Lab- 8

CSET340- Advanced Computer Vision and Video analytics

Task-1:- Interest Point Detection, **Feature Matching and Contour Detection,**

Interest Point Detection:- Apply **SIFT (Scale Invariant Feature Transform)** Detector function using cv.SIFT_create()

Feature Matching:- Feature matching is a fundamental technique in computer vision and image processing that involves finding correspondences between features detected in different images.

Use methods namely **ORB (Oriented FAST and Rotated BRIEF) and BFMatcher (Brute-Force Matcher).**

Contour Detection with Custom Seeds:- **Contour** represents the outline or boundary of an object, connecting continuous points of similar intensity or color.

In image processing, **edges** represent abrupt changes in brightness or color, while **contours** are closed curves that outline the shape or form of an object, often derived from edges.

Functions like markers, watershed, with some additional color placement functions can be used.

Task-2.1:- Image Classification using Resnet network on Cifar 100

Objective:

- Compare the performance of **Resnet 18** and **Resnet 34** an image classification task.
- Use **CIFAR-100**, a common dataset for image classification.
- Analyse model accuracy, loss, and inference time on a dataset.

Step 1: Installation of necessary libraries

Step 2: Load the dataset.

Step 3: Load the pretrained Model

Step 4: Train the Models

Step 5: Evaluate the Performances

Step 6: Compare the results.

Datasets-

1. CIFAR-100 dataset:- The CIFAR100 (Canadian Institute For Advanced Research) dataset consists of 100 classes with 600 color images of 32×32 resolution for each class.

This dataset is just like the CIFAR-10, except it has 100 classes containing 600 images each. There are 500 training images and 100 testing images per class. The 100 classes in the CIFAR-100 are grouped into 20 super classes. Each image comes with a "fine" label (the class to which it belongs) and a "coarse" label (the superclass to which it belongs).

2. Load CIFAR 100 Dataset Training Subset in Python
    a. import deeplake
    b. ds = deeplake.load("hub://activeloop/cifar100-train")
3. Load CIFAR 100 Dataset Testing Subset in Python
    a. import deeplake
    b. ds = deeplake.load("hub://activeloop/cifar100-test")
4. CIFAR 100 Dataset Structure
    a. **CIFAR 100 Data Fields**
        i. images: tensor containing images of the dataset.
        ii. labels: tensor containing labels for their respective image.
        iii. coarse_labels: tensor containing superclass for their respective image.

Task-2.2:- Meta learning approaches for image classification on MNIST dataset

Objective:

In this lab assignment, you will explore meta-learning techniques such as few-shot and one-shot learning for image classification using the MNIST dataset. You will perform data preprocessing, implement meta-learning models, and evaluate their performance.

Tasks Overview:

1. Dataset Preprocessing

- Load the MNIST dataset.
- Apply normalization (**apply min-max scaling**).
- Implement data augmentation (**apply Elastic Deformations -** It involves applying random distortions to images that simulate realistic variations while retaining the essential features of the objects within them.)
- Split the dataset into training, validation, and test sets.

2. Building a Meta-Learning Framework
    - Implement data sampling strategies for one-shot and few-shot learning.
    - Create a support set and a query set for meta-training.
    - Implement episodic training for meta-learning models.
3. Implementing Few-Shot Learning Models
    - Apply Prototypical Networks for few-shot classification.
    - Use Siamese Networks for similarity-based classification.
    - Train and evaluate the models using the meta-learning framework.
4. Implementing One-Shot Learning Models
    - Apply Matching Networks to perform one-shot classification.
    - Experiment with a modified Siamese Network for one-shot learning.
    - Evaluate model performance on unseen digits.
5. Performance Evaluation and Analysis
    - Compare accuracy across different meta models.
    - Analyse failure cases and suggest improvements.

Detailed Task Breakdown:

Task 1: Dataset Preprocessing

- Load the MNIST dataset using TensorFlow/Keras or PyTorch.
- Normalize pixel values to the range [0,1].
- Apply data augmentation techniques i.e. Elastic Deformations.
- Split the dataset into training (80%), and test (20%) sets.

Task 2: Building a Meta-Learning Framework

- Define episodic training by selecting N classes randomly.
- Create a support set (K examples per class) and a query set.

- Implement data pipeline for dynamically generating episodes.
- Set up evaluation metrics suitable for meta-learning.

Task 3: Few-Shot Learning Models

3.1 Prototypical Networks:

- Compute class prototypes using the mean embedding of support examples.
- Use Euclidean distance to classify query samples.
- Implement training and testing loops.

3.2 Siamese Networks:

- Train a convolutional network to learn feature embeddings.
- Use contrastive loss to measure similarity between pairs of images.
- Perform evaluation using nearest neighbour classification.

Task 4: One-Shot Learning Models

4.1 Matching Networks:

- Implement attention-based feature matching.
- Use cosine similarity for classification.
- Train and evaluate the model on MNIST.

4.2 Siamese Networks for One-Shot:

- Modify the Siamese Network to work with one-shot pairs.
- Train with a focus on minimizing intra-class variance.
- Also, Evaluate using unseen digits.

Task 5: Performance Evaluation and Analysis

- Compute accuracy, precision, recall, and F1-score.
- Compare the performance of different meta-learning models.
- Discuss the impact of training data size on few-shot classification.
- Identify challenges in one-shot classification and propose solutions.

Submission Requirements:

1. Code Implementation: Submit Notebooks code for all tasks.
2. Report: Summarize your findings, including visualizations of training curves and accuracy comparisons.

Links for help:- https://www.geeksforgeeks.org/contour-detection-with-custom-seeds-using-python-opencv/

https://www.geeksforgeeks.org/feature-matching-in-opencv/
https://www.geeksforgeeks.org/sift-interest-point-detector-using-python-opencv/
https://www.geeksforgeeks.org/check-if-image-contour-is-convex-or-not-in-opencv-python/

Link for meta learning:-
https://colab.research.google.com/github/phlippe/uvadlc_notebooks/blob/master/docs/tutorial_notebooks/tutorial16/Meta_Learning.ipynb

https://github.com/shruti-jadon/Hands-on-One-Shot-Learning/blob/master/Ch02-MetricsBasedMethods/Matching%20Networks.ipynb

https://medium.com/@heyamit10/few-shot-object-detection-with-meta-learning-f47bd876661e

Some libraries/ frameworks for use:-

Higher (for PyTorch)

- pip install higher
- Helps in **MAML** (Model-Agnostic Meta-Learning) by allowing differentiable optimization steps.

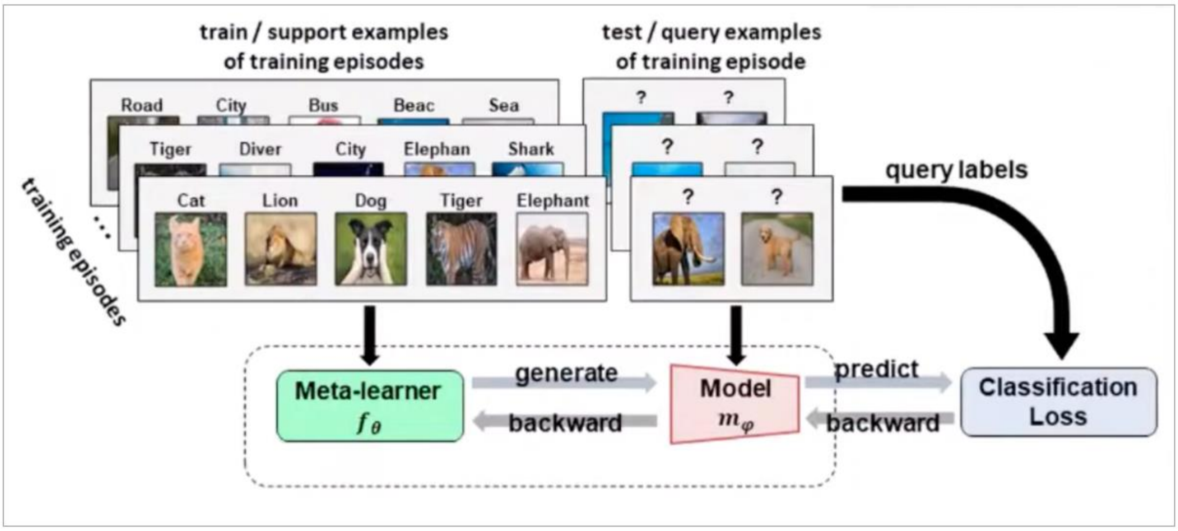
Torchmeta

- pip install torchmeta
- Provides prebuilt few-shot learning datasets and utilities for meta-learning in PyTorch.

Learn2Learn (L2L)

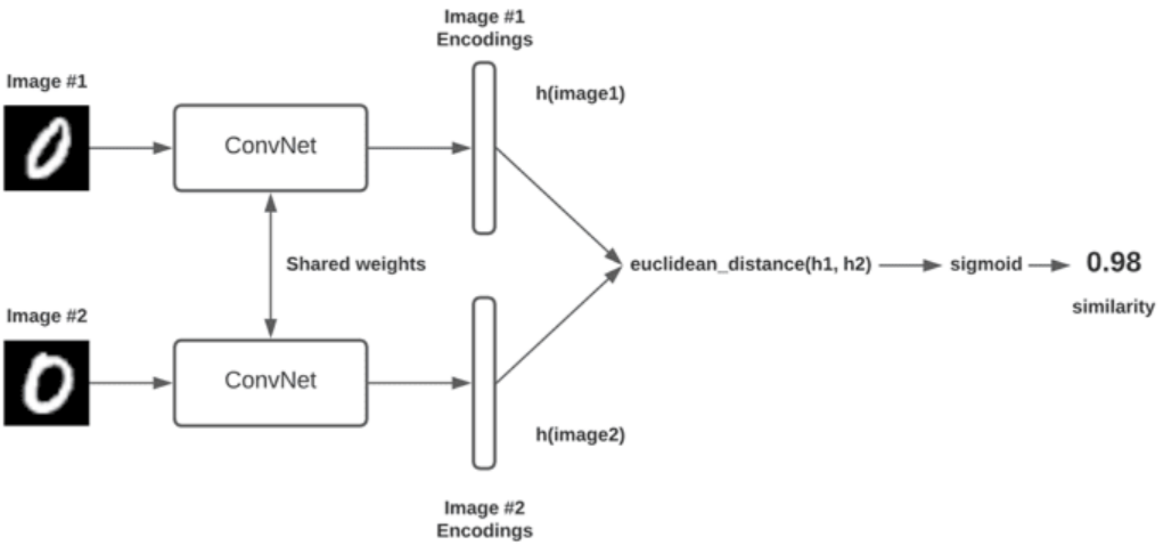
- pip install learn2learn
- A meta-learning framework for PyTorch supporting **MAML, Reptile, Prototypical Networks, and Meta-SGD**.

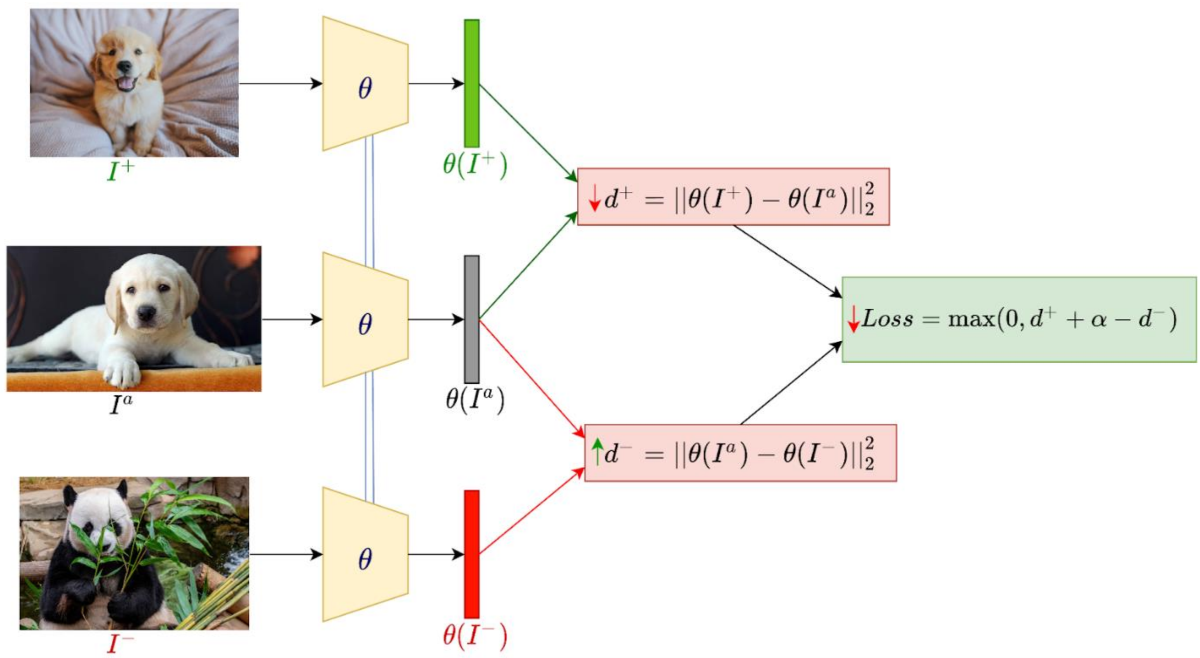
Prototypical Networks – few shot learning:-



Meta-Learning employs episodic training to produce a meta-learner capable of generalizing to unseen datasets.

Siamese Network architecture:-





Matching Network:- one shot learning:

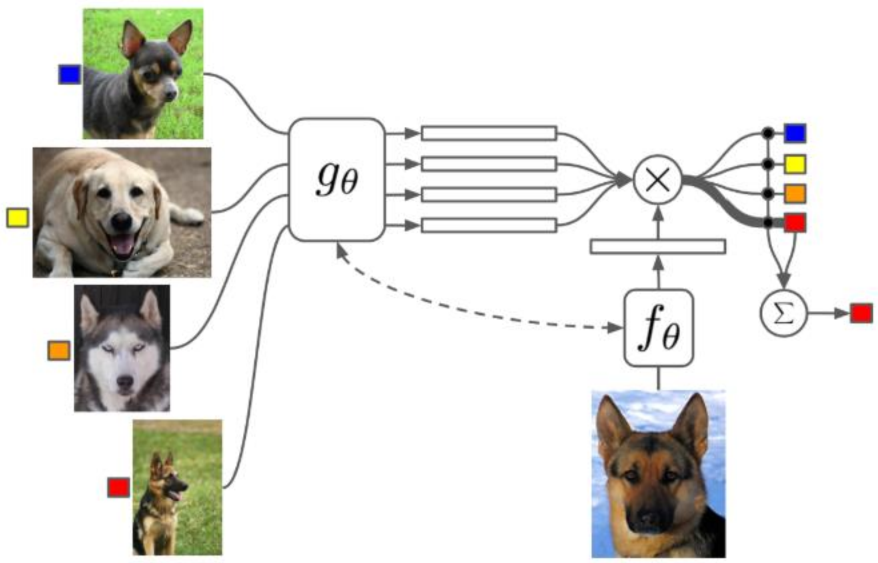


Figure 1: Matching Networks architecture