Week 8 | Lecture 09
Convolutional Networks

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Today’s Agenda

- **Convolutional Networks**
  - A Design Challenge in 3D Volumes
  - Convolutional Operation
  - The Design of a Convolutional Layer
- **Layers in ConvNets**
  - Three Stages of a Convolutional Layer
  - Common Architectures of ConvNets
  - CONV, POOL, FC Layers
- **A Universal Workflow**
  - Define the Problem & Dataset Assembly
  - Success Metric & Evaluation Protocol
  - Scale up the Model with Regularization
- **Learning a Transition Model**

Convolutional Networks

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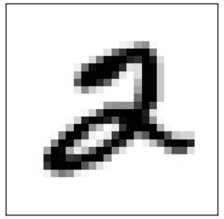
A Design Challenge with Increasing Dimensions

Regular Neural Nets don't scale well to full images

$\mathbf{512 \times 512 \times 3 = 765,432}$

Gray-scaled



MNIST

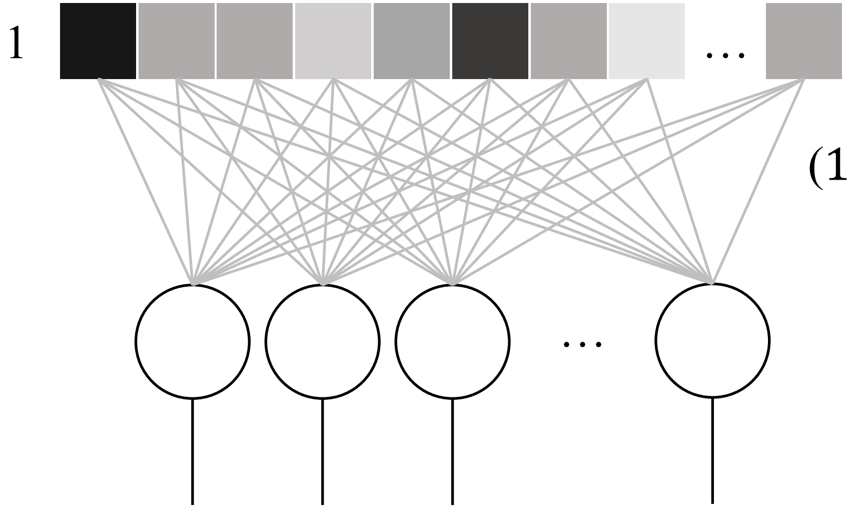
CIFAR-10

Color (RGB)

$28 \times 28 \times 1 = 784$

Input *Features*

$32 \times 32 \times 3 = 3{,}072$



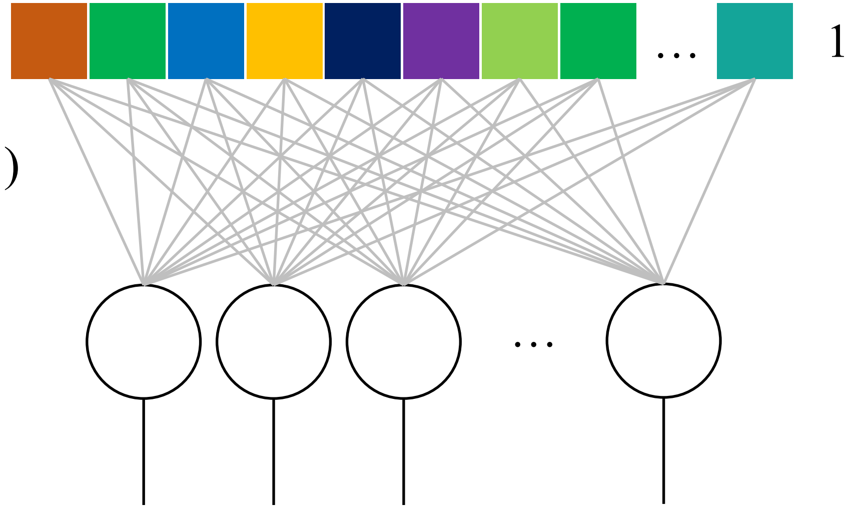
Weighted-Sum

$(10 \times 784 \leftarrow W \rightarrow 10 \times 3072)$

Activation

(?)

Output *Label*



0 1 2 9

airplane cat frog ship

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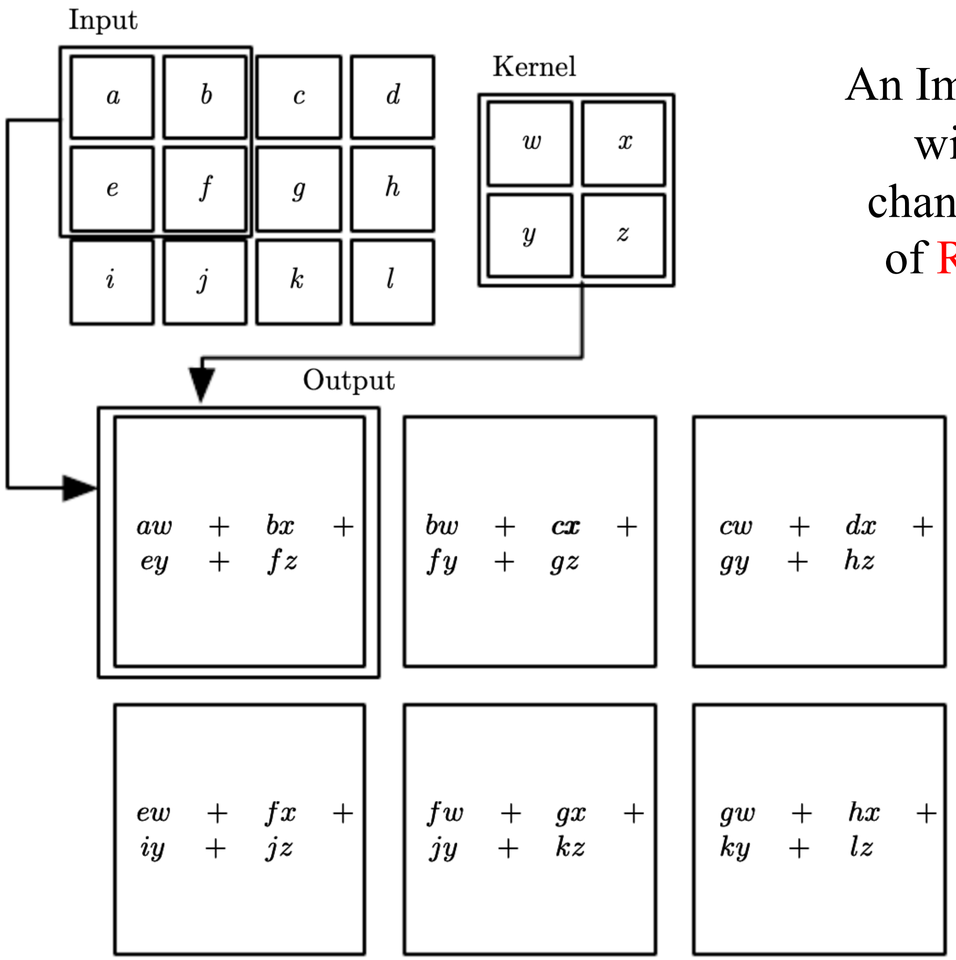
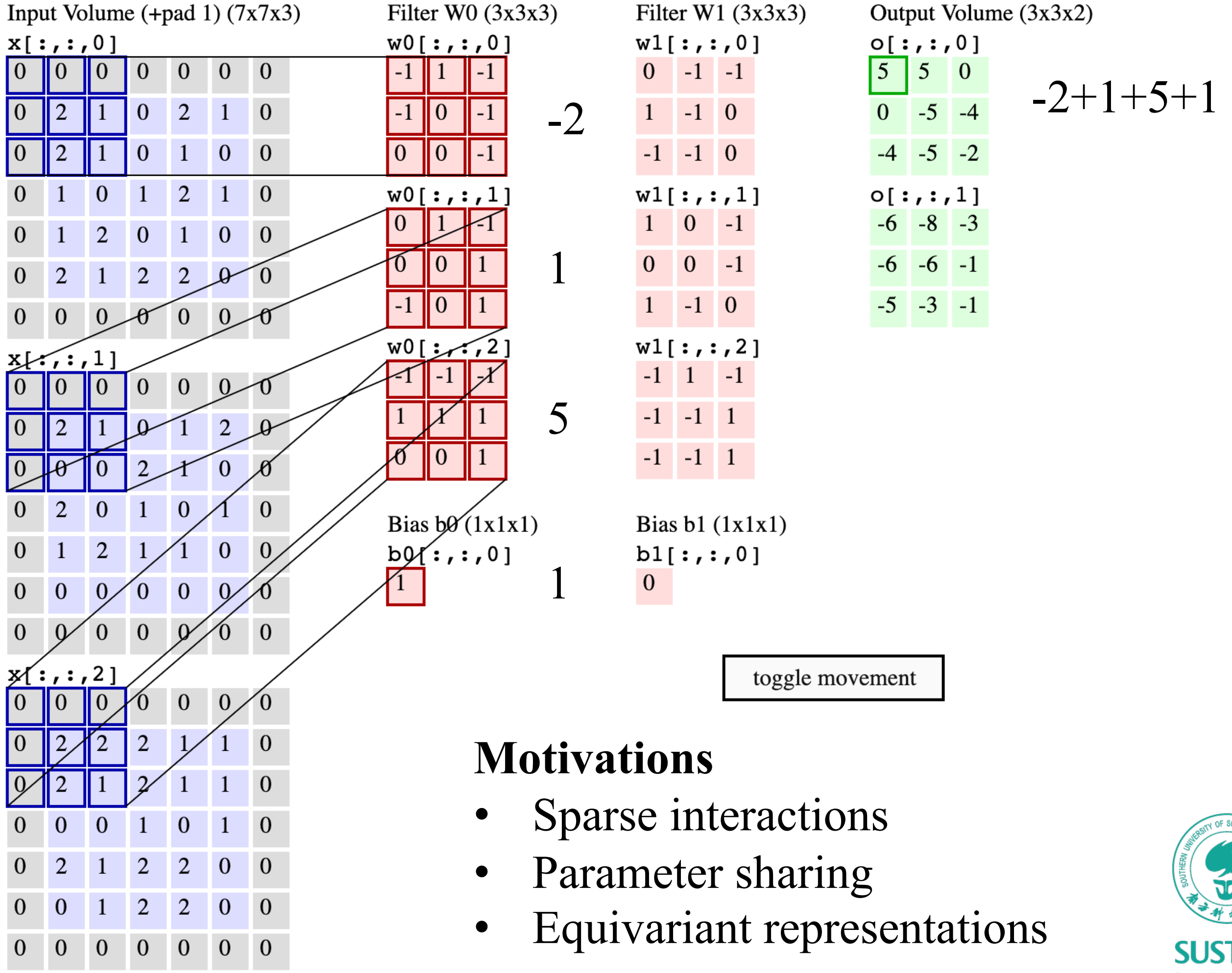
Convolutional Operation

$$s(t) = \int x(a)w(t-a)da = (x * w)(t)$$



An Image with 3 channels of RGB



Motivations

- Sparse interactions
- Parameter sharing
- Equivariant representations

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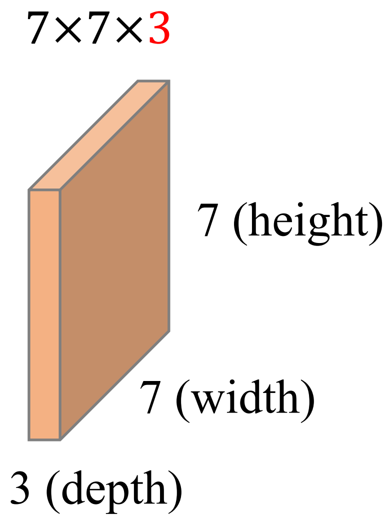
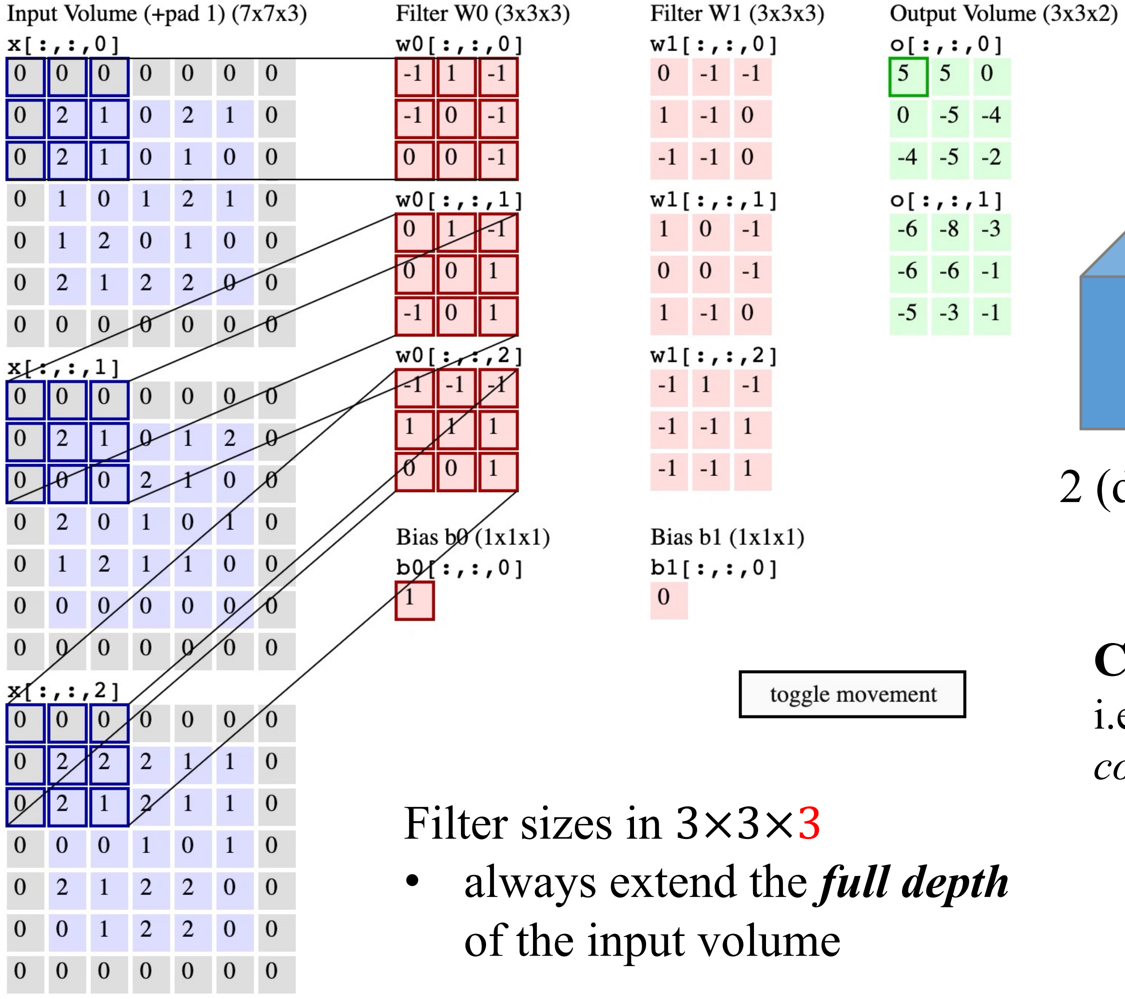
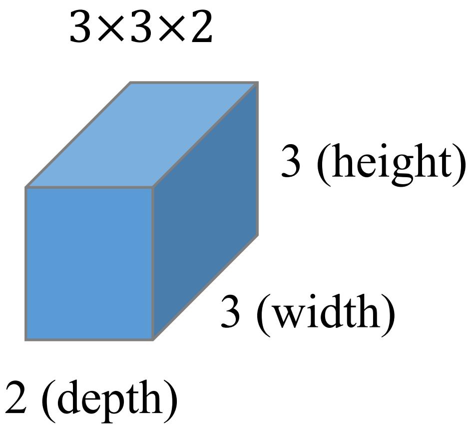
Convolution in 3D Volumes

Preserved spatial structure between the input and output volumes in width, height, number of channels

Input Volume in 3D







Output Volume in 3D

Layers in a ConvNet:
Transform an input 3D volume to an output 3D volume with some differentiable function that may or may not have parameters.

Filter sizes in 3×3×3
- always extend the ***full depth*** of the input volume

Convolve the filter with the image
i.e. "*slide over the image spatially, computing dot products*"

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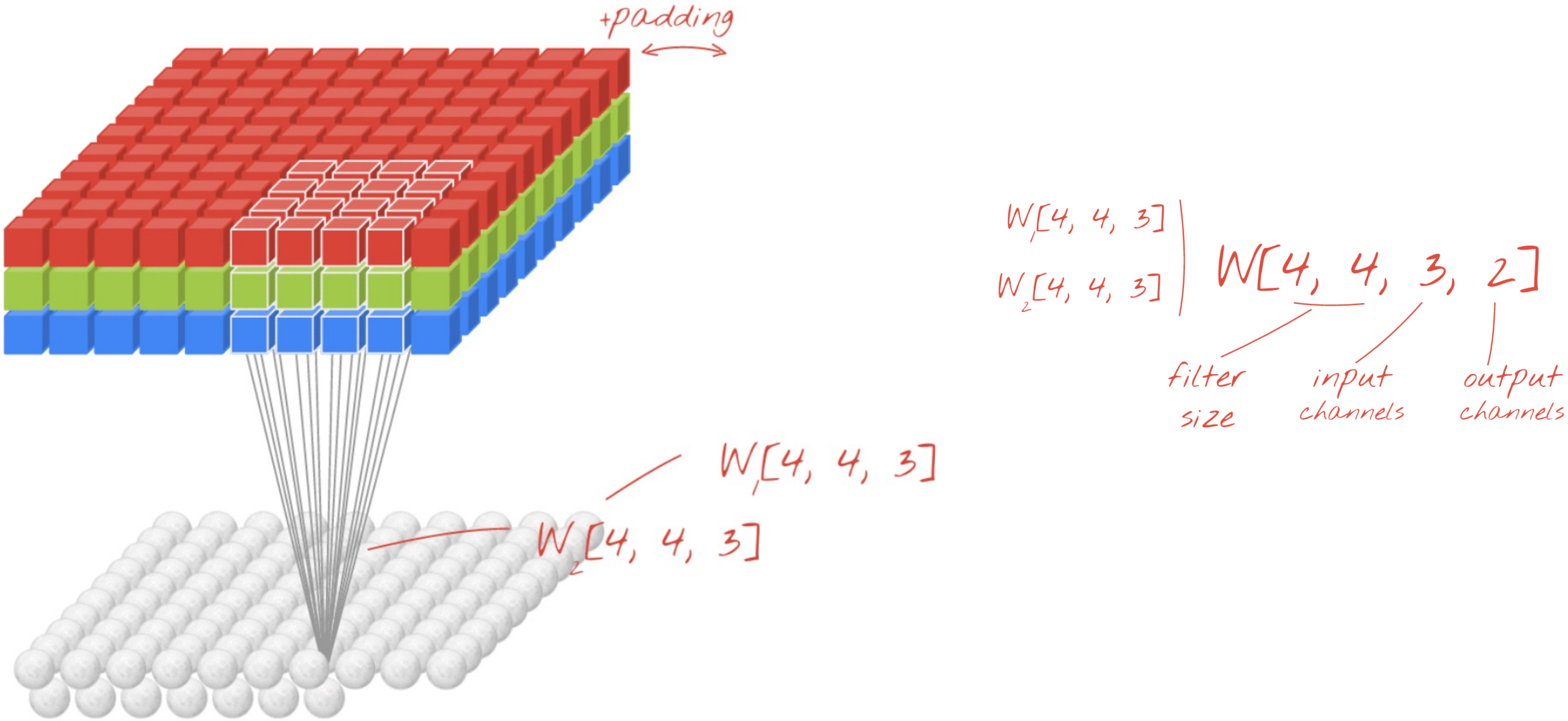
The Design of a Convolutional Layer

Defined by the filter (or kernel) size, the number of filters applied and the stride



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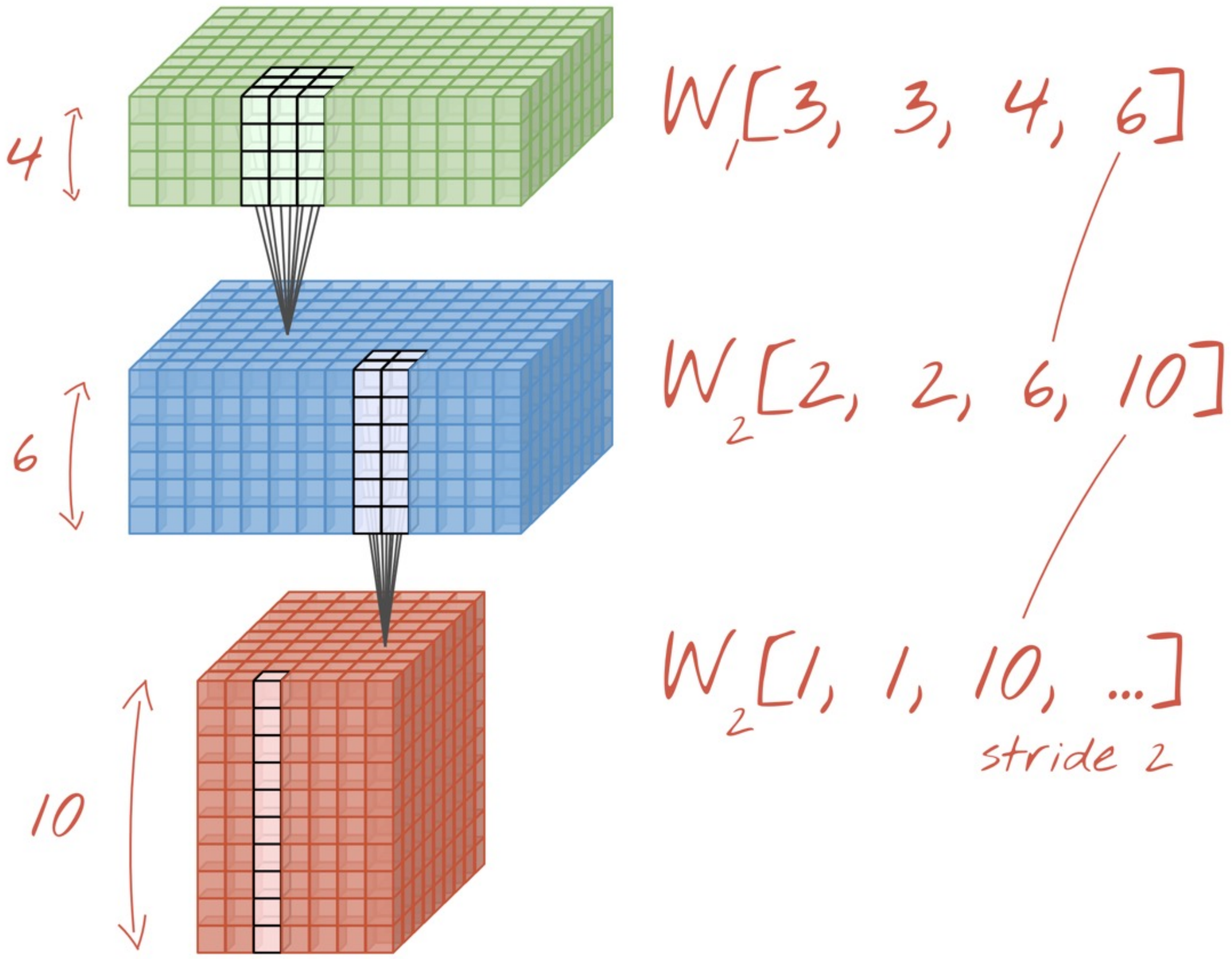
Output Volume Size

Defined by the filter (or kernel) size, the number of filters applied and the stride



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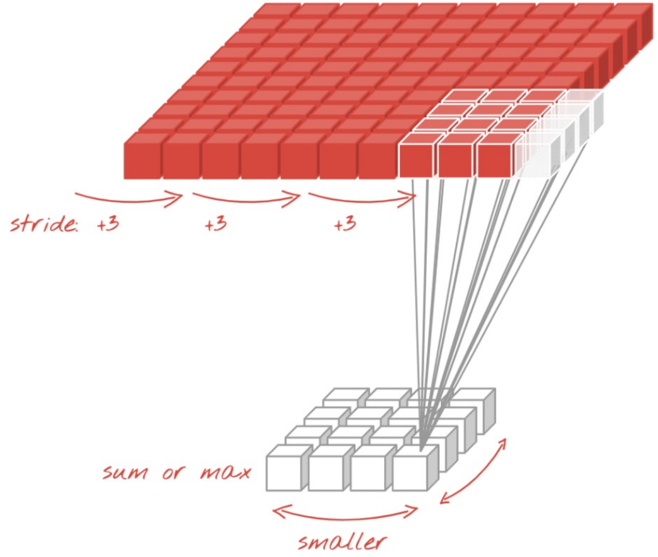
- Depth (number of channels):
  - *adjusted by using more or fewer filters*
- Width & Height:
  - *adjusted by using a stride >1*
  - *(or with a max-pooling operation)*



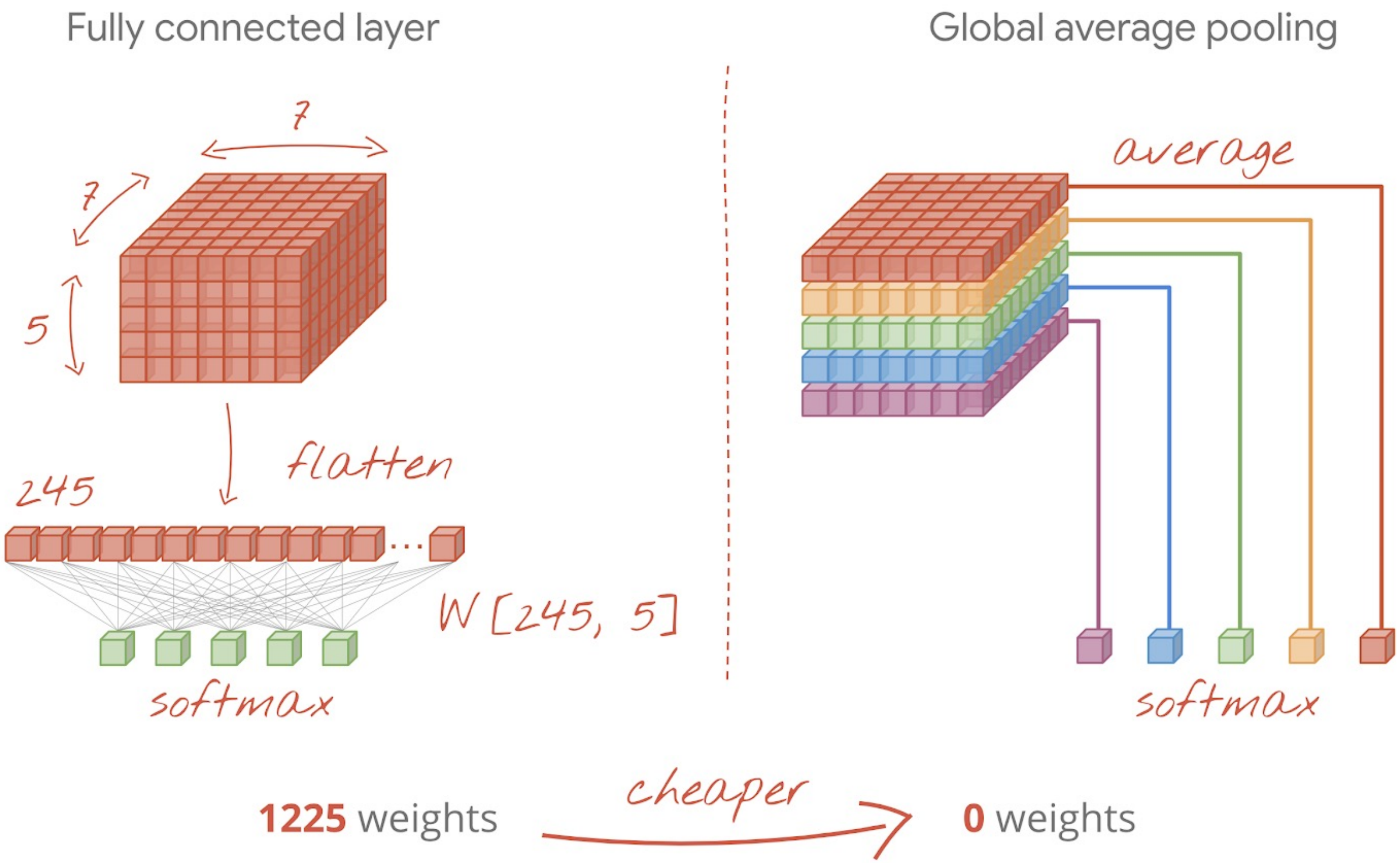
The Last Layer

From a Cubic Volume in 3D to predicted labels

Similar like a normal neural network

Expensive in #weights

But preseves the location data (x, y)



Much lighter in calculation

The average pooling explicitly discards all location data

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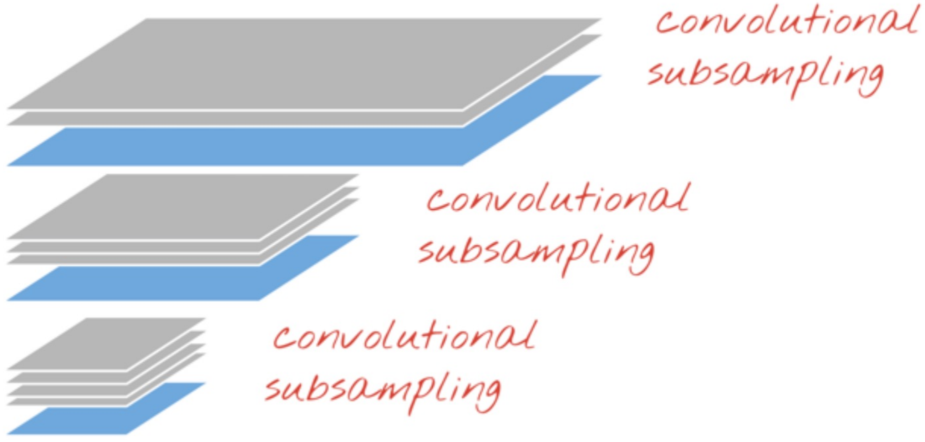
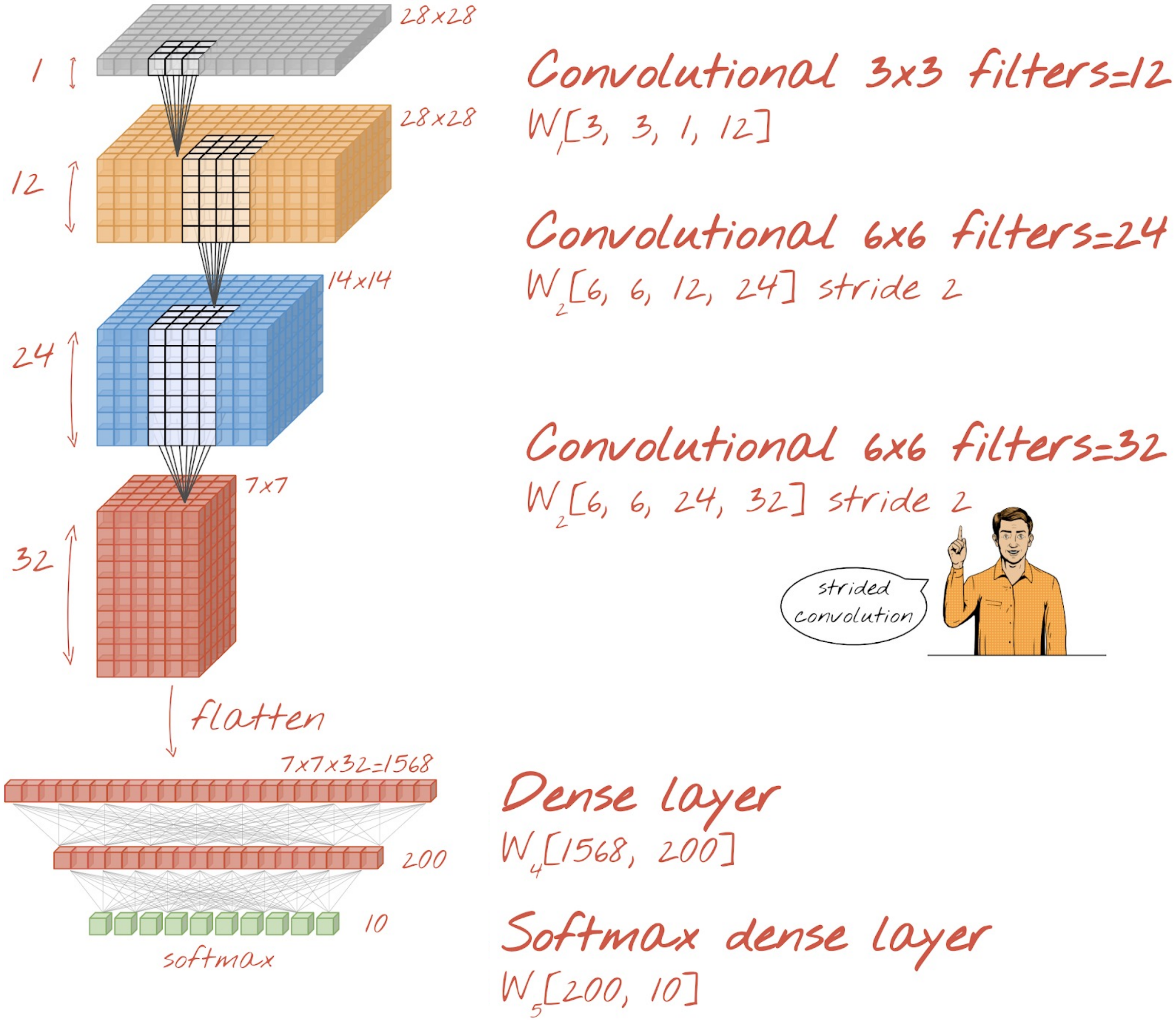
Stacking Up a ConvNet

Layer-by-layer





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Layers in ConvNets

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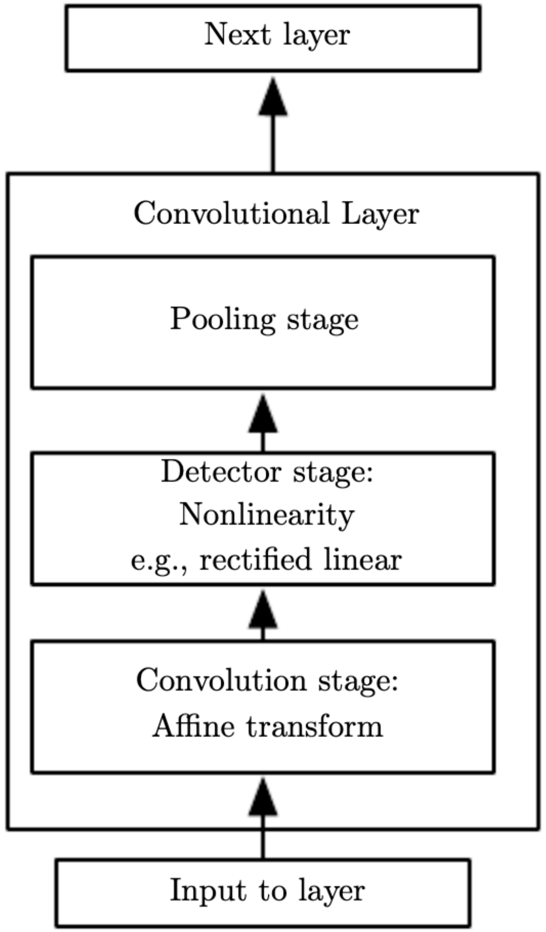
The Three Stages of a Typical ConvNet Layer

The Convolution, Detector and Pooling Stages



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- The maximum output within a rectangular neighborhood (max-pooling)
- The average of a rectangular neighborhood
- The L2 norm of a rectangular neighborhood
- A weighted average based on the distance from the central pixel

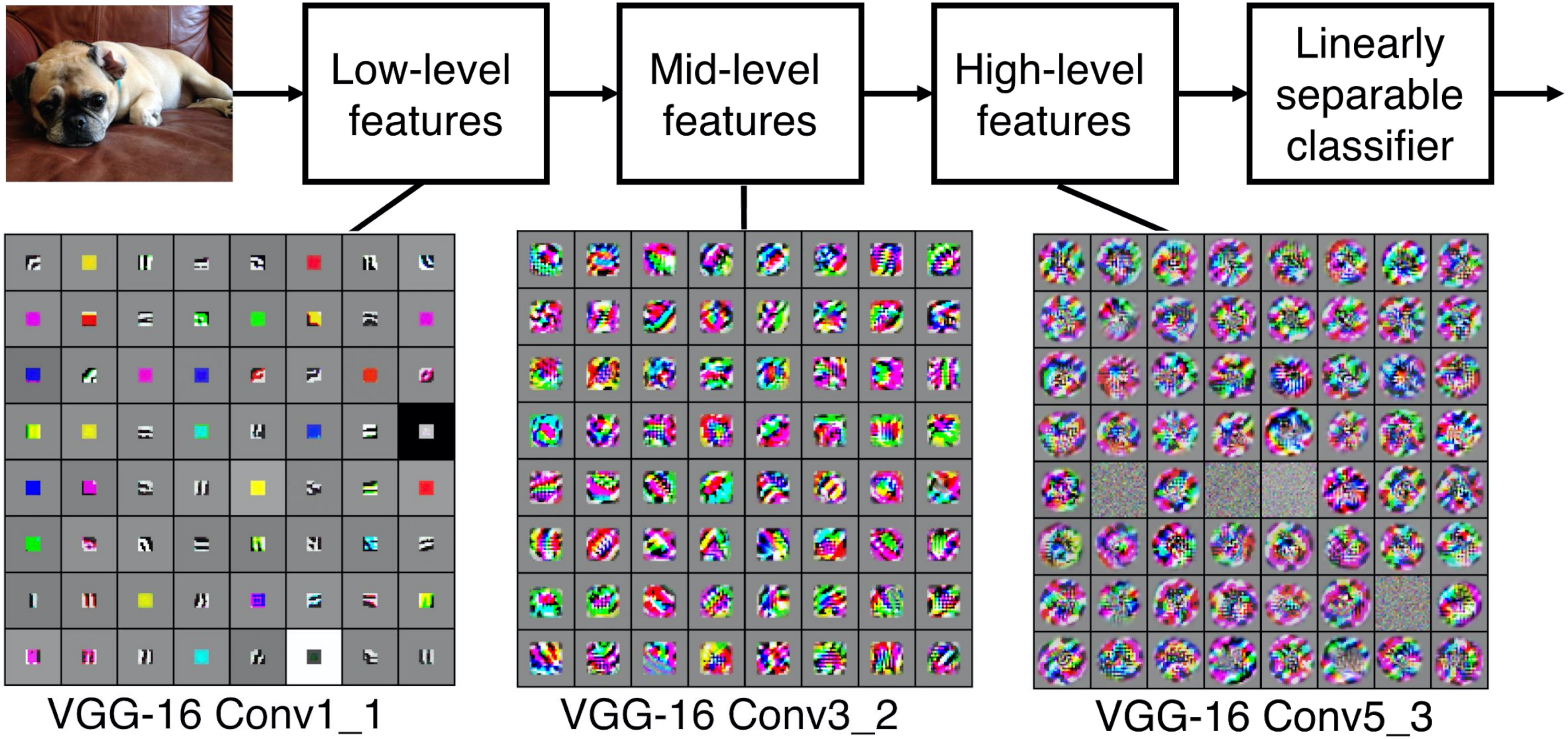
Replace the output of the net at a certain location with a summary statistic of the nearby outputs (can be viewed as a further abstraction of the learned features)

Each linear activation is run through a nonlinear activation function, such as ReLU (can be viewed as activation function)

Performs several convolutions in parallel to produce a set of linear activations (can be viewed as weighted-sum)

A Visualized Understanding of ConvNet

Multi-layered abstraction of 3D features towards a linerly separable classification



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https://arxiv.org/pdf/1311.2901.pdf

A Simple ConvNet for CIFAR-10 Classification

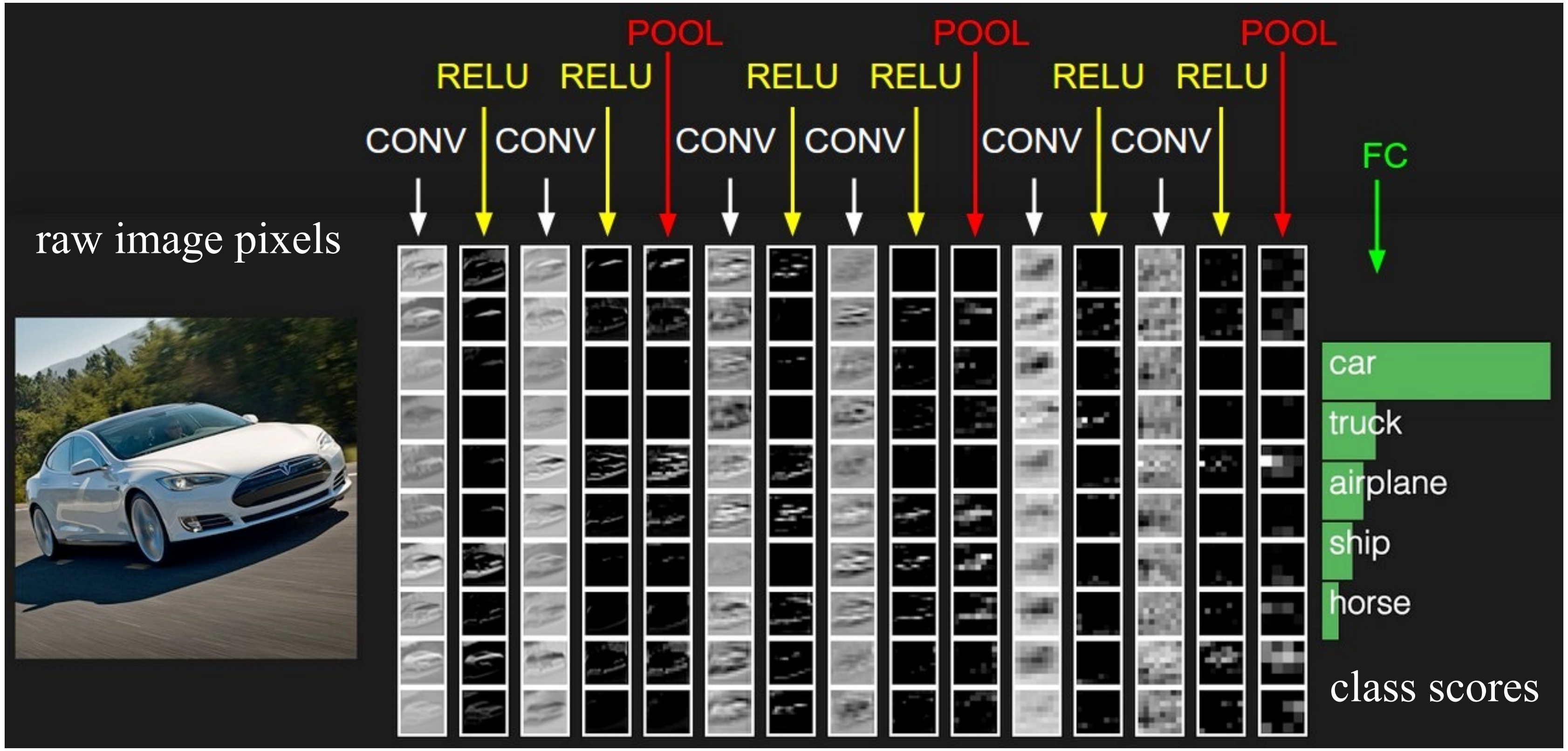
[INPUT - CONV - RELU - POOL - FC]

CONV layer compute the output of neurons that are connected to local regions in the input, i.e. [32x32x12] with 12 filters.

RELU layer will apply an elementwise activation function, such as the max(0,x) thresholding at zero. This leaves the size of the volume unchanged ([32x32x12]).

POOL layer will perform a downsampling operation along the spatial dimensions (width, height), resulting in volume such as [16x16x12].

INPUT layer [32x32x3] will hold the raw pixel values of the image



FC (i.e. fully-connected) layer will compute the class scores, resulting in volume of size [1x1x10], where each of the 10 numbers correspond to a class score

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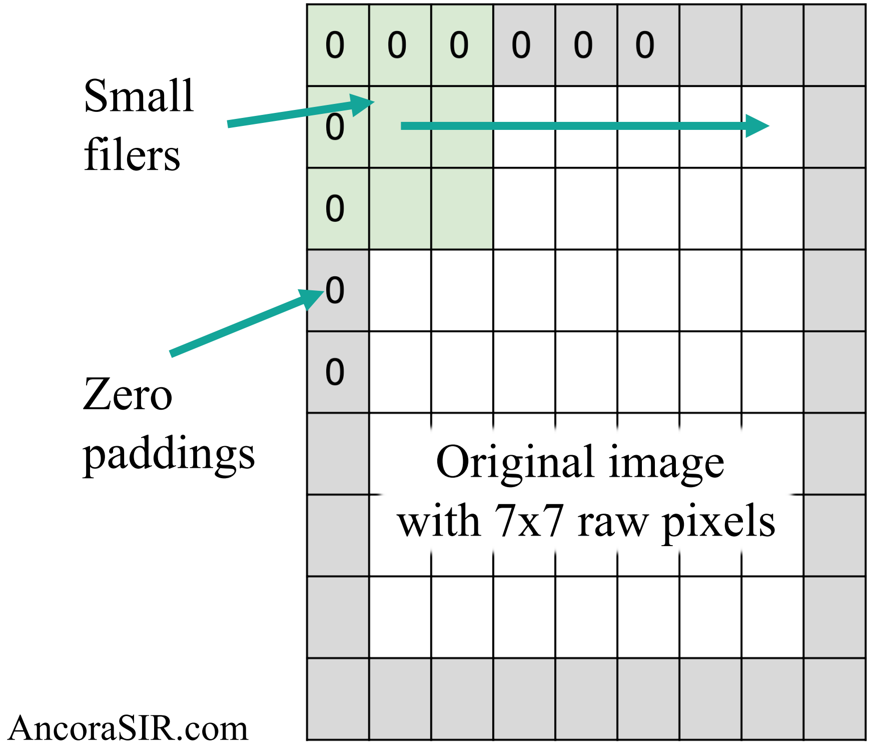
Convolutional Layer

Small filters that slide across the input volume

- Small-size filers
  - e.g. 3x3 or at most 5x5, using a stride of S=1,
  - Padding the input volume with zeros to avoid altering the spatial dimensions of the input.



INPUT features: 7x7

Filer size: 3x3

Stride: 1 (move step-by-step)

Padding: 1 pixel of 0 on all borders

OUTPUT features: 7x7

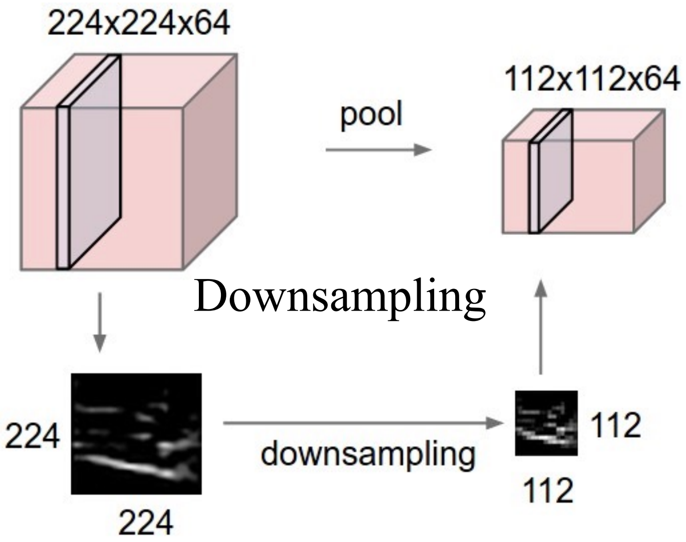
What if without paddings on the border?

- *The spatial dimensions of the input will be changed, causing information loss on the border*

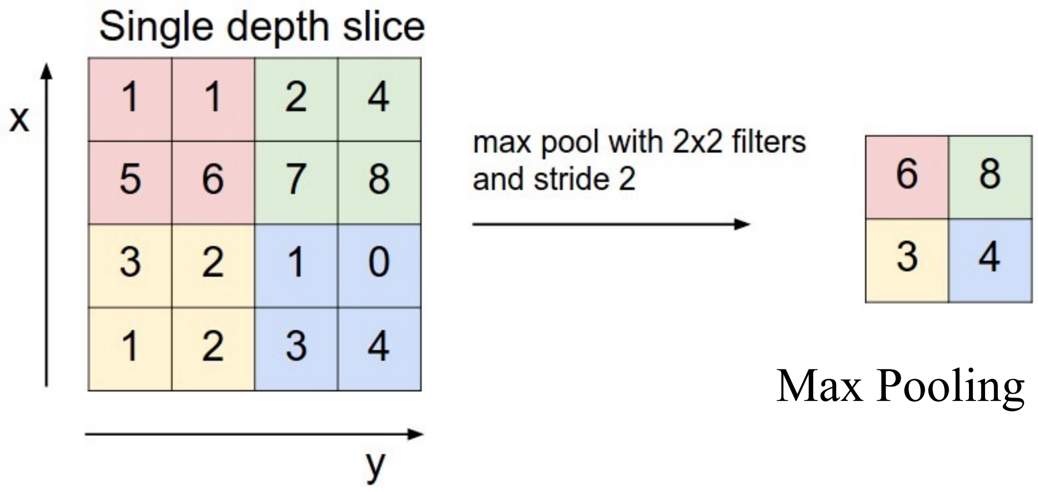
Pooling Layer

Downsampling the spatial dimensions of the input volume

- A network-wise regularization
  - Progressively reduce the spatial size of the representation to reduce the amount of parameters and computation in the network, and hence to also control overfitting
  - Operates over each activation map independently
  - Usually, no need to zero padding (no convolutional operations)



Downsampling



Max Pooling

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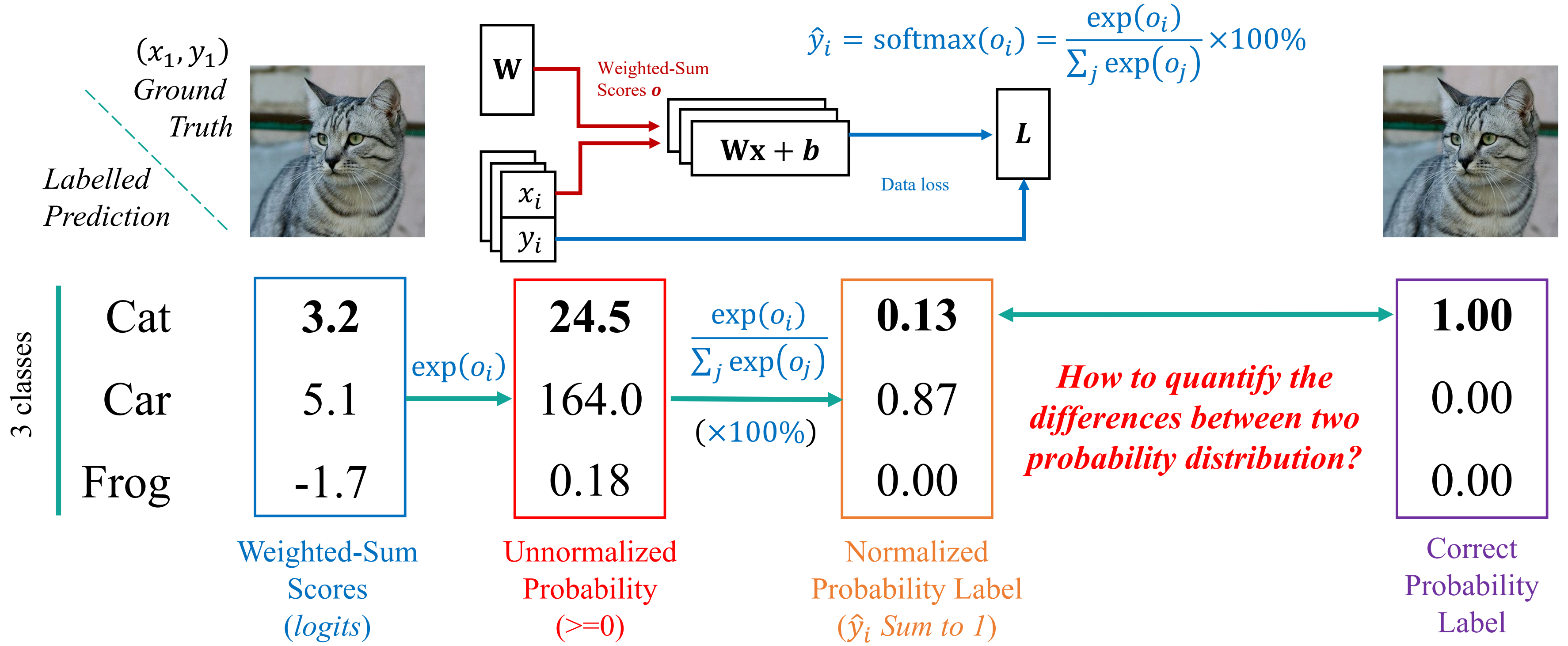
Fully-Connected Layer

Full connections to all activations in the previous layer, as seen in regular Neural Networks

- Contains neurons that connect to the entire input volume
- Softmax is a common choice



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ConvNet Architectures

Common choice of hyperparameters of ConvNet designs

- $\text{INPUT} \rightarrow \left[[\text{CONV} \rightarrow \text{RELU}] * \text{N} \rightarrow \text{POOL?}\right] * \text{M} \rightarrow [\text{FC} - \text{RELU}] * \text{K} \rightarrow \text{FC}$
  - the * indicates repetition,
  - the POOL? indicates an optional pooling layer.
  - N >= 0 (and usually N <= 3), M >= 0, K >= 0 (and usually K < 3)

- **INPUT** (that contains the image) should be divisible by 2 many times
  - 32 (e.g. CIFAR-10), 64, 96 (e.g. STL-10), or 224 (e.g. ImageNet), 384, and 512
- **CONV** should be using small filters using a stride of S=1
  - 3x3 or at most 5x5 with zero padding of the input volume
- **POOL** downsamples the spatial dimensions of the input
  - Common setting is to use max-pooling with 2x2 receptive fields with a stride of 2

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A Universal Workflow

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Defining the Problem

Assembling a Dataset

- **Data availability**
  - Usually the limiting factor at this stage.
- **Identifying the problem type**
  - Guide your choice of model architecture, loss function, etc.
- **A Hypothesis of Modeling**
  - *Can you build a model using price history to predict stock market? ☹*
- **Non-stationary Problem?**
  - *Will your data change over time?*

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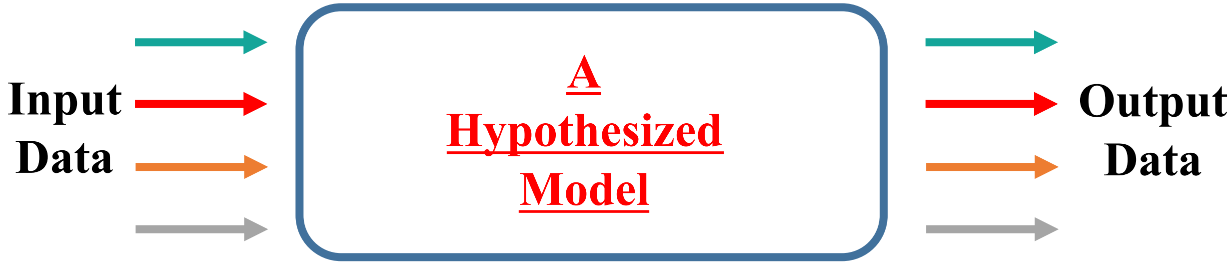
What will your input data be?
What are you trying to predict?

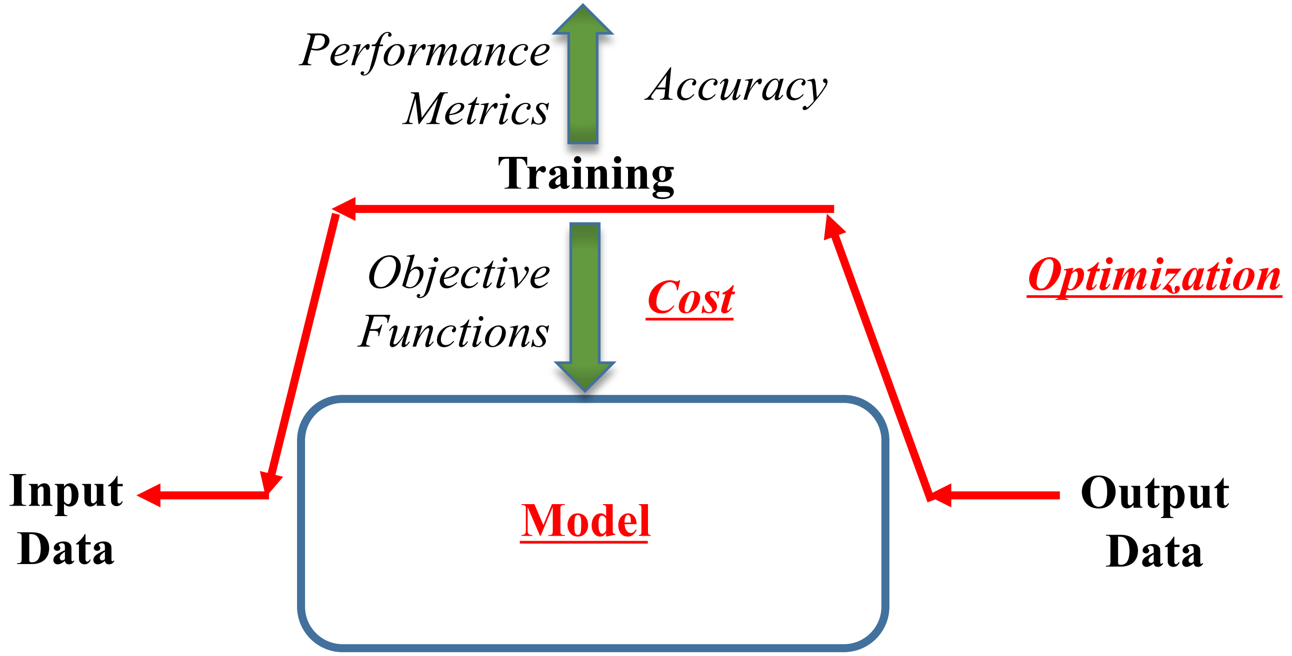
- Can only learn to predict something **if you have available training data**
- Can only be used to **learn patterns** that are present in training data
  - *A fundamental assumption that the future will behave like the past*



- *What type of problem are you facing?*
- *Is it binary classification?*
- *Multiclass classification?*
- *Scalar regression?*
- *Vector regression?*
- *Multiclass, multilabel classification?*
- *Something else, like clustering, generation, or reinforcement learning?*

Choosing a Measure of Success

You need to be able to observe it to control it



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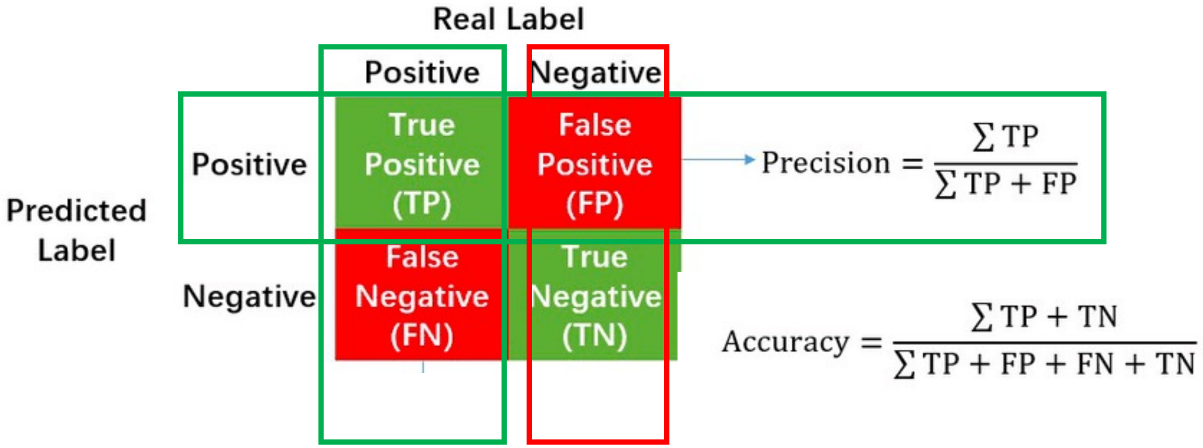


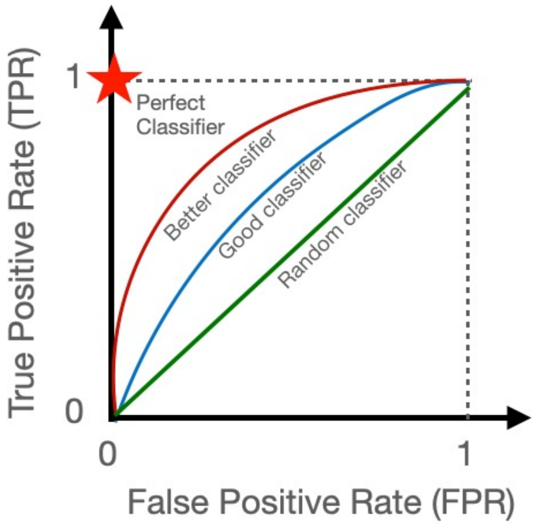
Your metric for success will guide the choice of a loss function

- Accuracy? Precision and recall? **What your model optimizes?**
- For balanced-classification problems (every class is equally likely): *accuracy and area under the receiver operating characteristic curve (ROC AUC)* are common metrics
- For class-imbalanced problems, you can use precision and recall

True Positive Rate (TPR)
= TP / (TP + FN)
= efficiency to identify the signal (Recall)

False Positive Rate (FPR)
= FP / (FP + TN)
= inefficiency to reject background

TP=63	FN=37	100
FP=28	TN=72	100
91	109	200



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Source

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It isn't uncommon to have to **define your own custom metric**.

- Common in Robotics
- Read more papers
- Be clear and direct about your modeling goal

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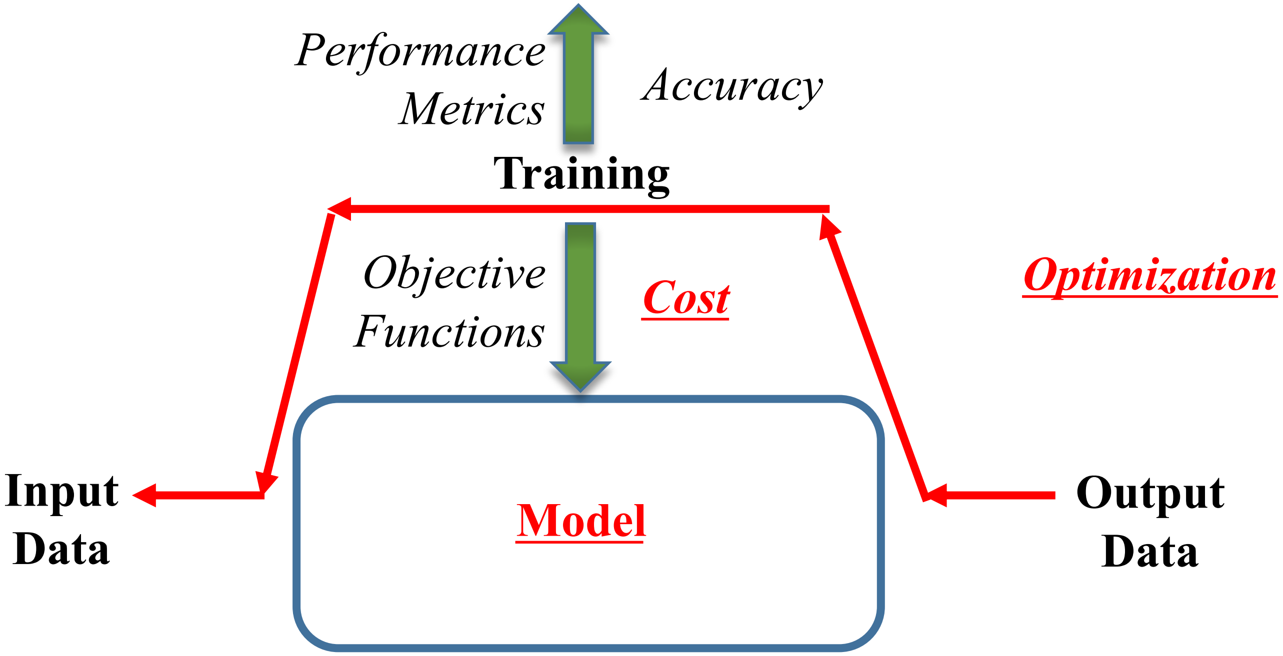

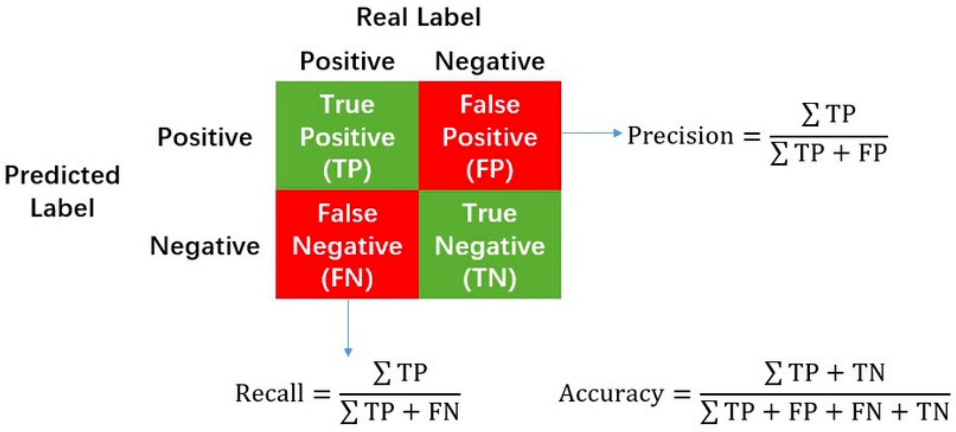

Deciding on an Evaluation Protocol

How you'll measure your current progress

Setting Hyperparameters

Idea #1: Choose hyperparameters that work best on the data

BAD: K = 1 always works perfectly on training data

Your Dataset

Maintaining a hold-out validation set

- The way to go when you have plenty of data

Doing K-fold cross-validation

- The right choice when you have too few samples for hold-out validation to be reliable

Doing iterated K-fold validation

- For performing highly accurate model evaluation when little data is available

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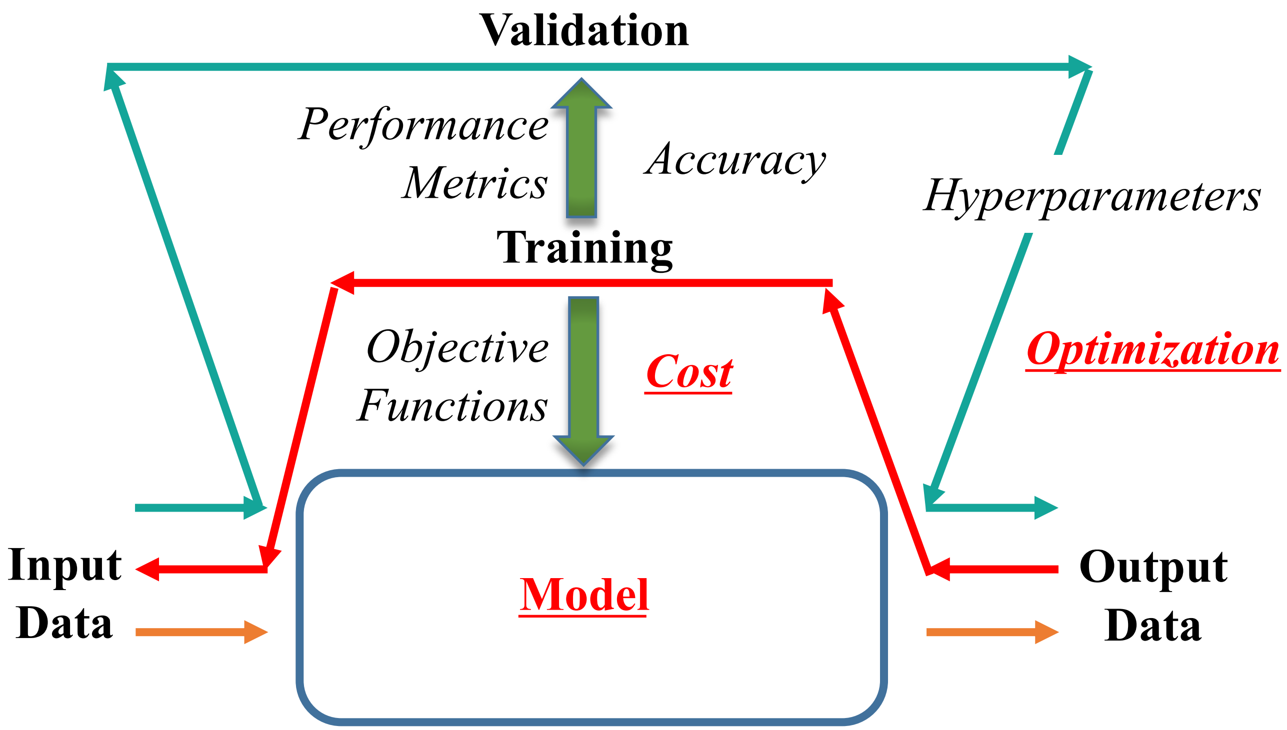


Idea #2: Split data into **train** and **test**, choose hyperparameters that work best on test data

BAD: No idea how algorithm will perform on new data

train	test

Idea #3: Split data into **train**, **val**, and **test**; choose hyperparameters on val and evaluate on test

Better!

train	validation	test

Idea #4: **Cross-Validation**: Split data into **folds**, try each fold as validation and average the results

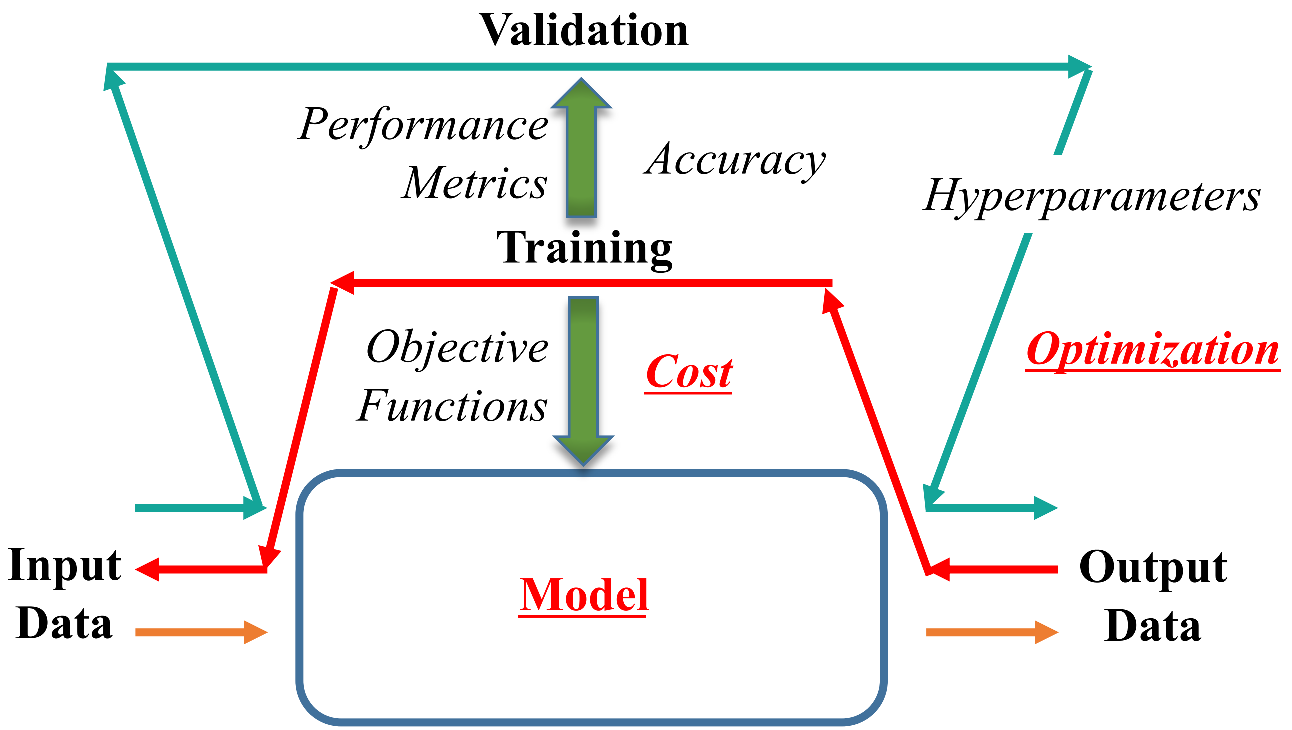
fold 1	fold 2	fold 3	fold 4	fold 5	test
fold 1	fold 2	fold 3	fold 4	fold 5	test
fold 1	fold 2	fold 3	fold 4	fold 5	test

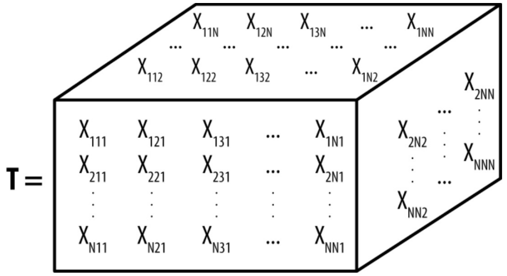
Useful for small datasets, but not used too frequently in deep learning

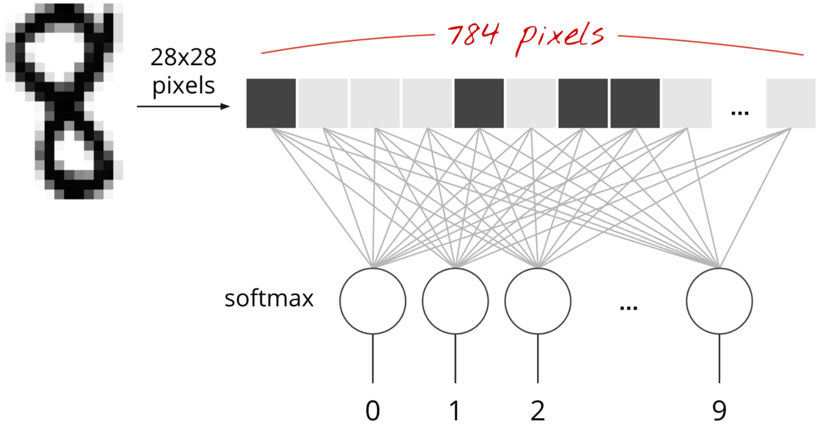
Preparing Your Data

Format your data in a way that can be fed into a model of deep neural network

- Your data should be formatted as **tensors**
- The values taken by these tensors should usually be **scaled** to small values
  - For example, in the [-1, 1] range or [0, 1] range
- **Normalize** the data if different features take values in different ranges







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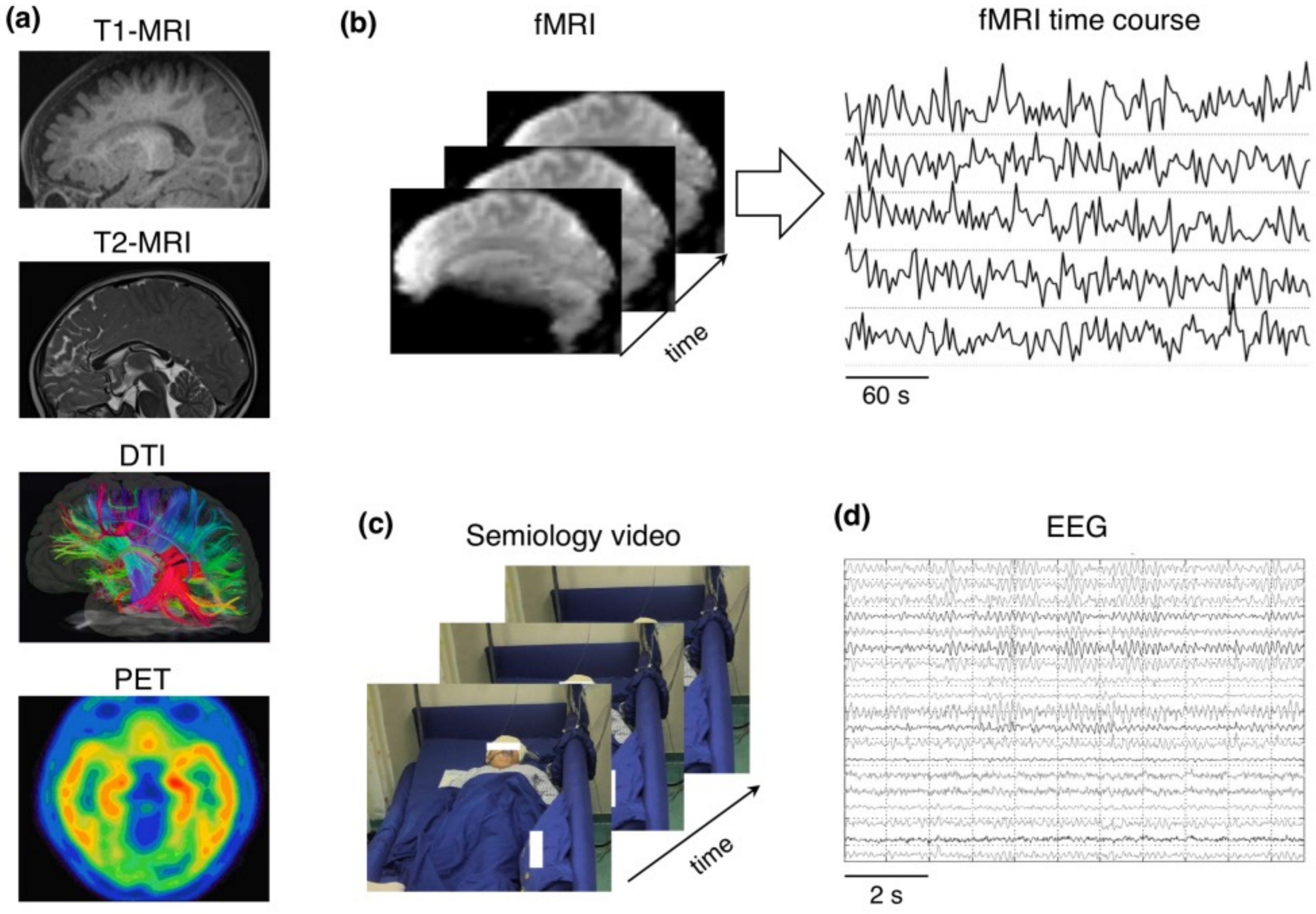
- **Feature engineering** may be required, especially for small-data problems



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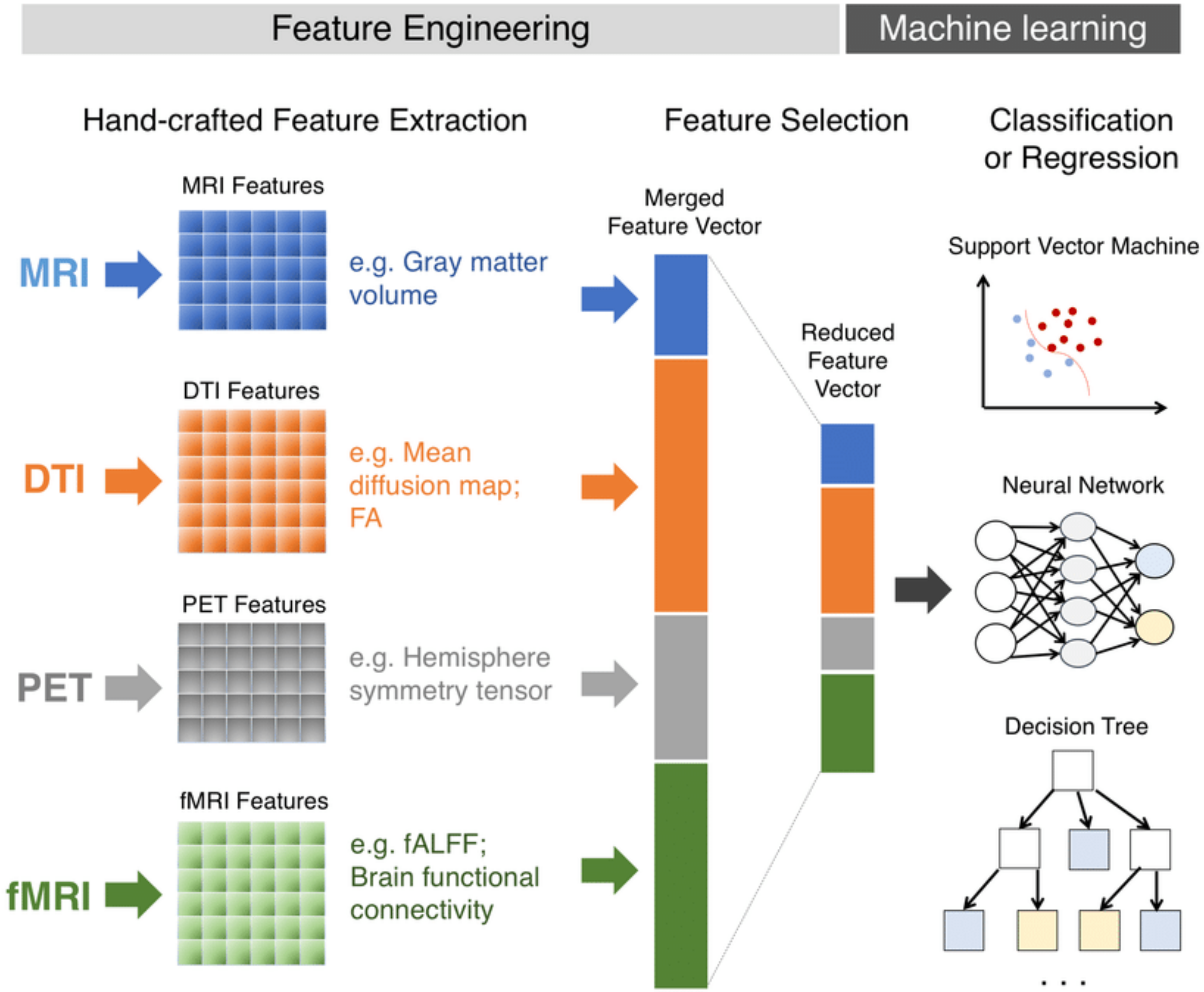

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Developing a Model Better than a Baseline

To achieve statistical power by building a small model that beats a dumb baseline

Check your assumptions agains a baseline model

- Your outputs can be predicted given your inputs.
- The available data is sufficiently informative to learn the relationship between inputs and outputs.
- (*asking the right questions to your data*)

Key choices to build a model

- *Last-layer activation*—This establishes useful constraints on the network's output.
- *Loss function*—This should match the type of problem you're trying to solve.
- *Optimization configuration*—What optimizer will you use? What will its learning rate be?

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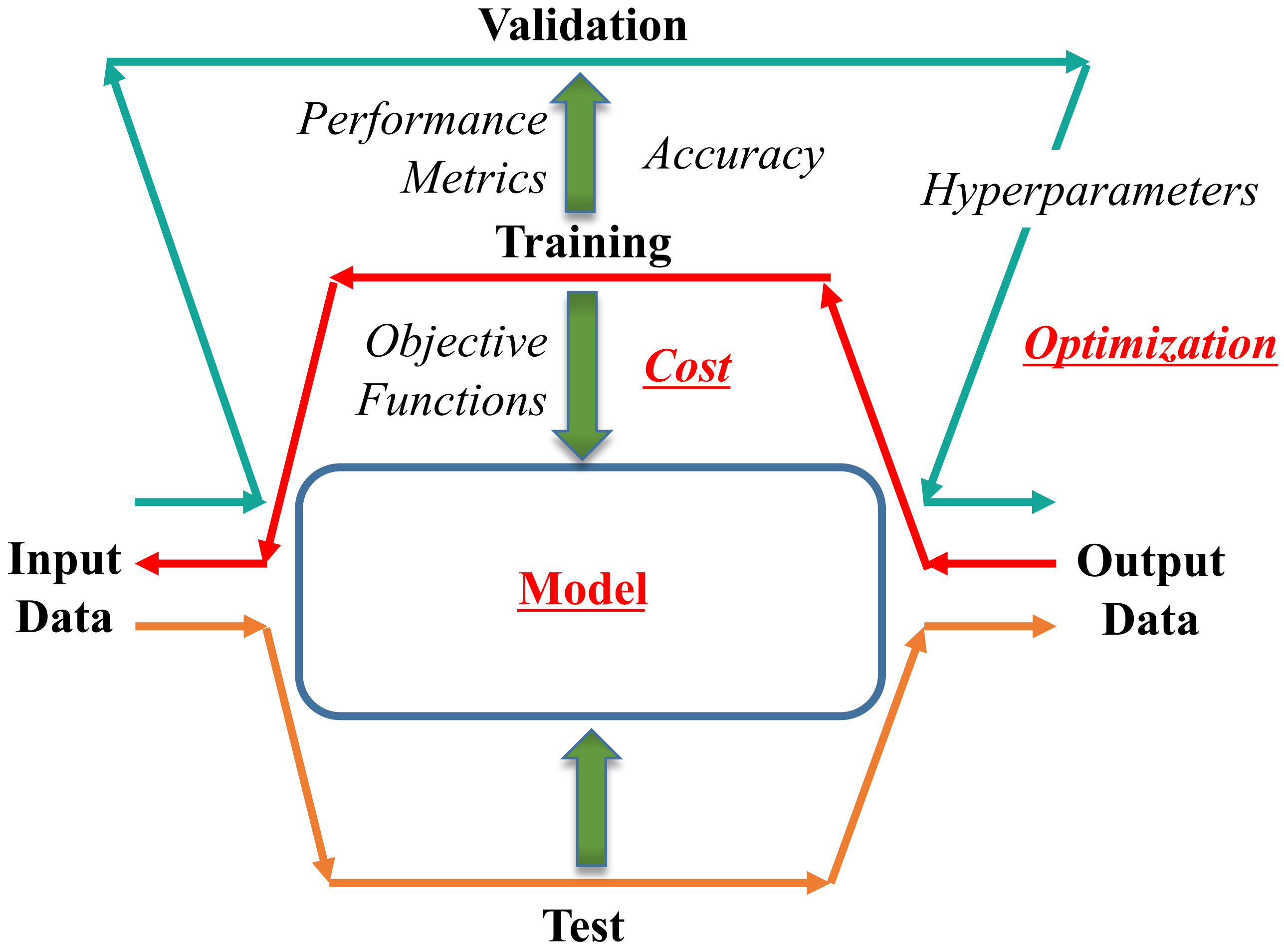
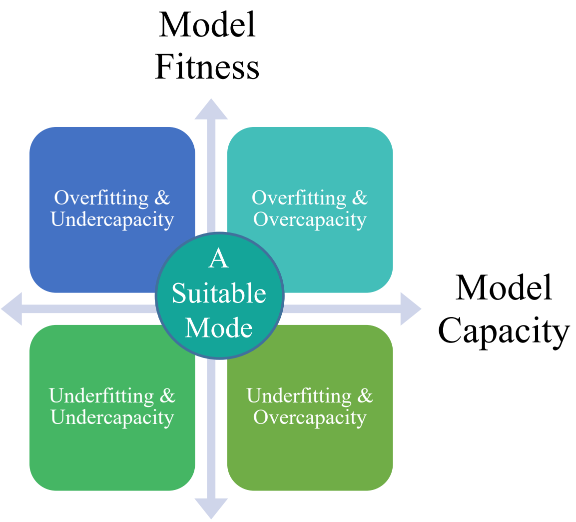
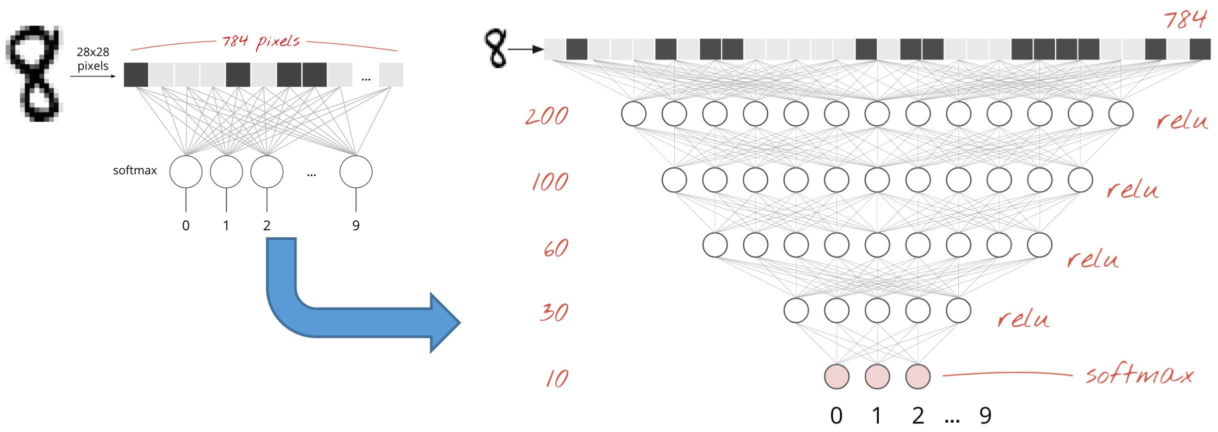


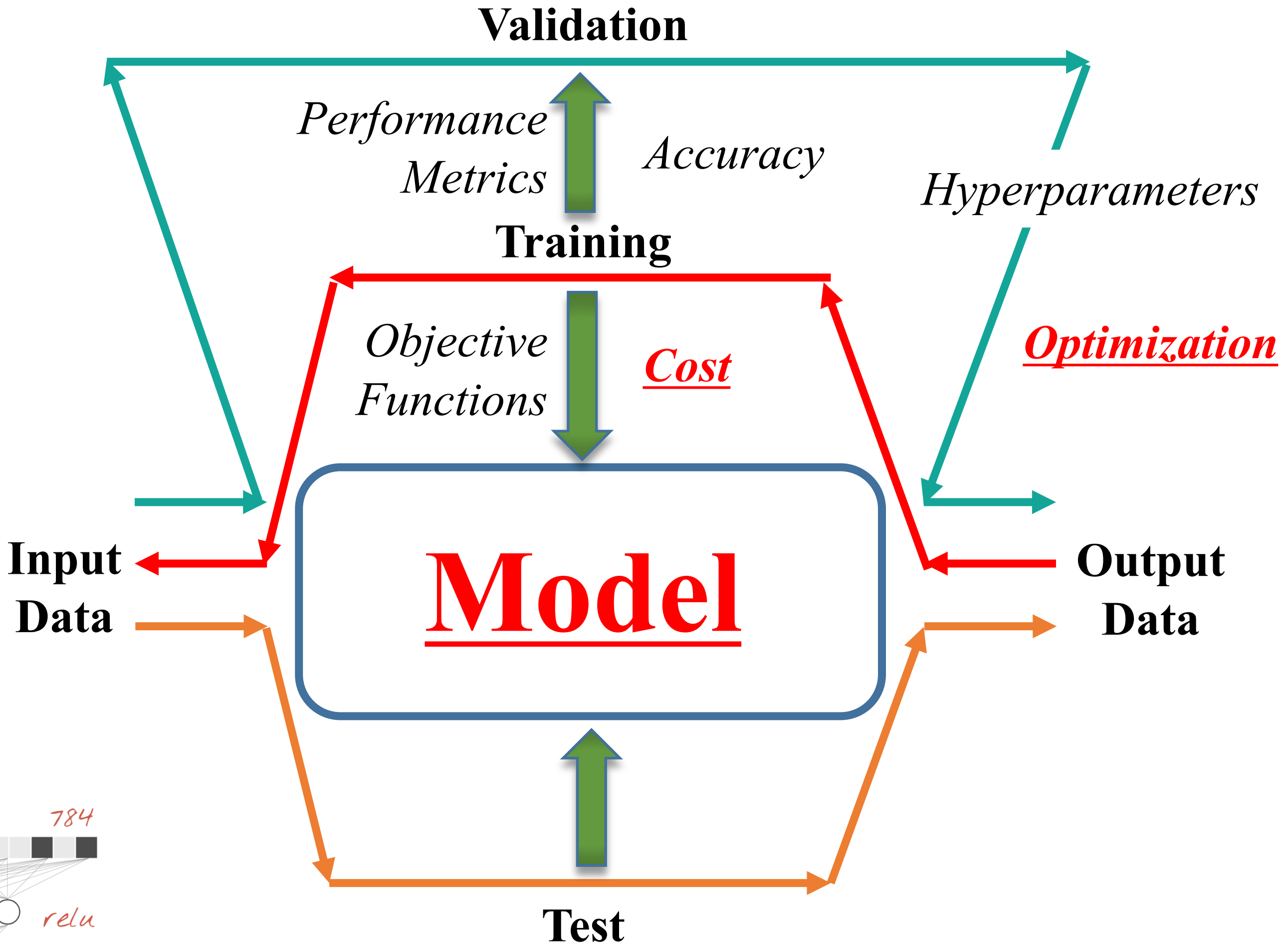
Problem type	Last-layer activation	Loss function
Binary classification	sigmoid	binary_crossentropy
Multiclass, single-label classification	softmax	categorical_crossentropy
Multiclass, multilabel classification	sigmoid	binary_crossentropy
Regression to arbitrary values	None	mse
Regression to values between 0 and 1	sigmoid	mse or binary_crossentropy

Scaling Up: Developing a Model that Overfits

1. Add layers.
2. Make the layers bigger.
3. Train for more epochs.







- *Is your model sufficiently powerful?*
- *Does it have enough layers and parameters to properly model the problem at hand?*

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Regularizing Your Model

The most time-consuming step …

- *Modify your model, train it, evaluate on your validation data (not the test data, at this point),*
- *Modify it again, and repeat, until the model is as good as it can get*

Things you can try

- Add dropout
- Try different architectures: add or remove layers
- Add L1 and/or L2 regularization
- Try different hyperparameters
  - such as the number of units per layer, or
  - the learning rate of the optimizer
- Optionally, iterate on feature engineering
  - add new features, or
  - remove features that don't seem to be informative

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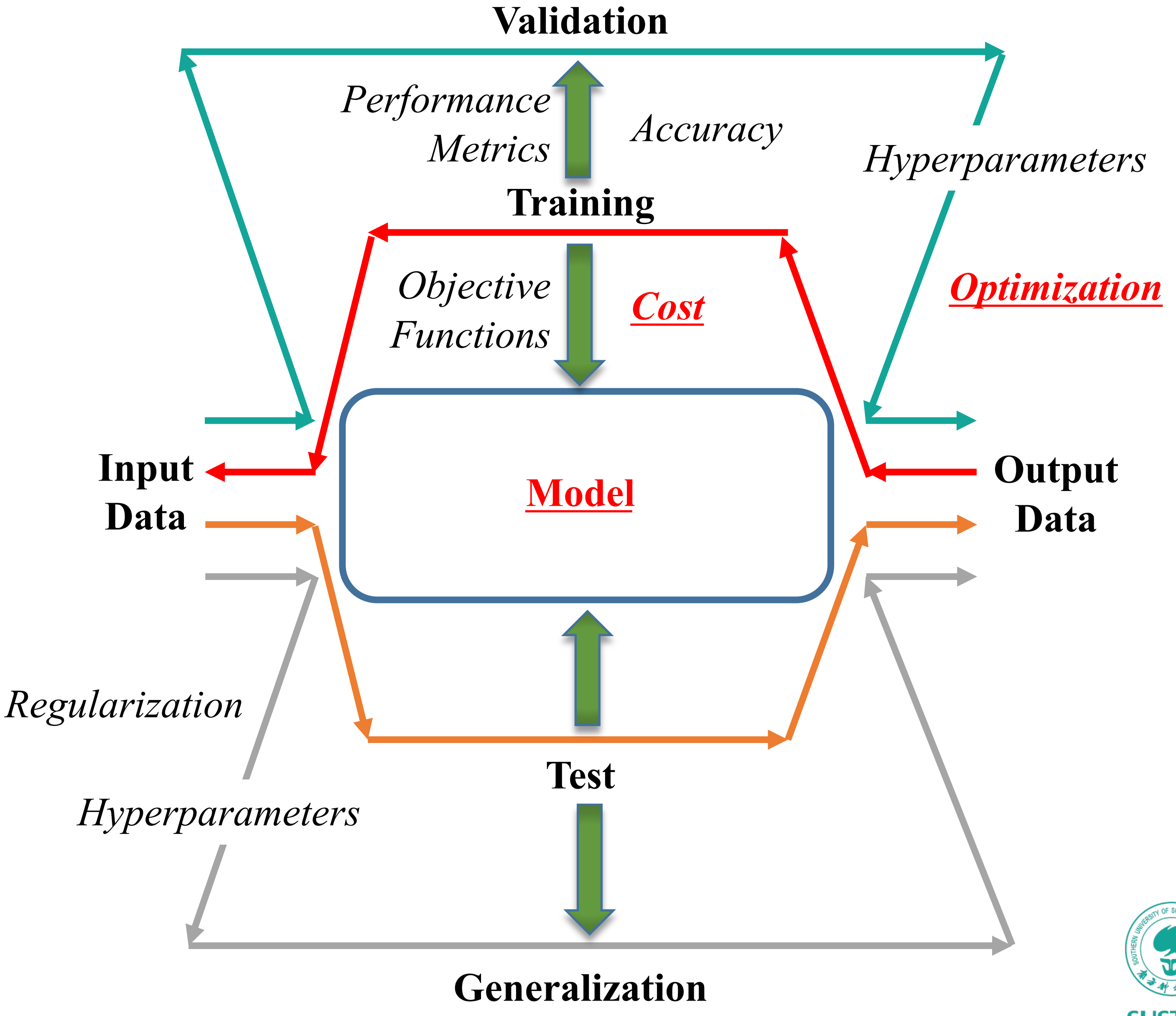


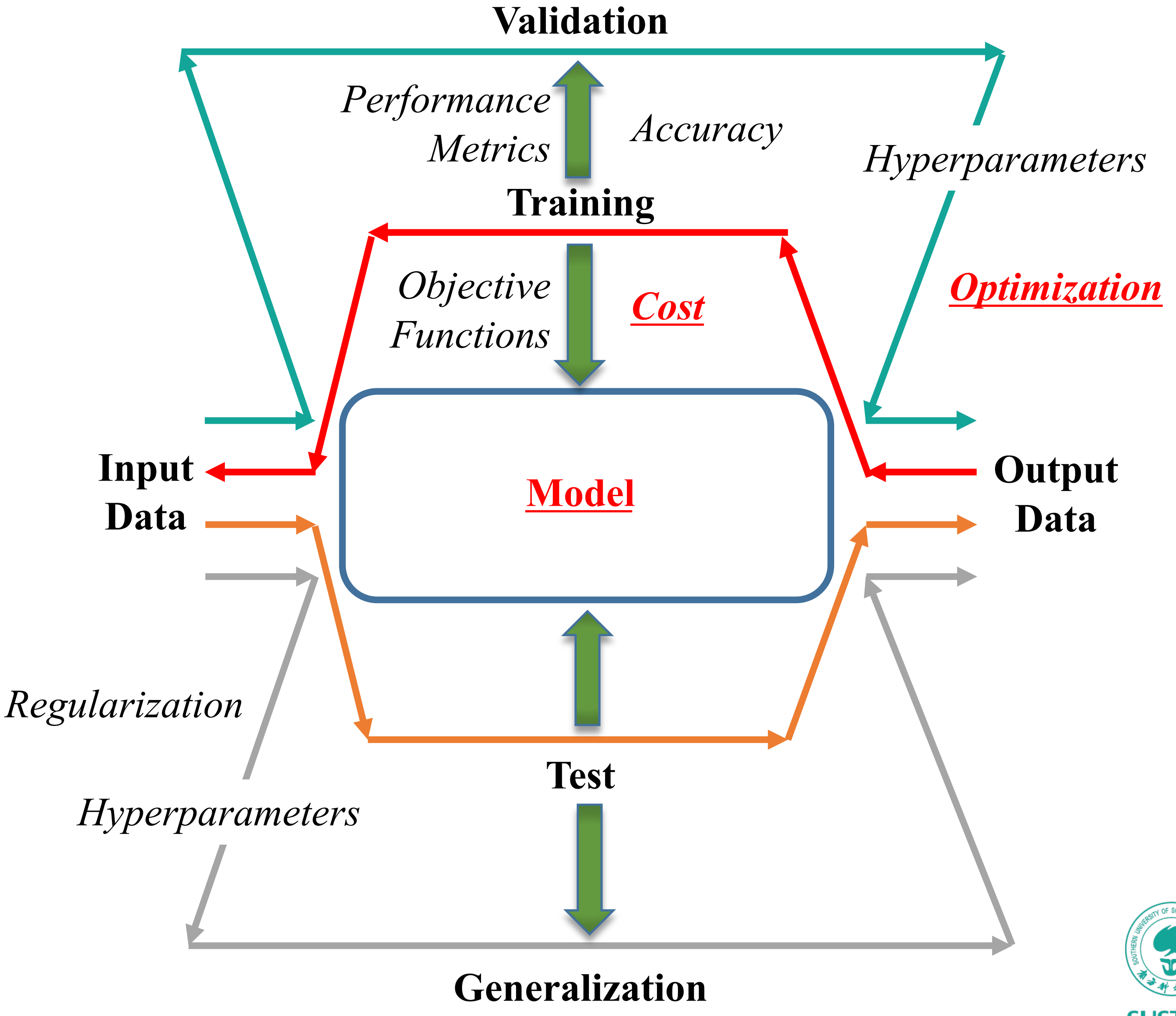
Tuning
Your Hyperparameters

Information Leak => Model Overfit

- Every time you use feedback from your validation process to tune your model, you leak information about the validation process into the model.
- This makes the evaluation process less reliable.

Once you've developed a satisfactory model configuration,

- you can train your final production model on all the available data (training and validation) and
- evaluate it one last time on the test set
- If good, then proceed
- Or if worse, you may want to switch to a more reliable evaluation protocol
(may be caused by overfitting)



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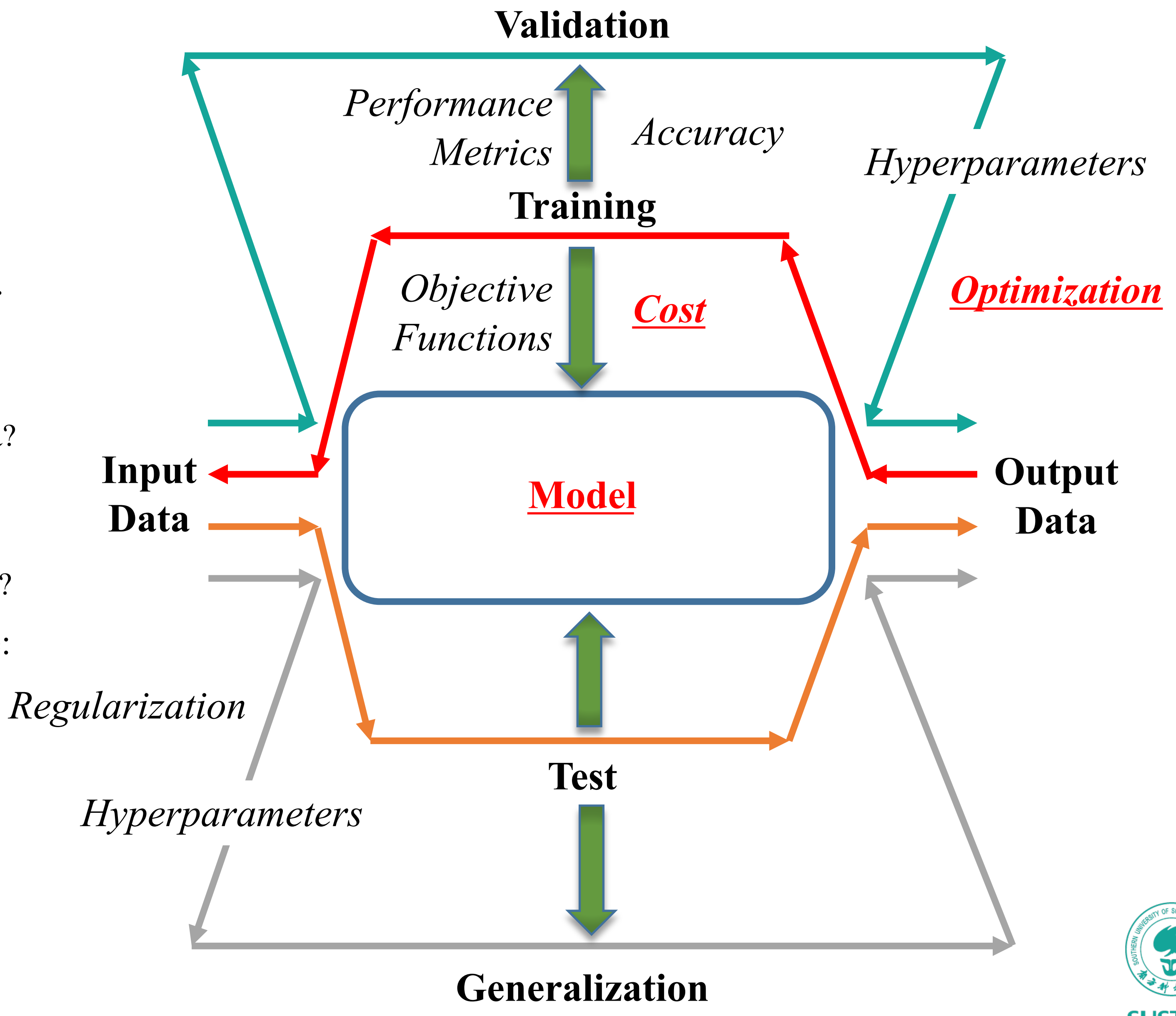
A Universal Workflow

- Define the problem and the data on which you'll train.
  - Collect this data or annotate it with labels if need be.
- Choose how you'll measure success on your problem.
  - Which metrics will you monitor on your validation data?
- Determine your evaluation protocol:
  - Hold-out validation? K-fold validation?
  - Which portion of the data should you use for validation?
- Develop a model that does better than a basic baseline:
  - A model with statistical power.
- Develop a model that overfits.
- Regularize your model and tune its hyperparameters,
  - Based on performance on the validation data.
  - A lot of machine-learning research tends to focus only on this step—but keep the big picture in mind.



Learning a Transition Model

Learning a Transition Model of the Environment

The robot must learn a model of how its actions affect the task state, and the resulting background cost, for use in planning

Transition Models of the Environment

Continuous, Discrete and Hybrid Models

↓

Stochasticity ← **Probabilistic Models** → **Uncertainty**

↓

Learning a New Model

Self-supervision and Exploration

Reuse an Existing Model

Transferring and Reusing

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Continuous Transition Models

*Regression methods can be used to learn **low-level** transition models for predicting the next state as a set of continuous values, even when the set of actions is discrete*

Scoop & Dump Task $l(h_0, a_0, ..., a_T, h_g) = \|\mathcal{F}(h_0, a_0, ..., a_T) - h_g\|_1$

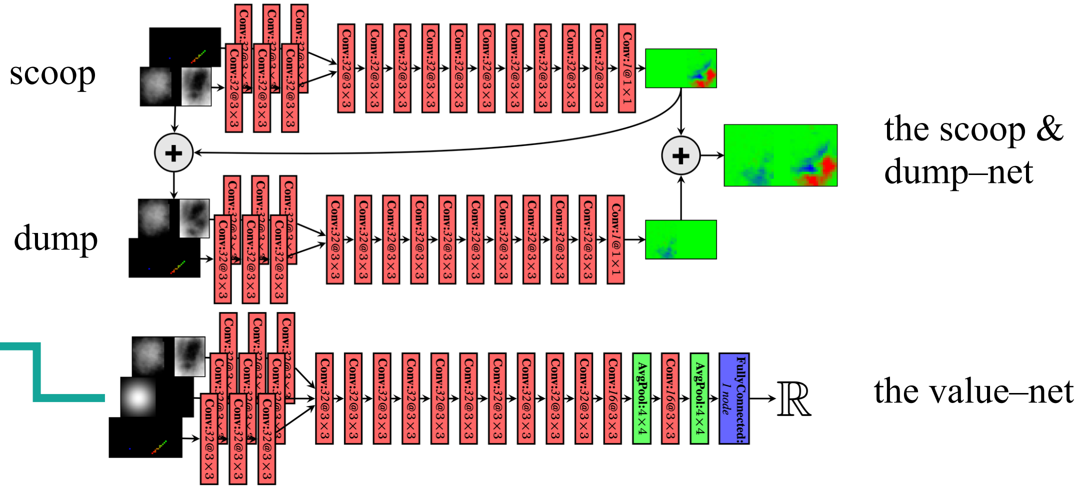
h_0: a given ***initial state*** of the environment

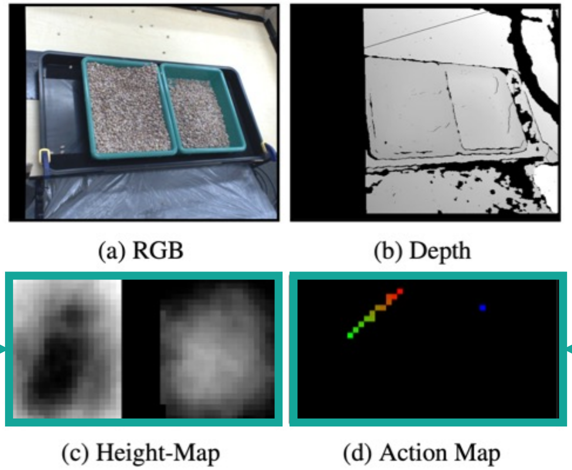
h_g: a given ***goal state*** of the environment

$a_{0,...,T}$: a series of ***robot actions***

$\|Norm\|_1$: L1 norm to be minimized as distance to the goal state

$\mathcal{F}(h_0, a_{0,...,T}) = h_{T+1}$ applies actions sequentiall to reach h_{T+1}



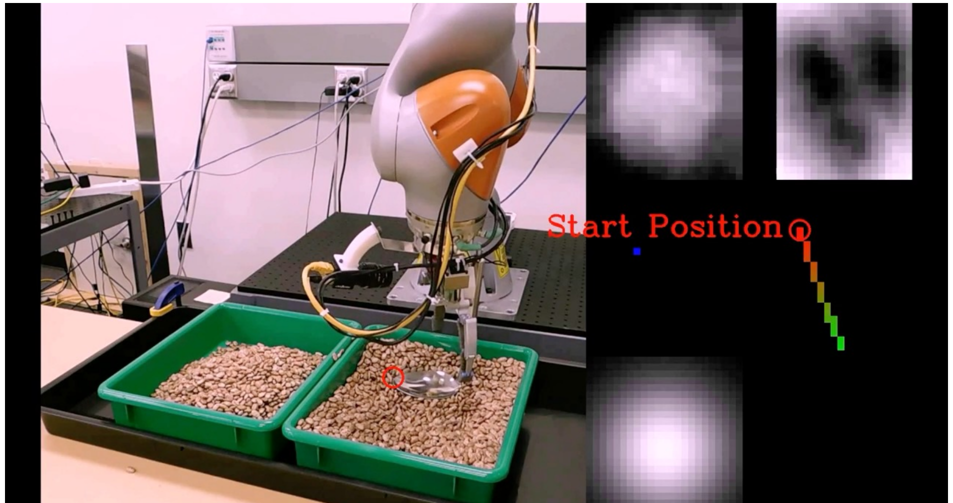


(a) RGB (b) Depth

(c) Height-Map (d) Action Map

Robot action (a 9D vector)

- *Scoop action*
  - the start location (2D)
  - the start angle (1D)
  - the end location (2D)
  - the end angle (1D)
  - the roll angle (1D)
- *Dump action*
  - the dump location (2D)



https://arxiv.org/pdf/1709.02833.pdf

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Thank you~

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