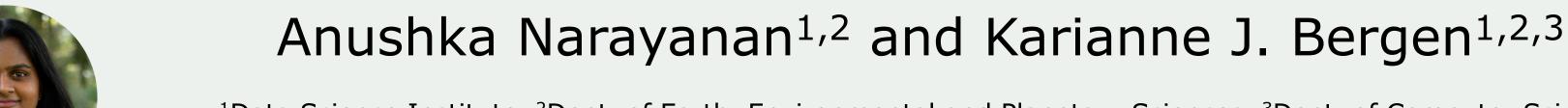
Prototype-Based Methods in Explainable-AI and Emerging Opportunities in Geosciences



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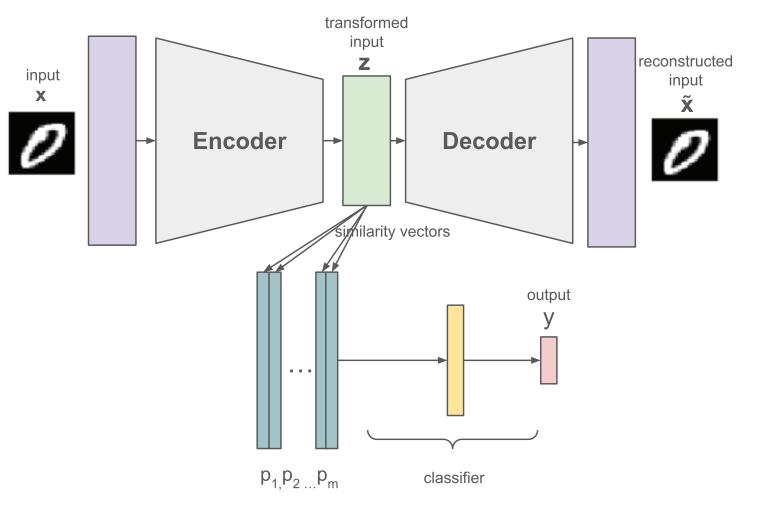
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Motivation: Why Prototype-XAI for Geosciences?

- Prototype-based methods are (1) **intrinsically interpretable**, (2) produce predictions & explanations by comparing data with "prototypical" instances (learned examples representative of the training data).
- Position:
 - Prototype-XAI offers an under-utilized alternative to post-hoc methods
 - Prototypes offer reasoning via inspection of similarity to prototypes (typical features / patterns in the data) mimics the human reasoning process
 - Prototype methods show potential for geoscientific learning tasks
- We highlight differences between geoscientific datasets and the standard benchmarks used to develop XAI methods, and discuss how specific geoscientific applications may benefit from modifying existing XAI methods

General Prototype-XAI Architecture



Case Studies: Prototype methods and their relevance to Geosciences

Development and Visualization

Image-Sized Prototypes [1]

- **Explanation:** This input image resembles a learned prototypical image of the target class.
- <u>Geoscientific use-cases</u>: climate phase prediction, dimensionality reduction

Patch-based Prototypes [2]

- This specific patch in input image resembles a learned prototypical local patch / pattern in a training image
- generating local spatial feature patterns

Spatially Deformable Prototypes [3]

- This organized cluster of prototypical patches resembles a set of prototypical patches within an image of the target class. (see Fig below)
- organization of feature patterns, detecting multi-scale feature patterns

Prototypical Evidence that Test Image Contains a Right-triangle Learned deformable prototypes with highest similarity Learned deformable prototypes with highest similarity

Types of Prototypes

Multi-Variable Prototypes [4]

- This multi-variable input shares similarities with single variables prototypes and their relationships with each other.
- multi-forcing classification, multi-variable feature attribution, multi-spectral imagery classification

Sequential Prototypes [5]

- A window of this input sequence resembles a prototypical window sequence in the target class.
- temporal forecasting, climate prediction

Anomaly Detection Prototypes [6]

- This input sequence significantly differs from prototypical sequences in the training data.
- anomaly detection, extreme event detection

Trivial and Support Prototypes [7]

- This input may resemble prototypes representative of a target class / boundary. (see Fig below)
- outlier detection, extreme event detection

Class 1 ★ ★ Support Prototypes Class 2 ★ Trivial Prototypes Classification Boundary • Data Samples

Prototypes for Various Learning Tasks

Decision Trees for Learning Tasks [8]

- The prediction is derived from a tree-like reasoning process on whether the input contains similarities to certain prototypes.
- multi-variable, extreme event prediction

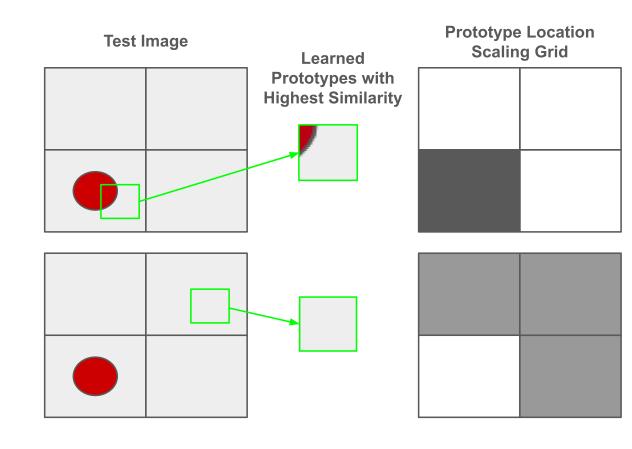
Learning Tasks with Negative Reasoning [9]

- This input image contains similar prototypical parts of the target class and does not contain prototypical parts from another class.
- climate prediction and classification, extreme event prediction

Learning Tasks with Location Scaling [10]

- This input image contains similar prototypical parts of the target class only in specific regions of the image. (see Fig below)
- generating spatially relevant feature patterns

Prototypical Evidence Object is in Quadrant III



Discussion

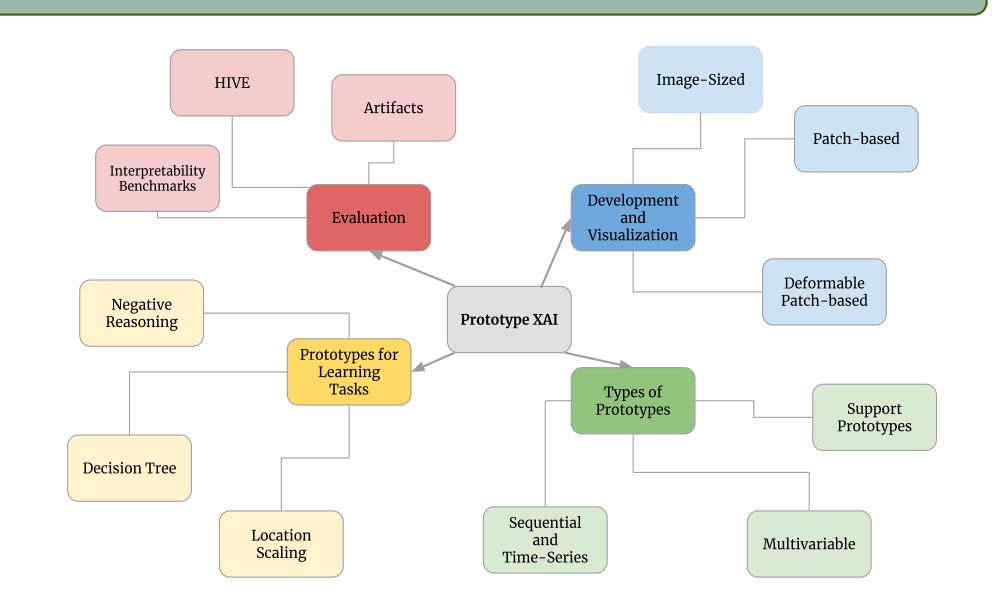
Geoscientific data has unique characteristics vs. natural images & text data typically used in prototype-based XAI research that require particular attention when using / developing prototype-based techniques.

Opportunities in Geosciences

- Image sized prototypes alternative to PCA-derived global climate modes vs patch prototypes for localized feature patterns
- Location- and channel-specific prototypes with sequential prototypes for interpretable spatiotemporal forecasting (ongoing!)
- Prototype anomaly scores, support prototypes for identifying subtle patterns, domain shift, extreme events
- Multi-variable prototypes for identifying salient individual and combined spectral channels for remote sensing

Limitations and Pitfalls of XAI

- Need **simple, non-duplicative** prototypes, e.g. scientist-in-the-loop pruning
- **Evaluation of robustness and reliability** to avoid artifact-induced explanation variability



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