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Multi-Task Deep Learning with Pytorch

Alessandro Lamberti · Follow
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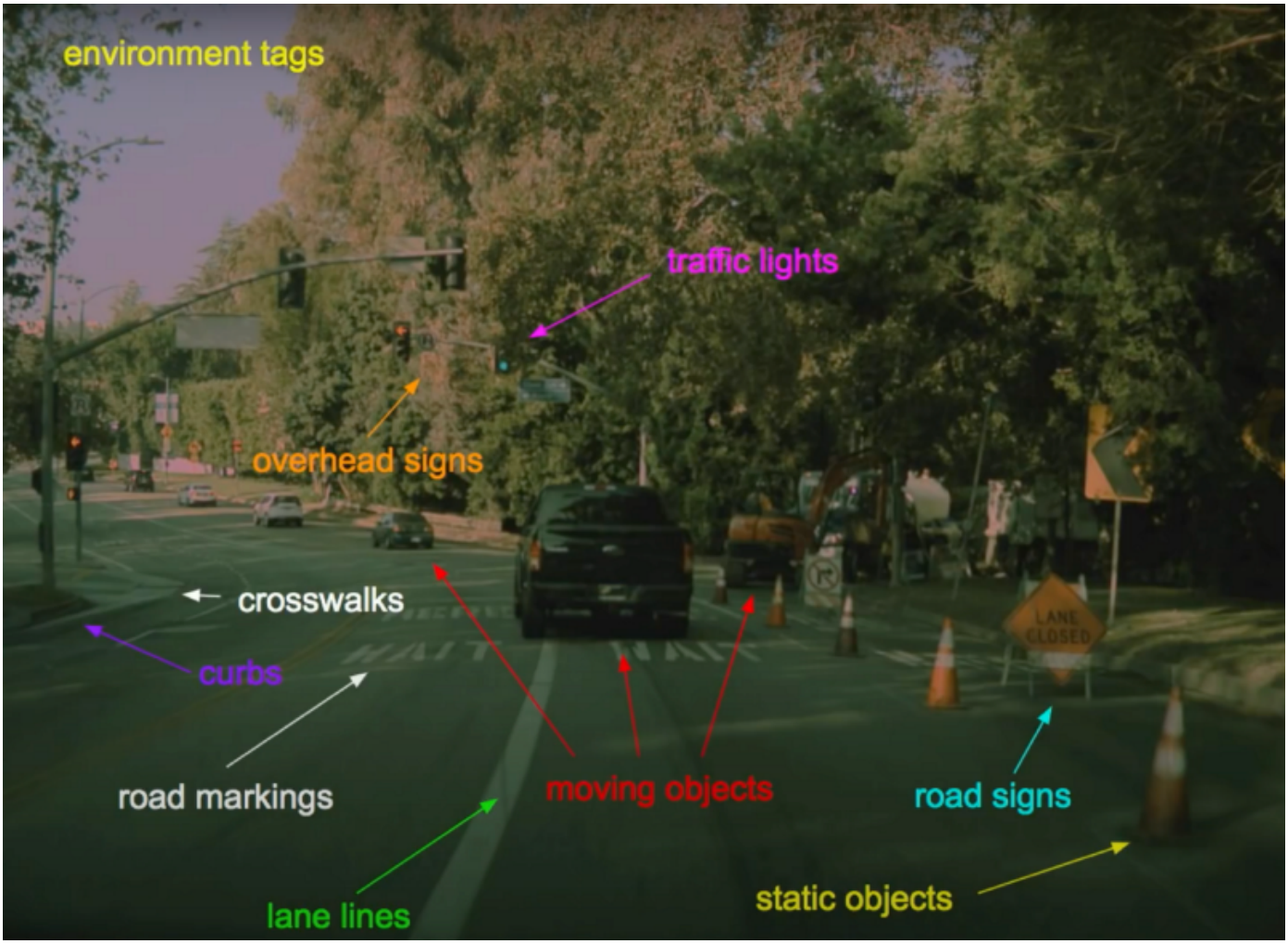

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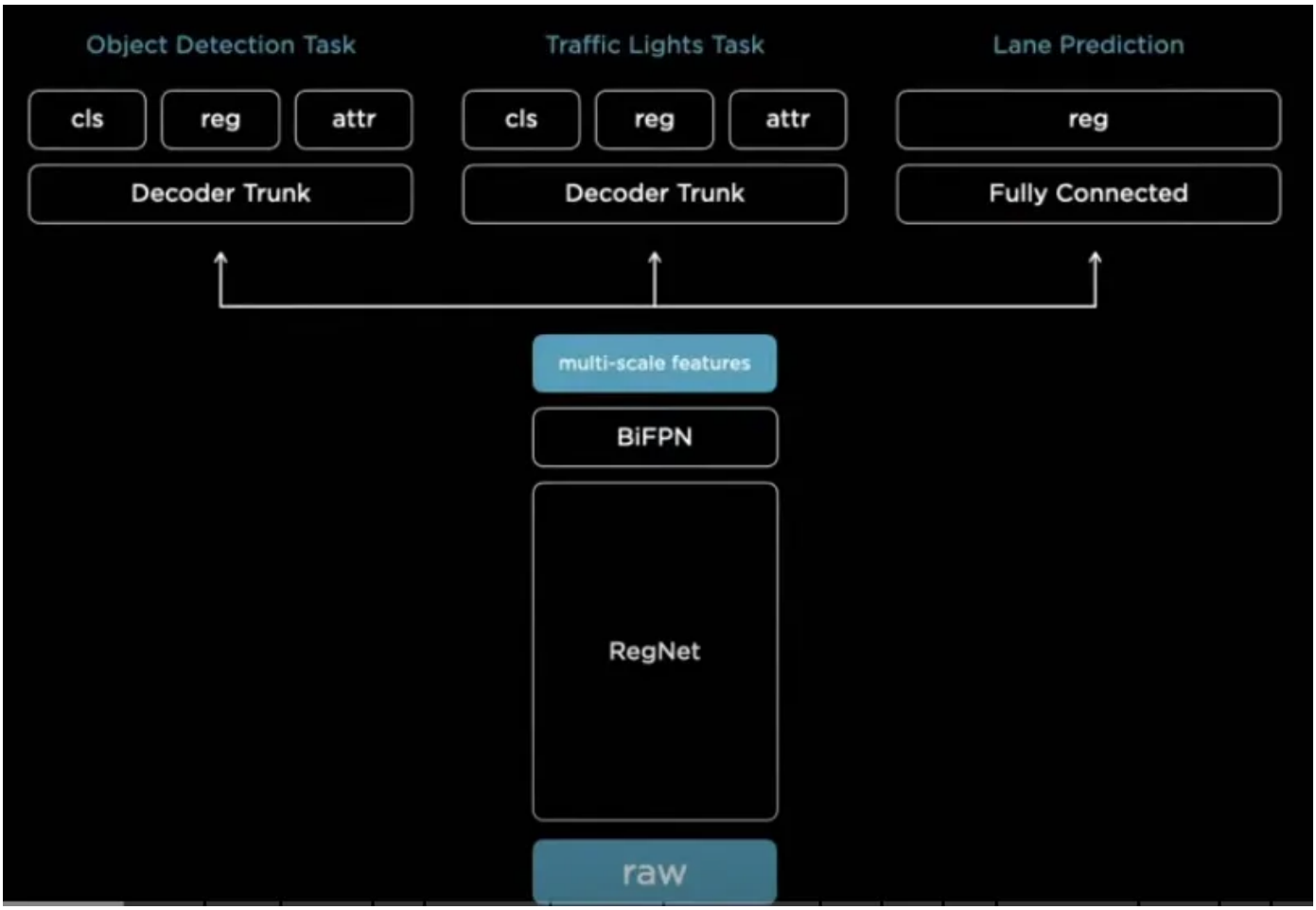
In Machine Learning, we typically aim to optimize for a single metric, for a single task. Multi-task learning (MTL) has led to successes in many applications of machine learning, from natural language processing and speech recognition to computer vision and drug discovery.

The most famous case of MTL is probably Tesla's autopilot.
You already know Tesla's goal is to solve a multitude of tasks like object detection, depth estimation, 3D reconstruction, video analysis, tracking, and more, and you might think they're implementing 10+ Deep Learning models that work together, but that's not the case.

Introduction to HydraNet

Tesla's main idea is fairly simple: one body, several heads. Leveraging a single model to solve multiple tasks.



Source

On a superficial scale, you can see images being extracted by feature extraction models. These images are then combined into a "super image", which are then combined again with previous super images, bringing time into the equation. That's usually done by using 3D CNNs, RNNs, Transformers, etc.

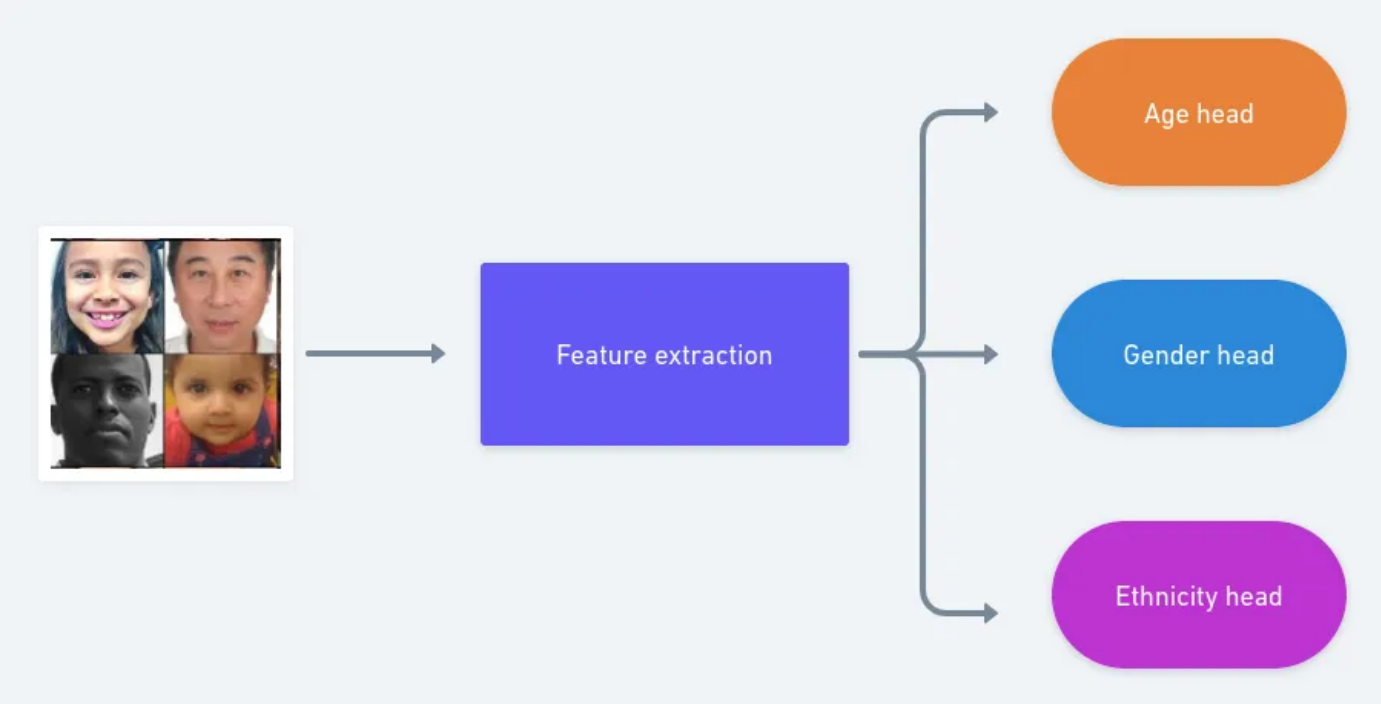
The output is finally split into heads, each one responsible for a specific case, and since they're independent from one another, they can also be fine-tuned individually!

I highly recommend checking out Tesla's keynote.

Multi-task learning project

In this article, we'll see how to implement a simpler HydraNet in Pytorch.
We'll be using the UTK Face dataset, a classification dataset with 3 labels (gender, race, age).

Our HydraNet will have three independent heads, and they'll all be different, because the prediction of age is a regression task, the race prediction is a multi-class classification problem, and the prediction of the gender is a binary classification task.



By the author

Data

We'll start by defining our custom Pytorch Dataset and DataLoader.

Keeping in mind that the name of the images give us the labels, e.g
UTKFace/30_0_3_20170117145159065.jpg.chip.jpg
where

- 30 is the age
- 0 is the gender (0: male, 1: female)
- 3 is the ethnicity (0:White, 1:Black, 2:Asian, 3:Indian, 4:Other)

a custom Dataset might look like this:

```python
class UTKFace(Dataset):
    def __init__(self, image_paths):
        self.transform = transforms.Compose([transforms.Resize((32, 32)), transforms.ToTensor(), t
        self.image_paths = image_paths
        self.images = []
        self.ages = []
        self.genders = []
        self.races = []

        for path in image_paths:
            filename = path[8:].split("_")

            if len(filename)==4:
                self.images.append(path)
                self.ages.append(int(filename[0]))
                self.genders.append(int(filename[1]))
                self.races.append(int(filename[2]))

    def __len__(self):
         return len(self.images)

    def __getitem__(self, index):
            img = Image.open(self.images[index]).convert('RGB')
            img = self.transform(img)

            age = self.ages[index]
            gender = self.genders[index]
            eth = self.races[index]

            sample = {'image':img, 'age': age, 'gender': gender, 'ethnicity':eth}

            return sample
```

dataset_utk.py hosted with ❤ by GitHub view raw

I'm assuming you know your way around Pytorch, but:

- The __init__ method is responsible for the various transformations and the extraction of the labels from the images paths.
- The __get_item__ will do what we defined in the first method: it'll load an image, apply the necessary transformation, get the labels, and it'll return an element of

the dataset.

At this point, we can easily define our data loaders:

```
train_dataloader = DataLoader(UTKFace(train_dataset), shuffle=True, batch_size=BATCH_SIZE)
val_dataloader = DataLoader(UTKFace(valid_dataset), shuffle=False, batch_size=BATCH_SIZE)
```

dataloaders.py hosted with ❤ by GitHub view raw

Model

Now that our data is ready, we can start thinking about the model itself.
We'll be using a pre-trained model as backbone, and we'll build 3 heads, as said before.

At the end, we'll have fc1, fc2 and fc3 for the age's, gender's and ethnicity's head respectively.

```python
class HydraNet(nn.Module):
    def __init__(self):
        super().__init__()
        self.net = models.resnet18(pretrained=True)
        self.n_features = self.net.fc.in_features
        self.net.fc = nn.Identity()

        self.net.fc1 = nn.Sequential(OrderedDict(
            [('linear', nn.Linear(self.n_features,self.n_features)),
            ('relu1', nn.ReLU()),
            ('final', nn.Linear(self.n_features, 1))]))

        self.net.fc2 = nn.Sequential(OrderedDict(
            [('linear', nn.Linear(self.n_features,self.n_features)),
            ('relu1', nn.ReLU()),
            ('final', nn.Linear(self.n_features, 5))]))

    def forward(self, x):
        age_head = self.net.fc1(self.net(x))
        gender_head = self.net.fc2(self.net(x))
        ethnicity_head = self.net.fc3(self.net(x))
        return age_head, gender_head, ethnicity_head
```

hydranet.py hosted with ❤ by GitHub view raw

As you can notice, the forward method will return every head independently.

Loss

You'll still be trying to minimize a loss, although with a catch: this loss will be the combination of more losses!

The simplest thing one could do is to naively sum the individual losses

$$L = L1 + L2 + L3$$

where:

- L1: the loss associated with the age, like a L1 loss (the mean absolute error), since it's a regression loss.
- L2: the one associated with the ethnicity, like a cross-entropy since it's a multi-class classification loss.
- L3: finally, the one associated with the gender, like binary cross-entropy.

Choosing the approach for the loss function can be tricky, because we're trying to optimize different losses, on different scales.
For example, a loss of 20 years in the age head becomes 400 if we decide to use the mean squared error, compared to the loss of gender which is 1. This will ensure our loss will only be affected by the age, hence we try to compare them on the same scale by using MAE.

Training loop

We'll start by instantiating our HydraNet, the optimizer, and the losses

```
model = HydraNet().to(device=device)

ethnicity_loss = nn.CrossEntropyLoss()
gender_loss = nn.BCELoss()
age_loss = nn.L1Loss()
sig = nn.Sigmoid()

optimizer = torch.optim.SGD(model.parameters(), lr=1e-4, momentum=0.09)
```

trainloop1.py hosted with ❤ by GitHub view raw

And the loop itself

```python
for epoch in range(n_epochs):
    model.train()
    total_training_loss = 0

     for i, data in enumerate(tqdm(train_dataloader)):
         inputs = data["image"].to(device=device)

         age_label = data["age"].to(device=device)
         gender_label = data["gender"].to(device=device)
         eth_label = data["ethnicity"].to(device=device)

         optimizer.zero_grad()
         age_output, gender_output, eth_output = model(inputs)

         loss_1 = ethnicity_loss(eth_output, eth_label)
         loss_2 = gender_loss(sig(gender_output), gender_label.unsqueeze(1).float())
         loss_3 = age_loss(age_output, age_label.unsqueeze(1).float())

         loss = loss_1 + loss_2 + loss_3
         loss.backward()
         optimizer.step()

         total_training_loss += loss
```

trainloop2.py hosted with ❤ by GitHub view raw

That's it! The same process applies for validation as well.

Stay tuned for more advanced things on multi-task learning!

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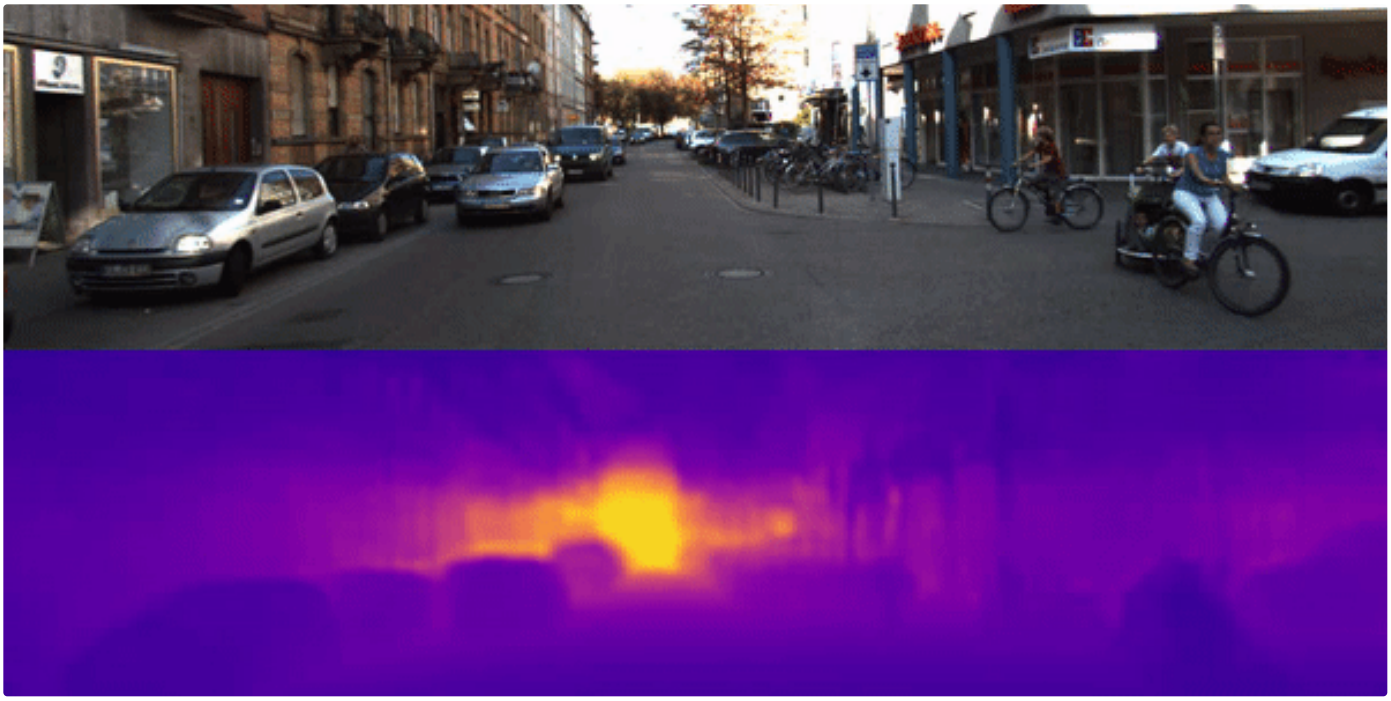

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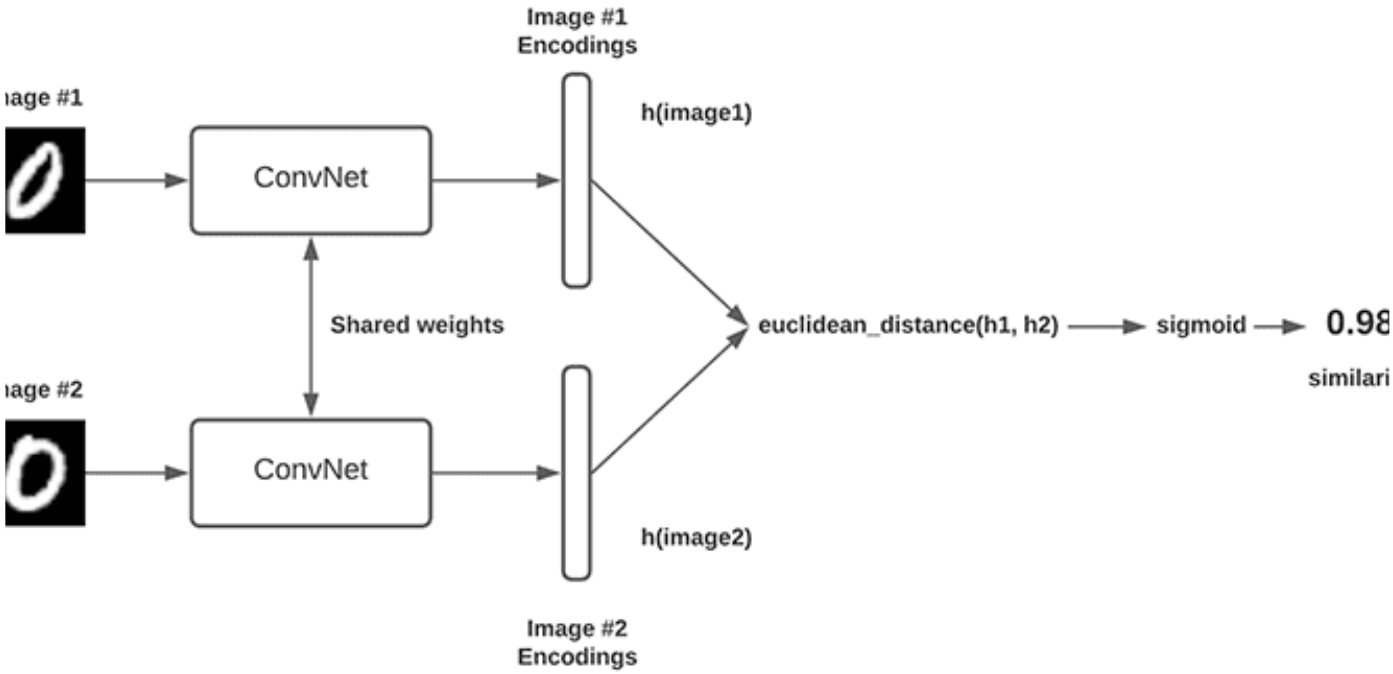

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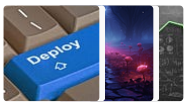

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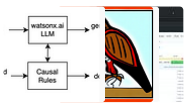

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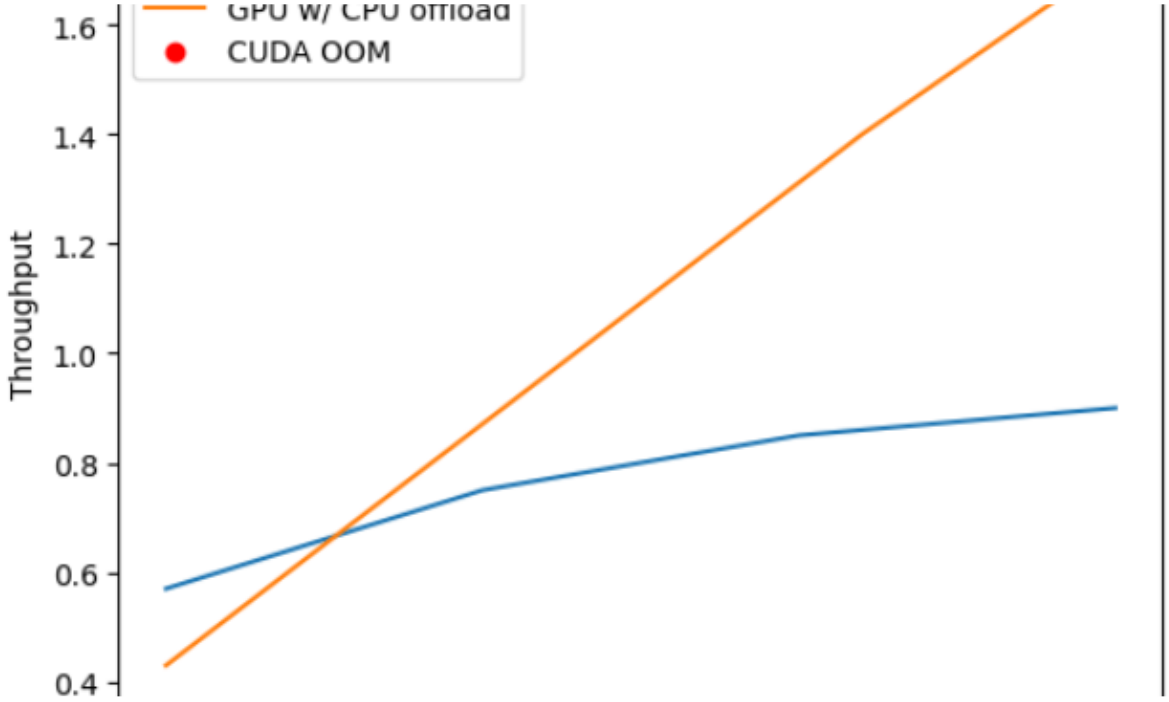

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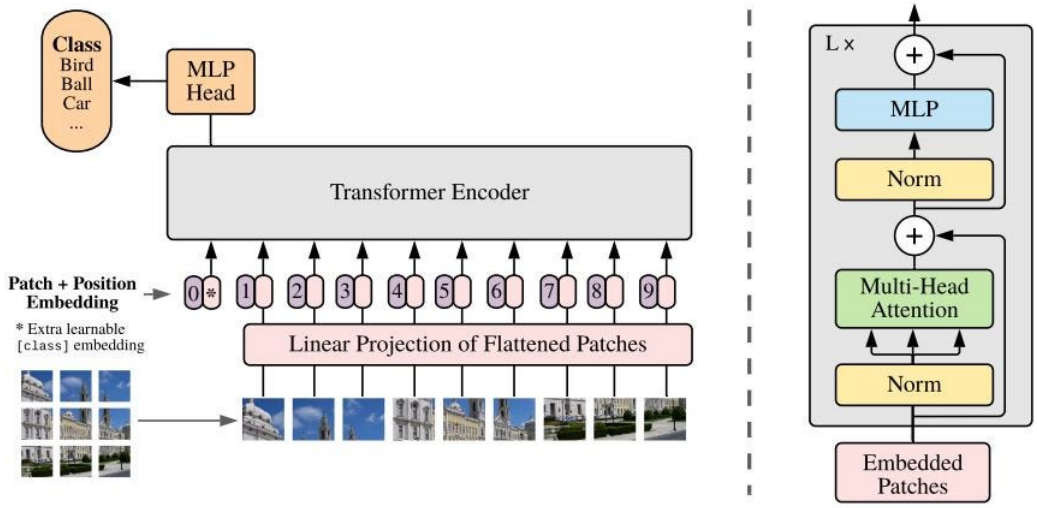

Figure 1: Model overview. We split an image into fixed-size patches, linearly embed each of them, add position embeddings, and feed the resulting sequence of vectors to a standard Transformer encoder. In order to perform classification, we use the standard approach of adding an extra learnable "classification token" to the sequence. The illustration of the Transformer encoder was inspired by

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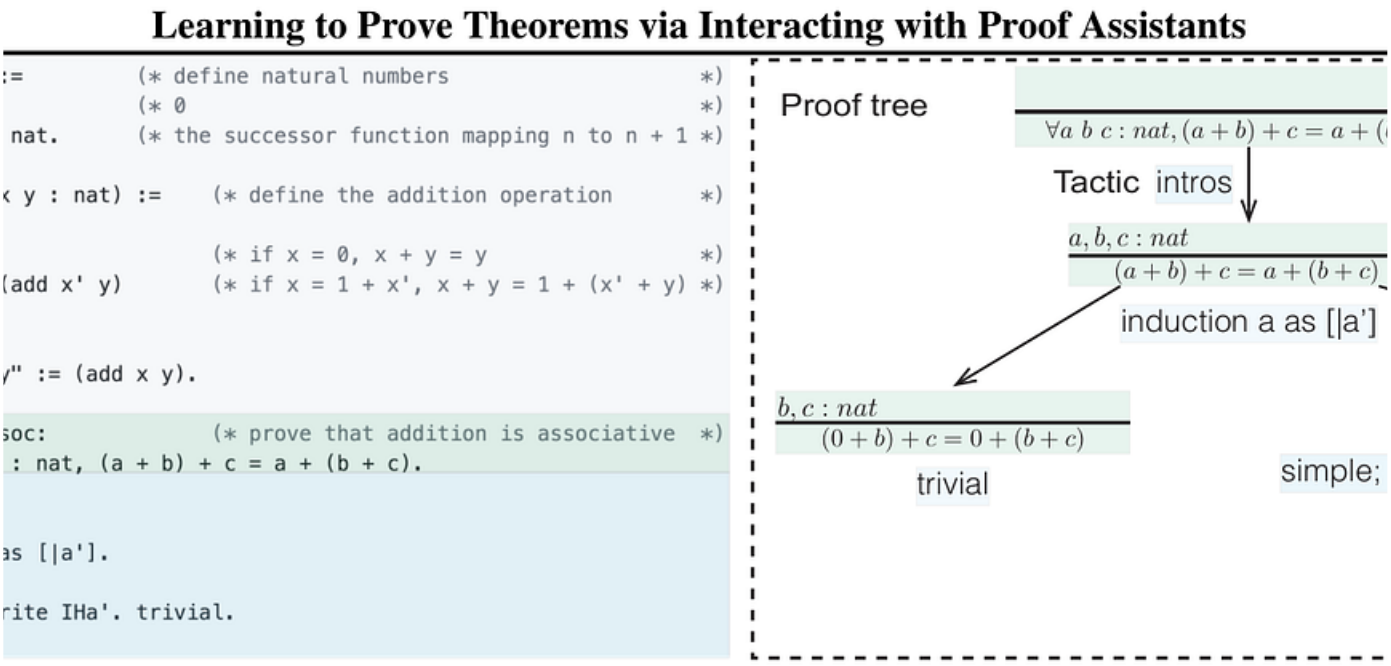

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