Handling images with PyTorch

INTERMEDIATE DEEP LEARNING WITH PYTORCH

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Clouds dataset

[1] https://www.kaggle.com/competitions/cloud-type-classification2/data

What is an image?

- Image consists of pixels ("picture elements")
- Each pixel contains color information
- Grayscale images: integer in 0 - 255
  - 30:

- Color images: three integers, one for each color channel (Red, Green, Blue)
  - RGB = (52, 171, 235):

Loading images to PyTorch

Desired directory structure:

```
clouds_train
  - cumulus
    - 75cbf18.jpg
    - ...
  - cumulonimbus
  - ...
clouds_test
  - cumulus
  - cumulonimbus
  - ...
```

- Main folders: `clouds_train` and `clouds_test`
- Inside each main folder: one folder per category
- Inside each class folder: image files

Loading images to PyTorch

```
from torchvision.datasets import ImageFolder
from torchvision import transforms

train_transforms = transforms.Compose([
    transforms.ToTensor(),
    transforms.Resize((128, 128)),
])

dataset_train = ImageFolder(
    "data/clouds_train",
    transform=train_transforms,
)
```

- Define transformations:
  - Parse to tensor
  - Resize to 128×128
- Create dataset passing:
  - Path to data
  - Predefined transformations

Displaying images

```
dataloader_train = DataLoader(
    dataset_train,
    shuffle=True,
    batch_size=1,
)

image, label = next(iter(dataloader_train))
print(image.shape)
```

```
torch.Size([1, 3, 128, 128])
```

```
image = image.squeeze().permute(1, 2, 0)
print(image.shape)
```

```
torch.Size([128, 128, 3])
```

```
import matplotlib.pyplot as plt
plt.imshow(image)
plt.show()
```

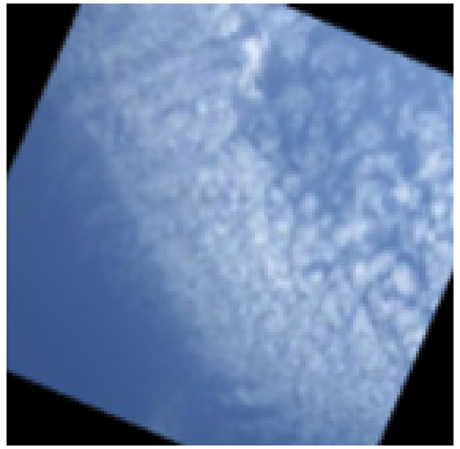
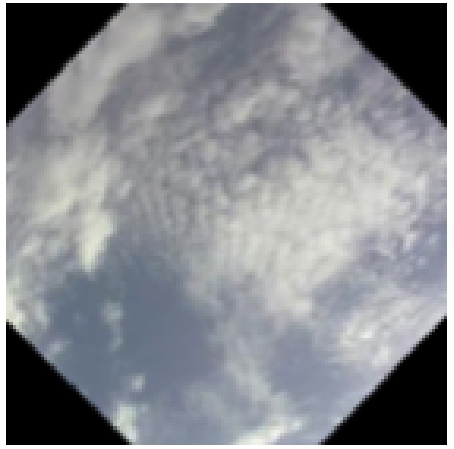
Data augmentation

```python
train_transforms = transforms.Compose([
    transforms.RandomHorizontalFlip(),
    transforms.RandomRotation(45),
    transforms.ToTensor(),
    transforms.Resize((128, 128)),
])

dataset_train = ImageFolder(
    "data/clouds/train",
    transform=train_transforms,
)
```

Data augmentation: Generating more data by applying random transformations to original images

- Increase the size and diversity of the training set
- Improve model robustness
- Reduce overfitting


Let's practice!

INTERMEDIATE DEEP LEARNING WITH PYTORCH

Convolutional Neural Networks

INTERMEDIATE DEEP LEARNING WITH PYTORCH

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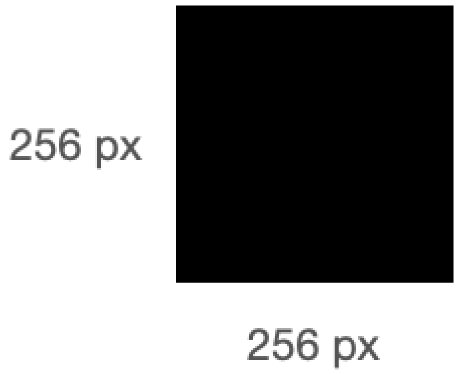
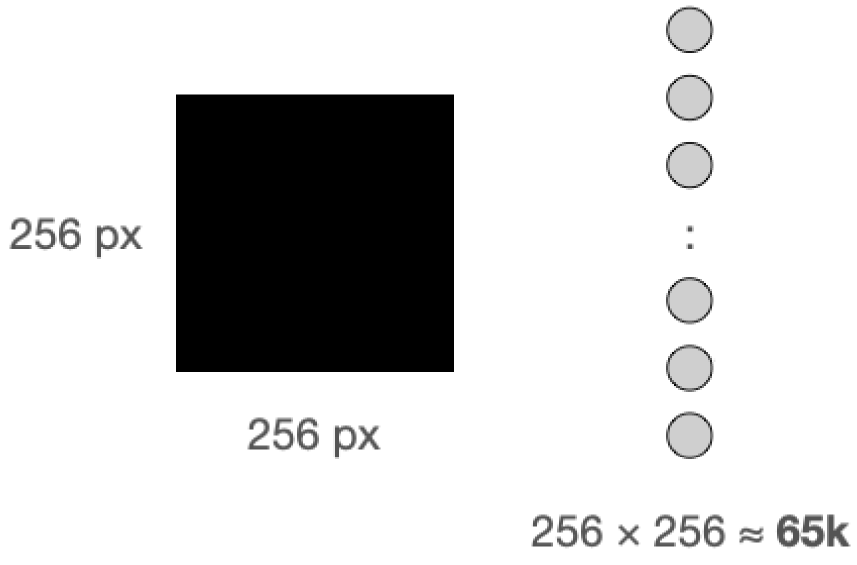
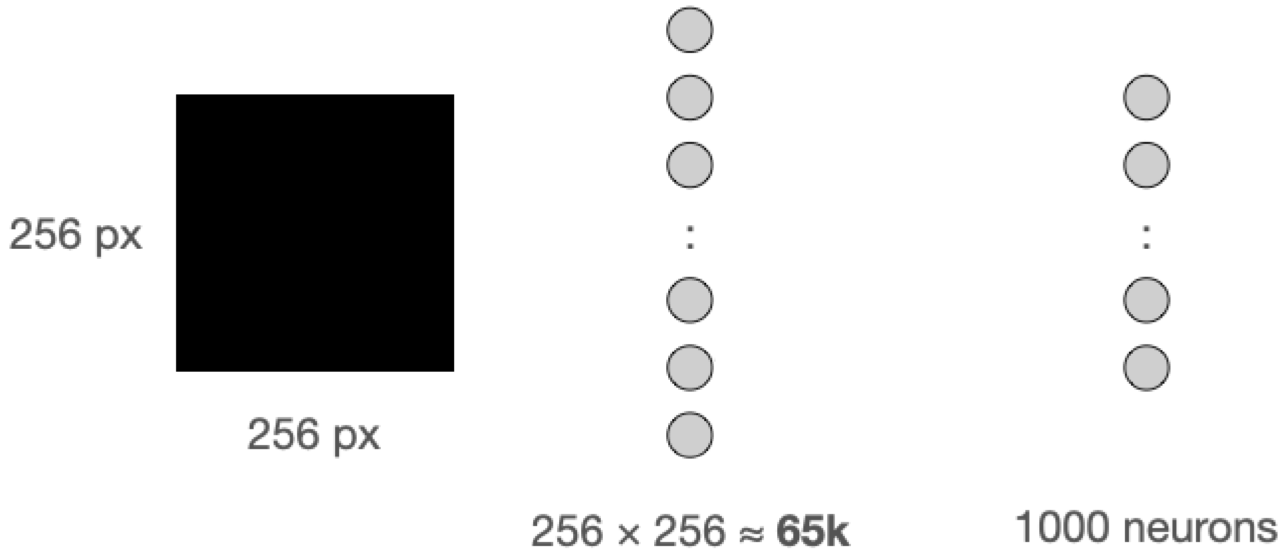
Why not use linear layers?



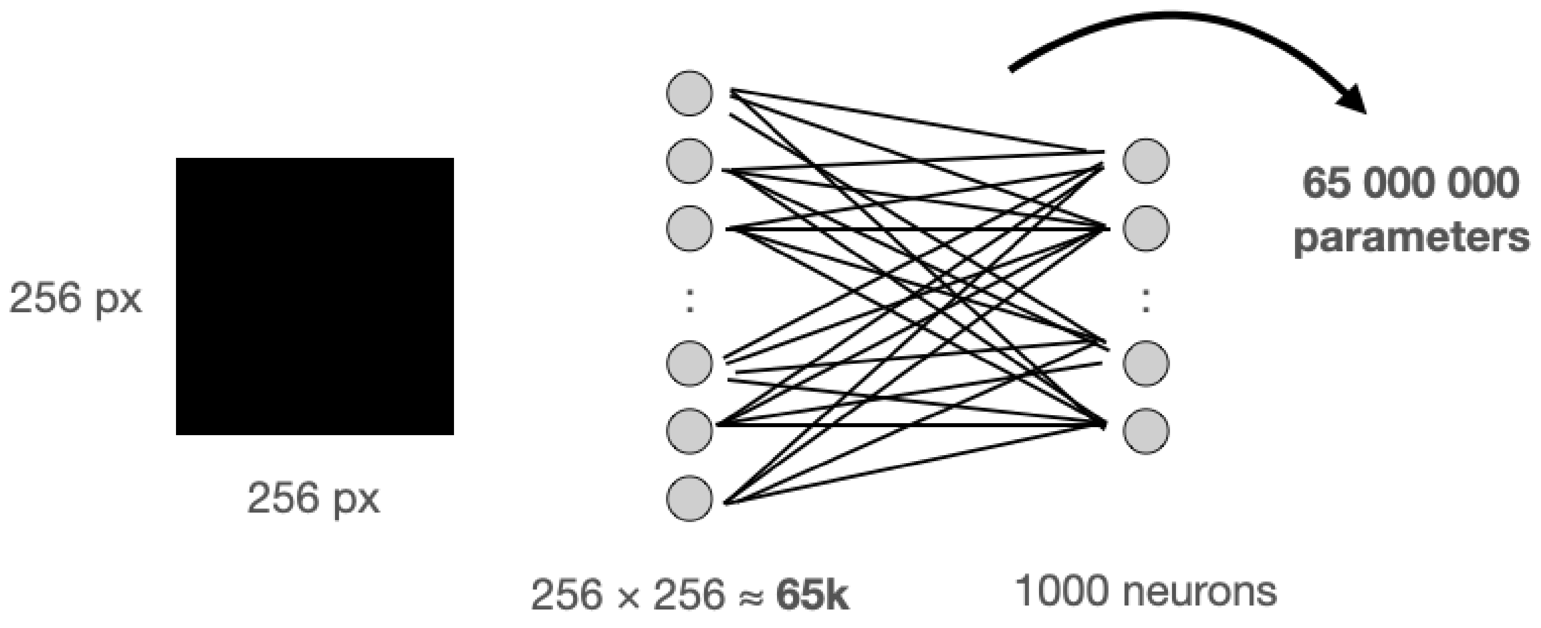
Why not use linear layers?



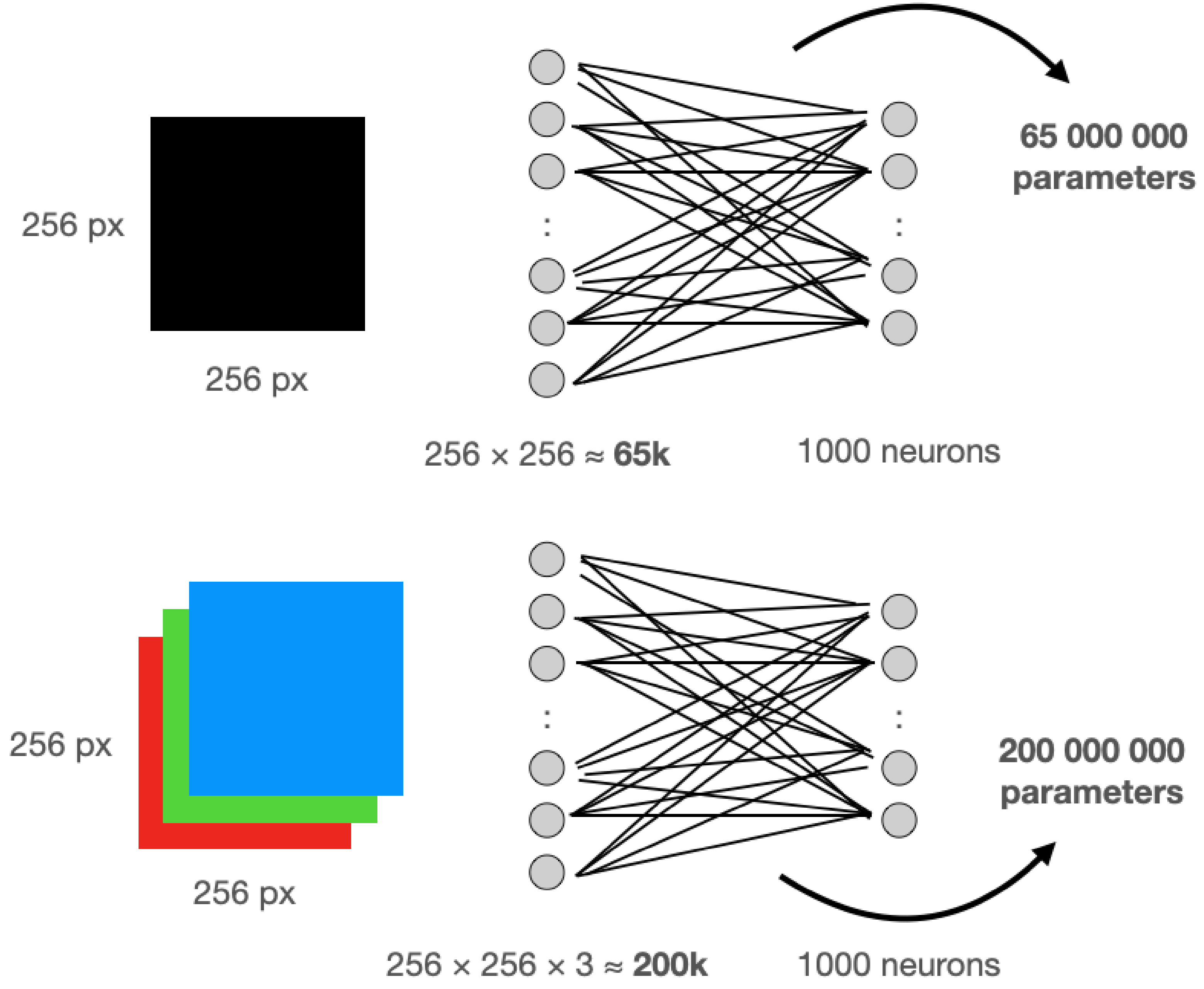
Why not use linear layers?



Why not use linear layers?

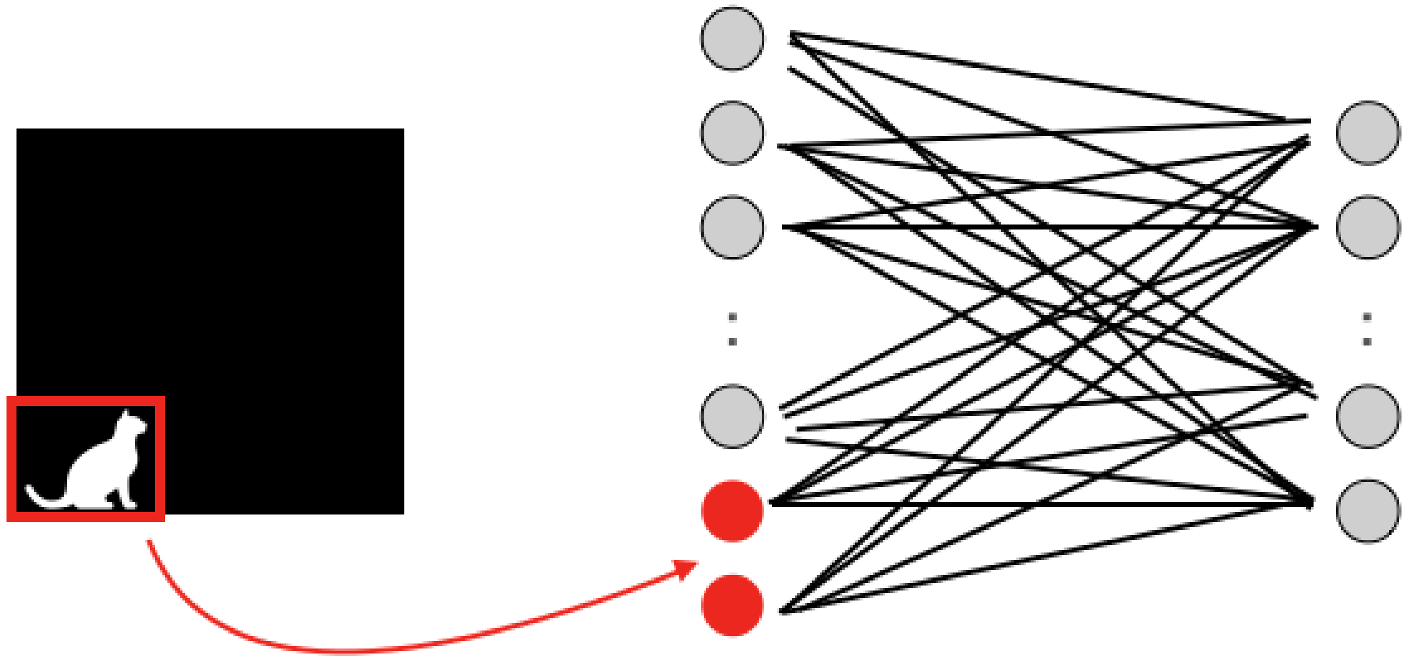


Why not use linear layers?

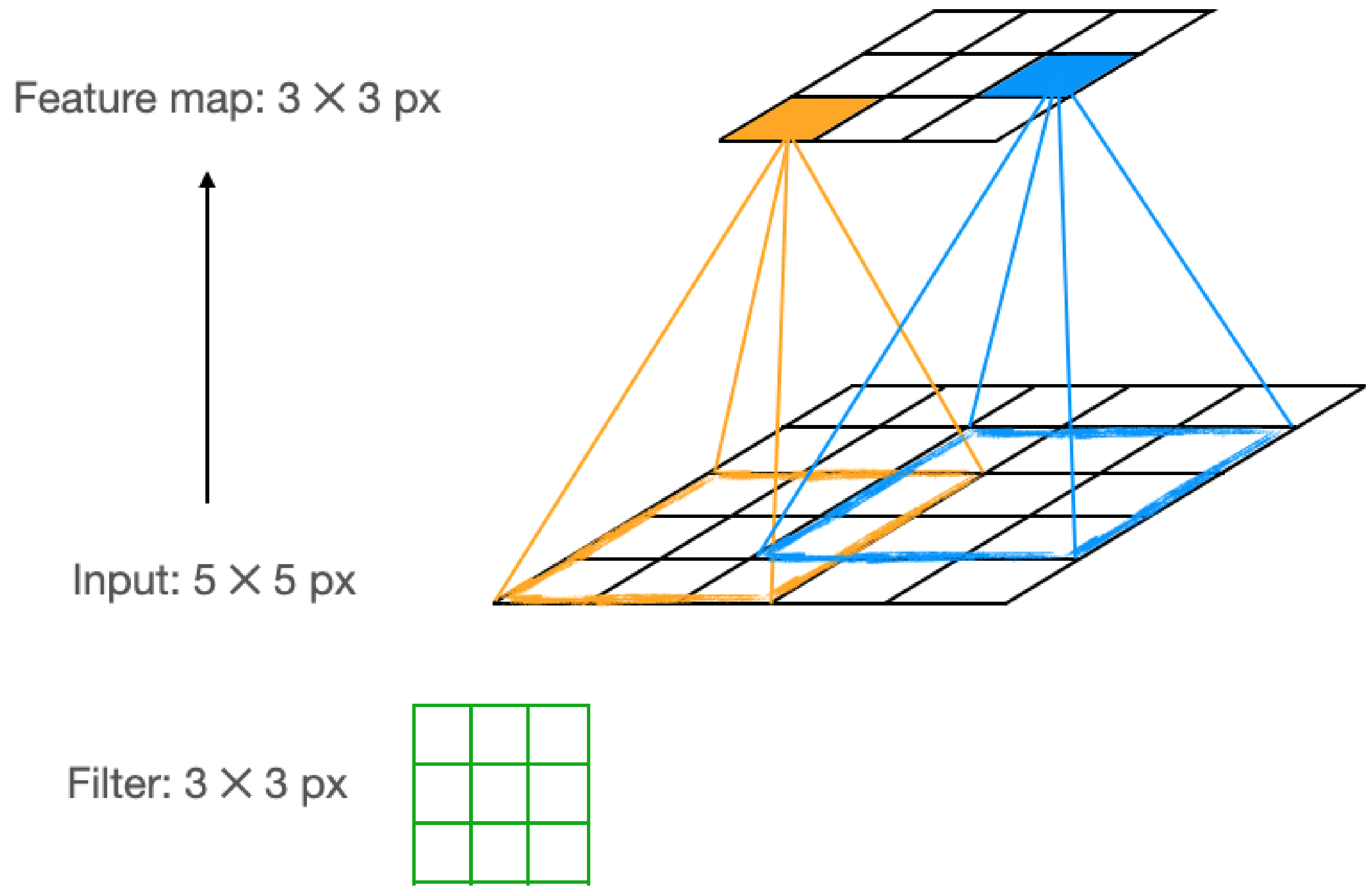


Why not use linear layers?

- Linear layers:
  - Slow training
  - Overfitting
  - Don't recognize spatial patterns
- A better alternative: convolutional layers!

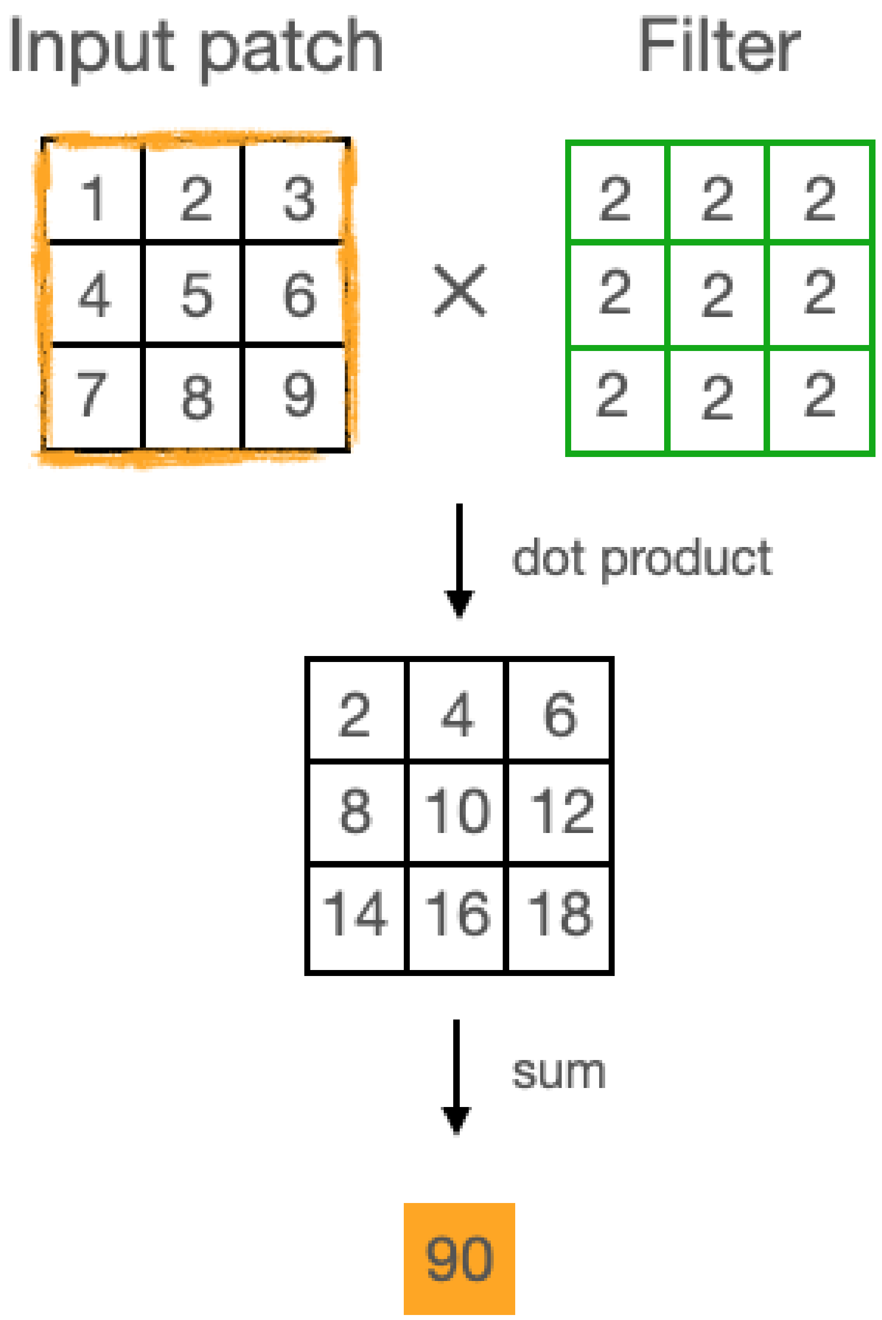


Convolutional layer



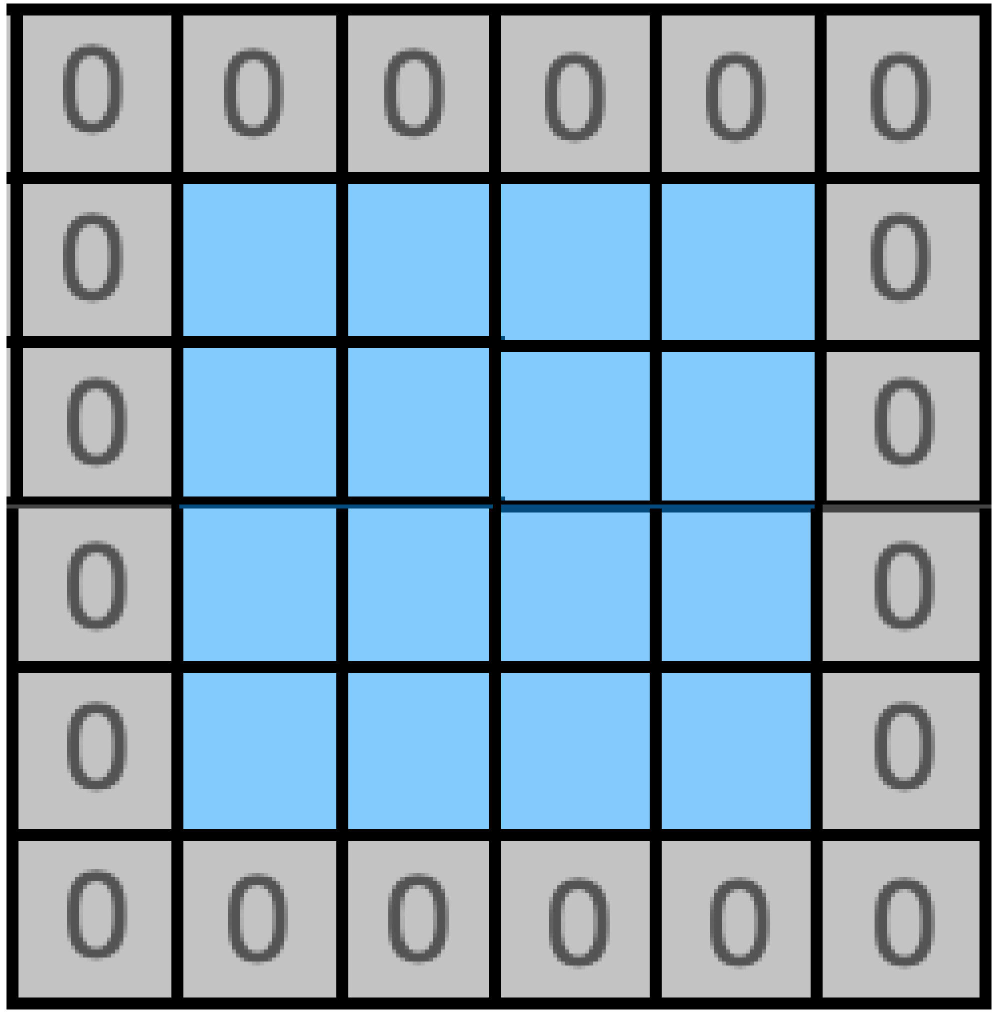
- Slide filter(s) of parameters over the input
- At each position, perform convolution
- Resulting feature map:
  - Preservers spatial patterns from input
  - Uses fewer parameters than linear layer
- One filter = one feature map
- Apply activations to feature maps
- All feature maps combined form the output
- `nn.Conv2d(3, 32, kernel_size=3)`

Convolution



1. Compute dot product of input patch and filter
   - Top-left field: $2 \times 1 = 2$
2. Sum the result

Zero-padding

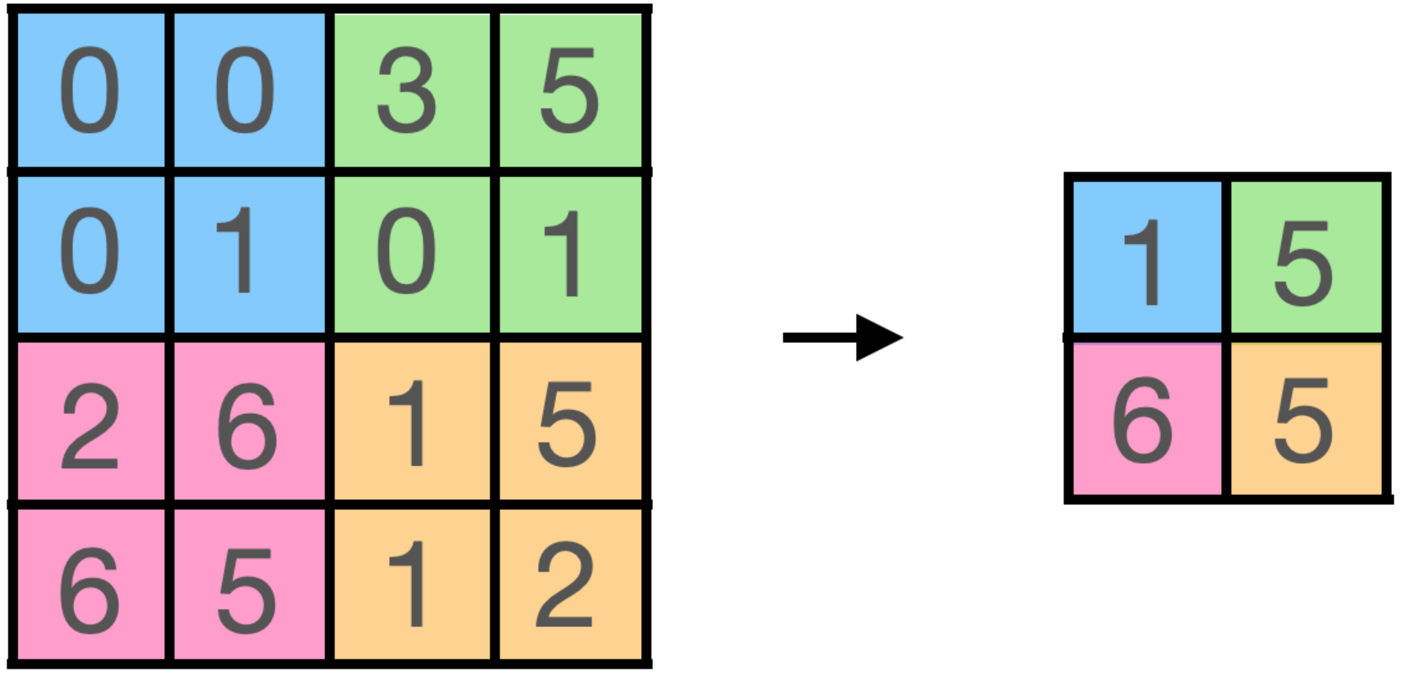


- Add a frames of zeros to convolutional layer's input

```
nn.Conv2d(
  3, 32, kernel_size=3, padding=1
)
```

- Maintains spatial dimensions of the input and output tensors
- Ensures border pixels are treated equally to others

Max Pooling



- Slide non-overlapping window over input
- At each position, retain only the maximum value
- Used after convolutional layers to reduce spatial dimensions
- `nn.MaxPool2d(kernel_size=2)`

Convolutional Neural Network

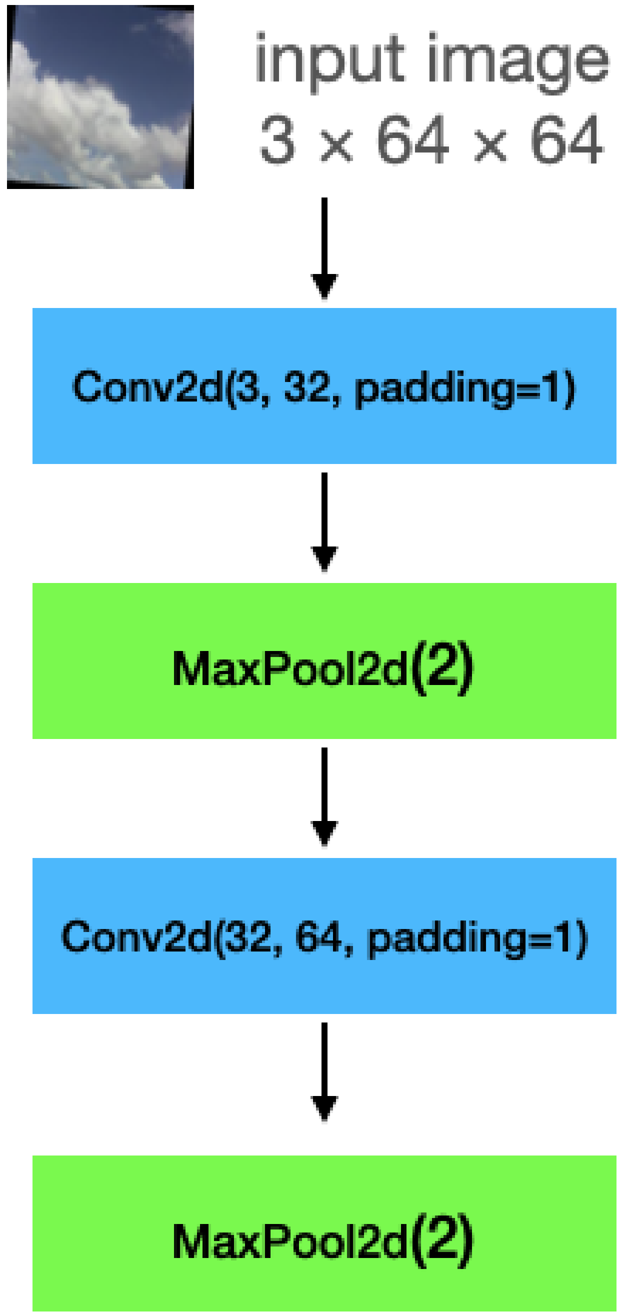
```
class Net(nn.Module):
    def __init__(self, num_classes):
        super().__init__()
        self.feature_extractor = nn.Sequential(
            nn.Conv2d(3, 32, kernel_size=3, padding=1),
            nn.ELU(),
            nn.MaxPool2d(kernel_size=2),
            nn.Conv2d(32, 64, kernel_size=3, padding=1),
            nn.ELU(),
            nn.MaxPool2d(kernel_size=2),
            nn.Flatten(),
        )
        self.classifier = nn.Linear(64*16*16, num_classes)

    def forward(self, x):
        x = self.feature_extractor(x)
        x = self.classifier(x)
        return x
```

- `feature_extractor` : (convolution, activation, pooling), repeated twice and flattened
- `classifier` : single linear layer
- `forward()` : pass input image through feature extractor and classifier

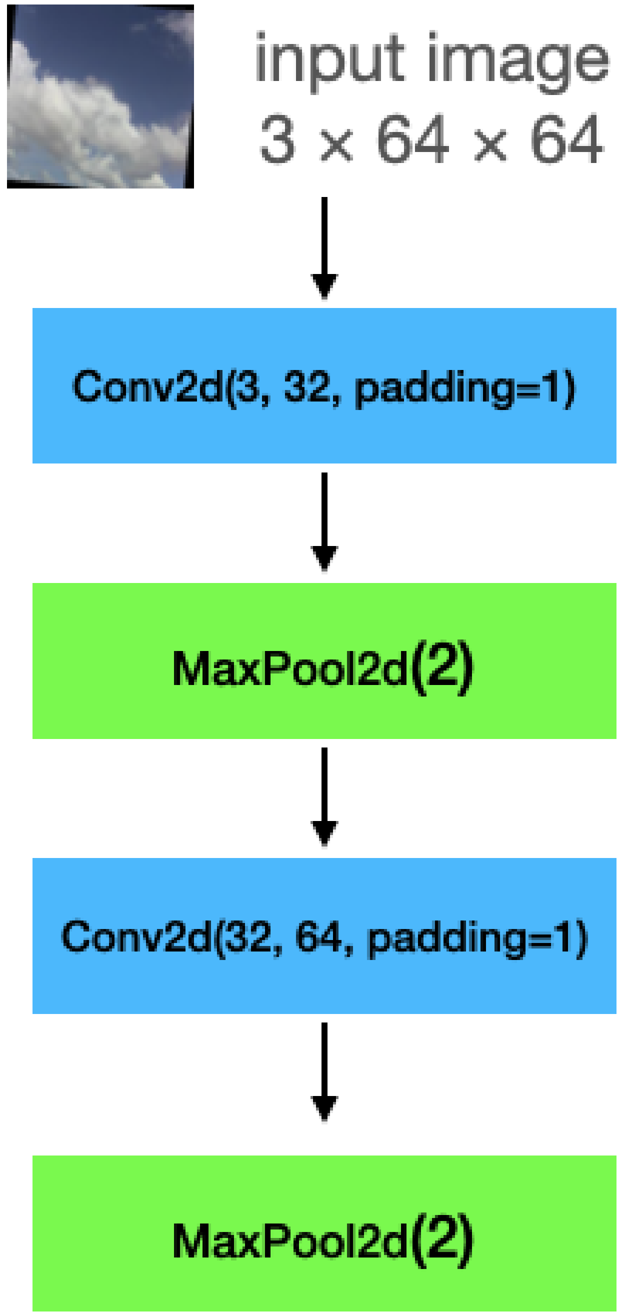
Feature extractor output size

```
self.feature_extractor = nn.Sequential(
  nn.Conv2d(3, 32, kernel_size=3, padding=1),
  nn.ELU(),
  nn.MaxPool2d(kernel_size=2),
  nn.Conv2d(32, 64, kernel_size=3, padding=1),
  nn.ELU(),
  nn.MaxPool2d(kernel_size=2),
  nn.Flatten(),
)
self.classifier = nn.Linear(64*16*16, num_classes)
`
```



Feature extractor output size

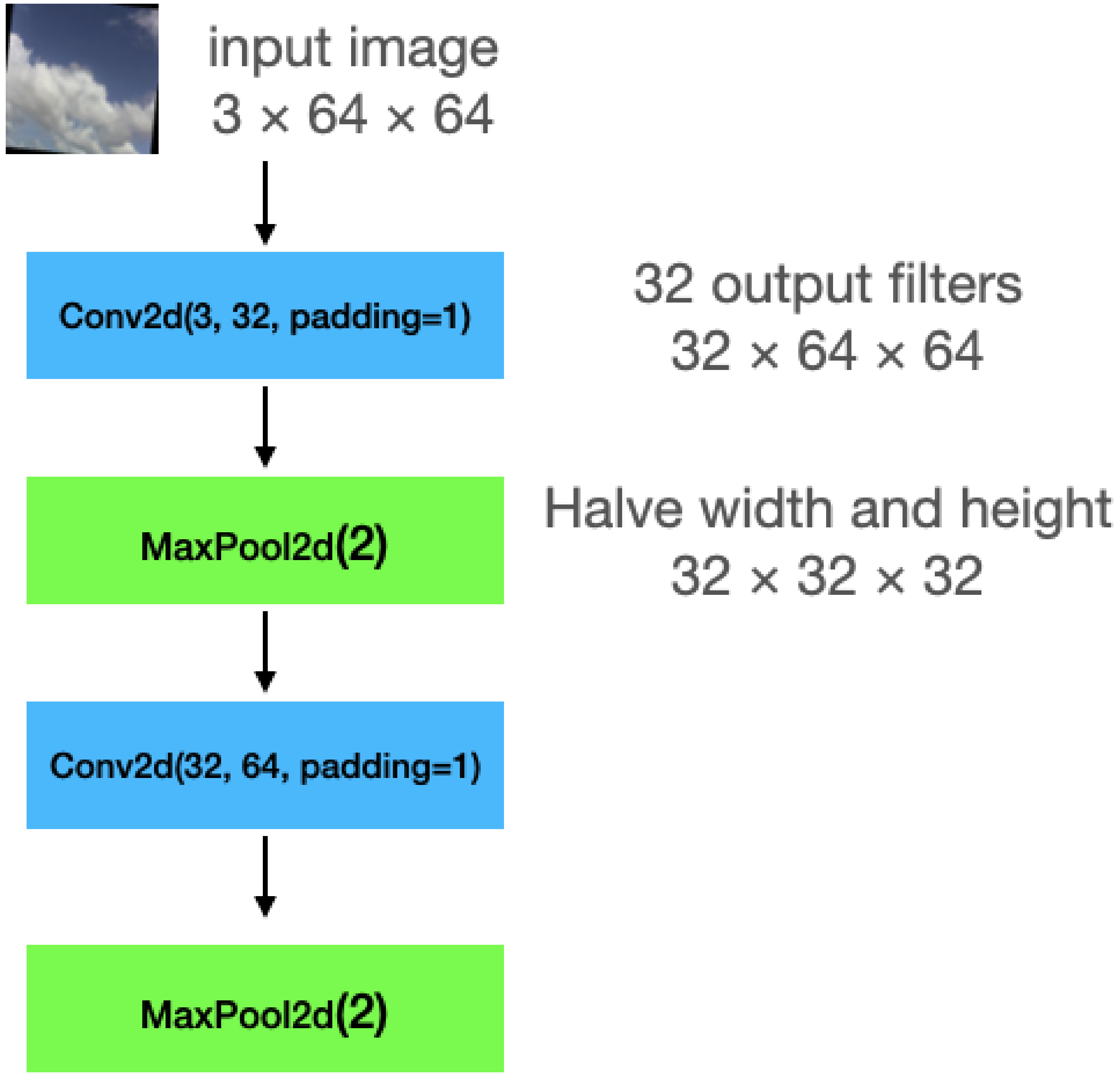
```
self.feature_extractor = nn.Sequential(
  nn.Conv2d(3, 32, kernel_size=3, padding=1),
  nn.ELU(),
  nn.MaxPool2d(kernel_size=2),
  nn.Conv2d(32, 64, kernel_size=3, padding=1),
  nn.ELU(),
  nn.MaxPool2d(kernel_size=2),
  nn.Flatten(),
)
self.classifier = nn.Linear(64*16*16, num_classes)
`
```



32 output filters
32 × 64 × 64

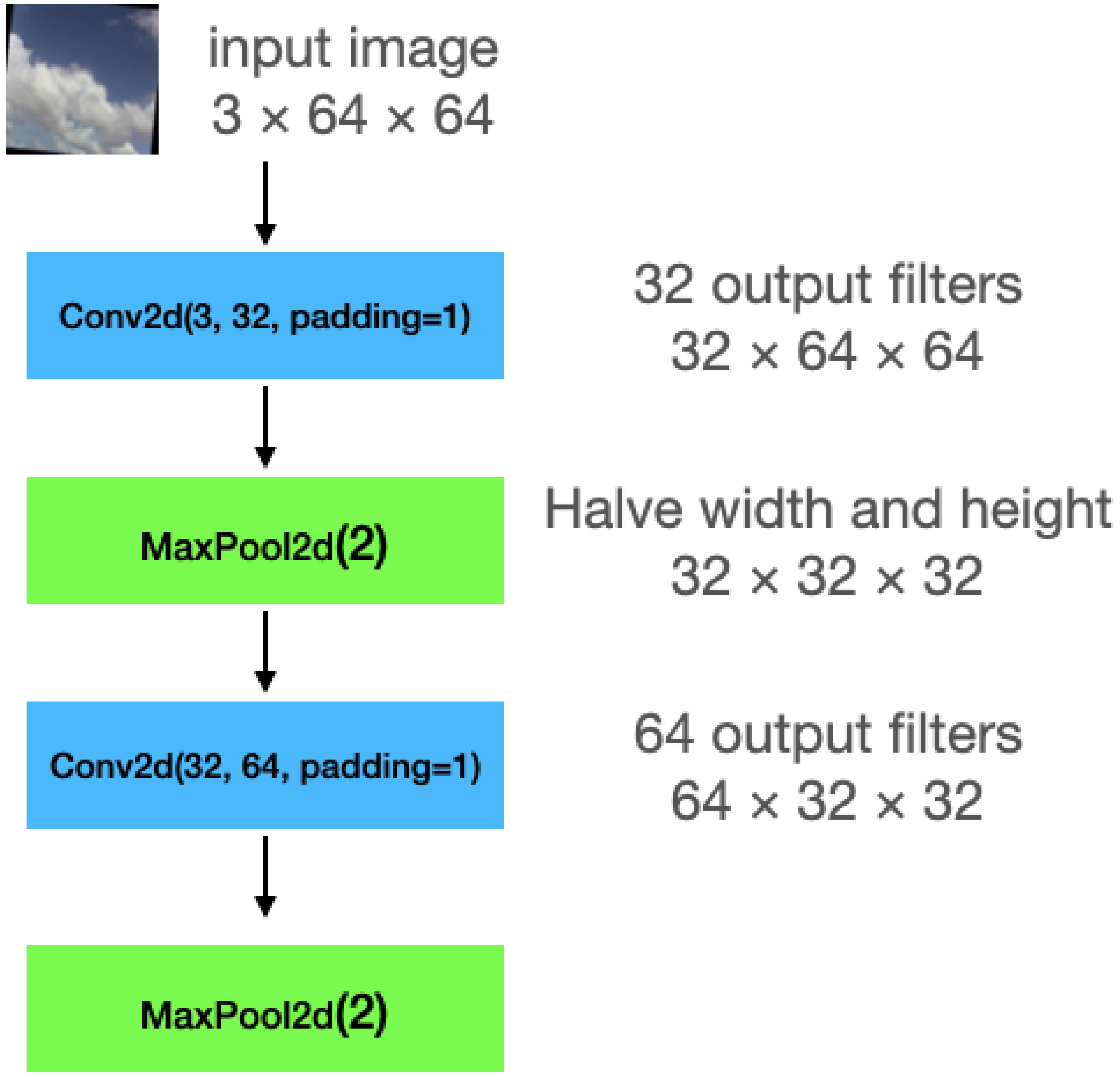
Feature extractor output size

```
self.feature_extractor = nn.Sequential(
  nn.Conv2d(3, 32, kernel_size=3, padding=1),
  nn.ELU(),
  nn.MaxPool2d(kernel_size=2),
  nn.Conv2d(32, 64, kernel_size=3, padding=1),
  nn.ELU(),
  nn.MaxPool2d(kernel_size=2),
  nn.Flatten(),
)
self.classifier = nn.Linear(64*16*16, num_classes)
`
```



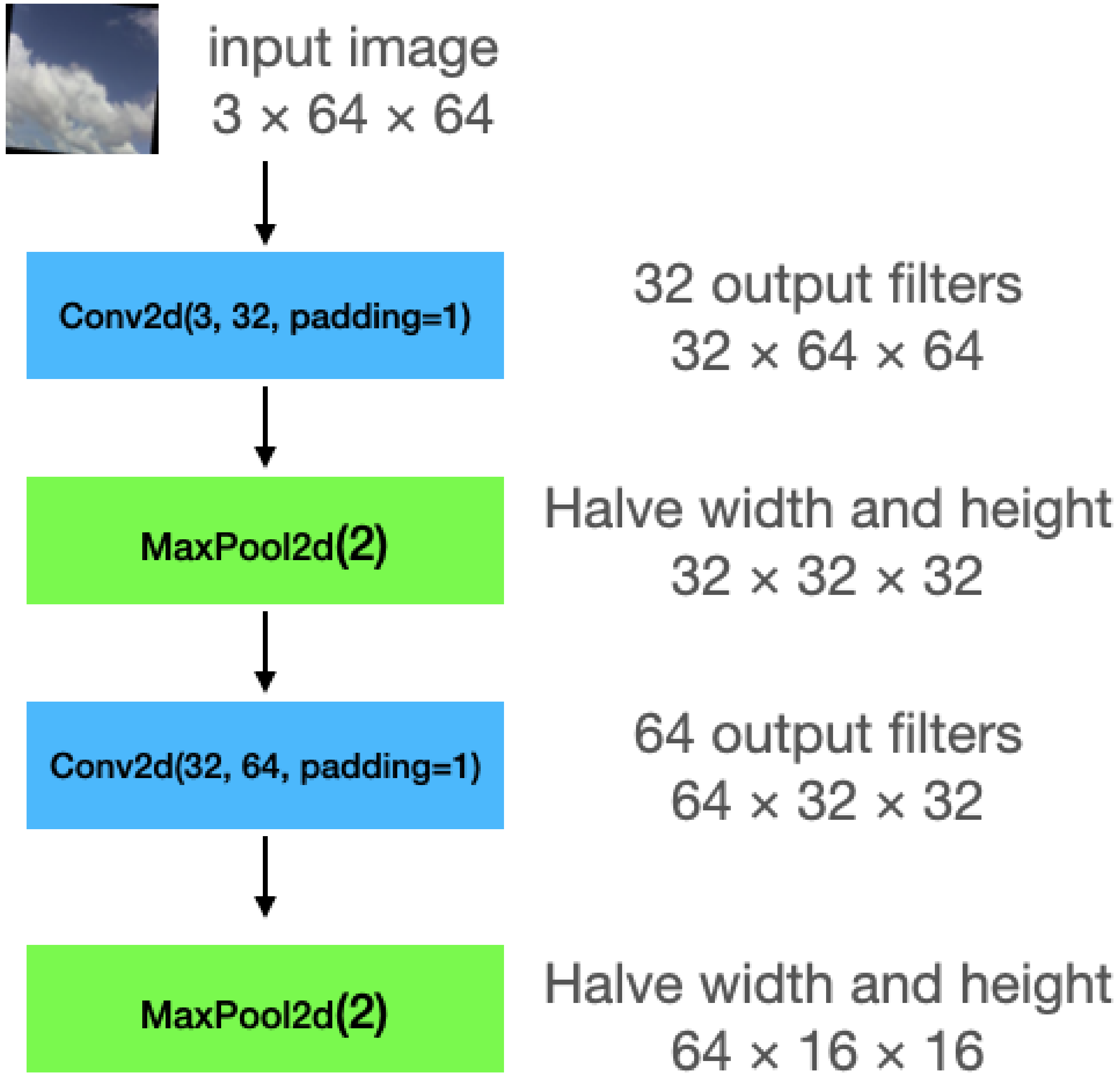
Feature extractor output size

```
self.feature_extractor = nn.Sequential(
  nn.Conv2d(3, 32, kernel_size=3, padding=1),
  nn.ELU(),
  nn.MaxPool2d(kernel_size=2),
  nn.Conv2d(32, 64, kernel_size=3, padding=1),
  nn.ELU(),
  nn.MaxPool2d(kernel_size=2),
  nn.Flatten(),
)
self.classifier = nn.Linear(64*16*16, num_classes)
`
```



Feature extractor output size

```
self.feature_extractor = nn.Sequential(
  nn.Conv2d(3, 32, kernel_size=3, padding=1),
  nn.ELU(),
  nn.MaxPool2d(kernel_size=2),
  nn.Conv2d(32, 64, kernel_size=3, padding=1),
  nn.ELU(),
  nn.MaxPool2d(kernel_size=2),
  nn.Flatten(),
)
self.classifier = nn.Linear(64*16*16, num_classes)
`
```



Let's practice!

INTERMEDIATE DEEP LEARNING WITH PYTORCH

Training image classifiers

INTERMEDIATE DEEP LEARNING WITH PYTORCH

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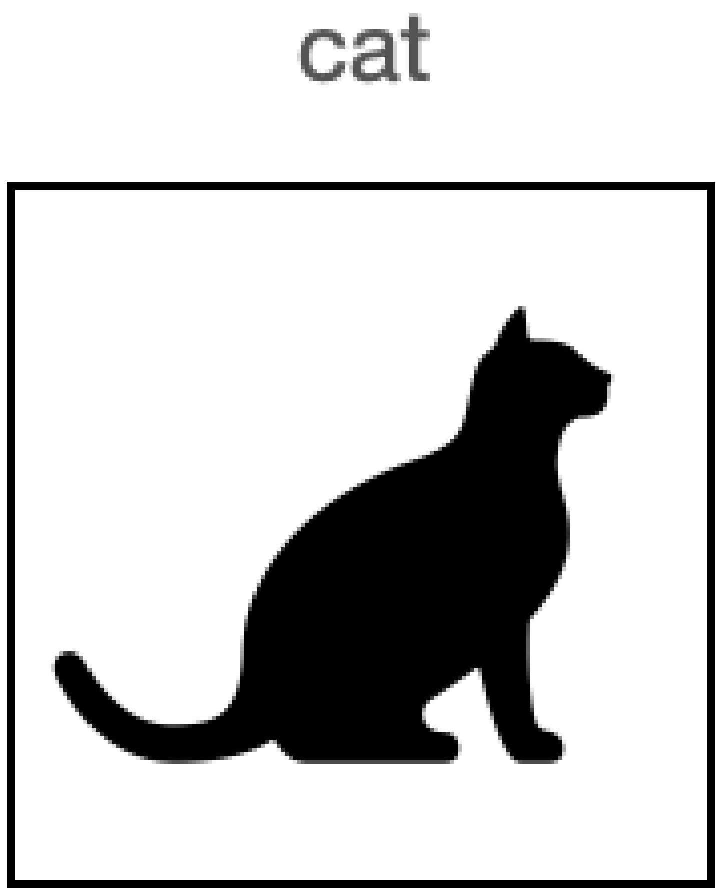
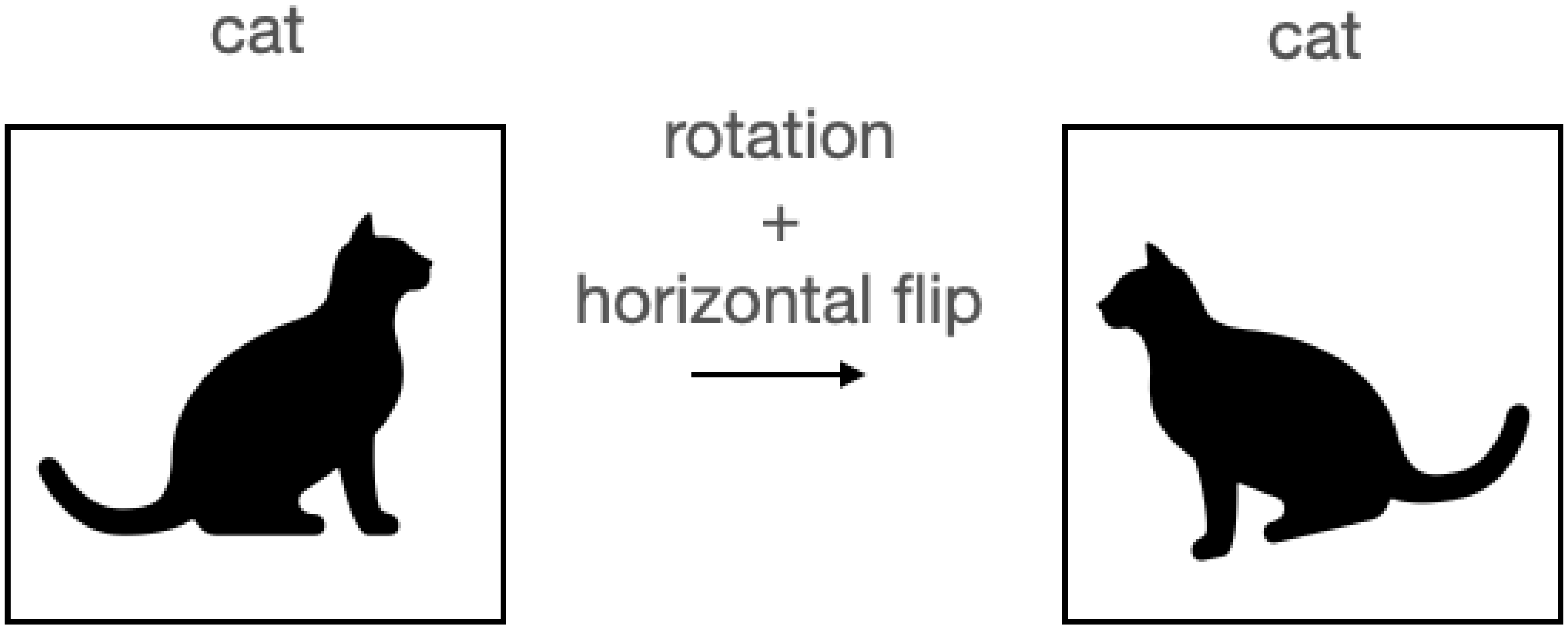
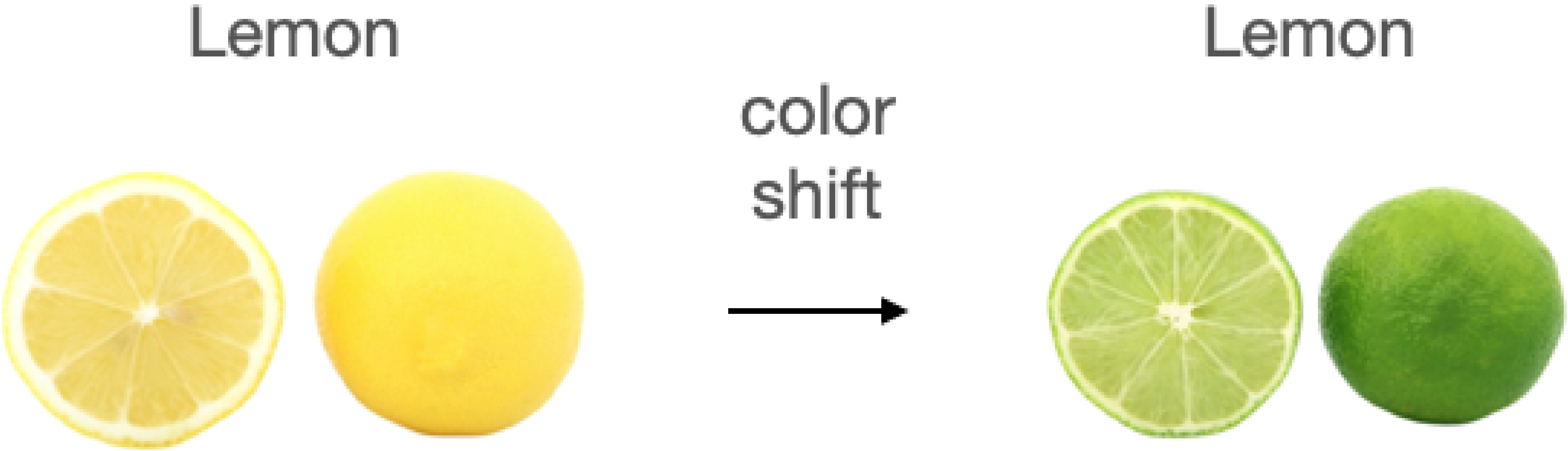
Data augmentation revisited



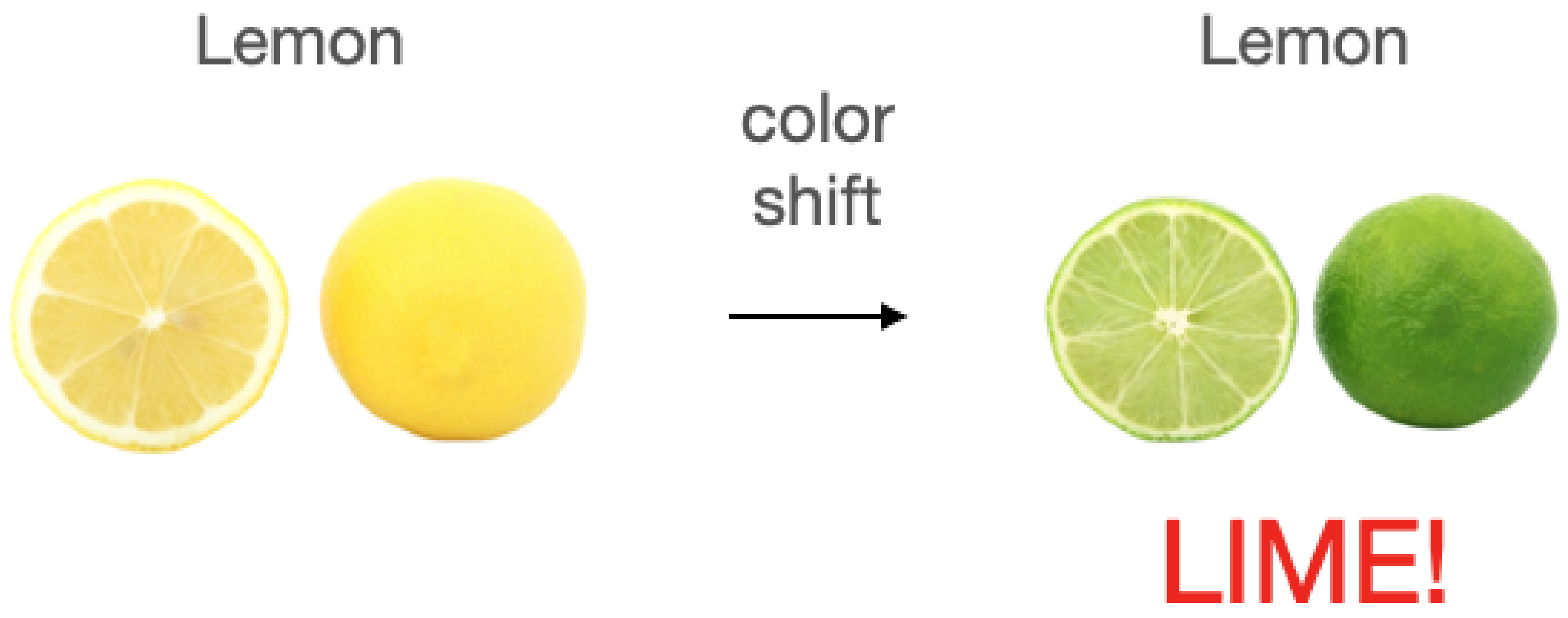
Data augmentation revisited



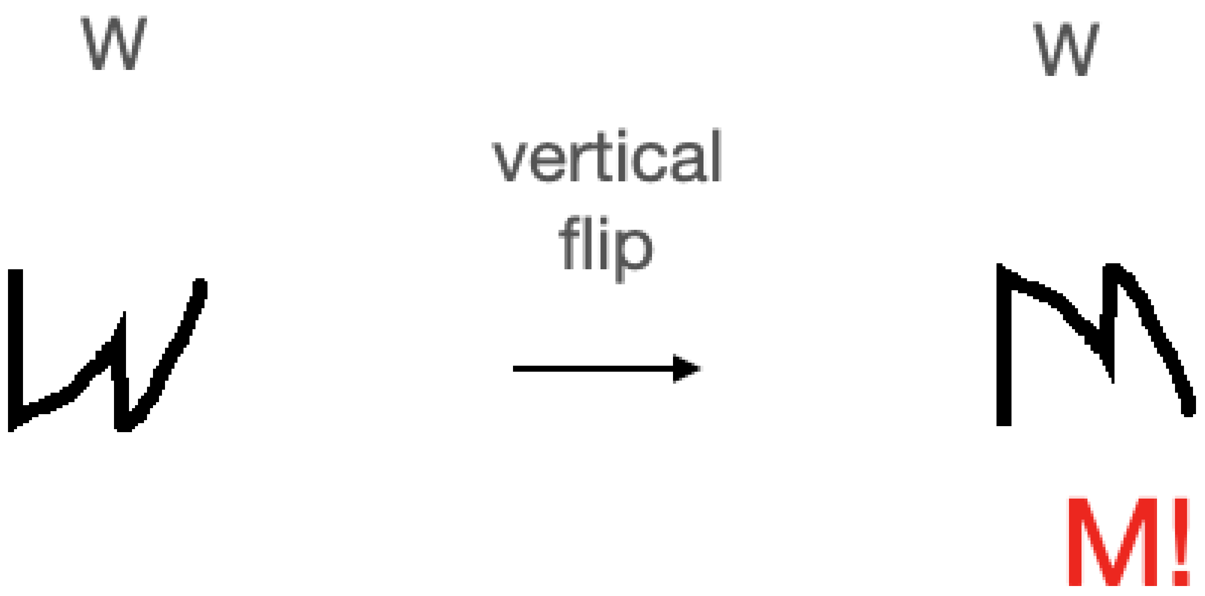
What should not be augmented



What should not be augmented



What should not be augmented



- Augmentations can impact the label
- Whether this is confusing depends on the task
- Always choose augmentations with the data and task in mind!

Augmentations for cloud classification




- **Random rotation:** expose model to different angles of cloud formations
- **Horizontal flip:** simulate different viewpoints of the sky
- **Auto contrast adjustment:** simulate different lighting conditions

```
train_transforms = transforms.Compose([
    transforms.RandomHorizontalFlip(),
    transforms.RandomRotation(45),
    transforms.RandomAutocontrast(),
    transforms.ToTensor(),
    transforms.Resize((128, 128))
])
```

Cross-Entropy loss

- Binary classification: binary cross-entropy (BCE) loss
- Multi-class classification: cross-entropy loss
- `criterion = nn.CrossEntropyLoss()`

Image classifier training loop

```
net = Net(num_classes=7)

criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(net.parameters(), lr=0.001)

for epoch in range(10):
    for images, labels in dataloader_train:
        optimizer.zero_grad()
        outputs = net(images)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
```

Let's practice!

INTERMEDIATE DEEP LEARNING WITH PYTORCH

Evaluating image classifiers

INTERMEDIATE DEEP LEARNING WITH PYTORCH

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Data augmentation at test time

Data augmentation for training data:

```
train_transforms = transforms.Compose([
    transforms.RandomHorizontalFlip(),
    transforms.RandomRotation(45),
    transforms.RandomAutocontrast(),
    transforms.ToTensor(),
    transforms.Resize((64, 64)),
])

dataset_train = ImageFolder(
  "clouds_train",
  transform=train_transforms,
)
```

Data augmentation for test data:

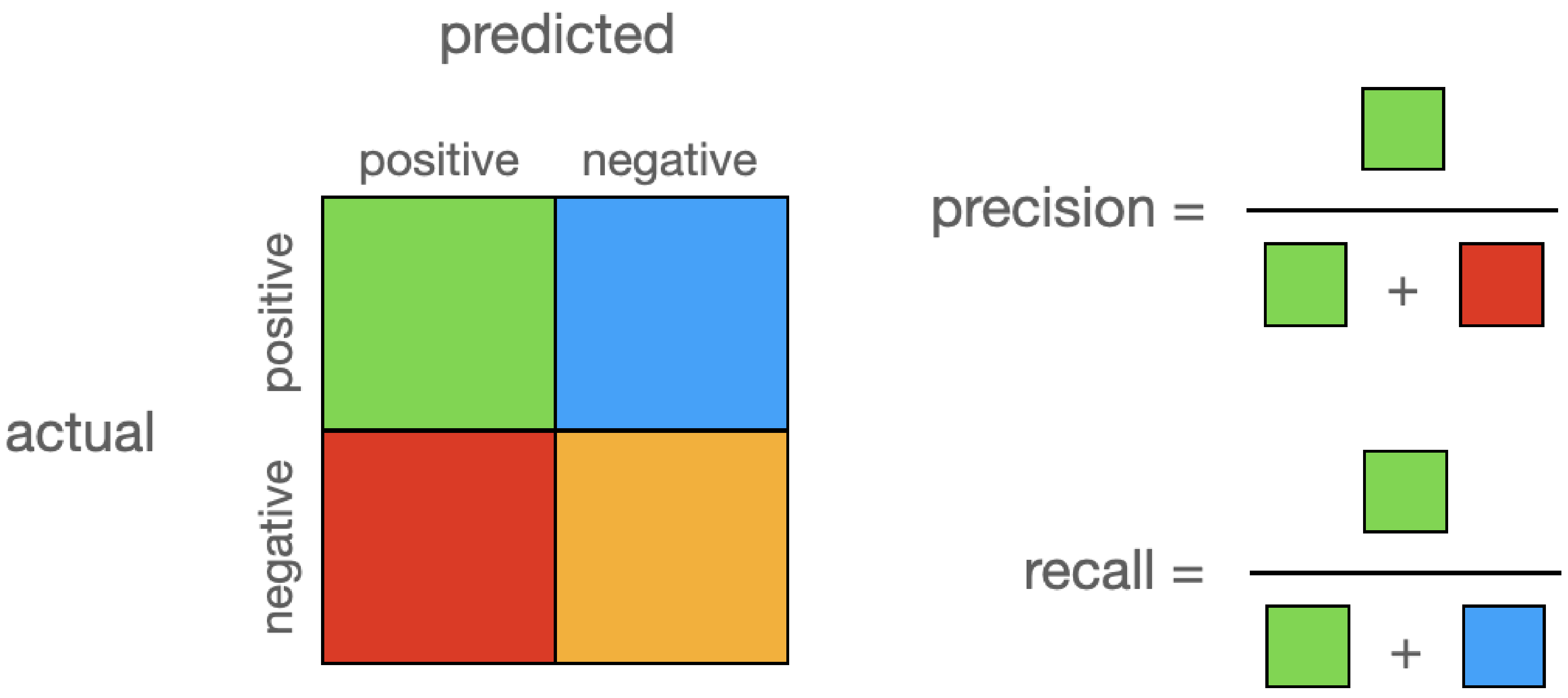
```
test_transforms = transforms.Compose([
    #
    # NO DATA AUGMENTATION AT TEST TIME
    #
    transforms.ToTensor(),
    transforms.Resize((64, 64)),
])

dataset_test = ImageFolder(
  "clouds_test",
  transform=test_transforms,
)
```

Precision & Recall: binary classification

In binary classification:

- **Precision:** Fraction of correct positive predictions
- **Recall:** Fraction of all positive examples correctly predicted



Precision & Recall: multi-class classification

In multi-class classification: separate precision and recall for each class

- **Precision:** Fraction of cumulus-predictions that were correct
- **Recall:** Fraction of all cumulus examples correctly predicted

Averaging multi-class metrics

- With 7 classes, we have 7 precision and 7 recall scores
- We can analyze them per-class, or aggregate:
  - **Micro average**: global calculation
  - **Macro average**: mean of per-class metrics
  - **Weighted average**: weighted mean of per-class metrics

Averaging multi-class metrics

```
from torchmetrics import Recall

recall_per_class = Recall(task="multiclass", num_classes=7, average=None)
recall_micro = Recall(task="multiclass", num_classes=7, average="micro")
recall_macro = Recall(task="multiclass", num_classes=7, average="macro")
recall_weighted = Recall(task="multiclass", num_classes=7, average="weighted")
```

When to use each:

- Micro: Imbalanced datasets
- Macro: Care about performance on small classes
- Weighted: Consider errors in larger classes as more important

Evaluation loop

```
from torchmetrics import Precision, Recall

metric_precision = Precision(
  task="multiclass", num_classes=7, average="macro"
)
metric_recall = Recall(
  task="multiclass", num_classes=7, average="macro"
)
net.eval()
with torch.no_grad():
    for images, labels in dataloader_test:
        outputs = net(images)
        _, preds = torch.max(outputs, 1)
        metric_precision(preds, labels)
        metric_recall(preds, labels)
precision = metric_precision.compute()
recall = metric_recall.compute()
```

- Import and define precision and recall metrics
- Iterate over test examples with no gradient
- For each test batch, get model outputs, take most likely class, and pass it to metric functions along with the labels
- Compute the metrics

```
print(f"Precision: {precision}")
print(f"Recall: {recall}")
```

```
Precision: 0.7284010648727417
Recall: 0.763038694858551
```

Analyzing performance per class

```
metric_recall = Recall(
  task="multiclass", num_classes=7, average=None
)
net.eval()
with torch.no_grad():
    for images, labels in dataloader_test:
        outputs = net(images)
        _, preds = torch.max(outputs, 1)
        metric_recall(preds, labels)
recall = metric_recall.compute()
```

```
print(recall)
```

```
tensor([0.6364, 1.0000, 0.9091, 0.7917,
        0.5049, 0.9500, 0.5493],
       dtype=torch.float32)
```

- Compute metric with `average=None`
- This gives one score per class
- `Dataset` 's `.class_to_idx` attribute maps class names to indices

```
dataset_test.class_to_idx
```

```
{'cirriform clouds': 0,
 'clear sky': 1,
 'cumulonimbus clouds': 2,
 'cumulus clouds': 3,
 'high cumuliform clouds': 4,
 'stratiform clouds': 5,
 'stratocumulus clouds': 6}
```

Analyzing performance per class

```
{
  k: recall[v].item()
  for k, v
  in dataset_test.class_to_idx.items()
}
```

```
{'cirriform clouds': 0.6363636255264282,
 'clear sky': 1.0,
 'cumulonimbus clouds': 0.9090909361839294,
 'cumulus clouds': 0.7916666865348816,
 'high cumuliform clouds': 0.5048543810844421,
 'stratiform clouds': 0.949999988079071,
 'stratocumulus clouds': 0.5492957830429077}
```

- `k` = class name, e.g. `cirriform clouds`
- `v` = class index, e.g. `0`
- `recall[v]` = `tensor(0.6364, dtype=torch.float32)`
- `recall[v].item()` = `0.6364`

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