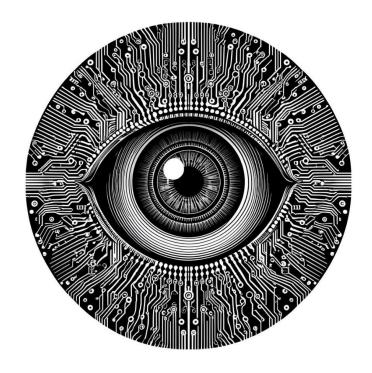


# **Image Data Augmentation**



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## **Learning goals**

- Use data augmentation to extend training datasets
- Gain familiarity with PyTorch's transforms.v2: affine transformations, vertical and horizontal flipping, and random crops

## **Data augmentation**













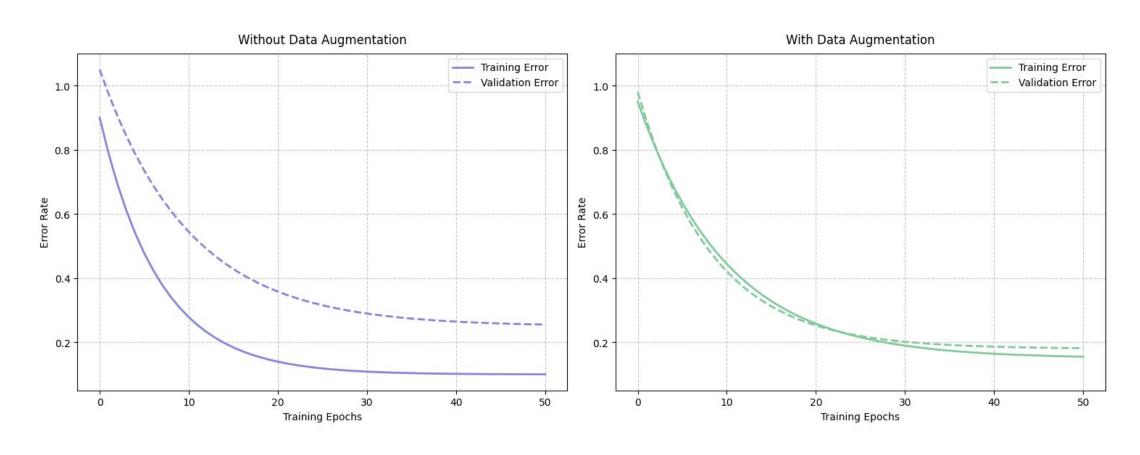




Image from <a href="https://docs.fast.ai/vision.augment">https://docs.fast.ai/vision.augment</a>

# Data augmentation as regularization

#### Impact of Data Augmentation on Model Training

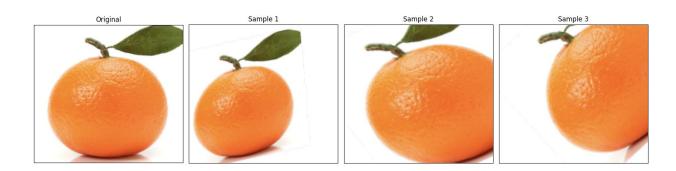


#### **Affine transformations**

$$egin{pmatrix} x' \ y' \end{pmatrix} = egin{pmatrix} a & b \ c & d \end{pmatrix} egin{pmatrix} x \ y \end{pmatrix} + egin{pmatrix} \Delta_x \ \Delta_y \end{pmatrix}$$

**Linear transformation** 

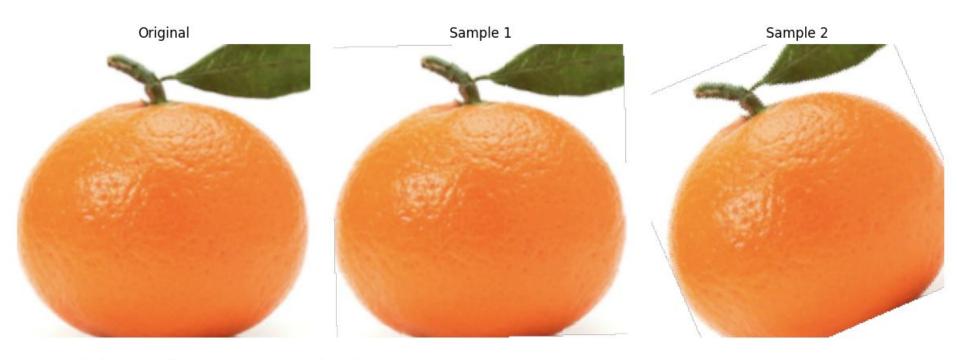
(Rotation, scaling, shear)



**Translation** 

(Moving along the axes)

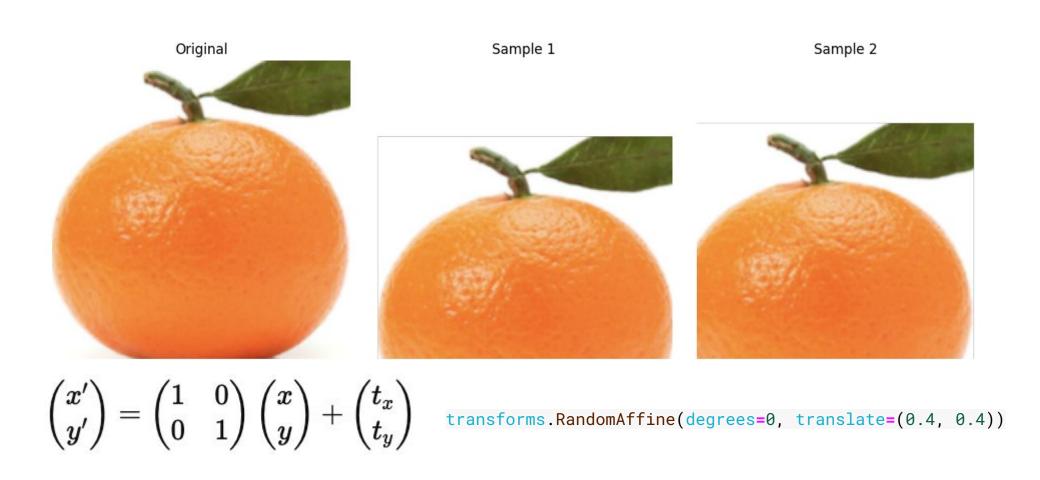
#### The RandomAffine transformation - rotation



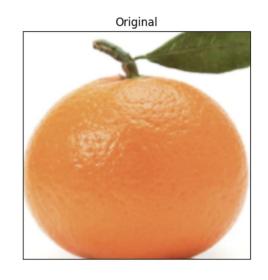
$$egin{pmatrix} x' \ y' \end{pmatrix} = egin{pmatrix} \cos heta & -\sin heta \ \sin heta & \cos heta \end{pmatrix} egin{pmatrix} x \ y \end{pmatrix}$$

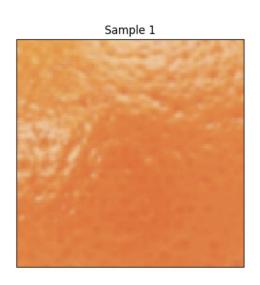
transforms.RandomAffine(degrees=45)

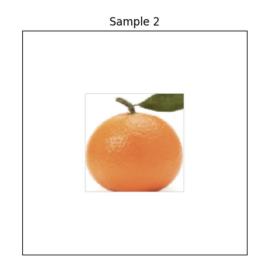
#### The RandomAffine transformation - translation



## The RandomAffine transformation - scaling



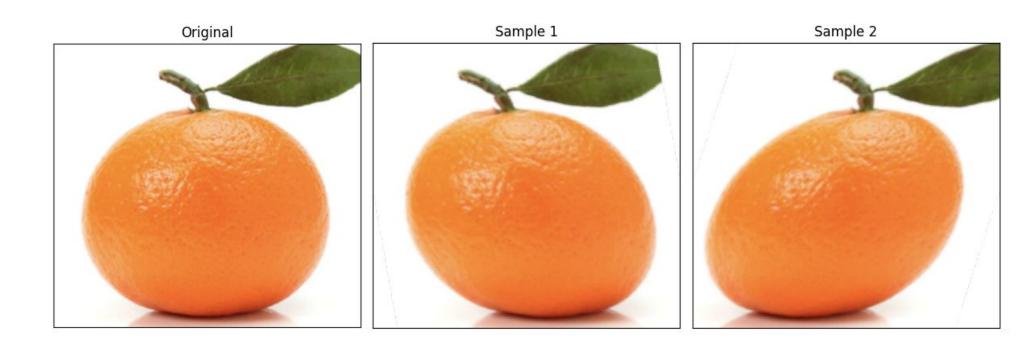




$$egin{pmatrix} x' \ y' \end{pmatrix} = egin{pmatrix} s_x & 0 \ 0 & s_y \end{pmatrix} egin{pmatrix} x \ y \end{pmatrix}$$

transforms.RandomAffine(degrees=0, scale=(0.25, 2.5))

#### The RandomAffine transformation - shear



$$egin{pmatrix} x' \ y' \end{pmatrix} = egin{pmatrix} 1 & s_x \ s_y & 1 \end{pmatrix} egin{pmatrix} x \ y \end{pmatrix}$$
 transforms.RandomAffine(degrees=0, shear=45)

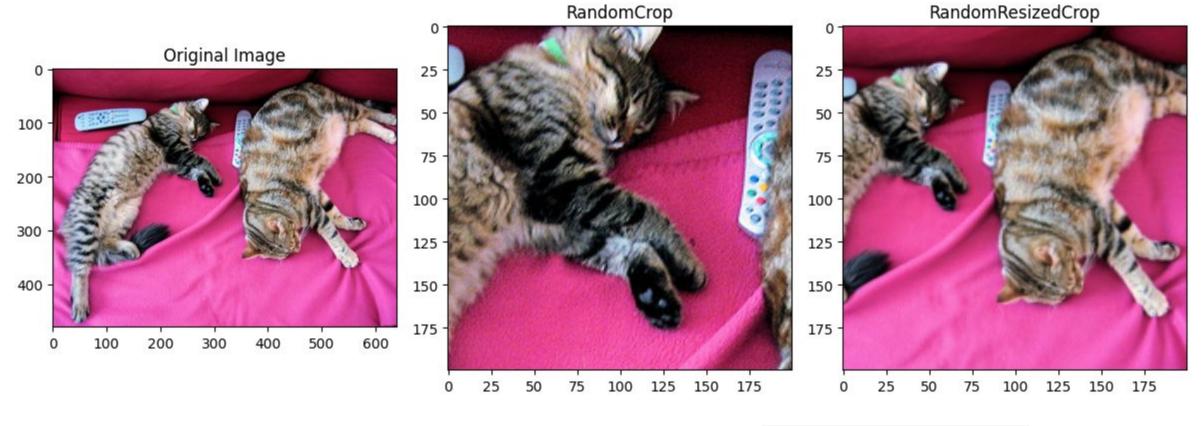
# Horizontal and vertical flipping







## RandomCrop and RandomResizedCrop

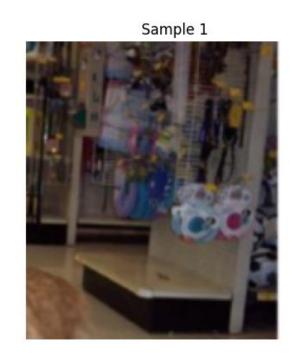


transforms.RandomCrop(size=224)

### Blind data augmentation can damage your model

 $\hat{y} = \text{golden retriever (unit 207 on Imagenet)}$ 





Cross Entropy Loss =  $-\log(0.003) = 5.809$ 



 $-\log(0.6) = 0.511$ 

# The validation set should not be augmented during training

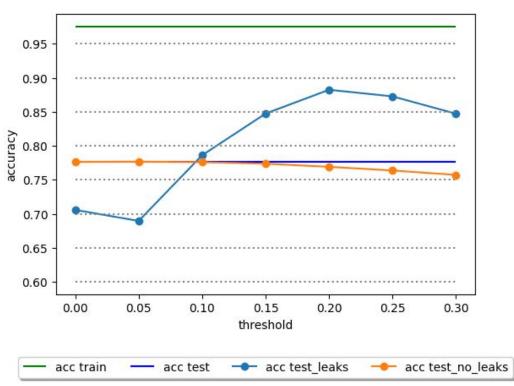


```
import torchvision.transforms.v2 as T
imagenet_mean = [0.485, 0.456, 0.406]
imagenet_std = [0.229, 0.224, 0.225]
transform = T.Compose([
# Resize to 224x224
T.Resize((224, 224)),
# Convert to torch Image
T.ToImage(),
# Convert to scaled float tensor
T.ToDtype(torch.float32, scale=True),
# Apply ImageNet normalization
T.Normalize(mean=imagenet_mean,
            std=imagenet_std)
```

# Augmentation should happen <u>after</u> train, validation, and test splitting









# **Summary**

#### Data augmentation creates synthetic input data

Data augmentation can improve the robustness of a model and prevent overfitting

#### PyTorch transforms are powerful and composable

- transforms.v2 provides rotation, scale, crop, and flip (+other) operations
- Each transform has specific parameters for fine control

#### Avoiding data leakage: best practices

Apply augmentations after train, validation, and test split. Never augment validation data.
 Test augmentation effects through observation and loss values



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## Further reading and references

#### Data augmentation is still data curation

https://voxel51.com/blog/data-augmentation-is-still-data-curation/

#### **Getting started with PyTorch's transforms v2**

https://pytorch.org/vision/main/auto\_examples/transforms/plot\_transforms\_getting\_started\_.html

#### Illustration of transforms

https://pytorch.org/vision/main/auto\_examples/transforms/plot\_transforms\_illustrations.ht
 ml#sphx-glr-auto-examples-transforms-plot-transforms-illustrations-py

