A Deep Generative+Self-Supervised Approach that Uses Physical Quantities to Generate and Retrieve Solar Images

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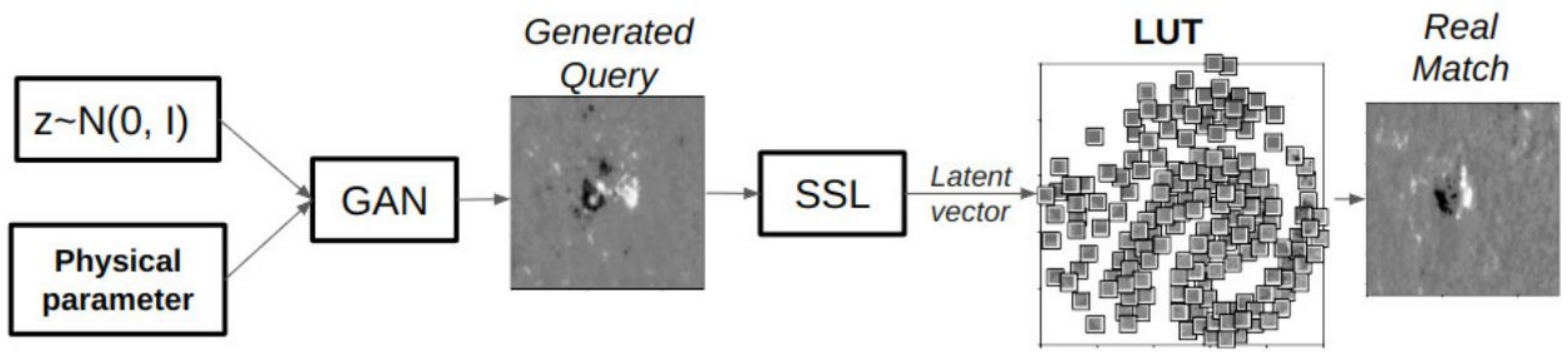
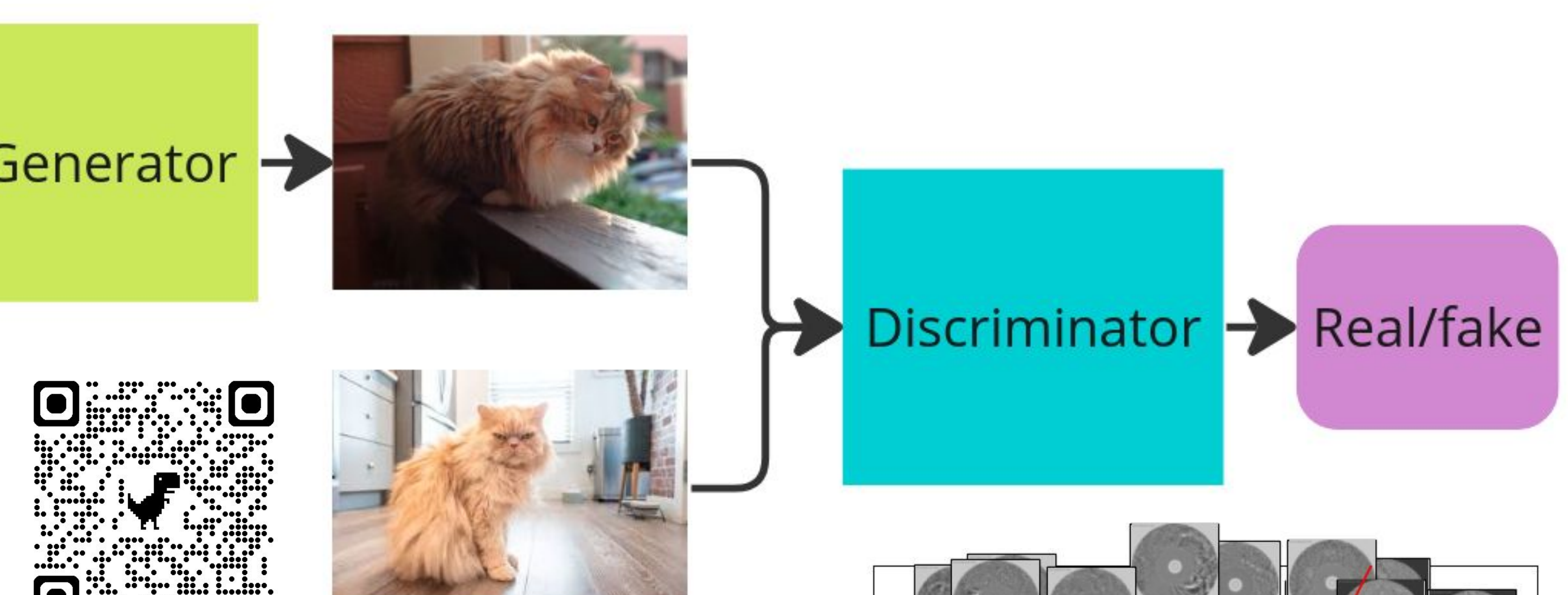


Figure 1

Motivation

- Deep generative models have shown immense potential in generating unseen data that has properties of real data.
- These models learn complex data-generating distributions starting from a smaller set of latent dimensions.
- Generative models have encountered great skepticism in scientific domains due to the disconnection between generative latent vectors and scientifically relevant quantities.
- ***In this study[1], we integrate three types of machine learning models to generate solar magnetic patches in a physically interpretable manner and use those as query to find matching patches in real observations. (see Figure 1)***
- We use the magnetic field measurements from Space-weather HMI Active Region Patches (SHARPs) to train a Generative Adversarial Network (GAN[2]). (see Figure 2)



Scan to access "Sun Generator"
https://sungenerator-subhamoy.streamlit.app/
This App that allows user to interact with latent space for tweaking solar magnetic patch generation

Figure 2

Potential Application on CME Data Mining

- ***Connecting CME properties to Generative Latent space will allow efficient exploration of CMEs***
- Latent vectors capture inherent structure of CME images (Figure 7)
- Generative models allow continuous changes in CME images by changing the input latent vectors
- Mapping latent vectors to CME properties allow generation of new CME images and mine rare cases that can be hidden in a large dataset

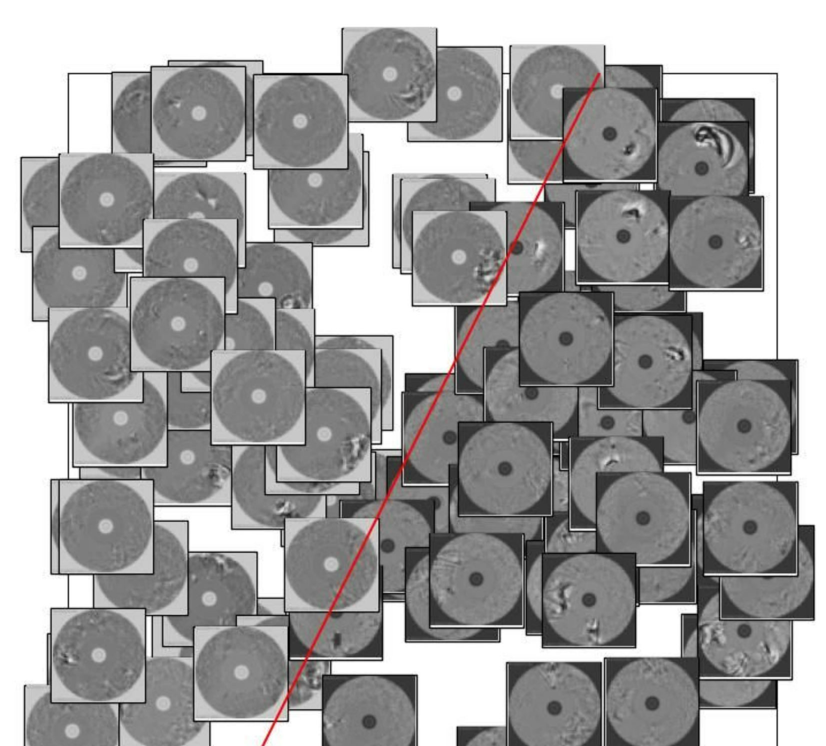


Figure 7

Supervised Learning on Generative Latent Space

- We calculate physical parameters from the generated images – Total Unsigned Field (TUF), Total Positive/Negative Field (TPF/TNF), polarity separation (PSEP) etc.
- ***We use supervised learning to learn decision boundaries (in red) that separate higher and lower values of physical parameters (see Figures 3, 4, 7)***
- Moving along direction normal to those decision boundaries makes smooth changes in those physical properties of the generated images[1]

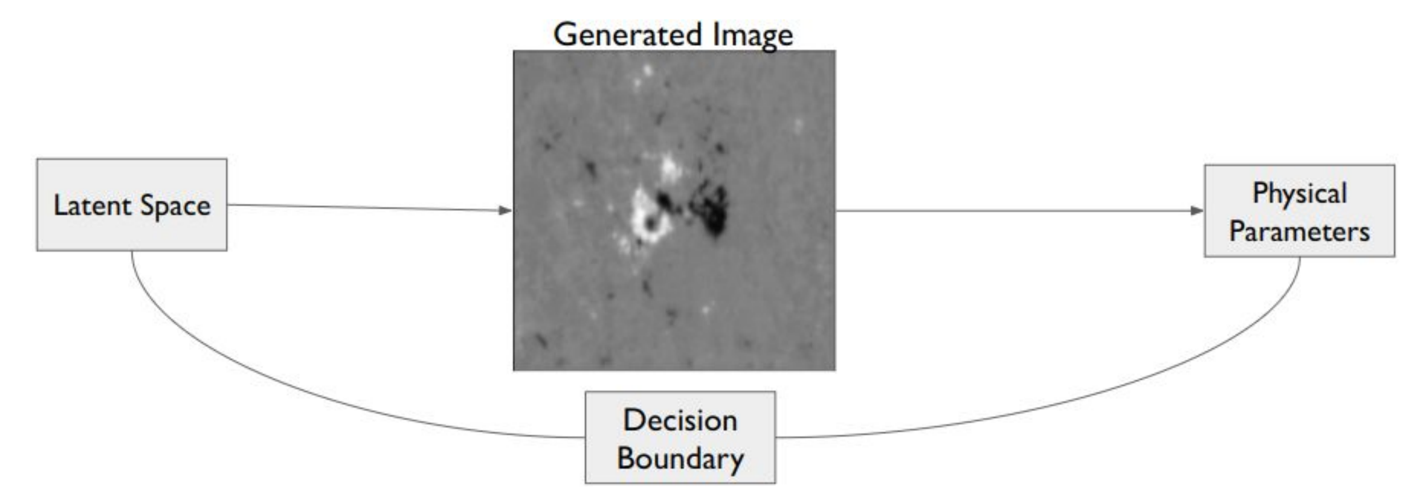


Figure 3

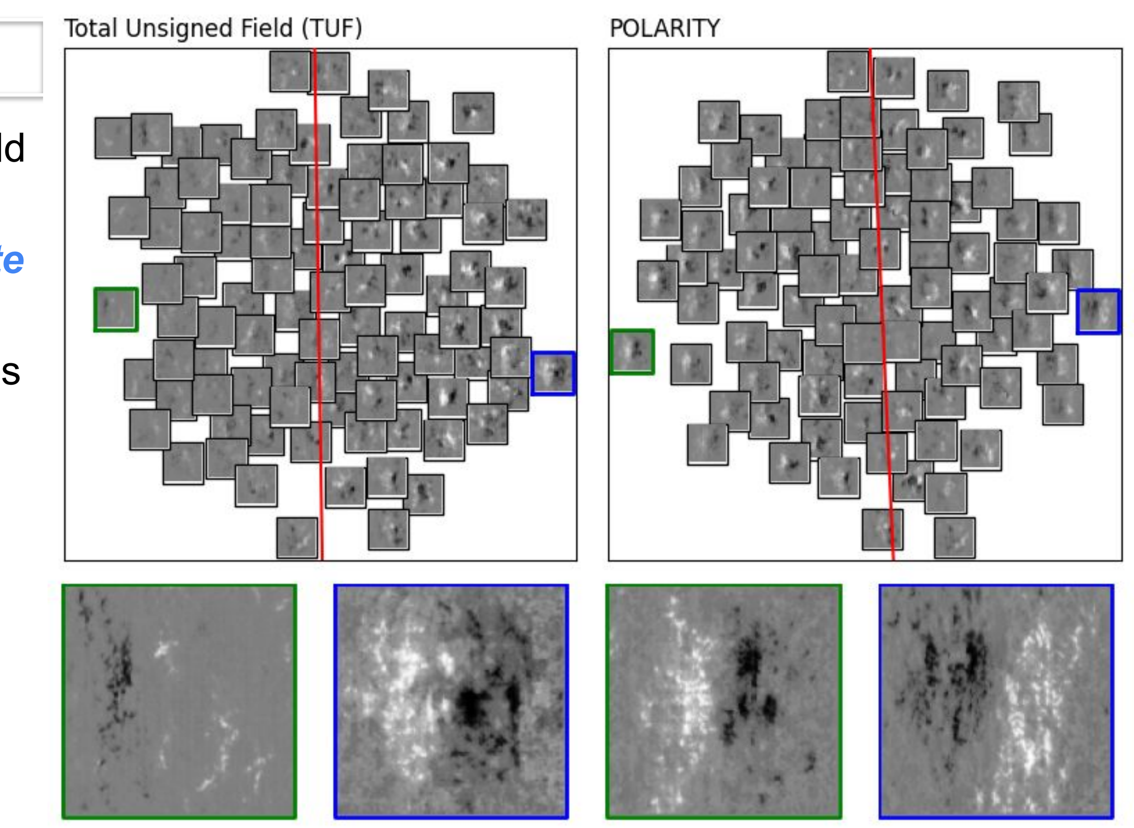


Figure 4

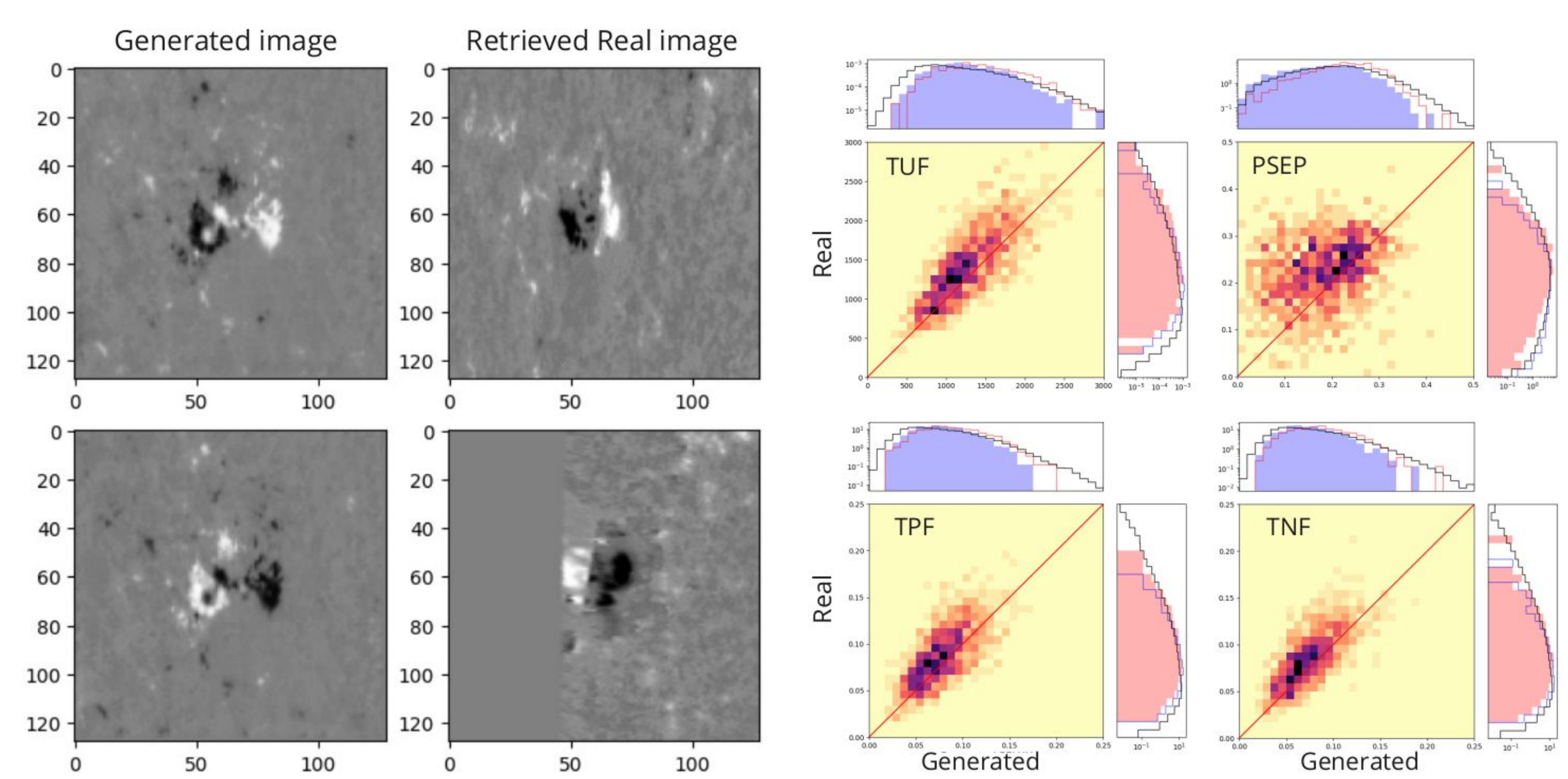


Figure 5

Self-Supervised Learning to find Nearest Observation

- We train a Self-Supervised Learning (SSL) model called SimSiam[3] on SHARP data to learn augmentation invariant latent representation
- We build a Look Up Table (LUT) that maps SHARPs to SSL-derived latent vectors. (see Figure 1)
- ***We use Generated Image as Query and find nearest observed SHARP using the SSL latent space. (see Figures 1, 5)***
- The physical properties of Generated Query and retrieved Real Match show high statistically significant correlation (2D histograms on Figure 5).
- Generated Queries match the physical domains of real images in terms of the derived physical properties. (marginal histograms on Figure 5).

SEARCH

- ***A community driven Self-Supervised Learning effort to build a reverse image search application on SDO Data***
- SEARCH = **S**DO **E**xploration **A**nd **R**esearch **C**ommunity for **H**eliophysics.
- Build SDO/AIA data downloader + AI/ML ready packager
- Trained SSL models on SDO/AIA mutli-wavelength images
- Built reverse image-search tool making use of SSL latent space (Figure 6)

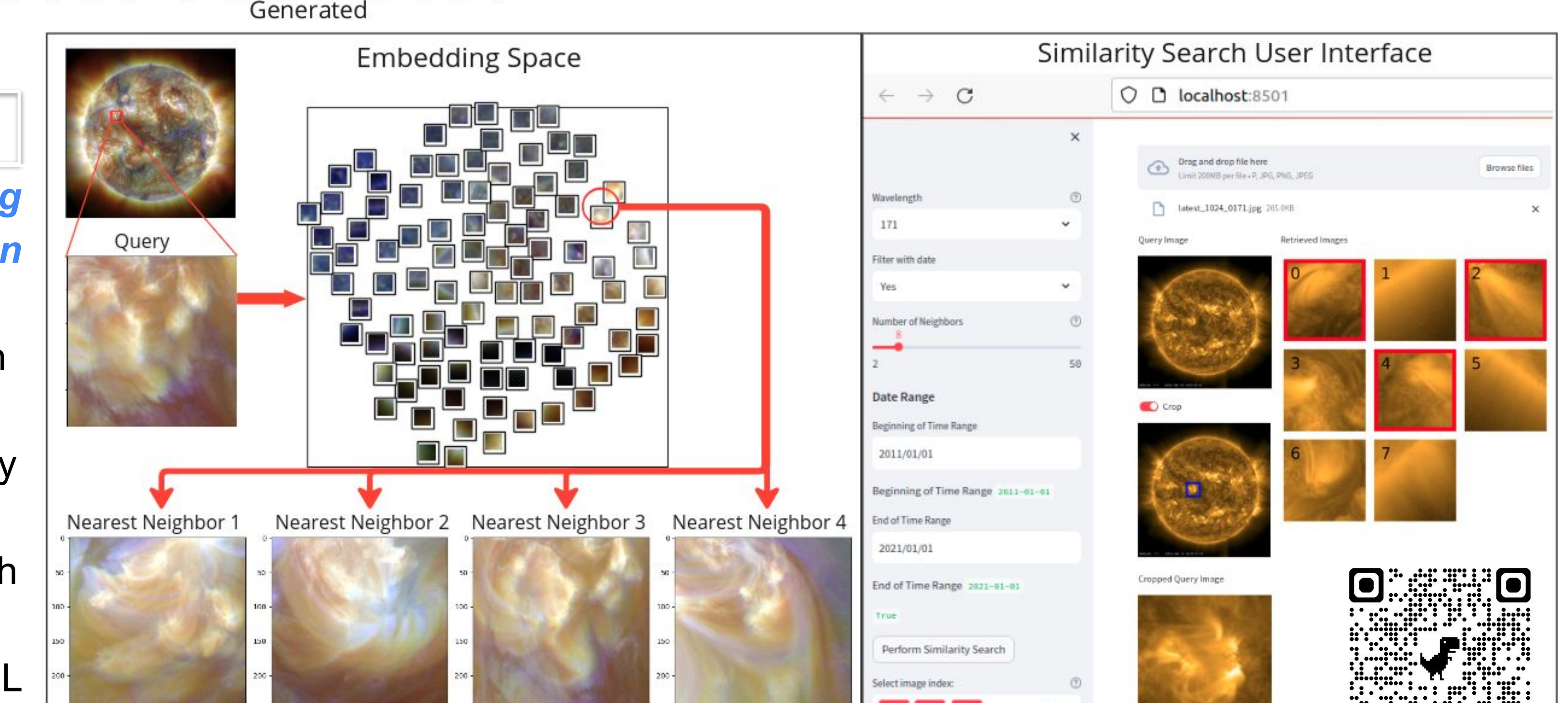


Figure 6

Conclusion

- We demonstrated that a Deep Generative model can be harnessed to generate scientifically meaningful queries to find matches in scientific datasets.
- This image generation can be tweaked along directions that reflect changes in any set of chosen physical quantities.
- We showed that the generated images can also be used as a query to the SSL-derived latent space to retrieve matches from solar images. These retrieved regions matched the query both visually and quantitatively.
- ***This approach thus elevates generative models from a means-to-generate-synthetic data to a novel tool for the efficient mining of real scientific data.***
- Even though we demonstrated this approach in a specific domain of solar astronomy, it can be easily adapted to any other field of astronomy dealing with big datasets of any modality and complexity.

References

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