Finding images with similar content elements based on LSH and ANN

FINAL PROGRESS REPORT

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Problem Definition

Build a python **framework** that takes a huge **database of images** as input and outputs a **structure** that can be **queried** for **approximate nearest neighbours** of an image or a slice of an image using **locality sensitive hashing**.

Problem Example

Image source: [1]

Given an image with trash containers

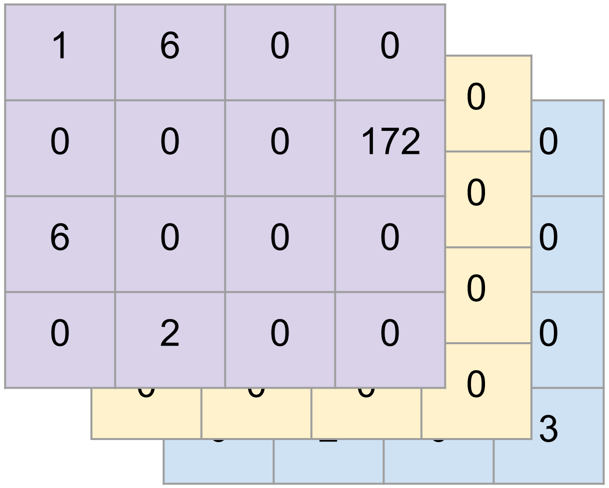
Reason:
Segmentation neural networks sometimes confuse trash containers with cars.

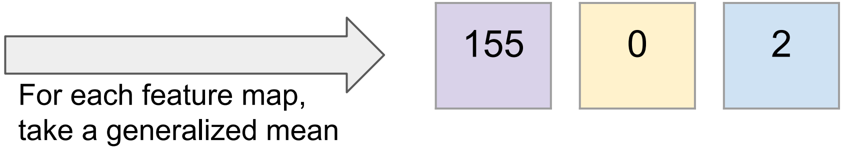
Find images in the database that also contain trash containers

Generalized Mean Pooling (GeM)

VGG16

Outputs 512 feature maps size H x W

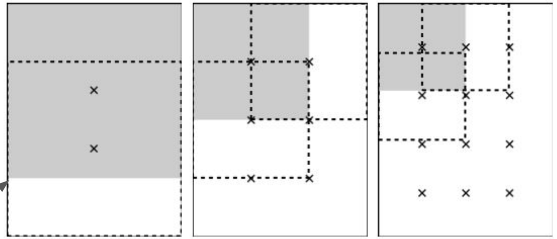


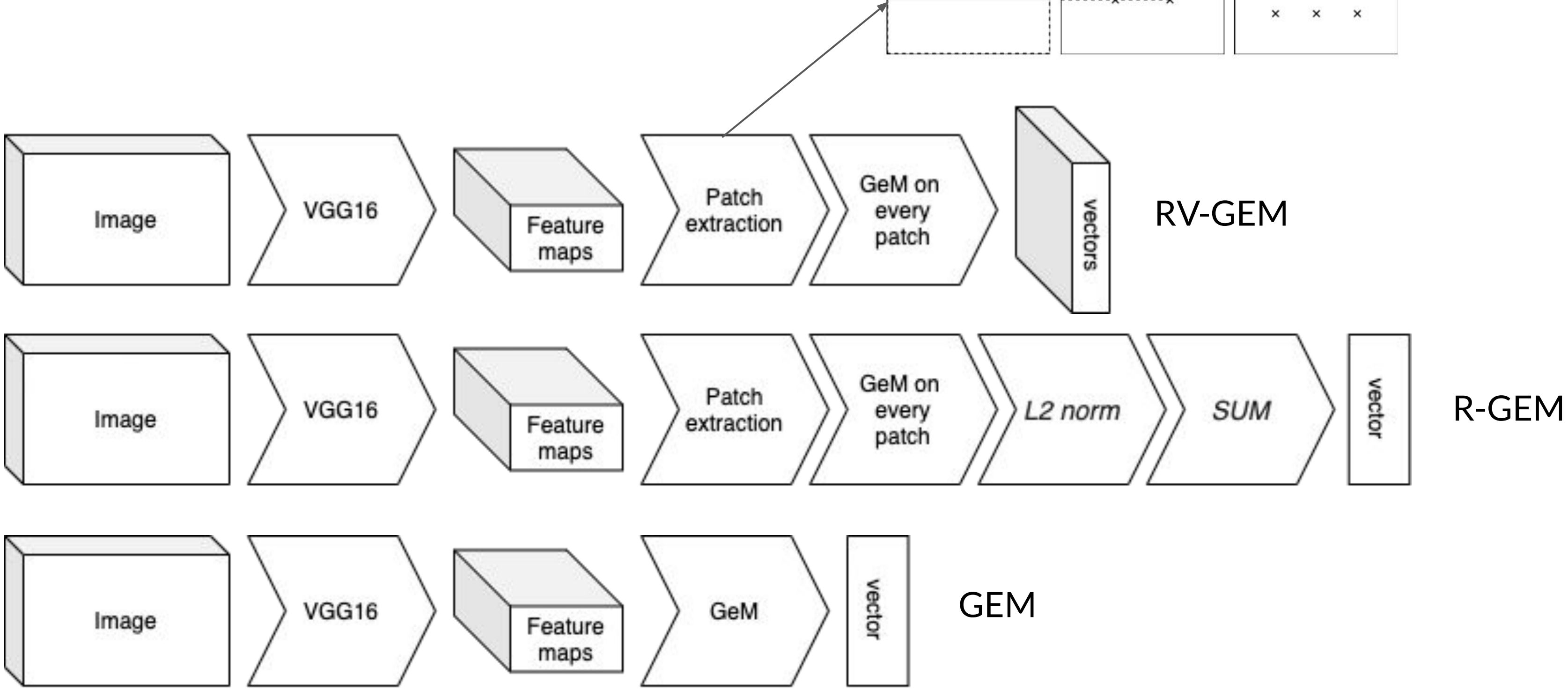


GeM

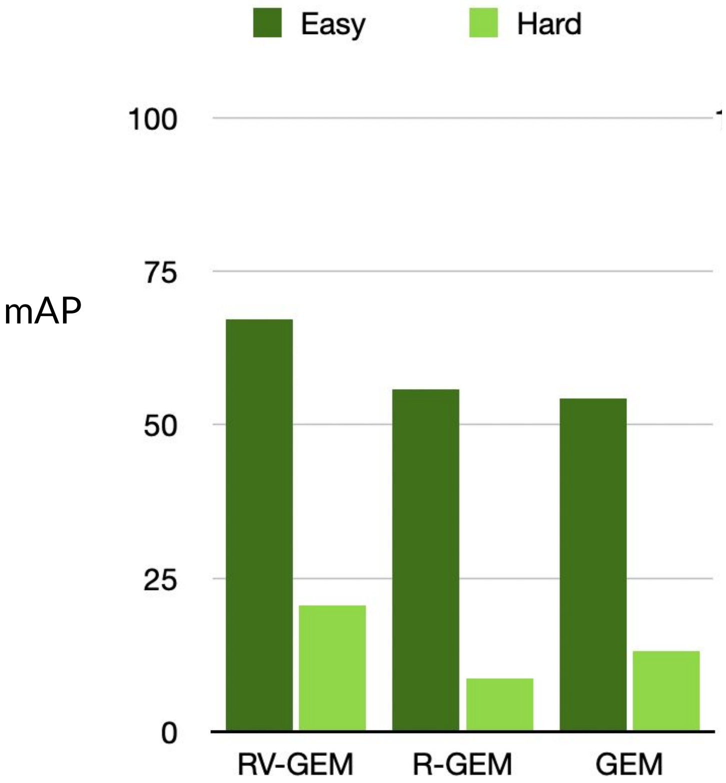
Outputs 512 feature maps of size 1 x 1
(Vector with 512 dimensions)

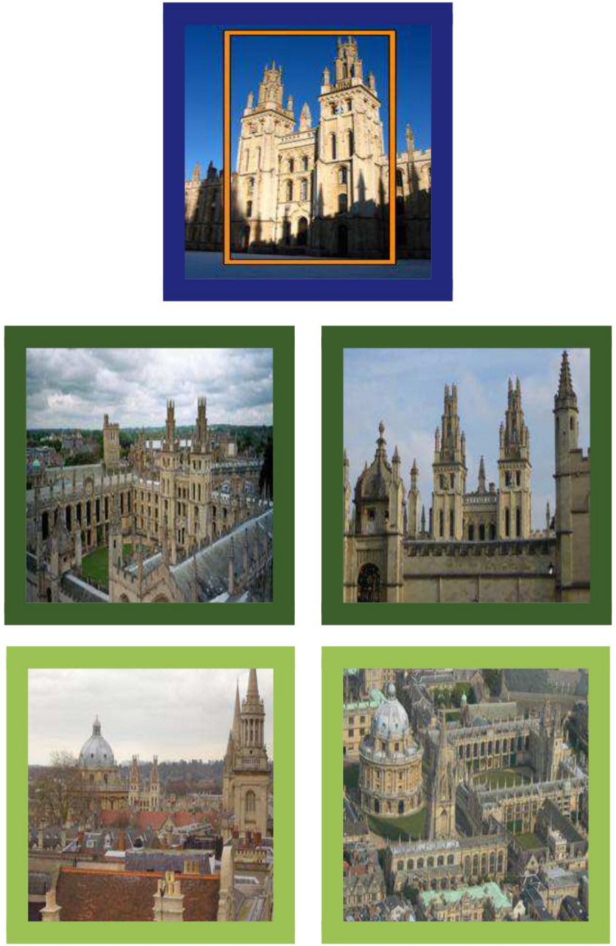
Feature Extraction Pipelines





Evaluation





[14]

Definitions

Near-Duplicate images:

Images that share the same content with only little modification
(e.g. all images that contain the same image of a horse)

Similar images:

Images that contain the same class of images
(e.g all images that contain any type of horse)

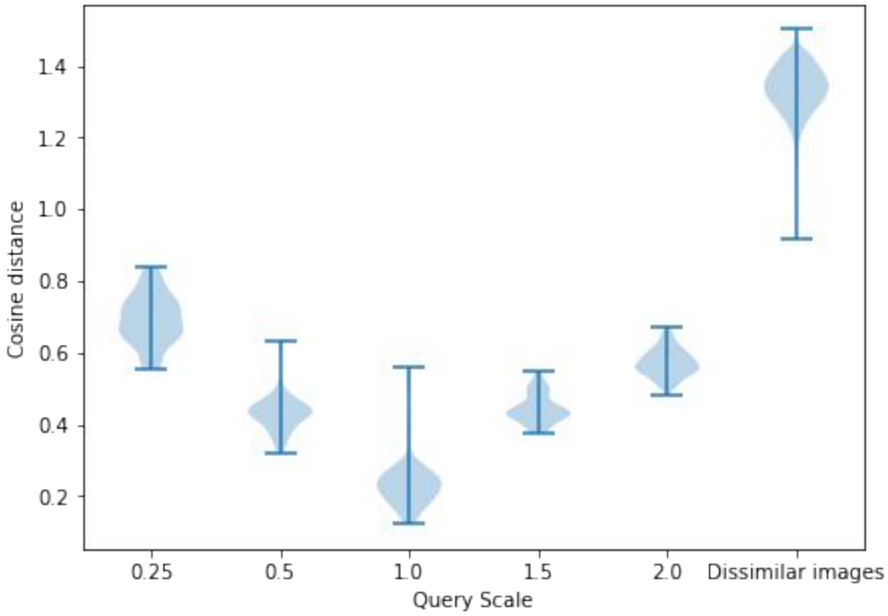
Query image:

The image for that we want to find similar content in a database

Target images:

All images that should be returned for a given query image

Query Scaling



Cosine distance of query image to target images

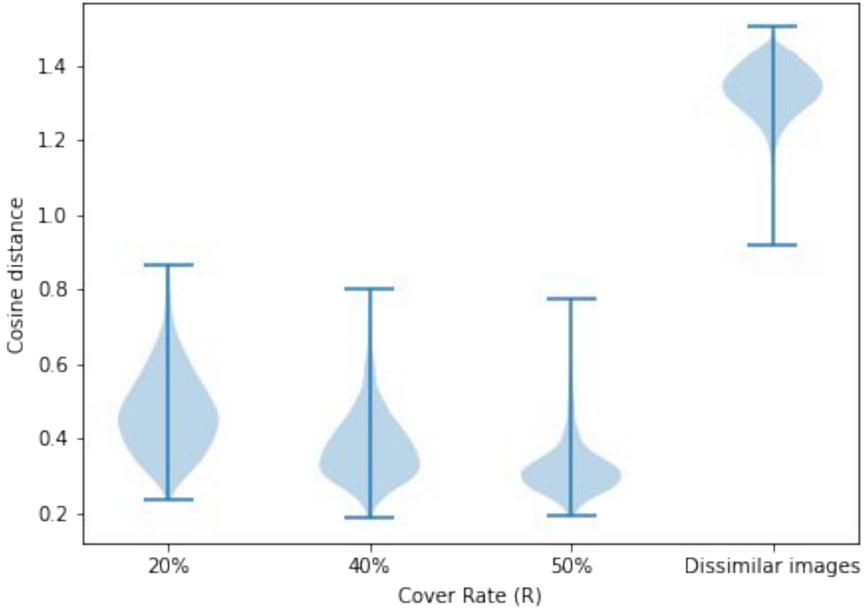
Effect of the query image and target image being differently scaled in a database with unscaled images (for near-duplicate images)

We observe higher cosine distances if query scale and target scale do not match up.

We achieve result improvement by querying the database with multiple differently scaled queries.

If query and target scale match, threshold of 0.4 distinguishes most near-duplicates from all dissimilar images

Patch Extraction of multiple sizes



Cosine distance of query image to target images

Cover Rate R determines how much percentage of the whole image was covered by the target image.

If target image has a big noisy background, the cosine distance increases

We improve performance by sampling multiple patch sizes from the GeM layer

If target image covers most of the area, threshold 0.4 contains most of our near duplicates

Examples:

Query image

Database

Locality Sensitive Hashing with random hyperplanes

$$H_{\cos} \text{ is } (\boxed{0.4}, \boxed{1.2}, \boxed{0.87}, \boxed{0.62}) - \text{sensitive}$$

Near-Duplicate Threshold

Upper threshold
(Dissimilar images)

Probability that near duplicates are in the same half space (bucket)

Probability that dissimilar images are in the same half space (bucket)

Locality Sensitive Hashing with random hyperplanes

AND-OR Amplification with random hyperplanes:

- Select k random hyperplanes
- Two images are stored in the same bucket if for all k hyperplanes, they lie in the same halfspace
- For every image, store it in L hash tables with k random hyperplanes each.

For L=50, k=20 (experimental result), this changes the sensitivity to:

$$H_{\cos,\, L=50,\, k=20} \text{ is } (0.4,\ 1.2,\ \boxed{0.97,\ 0.003}) - \text{sensitive}$$

Results

Results on a dataset that contains 10% augmented images with random images of horses

Model	GeM (3) (Exhaustive Search)			+ LSH, k=20, L=50				
Retrieval Type	R	P	A	R	P	A	% of DB	% below δ
Duplicates, δ=0.4	0.97	1.00	1.00	0.97	1.00	1.00	1.5%	26%
Duplicates, δ=0.6	0.99	0.86	0.99	0.99	0.93	0.99		32%
Similar Images, δ=0.8	0.38	1.00	0.92	0.12	1.00	0.9		45%
Similar Images, δ=1.0	0.91	1.00	0.92	0.15	1.00	0.92		65%
Similar Images, δ=1.2	0.96	0.98	0.92	0.15	0.97	0.94		70%

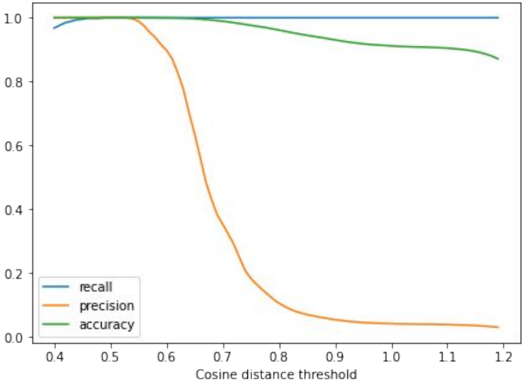
In a database with `200.000` images
Query time of exhaustive search: ~230 ms
Query time of LSH Method: ~19 ms

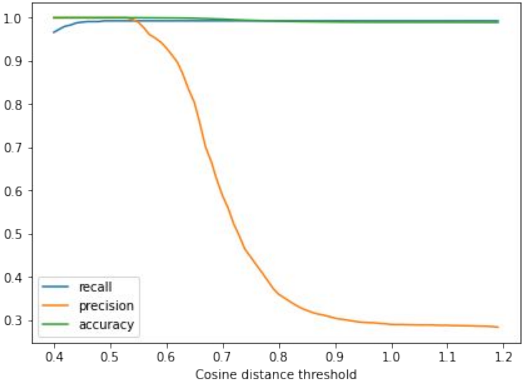
Machine: Google Colab Free plan
2 virtual cores

Exhaustive Search

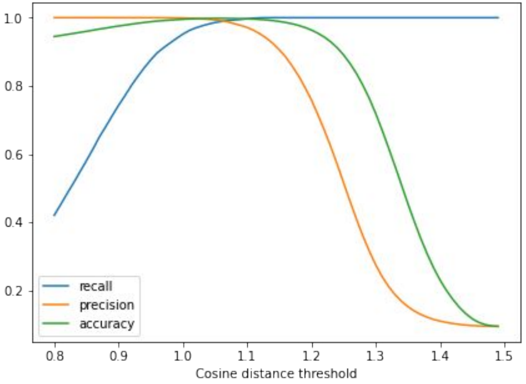
with LSH

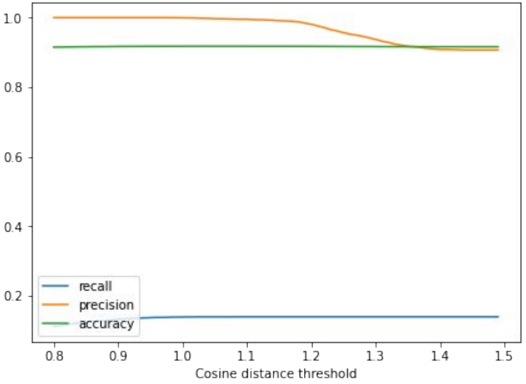
Near Duplicate Retrieval





Similar Image Retrieval



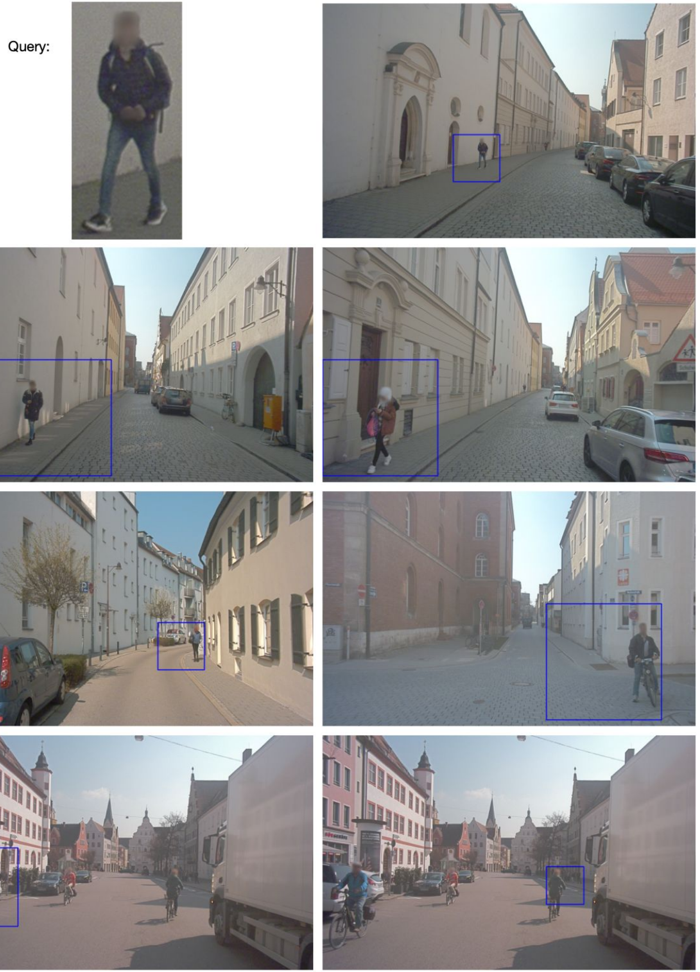


Demo

Demo (backup)

Query:

Demo (backup)



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