Lecture 3: computer vision, convolutional networks, transfer learning

Machine Learning - 2

Data Science and Business Analytics Program (DSBA) at HSE & LSE, 22/23

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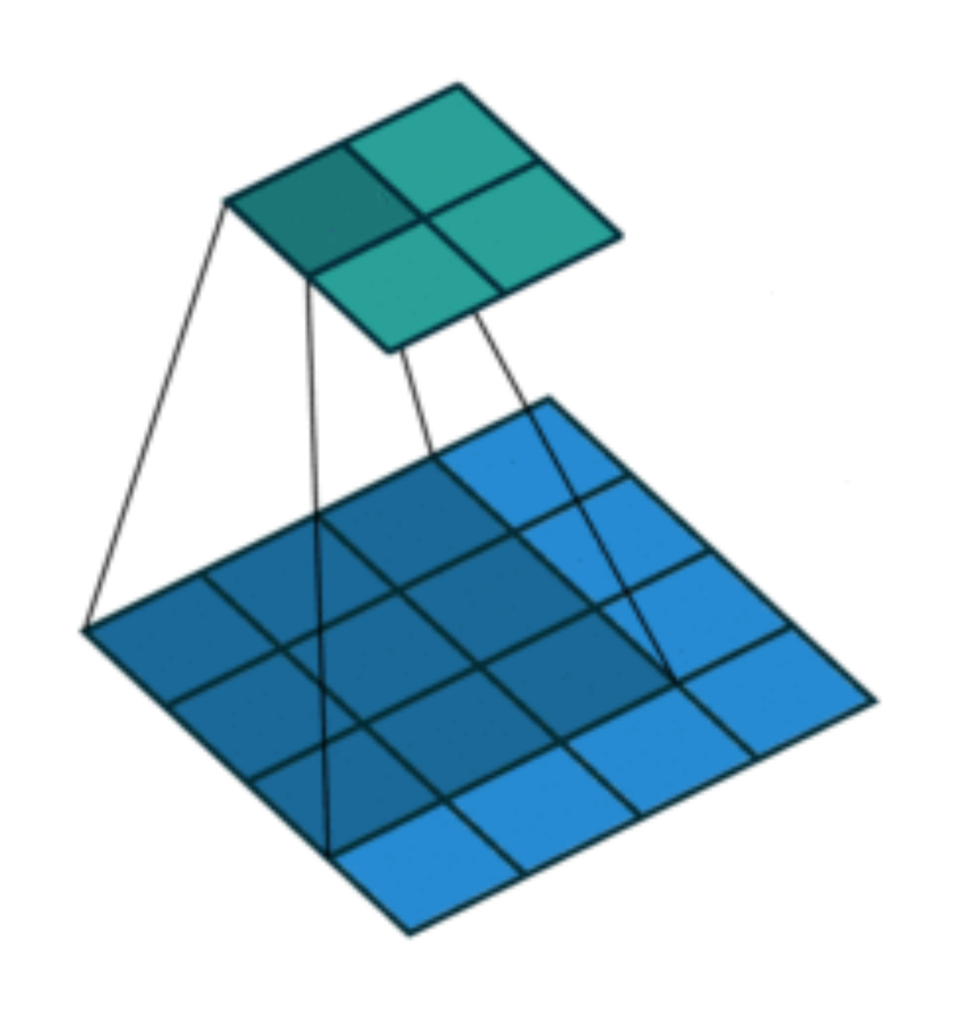
Convolutions, Pooling, Computer Vision Tasks

Source:

- https://stanford.edu/~shervine/teaching/cs-230/cheatsheet-convolutional-neural-networks
- https://stanford.edu/~shervine/teaching/cs-230/cheatsheet-deep-learning-tips-and-tricks
- https://cs231n.github.io/convolutional-networks/

Convolution examples



F - ?
Padding - ?
Stride - ?

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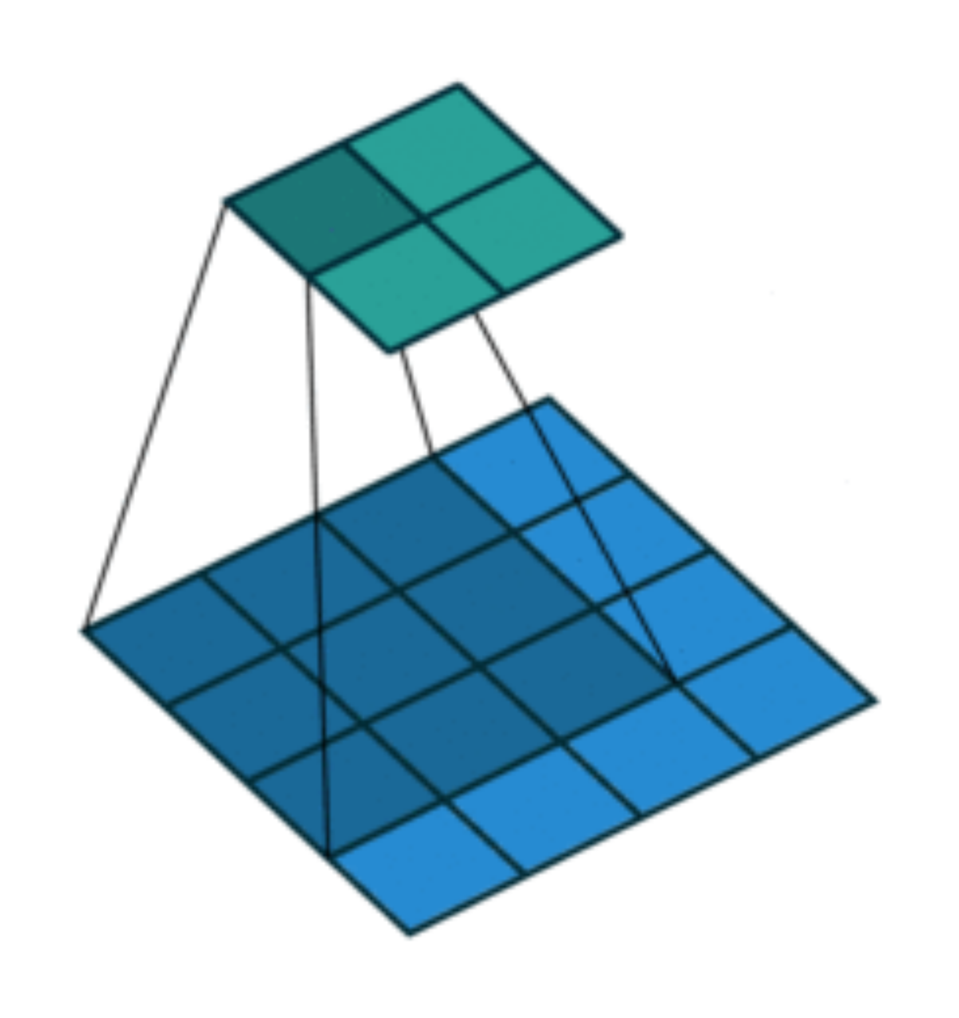
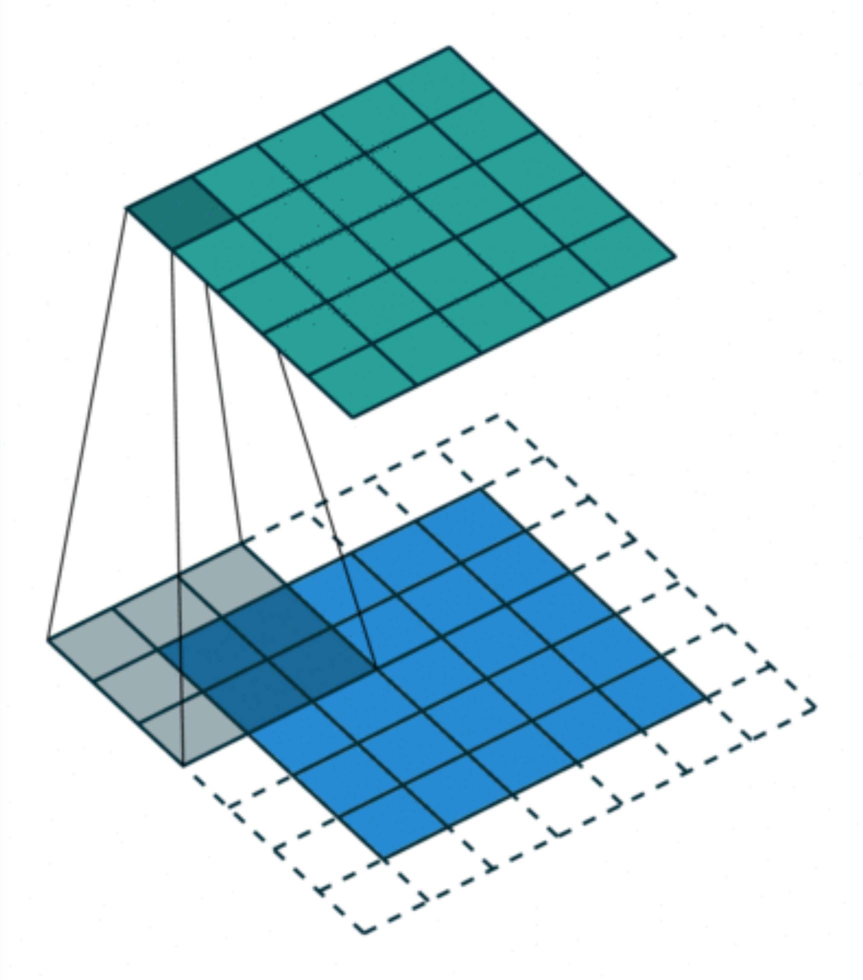
Convolution examples



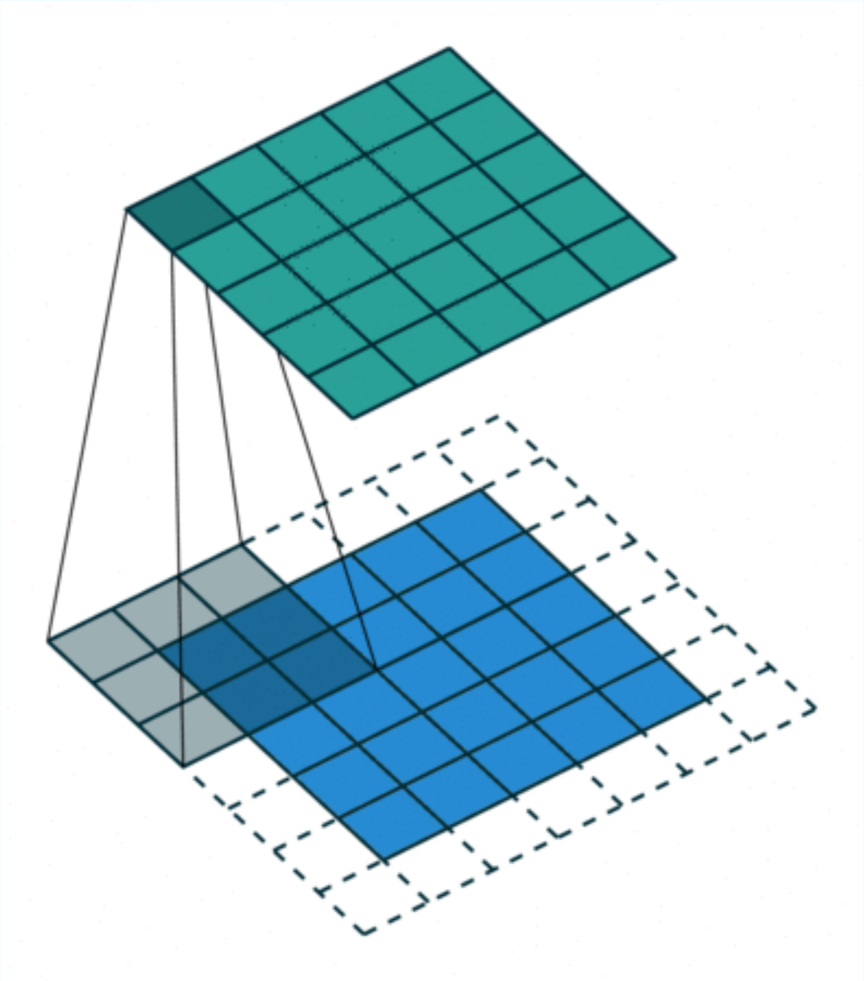
F = 3
Padding = 0
Stride = 1

Convolution examples



F - ?
Padding - ?
Stride - ?

Convolution examples



F = 3

Padding = same (half)

Stride = 1

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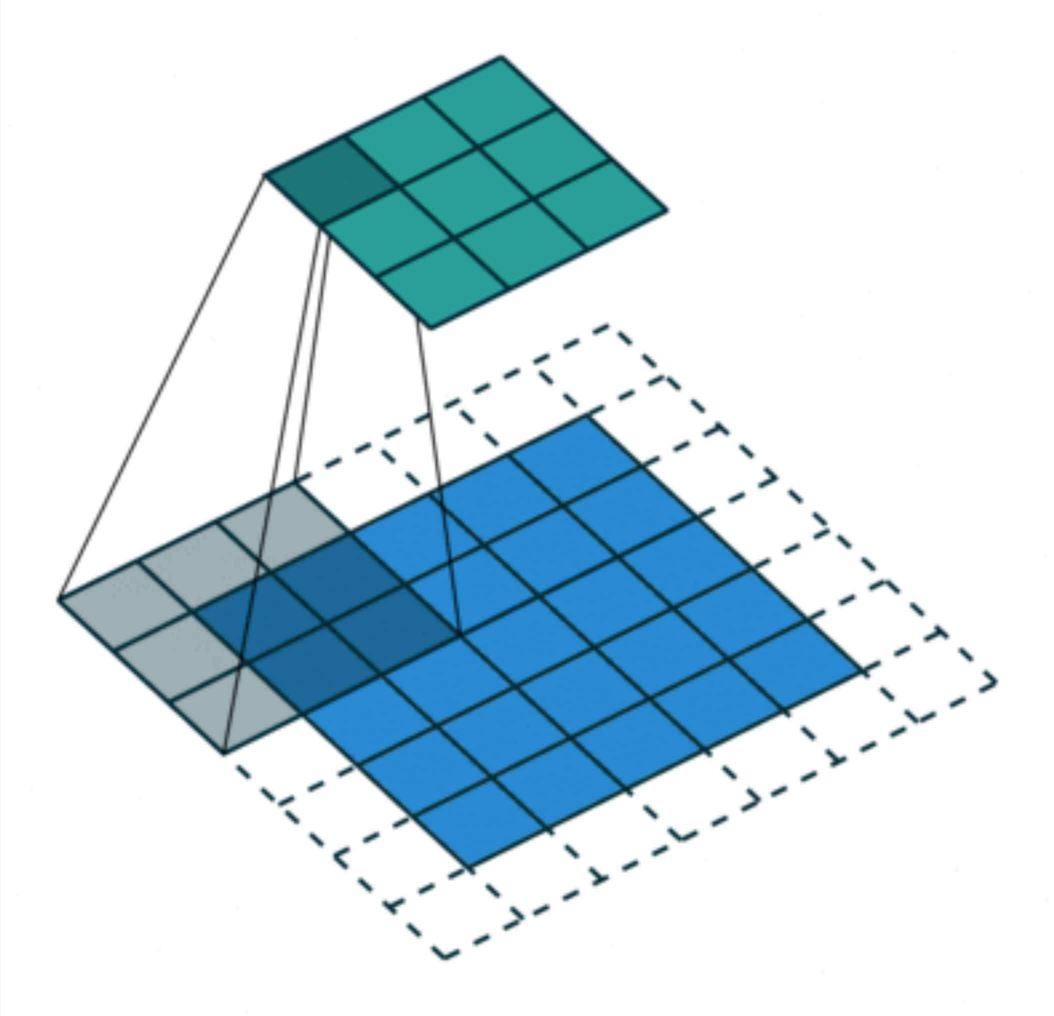
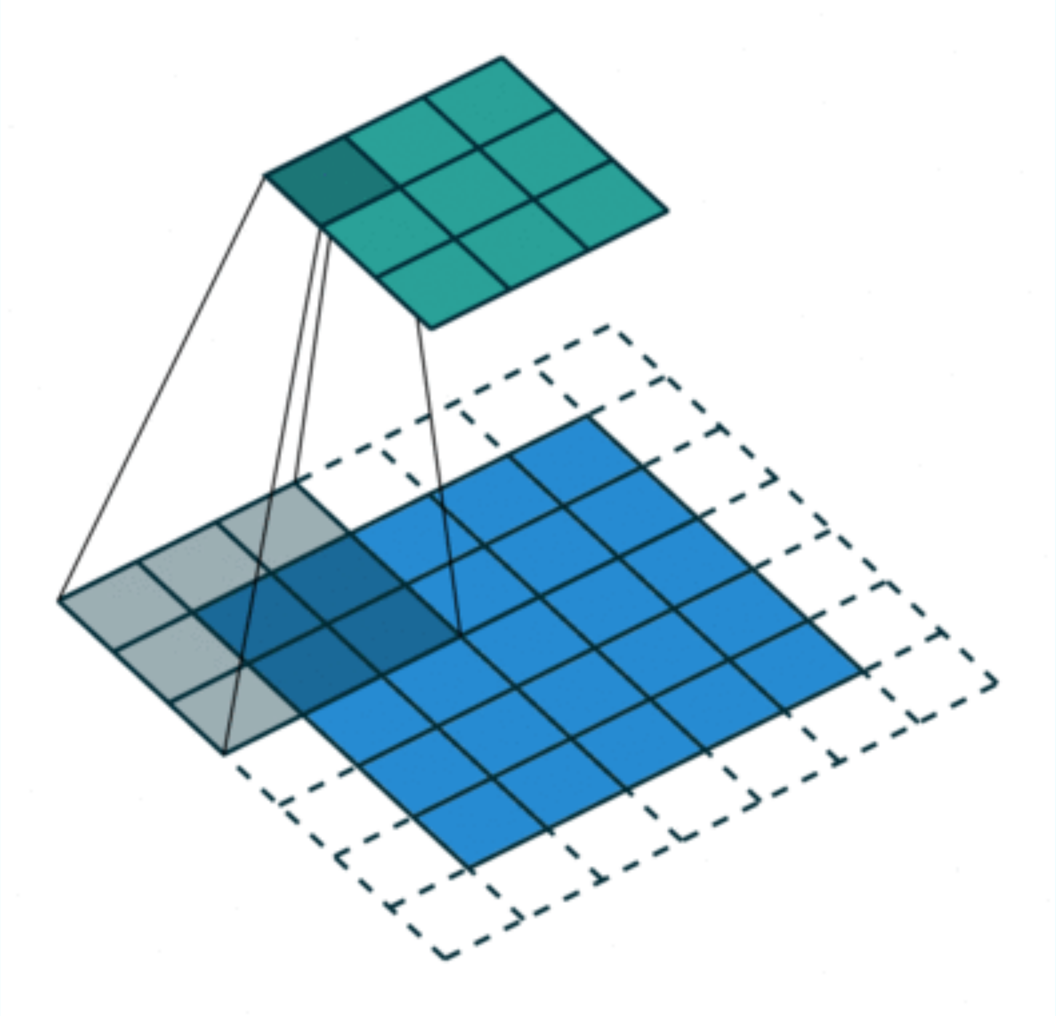
Convolution examples



F - ?
Padding - ?
Stride - ?

Convolution examples

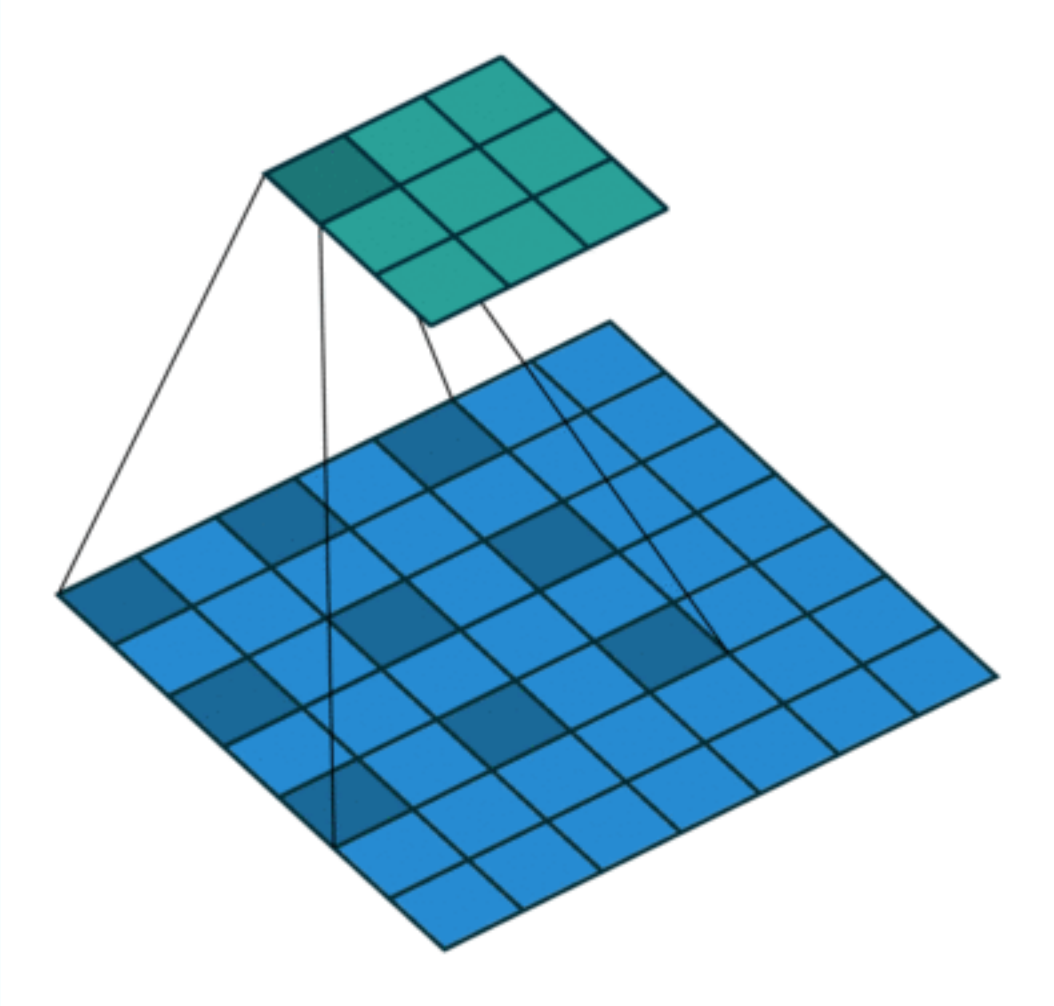


F = 3

Padding = same (half)

Stride = 2

Convolution examples

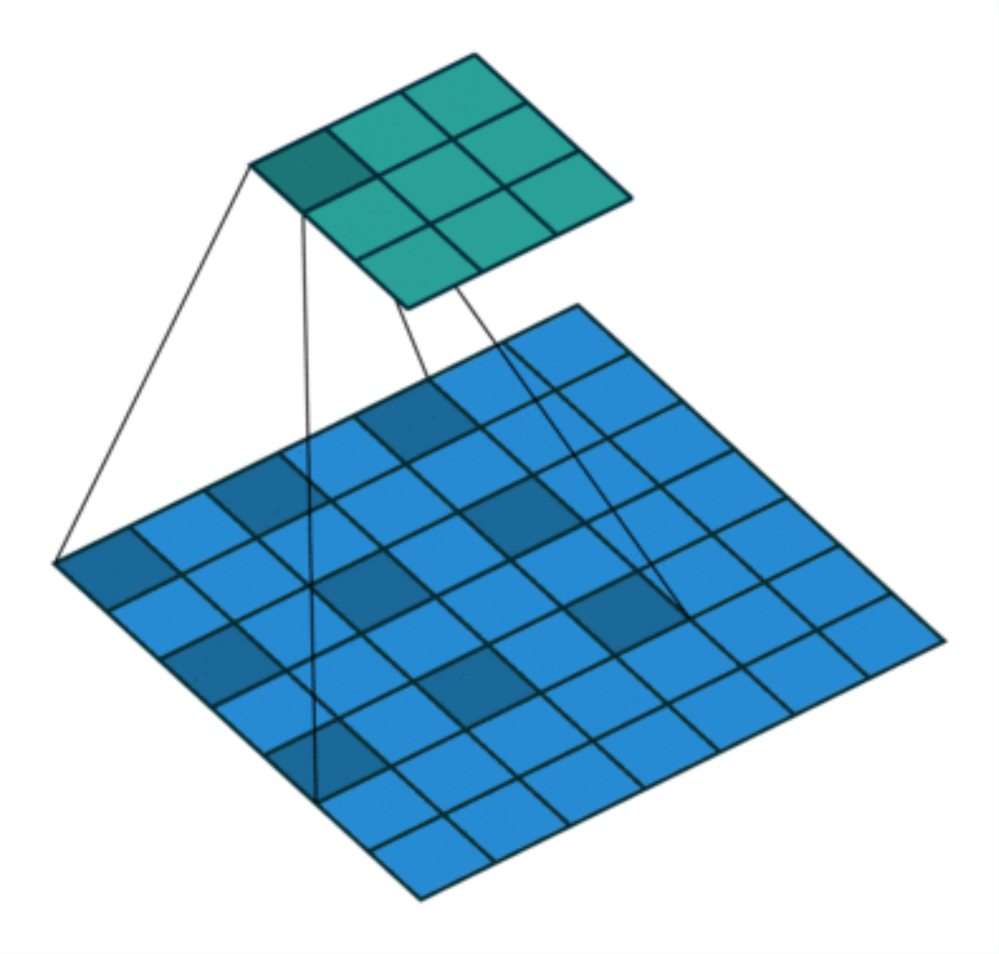


F - ?

Padding - ?

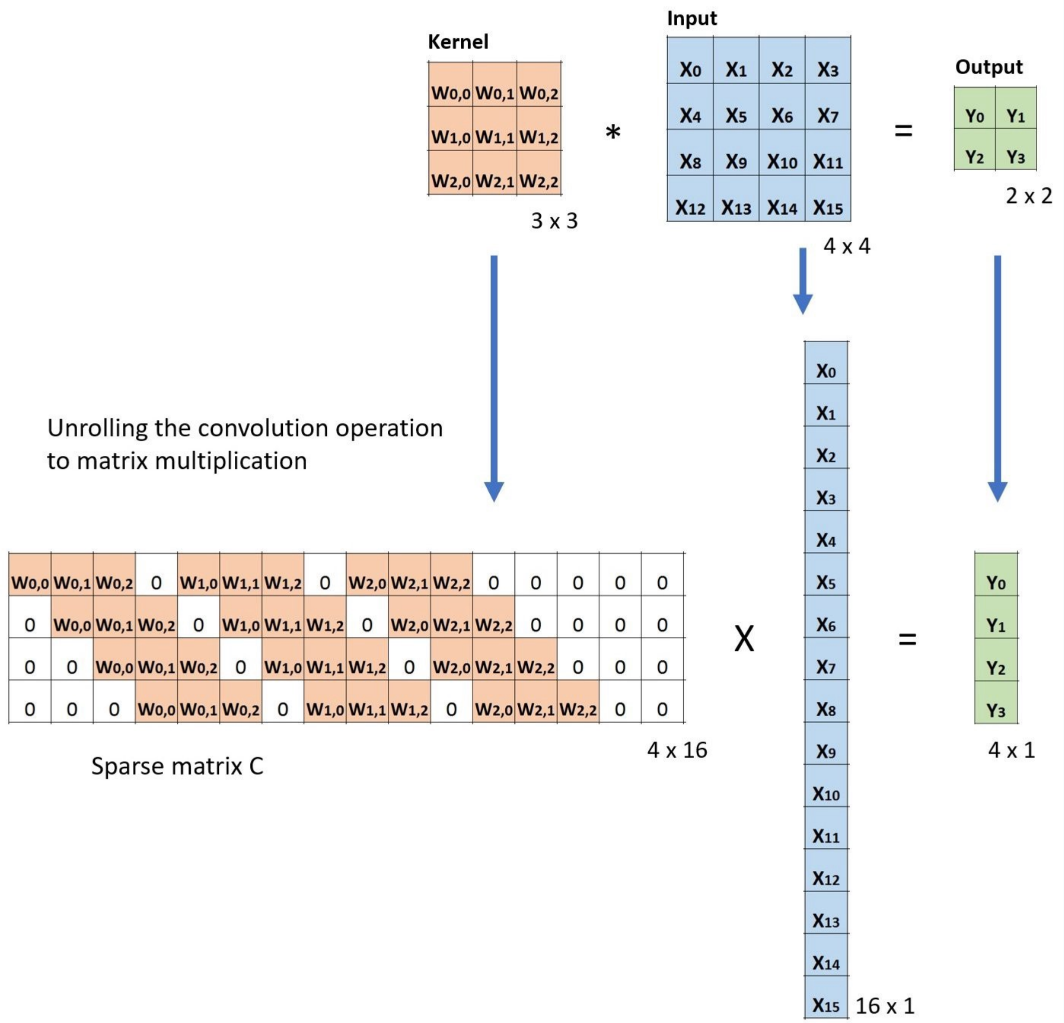
Stride - ?

Convolution examples



F = 3
Padding = 0
Stride = 1
Dilation = 2

Convolution as matrix multiplication



- Construct a sparse matrix which can be directly multiplied!

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Data Augmentation

- Train set:

- Test instance:

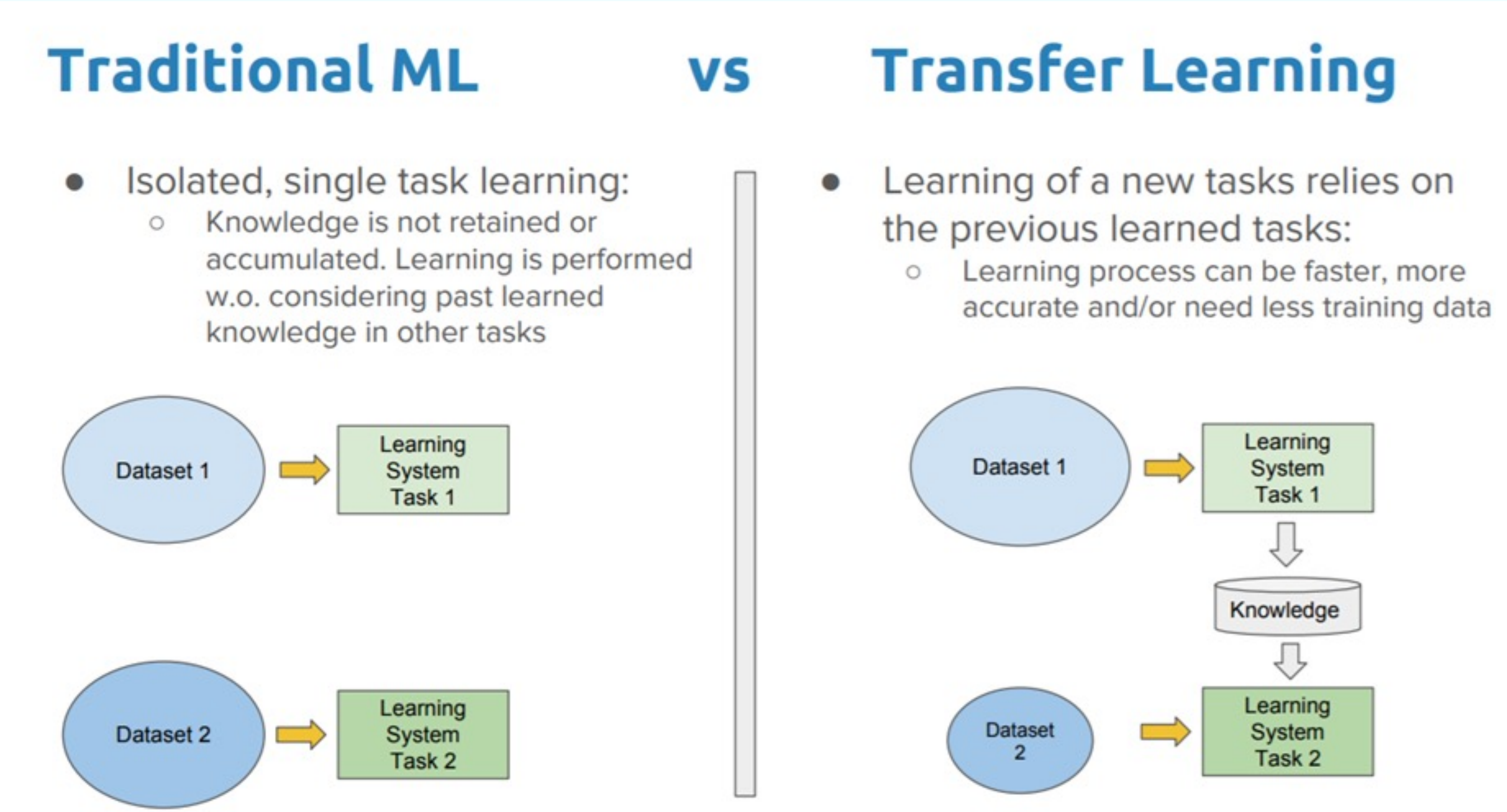
- Which class?

Data Augmentation

Source:

- **https://stanford.edu/~shervine/teaching/cs-230/cheatsheet-deep-learning-tips-and-tricks**

Transfer Learning & Fine-Tuning



Transfer Learning & Fine-Tuning

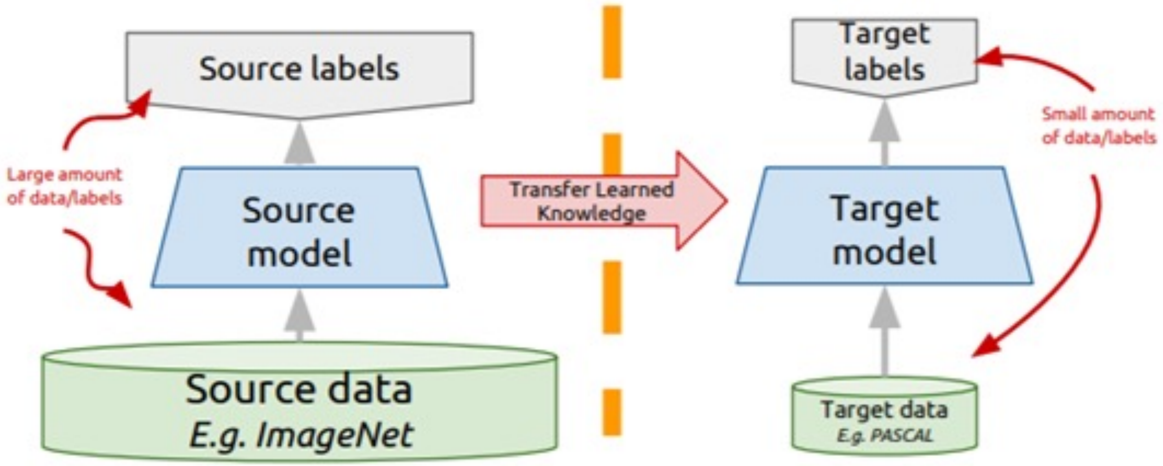
Transfer learning: idea

Instead of training a deep network from scratch for your task:

- Take a network trained on a different domain for a different **source task**
- Adapt it for your domain and your **target task**

Variations:

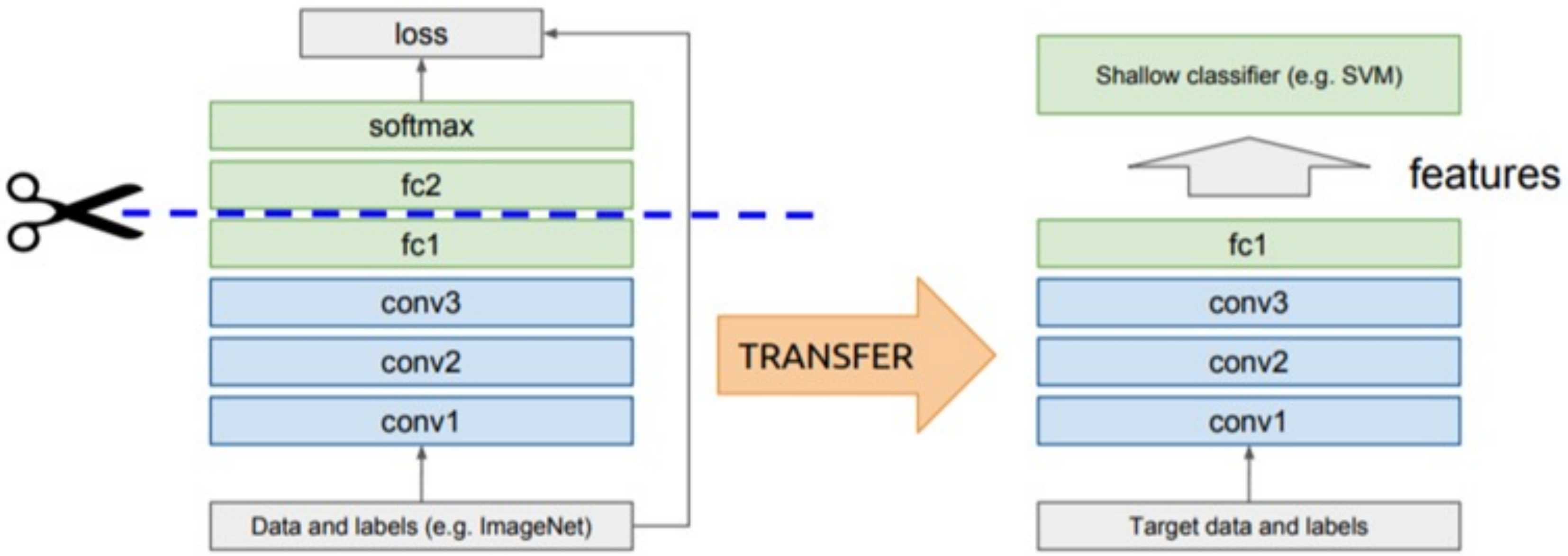
- Same domain, different task
- Different domain, same task



Transfer Learning & Fine-Tuning

Idea: use outputs of one or more layers of a network trained on a different task as generic feature detectors. Train a new shallow model on these features.

Assumes that $D_S = D_T$



Transfer Learning & Fine-Tuning

Freeze or fine-tune?

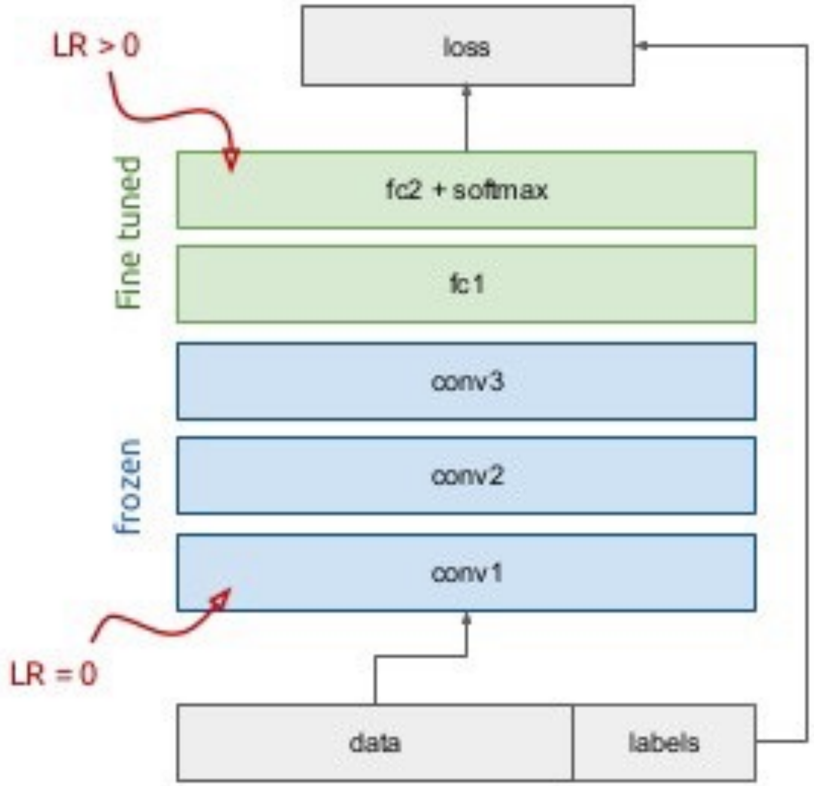
Bottom *n* layers can be frozen or fine tuned.

- **Frozen**: not updated during backprop
- **Fine-tuned**: updated during backprop

Which to do depends on target task:

- **Freeze**: target task labels are scarce, and we want to avoid overfitting
- **Fine-tune**: target task labels are more plentiful

In general, we can set learning rates to be different for each layer to find a tradeoff between freezing and fine tuning



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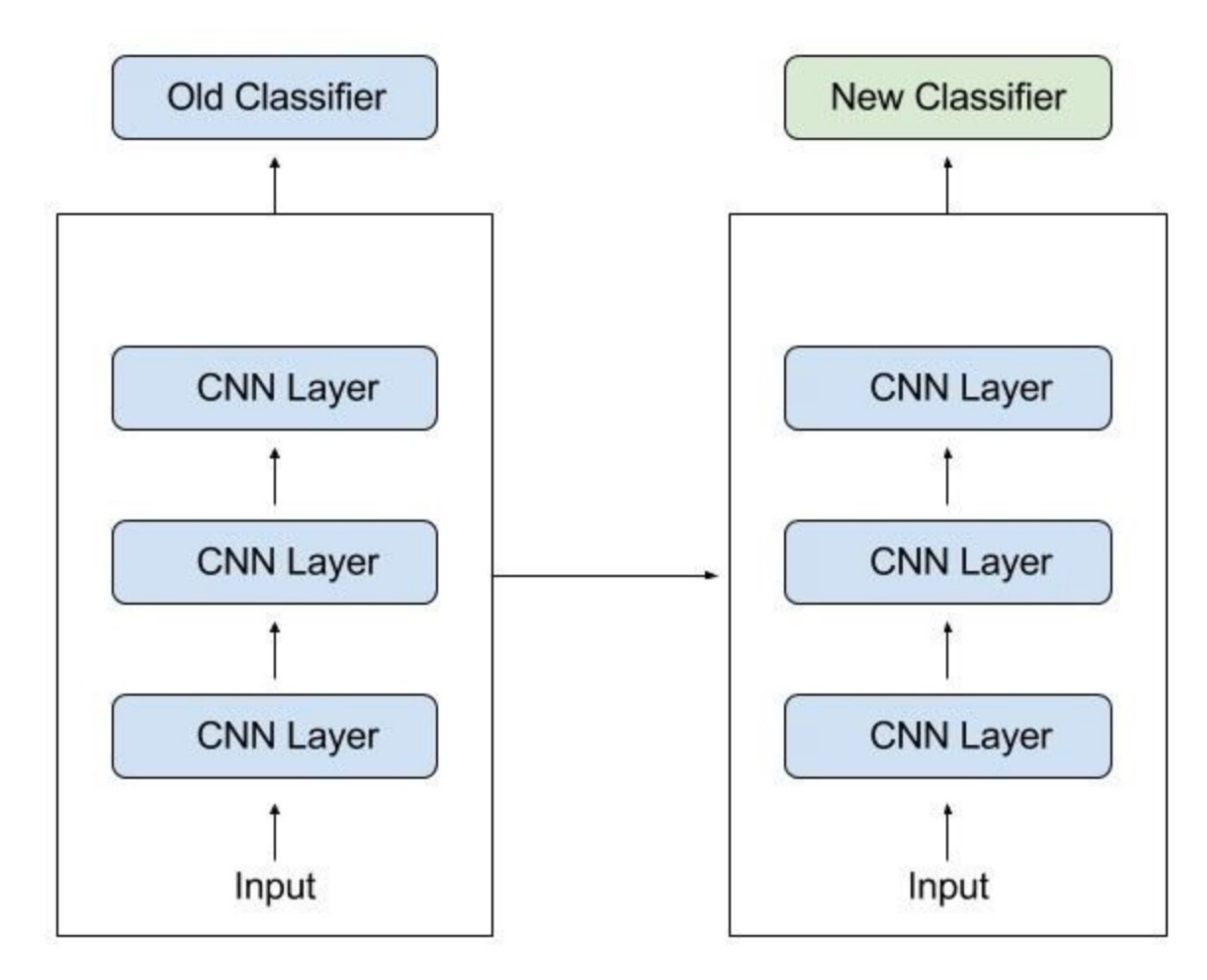
Transfer Learning & Fine-Tuning



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Self-learning

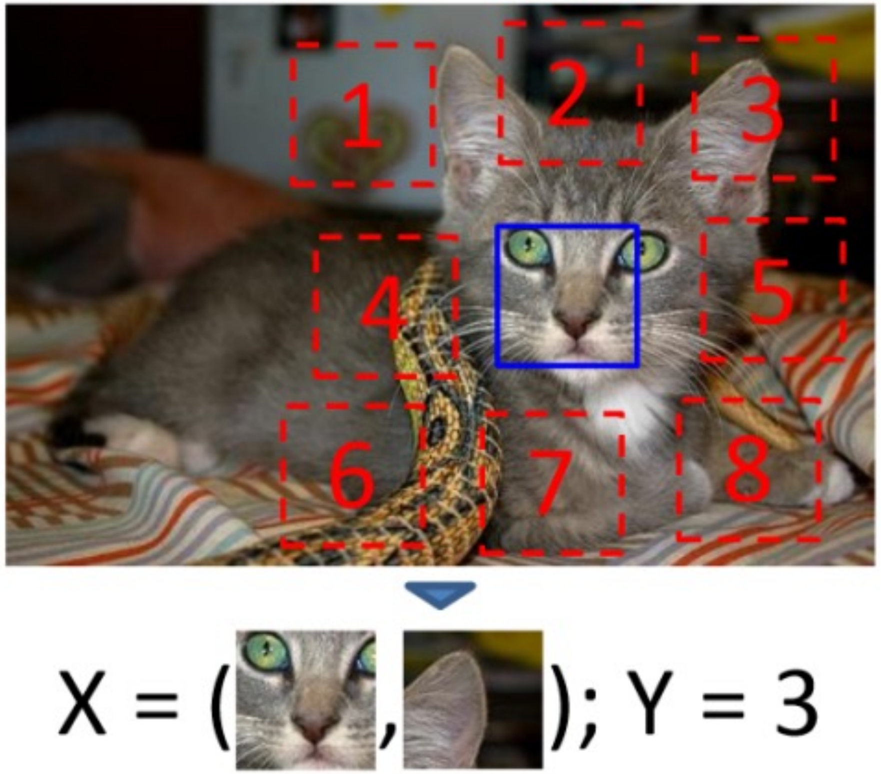
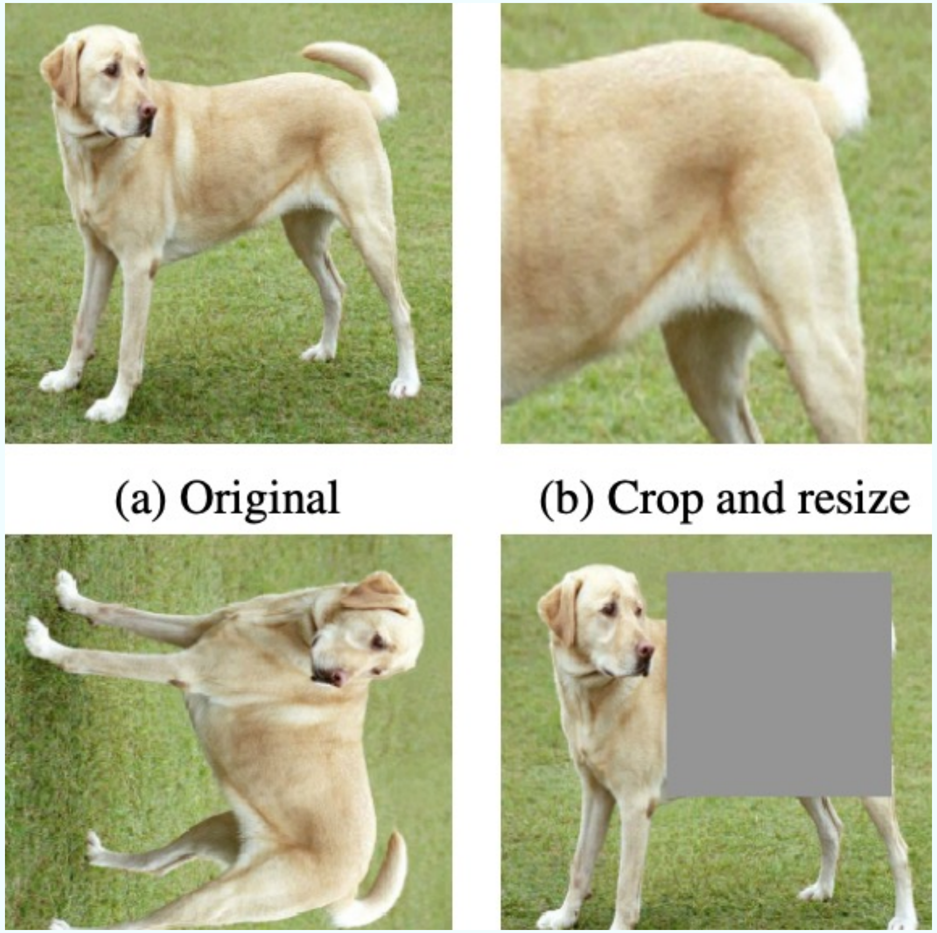


Figure 2. The algorithm receives two patches in one of these eight possible spatial arrangements, without any context, and must then classify which configuration was sampled.



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Summary

- Convolutional networks are mostly used in Computer Vision due to the benefits of convolutional & pooling layers
- Data augmentation allows to increase the performance of the model
- Transfer learning & fine-tuning significantly improve the performance of the models in CV / NLP by leveraging knowledge obtained while solving a large pre-training task onto the target task

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