similar images

Adaptation

Classification
Land use, Land cover

Object Detection
Irrigation, Dwellings, Anomaly detection

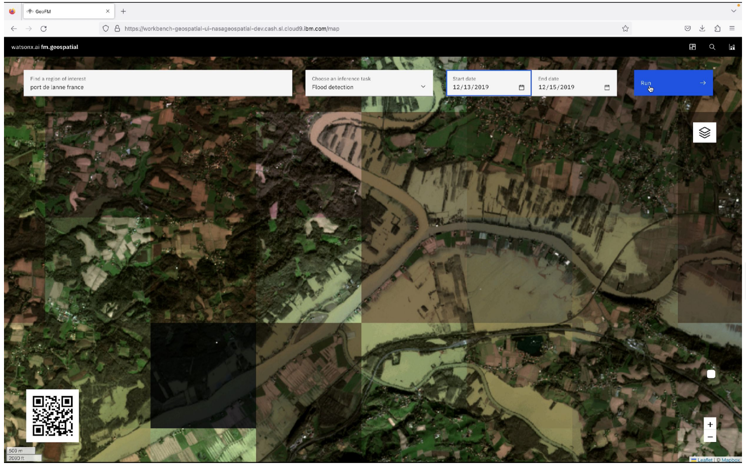
Adaptation

Science Data Product Generation
Harmonization with other optical sensors, Super resolution

Image to Image Translation
Optical to SAR (style transfer), Gap filling, Cloud removal

Increasing Task Complexity

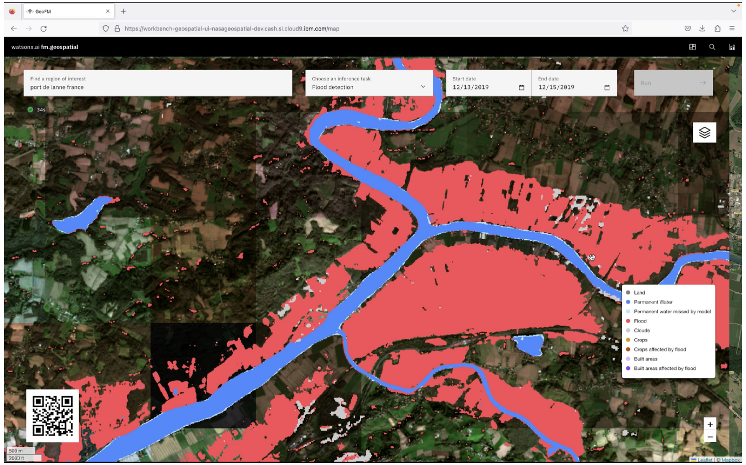
Inference by HLS GeoSpatial FM
Flood Mapping



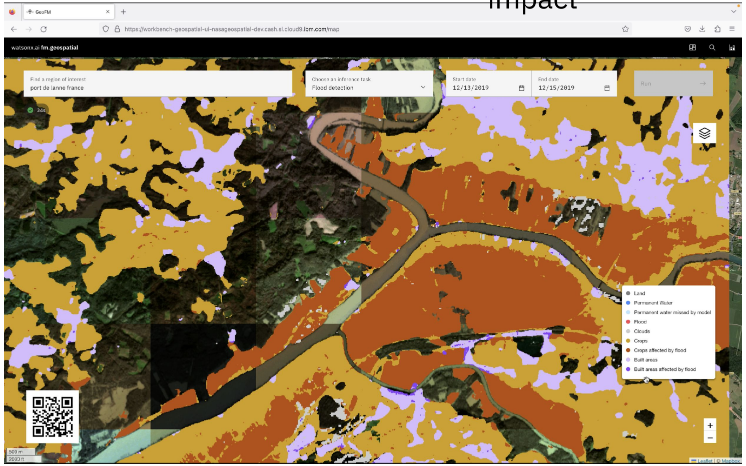
“**Prompt**”: Image(s) (spatial + temporal domains)

<< Inference>>
(e.g., flood task)

Insights: Flood detection



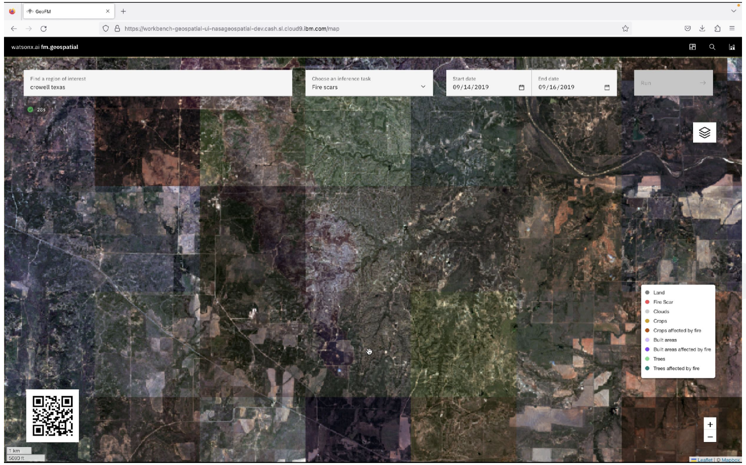
Insights: Flood impact



	IoU (water class)	F1 (water class)	IoU	F1 score	Accuracy
Baseline [44]	24.21	–	–	–	–
U-Net-based SOTA [43]	69.12	81.74	93.85	96.65	96.44
ViT-base [19]	66.52	79.89	90.92	94.97	94.97
Swin [46]	74.75	85.55	92.38	95.90	94.73
Prithvi (not pretrained)	79.23	88.41	94.52	97.09	97.07
Prithvi (pretrained)	**80.10**	**88.95**	**94.78**	**97.23**	**97.23**

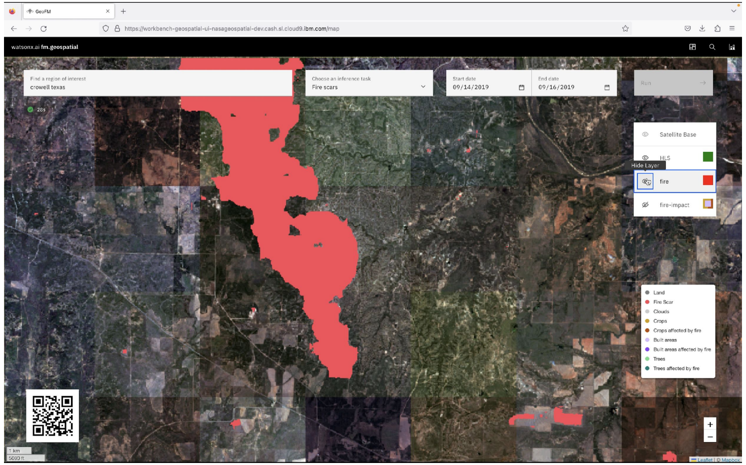
Inference by HLS GeoSpatial FM

Fire Scar Mapping

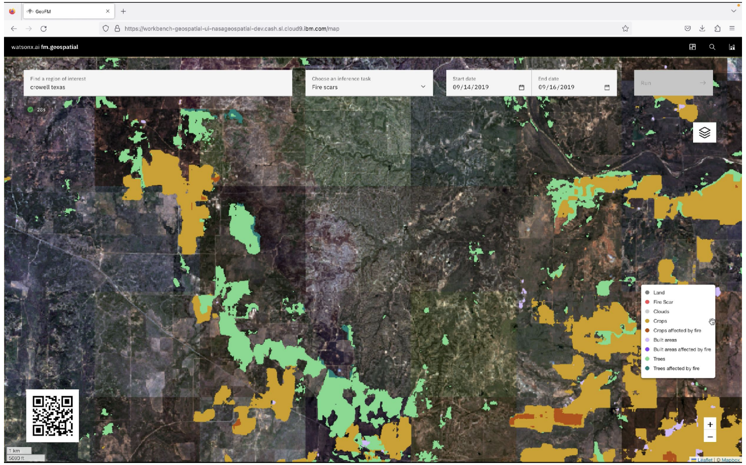


<< Inference>>

Insights: fire scar detection



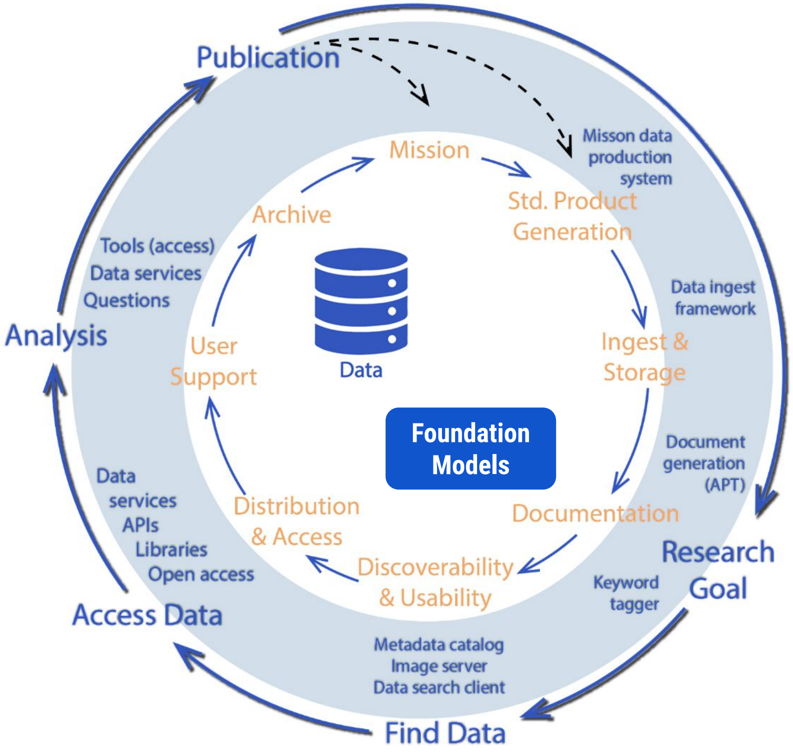
Insights: Fire impact



"**Prompt**": Image(s) (spatial + temporal domains)

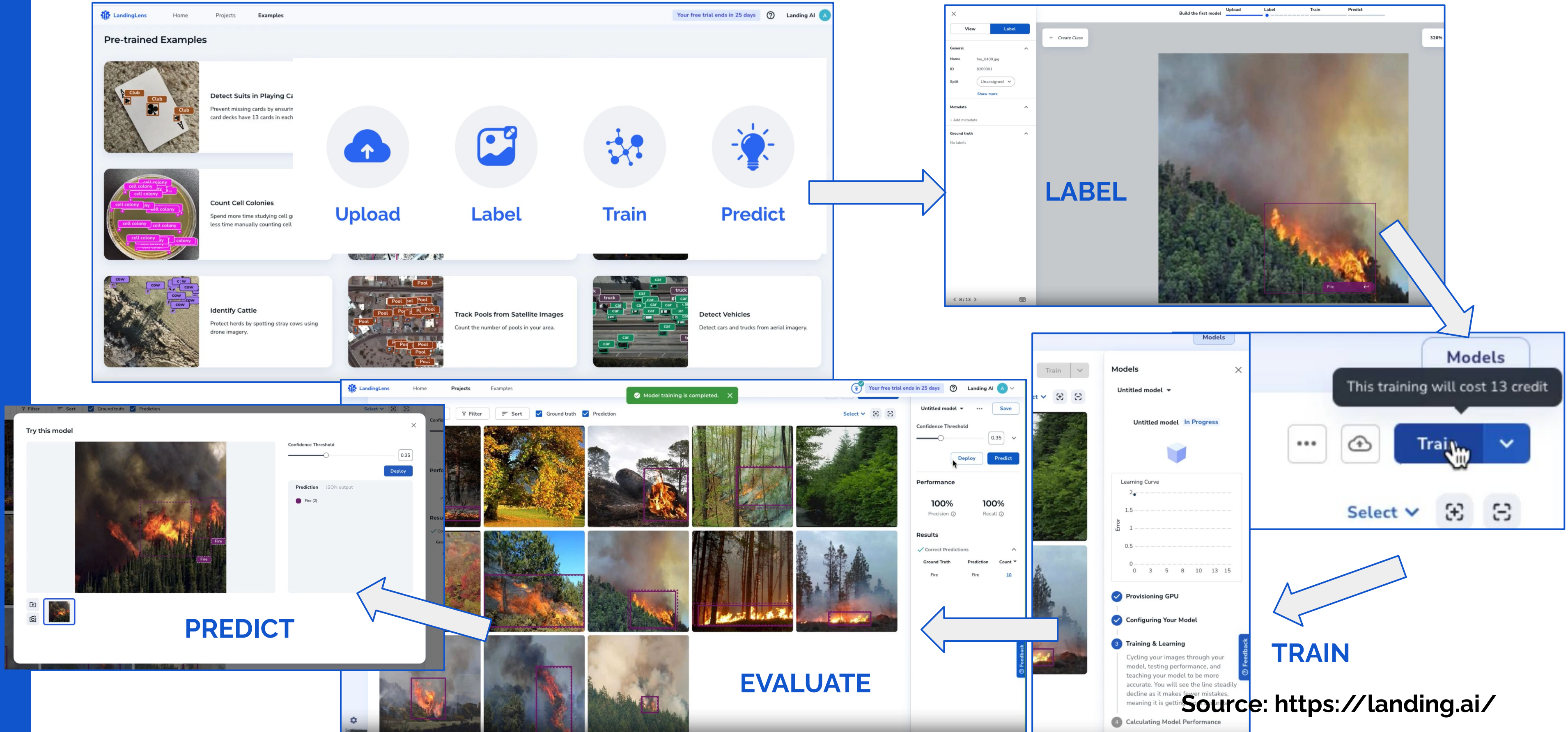
	IoU (fire scar class)	F1 (fire scar class)	IoU	F1 score	Accuracy
U-Net (DeepLabV3) [48]	45.96	62.98	93.38	96.11	96.22
ViT-base [19]	51.87	68.31	94.01	96.56	96.56
Swin [46]	56.04	71.83	94.16	96.71	96.50
Prithvi (not pretrained)	59.31	74.46	94.62	97.0	96.80
Prithvi (pretrained)	**61.55**	**76.20**	**95.04**	**97.25**	**97.10**

Building Blocks: Future State



Data + Tools/Infrastructure + AI Foundational Models -> *Accelerate Research and Applications*

What does the future look like?



Source: https://landing.ai/

Future Plans and Attributions

HLS FM
Early August Release

- Hugging Face
  - Pretrained HLS FM
  - Fine Tuned Flooding, Burn Scar Models
- Github
  - Flooding, Burnscar code, data

Late August Release

- Github
  - Pretraining source code
  - Other Fine Tuning examples

Science LLM - December Release (AGU)

Watch this space:
Earthdata | Earthdata (nasa.gov)
IMPACT Unofficial – Medium

NASA MSFC/IMPACT
Sujit Roy, Ankur Kumar, Chris Phillips, Iksha Gurung, Kumar,
Rahul Ramachandran, **Manil Maskey**

IBM Research
Johannes Jakubik, Linsong Chu, Paolo Fraccaro, Ranjini, Kamal Das, Daiki Kimura, Naomi Simumba, Daniela Szwarcman, Michal Muszynski, Carlos Gomes, **Kommy Weldemariam**, Bianca Zadrozny, **Raghu Ganti**

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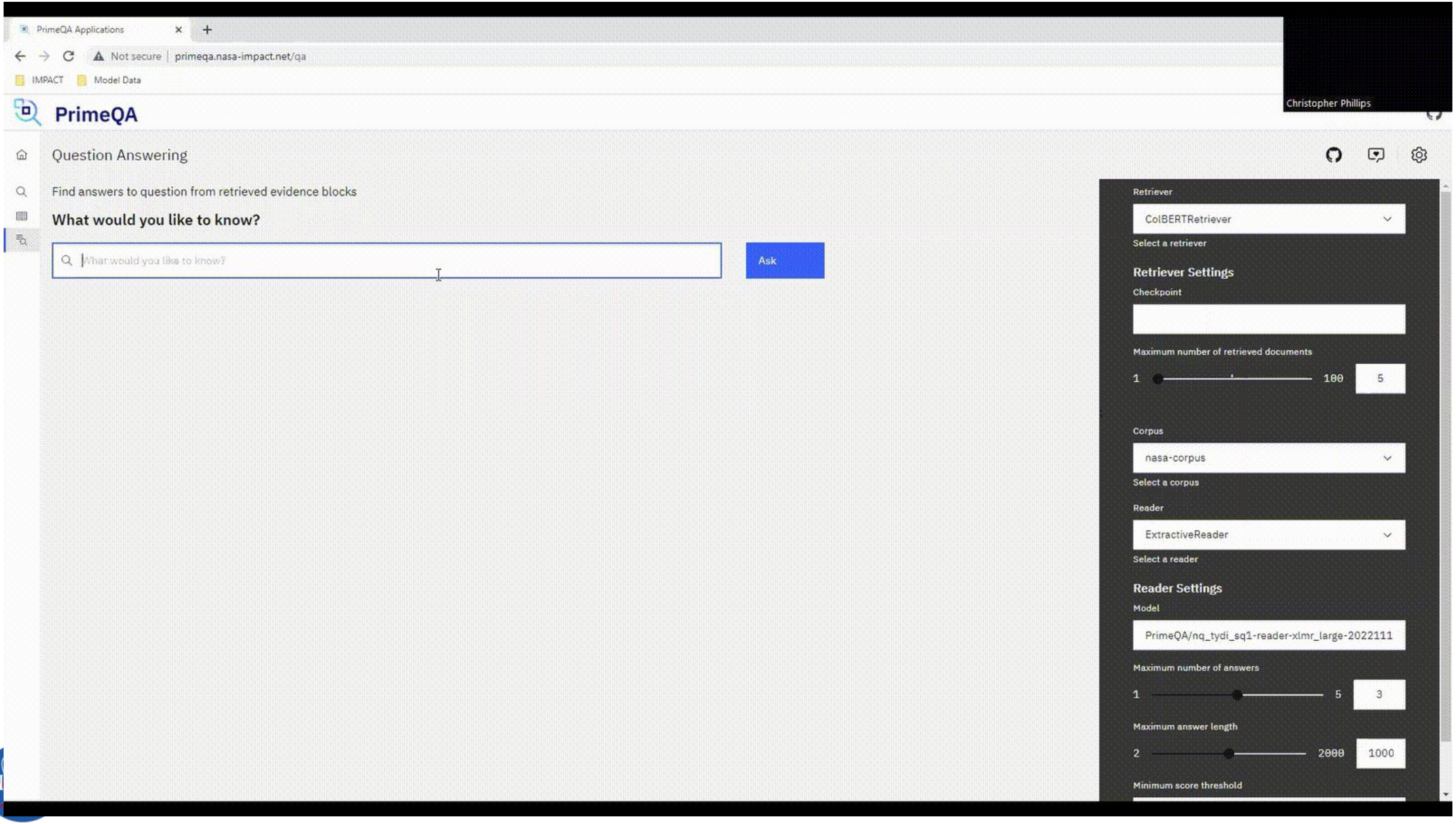
Hamed Alemohammad, Michael Cecil, Steve Li, Sam Khallaghi, Denys Godwin, Maryam Ahmadi, Fatemeh Kordi

NASA HQ
Tsengdar Lee, Kevin Murphy

NASA GSFC
Dan Duffy, Mike Little

Using the Language Model for Question Answering

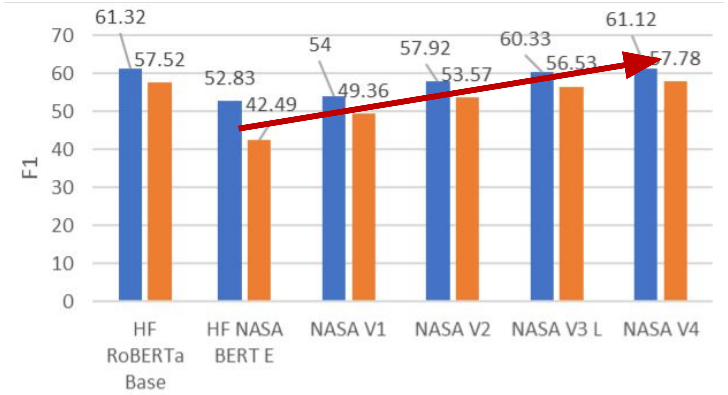
Proof of concept demo



Try live version trained on NASA ATBD and dataset description

Language Model for Earth Science: Q&A

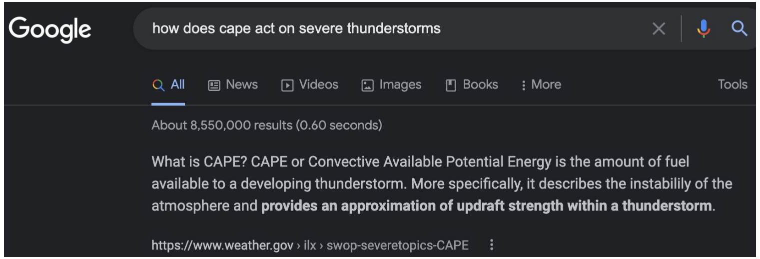
Integrate trained model with IBM's PrimeQA technology for natural language Q&A with provenance

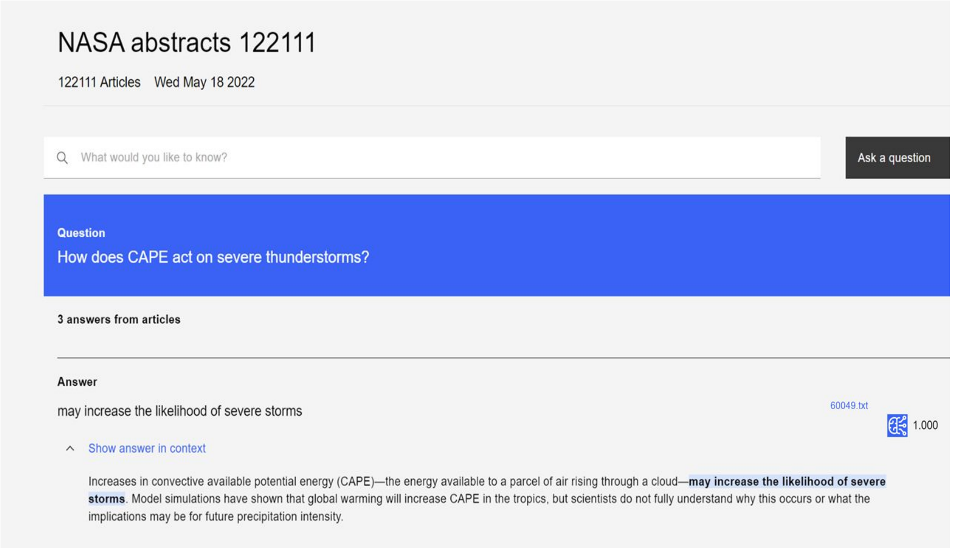


Validation on SQ2 pruned benchmark (F1, EM scores)

Next steps

- Improve model by adding relevant data
- Validation of Q&A responses underway by NASA
- Open-source model with Q&A service
- Expand to SMD wide Language Model





Slide source: Raghu Ganti/IBM Research