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TAKING THE PULSE OF OUR PLANET FROM SPACE

Deep Learning methods for monitoring volcanic activity globally with Sentinel-1 InSAR

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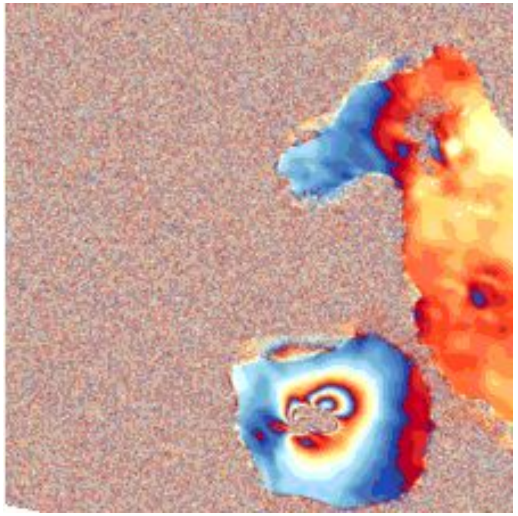
Motivation

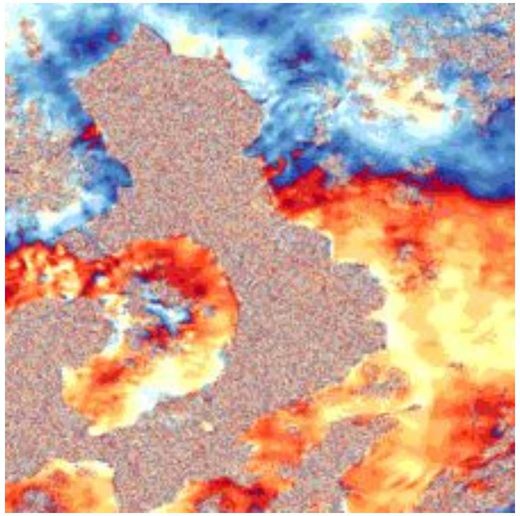
- More than 800 million people live within 100km from an active volcano
- A large eruption could have devastating results
- Detecting early signs of volcanic activity can be crucial for civil protection authorities
- What can we do?
  - Utilize Interferometric Synthetic Aperture Radar (InSAR) data from the Sentinel-1 missions to monitor volcanoes globally

Objective

- Exploit the abundance of freely available satellite data for volcanic unrest monitoring
- How?
    - Identify ground deformation patterns in interferograms



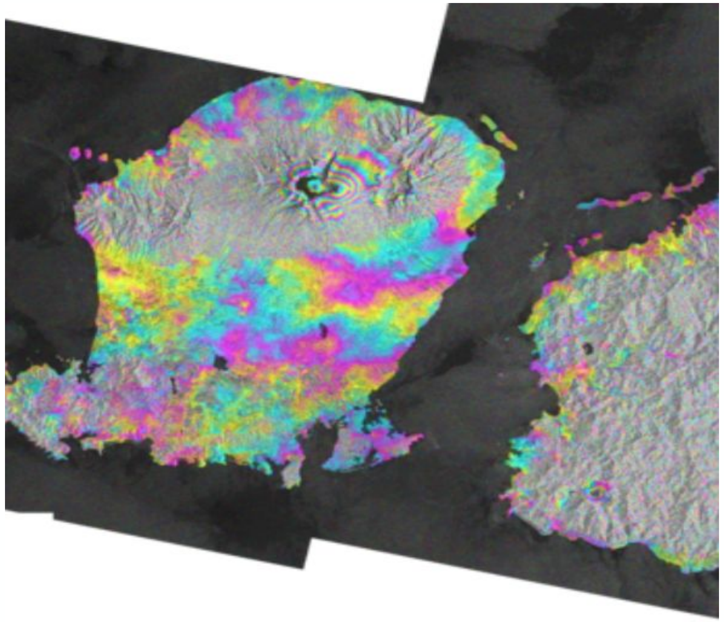
Ground Deformation



No Deformation

Challenges

- No large enough annotated dataset for this task
- Naturally occuring class imbalance making supervised learning challenging
- There are other factors that can produce similar patterns with ground deformation
    - e.g atmospheric contributions
        - Example:



Solutions?

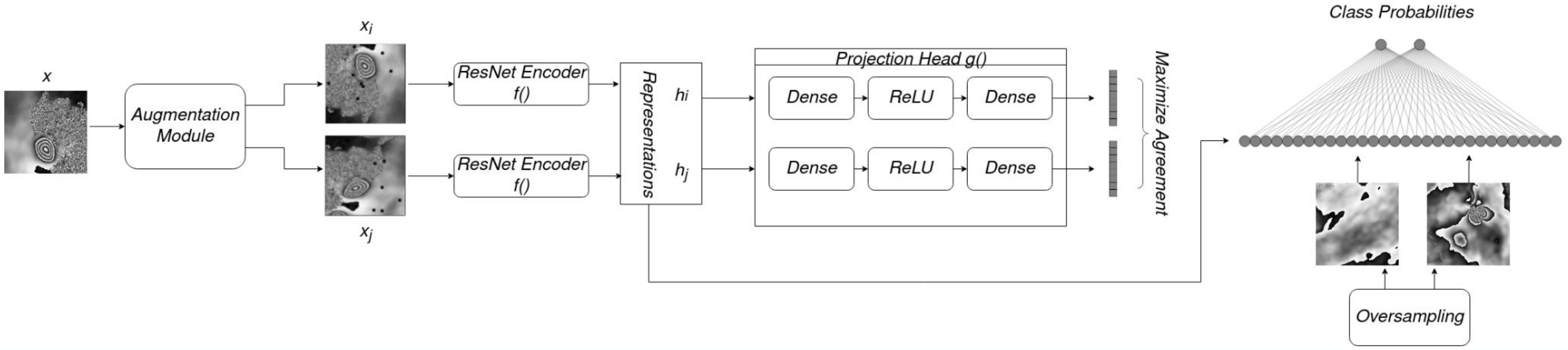
- Self supervised learning
    - Exploit the abundance of unlabeled satellite data to learn quality representations
    - These representations are task-agnostic and thus applicable to multiple downstream tasks
    - More robust to class imbalance when compared to supervised learning [1]
- Synthetic Data
    - We can produce any number of synthetic samples for each class
    - Create methods that exploit synthetically generated interferograms and try to adapt the learnt knowledge to the real domain
- Create large annotated datasets
    - This is crucial both for the task at hand and for boosting research on InSAR data

1. Liu, Hong, et al. "Self-supervised Learning is More Robust to Dataset Imbalance." *arXiv preprint arXiv:2110.05025* (2021).

Self-supervised learning for volcanic unrest detection

- SSL method for volcanic unrest based detection based on SimCLR [1]
- Self-supervised training on a highly imbalanced dataset
- Test on a balanced set from a different distribution

Data Source	Train		Test		Total
-	Positive	Negative	Positive	Negative	
S1	150	7386	32	32	7600
C1	-	-	404	365	769



Phase 1. Our encoder is trained for the task of maximizing agreement between two randomly augmented views of the same sample.

Phase 2. Extract data representations and train a linear classifier on top of them for the task at hand.

1. Bountos, Nikolaos Ioannis, et al. "Self-supervised contrastive learning for volcanic unrest detection." *IEEE Geoscience and Remote Sensing Letters* 19 (2021): 1-5.

Self-supervised learning for volcanic unrest detection

esa

- Core method: SimCLR
- Self-supervised training on a highly imbalanced dataset
- Test on a balanced set from a different distribution
- Results in 91% accuracy on C1 dataset.

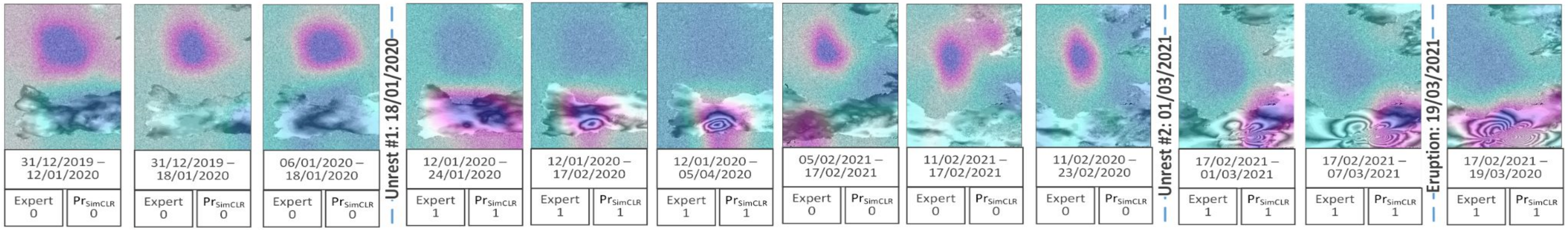
Data Source	Train		Test		Total
-	Positive	Negative	Positive	Negative	
S1	150	7386	32	32	7600
C1	-	-	404	365	769

Model	Accuracy	False Positives	True Positives	False Negatives	True Negatives
ResNet34-ImageNet	70%	3	181	223	362
ResNet34-SimCLR	91%	4	339	65	361
ResNet50-ImageNet	63%	1	125	279	364
ResNet50-SimCLR	91%	10	347	57	355

Comparison of performance of representations learnt via SimCLR vs ImageNet pretraining on C1 dataset.

Self-supervised learning for volcanic unrest detection

- How well does our model understand our task?

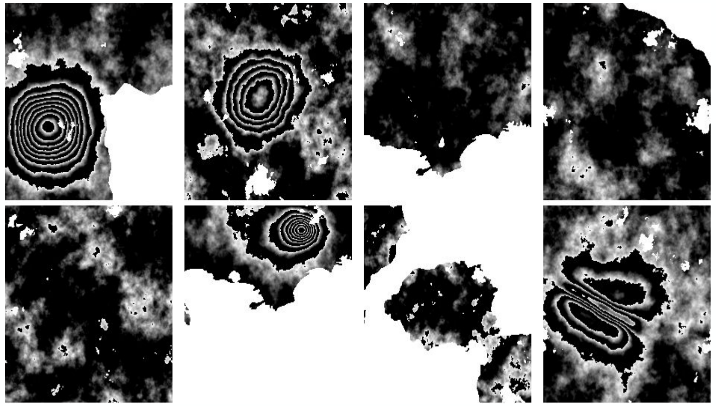


ResNet50 activations on Fagradalsfjall volcano. Pink represents the area that affected the network's decision the most. Pr_{SimCLR} and Expert are the predictions made by our method and the InSAR expert, respectively (1=positive, 0=negative)

Synthetic data exploitation for volcanic monitoring

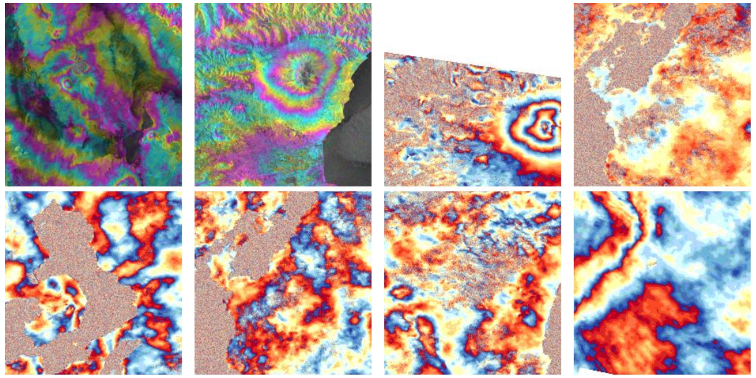
- Goal: Extract knowledge from synthetically generated InSAR data and adapt them to the real domain without human supervision.

Synthetic



Synthetic data generated from [1]

Real



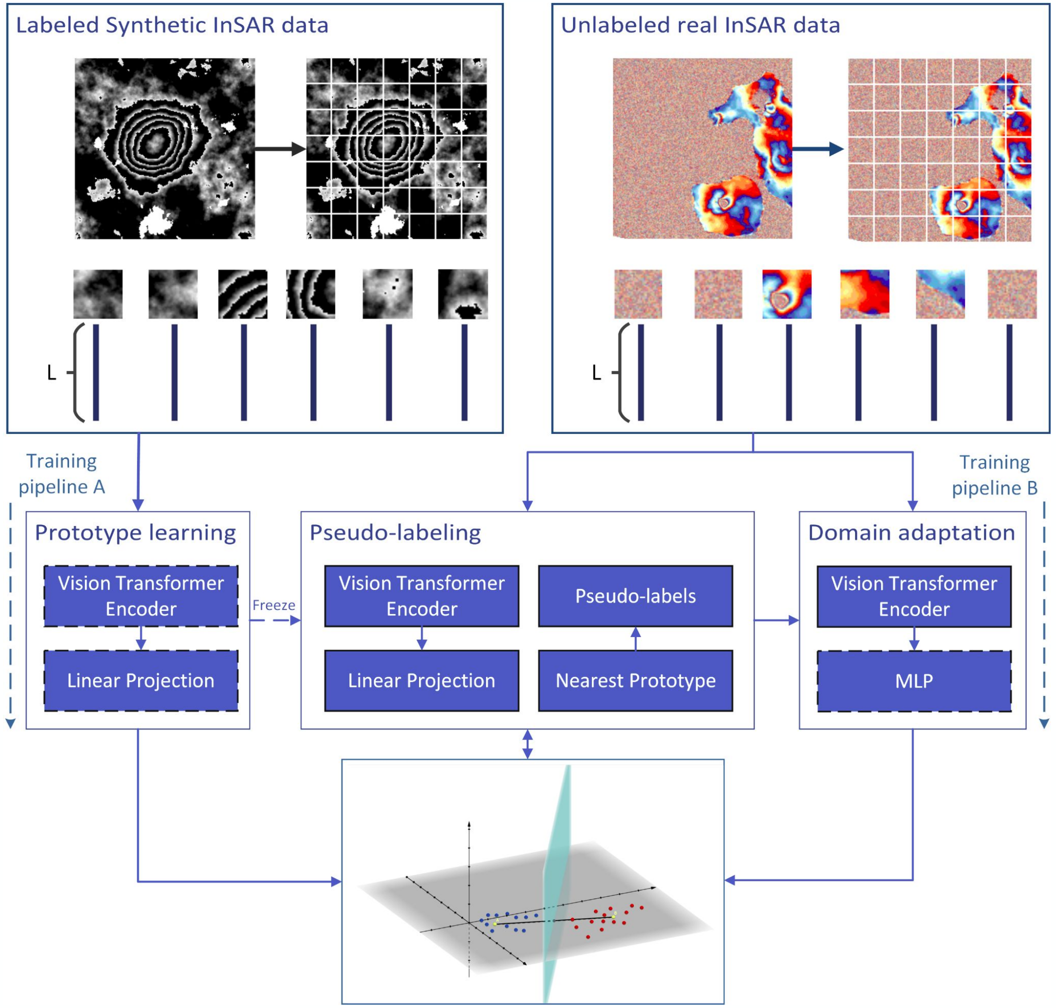
Real InSAR from Comet-LiCS

1. Gaddes, M. E., Andy Hooper, and Marco Bagnardi. "Using machine learning to automatically detect volcanic unrest in a time series of interferograms." *Journal of Geophysical Research: Solid Earth* 124.11 (2019): 12304-12322.

Synthetic data exploitation for volcanic monitoring

Method : Create robust classifiers from synthetic InSAR data by learning class prototypes[1]

- Phase 1
  - Synthetic InSAR are fed to a vision transformer encoder
  - The extracted representations are projected to a 3-D prototype space
  - The data points are classified via a nearest neighbor approach.
- Phase 2 (Domain Adaptation Module)
  - Produce pseudo-labels for an unlabeled real InSAR dataset using the trained vision transformer
  - Replace linear projection with a more complex, non-linear one
  - Freeze the rest of the network (including the prototypes) and train the new projection on the pseudo labels.



1. Bountos, Nikolaos Ioannis, Dimitrios Michail, and Ioannis Papoutsis. "Learning class prototypes from Synthetic InSAR with Vision Transformers." *arXiv preprint arXiv:2201.03016* (2022).

Synthetic data exploitation for volcanic monitoring

- Does the introduction of prototypes improve performance?
  - Methods trained with the prototype learning framework are denoted as Encoder-PL

Model	ACC	FP	TP	FN	TN
ResNet18	**85%**	7	296	108	358
DenseNet121	84.3%	22	306	98	343
VGG16	75.2%	132	346	58	233
ConvViT	**87.7%**	57	367	37	308
DeiT	81.4%	115	376	28	250
Swin	85.4%	7	299	105	358

Softmax based architectures

Model	ACC	FP	TP	FN	TN
ResNet18-PL	78%	2	237	167	363
DenseNet121-PL	82.4%	3	272	132	362
VGG16-PL	82.9%	123	396	8	242
ConvViT-PL	91.4%	28	366	38	337
DeiT-PL	92.7%	28	376	28	337
Swin-PL	93.8%	26	383	21	339

Prototype based architectures

Synthetic data exploitation for volcanic monitoring

- Does the introduction of the domain adaptation module improve performance?
  - Methods trained with the domain adaptation module are denoted as Encoder-PL-Pseudo
  - New SOTA on C1 at 97.1%

Model	ACC	FP	TP	FN	TN
ResNet18-PL	78%	2	237	167	363
DenseNet121-PL	82.4%	3	272	132	362
VGG16-PL	82.9%	123	396	8	242
ConvViT-PL	91.4%	28	366	38	337
DeiT-PL	92.7%	28	376	28	337
Swin-PL	93.8%	26	383	21	339

Prototype based architectures

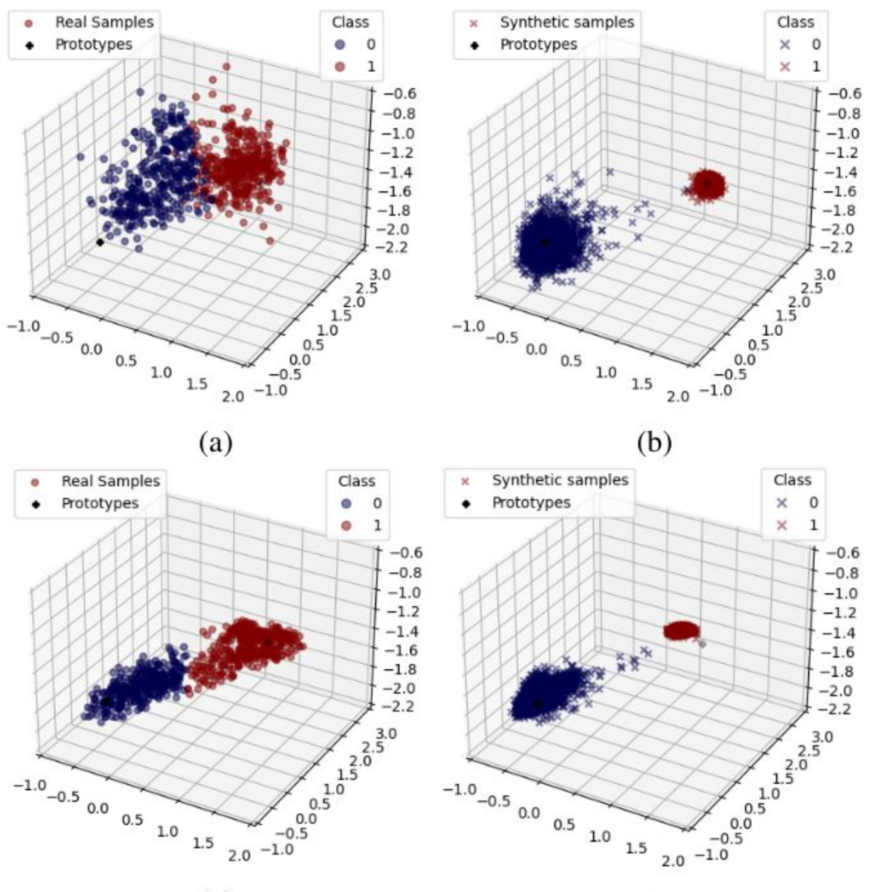
ConvViT-PL-Pseudo	95.1%	14	381	23	351
DeiT-PL-Pseudo	93.4%	37	391	13	328
Swin-PL-Pseudo	**97.1%**	16	398	6	349

DA Prototype based architectures

Synthetic data exploitation for volcanic monitoring

- Prototype space exploration

  - (a-b) Prototype learning based swin transformer without the domain adaptation module:
    - a) refers to the real test set while
    - b) refers to the synthetic validation set.
  - (c-d) Prototype learning based swin transformer with the domain adaptation module:
    - c) refers to the real test set,
    - d) refers to the synthetic validation set.



(a) (b) (c) (d)

Key takeaway:

- After the new projection is learnt there is greater inter-class seperation on the real test set, while maintaining the performance on the synthetic validation set.

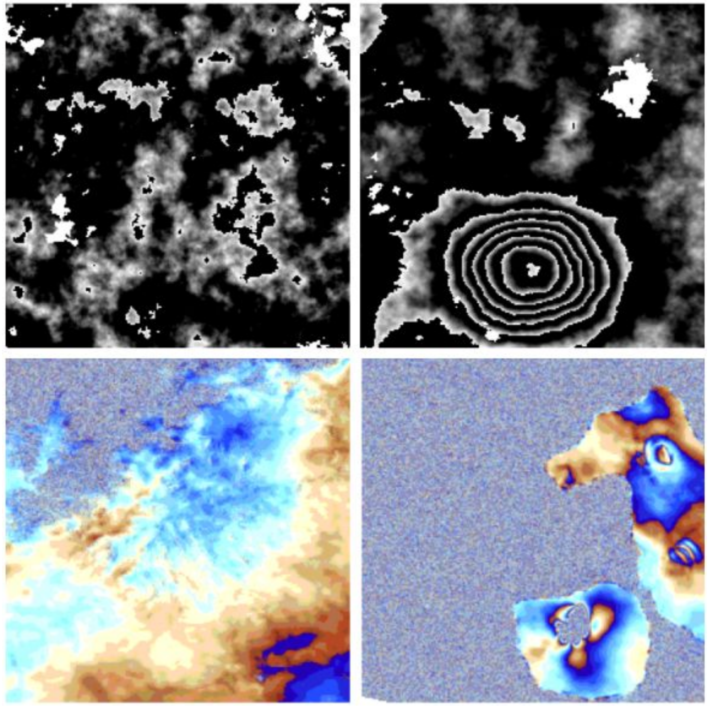
Synthetic data exploitation for volcanic monitoring

- How do these prototypes look like?

  - Since the prototypes lie in a 3D space we can inspect their characteristics based on their closest data samples.
  - The prototypes are learnt from the synthetic domain → these samples would be more representative.

Synthetic domain

Real domain

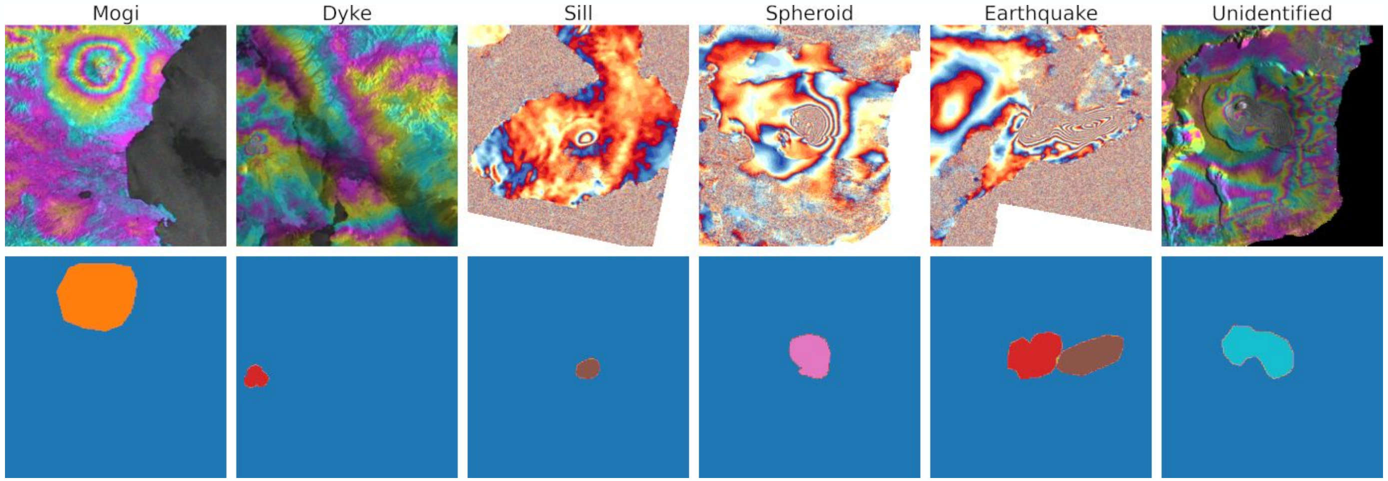


Linear Projection

Non linear projection

A large scale, multi-task InSAR dataset

- Hephaestus dataset towards InSAR understanding[1]
  - Global
  - Large Scale
    - 19.919 annotated interferograms resulting to more than 216,106 patches (224x224 pixels)
      - \+ random frames from all over the world for large scale self supervised learning
    - Total interferograms: 110,573
    - 38 frames containing 44 volcanoes
    - Source: Comet-LiCS
  - Diverse set of labels
  - Textual description



Example samples

1. Bountos, Nikolaos Ioannis, et al. "Hephaestus: A large scale multitask dataset towards InSAR understanding." *arXiv preprint arXiv:2204.09435* (2022).

https://github.com/Orion-AI-Lab/Hephaestus

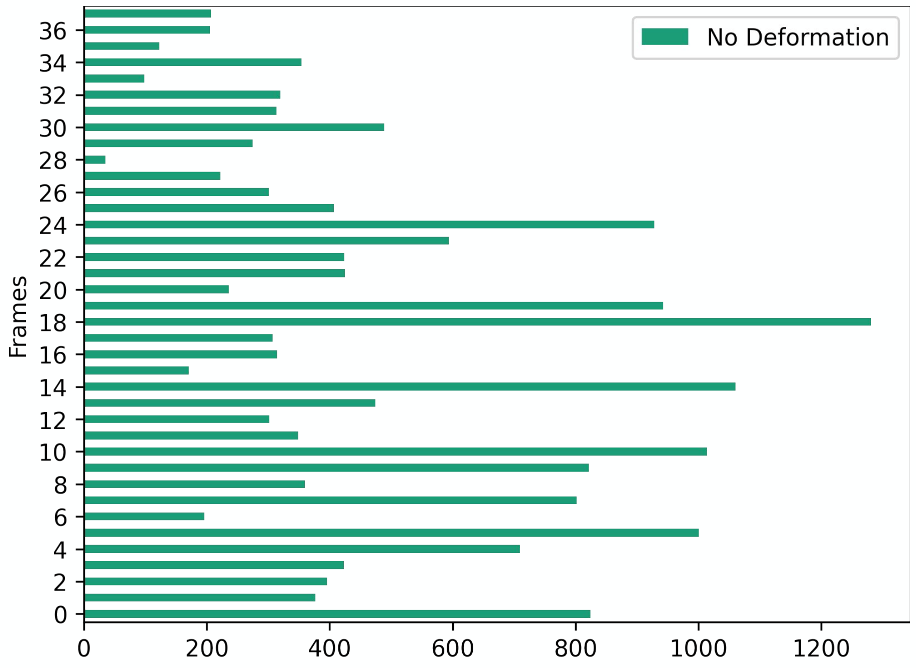
A large scale, multi-task InSAR dataset

- Hephaestus dataset towards InSAR understanding
  - Annotation file example

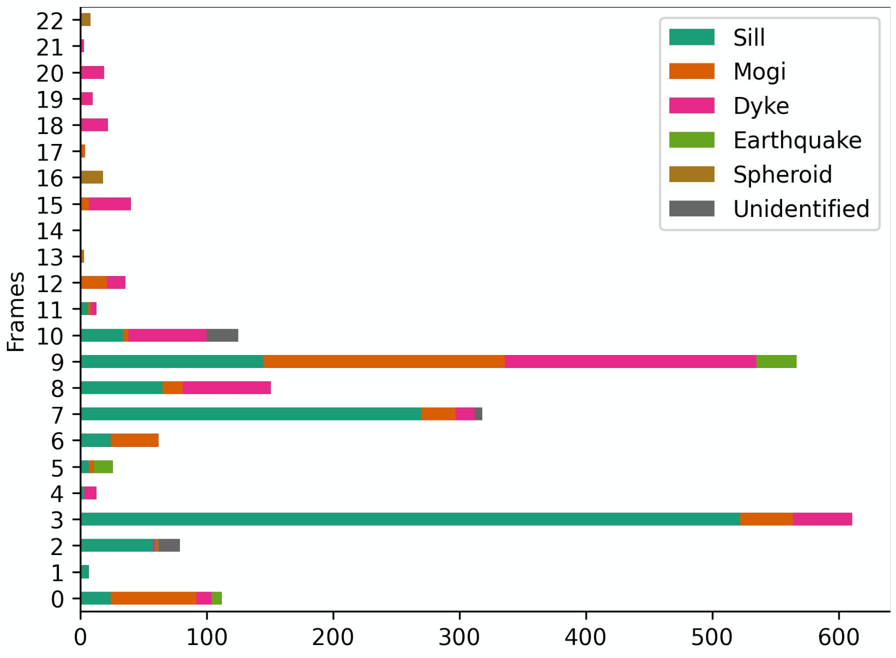
```json
{
  "uniqueID": 1957,
  "frameID": "124D_05291_081406",
  "primary_date": "20200110",
  "secondary_date": "20200122",
  "corrupted": 0,
  "processing_error": 0,
  "glacier_fringes": 0,
  "orbital_fringes": 0,
  "atmospheric_fringes": 1,
  "low_coherence": 0,
  "no_info": 0,
  "image_artifacts": 0,
  "label": [ "Deformation" ],
  "activity_type": [ "Mogi" ],
  "intensity_level": "Medium",
  "phase": "Unrest",
  "confidence": 0.6,
  "segmentation_mask": [
    [
      616.1845703125,
      121.2841796875,
      ...,
      618.5218671292696,
      116.14156159975028
    ]
  ],
  "is_crowd": 0,
  "caption": "Vertical stratification caused
by atmospheric delays can be detected in high
altitude areas. Medium deformation activity
can be detected."
}
```

A large scale, multi-task InSAR dataset

- Hephaestus dataset towards InSAR understanding
  - Class imbalance remains a problem



No deformation samples distribution along different frames



Ground deformation samples distribution along different frames

A large scale, multi-task InSAR dataset

- Next steps:
  - Exploration of self-supervised learning methods for general InSAR representation learning
    - exploitation of the temporal aspect of InSAR data
    - applicability to various tasks not covered in Hephaestus, or suffering from sample scarcity
      - E.g glacier detection
  - Creation of zero-shot classification (Text + Image modality combination?)
  - Automatic InSAR captioning
  - InSAR retrieval

Thanks!