How to navigate through the ML research information flood

Dmytro Mishkin. Faculty of Electrical Engineering, CTU in Prague

CFNet: Learning Correlation Functions for One-Stage Panoptic Segmentation

Yifeng Chen, Wenqing Chu, Fangfang Wang, Ying Tai, Ran Yi, Zhenye Gan, Liang Yao, Chengjie Wa...

Recently, there is growing attention on one-stage panoptic segmentation methods which aim to segment instances and stuff jointly within a fully convolutional pipeline efficiently. However, most of the existing works directly feed the backbone features to various segmentation heads ignoring the demands for semantic and instance segmentation are different: The former needs semantic-level discriminative features, while the latter requires features to be distinguishable across instances. To alleviate this, we propose to first predict semantic-level and instance-level correlations among different locations that are utilized to enhance the backbone features, and then feed the improved discriminative features into the corresponding segmentation heads,

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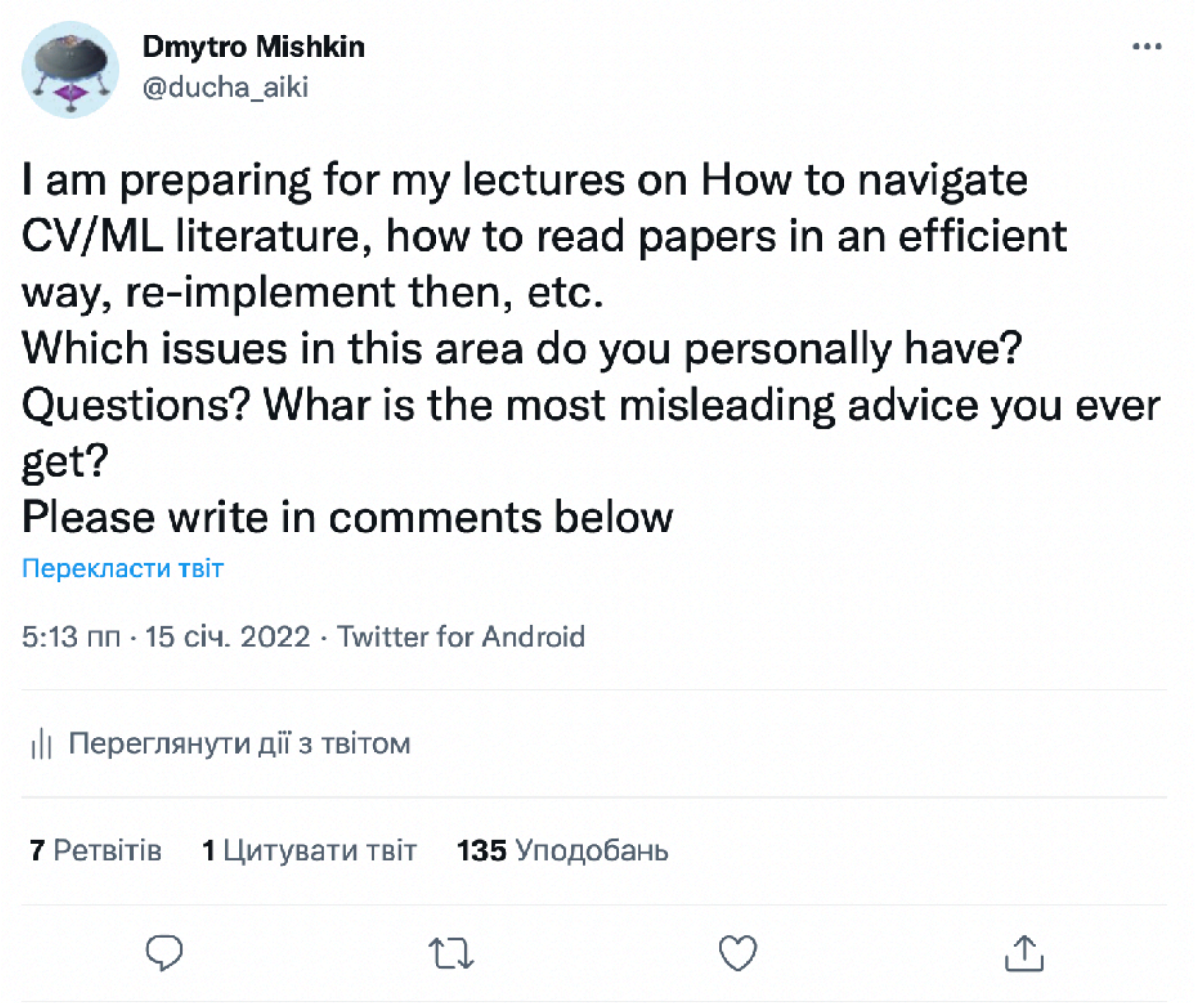

Dmytro Mishkin
@ducha_aiki

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Which issues in this area do you personally have? Questions? Whar is the most misleading advice you ever get?
Please write in comments below

Перекласти твіт

5:13 пп · 15 січ. 2022 · Twitter for Android

Переглянути дії з твітом

7 Ретвітів 1 Цитувати твіт 135 Уподобань

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Amy Tabb
@amy_tabb

У відповідь @ducha_aiki

Misleading advice: do *whatever* exactly the way someone else does it, whether it be read 10 papers a day, or none.

Your strategy should be allowed to change depending on the needs of the research problem, your own constraints & preferences, etc., and that's ok.

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1 Ретвіт 9 Уподобань

Foreword: trust noone in ML

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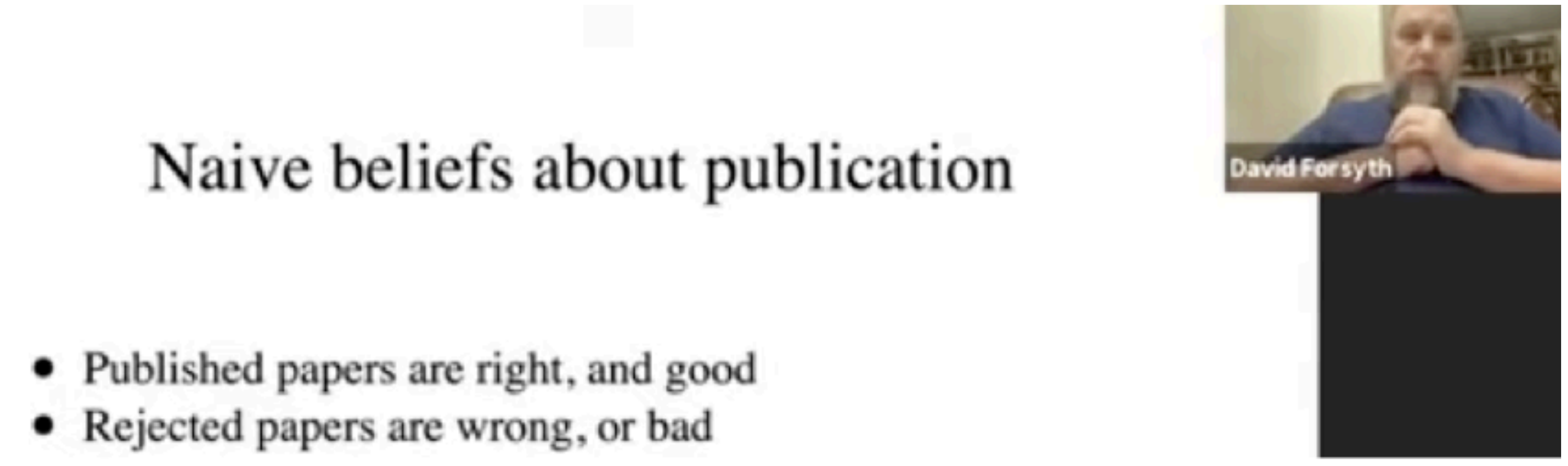

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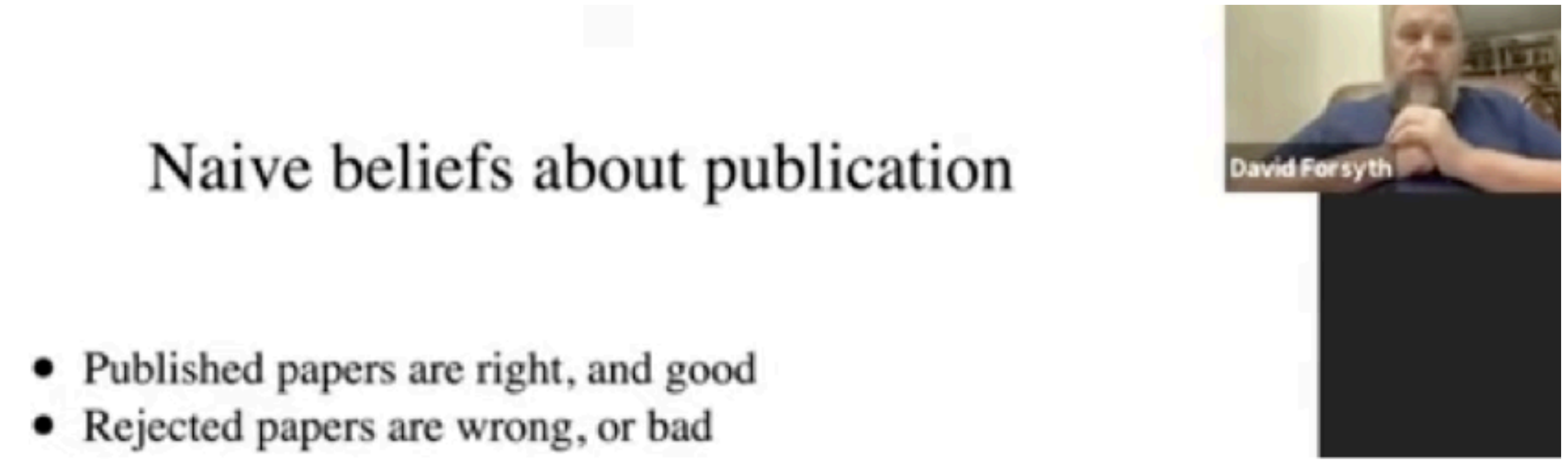
- OK, let's go



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What do I want to achieve?

Why do you need to read papers?

Use-cases

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Each of this cases requires a little bit different strategy

You are new to the field

and need to implement something ASAP (like, yesterday)

- That is really unfortunate situation.
- The only way to succeed is to be lucky and find ready implementation
- Check the following first:
  - Kaggle & DrivenData competitions
  - Papers With Code
  - fast.ai forums, pyimagesearch, etc.
  - Only then browse papers and github.

Kaggle

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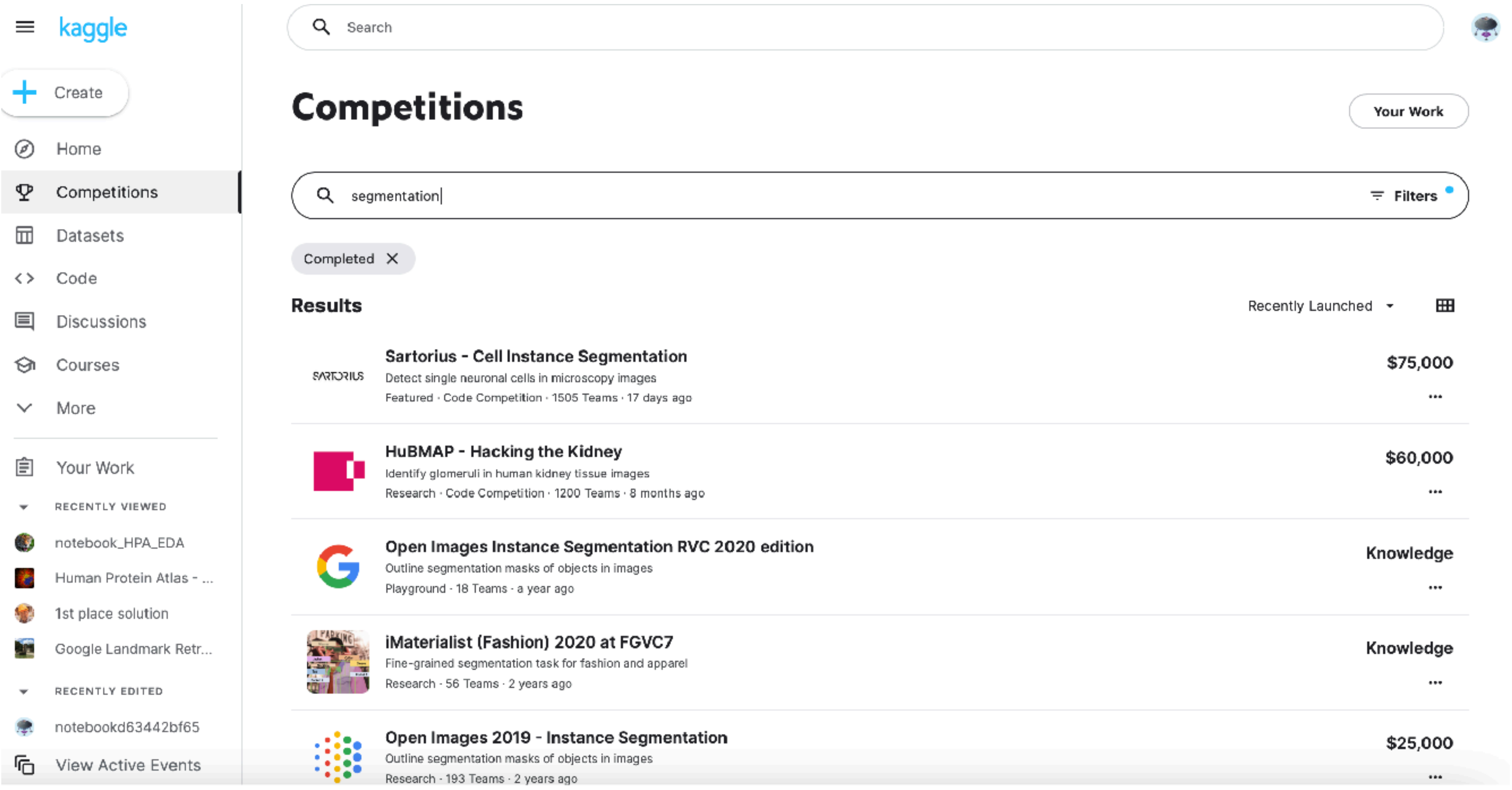

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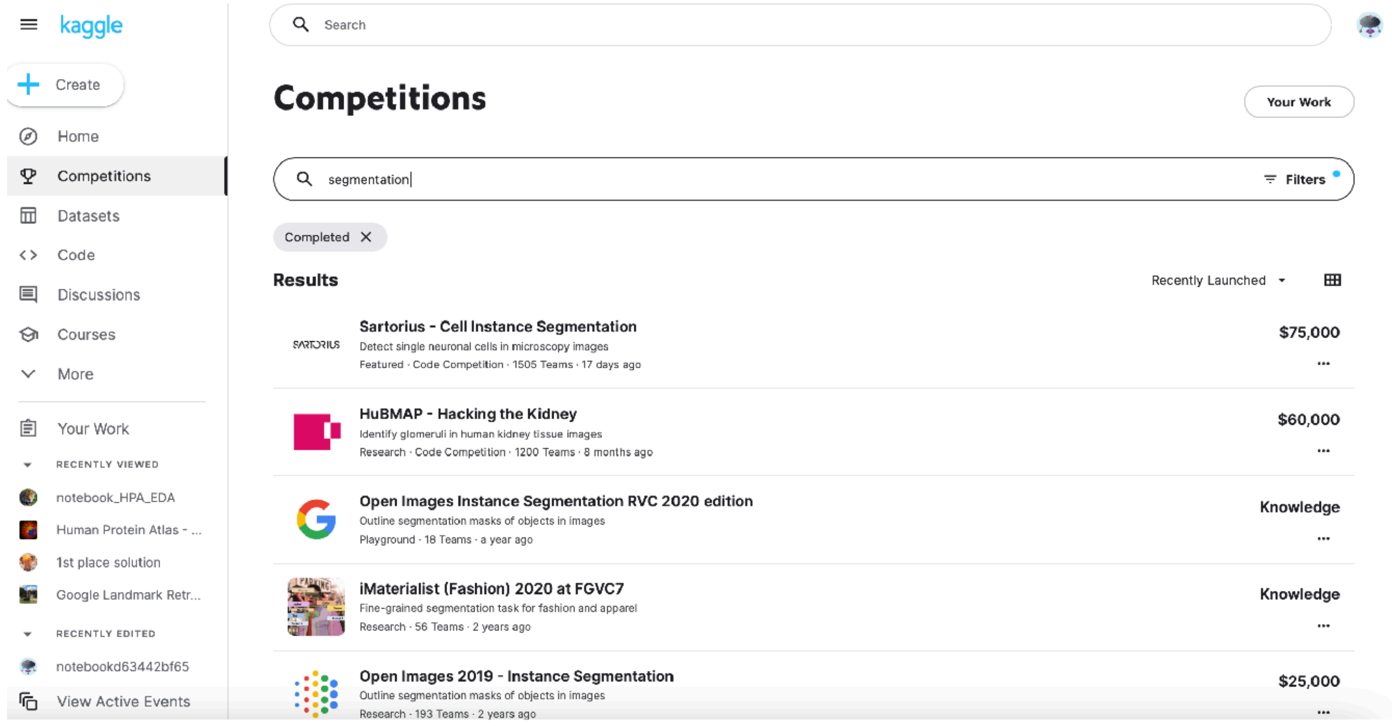

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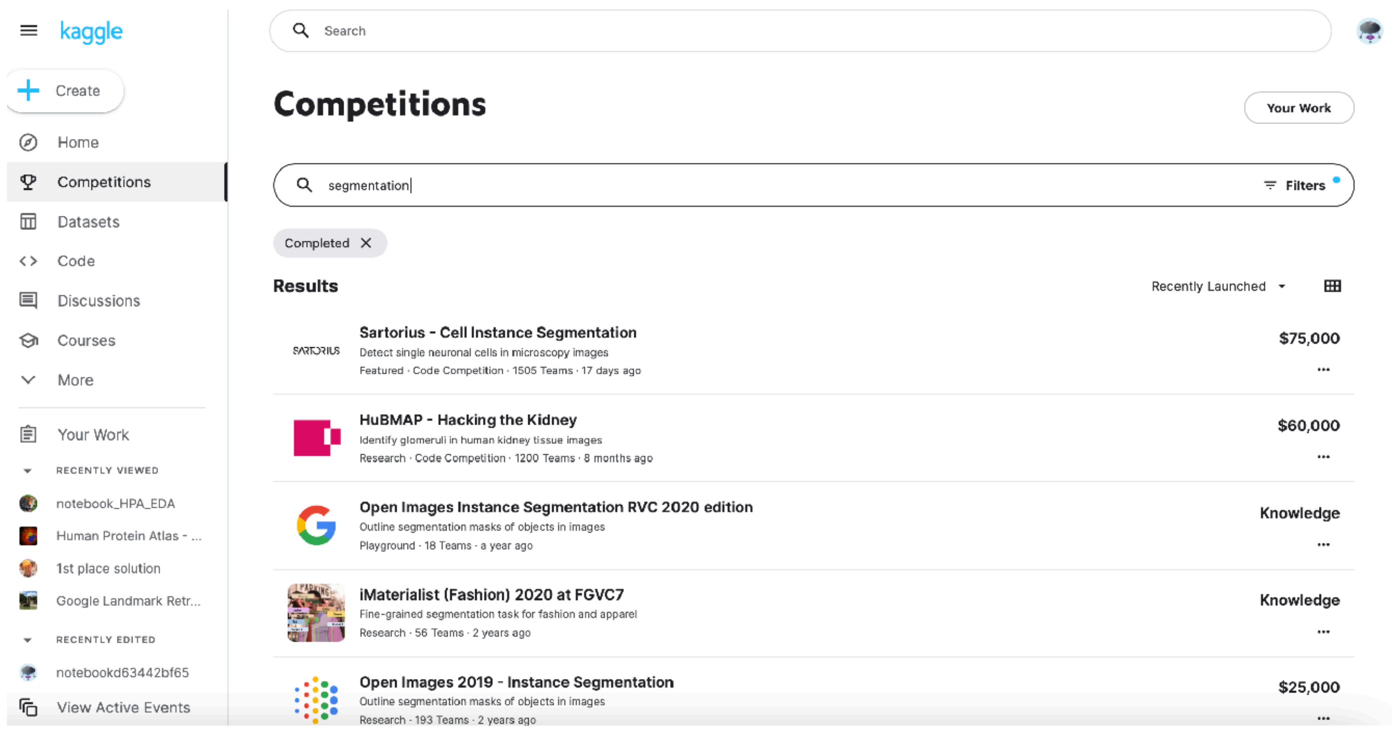

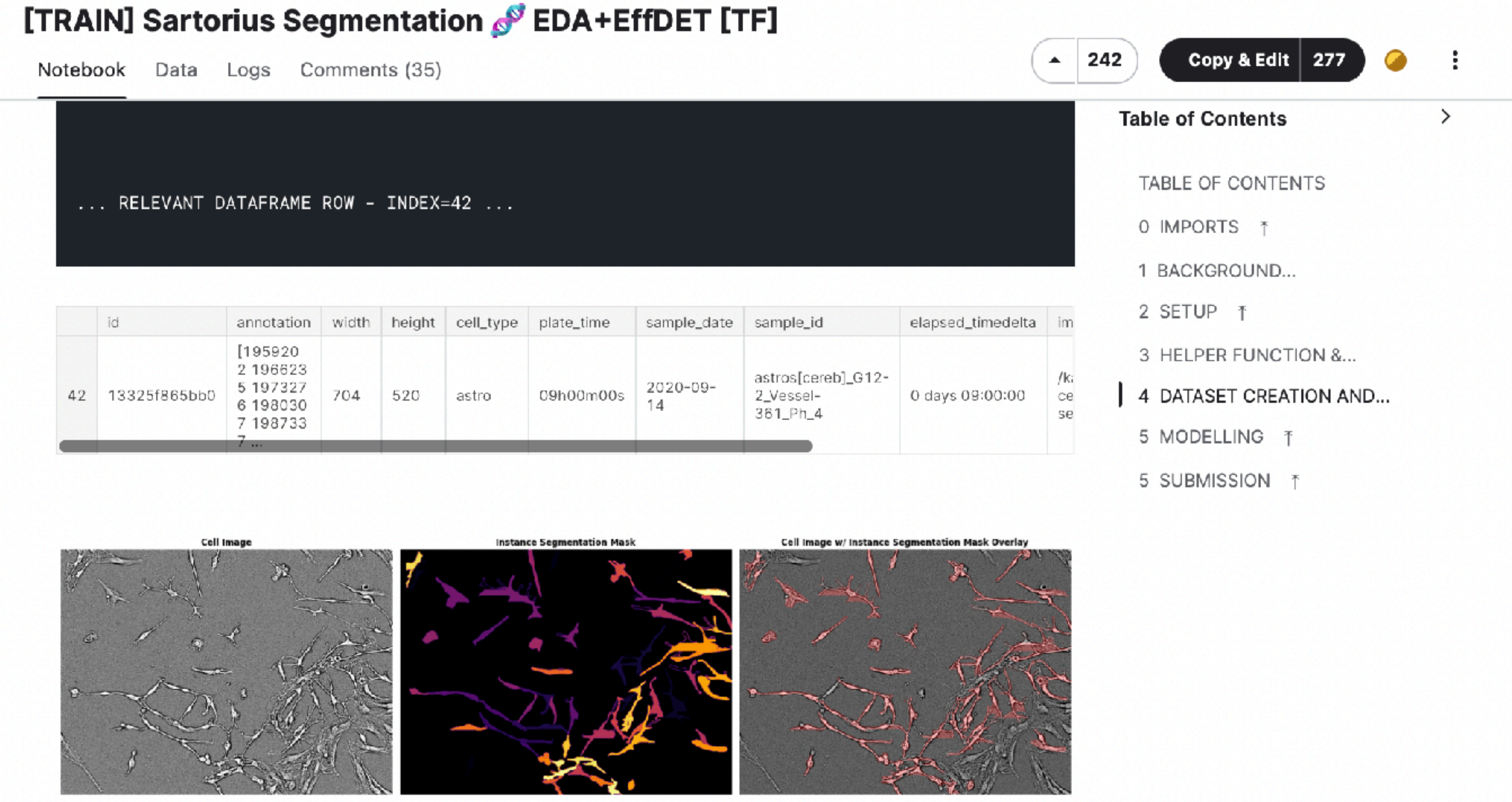

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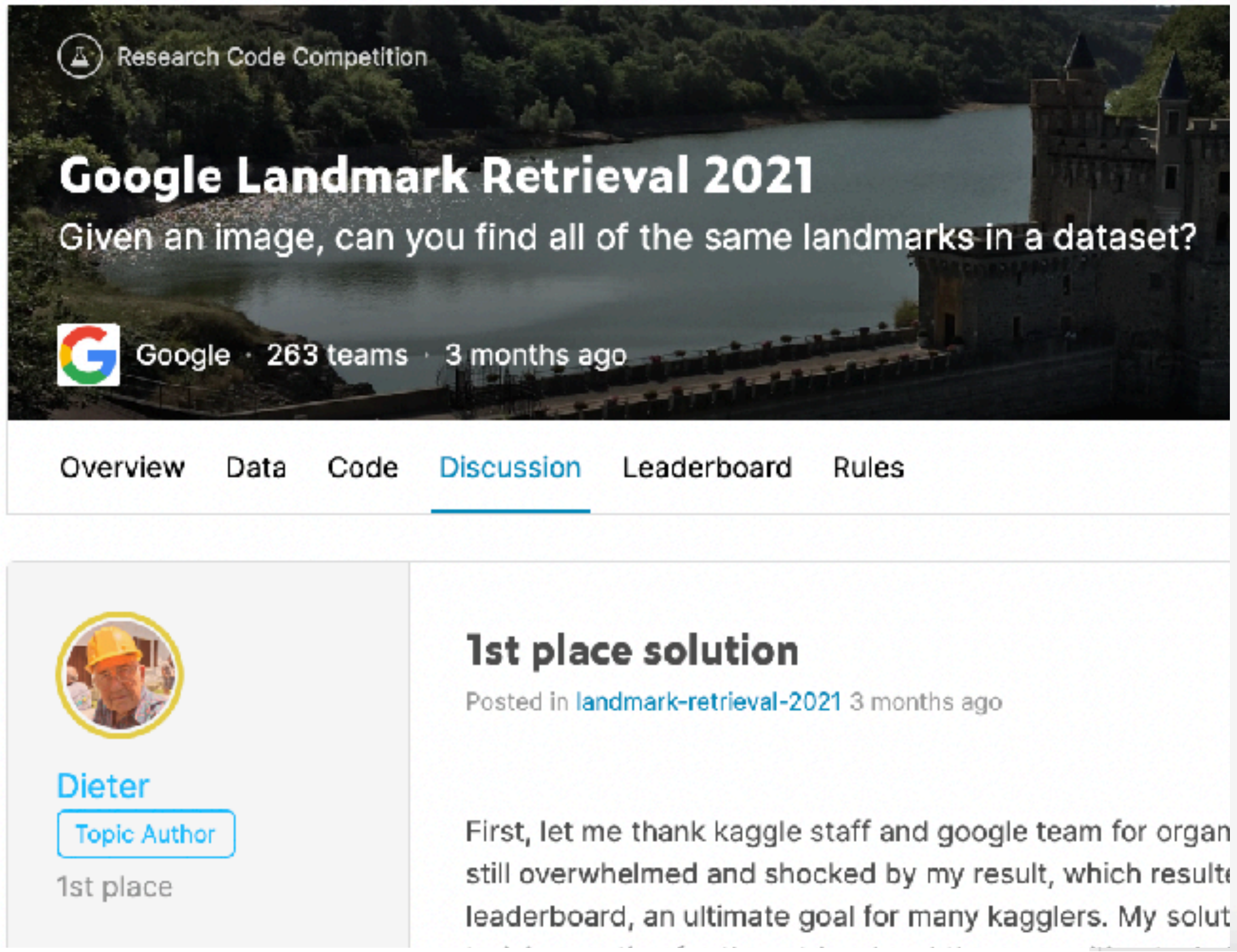
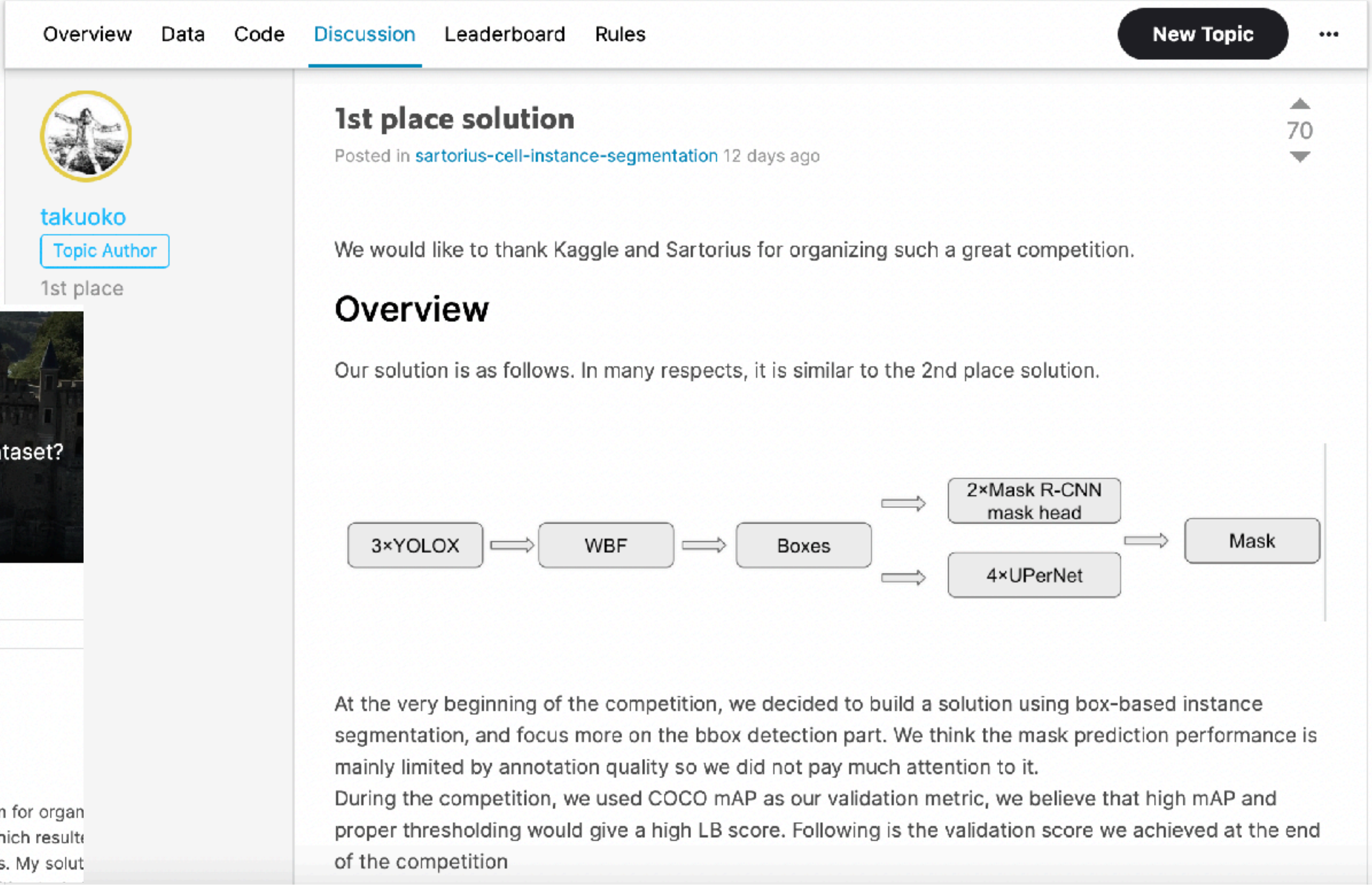
Kaggle

If task & competition is relevant to you, check solutions

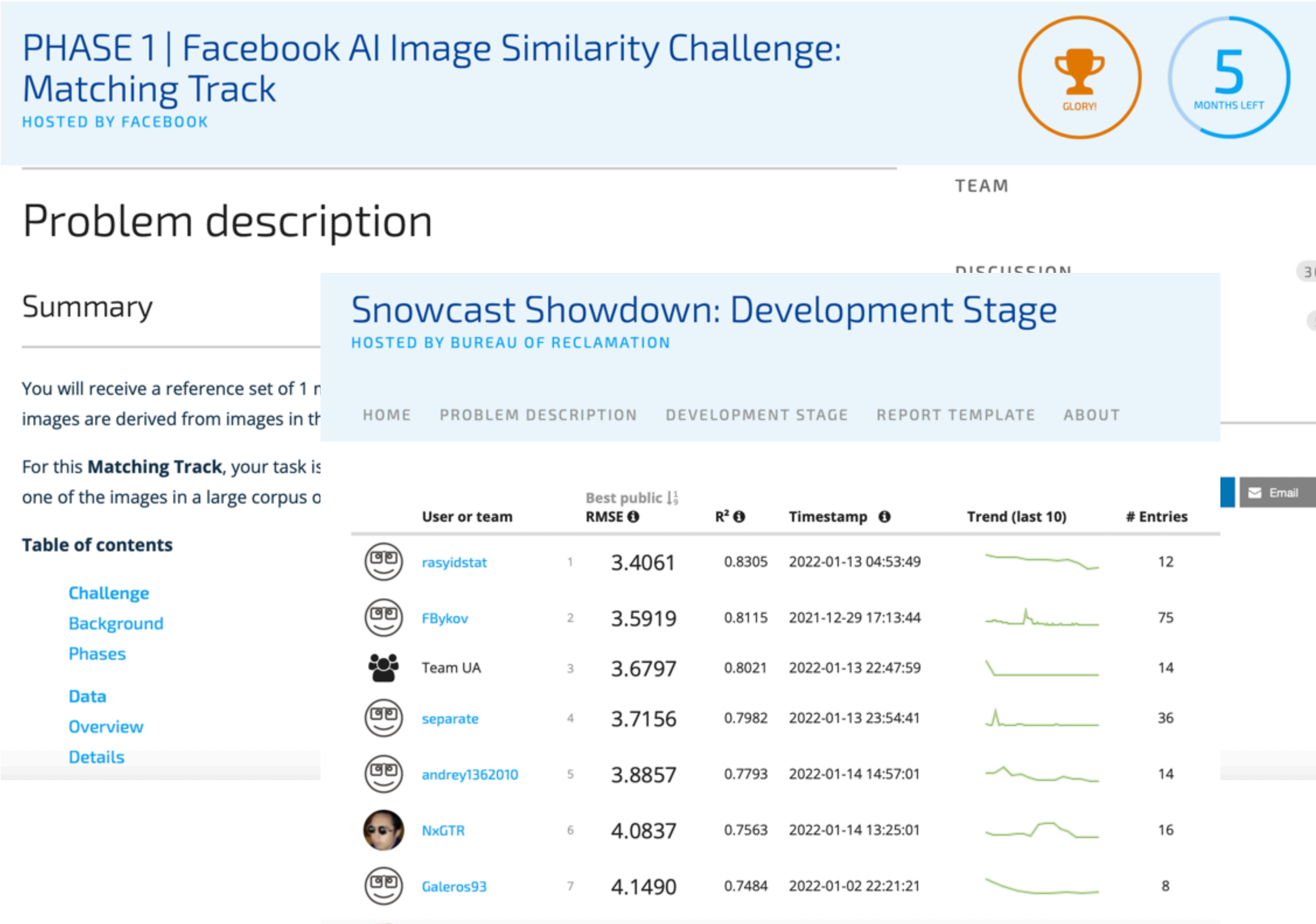
- Winning solutions
- Simple solutions





DrivenData

- Much smaller community than Kaggle, with much less forum life
- But contains some unique challenges



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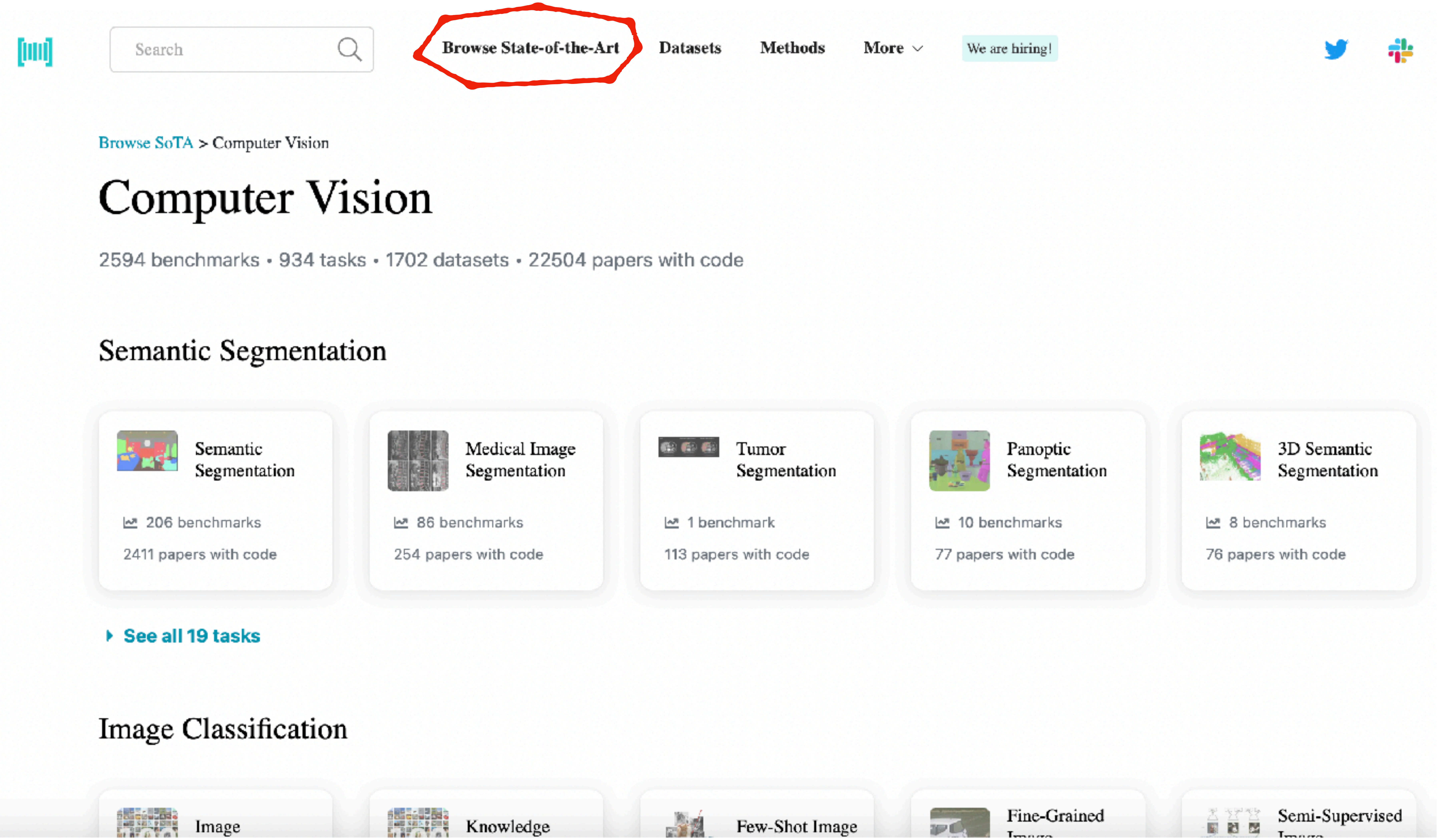
Papers With Code



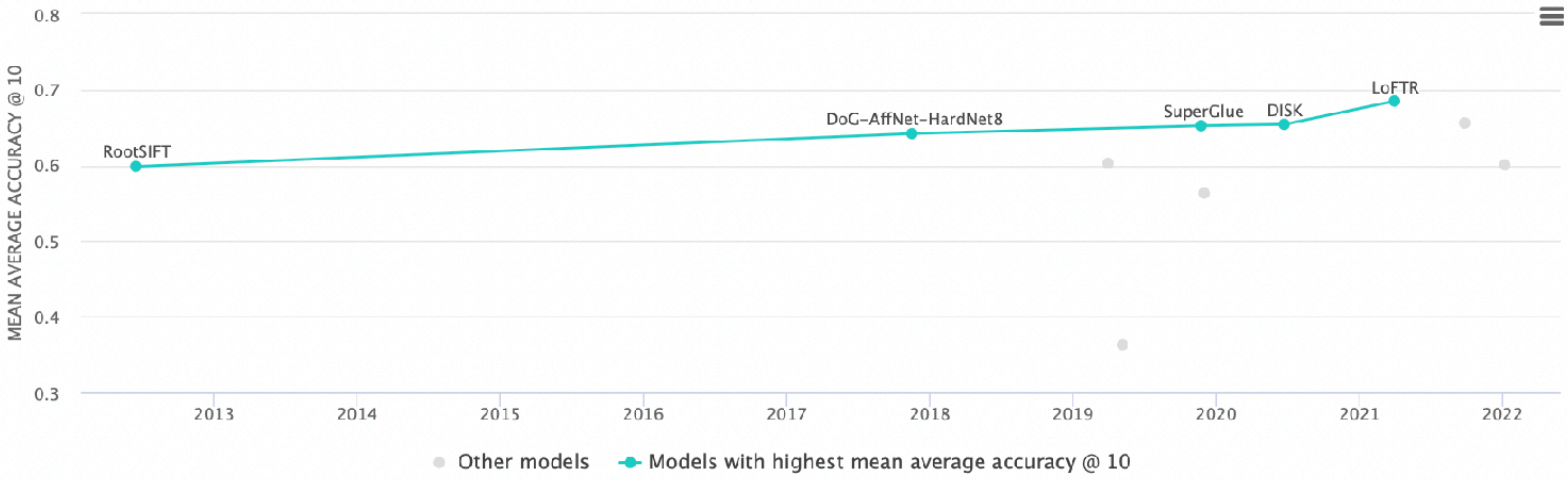
Papers With Code

Caveat: sparsely populated

Image Matching on IMC PhotoTourism

Leaderboard Dataset

View mean average accuracy @ 10 by Date for All models



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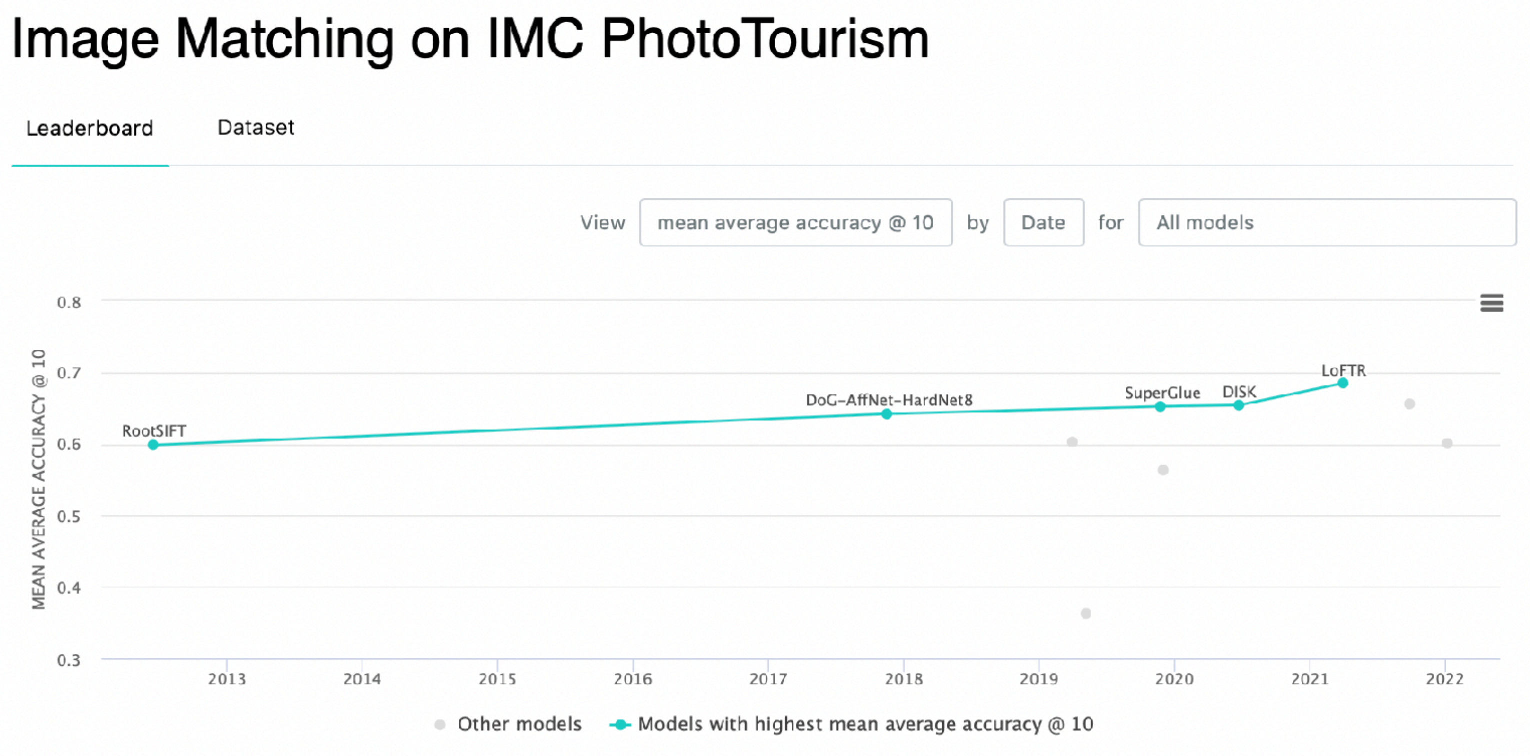

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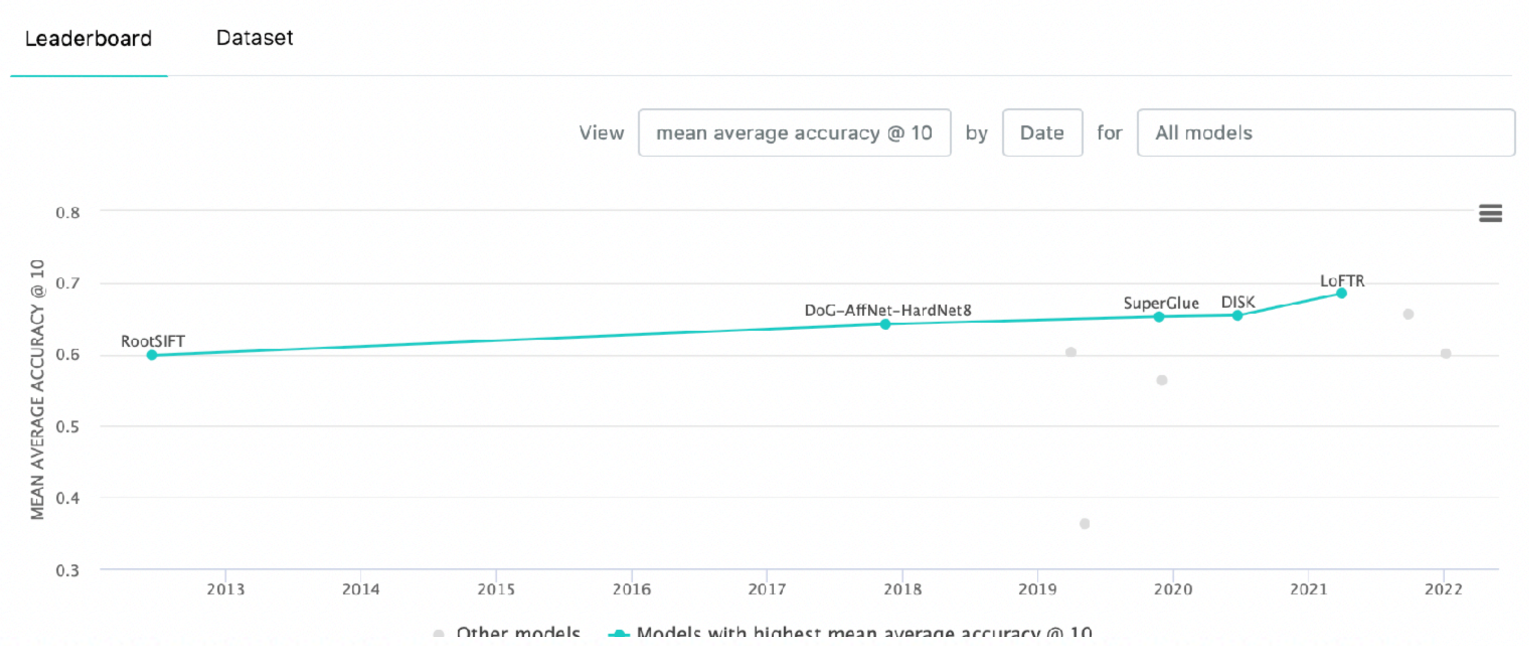

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1	**LoFTR**	0.68503	✓	LoFTR: Detector-Free Local Feature Matching with Transformers			2021	
2	**HarrisZ improved, Blob DTM**	0.65606	✗	HarrisZ^{+}: Harris Corner Selection for Next-Gen Image Matching Pipelines			2021	
3	**DISK**	0.65435	✓	DISK: Learning local features with policy gradient			2020	
4	**SuperGlue**	0.65248	✓	SuperGlue: Learning Feature Matching with Graph Neural Networks			2019	
5	**DoG-AffNet-HardNet8**	0.64212	✓	Repeatability Is Not Enough: Learning Affine Regions via Discriminability			2017	
6	**Key.Net-SOSNet**	0.60285	✗	Key.Net: Keypoint Detection by Handcrafted and Learned CNN Filters			2019	
7	**PoSFeat**	0.60072	✗	Decoupling Makes Weakly Supervised Local Feature Better			2022	
8	**RootSIFT**	0.59859	✗	Three things everyone should know to improve object retrieval			2012	
9	**R2D2**	0.56345	✓	R2D2: Reliable and Repeatable Detector and Descriptor			2019	

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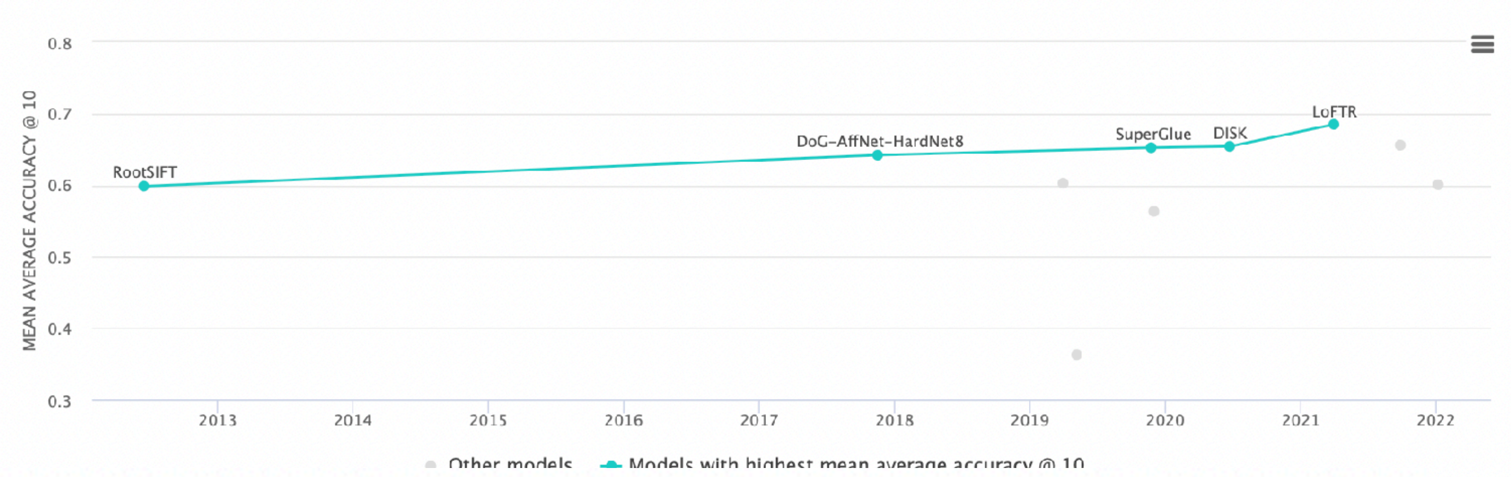

I have added this whole leaderboard

when preparing for this talk.

Before there was no leaderboard, and nobody checked it

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Methodology

Representation Learning

Edit

1643 papers with code • 2 benchmarks • 2 datasets

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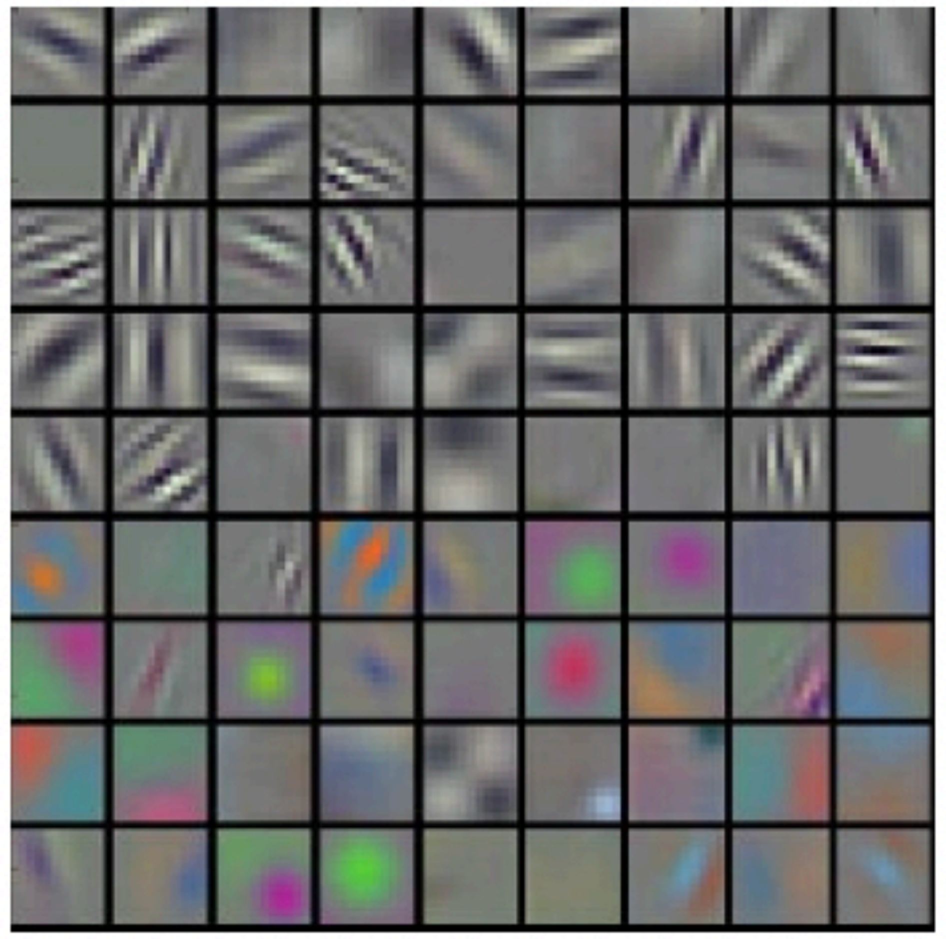

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Representation learning can be divided into:

- **Supervised representation learning**: learning representations on task A using annotated data and used to solve task B

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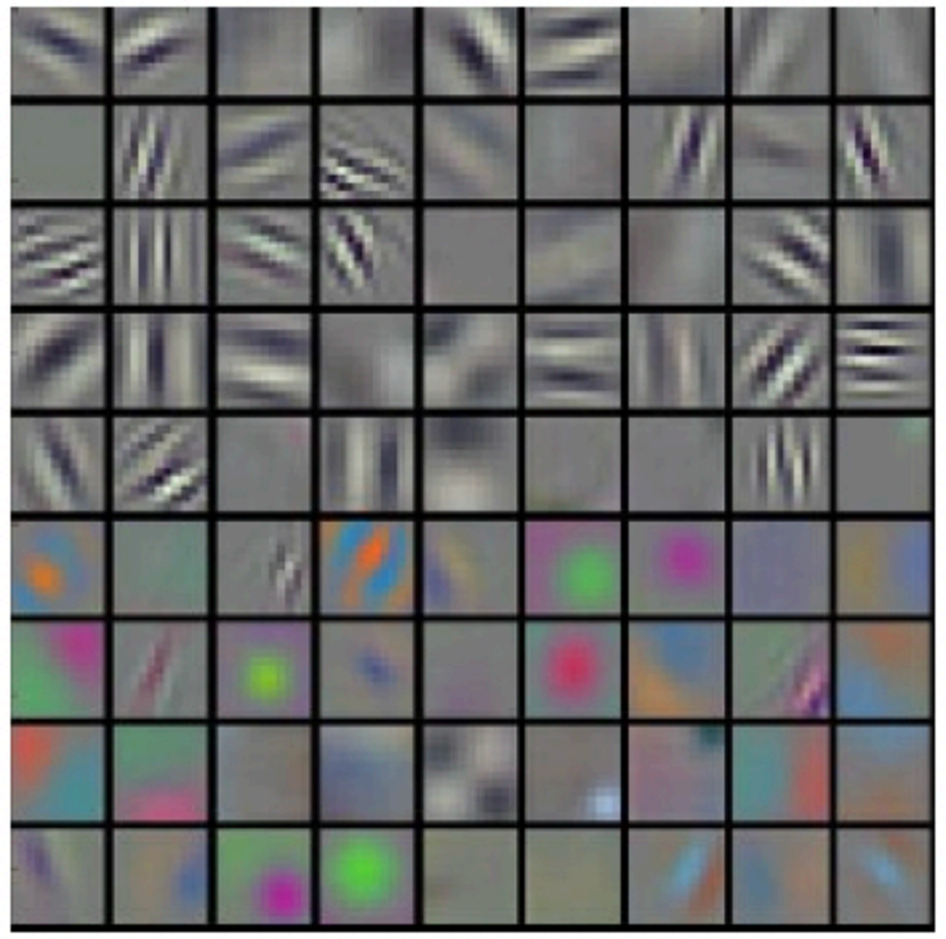

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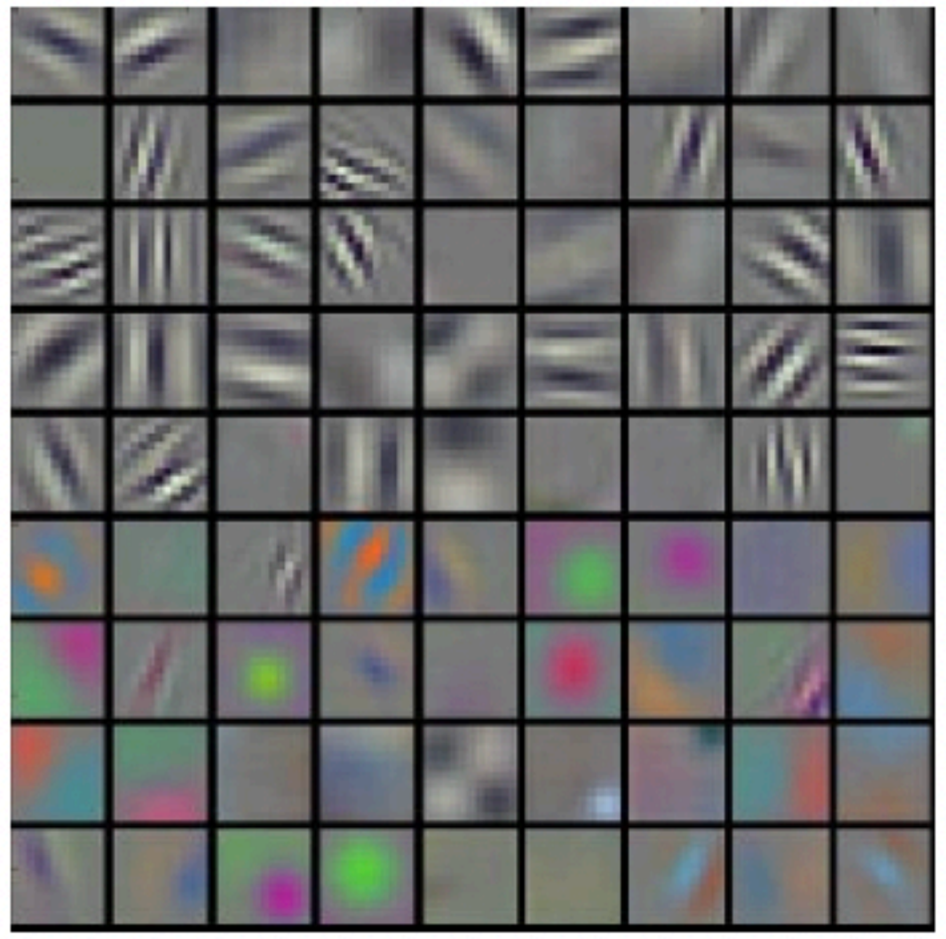

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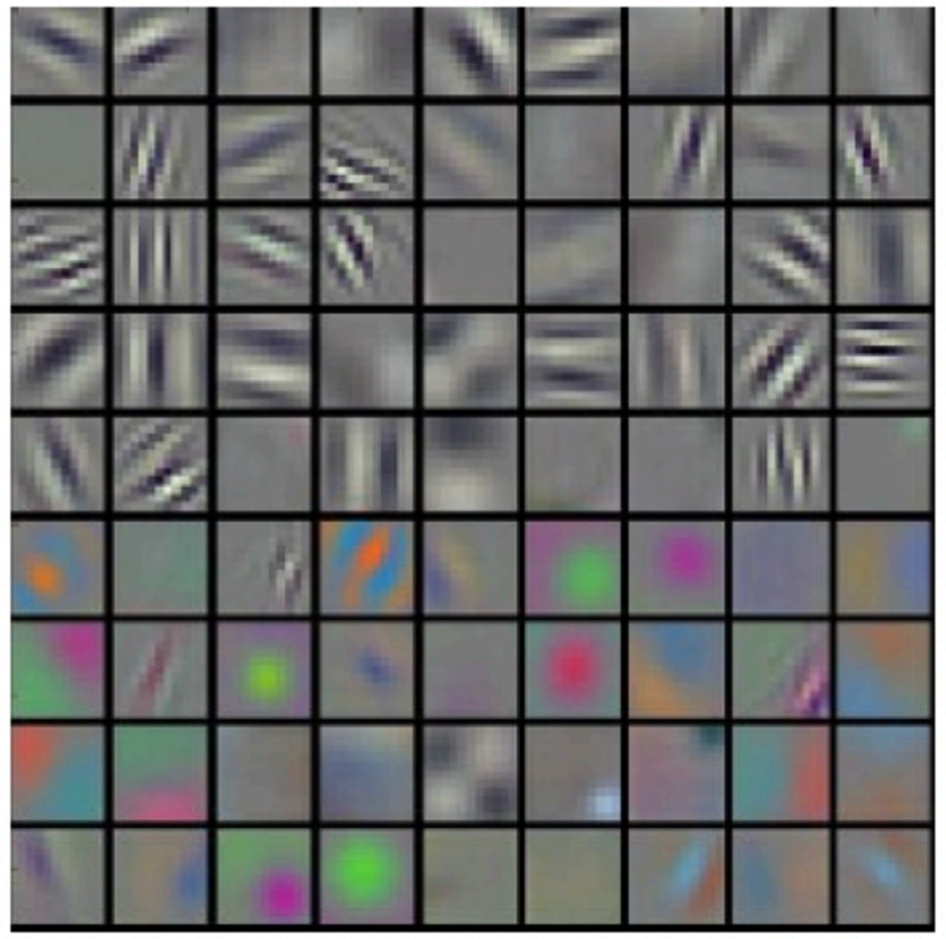

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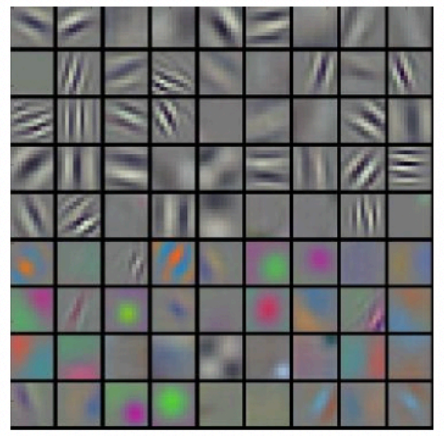

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Benchmarks

Add a Result

These leaderboards are used to track progress in Representation Learning

Trend	Dataset	Best Model	Paper	Code	Compare
	Circle Data	Morphological Network			See all
	Sports10	Max Margin Contrastive			See all

Papers With Code

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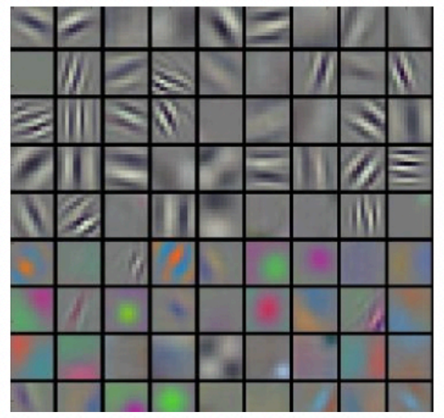

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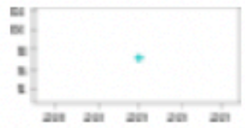	Circle Data	Morphological Network			See all
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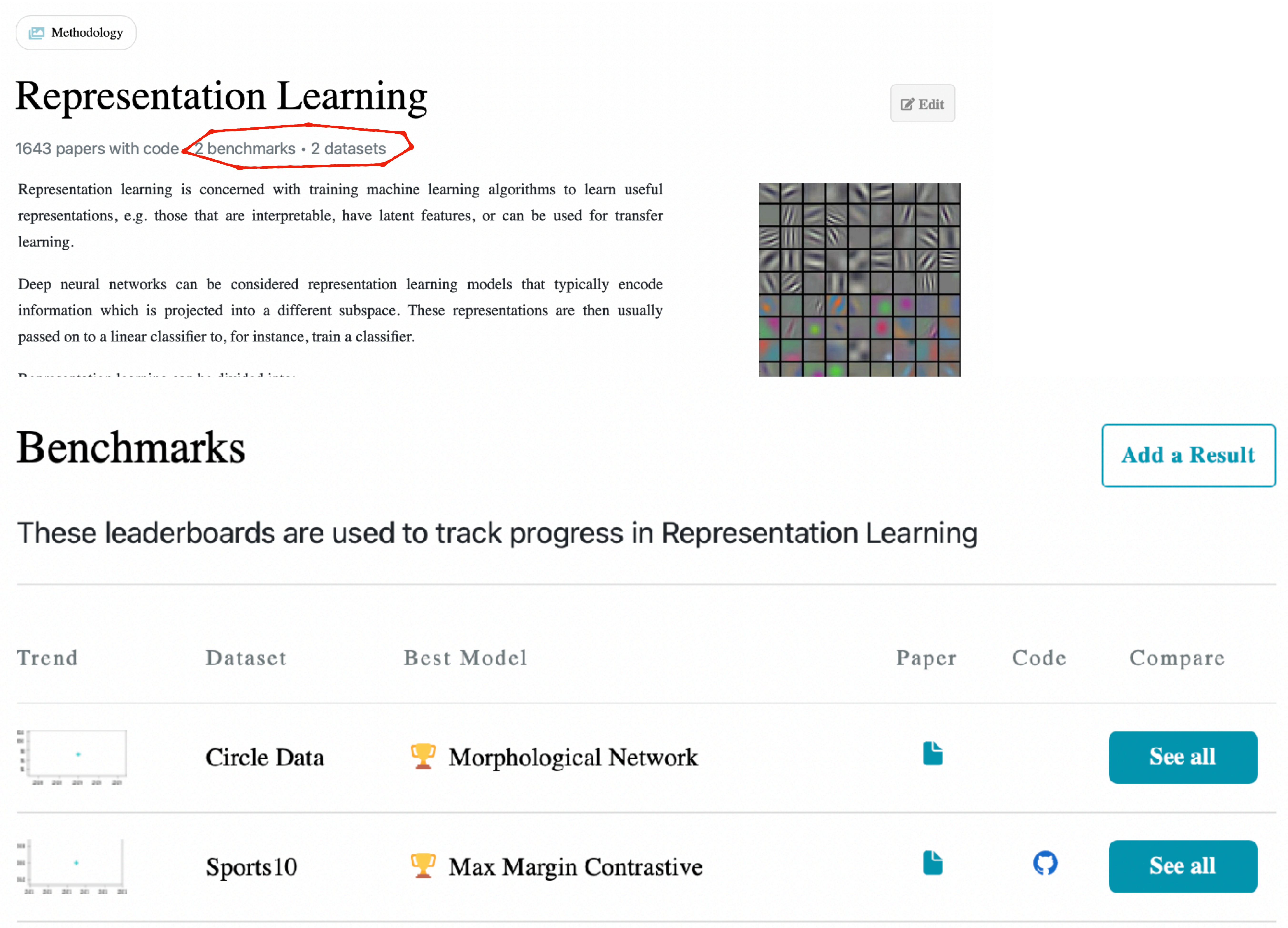

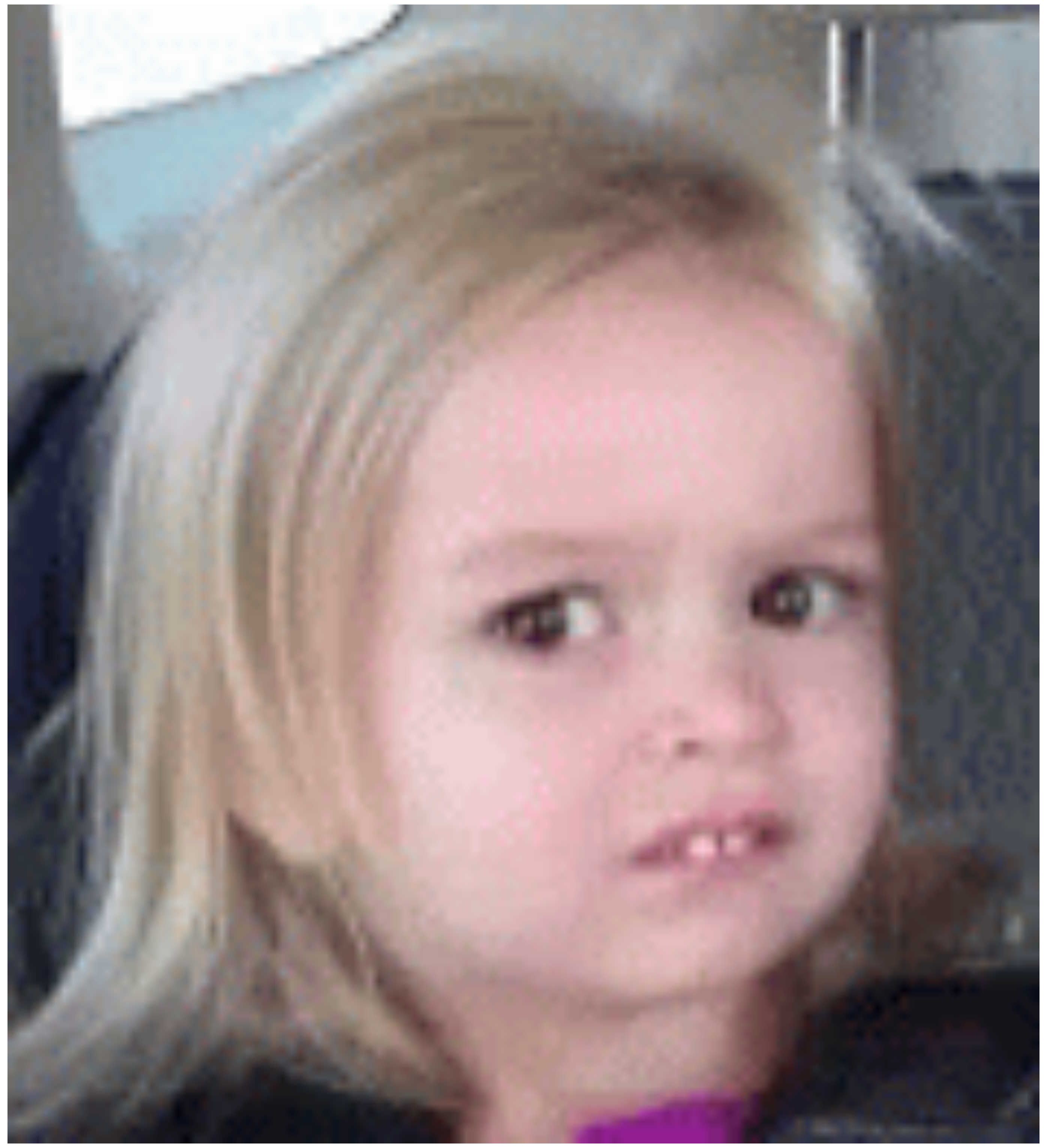

If both Kaggle & PapersWithCode fail

Then go to github + arXiv search

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- But that is later, now let’s assume you have some time…

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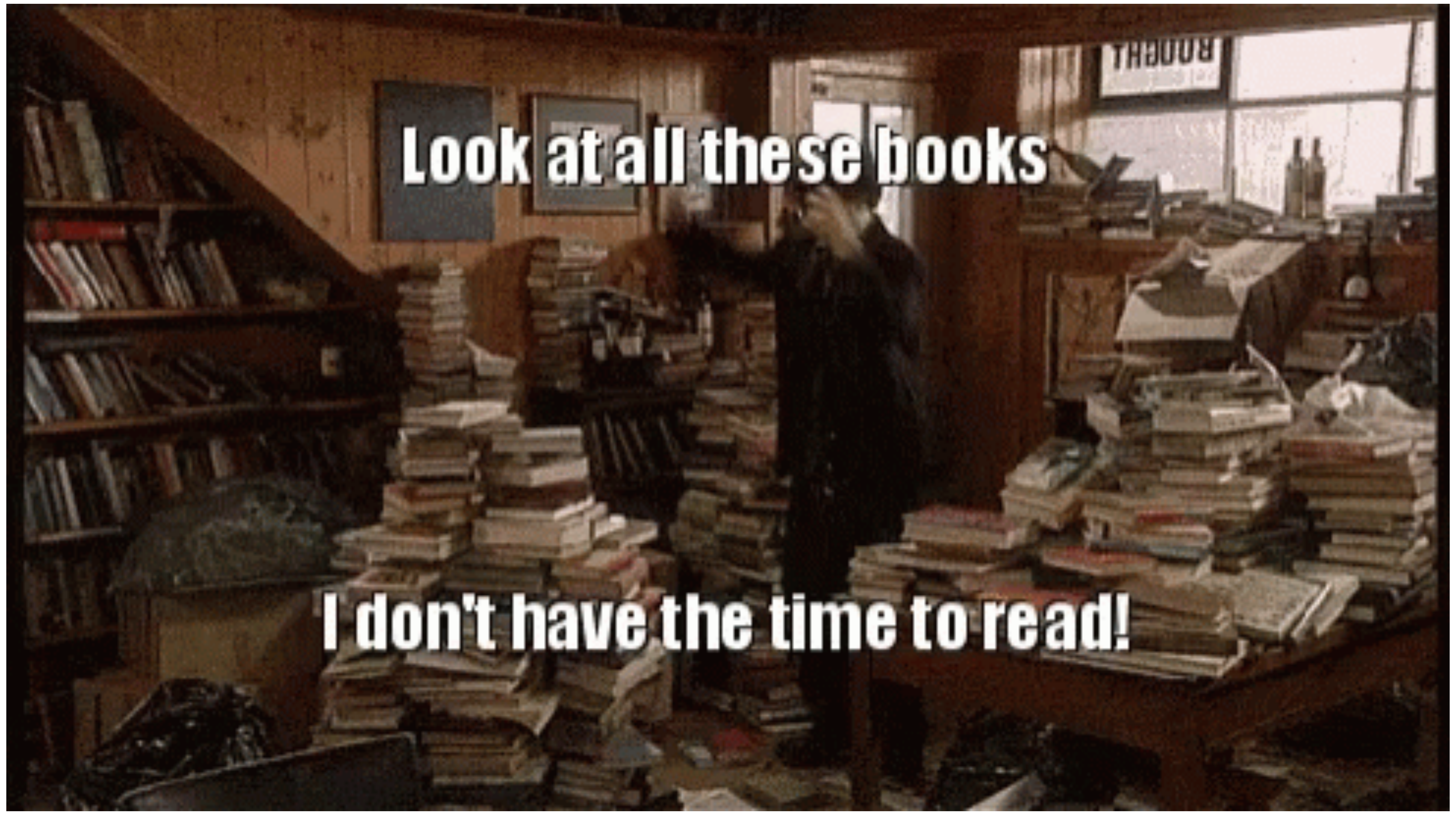

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- Starting with dataset to play with (see Kaggle, PapersWithCode) is also a good idea.
- Also a good idea is to start with a good benchmark paper
- Or a good survey paper
- But it is not always easy to find good survey paper, there many bad ones

How to spot good benchmark paper?

Citations

- It is used by community (unless it is just published 2 days ago), i.e. people cite it

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autor: F Radenović · 2018 · Počet citací tohoto článku: 203 — In this paper we address issues with image **retrieval** benchmarking on standard and popular **Oxford** 5k and **Paris** 6k datasets...

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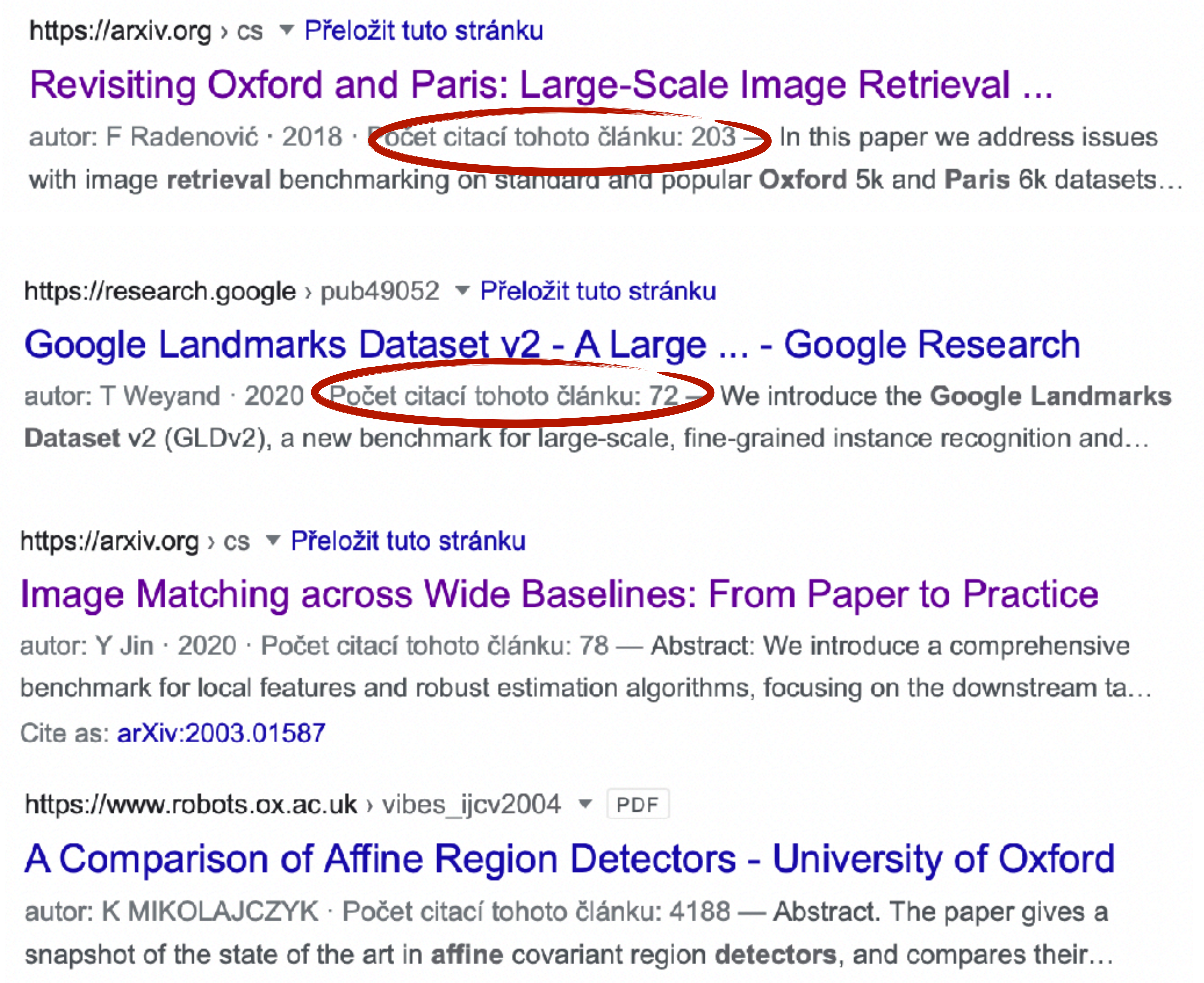

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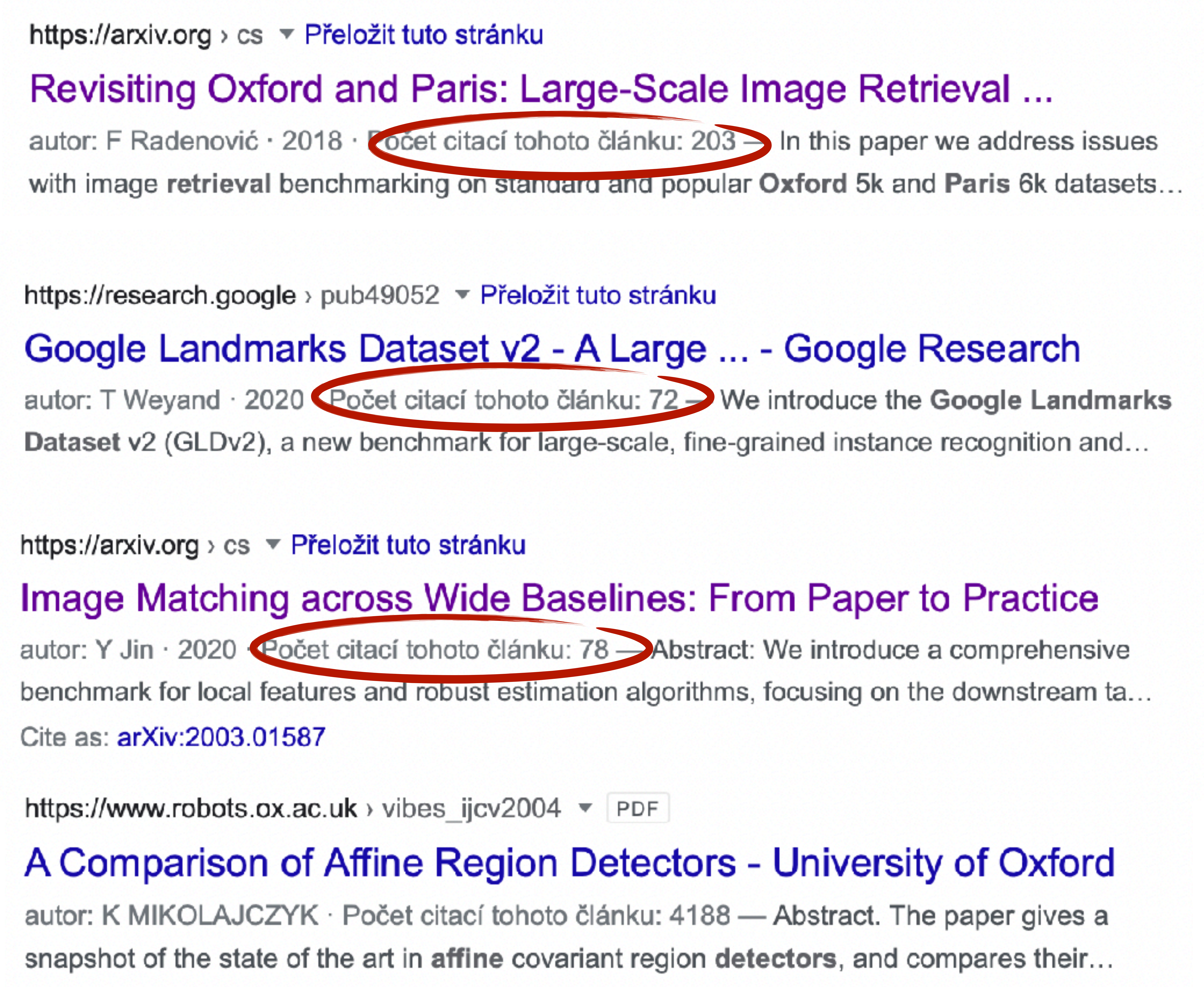

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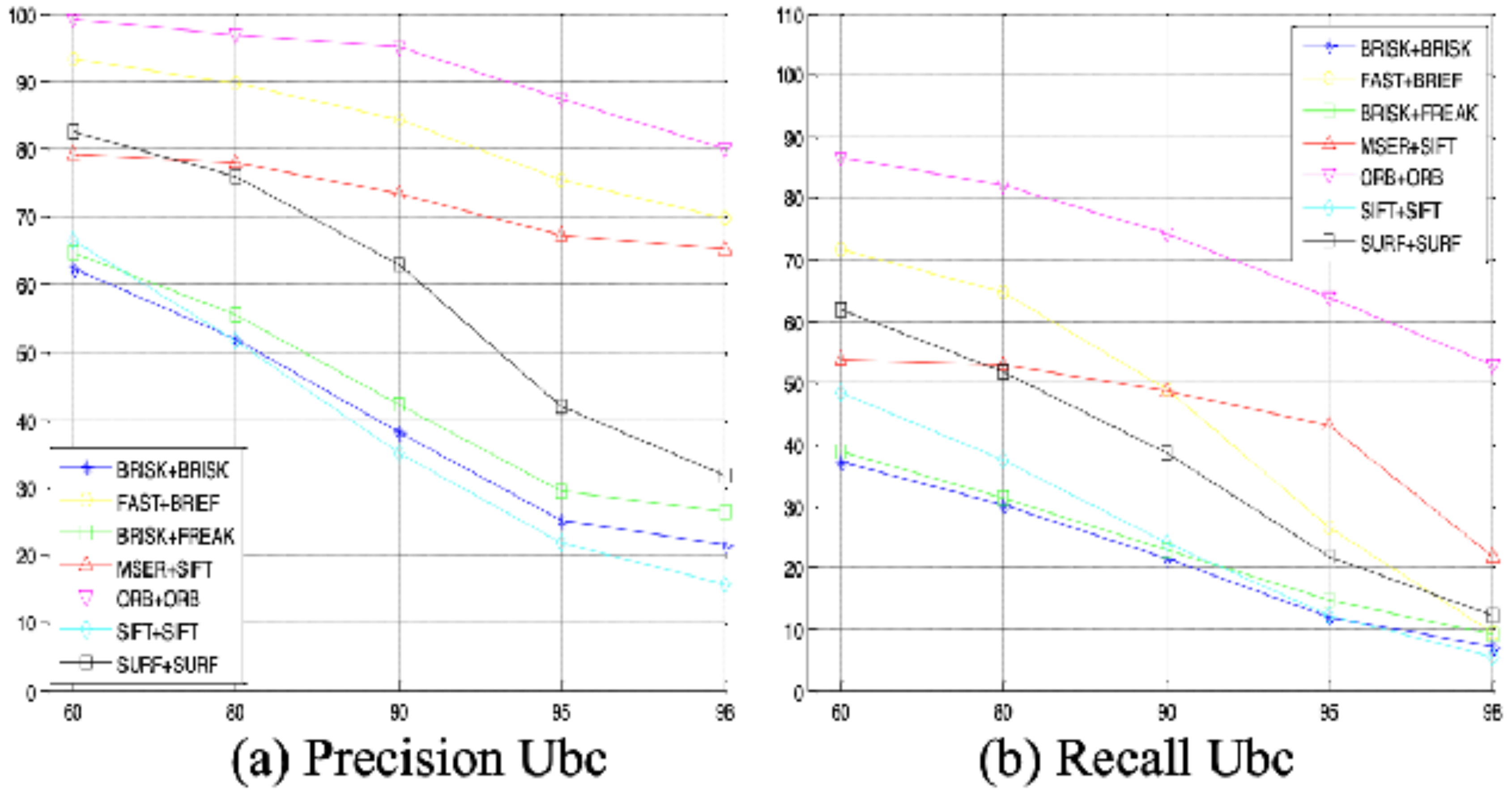

Figure 7: Precision and recall values for JPEG compression.

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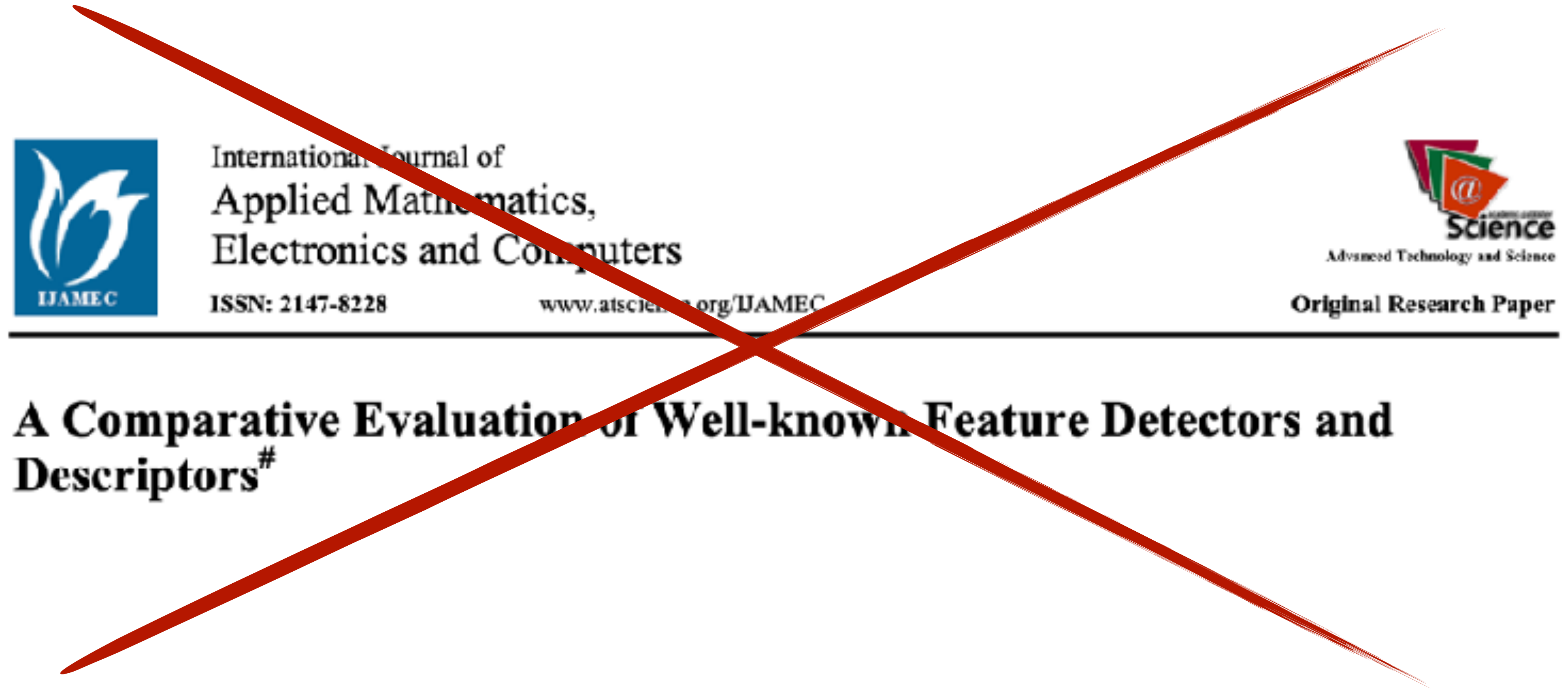

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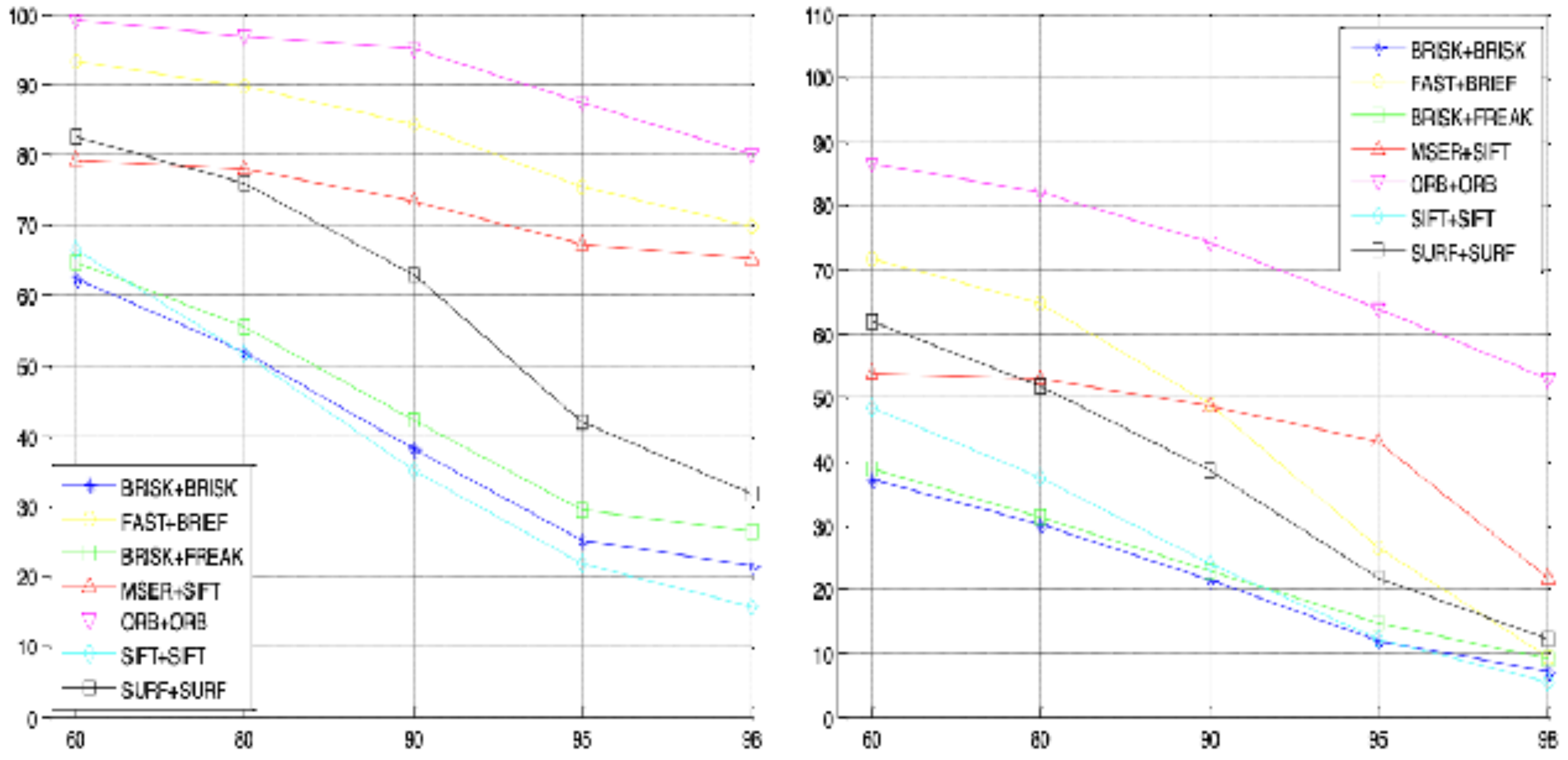

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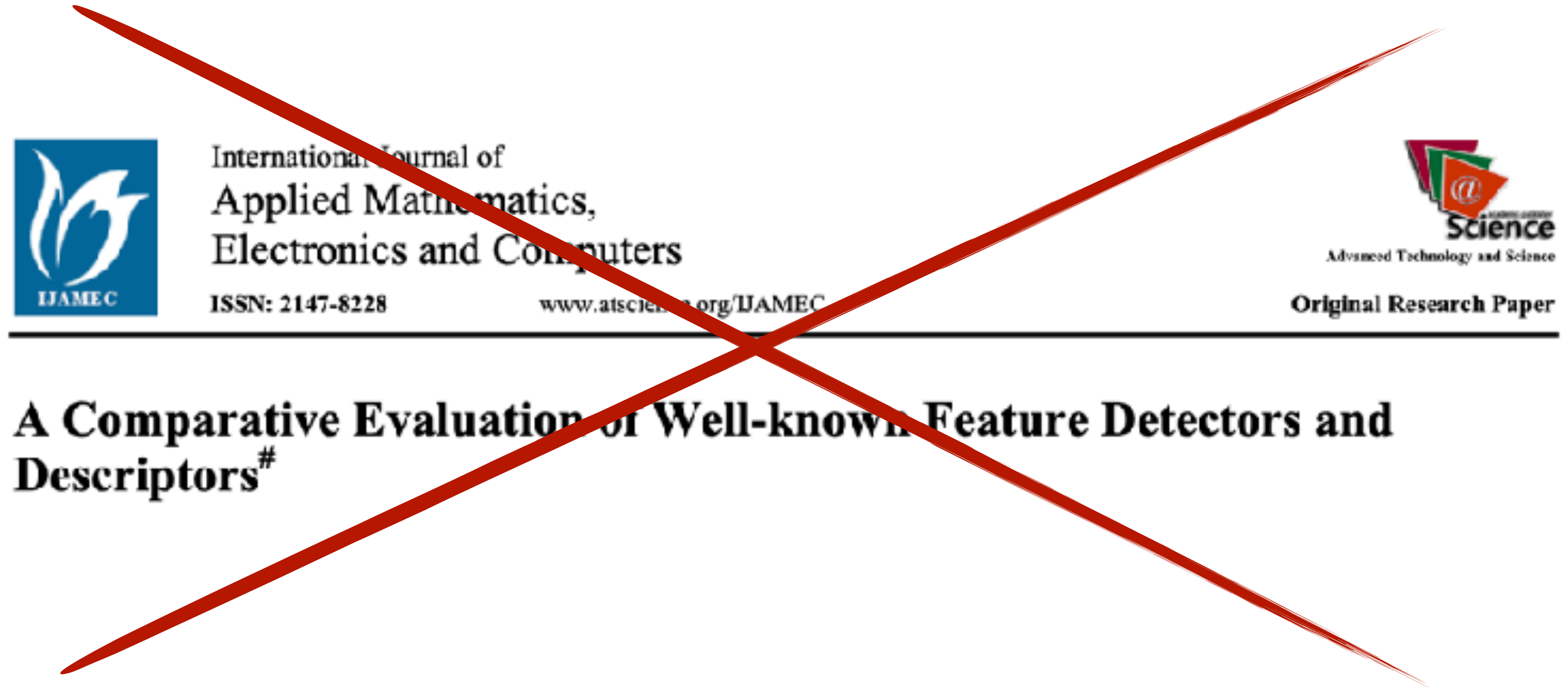

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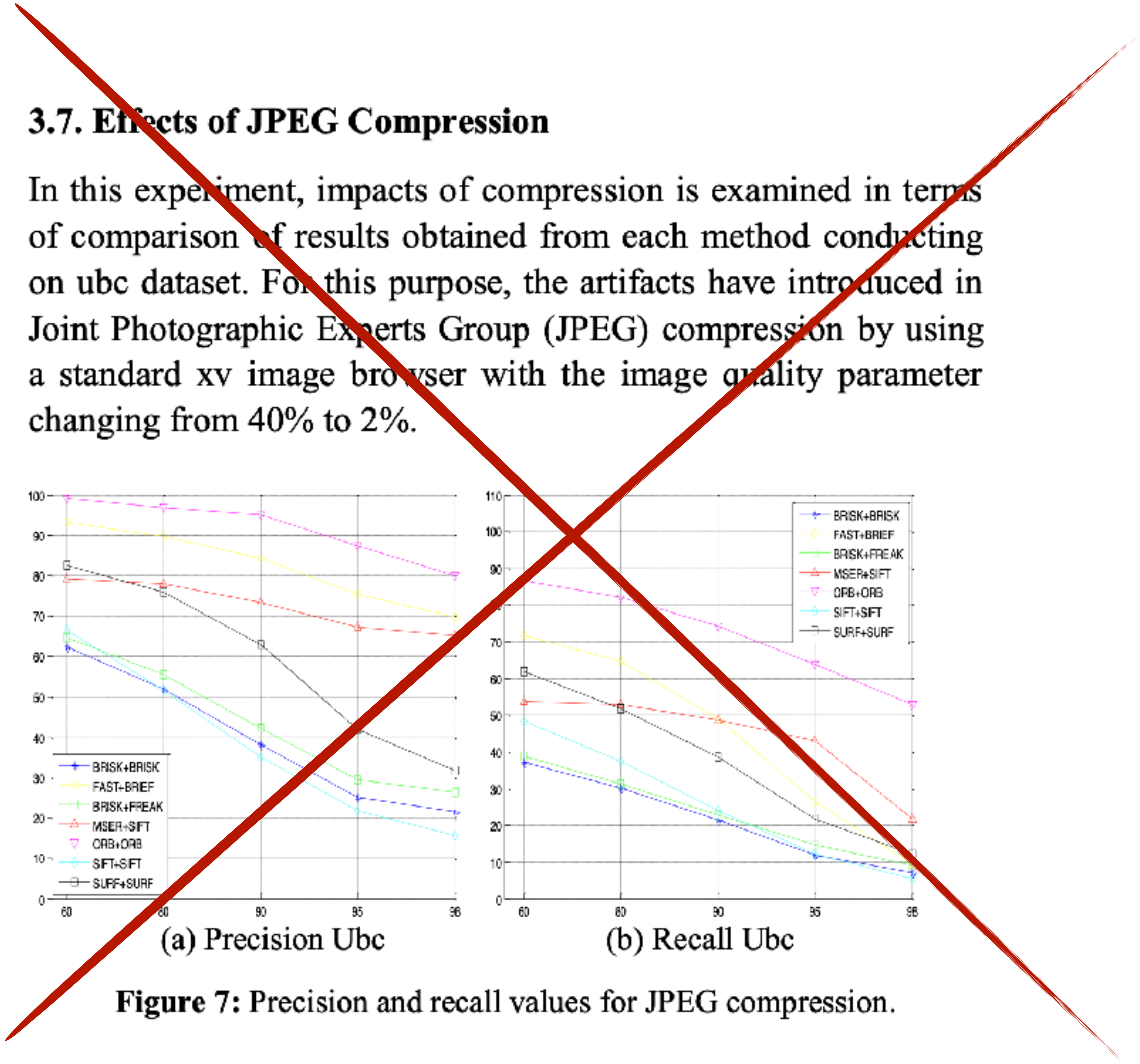

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LONG-TERM VISUAL LOCALIZATION

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Benchmark

Listed below are the public results on the three benchmark datasets. The localization results are reported as the perc
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Aachen Day-Night dataset

Localization thresholds:

All conditions: (0.25m, 2°) / (0.5m, 5°) / (5m, 10°)

Method	day
Combined tuned HLoc	89.7 / 95.8 / 98
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SuperGlue + Patch2Pix (HLoc)	89.2 / 95.5 / 98
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Benchmarks

Official results of past challenges are still available as a benchmark to researchers. We invite the visual tracking researchers to compare their methods with those results.

VOT2021 benchmark

The VOT2021 benchmark addresses short-term, long-term, real-time, RGB and RGBD trackers. Results were presented at the ICCV2021 VOT workshop.

VOT2020 benchmark

The VOT2020 benchmark addresses short-term, long-term, real-time, RGB, RGBT and RGBD trackers. Results were presented at the ECCV2020 VOT workshop.

VOT2019 benchmark

The VOT2019 benchmark addresses short-term, long-term, real-time, RGB, RGBT and RGBD trackers. Results were presented at the ICCV2019 VOT workshop.

VOT2018 benchmark

The VOT2018 benchmark introduced a long-term subchallenge VOT-LT2018. Results were presented at the VOT workshop at ECCV2018.

VOT2017 benchmark

The VOT2017 benchmark introduced a refreshed a dataset and a real-time experiment. The winner will was determined on sequestered dataset. The results were presented at the VOT workshop at ICCV2017.

VOT2016 benchmark

The fourth challenge updated the dataset of 60 sequences with new annotations. The results were published in a joint paper presented at a workshop at ECCV2016.

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It re-evaluates existing method on the common ground

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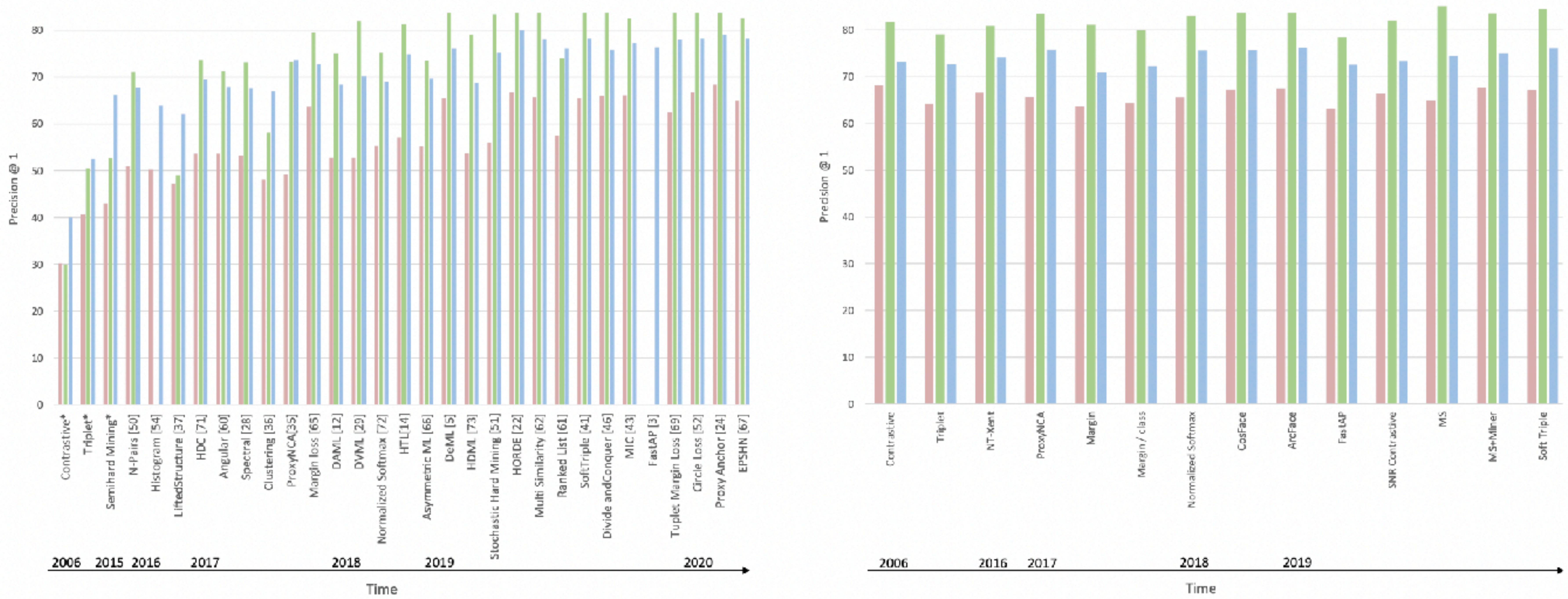

(a) The trend according to papers (b) The trend according to reality

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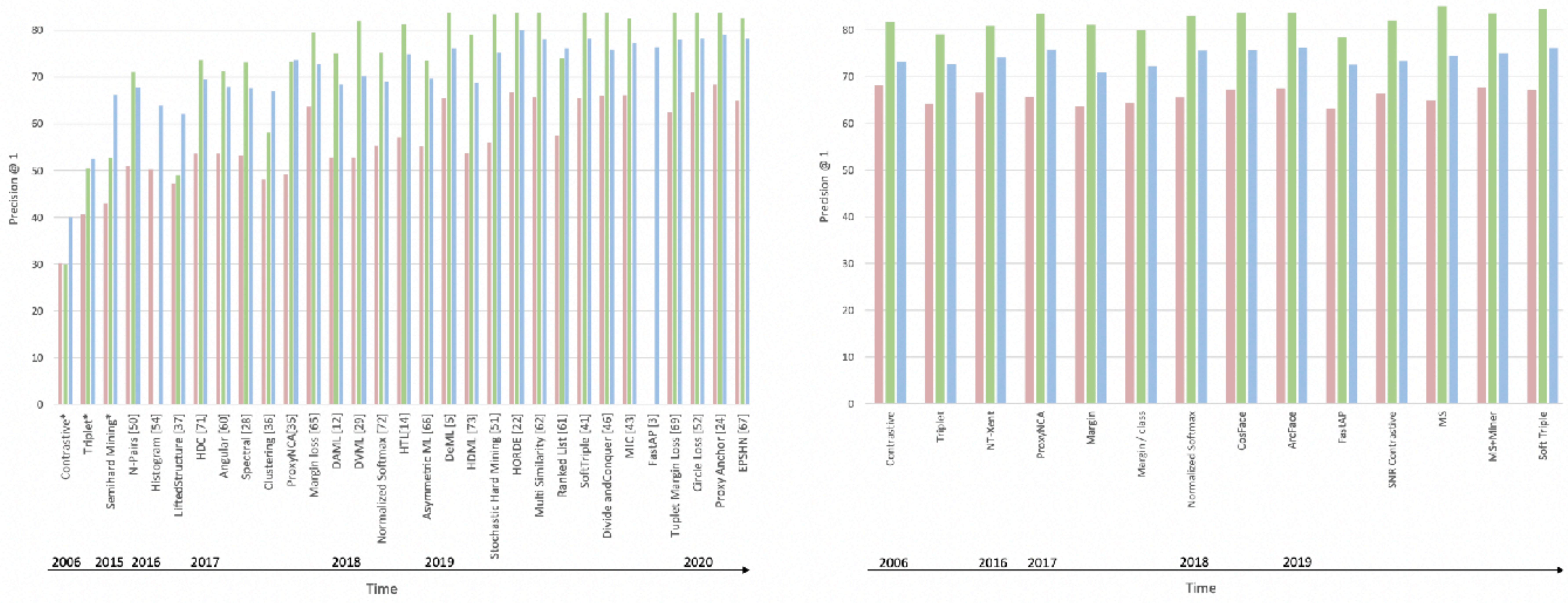

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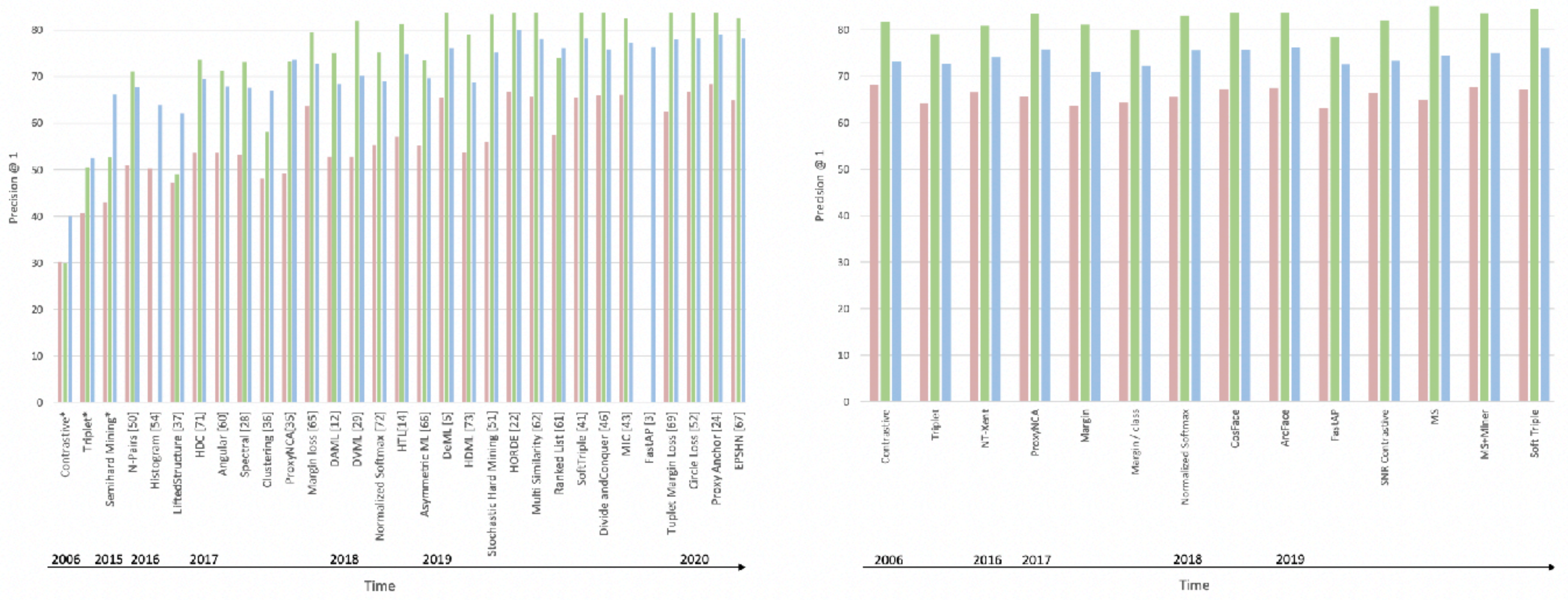

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But there are couple of heuristics

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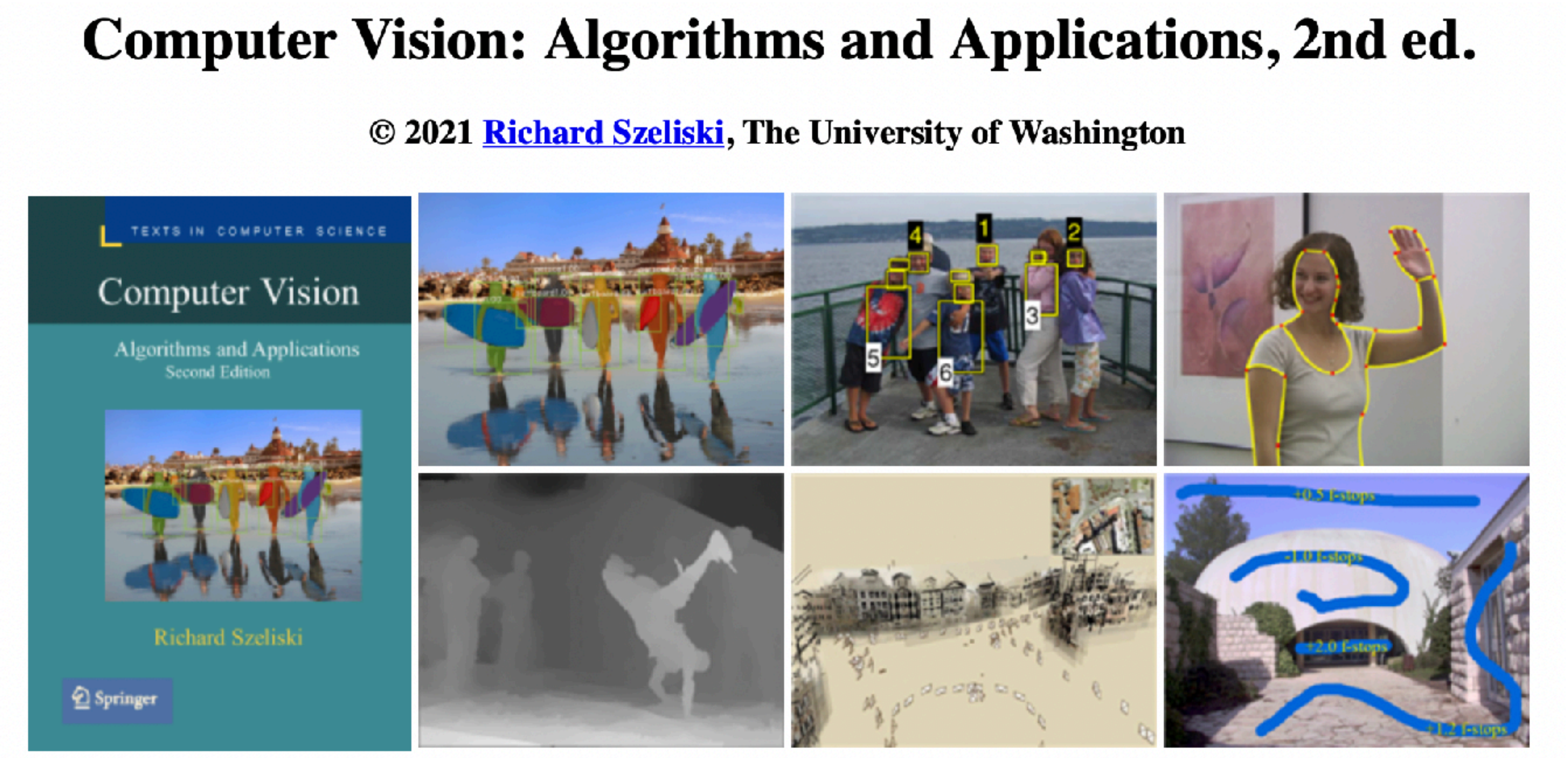

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  - Can we avoid solving this task at all?

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Image Matching Across Wide Baselines: From Paper to Practice

Yuhe Jin · Dmytro Mishkin · Anastasiia Mishchuk · Jiri Matas · Pascal Fua · Kwang Moo Yi · Eduard Trulls

arXiv:2003.01587v5 [cs.CV] 11 Feb 2021

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How to read benchmark/survey paper

if you are new to the field

- First, understand the task, by reading the intro and thinking. Write down:
- Who are the “users" of the algorithm?
    - Where is the result is going to be used?
    - What is important for the downstream task?
    - How one can measure it?
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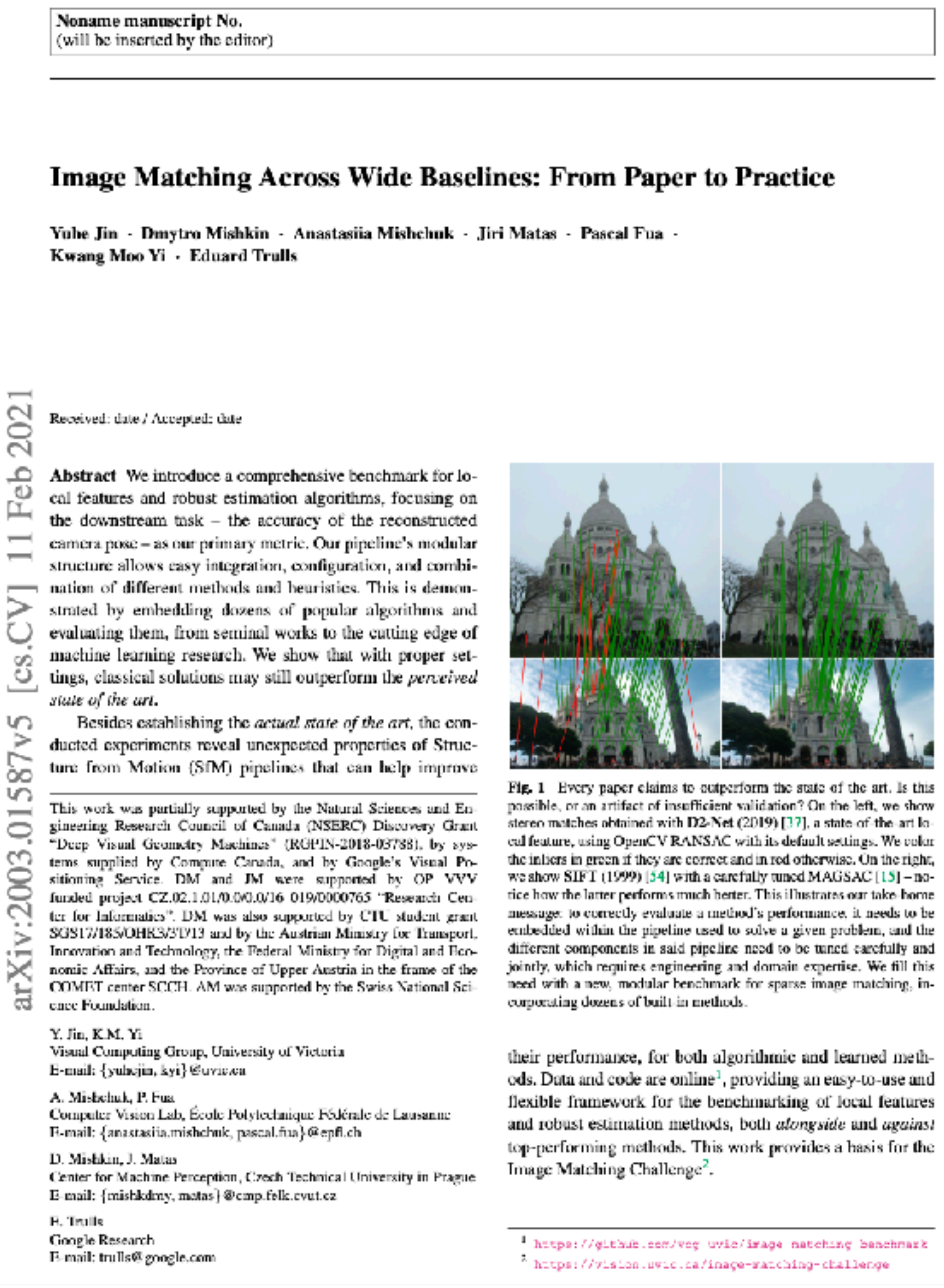
Case study: image matching

Task understanding (1)



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Case study: image matching

Task understanding (1)

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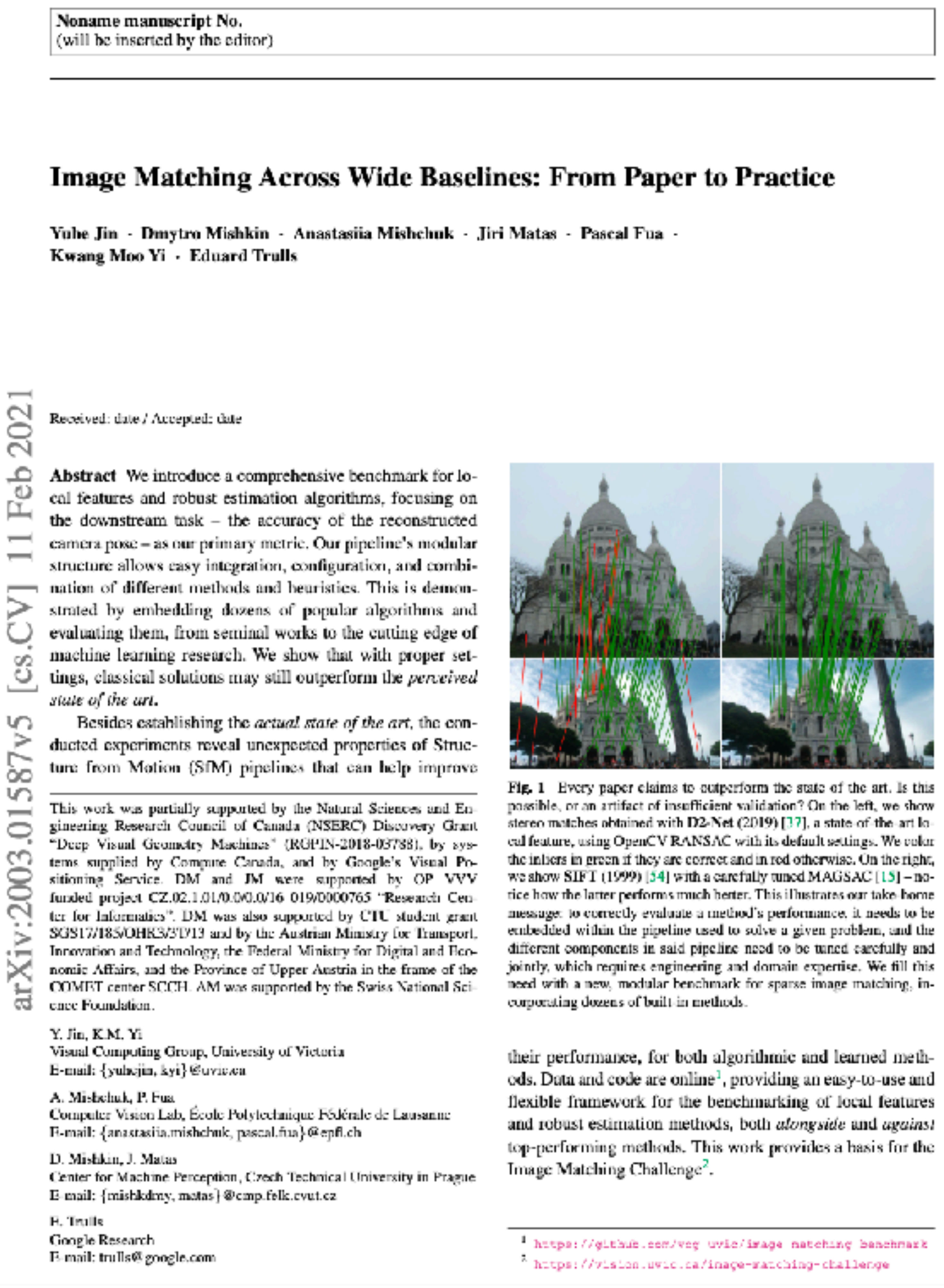

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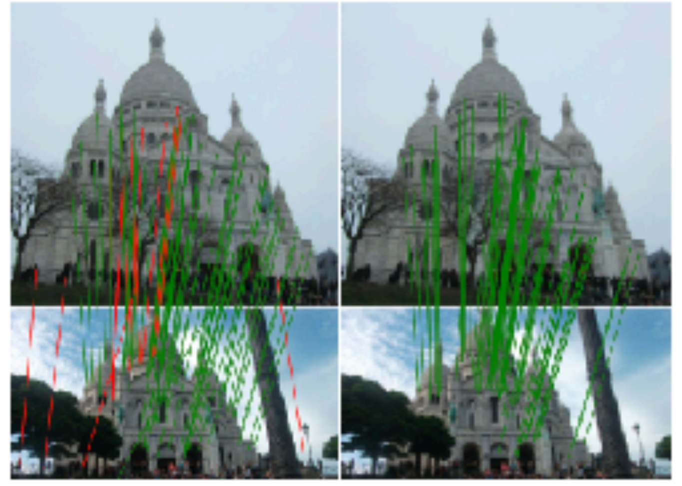

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Case study: image matching

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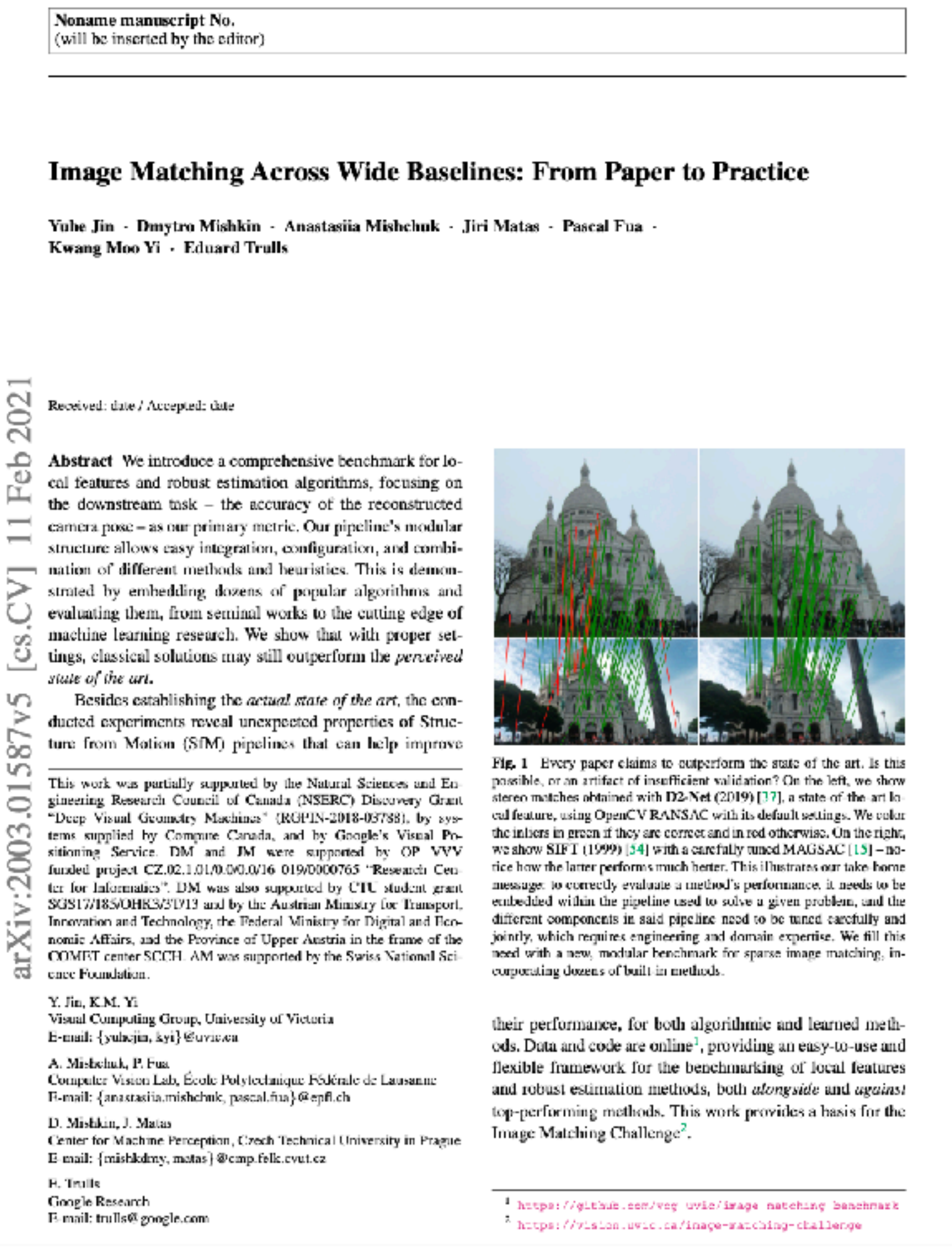

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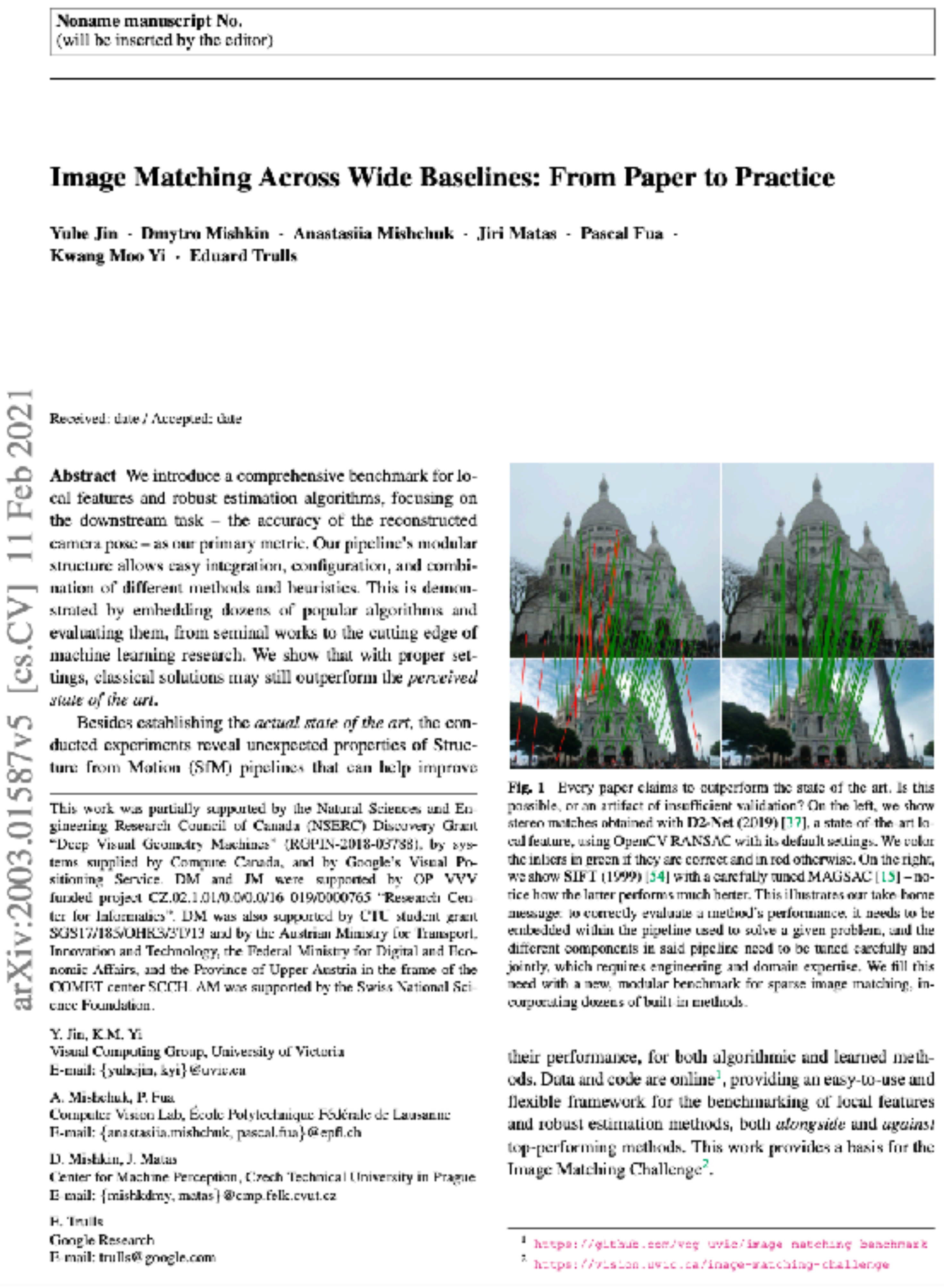

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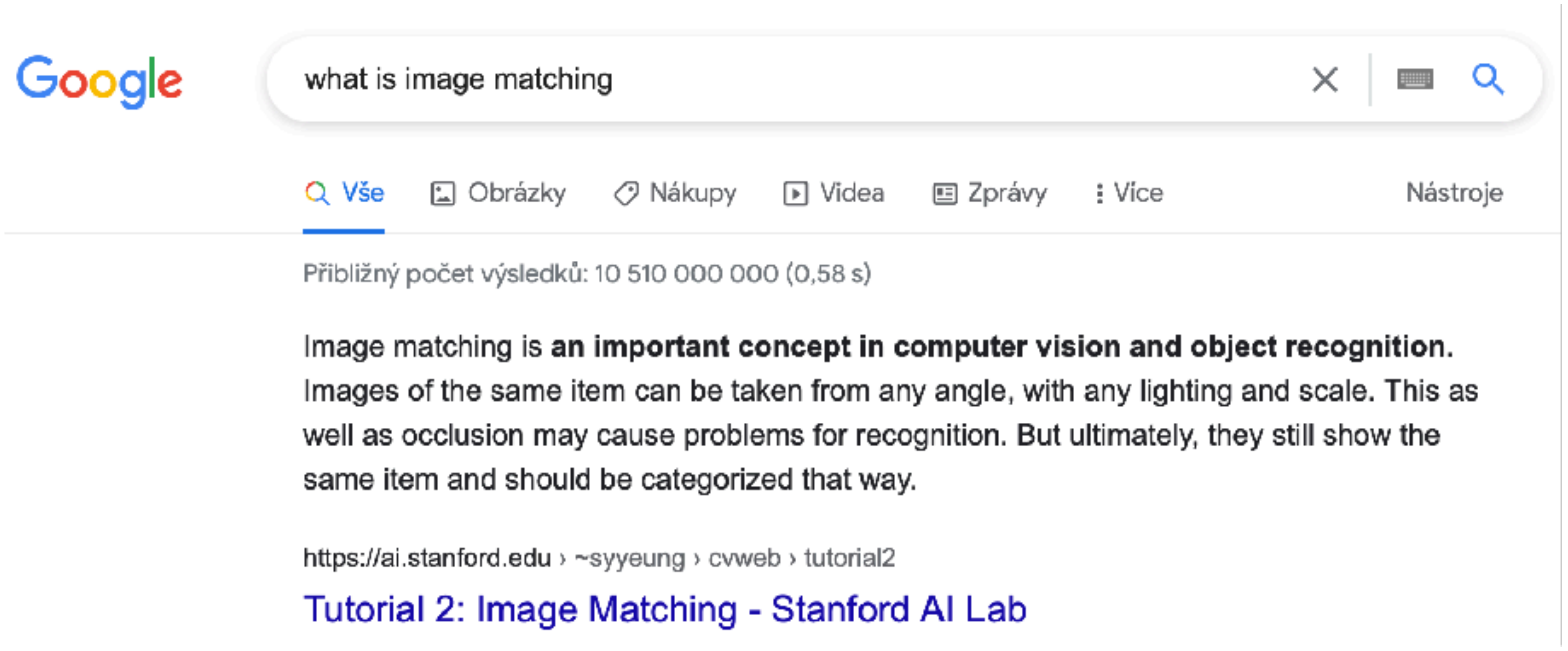

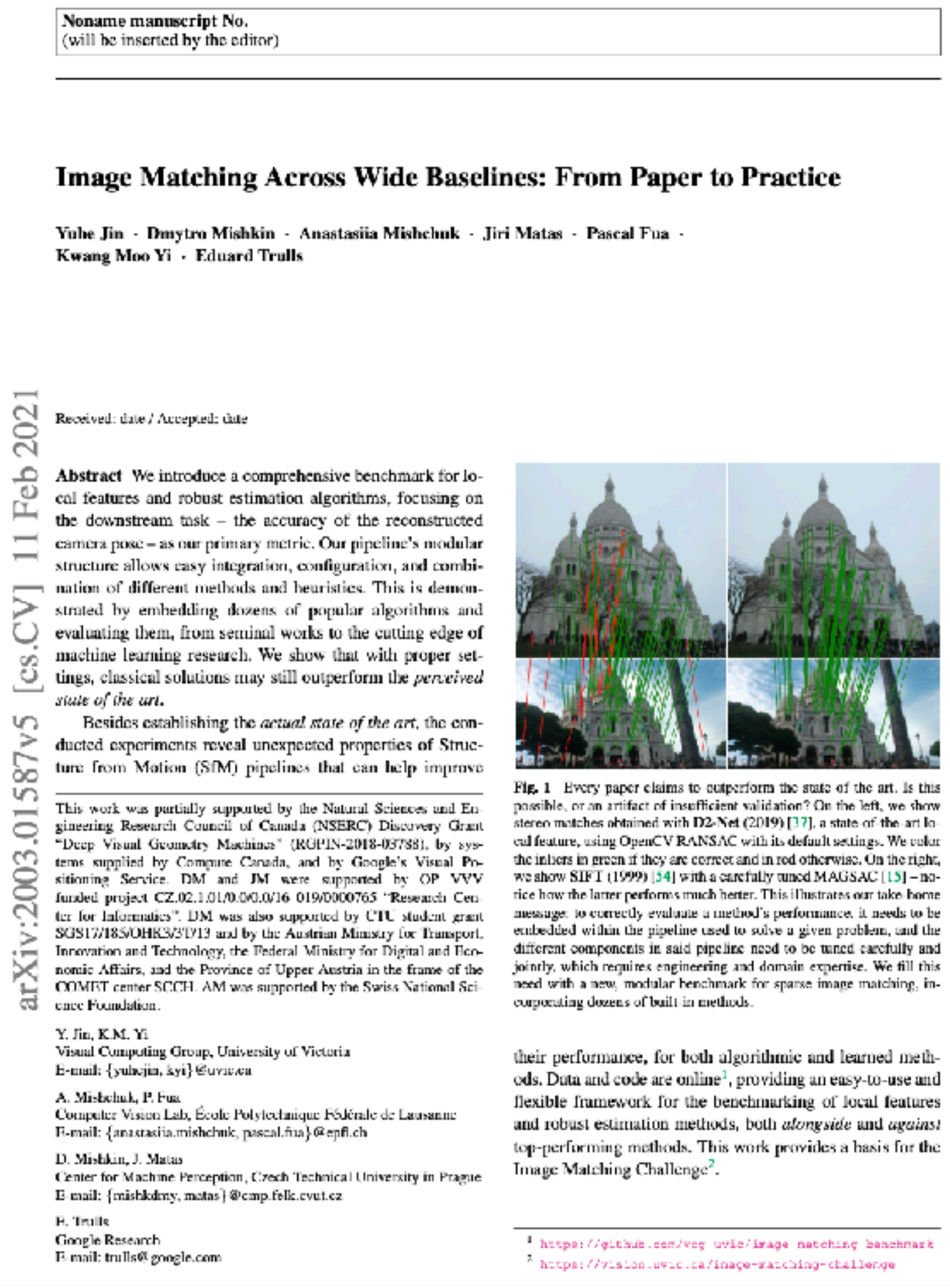

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Case study: image matching

Task understanding (1)

- Inputs: images of the “same item”.
- Output (after more googling): correspondences and relative camera pose
- Note: people can use different terms for the same thing:
  - "Image matching” == “Wide baseline stereo"

The wide multiple baseline stereo (WxBS) is **a process of establishing a sufficient number of pixel or region correspondences from two or more images depicting the same scene to estimate the geometric relationship between cameras, which produced these images**. Mar 27, 2020

https://ducha-aiki.github.io › 2020/03/27 › intro

The Role of Wide Baseline Stereo in the Deep Learning World

Case study: image matching

Task understanding (2)

Case study: image matching

Task understanding (2)

- Who are the “users" of the algorithm? Where is the result is going to be used?

Case study: image matching

Task understanding (2)

- Who are the “users" of the algorithm? Where is the result is going to be used?

1 Introduction

Matching two or more views of a scene is at the core of fundamental computer vision problems, including image retrieval [54,7,78,104,70], 3D reconstruction [3,47,90,122], re-localization [85,86,57], and SLAM [68,33,34]. Despite

Case study: image matching

Task understanding (2)

- Who are the “users" of the algorithm? Where is the result is going to be used?
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Case study: image matching

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Case study: image matching
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  - SLAM

1 Introduction

Matching two or more views of a scene is at the core of fundamental computer vision problems, including image retrieval [54,7,78,104,70], 3D reconstruction [3,47,90,122], re-localization [85,86,57], and SLAM [68,33,34]. Despite

- Now we may, or may not need to check about this “users"

Case study: image matching

Task understanding (2)

Case study: image matching

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- What is important for the downstream task?

Case study: image matching
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Is it relevant to me?

Case study: image matching

Task understanding (3)

Case study: image matching

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- We have already googled and checked other papers to answer the questions, which are necessary to understand the paper we are reading now

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Case study: image matching

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- It is OK to deviate (a lot), when you are reading
- Especially when you are new to the area
- It is a good idea to “learn in public” and write answers to the question in a blog post.

Case study: image matching
How can we measure that?

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Recall and precision

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Lots of metrics

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Pose error, accuracy

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Case study: image matching
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Back to the paper

What does the paper evaluate?

Case study: Image matching

- What does paper measure?
- Where the data in the paper comes from?
- Where the ground truth labels come from?

What does the paper evaluate?

Again, we are speaking purely about the task now

3 The Image Matching Challenge PhotoTourism Dataset

While it is possible to obtain very accurate poses and depth maps under controlled scenarios with devices like LIDAR, this is costly and requires a specific set-up that does not scale well. For example, Strecha's dataset [95] follows that approach but contains only 19 images. We argue that a truly representative dataset must contain a wider range of transformations – including different imaging devices, time of day, weather, partial occlusions, etc. Phototourism images satisfy this condition and are readily available.

We thus build on 25 collections of popular landmarks originally selected in [47, 101], each with hundreds to thousands of images. Images are downsampled with bilinear interpolation to a maximum size of 1024 pixels along the long-side and their poses were obtained with COLMAP [90], which provides the (pseudo) ground truth. We do exhaustive image matching before Bundle Adjustment – unlike [92], which uses only 100 pairs for each image – and thus provide enough matching images for any conventional SfM to return near-perfect results in standard conditions.

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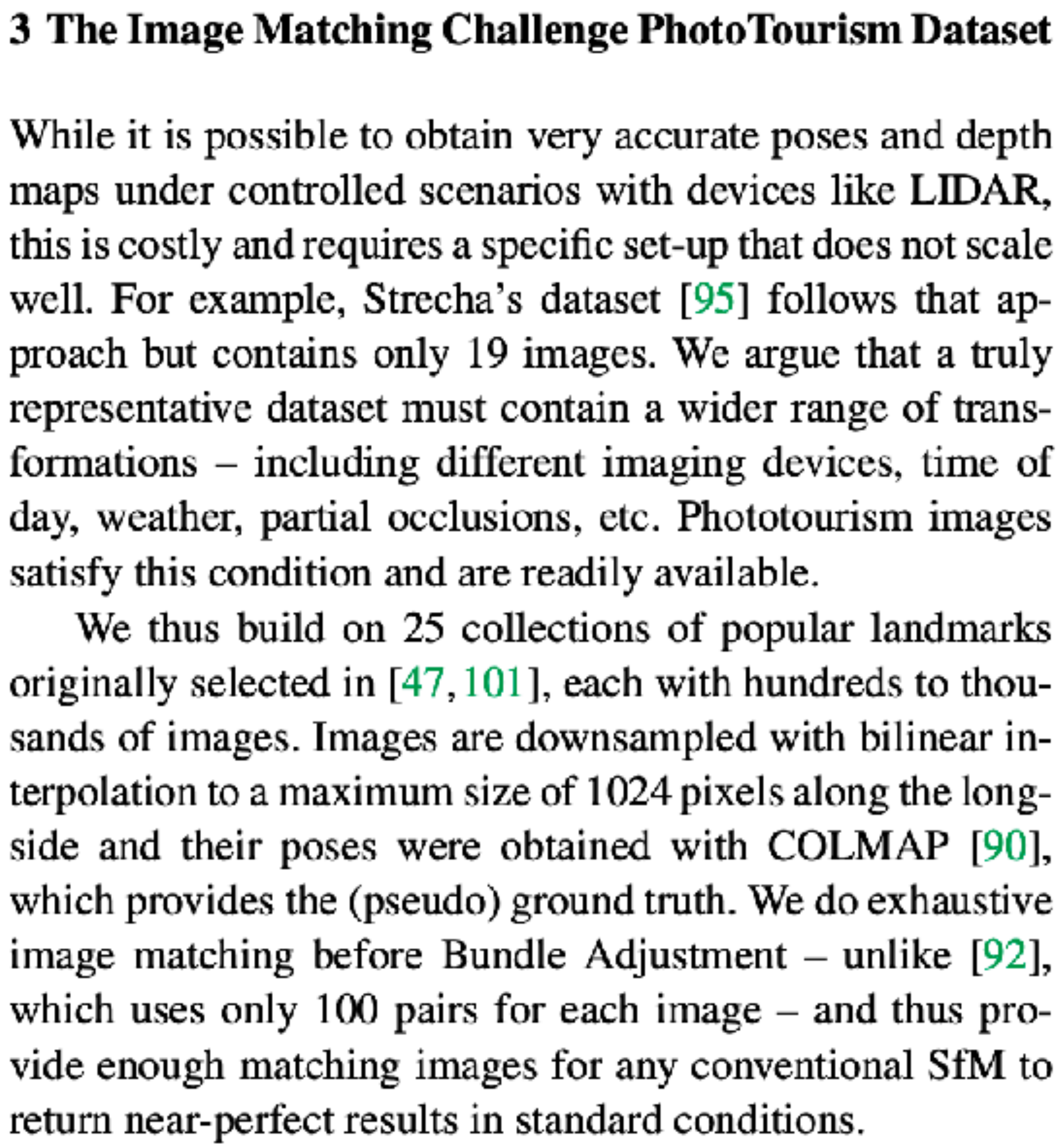

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Case study: image matching, metric

- User metrics:
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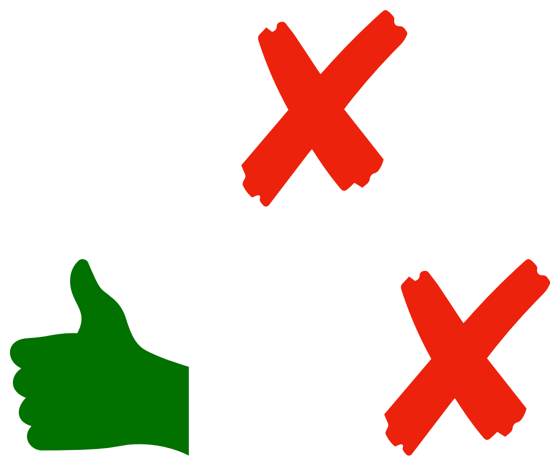

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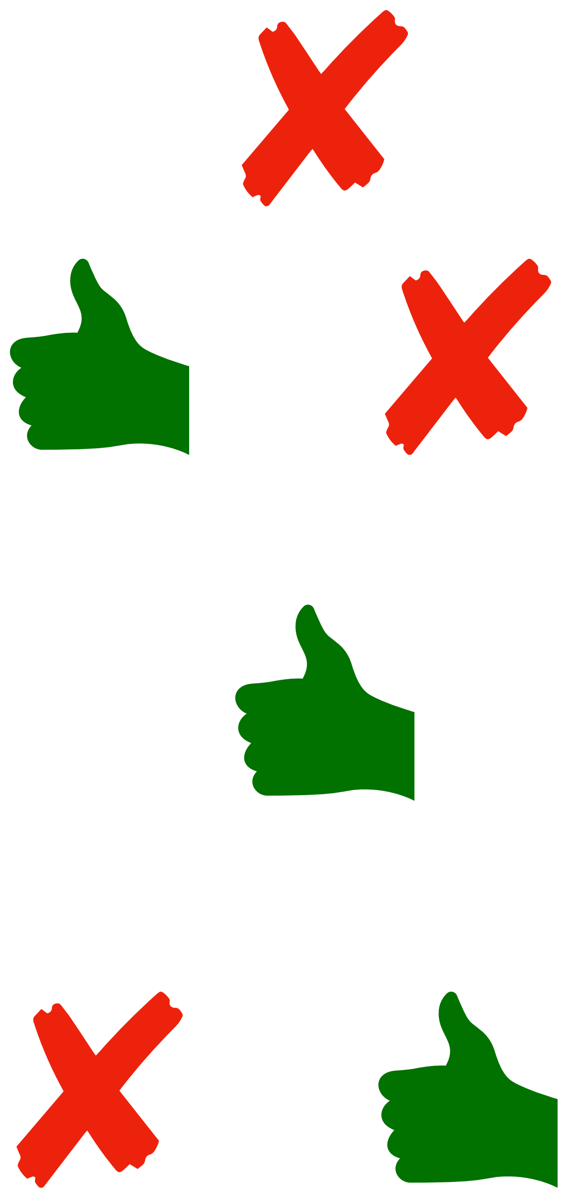

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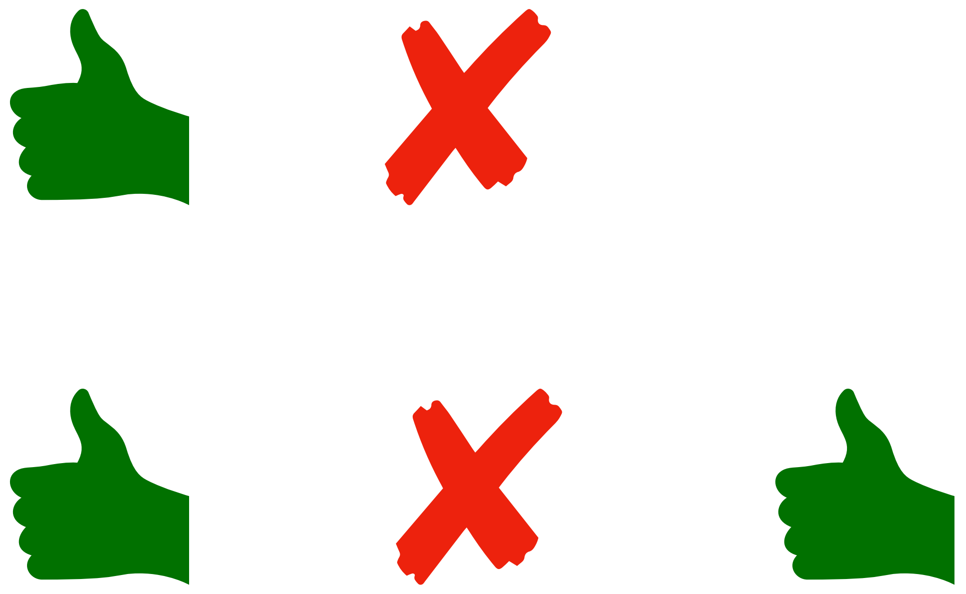

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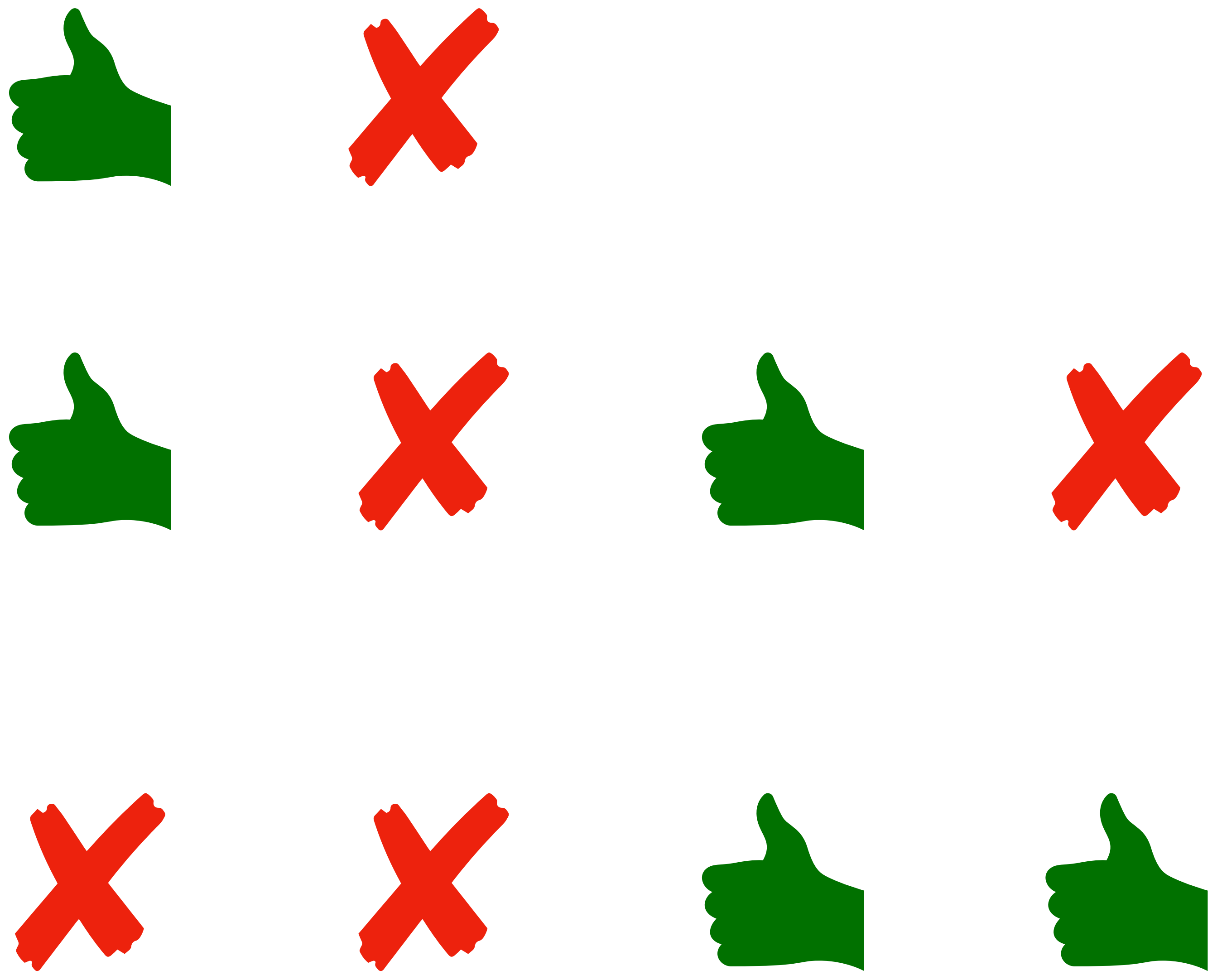

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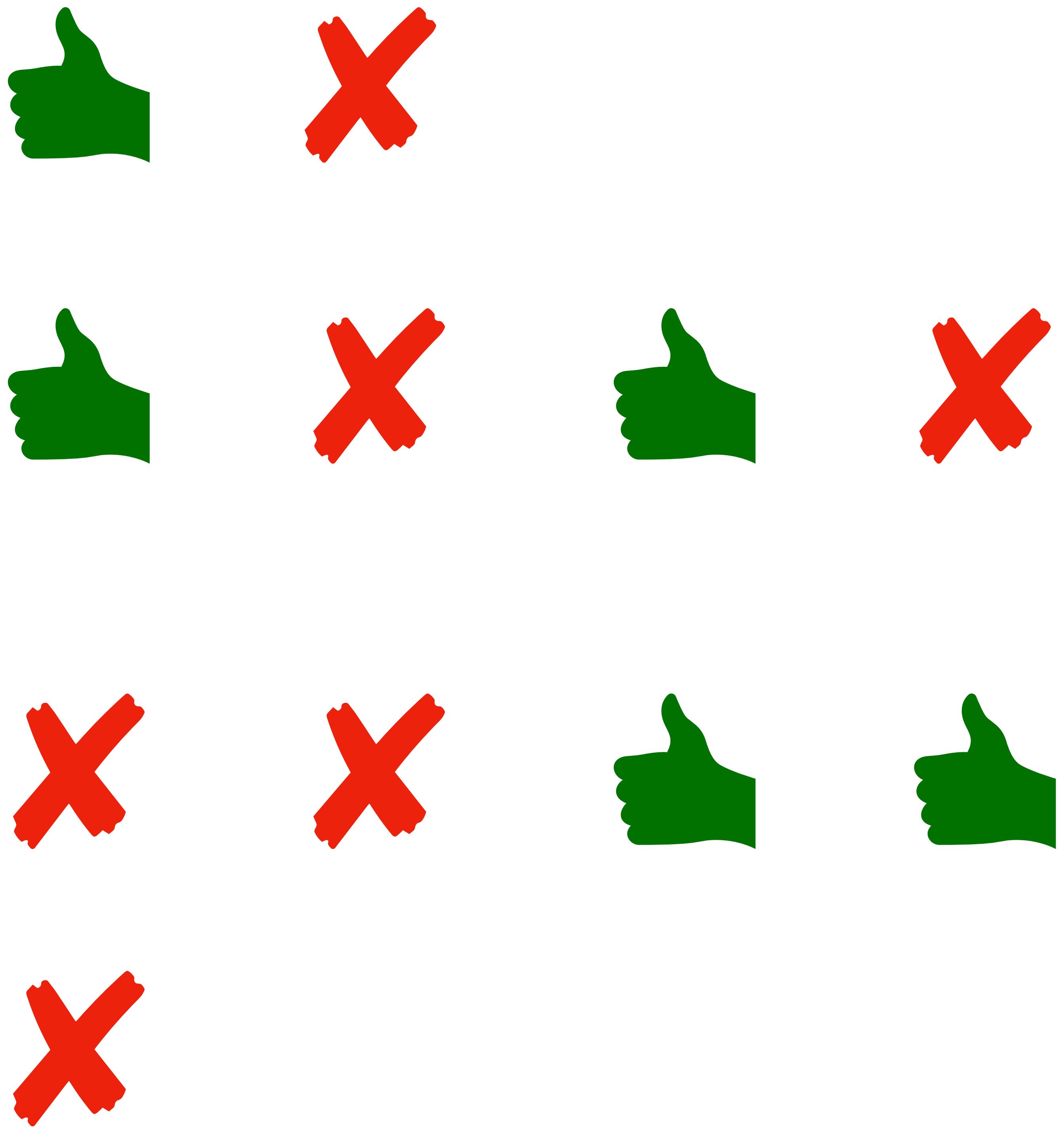

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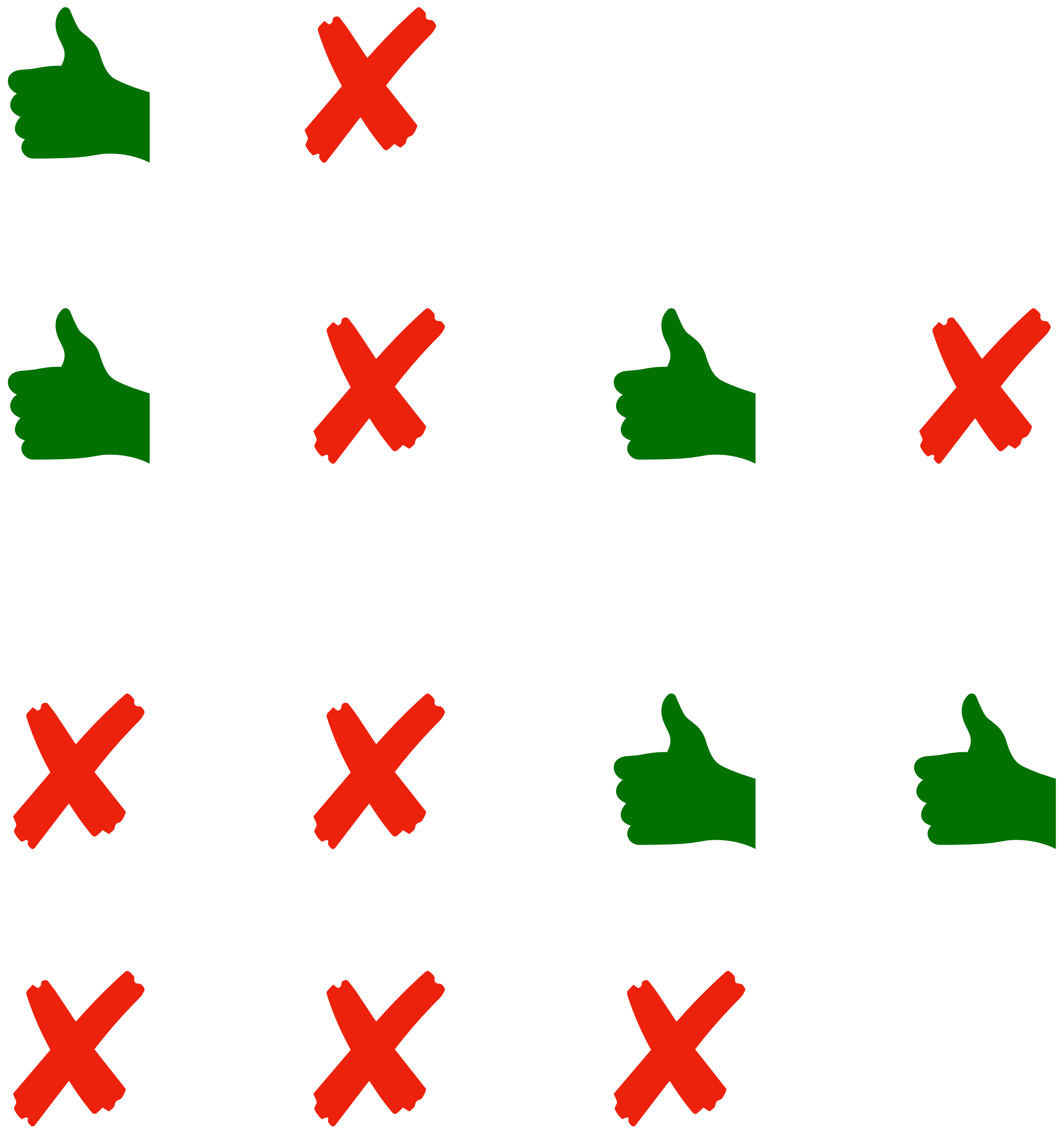

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- How the paper results are relevant for
  - Image retrieval
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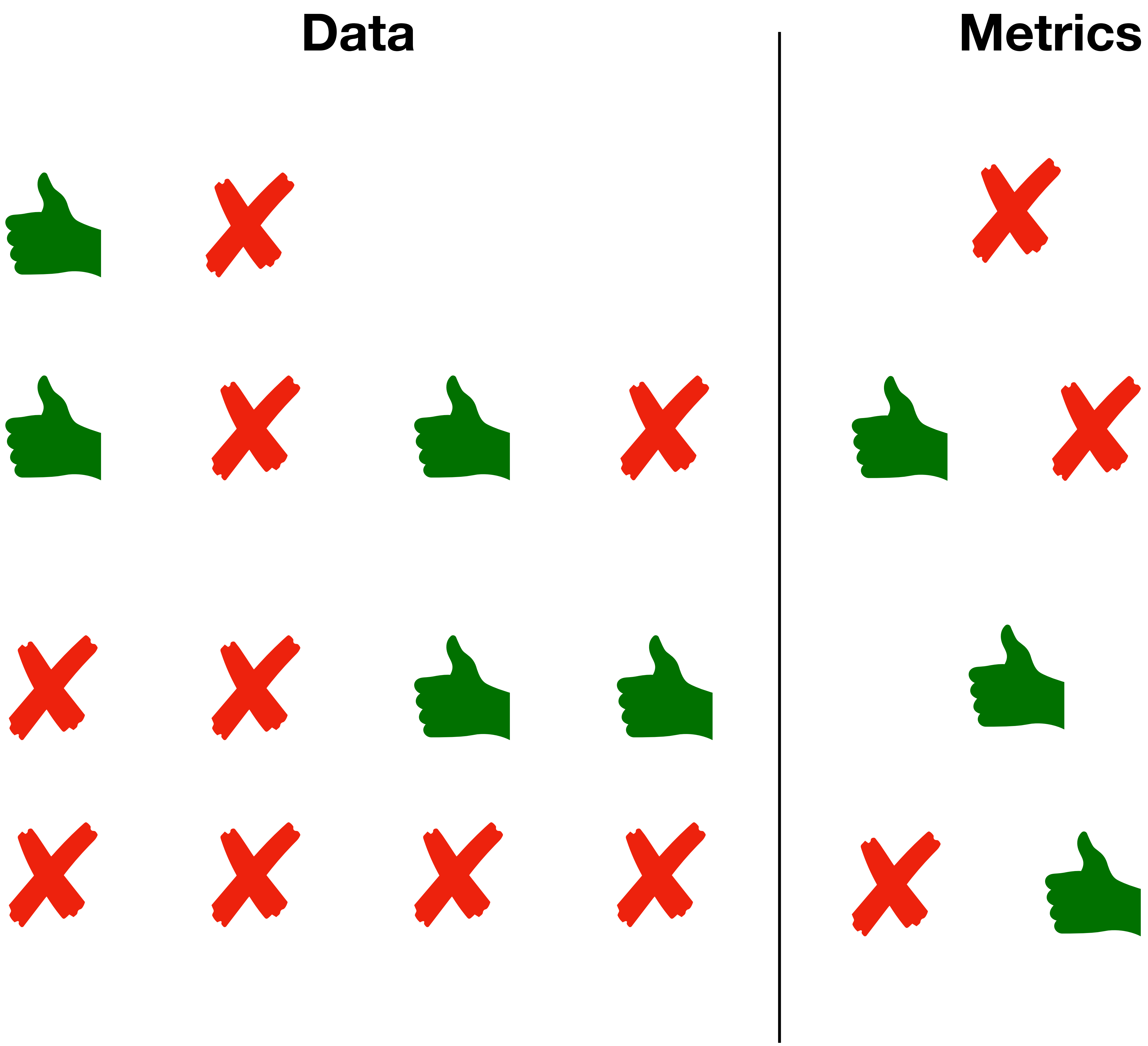
  - visual localization
  - SLAM



Intermediate conclusion

- The paper findings are partially relevant for some use-cases in
  - visual localization
  - 3D reconstruction
- Loosely relevant for the SLAM
- Not relevant at all for image retrieval

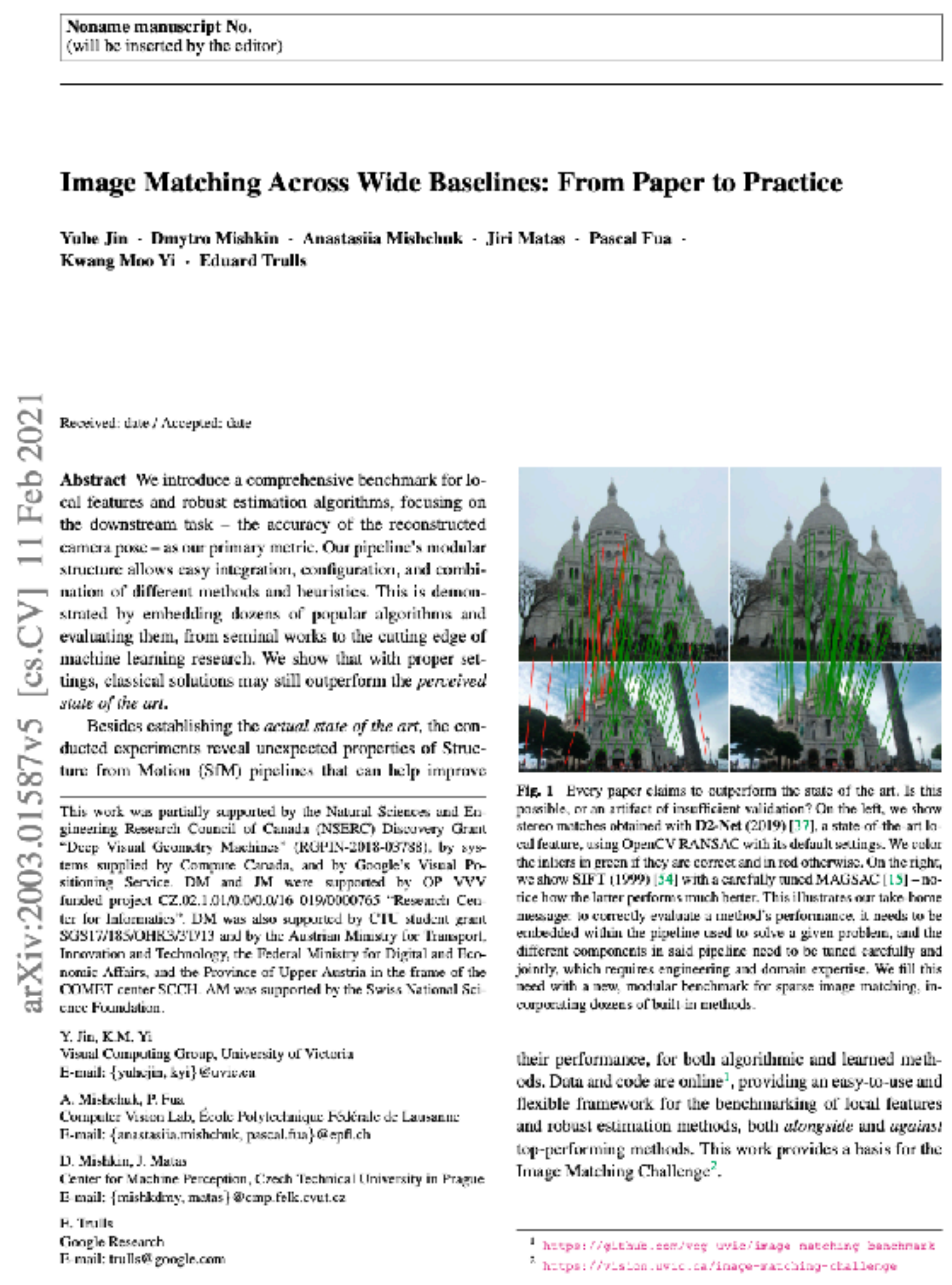


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Image Matching Across Wide Baselines: From Paper to Practice

Yuhe Jin · Dmytro Mishkin · Anastasiia Mishchuk · Jiri Matas · Pascal Fua · Kwang Moo Yi · Eduard Trulls

arXiv:2003.01587v5 [cs.CV] 11 Feb 2021

Received: date / Accepted: date

Abstract We introduce a comprehensive benchmark for local features and robust estimation algorithms, focusing on the downstream task – the accuracy of the reconstructed camera pose – as our primary metric. Our pipeline's modular structure allows easy integration, configuration, and combination of different methods and heuristics. This is demonstrated by embedding dozens of popular algorithms and evaluating them, from seminal works to the cutting edge of machine learning research. We show that with proper settings, classical solutions may still outperform the *perceived state of the art*.

Besides establishing the *actual state of the art*, the conducted experiments reveal unexpected properties of Structure from Motion (SfM) pipelines that can help improve their performance, for both algorithmic and learned methods. Data and code are online[1], providing an easy-to-use and flexible framework for the benchmarking of local features and robust estimation methods, both *alongside* and *against* top-performing methods. This work provides a basis for the Image Matching Challenge[2].

Fig. 1 Every paper claims to outperform the state of the art. Is this possible, or an artifact of insufficient validation? On the left, we show stereo matches obtained with D2-Net (2019) [17], a state-of-the-art local feature, using OpenCV RANSAC with its default settings. We color the inliers in green if they are correct and in red otherwise. On the right, we show SIFT (1999) [54] with a carefully tuned MAGSAC [15] – notice how the latter performs much better. This illustrates our take-home message: to correctly evaluate a method's performance, it needs to be embedded within the pipeline used to solve a given problem, and the different components in said pipeline need to be tuned carefully and jointly, which requires engineering and domain expertise. We fill this need with a new, modular benchmark for sparse image matching, incorporating dozens of built-in methods.

This work was partially supported by the Natural Sciences and Engineering Research Council of Canada (NSERC) Discovery Grant "Deep Visual Geometry Machines" (RGPIN-2018-03788), by systems supplied by Compute Canada, and by Google's Visual Positioning Service. DM and JM were supported by OP VVV funded project CZ.02.1.01/0.0/0.0/16 019/0000765 "Research Center for Informatics". DM was also supported by CTU student grant SGS17/185/OHK3/3T/13 and by the Austrian Ministry for Transport, Innovation and Technology, the Federal Ministry for Digital and Economic Affairs, and the Province of Upper Austria in the frame of the COMET center SCCH. AM was supported by the Swiss National Science Foundation.

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[1] https://github.com/vcg-uvic/image-matching-benchmark
[2] https://vision.uvic.ca/image-matching-challenge

Why should I do all this crap?

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Why should I do all this crap?

If you need a truck,
do not watch racing car reviews

Research sometimes deviates from practice

or often

https://twitter.com/ChristophMolnar/status/1485549716268109824

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A lot of machine learning research has detached itself from solving real problems, and created their own "benchmark-islands".

How does this happen? And why are researchers not escaping this pattern?

A thread 🧵

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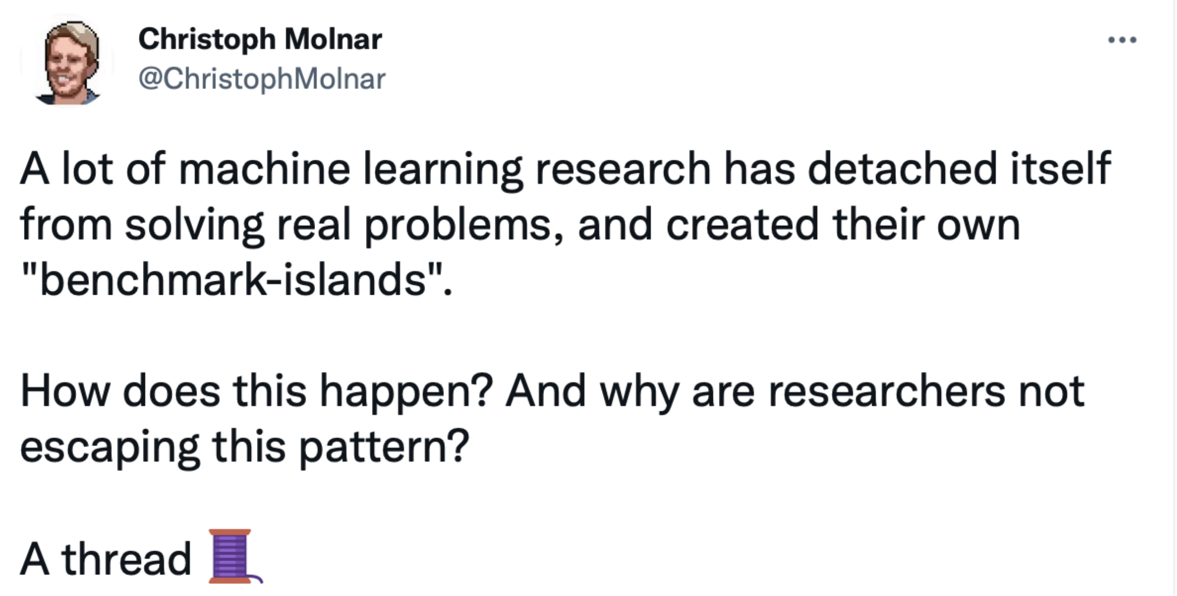
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1. Establish a research topic. For example: Detect COVID-19 from x-ray images with machine learning.
2. First papers on this topic appear, and provide motivation for this research topic.
3. A precedent has been established: The initial papers pave the way for further research papers on the same topic.
4. The original motivation and assumptions for developing these predictive models are no longer questioned.
5. More researchers publish data and predictive models.

Christoph Molnar
@ChristophMolnar

A lot of machine learning research has detached itself from solving real problems, and created their own "benchmark-islands".

How does this happen? And why are researchers not escaping this pattern?

A thread 🧵

https://twitter.com/ChristophMolnar/status/1485549716268109824

Research sometimes deviates from practice

or often

Christoph Molnar
@ChristophMolnar

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s not

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4. The original motivation and assumptions for developing these predictive models are no longer questioned.
5. More researchers publish data and predictive models.
6. A community forms that cites and reviews each other.
7. Certain datasets become benchmarks and certain predictive models become state-of-the-art.
8. Predictive performance becomes the sole measure of progress, although improvements are becoming smaller.
9. Actual progress in solving the initial research questions has become irrelevant, even discouraged.
10. Decoupling from reality is complete.

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OK, paper is relevant

https://www.youtube.com/watch?v=_MeY1_ph2P4

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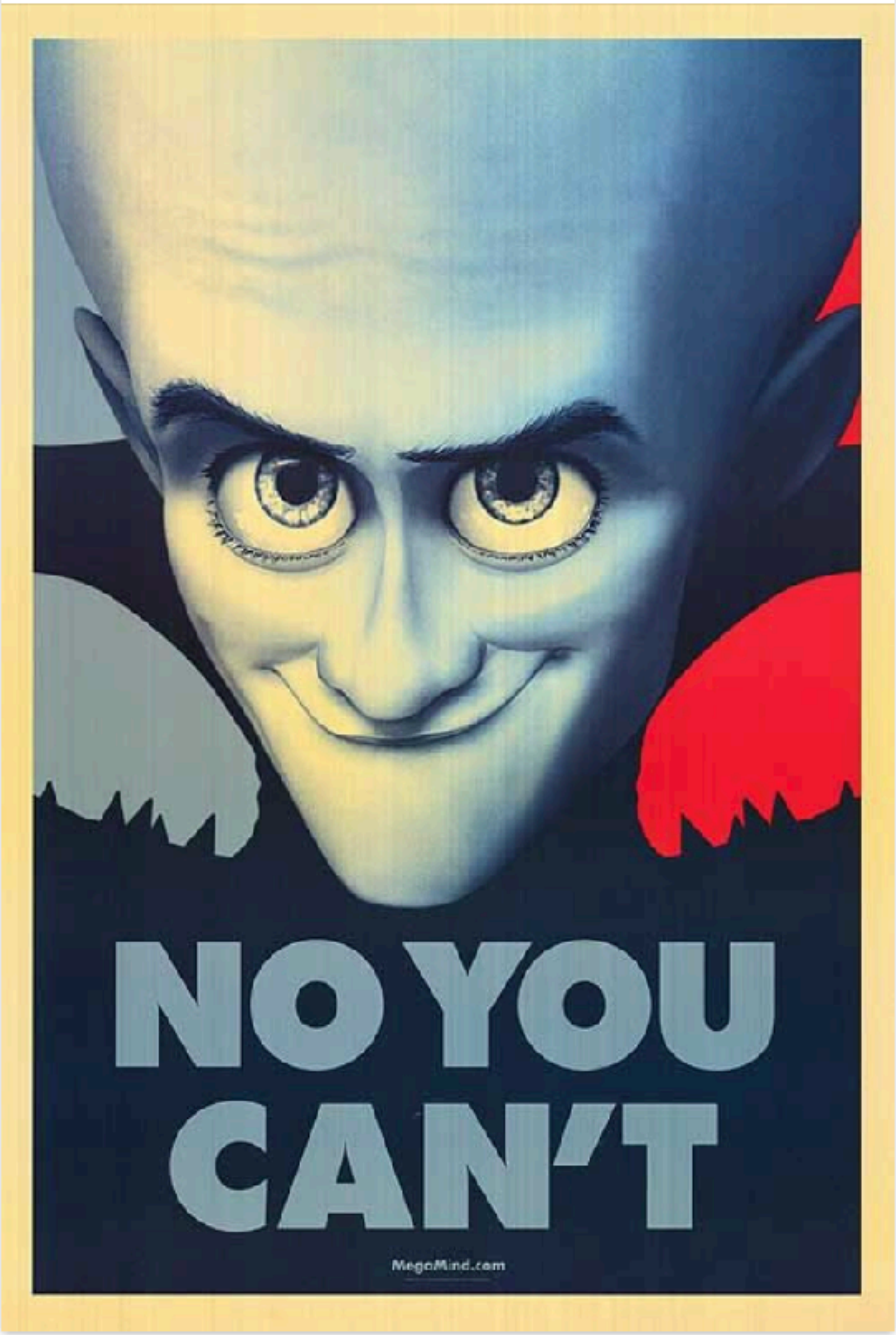

Can we trust the paper?

"The only correct attitude, when reading the paper is:
Why do these lying bastard lie to me?"
David Forsyth

Do the metrics in the paper make sense?

If you don't have experience, you can skip this

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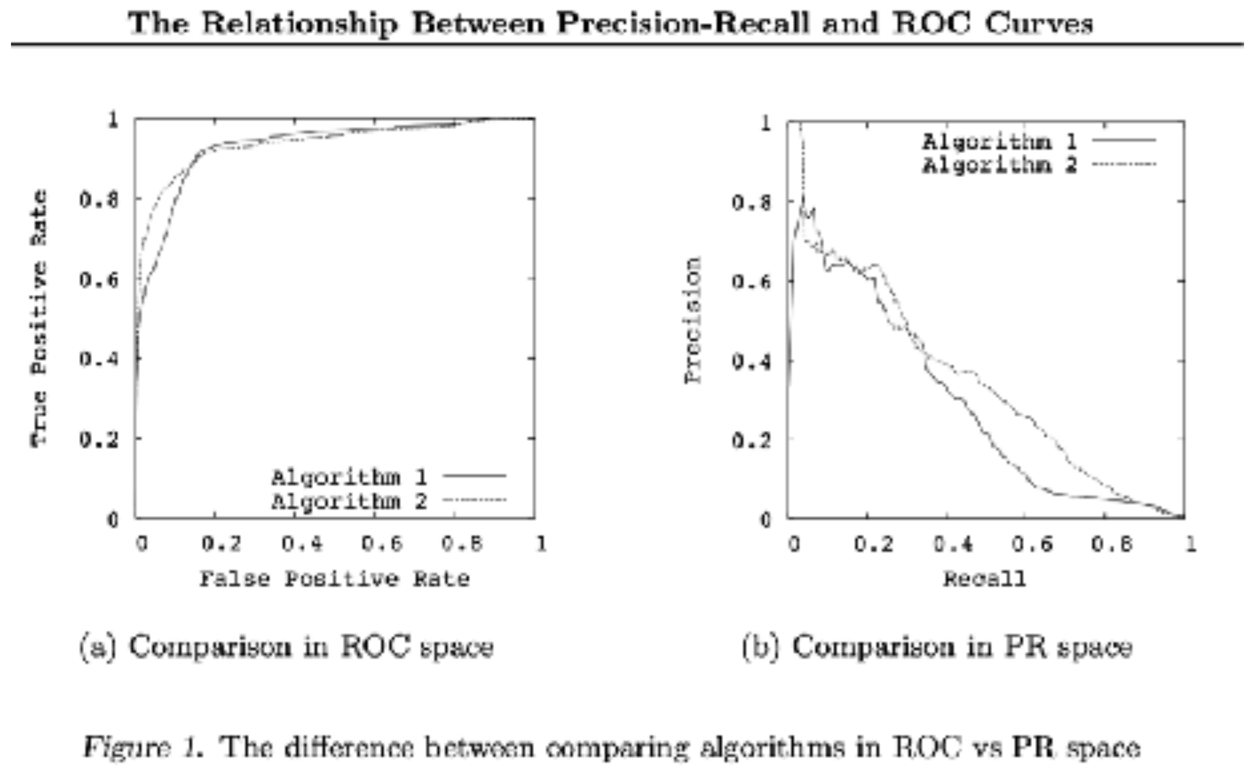


https://www.biostat.wisc.edu/~page/rocpr.pdf

How the ground truth labels were obtained?

- Check if the annotation process makes sense
- Is it biased?

Noname manuscript No.
(will be inserted by the editor)

ImageNet Large Scale Visual Recognition Challenge

Olga Russakovsky* · Jia Deng* · Hao Su · Jonathan Krause · Sanjeev Satheesh · Sean Ma · Zhiheng Huang · Andrej Karpathy · Aditya Khosla · Michael Bernstein · Alexander C. Berg · Li Fei-Fei

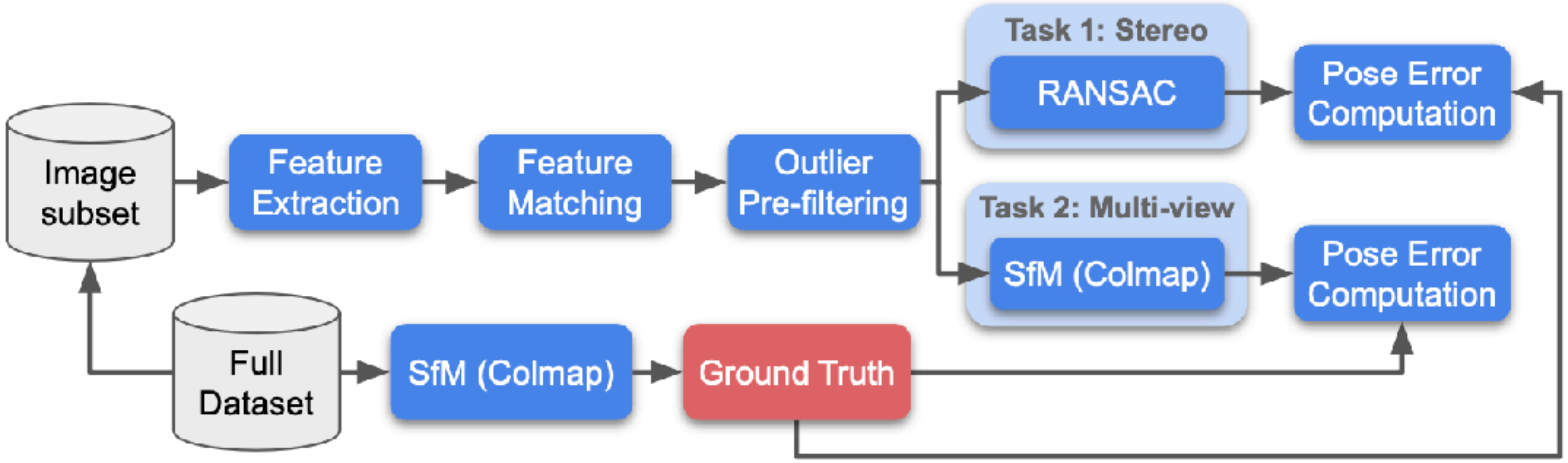
1. **Drawing** A worker draws one bounding box around one instance of an object on the given image.
2. **Quality verification** A second worker checks if the bounding box is correctly drawn.
3. **Coverage verification** A third worker checks if all object instances have bounding boxes.

https://arxiv.org/pdf/1409.0575.pdf

How the ground truth labels were obtained?

Case study: image matching

- Assumption: COLMAP reconstruction from the 1000 images outputs poses, which are good enough to evaluate stereo poses



How the ground truth labels were obtained?

Case study: image matching

- Assumption: COLMAP reconstruction from the 1000 images outputs poses, which are good enough to evaluate stereo poses
- Is it validated?

3.3 On the quality of the "ground-truth"

Our core assumption is that accurate poses can be obtained from large sets of images without human intervention. Such poses are used as the "ground truth" for evaluation of image matching performance on pairs or small subsets of images – a harder, proxy task. Should this assumption hold, the (relative) poses retrieved with a large enough number of images would not change as more images are added, and these poses would be the same regardless of which local feature is used. To validate this, we pick the scene "Sacre Coeur" and compute SfM reconstructions with a varying number of images: 100, 200, 400, 800, and 1179 images (the entire "Sacre Coeur" dataset), where each set contains the previous one; new images are being added and no images are removed. We run each reconstruction three times, and report the aver-

https://arxiv.org/pdf/1409.0575.pdf

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Case study: image matching

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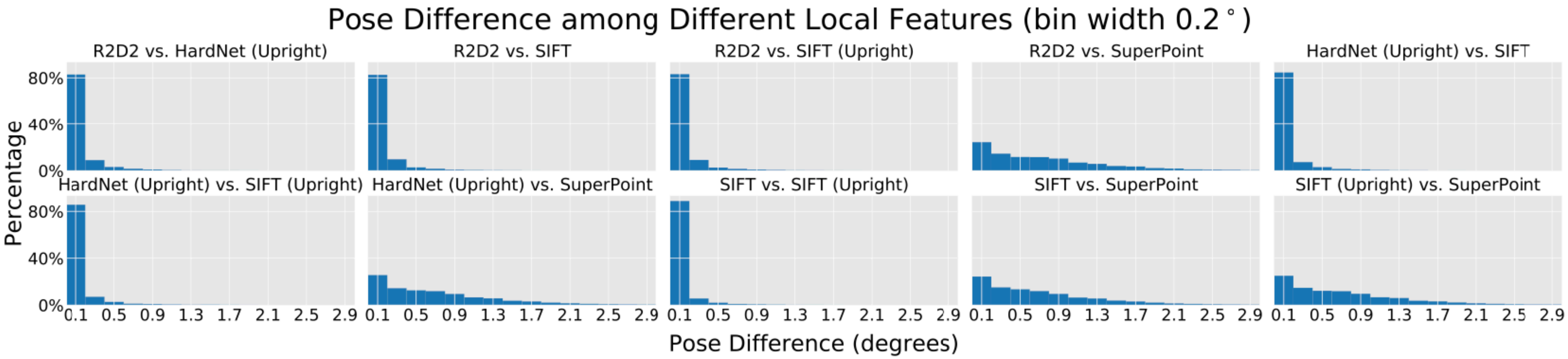

Fig. 7 Histograms of pose differences between reconstructions with different local feature methods. We consider five different local features – including rotation-sensitive and upright SIFT – resulting in 10 combinations. The plots show that about 80% percent of image pairs are within a 0.2^o pose difference, with the exception of those involving SuperPoint.

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Local featured type	Number of Images				
	100	200	400	800	all
SIFT [54]	0.06°	0.09°	0.06°	0.07°	0.09°
SIFT (Upright) [54]	0.07°	0.07°	0.04°	0.06°	0.09°
HardNet (Upright) [62]	0.06°	0.06°	0.06°	0.04°	0.05°
SuperPoint [34]	0.31°	0.25°	0.33°	0.19°	0.32°
R2D2 [80]	0.12°	0.08°	0.07°	0.08°	0.05°

Table 2 Standard deviation of the pose difference of three COLMAP runs with different number of images. Most of them are below 0.1°, except for SuperPoint.

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- Although we never can be sure

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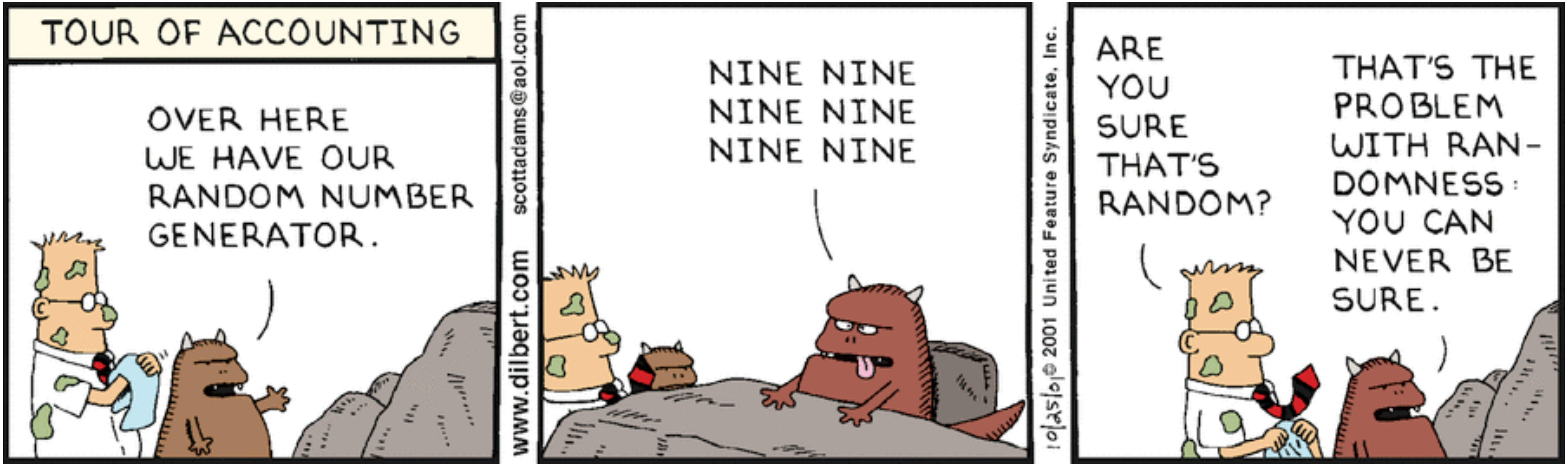

You should never be 100% sure

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- On the Limits of Pseudo Ground Truth in Visual Camera Re-localisation. Brachmann et.al ICCV 2021

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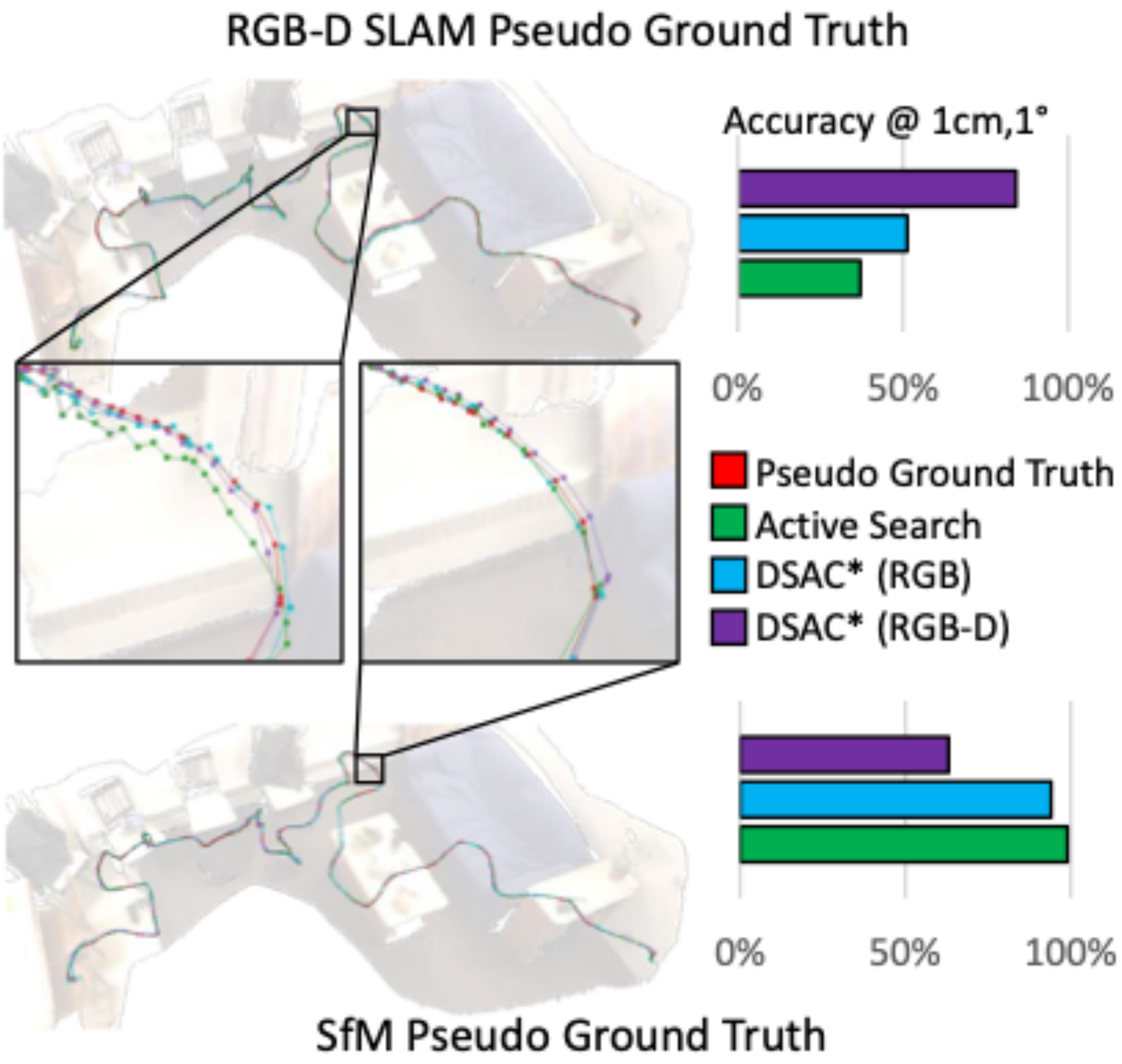

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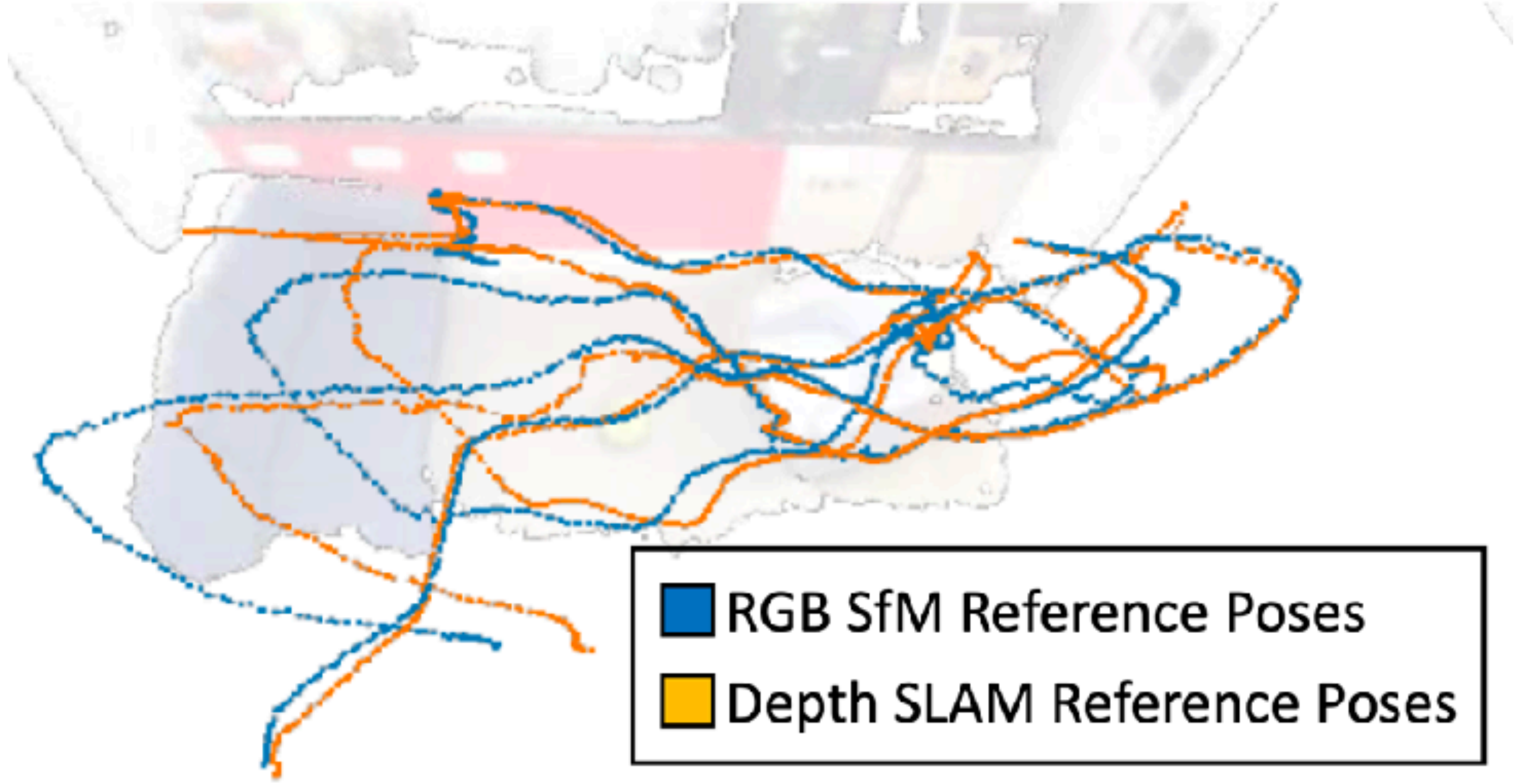

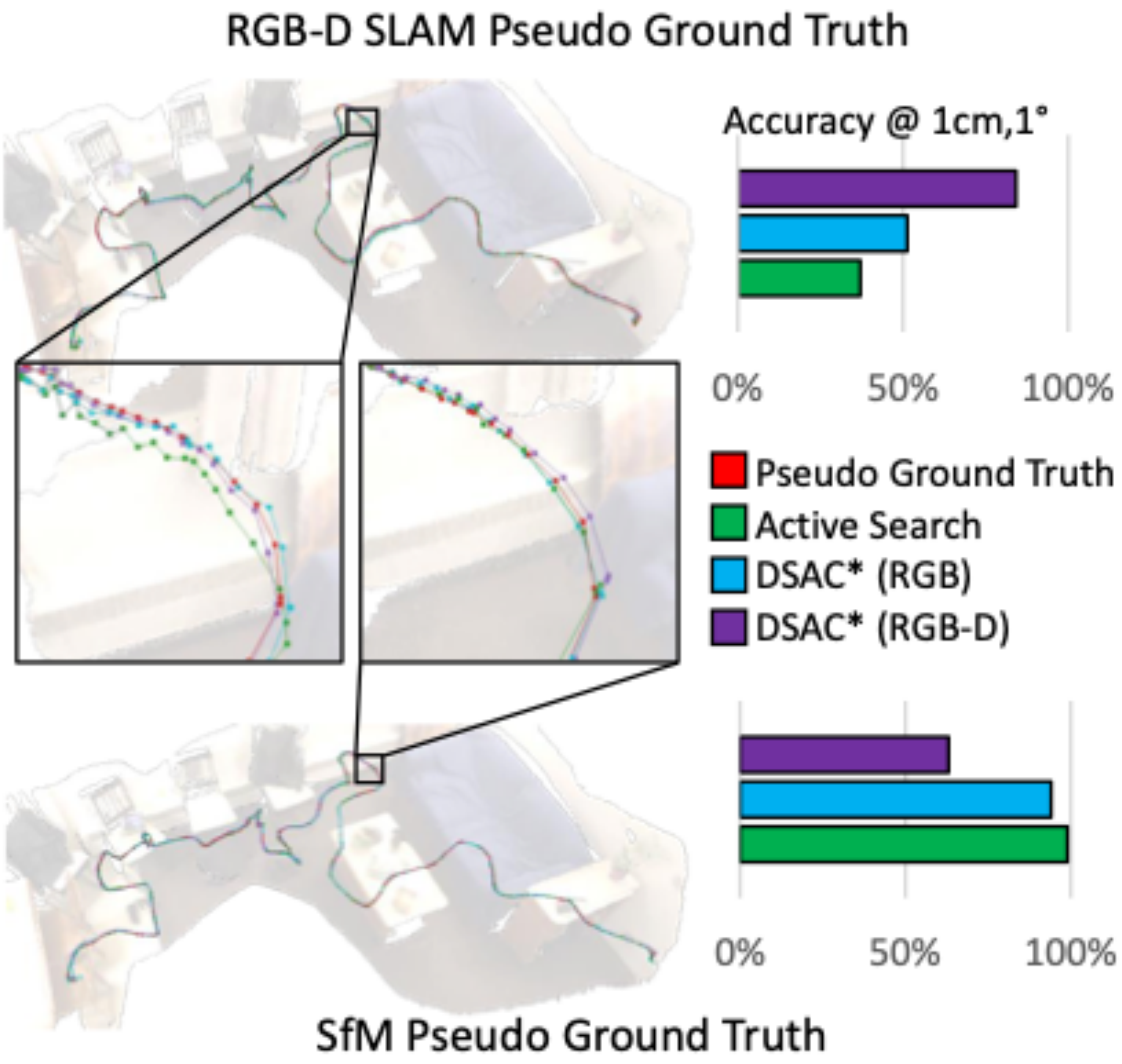

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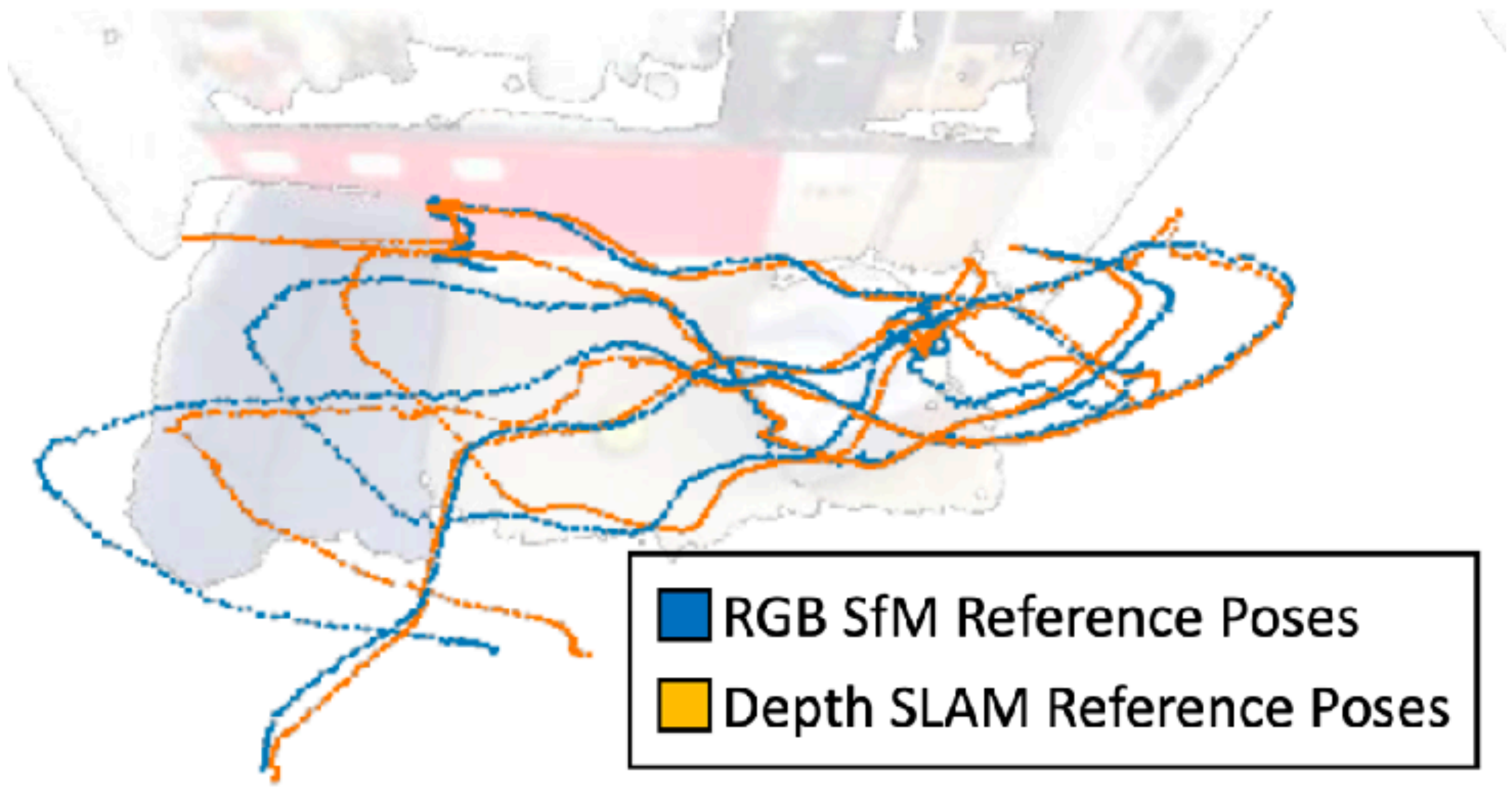

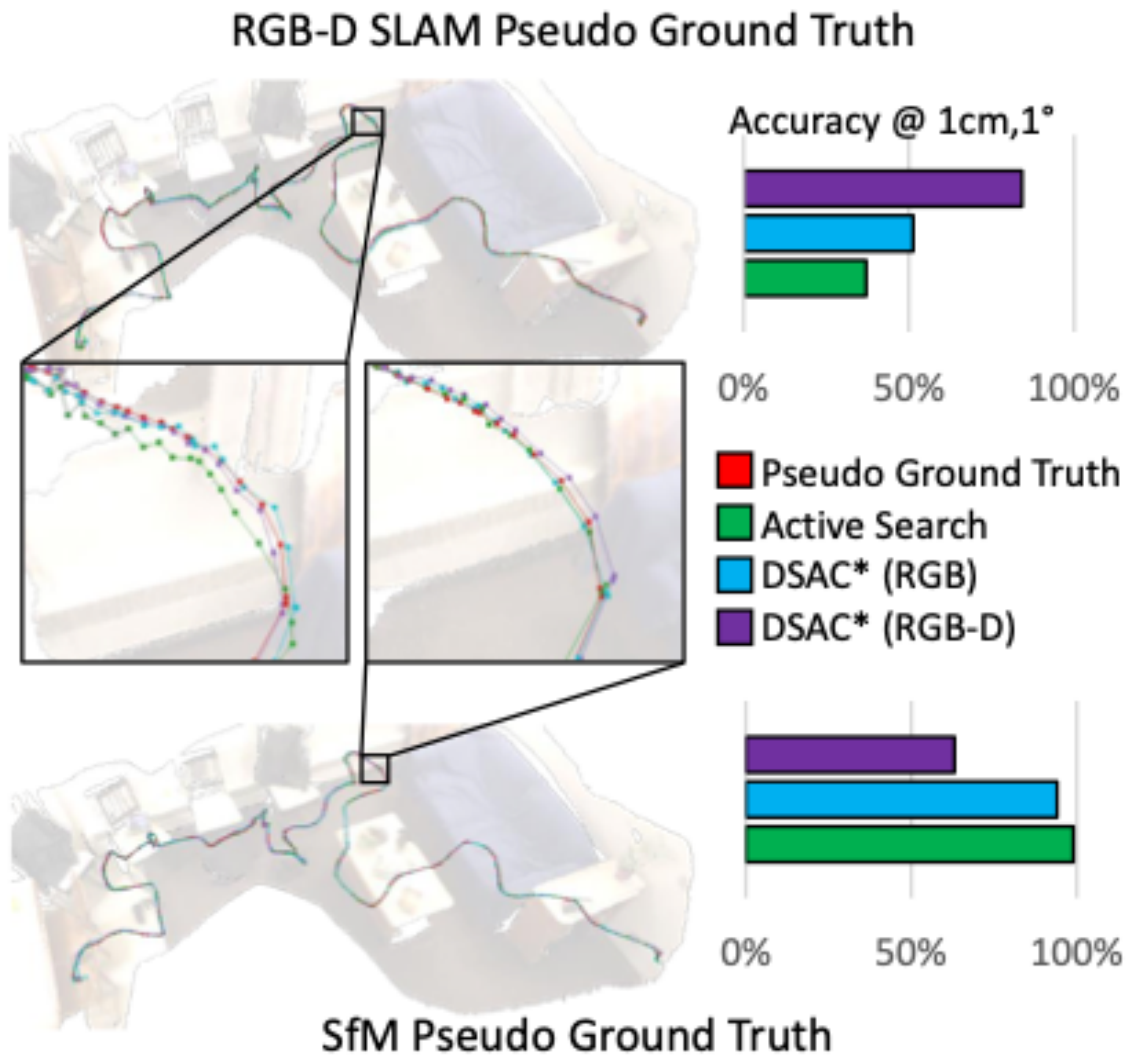

https://ducha-aiki.github.io/wide-baseline-stereo-blog/2021/09/04/review-of-pseudoGT-limitations.html

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Checking results and methods

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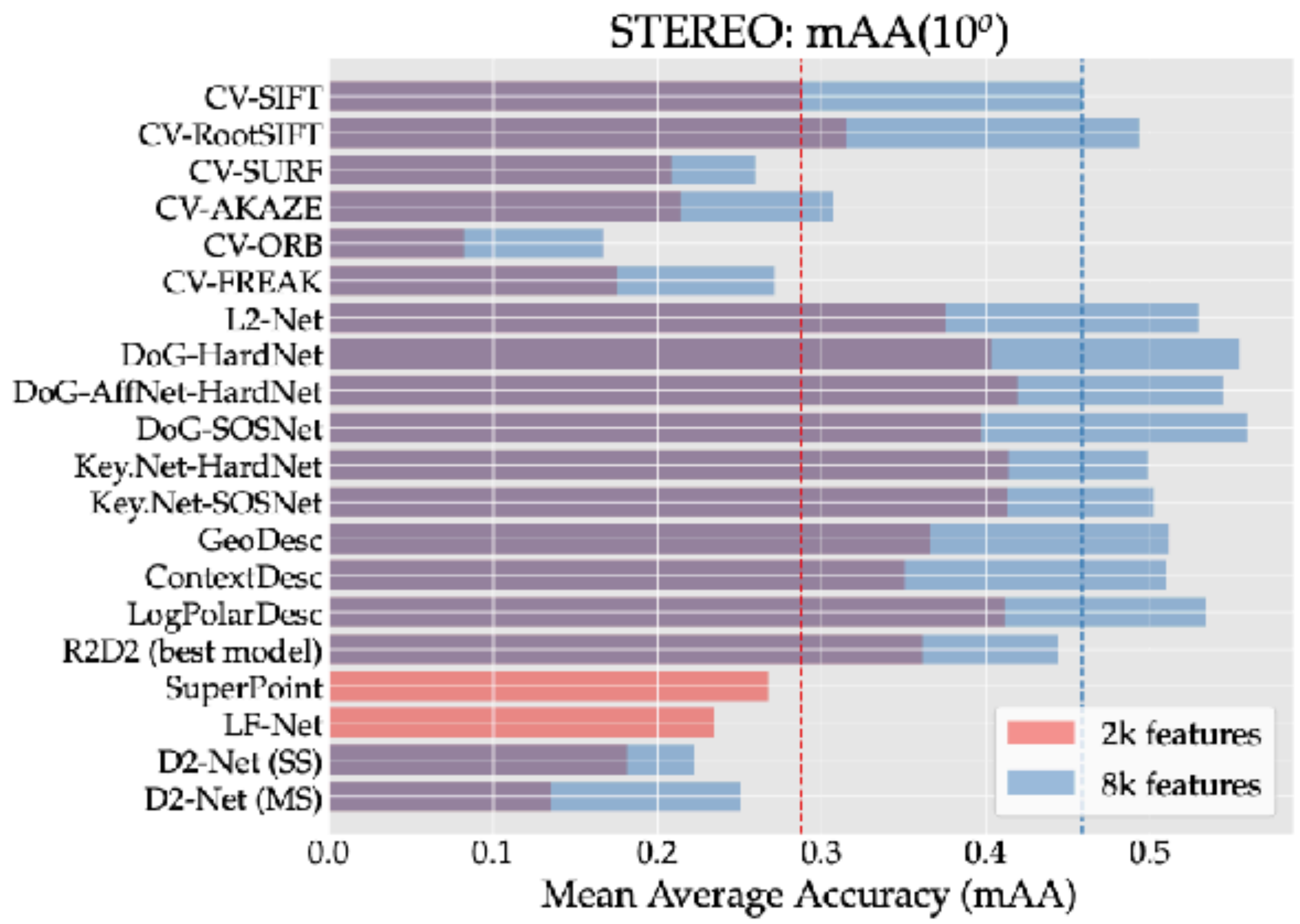

Fig. 17 Test – Stereo performance: 2k vs 8k features. We compare the results obtained with different methods using either 2k or 8k features – we use DEGENSAC, which performs better than other RANSAC variants under most circumstances. Dashed lines indicate SIFT's performance. For LF-Net and SuperPoint we do not include results with 8k features, as we failed to obtain meaningful results. For R2D2, we use the best model for each setting.

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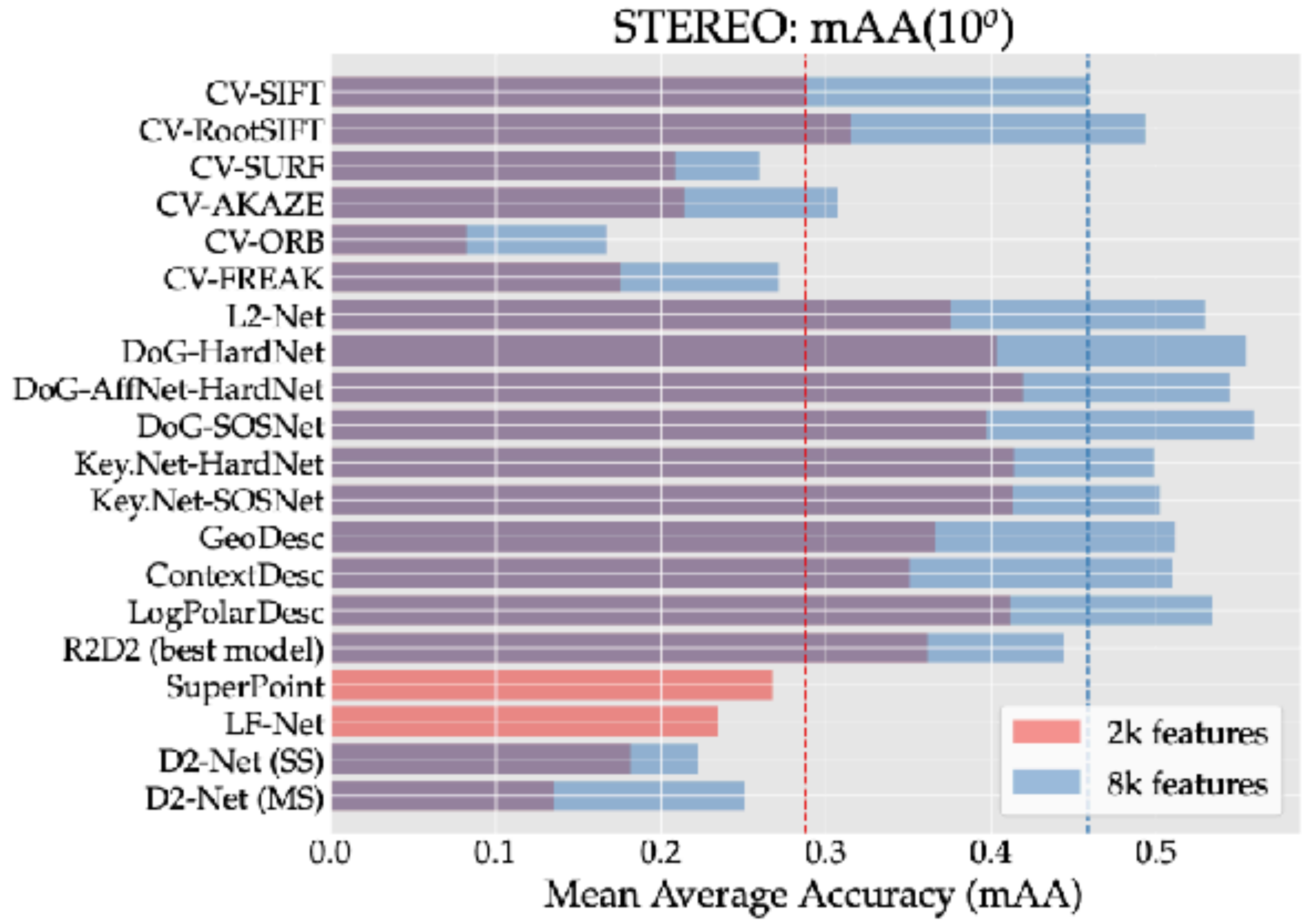

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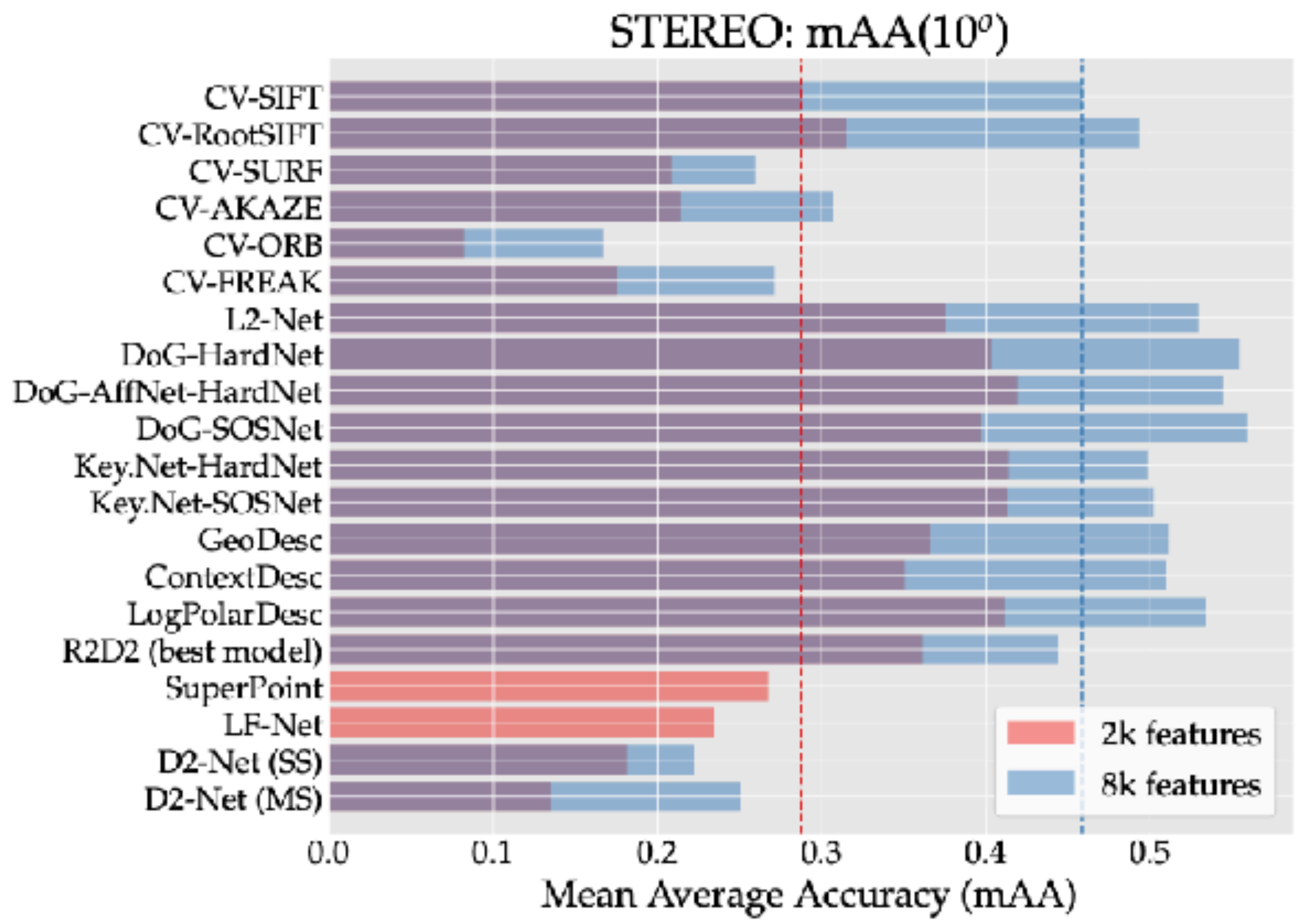

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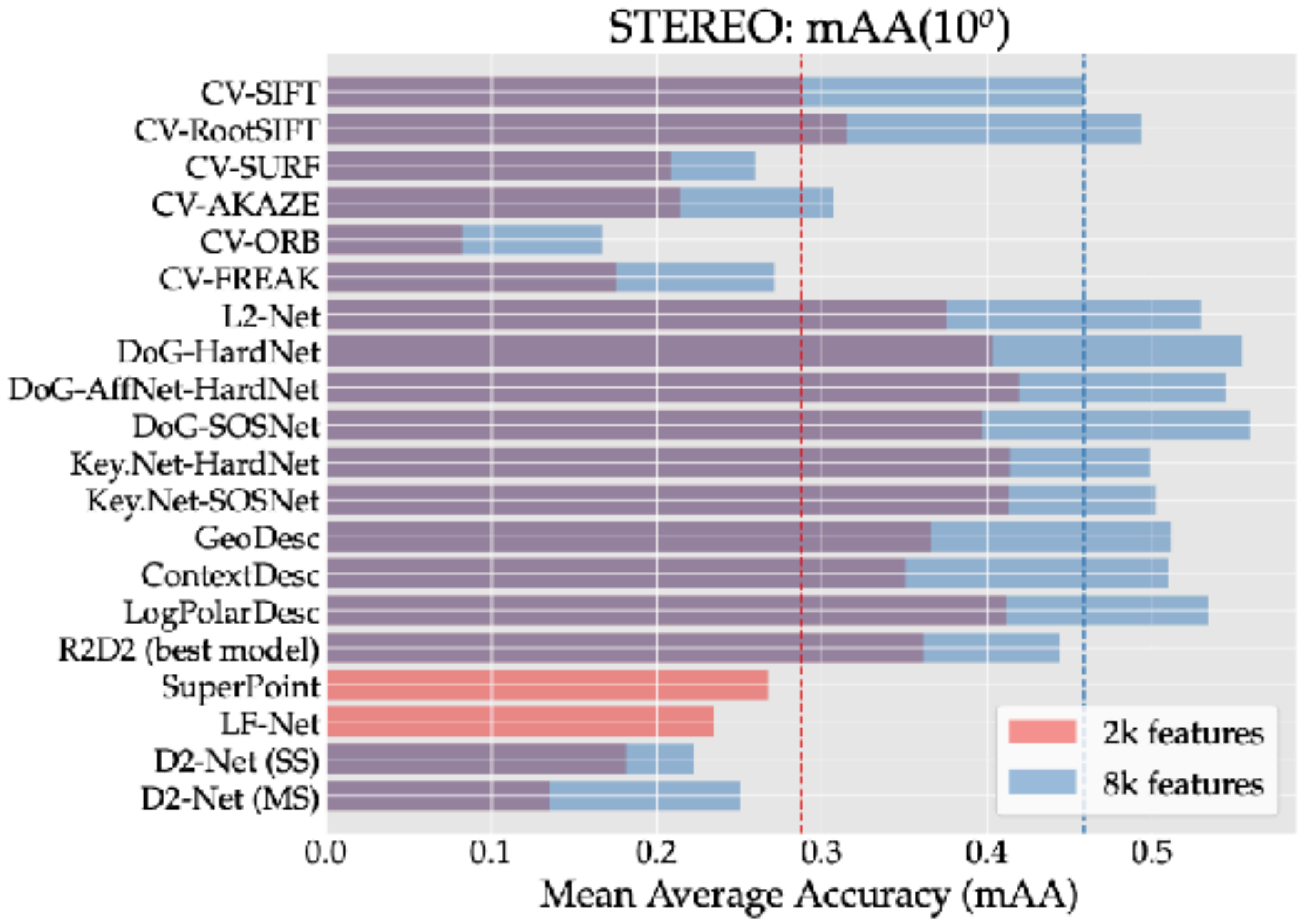

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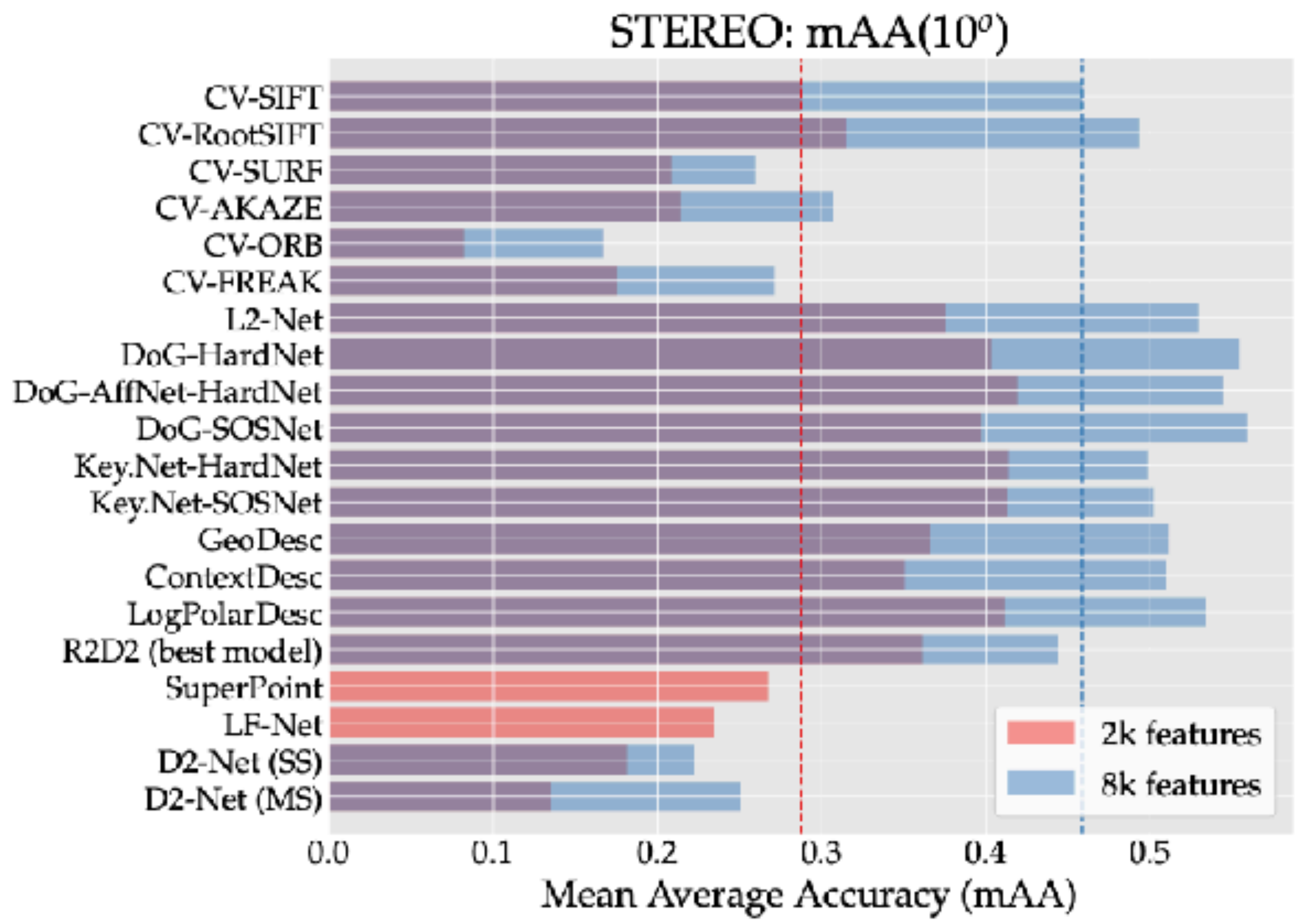

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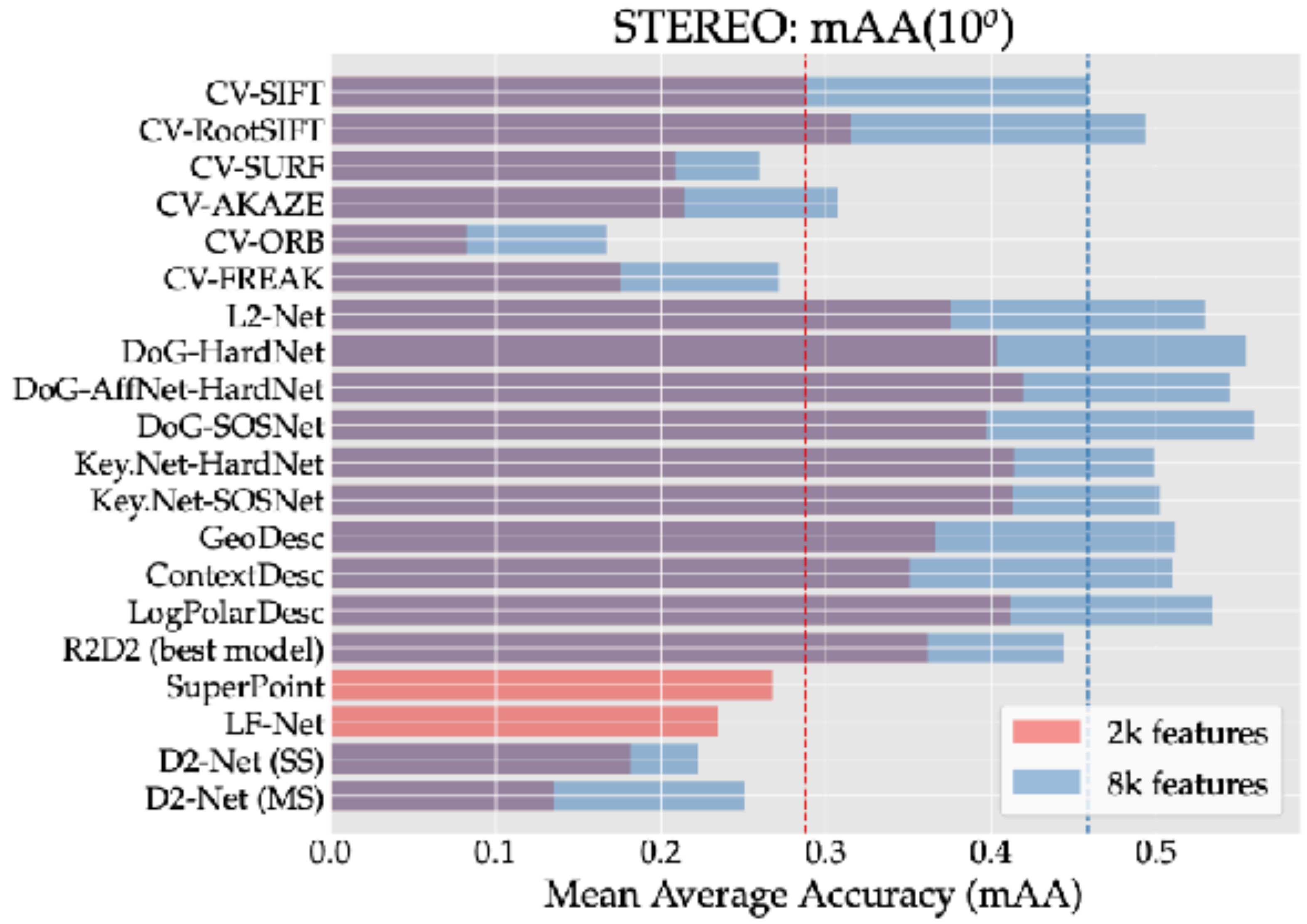

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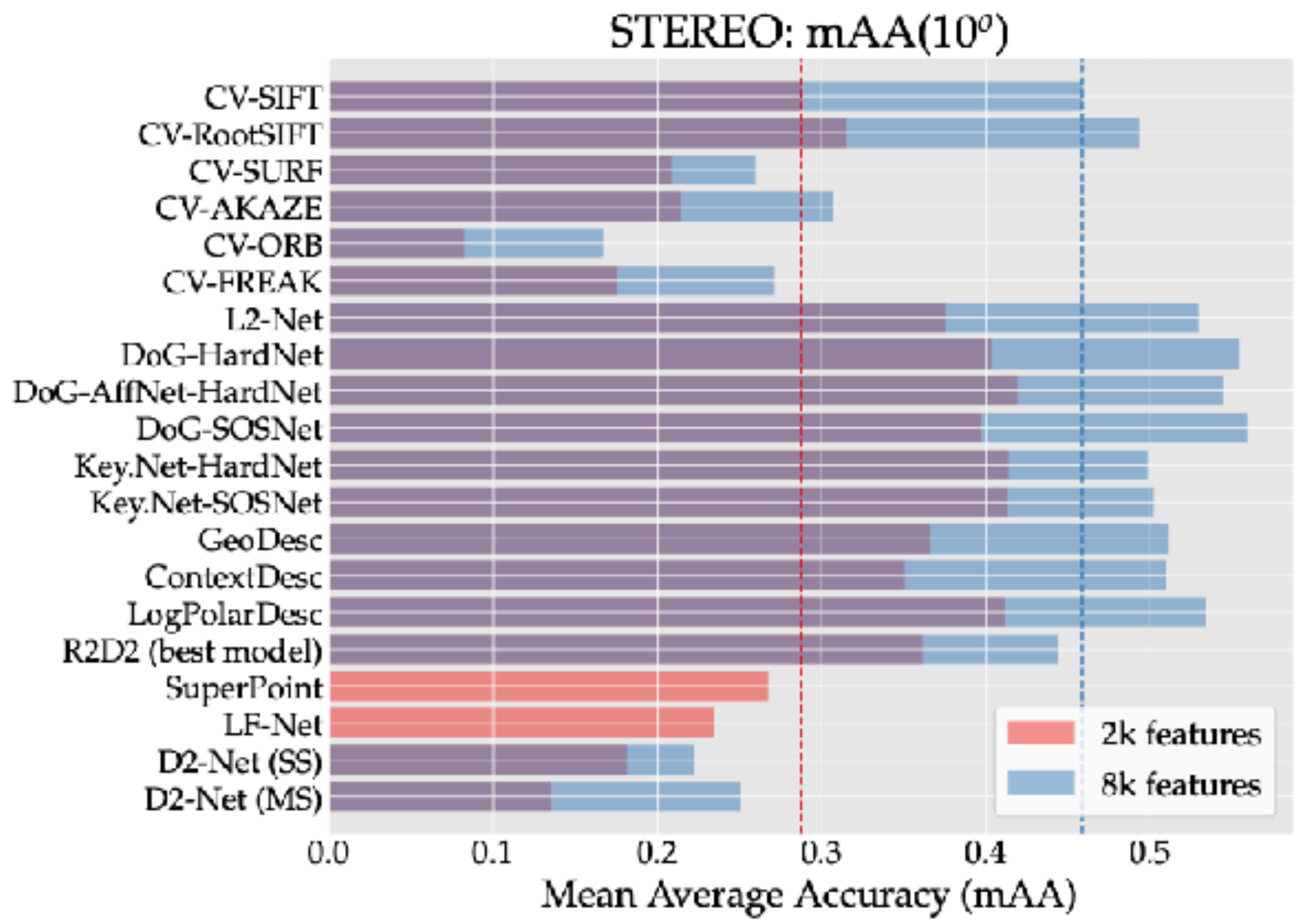
- Play selected (good and simple) methods
    - Maybe add their implementation to your ToDo



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How to “play with method”?

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- First, try to make it work

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  - Visualize, visualize, visualize
- Once it works, try to break it. Noise, transforms, data, etc.
  - that it is how understand its limits.
- Try to understand the ideas it is based on
- Only then try to implement it on your own

Playing with method

Case study

Playing with method
Case study

- I was working on some image-matching method with co-authors

Playing with method

Case study

- I was working on some image-matching method with co-authors
- They sent me the training code, I had to plug it into the benchmark

Playing with method
Case study

- I was working on some image-matching method with co-authors
- They sent me the training code, I had to plug it into the benchmark
- Instead I first wrote simple script to visualize keypoints

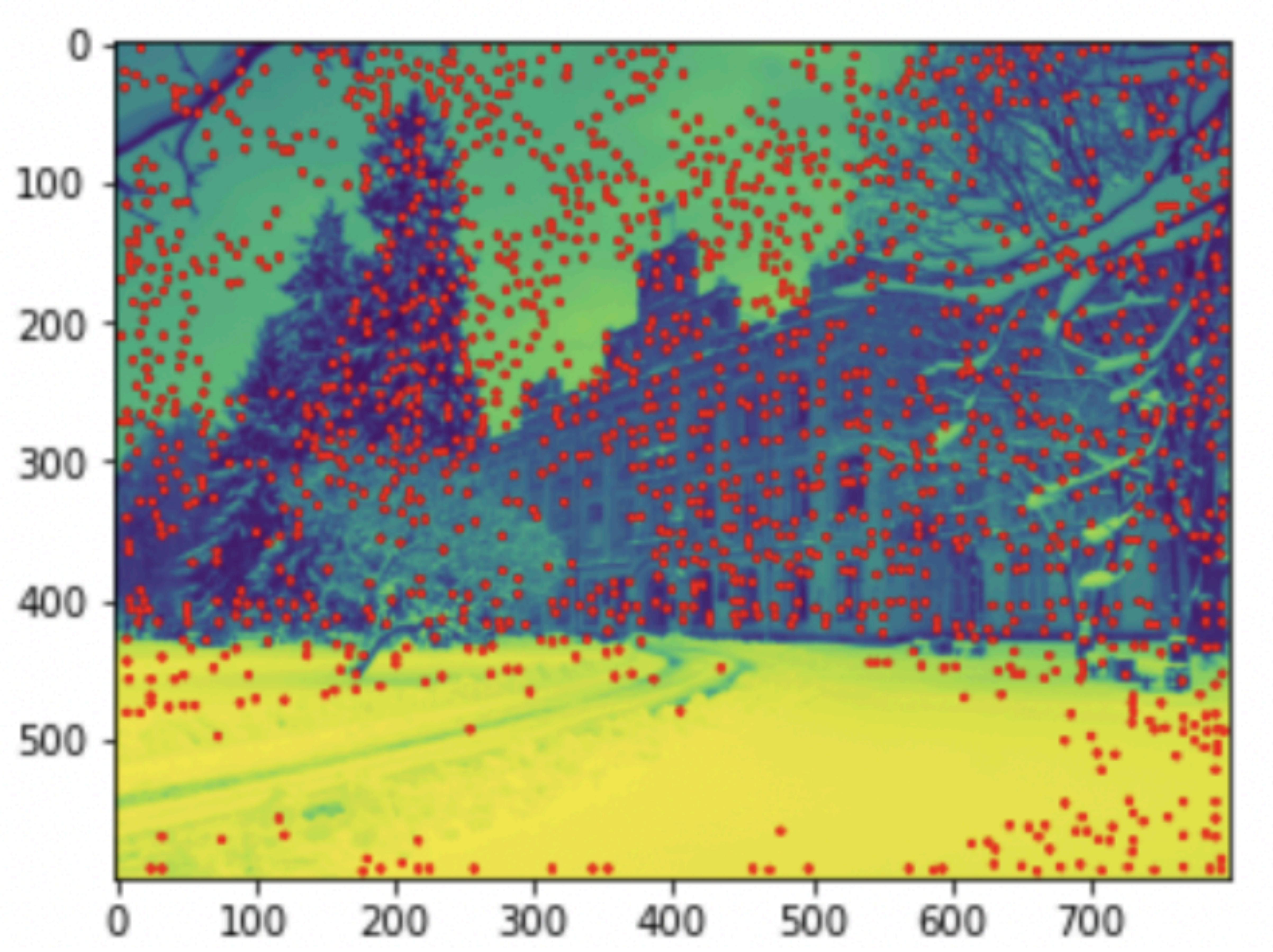
Playing with method

Case study

Playing with method

Case study

Model 1



Playing with method

Case study

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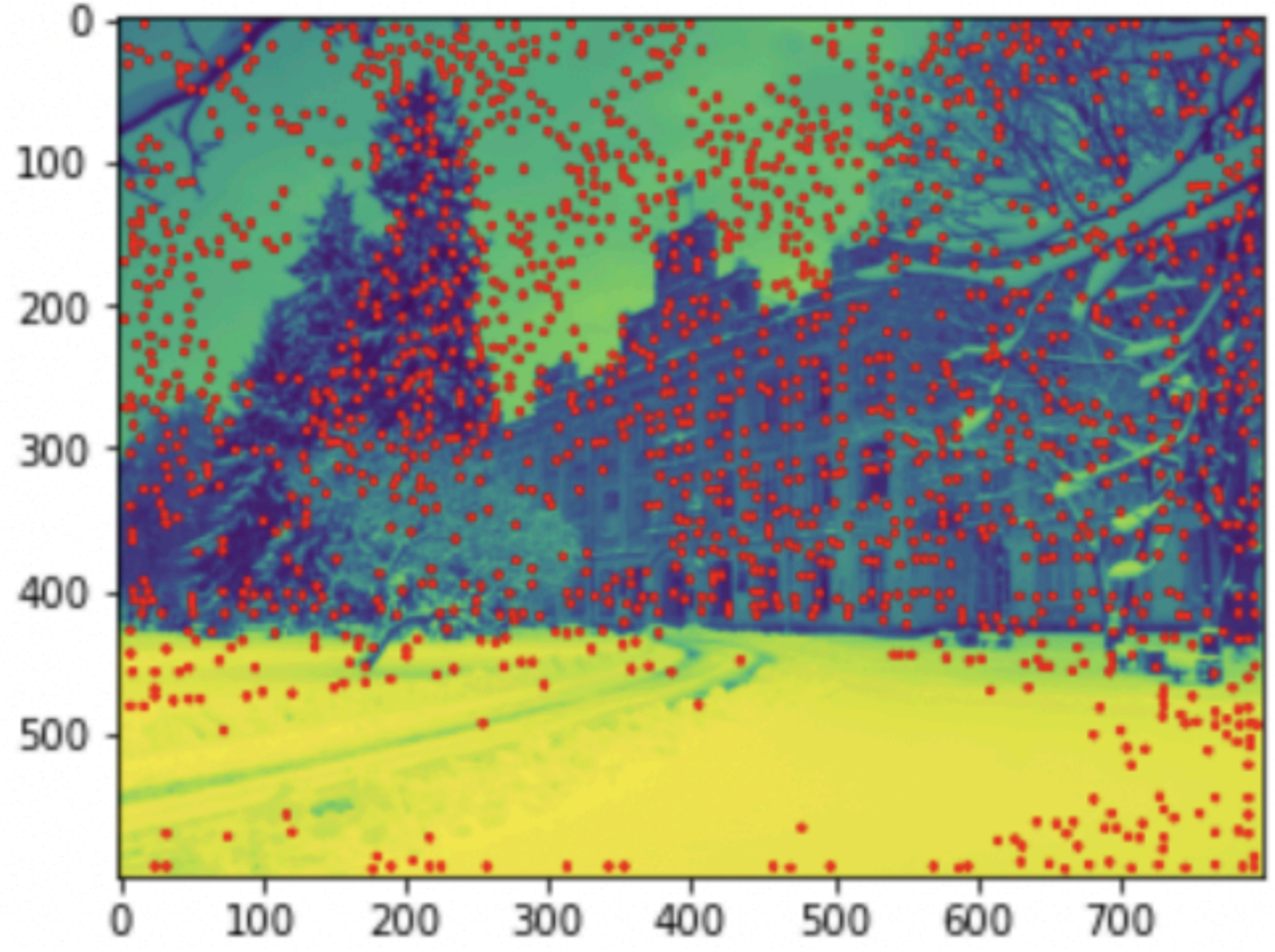
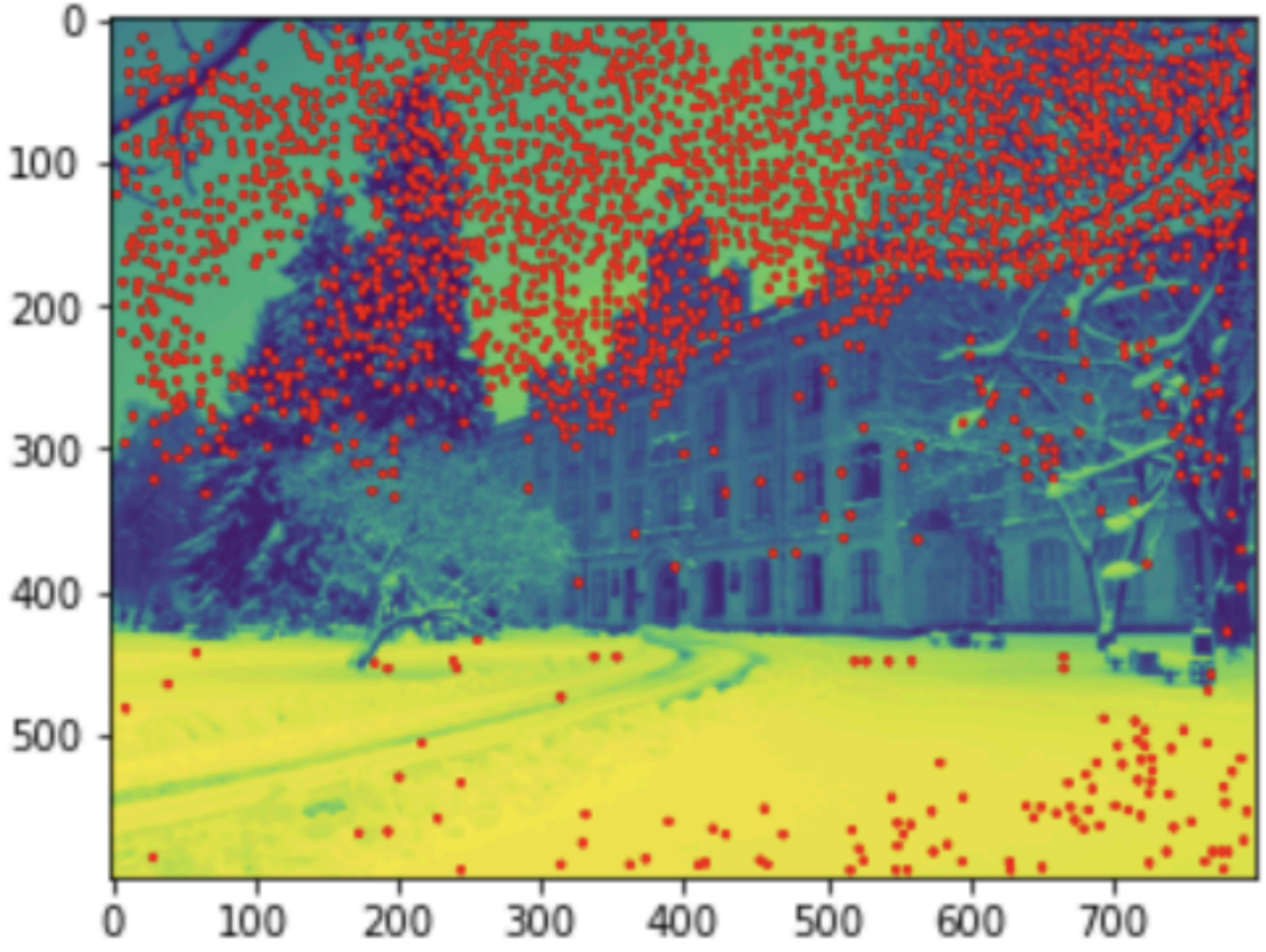


Model 2

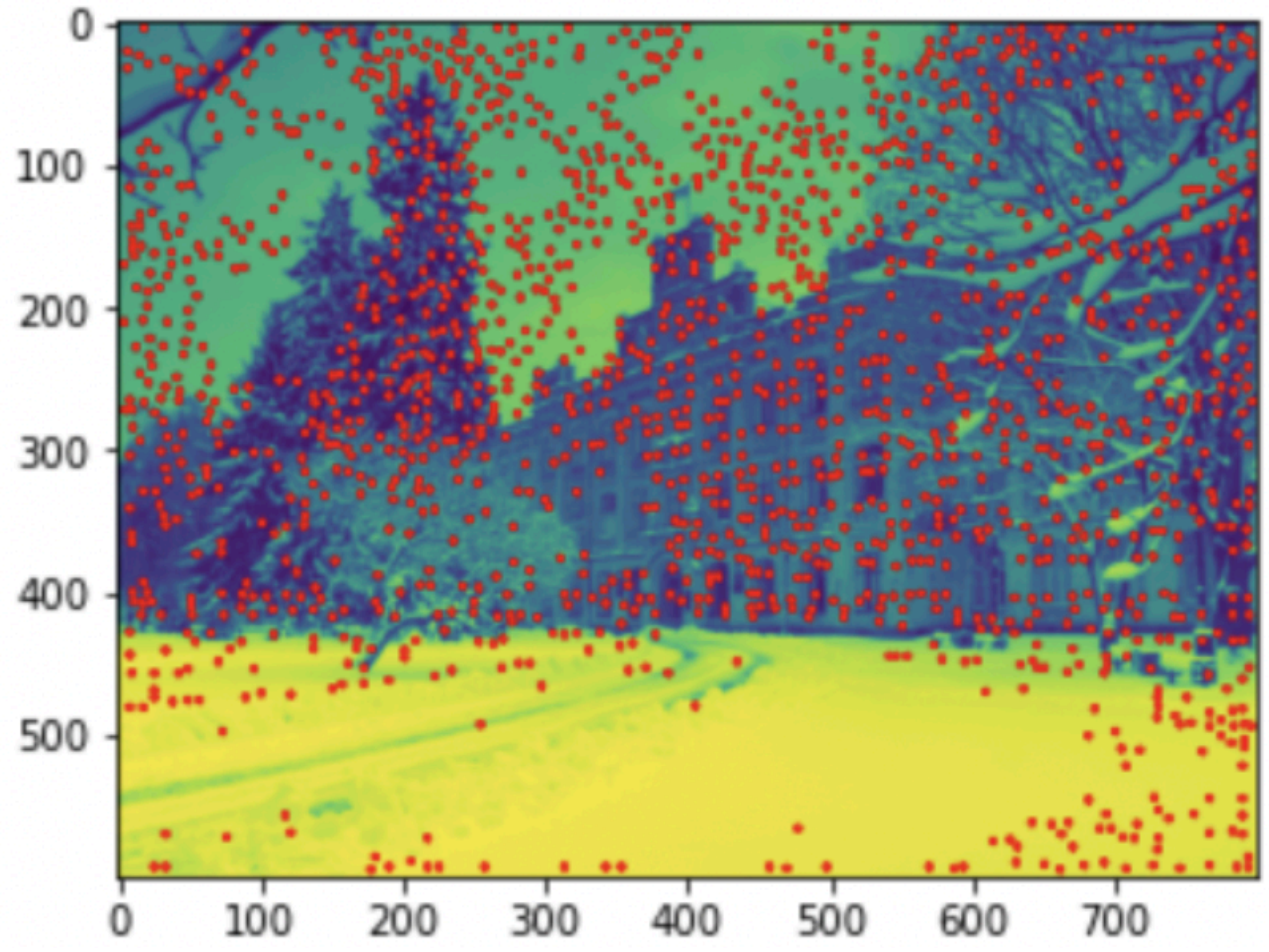


Playing with method

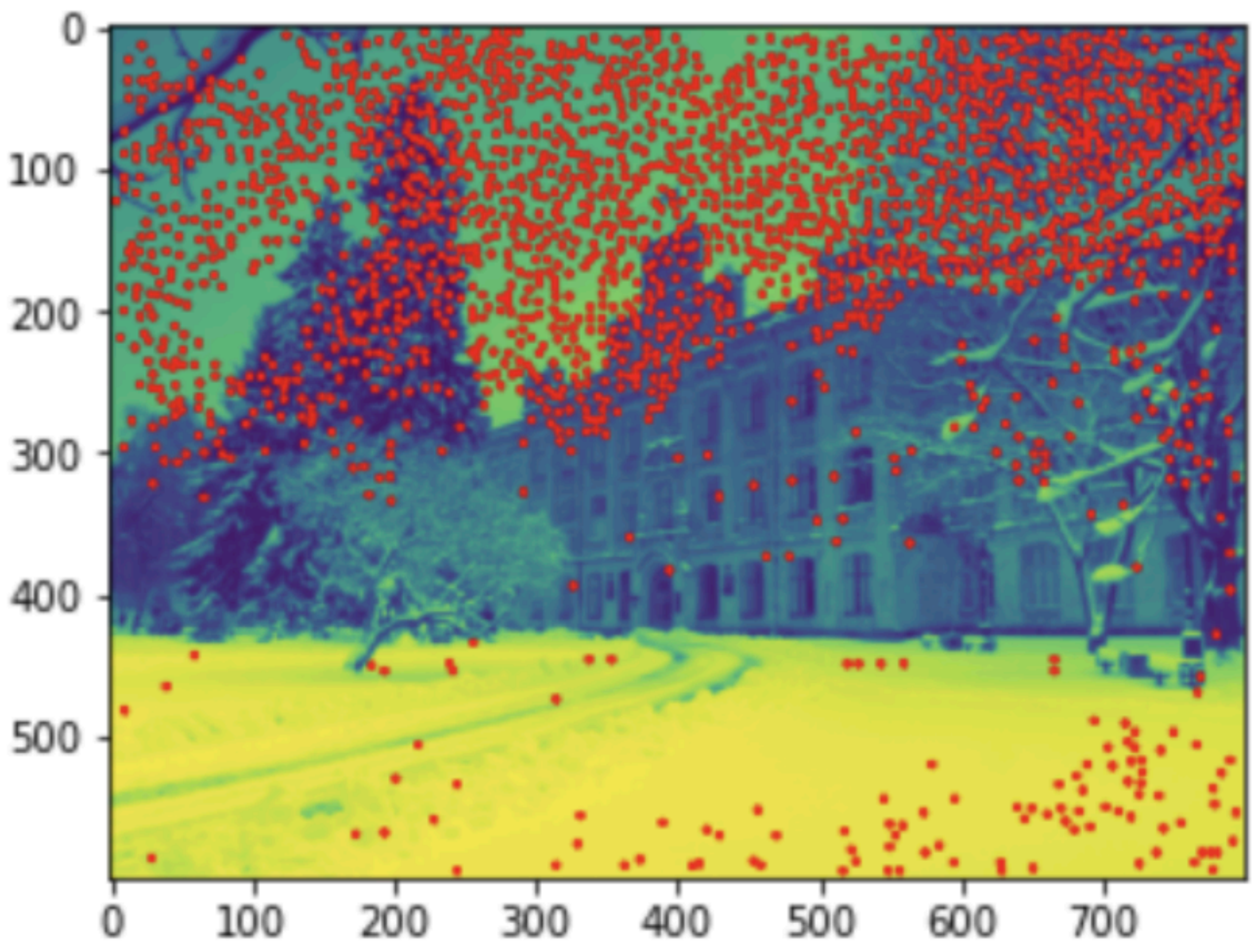
Case study

They were expected to look similar….

Model 1



Model 2



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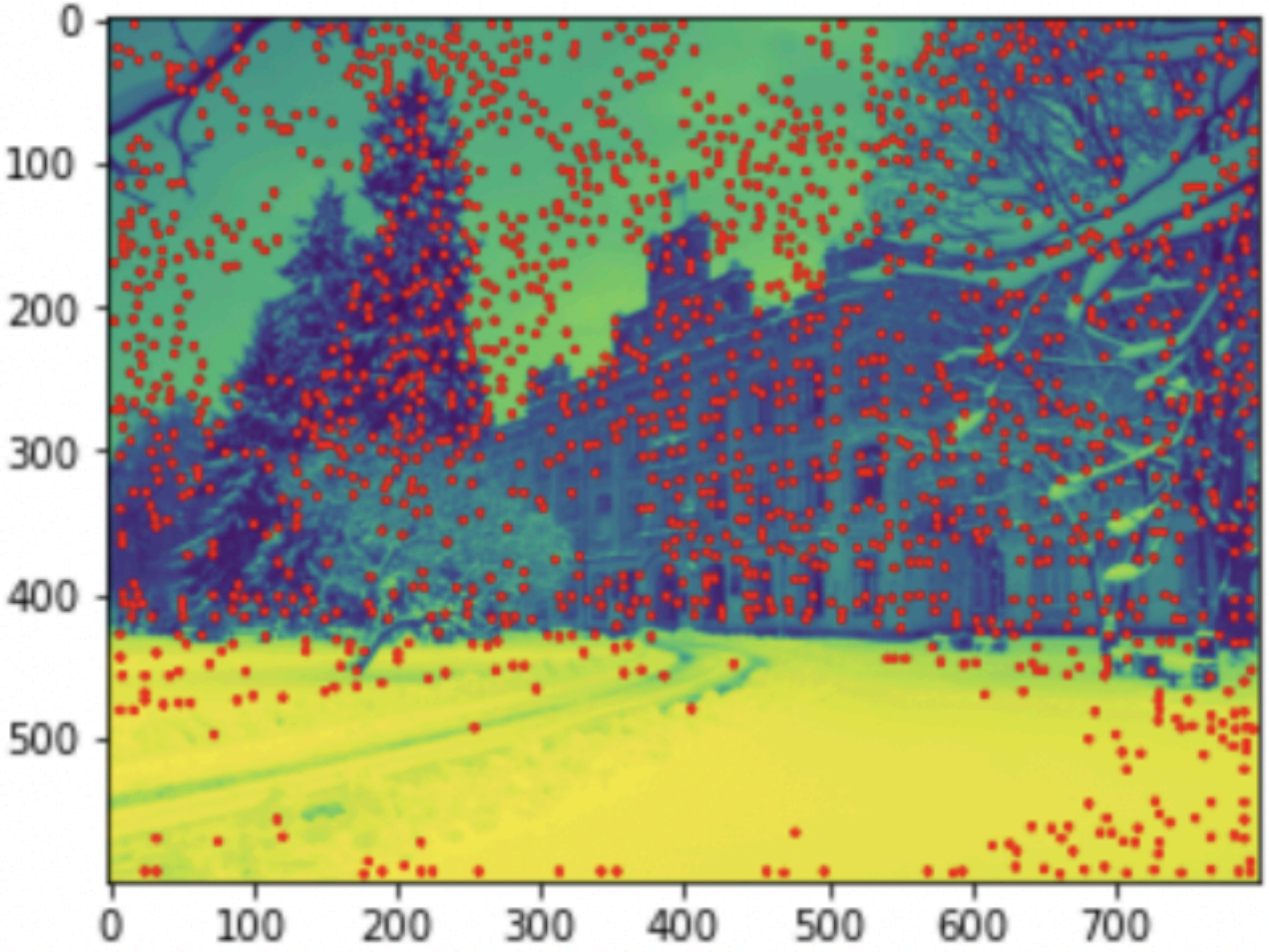

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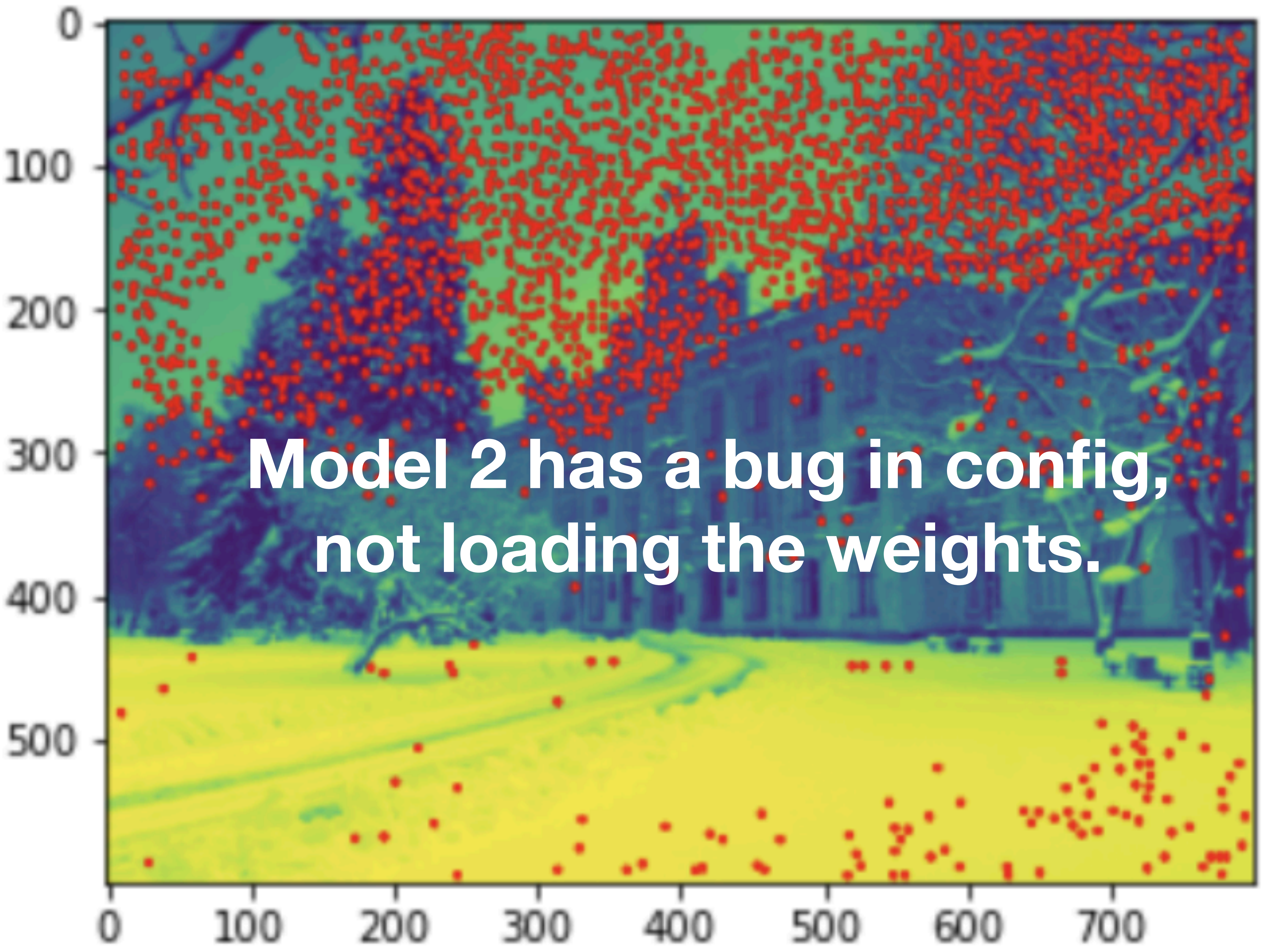

Playing with method

Case study

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Playing with method

Case study

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Playing with method
Case study

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Playing with method
Case study

- If it is possible, gather some data yourself, not from benchmarks
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- You can even build web demo for it
- If it is not fun, it is not “playing”
- You can think of this as “micro-benchmark”

Playing with method

Dmytro Mishkin
@ducha_aiki

R2D2 fails here, others are fine
9/

Перекласти твіт

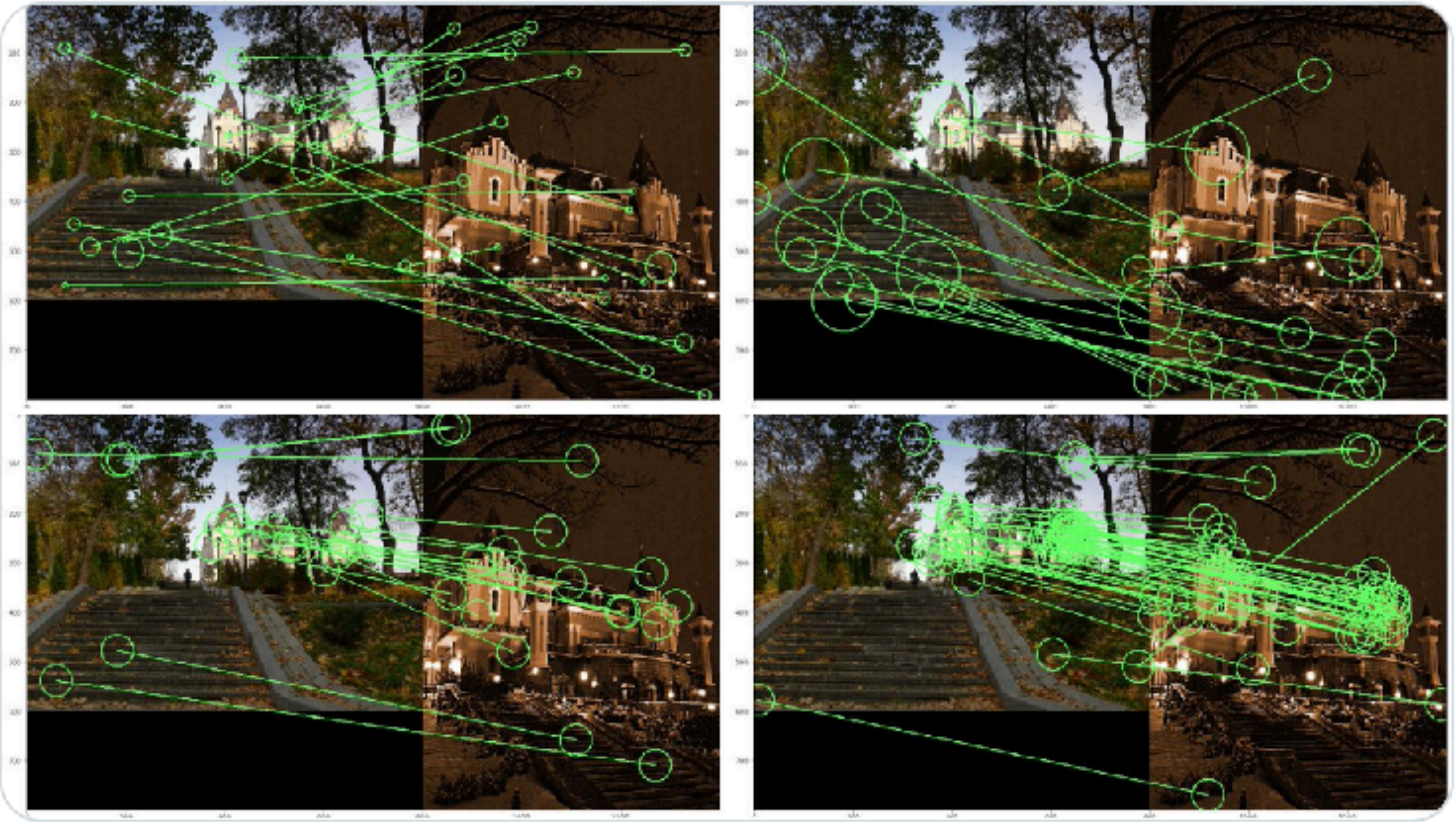
3:47 пп · 22 лист. 2020 · Twitter Web App

https://twitter.com/ducha_aiki/status/1330495426865344515

Dmytro Mishkin
@ducha_aiki

SIFT-HardNet and R2D2 fail here, SuperPoint rocks.
10/10
Overall, for random unknown upright pair of images with possible illumination change, I would go for SuperPoint, as least if we don't consider affine view synthesis.

Перекласти твіт



4:00 пп · 22 лист. 2020 · Twitter Web App

You know area well enough

and want to keep yourself up-to-date

You know area well enough

and want to keep yourself up-to-date

- You want to maximize useful information flow

You know area well enough

and want to keep yourself up-to-date

- You want to maximize useful information flow
- And minimize brain fuel & time spent

Where to look for papers on arXiv

arXiv itself?

- arxiv.org

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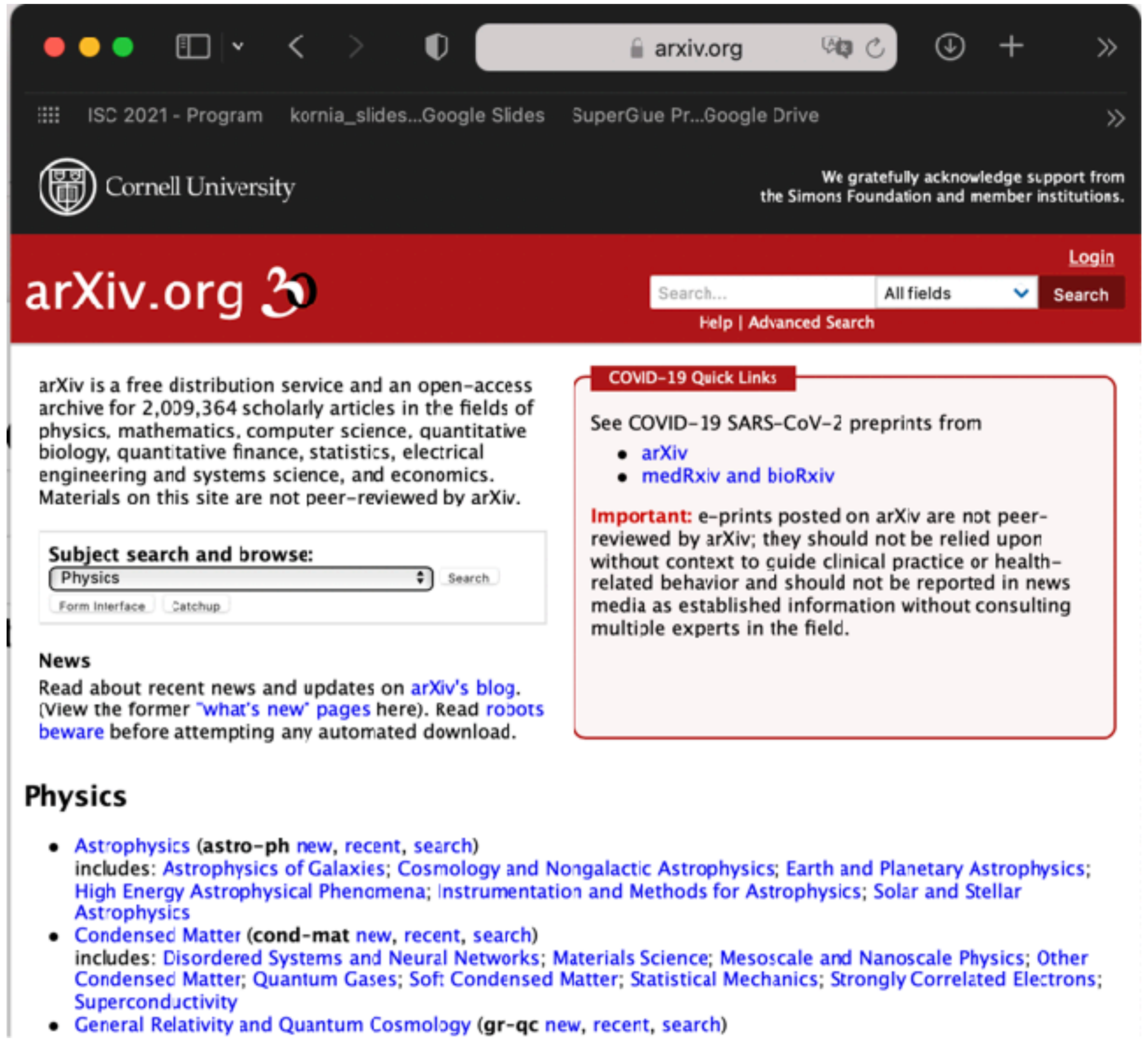

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Computer Science

- Computing Research Repository (CoRR new, recent, search)
  includes (see detailed description): Artificial Intelligence; Computation and Language; Computational Complexity; Computational Engineering, Finance, and Science; Computational Geometry; Computer Science and Game Theory; Computer Vision and Pattern Recognition; Computers and Society; Cryptography and Security; Data Structures and Algorithms; Databases; Digital Libraries; Discrete Mathematics; Distributed, Parallel, and Cluster Computing; Emerging Technologies; Formal Languages and Automata Theory; General Literature; Graphics; Hardware Architecture; Human-Computer Interaction; Information Retrieval; Information Theory; Logic in Computer Science; Machine Learning; Mathematical Software; Multiagent Systems; Multimedia; Networking and Internet Architecture; Neural and Evolutionary Computing; Numerical Analysis; Operating Systems; Other Computer Science; Performance; Programming Languages; Robotics; Social and Information Networks; Software Engineering; Sound; Symbolic Computation; Systems and Control

Quantitative Biology

- Quantitative Biology (q-bio new, recent, search)
  includes (see detailed description): Biomolecules; Cell Behavior; Genomics; Molecular Networks; Neurons and Cognition; Other Quantitative Biology; Populations and Evolution; Quantitative Methods; Subcellular Processes; Tissues and Organs

Quantitative Finance

- Quantitative Finance (q-fin new, recent, search)
  includes (see detailed description): Computational Finance; Economics; General Finance; Mathematical Finance; Portfolio Management; Pricing of Securities; Risk Management; Statistical Finance; Trading and Market Microstructure

Statistics

- Statistics (stat new, recent, search)
  includes (see detailed description): Applications; Computation; Machine Learning; Methodology; Other Statistics; Statistics Theory

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Quantitative Biology

- Quantitative Biology (q-bio new, recent, search)
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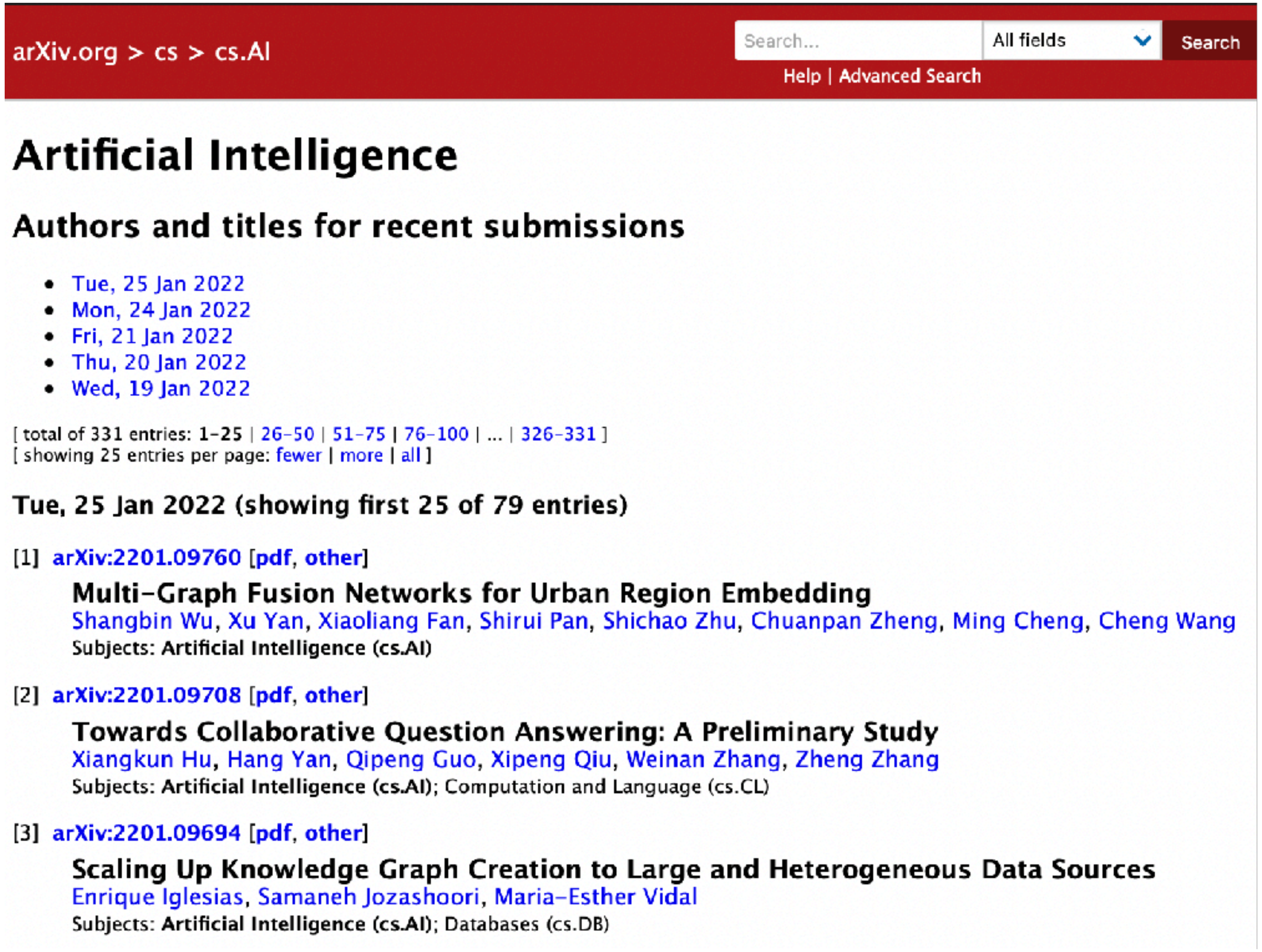

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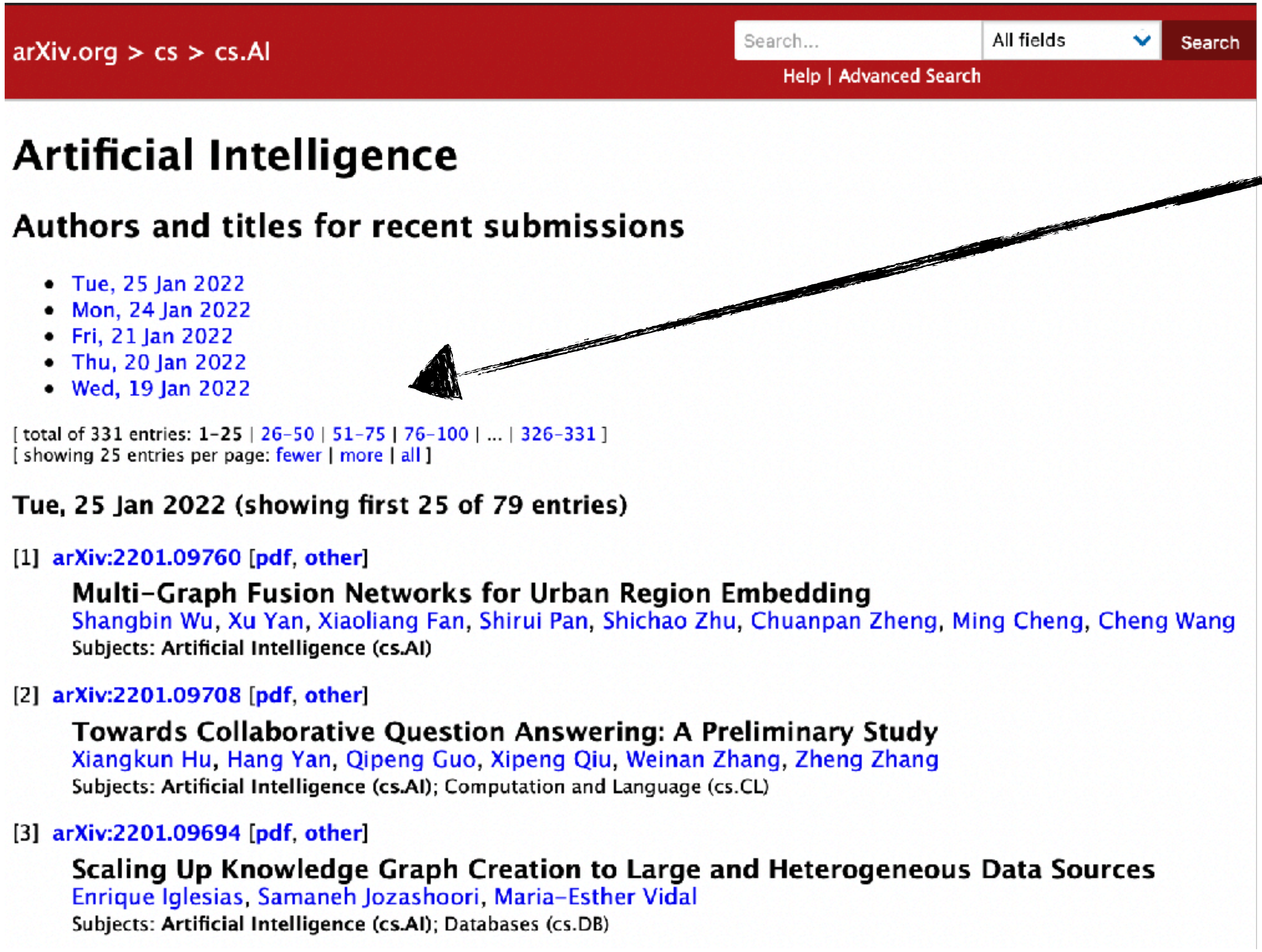
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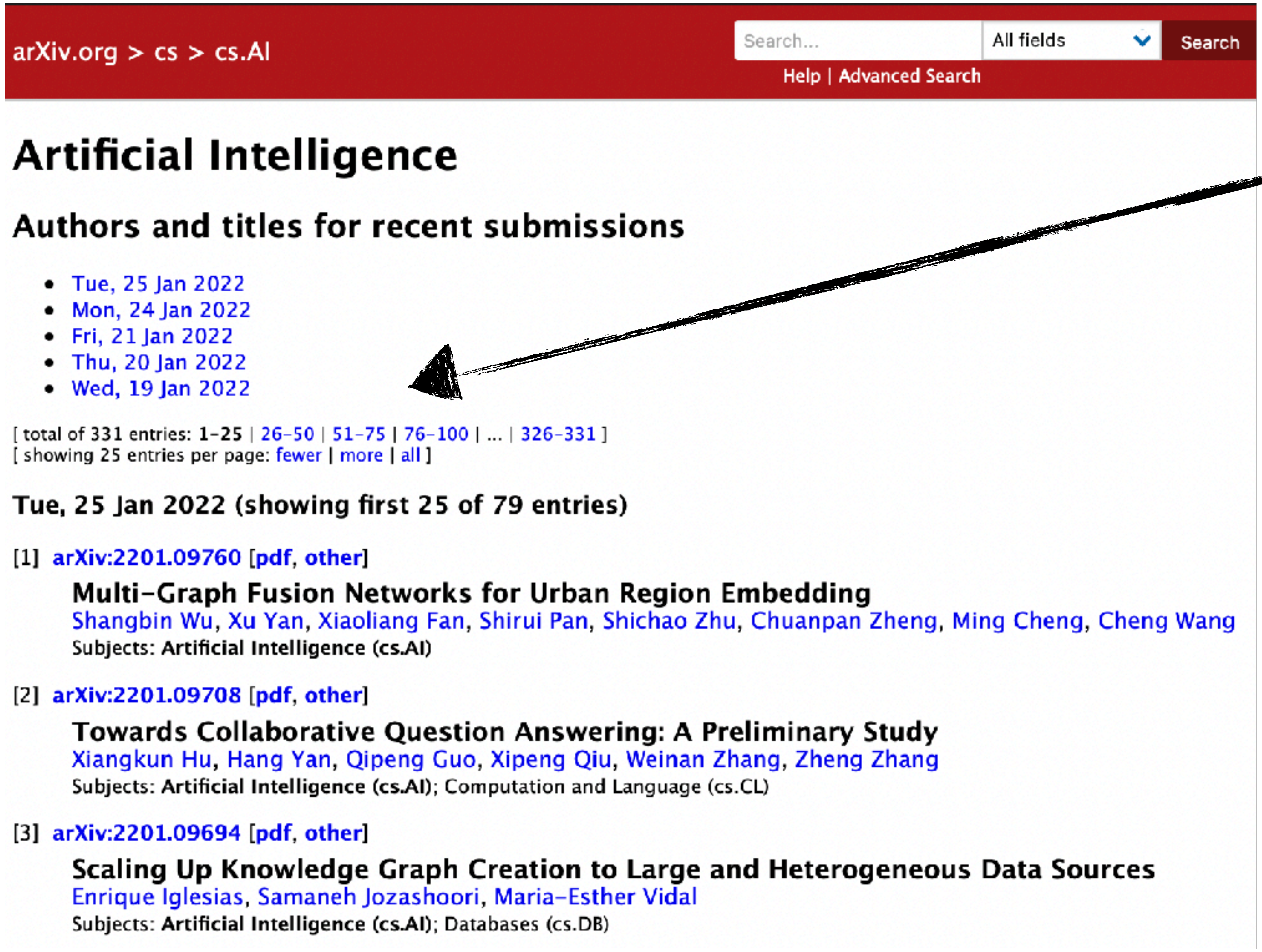
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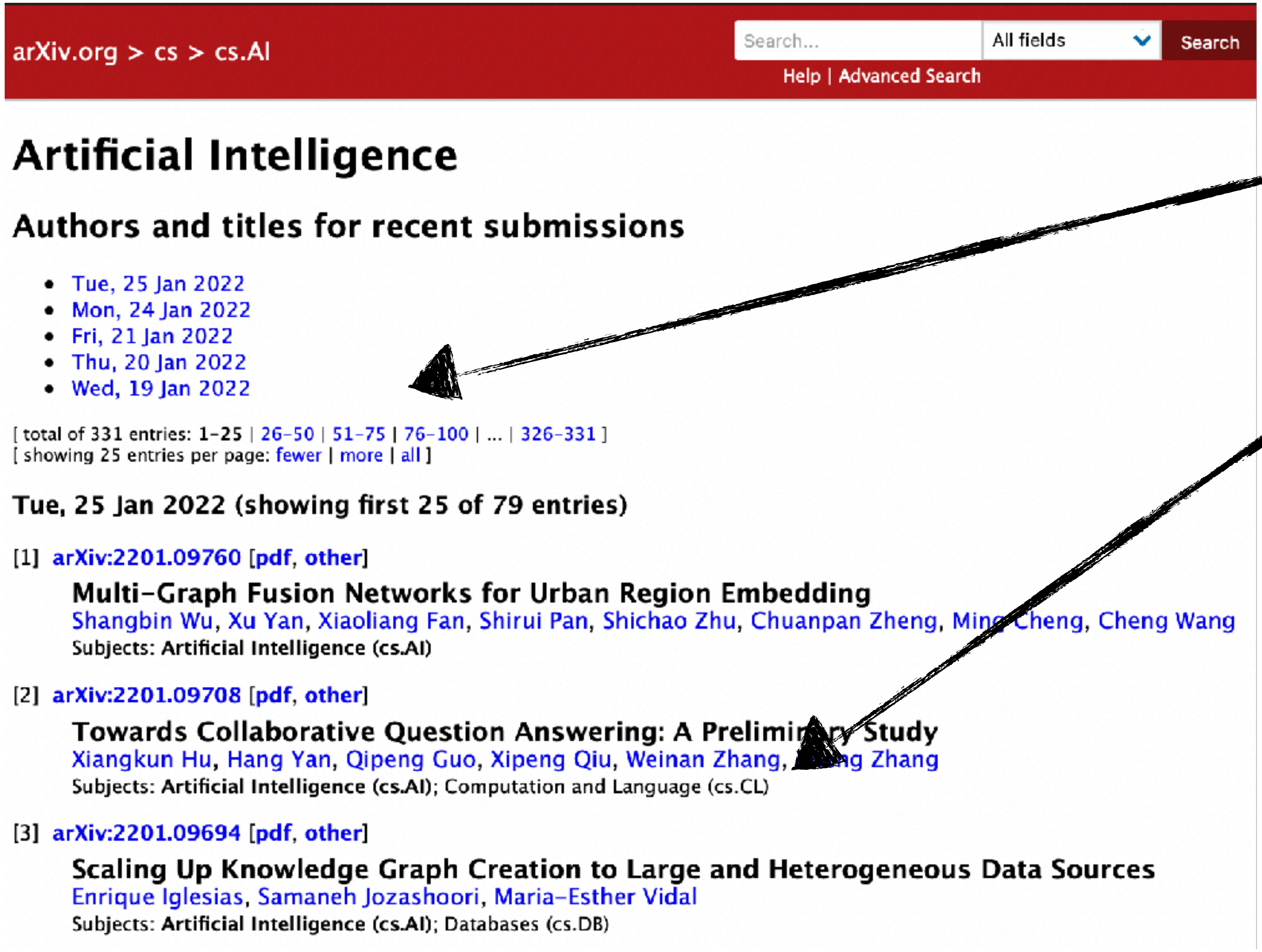
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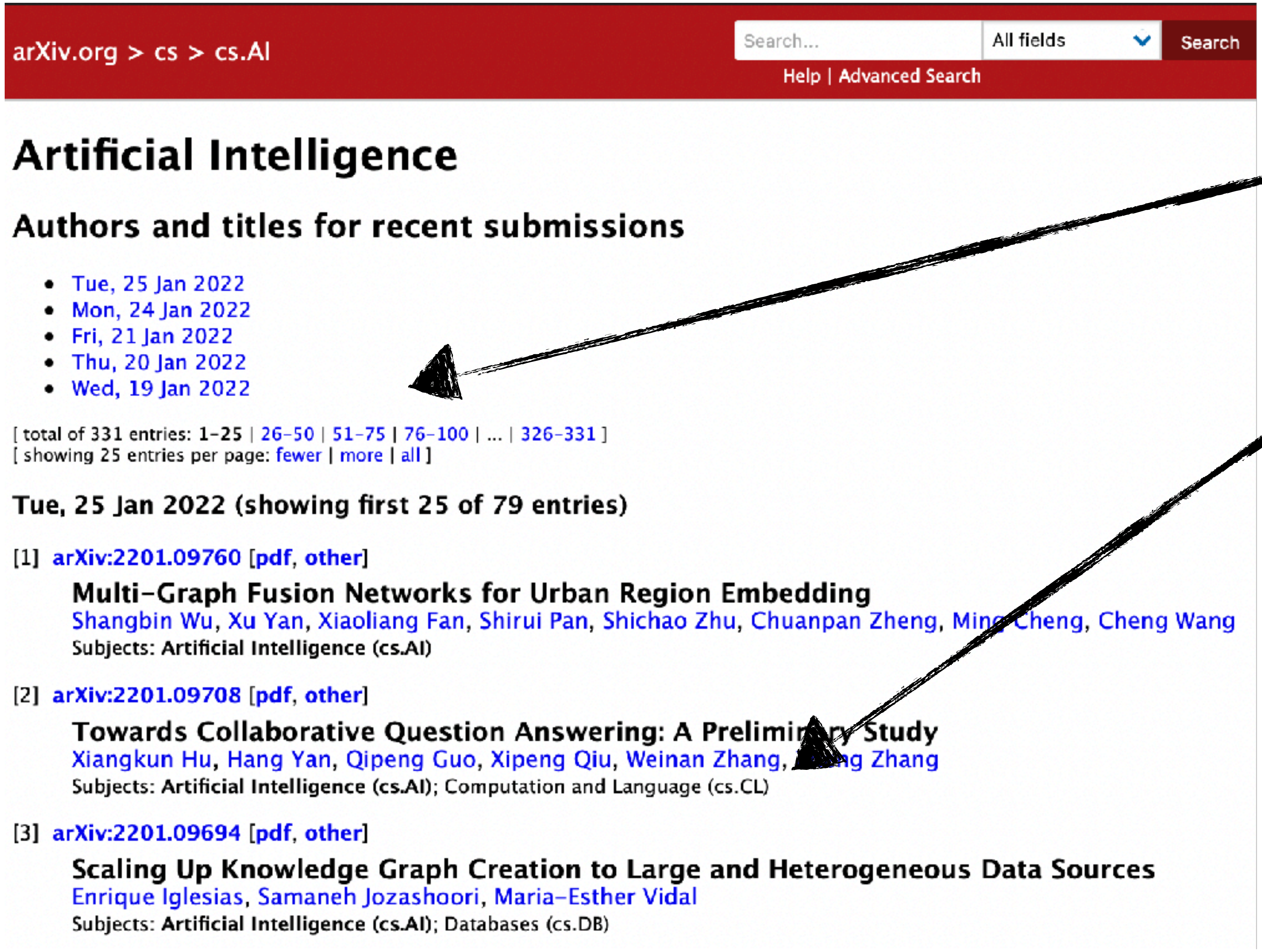

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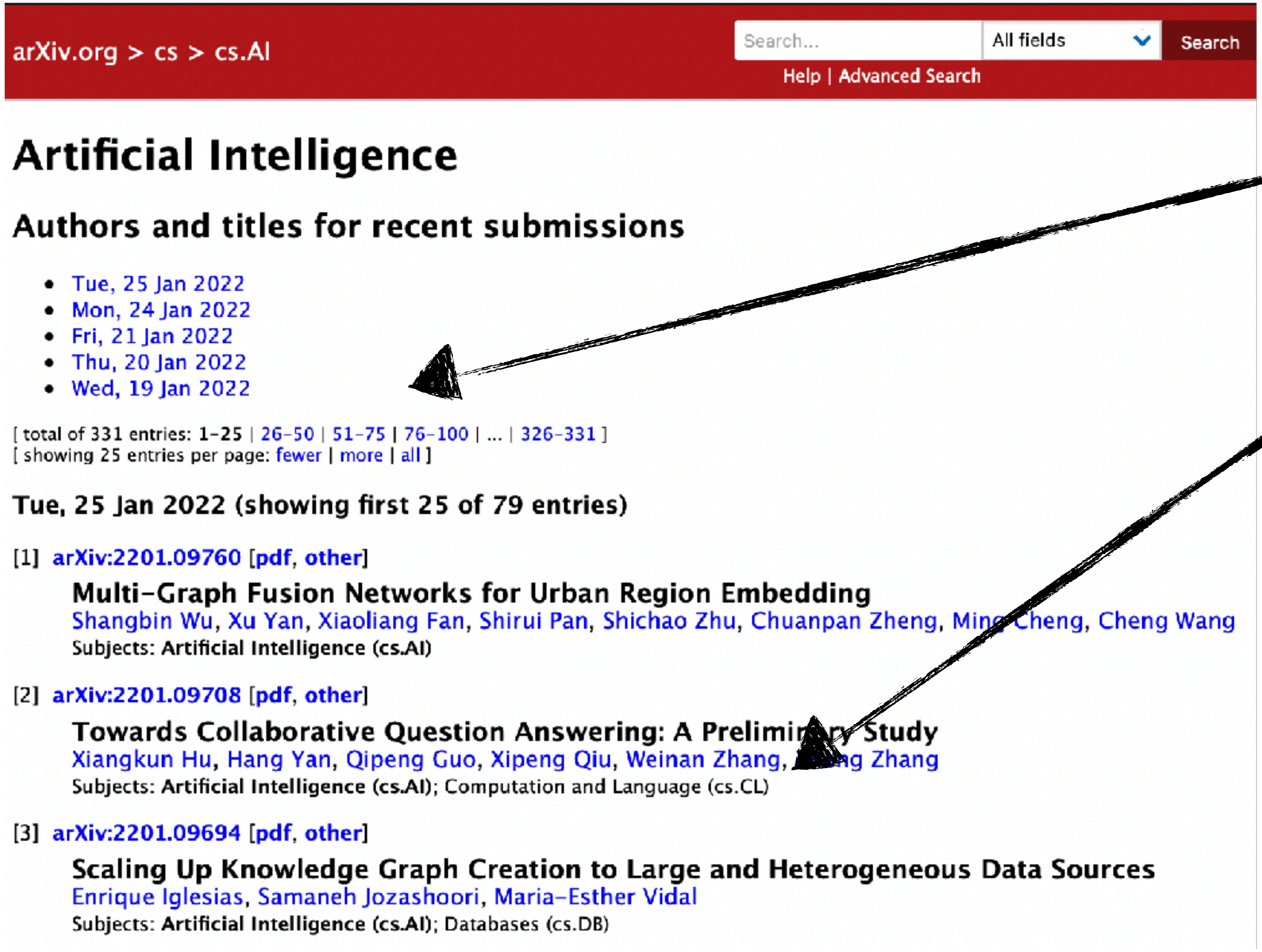

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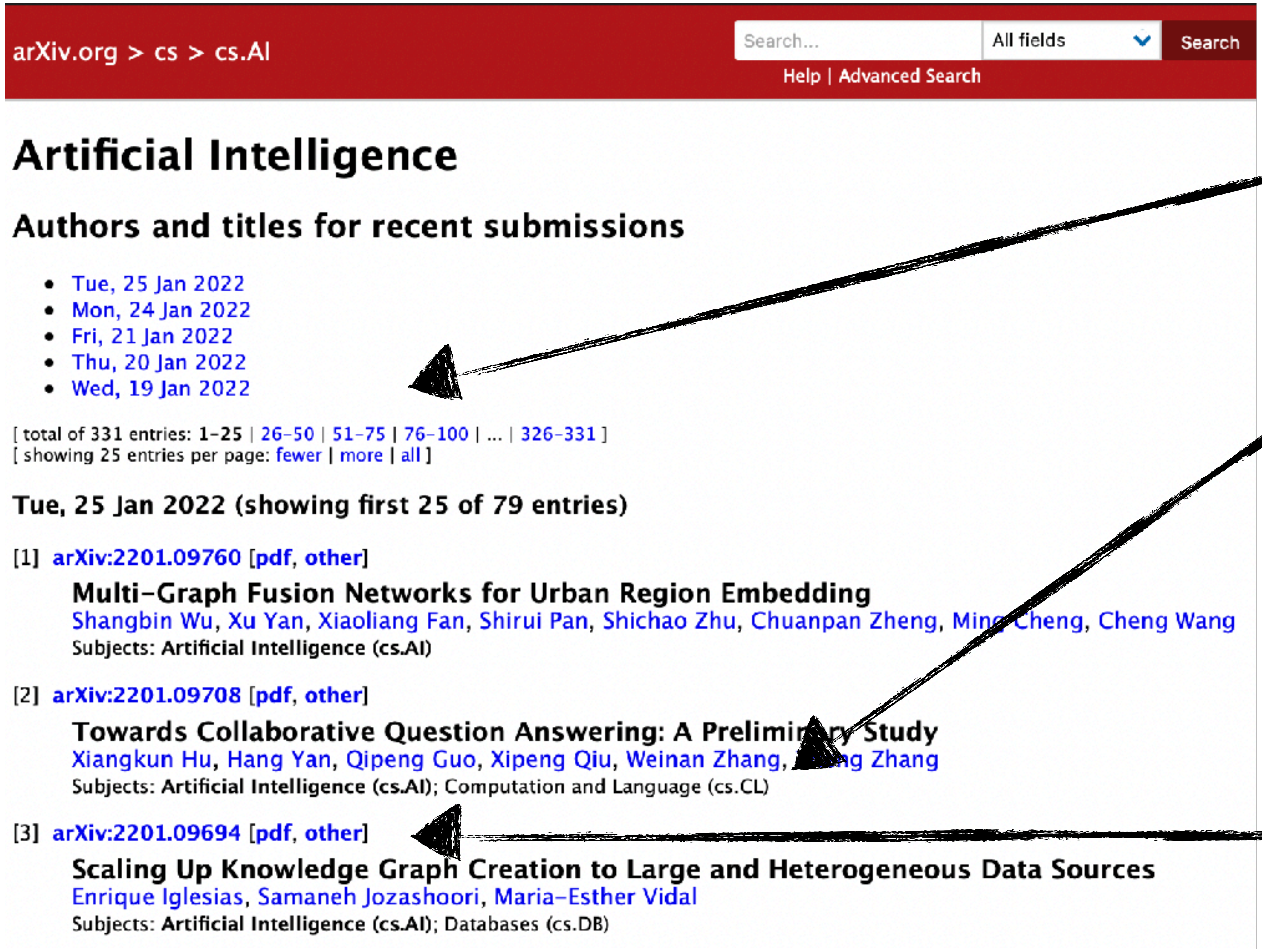

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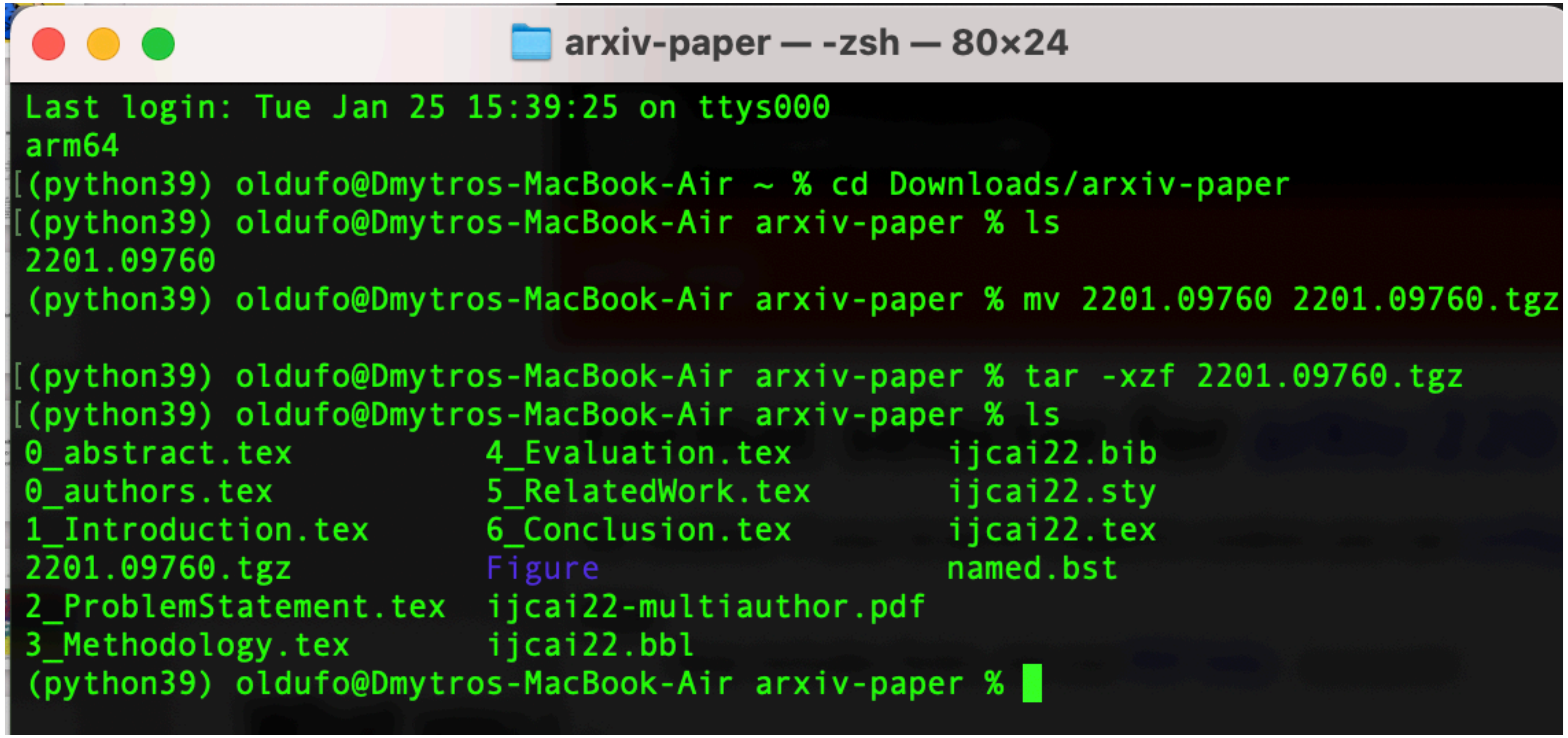

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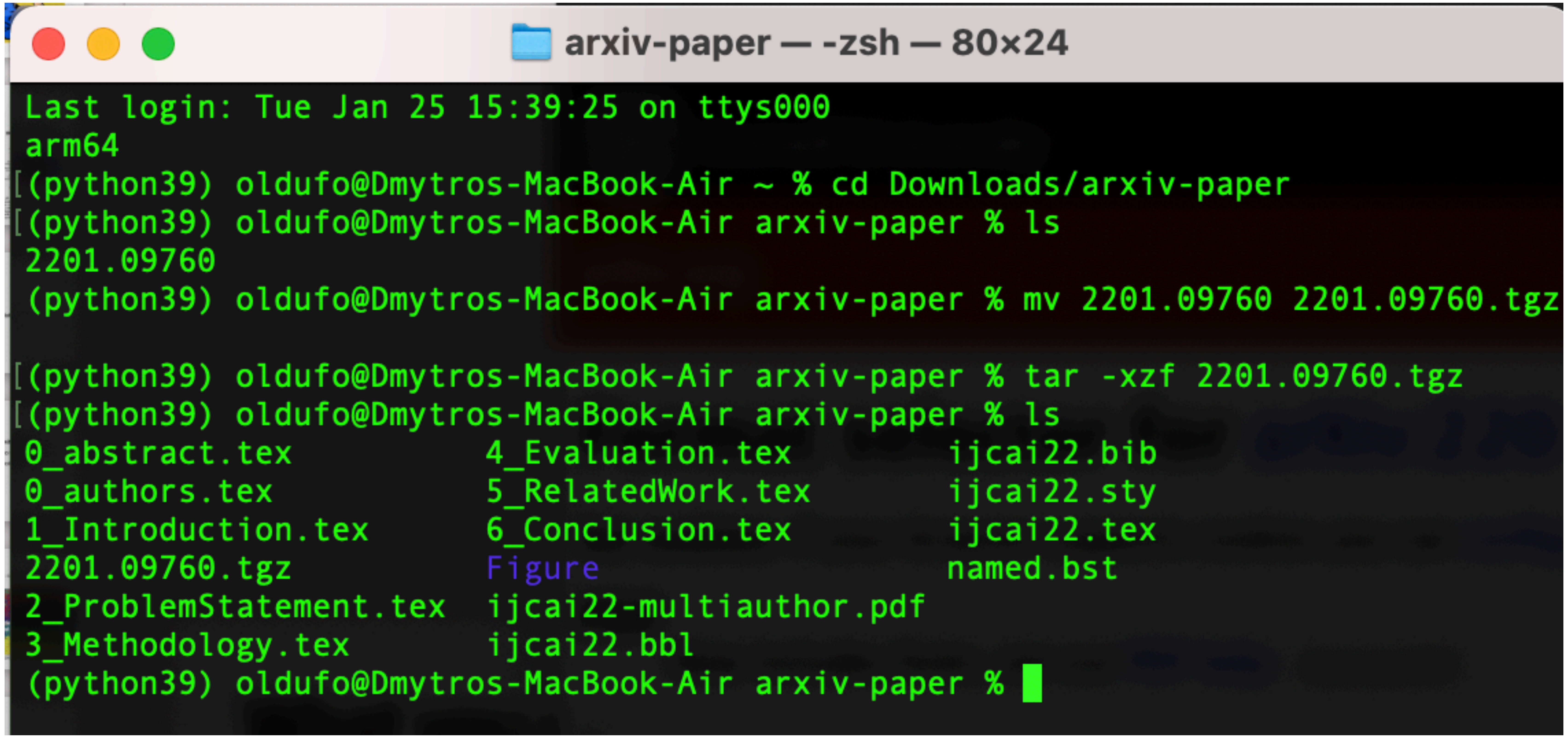

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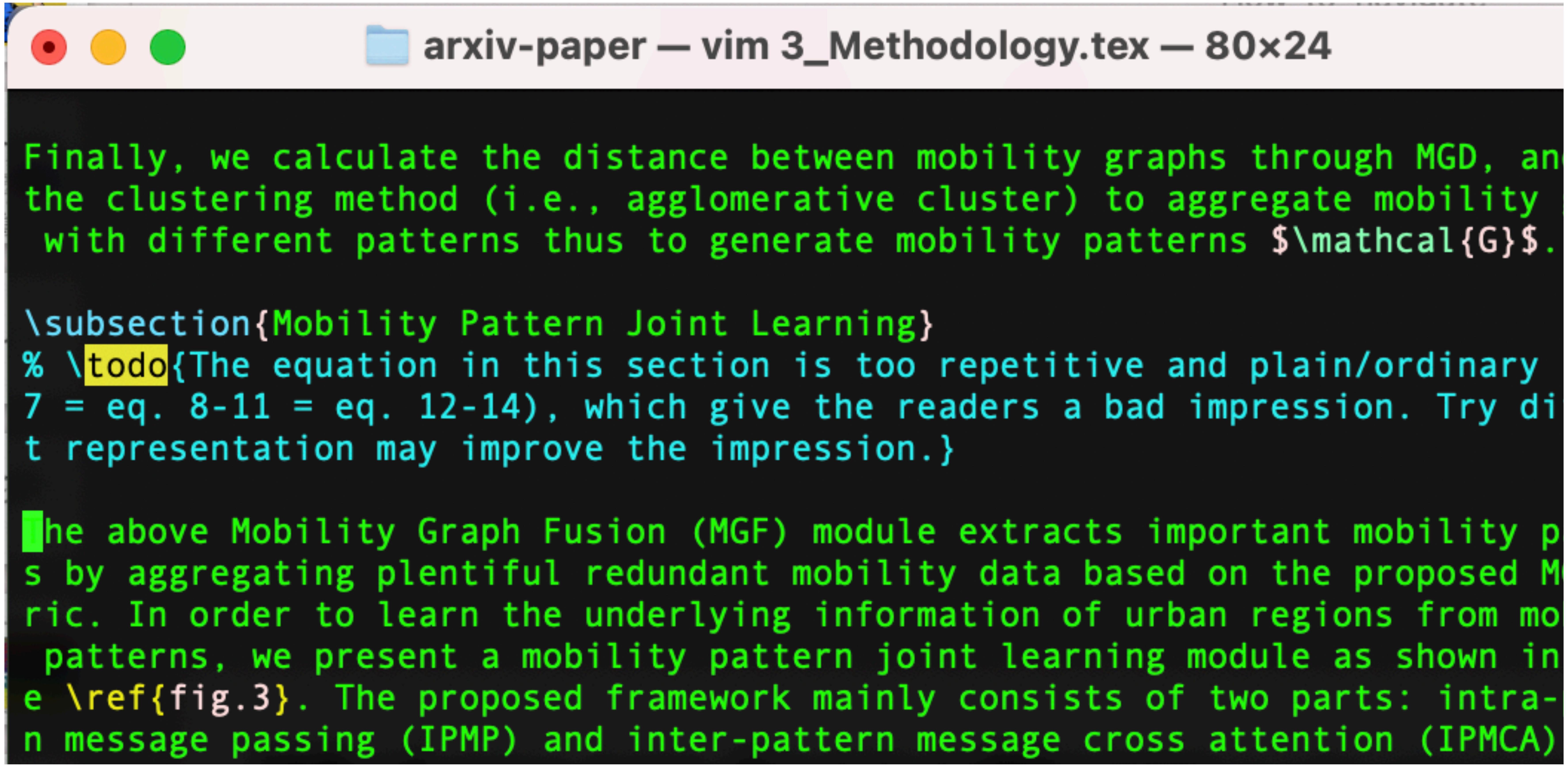

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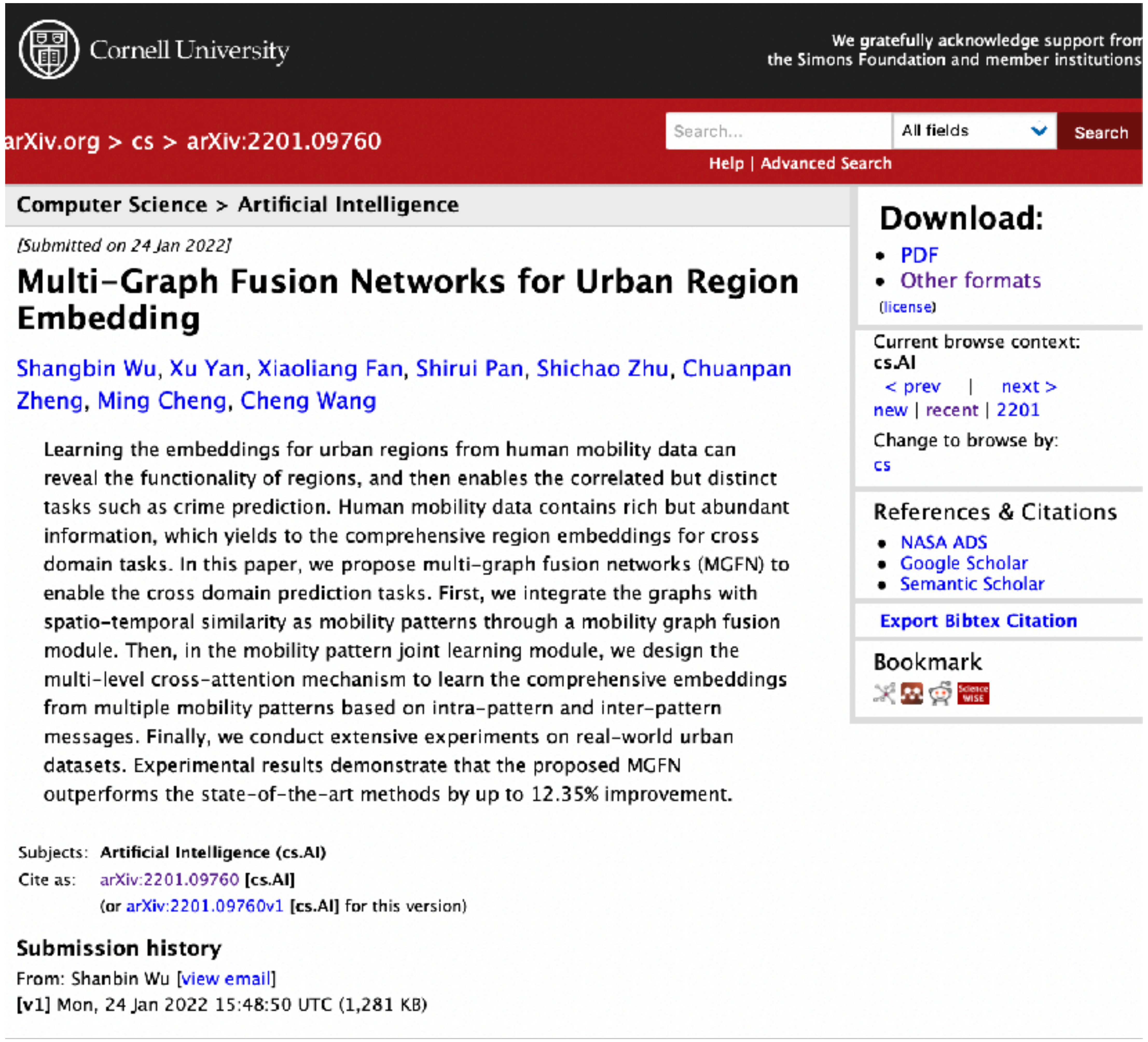

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Multi-Graph Fusion Networks for Urban Region Embedding

Shangbin Wu, Xu Yan, Xiaoliang Fan, Shirui Pan, Shichao Zhu, Chuanpan Zheng, Ming Cheng, Cheng Wang

Learning the embeddings for urban regions from human mobility data can reveal the functionality of regions, and then enables the correlated but distinct tasks such as crime prediction. Human mobility data contains rich but abundant information, which yields to the comprehensive region embeddings for cross domain tasks. In this paper, we propose multi-graph fusion networks (MGFN) to enable the cross domain prediction tasks. First, we integrate the graphs with spatio-temporal similarity as mobility patterns through a mobility graph fusion module. Then, in the mobility pattern joint learning module, we design the multi-level cross-attention mechanism to learn the comprehensive embeddings from multiple mobility patterns based on intra-pattern and inter-pattern messages. Finally, we conduct extensive experiments on real-world urban datasets. Experimental results demonstrate that the proposed MGFN outperforms the state-of-the-art methods by up to 12.35% improvement.

Subjects: **Artificial Intelligence (cs.AI)**
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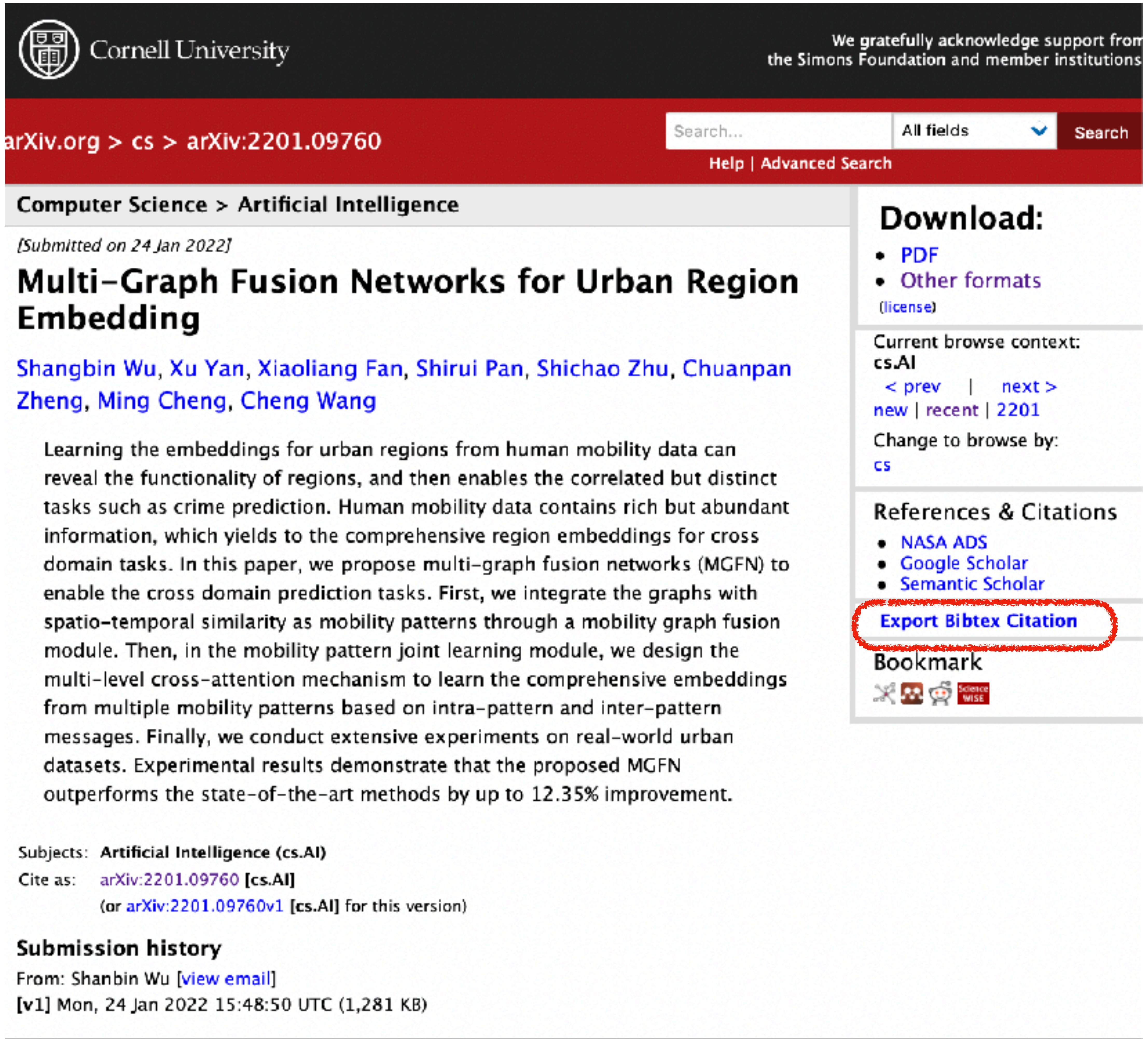

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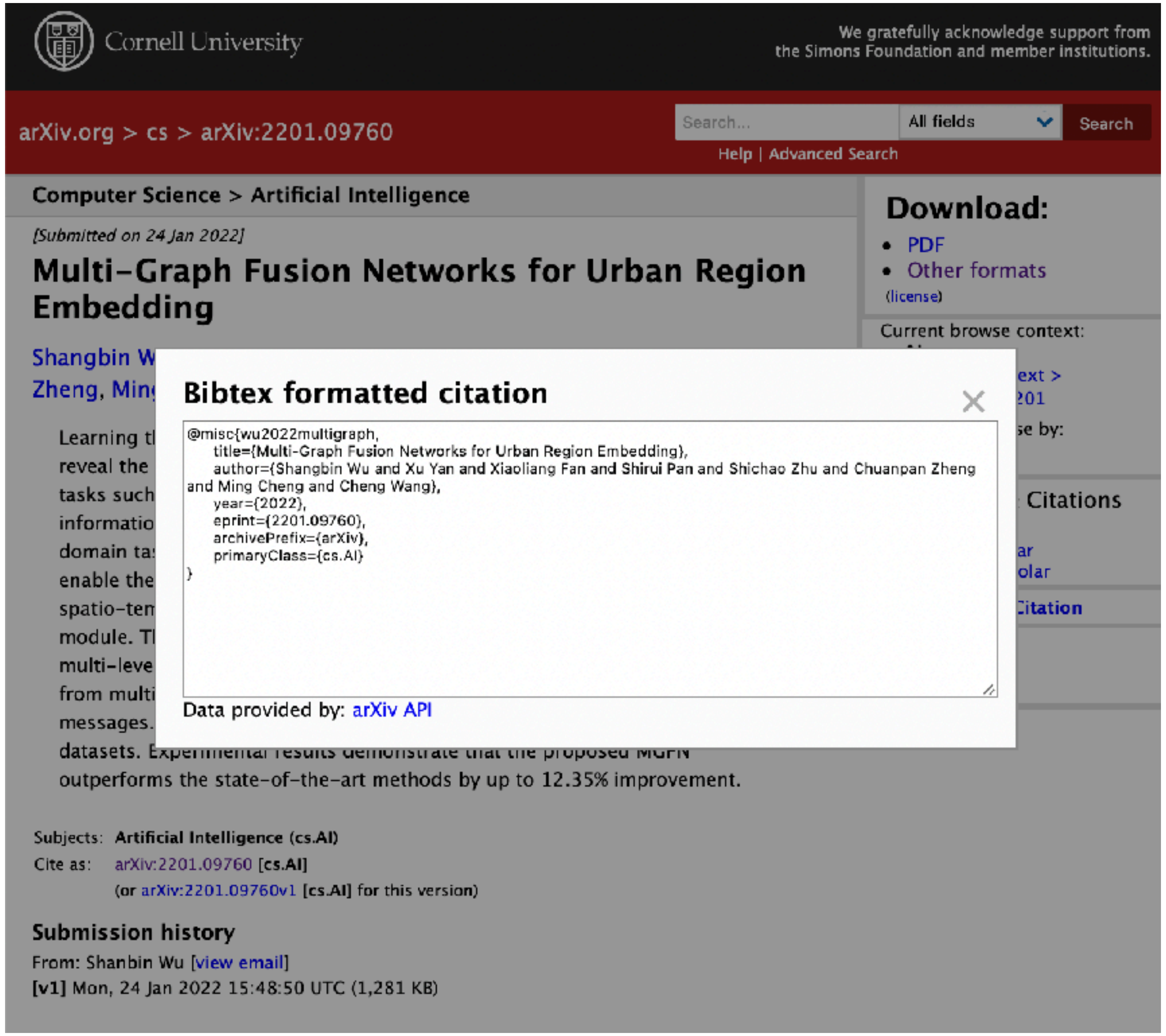

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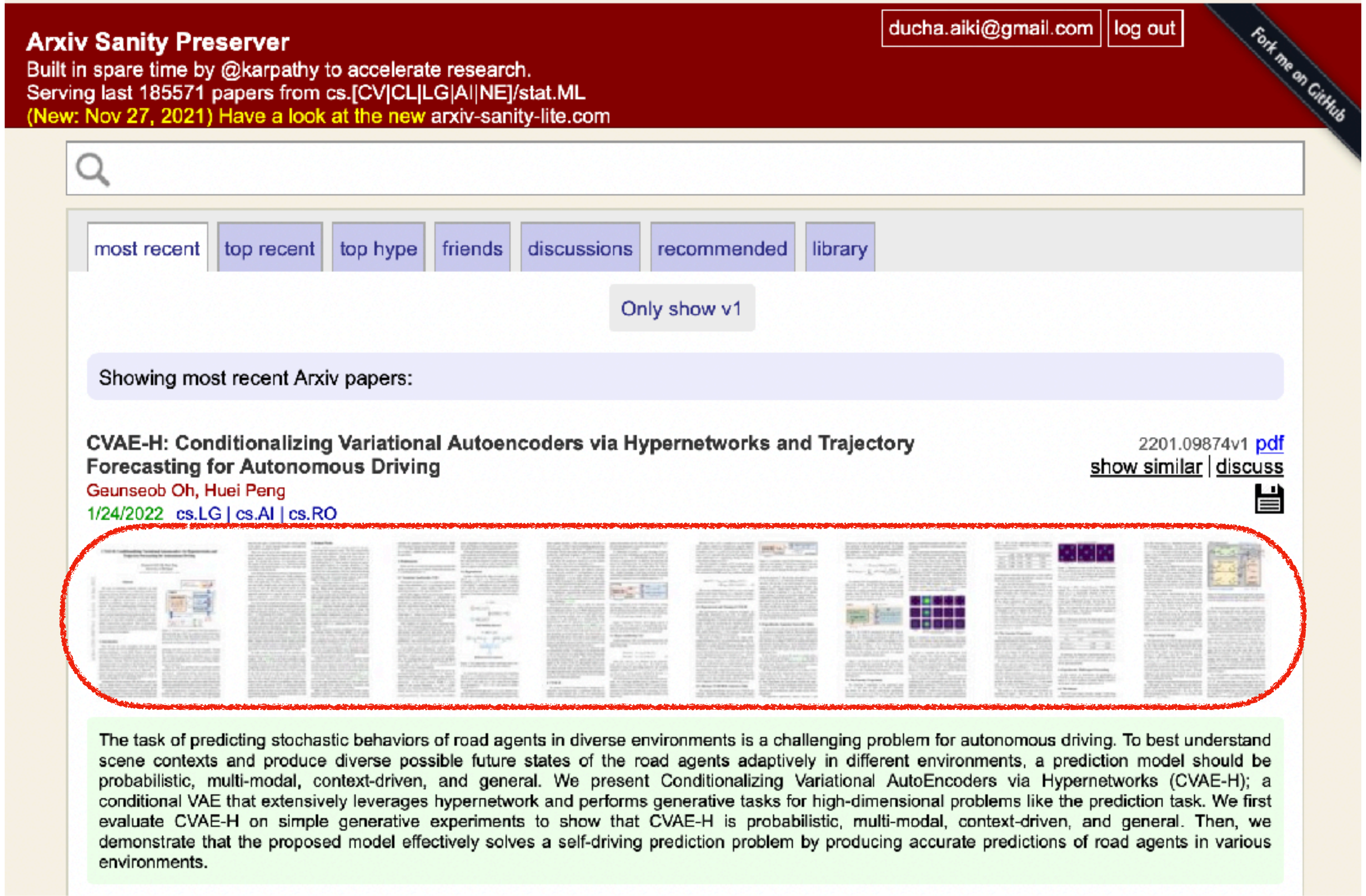

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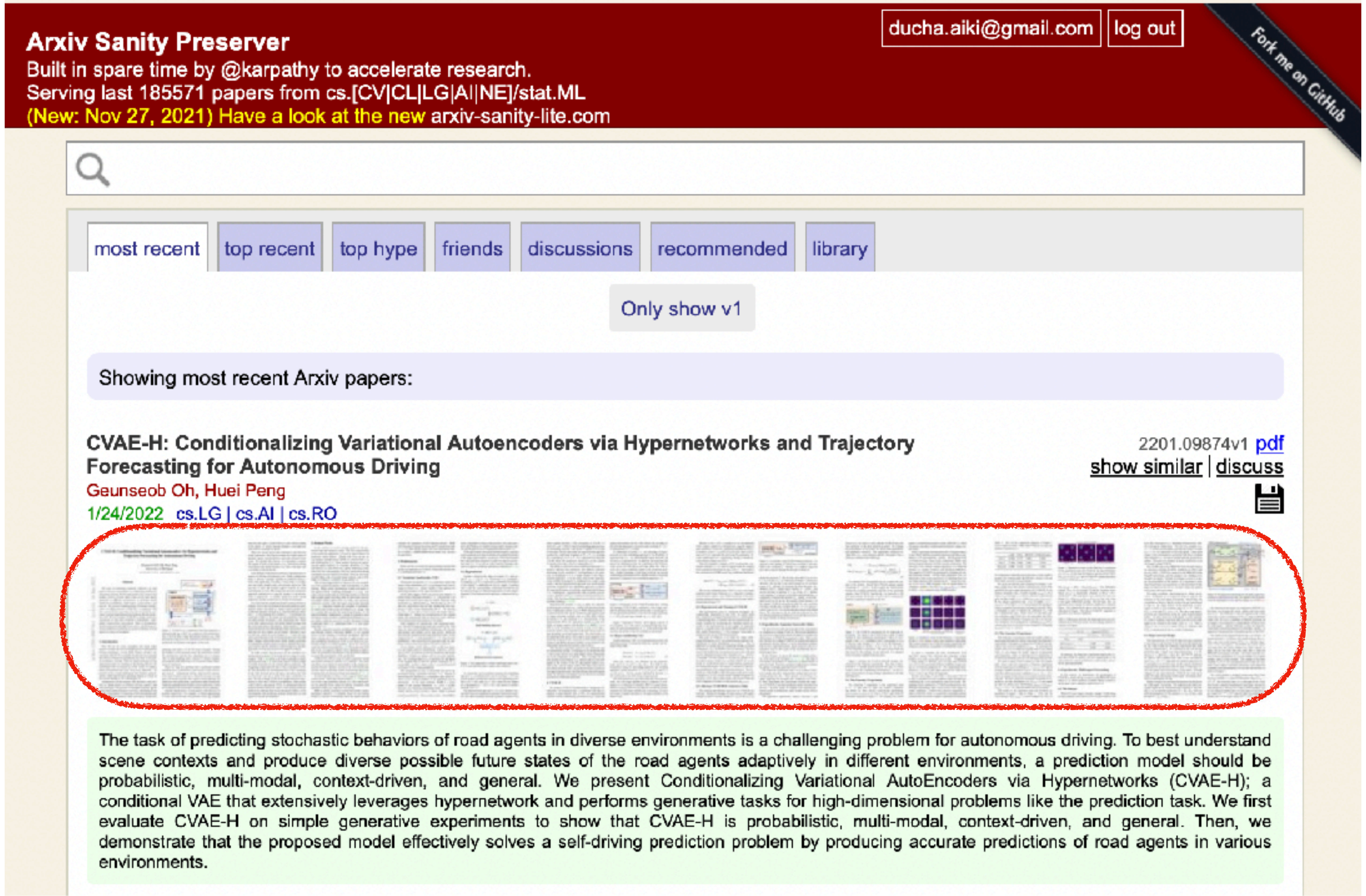

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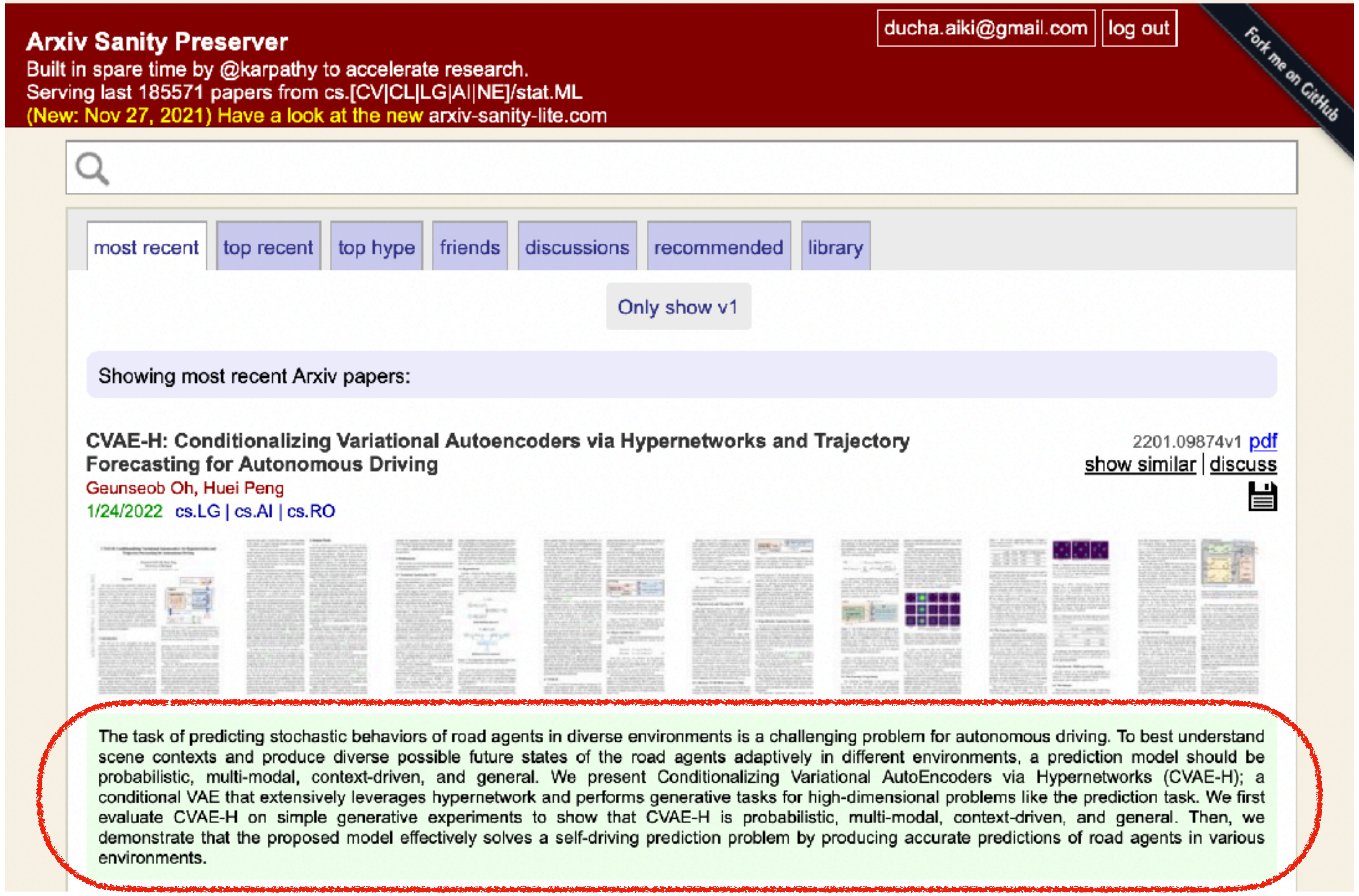

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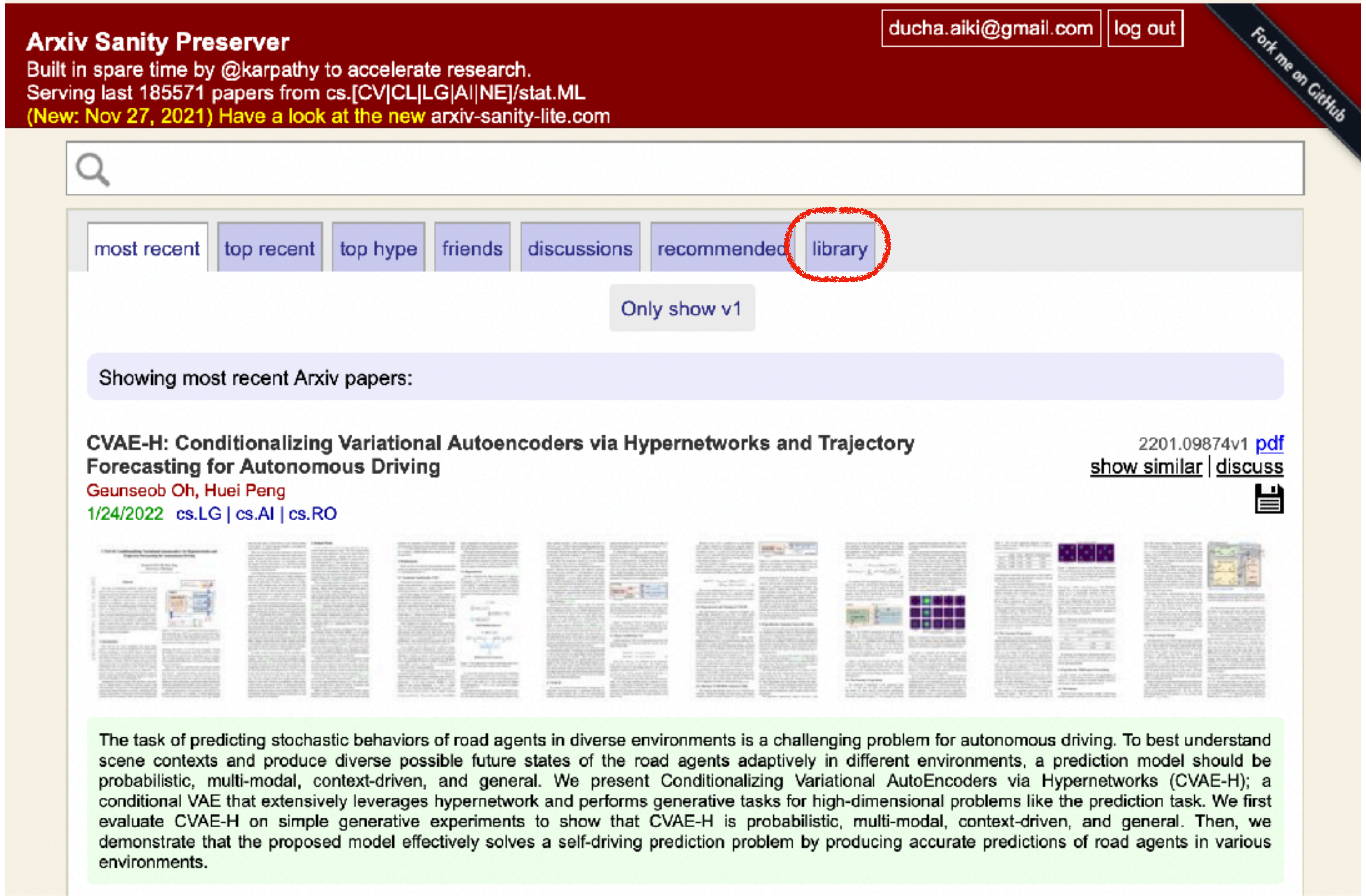

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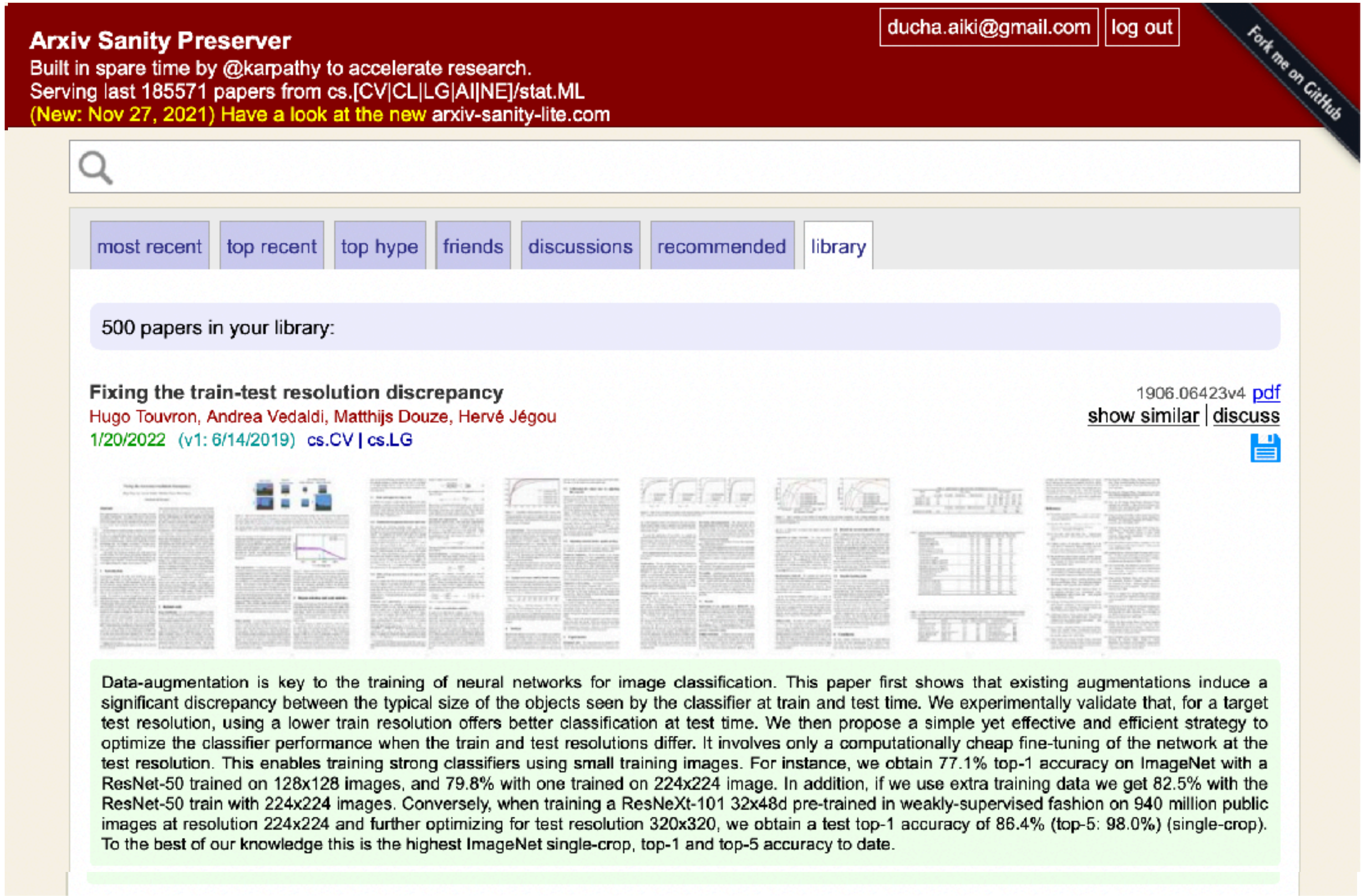

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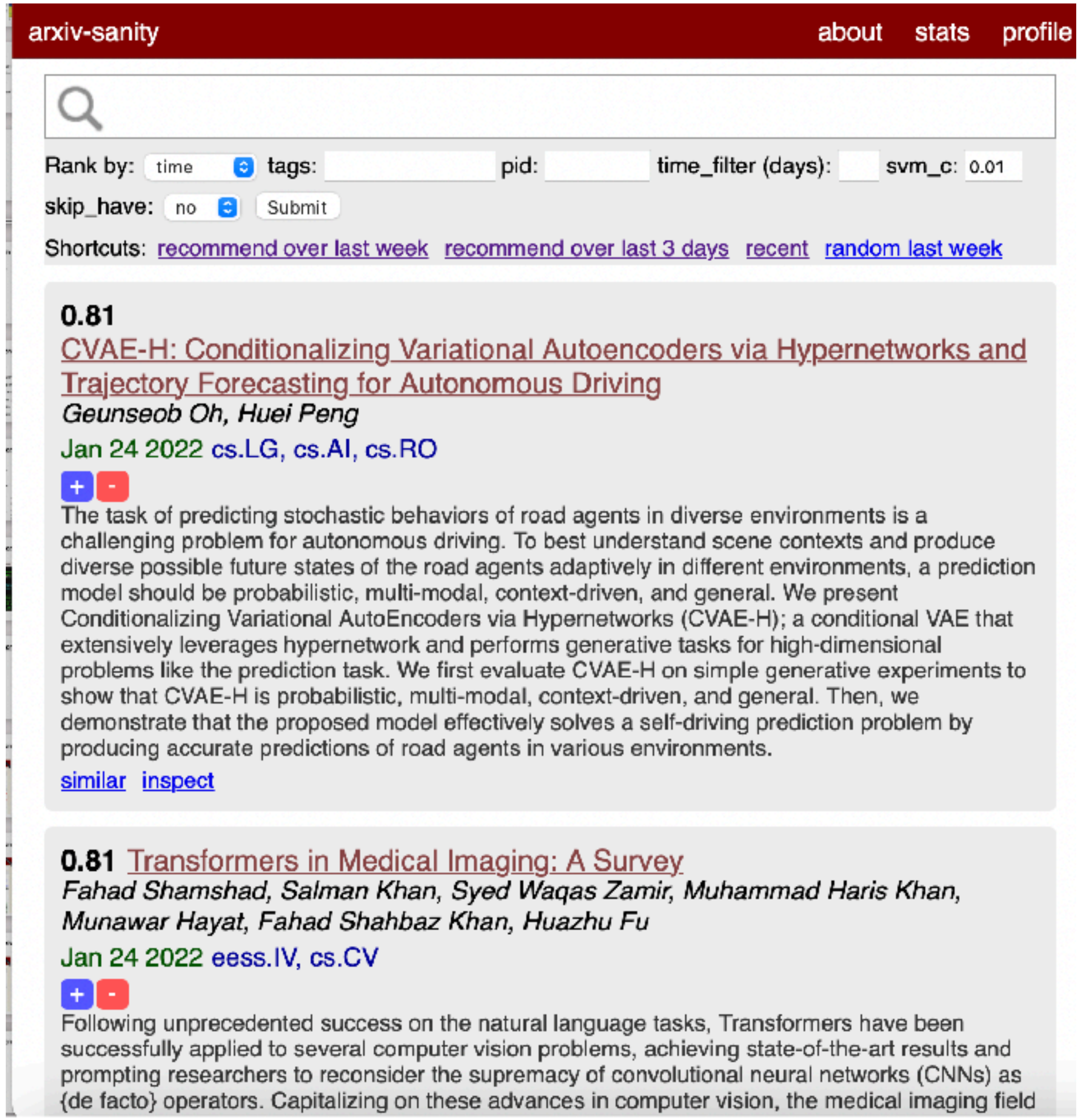

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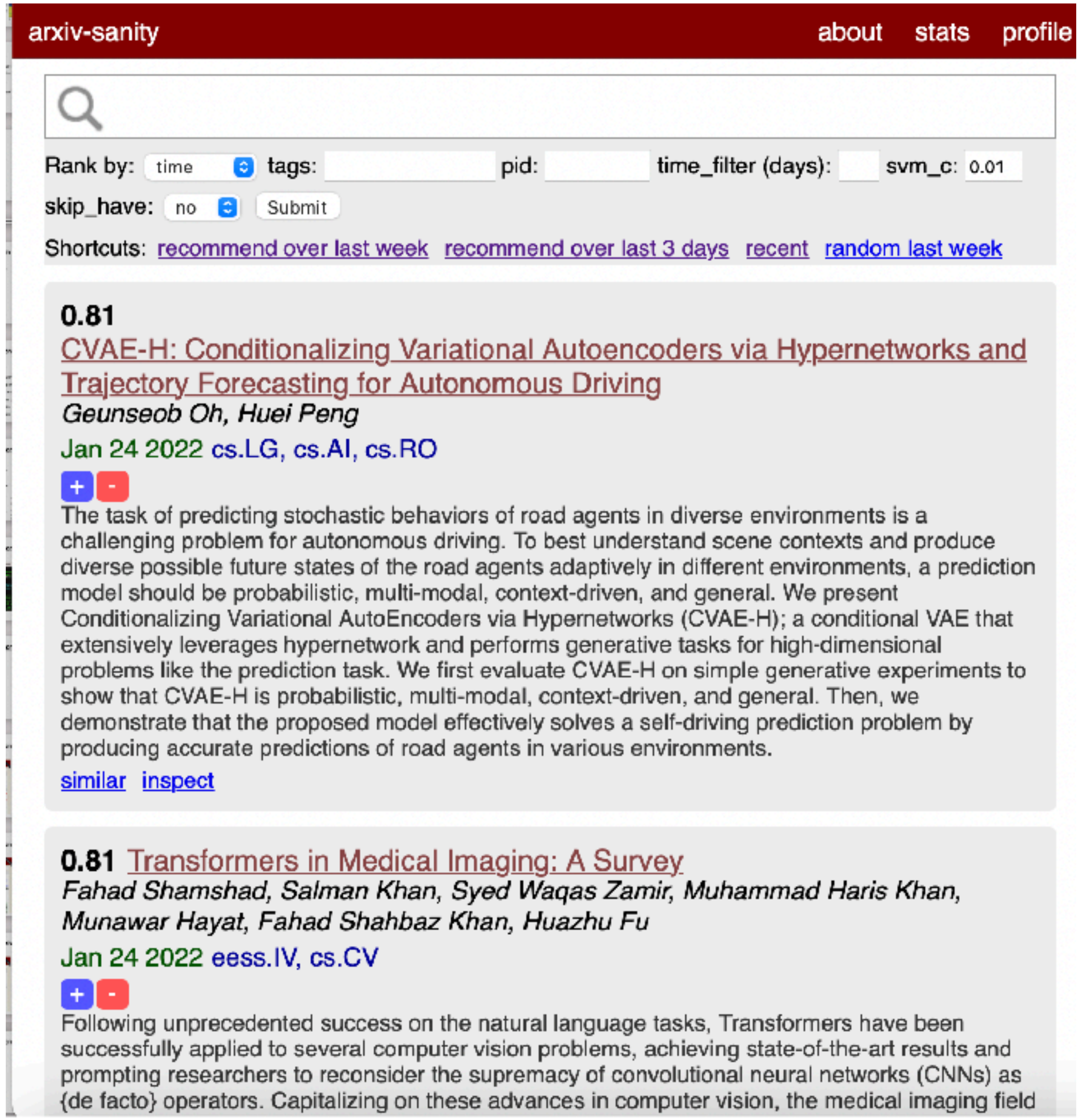

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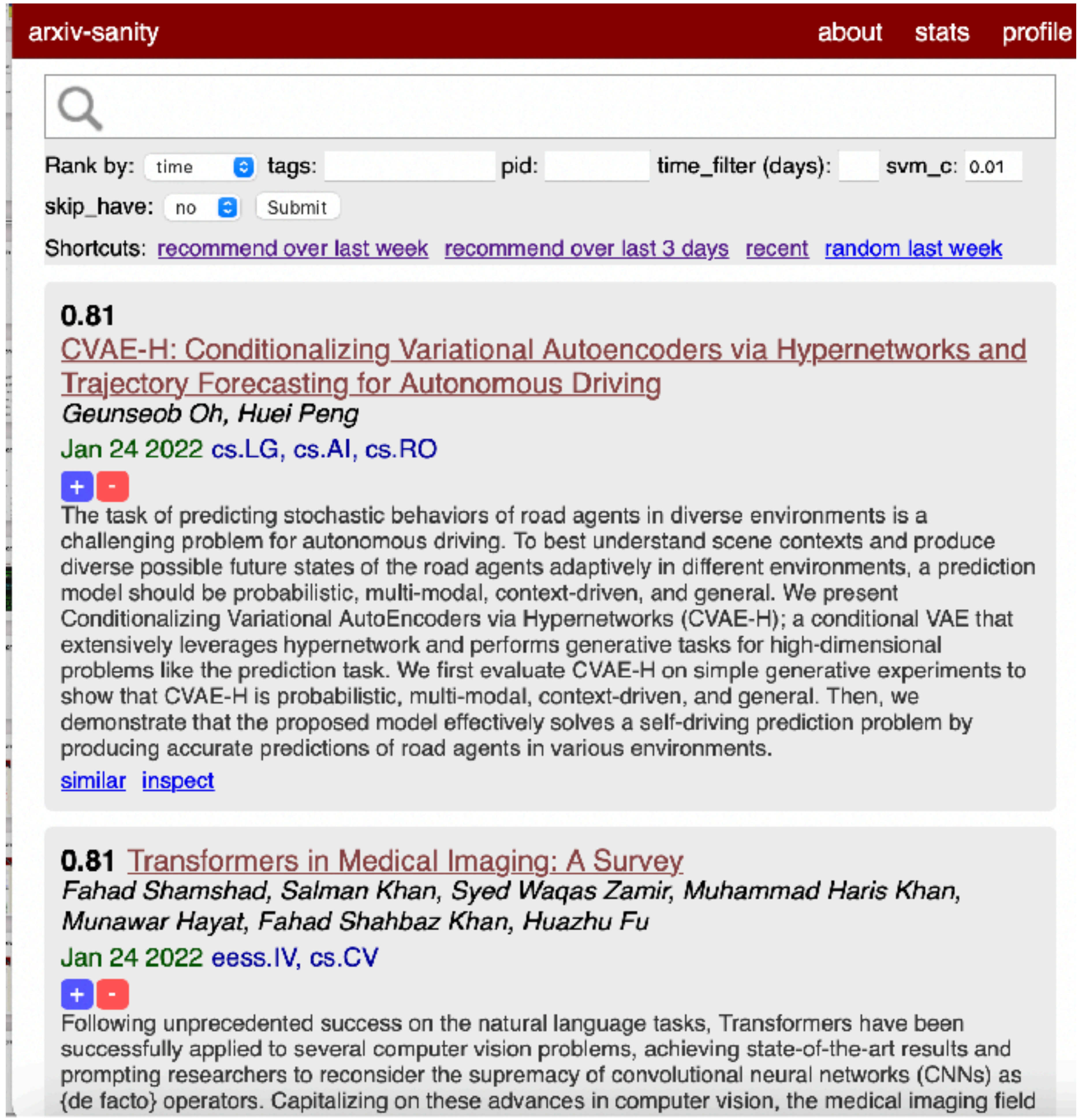

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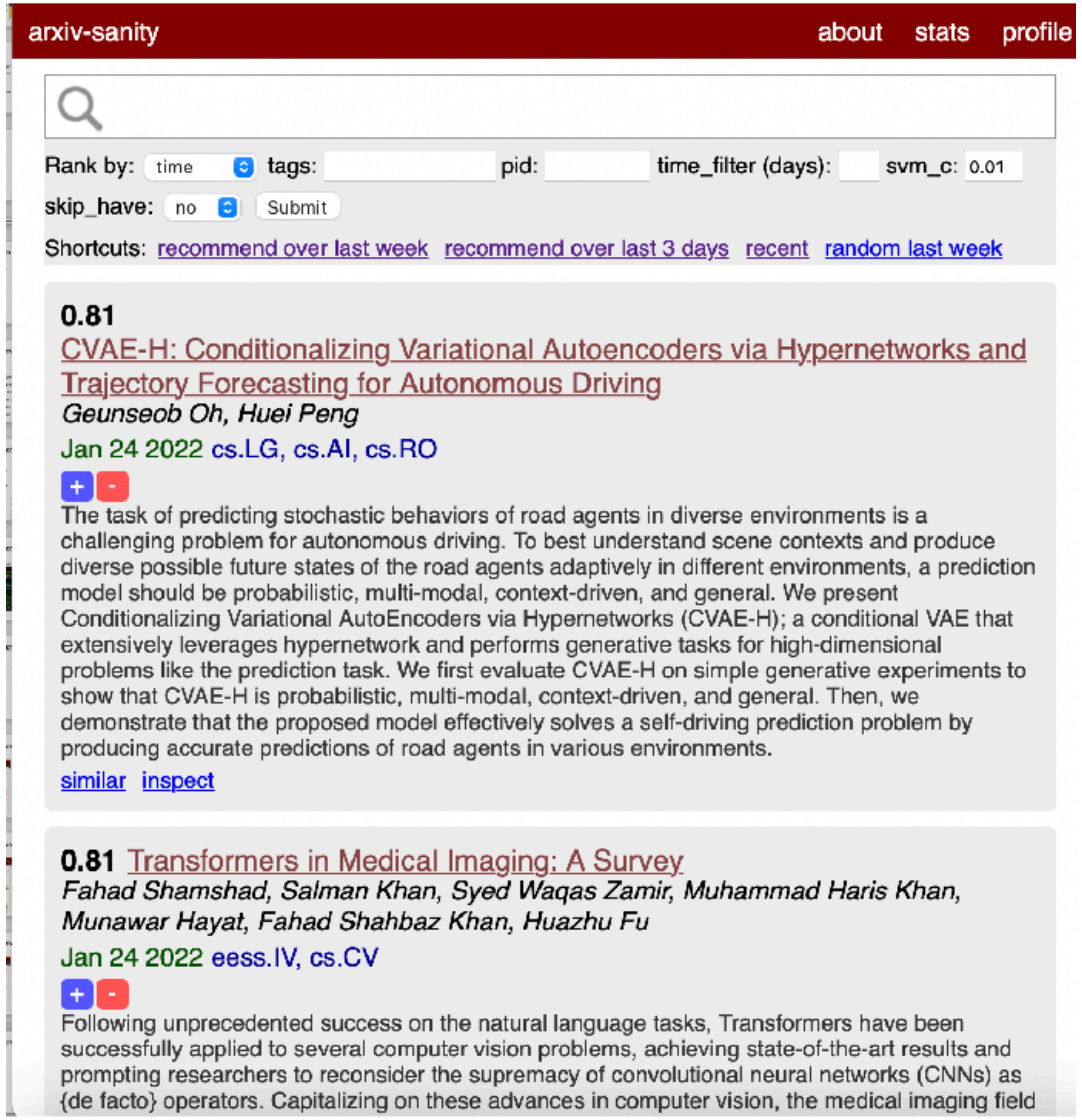

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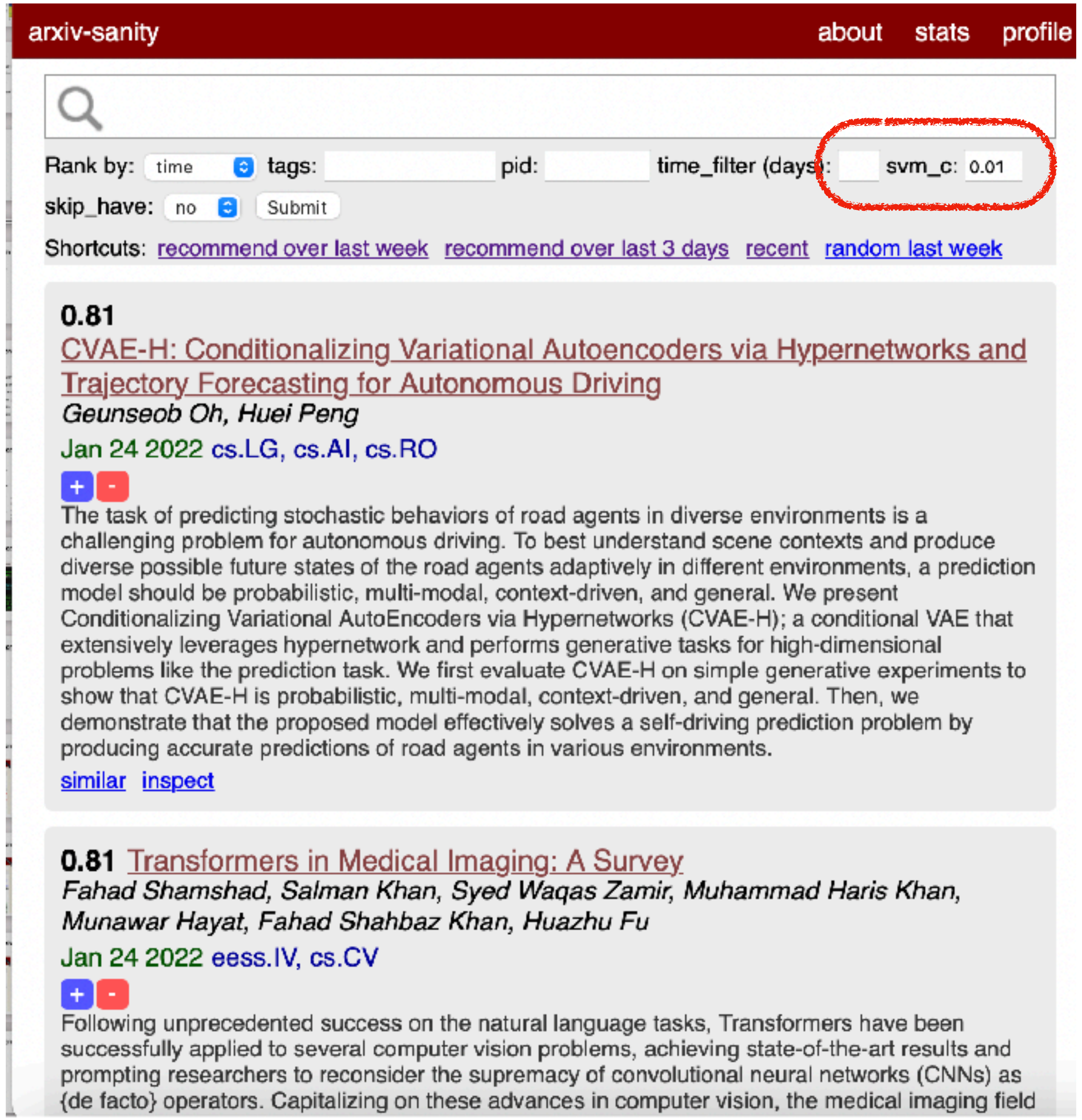

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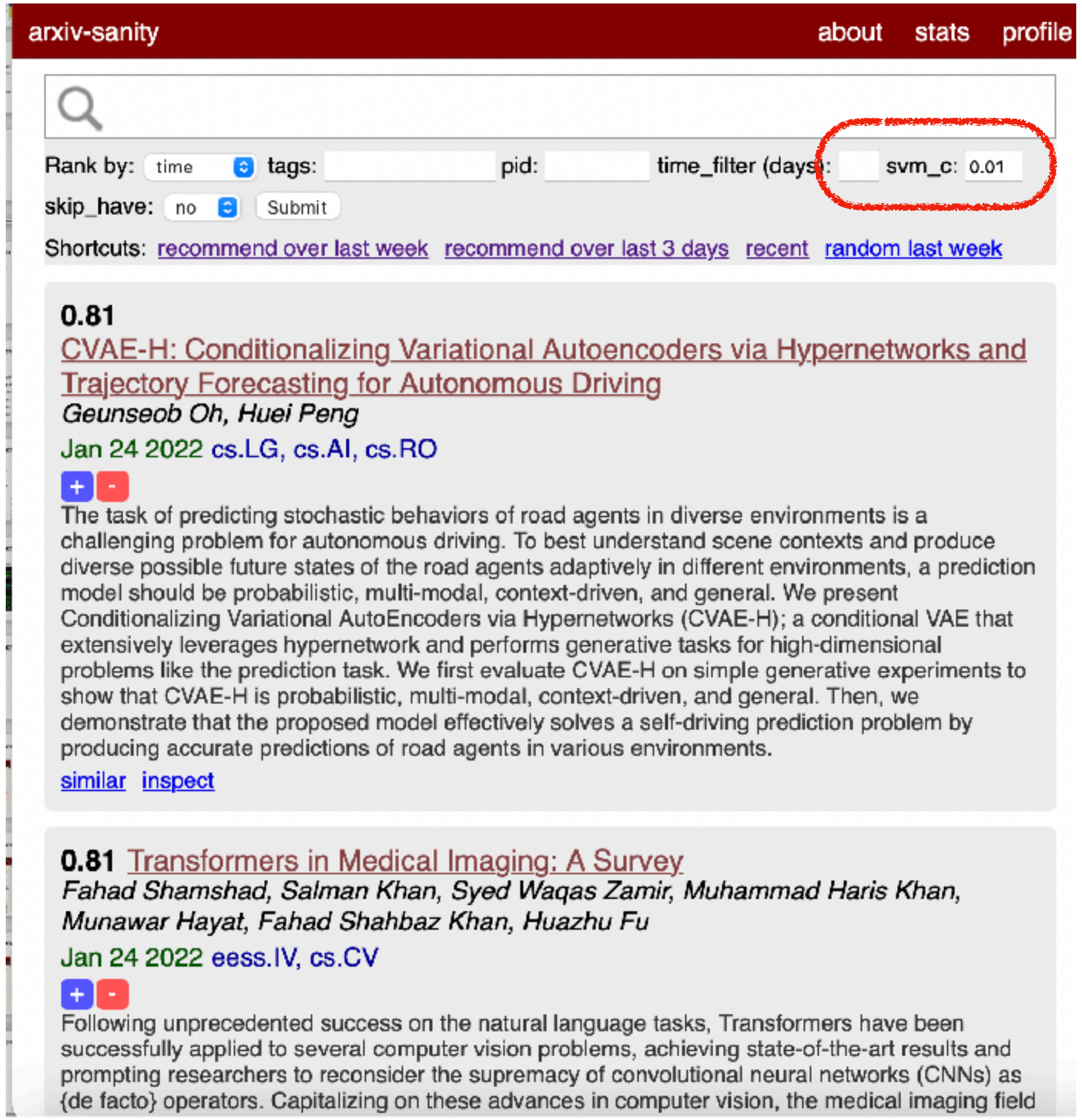

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- “Relevancy score”

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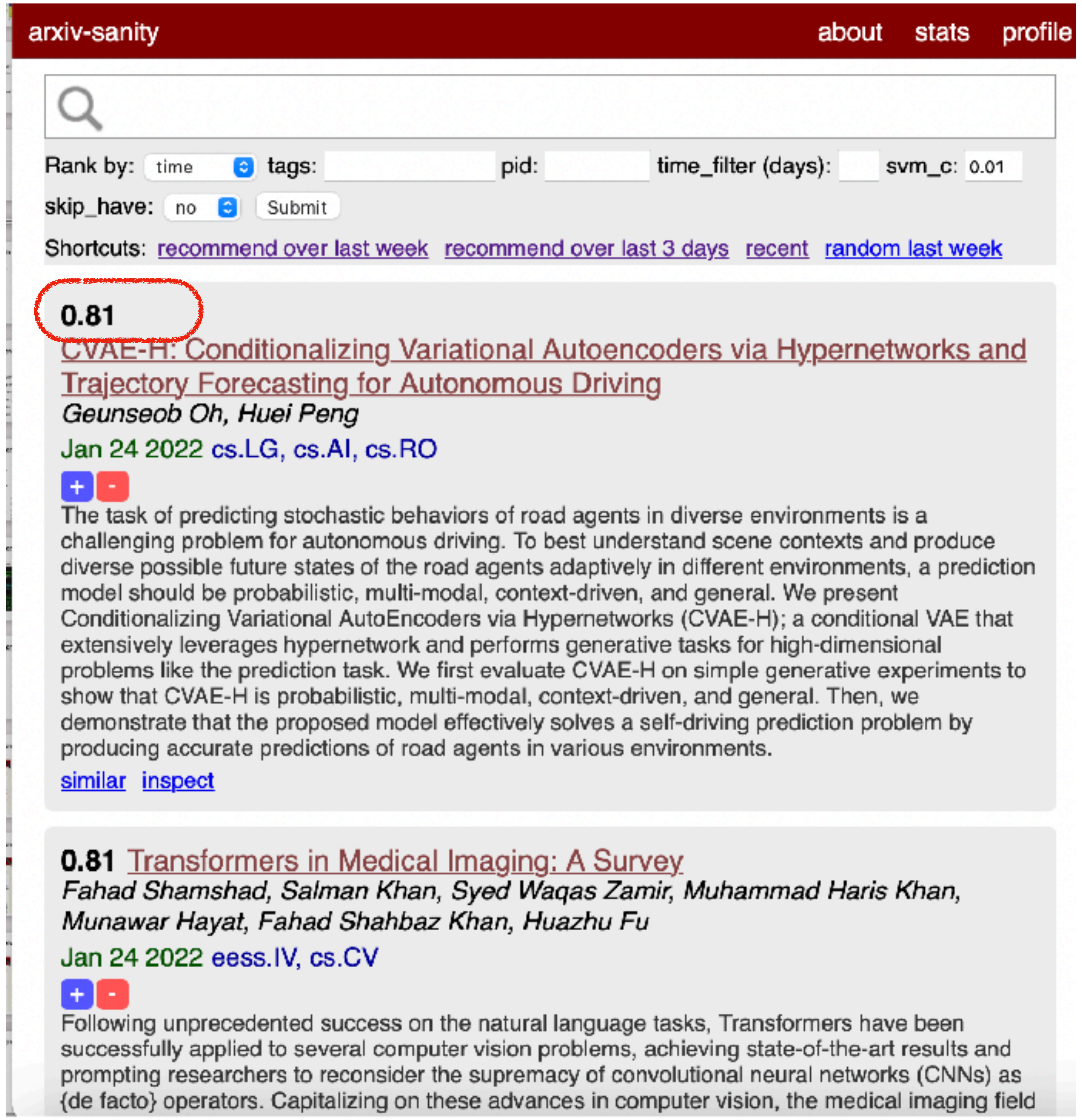

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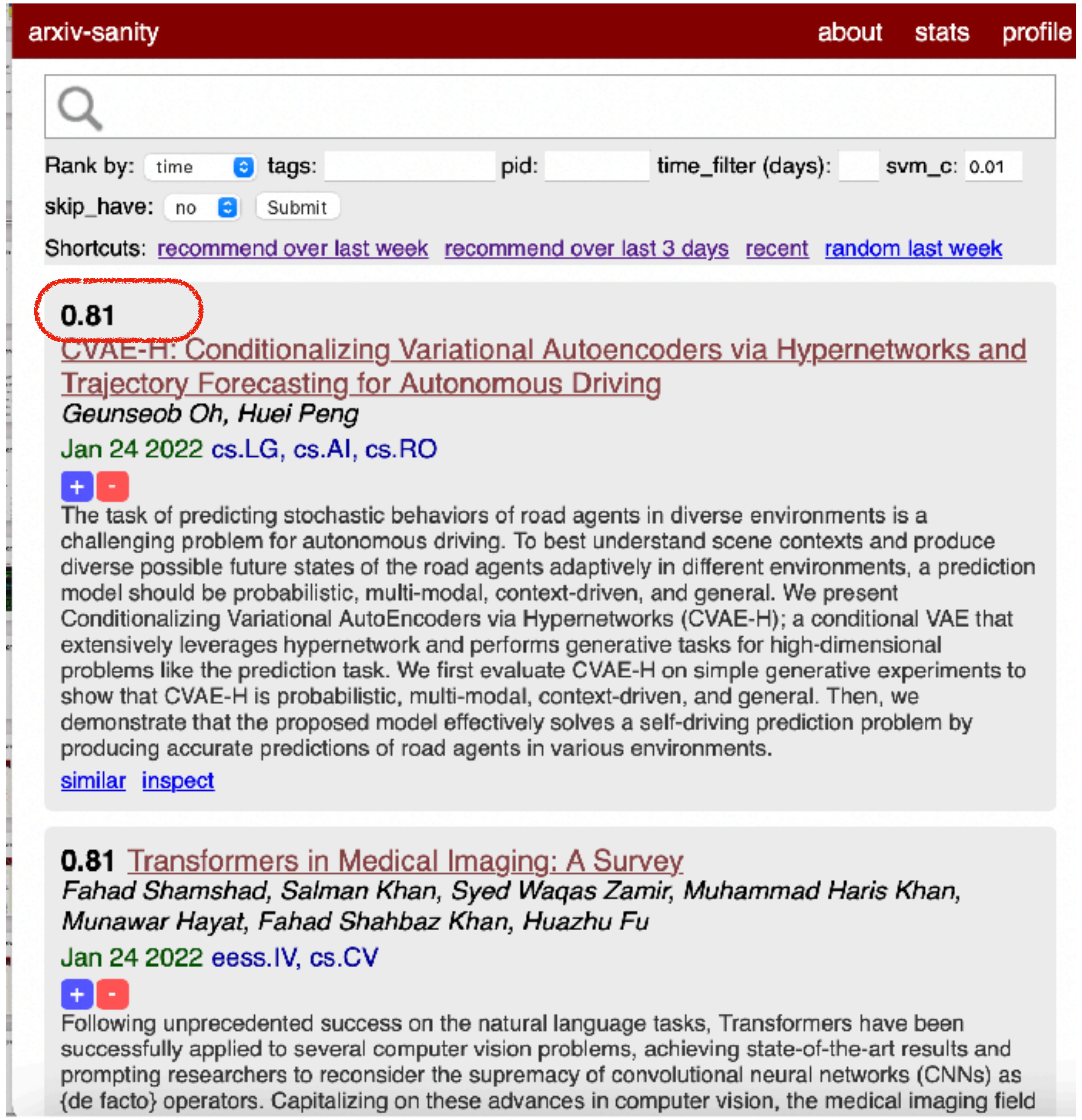

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- “Inspect" the terms used for relevancy score calculation

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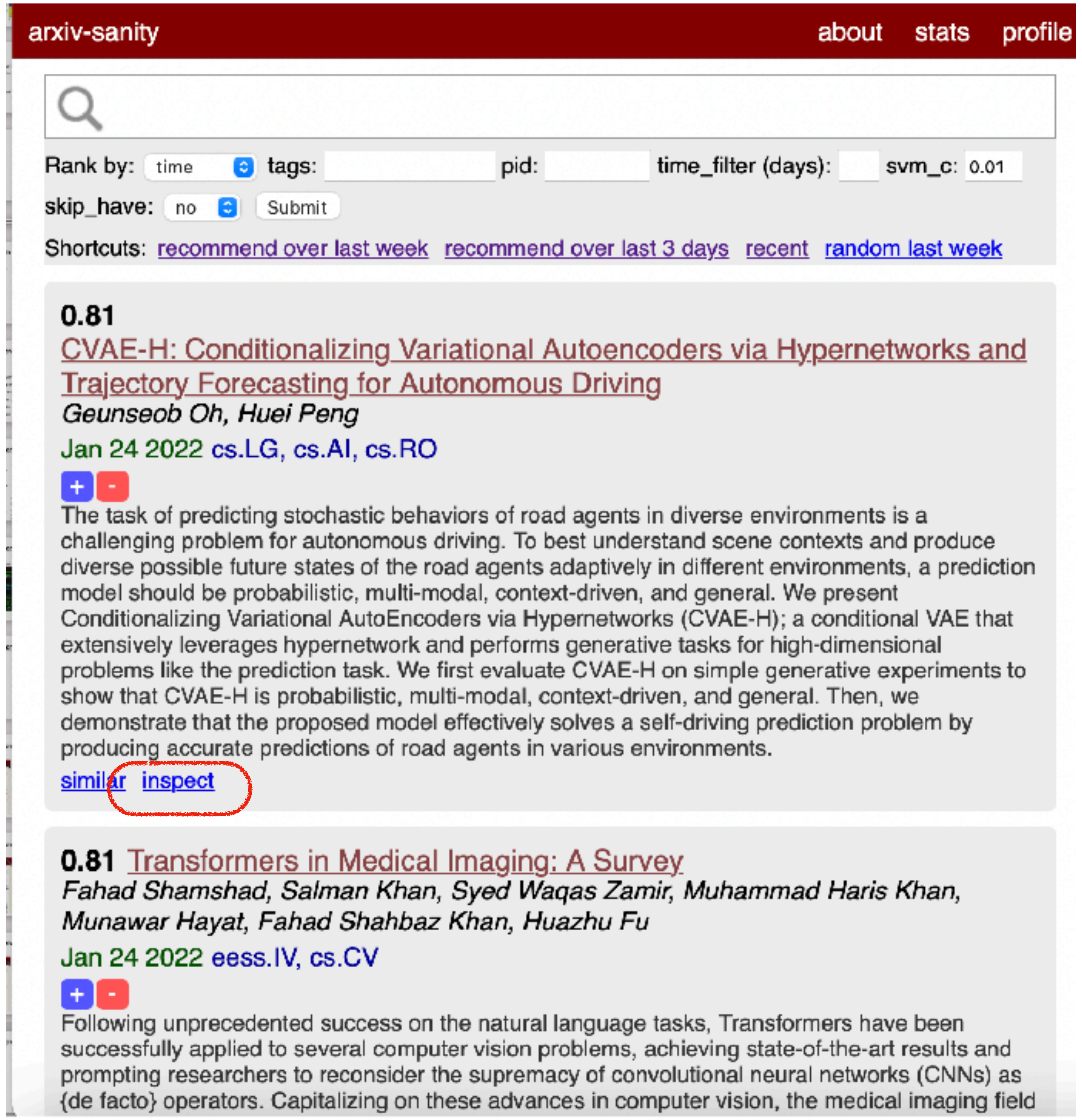

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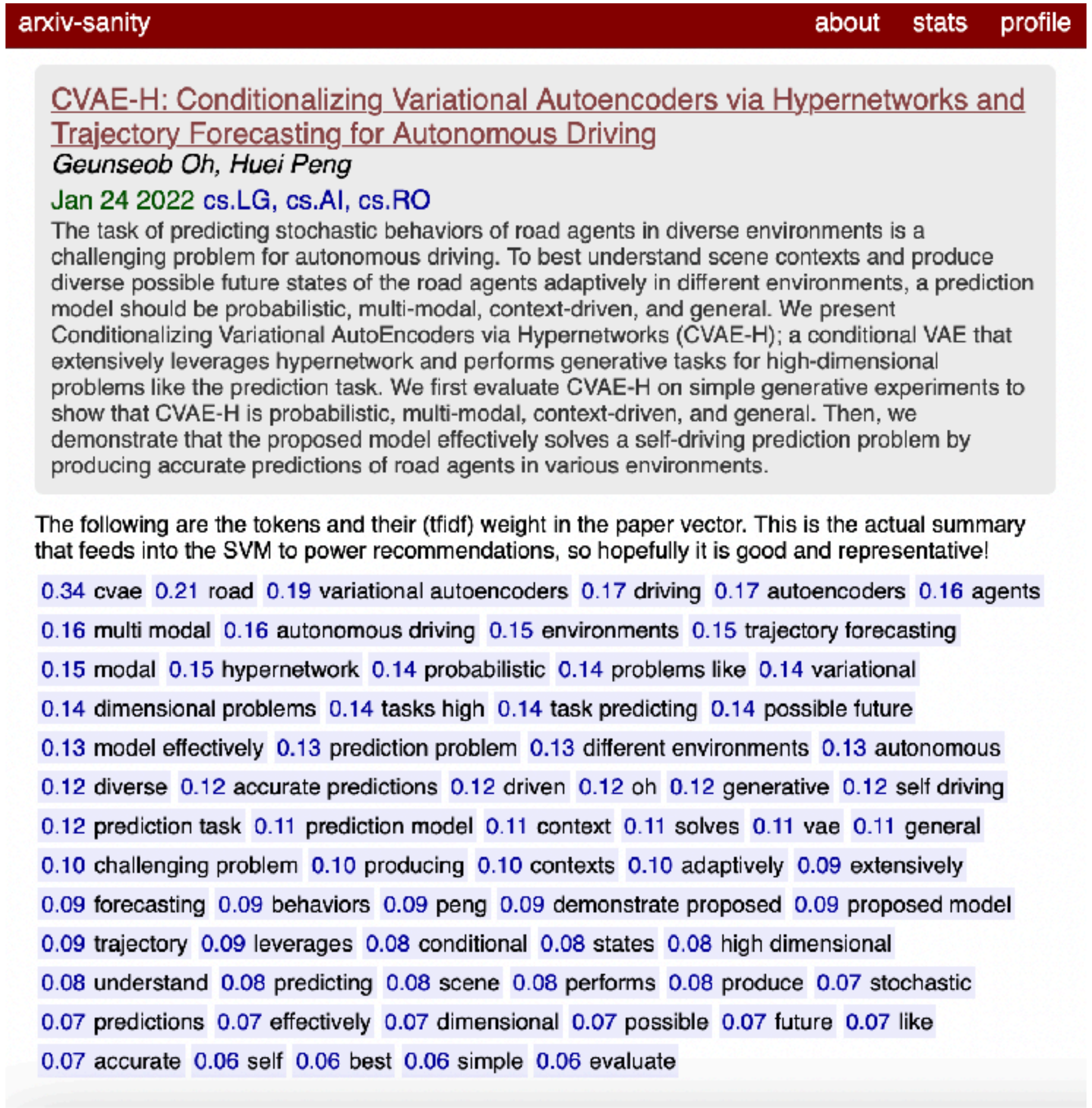
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CVAE-H: Conditionalizing Variational Autoencoders via Hypernetworks and Trajectory Forecasting for Autonomous Driving

Geunseob Oh, Huei Peng

Jan 24 2022 cs.LG, cs.AI, cs.RO

The task of predicting stochastic behaviors of road agents in diverse environments is a challenging problem for autonomous driving. To best understand scene contexts and produce diverse possible future states of the road agents adaptively in different environments, a prediction model should be probabilistic, multi-modal, context-driven, and general. We present Conditionalizing Variational AutoEncoders via Hypernetworks (CVAE-H); a conditional VAE that extensively leverages hypernetwork and performs generative tasks for high-dimensional problems like the prediction task. We first evaluate CVAE-H on simple generative experiments to show that CVAE-H is probabilistic, multi-modal, context-driven, and general. Then, we demonstrate that the proposed model effectively solves a self-driving prediction problem by producing accurate predictions of road agents in various environments.

The following are the tokens and their (tfidf) weight in the paper vector. This is the actual summary that feeds into the SVM to power recommendations, so hopefully it is good and representative!

0.34 cvae 0.21 road 0.19 variational autoencoders 0.17 driving 0.17 autoencoders 0.16 agents
0.16 multi modal 0.16 autonomous driving 0.15 environments 0.15 trajectory forecasting
0.15 modal 0.15 hypernetwork 0.14 probabilistic 0.14 problems like 0.14 variational
0.14 dimensional problems 0.14 tasks high 0.14 task predicting 0.14 possible future
0.13 model effectively 0.13 prediction problem 0.13 different environments 0.13 autonomous
0.12 diverse 0.12 accurate predictions 0.12 driven 0.12 oh 0.12 generative 0.12 self driving
0.12 prediction task 0.11 prediction model 0.11 context 0.11 solves 0.11 vae 0.11 general
0.10 challenging problem 0.10 producing 0.10 contexts 0.10 adaptively 0.09 extensively
0.09 forecasting 0.09 behaviors 0.09 peng 0.09 demonstrate proposed 0.09 proposed model
0.09 trajectory 0.09 leverages 0.08 conditional 0.08 states 0.08 high dimensional
0.08 understand 0.08 predicting 0.08 scene 0.08 performs 0.08 produce 0.07 stochastic
0.07 predictions 0.07 effectively 0.07 dimensional 0.07 possible 0.07 future 0.07 like
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2.00 Learning and Crafting for the Wide Multiple Baseline Stereo
Dmytro Mishkin
Dec 22 2021 cs.CV
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This thesis introduces the wide multiple baseline stereo (WxBS) problem. WxBS, a generalization of the standard wide baseline stereo problem, considers the matching of images that simultaneously differ in more than one image acquisition factor such as viewpoint, illumination, sensor type, or where object appearance changes significantly, e.g., over time. A new dataset with the ground truth, evaluation metric and baselines has been introduced. The thesis presents the following improvements of the WxBS pipeline. (i) A loss function, called HardNeg, for learning a local image descriptor that relies on hard negative mining within a mini-batch and on the maximization of the distance between the closest positive and the closest negative patches. (ii) The descriptor trained with the HardNeg loss, called HardNet, is compact and shows state-of-the-art performance in standard matching, patch verification and retrieval benchmarks. (iii) A method for learning the affine shape, orientation, and potentially other parameters related to geometric and appearance properties of local features. (iv) A tentative correspondences generation strategy which generalizes the standard first to second closest distance ratio is presented. The selection strategy, which shows performance superior to the standard method, is applicable to either hard-engineered descriptors like SIFT, LIOP, and MROGH or deeply learned like HardNet. (v) A feedback loop is introduced for the two-view matching problem, resulting in MODS -- matching with on-demand view synthesis -- algorithm. MODS is an algorithm that handles a viewing angle difference even larger than the previous state-of-the-art ASIFT algorithm, without a significant increase of computational cost over "standard" wide and narrow baseline approaches. Last, but not least, a comprehensive benchmark for local features and robust estimation algorithms is introduced.
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-69.66 Digging Into Self-Supervised Learning of Feature Descriptors
Iaroslav Melekhov, Zakaria Laskar, Xiaotian Li, Shuzhe Wang, Juho Kannala
Oct 10 2021 cs.CV
+ -
Fully-supervised CNN-based approaches for learning local image descriptors have shown remarkable results in a wide range of geometric tasks. However, most of them require per-pixel ground-truth keypoint correspondence data which is difficult to acquire at scale. To address this challenge, recent weakly- and self-supervised methods can learn feature descriptors from relative camera poses or using only synthetic rigid transformations such as homographies. In this work, we focus on understanding the limitations of existing self-supervised approaches and propose a set of improvements that combined lead to powerful feature descriptors. We show that increasing the search space from in-pair to in-batch for hard negative mining brings consistent improvement. To enhance the discriminativeness of feature descriptors, we propose a coarse-to-fine method for mining local hard negatives from a wider search space by using global visual image descriptors. We demonstrate that a combination of synthetic homography transformation, color augmentation, and photorealistic image stylization produces useful representations that are viewpoint and illumination invariant. The feature descriptors learned by the proposed approach perform competitively and surpass their fully- and weakly-supervised counterparts on various geometric benchmarks such as image-based localization, sparse feature matching, and image retrieval.
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-72.01 SIFT Matching by Context Exposed
Fabio Bellavia
Aug 27 2021 cs.CV
+ -
This paper investigates how to step up local image descriptor matching by exploiting matching context information. Two main contexts are identified, originated respectively from the descriptor space and from the keypoint space. The former is generally used to design the actual matching strategy while the latter to filter matches according to the local spatial consistency. On this basis, a new matching strategy and a novel local spatial filter, named respectively blob matching and Delaunay Triangulation Matching (DTM) are devised. Blob matching provides a general matching framework by merging together several strategies, including rank-based pre-filtering as well as many-to-many and symmetric matching, enabling to achieve a global improvement upon each individual strategy. DTM alternates between Delaunay triangulation contractions and expansions to figure out and adjust keypoint neighborhood consistency. Experimental evaluation shows that DTM is comparable or better than the state-of-the-art in terms of matching accuracy and robustness. Evaluation is carried out according to a new benchmark devised for analyzing the matching pipeline in terms of correct correspondences on both planar and non-planar scenes, including several state-of-the-art methods as well as the common SIFT matching approach for reference. This evaluation can be of assistance for future research in this field.
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Should read this paper?

Questions I ask myself (1)

Should read this paper?

Questions I ask myself (1)

- My areas? Yes → read.

Should read this paper?

Questions I ask myself (1)

- My areas? Yes → read.
- Opens a new (sub-)area of research? Yes → read. E.g. GAN in 2014, NERF

Should read this paper?

Questions I ask myself (1)

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- From the crowded area? Yes → skip. E.g GANs now

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- Dataset or large-scale benchmark paper? Yes → read

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- Simple baseline? Yes → read, regadless of the area.

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- From the crowded area? Yes → skip. E.g GANs now
- Dataset or large-scale benchmark paper? Yes → read
- Simple baseline? Yes → read, regadless of the area.
- About understanding some aspect of machine learning? Yes → read if have time. E.g. padding, double descent, over-parametrization

Should read this paper?

Questions I ask myself (2)

Should read this paper?

Questions I ask myself (2)

- Theory paper? Yes → skip

Should read this paper?

Questions I ask myself (2)

- Theory paper? Yes → skip
- Relevant for me as a user? Yes → read if have time. E.g. new non-linearity, optimizer, etc.

Should read this paper?

Questions I ask myself (2)

- Theory paper? Yes → skip

- Relevant for me as a user? Yes → read if have time. E.g. new non-linearity, optimizer, etc.

- Isn't the title over-keyworded and so on? E.g. "Adaptive DropBlock Enhanced Generative Adversarial Networks for Hyperspectral Image Classification”. This kind of things are hard to verbalize.

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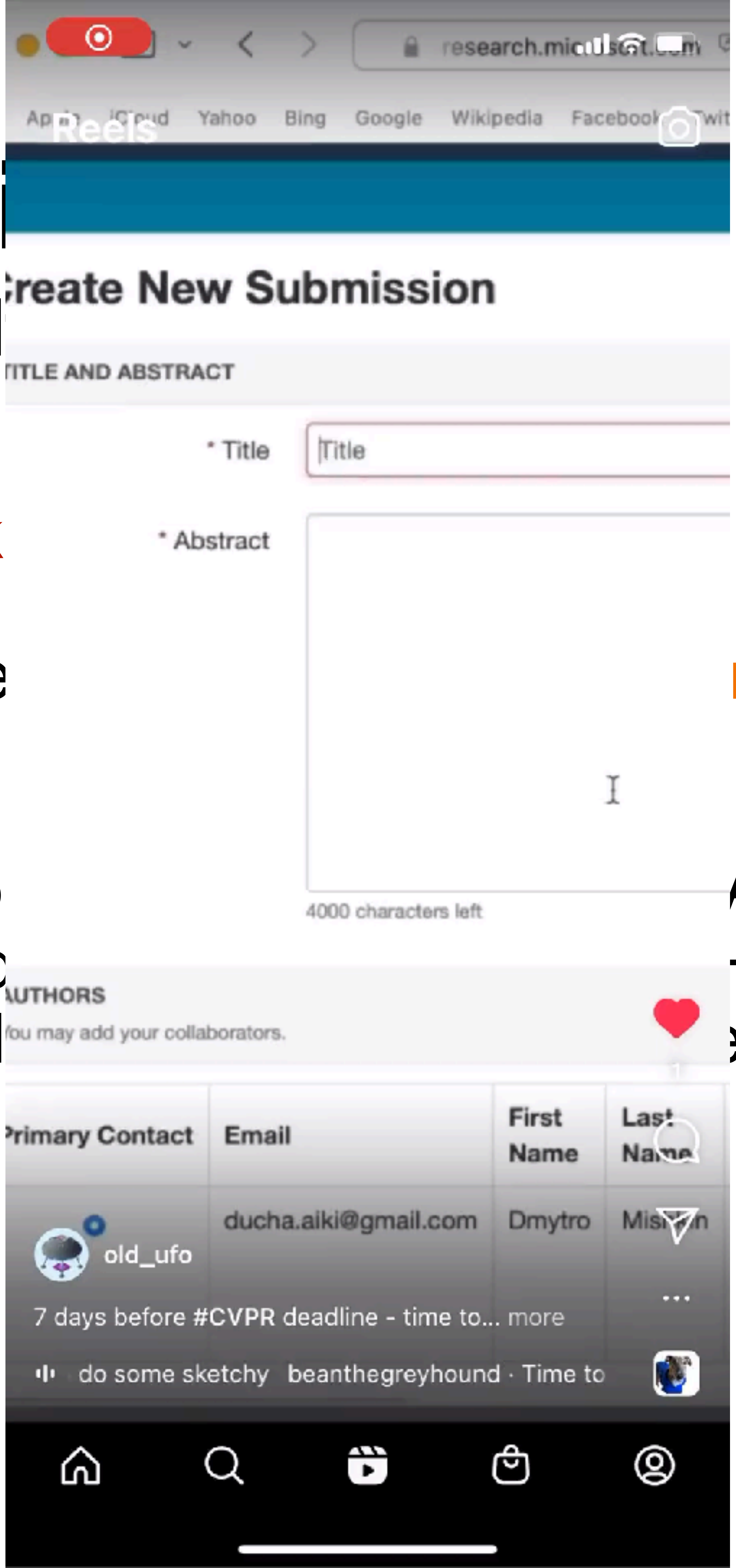
Questions I ask mysel



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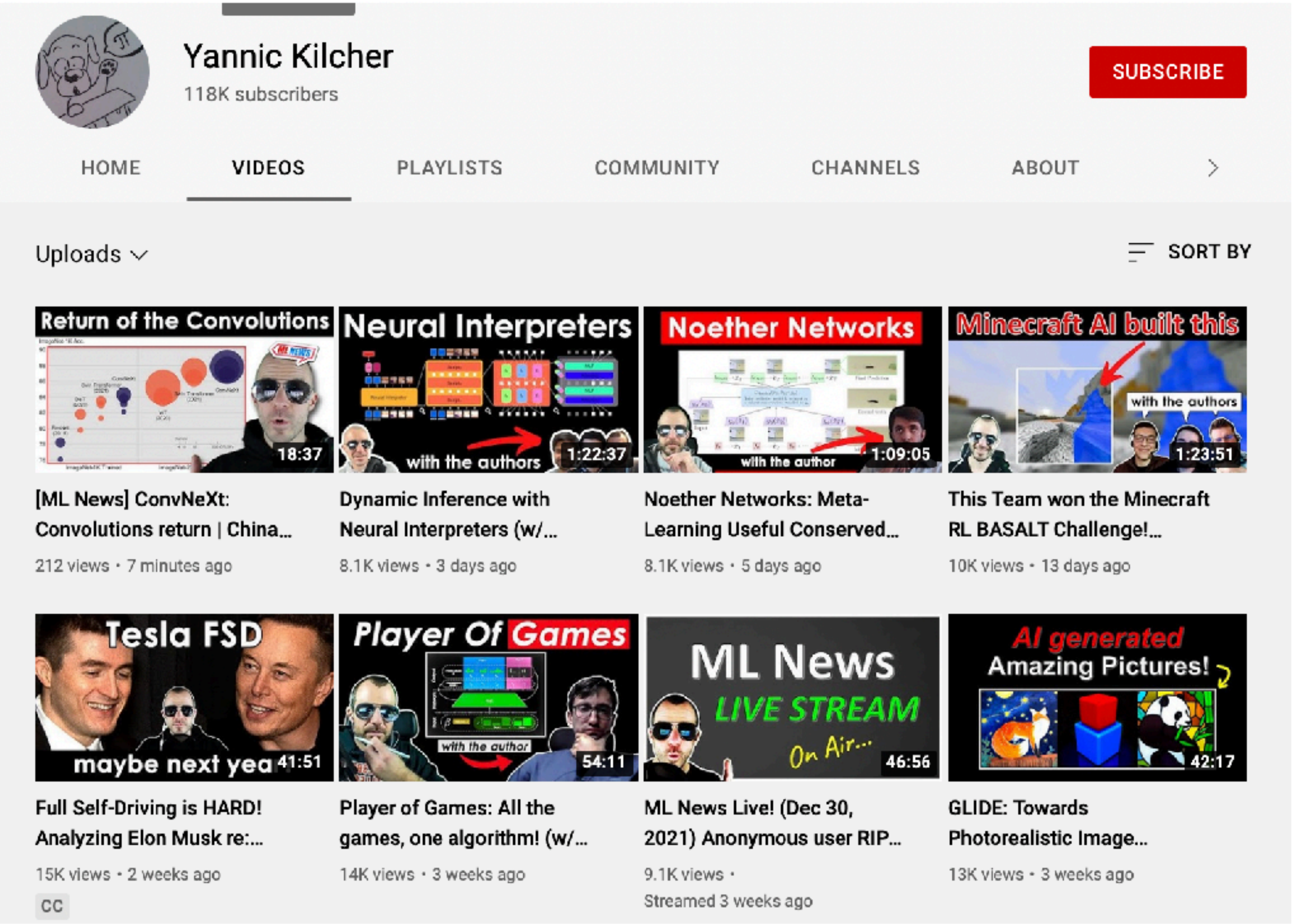
Additional paper sources

Yannic Kilcher



Additional paper sources

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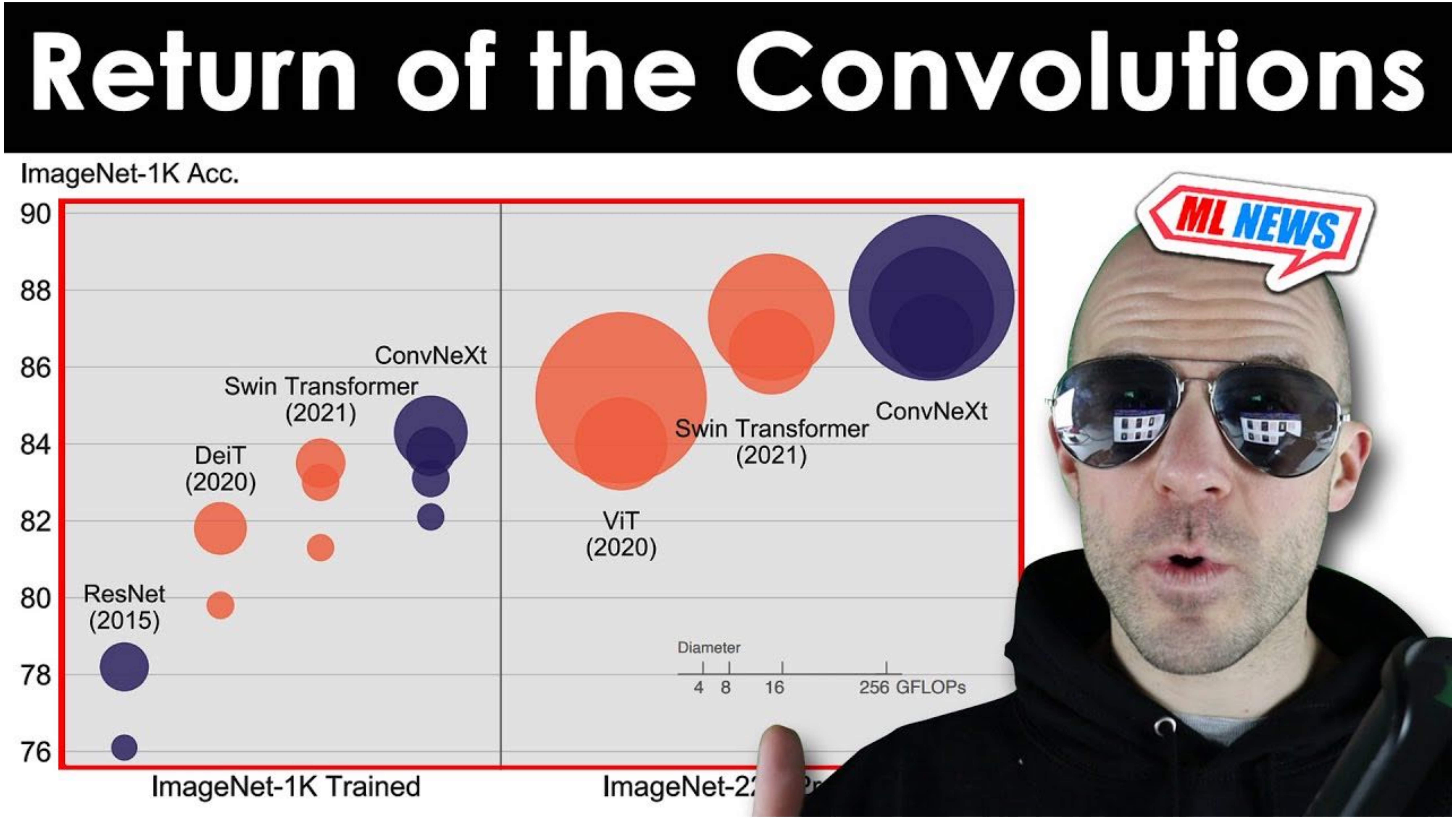
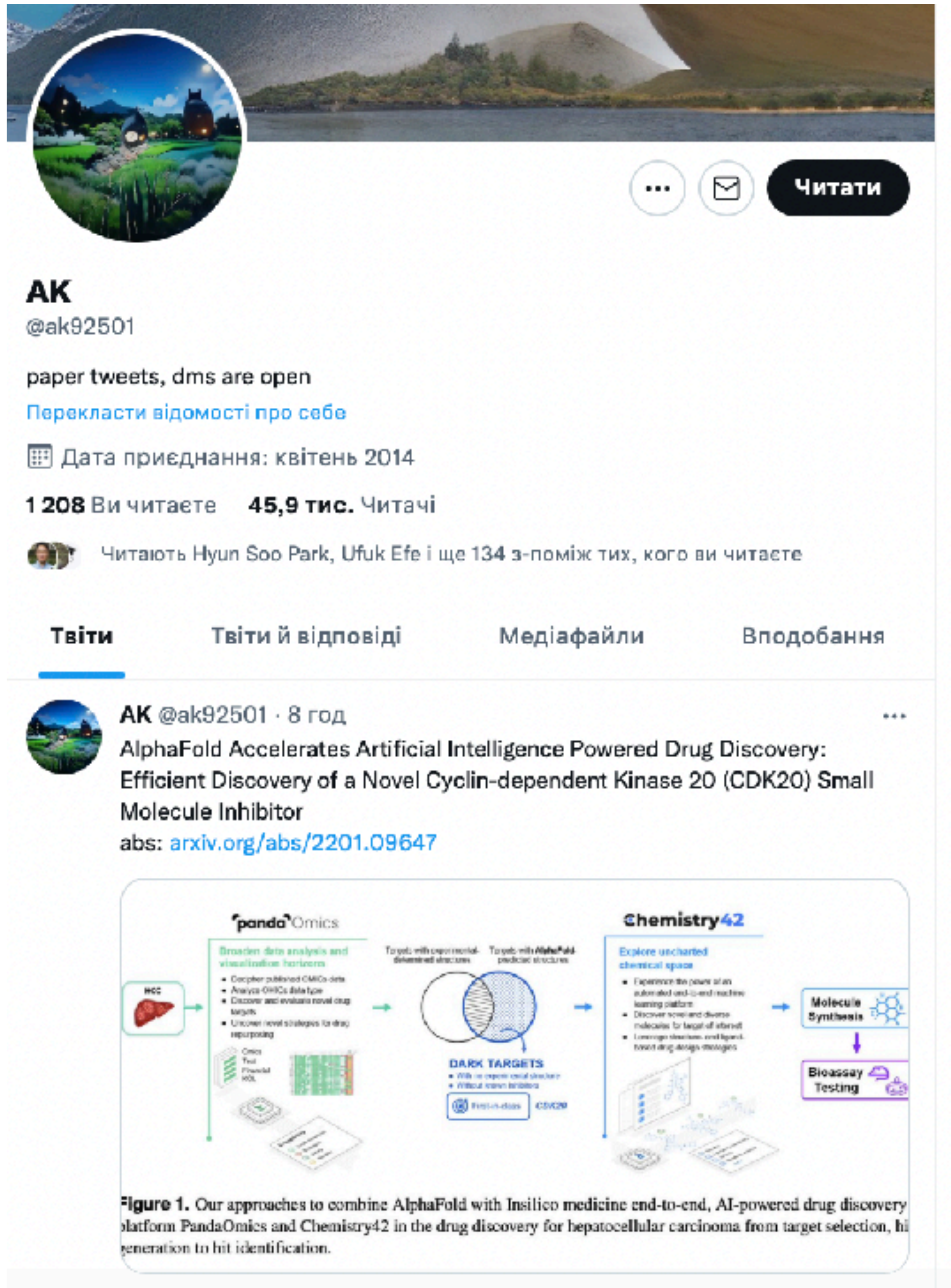


Twitter AK feed — general purpose interesting

@ak92501



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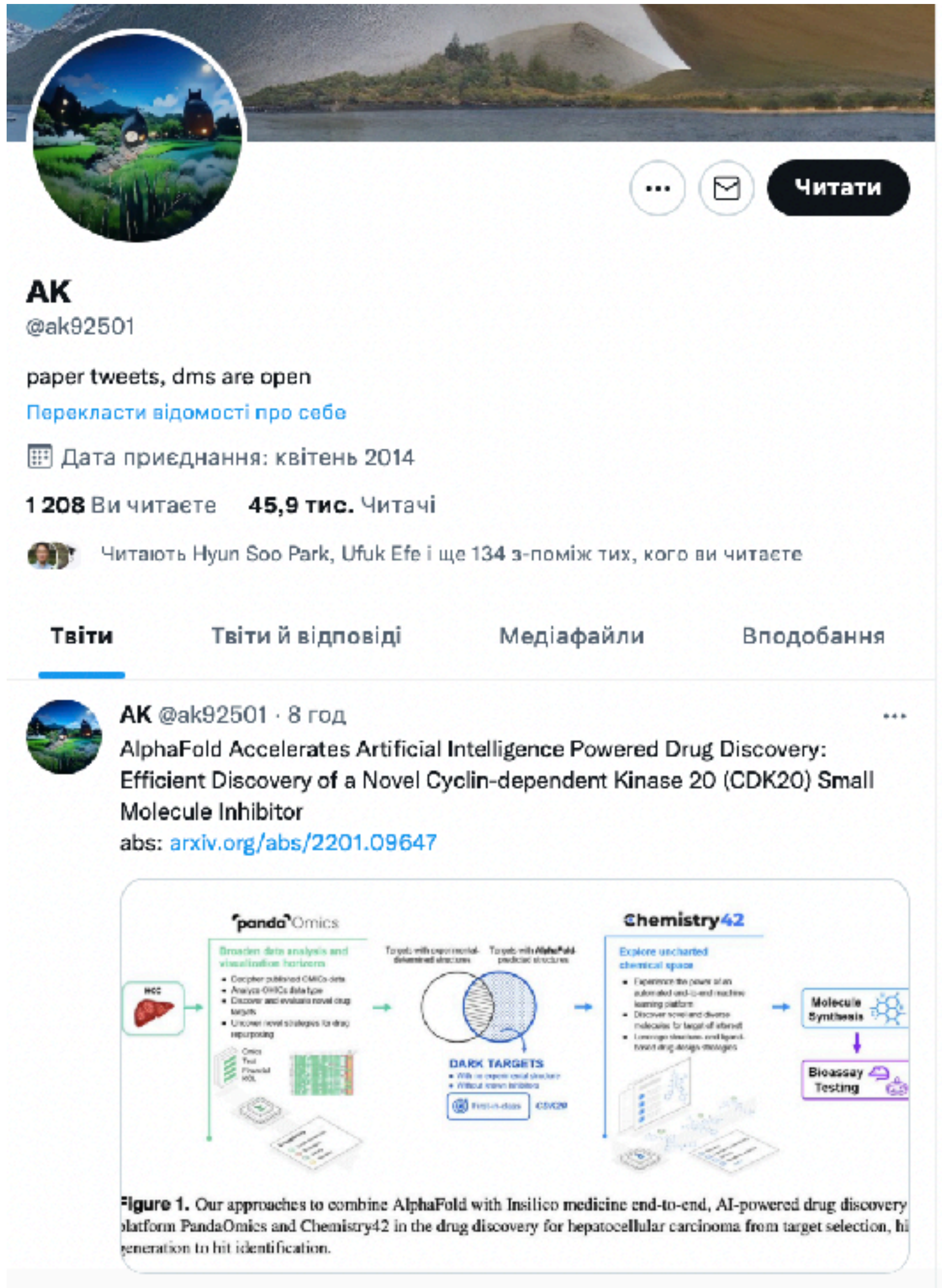

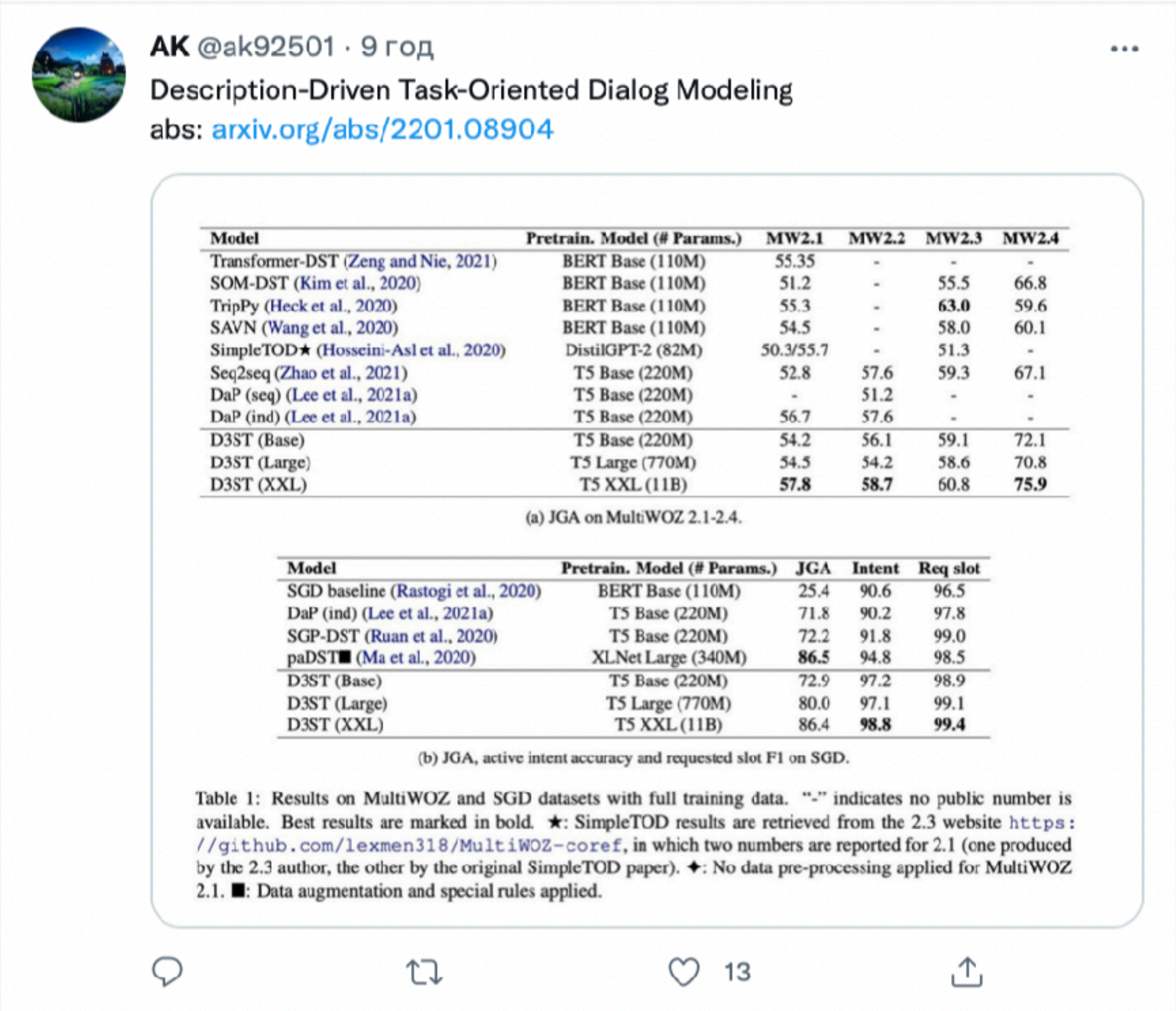

Model	Pretrain. Model (# Params.)	MW2.1	MW2.2	MW2.3	MW2.4
Transformer-DST (Zeng and Nie, 2021)	BERT Base (110M)	55.35	-	-	-
SOM-DST (Kim et al., 2020)	BERT Base (110M)	51.2	-	55.5	66.8
TripPy (Heck et al., 2020)	BERT Base (110M)	55.3	-	**63.0**	59.6
SAVN (Wang et al., 2020)	BERT Base (110M)	54.5	-	58.0	60.1
SimpleTOD★ (Hosseini-Asl et al., 2020)	DistilGPT-2 (82M)	50.3/55.7	-	51.3	-
Seq2seq (Zhao et al., 2021)	T5 Base (220M)	52.8	57.6	59.3	67.1
DaP (seq) (Lee et al., 2021a)	T5 Base (220M)	-	51.2	-	-
DaP (ind) (Lee et al., 2021a)	T5 Base (220M)	56.7	57.6	-	-
D3ST (Base)	T5 Base (220M)	54.2	56.1	59.1	72.1
D3ST (Large)	T5 Large (770M)	54.5	54.2	58.6	70.8
D3ST (XXL)	T5 XXL (11B)	**57.8**	**58.7**	60.8	**75.9**

(a) JGA on MultiWOZ 2.1-2.4.

Model	Pretrain. Model (# Params.)	JGA	Intent	Req slot
SGD baseline (Rastogi et al., 2020)	BERT Base (110M)	25.4	90.6	96.5
DaP (ind) (Lee et al., 2021a)	T5 Base (220M)	71.8	90.2	97.8
SGP-DST (Ruan et al., 2020)	T5 Base (220M)	72.2	91.8	99.0
paDST■ (Ma et al., 2020)	XLNet Large (340M)	**86.5**	94.8	98.5
D3ST (Base)	T5 Base (220M)	72.9	97.2	98.9
D3ST (Large)	T5 Large (770M)	80.0	97.1	99.1
D3ST (XXL)	T5 XXL (11B)	86.4	**98.8**	**99.4**

(b) JGA, active intent accuracy and requested slot F1 on SGD.

Table 1: Results on MultiWOZ and SGD datasets with full training data. "-" indicates no public number is available. Best results are marked in bold. ★: SimpleTOD results are retrieved from the 2.3 website `https://github.com/lexmen318/MultiWOZ-coref`, in which two numbers are reported for 2.1 (one produced by the 2.3 author, the other by the original SimpleTOD paper). ✦: No data pre-processing applied for MultiWOZ 2.1. ■: Data augmentation and special rules applied.

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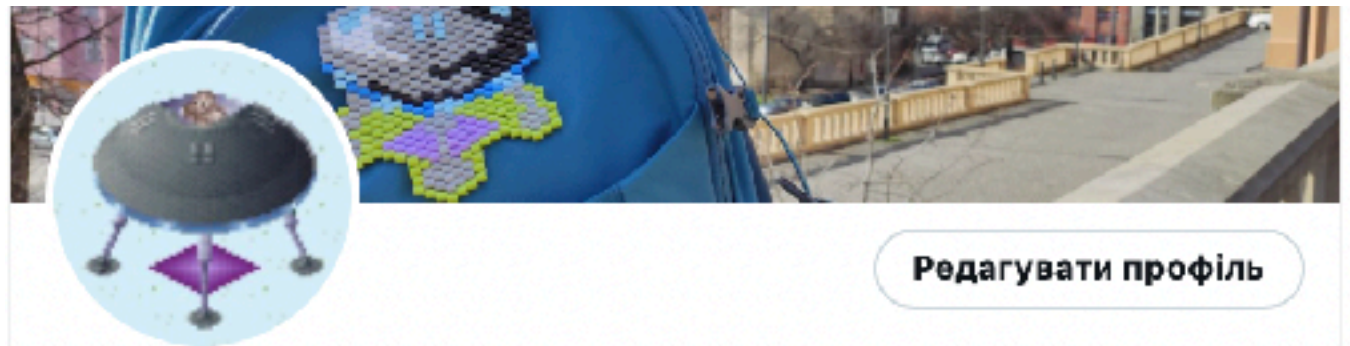

Редагувати профіль

Dmytro Mishkin
@ducha_aiki

Marrying classical CV and Deep Learning. I do things, which work, rather than being novel, but not working.
Перекласти відомості про себе

Ukraine dmytro.ai Дата приєднання: липень 2017

441 Ви читаєте **5 852** Читачі

Твіти Твіти й відповіді Медіафайли Вподобання

Закріплений твіт
Dmytro Mishkin @ducha_aiki · 13 жовт. 2020
ArXiving before submission :

- helps professional identity building;
-protects against idea re-discovery/theft/gate-keeping
- facilitates open research distribution
- reduces inequality.

our refined statement, with @amy_tabb & Jiri Matas, now on arXiv

arxiv.org
ArXiving Before Submission Helps Everyone
We claim, and present evidence, that allowing arXiv publication before a conference or journal ...

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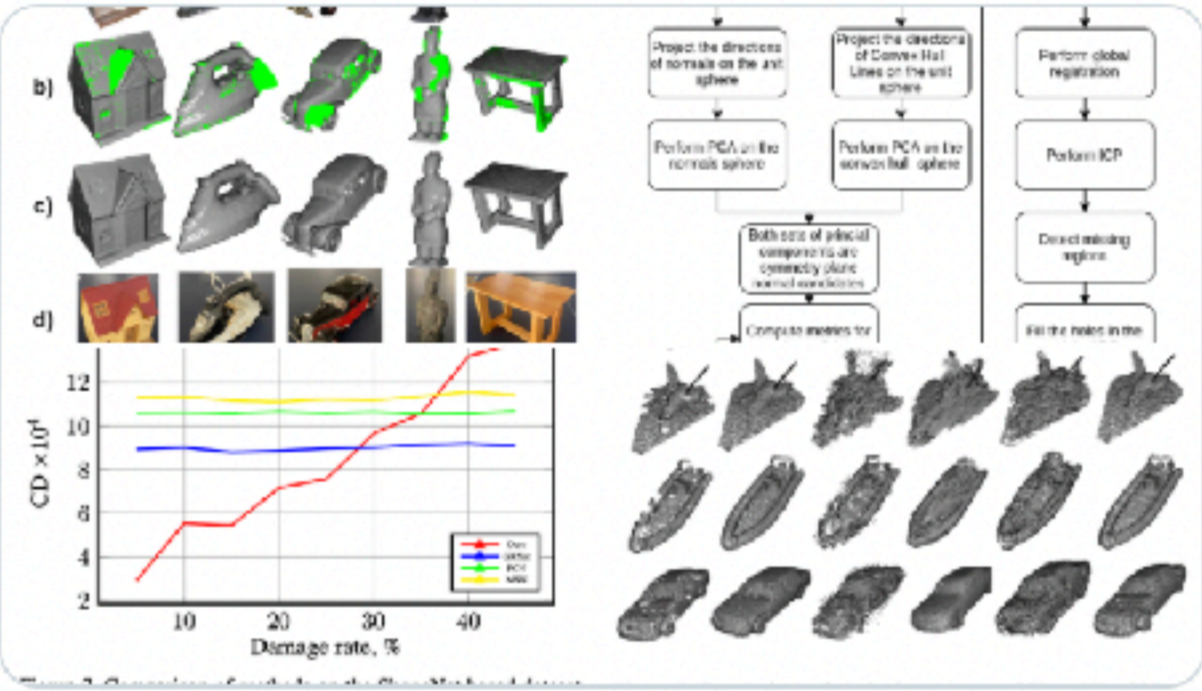
Dmytro Mishkin @ducha_aiki · 7 січ.
Towards realistic symmetry-based completion of previously unseen point clouds

Taras Rumezhak, @dobosevych , Rostyslav Hryniv, Vladyslav Selotkin, Volodymyr Karpiv, Mykola Maksymenko, @ucu_apps

tl;dr: good handcrafted method for point cloud completion

arxiv.org/abs/2201.01858



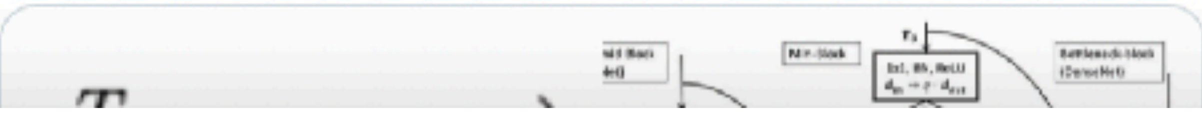
1 7 15

Dmytro Mishkin @ducha_aiki · 7 січ.
Bio-inspired Min-Nets Improve the Performance and Robustness of Deep Networks

Philipp Grüning, Erhardt Barth

tl;dr: out = min(ReLU(convA(BN(x))), ReLU(convB(BN((x)))
Idea: both filters should fire for reliable detection, kind of opposite of maxout idea.

arxiv.org/abs/2201.02149...



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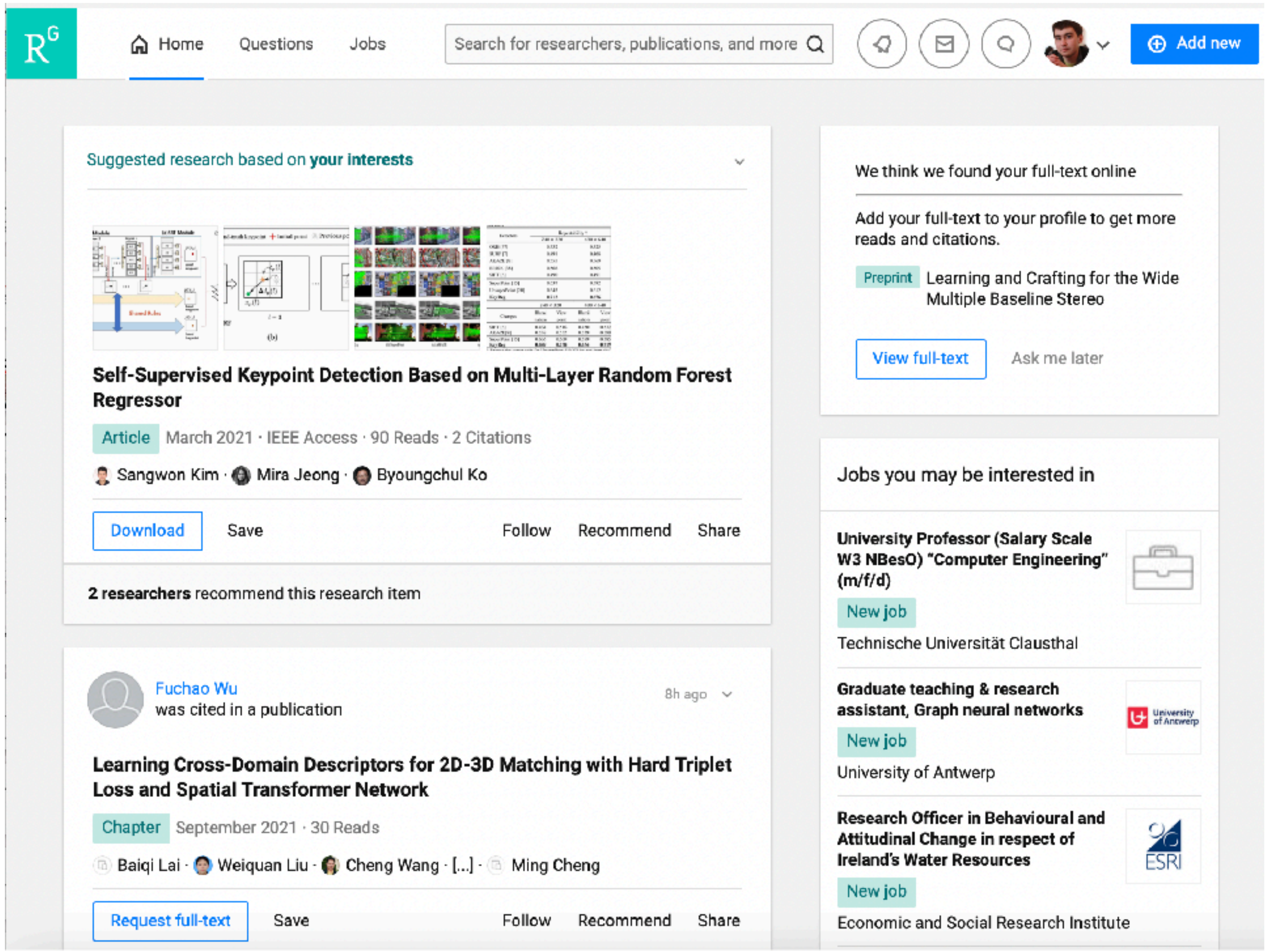
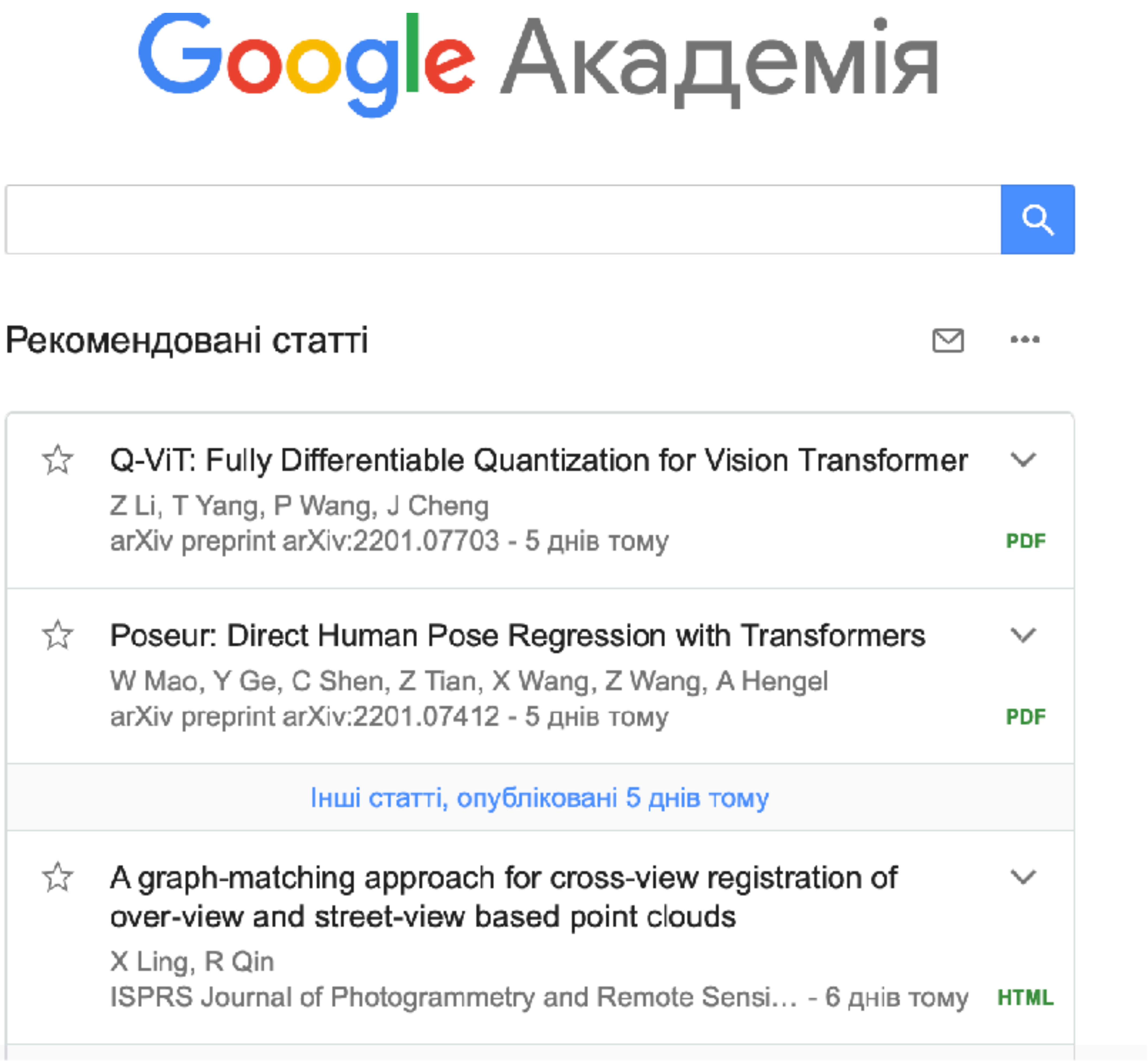


Google Scholar recommendations



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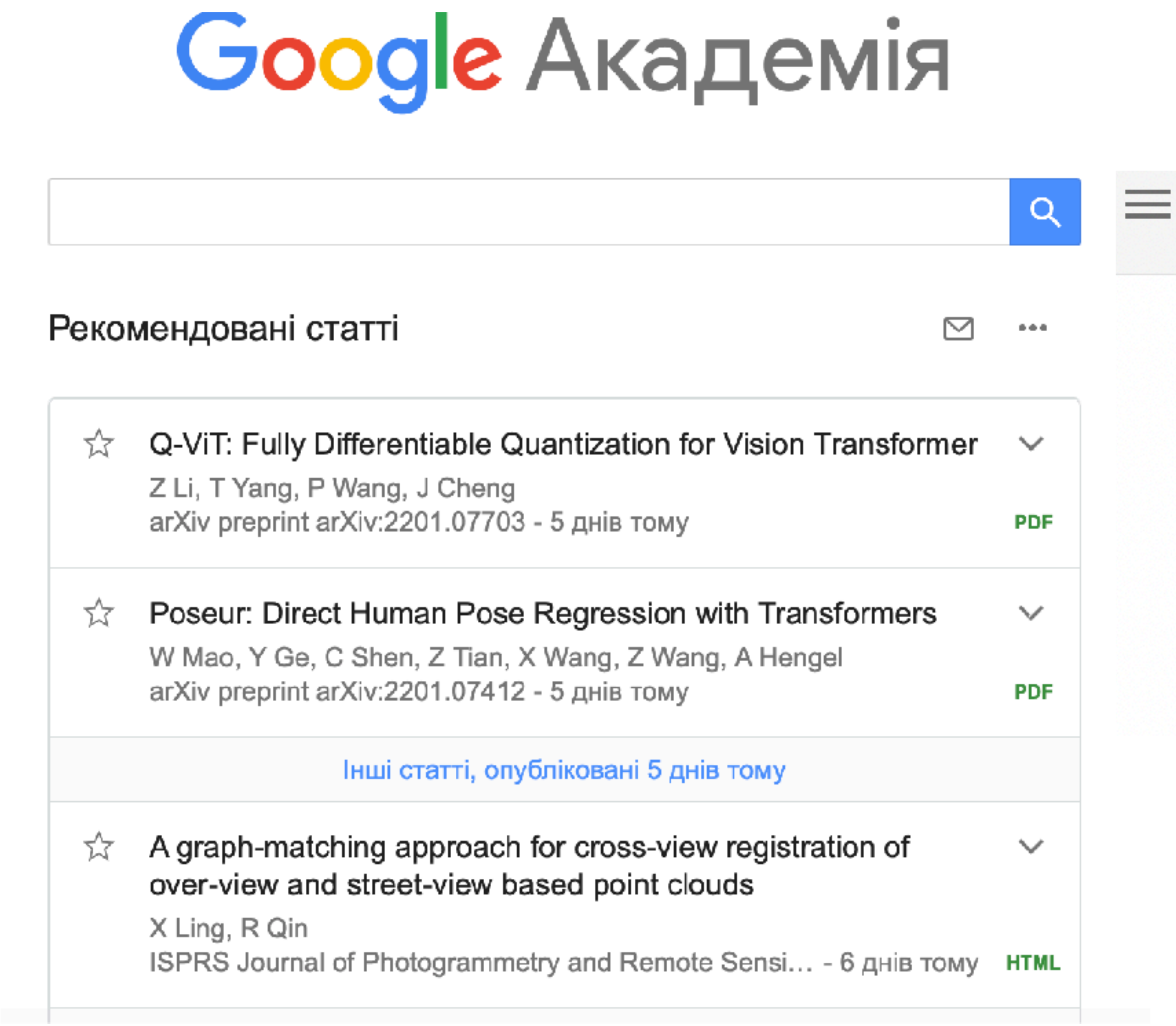

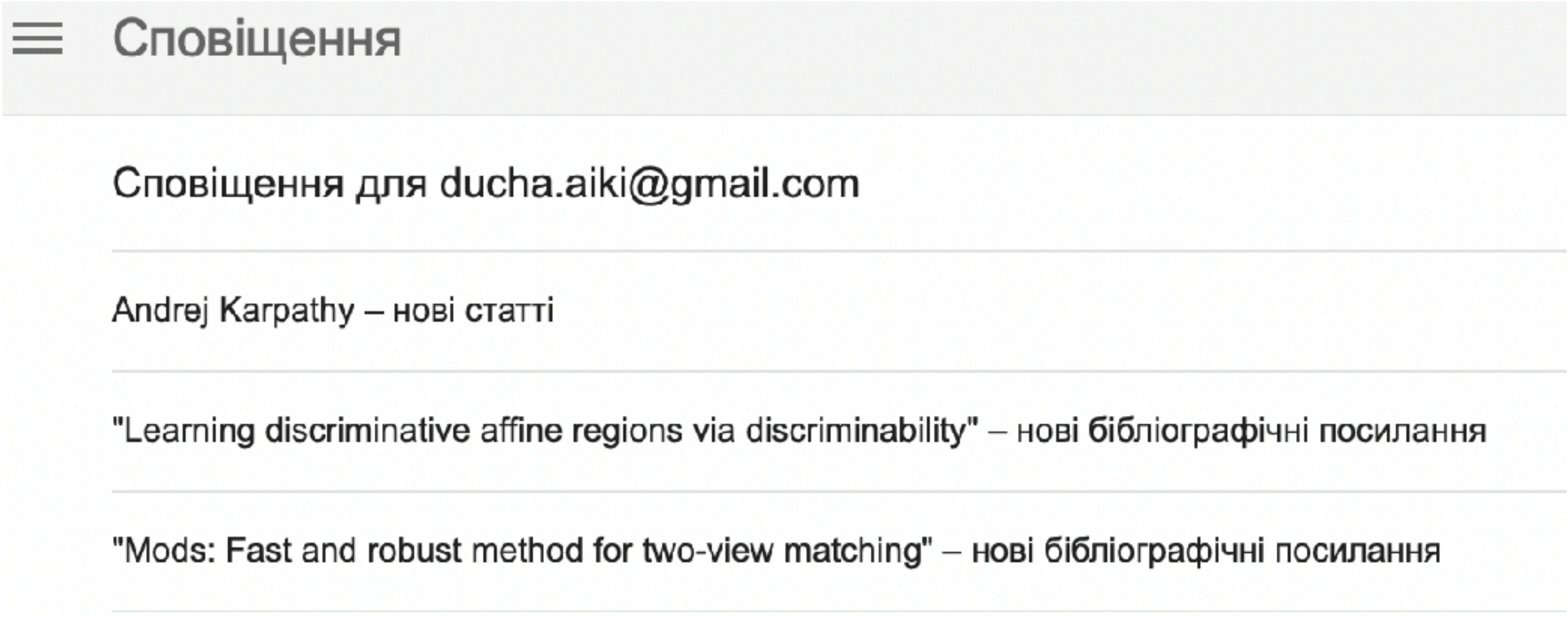

How to read a method paper?

The reading order of the method paper

Working hard to know your neighbor's margins: Local descriptor learning loss

Thanks to François Fleuret and Darshan Deshpande for help with this slide

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- Abstract

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We introduce a loss for metric learning, which is inspired by the Lowe's matching criterion for SIFT. We show that the proposed loss, that maximizes the distance between the closest positive and closest negative example in the batch, is better than complex regularization methods; it works well for both shallow and deep convolution network architectures. Applying the novel loss to the L2Net CNN architecture results in a compact descriptor named HardNet. It has the same dimensionality as SIFT (128) and shows state-of-art performance in wide baseline stereo, patch verification and instance retrieval benchmarks.

Thanks to François Fleuret and Darshan Deshpande for help with this slide

The reading order of the method paper

Working hard to know your neighbor's margins: Local descriptor learning loss

- Abstract
- Method figure

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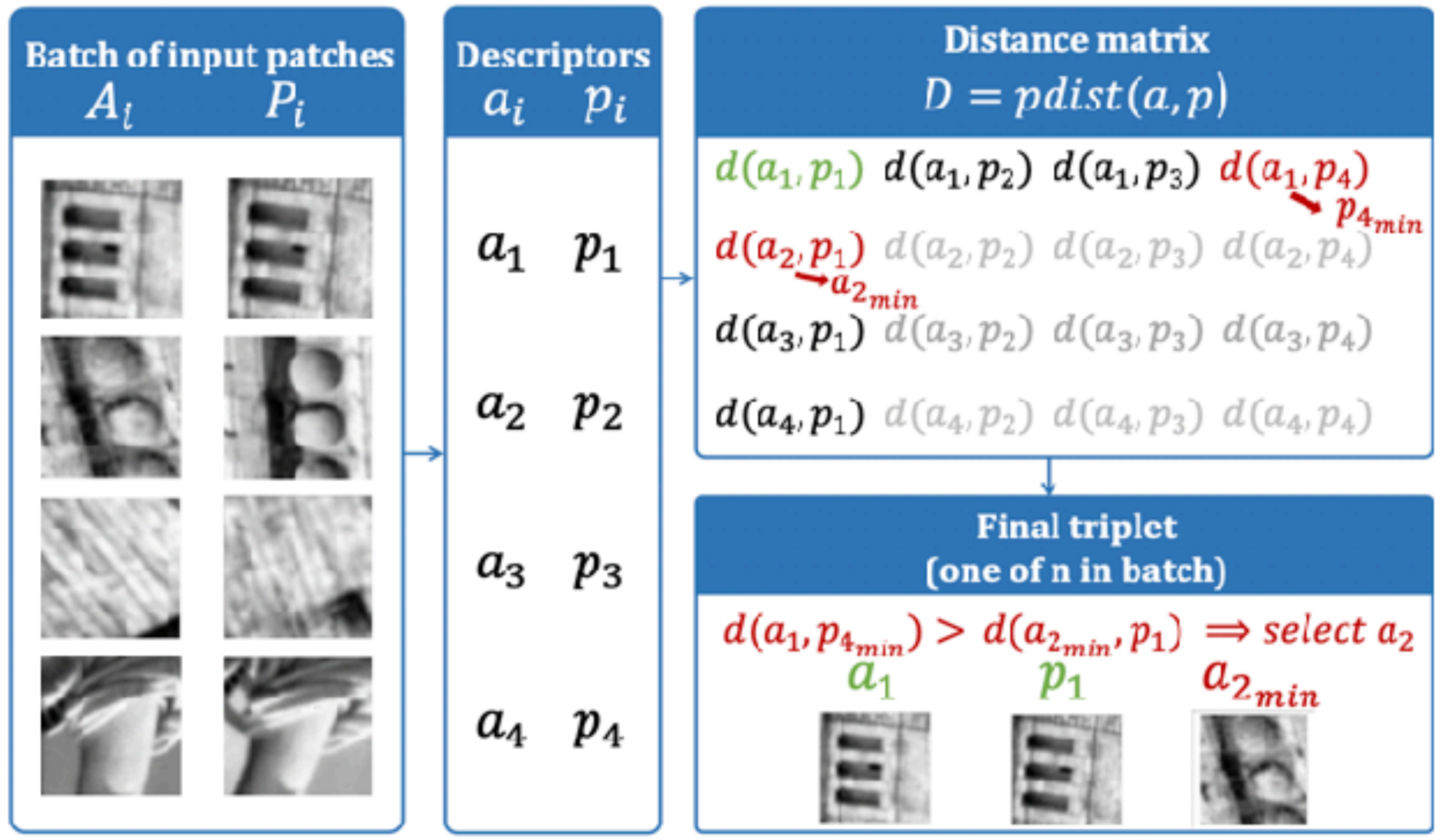

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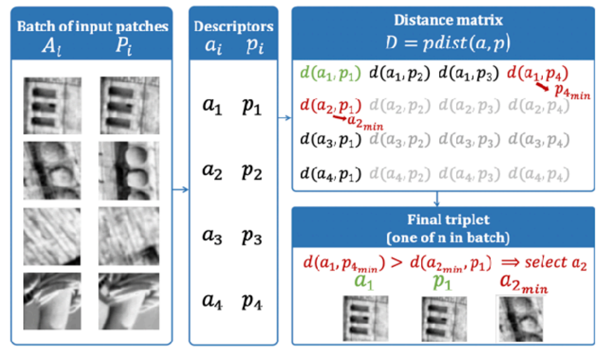

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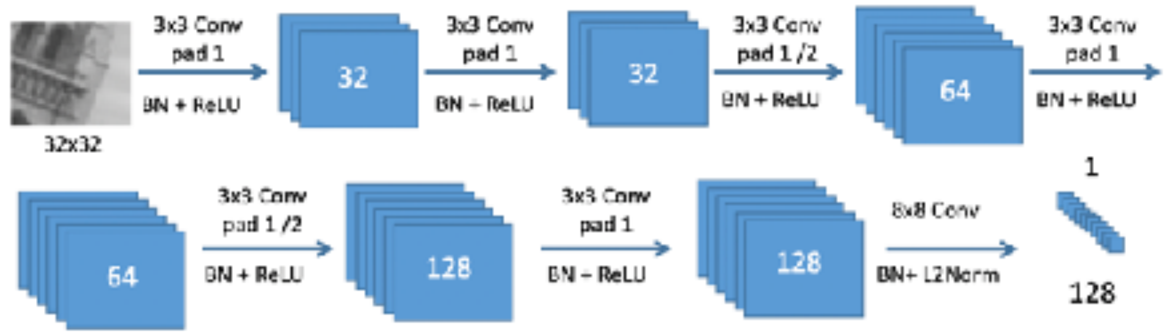

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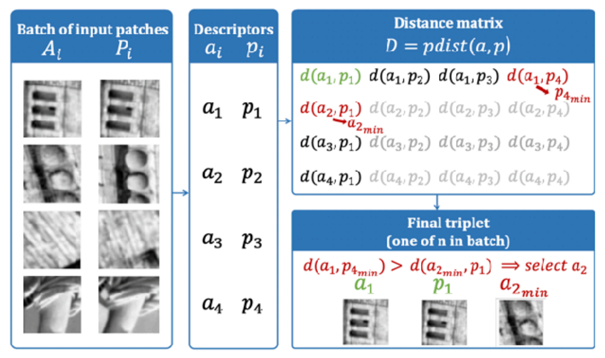

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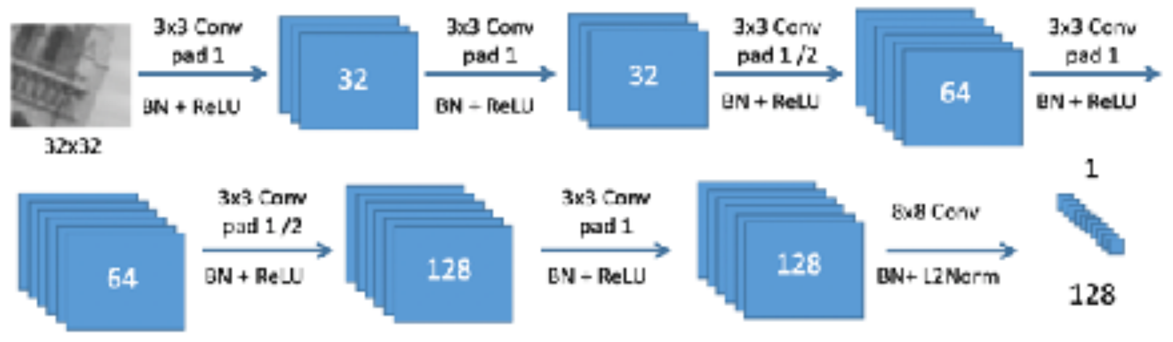

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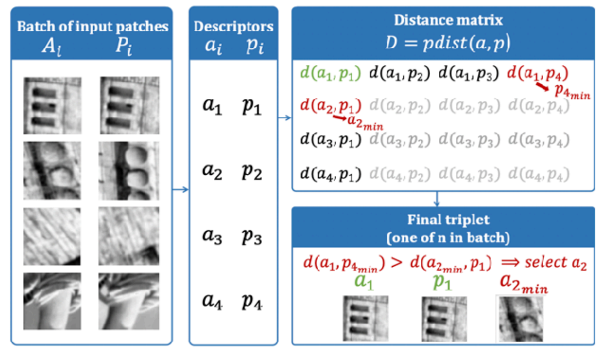

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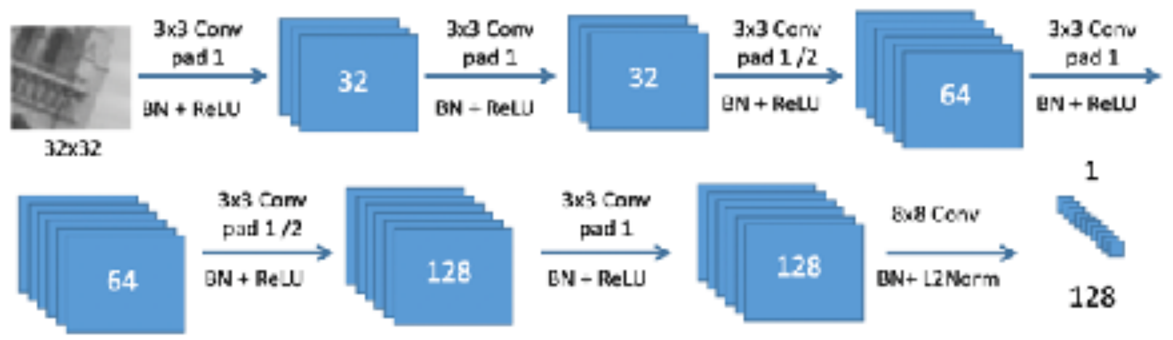

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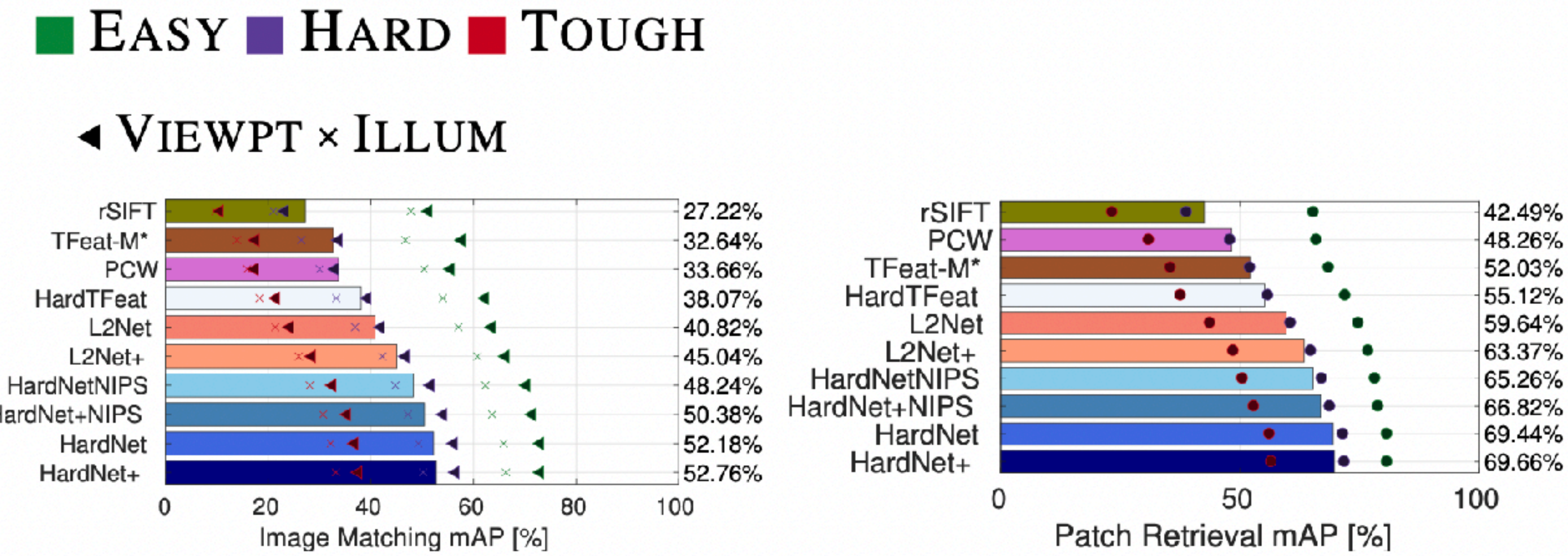

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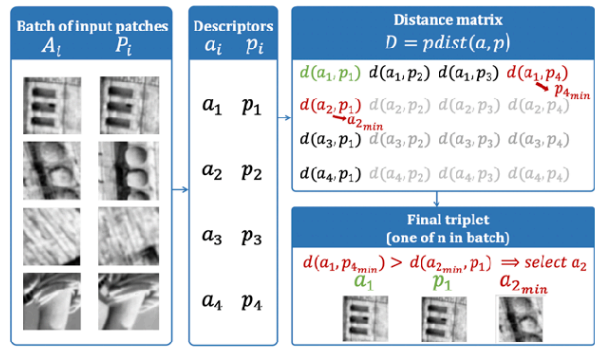

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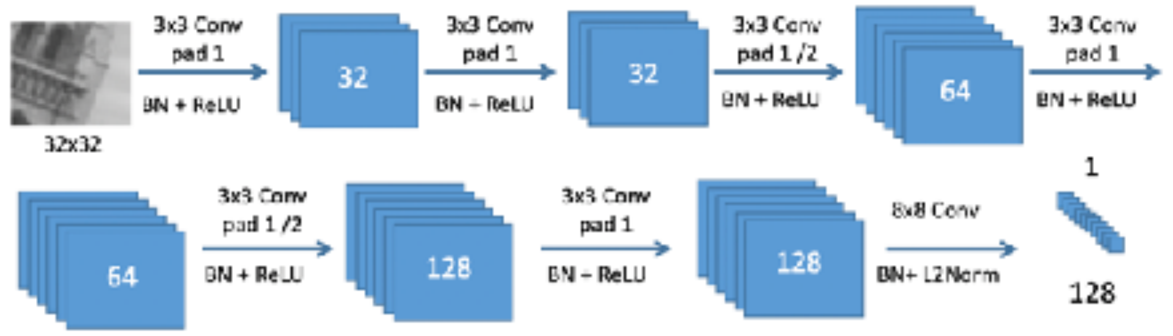

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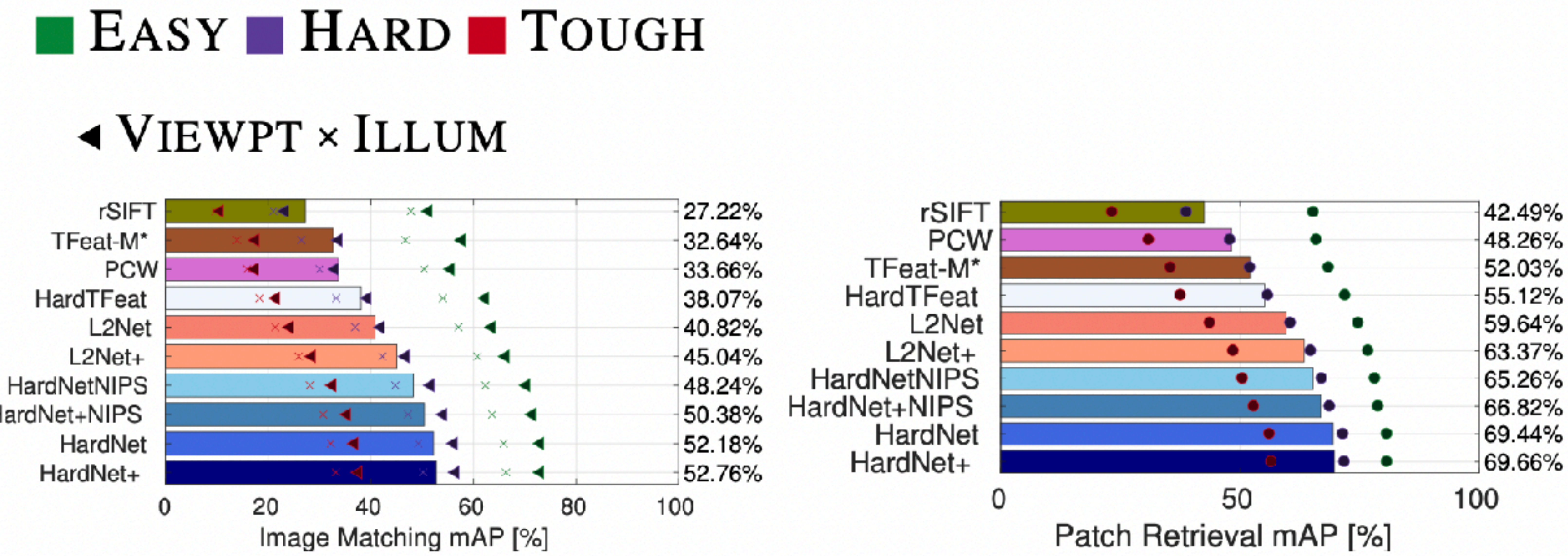

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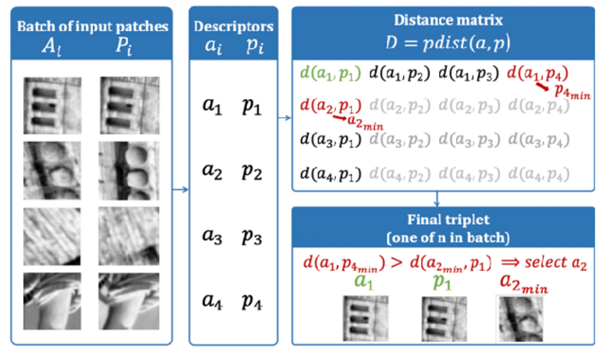

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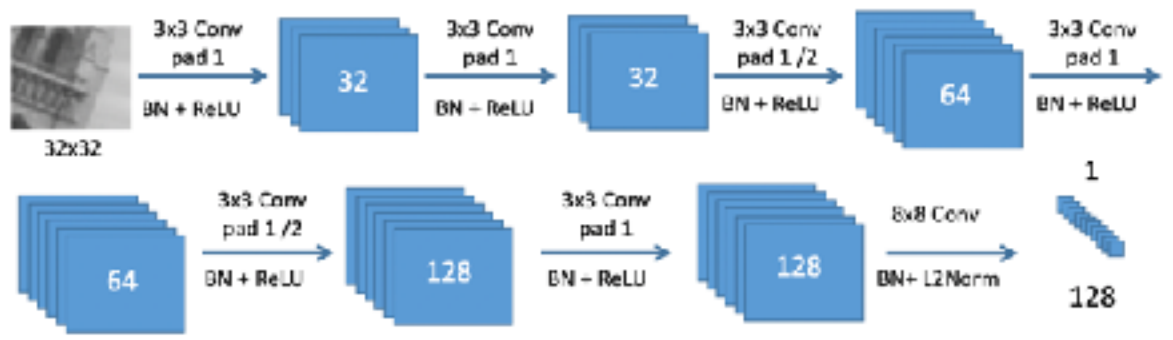

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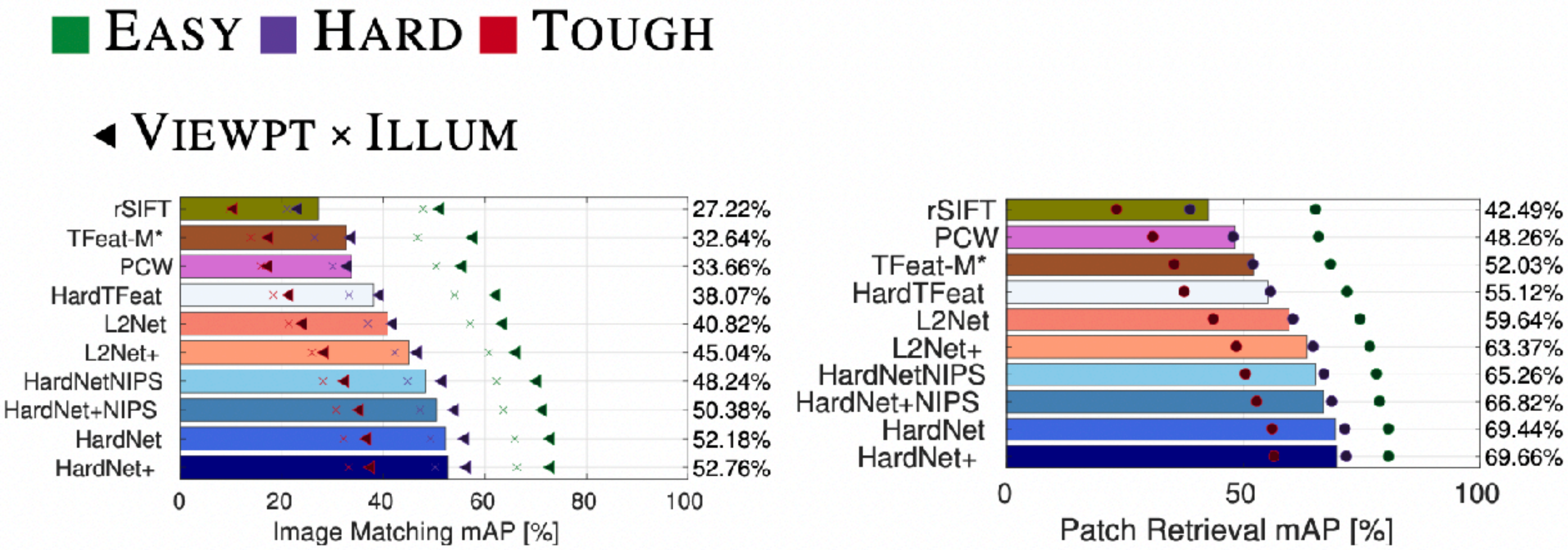

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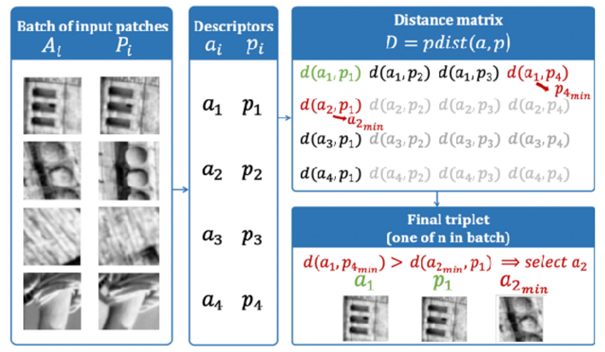

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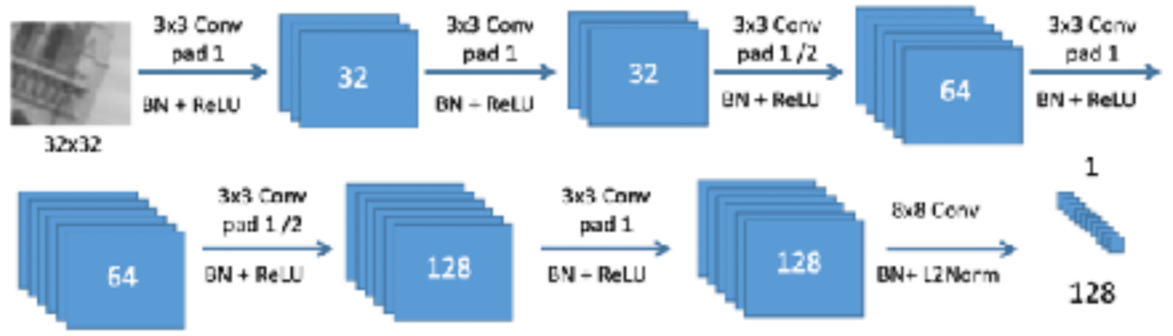

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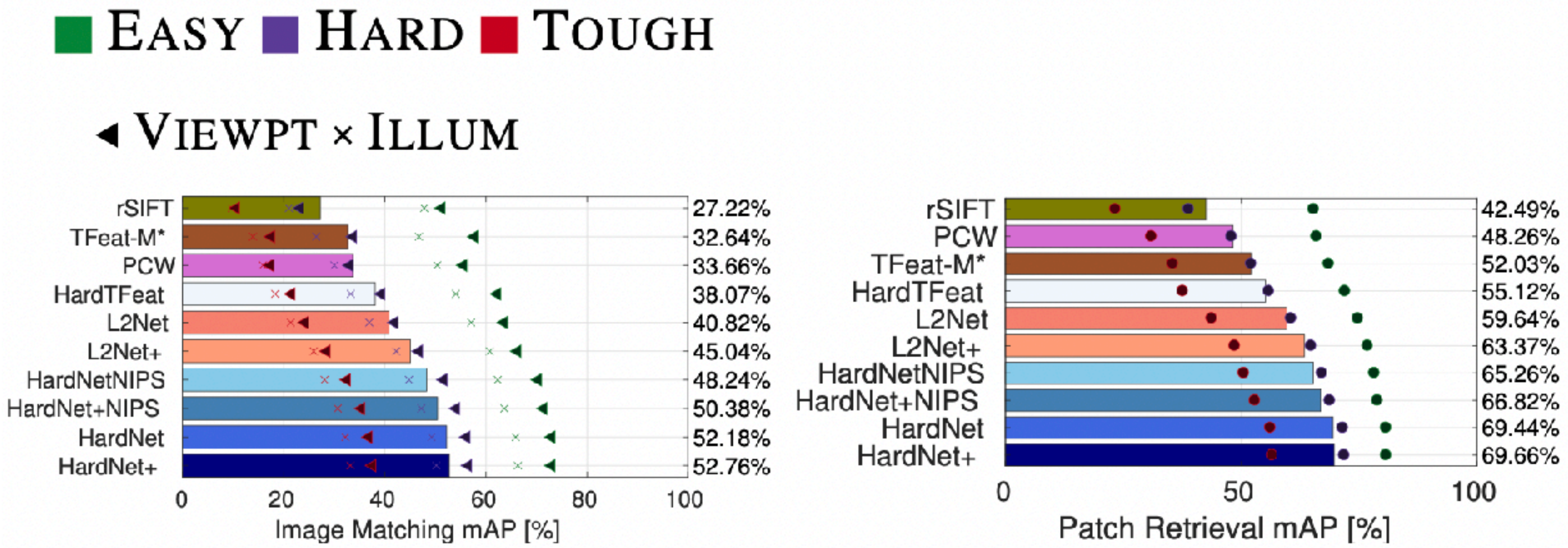

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Advice by Dushyant Mehta

From personal painful experience

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    - There is immense advantage to the simple. Less finicky training, less faff in deployment, faster experiment iteration,

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    - Very simple/subtle sampling differences can cause a huge difference in your metrics, without anything about the method changing.

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   - What metrics would better reflect what matters the most for your deployment scenario?

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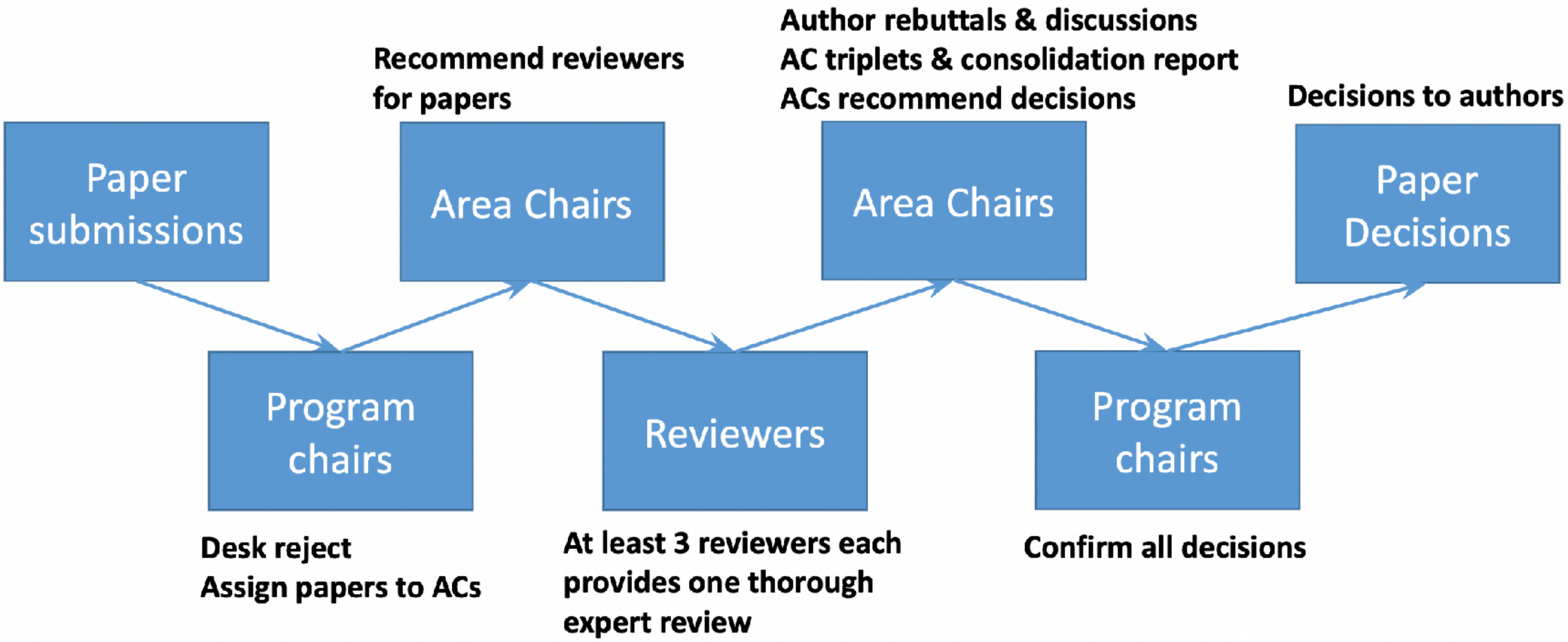
What does peer review mean?

The process of accepting/rejecting a paper



The role of reviewers in the process

- Provide an independent, objective, critical, and comprehensive review
  - **Key**: What is the knowledge advancement in the paper?
- Discuss with AC and reviewer buddies to (hopefully) reach consensus
  - Explain clearly the basis of your review and recommendation
  - It is OK if the reviewers disagree with one another even after discussions
  - AC will form recommendations weighing in reviews, rebuttals, and discussions
- Make your final recommendations with solid justifications
  - Read the rebuttal and discussions. Do they change your position? Why?
  - This facilitates the ACs to make final recommendations for the paper

What paper should be accepted?

- Any paper that, in accordance with CVPR community standards,
  - presents **sufficient knowledge advancement** that is **well grounded**;
  - is of **sufficient interest** to some **CVPR audiences** who could **benefit** from it

- Note: CVPR is very inclusive
  - Historically rejection solely for out-of-scope is rather rare

What should be included in the review?

- A concise summary of the paper
  - What problem is addressed in the paper?
  - Is it a new problem? If so, why does it matter? If not, why does it still matter?
  - What is the key to the solution? What is the main contribution?
  - Do the experiments sufficiently support the claims?
- A clear statement of strengths and weaknesses
  - What are the key contributions and why do they matter?
  - What aspects of the paper most need improvement?
- A comprehensive check of potential fundamental flaws in the paper
  - Are the assumptions and theories (mathematically) sound?
  - Are the experiments scientifically sound and valid?
  - Is the problem addressed trivial?
  - Did the paper miss important prior work? Has it been done before? If yes, where?

CVPR 2022 Reviewer tutorial

What should be avoided in the review?

- Common mistakes in a sloppy review
  - Arrogance, ignorance, and inaccuracy
    - Be responsible!
  - Pure opinions
    - Be grounded!
  - Novelty fallacy
    - Be knowledge-driven!
  - Blank assertions
    - Be substantial!
  - Policy entrepreneurism
    - Be sensible!
  - Intellectual laziness
    - Be active!

[Developed from: Reviewer Slides for CVPR’21]

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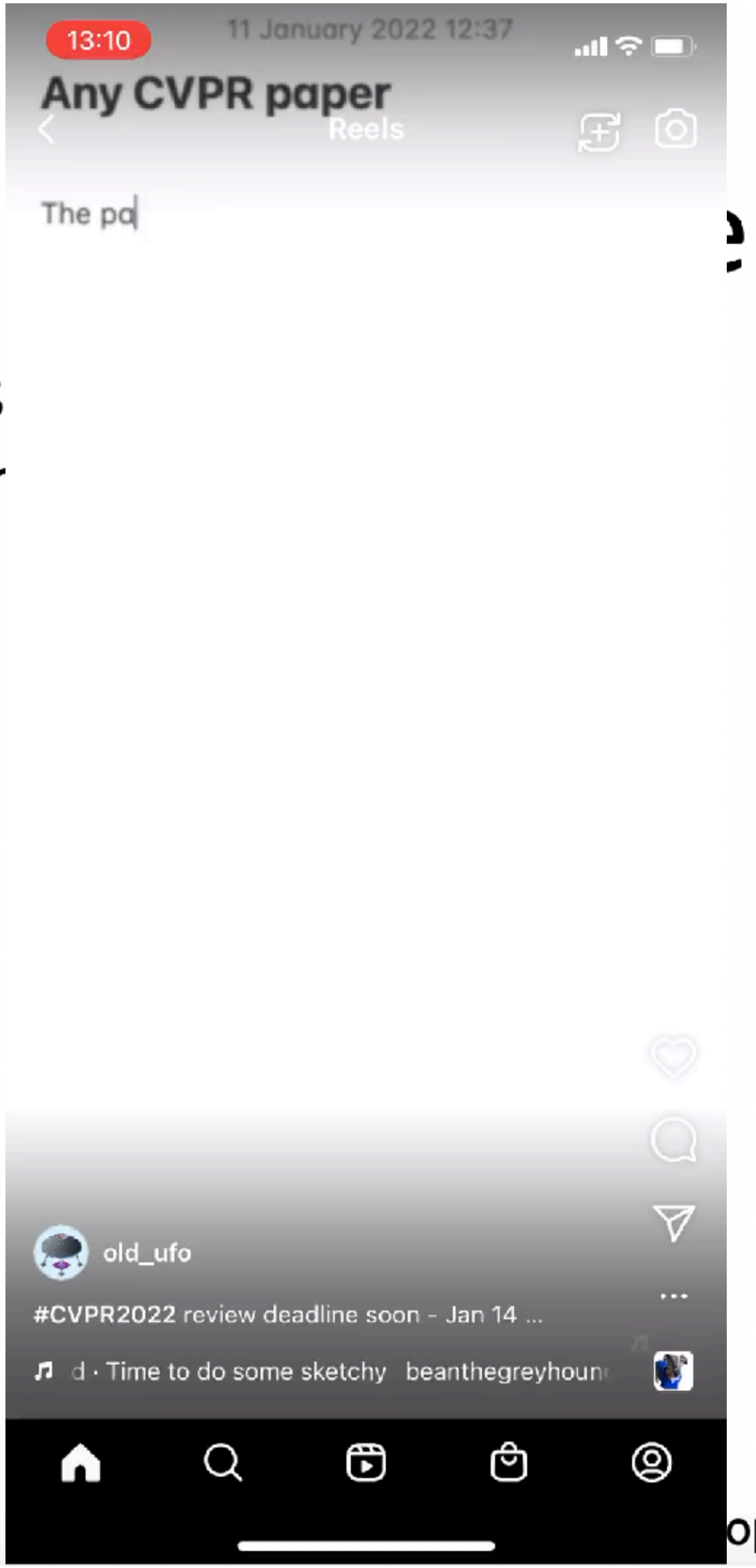

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Functions of the conferences

Why authors submit

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- **Knowledge dissemination**: "I want people to know about the new knowledge I discovered." The conference promises a certain minimum level of attention one's work gets. In other words, if you don't publish at top conferences, nobody would read your work.

https://ducha-aiki.medium.com/what-does-it-mean-to-publish-your-scientific-paper-in-2020-9ec3a8a90fe8 https://amytabb.com

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- **Networking**: meeting with peers, potential employers, etc

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Functions of the conferences

Why people attend

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- **Prefiltering**: time is limited, so we outsource the selection of what we are reading to the reviewers.

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- **Authors promise to answer our questions** (symmetrical to “attention for the author from audience,” and audience gets the guarantee that questions about the work will be answered at the talk or poster session).

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