UiT The Arctic University of Norway

NORA summer school on multi-modal learning

Multi-Modal Learning: Beyond Vision and Language

Challenges in Remote Sensing

Rwiddhi Chakraborty
UiT Machine Learning Group and Visual Intelligence

Schedule Today

- 09 - 12: Beyond Vision-Language – I and II
- 12 – 13: Lunch
- 13 – 16: Group Project

In this talk

Domain Challenges

Remote Sensing

Pre-training

Zero-Shot

In this talk

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Beyond Vision and Language

Pre-trained vision-language models lack fine-grained understanding

Unsuitable for domains where specificity is key – e.g. remote sensing, biology, etc.

Text as a data mode has its own issues

Beyond Vision and Language

Real world datasets exist in multiple views and modalities

Only vision-language as a pre-training objective is too restrictive

We want to leverage similar ideas for diverse tasks

In this talk

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Monitoring Deforestation in the Amazon

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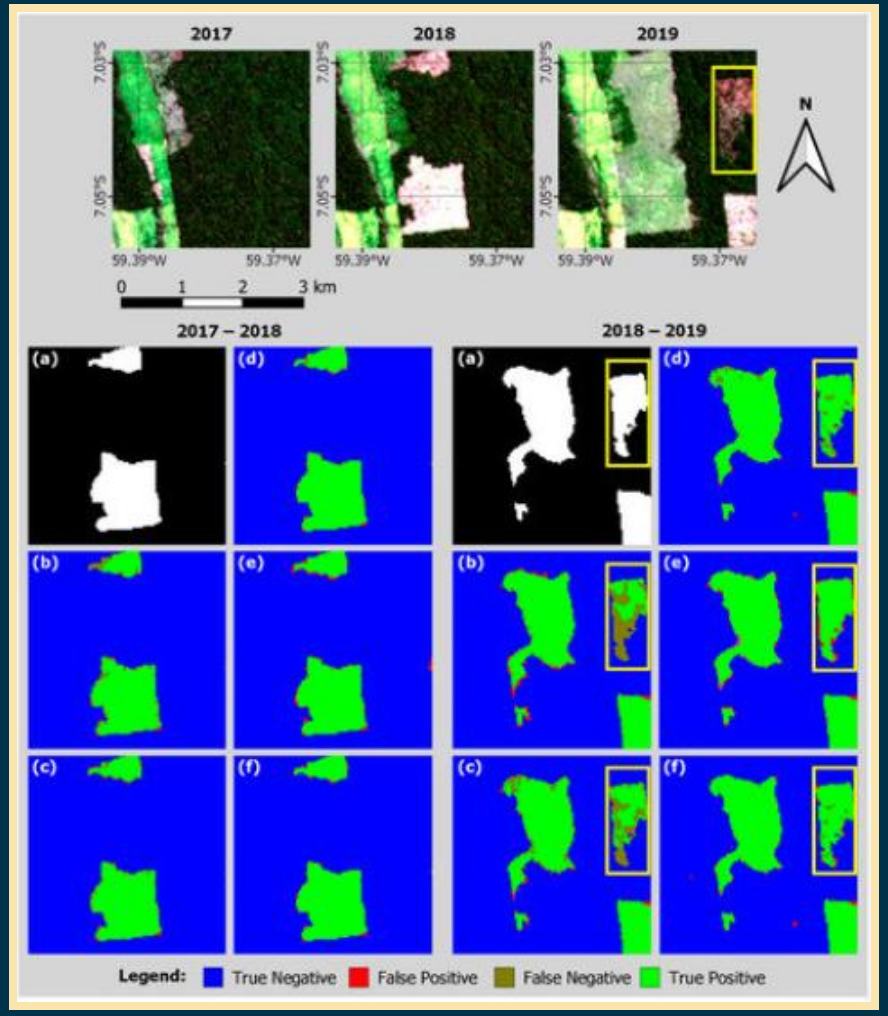
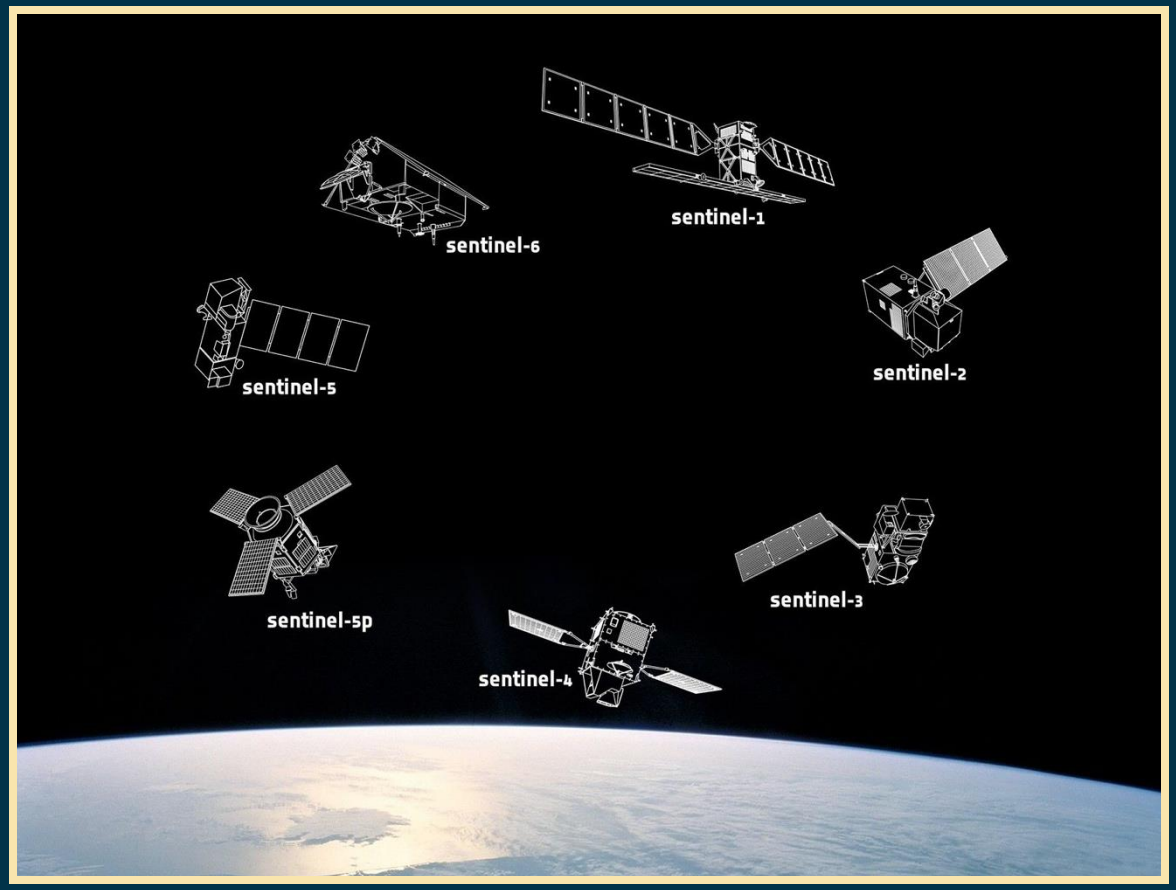


de Bem, P.P.; de Carvalho Junior, O.A.; Fontes Guimarães, R.; Trancoso Gomes, R.A. Change Detection of Deforestation in the Brazilian Amazon Using Landsat Data and Convolutional Neural Networks. *Remote Sens.* **2020**

Remote Sensing: The Sentinels

Part of Europe's *Copernicus program*

Monitor changes on the Earth's surface



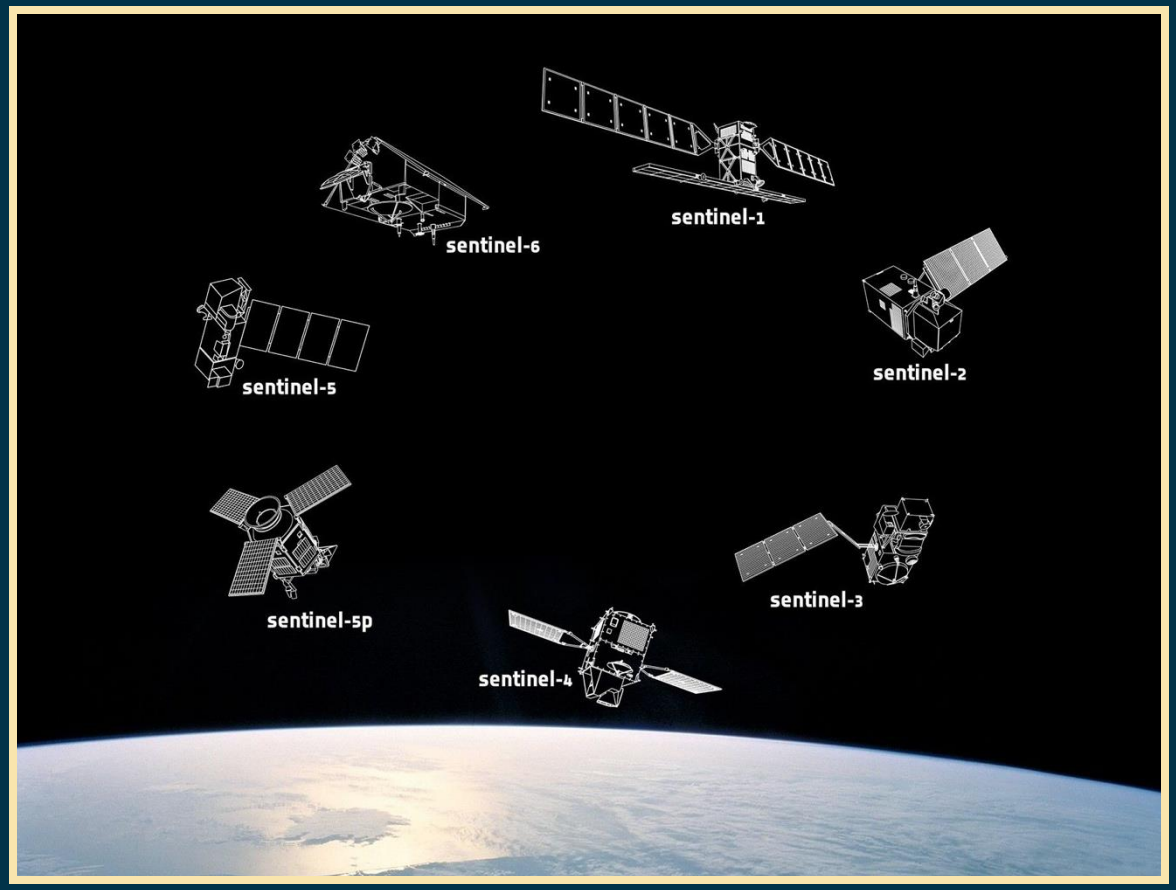
Multispectral optical (MO) imagery

Synthetic Aperture Radar (SAR) data

Remote Sensing: The Sentinels

MO imagery reveals material composition of objects (440-2200nm)

SAR reveals geometry, roughness, and electrical properties of objects (5.5cm)



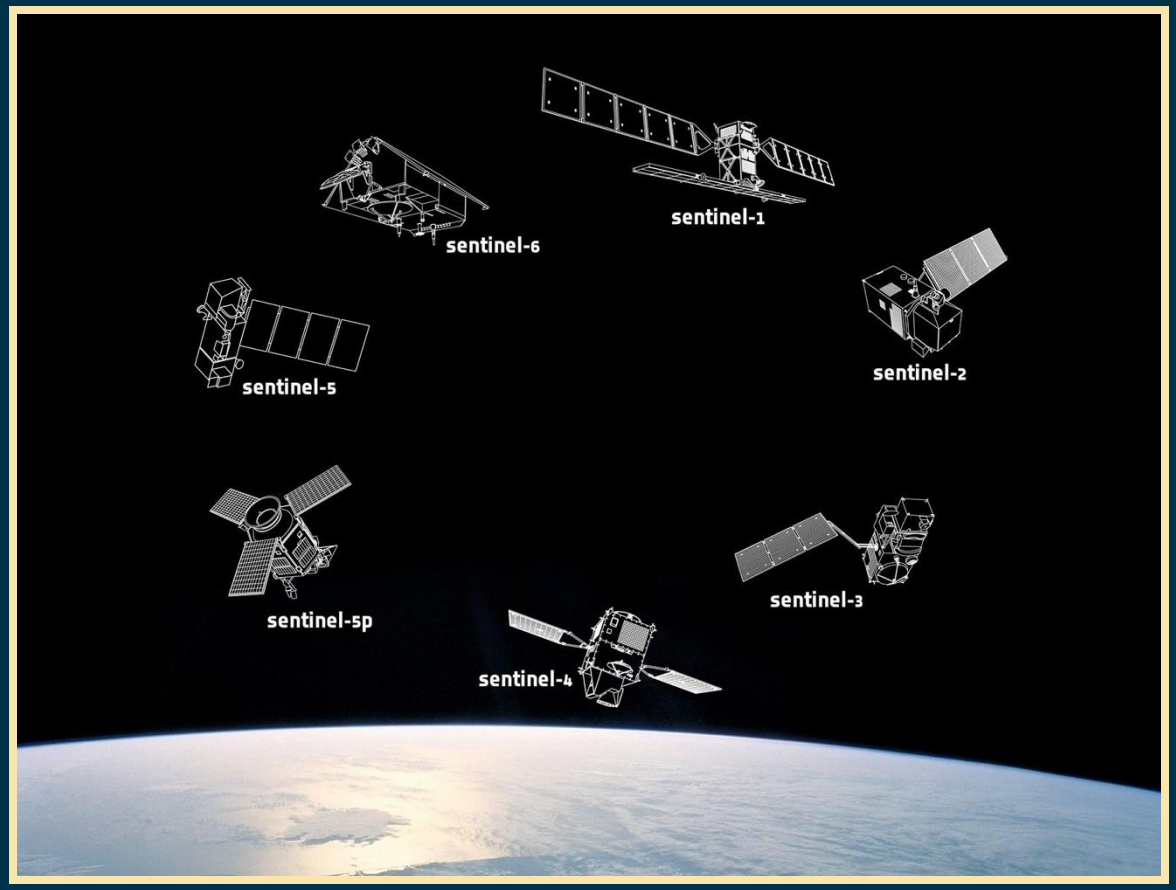
Agriculture, Climate Change, Forestry….

Cornerstone of Earth Observation

Remote Sensing: The Sentinels

Multiple views of the same features on ground

Spatially aligned



Can self-supervised learning help?

Remote Sensing: The Sentinels

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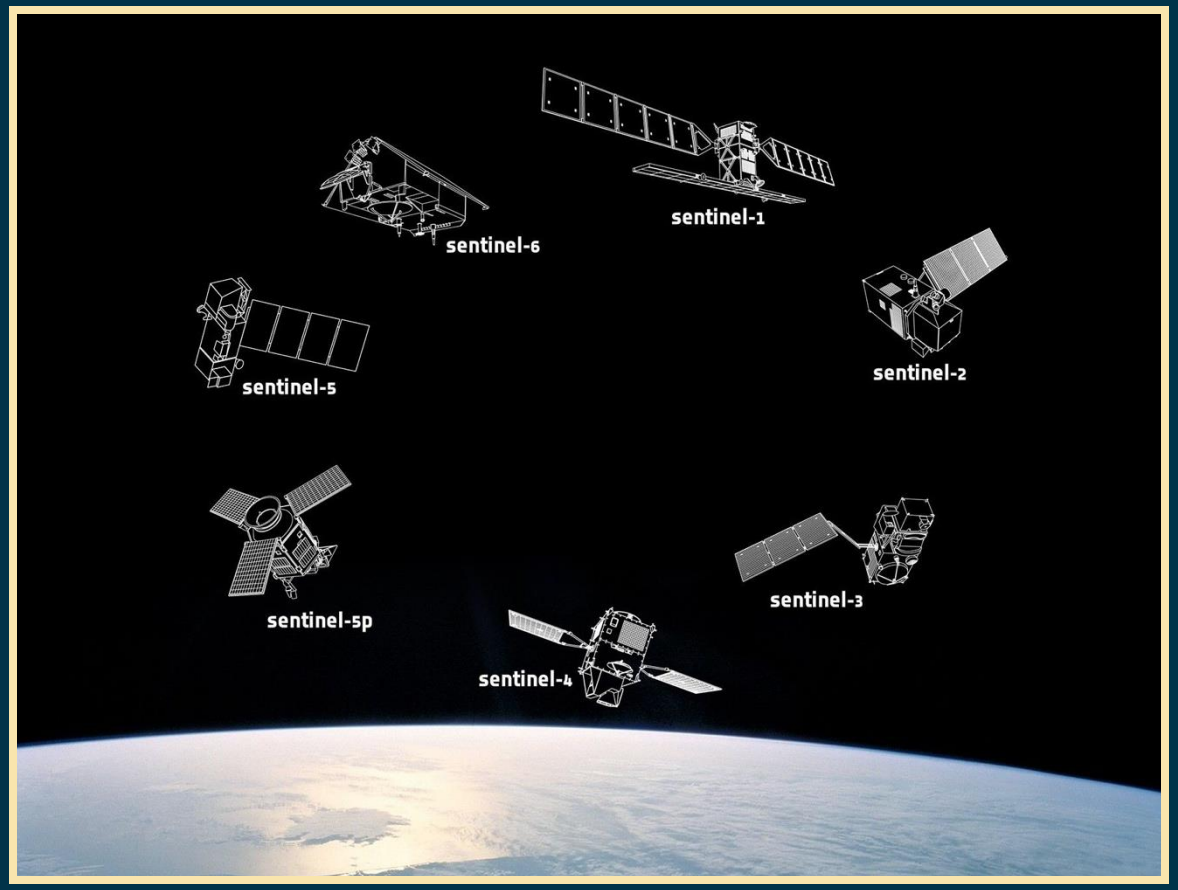

Can self-supervised learning help?

Yes

In this talk

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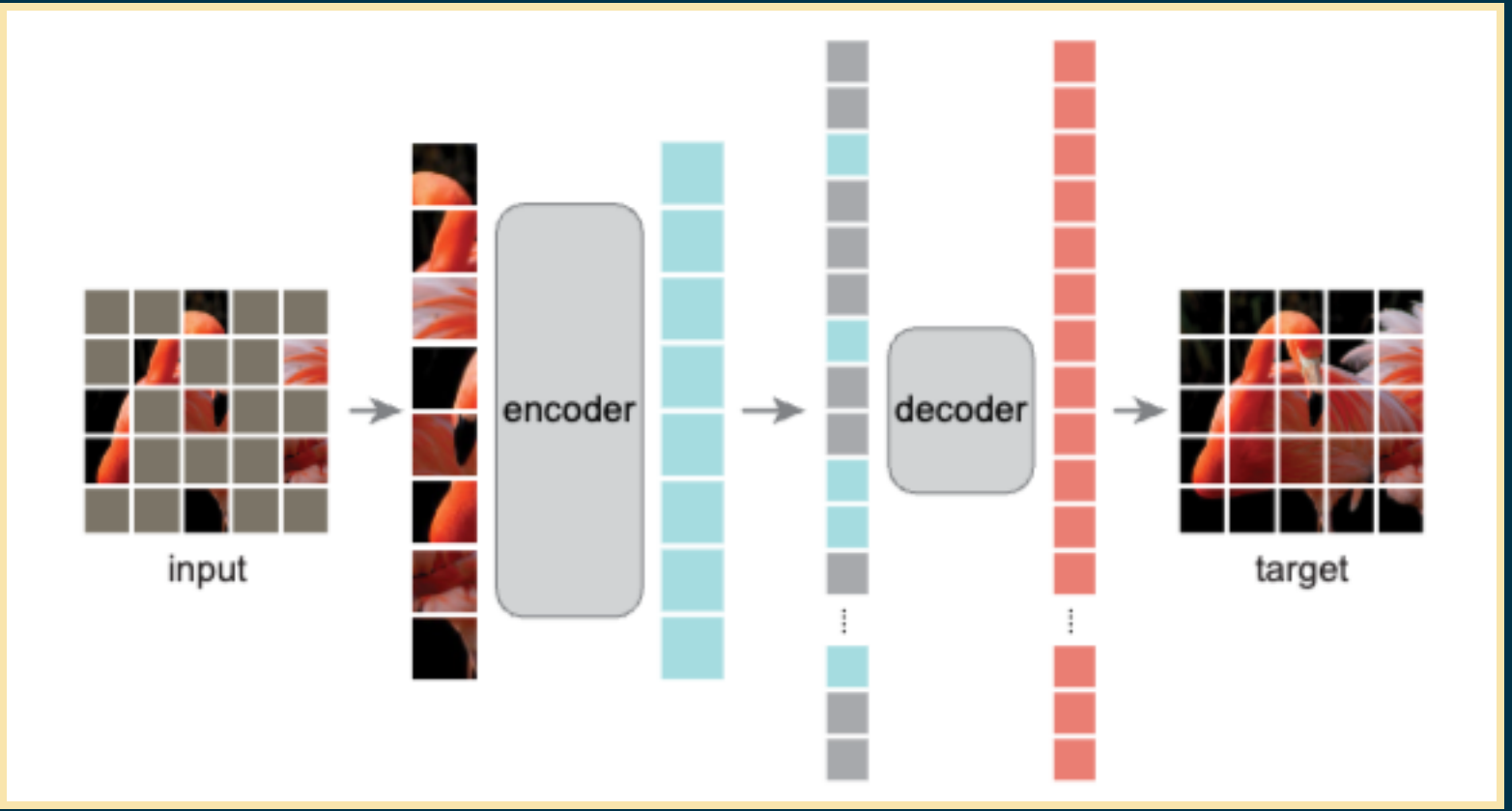
The Masked Autoencoder



He, Kaiming, et al. "Masked autoencoders are scalable vision learners." Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2022.

MAE in Remote Sensing?

Good starting point

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Does *not* leverage scale

Absolute/Relative positional encoding

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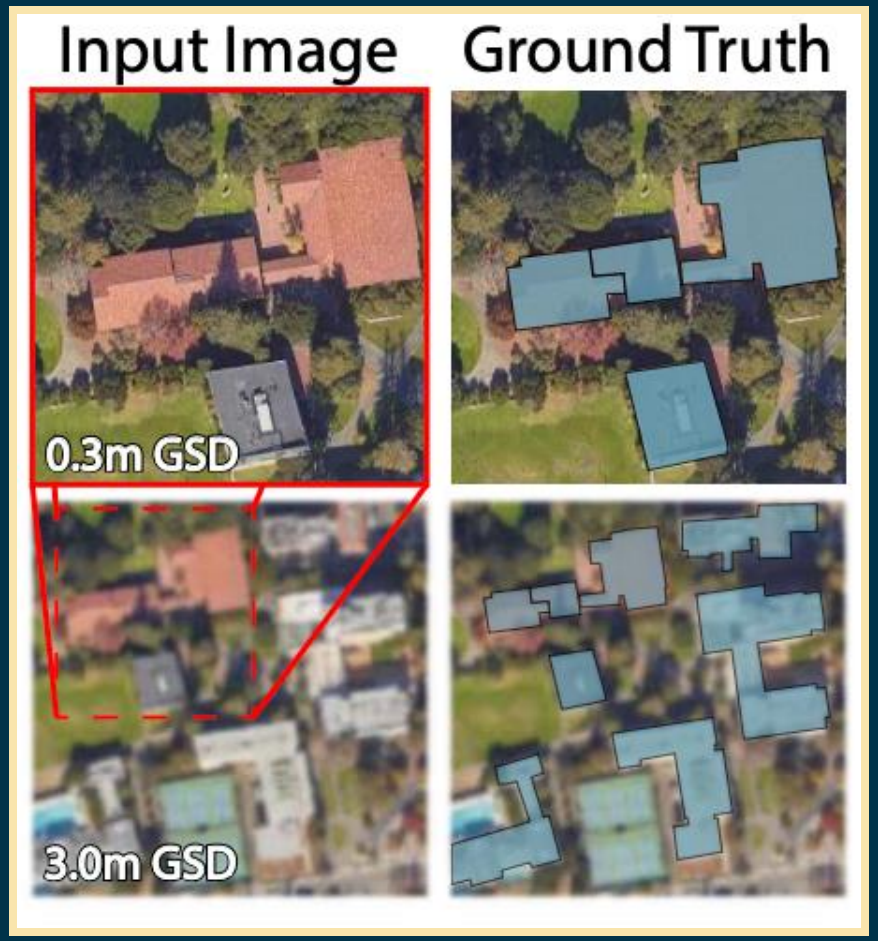

Reed, Colorado J., et al. "Scale-mae: A scale-aware masked autoencoder for multiscale geospatial representation learning." Proceedings of the IEEE/CVF International Conference on Computer Vision. 2023.

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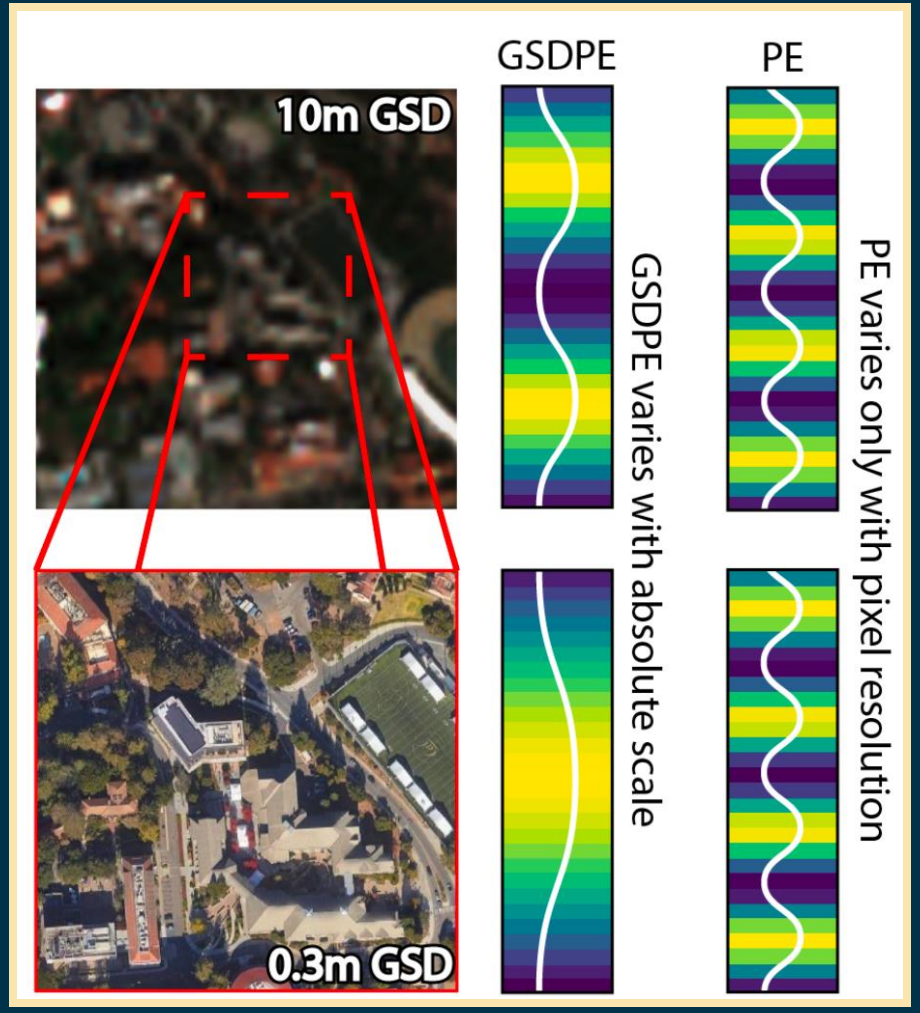

Reed, Colorado J., et al. "Scale-mae: A scale-aware masked autoencoder for multiscale geospatial representation learning." Proceedings of the IEEE/CVF International Conference on Computer Vision. 2023.

MAE in Remote Sensing?

In essence, we need a decoder that has:

(i) Scale-aware positional encoding
(ii) Multi-resolution sampling

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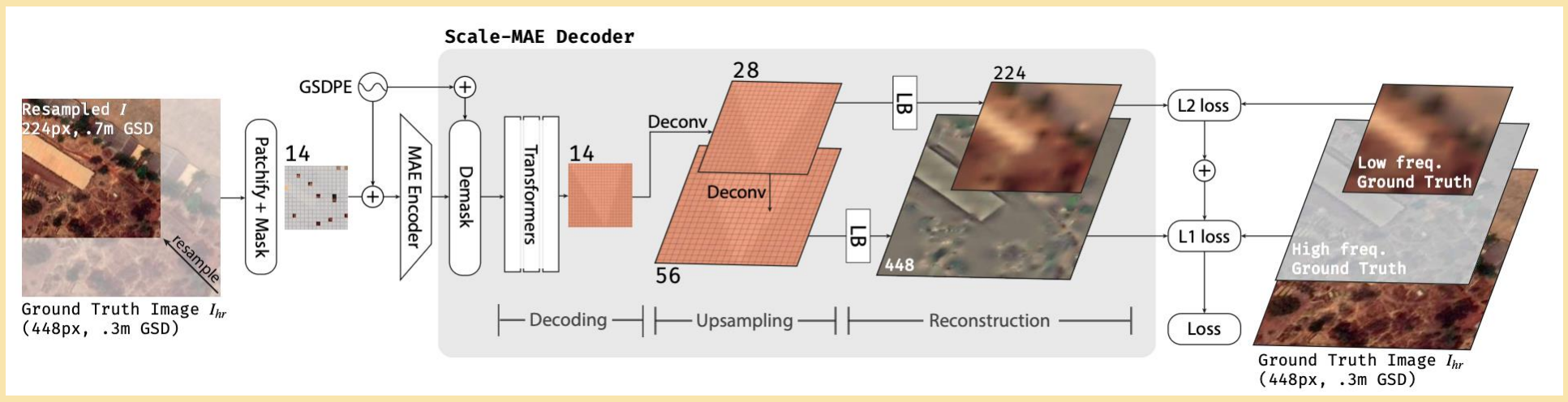
ScaleMAE for Remote Sensing



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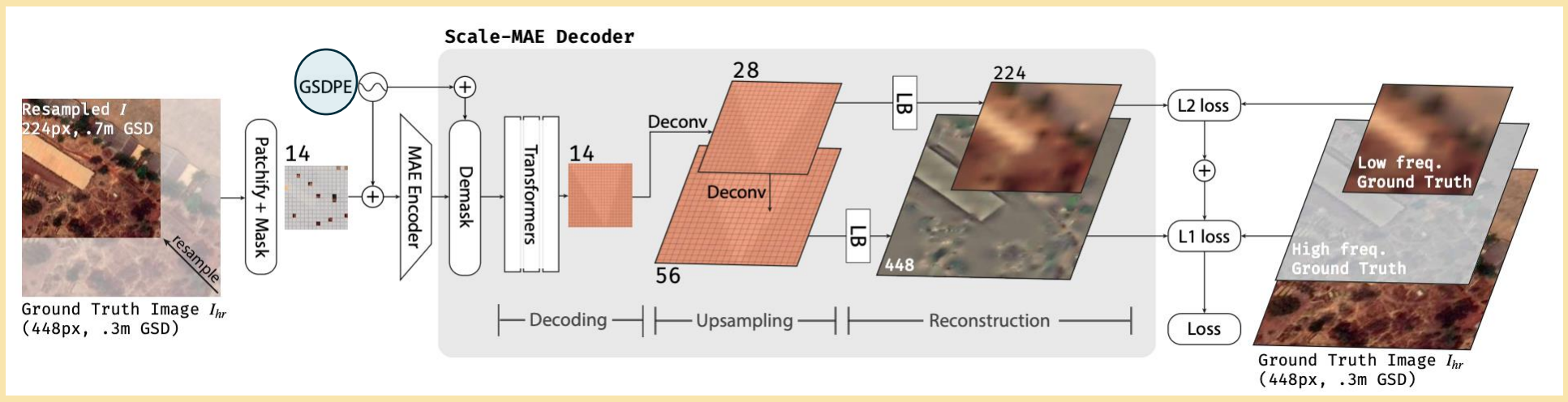

Reed, Colorado J., et al. "Scale-mae: A scale-aware masked autoencoder for multiscale geospatial representation learning." Proceedings of the IEEE/CVF International Conference on Computer Vision. 2023.

ScaleMAE for Remote Sensing

$$v_x(pos, 2i) = \sin \frac{pos}{10000^{\frac{2i}{D}}}$$
$$v_y(pos, 2i+1) = \cos \frac{pos}{10000^{\frac{2i}{D}}}$$

Before

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Now

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Now

An object at a finer resolution has more pixels representing it
The same object at a coarser resolution must then map to fewer pixels

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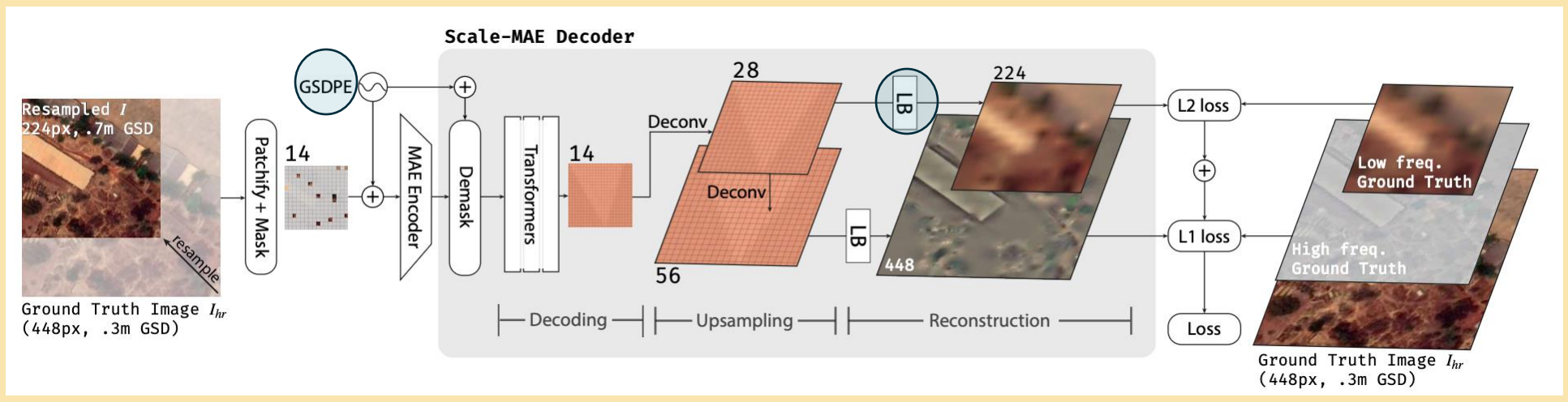

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ScaleMAE for Remote Sensing

The Laplacian Block (LB) helps sample at a specified frequency (resolution)

Reconstruct low res images for low frequencies, high res images for high frequencies

Final image reconstruction combines these two resolutions

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Multi-scale reconstruction like this leads to the term Laplacian *pyramid*

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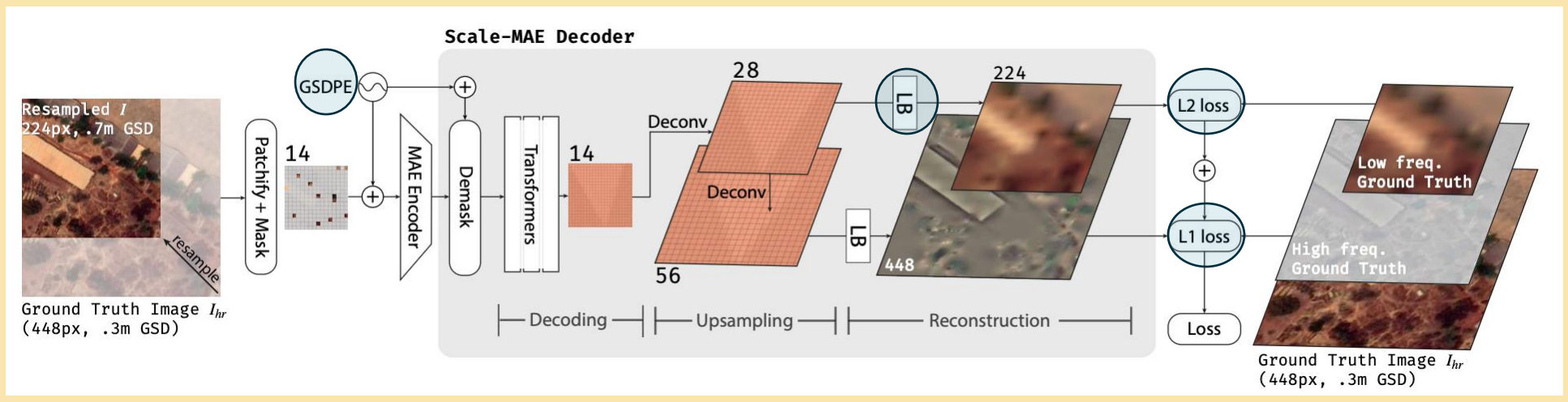

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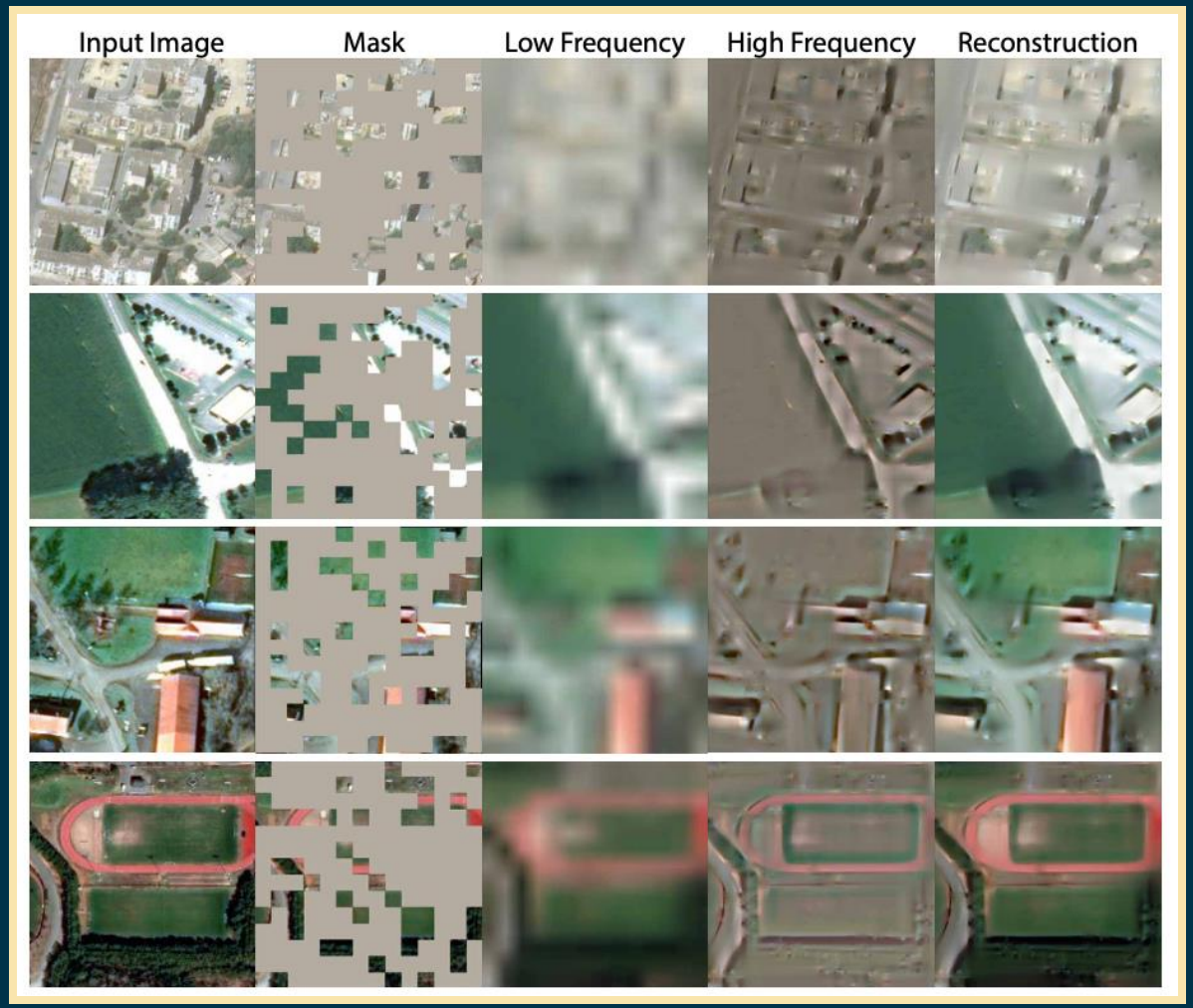

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In this talk

Domain Challenges

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Zero-Shot

Contrastive ideas as well?

Masked reconstruction algorithms are great:

(i) Scalable
(ii) No need for paired data

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Data and compute hungry
Sensitive to paired info

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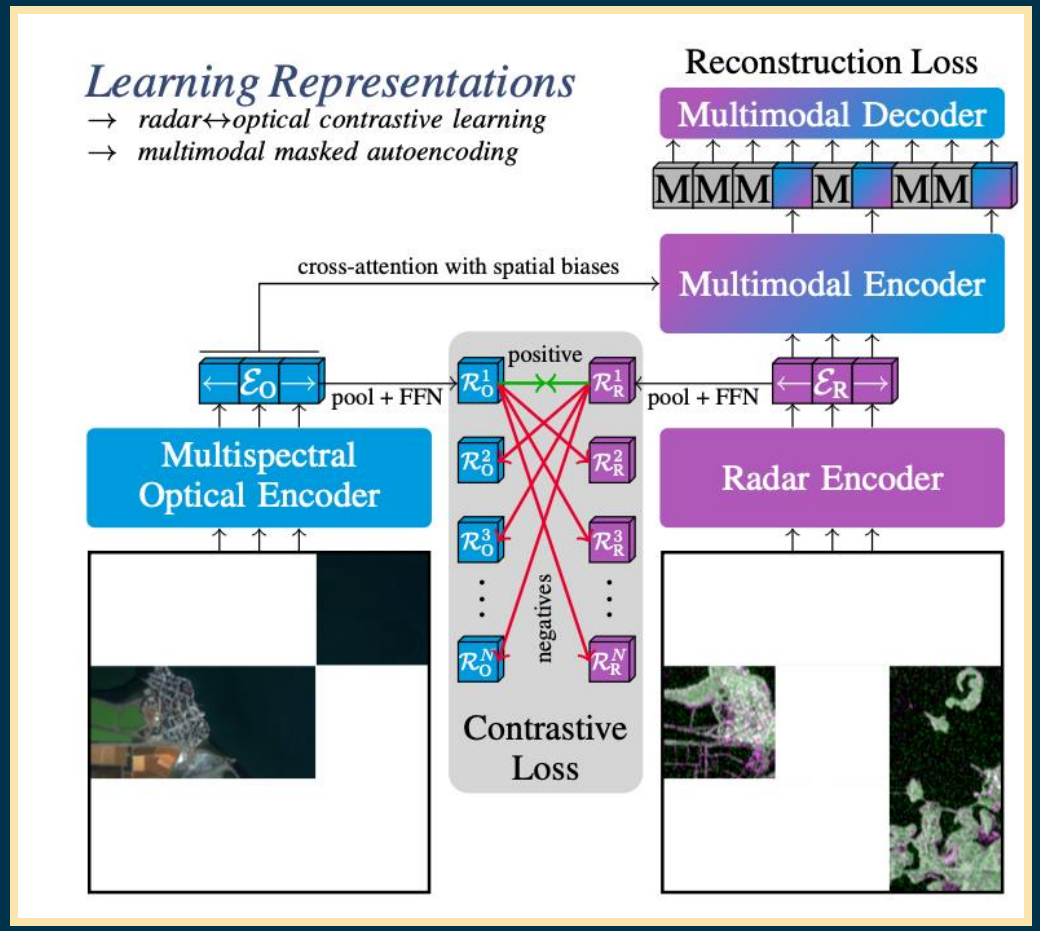
Contrastive + Masked Reconstruction!

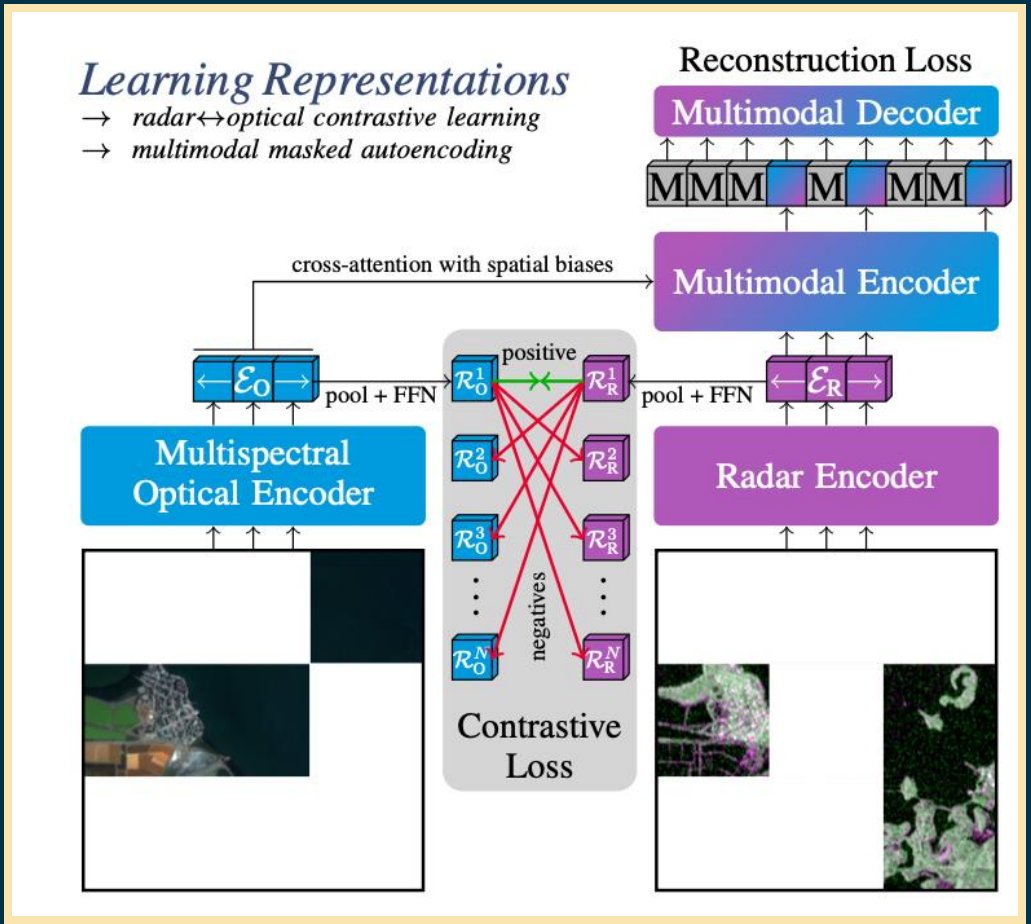


Fuller, A., Millard, K., & Green, J. (2023). CROMA: Remote sensing representations with contrastive radar-optical masked autoencoders. *Advances in Neural Information Processing Systems*, *36*, 5506-5538.

Contrastive + Masked Reconstruction!

Optical Data:
12-channel MO from Sentinel-2

Radar data:
2-channel backscatter from Sentinel-1



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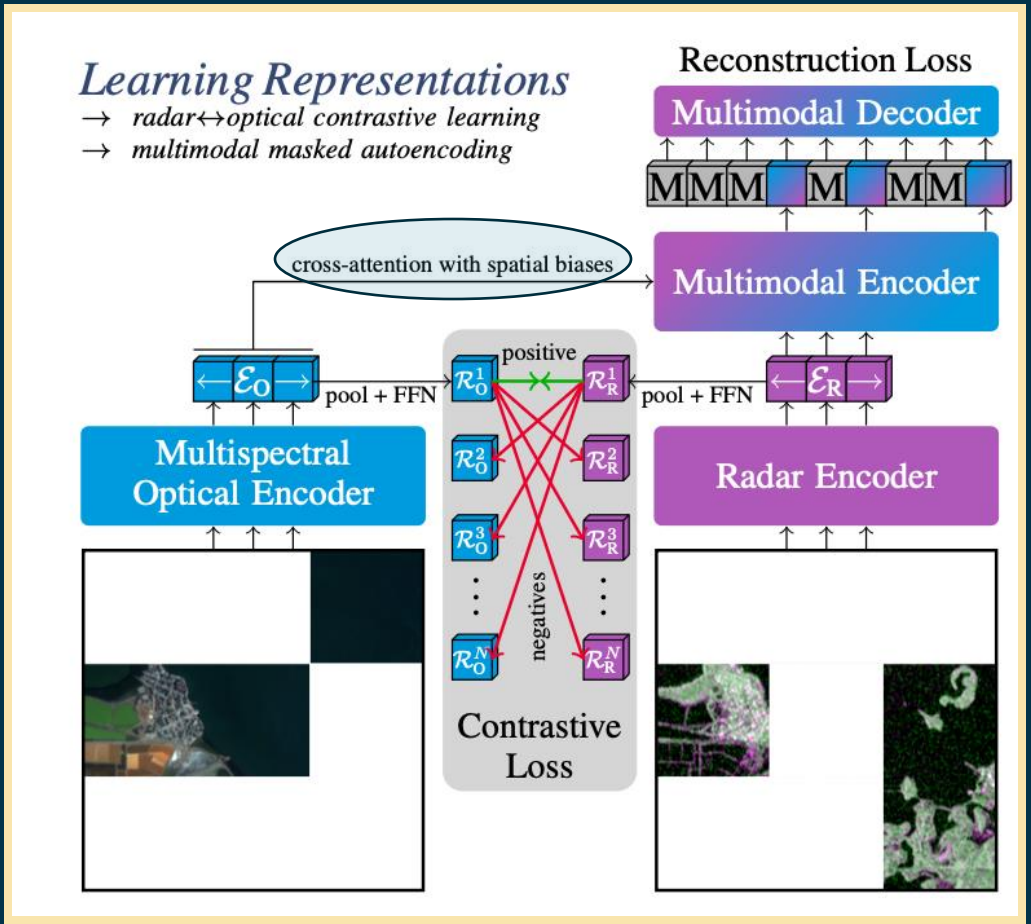

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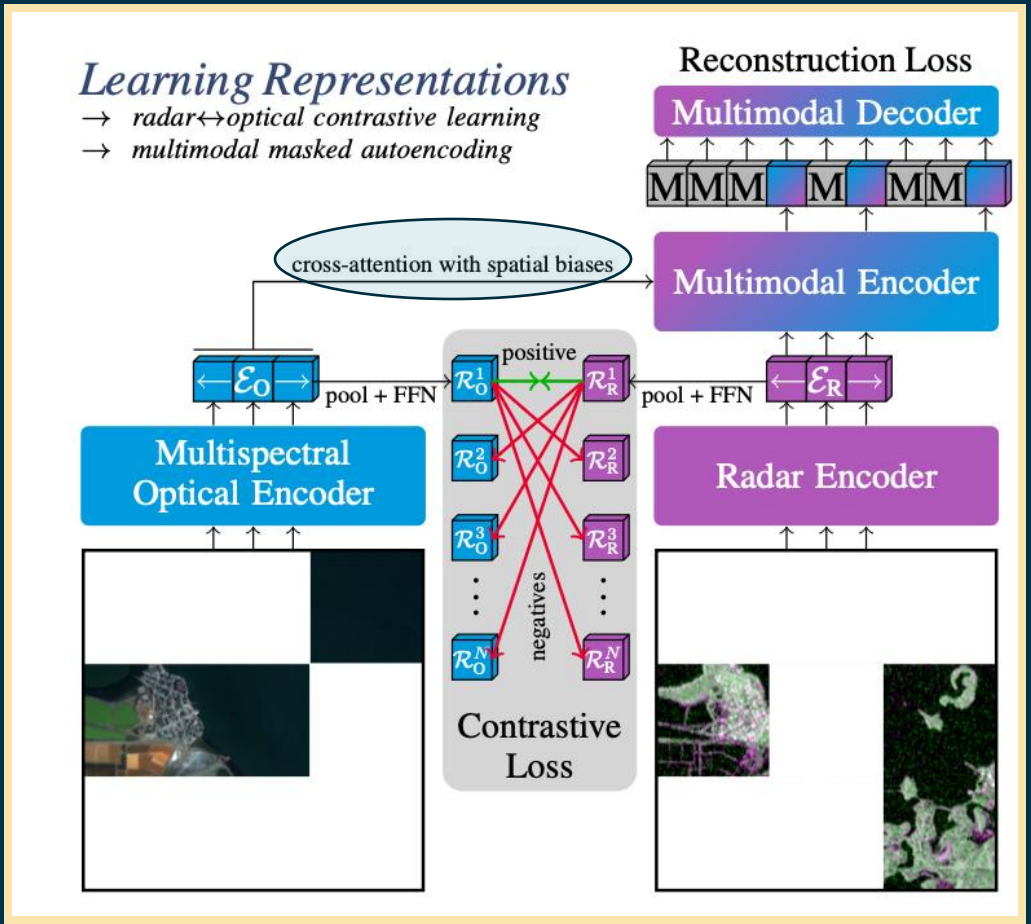
Each ViT backbone has its self-attention heads biased based on the Euclidean distance between query-key pairs



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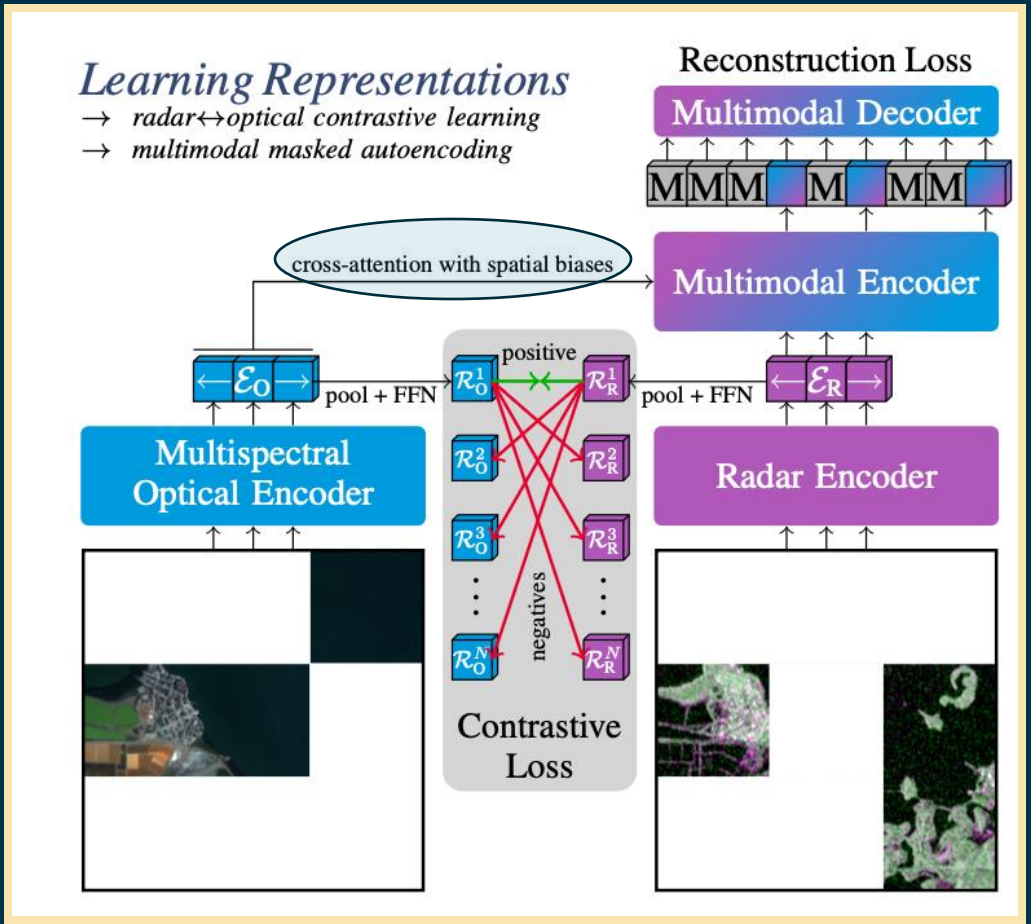

The cross-attention matrix is modified by the Euclidean distance between *cross-modal* key-query pairs

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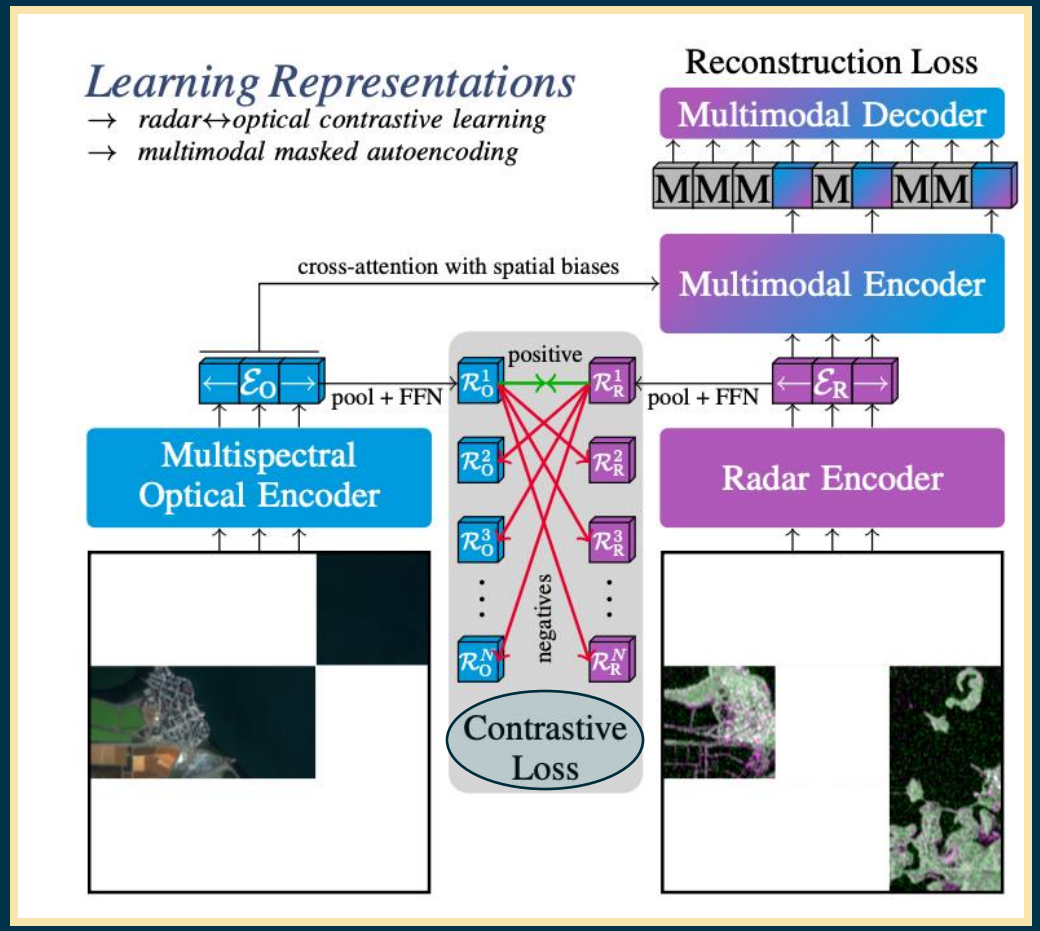
Contrastive + Masked Reconstruction!



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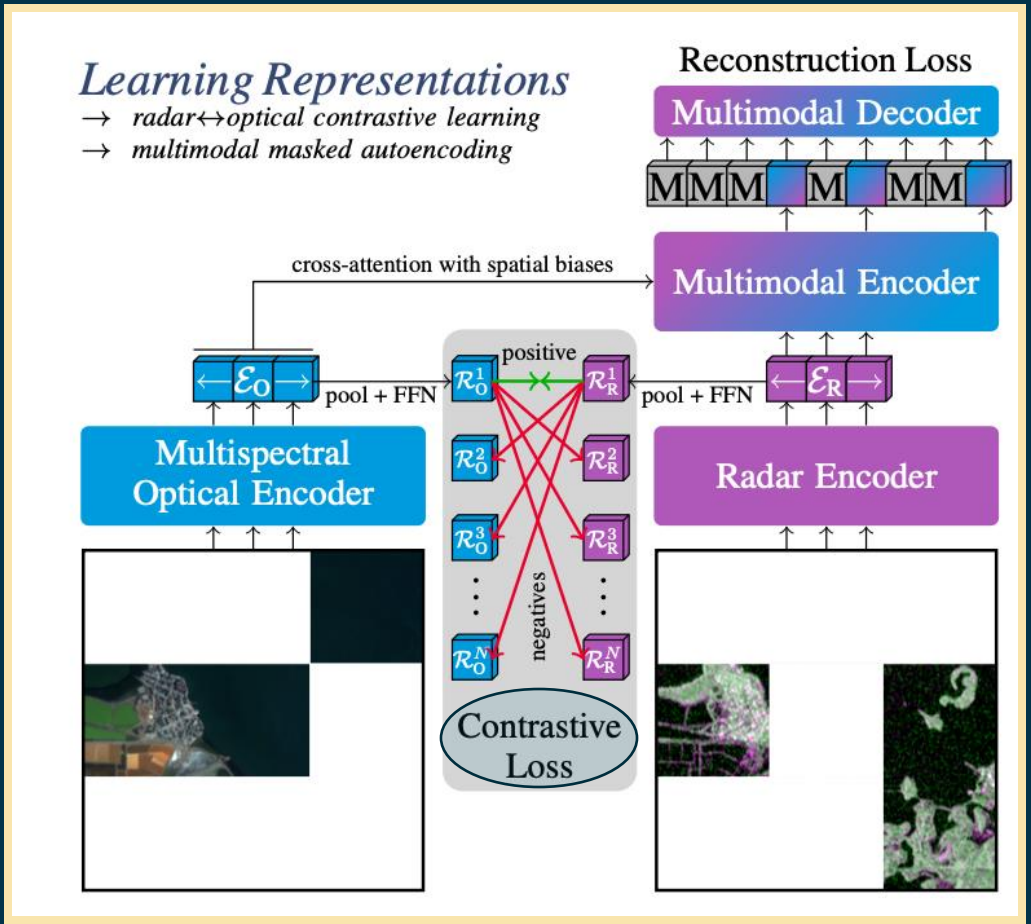
Contrastive + Masked Reconstruction!

For optical anchor image, positive sample is the geographic, temporal match in the radar sample

Negative sample? *All other radar samples in the batch!*



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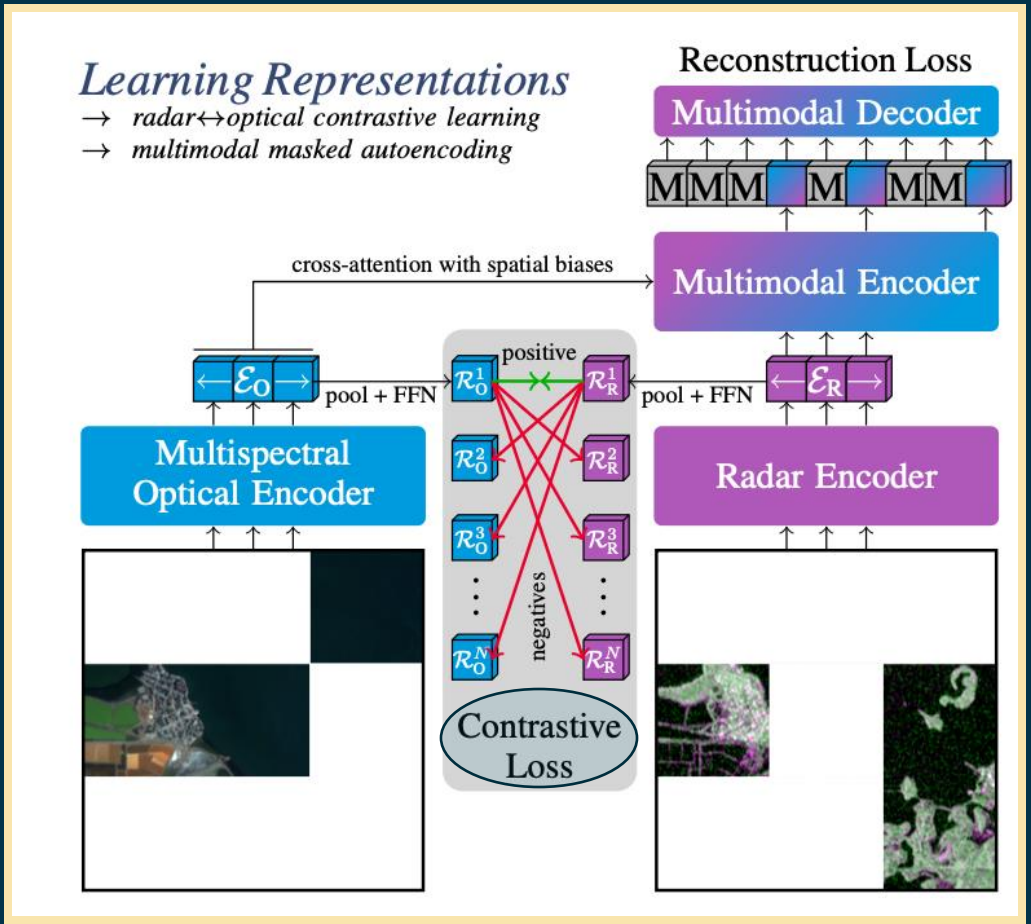
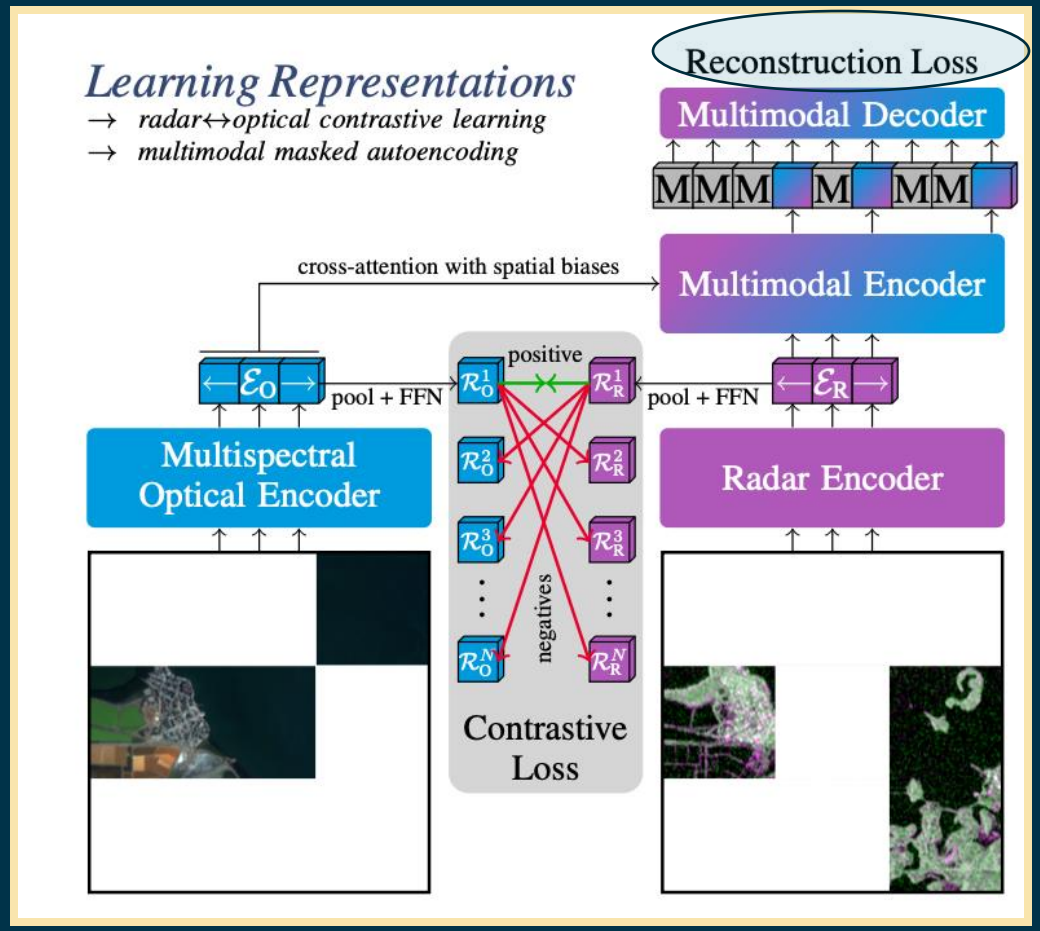


And vice versa!

Fuller, A., Millard, K., & Green, J. (2023). CROMA: Remote sensing representations with contrastive radar-optical masked autoencoders. *Advances in Neural Information Processing Systems*, *36*, 5506-5538.

Contrastive + Masked Reconstruction!

Independently mask 75% of radar and optical patches



Loss term incorporates both radar and optical reconstruction distances

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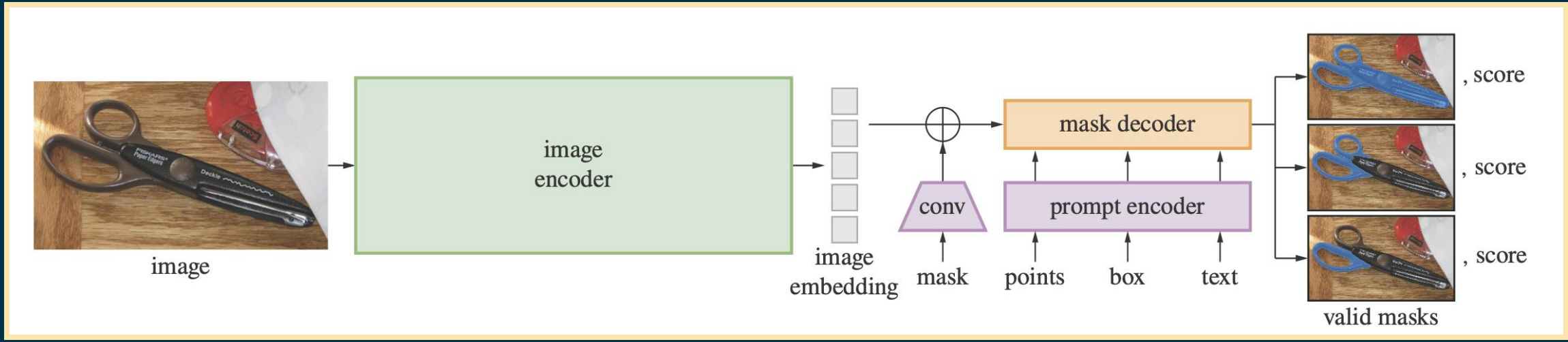
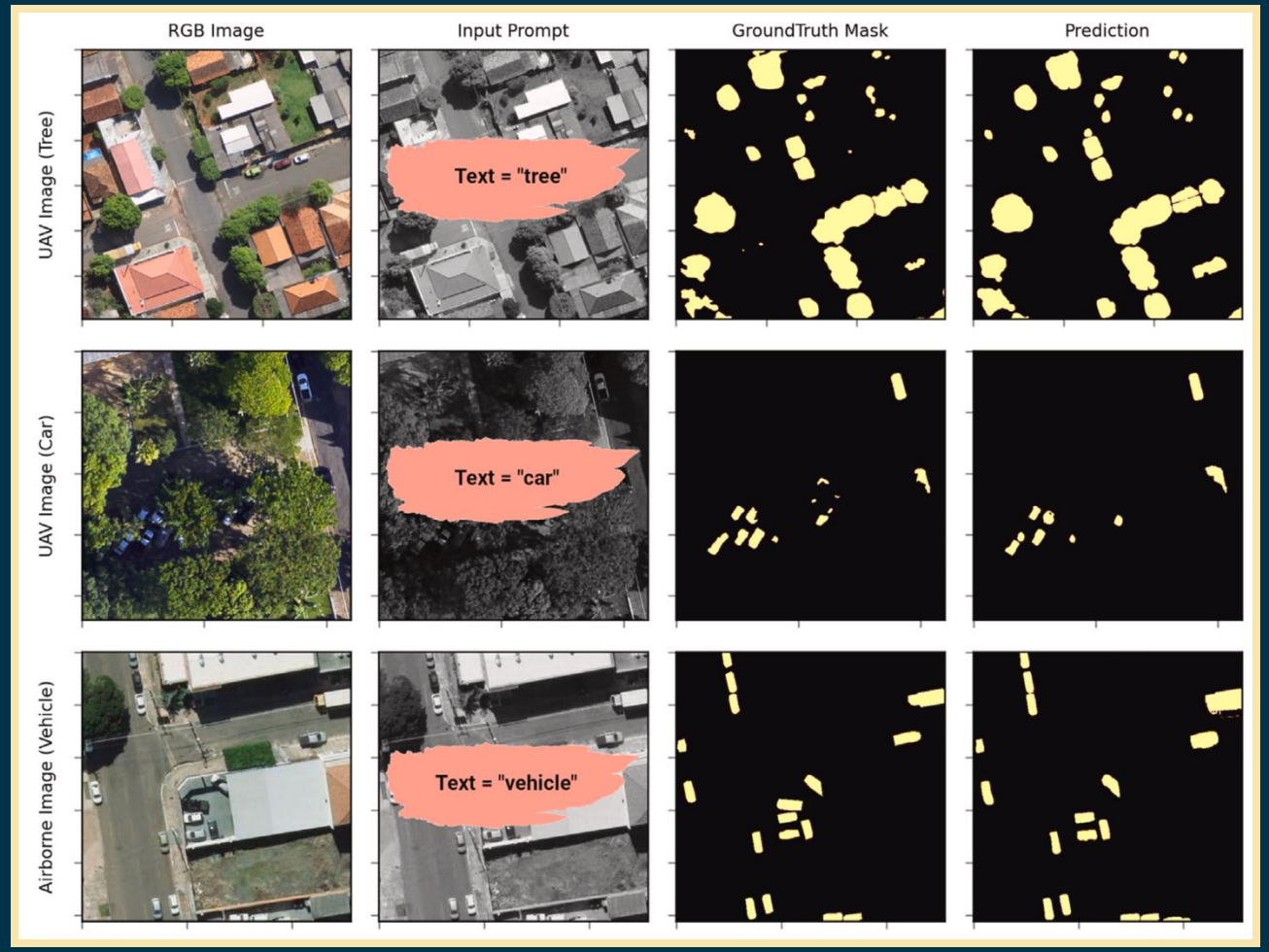
Segment Anything



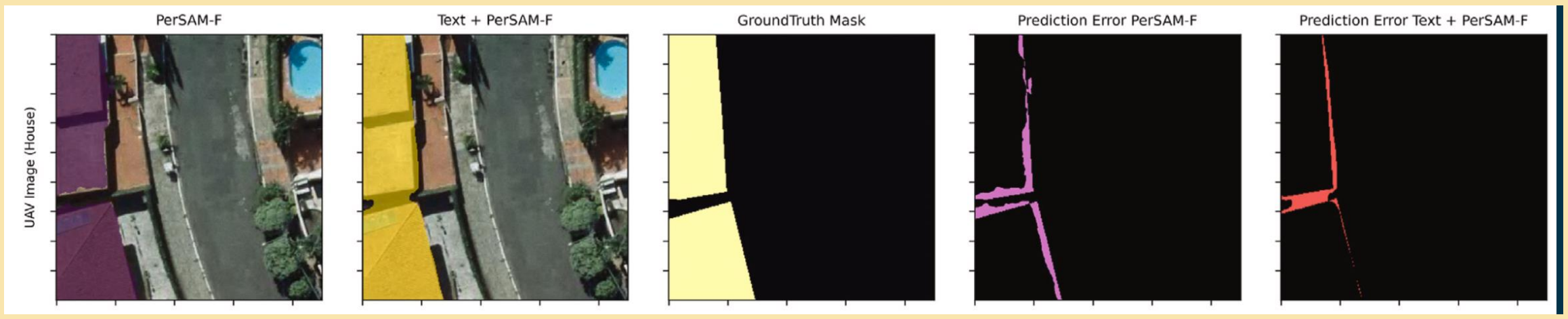
Kirillov, Alexander et al. "Segment Anything." *2023 IEEE/CVF International Conference on Computer Vision (ICCV)* (2023): 3992-4003.

Zero-Shot with SAM



Osco, Lucas Prado, et al. "The segment anything model (sam) for remote sensing applications: From zero to one shot." *International Journal of Applied Earth Observation and Geoinformation* 124 (2023): 103540.

One-Shot with SAM



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Caution!

Concepts are still broad – special cases may be challenging

Tends to overestimate object boundaries – may be a prompt issue

Summary

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