University of Antwerp

Artificial Neural Networks

[2500WETANN]

José Oramas

Convolutional Neural Networks

[Part 3 – Use Case Discussion]

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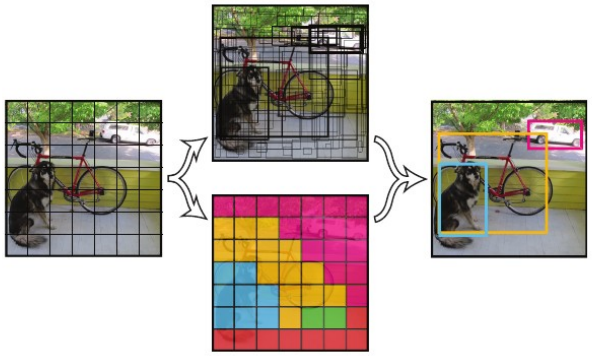
Summarizing

- **Convolutions go beyond simple classification**

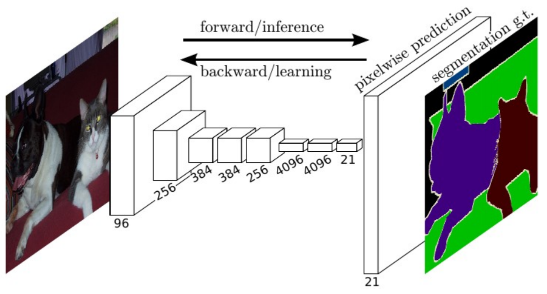
  localization | dense prediction



- **Additional use of convolutions**

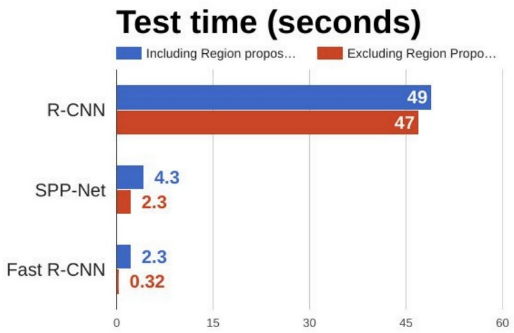
  Transpose → Useful for upscaling operations

  FC Layers as Convolutions → useful for resolution invariance



- **Suitable designs → better performance**

  time invested at design-time eventually pays off



Learning & Optimization

[... for Deep Neural Networks]

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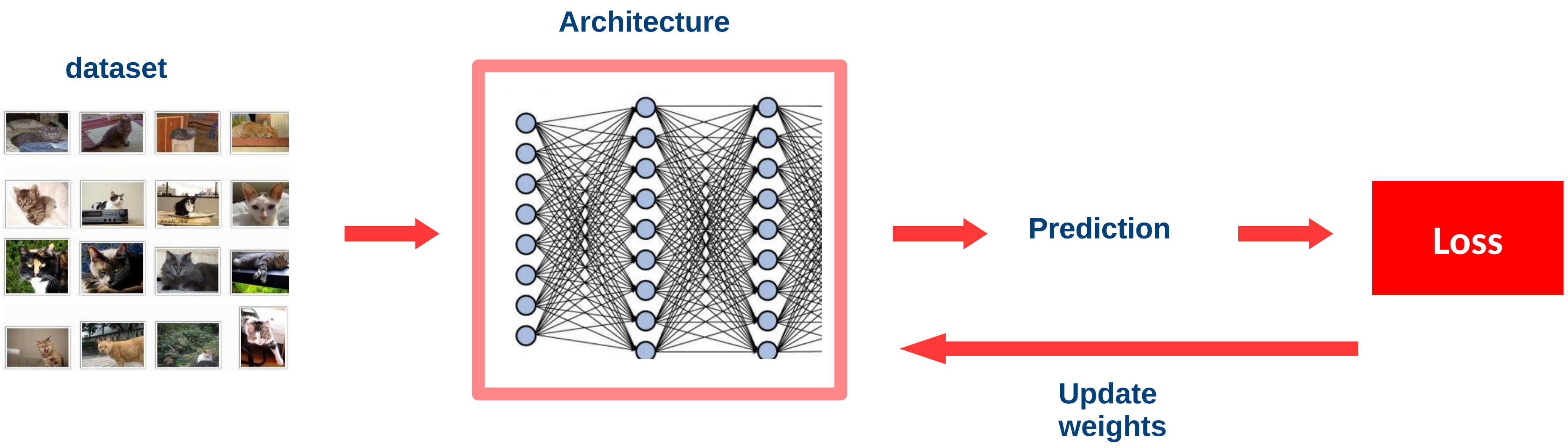
Learning and Optimization

Training Pipeline

- Techniques Applicable at Different Stages



Prior-Training

[The Calm Before the Storm]

Data Augmentation

What?

- Apply a set of operations on a given data sample to produce additional samples

Original Image

Cropped samples

Mirrored samples

Benefits

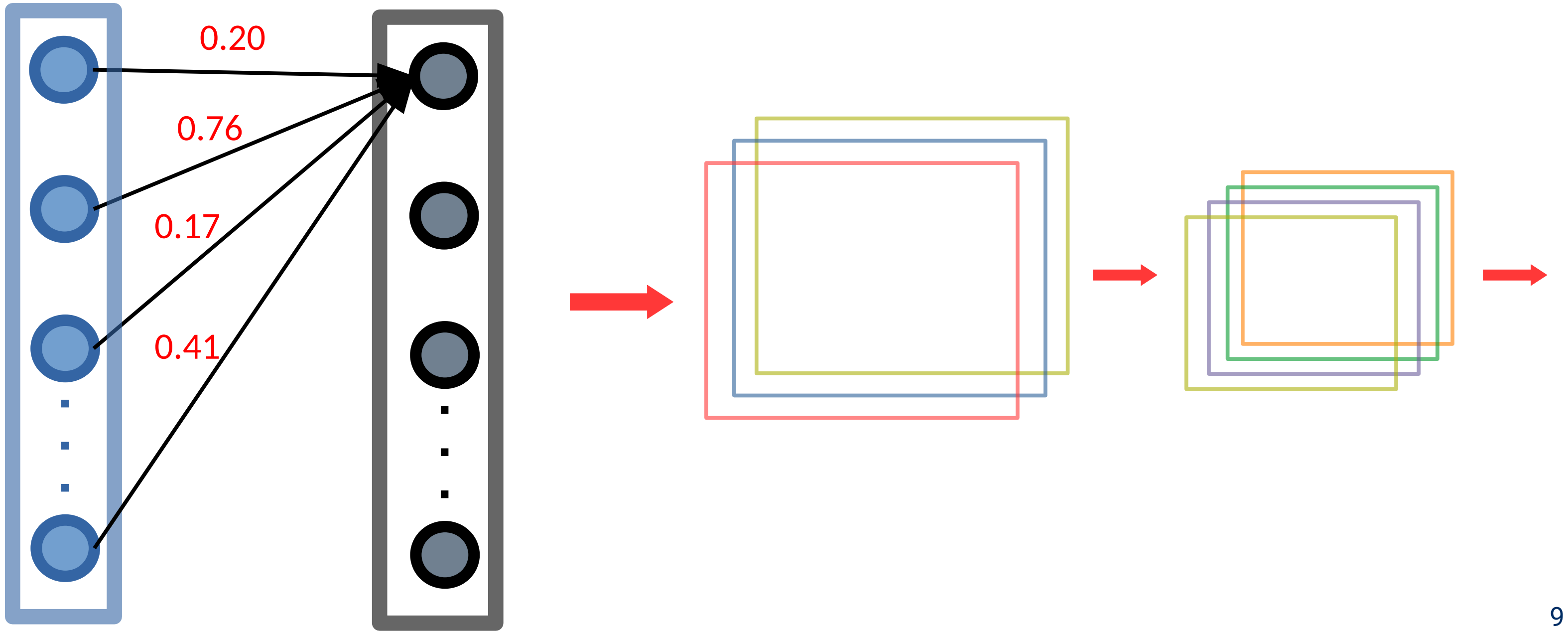
- Increase training data
- Introduce variability

Q: What happens at test time?

Input Normalization

Common Practice

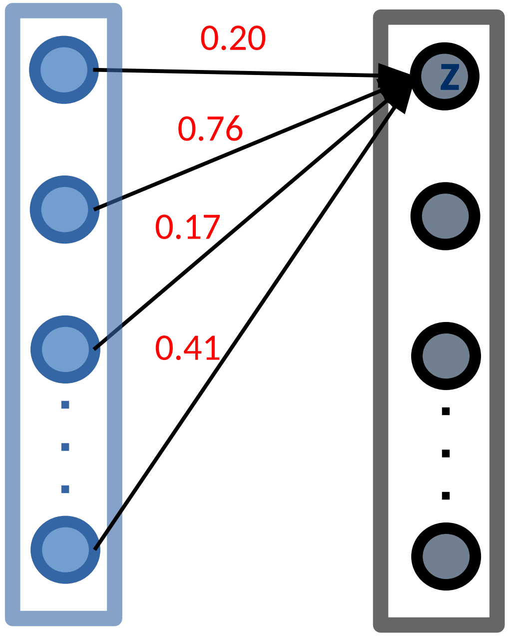
- Remove the "mean image"
- Standarize the inputs



Initializating Weights of the Network

Common Practice

- Random Initialization
- Ensure the weights have a known mean and variance



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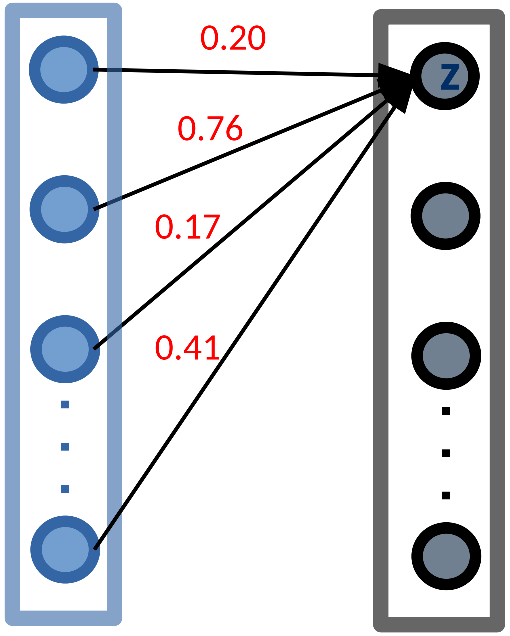

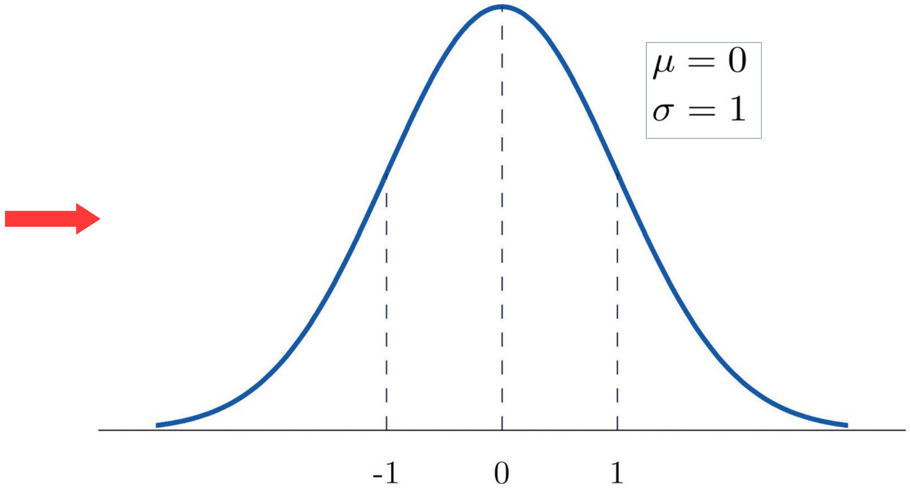

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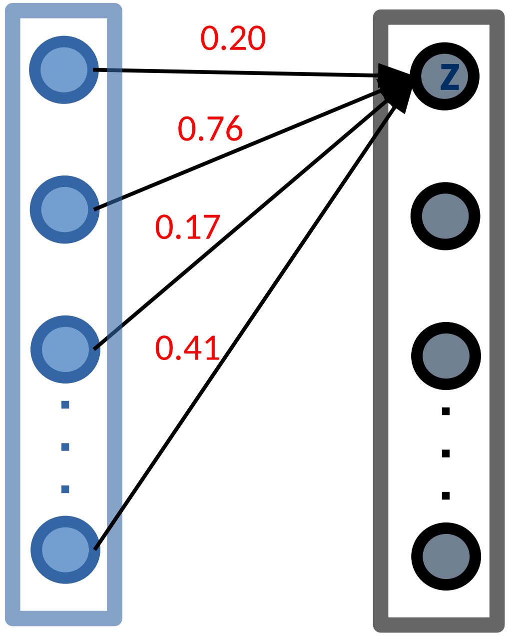

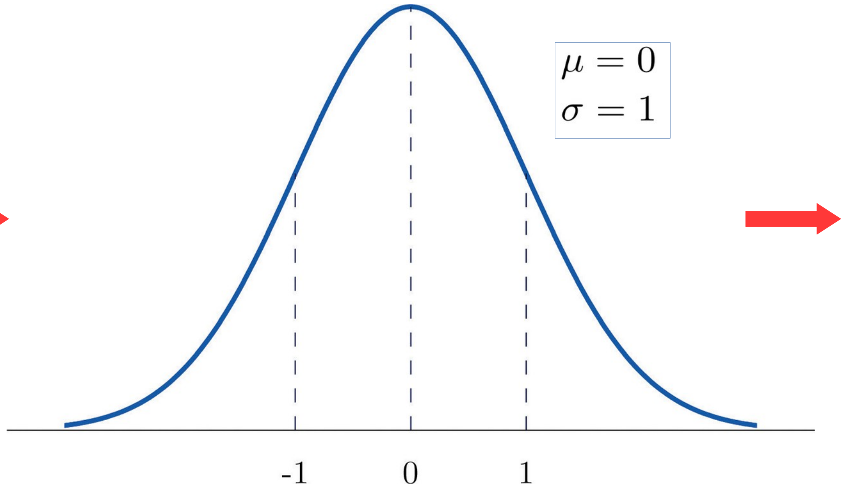

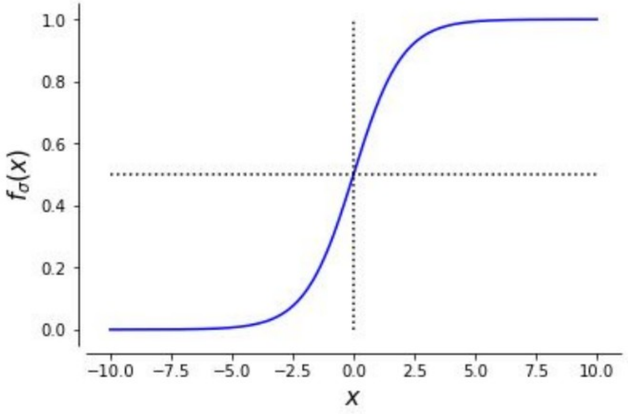

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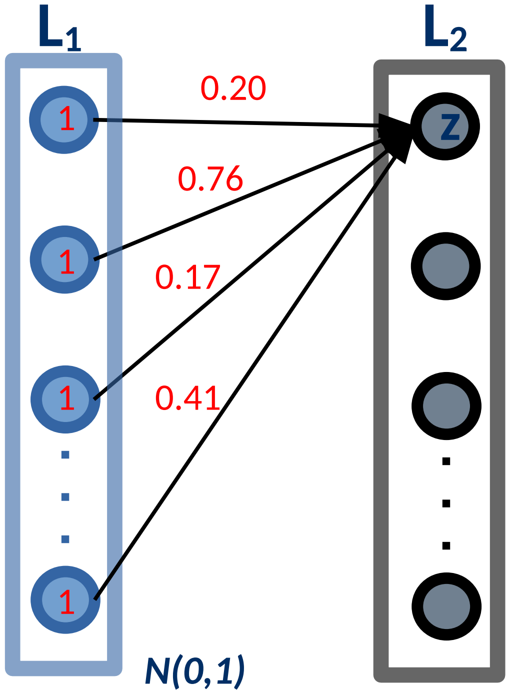
Initializating Weights of the Network

Common Practice – What Happens in the Next Layer?

- Random Initialization
- Let’s consider a simple setting (n=4 inputs, all set to 1)



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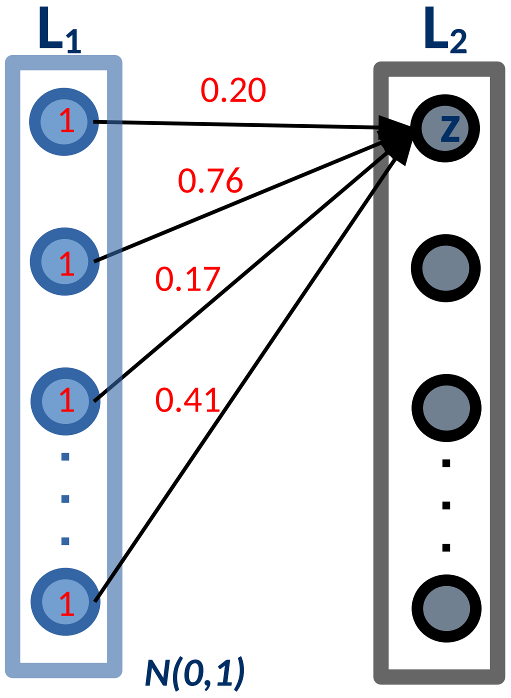

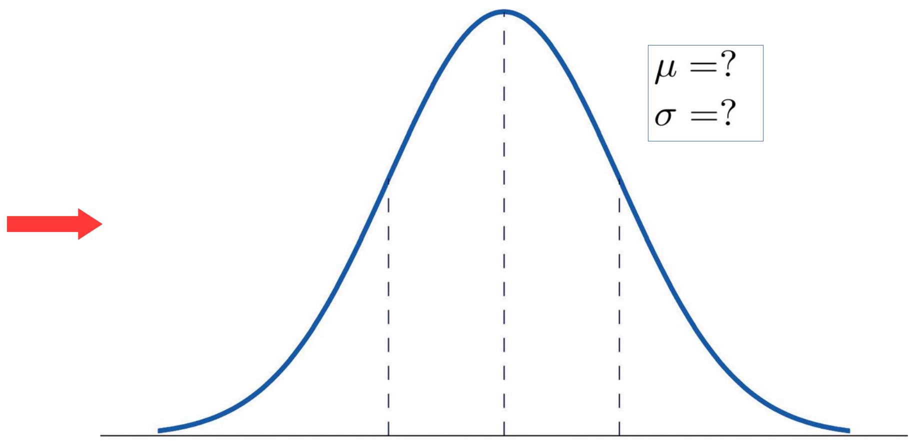

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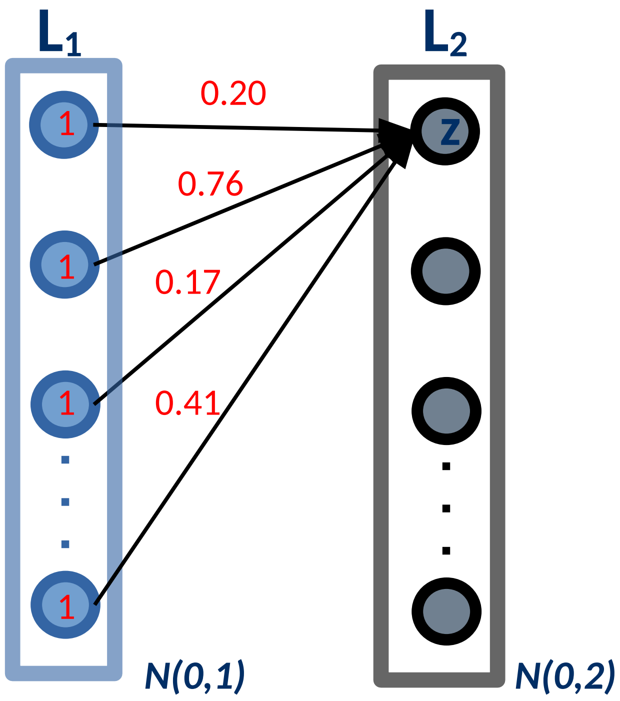

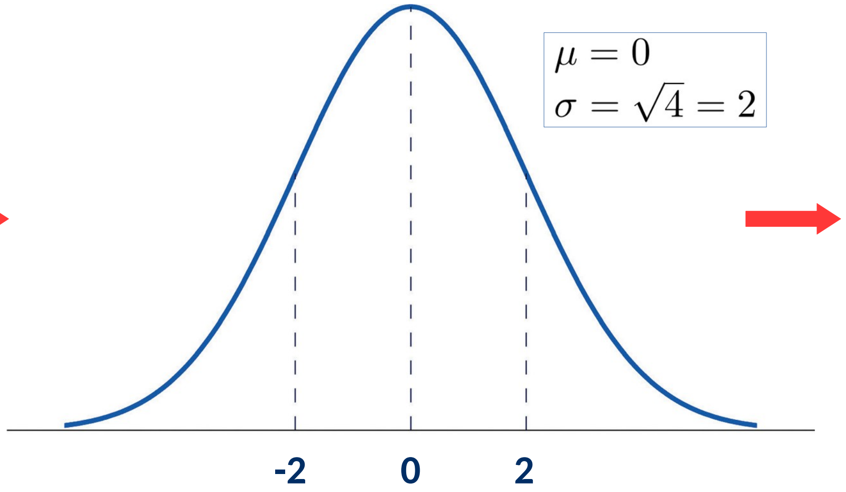

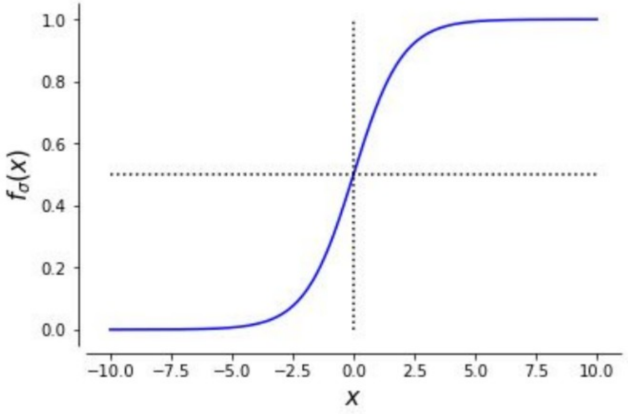

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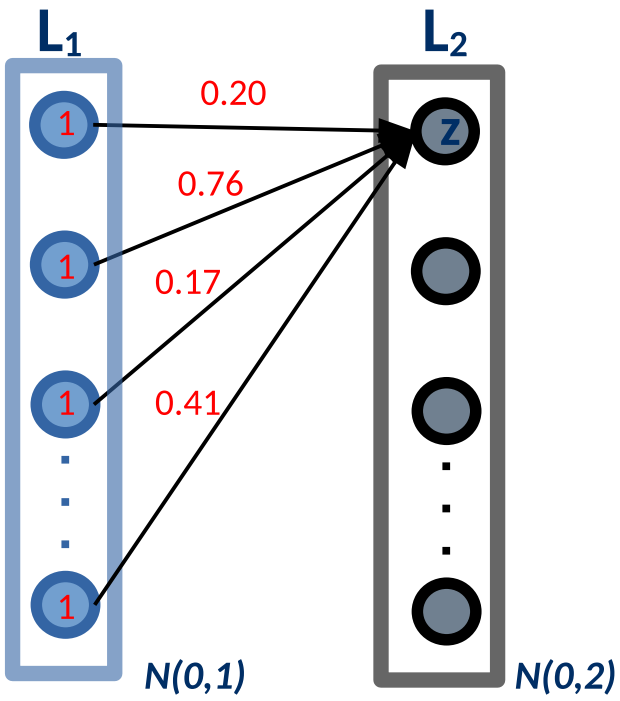

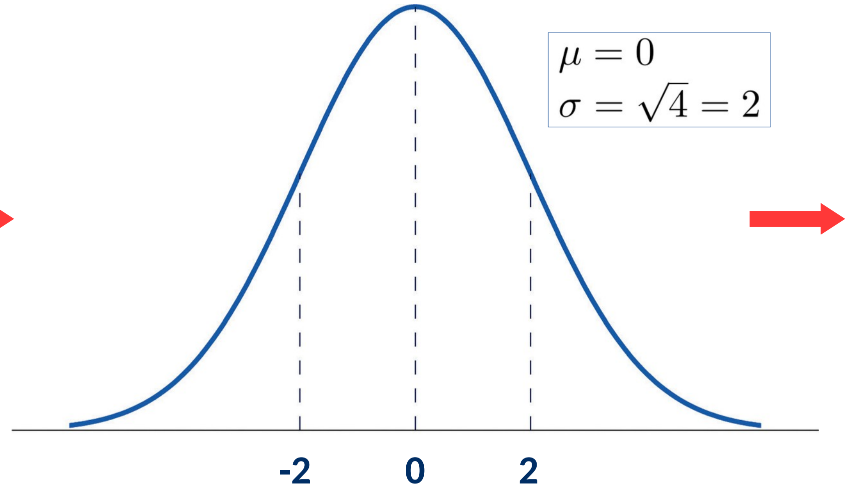

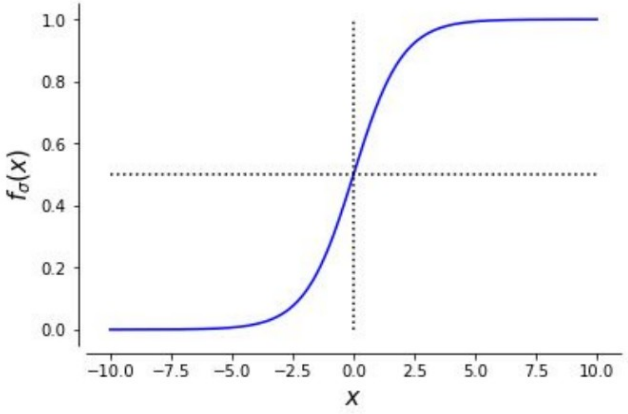

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Q2: What would happen if my architecture is deeper?

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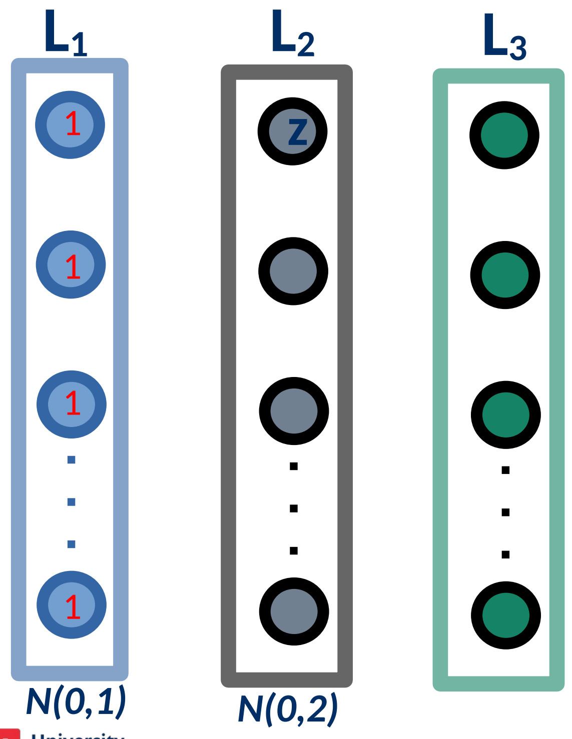

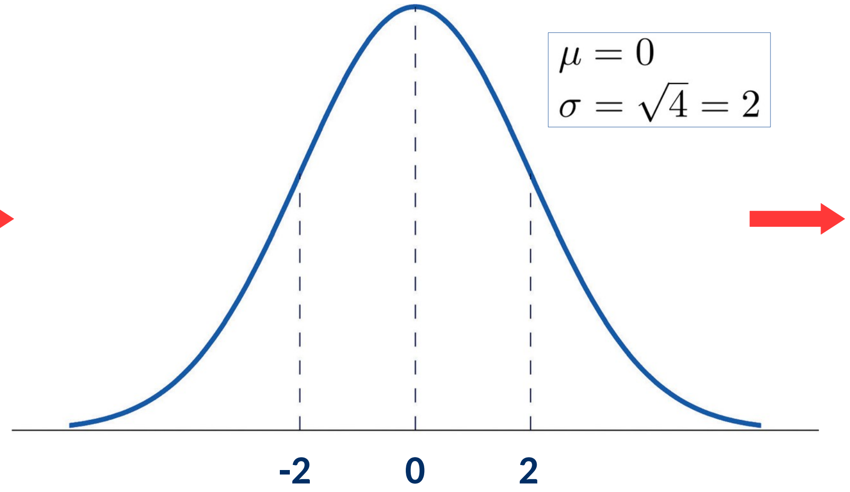

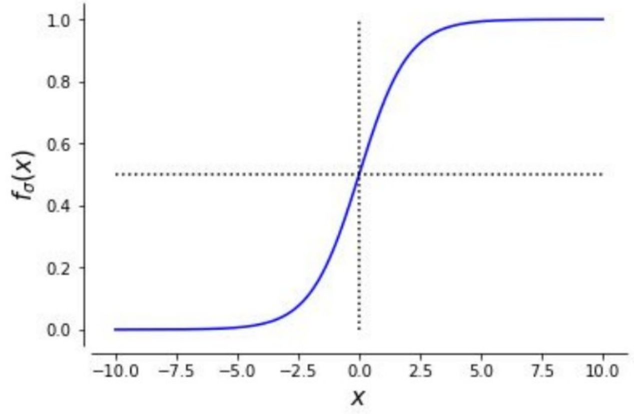

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Solution – Xavier/Glorot Initialization

- **Problem:** large variance – *var(z)*
- **Solution:** let's make it smaller → *var(z) = 1/n*

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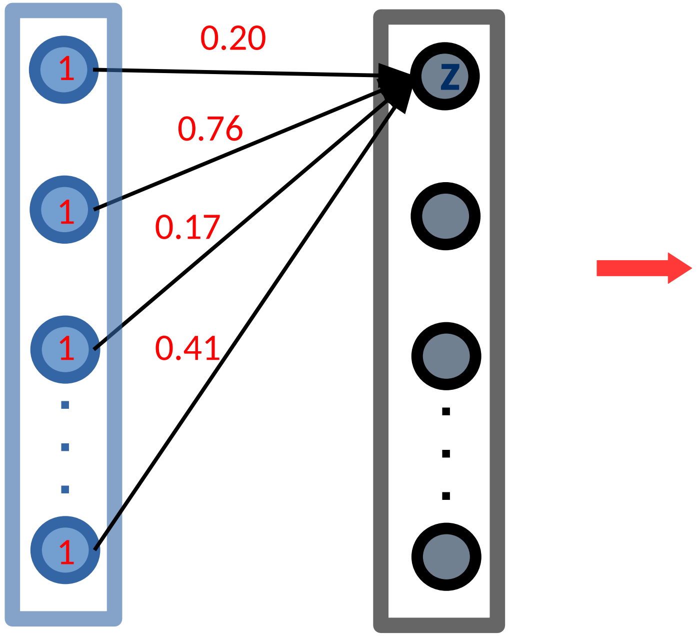

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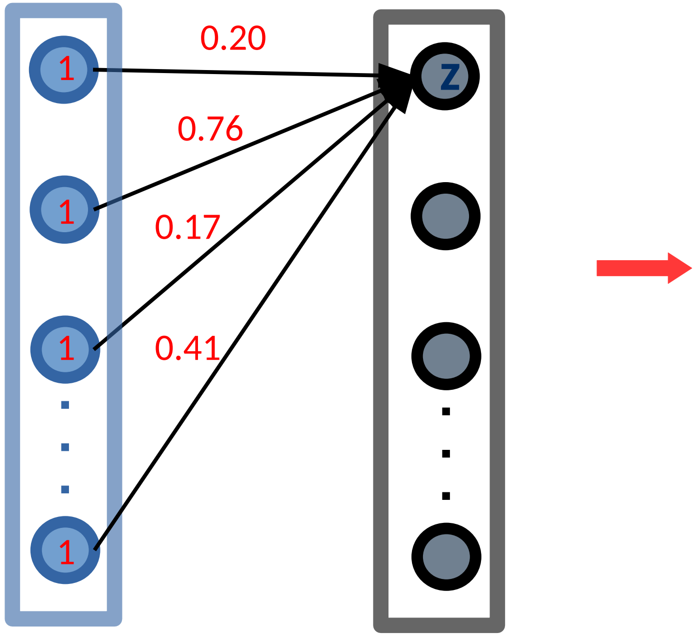

How to do it?

$$w_i = w_i \times \sqrt{1/n}$$

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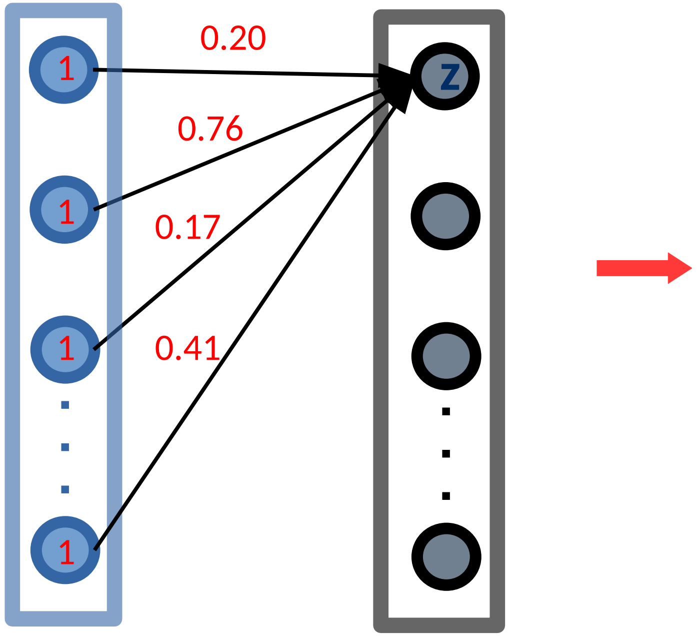

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For ReLU layers

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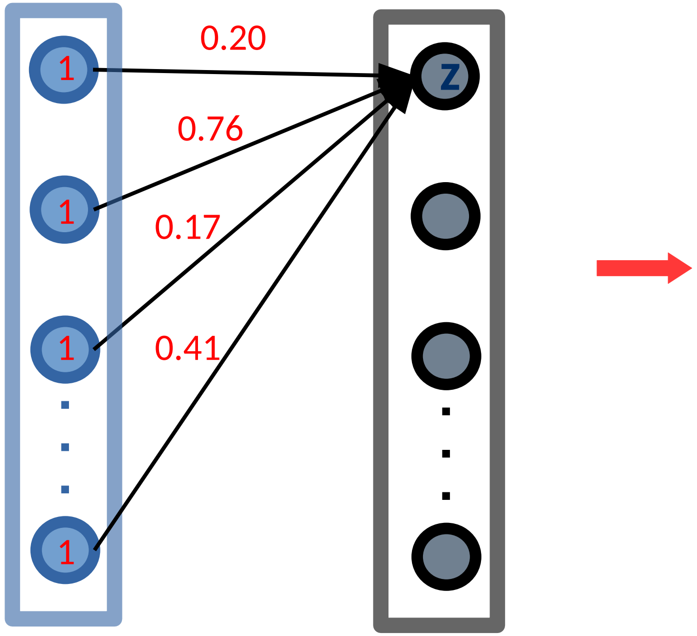

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For ReLU layers

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Previously (for reference)

$$w_i = w_i \times \sqrt{\frac{2}{n_{in}+n_{out}}}$$

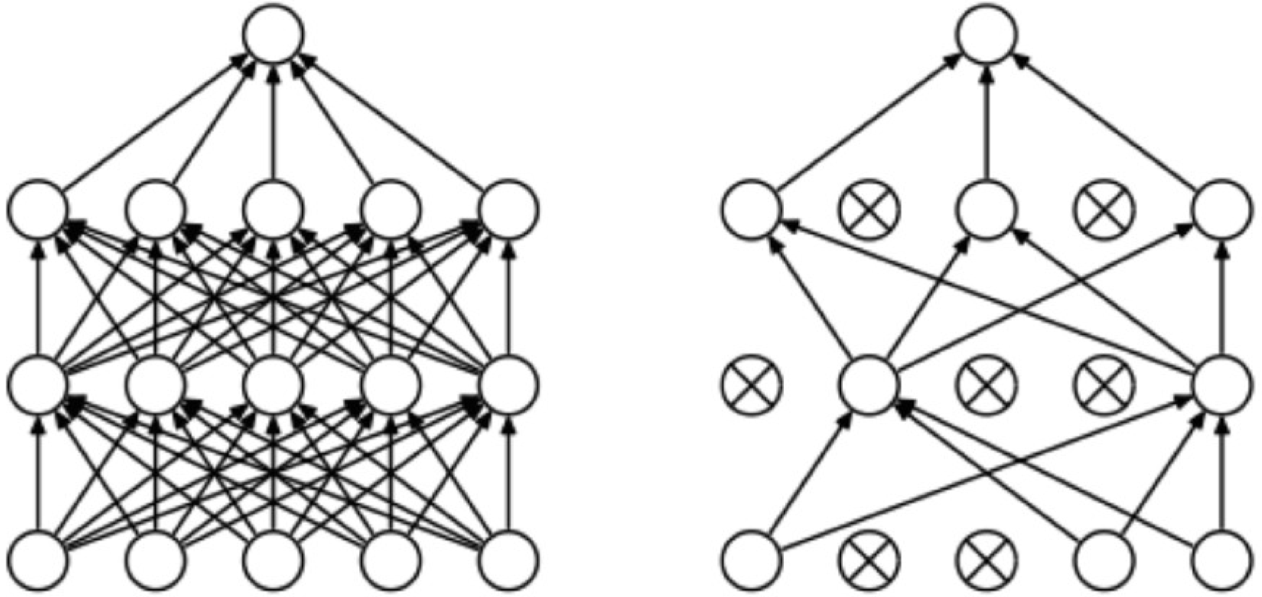
During Training

[While the Computer is Hard at Work]

Updating Weights of the Network

Dropout

- **Problem:** dicrease dependence of a given feature
- **Solution:** randomly deactivate neurons



Standard Neural Net

After applying dropout.

Benefits
Avoid over-fitting
Promote ensemble learning

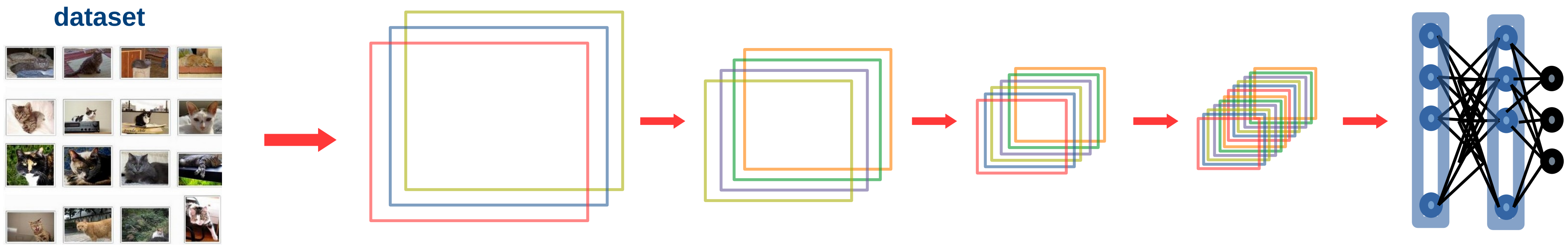
Q: What happens at test time?

[Krizhevsky et al., 2012]

Updating Weights of the Network

During Training

- **Problem:** Updates on weights at a later layers should take into account changes at earlier layers (covariate shift)
  - Introduces changes in the distribution of internal activations
  - Requires careful initialization and a small learning rate



Desiderata: Distribution of inputs (*x*) should be fixed over time

Updating Weights of the Network

Batch Normalization

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1\ldots m}\}$;
Parameters to be learned: γ, β

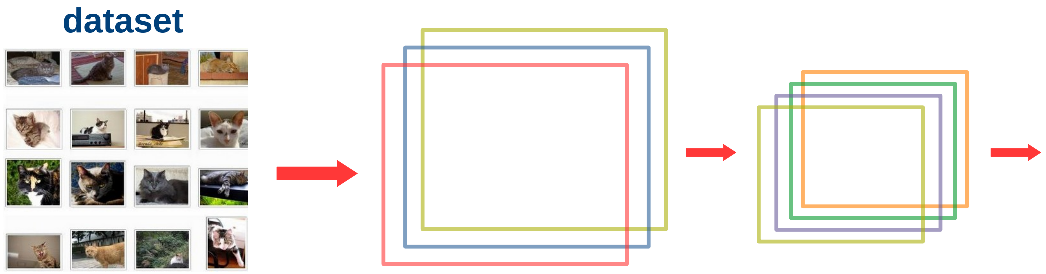
Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

- **Solution:** Normalize internal acrtivations by considering dataset statistics
  - Stochastic optimization

    → batch-level statistics



[Loffe & Szegedy., 2015]

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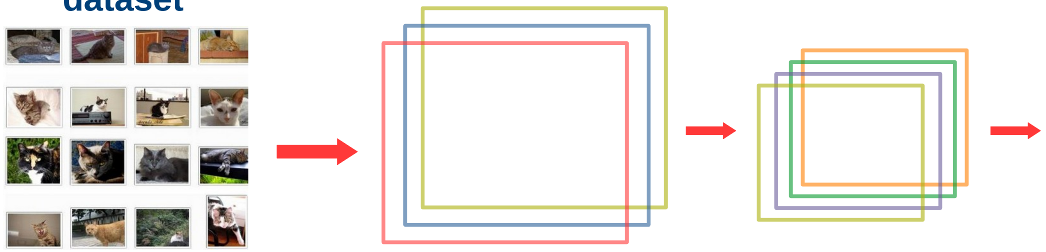

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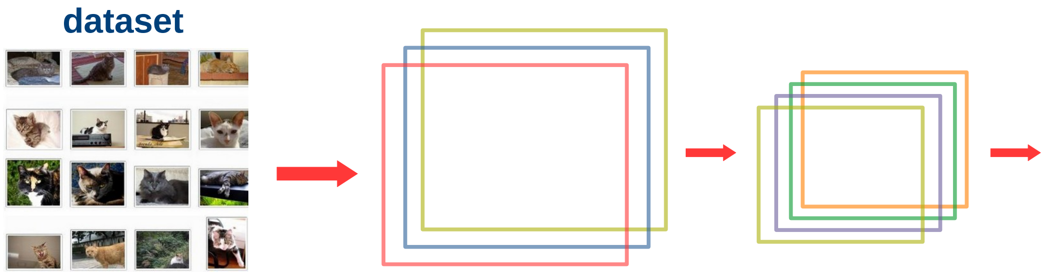

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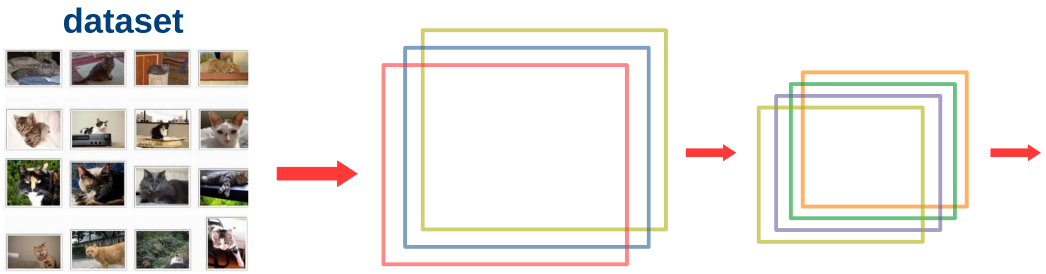
Benefits

- Less sensitivity to initialization
- Allows using larger learning rates (faster training)



[Loffe & Szegedy., 2015]

Computing the Loss

[While Checking How Well It Works]

Break

[See you in 15 mins.]

Computing the Loss

[While Checking How Well It Works]

Training with Weighted Examples

Let’s revisit the computation of the gradient of the loss

- Gradient Descend

$$\theta_{t+1} = \theta_t - \alpha_t \nabla_\theta L(\theta_t)$$

where,

$$\nabla_\theta L(\theta_t) = \nabla_\theta \sum_i l(f(x^{(i)}, \theta_t), y^{(i)})$$

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re-weighting,

$$= \sum_i \frac{1}{Z(y^{(i)})} \nabla_\theta l(f(x^{(i)}, \theta_t), y^{(i)})$$

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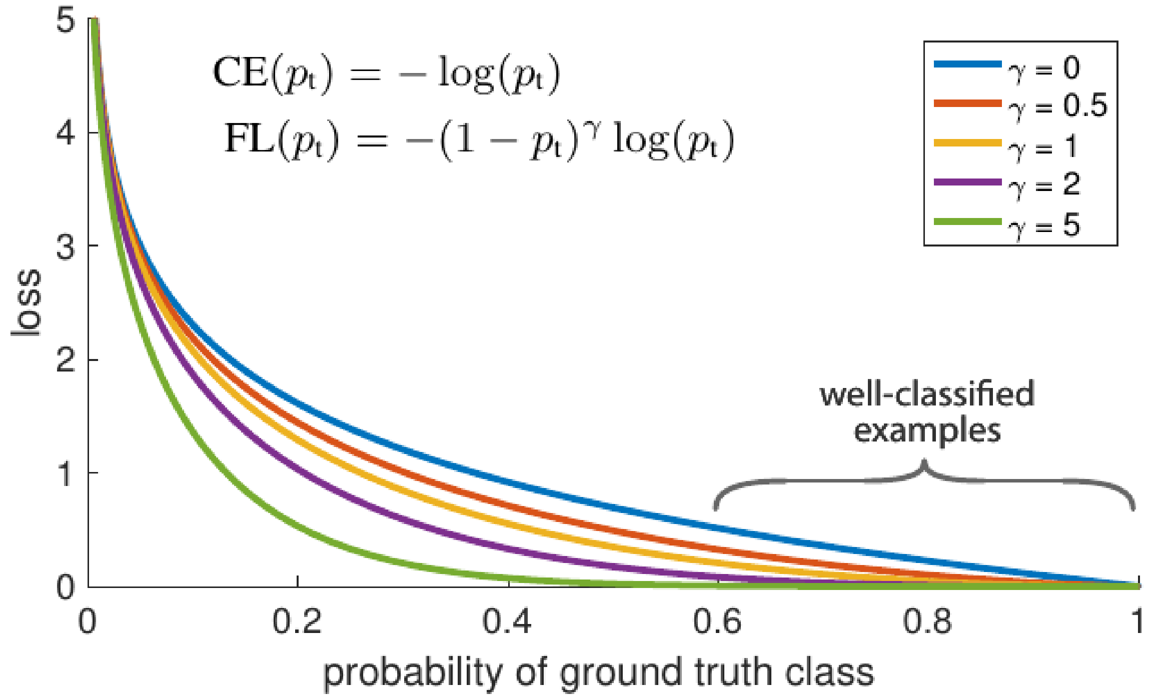
Training with Examples of Different Complexity

Focal Loss



$$\mathrm{FL}(p_t) = -(1-p_t)^\gamma \log(p_t)$$

What it does?

- Down-weights the loss from well-classified examples
- Focusses training on sparse set of hard examples

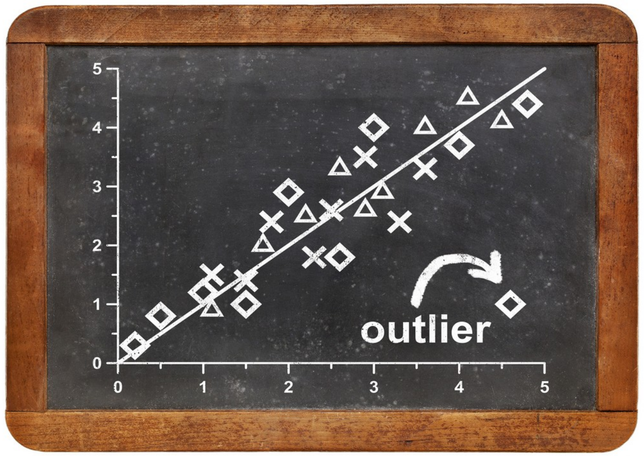
[Lin et al., 2017]

Training with Examples of Different Complexity

Focal Loss

Where it could be useful?

- Dense predictions tasks
- In the presence of outliers



Learning Representations by Comparison

Triplet Loss

- Given three examples (Anchor, Positive, Negative)
- Learn a representation that distance(positive, anchor) < distance(negative, anchor)

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Using the L2-distance

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Using in a cost function $= \sum_{i=1}^{M} L(\ A^{(i)}, P^{(i)}, N^{(i)}\ )$

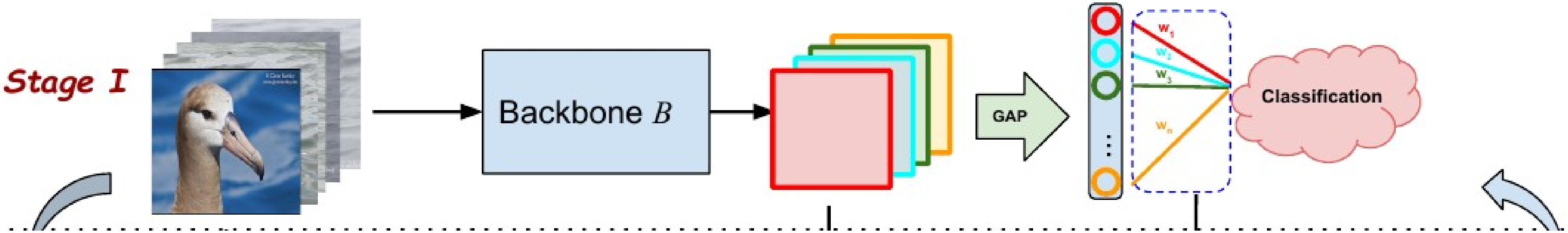
Triplet Loss

[Wang et al., 2018]

Using Multiple Loss Functions

Object Localization – MinMaxCAM [Wang et al., 2021]

Idea: Regularize a high-performing classifier to enable localization



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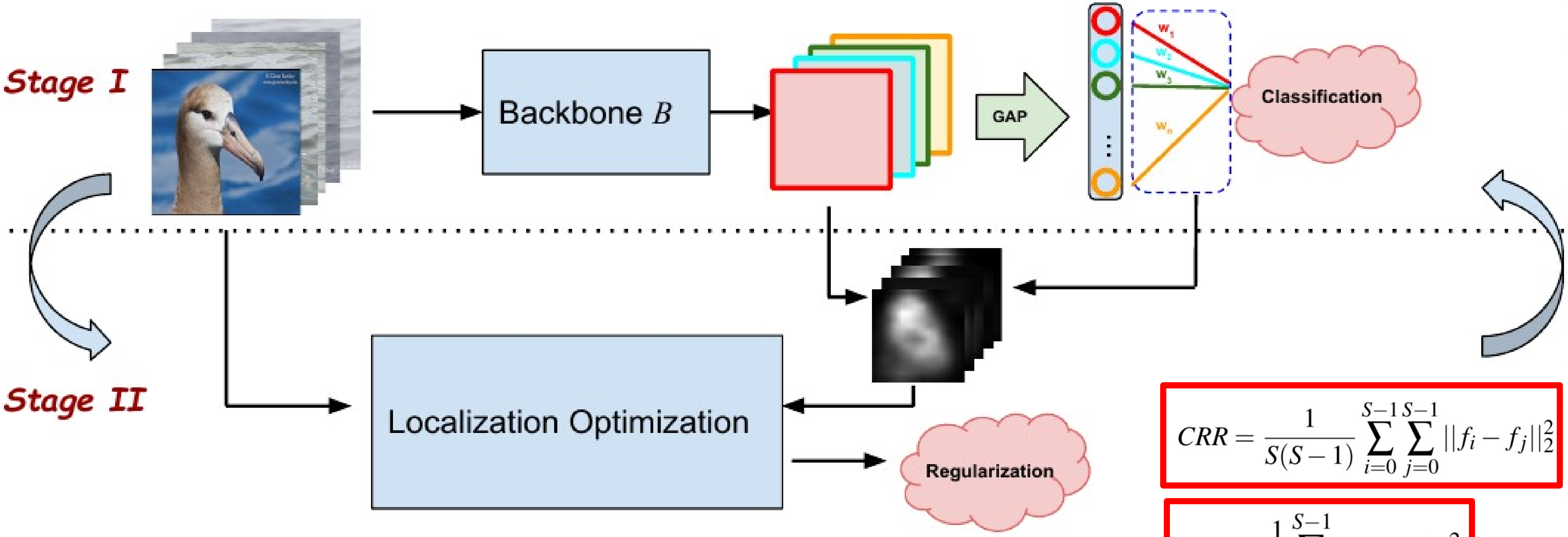


$$CRR = \frac{1}{S(S-1)} \sum_{i=0}^{S-1} \sum_{j=0}^{S-1} ||f_i - f_j||_2^2$$

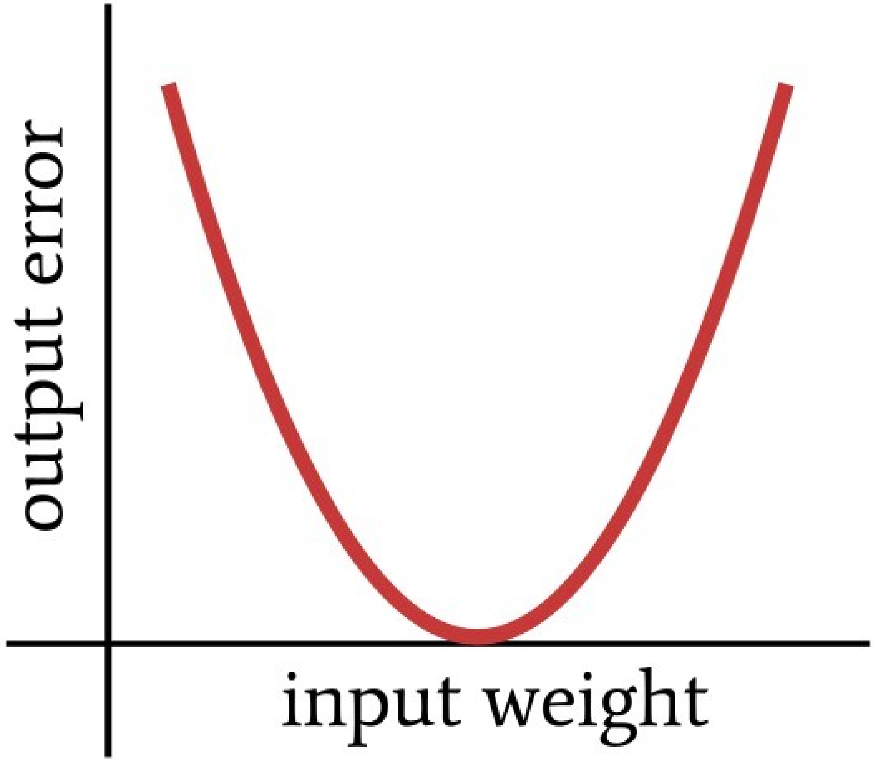
$$FRR = \frac{1}{S} \sum_{i=0}^{S-1} ||f_i - f_i^o||_2^2$$

Optimization

[While Searching for the Best Solution]

Optimizing the Training Procedure

Fixed VS Variable Learning Rate



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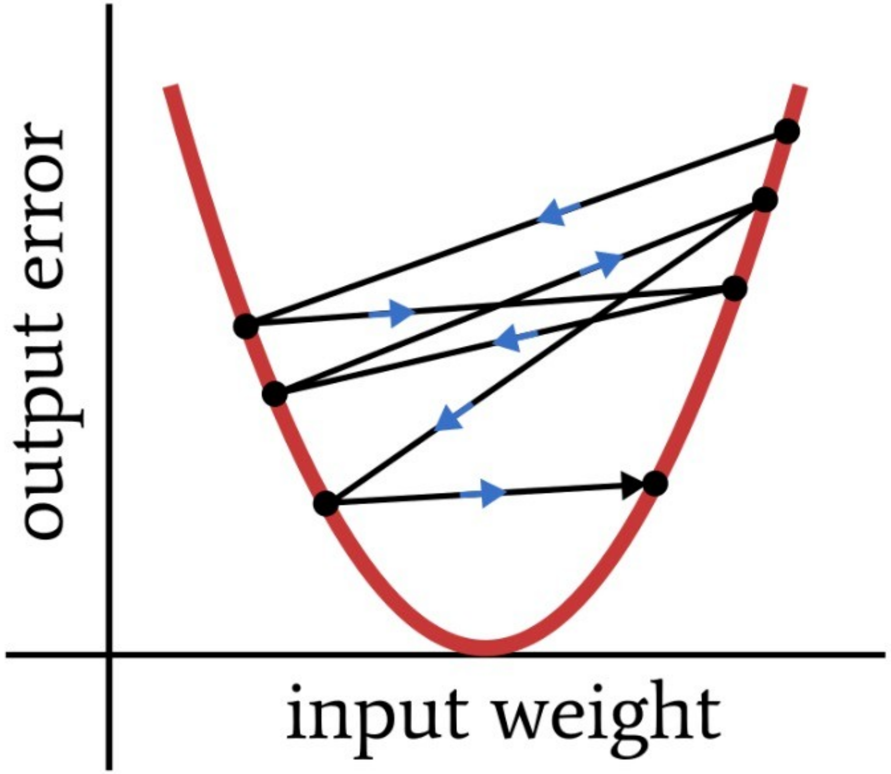

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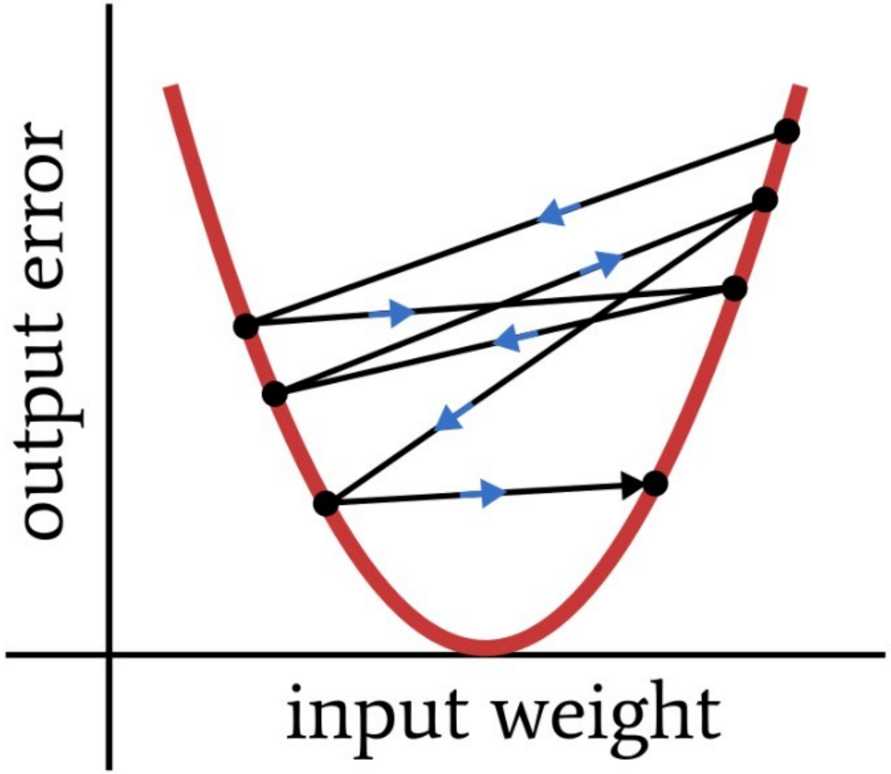
Optimizing the Training Procedure

Fixed VS Variable Learning Rate



$$\theta_{t+1} = \theta_t - \alpha_t \nabla_\theta L(\theta_t)$$

- **Problem:** As training progresses taken steps might be to large to reach the optimum

- **Solution:** dicrease the learning rate as training progresses.

  (Annealing)

Combinations

[A bit of everything]

Self-Supervised Learning

- Problem: data annotation is expensive
- Solution: supervise using labels generated from data (without manual annotation)

Image X

[Gidaris et al., 2018]

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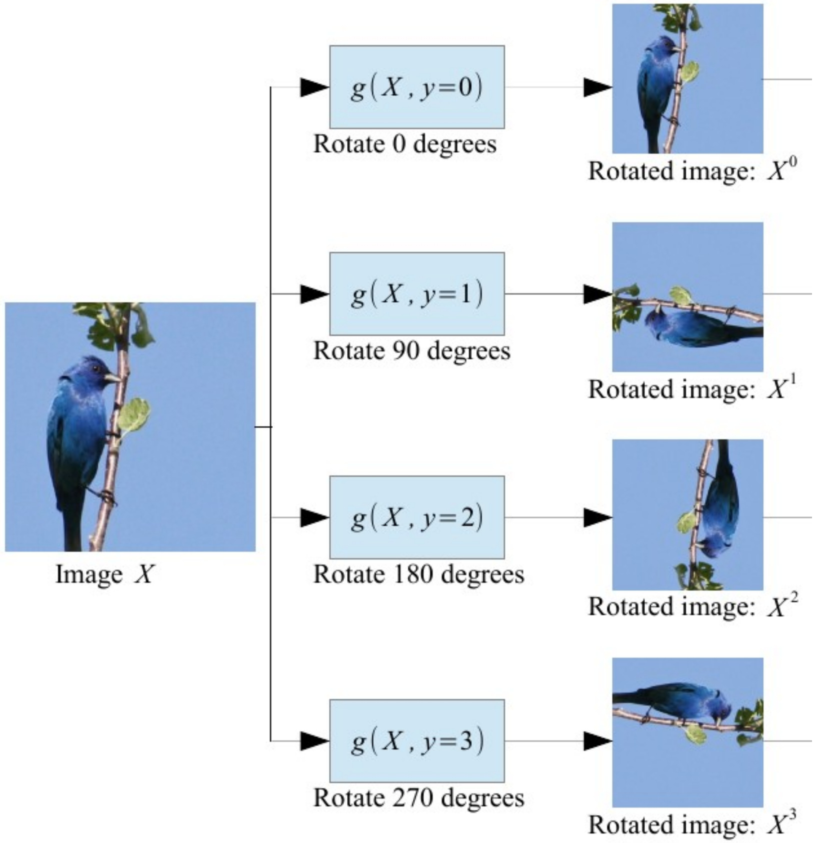

[Gidaris et al., 2018]

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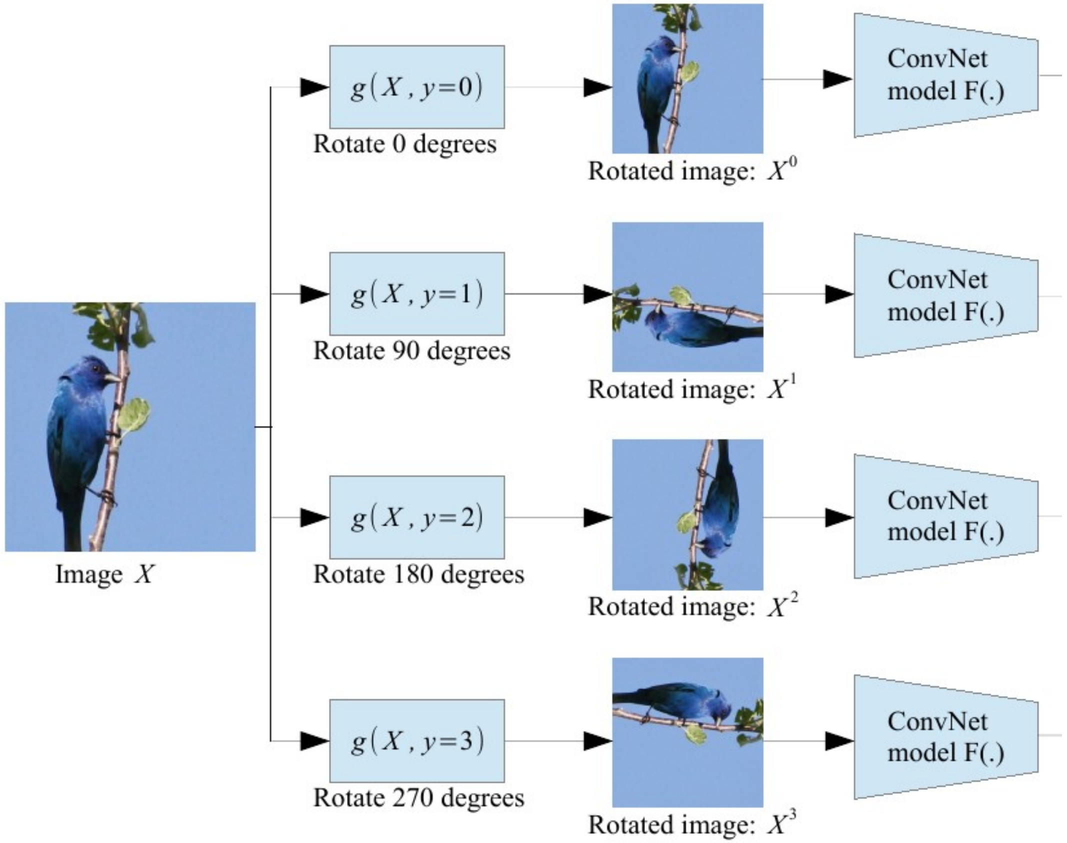

[Gidaris et al., 2018]

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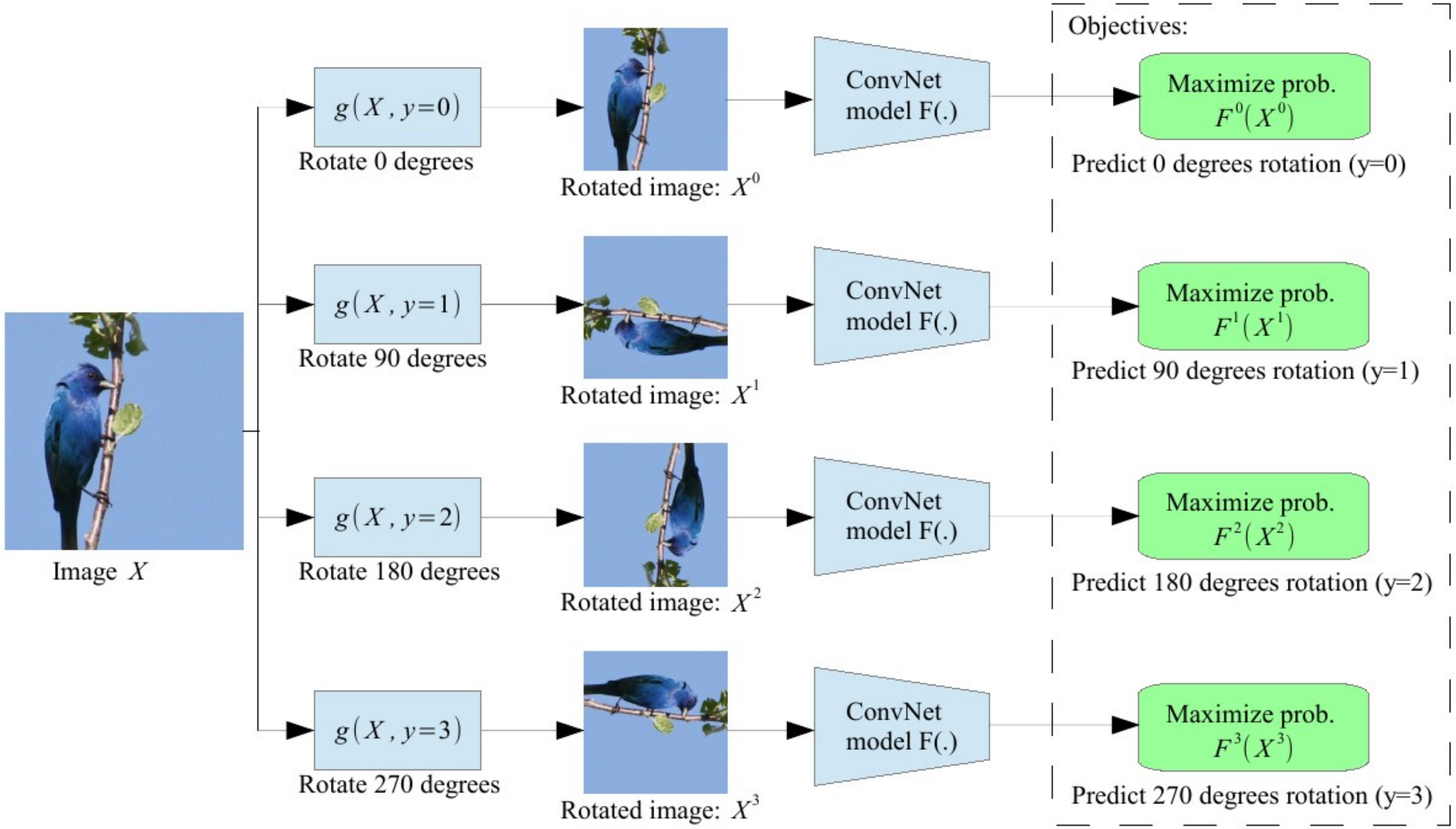

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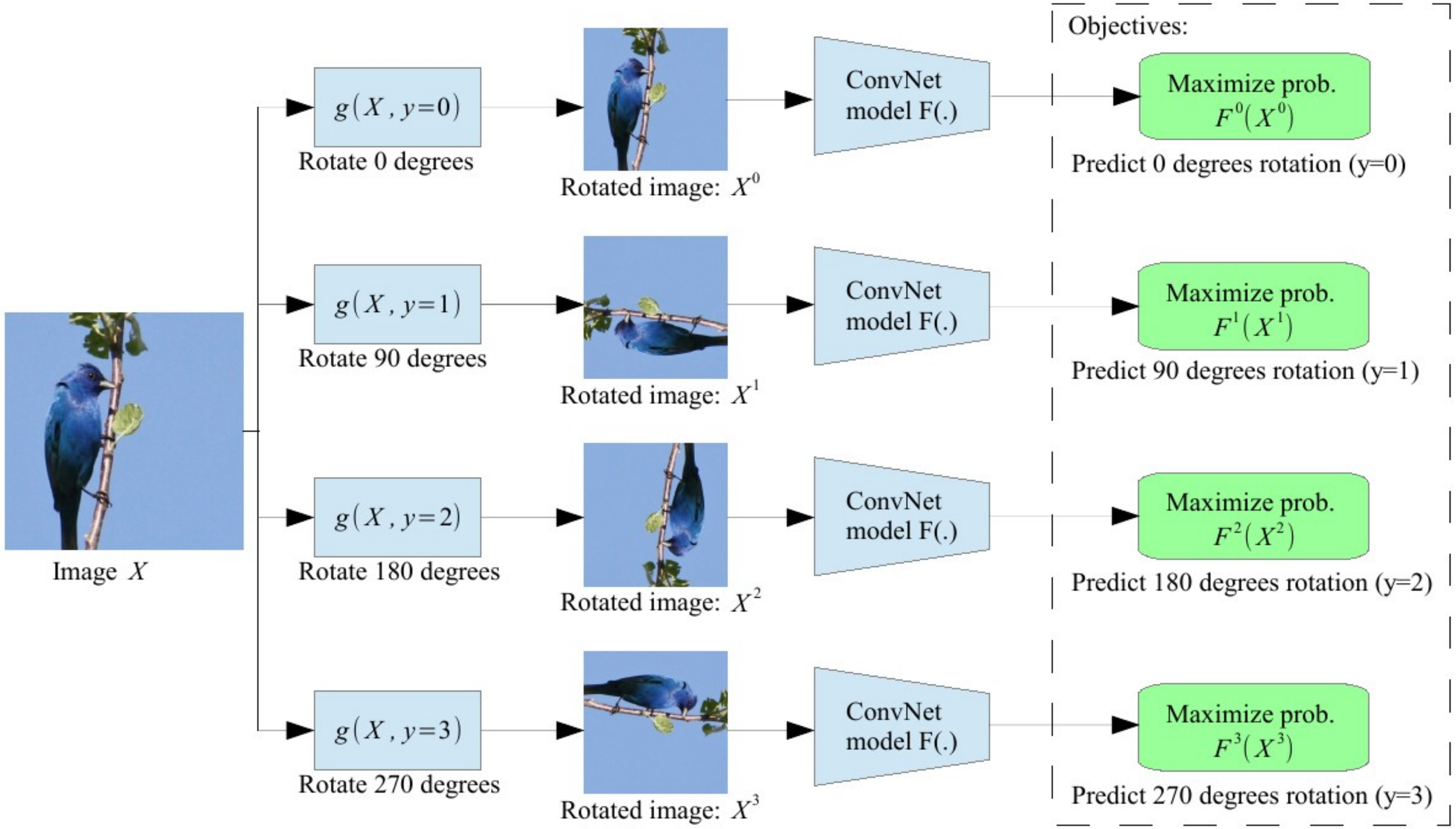

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Summarizing

[Finally :D]

Summarizing

- **Different techniques possible**
    - **Additional adaptation to the problem at hand might be required**

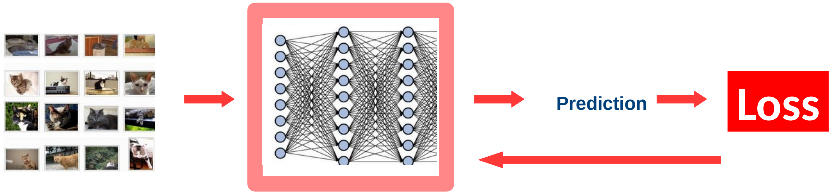
Summarizing

- **Different techniques possible**

  Additional adaptation to the problem at hand might be required

- **Can be applied at different stages of training**

  pre/during training | computing the loss | updating the weights



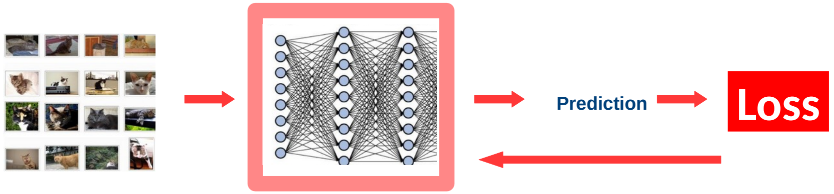
Summarizing

- **Different techniques possible**

  Additional adaptation to the problem at hand might be required

- **Can be applied at different stages of training**

  pre/during training | computing the loss | updating the weights



- **Nothing but the tip of very huge iceberg**

  lots of other techniques available

Pay Attention to...

- When the techniques are applied?
  - Additional actions to be taken at different times
- What is the problem they address?
- How these techniques operate and what is their effect
  - How to adapt them to specific architectures?

Questions?

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Artificial Neural Networks

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