

# SEARCH

SDO Exploration And Research Community for Heliophysics

## An experiment on using applied AI research to educate a diverse workforce

Subhamoy Chatterjee, Nadia Ahmed, & Andrés Muñoz-Jaramillo <u>andres.munoz@swri.org</u>

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Priviledge

Disadvantage

Our lives are very random. They are NOT the deterministic outcome of the choices we make.

Our birth has an outsize influence on the rest of our lives. We do NOT start with the same circumstances and opportunities.









Education is one of the main ways we have to help disadvantaged populations.

Most educational oportunities are gated, which tends to help those that are ahead get farther ahead.

Disadvantage Priviledge







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So we restrict them, and it helps, up to a point.



advantagePriviledge





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So we restrict them, and it helps, up to a point.

Because priviledge is relative.

# Sources of priviledge we wanted to offset



- Socio-economic status, wealth, and place of origin:
  - Limited access to educational opportunities.
  - Significant difference in skillsets.
  - Limited access to computational resources.
- Gender, race, ethnicity, religion, and sexual orientation:
  - Subconcious and concious bias.
  - Harder access to opportunities.
- Age, employment, family responsibility, veteran status:
  - Scientific education is focused on students.
  - Limited time availability to learn.
  - Reduced access to new techniques and technologies.





Significant difference in skillsets. C Reduced access to new techniques and technologies.

Collaborative programing (mob-coding)

- Equal sharing of development responsibility.
- Short, low-stakes rotations.
- Simultaneous development and documentation of code.
- Mob efficienly finds solutions to obstacles.
- Effective learning environment for equalizing skillsets.







Significant difference in skillsets. Reduced access to new techniques and technologies.	Collaborative programing (mob-coding)
Limited time availability to learn	4 hours/week commitment, no assignments
Limited access to computational resources.	Development uses Google colab and visual studio code liveshare sessions
Limited access to educational opportunities. Harder access to opportunities. Scientific education is focused on students.	Anyone can join as long as they show up and actively engage in collaborative programming.











Subhamoy C.

Jasper D.



Maxwell R.

Cameron W.





Matin Q.

Daniel G.









Jennifer L.





Sierra M.





Spencer G.

Jonathan V.





Andres M.

Julie C.





Justin G.





Miguel T.

David S.









- To perform cutting edge Machine Learning (ML) research in heliophysics involving a diverse group of people without requiring any prior ML technical expertise.
- □ To create a space where all are welcome and where all participants level up and work together towards common technical goals.

## **Opening:** Team Organization and Workflow

- VSCode Liveshare
- Google <mark>Colab</mark>
- Github

- Mob programming -
- Team member rotation -
  - Weekly Code review -
    - Agile workflow -



Mob Programming

module2/Sunshine/

module3/Sunbird/

module1/Sunflowers/

# Diservatory



AIA (Atmospheric Imaging Assembly)

# **Introduction:** AIA Data Volume & Motivation

- Petabytes of data
- Data must be manually searched through



2012, J.B Gurman





















AI/ML Ready Packager

Similarity Search Engine







#### Introduction to Self-Supervised Learning: General Overview (Model-Agnostic)



#### Trained by comparing:

Image vs. transformed image (and/or a contrasting image)

Allows us to discern similar & dissimilar images.

#### **Returns:**

Similar embeddings for an image & its transformed counterpart.

For **dissimilar** images the embeddings should be very different.

#### Introduction to Self-Supervised Learning: General Overview (Model-Agnostic)



#### Collapse:

Solution collapse can occur when a model fails to learn meaningful feature representations from the data and converges on a single embedding or limited embedding space.



#### Introduction to Self-Supervised Learning: General Overview (Model-Agnostic)



ML algorithms we used:

SimSiam; SimCLR; BYOL
("Bootstrap Your Own
Latent").







#### Introduction to Self Supervised Learning: Metrics and Losses





#### **Cosine Similarity**

Euclidean Distance



Contrastive Loss

Measures how well the model can contrast between similar and dissimilar data points

1) Augmented Image in Batch





Chen, Kornblith, Norouzi, Hinton, A Simple Framework for Contrastive Learning of Visual Representations (2020)







Chen, Kornblith, Norouzi, Hinton, A Simple Framework for Contrastive Learning of Visual Representations (2020)





Shifts





✓ Augmentations, and train/val split creates gaps

✓ Nearest neighbor VS Iterative filling

✓ Iterative filling creates improvement in terms of collapse







#### Augmenting Data

 Augmentations, and train/val split creates gaps

✓ Nearest neighbor VS Iterative filling

✓ Iterative filling
creates improvement in
terms of collapse











SEARCH Projection Head

SEARCH Backbone



NEW Projection Head

SEARCH Backbone





## BYOL: Bootstrap Your Own Latent





Chen & He, Exploring Simple Siamese Representation Learning (2020)

# •••• Introduction to Self Supervised Learning: O Clustering





## SimCLR: Similarity Search 🔮



(mail)				
\$ python model_run.py				
Slobal seed set to 1				
wandb: Currently logged in as: martinsierrasue (search-byol).	Use `wandb loginrelogin`	to force r		
elogin				
wandb: wandb version 0.15.11 is available! To upgrade, pleas	e run:			
wandb: \$ pip install wandbupgrade				
wandb: Tracking run with wandb version 0.15.8				
wandb: Run data is saved locally in D:\source\repos\hits-sdo-	similaritysearch\search_simc	:lr\visualiz		
ations\simclr_knn\wandb\run-20230929_143018-27148n46				
wandb: Run `wandb offline` to turn off syncing.				
wandb: Syncing run sweet-paper-175				
wandb: View project at <a href="https://wandb.ai/search-byol/search_s">https://wandb.ai/search-byol/search_s</a>	<u>imclr</u>			
<pre>wandb: View run at <u>https://wandb.ai/search-byol/search_simcl</u></pre>	r/runs/27148n46			
Not using wandb config				
100%		10000		
/10000 [00:00<00:00, 4996788.18it/s]		1. S.		
100%		800		
0/8000 [00:00<00:00, 3996002.38it/s]				
100%		200		
0/2000 [00:00<00:00, 1996336.98it/s]				
			_	
A 1			_	
	completed 350 / 500 (	epocns		
	Epochs completed: 76%			
	completed 400 / 500 (	epochs		
	Epochs completed: 87%			
	completed 450 / 500 (	epochs		
	Epochs completed: 100%			



### SimCLR: Sweep





#### Features:

- "NT-Xent loss" (Normalized Temperature-Scaled Cross-Entropy Loss)
- Additional augmentations



### SimCLR: Hyperparameters













## SimCLR: K-Nearest Neighbors







## SimCLR: K-Nearest Neighbors







## SimCLR: K-Nearest Neighbors





# •o<sup>O</sup> Team Highlights: Diverse sampling and O<sup>O</sup>, Iterative training





Patel, Gao, Koul, Ganju & Kasam, Scalable Data Balancing for Unlabeled Satellite Imagery (2021)

# o<sup>O</sup> Team Highlights: Diverse sampling and O<sup>O</sup>, Iterative training





Enhanced Training with Diverse Sampling:

- Custom training loop integration.
- Iteratively update dataset with diverse samples.
- Broaden model exposure to capture data variations.

Patel, Gao, Koul, Ganju & Kasam, Scalable Data Balancing for Unlabeled Satellite Imagery (2021)

## O Team Highlights: Contrastive vs. Non O , contrastive losses on embedding space



#### 2D Histogram of Embedding Spaces





#### Non-Contrastive Loss

**Contrastive Loss** 









Collaborative Learning Automation

Advances in Heliophysics

![](_page_46_Picture_0.jpeg)

![](_page_46_Picture_1.jpeg)

#### □ Fine-Tuning

- Using Labeled Data
- Different Algorithms and Architecture
- Improving JSOC Usability & Accessibility
- Optimization & Expansion
- ML Democratization outside Educational Institutions & Open Research Accessibility
- Continue Experimentation

![](_page_47_Picture_0.jpeg)

- We have brought together passionate individuals from diverse backgrounds in machine learning and heliophysics
- From humble beginnings, we have built advanced data and machine learning systems that have made the intricate world of scientific research a bit more approachable
- We are also **proud** of what we have done and we look forward to accomplishing more in the **future**

![](_page_47_Picture_4.jpeg)