4.0 Data Cleaning and Collection

With our ResNet-50 model constructed. Data are required to train our model so that we can classify our pictures into "Dog", "Cat", or neither. We will work through by first sourcing the data, then we would rescale it, and finally, convert it into a suitable `DataLoader` class.

4.1 Data Sourcing

Kaggle is a great site to find datasets and even test your model on them to compare it to others. We will use this Kaggle dataset for dogs and cats classification.

Let's export the kaggle dataset into `data/raw`

```python
from zipfile import ZipFile
import os
import shutil
import matplotlib.pyplot as plt
import random
import cv2
import json
from torch.utils.data import Dataset, DataLoader
import torch
```

```
!kaggle datasets download -d bhavikjikadara/dog-and-cat-classification-dataset -p ../data/raw
```

```
Dataset URL: https://www.kaggle.com/datasets/bhavikjikadara/dog-and-cat-
classification-dataset
License(s): apache-2.0
dog-and-cat-classification-dataset.zip: Skipping, found more recently modified
local copy (use --force to force download)
```

With the dataset downloaded, then we unzip it.

```python
raw_folder = '../data/raw'

def extract_data(folder):
    zip_file_path = os.path.join(folder, 'dog-and-cat-classification-dataset.zip')
    extract_to_path = folder

    with ZipFile(zip_file_path, 'r') as zip_ref:
        zip_ref.extractall(extract_to_path)

    # Move files from PetImages to the raw_folder
    source_dir = os.path.join(folder, 'PetImages')
    for item in os.listdir(source_dir):
        source_item_path = os.path.join(source_dir, item)
        destination_item_path = os.path.join(folder, item)
        shutil.move(source_item_path, destination_item_path)

    os.rmdir(source_dir)

extract_data(raw_folder)
```

```
---------------------------------------------------------------------------
Error                                     Traceback (most recent call last)
Cell In[3], line 19
     15         shutil.move(source_item_path, destination_item_path)
     17     os.rmdir(source_dir)
---> 19 extract_data(raw_folder)

Cell In[3], line 15, in extract_data(folder)
```

```
     13     source_item_path = os.path.join(source_dir, item)
     14     destination_item_path = os.path.join(folder, item)
---> 15     shutil.move(source_item_path, destination_item_path)
     17 os.rmdir(source_dir)

File /opt/miniconda3/envs/dog_and_cat_classifier_cnn_from_scratch/lib/python3.10/shutil.py:814, in
move(src, dst, copy_function)
    811     real_dst = os.path.join(dst, _basename(src))
    813     if os.path.exists(real_dst):
--> 814         raise Error("Destination path '%s' already exists" % real_dst)
    815 try:
    816     os.rename(src, real_dst)

Error: Destination path '../data/raw/Cat/Cat' already exists
```

With the image dataset exported to our raw folder. Let's load them into our notebook.

```python
def load_raw_images():
    raw_cat_images = []
    raw_dog_images = []

    for filename in os.listdir(raw_folder + '/Cat'):
        img = cv2.imread(raw_folder + '/Cat/' + filename)
        if img is None:
            continue
        img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
        raw_cat_images.append(img)

    for filename in os.listdir(raw_folder + '/Dog'):
        img = cv2.imread(raw_folder + '/Dog/' + filename)
        if img is None:
            continue
        img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)  # BGR -> RGB
        raw_dog_images.append(img)

    return (raw_cat_images, raw_dog_images)
```

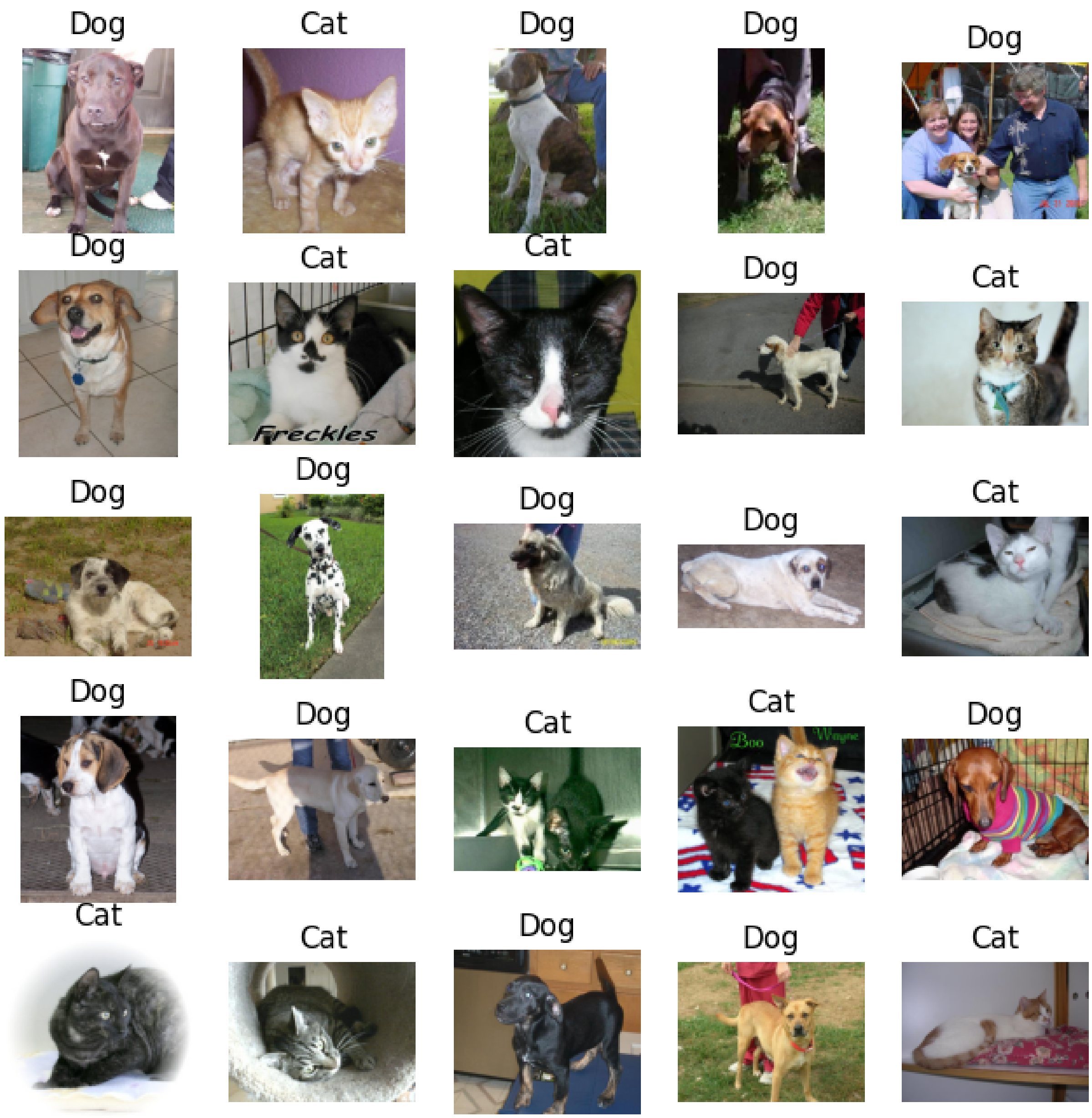
```python
raw_cat_images, raw_dog_images = load_raw_images()
```

```
Corrupt JPEG data: 214 extraneous bytes before marker 0xd9
Corrupt JPEG data: 1153 extraneous bytes before marker 0xd9
Corrupt JPEG data: 99 extraneous bytes before marker 0xd9
Corrupt JPEG data: 128 extraneous bytes before marker 0xd9
Corrupt JPEG data: 239 extraneous bytes before marker 0xd9
Corrupt JPEG data: 65 extraneous bytes before marker 0xd9
Corrupt JPEG data: 226 extraneous bytes before marker 0xd9
Corrupt JPEG data: 162 extraneous bytes before marker 0xd9
Warning: unknown JFIF revision number 0.00
Corrupt JPEG data: 2230 extraneous bytes before marker 0xd9
Corrupt JPEG data: 254 extraneous bytes before marker 0xd9
Corrupt JPEG data: 399 extraneous bytes before marker 0xd9
Corrupt JPEG data: 1403 extraneous bytes before marker 0xd9
```

With the raw images loaded, let's build a function to visualize it. It'll be super cute!

```python
def visualize_raw_pet_images(cat_images, dog_images):
    _, ax = plt.subplots(5, 5, figsize=(8, 8))
    for i in range(5):
        for j in range(5):
            is_cat = random.randint(0, 1)
```

```
            cat_images_len = len(cat_images)
            dog_images_len = len(dog_images)

            label = "Cat" if is_cat else "Dog"

            ax[i, j].imshow(cat_images[random.randint(0, cat_images_len - 1)] if is_cat
                            else dog_images[random.randint(0, dog_images_len - 1)])
            ax[i, j].axis("off")
            ax[i, j].set_title(label)
visualize_raw_pet_images(raw_cat_images, raw_dog_images)
```



Cute huh! We now move to processing it.

4.2 Data Processing

The standard de facto image size of ML/AI is 224x224 (even in our ResNet paper!). We should resize everything to 224x224, and then save it to `data/processed`. Here we implement an image processing function

```
def process_image (img, filename, dimension=(224, 224)):
    resized_image = cv2.resize(img, dimension, cv2.INTER_AREA)
```

```
    resized_image = cv2.cvtColor(resized_image, cv2.COLOR_RGB2BGR)

    cv2.imwrite(filename, resized_image)

def process_raw_images(images, label, folderpath, counter=0, dimension=(224, 224)):
    for i, img in enumerate(images):
        process_image(img, folderpath + f"/{counter}-{label}.jpg", dimension)
        counter += 1
    return counter
def save_metadata(metadata, outpath="../data/processed/metadata.json"):
    with open(outpath, "w") as f:
        json.dump(metadata, f, indent=4)
```

```
total_cats = process_raw_images(raw_cat_images, "cat", "../data/processed")
total_imgs = process_raw_images(raw_dog_images, "dog", "../data/processed", total_cats)

metadata = {
    "num_images": total_imgs,
    "dimension": [224, 224],
    "format": "jpg"
}

save_metadata(metadata)
```

4.3 Cat and Dog Dataset

Let's implement a `Dataset` and `DataLoader` class to get images from our `data/processed` folder.

When feeding the inputs to our model's training, we would like normalize our images RGB's value, ranging from 0-255, to a smaller value. We can simply just divide each RGB values by 255, transforming each values to somewhere in between 0 and 1. This crucial normalization prevents our model from numerical instability and in fact would help it converge.

Additionally, we would further normalize the images using PyTorch's normalization of means $[0.485, 0.456, 0.406]$ and std $[0.229, 0.224, 0.225]$, whose values are derived from millions of images from ImageNet.

When applying these transformations for our dataset, we must remember to also use it during the inference phase, the phase where test our model with inputs not from the dataset. Otherwise, we would not yield the correct results, which I found out the hard way as of the time of writing this sentence.

We will add some transformation to both the training dataset to add randomness to our data and prevent our model from overfitting. This is also known as **Data Augmentation**.

The transformation includes

- Rotations
- Horizontal flips
- Color jitters
- Random affine transformations
- Random grayscale filters

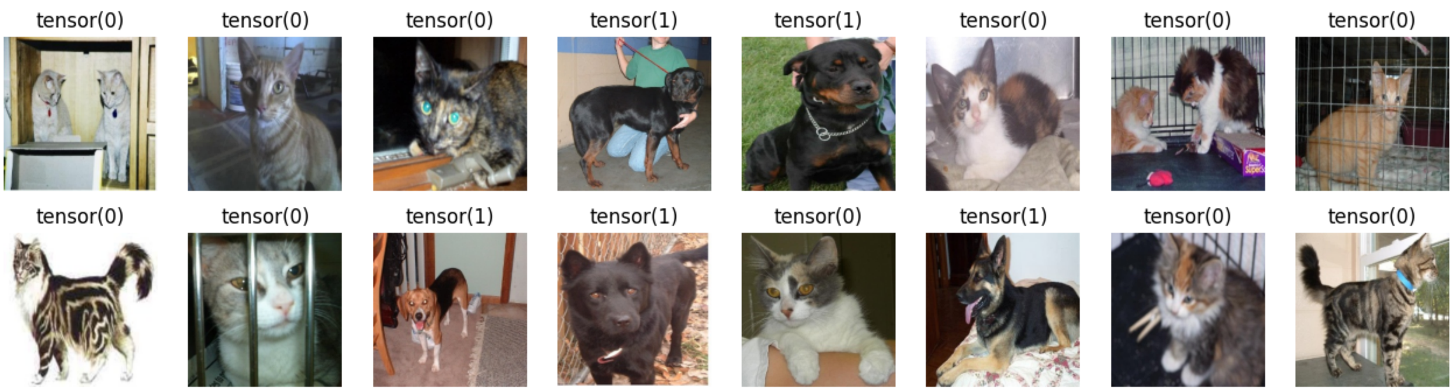
```
from torchvision import transforms
class CatAndDogDataset(Dataset):
    def __init__(self, img_dir, transform=None, target_transform=None, train=True):
        with open(img_dir + "/metadata.json", "r") as f:
            metadata = json.load(f)
        self.metadata = metadata
        self.img_dir = img_dir
        self.img_files = sorted([f for f in os.listdir(img_dir) if f.endswith(".jpg")],
                                key=lambda x: int(x.split('-')[0])) # Sort files by their numerical ID
```

```python
        self.train = train
        self.transform = transform
        self.target_transform = target_transform
        self.class_map = {"cat": 0, "dog": 1}

        # If no transform provided, use appropriate defaults
        if self.transform is None:
            self.transform = self.get_default_transforms(train)

    def get_default_transforms(self, train=True):
        if train:
            # Training transforms with heavy augmentation
            return transforms.Compose([
                transforms.Lambda(lambda x: x / 255.0),  # Normalize to [0, 1]
                transforms.RandomHorizontalFlip(p=0.5),
                transforms.RandomRotation(degrees=15),
                transforms.ColorJitter(brightness=0.2, contrast=0.2, saturation=0.2, hue=0.1),
                transforms.RandomAffine(degrees=0, translate=(0.1, 0.1), scale=(0.9, 1.1)),
                transforms.RandomGrayscale(p=0.1),
                transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]),
            ])
        else:
            # Validation transforms (only normalization)
            return transforms.Compose([
                transforms.Lambda(lambda x: x / 255.0),  # Normalize to [0, 1]
                transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]),
            ])

    def __len__(self):
        return self.metadata['num_images']

    def __getitem__(self, idx):
        img_name = self.img_files[idx]
        img_path = os.path.join(self.img_dir, img_name)

        # load image with cv2
        image = cv2.imread(img_path)
        image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)  # OpenCV loads BGR

        image = torch.from_numpy(image).permute(2, 0, 1).float()

        # parse label from filename ("1-cat.jpg" -> "cat")
        label_str = img_name.split("-")[1].split(".")[0]  # "cat" or "dog"
        label = self.class_map[label_str]

        if self.transform:
            image = self.transform(image)
        if self.target_transform:
            label = self.target_transform(label)

        return image, label
```

Let's use a `DataLoader` to retrieve our processed data now, all the images should be 224x224, and it should come with its label automatically.

```python
def visualize_pet_images(images, labels):
    _, ax = plt.subplots(2, 8, figsize=(16, 4))
    img_idx = 0
    for i in range(2):
```

```
        for j in range(8):
            ax[i, j].imshow(images[img_idx])
            ax[i, j].axis("off")
            ax[i, j].set_title(labels[img_idx])
            img_idx += 1

dataset = CatAndDogDataset("../data/processed")
dataloader = DataLoader(dataset, batch_size=16, shuffle=True)
images, labels = next(iter(dataloader))
visualize_pet_images(images, labels)
```



We are finally done. Here we go to the most exciting part!