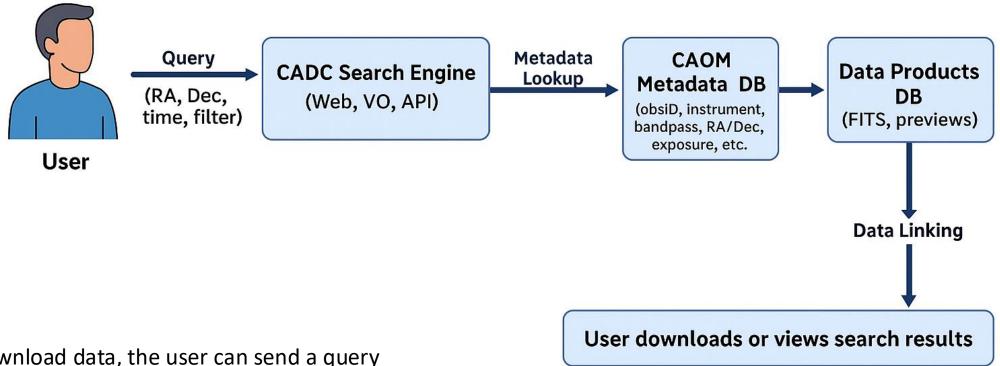
# Hossen Teimoorinia Patrick Dowler

(Canadian Astronomy Data Centre)

ADASS, Görlitz (DE) Nov, 2025 CAOM-AI: Content-Based Image Search System

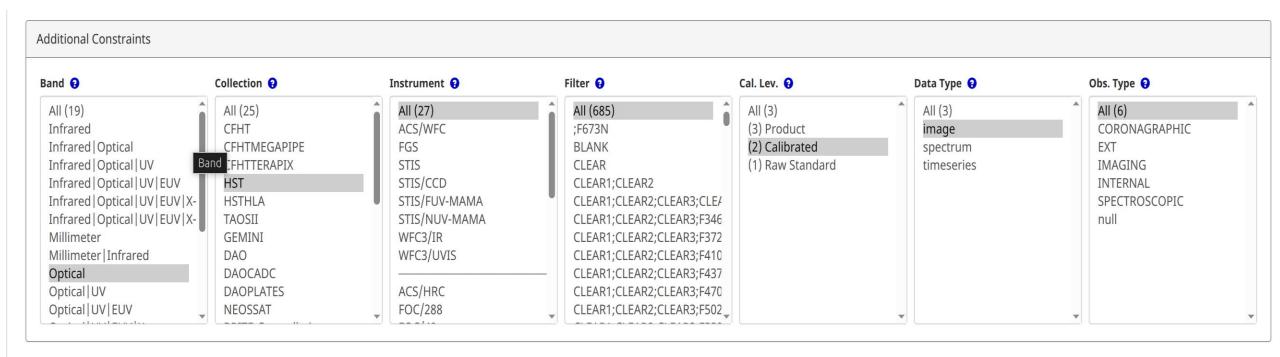
From Unsupervised to Self-Supervised Representation Learning:

Implementing Content-Based Search in Astronomical Data Archives



To download data, the user can send a query to the CADC, and the CAOM model can match metadata with relevant images, returning a list of downloadable images.

#### An example of CADC Advanced Search



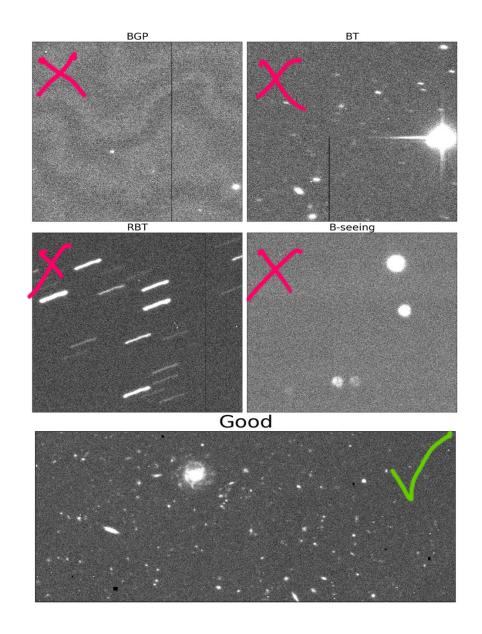
Search Reset

This is an example of what you could see in CADC, the advanced search page, choose your metadata like filters, instruments and then click search

Mark 🗌	Preview	Collection	Proposal	Obs. ID	Product ID	RA (J2000.0)	Dec. (J2000.0)	Target Na	"Start Date	Int. Time	Instrument	Filter	Cal. Lev.	Obs. Ty
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		HST	CAL/STIS	<u>ofdajnrqq</u>	ofdajnrqq-CALIBRATED	03:33:03.80	-02:48:02.2	DARK	2025-10-23 05:45:			MIRVIS	2	IMAGIN
		HST	CAL/STIS	ofdajnrpq	ofdajnrpq-CALIBRATED	03:33:03.80	-02:48:02.2	DARK	2025-10-23 05:26:			MIRVIS	2	IMAGIN
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	Preview			<u>jfg702q4q</u>	jf9s12cbq-CALIBRATED ifq702q4q-CALIBRATED	05:17:05.83	-44:10:44.3		2025-08-11 08:51:3 2025-04-24 06:17:3			F814W	2	IMAGIN
	Preview			jdua10tag	jdua10tag-CALIBRATED	00:03:31.72	+70:18:58.7		2018-12-02 03:05:			F775W;CLEAR2L	2	INTERN
	Preview			jdua10t8q	idua10t8g-CALIBRATED	09:59:03.97	+01:55:05.3		2018-12-02 02:57:2			F775W;CLEAR2L	2	INTERN
			;	j <u>dua10010</u>	idua10011-CALIBRATED	09:59:01.38	+01:55:36.8		2018-12-02 02:49::			F775W;CLEAR2L	2	INTERN
	Preview	HST	CAL/ACS	jdua04s6q	jdua04s6q-CALIBRATED	09:59:03.97	+01:55:05.3		2018-12-02 01:07:			F550M;CLEAR2L	2	INTERN
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	Preview	HST	CAL/ACS	j <u>dua09roq</u>	jdua09roq-CALIBRATED	09:59:03.94	+01:55:05.7	<b>TUNGSTEN</b>	2018-12-01 23:41:4	140.000	ACS/WFC	CLEAR1L;F660N	2	INTERN
	<u>Preview</u>	HST	CAL/ACS	<u>jdua09rmq</u>	jdua09rmq-CALIBRATED	09:59:03.94	+01:55:05.7	TUNGSTEN	2018-12-01 23:31:	140.000	ACS/WFC	CLEAR1L;F660N	2	INTERN
N/A		HST	GO	jf9s12ceq	jf9s12ceq-CALIBRATED	00:54:24.70	-37:45:49.0	N300-D	2025-08-11 09:03:	C457.000	ACS/WFC	F606W	2	IMAGIN
N/A				jf9s12cbq	f9s12cbq-CALIBRATED	00:54:24.80	-37:45:50.1	N300-D	2025-08-11 08:51:	3525.000	ACS/WFC	F606W	2	IMAGIN
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		HST	CAL/ACS	idua10010	idua10011-CALIBRATED	09:59:01.38	+01:55:36.8		2018-12-02 02:49:		ACS/WFC	F775W;CLEAR2L	2	INTERN
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	Preview	HST	CAL/ACS	idua04s2g	idua04s2q-CALIBRATED	09:59:03.97	+01:55:05.3		2018-12-02 00:51		ACS/WFC	F550M;CLEAR2L	2	INTER

This is an example of what you could see. More than 30,000 downloadable images. You can see some of them to explore them, but it is still very challenging without any prior knowledge to know which one should be downloaded

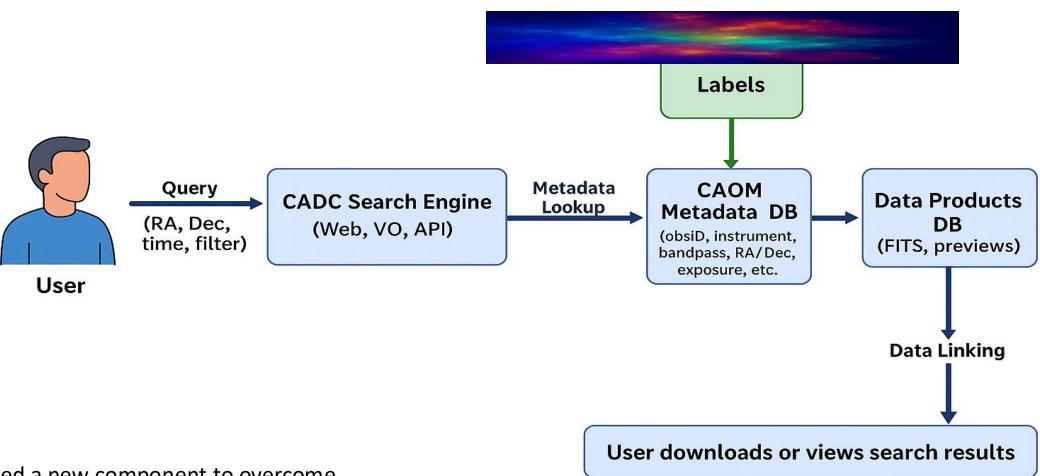
Sometimes you would end up downloading garbage, the images that you don't need



No content-based information.

## (Annotations)

(AI content-based information)



We need a new component to overcome this problem, and would like to talk about this interpretable component here.

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## An Astronomical Image Content-based Recommendation System Using Combined Deep Learning Models in a Fully Unsupervised Mode

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Department of Statistics, Faculty of Science, University of British Columbia, Vancouver, BC V6T 1Z4, Canada

Department of Astronomy and Astrophysics, University of Toronto, ON M5S 3H4, Canada

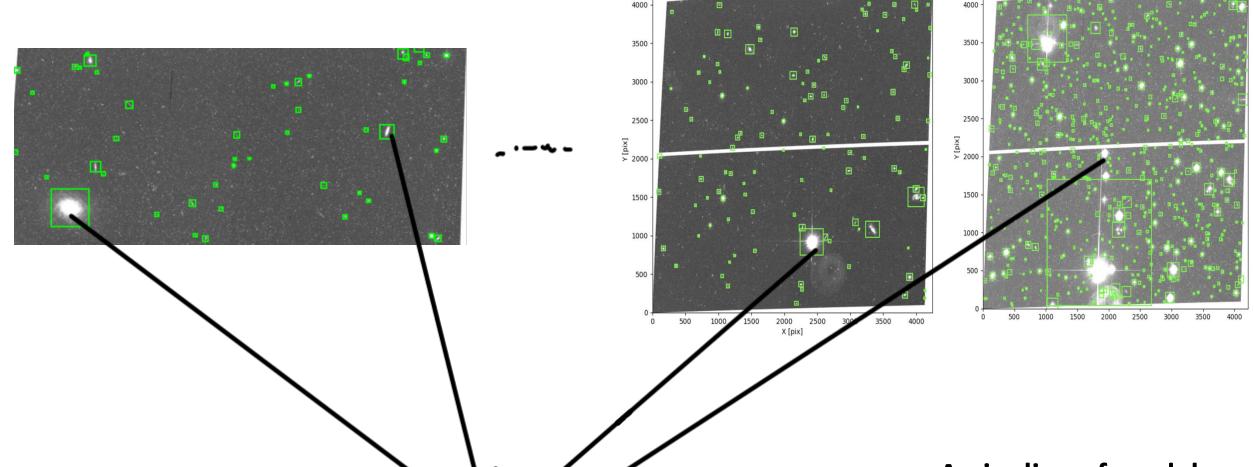
Received 2021 January 19; revised 2021 February 21; accepted 2021 February 26; published 2021 April 19

#### Abstract

We have developed a method that maps large astronomical images onto a two-dimensional map and clusters them. A combination of various state-of-the-art machine-learning algorithms is used to develop a fully unsupervised image-quality assessment and clustering system. Our pipeline consists of a data pre-processing step where individual image objects are identified in a large astronomical image and converted to smaller pixel images. This data is then fed to a deep convolutional auto-encoder jointly trained with a self-organizing map (SOM). This part can be used as a recommendation system. The resulting output is eventually mapped onto a two-dimensional grid using a second, deep, SOM. We use data taken from ground-based telescopes and, as a case study, compare the system's ability and performance with the results obtained by supervised methods presented by Teimoorinia et al. The availability of target labels in this data allowed for a comprehensive performance comparison between our unsupervised and supervised methods. In addition to image-quality assessments performed in this project, our method can have various other applications. For example, it can help experts label images in a considerably shorter time with minimum human intervention. It can also be used as a content-based recommendation system capable of filtering images based on the desired content.

Unified Astronomy Thesaurus concepts: Astronomy data analysis (1858); Astronomy data modeling (1859)

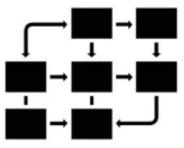
We addressed the problem during the 2020 pandemic, but we couldn't implement it. We use deep learning and self-organizing maps to show the method. The idea is more or less the same, but we use more advanced models and no Self-Organizing Map in the new work.

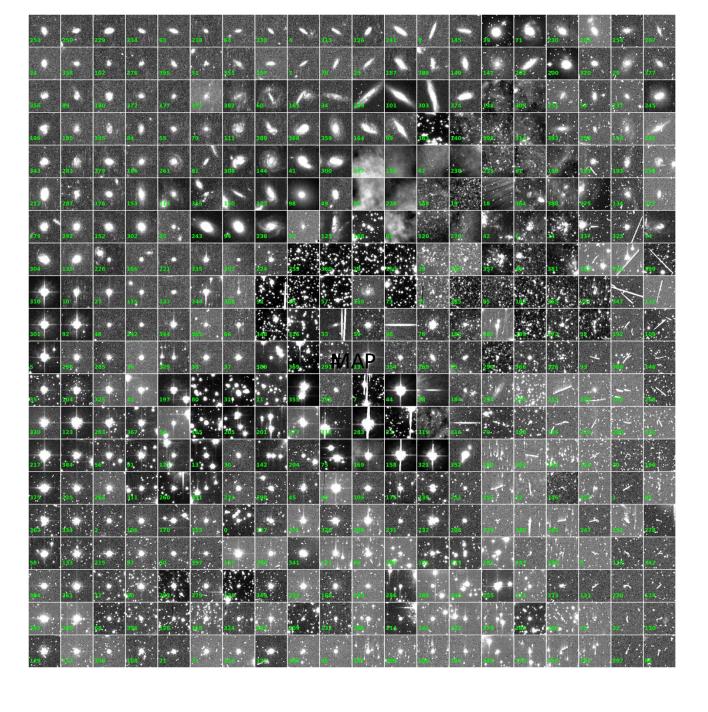


The main idea is simple: focus on detectable objects within images. Cut them out, gather them in one place, and use a pipeline of models to analyze and organize these cutouts

4,000,000 random cutouts from 20000 random images

## A pipeline of models



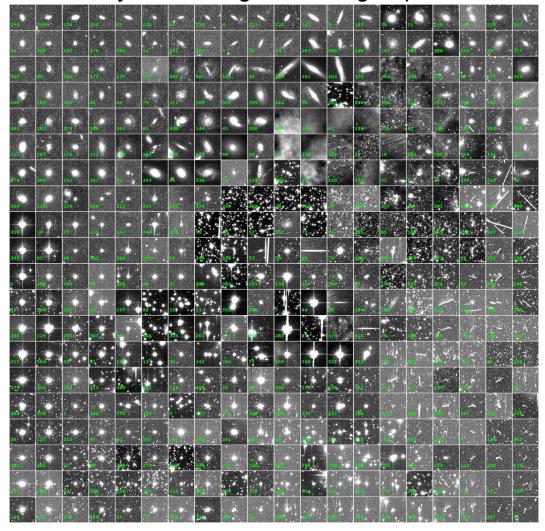


## MAP #1: the model #1, for finding the **objects** of interest

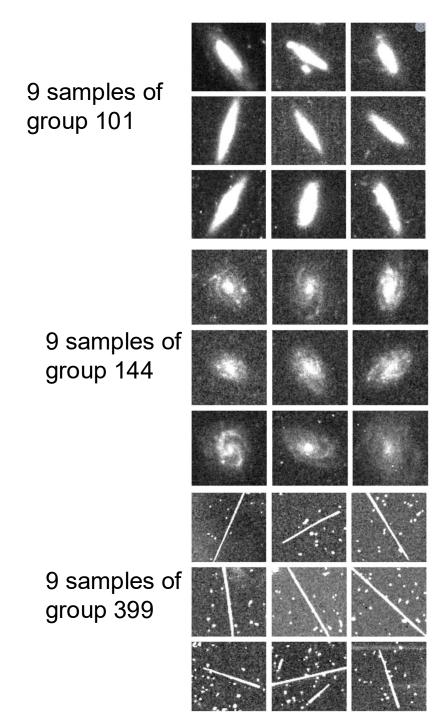
This slide shows the result of that pipeline. It arranges all the cutouts into a map with 400 nodes or groups. Each node represents a typical object type found in the survey. We call this Map 1.

Next, we need to verify the reliability of this map.

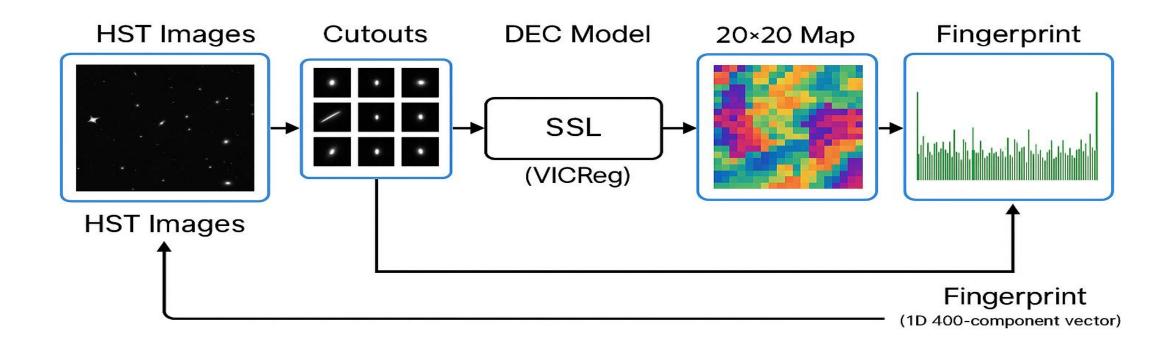
The model that can cluster detected objects in images in 400 groups



Once the model performs well, we can use it to create the content-based component required for CADC. Now, let's see how that content information is actually built.

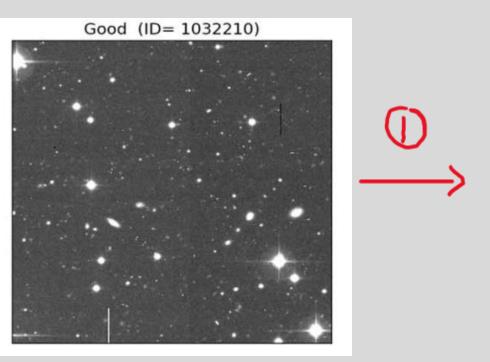


This slide shows how we create that content information. The cutout objects of an image are fed to the model, which produces a histogram or vector of 400 components. Each component represents the number of similar objects in a single node on Map 1. We call this vector the fingerprint, or FP, of an image.

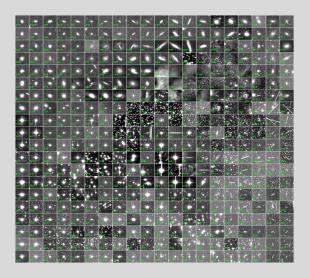


The two-dimensional distribution of objects (existing in the input image) on the model

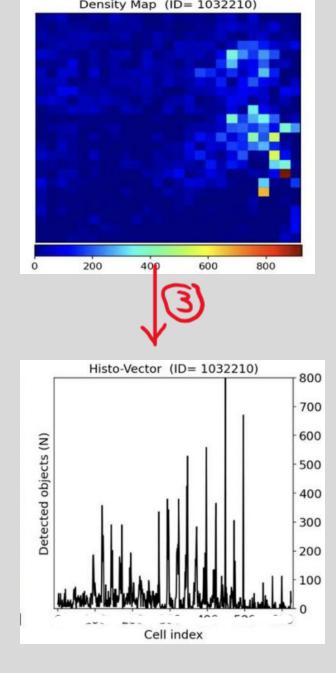




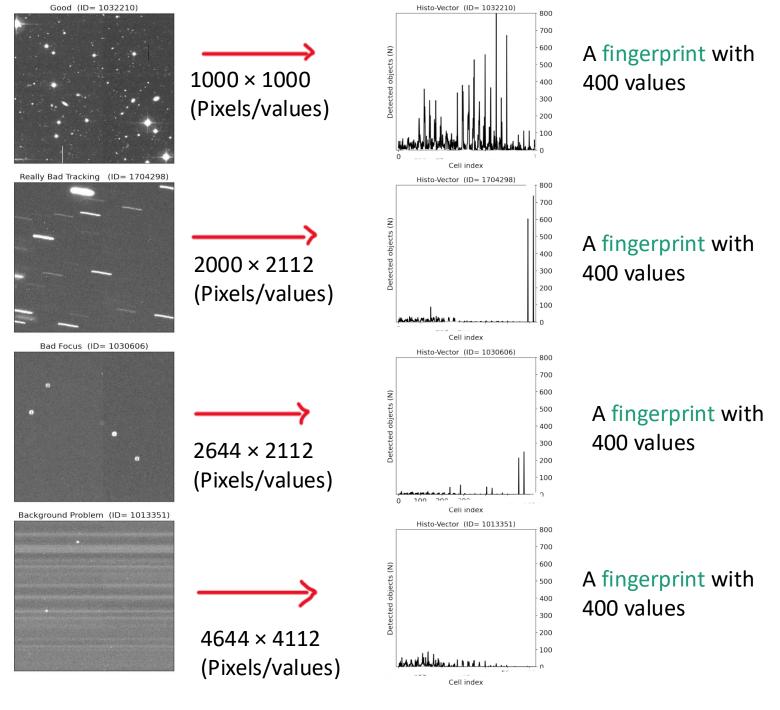
The input Image



The model



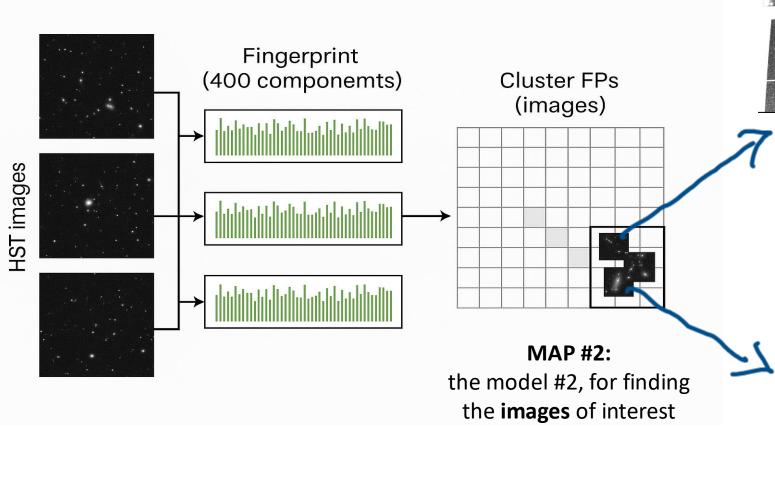
One dimensional distribution version (the fingerprint)

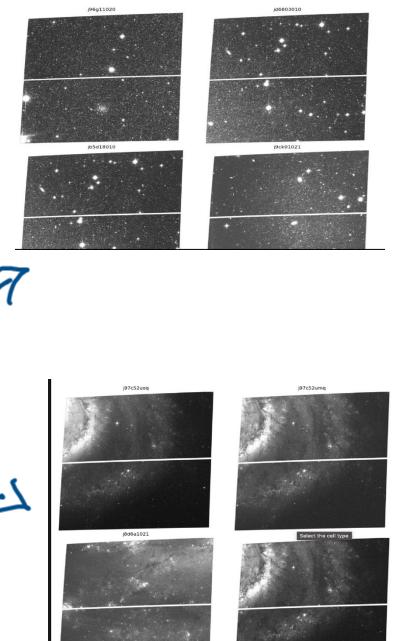


Fingerprints are tiny vectors, representing images that are ~ 10000 times smaller than the original.

This slide shows more examples, comparing fingerprints with their corresponding large images. No matter what the original image size is, each image is converted into a 400dimensional vector. These vectors are perfect for clustering in machine learning. We use them to build a second map, Map 2, where each node represents similar images.

Here you can see the clustering process. Similar fingerprints fall into the same node, so each node on Map 2 contains similar FPs, or equivalently, similar images. Now imagine using this in a large-scale search.

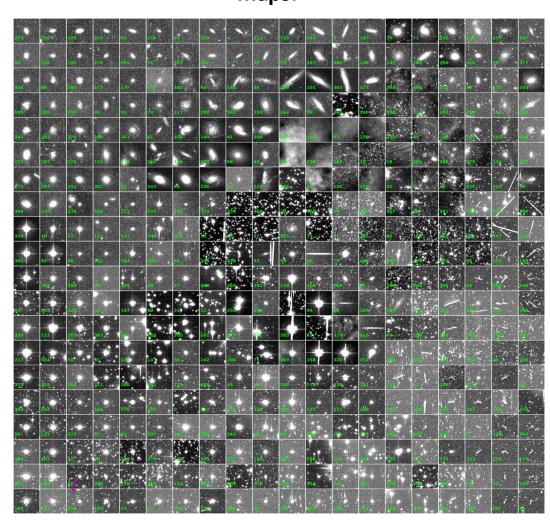




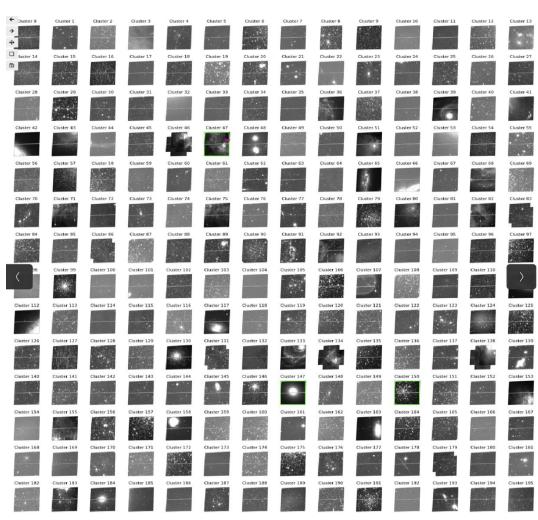
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		HST	CAL/STIS	ofdajos0q	ofdajos0q-CALIBRATED	03:52:25.98	+19:59:22.2	DARK	2025-10-23 06:48:	60.000	STIS/CCD	MIRVIS	2	IMAGIN
		HST	CAL/STIS	<u>ofdajorzq</u>	ofdajorzq-CALIBRATED	03:33:03.79	-02:48:02.0	DARK	2025-10-23 06:29:	1100.000	STIS/CCD	MIRVIS	2	IMAGIN
		HST	CAL/STIS	<u>ofdajnrrq</u>	ofdajnrrq-CALIBRATED	03:33:03.80	-02:48:02.2	DARK	2025-10-23 05:46:	60.000	STIS/CCD	MIRVIS	2	IMAGIN
		HST	CAL/STIS	<u>ofdajnrqq</u>	ofdajnrqq-CALIBRATED	03:33:03.80	-02:48:02.2	DARK	2025-10-23 05:45:	160.000	STIS/CCD	MIRVIS	2	IMAGIN
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	<u>Preview</u>	HST	CAL/ACS CAL/ACS	jdua09roq	jdua09roq-CALIBRATED	09:59:03.94	+01:55:05.7		2018-12-01 23:41:		ACS/WFC	CLEAR1L;F660N	2	INTERN
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		HST	CAL/ACS	idua10010	idua10011-CALIBRATED	09:59:01.38	+01:55:36.8		2018-12-02 02:49:			F775W;CLEAR2L	2	INTERN
	Preview	HST	CAL/ACS	idua04s6q	idua04s6q-CALIBRATED	09:59:03.97	+01:55:05.3		2018-12-02 01:07:		ACS/WFC	F550M;CLEAR2L	2	INTERN
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Imagine a massive search where you checkmark one image. All other similar images in the same node on Map 2 can be automatically selected. This makes large searches much easier to handle.

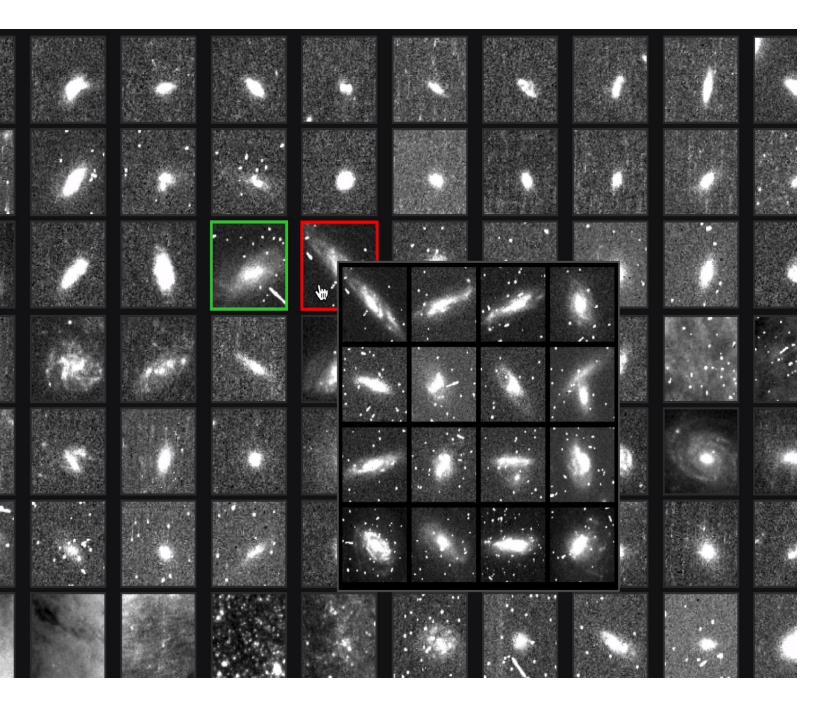
So now we have two maps to help download images:From Map 1, you can select objects that interest you, and from Map 2, you can select similar fields or images. To make it even more user-friendly, we built interactive versions of these maps.



MAP #1 for choosing the objects of interest



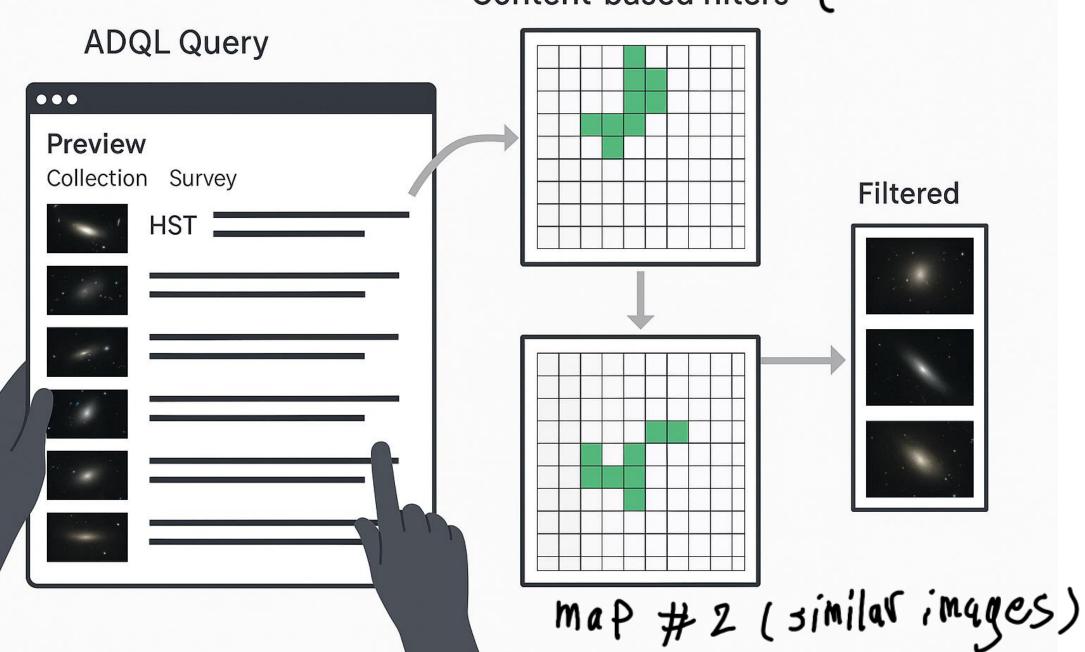
MAP #2 for choosing the images of interest



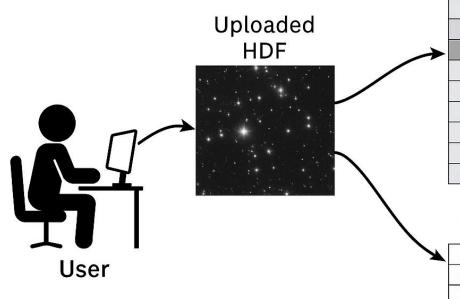
We created interactive maps that make this process simple. Users can hover over a node to see a sample of its content and statistics. You can include objects by marking nodes green, or exclude them by marking them red. Next, let's look at how all of this fits together in the full system.

**Interactive MAP 1** 

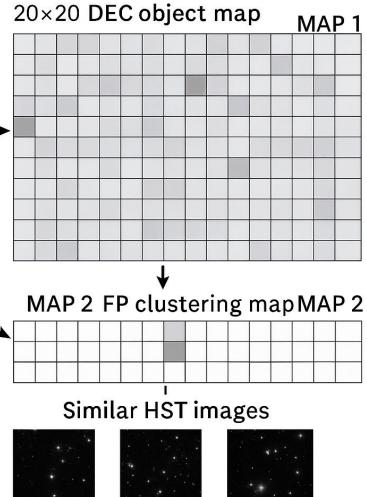
Shaylin Thahdani Shavon Thahdani (U of Ottawa) Map #1
Content-based filters (similar objects)

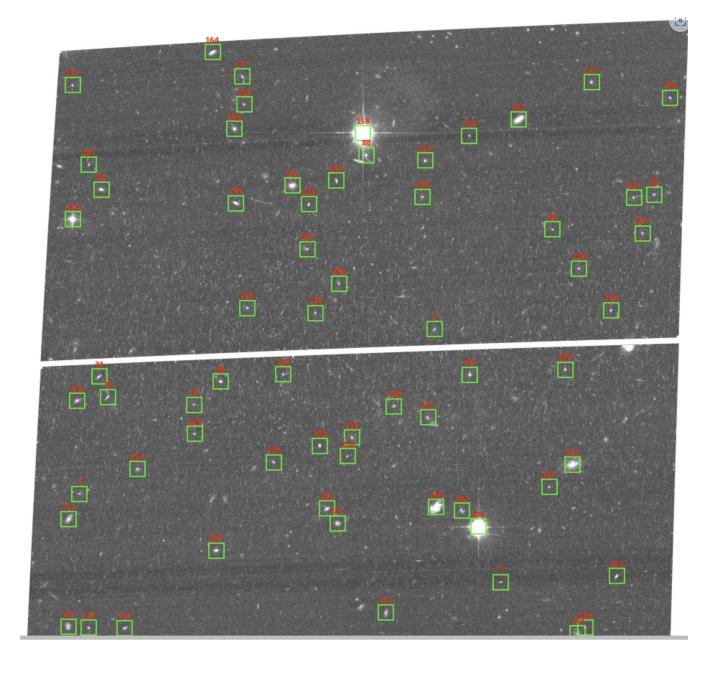


## Another application of it is to find similar images to those we have

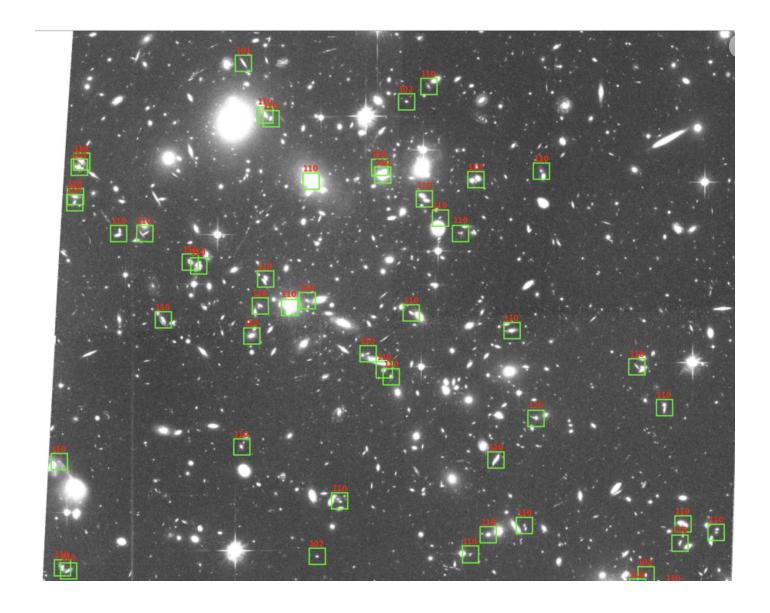


Also, a user can upload an image. The pipeline can create its fingerprint, which then falls into a node on Map 2. This allows the system to suggest similar images from the archive. It's a powerful potential application for future use.





The model can also annotate all detected objects in an image, assigning each one to its matching node on Map 1. This gives us automatic, large-scale labeling and classification. And we can even customize it for specific science goals.



Also, it can list images in a collection in CADC with a desired shape and character, such as mergers.

Pat (**Patrick Dowler** from CADC) can show you some examples of searches and the interactive maps, if you are interested.

## Thanks!