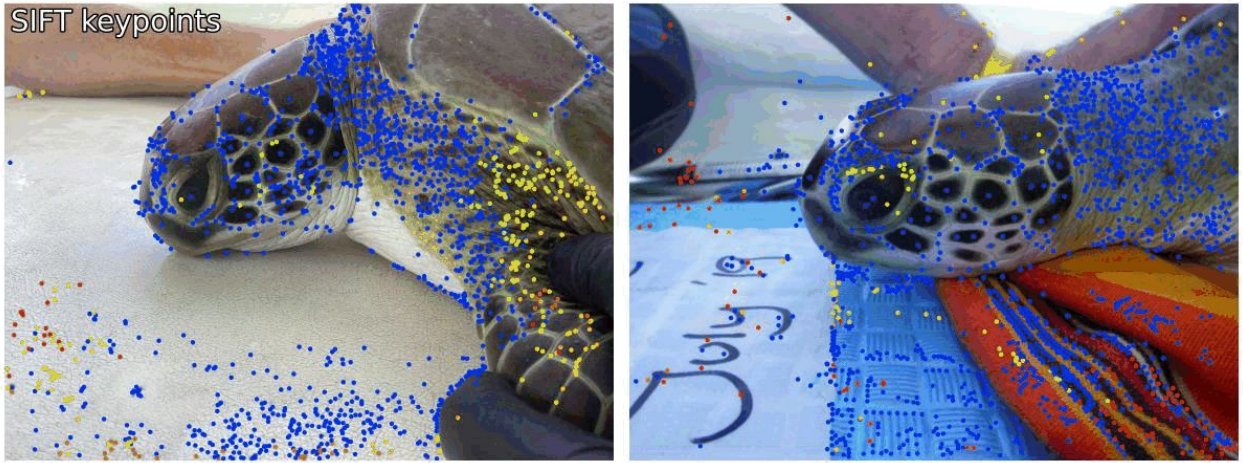
Feature Matching with LightGlue



FruitPunch AI

Why we're here

Metric Learning

- Learn to identify turtles in feature space
- Convolutional Neural Networks (CNN)
- Lightweight
- 16% accuracy

sub-team members

Davide	Rodrigo
Ahmed	Thor

LightGlue

- Learn to match keypoints in images
- Two-step algorithm
- CNN + Transformers
- 100% accuracy

Eelke	Miruna
Laurenz	Marcus

LoFTR

- State-of-the-art keypoint matching
- Transformer-based
- Big and heavy
- 84% accuracy

Enrico	Deb
Lennart	Sonny

Slide courtesy of Davide Coppola

Who we are

Marcus Leiwe
Consultant Data Scientist,
Metacell

METACELL

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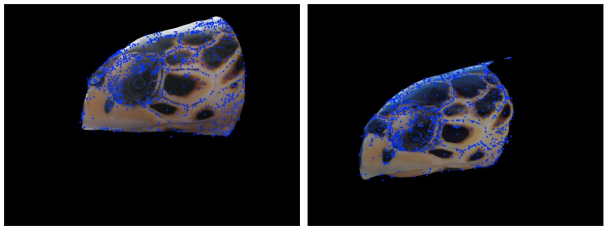
Student,
Radboud University

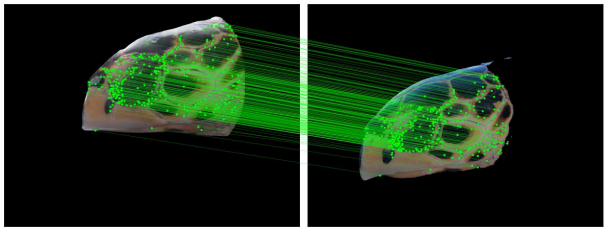
Radboud Universiteit

NB With help from Eelke Folmer and Miruna Morarasu

Keypoint Feature Extraction → **LightGlue Matcher** → **Identifying the best matches**



What are keypoints?
Classical approaches
Deep Learning



Output
LightGlue architecture
Augmenting matching

Donatello
64%

Raphael
16%

Michelangelo
11%

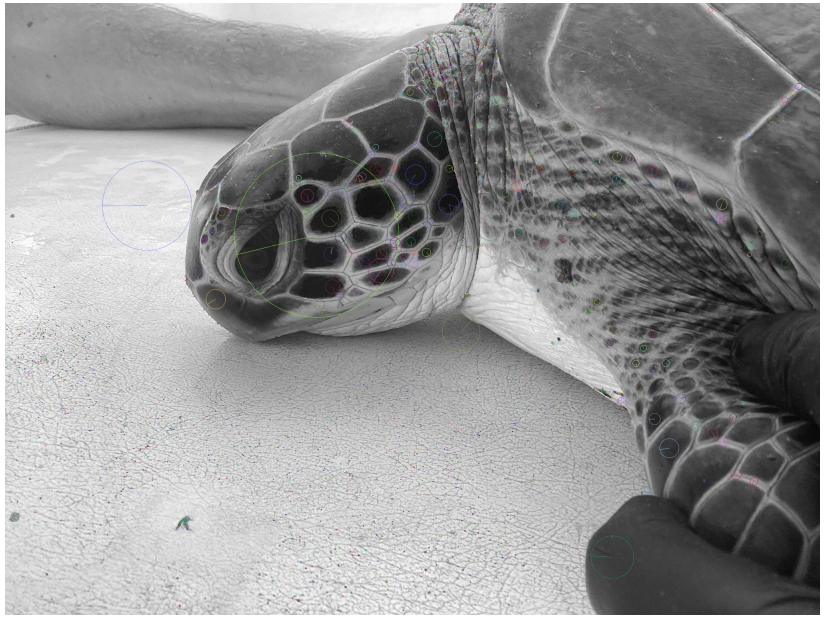
others...

Feature Extraction is ...

“Converting key parts of the image into vectors.”

But...

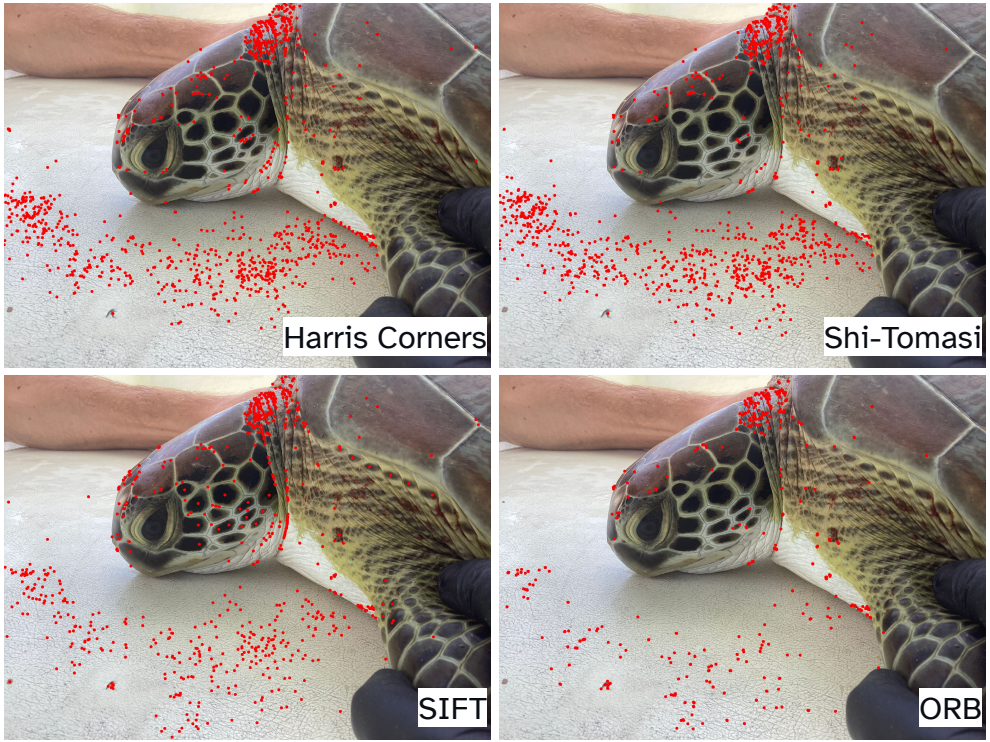
1. How do you find what is a key part (aka “keypoint”)?
2. What information do you store in the vector (“descriptors”)?



Classical Feature Extraction

Relies on hard rules to find keypoints.

SIFT is the gold-standard for classical techniques



Tabular Summary for Reference

	Strengths	Weaknesses
Harris Corners	• Good at finding corners in an image • Less sensitive to noise and different scales	• Computationally more expensive • Sensitive to image rotation
Shi-Tomasi	• Improvement over Harris Corner Detector by changing the scoring	• Computationally more expensive • Sensitive to image rotation
SIFT	• Scale-invariant feature detection • Robust to changes in illumination and viewpoint	• Computationally expensive • Requires a lot of memory (we used batching)
SURF (Patented $)	• Faster than SIFT • Robust to changes in scale and rotation	• Computationally more expensive than FAST and BRIEF • Sensitive to changes in illumination
FAST	• Fast corner detection method • Good for real-time applications	• Sensitive to scale and rotation changes • Less robust than SIFT and SURF
BRIEF	• Computationally efficient • Good for real-time applications	• Sensitive to scale and rotation • Less robust than SIFT and SURF
ORB (Orientated fast, Rotated Brief)	• Fast and efficient • Combines features of FAST and BRIEF	• Not as distinctive as SIFT and SURF • Less robust than SIFT and SURF

Good introduction is here : https://towardsdatascience.com/image-feature-extraction-traditional-and-deep-learning-techniques-ccc059195d04

SIFT - Identifying Features

Process

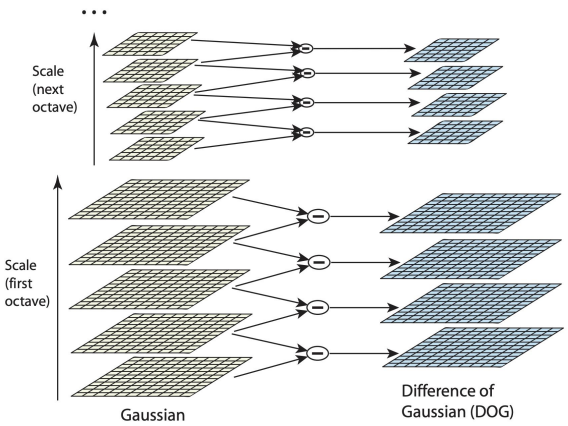
1. Grayscale
2. Scale-space Extrema Detection
3. Keypoint Refinement
4. Orientation Assignment and Refinement
5. Descriptor Computation

Take home message:
“SIFT works by identifying areas of high contrast that are insensitive to scaling”

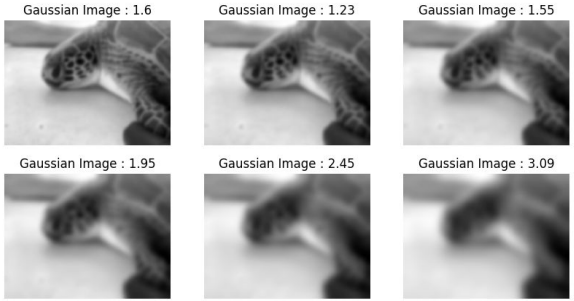
Check out OpenCV’s description for a more detailed description, or the original paper

SIFT - Scale-space Extrema Detection

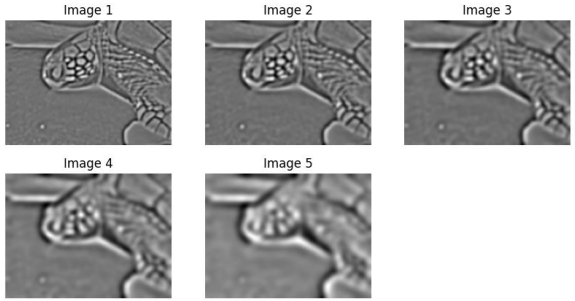
Difference of Gaussians highlight edges of the image at different **Octaves** (scales)



Example Octave



Example Differences of Gaussians

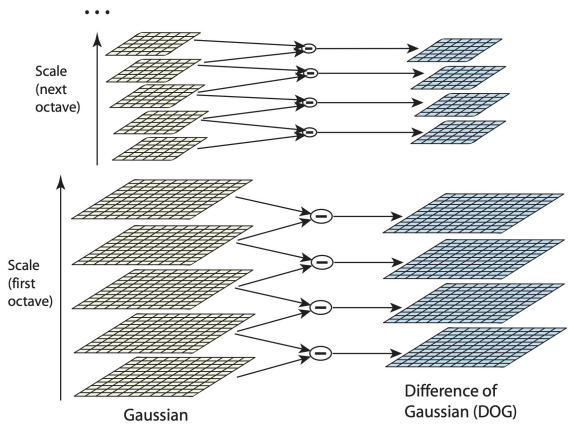


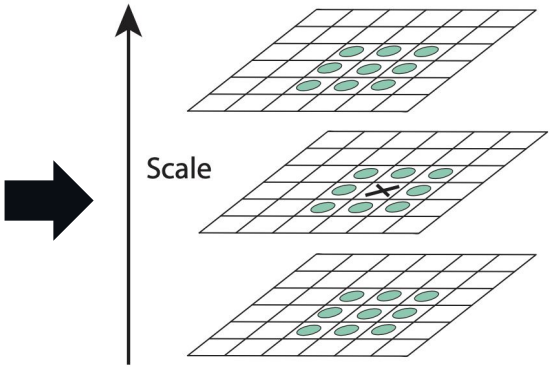
Octaves = Recommended number is 4 but this is tunable

Russ Islam, https://medium.com/@russmislam/implementing-sift-in-python-a-complete-guide-part-1-306a99b50aa5

SIFT - Scale-space Extrema Detection

Finding all **minima and maxima (extrema)** to generate keypoints





Further refined by...

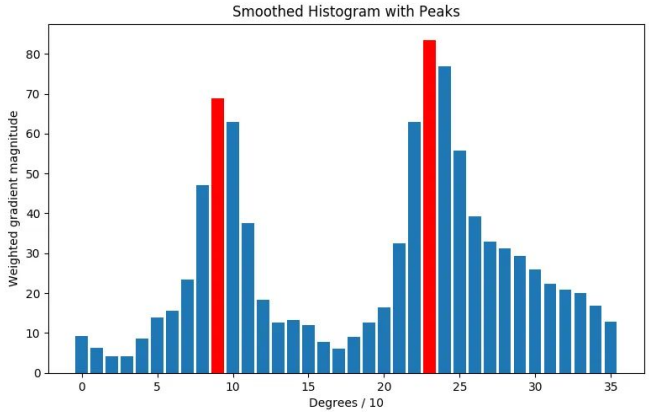
1. Taylor series expansion to locate the extrema in it's octave.
2. Intensity thresholding (<0.03 = no keypoint)

X must be the lowest or highest value compared to its neighbours (n=26) to be a provisional keypoint

SIFT - Orientation Assignment

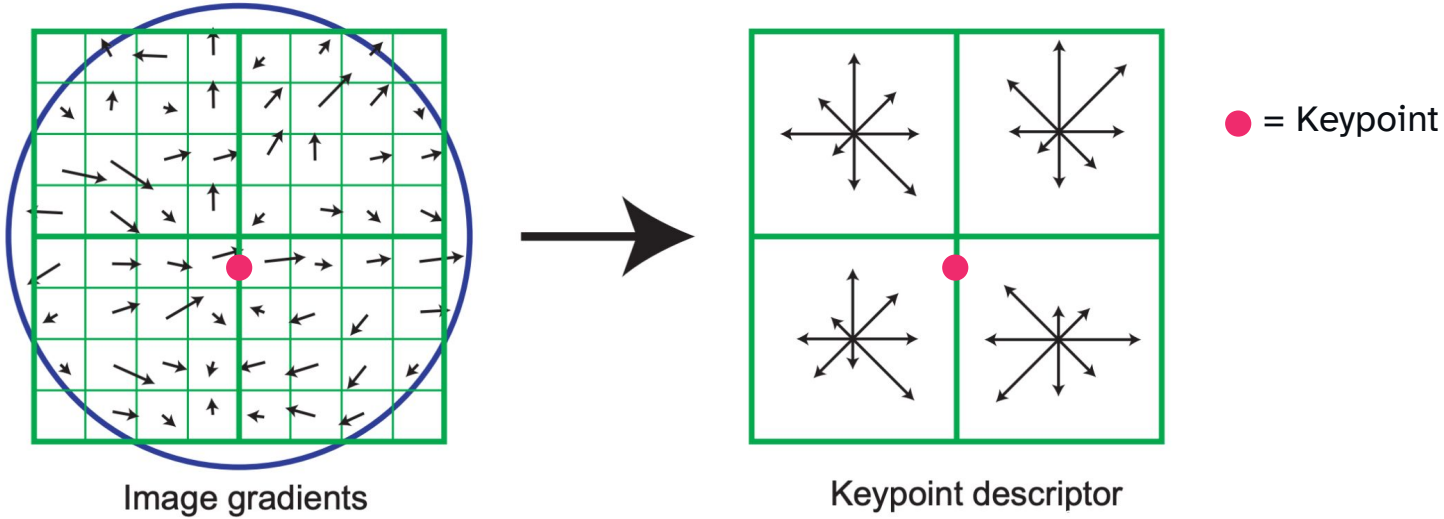
An **orientation** also is assigned to each key-point. This is done by extracting the neighborhood around the key-point and creating a **orientation histogram**, the peak of the histogram is used as the orientation.

No clear peak = no keypoint
2 peaks = 2 keypoints



Credit: Russ Islam, https://medium.com/@russmislam/implementing-sift-in-python-a-complete-guide-part-2-c4350274be2b

SIFT - Descriptor



128 point tensor from an orientation-corrected 8x8 grid that **describes the direction and magnitude of gradients**

Deep Learning Feature Extraction

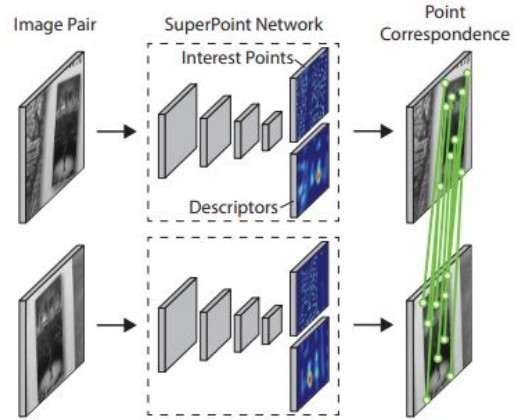
- Hand-crafted methods rely heavily on assumptions and heuristics
  - No guarantee for efficiency or robustness

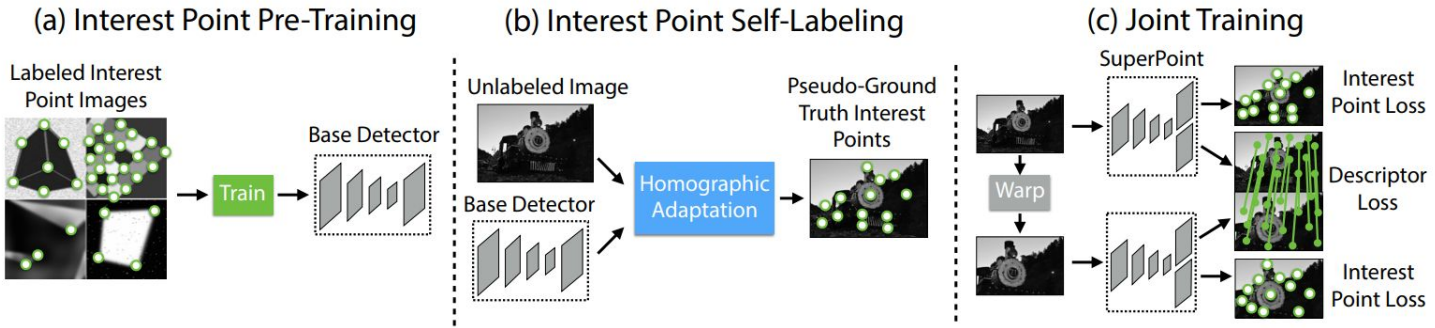
➡ **Data-driven** approach to keypoint extraction

- Goal: Improve Keypoint location and Descriptor embedding
- 3 supported implementations for LightGlue:
  - SuperPoint
  - DISK
  - ALIKED
  - (DoG HardNet)

SuperPoint

CNN for computing keypoint-locations and descriptors in single forward pass





Check out the paper here

DISK

- Reinforcement Learning (RL) for keypoint extraction
  - Probabilistic framework in training procedure
- U-Net (CNN) based architecture
  - output channels for both keypoints and descriptors -> computed in one forward pass

Training Procedure:

1. obtain feature maps $\mathbf{K}$ (keypoints) and $\mathbf{D}$ (descriptors) for images $\mathbf{A}$, $\mathbf{B}$
   - find most probable feature locations in $\mathbf{K}$
   - combine with corresponding descriptors in $\mathbf{D}$, obtaining $\mathbf{F}$ (feature set)
2. match feature-sets $\mathbf{F}_{\mathbf{A}}$, $\mathbf{F}_{\mathbf{B}}$ based on Euclidean distance
3. Reward correct matches, penalize incorrect matches
   - based on ground-truth pose and depth-maps

Check out the paper here

ALIKED

- Improve geometric invariance using Deformable Convolution Networks (DCN)
- Separation of keypoint and descriptor extraction through Sparse Deformable Descriptor Head (SDDH)

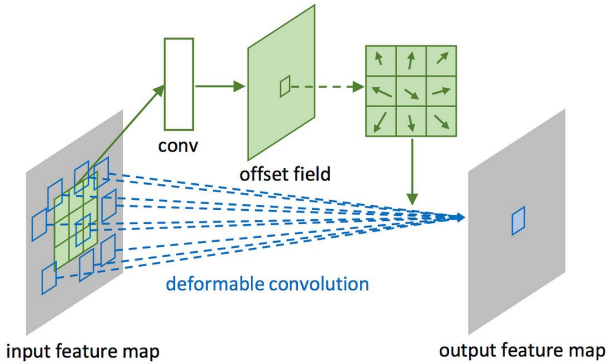
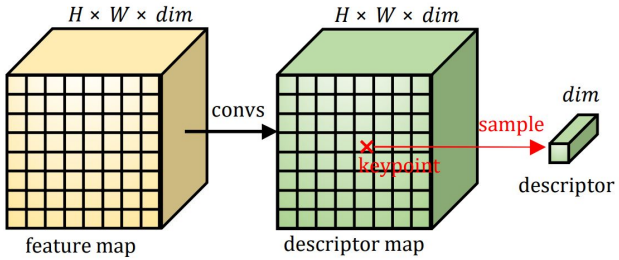


Figure 2: Illustration of 3×3 deformable convolution.

Check out the paper here

ALIKED

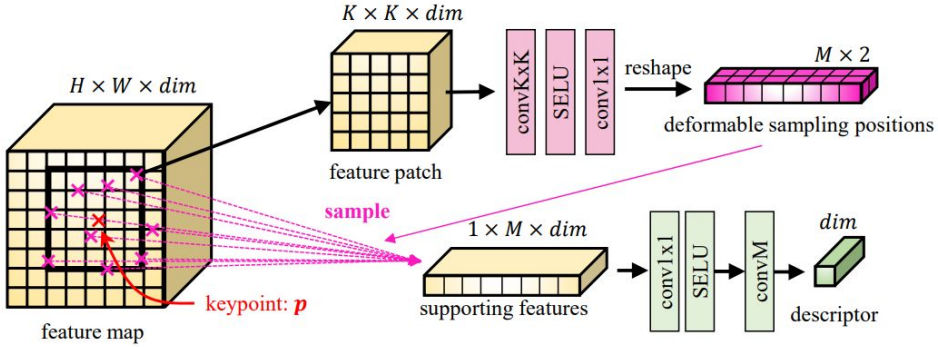
Dense Descriptor Map



expensive, often downsampled -> lower descriptor quality

vs.

SDDH



lower computational efforts, more powerful descriptors

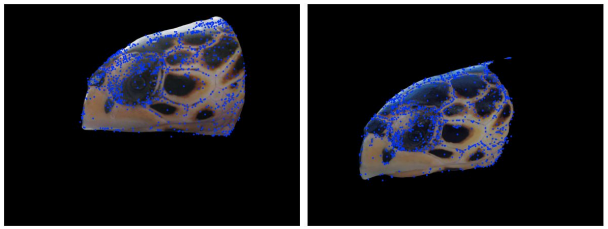
Check out the paper here

Deep Learning Feature Extraction in practice

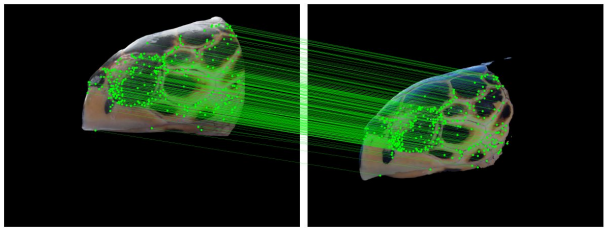
- There is no 'best' approach
  - (SIFT worked best for us)
- Trained/Evaluated on landmark datasets
  - Performance comparisons limited to this domain
  - Not necessarily translatable to your problem

Feel free to experiment!

Keypoint Feature Extraction → LightGlue Matcher → Identifying the best matches



Four Algorithms
Superpoint, DISK, aliked, SIFT



Output
Matching points and confidence scores

Donatello
64%

Raphael
16%

Michelangelo
11%

others...

LightGlue: State-of-the-art feature matching

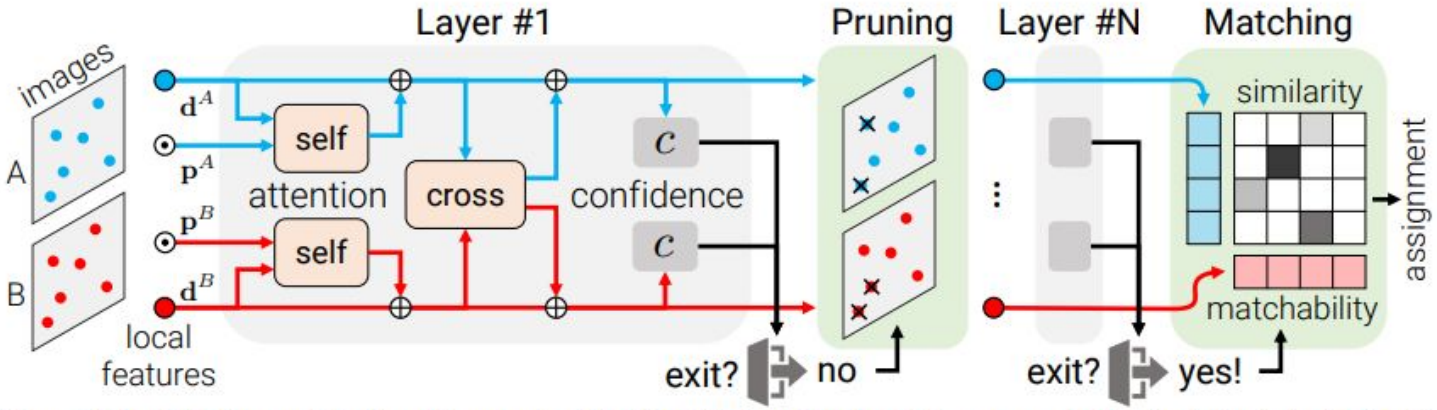
- Reworked version of SuperGlue[1]
- Sparse feature matcher:
  - Computes matchability given two Keypoint/Descriptor-Sets

Improvements:

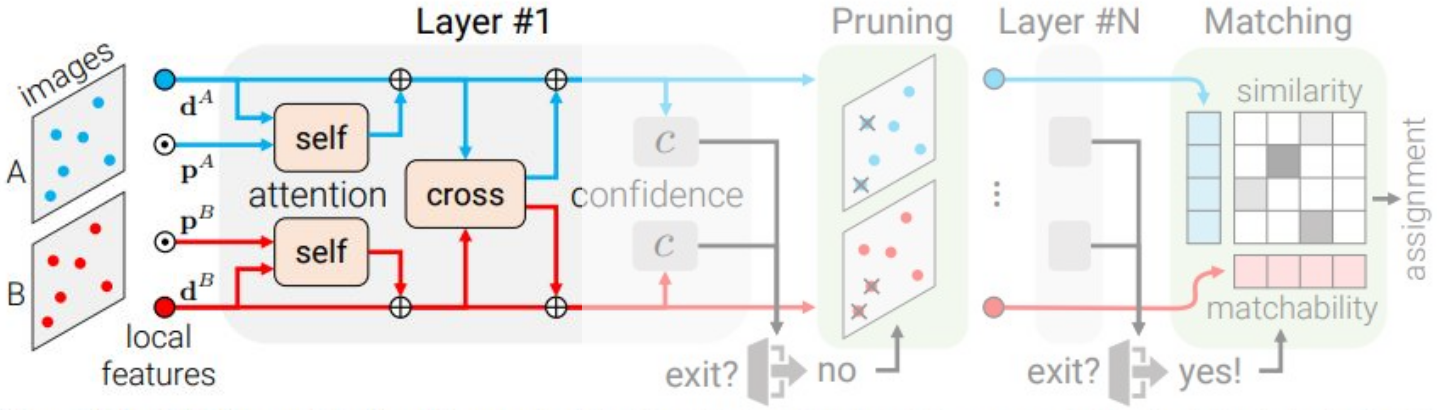
- **Efficiency** - Premature stopping at varying depth into the network
- **Accuracy** - Change in positional encoding of keypoints yields a more stable result
- **Training** - Reworked architecture leads to easier training

[1] Sarlin, Paul-Edouard, et al. "Superglue: Learning feature matching with graph neural networks." *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2020.

Model Architecture: Overview



Model Architecture: Updating descriptors

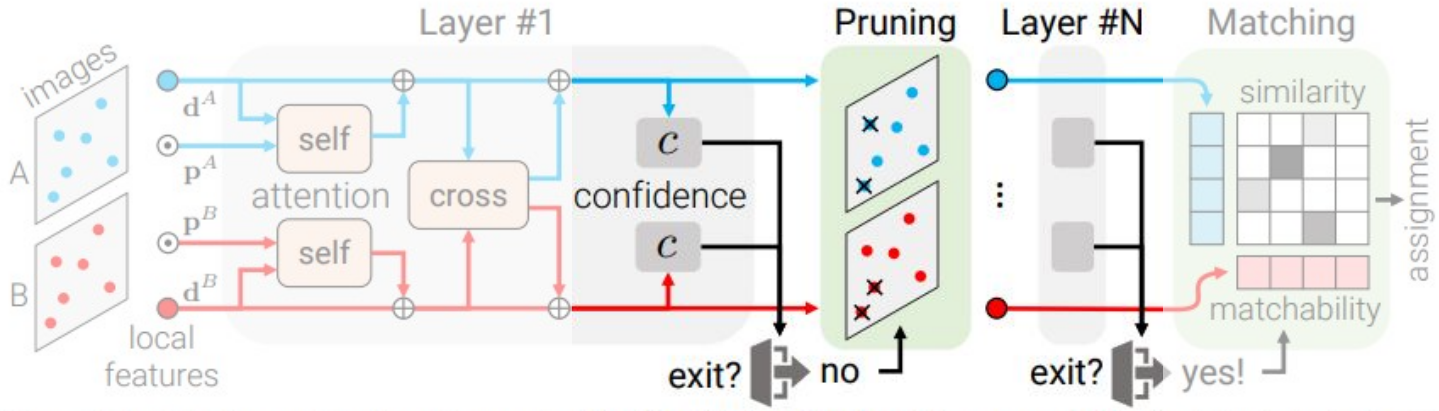


Self-Attention: every point attends to all points extracted from one image + rotary (relative) positional encoding

Cross-Attention: every point attends to all points extracted from the other image, positional information not added

Correspondence matrix between the local features, composed of matchability and similarity scores

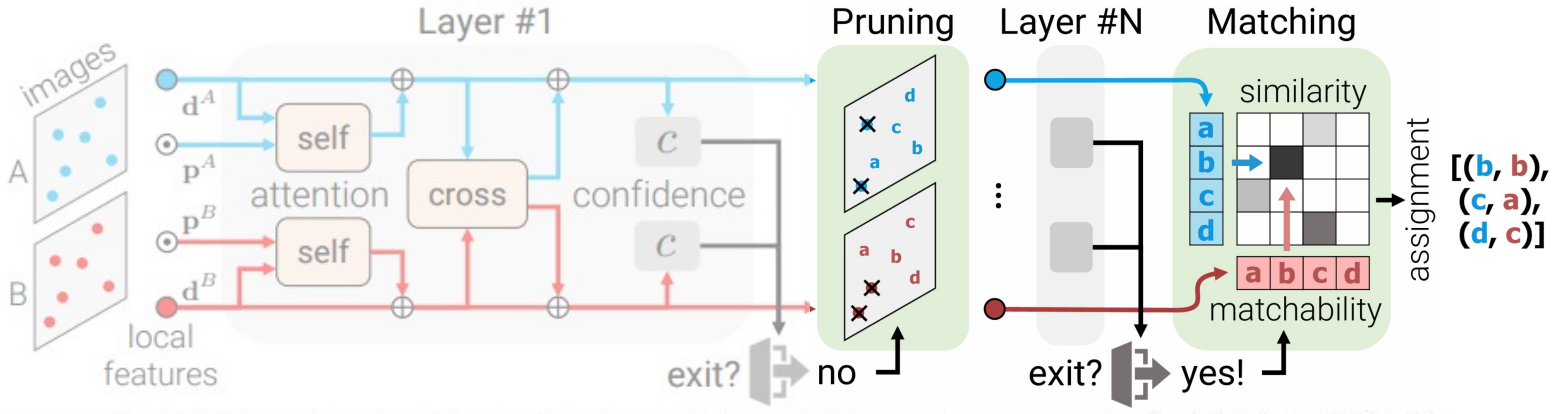
Model Architecture: Exit criterion



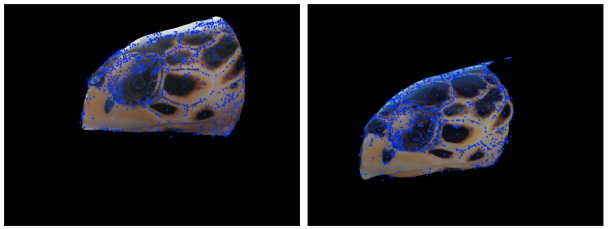
Confidence classifier: trained to predict whether current feature representations are 'final', exit if sufficient ratio of points is confident enough

Point Pruning: points predicted confident and unmatchable are removed

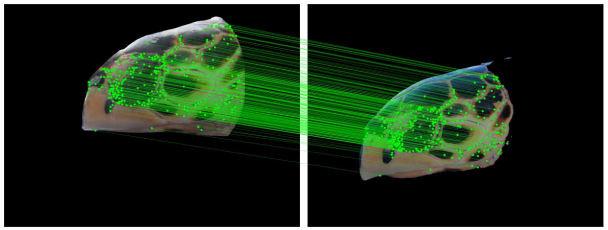
Model Architecture - Output



Keypoint Feature Extraction → LightGlue Matcher → Identifying the best matches



Four Algorithms
Superpoint, DISK, aliked, SIFT



Output
Matching points and confidence scores

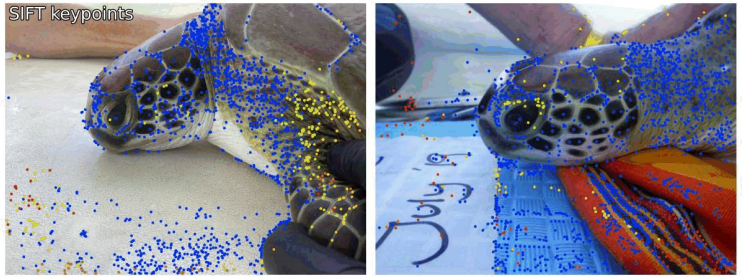
Donatello
64%

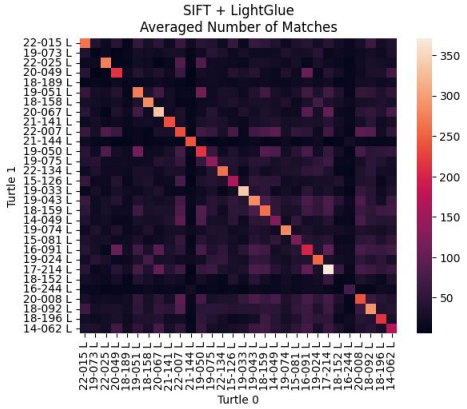
Raphael
16%

Michelangelo
11%

others...

Initial output: # of matching keypoints





The base method for comparison is finding the image with the most matching points.

This gave us a 77% accuracy score on a trial dataset.

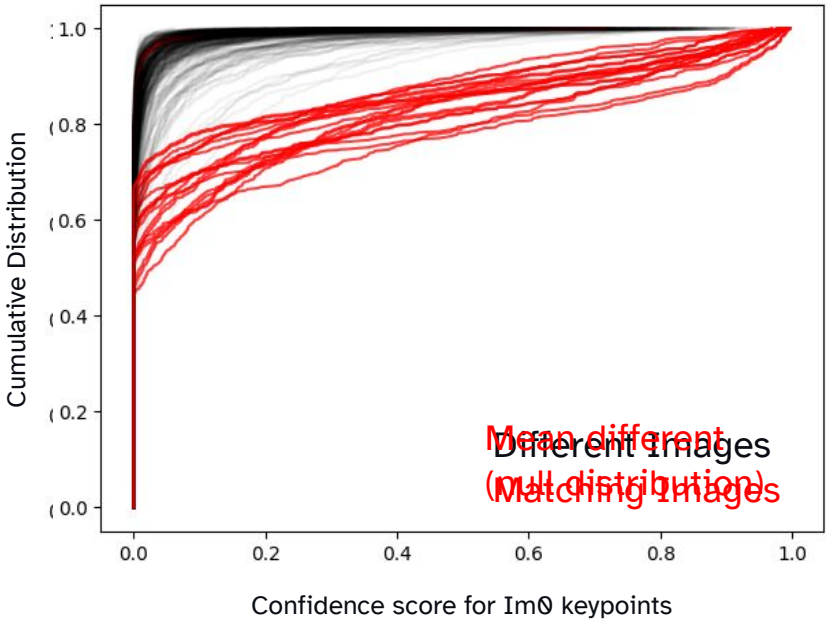
Possible reasons for suboptimal performance...

- # keypoints is not consistent across images.
- # thresholding scores also throws away a lot of information.

In other words we are throwing a lot of information away.

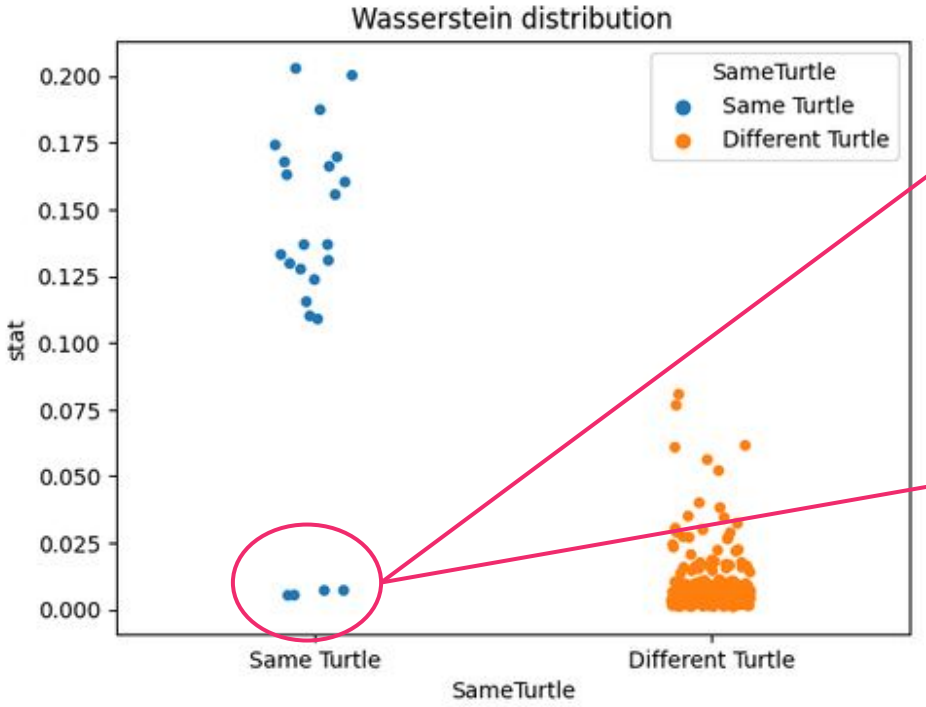
Solution: Look at the **distributions of scores** instead

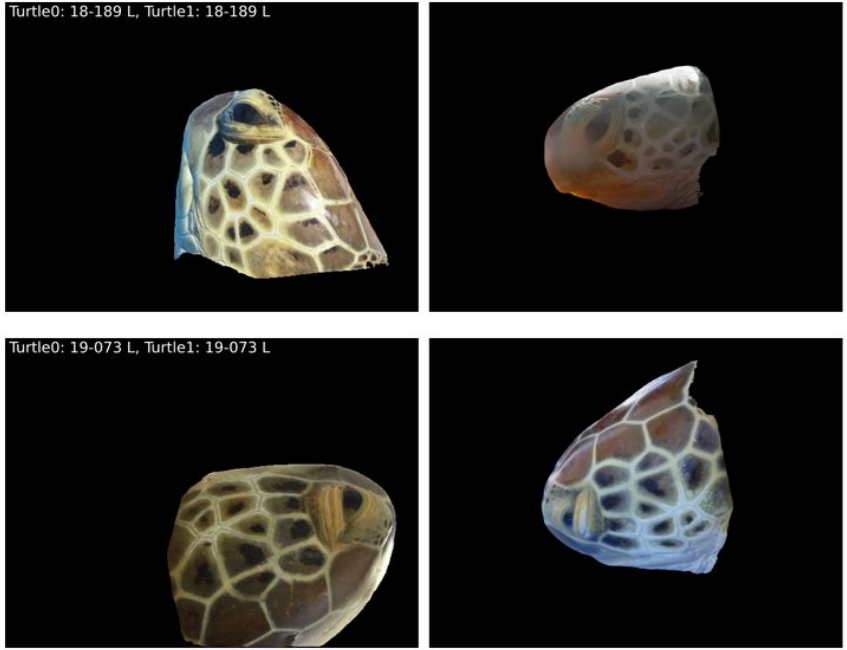
Matching images (Turtles) have different distributions



- Cumulative frequency plots
- Keypoint scores from matching images are much higher (curve shifts right/down)
- So what we are really doing is comparing two distributions.
- With the Wasserstein distances we can calculate how much “energy” is required to match the null distribution
  - Large number = Matching image
  - Small number = Non-matching

Wasserstein distribution scores accurately split the data





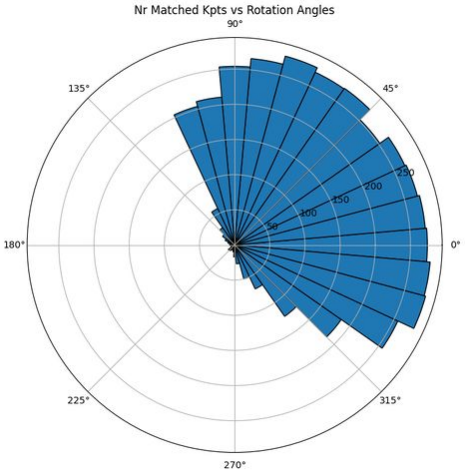
These four images are wrongly paired/rotated

Demo Notebook

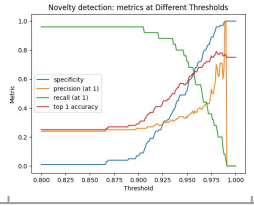
https://colab.research.google.com/drive/1094zv0A5CaCNDs7z8Ae8fN6Og3YcZ0iY?usp=sharing

Additional factors to consider

- Segmentation
- Image quality
- Rotational angle, we found large angle differences (~>90 degrees) tricky
- Processing time
- Novelty detection is a separate question

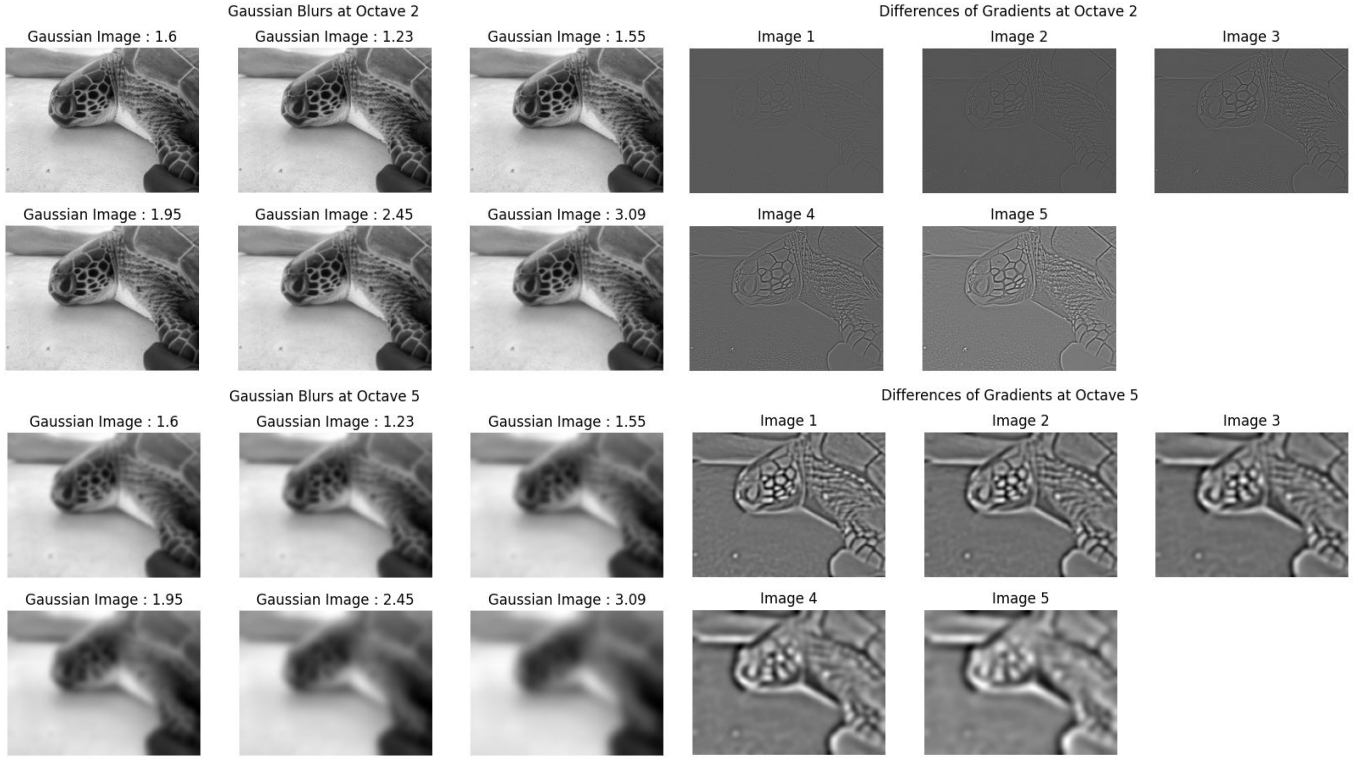


Model comparisons

Model / Algorithm	Accuracy at 1/3/5 (%)	Novelty detection (%)	Inference Time on 1 query (s)	👍Advantages	👎 Disadvantages
Metric Learning (ConvNeXt-Small +/Circle Loss)	8/12/16	76	<10s [Colab]	Fast inference with current size of reference set	Hard to train with too few hard pairs
LightGlue	100/100/100	0.9 accuracy	~ 30s [T4 on Colab]	Fast, accurate with current reference set.	Requires a GPU for quick evaluations.
LoFTR	64/80/84		1,5 hour [locally on macbook (mps)]	Fine grained/Low contrast feature extraction (not needed for turtles)	Inference time is very long and therefore not suitable for turtle reID

EXTRA SLIDES

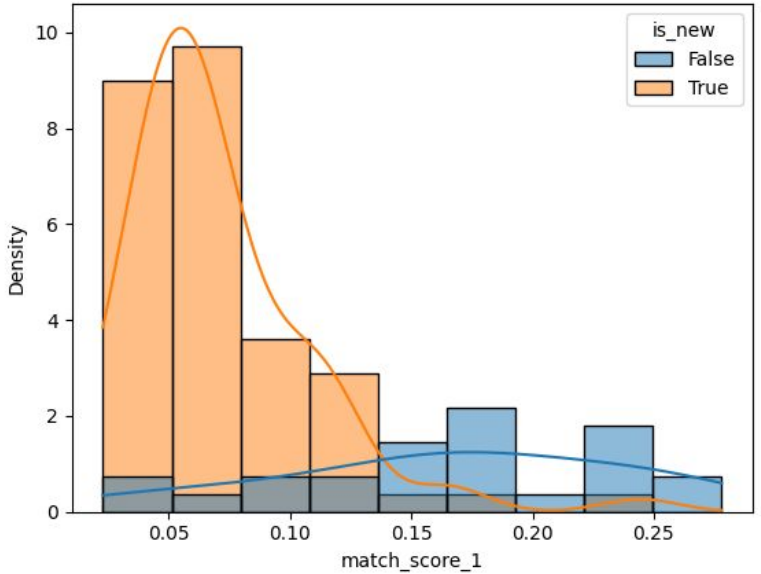
SIFT: The effect of DoG at different octaves



Identifying Novel turtles

- Novel turtles should generate low wasserstein distance scores for every comparison.
- If we model the probability distribution of matching scores we can come up a prediction/confidence on whether this is a new turtle or not.
- NB 90% accurate on identifying new turtles, so not perfect

Largest Wasserstein score per image



Comparison with other approaches

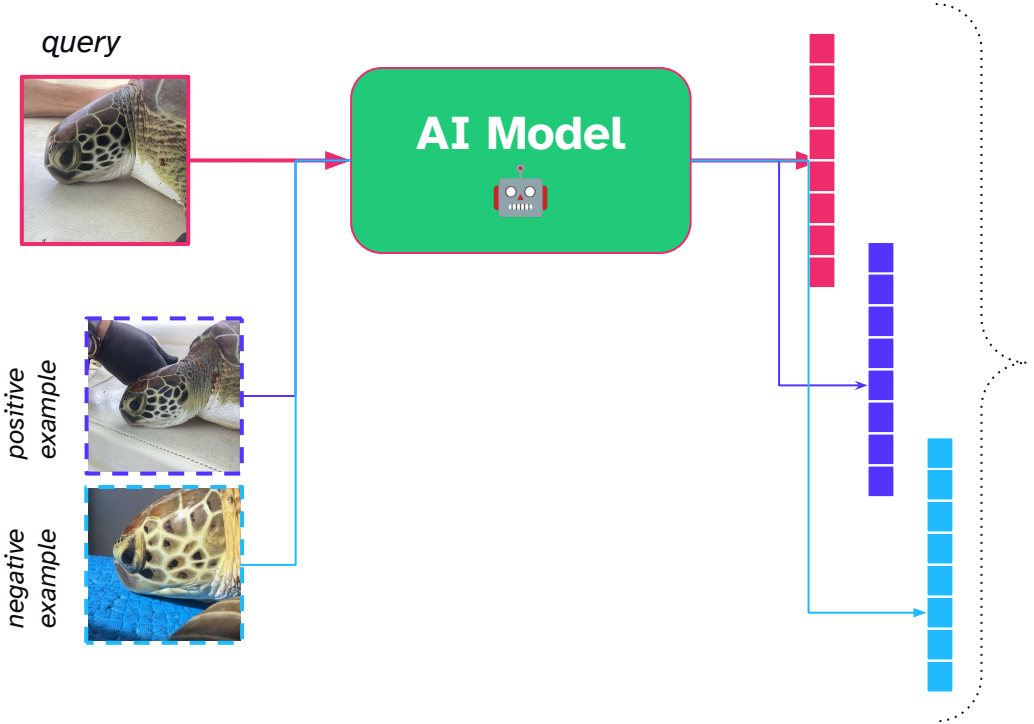
Metric Learning

- Utilize Convolutional Neural Networks (CNN) to find discriminative feature (embedding) space
- One possibility: *Triplet Loss*
  - For every training image, two additional images are provided:
    - positive example (same instance, different image)
    - negative example (different instance)
  - requires lots of (reoccurring) data
- **Fast, but difficult to train**

LoFTR (dense matcher)

- Extraction and matching of keypoints in one model
- Keypoints are extracted densely -> many more keypoints to be matched
- State-of-the-art performance
- **Long inference time**

Metric Learning: learning similarity in the feature space



many metric learning approaches in literature

experiments with various combinations of methods to find the best

Slide courtesy of Davide Coppola