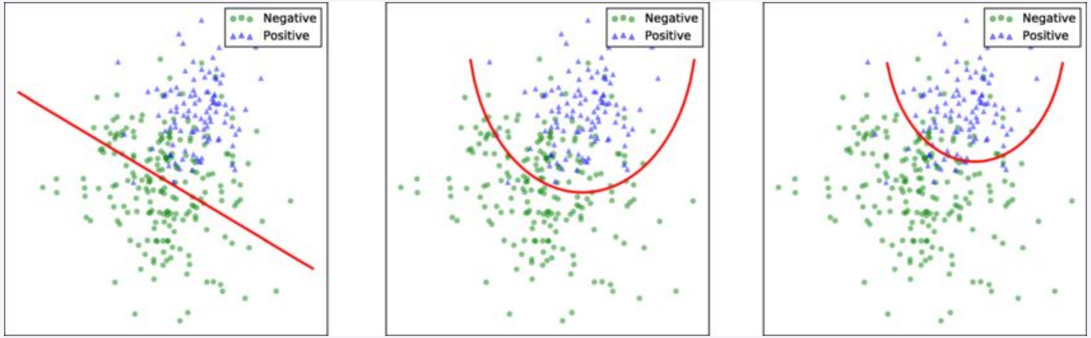
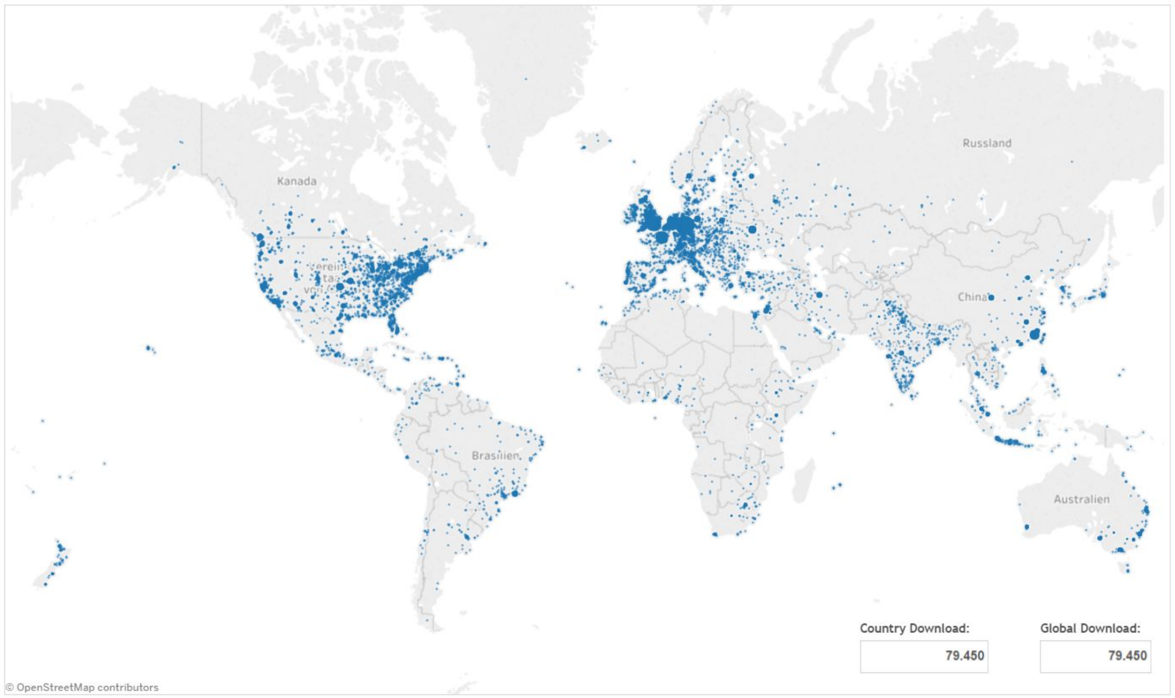
What’s the problem, why does it matter?

- **Problem Identification**: Existing self-supervised classification methods rely on random selection of negative samples which may not be as effective in creating distinguishing features.



Example images of 2D graphs with points representing samples. Positive samples are clustered in a certain area, but negative samples are spread randomly across the entire graph. This can show how a lack of strategic negative sampling affects the classifier's ability to create a useful boundary.

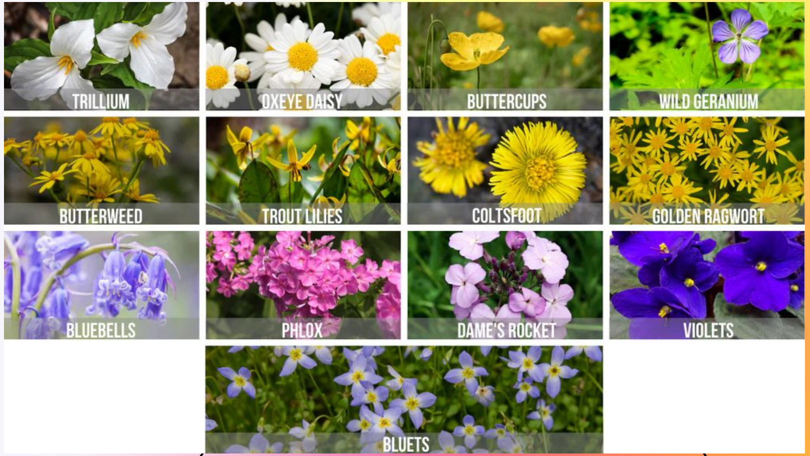
Contextual Relevance: These methods neglect the potential information available in the broader context of unlabeled image collections, like **geolocation data**.



Example image of geolocation data

Implication in Practice: Current models have limitations in accurately classifying complex image sets such as wildflower species across different geographical regions.

- impacts ecological monitoring
- conservation efforts
- rely heavily on the accurate classification of species



Significance of the Issue

The ability to classify accurately from unlabeled image collections has wide-ranging implications, beyond ecology

Obstacles in Prior Work

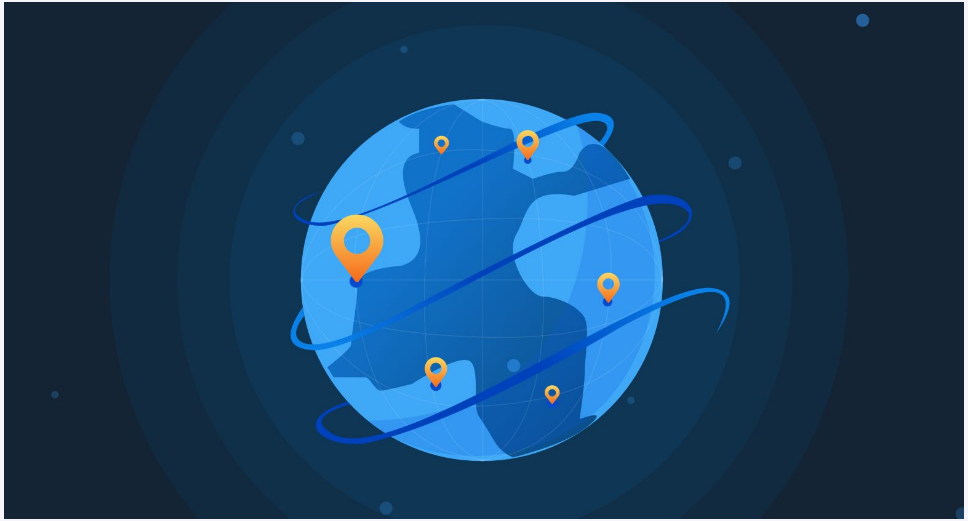
Reliance on Supervised Learning

Current research on wildflower classification relies on fully supervised models, but this is impractical for biodiversity monitoring since data is often under labeled.

Focus on Positive Pairs

Previous self-supervised contrastive models across various research fields have focused on selecting context aware positives and randomly selecting negatives

Bit Flip



- Geospatial context in selection of positive and negative pairs
- Observe how different strategies affect accuracy

Technical detail of what we did

Technical Approach

01

Supervised

Ran batches of 64 random iNaturalist images through a 5 layer network, then tested on 75,000 new images in batches of 64

02

Baseline Contrastive

Self-supervised for iNaturalist images with augmented image for positive and random image for negative; pretrain with random 10% labeled fine-tune

03

Context Aware Selection

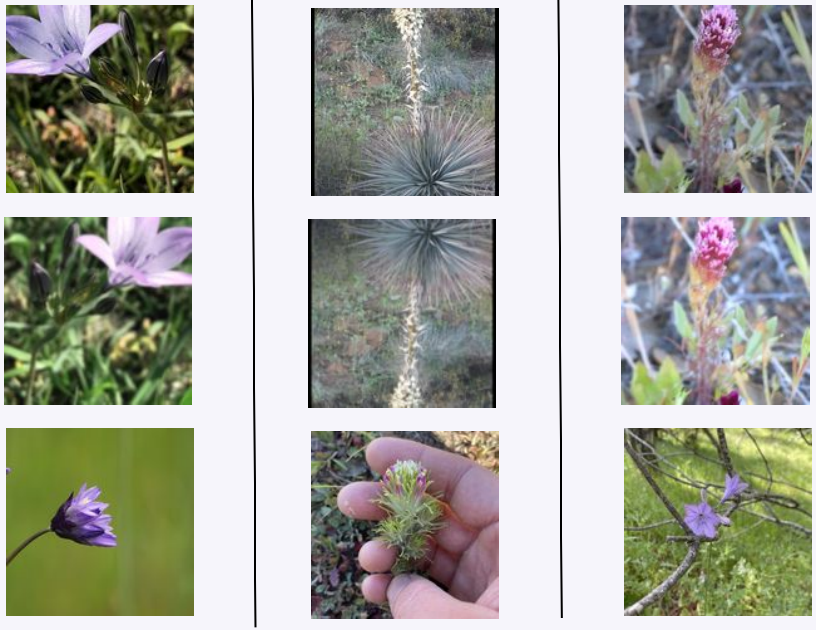
Self-supervised with geolocation selection for positive and random image for negative. Used a cKDTree data structure to find other images within a radius of the anchor and then pick one at random. Pretrain with random 10% fine-tune

Augmented Pairs

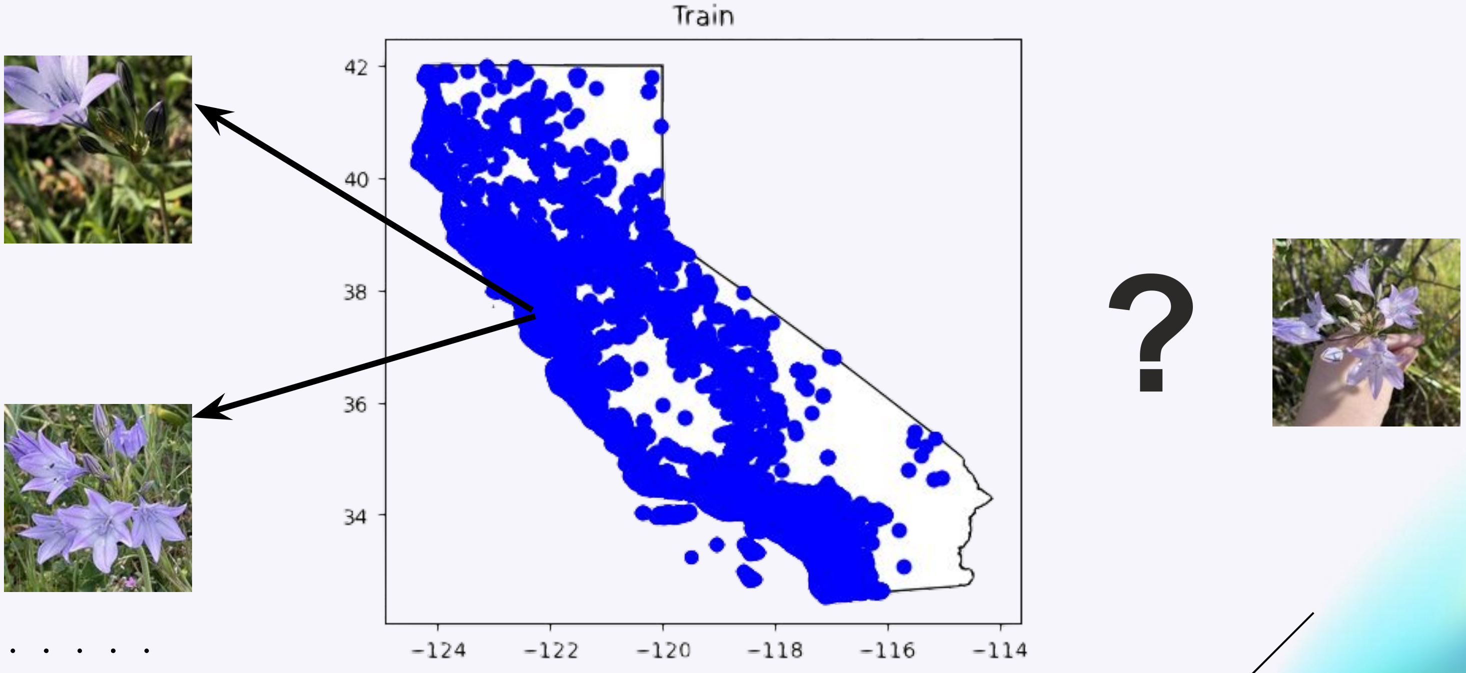
Original Image

Augmented Positive Pair

Random Negative Pair



Utilizing Geolocation Context for Positive Pair Selection



Context-Aware Positive Pairs

Original Image

Triteleia laxa

Hesperoyuuca whipplei

Castilleja exserta exserta

Context Aware Positive Pair

Triteleia laxa

Hesperoyuuca whipplei

Sisyrinchium bellum

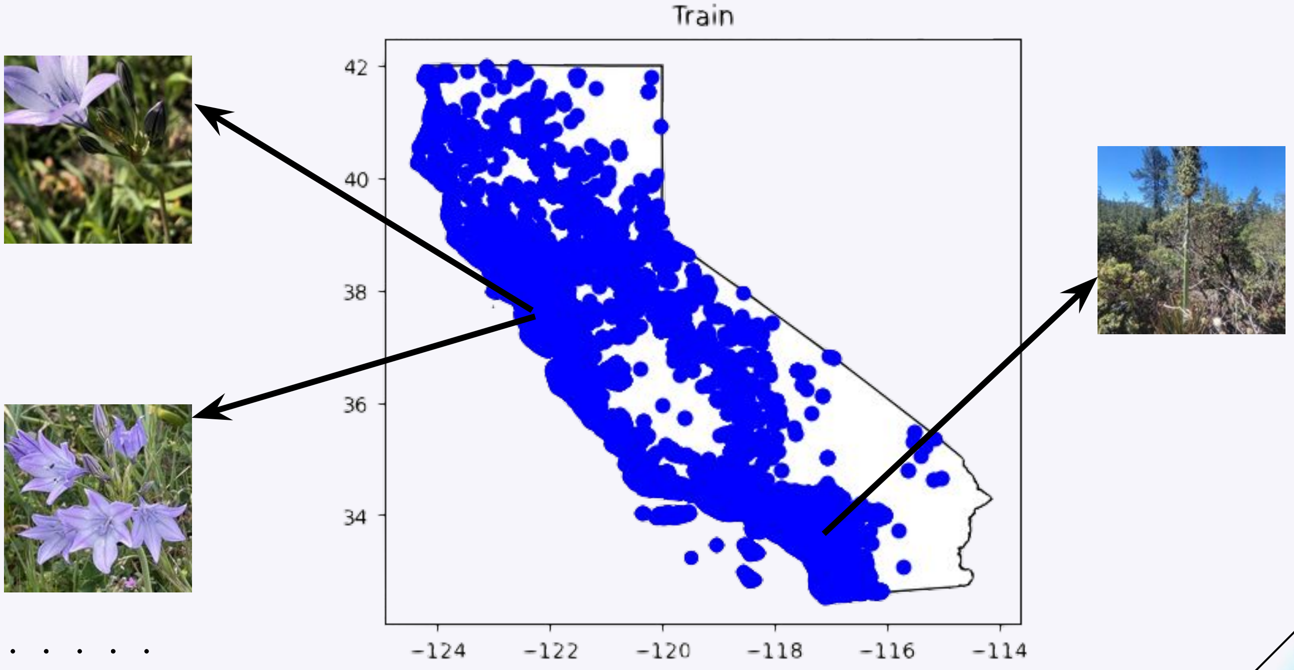
Random Negative Pair

Triteleia laxa

Sambucus cerulea

Acmispon glaber

Utilizing Geolocation Context for Positive and Negative Pair Selection



Context-Aware Positive and Negative Pairs

Original Image


Triteleia laxa


Hesperoyucca whipplei


Castilleja exserta exserta

Context Aware Positive Pair


Triteleia laxa


Hesperoyucca whipplei


Dipterostemon capitatus

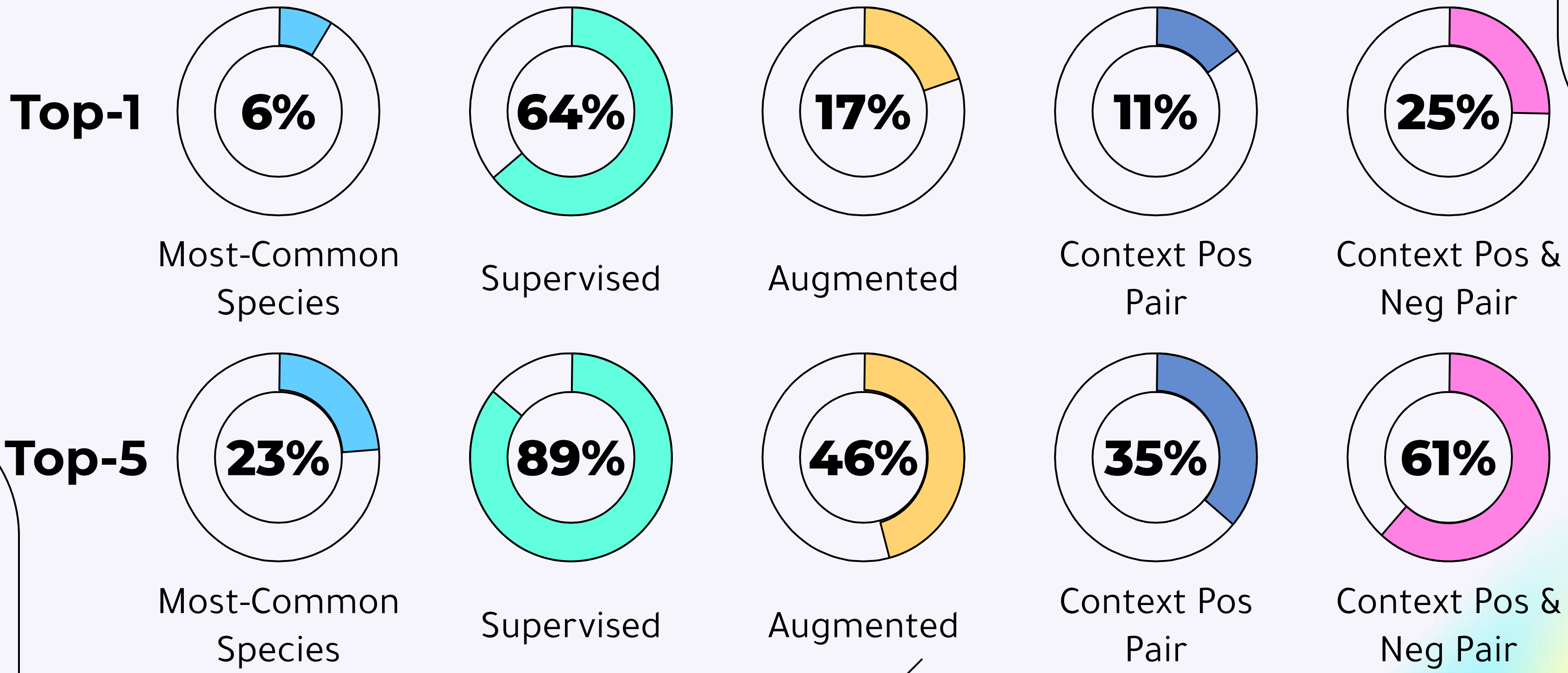
Context Aware Negative Pair


Hesperoyucca whipplei


Escscholzia californica


Aesculus californica

Results


Top-1
6%
Most-Common Species
64%
Supervised
17%
Augmented
11%
Context Pos Pair
25%
Context Pos & Neg Pair
Top-5
23%
Most-Common Species
89%
Supervised
46%
Augmented
35%
Context Pos Pair
61%
Context Pos & Neg Pair

Conclusion

Utilizing context in negative pair selection outperforms traditional augmented image contrastive learning and only utilizing context for the positive pair selection