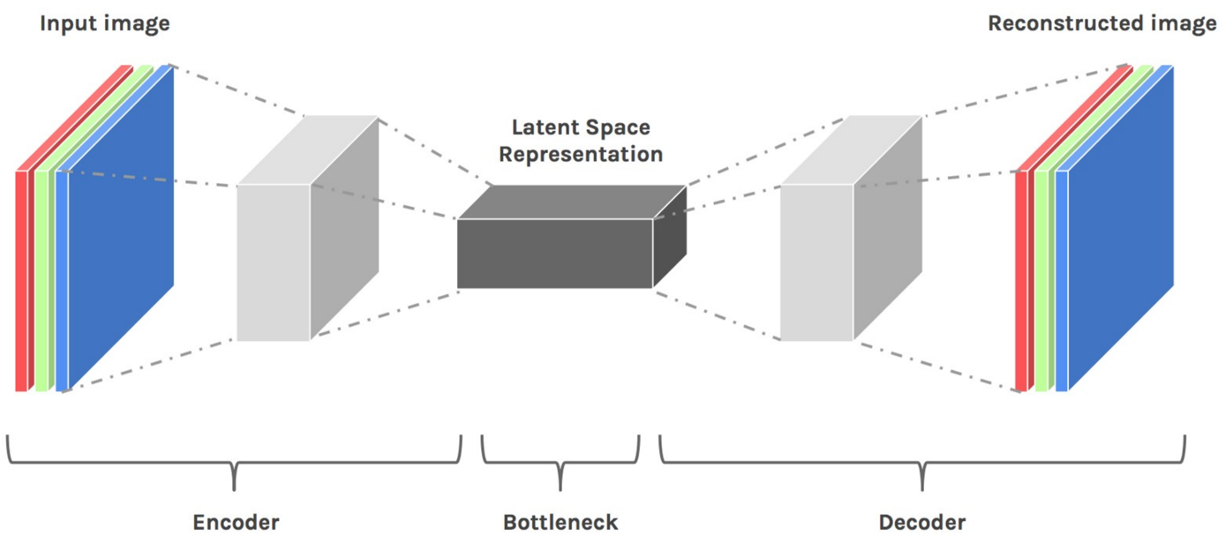
```
from google.colab import files
files.upload()

! chmod 600 kaggle.json

! kaggle datasets download -d theaayushbajaj/cbir-dataset --unzip

# کتابخانه اصلی مورد نیاز برای اجرای پروژه
!pip install barbar torchsummary

!pip install barbar

from sklearn.model_selection import train_test_split
from torch.utils.data.dataset import Dataset
from torch.utils.data import DataLoader
from torchvision import transforms
from torchsummary import summary
from pathlib import Path
from barbar import Bar
from tqdm import tqdm
from PIL import Image
from torch import nn

%matplotlib inline

import pandas as pd # پردازش داده های درون فایل CSV I/O (e.g.
pd.read_csv)
import numpy as np # برای استفاده از جبر خطی
import matplotlib.pyplot as plt
import torchvision
import pickle
import time
import copy
import scipy
import torch
import cv2
import os
import gc

RANDOMSTATE = 0

# از مدل اموزش سرعت سازی بهینه برای cuda از نبود اگر میکنیم استفاده cpu
device = torch.device('cuda:0' if torch.cuda.is_available() else
'cpu')
print(device)

cpu

# آماده سازی DataFrame
datasetPath = Path('/content/dataset/')
```

```python
df = pd.DataFrame()
df['image'] = [f for f in os.listdir(datasetPath) if
os.path.isfile(os.path.join(datasetPath, f))]
df['image'] = '/content/dataset/' + df['image'].astype(str)
df.head()

class CBIRDataset(Dataset):
    def __init__(self, dataFrame):
        self.dataFrame = dataFrame

        self.transformations = transforms.Compose([
            transforms.ToTensor(),
            transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
        ])

    def __getitem__(self, key):
        if isinstance(key, slice):
            raise NotImplementedError('slicing is not supported')

        row = self.dataFrame.iloc[key]
        image = self.transformations(Image.open(row['image']))
        return image

    def __len__(self):
        return len(self.dataFrame.index)

# تابع میانی برای پردازش داده ها از کلاس بازیابی داده ها
def prepare_data(DF):
    trainDF, validateDF = train_test_split(DF, test_size=0.15,
random_state=RANDOMSTATE)
    train_set = CBIRDataset(trainDF)
    validate_set = CBIRDataset(validateDF)

    return train_set, validate_set
```

ساختار سطح بالای یک AutoEncoder




```
class ConvAutoencoder(nn.Module):
    def __init__(self):
        super(ConvAutoencoder, self).__init__()
        self.encoder = nn.Sequential(# in- (N,3,512,512)

            nn.Conv2d(in_channels=3,
                      out_channels=16,
                      kernel_size=(3,3),
                      stride=3,
                      padding=1),  # (32,16,171,171)
            nn.ReLU(True),
            nn.MaxPool2d(2, stride=2),  # (N,16,85,85)

            nn.Conv2d(in_channels=16,
                      out_channels=8,
                      kernel_size=(3,3),
                      stride=2,
                      padding=1),  # (N,8,43,43)
            nn.ReLU(True),
            nn.MaxPool2d(2, stride=1)  # (N,8,42,42)
        )
        self.decoder = nn.Sequential(

            nn.ConvTranspose2d(in_channels = 8,
                               out_channels=16,
                               kernel_size=(3,3),
                               stride=2),  # (N,16,85,85)
            nn.ReLU(True),

            nn.ConvTranspose2d(in_channels=16,
                               out_channels=8,
                               kernel_size=(5,5),
                               stride=3,
```

```python
                                padding=1),  # (N,8,255,255)
            nn.ReLU(True),

            nn.ConvTranspose2d(in_channels=8,
                               out_channels=3,
                               kernel_size=(6,6),
                               stride=2,
                               padding=1),  # (N,3,512,512)
            nn.Tanh()
        )

    def forward(self, x):
        x = self.encoder(x)
        x = self.decoder(x)
        return x

class ConvAutoencoder_v2(nn.Module):
    def __init__(self):
        super(ConvAutoencoder_v2, self).__init__()
        self.encoder = nn.Sequential(# in- (N,3,512,512)

            nn.Conv2d(in_channels=3,
                      out_channels=64,
                      kernel_size=(3,3),
                      stride=1,
                      padding=1),
            nn.ReLU(True),
            nn.Conv2d(in_channels=64,
                      out_channels=64,
                      kernel_size=(3,3),
                      stride=1,
                      padding=1),
            nn.ReLU(True),
            nn.MaxPool2d(2, stride=2),

            nn.Conv2d(in_channels=64,
                      out_channels=128,
                      kernel_size=(3,3),
                      stride=2,
                      padding=1),
            nn.ReLU(True),
            nn.Conv2d(in_channels=128,
                      out_channels=128,
                      kernel_size=(3,3),
                      stride=1,
                      padding=0),
            nn.ReLU(True),
            nn.MaxPool2d(2, stride=2),

            nn.Conv2d(in_channels=128,
```

```
                      out_channels=256,
                      kernel_size=(3,3),
                      stride=2,
                      padding=1),
            nn.ReLU(True),
            nn.Conv2d(in_channels=256,
                      out_channels=256,
                      kernel_size=(3,3),
                      stride=1,
                      padding=1),
            nn.ReLU(True),
            nn.Conv2d(in_channels=256,
                      out_channels=256,
                      kernel_size=(3,3),
                      stride=1,
                      padding=1),
            nn.ReLU(True),
            nn.MaxPool2d(2, stride=2)
        )
        self.decoder = nn.Sequential(

            nn.ConvTranspose2d(in_channels = 256,
                               out_channels=256,
                               kernel_size=(3,3),
                               stride=1,
                              padding=1),

            nn.ConvTranspose2d(in_channels=256,
                               out_channels=256,
                               kernel_size=(3,3),
                               stride=1,
                               padding=1),
            nn.ReLU(True),

            nn.ConvTranspose2d(in_channels=256,
                               out_channels=128,
                               kernel_size=(3,3),
                               stride=2,
                               padding=0),

            nn.ConvTranspose2d(in_channels=128,
                               out_channels=64,
                               kernel_size=(3,3),
                               stride=2,
                               padding=1),
            nn.ReLU(True),
            nn.ConvTranspose2d(in_channels=64,
                               out_channels=32,
                               kernel_size=(3,3),
                               stride=2,
```

```
                                padding=1),

            nn.ConvTranspose2d(in_channels=32,
                               out_channels=32,
                               kernel_size=(3,3),
                               stride=2,
                               padding=1),
            nn.ReLU(True),

            nn.ConvTranspose2d(in_channels=32,
                               out_channels=3,
                               kernel_size=(4,4),
                               stride=2,
                               padding=2),
            nn.Tanh()
        )

    def forward(self, x):
        x = self.encoder(x)
        x = self.decoder(x)
        return x

summary(ConvAutoencoder_v2().to(device),(3,512,512))
```

Training Function

```
def load_ckpt(checkpoint_fpath, model, optimizer):

    # load check point
    checkpoint = torch.load(checkpoint_fpath)

    # initialize state_dict from checkpoint to model
    model.load_state_dict(checkpoint['model_state_dict'])

    # initialize optimizer from checkpoint to optimizer
    optimizer.load_state_dict(checkpoint['optimizer_state_dict'])

    # initialize valid_loss_min from checkpoint to valid_loss_min
    #valid_loss_min = checkpoint['valid_loss_min']

    # return model, optimizer, epoch value, min validation loss
    return model, optimizer, checkpoint['epoch']

def save_checkpoint(state, filename):
    """Save checkpoint if a new best is achieved"""
    print ("=> Saving a new best")
    torch.save(state, filename)  # save checkpoint

def train_model(model,
```

```
                criterion,
                optimizer,
                #scheduler,
                num_epochs):
    since = time.time()

    best_model_wts = copy.deepcopy(model.state_dict())
    best_loss = np.inf

    for epoch in range(num_epochs):
        print('Epoch {}/{}'.format(epoch, num_epochs))
        print('-' * 10)

        # Each epoch has a training and validation phase
        for phase in ['train', 'val']:
            if phase == 'train':
                model.train()  # Set model to training mode
            else:
                model.eval()   # Set model to evaluate mode

            running_loss = 0.0

            # Iterate over data.
            for idx,inputs in enumerate(Bar(dataloaders[phase])):
                inputs = inputs.to(device)

                # zero the parameter gradients
                optimizer.zero_grad()

                # forward
                # track history if only in train
                with torch.set_grad_enabled(phase == 'train'):
                    outputs = model(inputs)
                    loss = criterion(outputs, inputs)

                    # backward + optimize only if in training phase
                    if phase == 'train':
                        loss.backward()
                        optimizer.step()

                # statistics
                running_loss += loss.item() * inputs.size(0)
            #if phase == 'train':
            #    scheduler.step()

            epoch_loss = running_loss / dataset_sizes[phase]

            print('{} Loss: {:.4f}'.format(
                phase, epoch_loss))
```

```
            # deep copy the model
            if phase == 'val' and epoch_loss < best_loss:
                best_loss = epoch_loss
                best_model_wts = copy.deepcopy(model.state_dict())
                save_checkpoint(state={
                                    'epoch': epoch,
                                    'state_dict': model.state_dict(),
                                    'best_loss': best_loss,

'optimizer_state_dict':optimizer.state_dict()
                                },filename='ckpt_epoch_{}.pt'.format(e
poch))

        print()

    time_elapsed = time.time() - since
    print('Training complete in {:.0f}m {:.0f}s'.format(
        time_elapsed // 60, time_elapsed % 60))
    print('Best val Loss: {:4f}'.format(best_loss))

    # load best model weights
    model.load_state_dict(best_model_wts)
    return model, optimizer, epoch_loss

EPOCHS = 150
NUM_BATCHES = 32
RETRAIN = False

train_set, validate_set = prepare_data(DF=df)

dataloaders = {'train': DataLoader(train_set, batch_size=NUM_BATCHES,
shuffle=True, num_workers=1) ,
                'val':DataLoader(validate_set, batch_size=NUM_BATCHES,
num_workers=1)
                }

dataset_sizes = {'train': len(train_set),'val':len(validate_set)}

model = ConvAutoencoder_v2().to(device)

criterion = nn.MSELoss()
# Observe that all parameters are being optimized
optimizer = torch.optim.Adam(model.parameters(), lr=3e-4)
# Decay LR by a factor of 0.1 every 7 epochs
#exp_lr_scheduler = lr_scheduler.StepLR(optimizer, step_size=7,
gamma=0.1)

# If re-training is required:
# Load the old model
if RETRAIN == True:
```

```
    # load the saved checkpoint
    model, optimizer, start_epoch =
load_ckpt('/content/conv_autoencoder.pt', model, optimizer)
    print('Checkpoint Loaded')

from google.colab import drive
drive.mount('/gdrive')


model, optimizer, loss = train_model(model=model,
                    criterion=criterion,
                    optimizer=optimizer,
                    #scheduler=exp_lr_scheduler,
                    num_epochs=EPOCHS)

model.save('modelh5', save_format="h5")

# Save the Trained Model
torch.save({
            'epoch': EPOCHS,
            'model_state_dict': model.state_dict(),
            'optimizer_state_dict': optimizer.state_dict(),
            'loss': loss,
            }, 'conv_autoencoderv2_200ep.pt')
```

Inference

1. Indexing

```
transformations = transforms.Compose([
            transforms.ToTensor(),
            transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
        ])

# Load Model in Evaluation phase
model = ConvAutoencoder_v2().to(device)
model.load_state_dict(torch.load('/content/conv_autoencoderv2_200ep.pt
', map_location=device)['model_state_dict'], strict=False)

model.eval()

def get_latent_features(images, transformations):

    latent_features = np.zeros((4738,256,16,16))
    #latent_features = np.zeros((4738,8,42,42))

    for i,image in enumerate(tqdm(images)):
        tensor = transformations(Image.open(image)).to(device)
        latent_features[i] =
model.encoder(tensor.unsqueeze(0)).cpu().detach().numpy()
```

```
    del tensor
    gc.collect()
    return latent_features

images = df.image.values
latent_features = get_latent_features(images, transformations)

indexes = list(range(0, 4738))
feature_dict = dict(zip(indexes,latent_features))
index_dict = {'indexes':indexes,'features':latent_features}

# write the data dictionary to disk
with open('features.pkl', "wb") as f:
    f.write(pickle.dumps(index_dict))
```

1. Image Retrieval¶ This will be approached with two ways as discussed in the start:

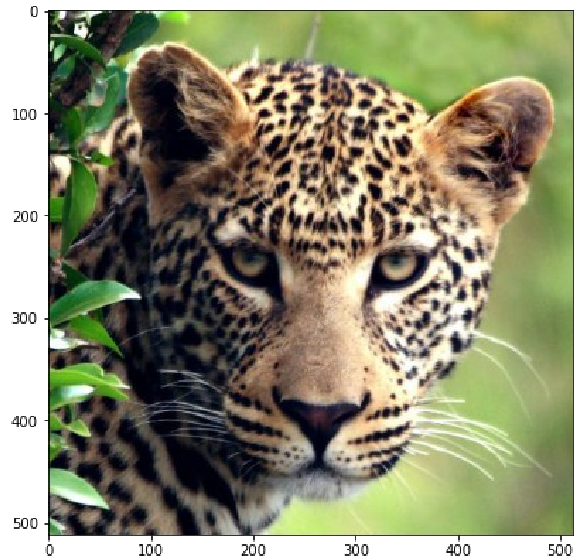
- Euclidean Search:
  - Identifying the Latent Features
  - Calculating the Euclidean Distance between them
  - Returning the closest N indexes (of images)
- Locality Sensitive Hashing
  - Create hashes of the feature vector from Encoder
  - Store it in a Hashing Table
  - Identify closest images based on hamming distance
- 2.1 Euclidean Search Method¶

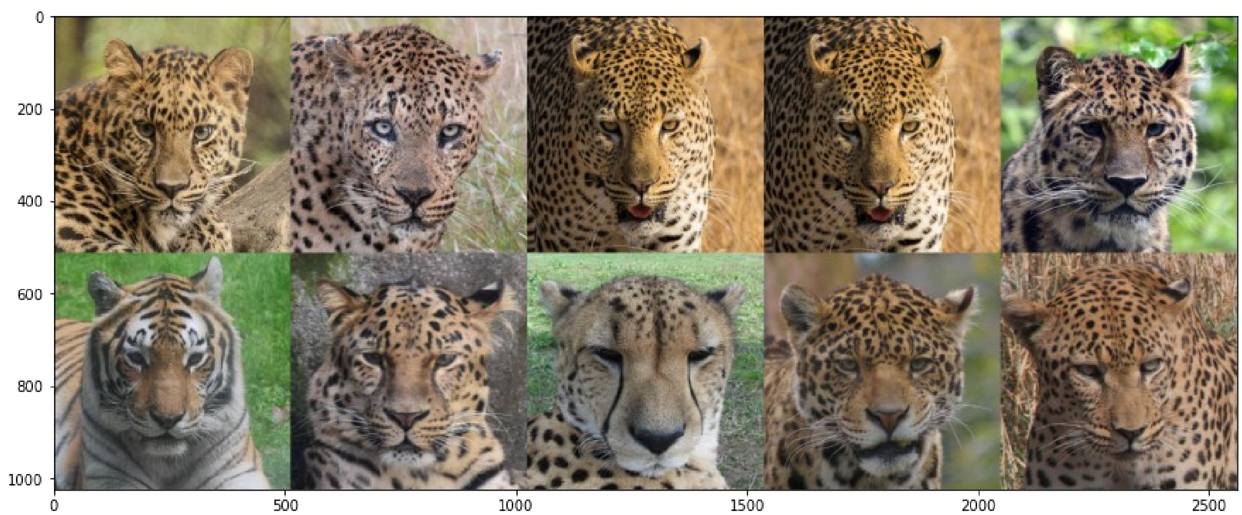
```
def euclidean(a, b):
    # compute and return the euclidean distance between two vectors
    return np.linalg.norm(a - b)

def cosine_distance(a,b):
    return scipy.spatial.distance.cosine(a, b)

def perform_search(queryFeatures, index, maxResults=64):

    results = []

    for i in range(0, len(index["features"])):
        # compute the euclidean distance between our query features
        # and the features for the current image in our index, then
        # update our results list with a 2-tuple consisting of the
        # computed distance and the index of the image
        d = euclidean(queryFeatures, index["features"][i])
        results.append((d, i))

    # sort the results and grab the top ones
    results = sorted(results)[:maxResults]
    # return the list of results
    return results
```

```
def build_montages(image_list, image_shape, montage_shape):

    if len(image_shape) != 2:
        raise Exception('image shape must be list or tuple of length 2
(rows, cols)')
    if len(montage_shape) != 2:
        raise Exception('montage shape must be list or tuple of length
2 (rows, cols)')
    image_montages = []
    # start with black canvas to draw images onto
    montage_image = np.zeros(shape=(image_shape[1] *
(montage_shape[1]), image_shape[0] * montage_shape[0], 3),
                          dtype=np.uint8)
    cursor_pos = [0, 0]
    start_new_img = False
    for img in image_list:
        if type(img).__module__ != np.__name__:
            raise Exception('input of type {} is not a valid numpy
array'.format(type(img)))
        start_new_img = False
        img = cv2.resize(img, image_shape)
        # draw image to black canvas
        montage_image[cursor_pos[1]:cursor_pos[1] + image_shape[1],
cursor_pos[0]:cursor_pos[0] + image_shape[0]] = img
        cursor_pos[0] += image_shape[0]  # increment cursor x position
        if cursor_pos[0] >= montage_shape[0] * image_shape[0]:
            cursor_pos[1] += image_shape[1]  # increment cursor y
position
            cursor_pos[0] = 0
            if cursor_pos[1] >= montage_shape[1] * image_shape[1]:
                cursor_pos = [0, 0]
                image_montages.append(montage_image)
                # reset black canvas
                montage_image = np.zeros(shape=(image_shape[1] *
(montage_shape[1]), image_shape[0] * montage_shape[0], 3),
                                      dtype=np.uint8)
                start_new_img = True
    if start_new_img is False:
        image_montages.append(montage_image)  # add unfinished montage
    return image_montages

# take the features for the current image, find all similar
# images in our dataset, and then initialize our list of result
# images
fig, ax = plt.subplots(nrows=2,figsize=(15,15))
queryIdx = 3166# Input Index for which images
MAX_RESULTS = 10


queryFeatures = latent_features[queryIdx]
```

```
results = perform_search(queryFeatures, index_dict,
maxResults=MAX_RESULTS)
imgs = []

# loop over the results
for (d, j) in results:
    img = np.array(Image.open(images[j]))
    print(j)
    imgs.append(img)

# display the query image
ax[0].imshow(np.array(Image.open(images[queryIdx])))

# build a montage from the results and display it
montage = build_montages(imgs, (512, 512), (5, 2))[0]
ax[1].imshow(montage)

testpath = Path('../input/testcbir/Test_Images')
testdf = pd.DataFrame()

testdf['image'] = [f for f in os.listdir(testpath) if
os.path.isfile(os.path.join(testpath, f))]
testdf['image'] = '../input/testcbir/Test_Images/' +
testdf['image'].astype(str)

testdf.head()

testimages = testdf.image.values
test_latent_features = get_latent_features(testimages,
transformations)

test_latent_features.shape

fig, ax = plt.subplots(nrows=2,figsize=(15,15))
MAX_RESULTS = 10
queryIdx = 12

queryFeatures = test_latent_features[queryIdx]
results = perform_search(queryFeatures, index_dict,
maxResults=MAX_RESULTS)
imgs = []

# loop over the results
for (d, j) in results:
    img = np.array(Image.open(images[j]))
    print(j)
    imgs.append(img)

# display the query image
ax[0].imshow(np.array(Image.open(testimages[queryIdx])))
```

```python
# build a montage from the results and display it
montage = build_montages(imgs, (512, 512), (5, 2))[0]
ax[1].imshow(montage)
```





2.2 LSHashing Method

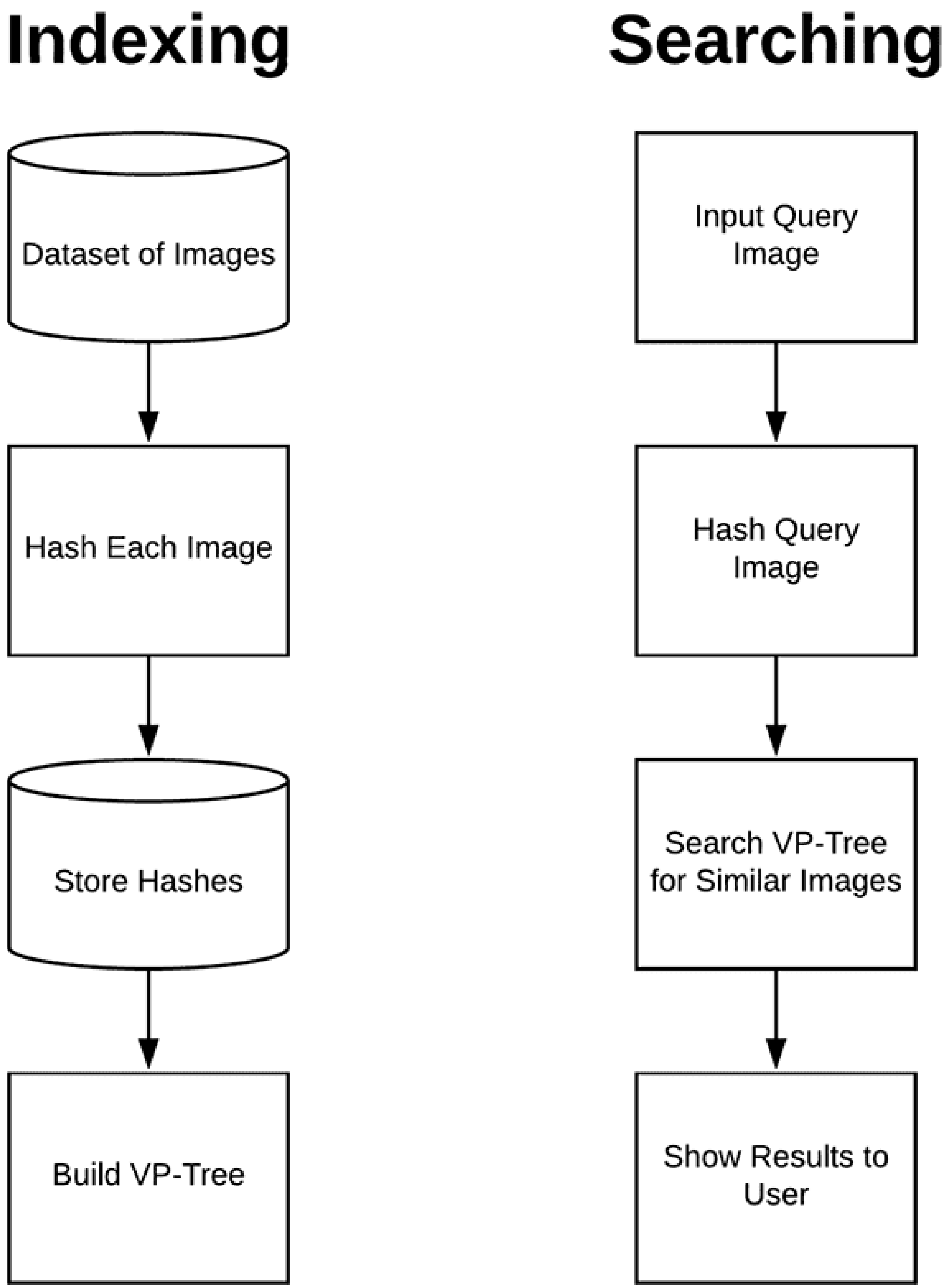
```python
!pip install lshashpy3

from lshashpy3 import LSHash

# Locality Sensitive Hashing
params
k = 12 # hash size
L = 5  # number of tables
```

```
d = 14112 # Dimension of Feature vector
lsh = LSHash(hash_size=k, input_dim=d, num_hashtables=L)

# LSH on all the images
for idx,vec in tqdm(feature_dict.items()):
    lsh.index(vec.flatten(), extra_data=idx)

# Exporting as pickle
pickle.dump(lsh, open('lsh.p', "wb"))

def get_similar_item(idx, feature_dict, lsh_variable, n_items=10):
    response =
lsh_variable.query(feature_dict[list(feature_dict.keys())
[idx]].flatten(),
                     num_results=n_items+1, distance_func='hamming')

    imgs = []
    for i in range(1, n_items+1):
        imgs.append(np.array(Image.open(images[response[i][0][1]])))
    return imgs

fig, ax = plt.subplots(nrows=2,figsize=(15,15))
queryIdx = 5

ax[0].imshow(np.array(Image.open(images[queryIdx])))

montage = build_montages(get_similar_item(queryIdx, feature_dict,
lsh,10),(512, 512), (5, 2))[0]
ax[1].imshow(montage)
```

End Notes

We started with the approach of AutoEncoders for Image Latent Features extraction followed by Image retrieval using Euclidean Distance which was an O(NlogN) approach (Time-Complexity) to Hashing which gave us an ~O(logN) approach

Another approach was to use Hashing on features obtained from SIFT, SURF, OBS and building the VP Trees ans search the images in it.


Indexing
Searching
Dataset of Images
Hash Each Image
Store Hashes
Build VP-Tree
Input Query Image
Hash Query Image
Search VP-Tree for Similar Images
Show Results to User

Clustering of Images

```
from sklearn.cluster import KMeans, MiniBatchKMeans
from scipy.spatial.distance import cdist
from sklearn.metrics import silhouette_samples, silhouette_score

import matplotlib.cm as cm
%matplotlib inline

def get_latent_features1D(images, transformations):

    latent_features1d = []

    for i,image in enumerate(tqdm(images)):
        tensor = transformations(Image.open(image)).to(device)

latent_features1d.append(model.encoder(tensor.unsqueeze(0)).cpu().deta
ch().numpy().flatten())

    del tensor
    gc.collect()
    return latent_features1d

images = df.image.values
latent_features1d = get_latent_features1D(images, transformations)

latent_features1d = np.array(latent_features1d)

distortions = []
inertias = []
mapping1 = {}
mapping2 = {}
K = range(4,10)

for k in tqdm(K):
    #Building and fitting the model
    kmeanModel = KMeans(n_clusters=k).fit(latent_features1d)

    distortions.append(sum(np.min(cdist(latent_features1d,
kmeanModel.cluster_centers_,
                      'euclidean'),axis=1)) /
latent_features1d.shape[0])
    inertias.append(kmeanModel.inertia_)

    mapping1[k] = sum(np.min(cdist(latent_features1d,
kmeanModel.cluster_centers_,
                 'euclidean'),axis=1)) / latent_features1d.shape[0]
    mapping2[k] = kmeanModel.inertia_

plt.plot(K, distortions, 'bx-')
plt.xlabel('Values of K')
```

```
plt.ylabel('Distortion')
plt.title('The Elbow Method using Distortion')
plt.show()

X = np.array(latent_features1d)
K = range(3,10)

for n_clusters in tqdm(K):
    # Create a subplot with 1 row and 2 columns
    fig, (ax1, ax2) = plt.subplots(1, 2)
    fig.set_size_inches(18, 7)

    # The 1st subplot is the silhouette plot
    # The silhouette coefficient can range from -1, 1 but in this
example all
    # lie within [-0.1, 1]
    ax1.set_xlim([-0.1, 1])
    # The (n_clusters+1)*10 is for inserting blank space between
silhouette
    # plots of individual clusters, to demarcate them clearly.
    ax1.set_ylim([0, len(X) + (n_clusters + 1) * 10])

    # Initialize the clusterer with n_clusters value and a random
generator
    # seed of 10 for reproducibility.
    clusterer = KMeans(n_clusters=n_clusters,
random_state=RANDOMSTATE)
    cluster_labels = clusterer.fit_predict(X)

    # The silhouette_score gives the average value for all the
samples.
    # This gives a perspective into the density and separation of the
formed
    # clusters
    silhouette_avg = silhouette_score(X, cluster_labels)
    print("For n_clusters =", n_clusters,
          "The average silhouette_score is :", silhouette_avg)

    # Compute the silhouette scores for each sample
    sample_silhouette_values = silhouette_samples(X, cluster_labels)

    y_lower = 10
    for i in range(n_clusters):
        # Aggregate the silhouette scores for samples belonging to
        # cluster i, and sort them
        ith_cluster_silhouette_values = \
            sample_silhouette_values[cluster_labels == i]

        ith_cluster_silhouette_values.sort()
```

```
        size_cluster_i = ith_cluster_silhouette_values.shape[0]
        y_upper = y_lower + size_cluster_i

        color = cm.nipy_spectral(float(i) / n_clusters)
        ax1.fill_betweenx(np.arange(y_lower, y_upper),
                          0, ith_cluster_silhouette_values,
                          facecolor=color, edgecolor=color, alpha=0.7)

        # Label the silhouette plots with their cluster numbers at the
middle
        ax1.text(-0.05, y_lower + 0.5 * size_cluster_i, str(i))

        # Compute the new y_lower for next plot
        y_lower = y_upper + 10  # 10 for the 0 samples

    ax1.set_title("The silhouette plot for the various clusters.")
    ax1.set_xlabel("The silhouette coefficient values")
    ax1.set_ylabel("Cluster label")

    # The vertical line for average silhouette score of all the values
    ax1.axvline(x=silhouette_avg, color="red", linestyle="--")

    ax1.set_yticks([])  # Clear the yaxis labels / ticks
    ax1.set_xticks([-0.1, 0, 0.2, 0.4, 0.6, 0.8, 1])

    # 2nd Plot showing the actual clusters formed
    colors = cm.nipy_spectral(cluster_labels.astype(float) /
n_clusters)
    ax2.scatter(X[:, 0], X[:, 1], marker='.', s=30, lw=0, alpha=0.7,
                c=colors, edgecolor='k')

    # Labeling the clusters
    centers = clusterer.cluster_centers_
    # Draw white circles at cluster centers
    ax2.scatter(centers[:, 0], centers[:, 1], marker='o',
                c="white", alpha=1, s=200, edgecolor='k')

    for i, c in enumerate(centers):
        ax2.scatter(c[0], c[1], marker='$%d$' % i, alpha=1,
                    s=50, edgecolor='k')

    ax2.set_title("The visualization of the clustered data.")
    ax2.set_xlabel("Feature space for the 1st feature")
    ax2.set_ylabel("Feature space for the 2nd feature")

    plt.suptitle(("Silhouette analysis for KMeans clustering on sample
data "
                  "with n_clusters = %d" % n_clusters),
                 fontsize=14, fontweight='bold')
```

```
plt.show()
```

- The Silhouette score isn't significant for any cluster since its close to 0 for every k, that translates to less differentiability for a point to belong to a particular cluster.

- GMM can help in this case because animals share a lot of similar traits with each other in terms of appearance but we have to get the bottleneck case since an animal can only belong to one cluster, so kmeans will be the way to go but a different feature/keypoint detection might help identify right number of clusters.

Using SIFT/SURF/ORB technique

```
def build_dictionary(xfeatures2d, images, n_clusters):
    #print('Computing descriptors..')
    desc_list = []

    for image_path in images:
        image = cv2.imread(image_path)
        gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
        kp, dsc = xfeatures2d.detectAndCompute(gray, None)
        desc_list.extend(dsc)

    desc = np.array(desc_list)
    #print('Creating BoW dictionary using K-Means clustering with
k={}..'.format(n_clusters))
    dictionary = MiniBatchKMeans(n_clusters=n_clusters,
batch_size=100, verbose=0)
    dictionary.fit(desc)

    distortion = sum(np.min(cdist(desc, dictionary.cluster_centers_,
                      'euclidean'),axis=1)) / desc.shape[0]

    return distortion

orb = cv2.ORB_create()
images = df.image.values
K = range(4,10)
distortions = []

for k in tqdm(K):
    distortions.append(build_dictionary(orb, images, n_clusters=k))

plt.plot(K, distortions, 'bx-')
plt.xlabel('Values of K')
```

```
plt.ylabel('Distortion')
plt.title('The Elbow Method using Distortion')
plt.show()
```

- The ORB technique tells us there are 6/7 major clusters that are persistent in the data