Handling images with PyTorch

INTERMEDIATE DEEP LEARNING WITH PYTORCH

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Clouds dataset

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

```python
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

```python
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])
```

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

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

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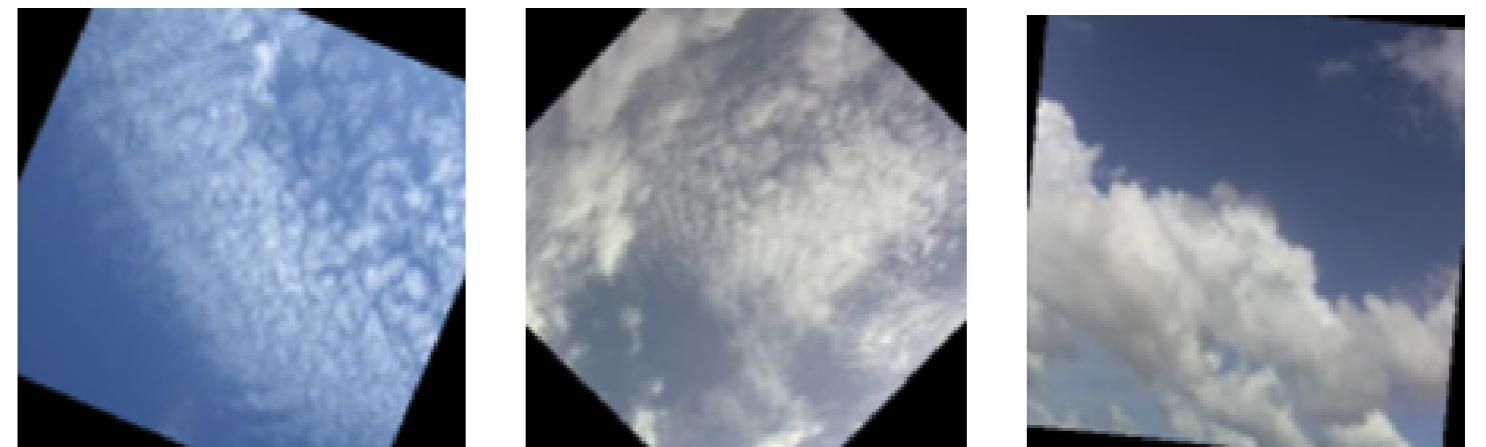
Data augmentation

```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
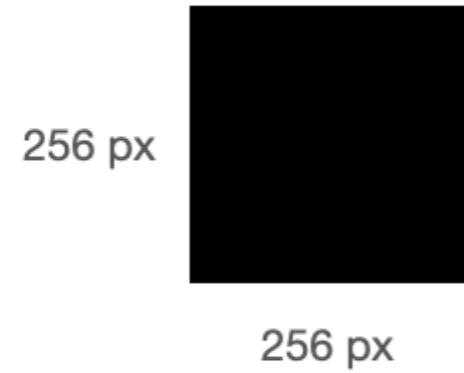
- Reduce overfitting

Let's practice!

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Convolutional Neural Networks

INTERMEDIATE DEEP LEARNING WITH PYTORCH

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Why not use linear layers?
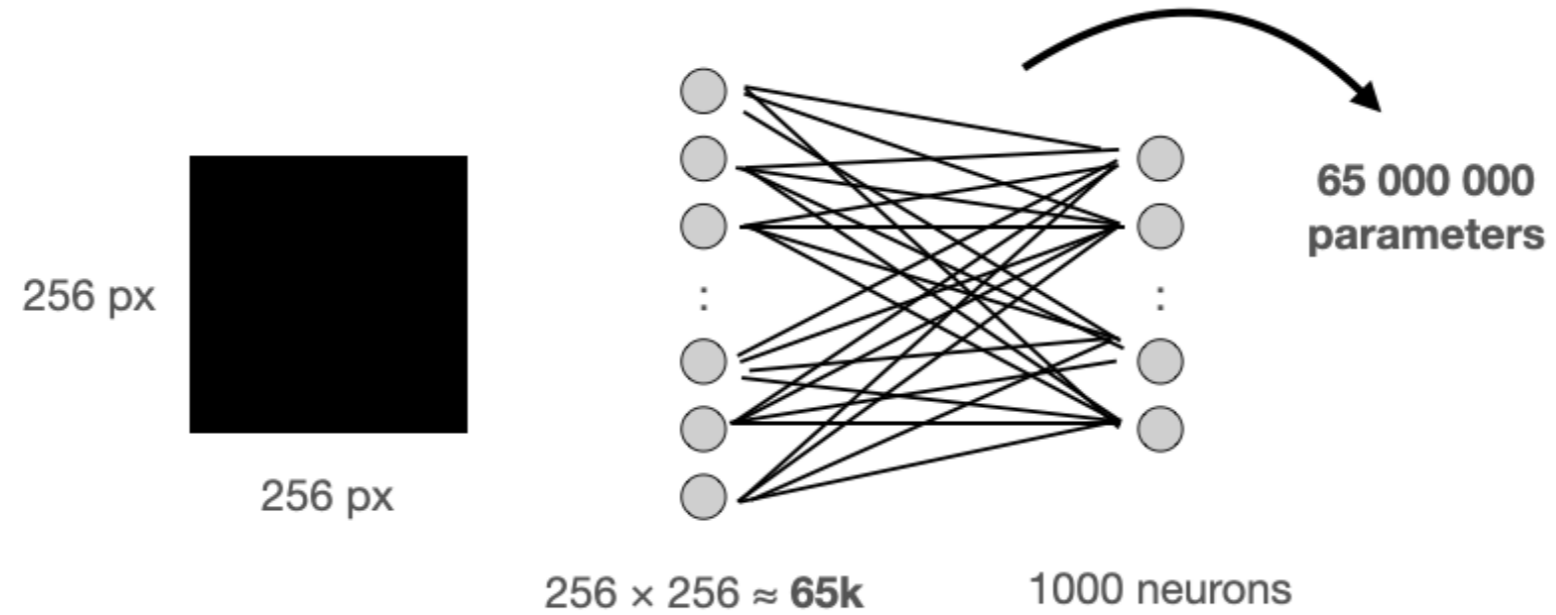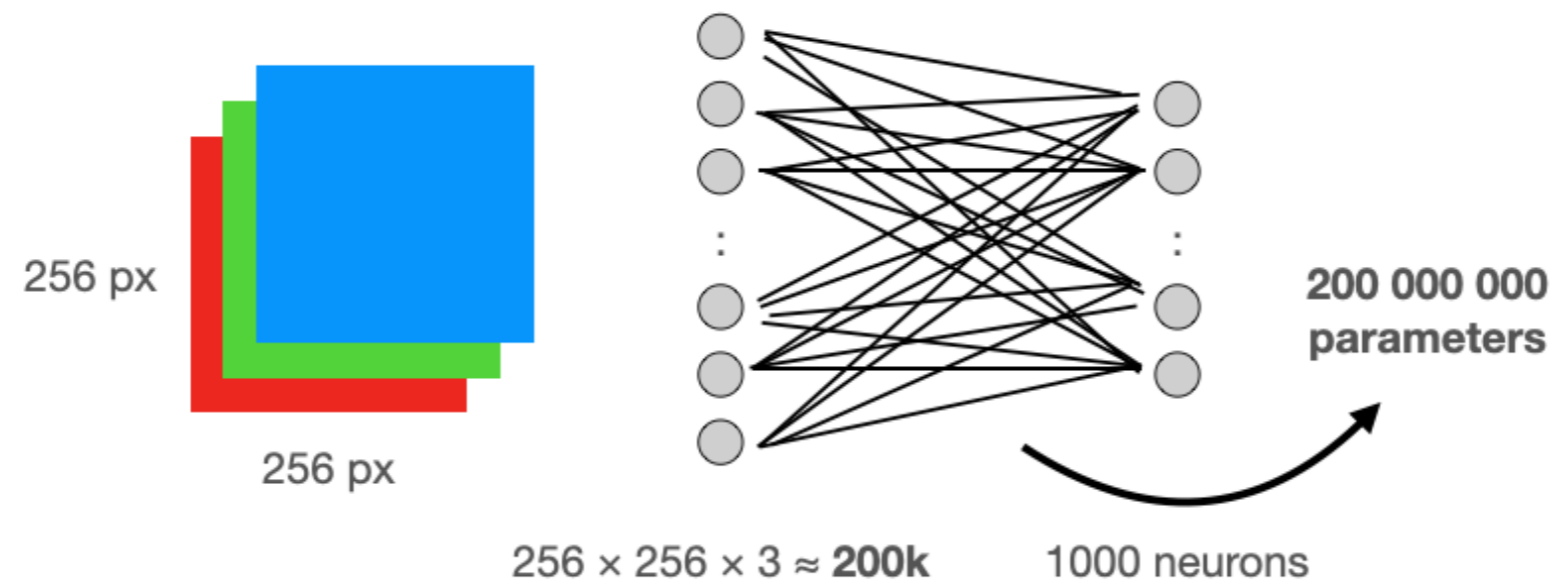

256 px

256 px

Why not use linear layers?

256 px

256 px

$256 \times 256 \approx$ **65k**

Why not use linear layers?

256 px

256 px

$256 \times 256 \approx$ **65k**

1000 neurons

Why not use linear layers?

256 px

256 px

$256 \times 256 \approx$ **65k**

1000 neurons

65 000 000 parameters

Why not use linear layers?

256 px

256 px

256 × 256 ≈ **65k**   1000 neurons

65 000 000 parameters

256 px

256 px

256 × 256 × 3 ≈ **200k**   1000 neurons

200 000 000 parameters
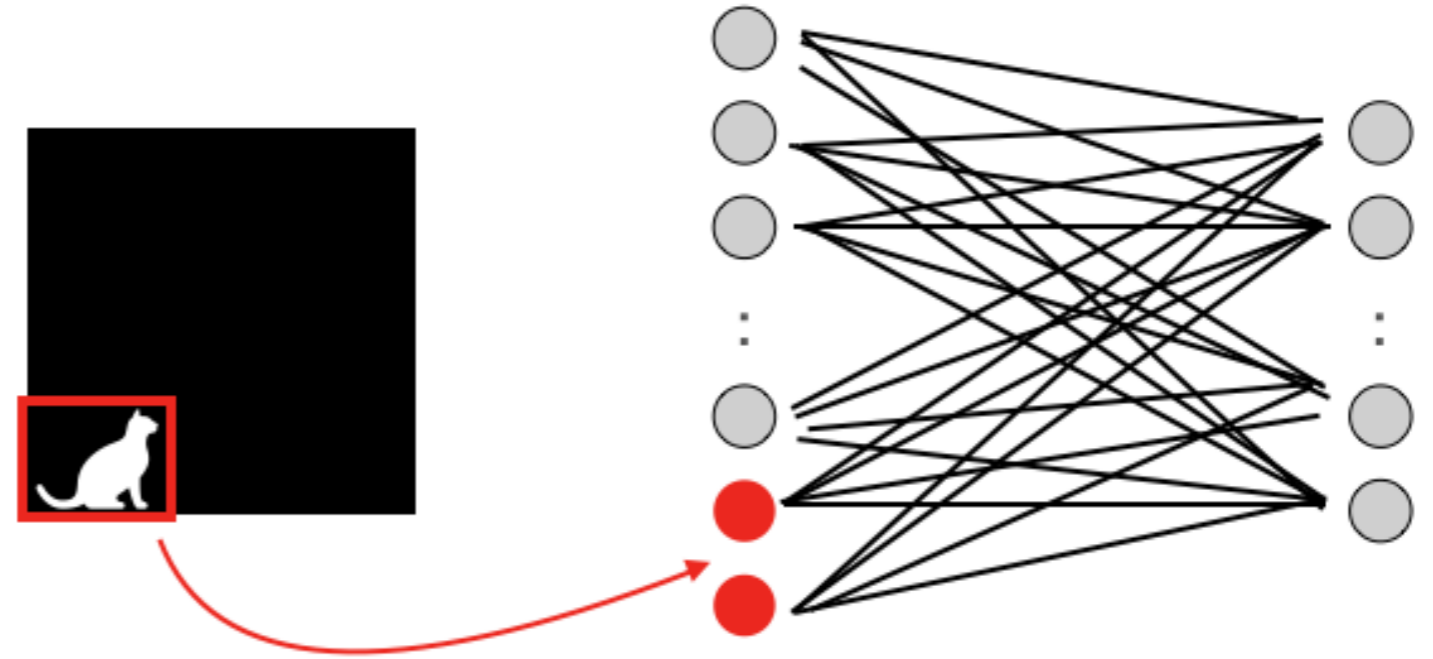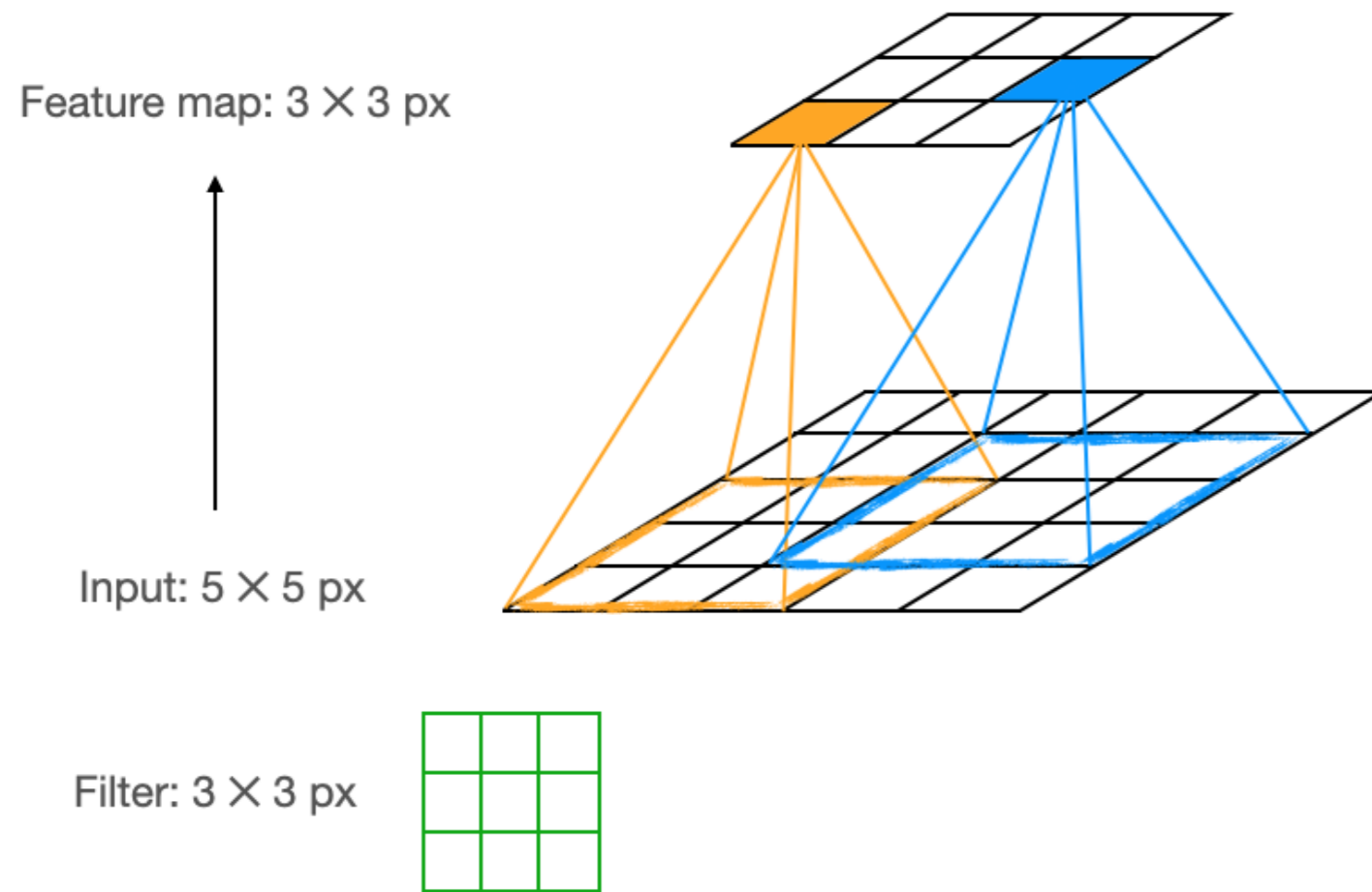
Why not use linear layers?

- Linear layers:
  - Slow training

  - Overfitting

  - Don't recognize spatial patterns

- A better alternative: convolutional layers!

Convolutional layer

Feature map: 3 × 3 px

Input: 5 × 5 px

Filter: 3 × 3 px

- 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

Input patch   Filter

1	2	3
4	5	6
7	8	9

$\times$

2	2	2
2	2	2
2	2	2

dot product

2	4	6
8	10	12
14	16	18

sum

90

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)`

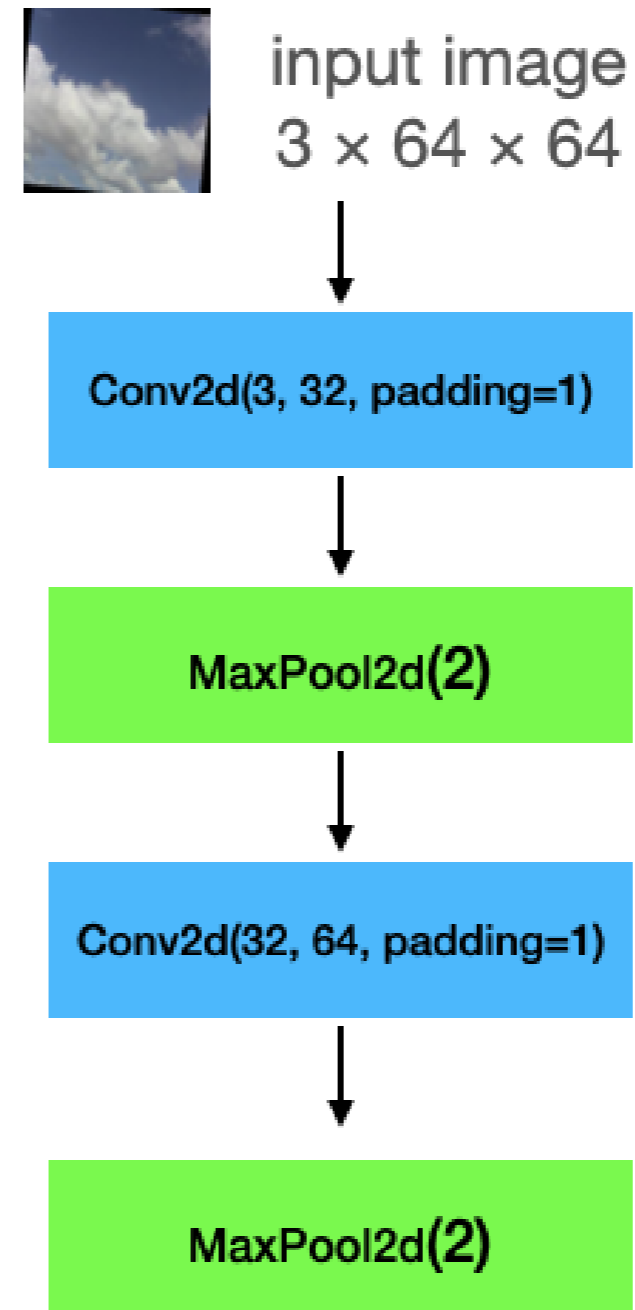# Convolutional Neural Network

```python
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

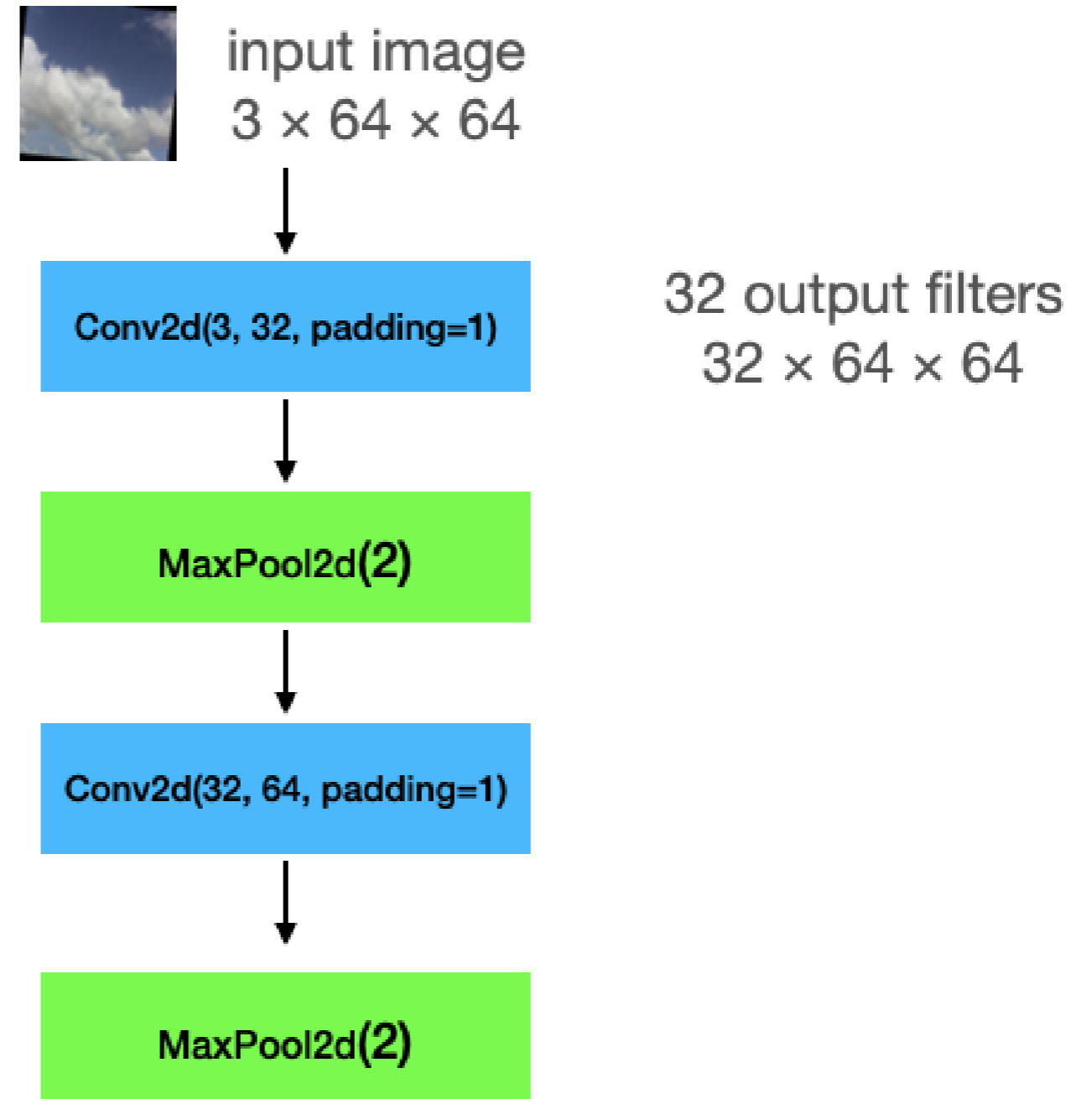- `forward()` : pass input image through feature extractor and classifier

Feature extractor output size

```python
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)
`
```


input image
3 × 64 × 64

Conv2d(3, 32, padding=1)

MaxPool2d(2)

Conv2d(32, 64, padding=1)

MaxPool2d(2)

Feature extractor output size

```python
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)
`
```
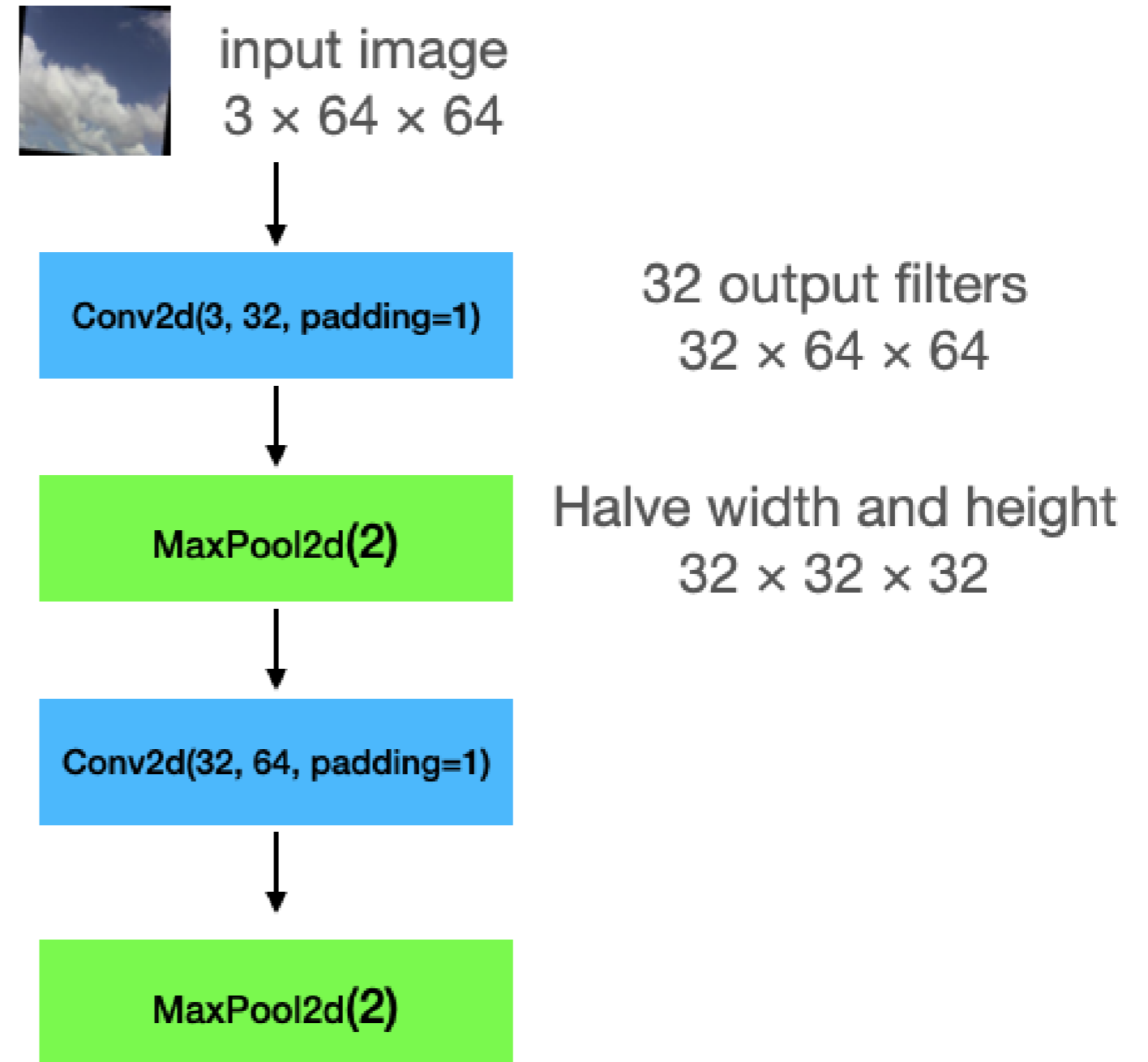
input image
3 × 64 × 64

Conv2d(3, 32, padding=1)

32 output filters
32 × 64 × 64

MaxPool2d(2)

Conv2d(32, 64, padding=1)

MaxPool2d(2)

Feature extractor output size

```python
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)
`
```
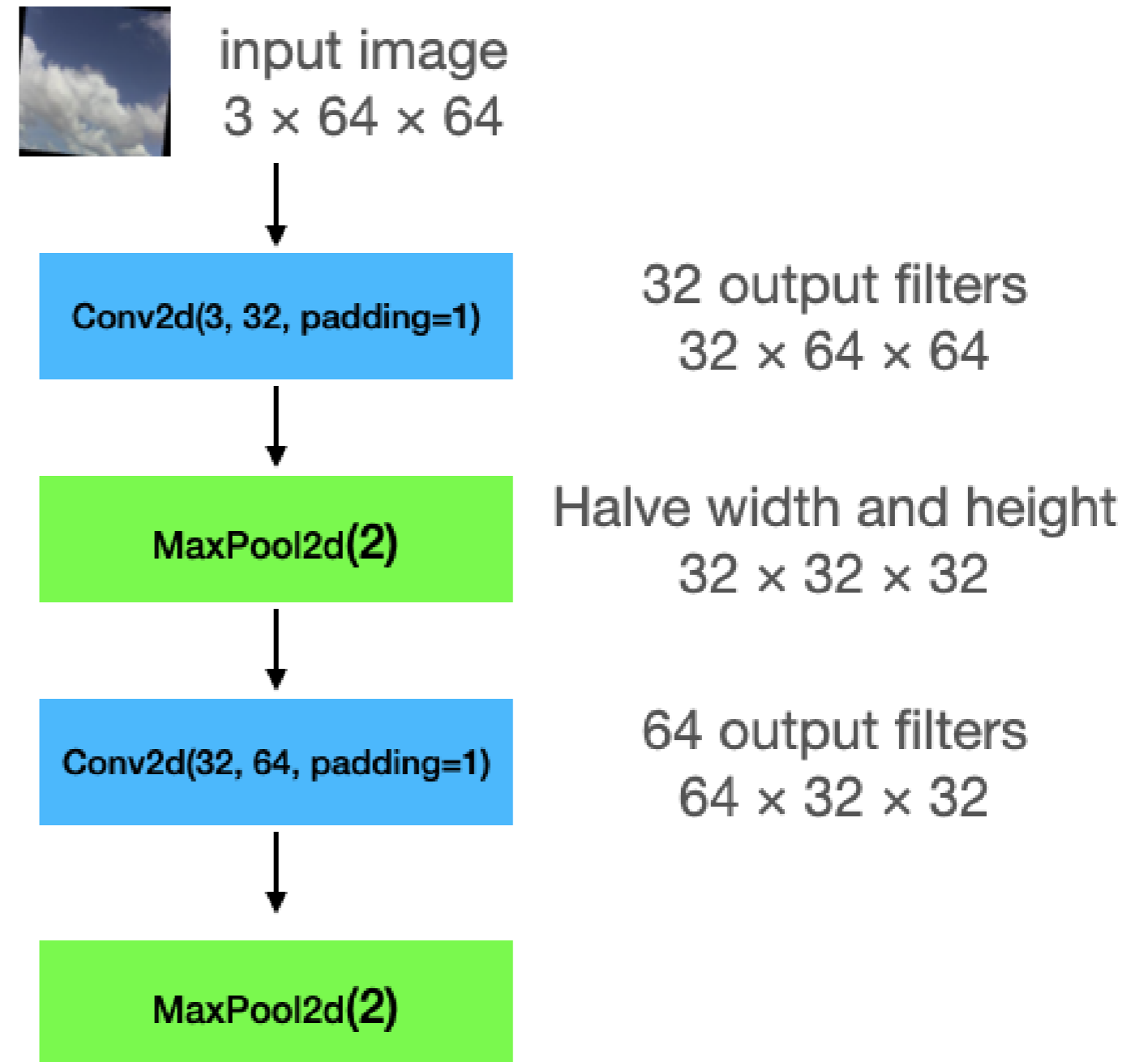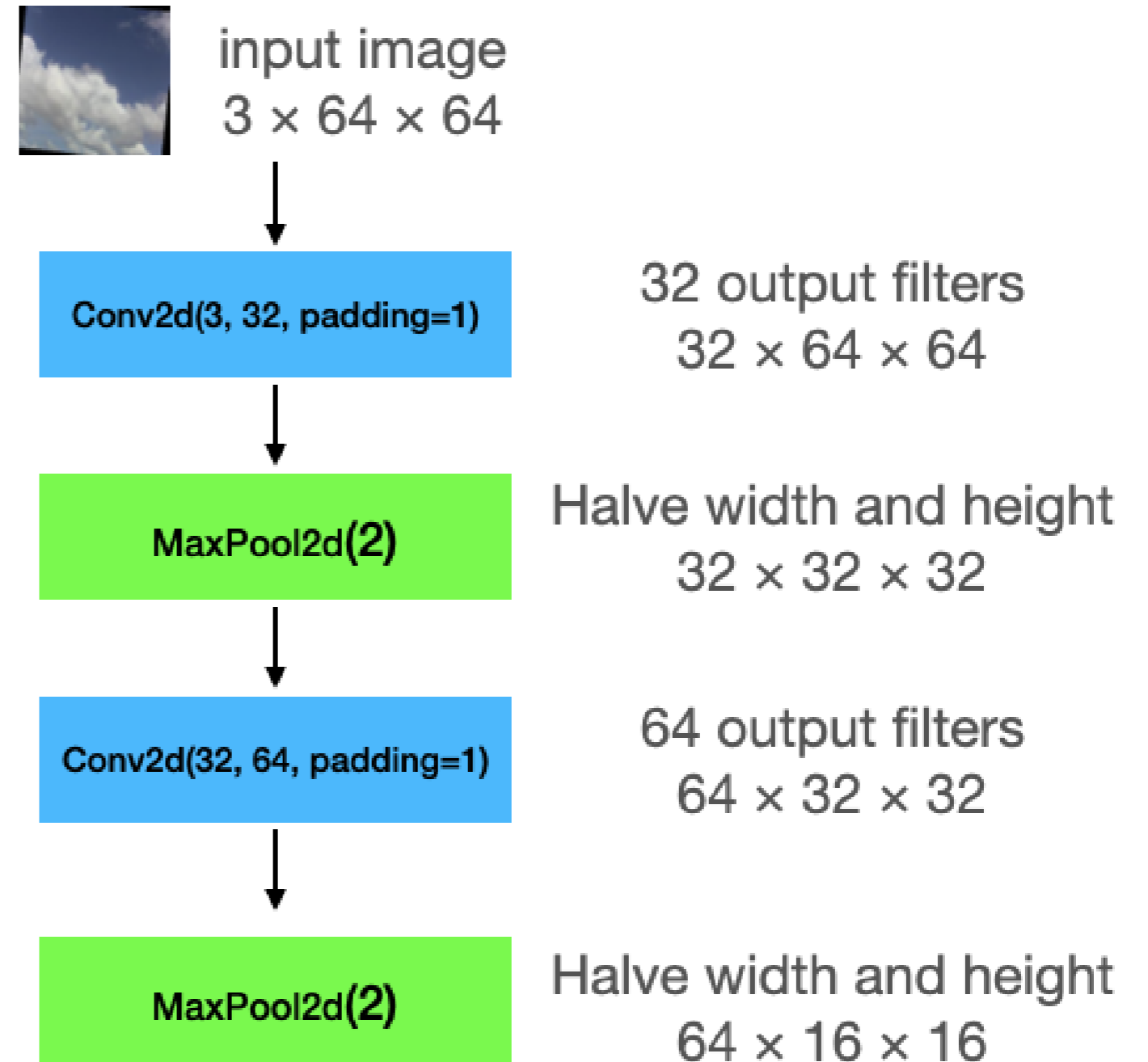

input image
3 × 64 × 64

Conv2d(3, 32, padding=1)

32 output filters
32 × 64 × 64

MaxPool2d(2)

Halve width and height
32 × 32 × 32

Conv2d(32, 64, padding=1)

MaxPool2d(2)

Feature extractor output size

```python
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)
`
```


input image
3 × 64 × 64

Conv2d(3, 32, padding=1)

32 output filters
32 × 64 × 64

MaxPool2d(2)

Halve width and height
32 × 32 × 32

Conv2d(32, 64, padding=1)

64 output filters
64 × 32 × 32

MaxPool2d(2)

Feature extractor output size

```python
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)
`
```

input image
$3 \times 64 \times 64$

Conv2d(3, 32, padding=1)

32 output filters
$32 \times 64 \times 64$

MaxPool2d(2)

Halve width and height
$32 \times 32 \times 32$

Conv2d(32, 64, padding=1)

64 output filters
$64 \times 32 \times 32$

MaxPool2d(2)

Halve width and height
$64 \times 16 \times 16$

Let's practice!

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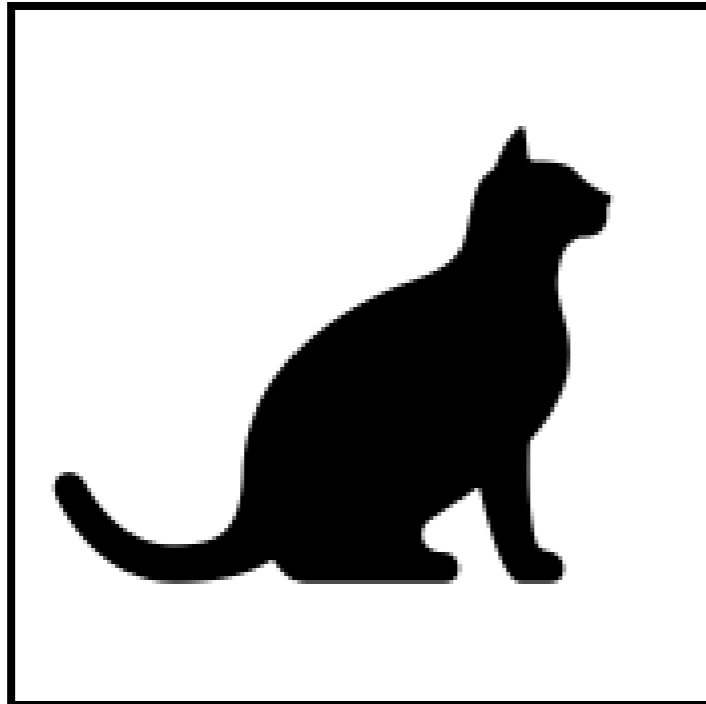
Training image classifiers

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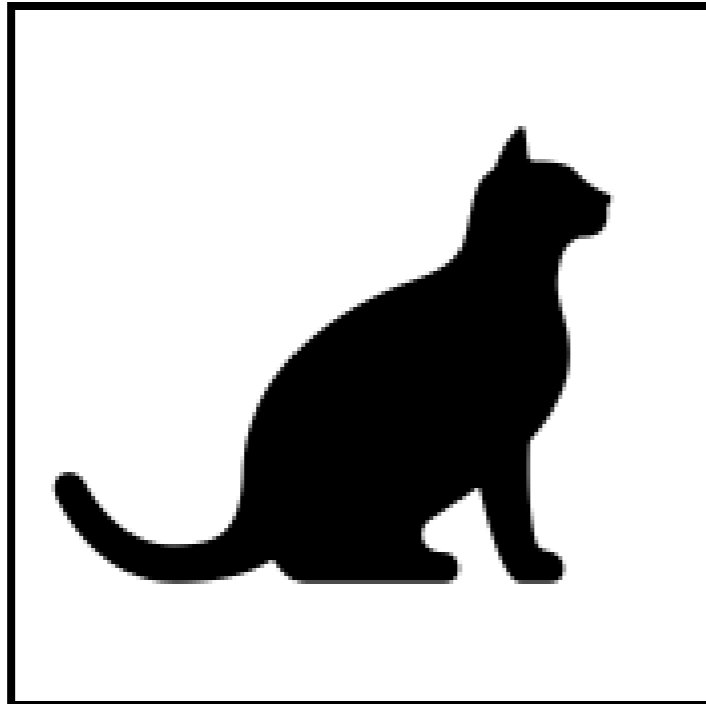Machine Learning Engineer

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Data augmentation revisited
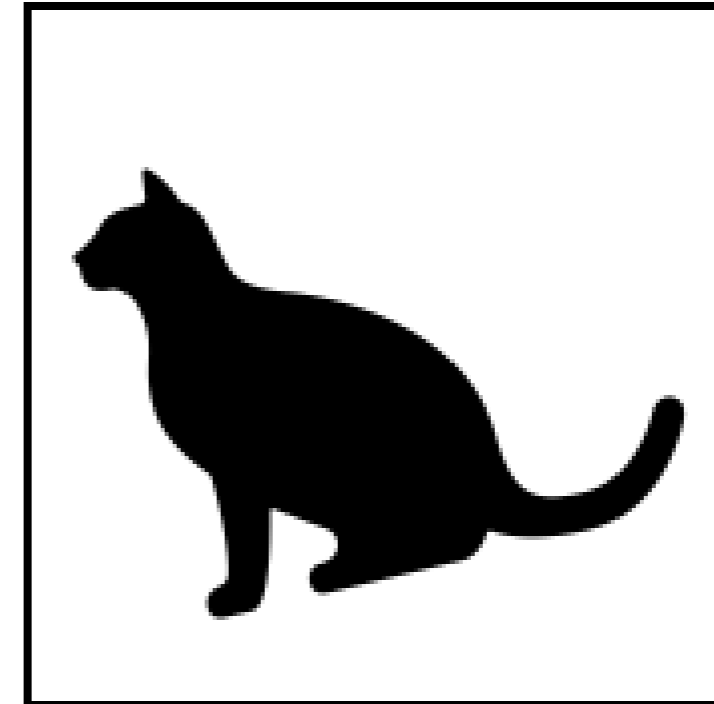
cat

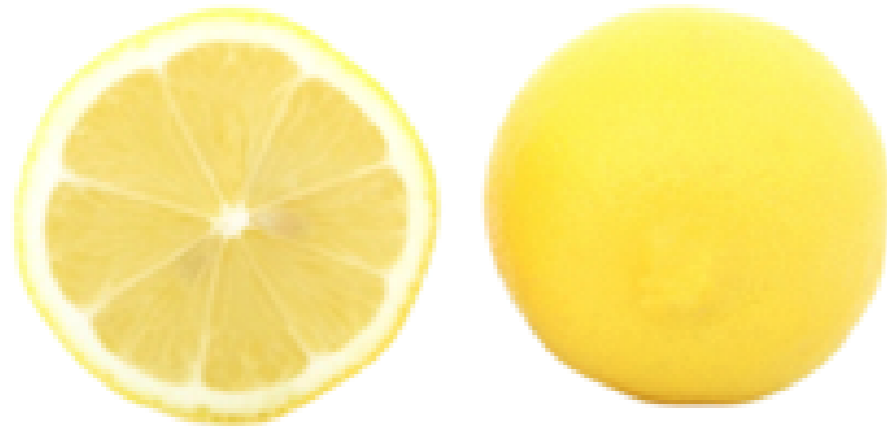# Data augmentation revisited

cat

rotation
+
horizontal flip

→
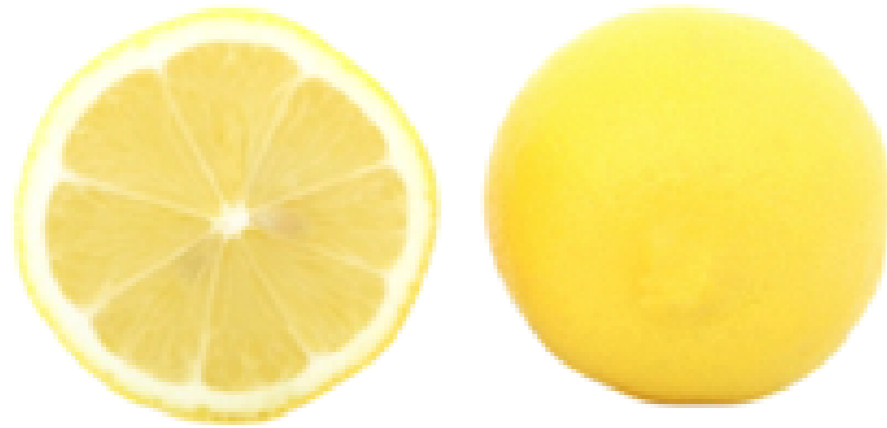
cat

What should not be augmented

Lemon

color shift

Lemon
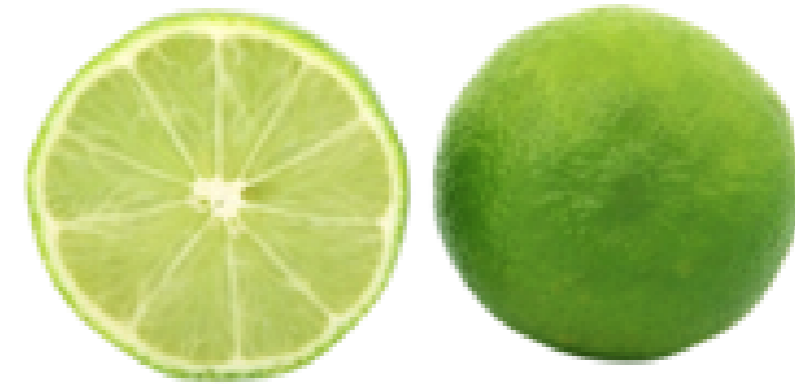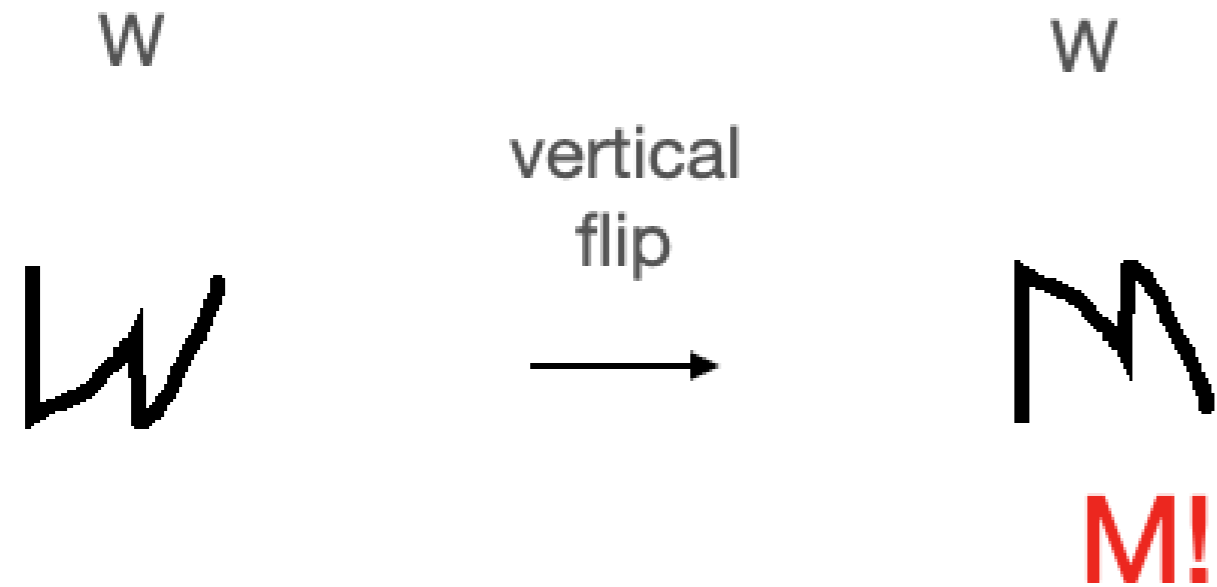
What should not be augmented

Lemon

color
shift

Lemon

LIME!

What should not be augmented

W

vertical
flip

$\longrightarrow$

W

M!

- 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

```python
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

```python
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!

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Evaluating image classifiers

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Data augmentation at test time

Data augmentation for training data:

```python
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,
)
```
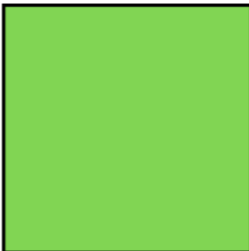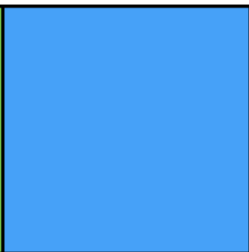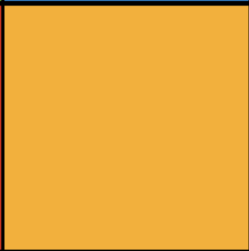
Data augmentation for test data:

```python
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

```python
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

```python
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

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

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

Analyzing performance per class

```python
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()
```

```python
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

```python
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`

Let's practice!

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