Deep Learning for Computer Vision

Andrii Liubonko

Grammarly*

* The opinions expressed in this presentation and on the following slides are solely those of the presenter and not necessarily those of Grammarly

Logistics

4 units

2 types of homework:

- notebooks [30 % of FINAL SCORE]
- paper review [20 % of FINAL SCORE]
- mini-project [50 % of FINAL SCORE]

important dates (preliminary):

15 January, 23:59 : SOFT

29 January, 23:59 : HARD, PENALTY 30%

course repo:

https://github.com/lyubonko/ucu2022cv

Overview of the course

Unit I

[T] Intro
[P] pytorch

Unit II

[T] CNNs in depth, Object Detection
[P] simple nets

Unit III

[T] Attention in CV, Transformers
[P] classification

Unit IV

[T] Generative models, Diffusion Models
[P] project structure, stable diffusion

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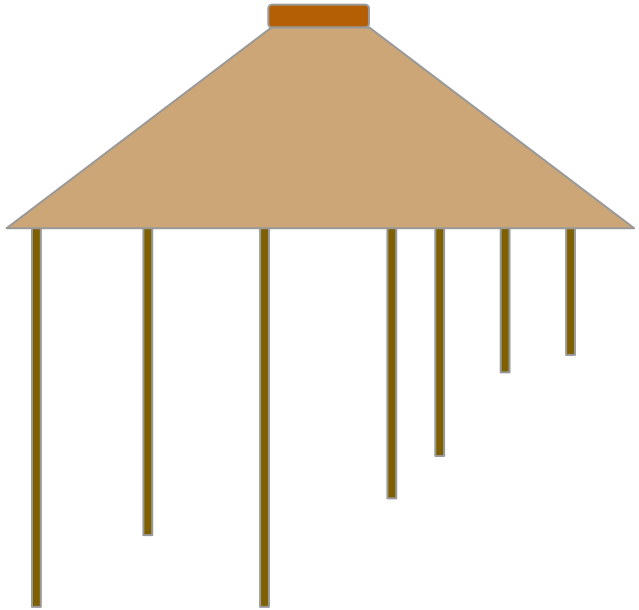
Goals of the Course

- working knowledge of essential elements/blocks of **Convolutional Neural Networks [CNNs]**
- modern **CNNs architectures**
- get deeper with one particular problem (**Object Detection**)
- attention in Computer Vision, **Transformers** in Computer Vision
- get flavor of **Generative Modeling,** vis **Diffusion Models**

Goals of the Course



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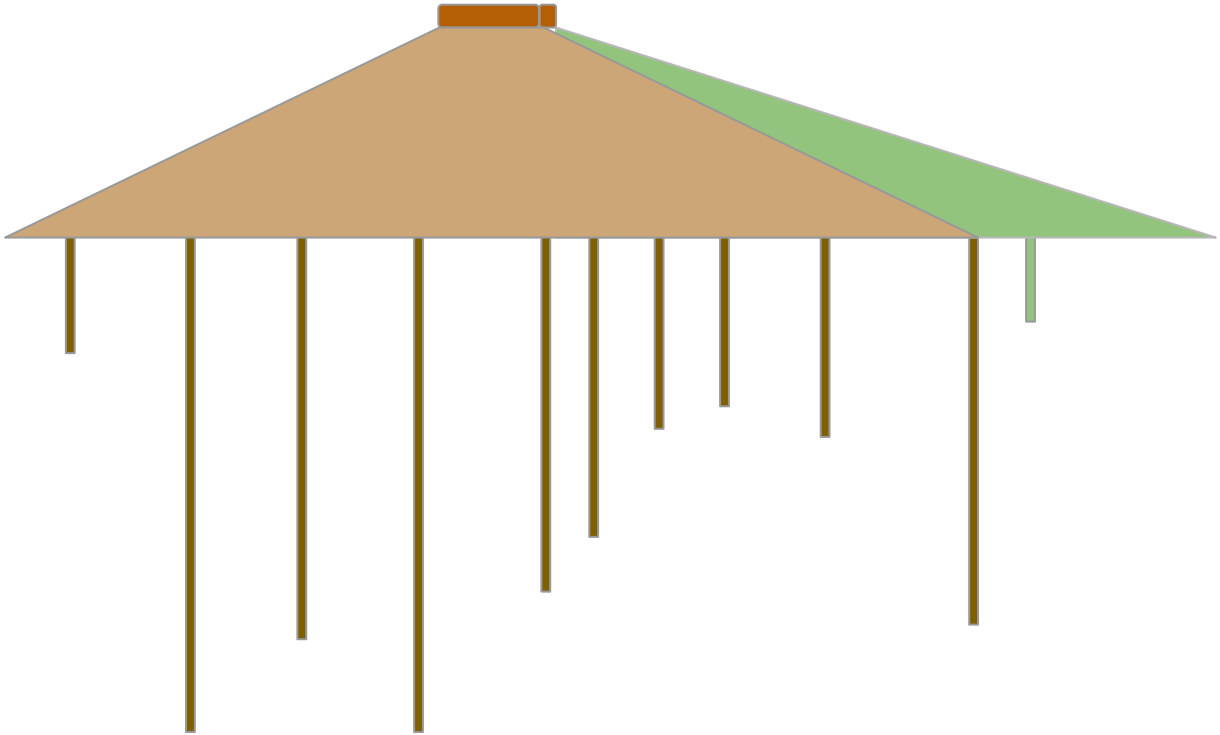

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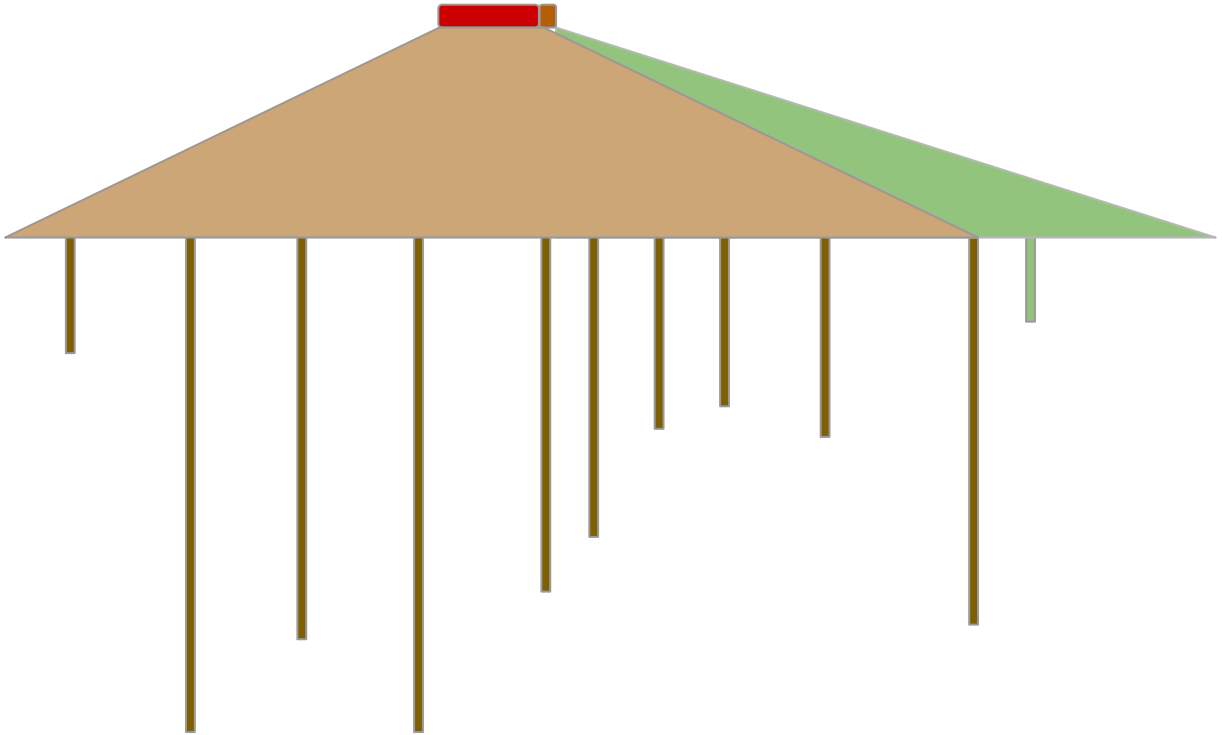
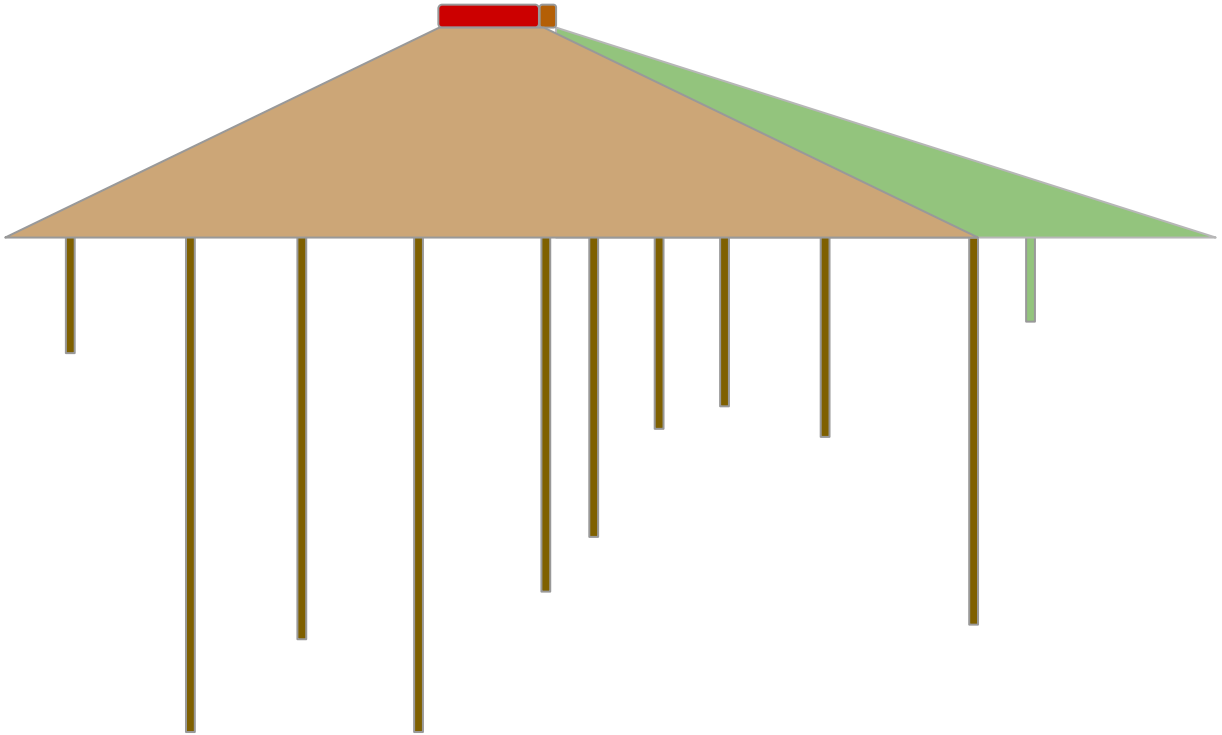


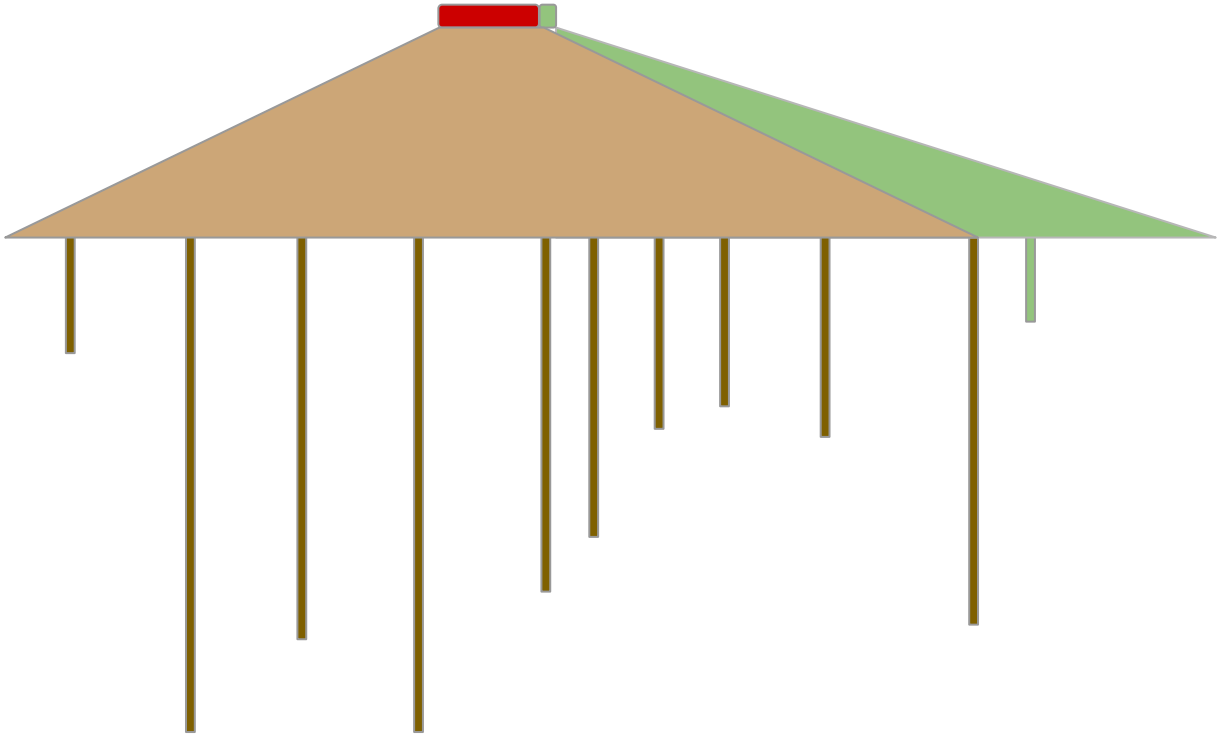
- essential elements/blocks

Goals of the Course



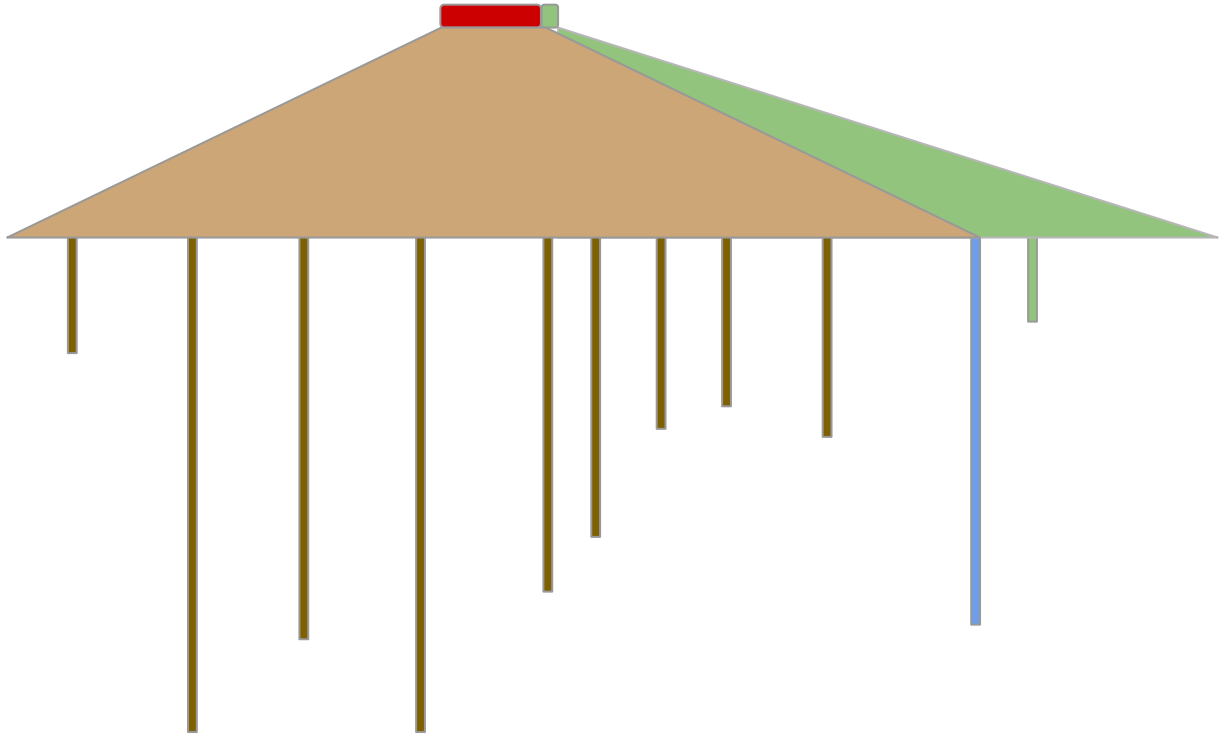
- essential elements/blocks
- modern architectures

Goals of the Course



- essential elements/blocks
- modern architectures
- attention in CV

Goals of the Course



- essential elements/blocks
- modern architectures
- attention in CV
- Object Detection

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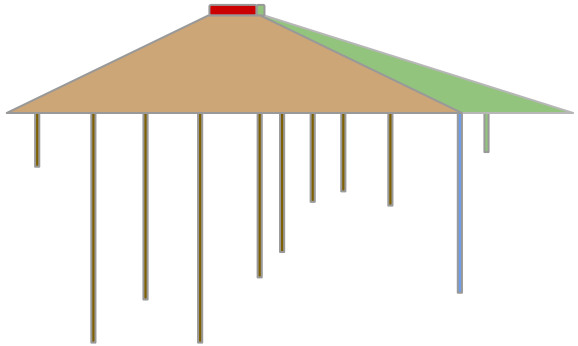

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- modern **modern CNNs architectures**
- **attention** in Computer Vision, **Transformers** in Computer Vision
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Content of today lecture

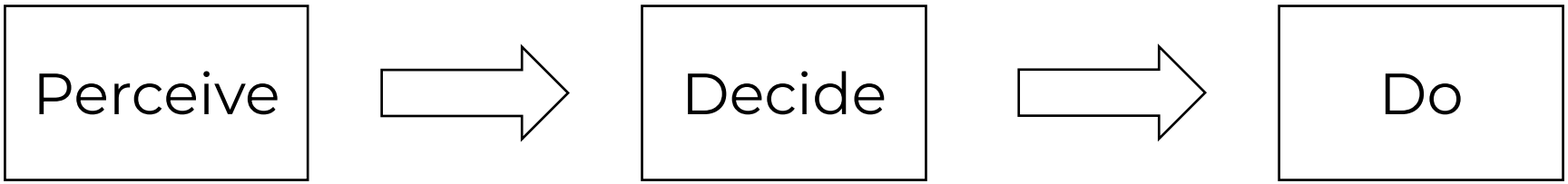
- **Intro, Context**

- ML/DL review
  - training & testing
  - neural networks

- CV specific setups
  - supervised, semi-supervised,
  - self-supervised, auto-encoders

- Main components of CNNs (motivation and details)
  - convolutional layer
  - pooling layer

Intro



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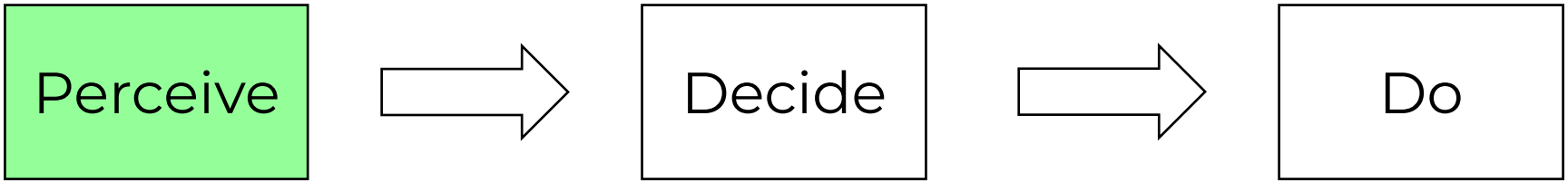
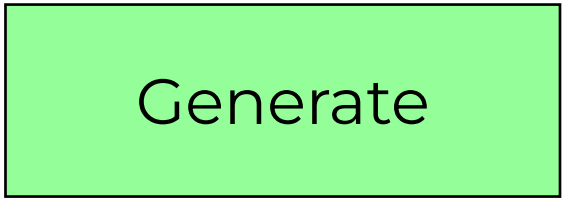


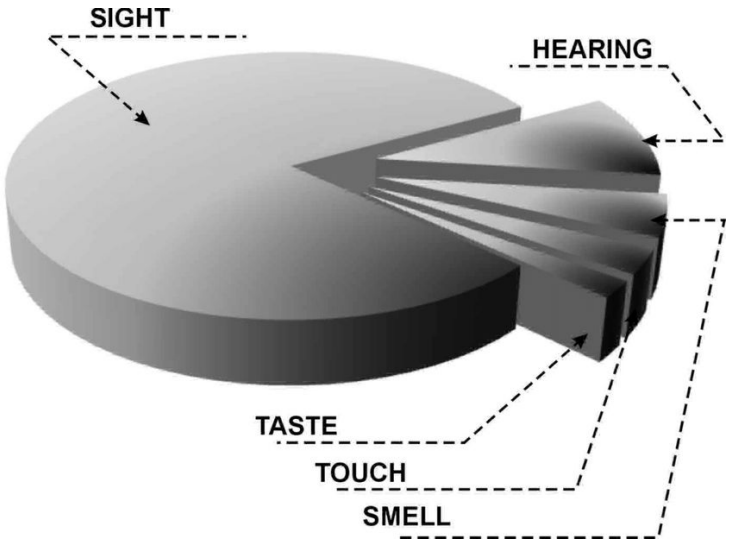
Intro



Intro

Generate

Intro



*The goal of **computer vision** is to perceive [extract useful information] from visual input, like images and video*

Intro

- indoor/outdoor? [image classification]
- Where are the objects? [object detection]
- How far is the object ? [depth estimation]
- What people are doing? [activity recognition]
- Is the state of the environment normal? [anomaly detection]
- ...

Intro

- scale variations
- occlusions
- illuminations
- deformations
- ....
-

Intro

what humans see

0	3	2	5	4	7	6	9	8
3	0	1	2	3	4	5	6	7
2	1	0	3	2	5	4	7	6
5	2	3	0	1	2	3	4	5
4	3	2	1	0	3	2	5	4
7	4	5	2	3	0	1	2	3
6	5	4	3	2	1	0	3	2
9	6	7	4	5	2	3	0	1
8	7	6	5	4	3	2	1	0

what computers see

Intro

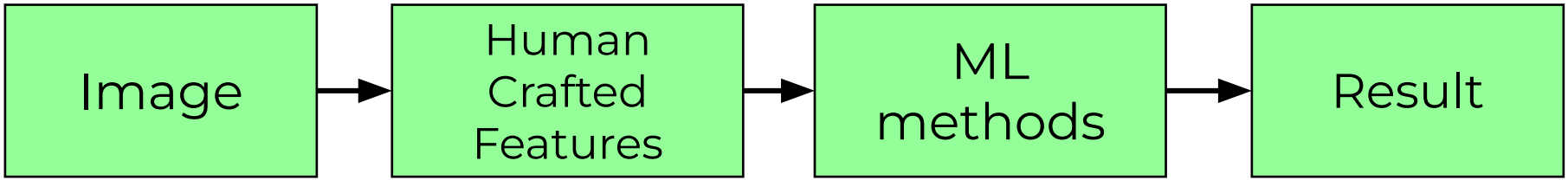
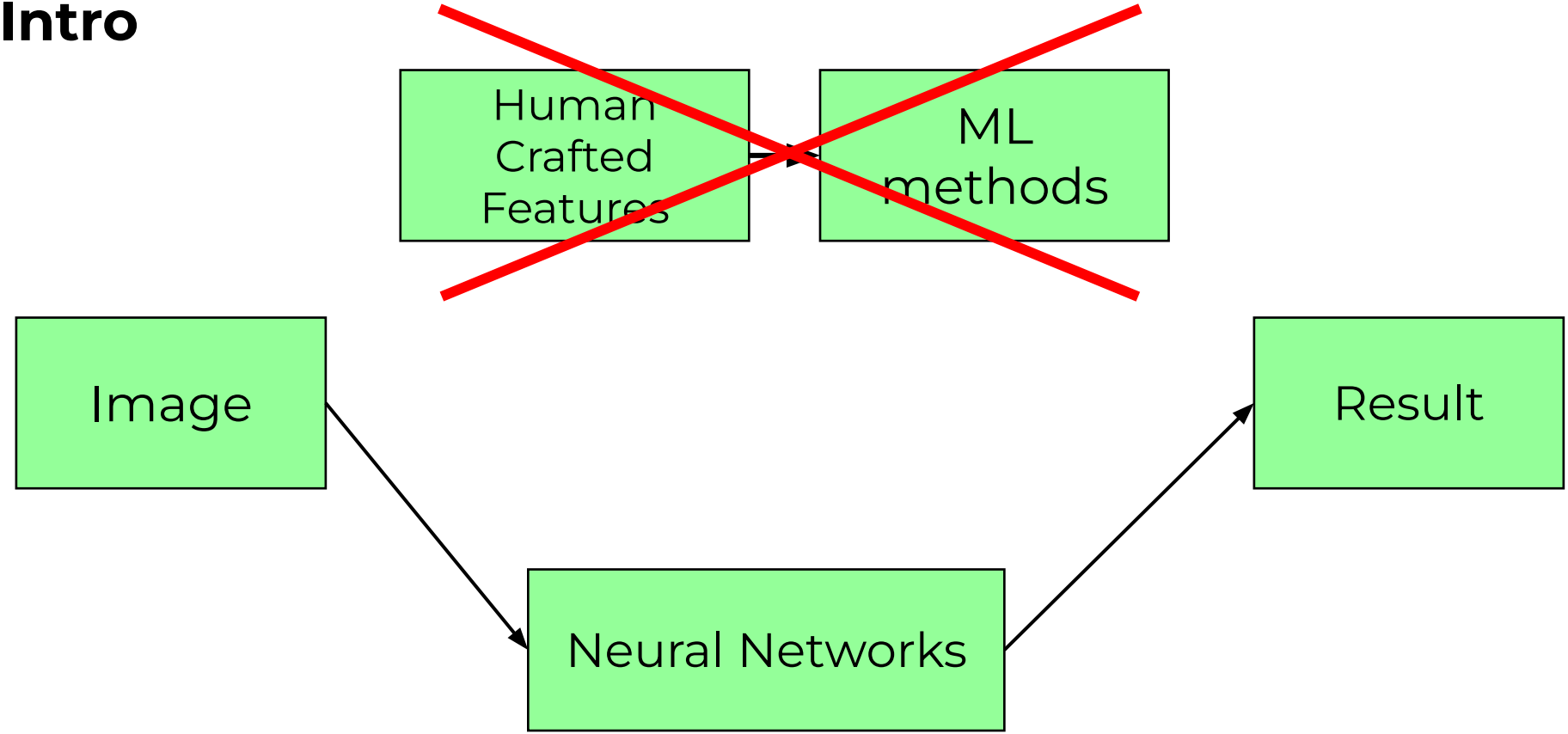
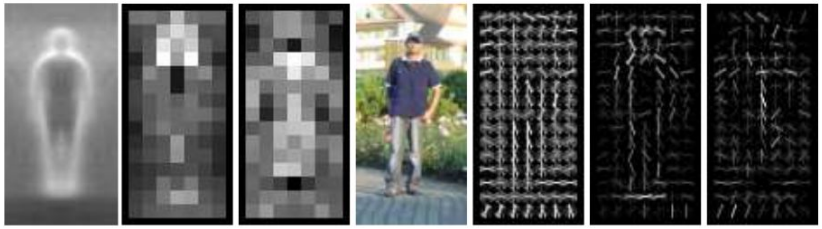


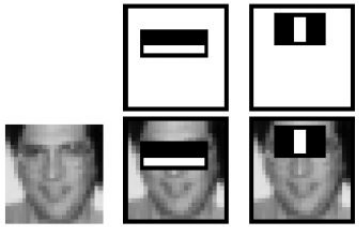
Image
Human Crafted Features
ML methods
Result
Descriptors: SIFT, SURF, etc.
Linear, SVM, Trees

Intro

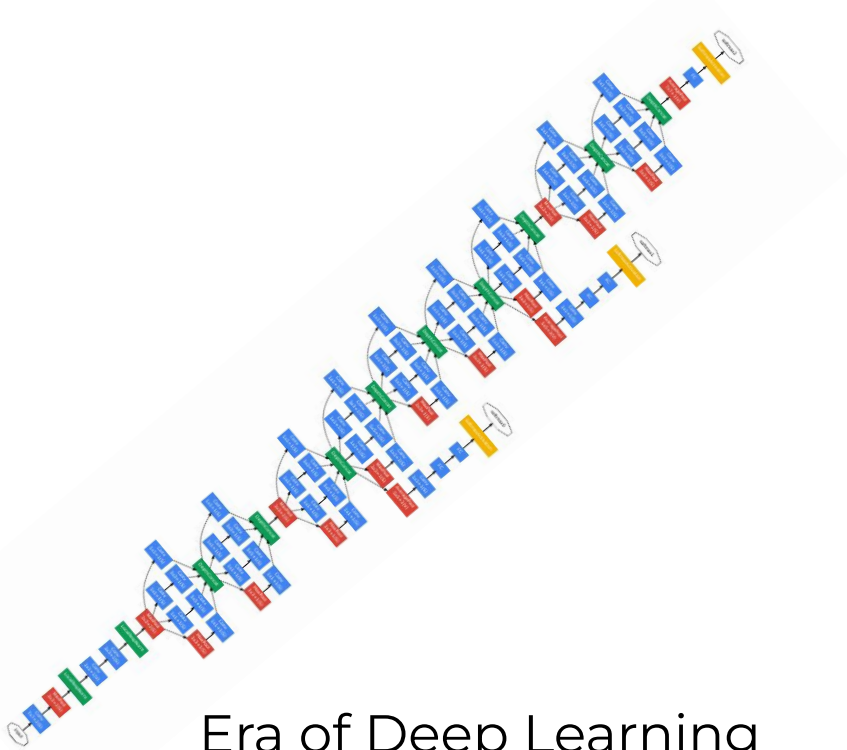

Human Crafted Features
ML methods
Image
Neural Networks
Result

Intro





Era of Human-Crafter Features



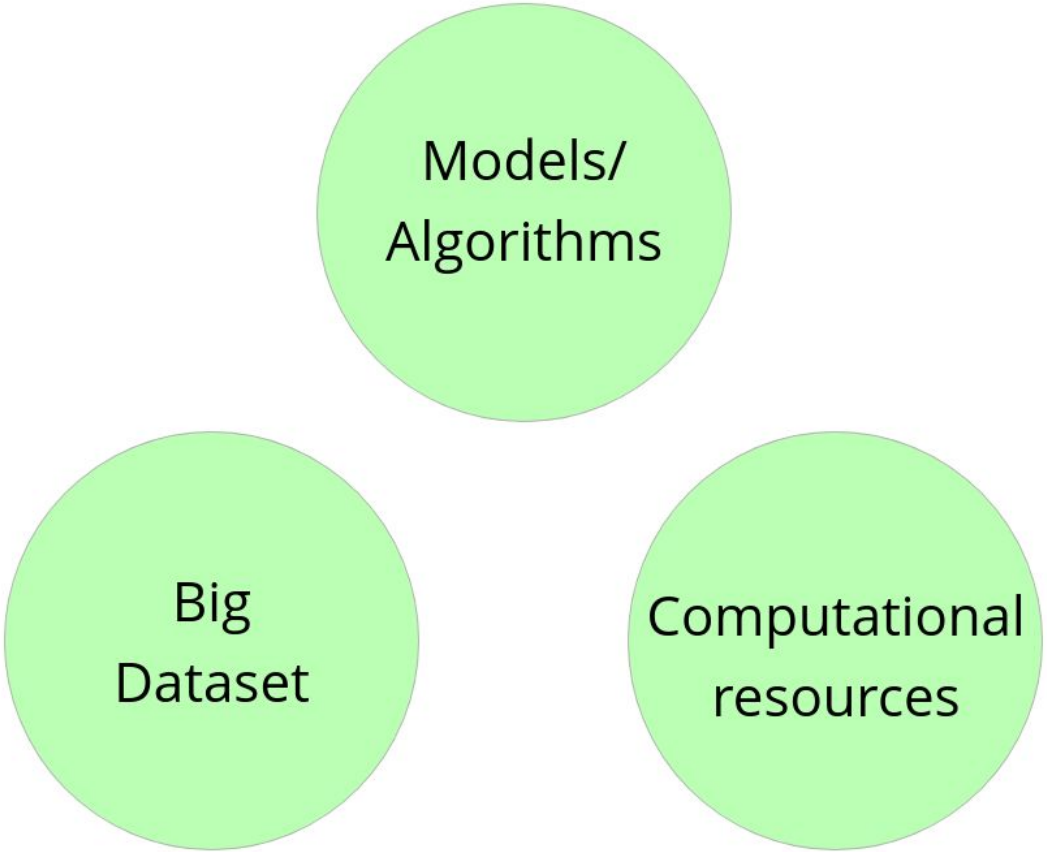
Era of Deep Learning

1986
BackProp

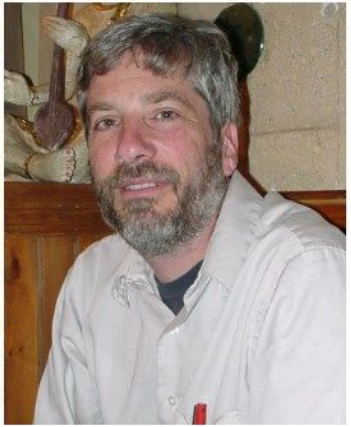
1998
LeNet

2012
AlexNet

Intro



Intro



Vladimir Vapnik **Larry Jackel**

1. Jackel bets (one fancy dinner) that by March 14, 2000, people will understand
quantitatively why big neural nets working on large databases are not so bad. (Understanding means that there will be clear conditions and bounds)

Vapnik bets (one fancy dinner) that Jackel is wrong.

But .. If Vapnik figures out the bounds and conditions, Vapnik still wins the bet.

****

2. Vapnik bets (one fancy dinner) that by March 14, 2005, no one in his right mind will use neural nets that are essentially like those used in 1995.

Jackel bets (one fancy dinner) that Vapnik is wrong

3/14/95
V. Vapnik

3/14//95
L. Jackel

3/14/95
Witnessed by Y. LeCun

Content

- Intro, Context

- **ML/DL review**
  - training & testing
  - neural networks

- CV specific setups
  - supervised, semi-supervised,
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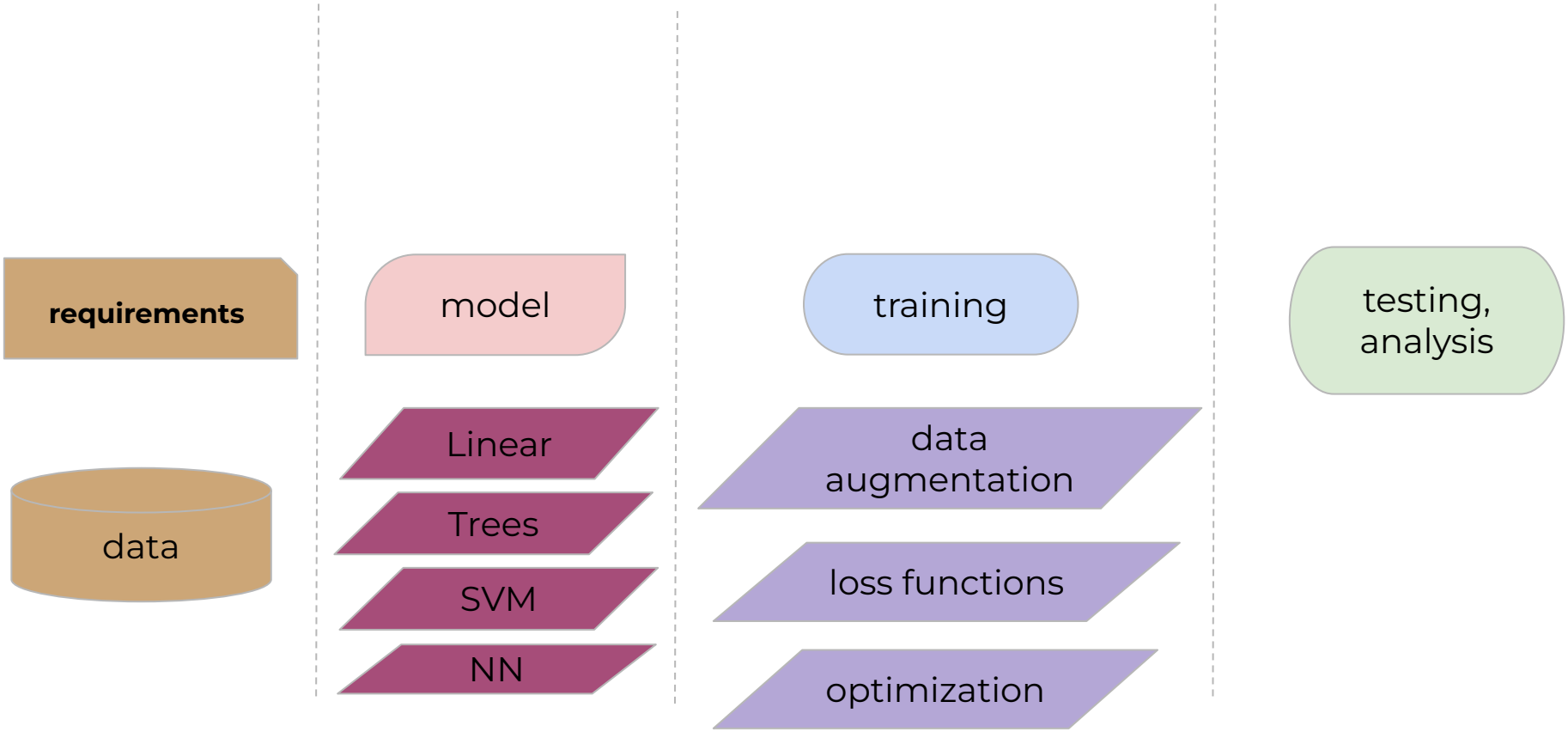
- Main components of CNNs (motivation and details)
  - convolutional layer
  - pooling layer

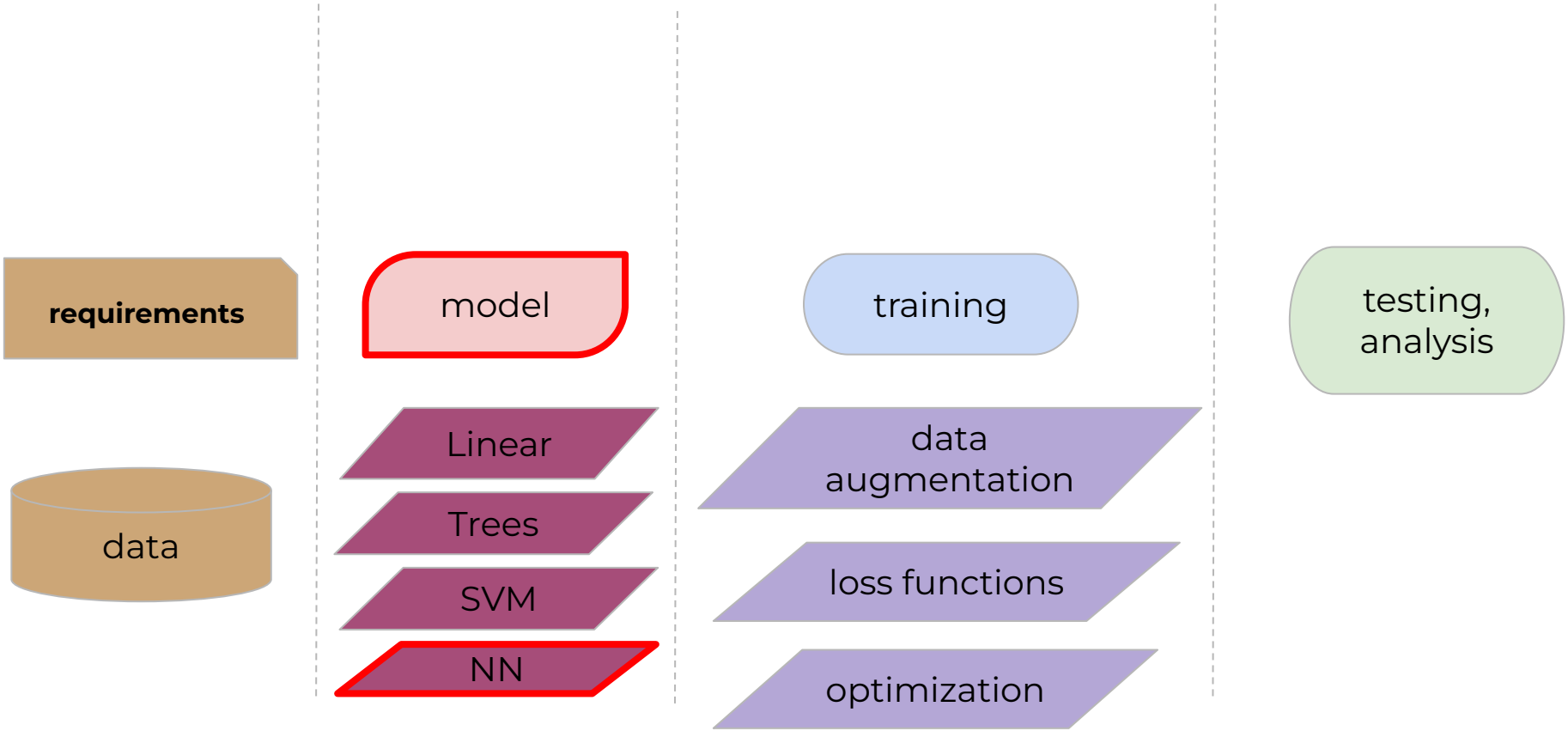
Machine Learning - types of learning

- Supervised
- Unsupervised
- Semi-supervised
- RL

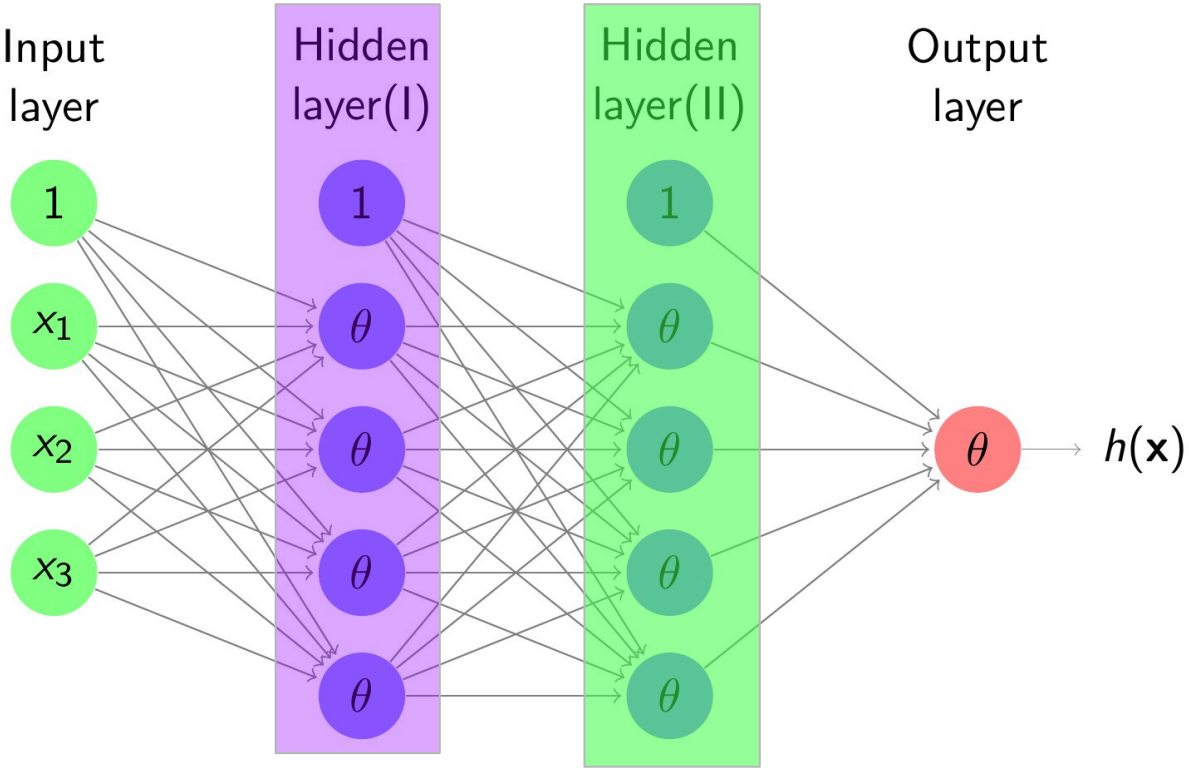
Machine Learning essential blocks



Machine Learning essential blocks

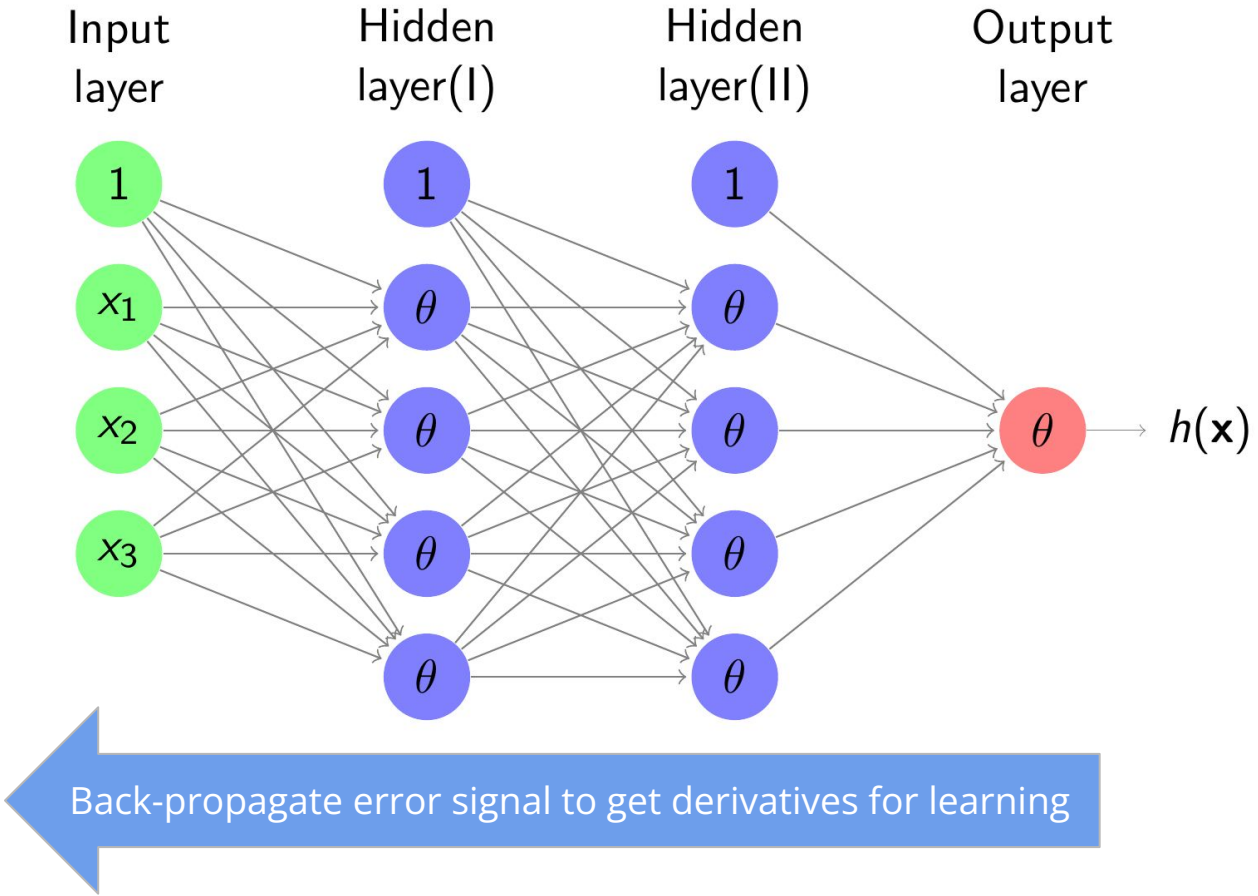


Model [Neural Networks]

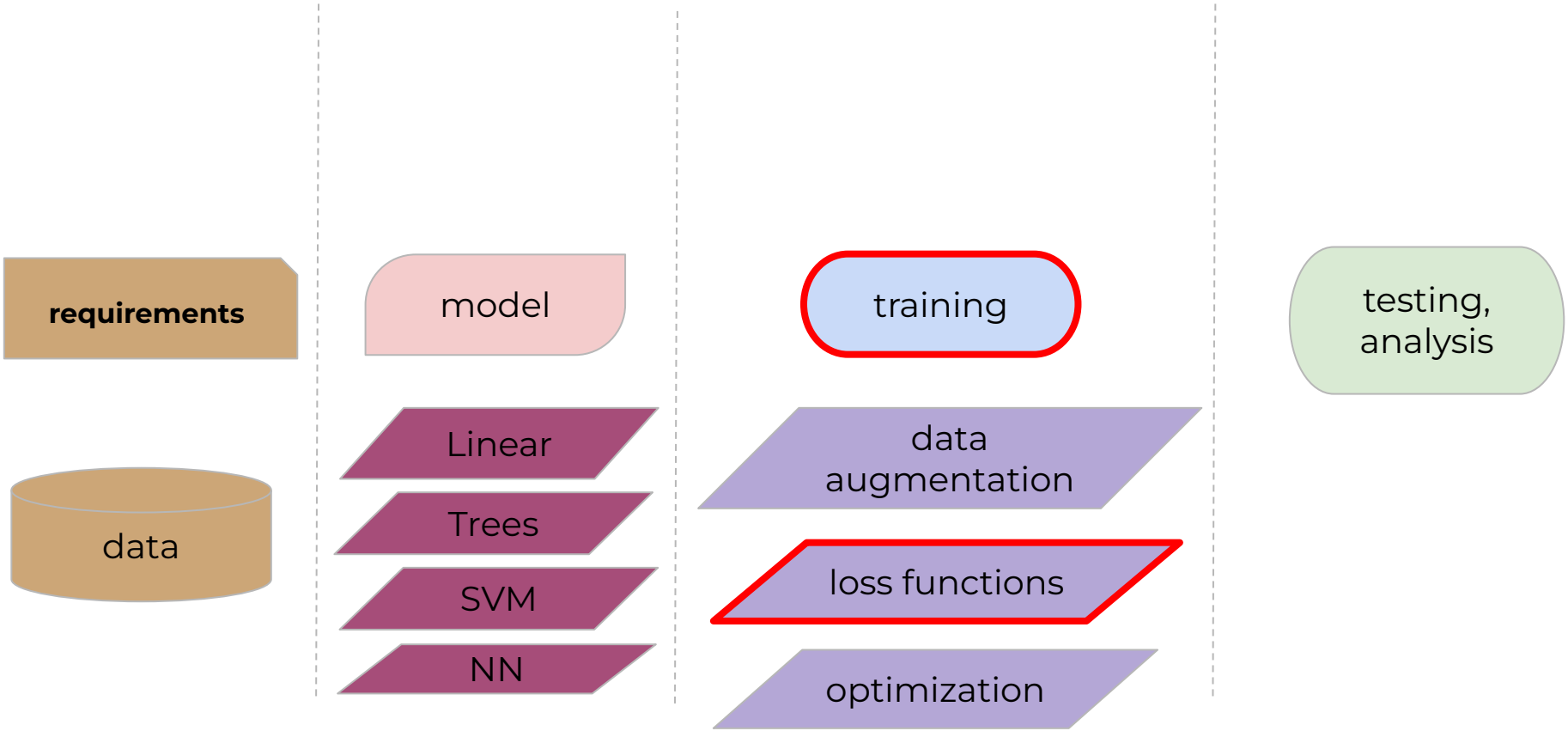


$$\left\{ f(\boldsymbol{x};\boldsymbol{\theta}) = \mathbf{W}_L \boldsymbol{\sigma}_L(\mathbf{W}_{L-1} \cdots \boldsymbol{\sigma}_2(\mathbf{W}_2 \boldsymbol{\sigma}_1(\mathbf{W}_1 \boldsymbol{x}))) \;\middle|\; \boldsymbol{\theta} = \{\mathbf{W}_1, \ldots, \mathbf{W}_L\} \right\}$$

Model [Neural Networks]



Machine Learning essential blocks



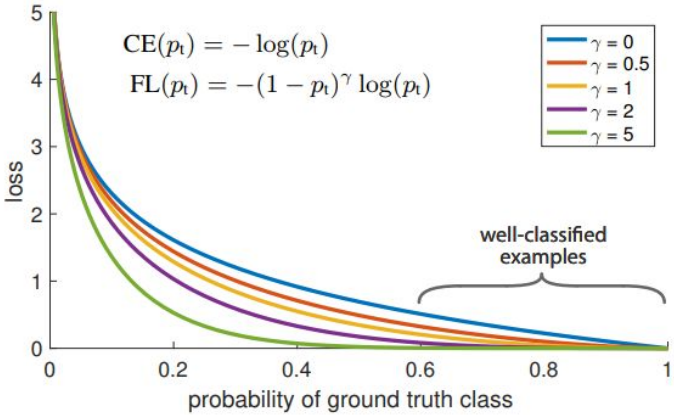
Loss function

Losses for classification, regression:

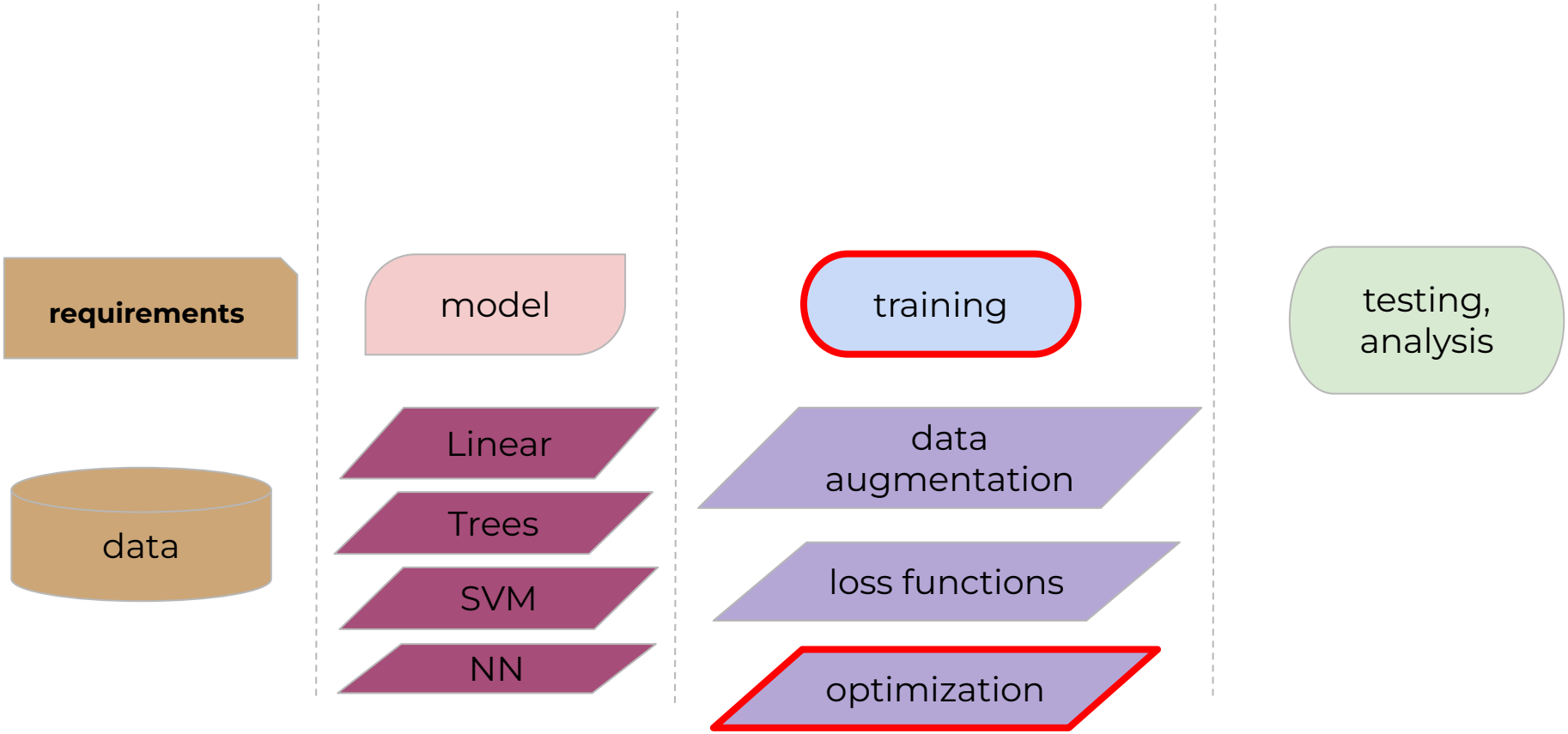
$$L_{logloss} = \frac{1}{N}\sum_{n=1}^{N}\sum_{k=1}^{M} y_{nk} \cdot log(p_{nk})$$

$$L_{rmse} = \frac{1}{N}\sum_{n=1}^{N} \parallel F(\mathbf{x_n}) - y_i \parallel_2$$

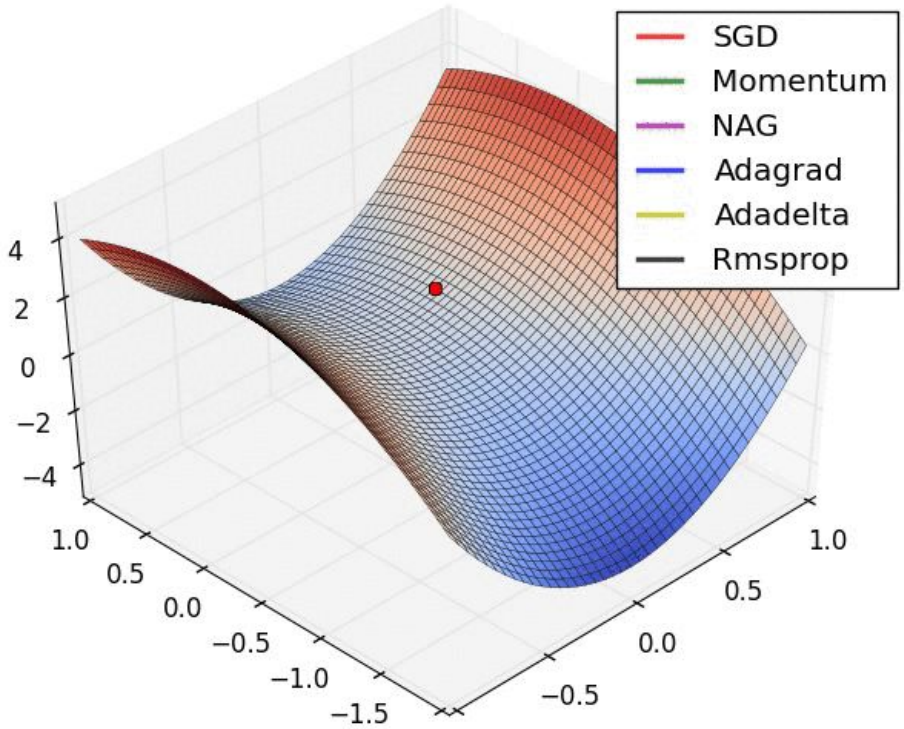
Focal Loss:



Machine Learning essential blocks



Optimization



Optimization

Input: Training set $\mathcal{S} \triangleq \cup_{i=1}^{n}\{(\boldsymbol{x}_i, \boldsymbol{y}_i)\}$, Loss function $l : \mathcal{W} \times \mathcal{X} \times \mathcal{Y} \rightarrow \mathbb{R}_+$, Batch size b, Step size $\eta > 0$, Neighborhood size $\rho > 0$.
Output: Model trained with SAM
Initialize weights $\boldsymbol{w}_0$, $t = 0$;
while *not converged* **do**
  Sample batch $\mathcal{B} = \{(\boldsymbol{x}_1, \boldsymbol{y}_1), ...(\boldsymbol{x}_b, \boldsymbol{y}_b)\}$;
  Compute gradient $\nabla_{\boldsymbol{w}} L_{\mathcal{B}}(\boldsymbol{w})$ of the batch's training loss;
  Compute $\hat{\boldsymbol{\epsilon}}(\boldsymbol{w})$ per equation 2;
  Compute gradient approximation for the SAM objective (equation 3): $\boldsymbol{g} = \nabla_w L_{\mathcal{B}}(\boldsymbol{w})|_{\boldsymbol{w}+\hat{\boldsymbol{\epsilon}}(\boldsymbol{w})}$;
  Update weights: $\boldsymbol{w}_{t+1} = \boldsymbol{w}_t - \eta \boldsymbol{g}$;
  $t = t + 1$;
end
return $\boldsymbol{w}_t$

Algorithm 1: SAM algorithm

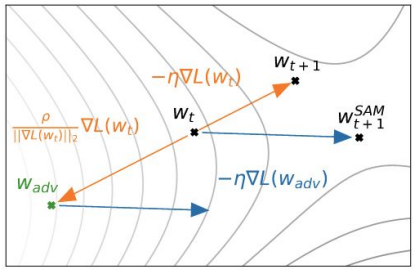
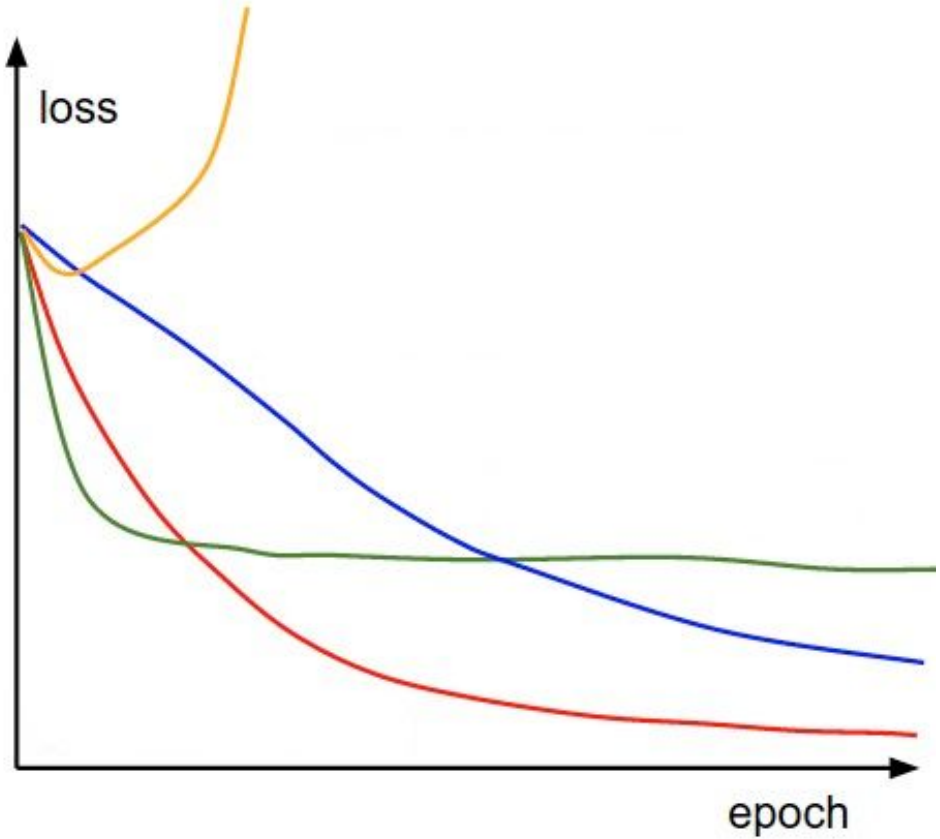


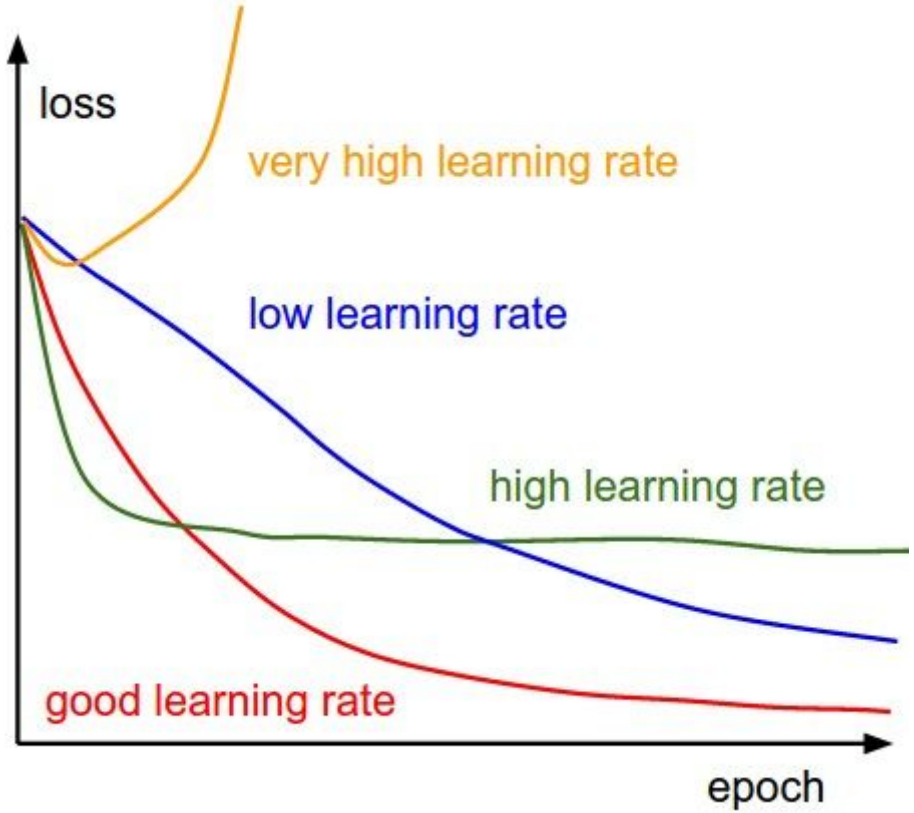
Figure 2: Schematic of the SAM parameter update.

2010.01412,
JAX(official), pytorch

Neural Networks



Neural Networks



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  - neural networks

- **CV specific setups**
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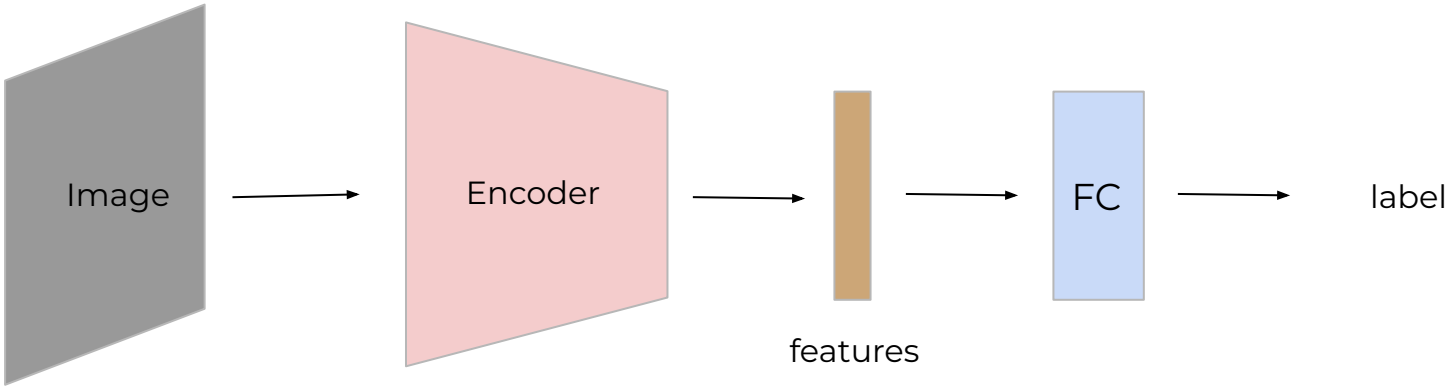
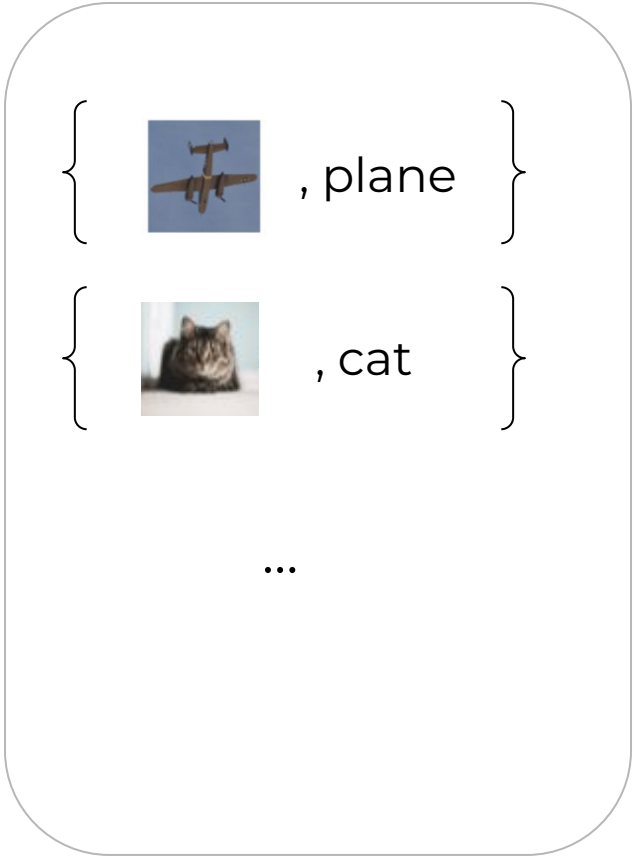
- Main components of CNNs (motivation and details)
  - convolutional layer
  - pooling layer

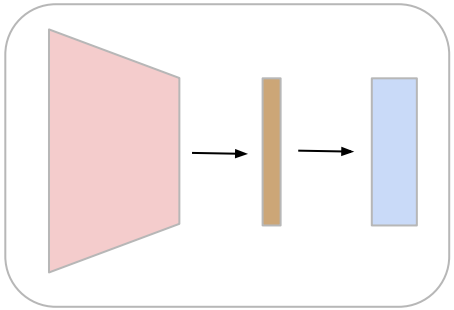
Neural Networks (supervised way)



Neural Networks (supervised way)



$F(\mathbf{x_n})$



$e(F(\mathbf{x_n}), y_n)$

$e(F(\mathbf{x_n}), y_n)$

...

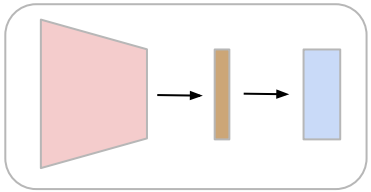
$$L_{train}(\omega) = \frac{1}{N}\sum_{n=1}^{N} e(F(\mathbf{x_n}), y_n)$$

Neural Networks (semi-supervised)

{  , plane }

{  , cat }

...



Train teacher model with labeled data

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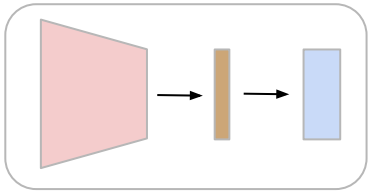
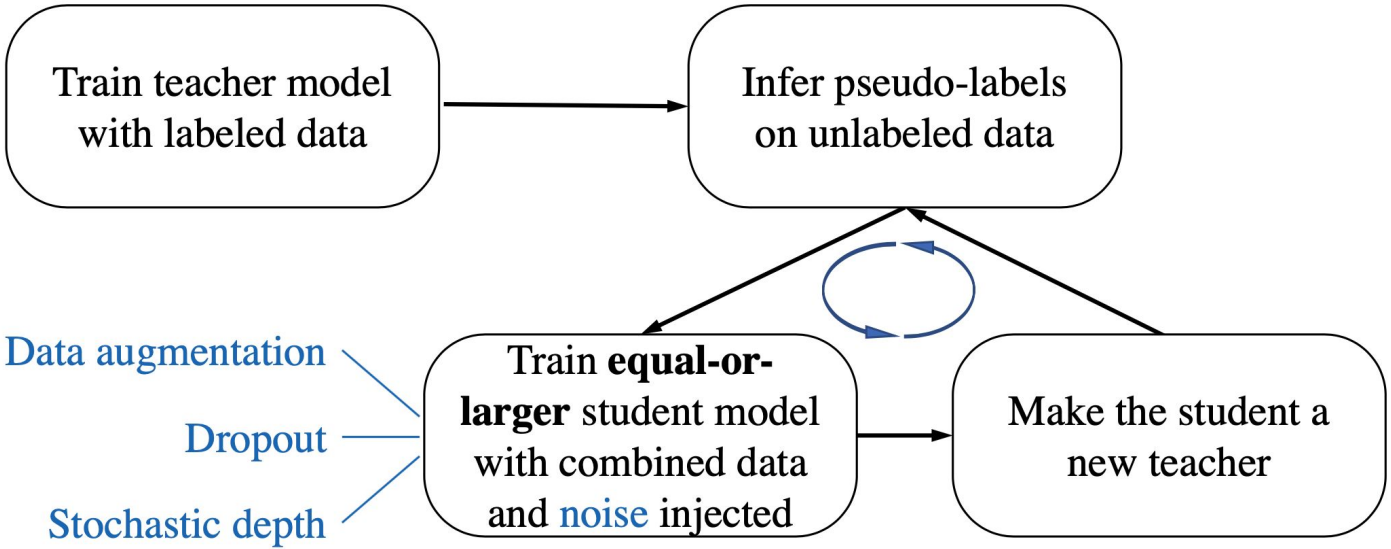
Neural Networks (semi-supervised)





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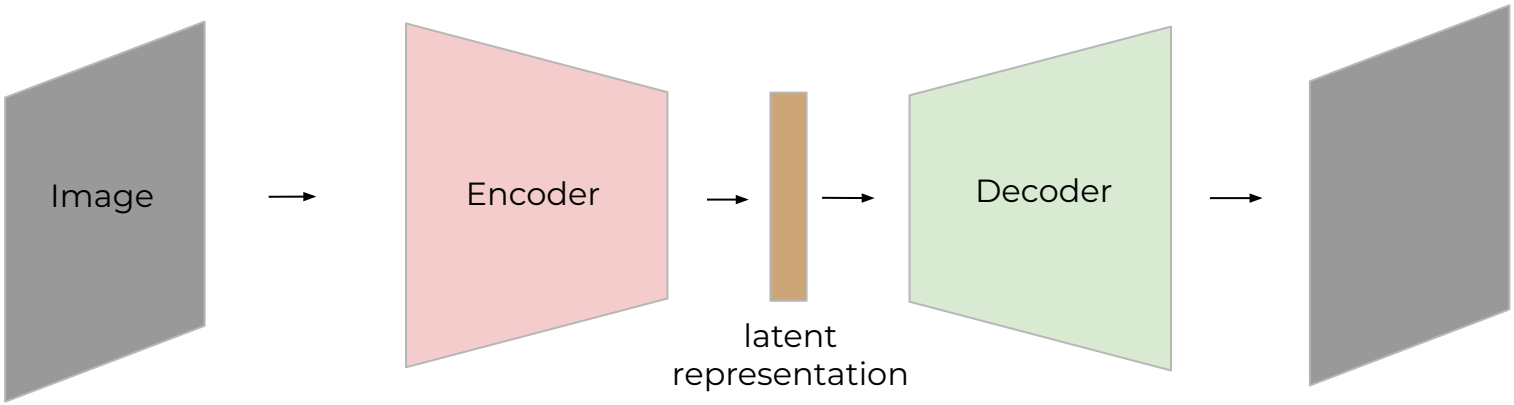
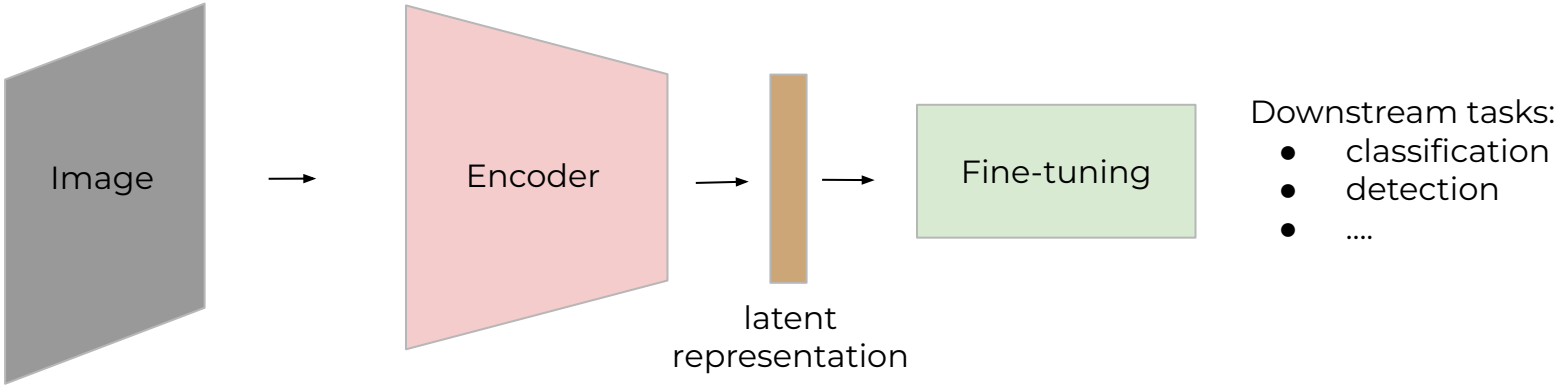
Neural Networks (auto-encoder way)

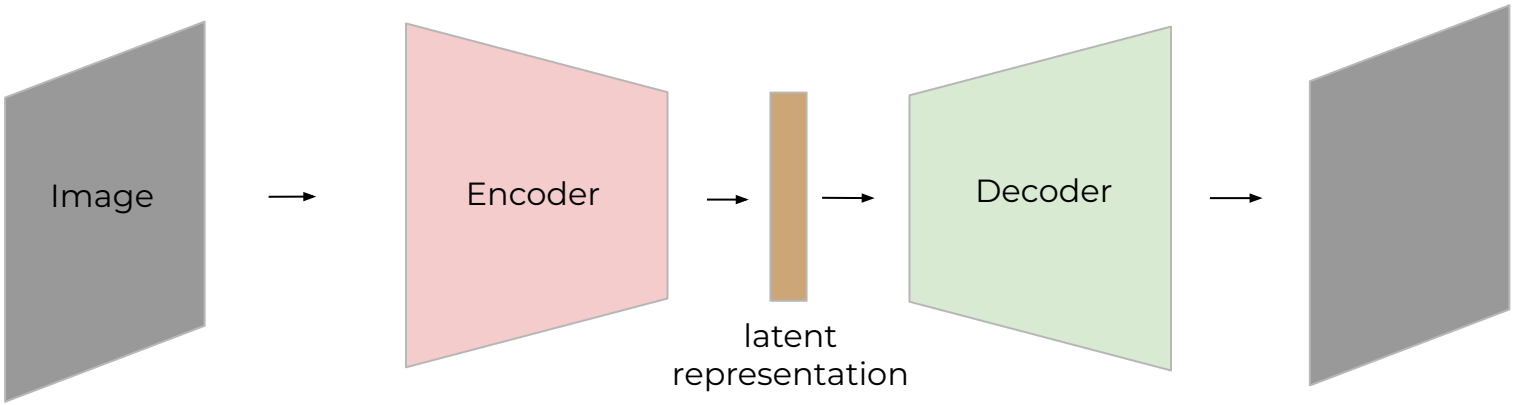


Neural Networks (discrimination)

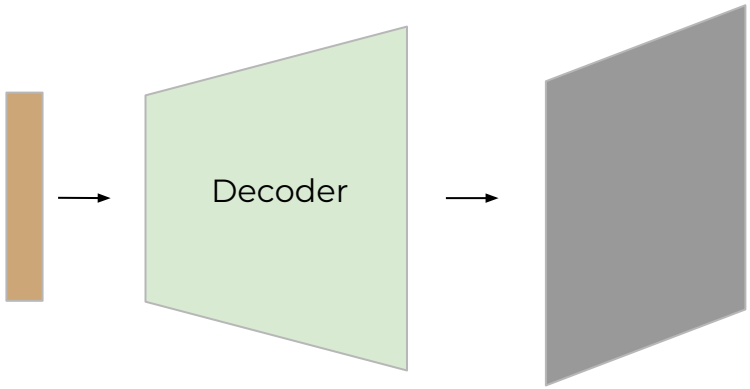
Fine-tuning



Neural Networks (generation)

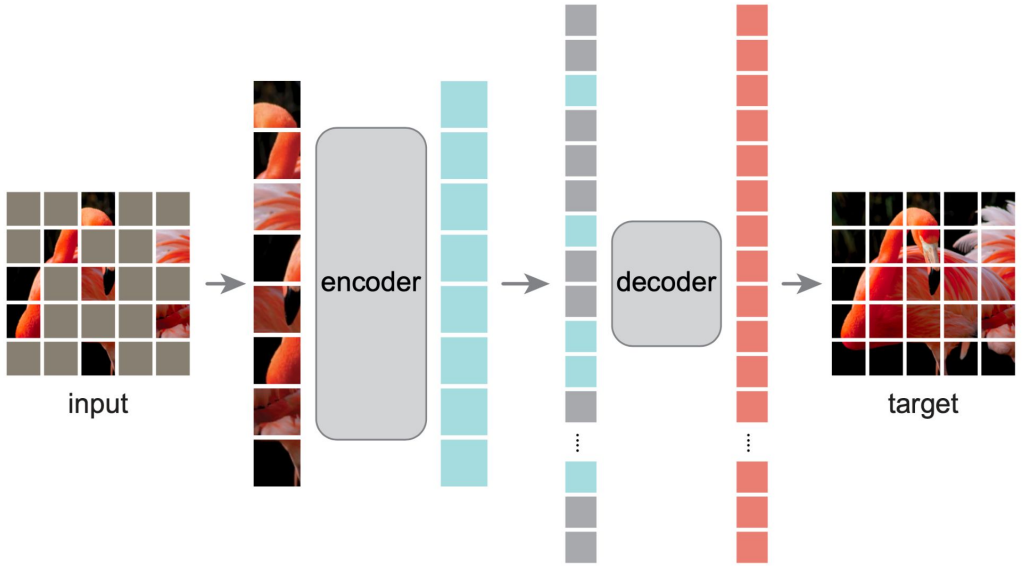


Neural Networks (generation)



Neural Networks (auto-encoder way)

MAE



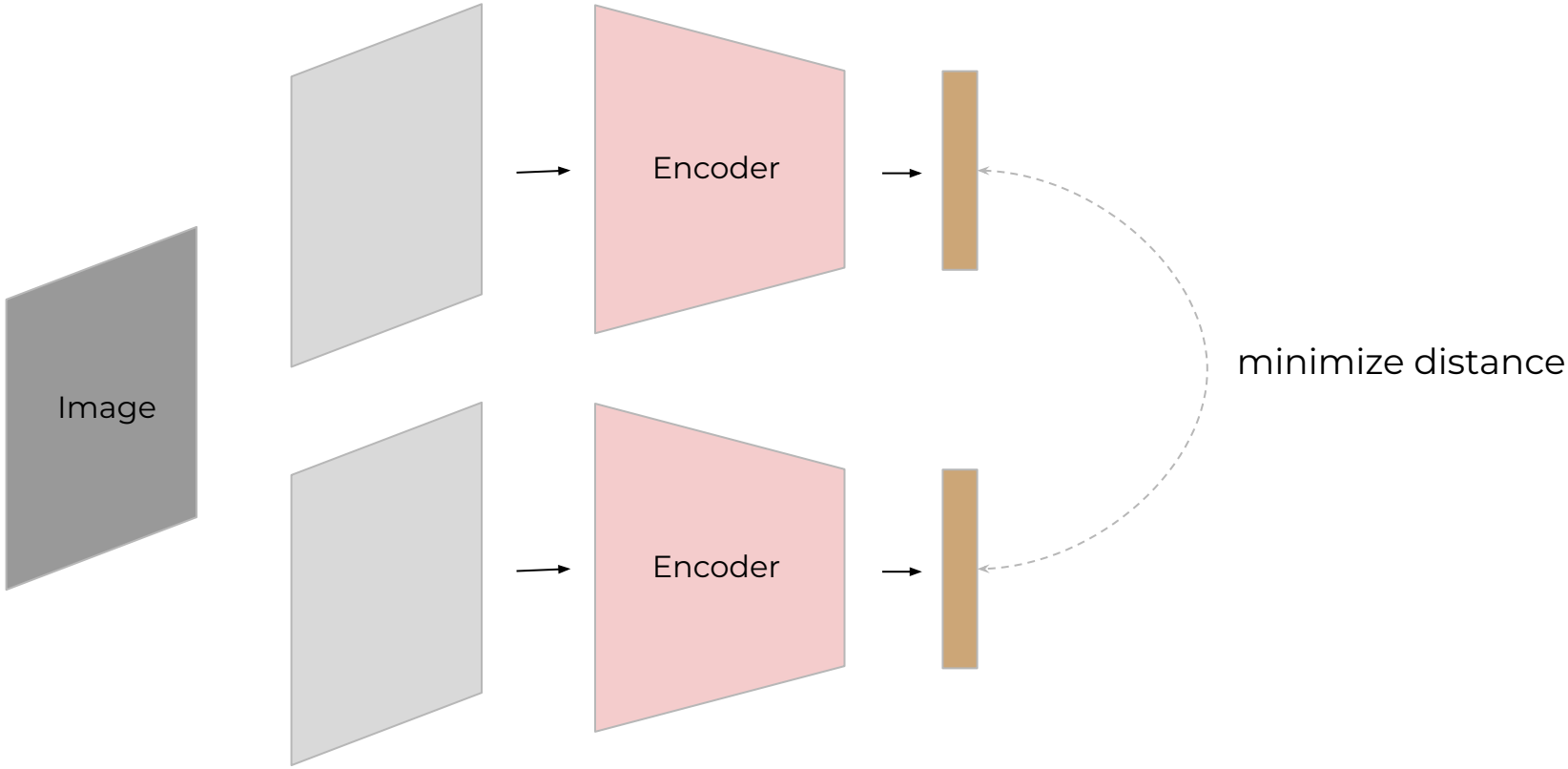
2111.06377

Neural Networks (auto-encoder way)

MAE

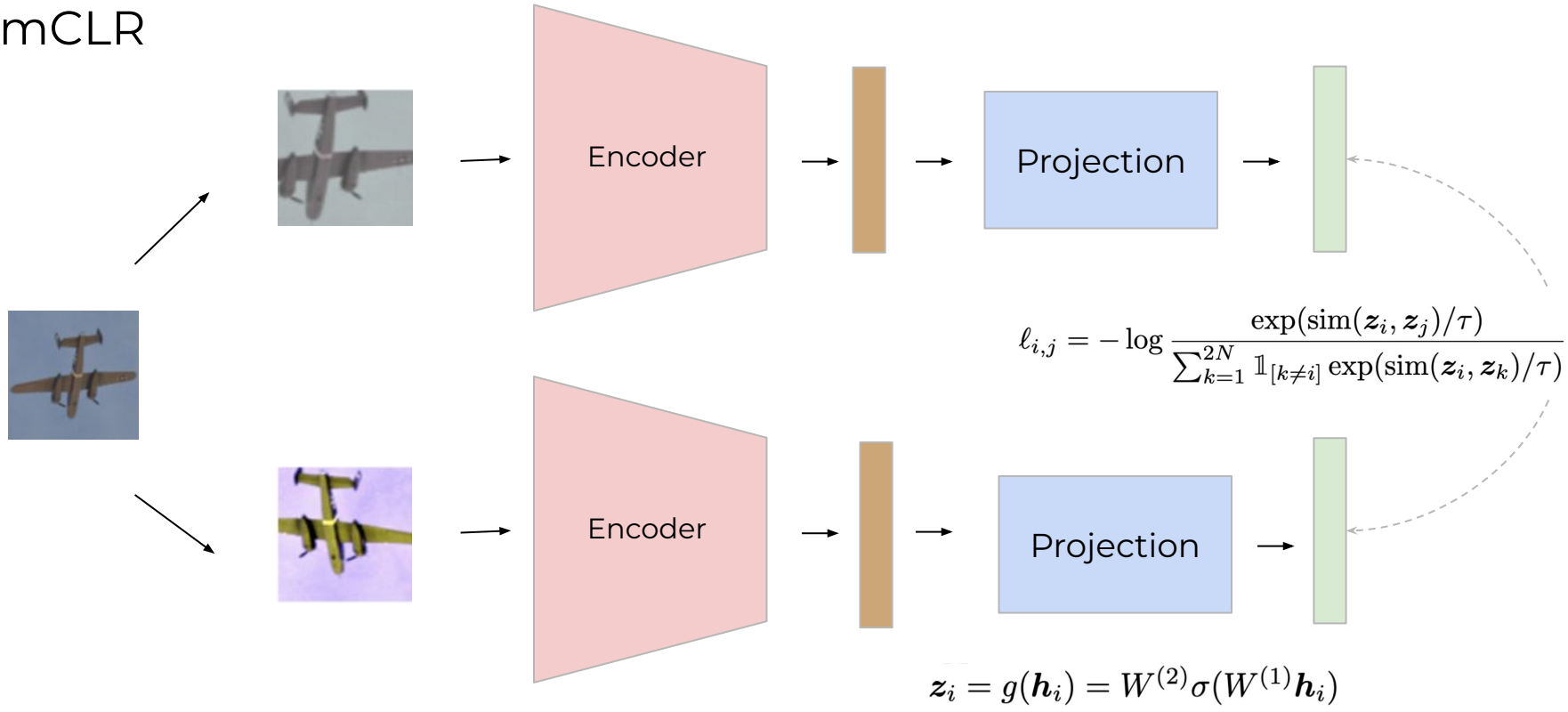
2111.06377

Neural Networks (self-supervised way)



Neural Networks (self-supervised way)

SimCLR



$$\ell_{i,j} = -\log \frac{\exp(\text{sim}(\boldsymbol{z}_i, \boldsymbol{z}_j)/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(\text{sim}(\boldsymbol{z}_i, \boldsymbol{z}_k)/\tau)}$$

$$\boldsymbol{z}_i = g(\boldsymbol{h}_i) = W^{(2)}\sigma(W^{(1)}\boldsymbol{h}_i)$$

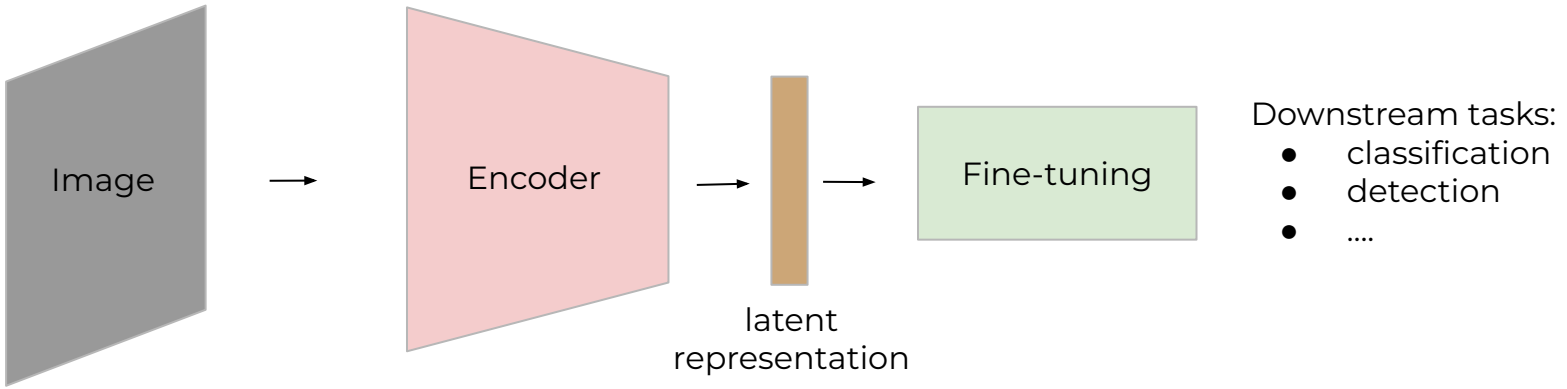
$$\boldsymbol{h}_i = f(\tilde{\boldsymbol{x}}_i) = \text{ResNet}(\tilde{\boldsymbol{x}}_i)$$

2002.05709

Neural Networks (self-supervised way)

SimCLR

Fine-tuning



2002.05709

Content

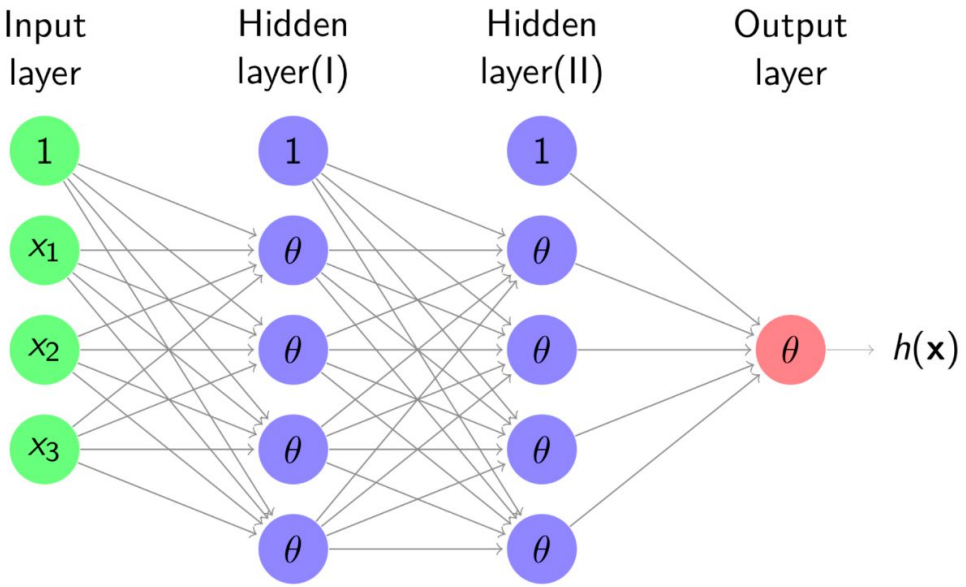
- Intro, Context

- ML/DL review
  - training & testing
  - neural networks

- CV specific setups
  - supervised, semi-supervised,
  - self-supervised, auto-encoders

- **Main components of CNNs (motivation and details)**
  - convolutional layer
  - pooling layer

Intro to CNN



Input layer
$64 \times 64 = 4096$

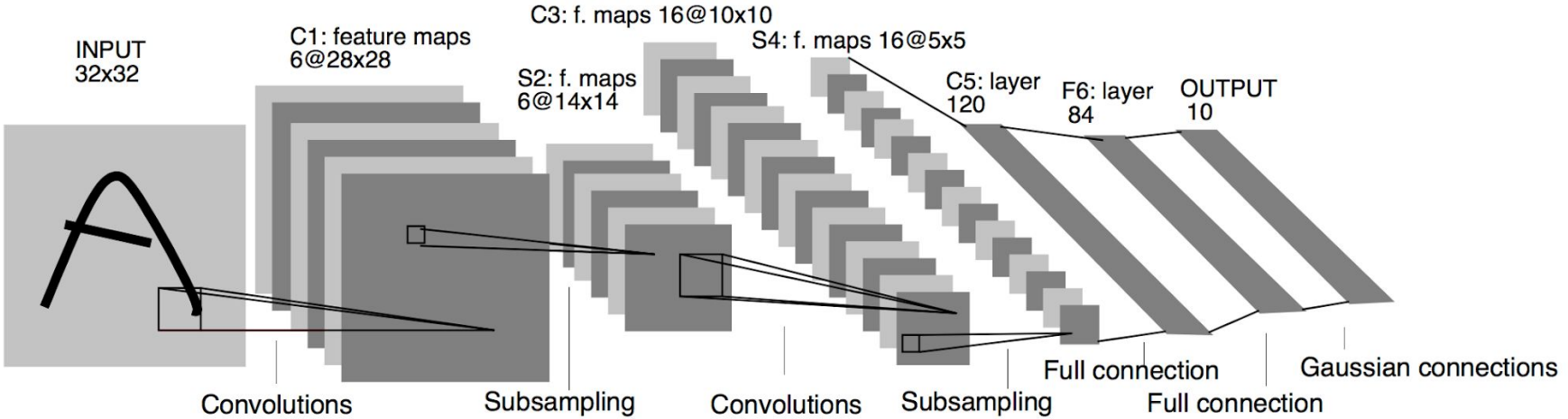
Weights: $4096\times$ (size of second layer)

$=>$ millions of parameters (for just one layer)

Need for alternative architecture

Intro to CNN

LeNet-5 [1998, paper by LeCun et al.]



Intro to CNN

- INPUT holds the raw pixel values of the image.
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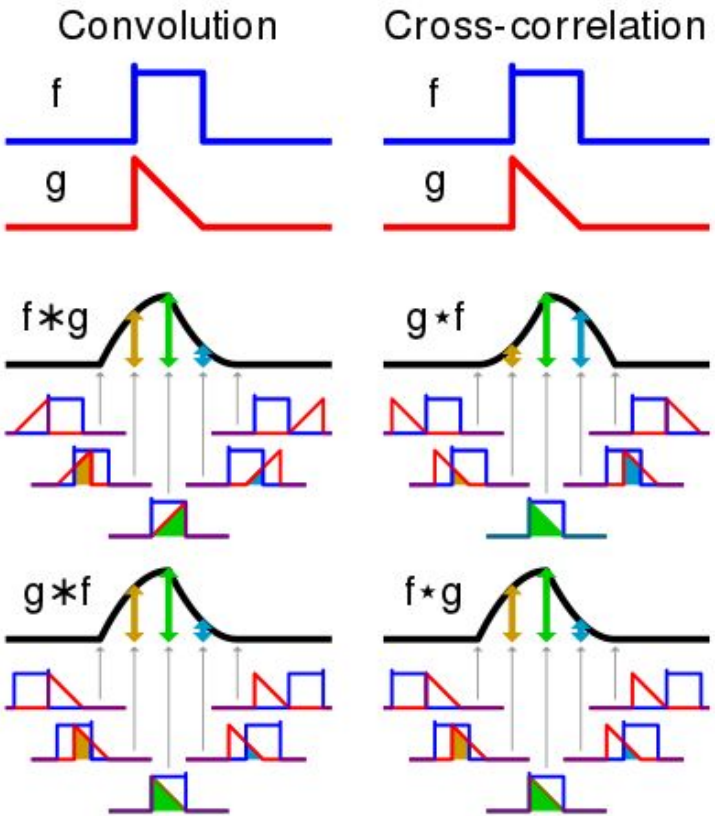
Intro to CNN



a function derived from two given functions by integration that expresses how the shape of one is modified by the other

$$(f * g)(t) \triangleq \int_{-\infty}^{\infty} f(\tau) g(t - \tau)\, d\tau.$$

https://en.wikipedia.org/wiki/Convolution

Intro to CNN

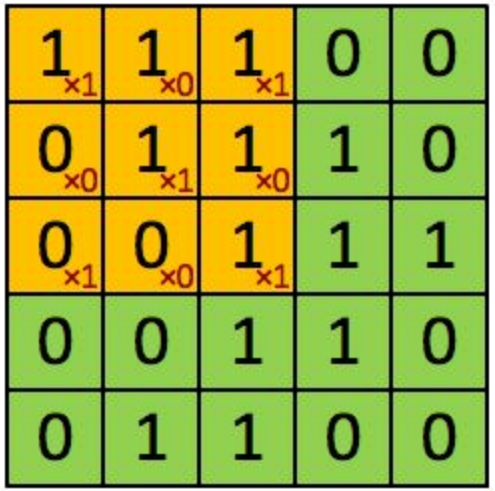
1	0	1
0	1	0
1	0	1

Kernel

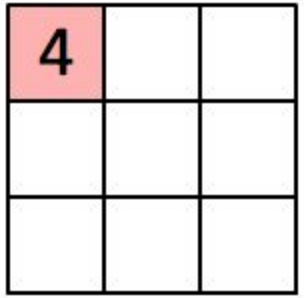
1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

Image

Intro to CNN



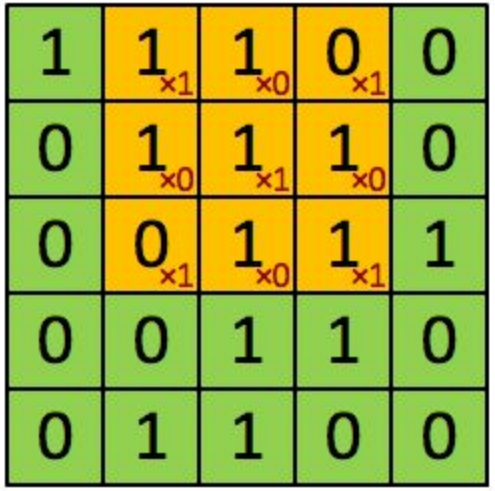
Image



Convolved Feature

images from http://cs231n.stanford.edu/

Intro to CNN



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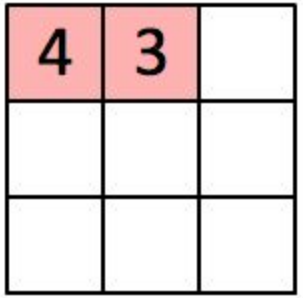

Convolved Feature

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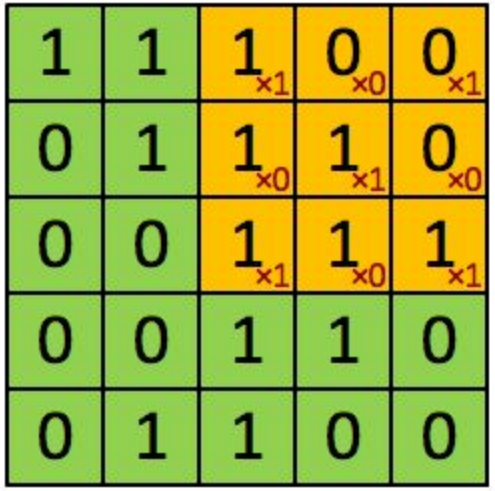
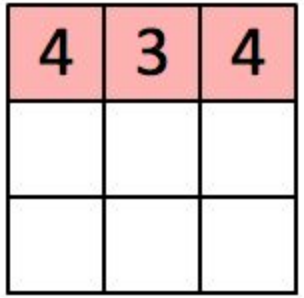
Intro to CNN



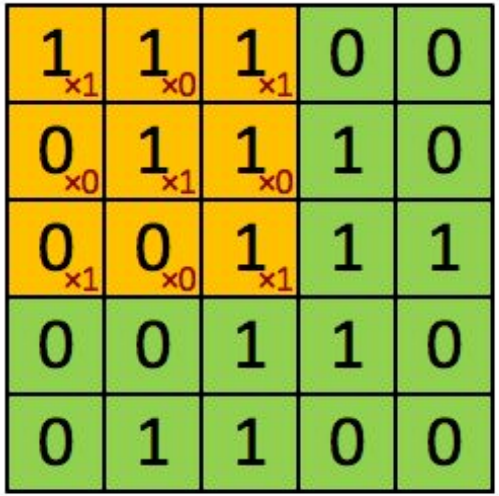
Image



Convolved Feature

images from http://cs231n.stanford.edu/

Intro to CNN



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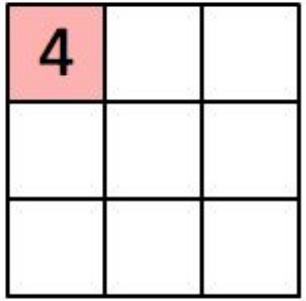
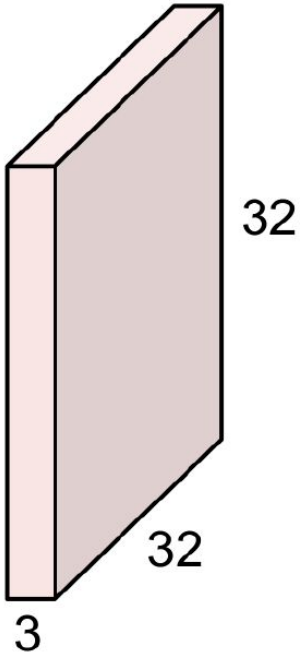


Convolved Feature

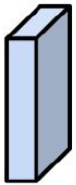
images from http://cs231n.stanford.edu/

Intro to CNN

32x32x3 image



5x5x3 filter

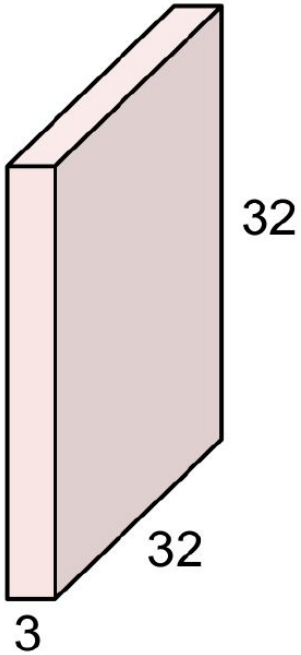


Convolve the filter with the image
i.e. “slide over the image spatially,
computing dot products”

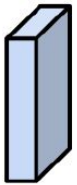
images from http://cs231n.stanford.edu/

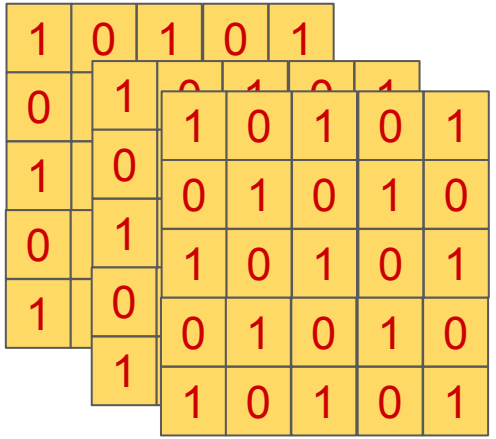
Intro to CNN

32x32x3 image



5x5x3 filter





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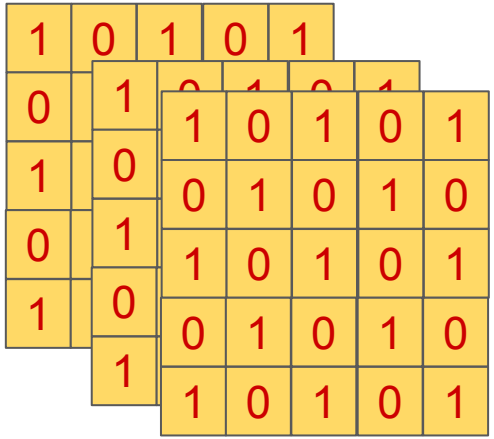
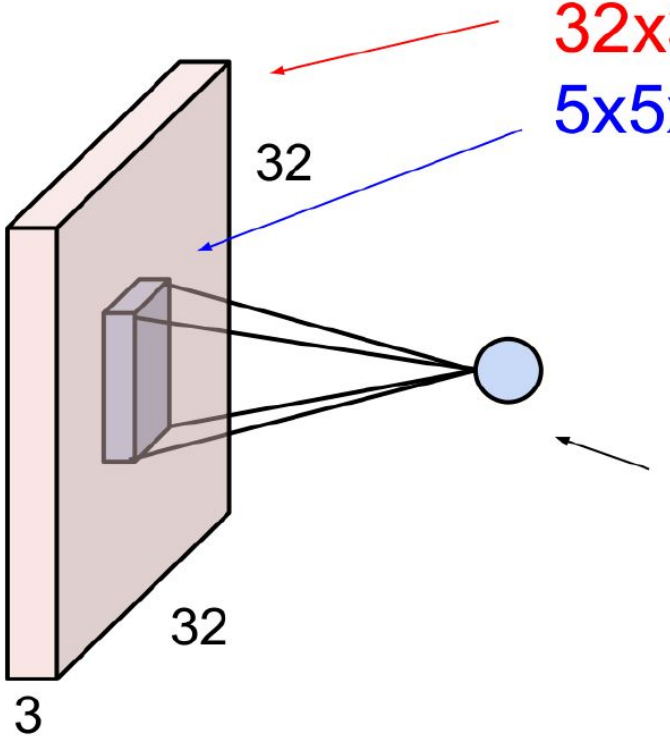
Intro to CNN





1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image (i.e. 5*5*3 = 75-dimensional dot product + bias)

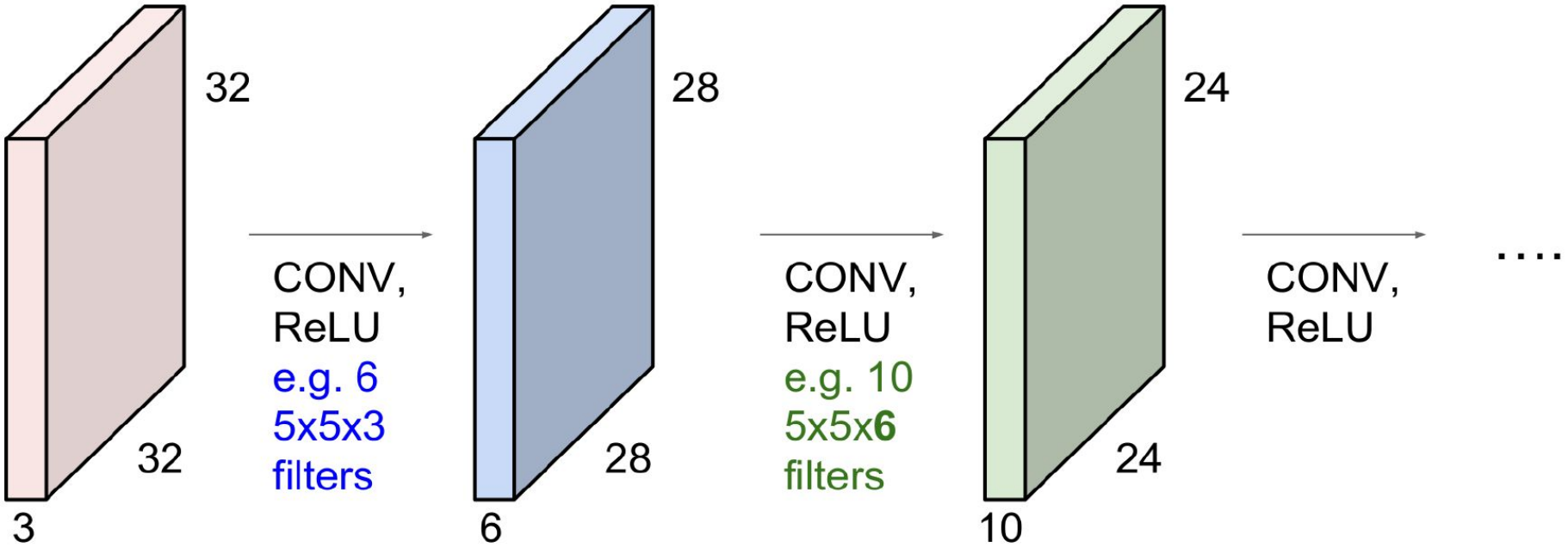
$$w^T x + b$$

images from http://cs231n.stanford.edu/

Intro to CNN

images from http://cs231n.stanford.edu/

Intro to CNN



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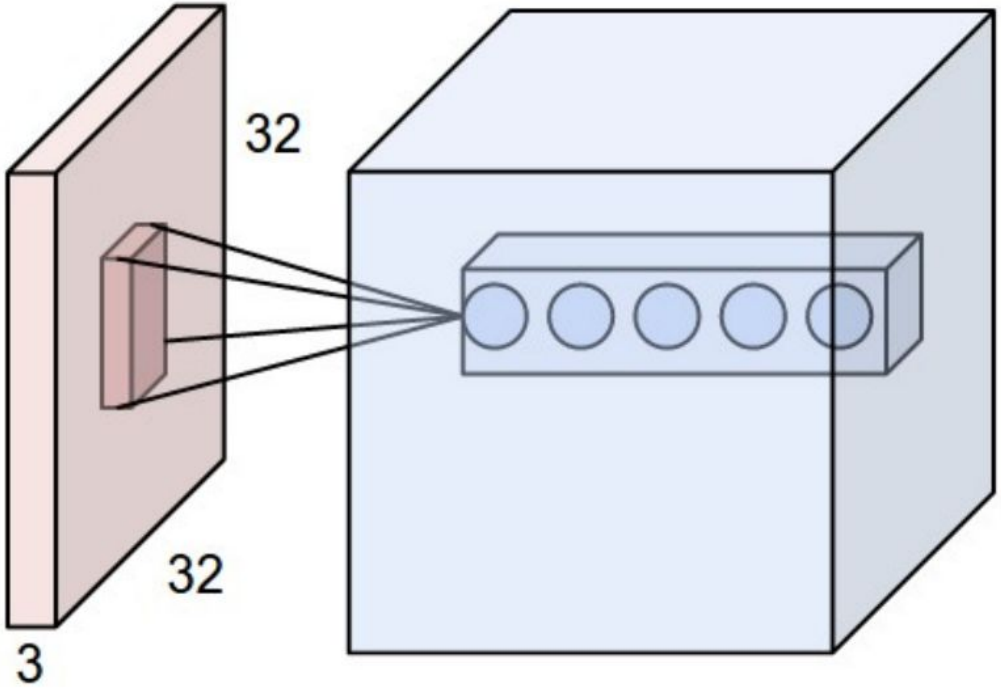
Intro to CNN



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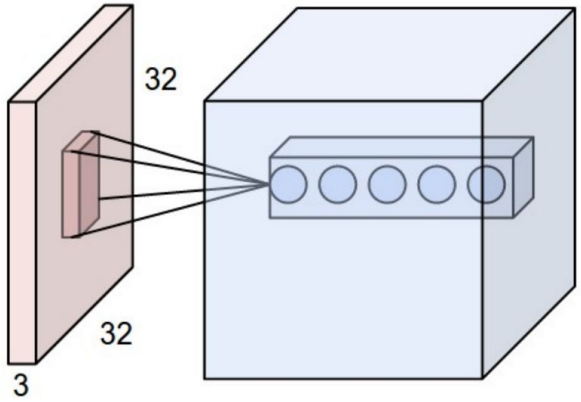
Intro to CNN

- Accepts a volume of size $W1 \times H1 \times D1$
- Requires four hyperparameters:
  - Number of filters K,
  - their spatial extent F,
  - the stride S,
  - the amount of zero padding P.
- Produces a volume of size $W2 \times H2 \times D2$ where:
  - $W2 = (W1 - F + 2P)/S + 1$,
  - $H2 = (H1 - F + 2P)/S + 1$
  - $D2 = K$
- With parameter sharing, it introduces $F \times F \times D1$ weights per filter, for a total of $(F \times F \times D1) \times K$ weights and K biases.



Intro to CNN

- Convolution leverages four ideas that can help ML systems:
  - Sparse interactions
  - Parameter sharing
  - Equivariant representations $f(g(\mathbf{x})) = g(f(\mathbf{x}))$
  - Ability to work with inputs of variable size

Intro to CNN

We can use one single convolutional layer to modify a certain image

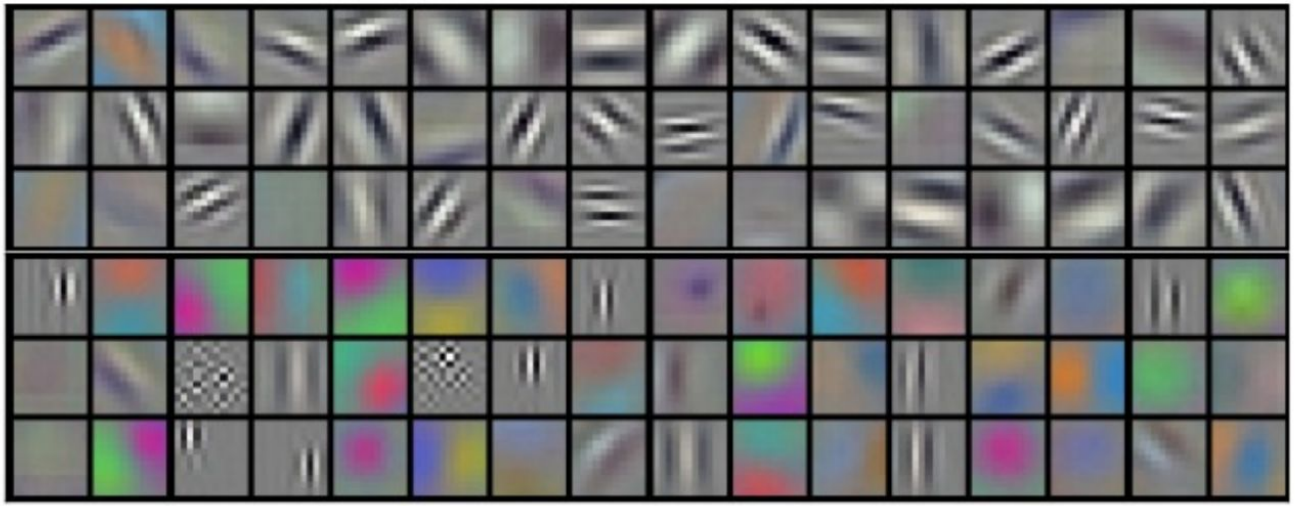
$$\begin{bmatrix} 1. & 1. & 1. \\ 1. & 1. & 1. \\ 1. & 1. & 1. \end{bmatrix}$$

$$\begin{bmatrix} 1. & 2. & 1. \\ 0. & 0. & 0. \\ -1. & -2. & -1. \end{bmatrix}$$

$$\begin{bmatrix} 0. & -1. & 0. \\ -1. & 5. & -1. \\ 0. & -1. & 0. \end{bmatrix}$$

Intro to CNN

In training, we don't
specify kernels.
We learn kernels!



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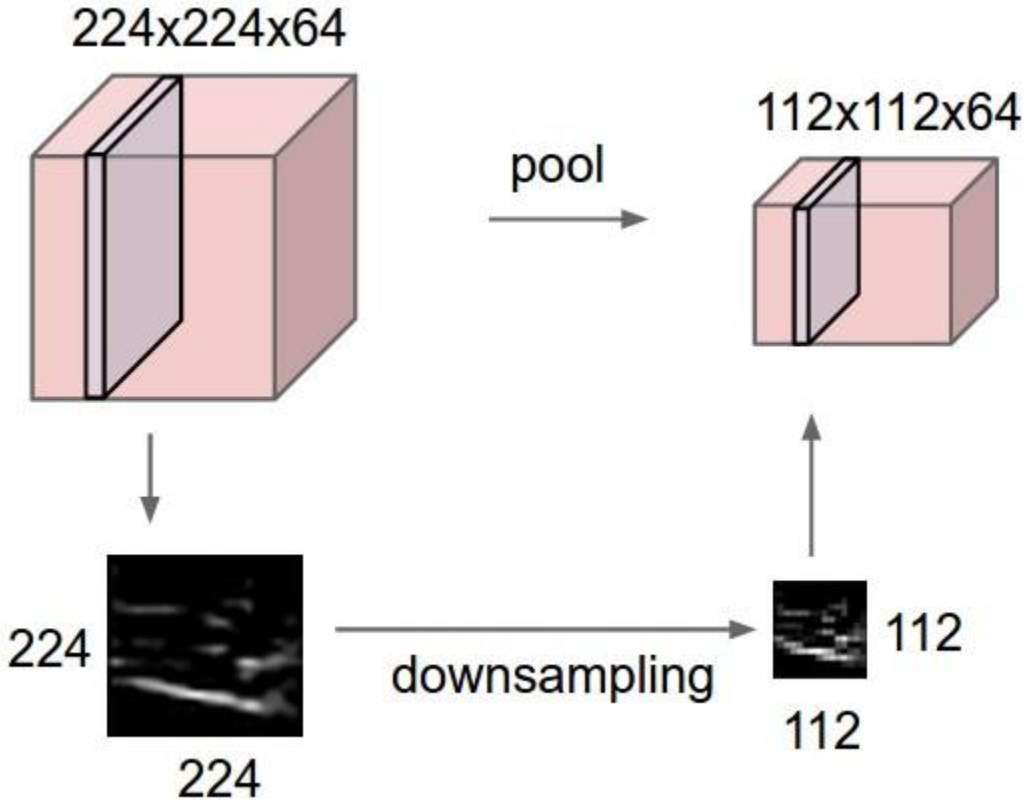
Intro to CNN



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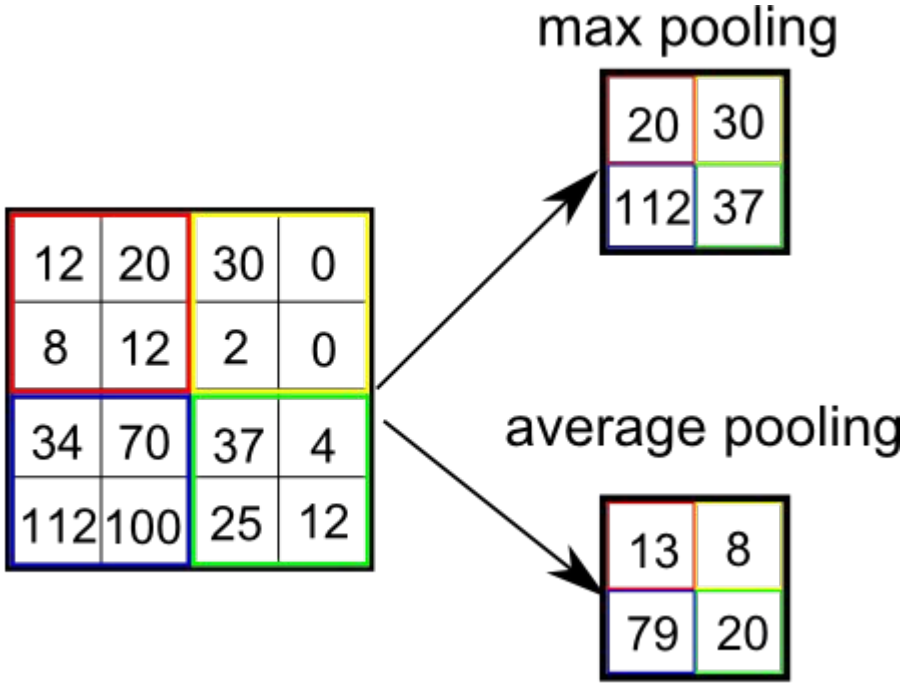
Intro to CNN



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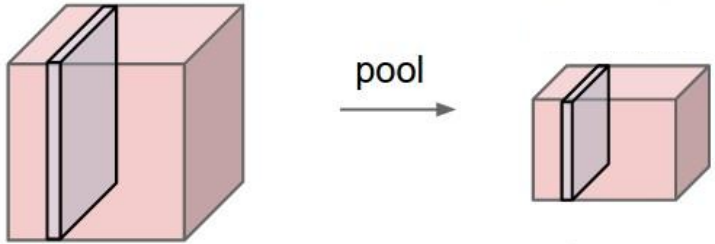
Intro to CNN



- Accepts a volume of size $W1 \times H1 \times D1$
- Requires three hyperparameters:
  - their spatial extent F,
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- Produces a volume of size $W2 \times H2 \times D2$ where:
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  - $D2 = D1$

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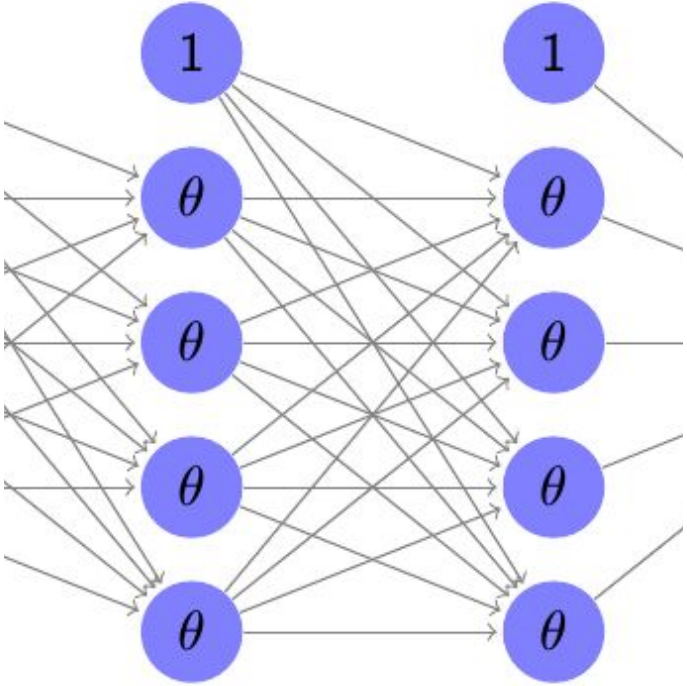
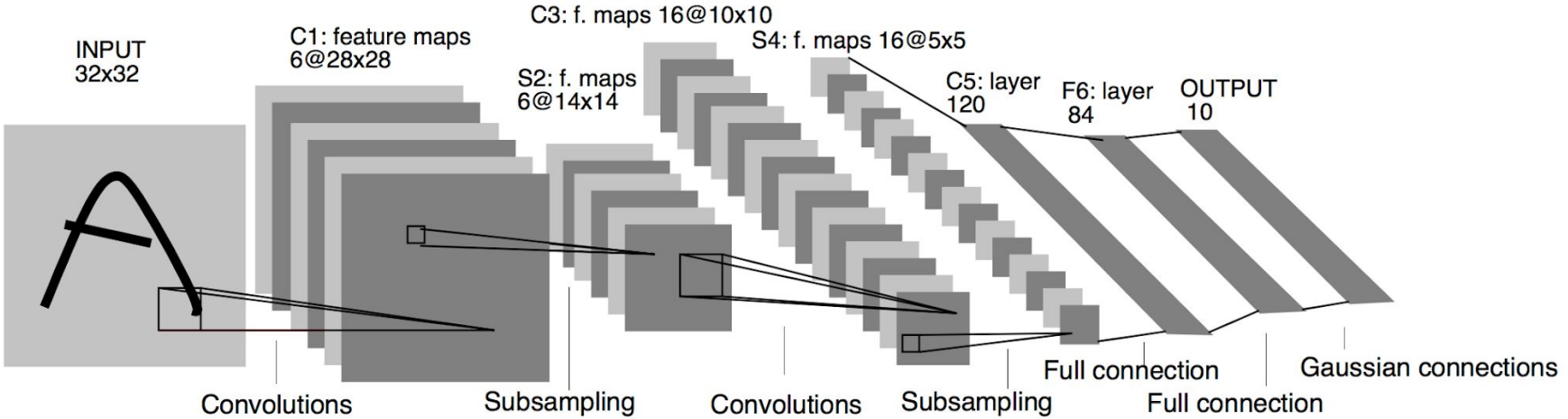


Intro to CNN

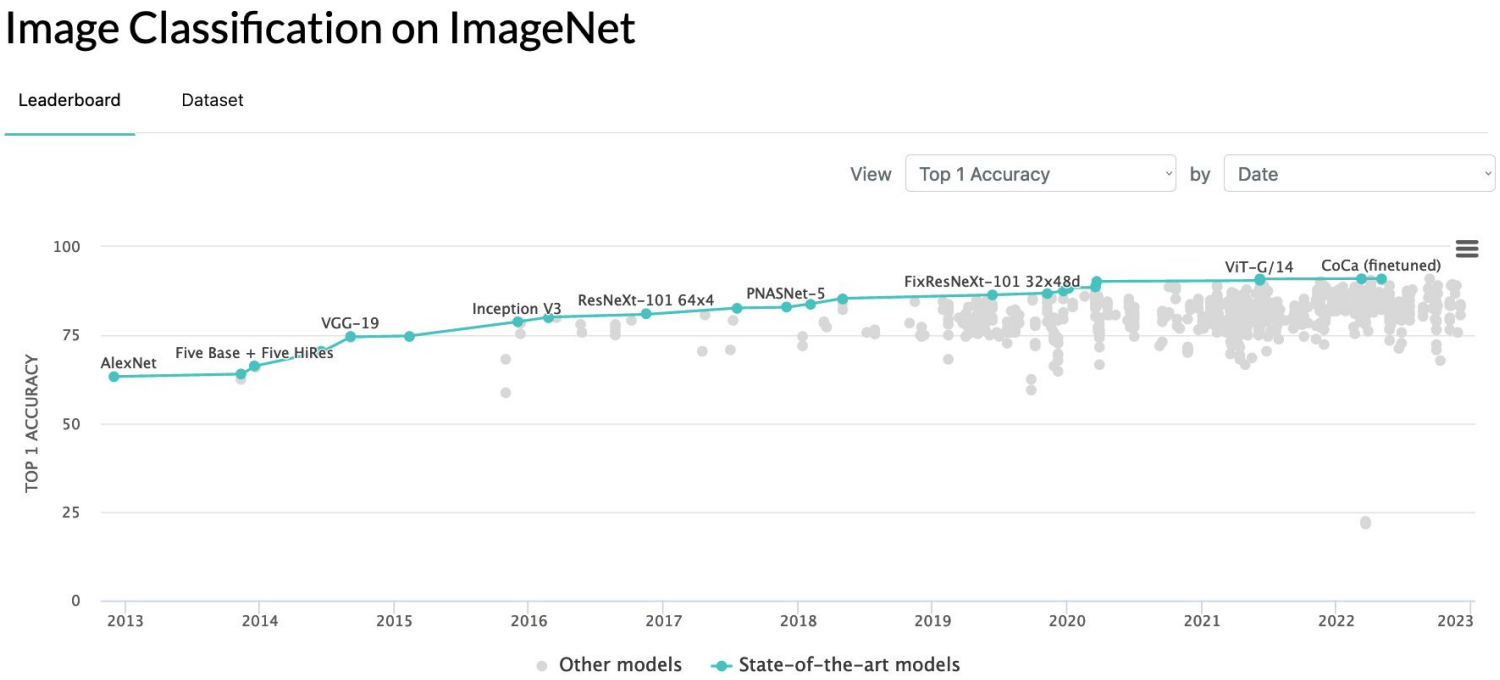
LeNet-5 [1998, paper by LeCun et al.]



Intro to CNN

CNN explainer

Intro to CNN



https://paperswithcode.com/sota/image-classification-on-imagenet

Intro to CNN