

Exercise Class

Pretrained Models Image Retrieval using Vector DB

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CONTENT

(1) – Pretrained Models

(2) – Flower Classification

(3) – Image Retrieval

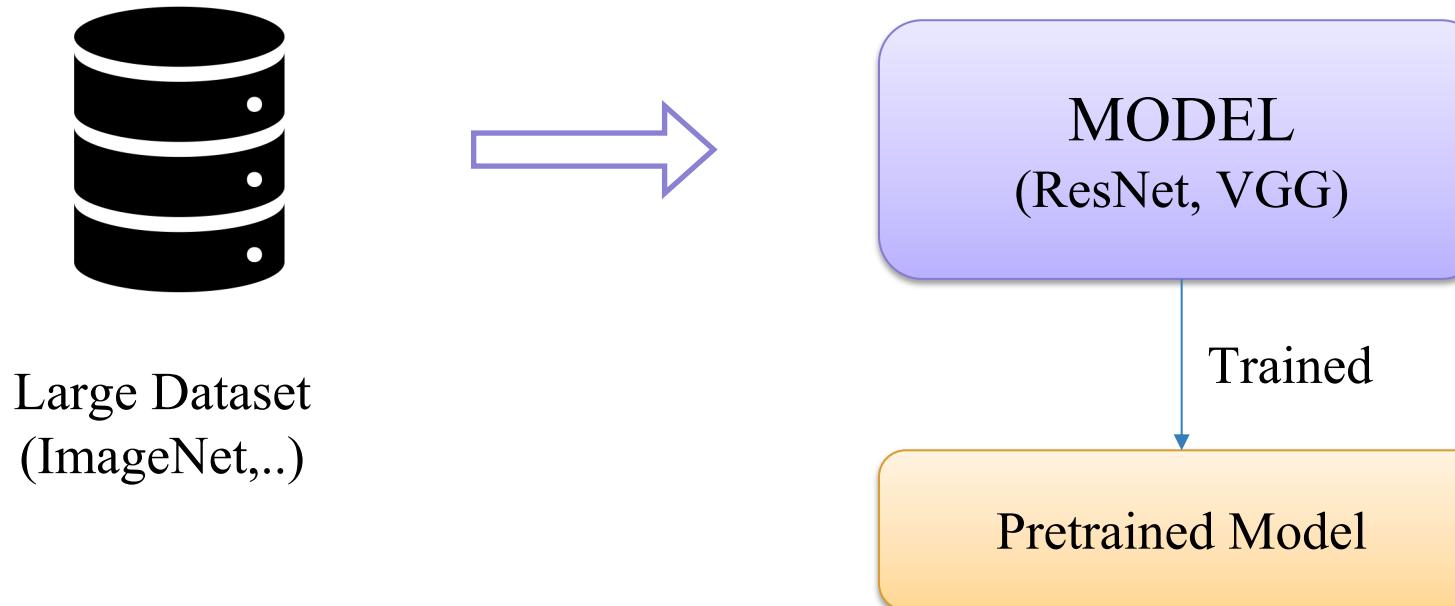
(4) – Image Retrieval with Vector Database

1 – Pretrained Models



Pretrained Models

- ❖ A model created by some one else to solve a similar problem

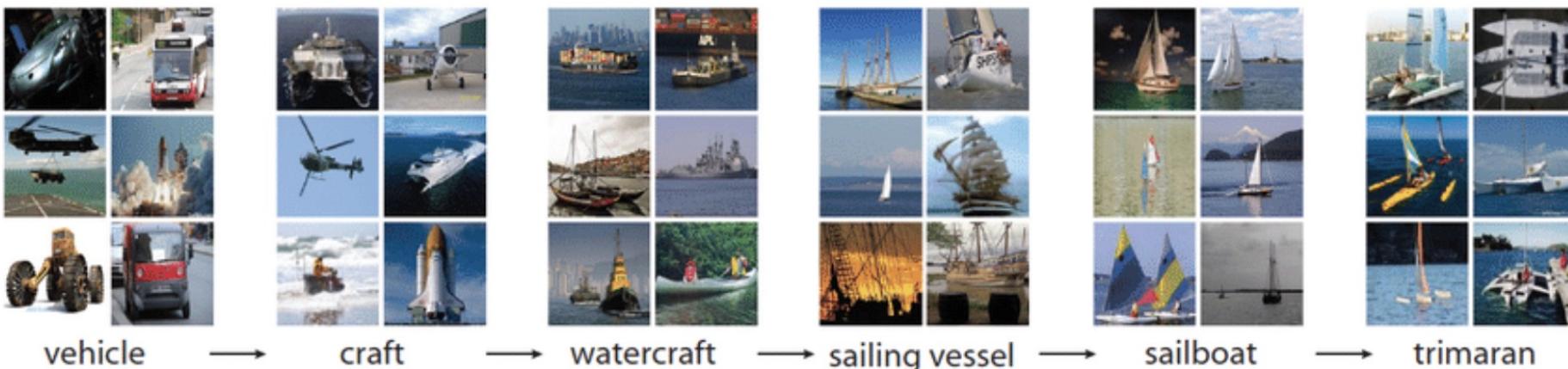
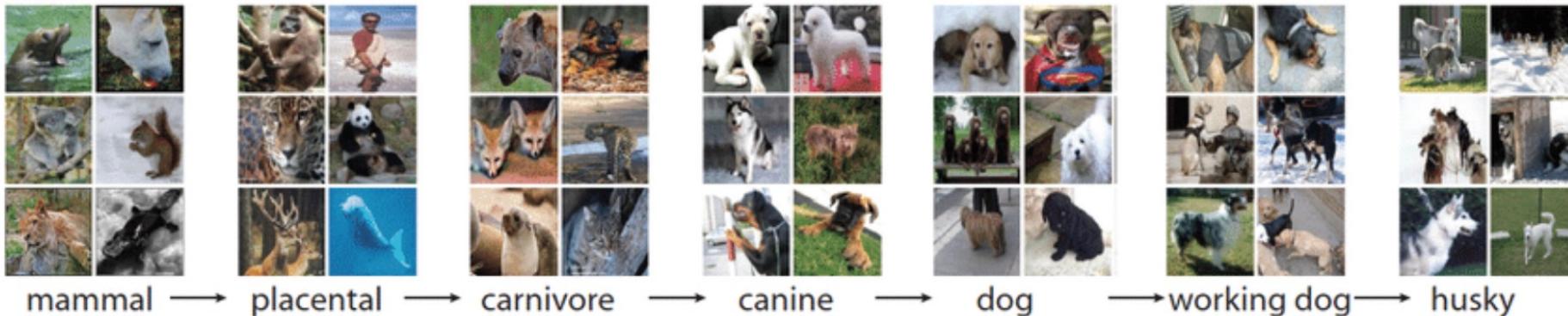


1 – Pretrained Models



Pretrained Models

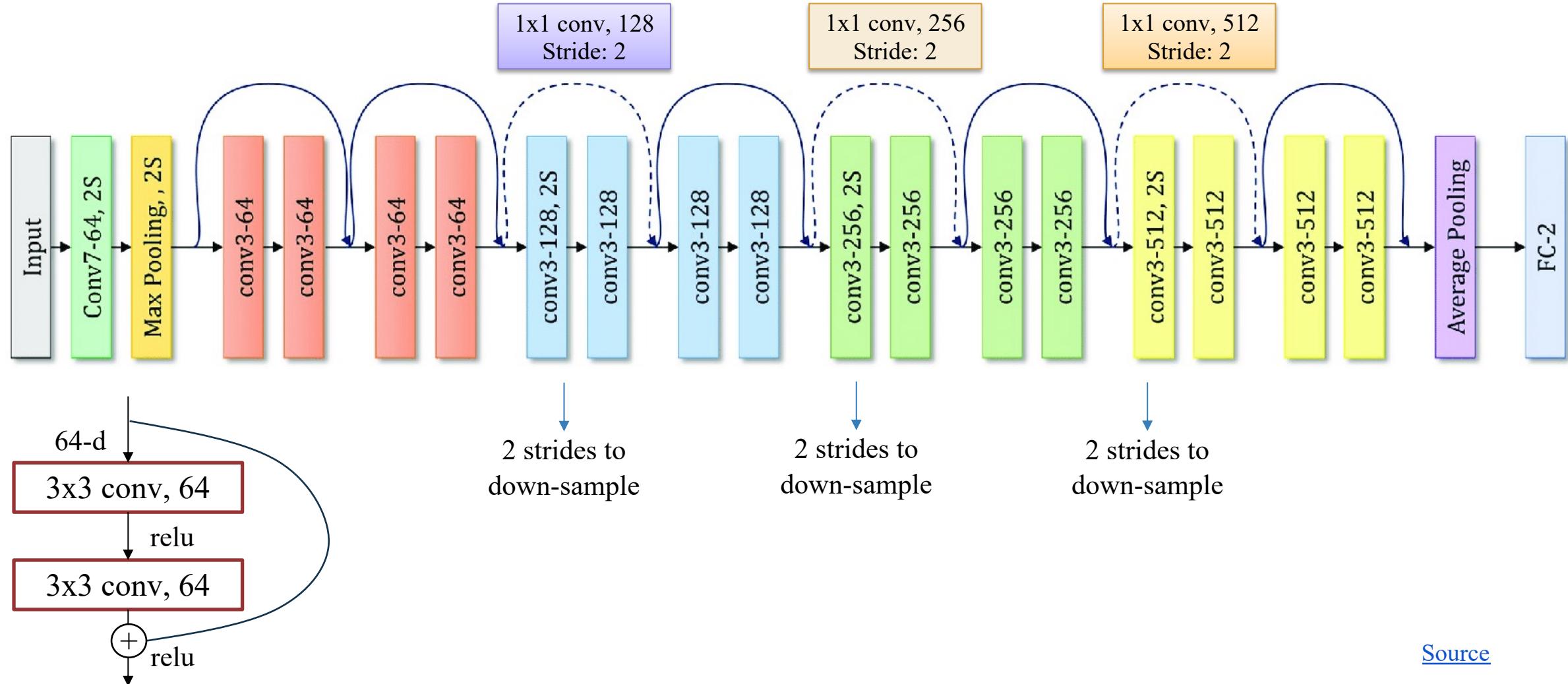
- ❖ Training: 1,281,167 images. Validation: 50,000 images. Testing: 100,000 images
- ❖ Object classes: 1,000



1 – Pretrained Models



ResNet18



1 – Pretrained Models

!

ResNet

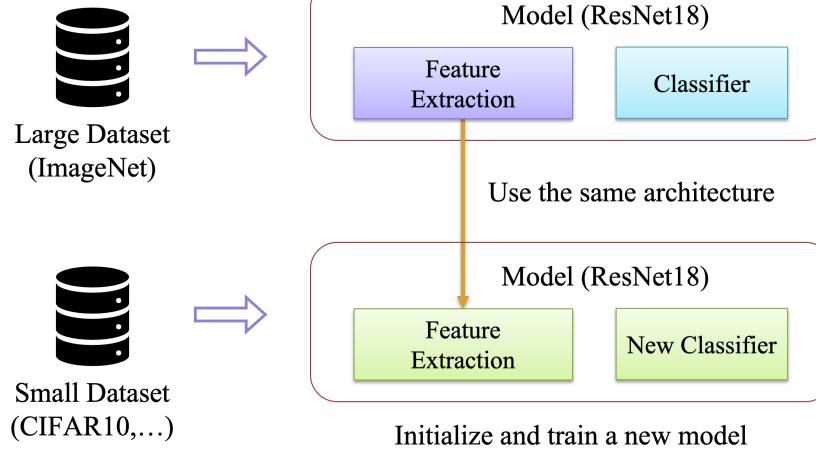
layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112			7×7, 64, stride 2		
conv2_x	56×56	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix} \times 2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix} \times 3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix} \times 2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix} \times 4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix} \times 8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix} \times 2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix} \times 6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix} \times 6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix} \times 23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix} \times 36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix} \times 2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix} \times 3$
	1×1	average pool, 1000-d fc, softmax				

1 – Pretrained Models

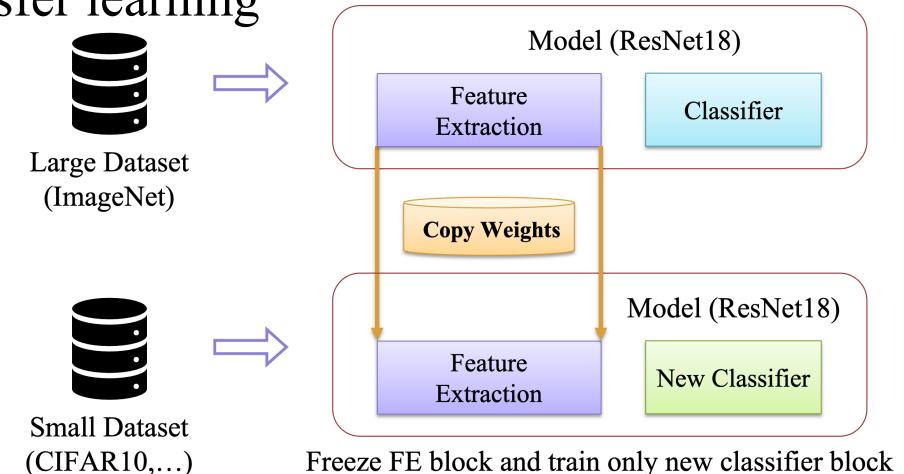


Training with Pretrained Models

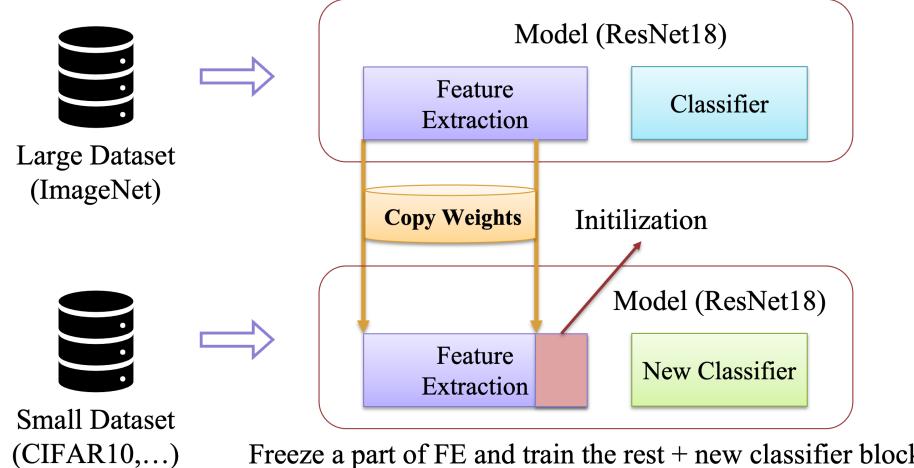
Train from scratch



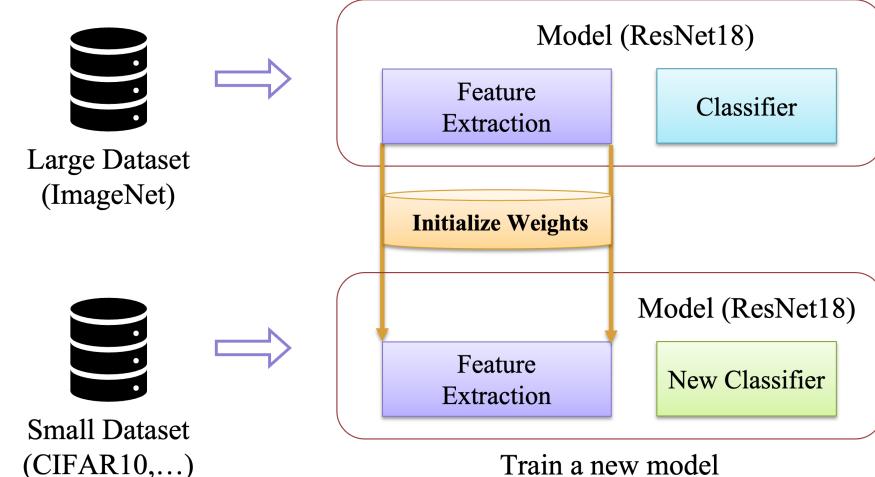
Transfer learning



Fine Tuning



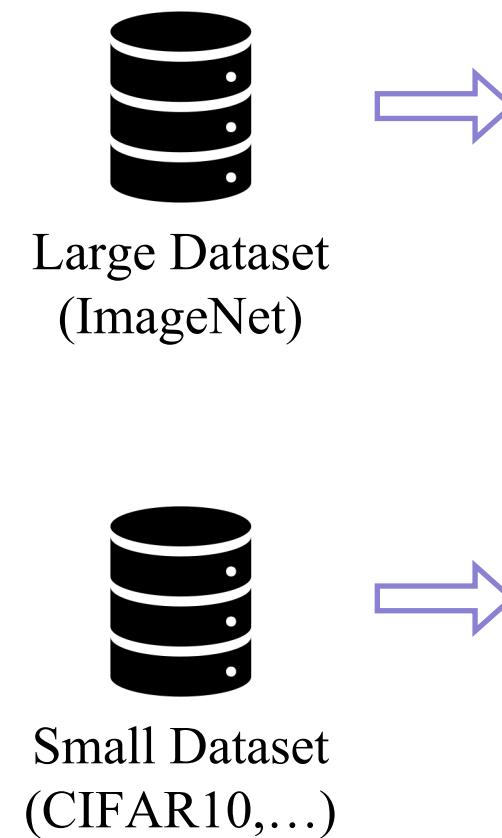
Fine Tuning (As Initialization)



1 – Pretrained Models



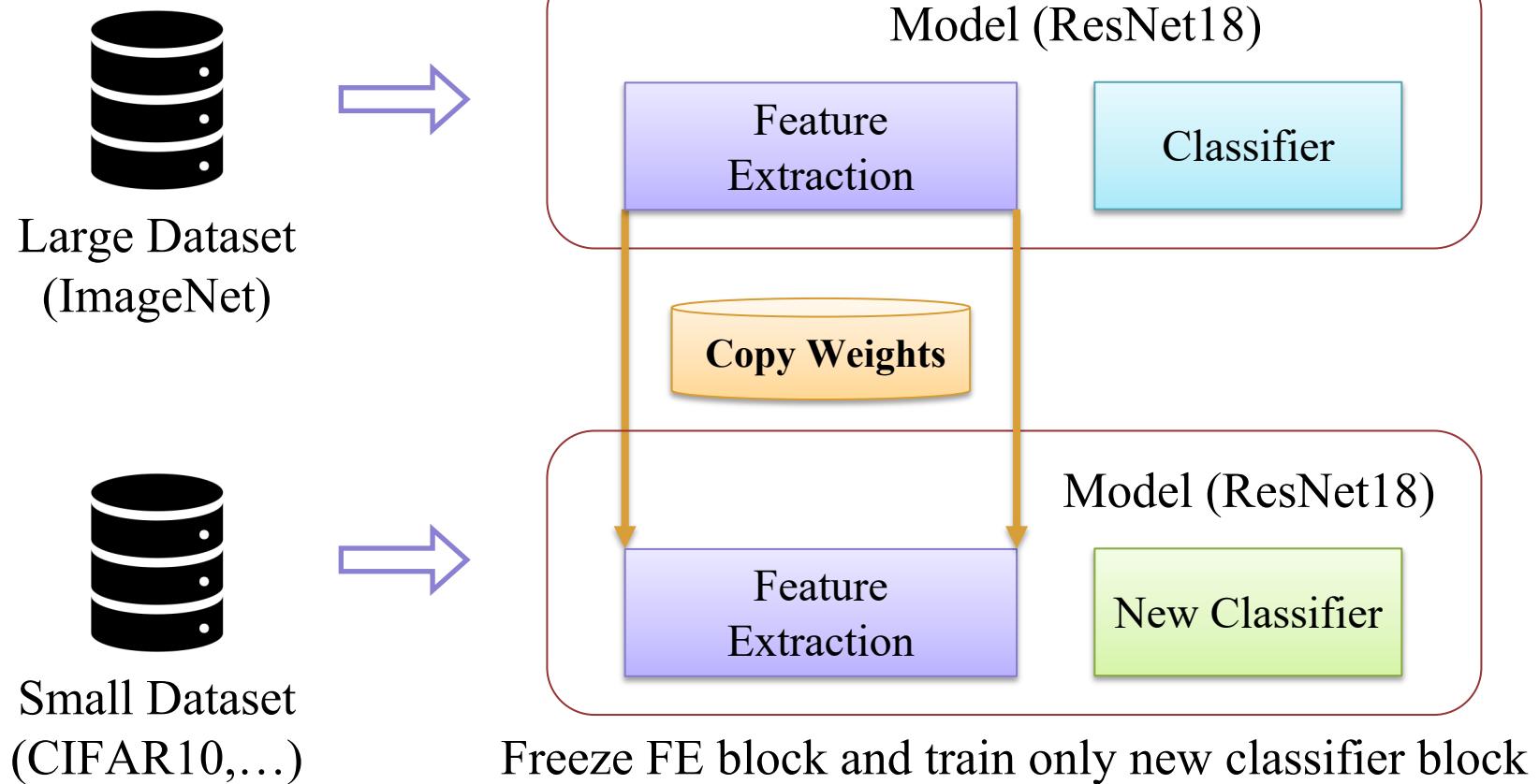
Train from Scratch



1 – Pretrained Models

!

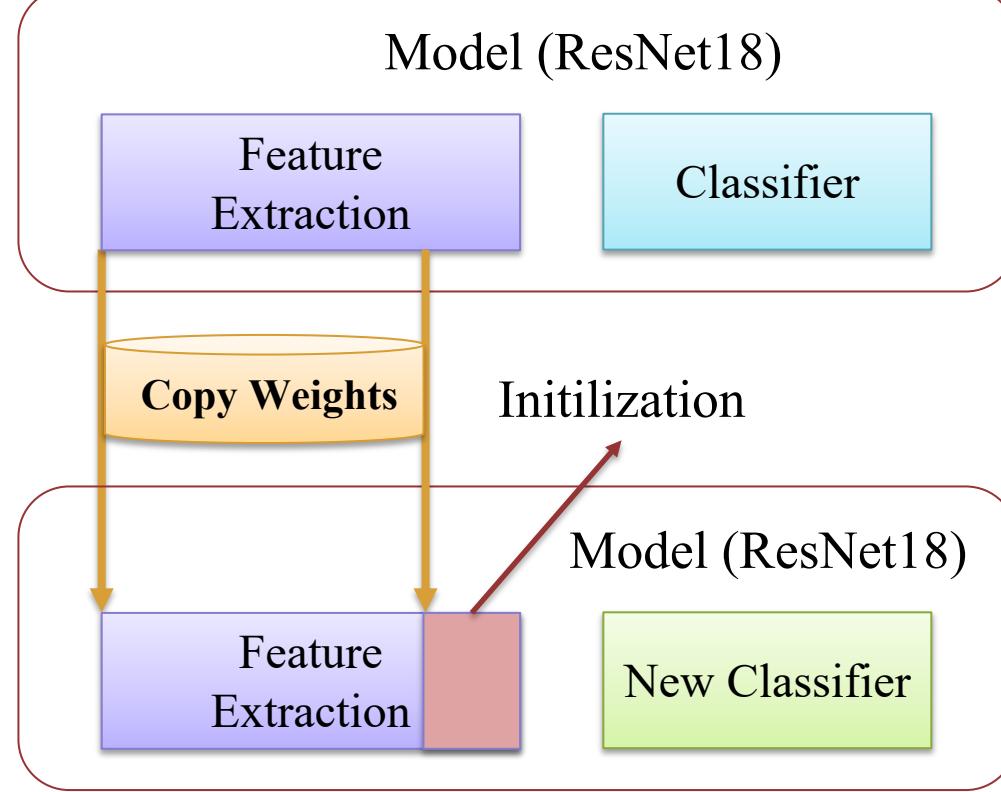
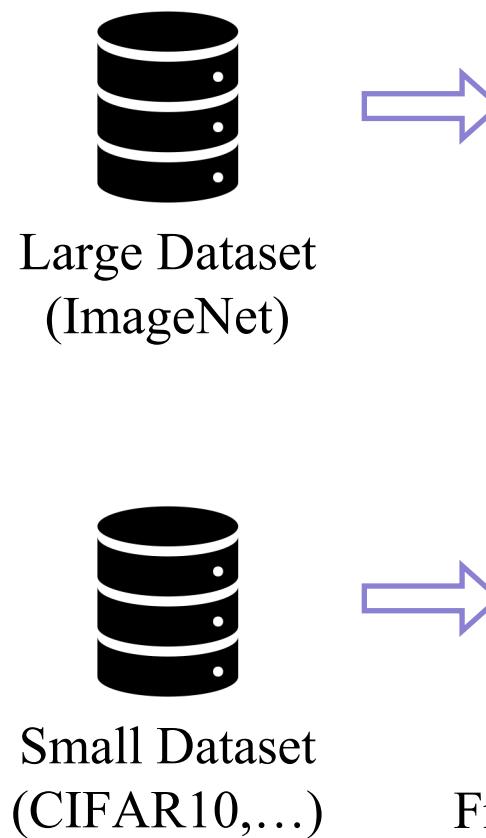
Transfer Learning (Feature Extractor)



1 – Pretrained Models



Fine Tuning

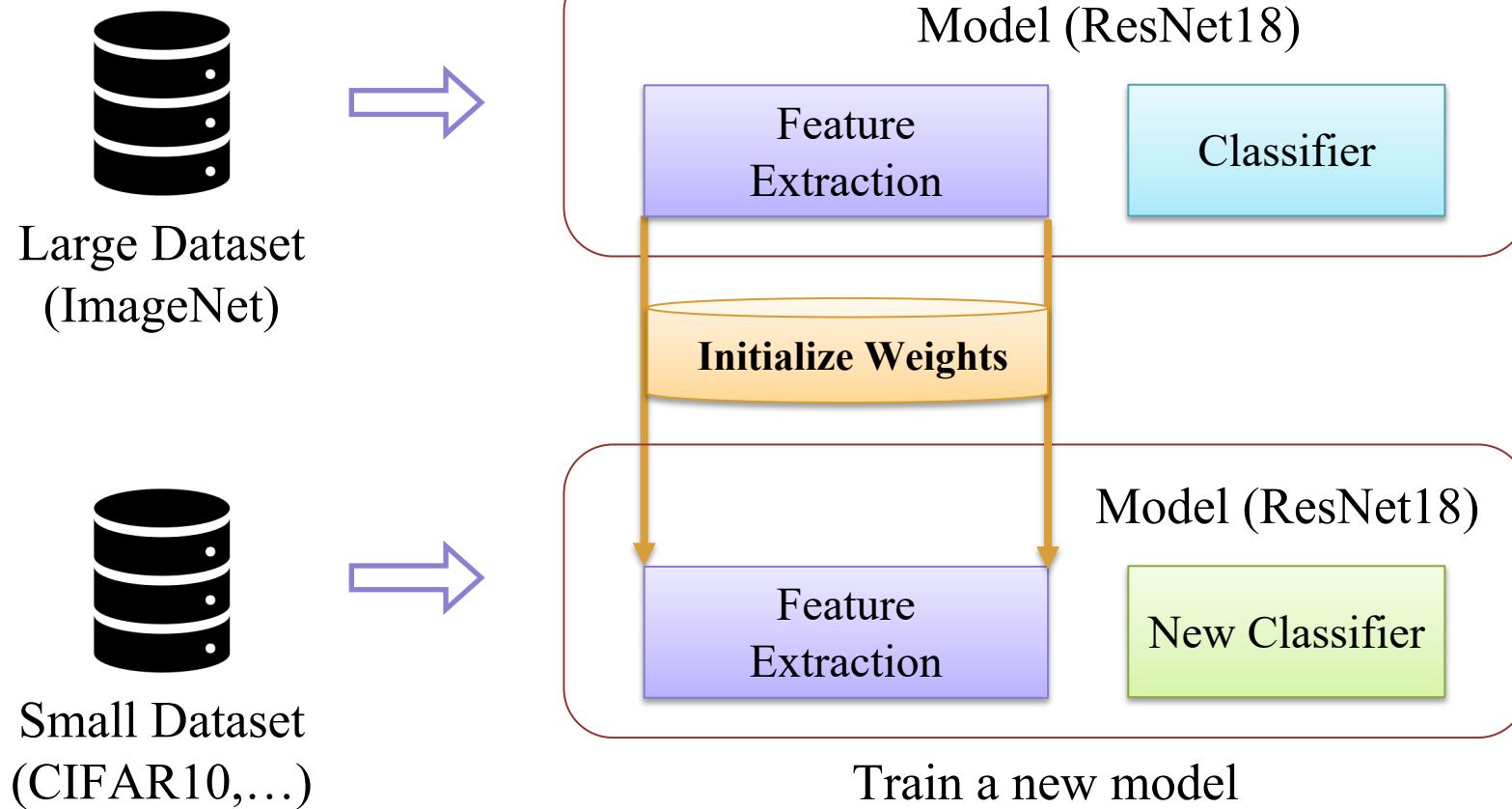


Freeze a part of FE and train the rest + new classifier block

1 – Pretrained Models



Fine Tuning (As Initialization)

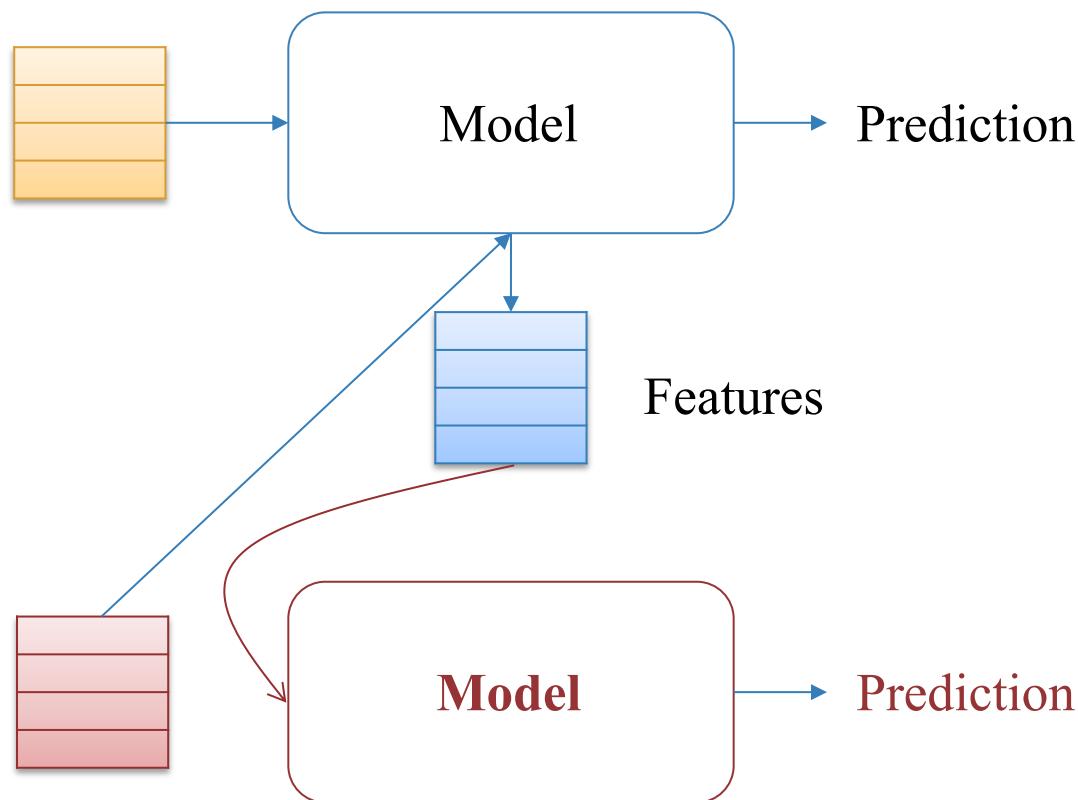


1 – Pretrained Models

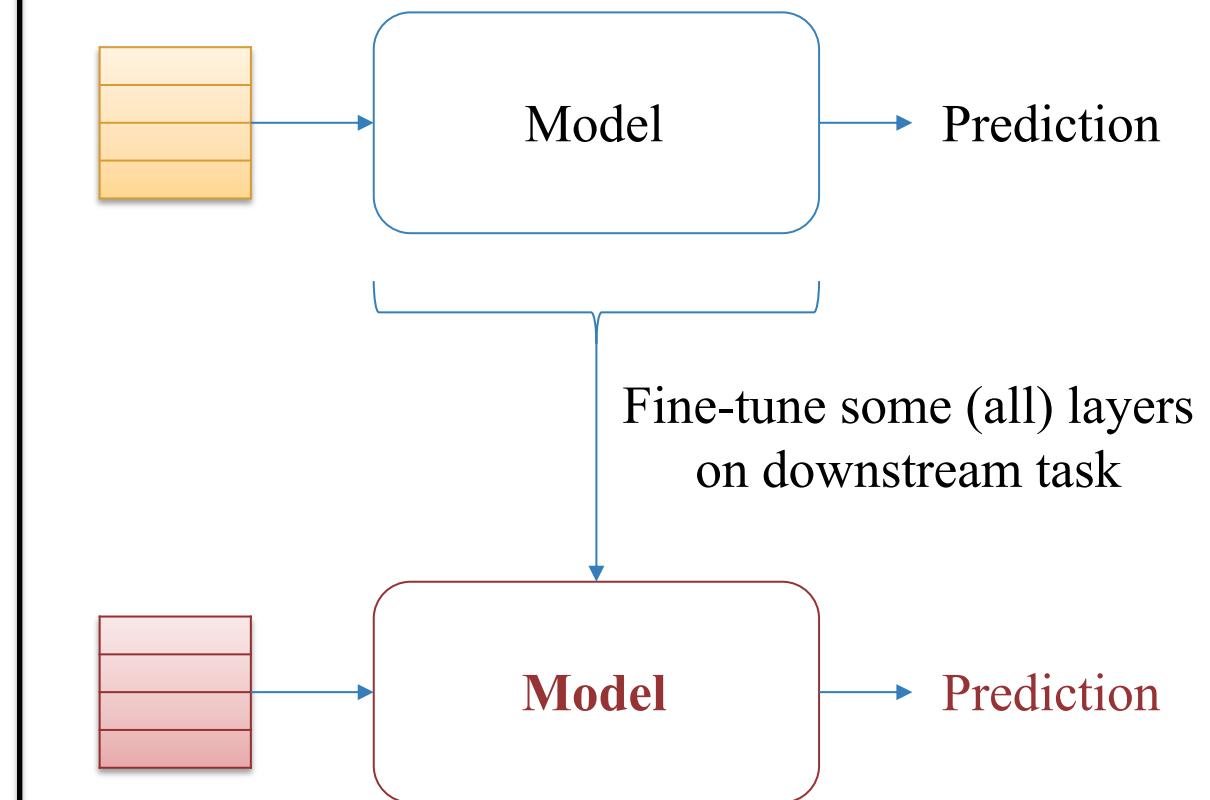


Transfer Learning and Fine Tuning using Pretrained Models

❖ Transfer Learning



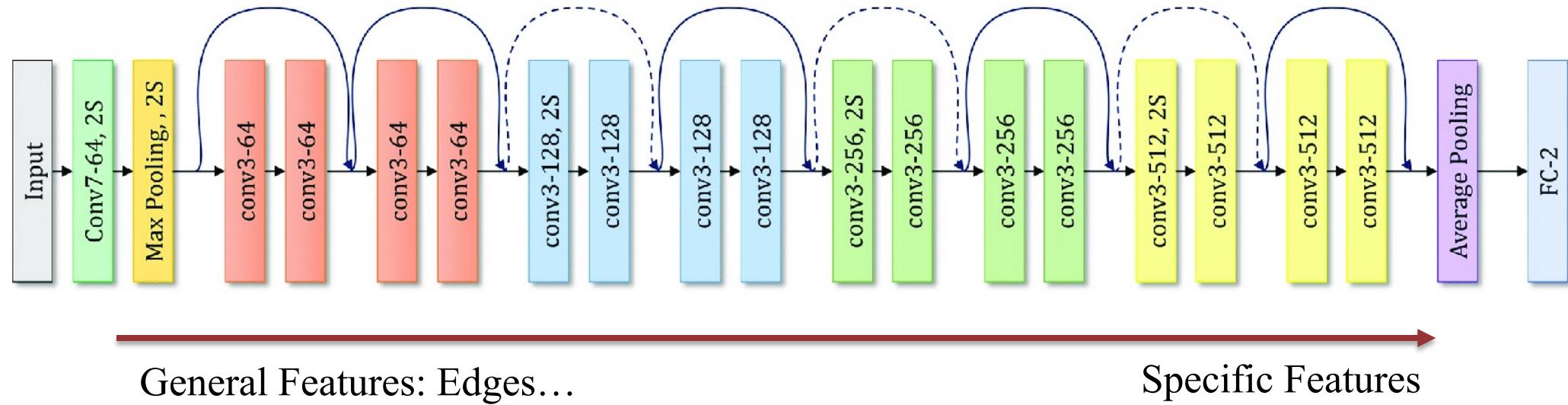
❖ Fine Tuning



1 – Pretrained Models



Transfer Learning and Fine Tuning using Pretrained Models



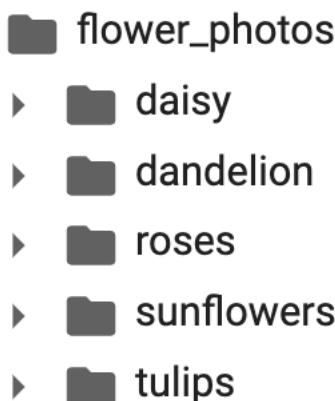
	Similar Dataset	Different Dataset
Small Dataset	Transfer Learning Highest Level Features	Transfer Learning Lower Level features
Large Dataset	Fine Tuning	Fine Tuning

2 – Flower Classification



Flower Dataset - Demo

❖ Folder Structure



```
[ ] data_path = "./dataset/flower_photos"  
  
[ ] # load image from path  
dataset = datasets.ImageFolder(root=data_path)  
  
[ ] dataset  
Dataset ImageFolder  
Number of datapoints: 3670  
Root location: ./dataset/flower_photos  
  
[ ] num_samples = len(dataset)  
num_samples  
3670  
  
[ ] dataset.classes  
['daisy', 'dandelion', 'roses', 'sunflowers', 'tulips']  
  
[ ] num_classes = len(dataset.classes)
```

2 – Flower Classification



Preprocessing - Demo

❖ Training : Validation : Testing = 0.9 : 0.1 : 0.1

```
TRAIN_RATIO, VALID_RATIO = 0.8, 0.1

n_train_examples = int(num_samples * TRAIN_RATIO)
n_valid_examples = int(num_samples * VALID_RATIO)
n_test_examples = num_samples - n_train_examples - n_valid_examples
```

```
n_train_examples, n_valid_examples, n_test_examples
```

```
(2936, 367, 367)
```

```
train_dataset, valid_dataset, test_dataset = data.random_split(
    dataset,
    [n_train_examples, n_valid_examples, n_test_examples]
)
```

2 – Flower Classification



Preprocessing - Demo

❖ Transform

```
# resize + convert to tensor
IMG_SIZE = 224

train_transforms = transforms.Compose([
    transforms.Resize((IMG_SIZE, IMG_SIZE)),
    transforms.RandomHorizontalFlip(),
    transforms.RandomRotation(0.2),
    transforms.ToTensor(),
    transforms.Normalize([0.5, 0.5, 0.5], [0.5, 0.5, 0.5])
])

test_transforms = transforms.Compose([
    transforms.Resize((IMG_SIZE, IMG_SIZE)),
    transforms.ToTensor(),
    transforms.Normalize([0.5, 0.5, 0.5], [0.5, 0.5, 0.5])
])

train_dataset.dataset.transform = train_transforms
valid_dataset.dataset.transform = test_transforms
test_dataset.dataset.transform = test_transforms
```

2 – Flower Classification



Dataloader - Demo

- ❖ Batch size: 256

```
BATCH_SIZE = 256

train_dataloader = data.DataLoader(
    train_dataset,
    shuffle=True,
    batch_size=BATCH_SIZE
)

valid_dataloader = data.DataLoader(
    valid_dataset,
    batch_size=BATCH_SIZE
)

test_dataloader = data.DataLoader(
    test_dataset,
    batch_size=BATCH_SIZE
)
```

2 – Flower Classification



Model – Train from Scratch - Demo

```
model = models.resnet18(weights=None)
```

```
in_features = model.fc.in_features
model.fc = nn.Linear(in_features, num_classes)
```

```
(avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
(fc): Linear(in_features=512, out_features=1000, bias=True)
```

```
(avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
(fc): Linear(in_features=512, out_features=5, bias=True)
```

Total params: 11,179,077
Trainable params: 11,179,077
Non-trainable params: 0

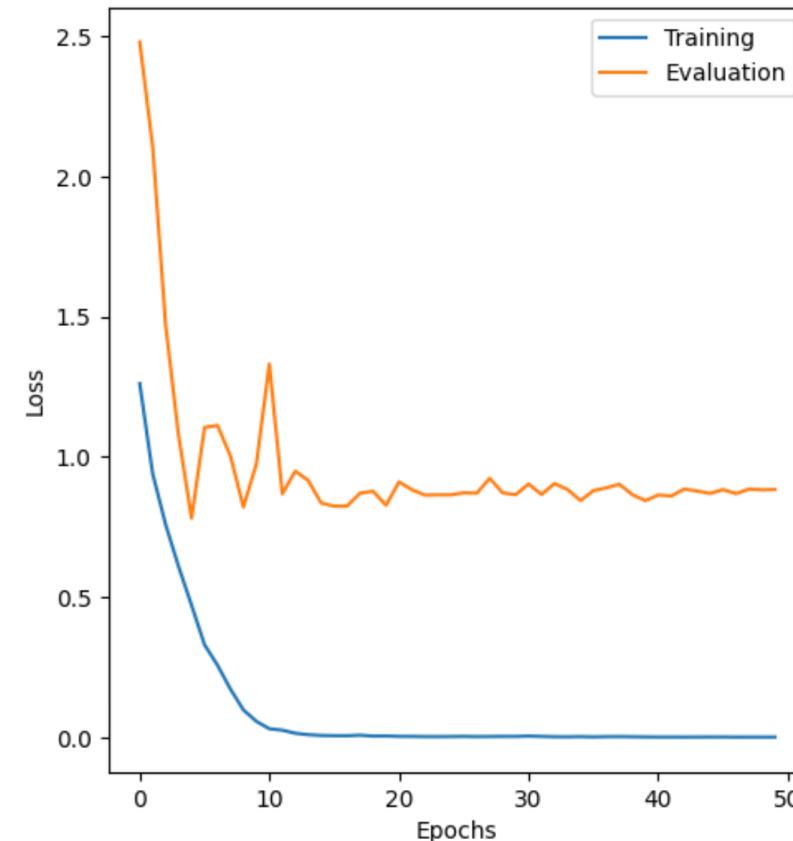
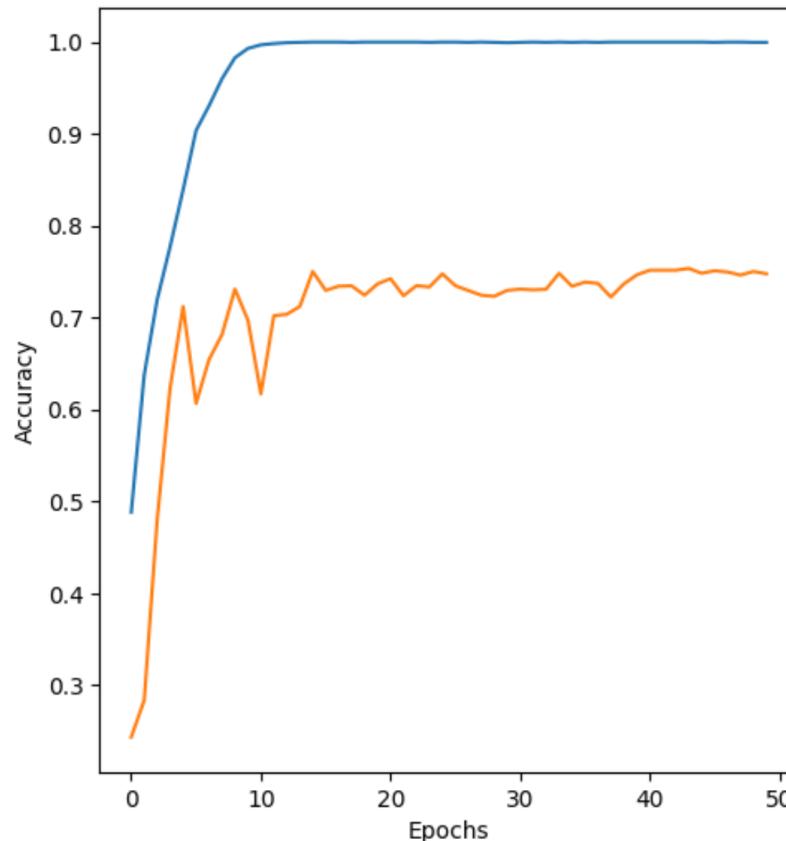
Input size (MB): 0.57
Forward/backward pass size (MB): 62.79
Params size (MB): 42.64
Estimated Total Size (MB): 106.00

2 – Flower Classification



Model – Train from Scratch - Demo

- ❖ Testing: 73.11%



2 – Flower Classification



Model – Transfer Learning - Demo

- ❖ Weight: ImageNet1K

```
transfer_model = models.resnet18(  
    weights=models.ResNet18_Weights.IMGNET1K_V1  
)  
# freeze FE  
for param in transfer_model.parameters():  
    param.requires_grad = False  
  
in_features = transfer_model.fc.in_features  
transfer_model.fc = nn.Linear(in_features, num_classes)
```

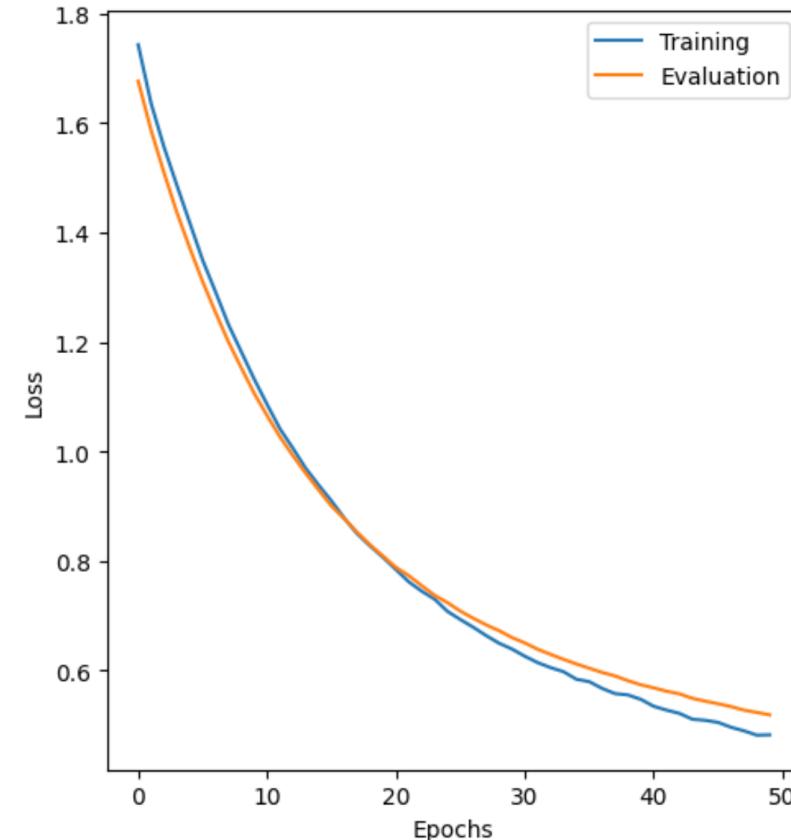
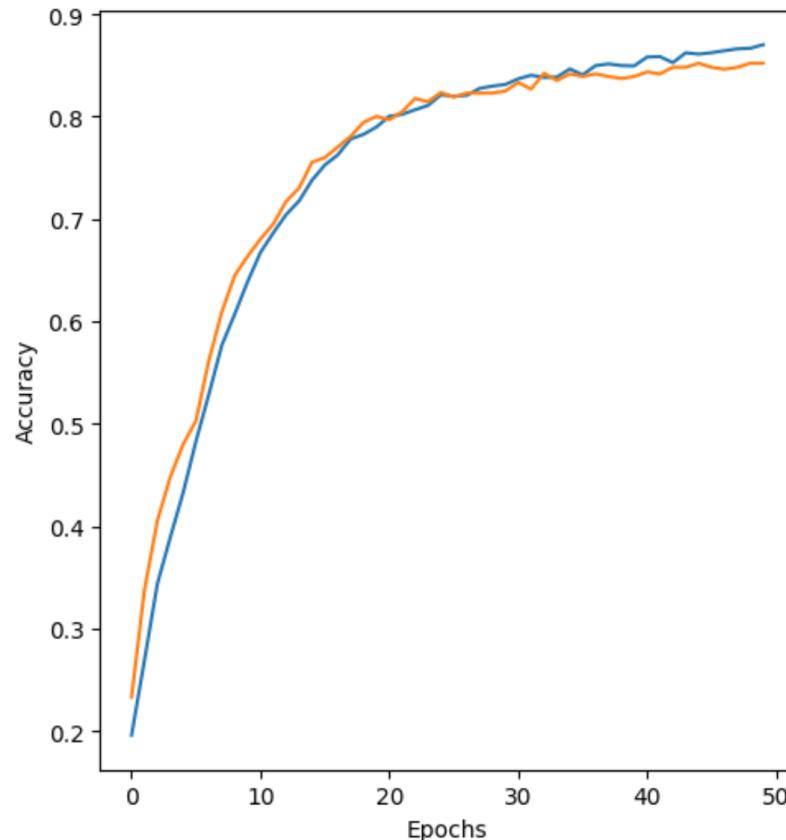
AdaptiveAvgPool2d-67	[-1, 512, 1, 1]	0
Linear-68	[-1, 5]	2,565
<hr/>		
Total params:	11,179,077	
Trainable params:	2,565	
Non-trainable params:	11,176,512	

2 – Flower Classification



Model – Transfer Learning - Demo

- ❖ Testing: 86.98%



2 – Flower Classification



Model – Fine Tuning - Demo

- ❖ Freeze the first 50 layers

```
fine_tuning_model = models.resnet18(  
    weights=models.ResNet18_Weights.IMAGENET1K_V1  
)  
  
# freeze the first 50 layers  
num_layers = 50  
for index, param in enumerate(fine_tuning_model.parameters()):  
    if index < num_layers:  
        param.requires_grad = False
```

AdaptiveAvgPool2d-67	[-1, 512, 1, 1]	0
Linear-68	[-1, 5]	2,565

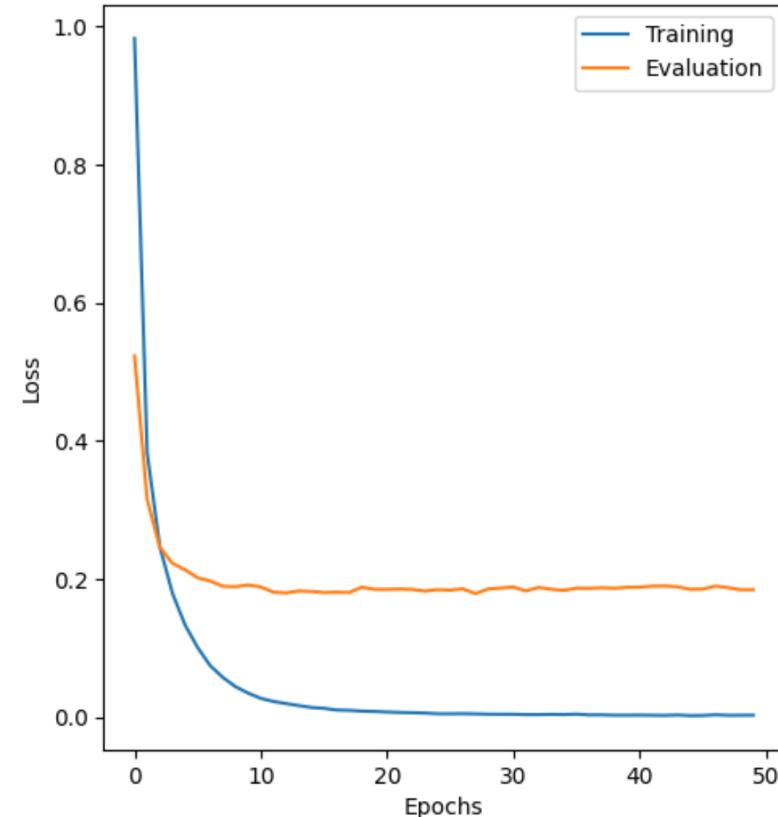
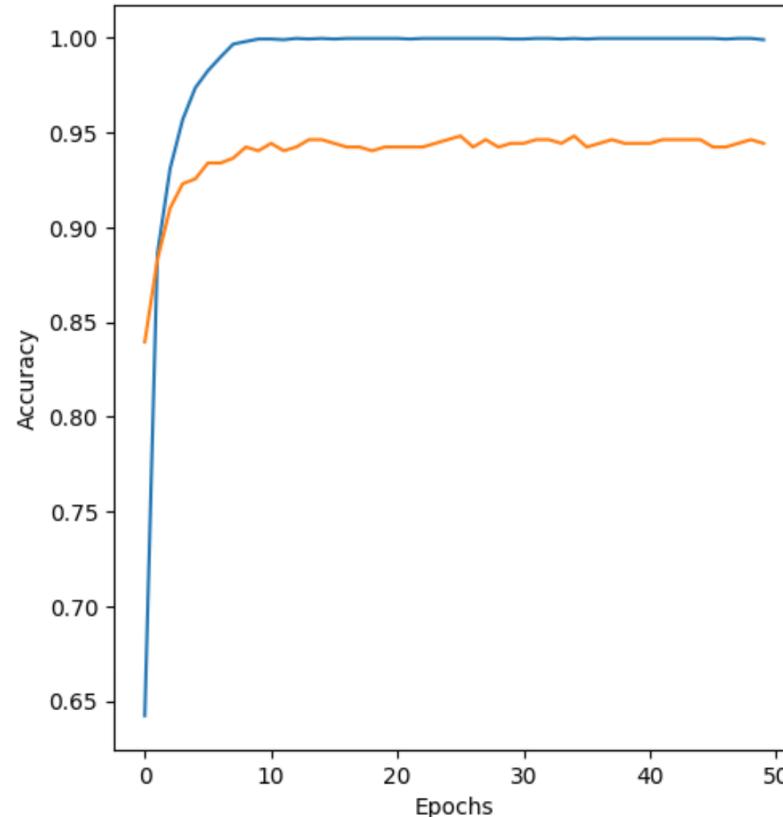
Total params: 11,179,077
Trainable params: 4,855,301
Non-trainable params: 6,323,776

2 – Flower Classification



Model – Fine Tuning - Demo

- ❖ Testing: 93.13%



2 – Flower Classification



Model – Fine Tuning (As Initialization) - Demo

- ❖ Unfreeze all layers

```
initialization_model = models.resnet18(  
    weights=models.ResNet18_Weights.IMGNET1K_V1  
)  
  
in_features = initialization_model.fc.in_features  
initialization_model.fc = nn.Linear(in_features, num_classes)
```

AdaptiveAvgPool2d-67	$[-1, 512, 1, 1]$	0
Linear-68	$[-1, 5]$	2,565

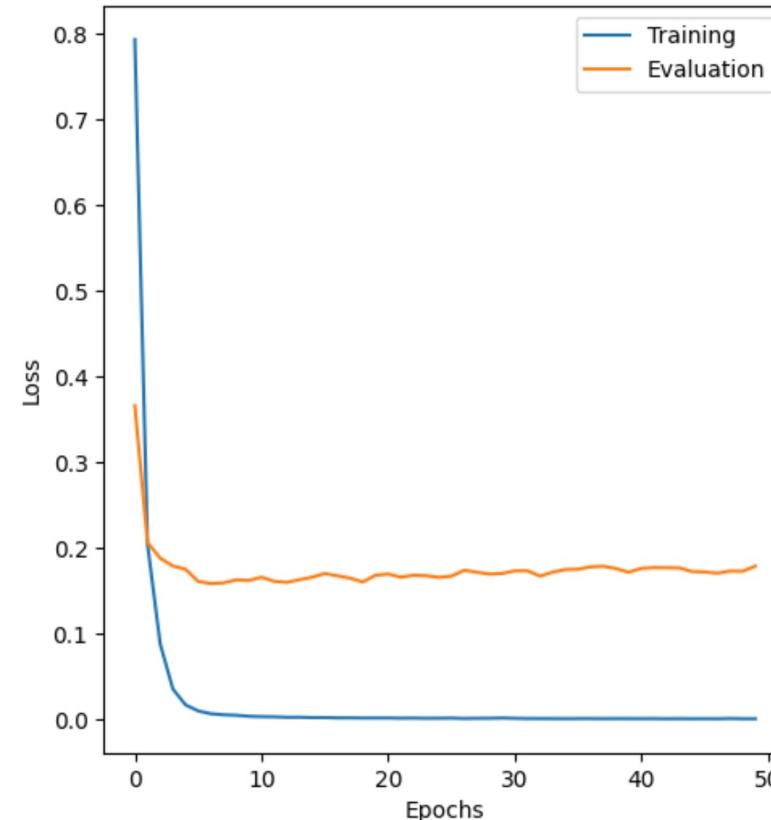
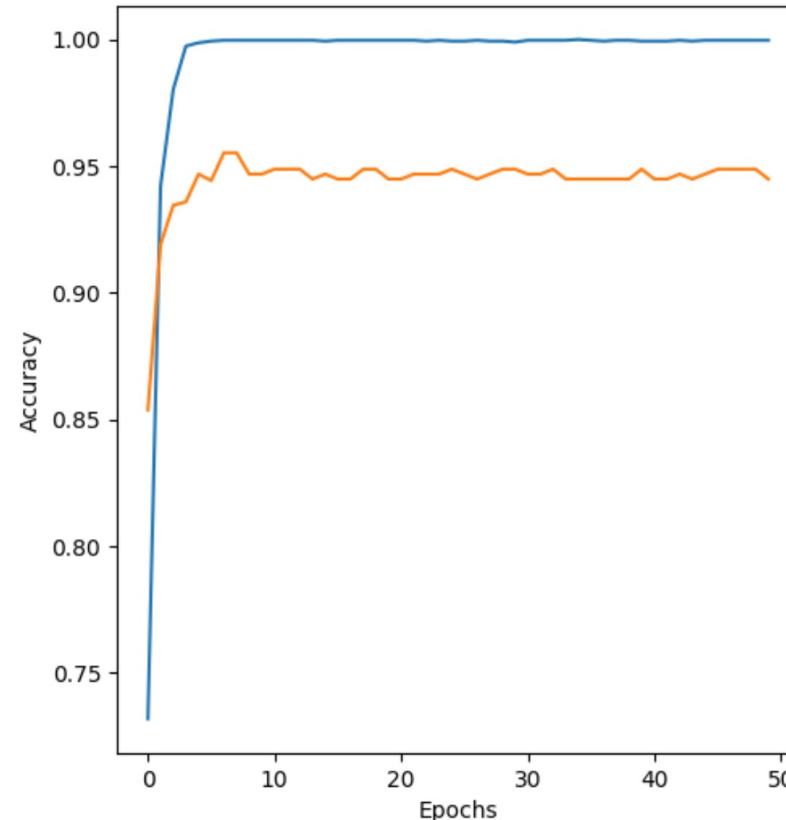
Total params: 11,179,077
Trainable params: 11,179,077
Non-trainable params: 0

2 – Flower Classification



Model – Fine Tuning (As Initialization) - Demo

- ❖ Testing: 95.27%

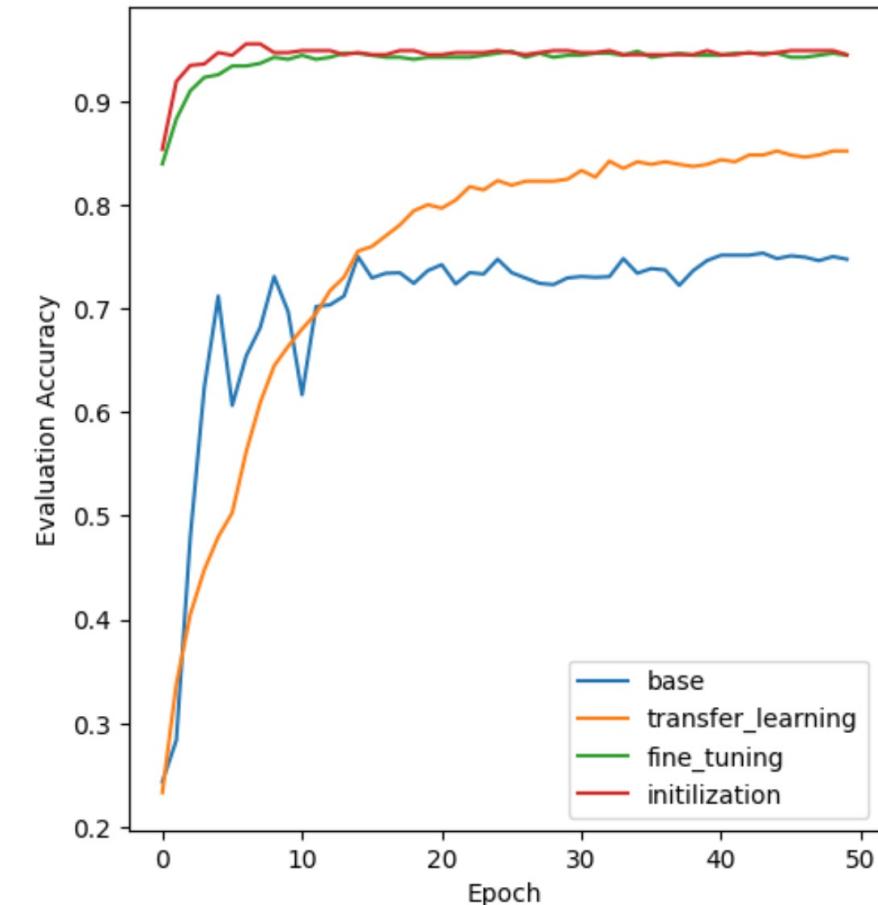
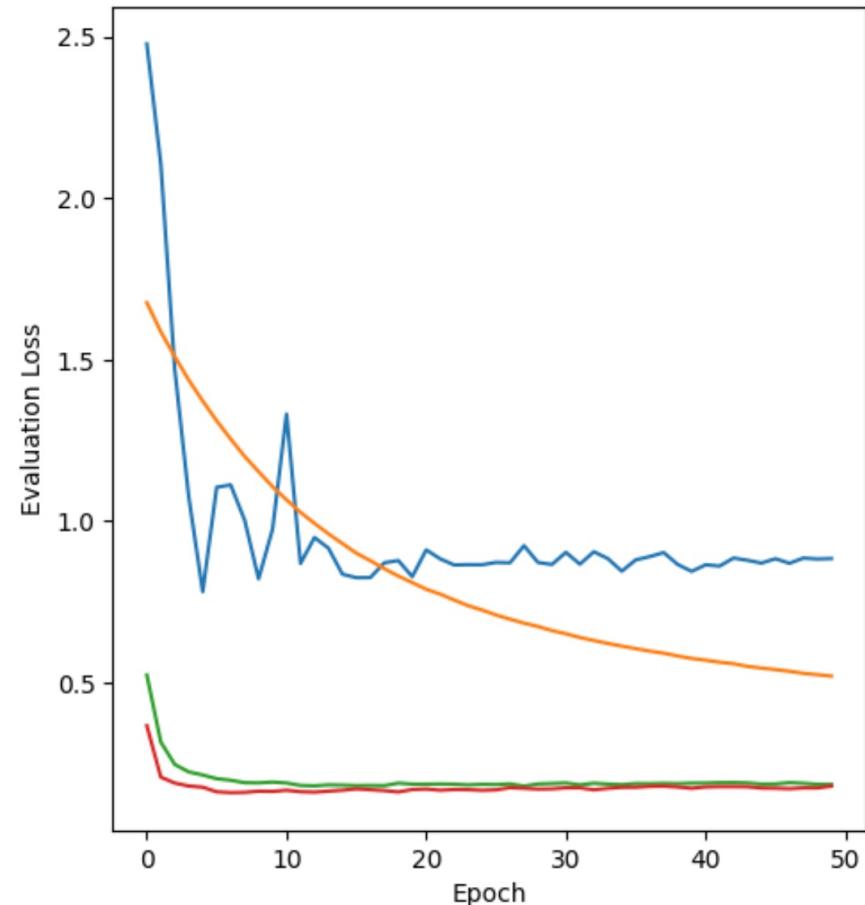


2 – Flower Classification

!

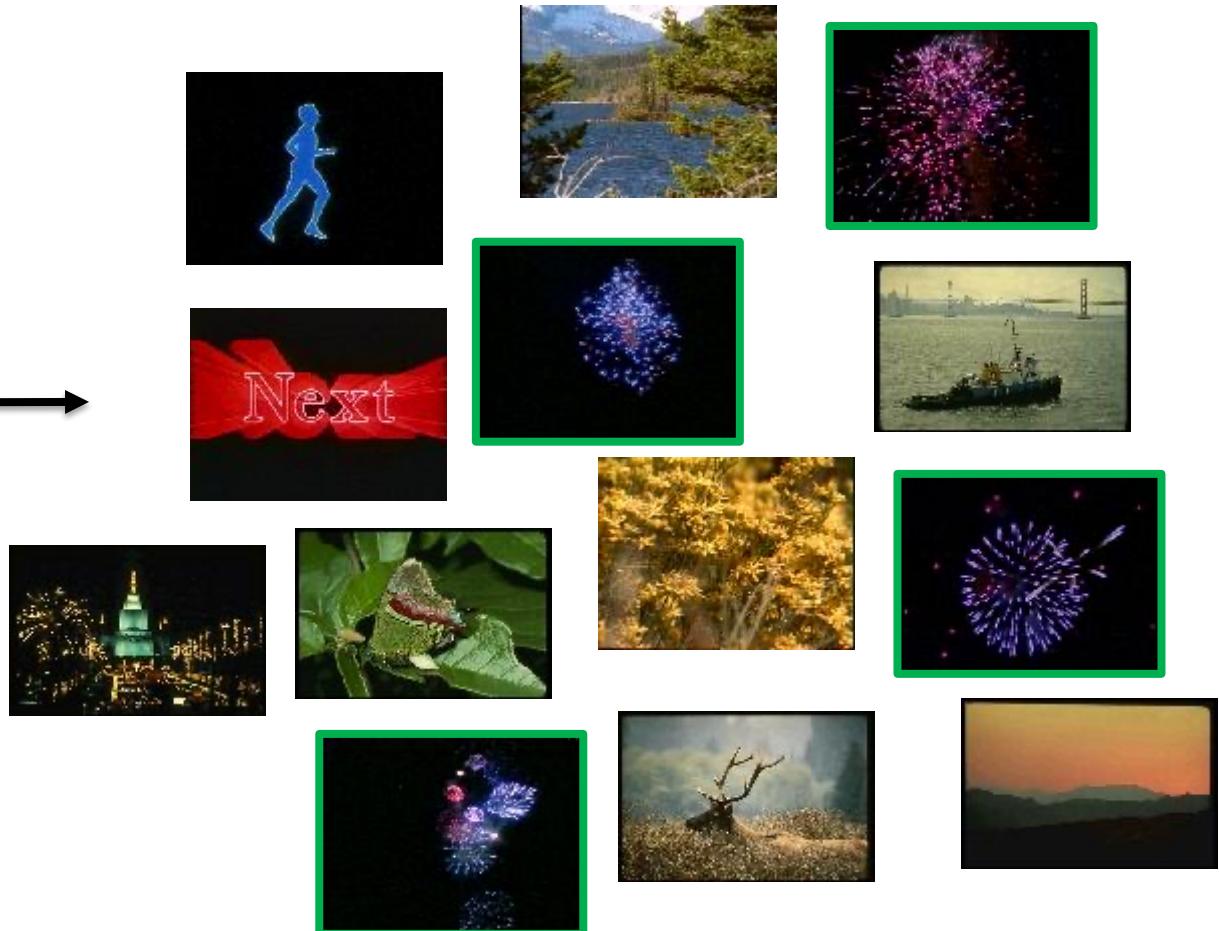
Comparing

Model	Accuracy
Base	73.11
Transfer	86.98
Fine-Tune	93.11
Initialization	95.27



3 – Image Retrieval

!

Database**Image Database****Query Image****Search for****Similar images**

3 – Image Retrieval



Image Similarity



MSE
L1 – Distance
L2 – Distance
Cosine Similarity
Normalized Cross-Correlation

Similarity Score /
Distance

3 – Image Retrieval



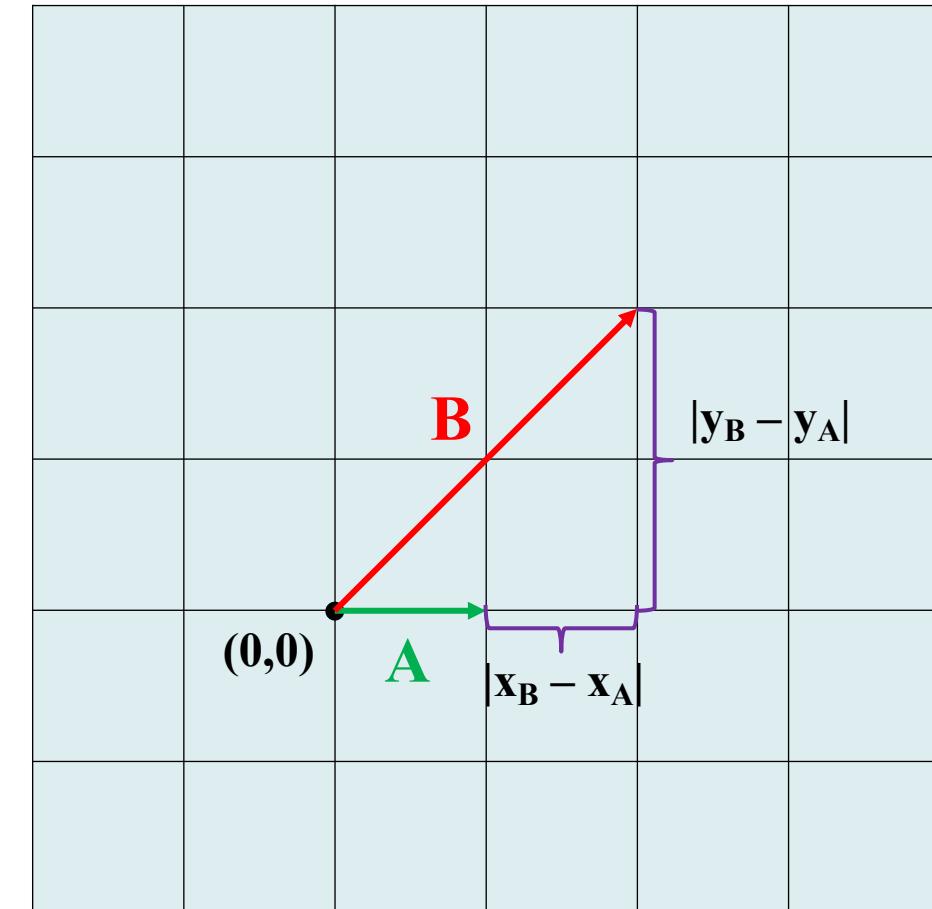
L1 Distance

- ❖ Compute L1 distance of 2 vectors

$$L1 = \sum_{i=1}^n |x_i - y_i|$$

A 

B 



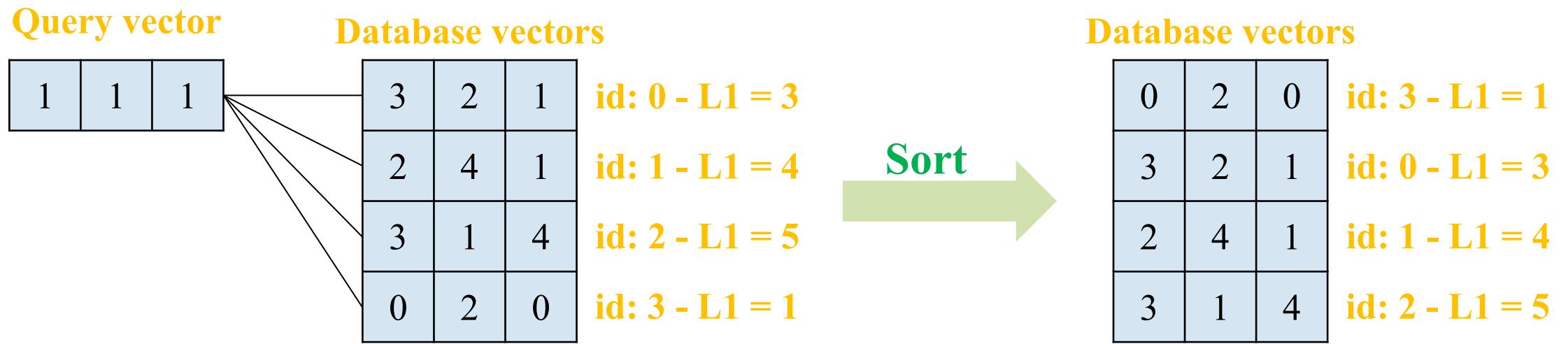
3 – Image Retrieval



L1 Distance

- ❖ Compute L1 distance of 2 vectors

$$L1 = \sum_{i=1}^n |x_i - y_i|$$



3 – Image Retrieval



Cosine Similarity

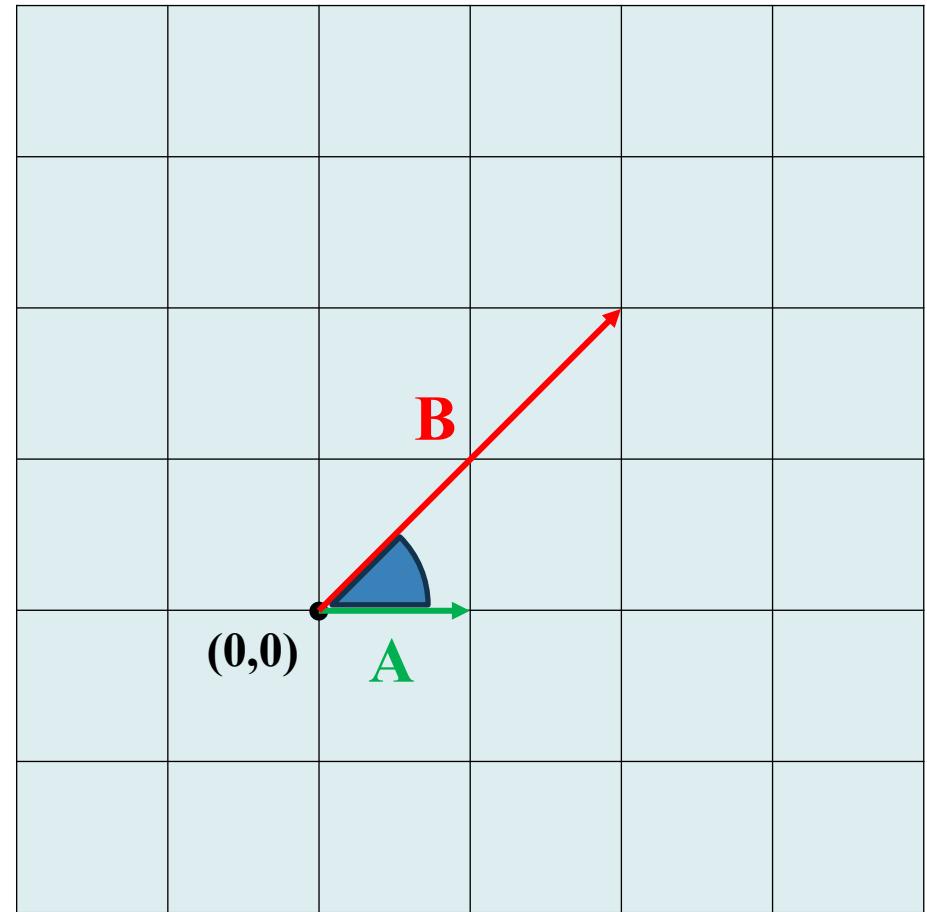
- ❖ Compute Cosine Similarity of 2 vectors

$$\text{Cos}(A, B) = \frac{A \cdot B}{\|A\| \|B\|}$$

A 

B 

(0,0)



3 – Image Retrieval



Cosine Similarity

- ❖ Compute Cosine Similarity of 2 vectors

$$\text{Cos}(A, B) = \frac{A \cdot B}{\|A\| \|B\|}$$

Query vector

1	1	1
---	---	---

Database vectors

3	2	1
2	4	1
3	1	4
0	2	0

id: 0 - Cs = 0.93
id: 1 - Cs = 0.88
id: 2 - Cs = 0.91
id: 3 - Cs = 0.58



Database vectors

3	2	1
3	1	4
2	4	1
0	2	0

id: 0 - Cs = 0.93
id: 2 - Cs = 0.91
id: 1 - Cs = 0.88
id: 3 - Cs = 0.58

3 – Image Retrieval



Naïve Approach



Similarity/
Distance Function



MSE
L1 – Distance
L2 – Distance
Cosine Similarity
Normalized Cross-Correlation

Similar Score /
Distance

3 – Image Retrieval

!

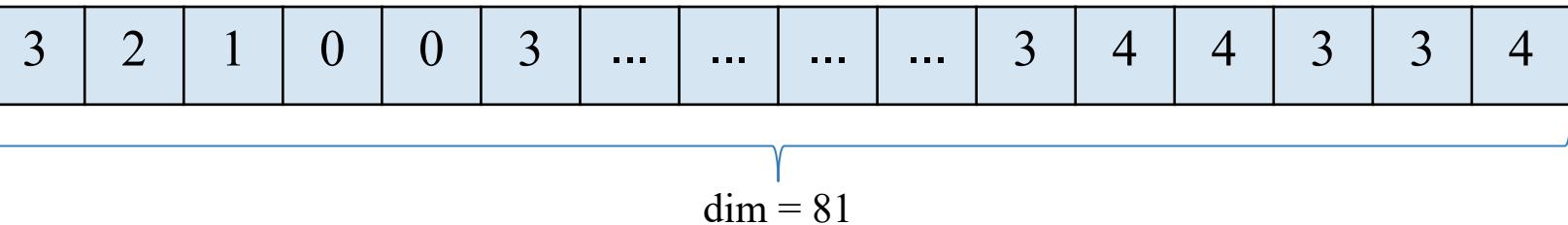
Naïve Approach



3	2	1	0	0	3
0	3	3	1	1	0
3	1	4	1	1	0
2	4	1	1	0	4
1	0	3	0	3	0
3	4	4	3	3	4

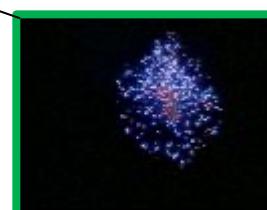
Example: size 9 x 9 image

Flatten into a vector with $9 \times 9 = 81$ dimension

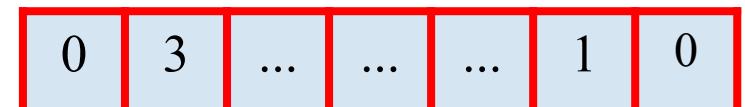


Similarity / Distance Function

Similar
Vector



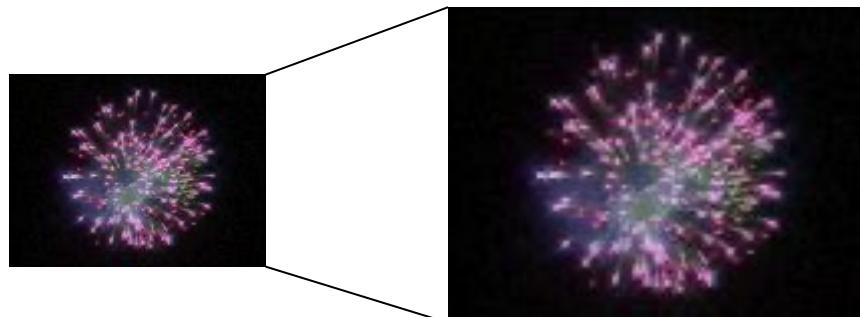
Different
Vector



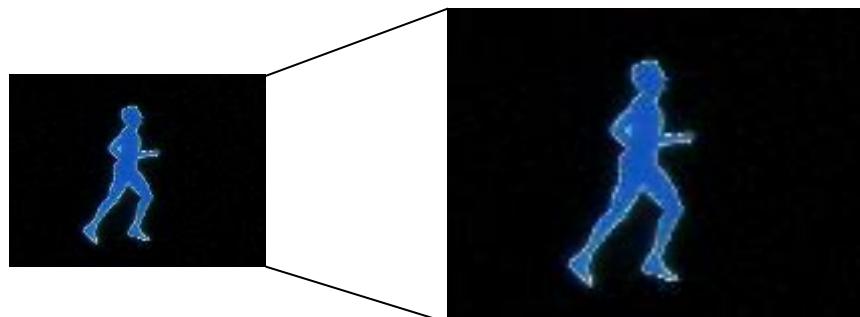
3 – Image Retrieval



Naïve Approach – Data Preparation – Demo



86



86

```
# Image transformation: resize and convert to tensor
transform = transforms.Compose([
    transforms.Resize(86, 128),
    transforms.ToTensor(),
])

# Function to load and preprocess the image
def load_image(path, transform):
    img = Image.open(path).convert('RGB')
    img_tensor = transform(img)
    return img_tensor
```

3 – Image Retrieval

!

Naïve Approach – L1 Distance – Demo

Query image



```
# Load query image
query_img_path = '/content/drive/MyDrive/img/q2.jpg'
query_tensor = load_image(query_img_path, transform)
print(f'Img tensor shape: {query_tensor.shape}')

# Display query image
plt.figure(figsize=(4, 4))
plt.imshow(transforms.ToPILImage()(query_tensor))
plt.title("Query Image")
plt.axis('off')
plt.show()
```

3 – Image Retrieval



Naïve Approach – L1 Distance – Demo

```
# Calculate L1 distance (absolute difference)
distances = torch.abs(data_tensors_flat - query_tensor_flat)
distances = torch.sum(distances, dim=1)

# Sort the distances and get indices
sorted_indices = torch.argsort(distances, descending=False)

# Print top 8 values and their indices
for i in range(8):
    index = sorted_indices[i].item()
    distance = distances[index].item()
    print(f'Index: {index}, Distance: {distance}')
```

```
Index: 3425, Distance: 0.0
Index: 3077, Distance: 5221.431640625
Index: 2611, Distance: 5247.2900390625
Index: 3109, Distance: 5289.16845703125
Index: 3445, Distance: 5358.61962890625
Index: 960, Distance: 5378.94873046875
Index: 4788, Distance: 5395.0078125
Index: 3094, Distance: 5435.6904296875
```

3 – Image Retrieval

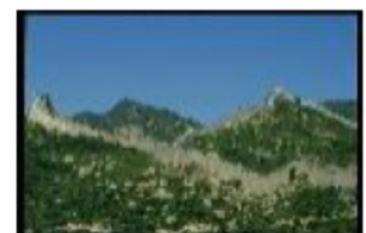


Naïve Approach – L1 Distance – Demo

```
# Display top 8 similar images
fig = plt.figure(figsize=(8, 8))
columns = 3
rows = 3
for i in range(columns * rows):
    index = sorted_indices[i].item()
    img = data_tensors[index]

    ax = fig.add_subplot(rows, columns, i + 1)
    ax.axis('off')
    ax.imshow(to_pil_image(img))

plt.show()
```



3 – Image Retrieval

!

Naïve Approach – Cosine Similarity– Demo

Query image



```
# Load query image
query_img_path = '/content/drive/MyDrive/img/q2.jpg'
query_tensor = load_image(query_img_path, transform)
print(f'Img tensor shape: {query_tensor.shape}')

# Display query image
plt.figure(figsize=(4, 4))
plt.imshow(transforms.ToPILImage()(query_tensor))
plt.title("Query Image")
plt.axis('off')
plt.show()
```

3 – Image Retrieval



Naïve Approach – Cosine Similarity– Demo

```
# Calculate cosine similarity
sims = cosine_similarity(query_tensor_flat, data_tensors_flat)

# Sort the similarities and get indices
sorted_indices = torch.argsort(sims, descending=True)

# Print top 8 values and their indices
for i in range(8):
    index = sorted_indices[i].item()
    similarity = sims[index].item()
    print(f'Index: {index}, Similarity: {similarity}')
```

```
Index: 3425, Similarity: 0.999997615814209
Index: 3306, Similarity: 0.8691879510879517
Index: 4645, Similarity: 0.8683653473854065
Index: 3330, Similarity: 0.8676211833953857
Index: 3374, Similarity: 0.867255449295044
Index: 4317, Similarity: 0.8664509057998657
Index: 3053, Similarity: 0.8658316135406494
Index: 3780, Similarity: 0.8647940158843994
```

3 – Image Retrieval

!

Naïve Approach – Cosine Similarity– Demo

```
# Display top 8 similar images
fig = plt.figure(figsize=(8, 8))
columns = 3
rows = 3
for i in range(columns * rows):
    index = sorted_indices[i].item()
    img = data_tensors[index]

    ax = fig.add_subplot(rows, columns, i + 1)
    ax.axis('off')
    ax.imshow(to_pil_image(img))

plt.show()
```



3 – Image Retrieval



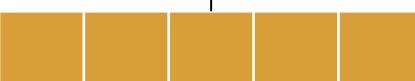
Using Pretrained Model



Feature Extractor
(ResNet18)



Similarity/
Distance Function



Feature Extractor
(ResNet18)

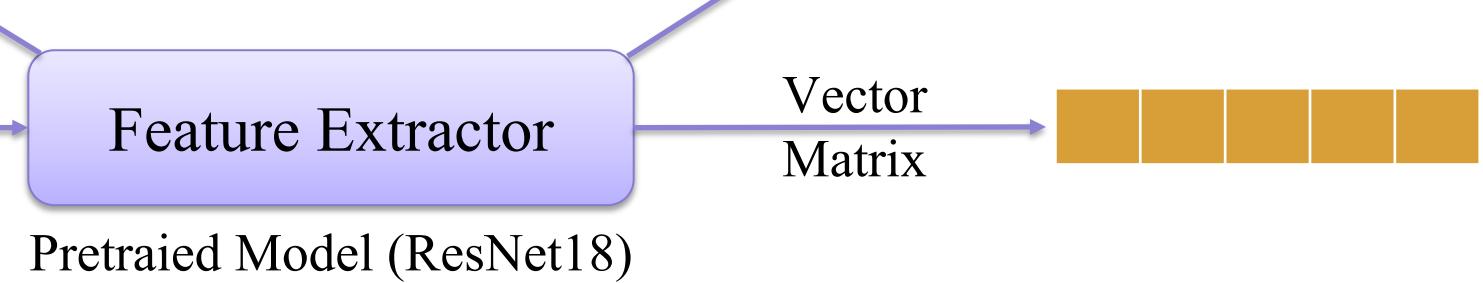
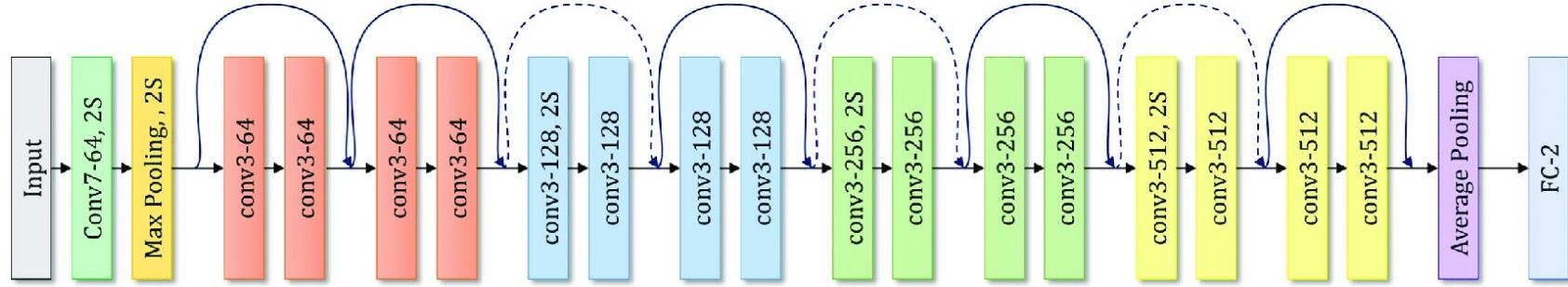
MSE
L1 – Distance
L2 – Distance
Cosine Similarity
Normalized Cross-Correlation

Similarity Score /
Distance

3 – Image Retrieval

!

Using Pretrained Model



Pretraied Model (ResNet18)

3 – Image Retrieval



Using Pretrained Model – Demo

- ❖ Load pretrained ResNet18 model

```
# Load the pretrained ResNet18 model
resnet18 = models.resnet18(
    weights=models.ResNet18_Weights.IMGNET1K_V1
)
# Remove the last layer to use as a feature extractor
modules = list(resnet18.children())[:-1]
resnet18 = torch.nn.Sequential(*modules)

resnet18.eval() # Set the model to evaluation mode
```

3 – Image Retrieval



Using Pretrained Model – Demo

❖ Feature Extraction

```
# Function to preprocess and extract features
def extract_features(tensor, model):
    with torch.no_grad():
        # Add batch dimension and get features
        features = model(tensor.unsqueeze(0))
        # Flatten the features
        features = features.view(features.size(0), -1)
    return features

# Extract features for each image and store them
feature_list = []
for tensor in data_tensors:
    # print(tensor.unsqueeze(0).shape)
    features = extract_features(tensor, resnet18)
    feature_list.append(features)

# Stack all features into a single tensor
feature_tensor = torch.stack(feature_list).squeeze()
print(feature_tensor.shape)
torch.save(feature_tensor, '/content/drive/MyDrive/img/images_mr_features.pt')
```

3 – Image Retrieval



Using Pretrained Model – Demo

❖ Result

```
# Load the query image and extract features
query_tensor = load_image(query_img_path, transform)
query_features = extract_features(query_tensor, resnet18)

# Load the feature tensor
feature_tensor = torch.load('/content/drive/MyDrive/img/images_mr_features.pt')

# Calculate cosine similarity
sims = cosine_similarity(query_features, feature_tensor)

# Sort the similarities and get indices
sorted_indices = torch.argsort(sims, descending=True)

# Print top 8 values and their indices
for i in range(8):
    index = sorted_indices[i].item()
    similarity = sims[index].item()
    print(f'Index: {index}, Similarity: {similarity}')
```

```
Index: 3425, Similarity: 1.0000001192092896
Index: 3407, Similarity: 0.6934022903442383
Index: 370, Similarity: 0.687757670879364
Index: 3214, Similarity: 0.6866506338119507
Index: 3667, Similarity: 0.6857972741127014
Index: 3509, Similarity: 0.6846740245819092
Index: 248, Similarity: 0.6844337582588196
Index: 3793, Similarity: 0.6839574575424194
```

4 – IR with Vector Databases



Database

Data

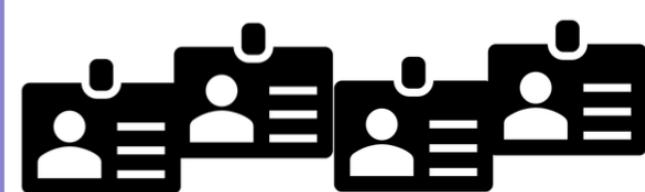
- Refers to a collection of information
- Forms: numbers, text, or other types of media

Name: Thai
Age: 20
Image: [link](#)



Database

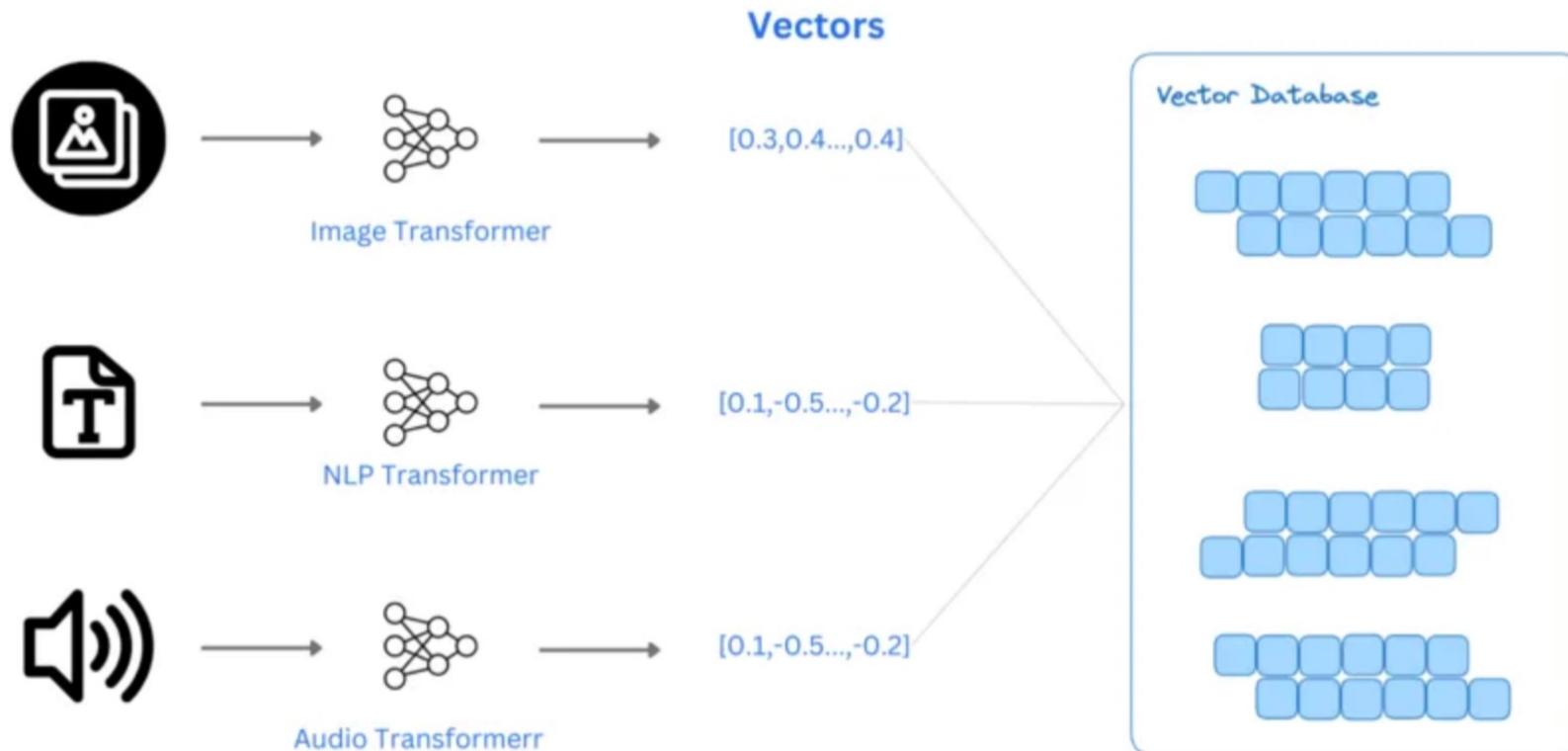
- An organized collection of structured information, or data
- Can be easily accessed, restored, administered and updated



4 – IR with Vector Databasse



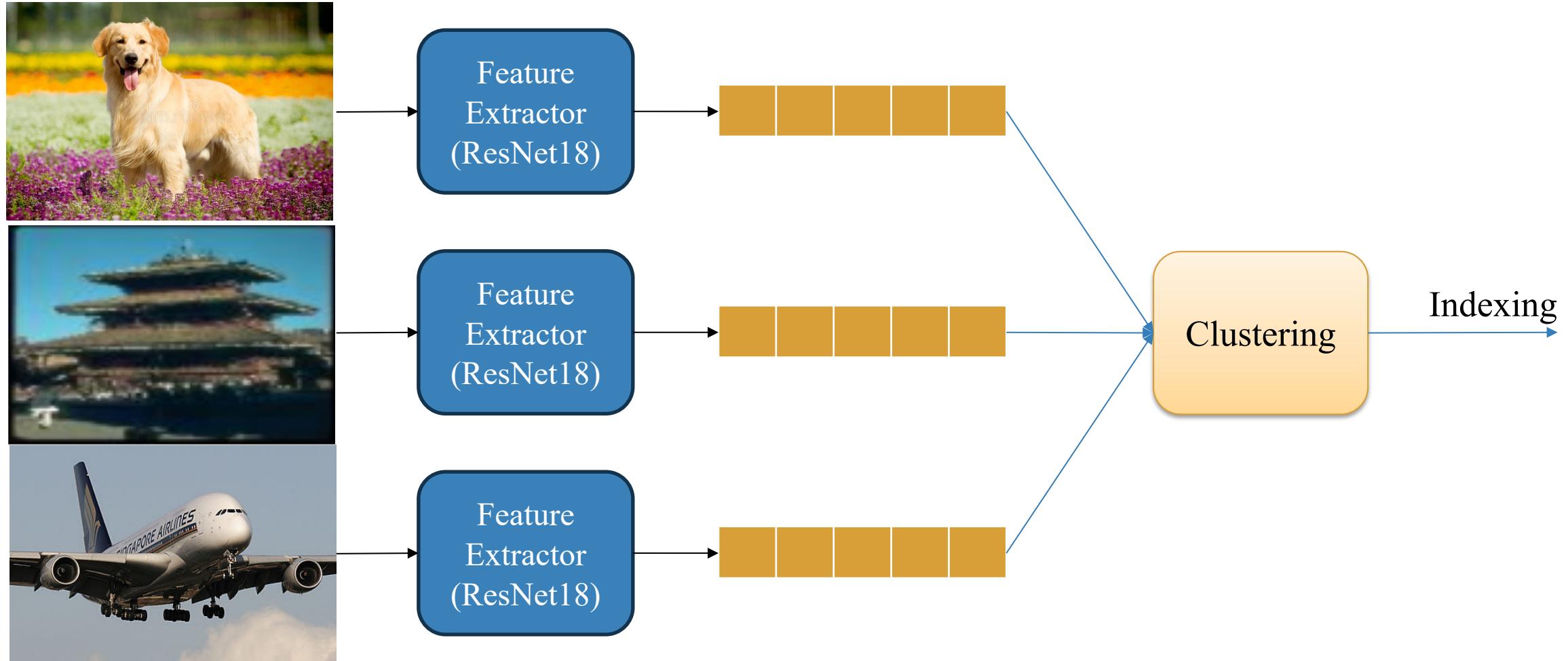
Vector Database



4 – IR with Vector Databasse

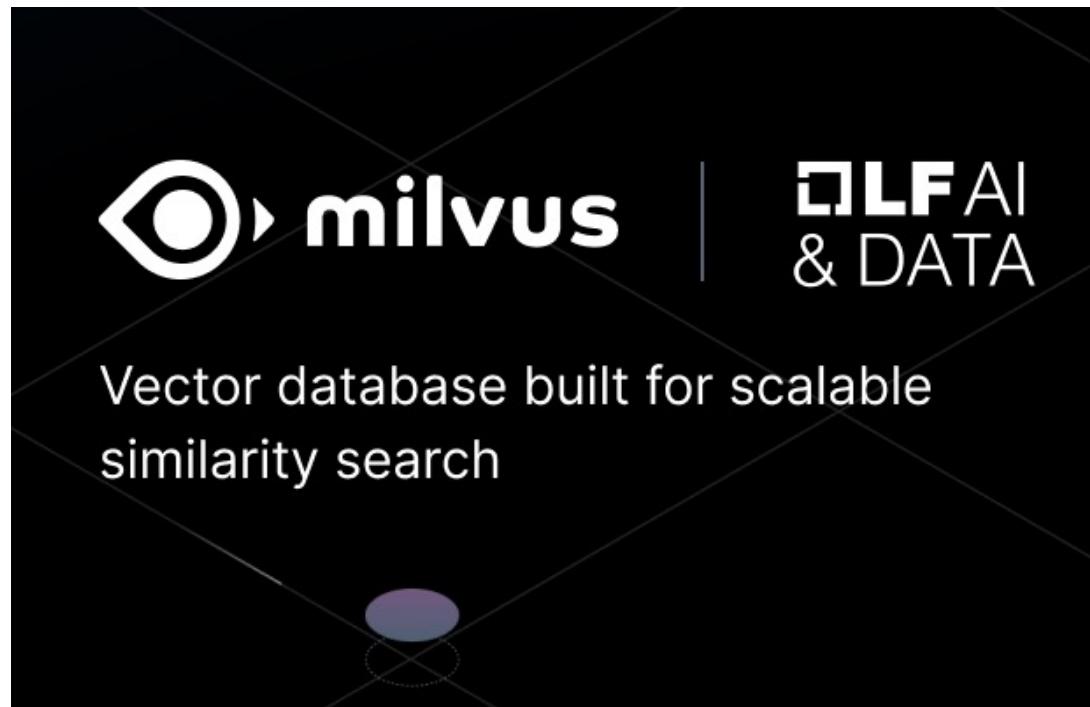
!

Indexing



4 – IR with Vector Databasse

!

PyMilvus

4 – IR with Vector Databasse

!

Zilliz Cloud

The screenshot shows the Zilliz Cloud interface. On the left, there's a sidebar with options like Default project, Clusters (which is selected and highlighted in blue), Collaborators, API Keys, Security, Monitoring, and Playground. A yellow badge at the bottom indicates \$100 credits left, with an Upgrade button below it. The main area shows a navigation path: AISOLUS > Default project > ImageRetrieval > ResNet18. The ResNet18 collection is currently loaded. The interface includes tabs for Collection Details, Schema, Data Preview (which is active), and Vector Search. Under the Data Preview tab, it says "1-10 of 100 Datasets" and lists four datasets with their image IDs and embeddings. Each dataset has a "Vector search" button next to it.

AISOLUS > Default project > ImageRetrieval > ResNet18

ResNet18 LOADED

Collection Details Schema Data Preview Vector Search

1-10 of 100 Datasets

"image_id": 1123
"image_embedding": [0.20781682, 0.98557526, 1.0439999, 0.82633895, 1.4744401, 0.30633506, 0.6637236, 1.5632436, 1.1156428, 1.1061236, 0.8463035, 0....

"image_id": 1190
"image_embedding": [0.33223343, 0.4924078, 0.99724513, 0.6812632, 0.7886206, 0.086395204, 0.24000072, 0.49062985, 0.893631, 1.156685, 0.37443095, ...]

"image_id": 1682
"image_embedding": [1.3943827, 0.82332003, 2.0007038, 0.71553147, 0.46676317, 0.62527215, 1.0464592, 1.6463325, 1.1128753, 1.3075048, 1.3037924, 0....]

"image_id": 5486
"image_embedding": [0.9557475, 0.6131335, 0.7220886, 1.1494548, 0.120158106, 0.3496582, 0.37944207, 0.99652904, 1.3610817, 0.79706025, 0.20960505...]

4 – IR with Vector Databasse



Connect a Database – Demo

```
# connect database
from pymilvus import MilvusClient, connections

CLUSTER_ENDPOINT = "###"
TOKEN = "###"

connections.connect(
    "default",
    uri=CLUSTER_ENDPOINT,
    token=TOKEN
)

client = MilvusClient(
    uri=CLUSTER_ENDPOINT,
    token=TOKEN
)
```

4 – IR with Vector Databases



Create a Collection – Demo

```
from pymilvus import Collection, DataType, FieldSchema, CollectionSchema, utility

# create a collection
COLLECTION_NAME = "ResNet18"
check_collection = utility.has_collection(COLLECTION_NAME)
if check_collection:
    drop_result = utility.drop_collection(COLLECTION_NAME)

EMBEDDING_DIM=512
image_id = FieldSchema(
    name="image_id",
    dtype=DataType.INT64,
    is_primary=True,
    description="Image ID"
)

image_embedding = FieldSchema(
    name="image_embedding",
    dtype=DataType.FLOAT_VECTOR,
    dim=EMBEDDING_DIM
)

schema = CollectionSchema(
    fields=[image_id, image_embedding],
    auto_id=False,
    description="Image Retrieval Using ResNet18")

collection = Collection(
    name=COLLECTION_NAME,
    schema=schema
)
```

4 – IR with Vector Databases



Insert Entities – Demo

```
transform = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor(),
])

def preprocess_image(image_path):
    img = Image.open(image_path).convert('RGB')
    processed_img = transform(img)
    return processed_img

def extract_feature(processed_image):
    input = processed_image.unsqueeze(0).to(device)
    with torch.no_grad():
        prediction = resnet18_model(input)
    return prediction.squeeze().cpu().tolist()

# extract feature
image_ids = sorted([
    int(image_name.split(".")[0]) for image_name in os.listdir(image_folder)
])
image_embeddings = []
for file_name in tqdm(image_ids):
    file_name = str(file_name) + ".jpg"
    image_path = os.path.join(image_folder, file_name)
    processed_image = preprocess_image(image_path)
    processed_image = extract_feature(processed_image)
    image_embeddings.append(processed_image)
```

4 – IR with Vector Databases



Indexing – Demo

```
collection.num_entities
```

```
9908
```

```
index_params = {  
    "index_type": "IVF_FLAT",  
    "metric_type": "L2",  
    "params": {}  
}  
collection.create_index(  
    field_name=image_embedding.name,  
    index_params=index_params  
)
```

```
Status(code=0, message=)
```

```
collection.drop_index()
```

```
collection.has_index()
```

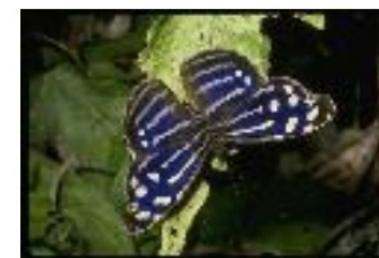
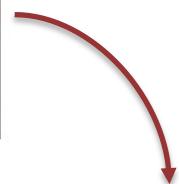
```
True
```

4 – IR with Vector Databases



Searching – Demo

```
# search
search_params = {
    "metric_type": "L2",
    "params": {"level": 2}
}
def search_images(image_path, topk=5):
    processed_image = preprocess_image(image_path)
    processed_image = extract_feature(processed_image)
    results = collection.search(
        [processed_image],
        anns_field=image_embedding.name,
        param=search_params,
        limit=topk,
        guarantee_timestamp=1
    )
    return results[0]
```



Thanks!

Any questions?