CS540 Introduction to Artificial Intelligence
AI in the Real World

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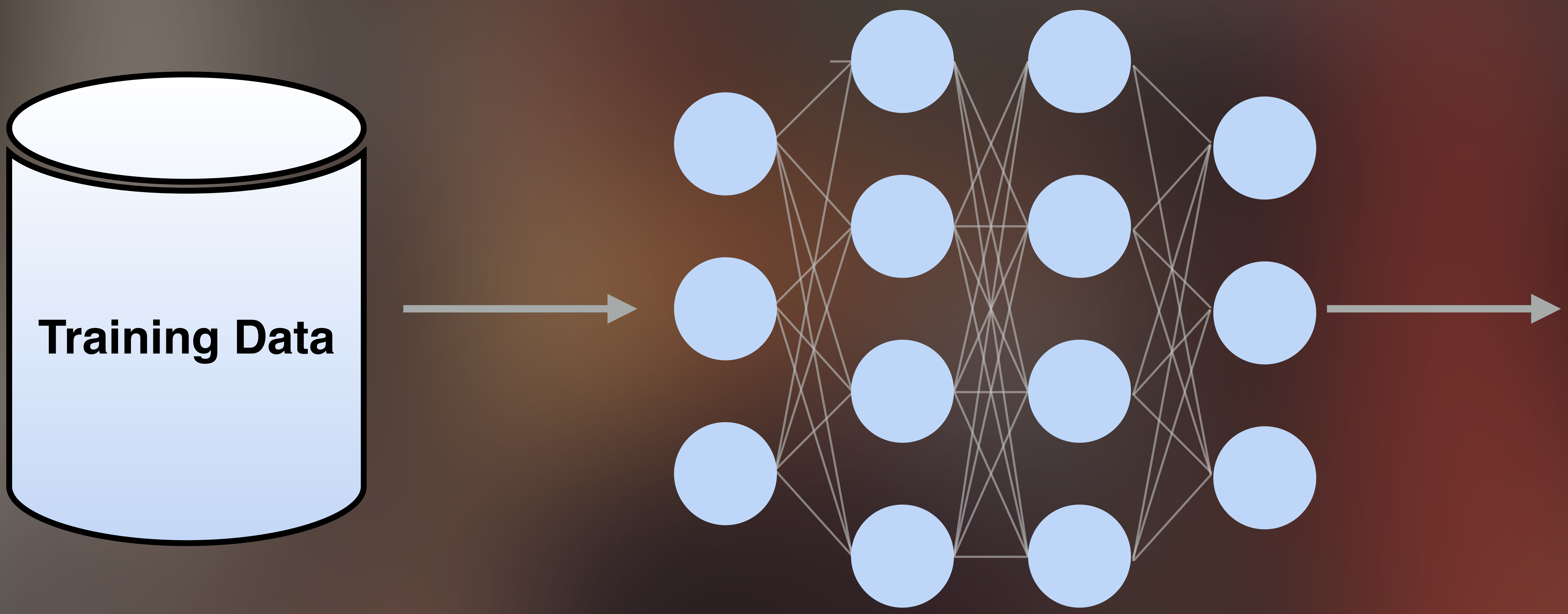
A running example

Food Image Classifier



Basic steps to build an ML system

The steps overview

- Step 1: collect data
- Step 2: look at your data
- Step 3: Create train/dev/test splits
- Step 4: build model
- Step 5: Evaluate your model
- Step 6: Diagnose error and repeat

Acquire and annotate data

Data should be **diverse**

(annotation can be expensive)

Data should be **realistic**

Ideal data sampled from the distribution your product will be run on.

Real photo taken by users

Professional ads photo

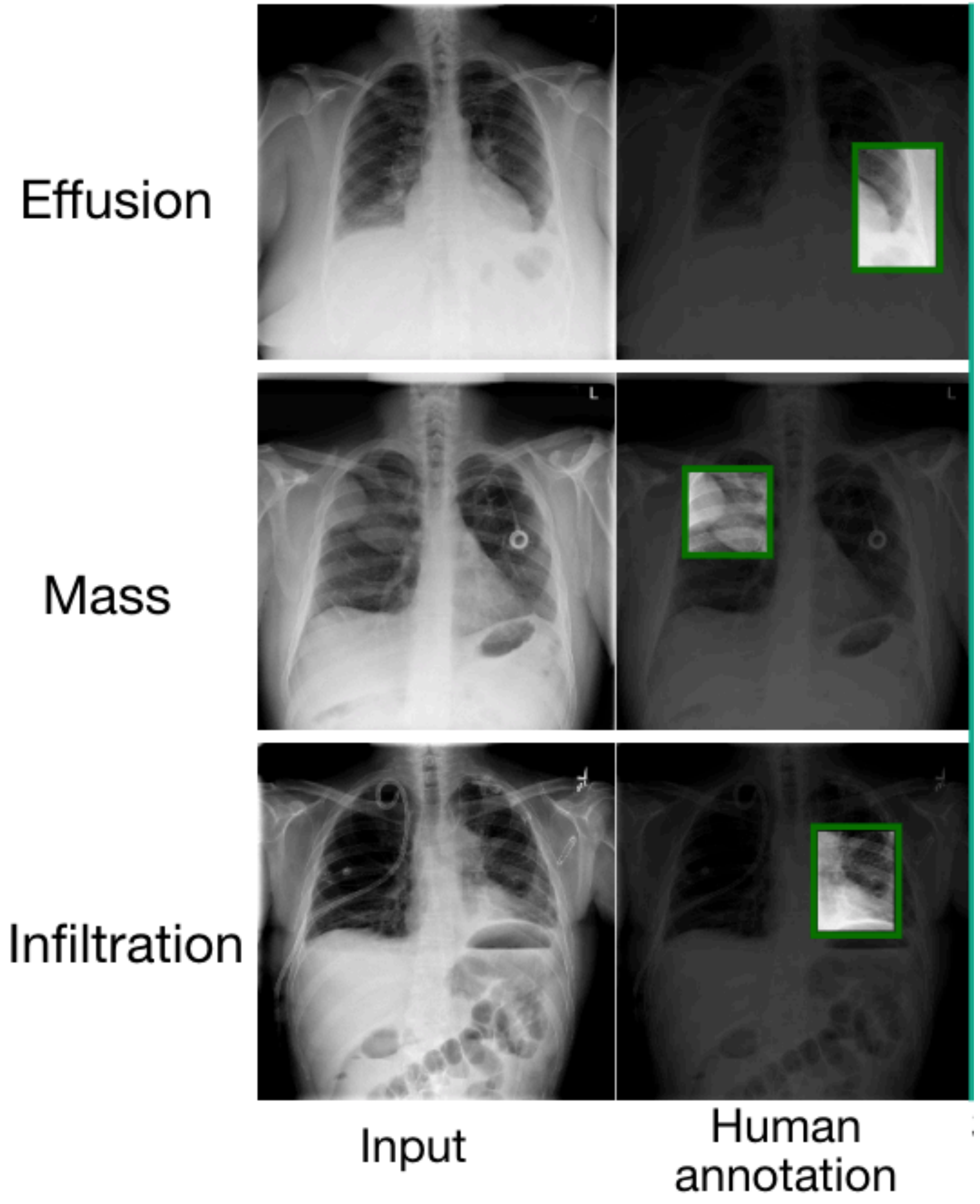
Look at your data.

Look at your data.

- You have some food images, take a closer look at them!
- Food from Europe different than from Africa? from Asia?
- Any potential bias in your data?
- Have the right people look at your data.
- Do this at every stage!

Expertise sometimes can be required

- Biomedical imaging annotation can be expensive
- Professionally trained radiologists
- Domain knowledge



Train/Dev/Test Split

Partitioning Data: Train, Test, and Validation

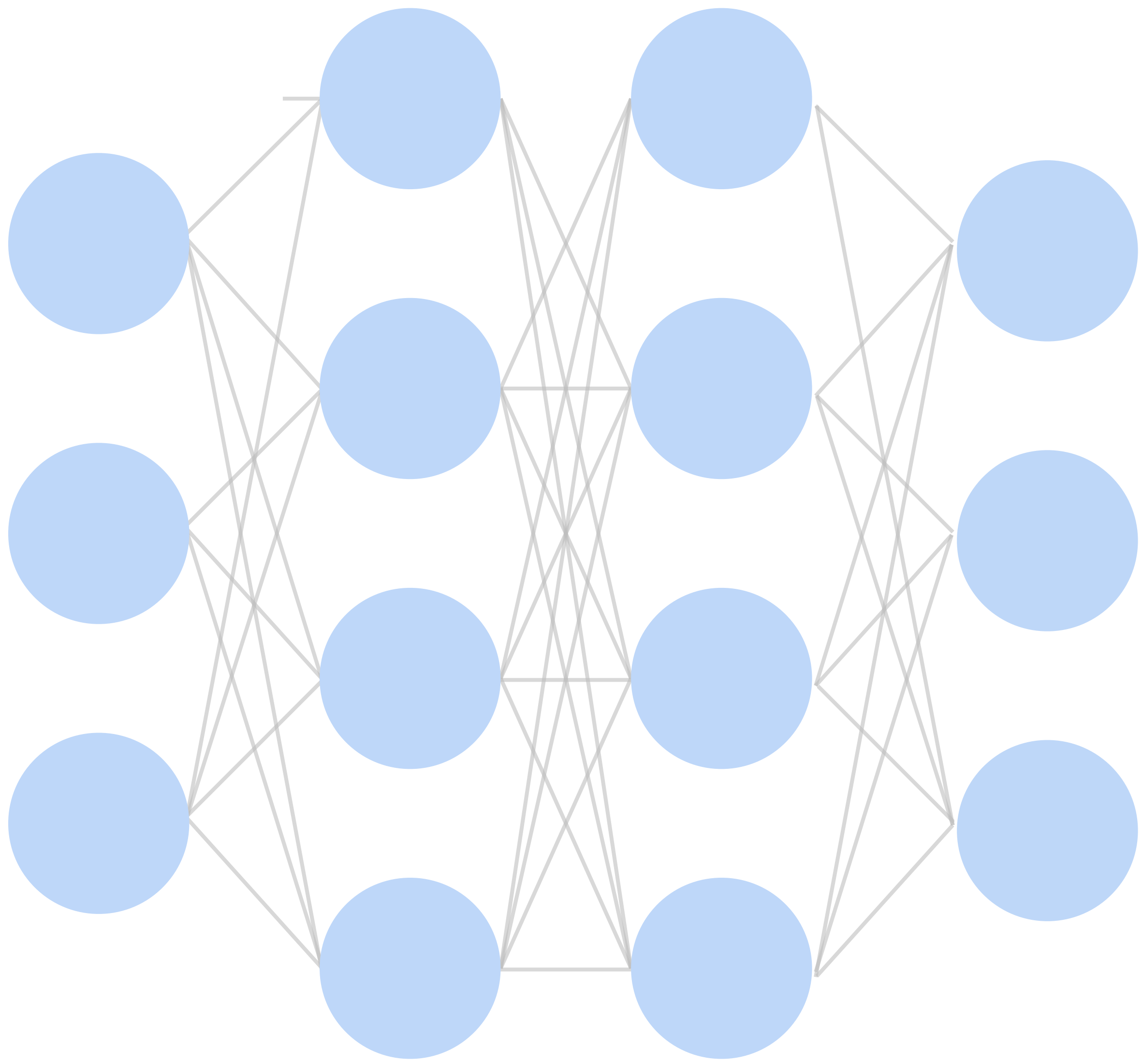
Slides credit: Chris Ré, Stanford CS229

What makes a good split?

- **Ideal**: Train, test, & dev randomly sampled
  - Allows us to say train quality is approximately test quality
- Test is a **proxy** for the real world!
  - We'll talk more about this later…
- **Challenge**: Leakage.
  - (Nearly) same example in train and dev.
  - Causes performance to be overstated!
    - Eg., same senders in train and test?

Slides credit: Chris Ré, Stanford CS229

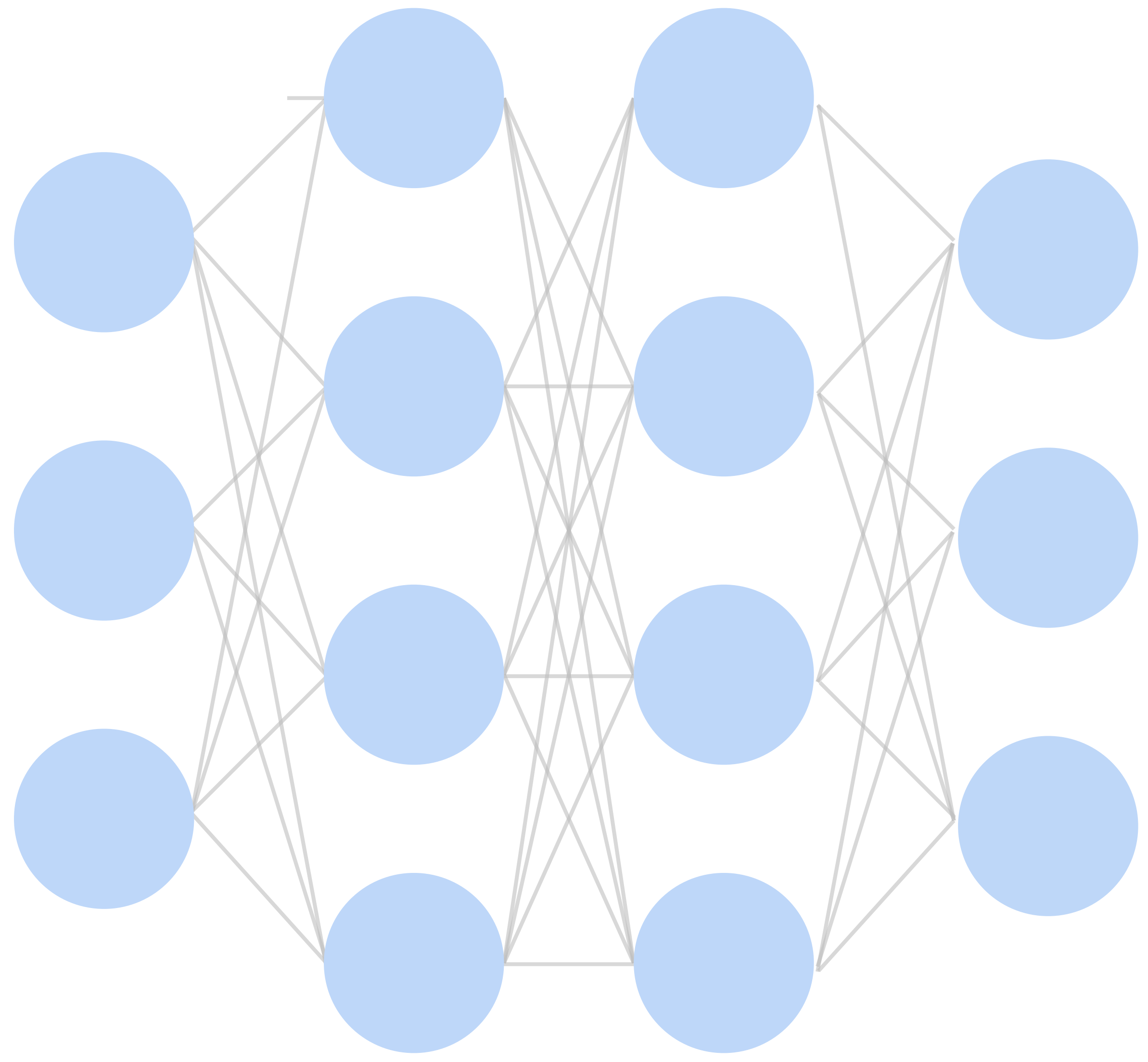
Build your model.



Build your model.

- A bag of learning algorithms learned from class.

- Simple model vs. deep models

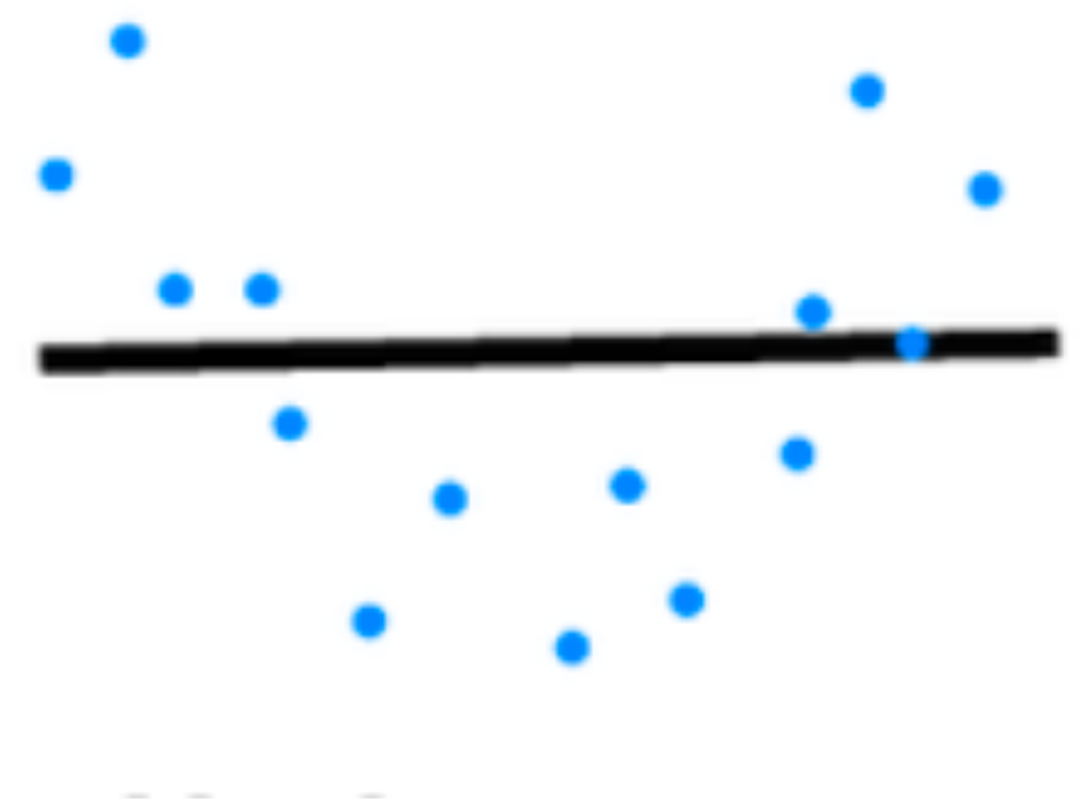


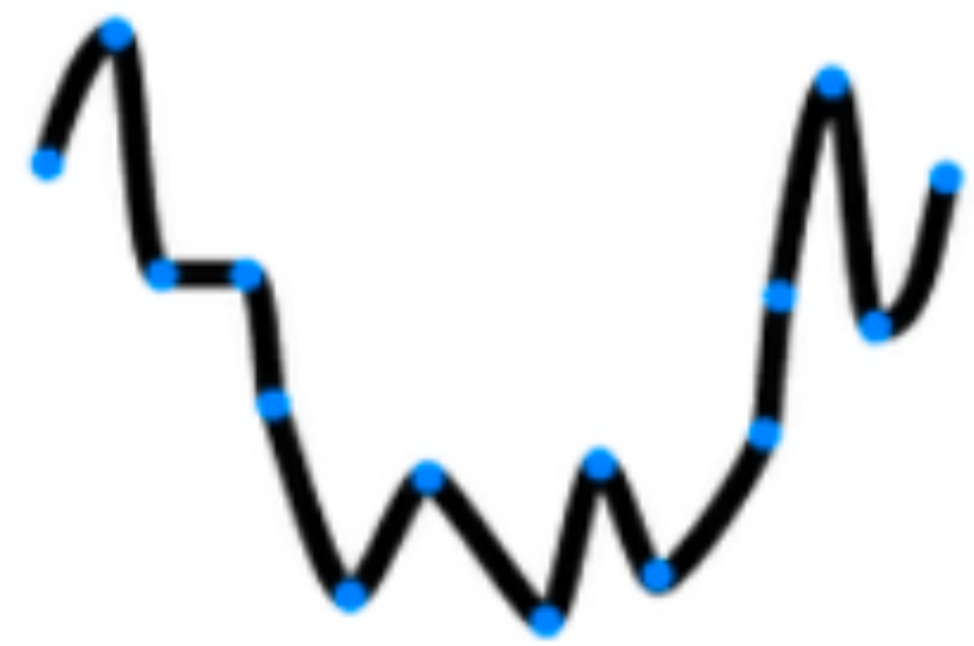
Underfitting
Overfitting

Image credit: hackernoon.com

Model Capacity

- The ability to fit variety of functions
- Low capacity models struggles to fit training set
  - Underfitting
- High capacity models can memorize the training set
  - Overfitting





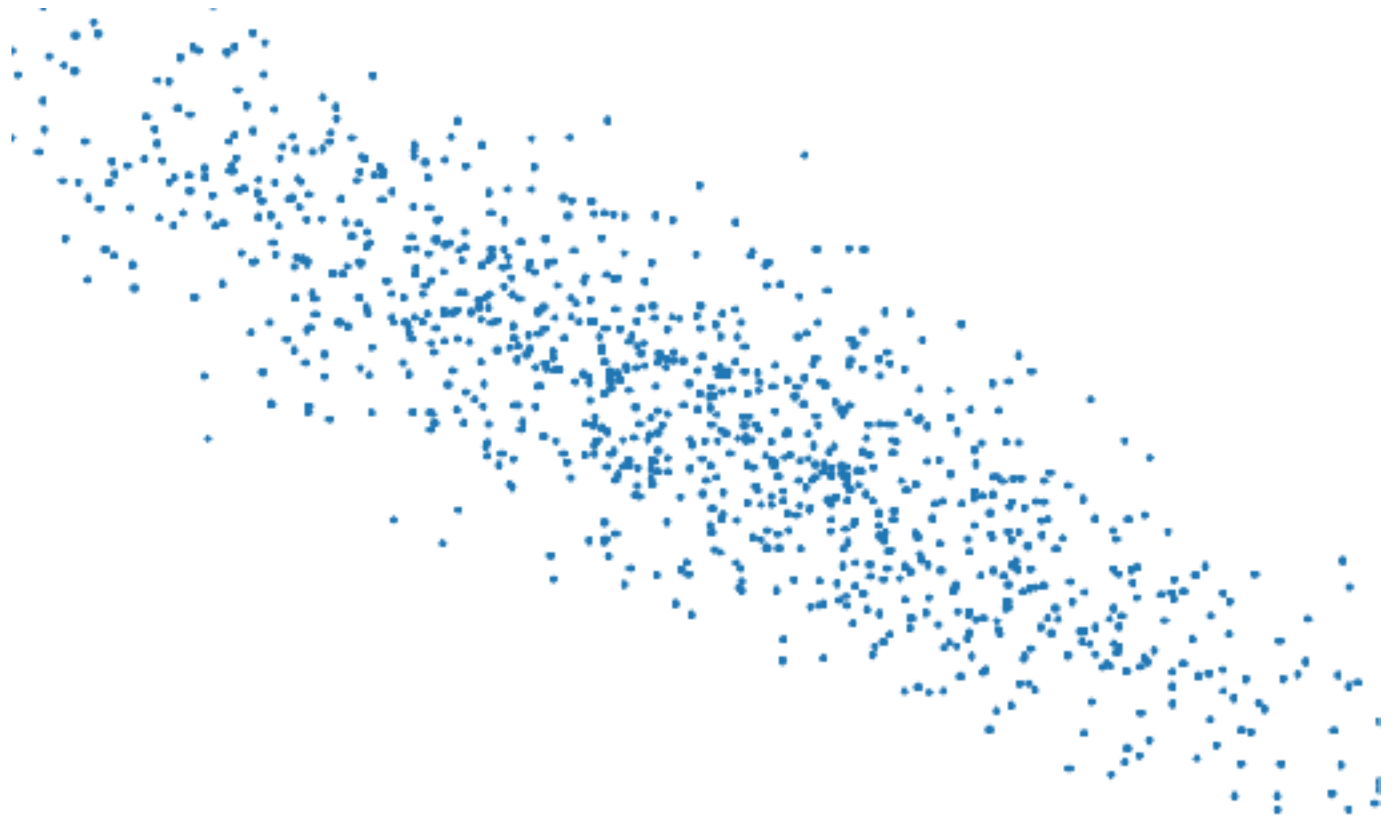
Underfitting and Overfitting

Data complexity

Model capacity		Simple	Complex
	Low	Normal	Underfitting
	High	Overfitting	Normal

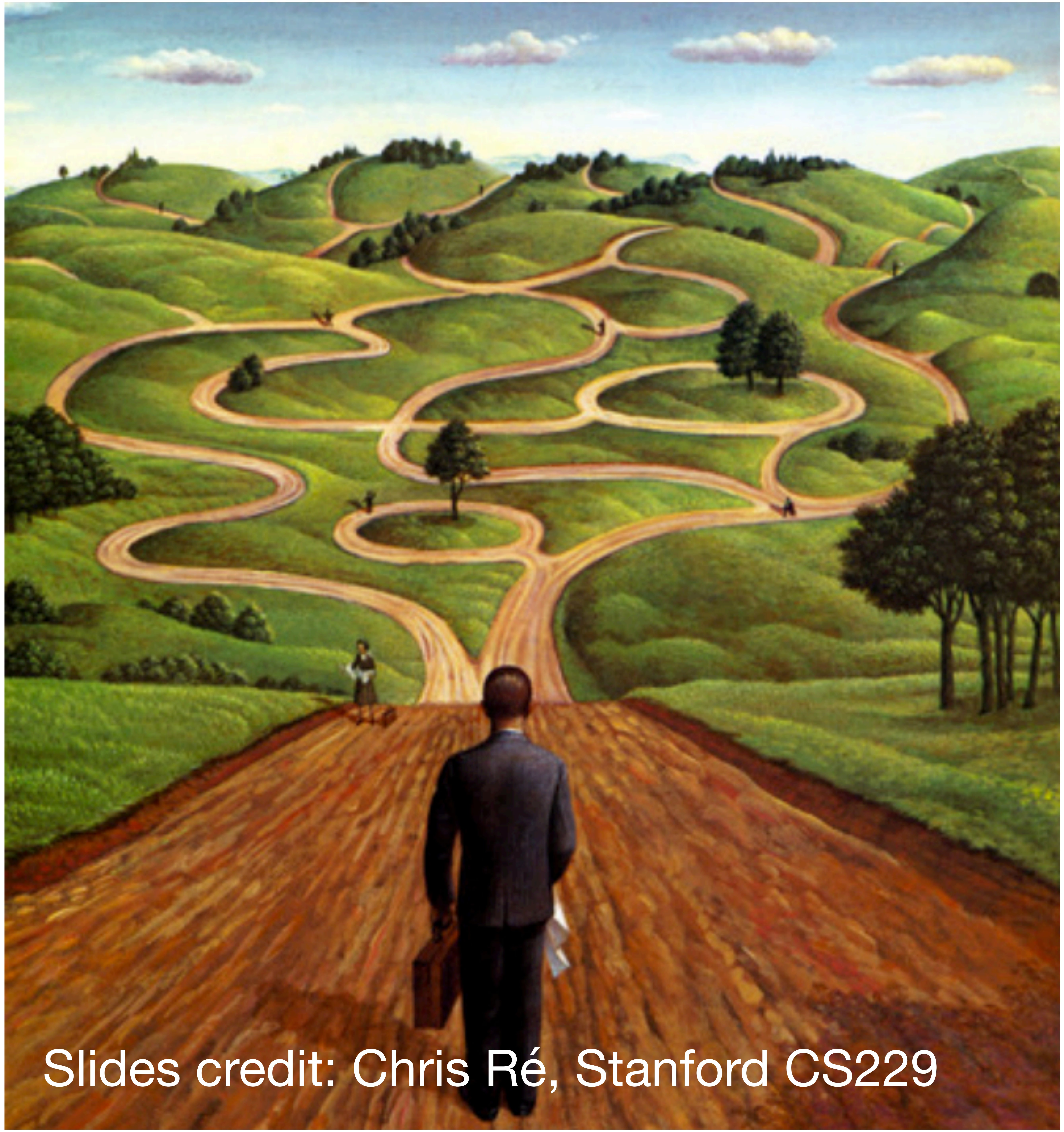
Data Complexity

- Multiple factors matters
  - # of examples
  - # of features in each example
  - time/space structure
  - # of labels



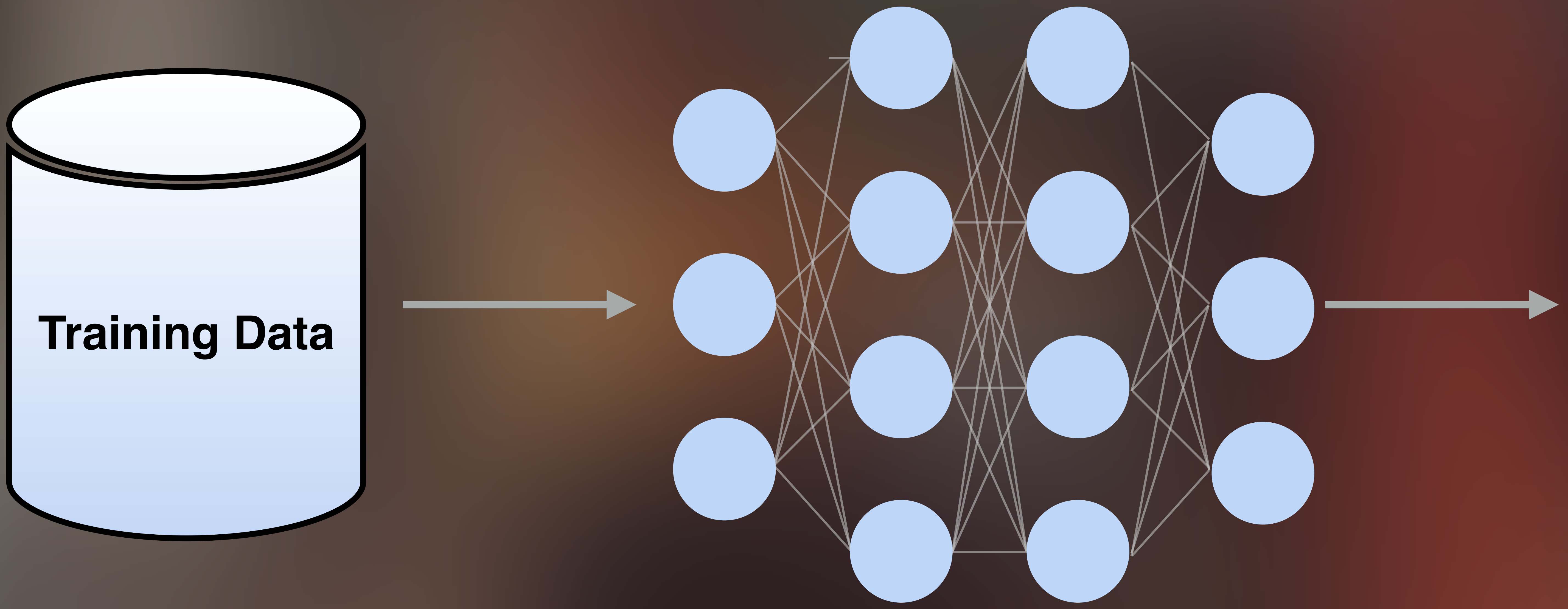
Ablation studies.

- You've built up a model, it has many different components.
  - Which matter?
  - which are stable?
- Remove one feature at a time!
  - *Adding* features + baseline could overestimate overlap. How?
- Measure performance.
  - Critical for research!



A running example

Food Image Classifier

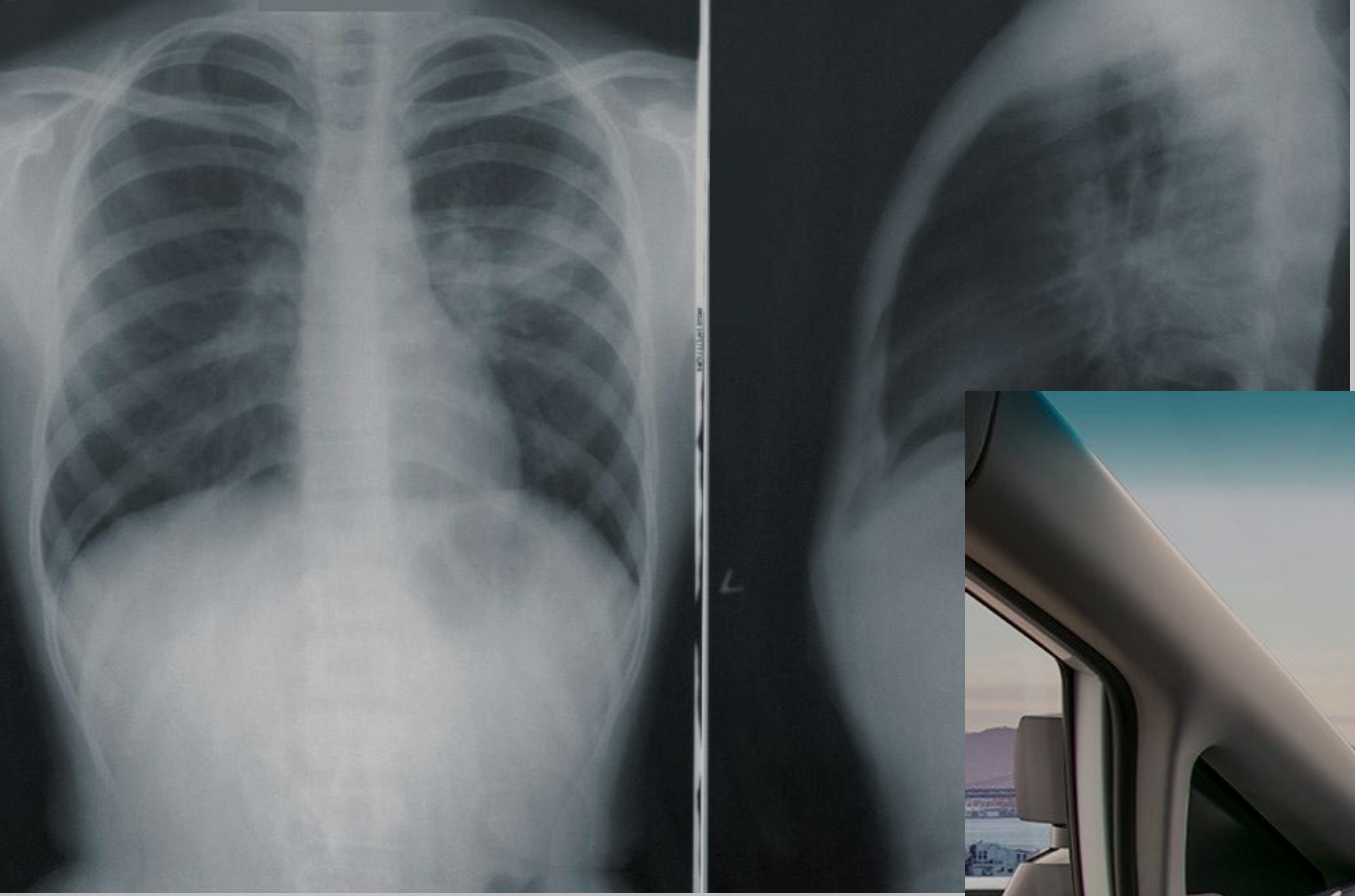


Closed-world: Training and testing distributions **match**

Open-world: Training and testing distributions **differ**

How to build machine learning models that function reliably in an open world?


Food Image Classifier
This is "out of distribution"!
Out-of-distribution Uncertainty



Photos from: CDC/GM

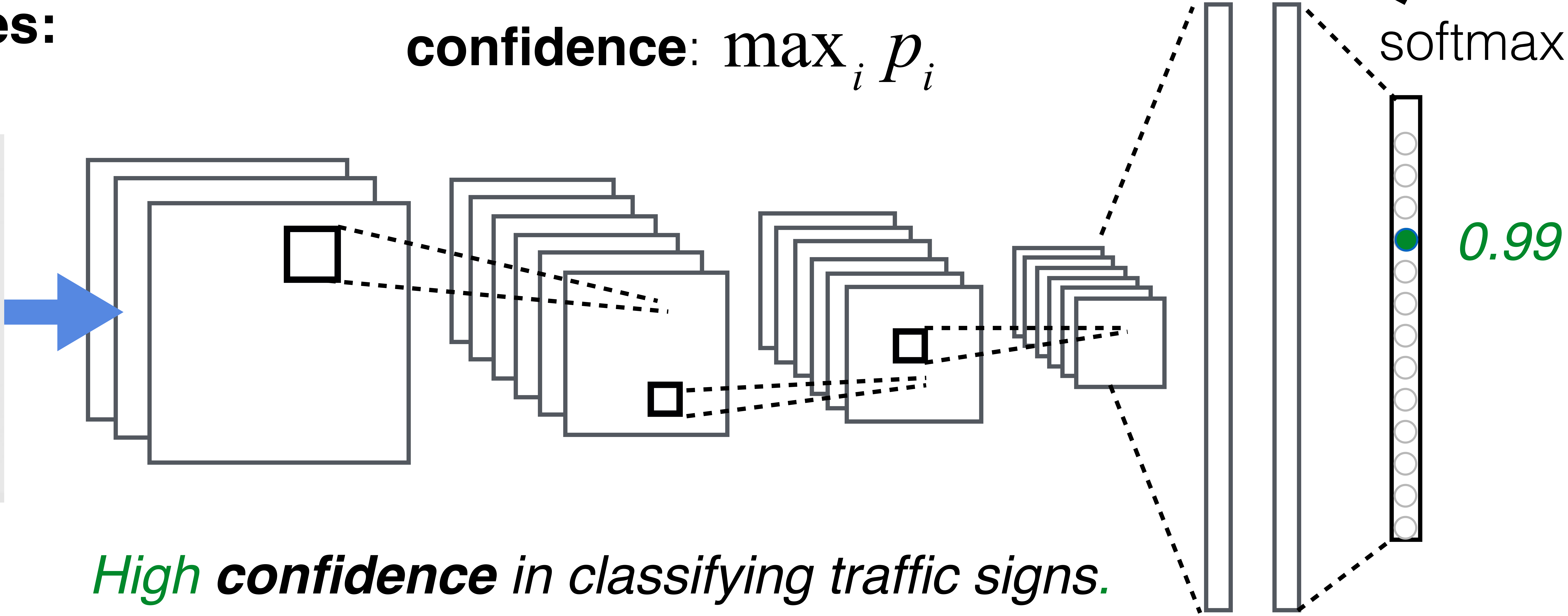
Out-of-distribution Uncertainty

For safety critical applications

$$p_i(\boldsymbol{x}) = \frac{\exp\left(f_i(\boldsymbol{x})\right)}{\sum_{j=1}^{N} \exp\left(f_j(\boldsymbol{x})\right)},$$

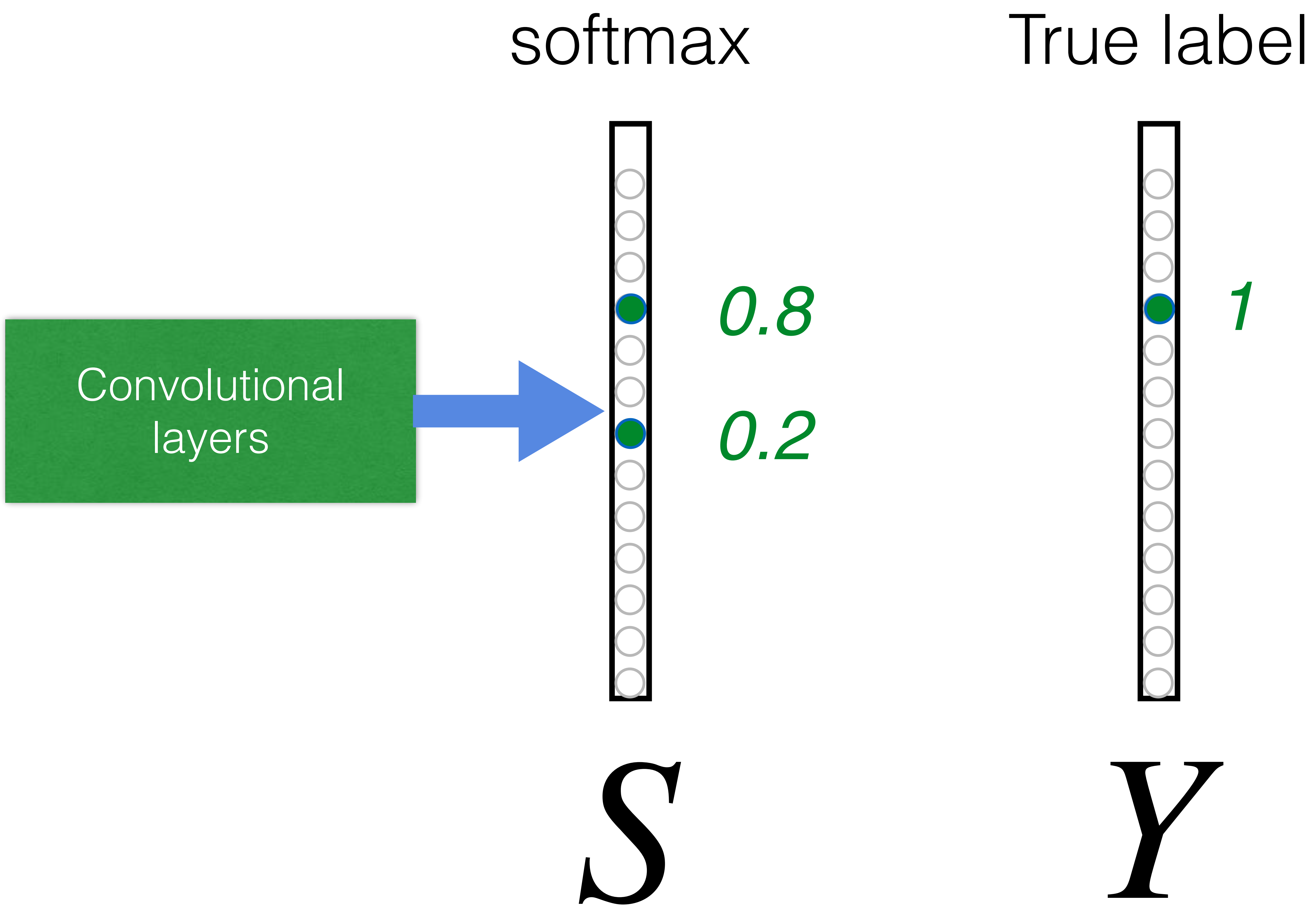
Training examples: traffic signs

confidence: $\max_i p_i$



*High **confidence** in classifying traffic signs.*

Cross-Entropy Loss



$$L_{CE} = \sum_i - Y_i \log(S_i)$$

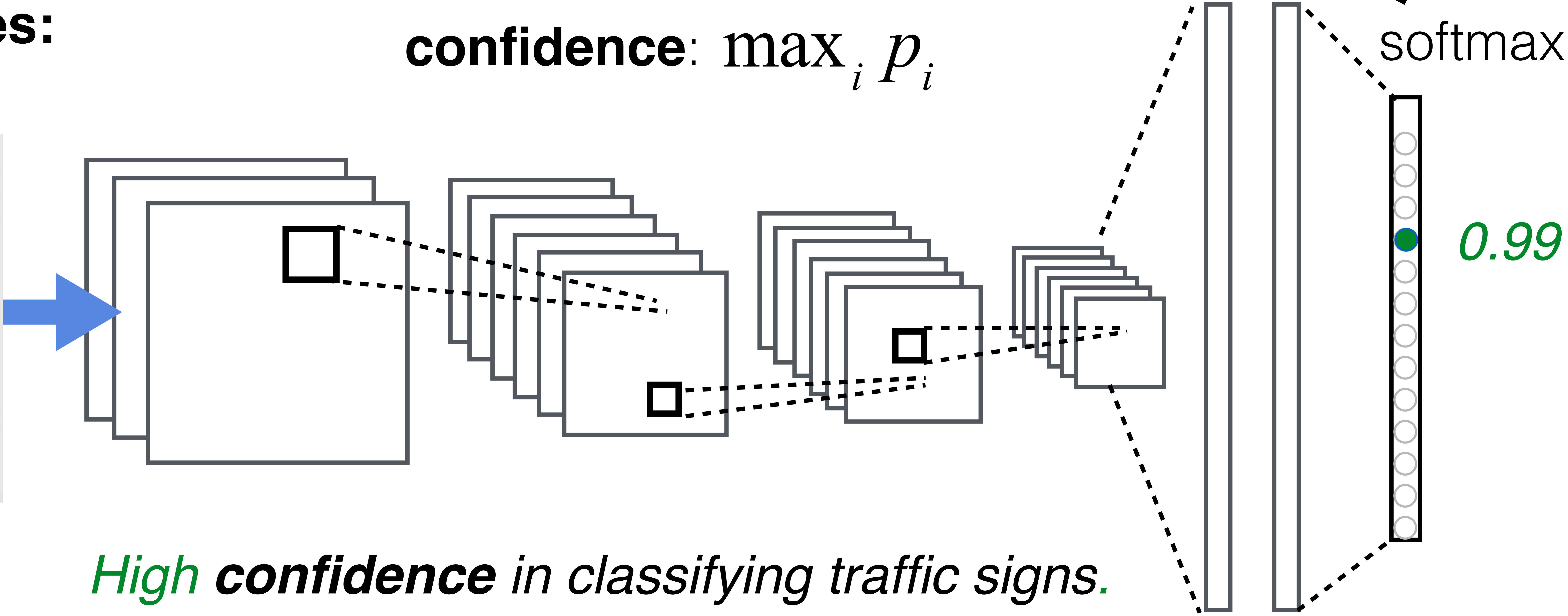
$$= -\log(0.8)$$

Goal: push **S** and **Y** to be identical

$$p_i(\boldsymbol{x}) = \frac{\exp\left(f_i(\boldsymbol{x})\right)}{\sum_{j=1}^{N} \exp\left(f_j(\boldsymbol{x})\right)},$$

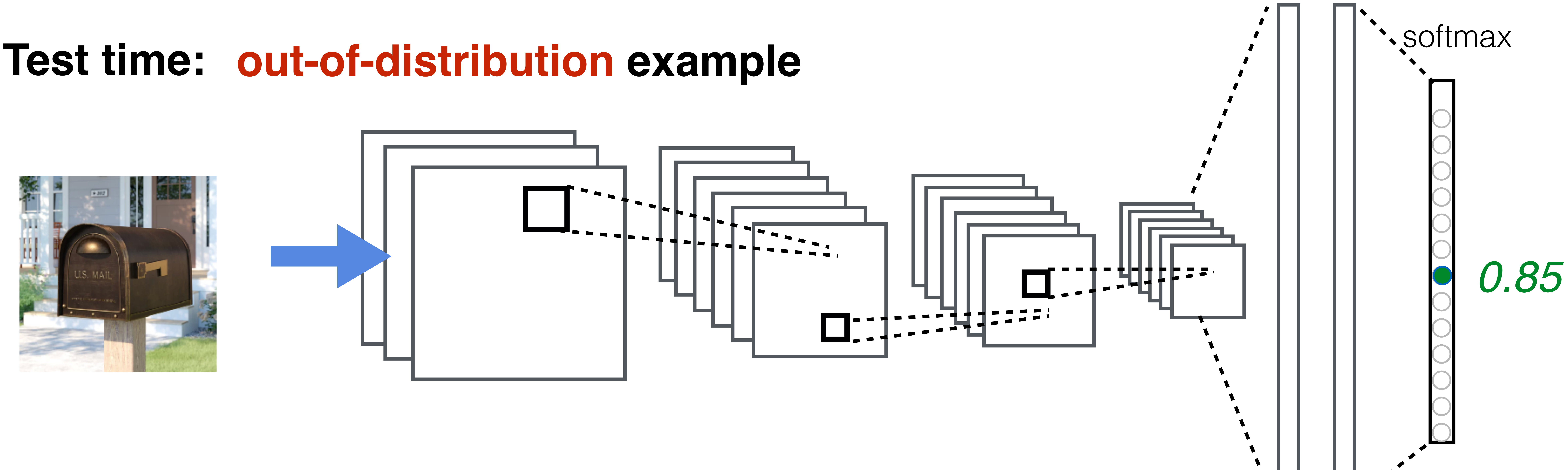
Training examples: traffic signs

confidence: $\max_i p_i$



High ***confidence*** *in classifying traffic signs.*

Test time: out-of-distribution example

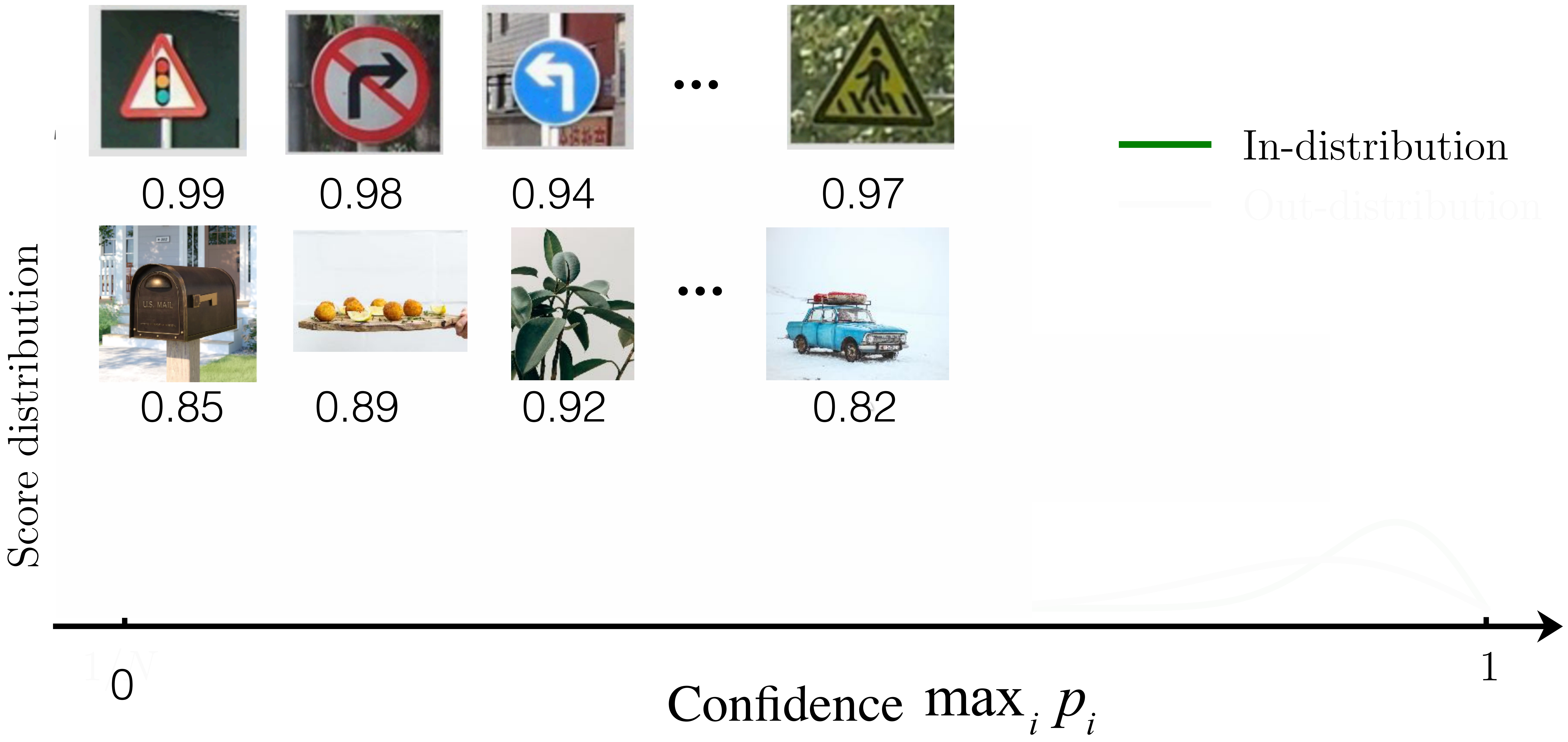


Ideally: Low confidence in predicting as traffic sign

Neural networks can be over-confident to *out-of-distribution (OOD)* examples.

[Nguyen et al. 2015]

Confidence Score Distribution



How can we distinguish out-of-distribution examples from in-distribution data?

ODIN: Out-of-distribution Image Detector

[Liang et al. ICLR 2018]

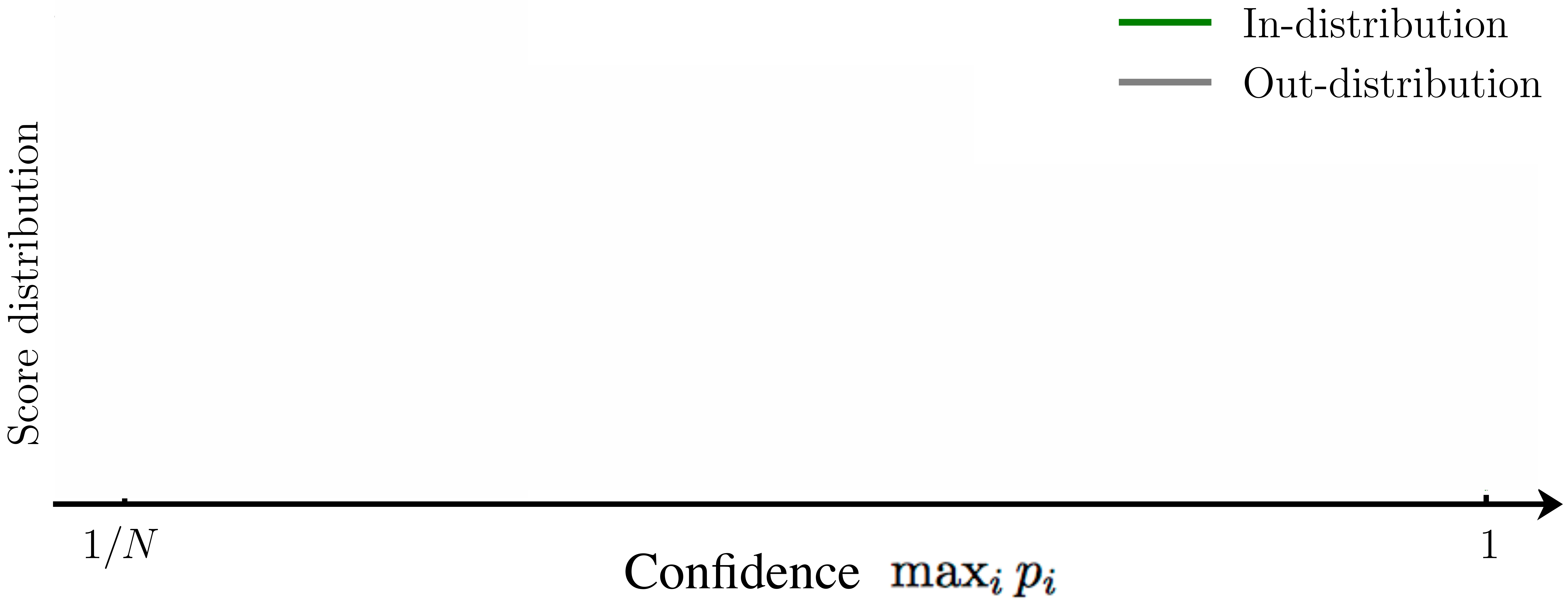
Shiyu Liang

Sharon Y. Li

R. Srikant

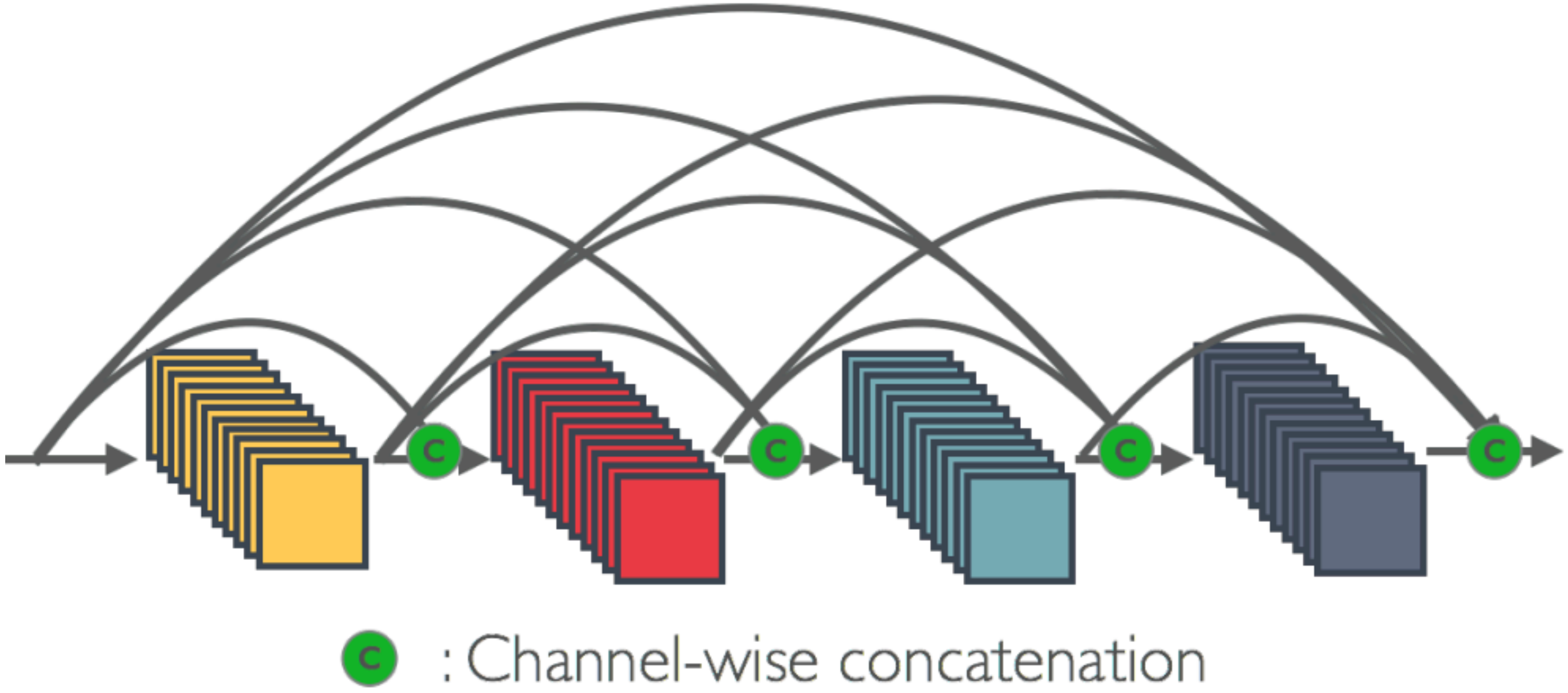
ODIN: Out-of-distribution Image Detector

$$p_i(\boldsymbol{x};T) = \frac{\exp\left(f_i(\boldsymbol{x})/T\right)}{\sum_{j=1}^{N}\exp\left(f_j(\boldsymbol{x})/T\right)},$$



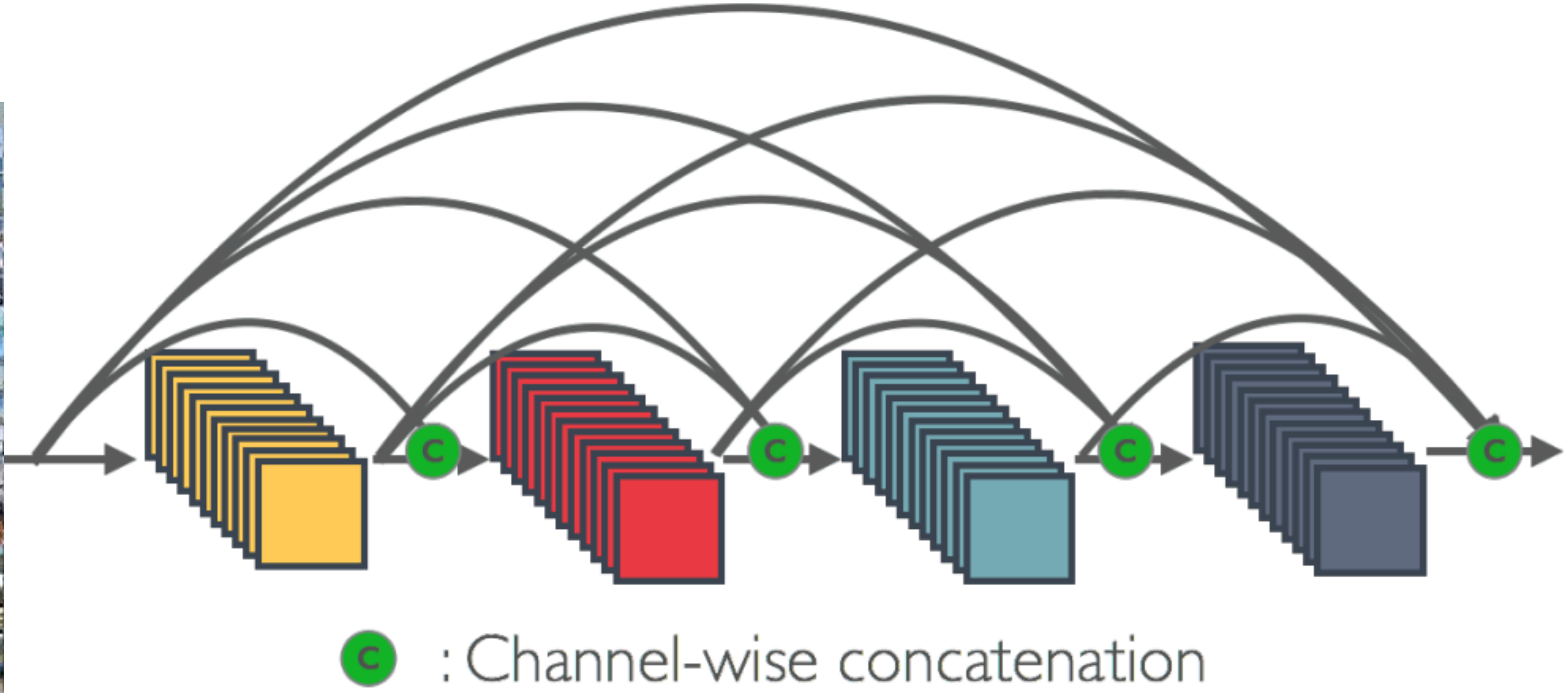
Training Task

In-distribution data: CIFAR-10

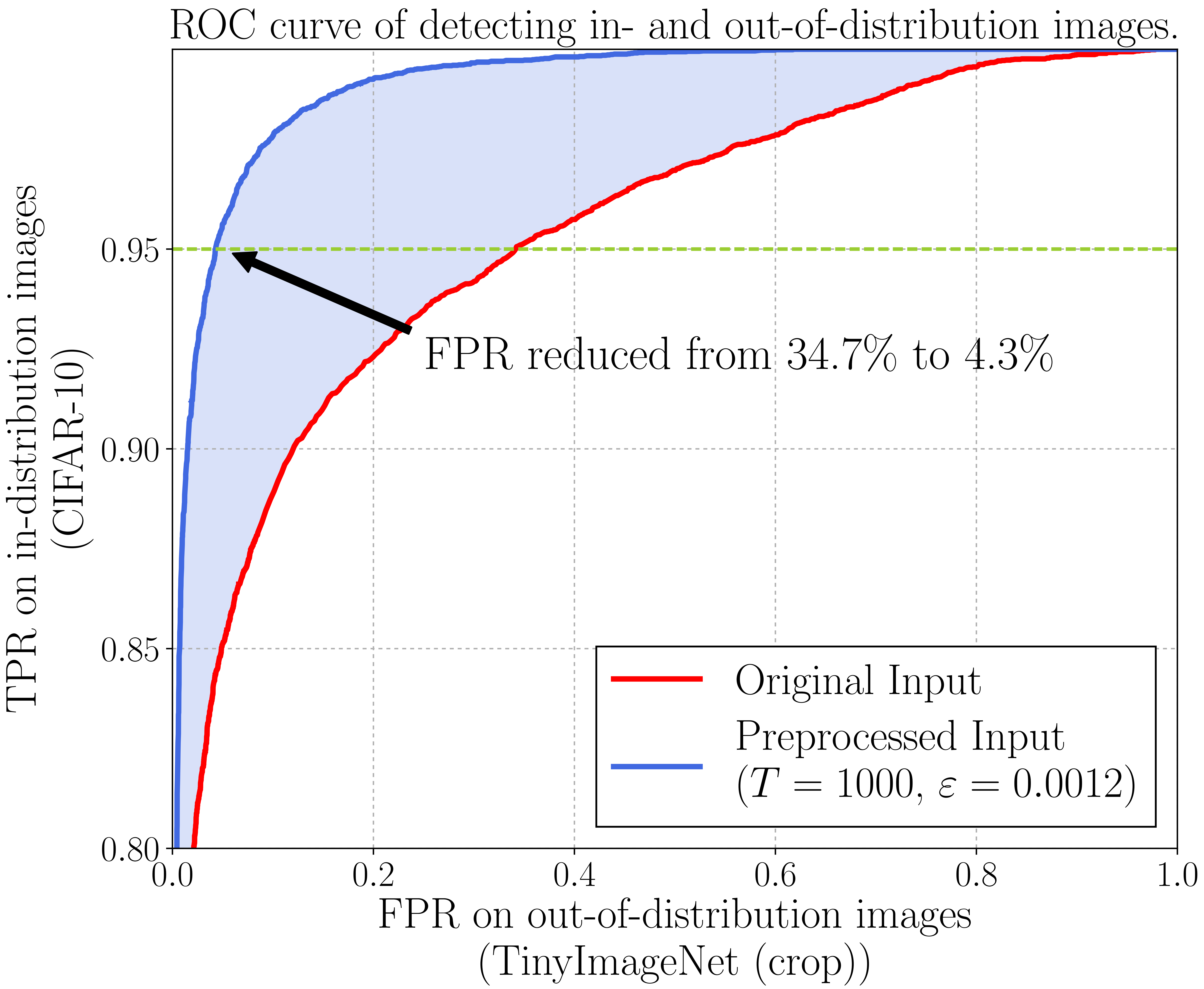


Detection Task

Out-of-distribution data



Results



ROC curve of detecting in- and out-of-distribution images.
FPR reduced from 34.7% to 4.3%
Original Input
Preprocessed Input
($T = 1000$, $\varepsilon = 0.0012$)
TPR on in-distribution images
(CIFAR-10)
FPR on out-of-distribution images
(TinyImageNet (crop))
0.80
0.85
0.90
0.95
0.0
0.2
0.4
0.6
0.8
1.0

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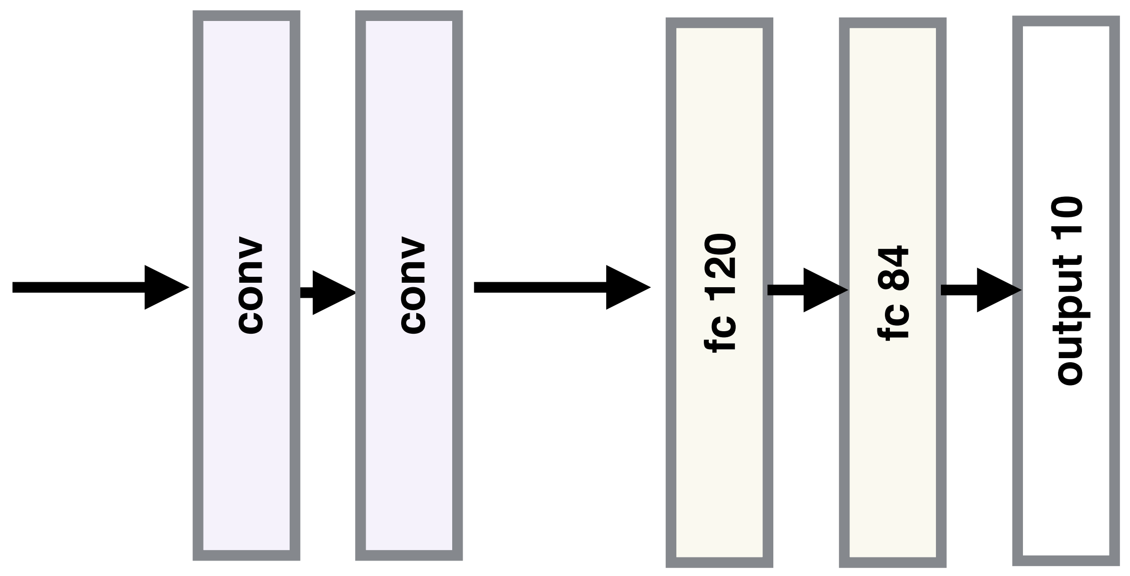
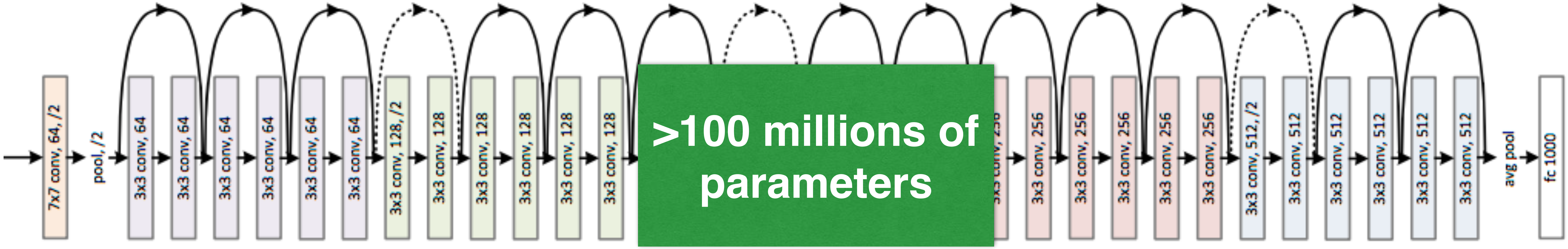
Industry-scale Machine Learning

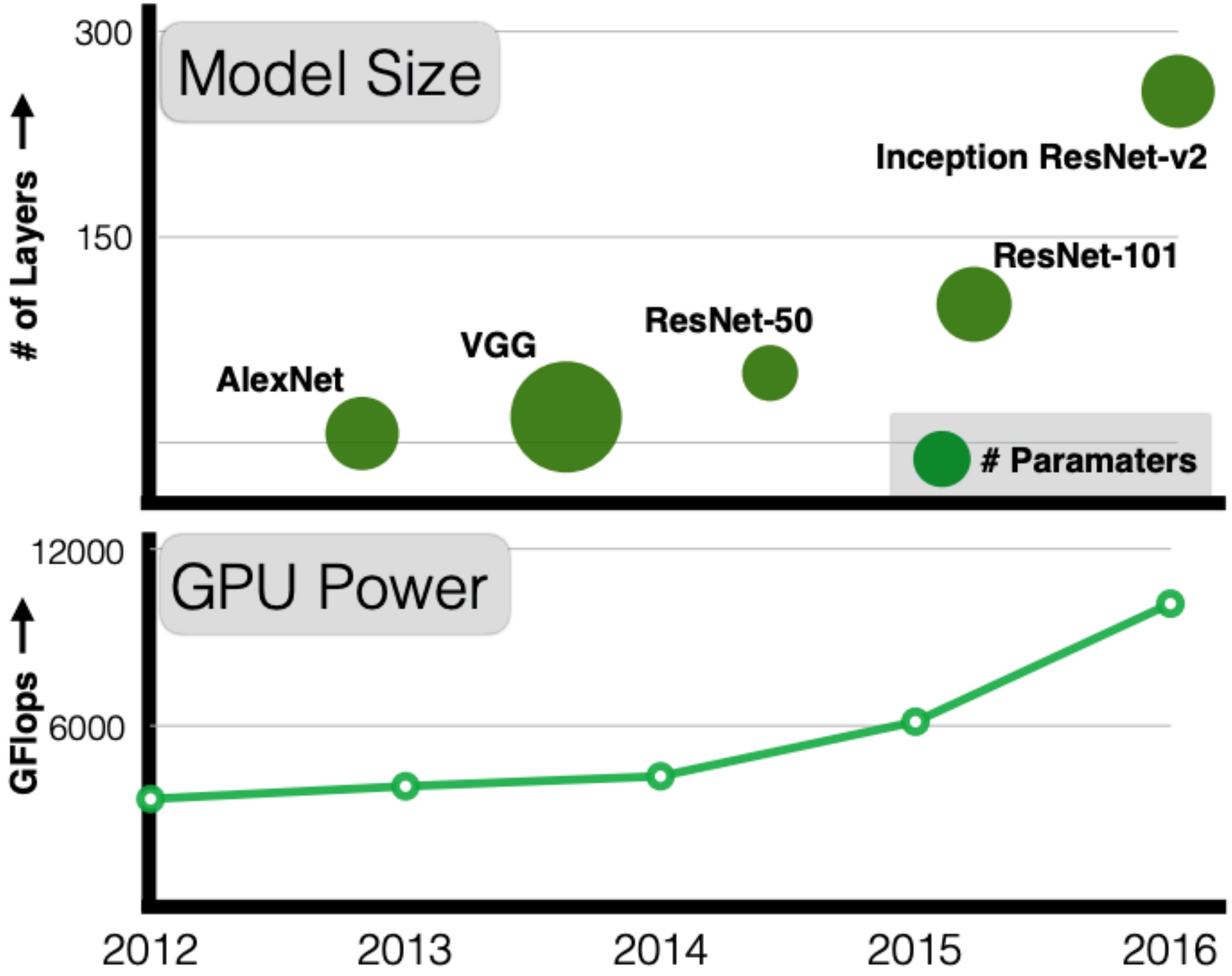
Model Complexity Keeps Increasing



LeNet (Lecun et al. 1998)

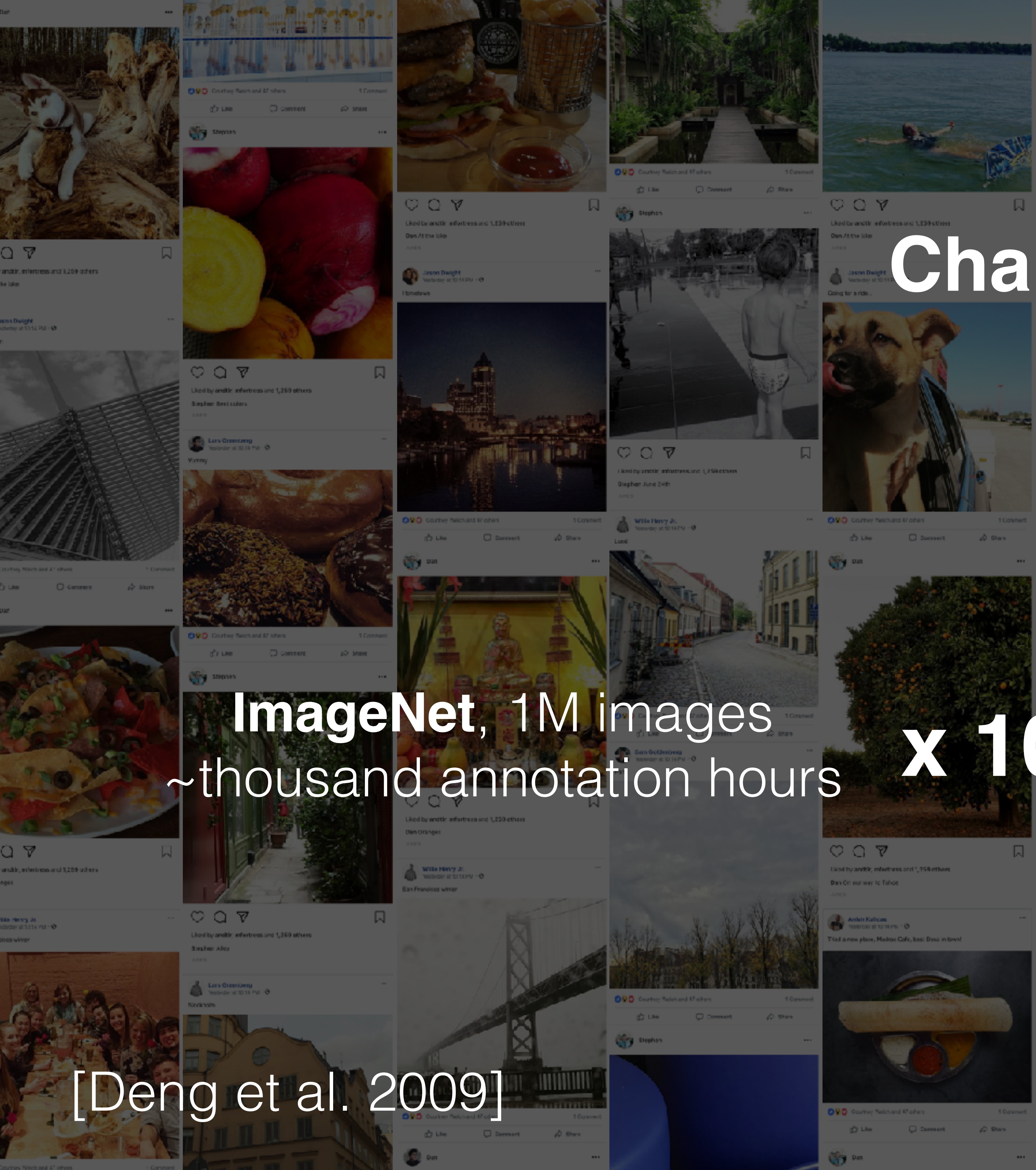


ResNet (He et al. 2016)



[Sun et al. 2017]

Challenge: Limited labeled data



ImageNet, 1M images
~thousand annotation hours

x 1000

1B images
~million annotation hours

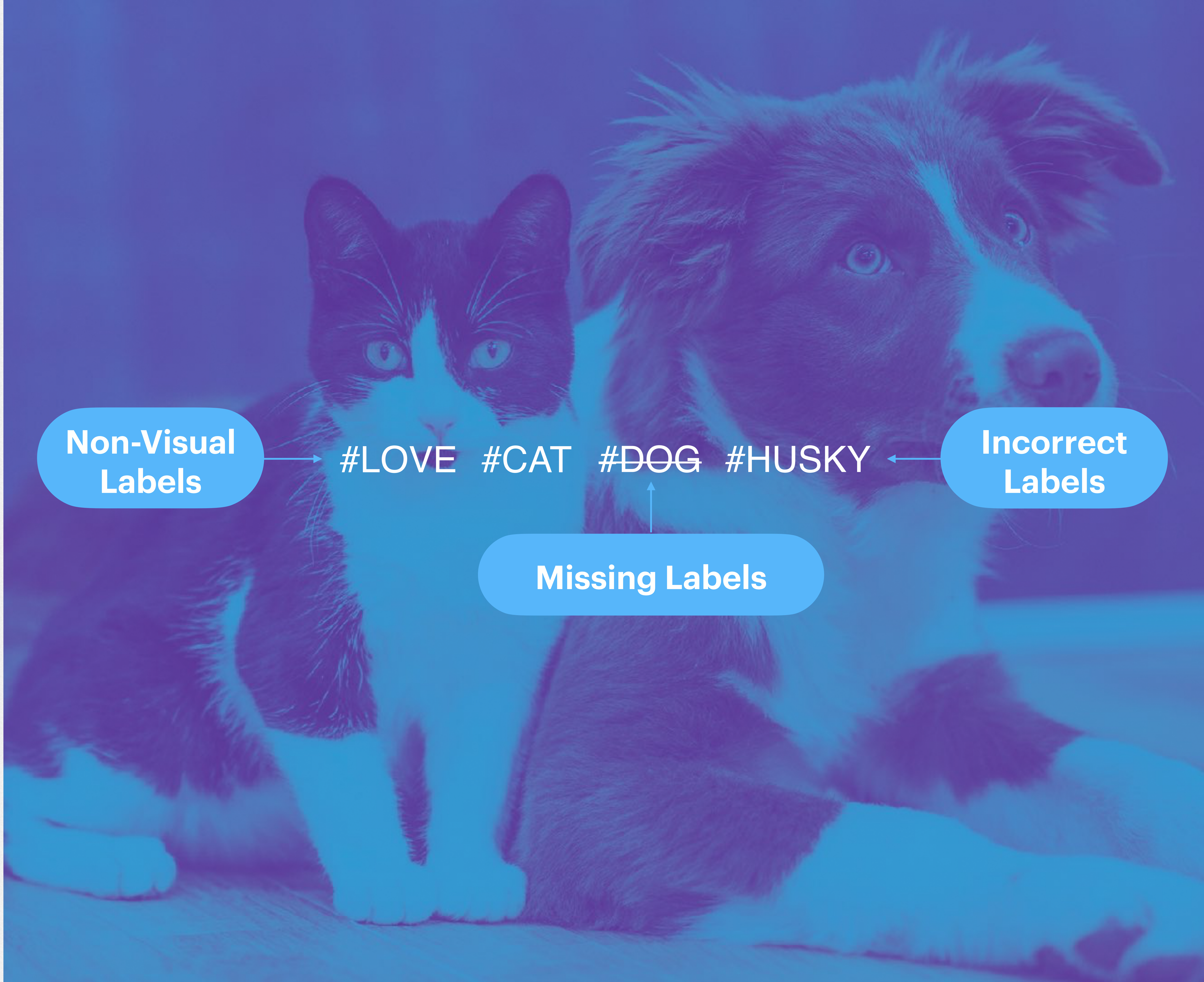
[Deng et al. 2009]

TRAINING AT SCALE

Levels of Supervision

TRAINING AT SCALE

Noisy Data



Can we use images with noisy labels for training?

[Mahajan et al. 2018]

Largest Weakly Supervised Training

3.5B
PUBLIC INSTAGRAM
IMAGES

LARGE CAPACITY MODEL
(RESNEXT101-32X48)

17K UNIQUE LABELS

DISTRIBUTED
TRAINING
(350 GPUS)

[Mahajan et al. 2018]

Self-supervised Learning
(no label)

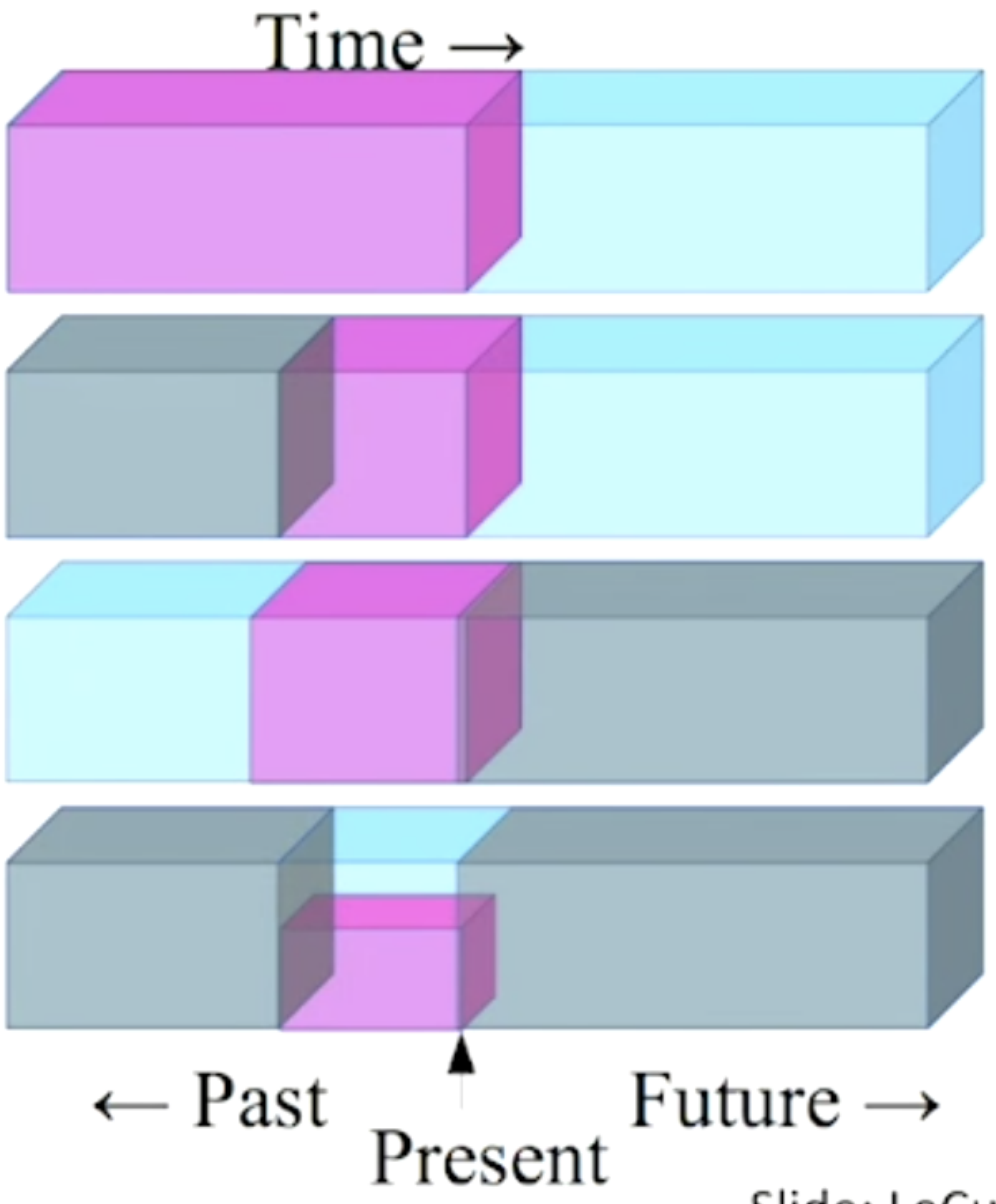
- **“Pure” Reinforcement Learning (cherry)**
  - The machine predicts a scalar reward given once in a while.
  - **A few bits for some samples**
- **Supervised Learning (icing)**
  - The machine predicts a category or a few numbers for each input
  - Predicting human-supplied data
  - **10→10,000 bits per sample**
- **Self-Supervised Learning (cake génoise)**
  - The machine predicts any part of its input for any observed part.

Source: Yann LeCun’s talk

What if we can get labels for free for unlabelled data
and train unsupervised dataset in a supervised manner?

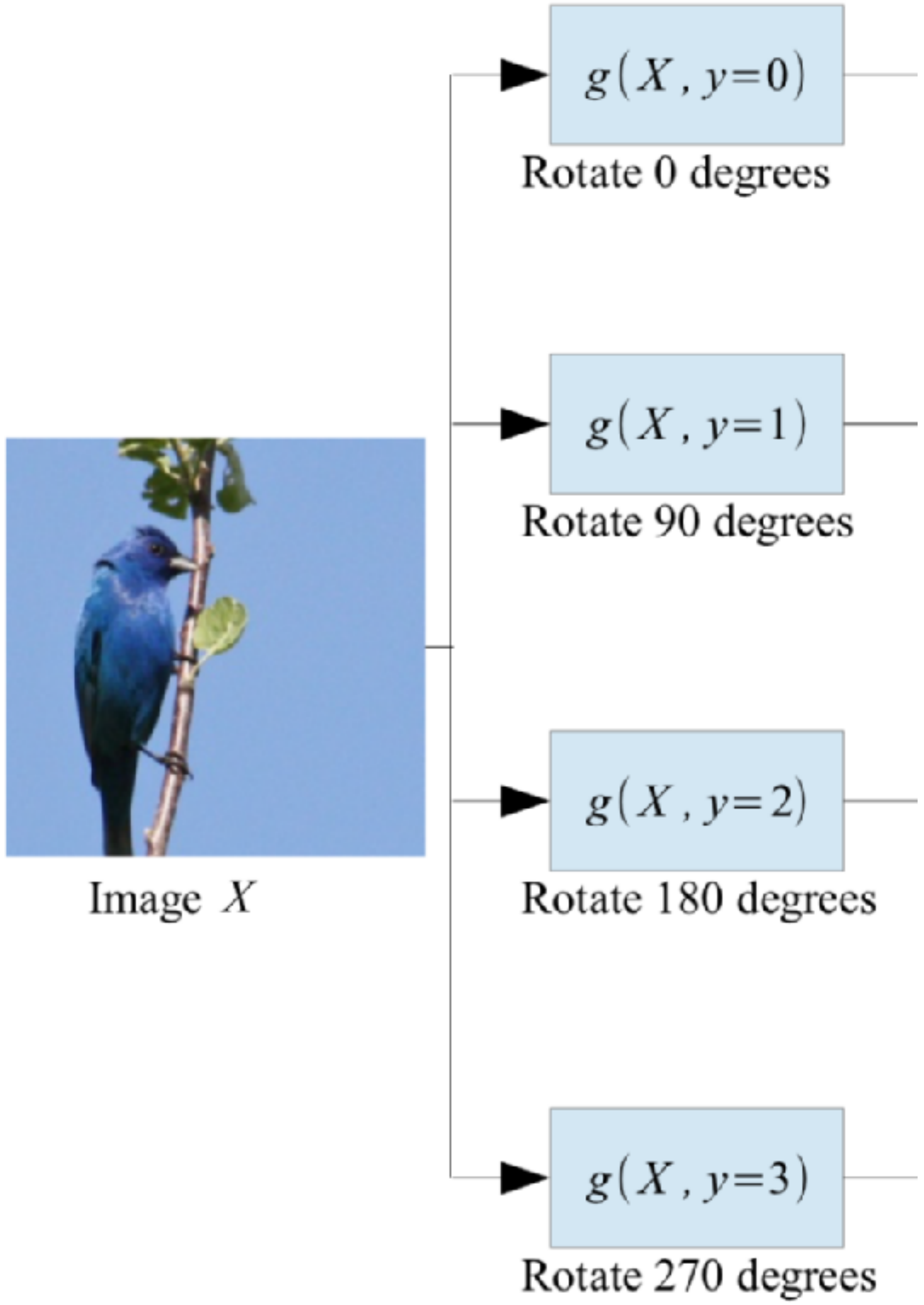
Pretext Tasks

- **Predict any part of the input from any other part.**
- **Predict the future from the past.**
- **Predict the future from the recent past.**
- **Predict the past from the present.**
- **Predict the top from the bottom.**
- **Predict the occluded from the visible**
- **Pretend there is a part of the input you don't know and predict that.**



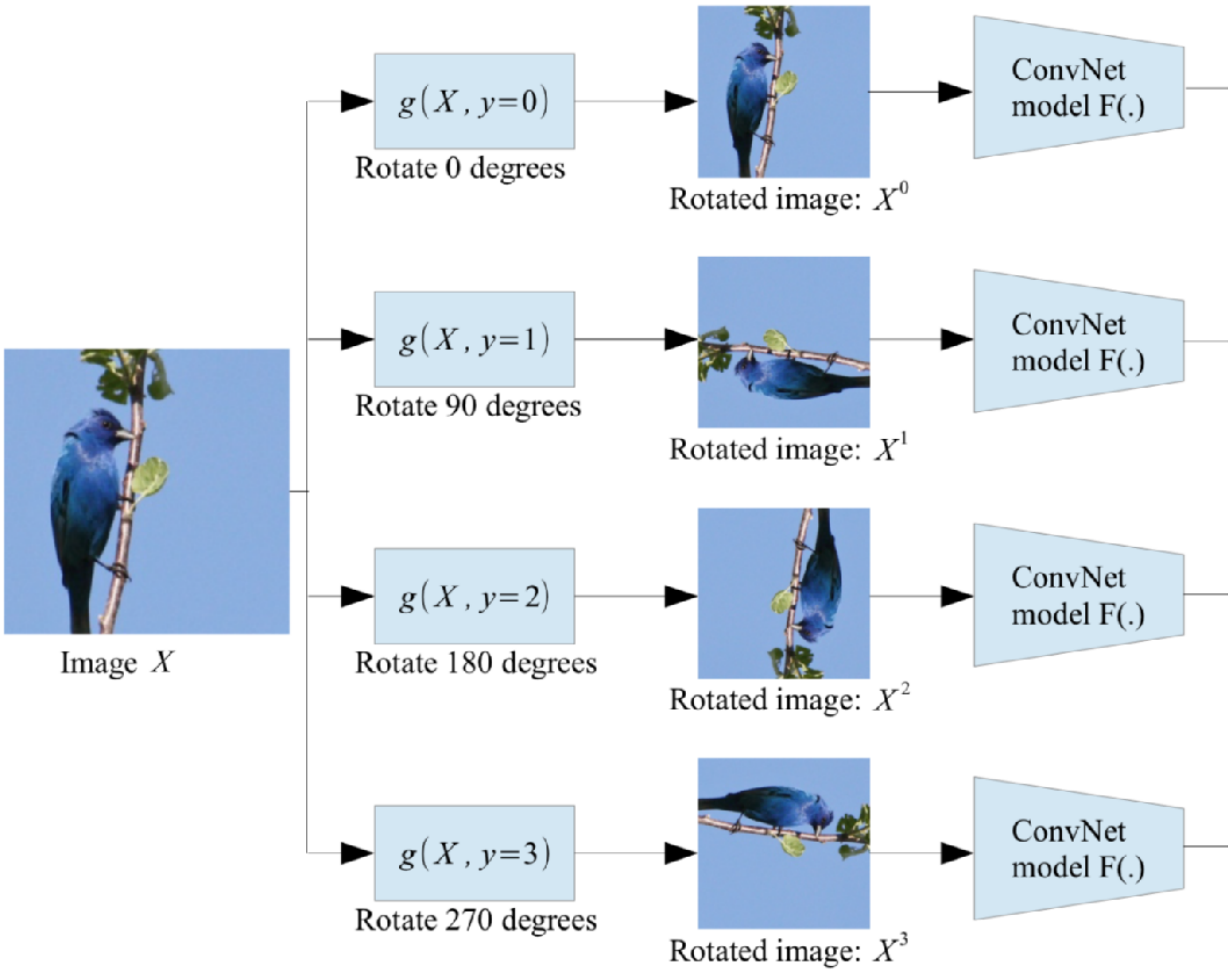
Slide: LeCun

Rotation



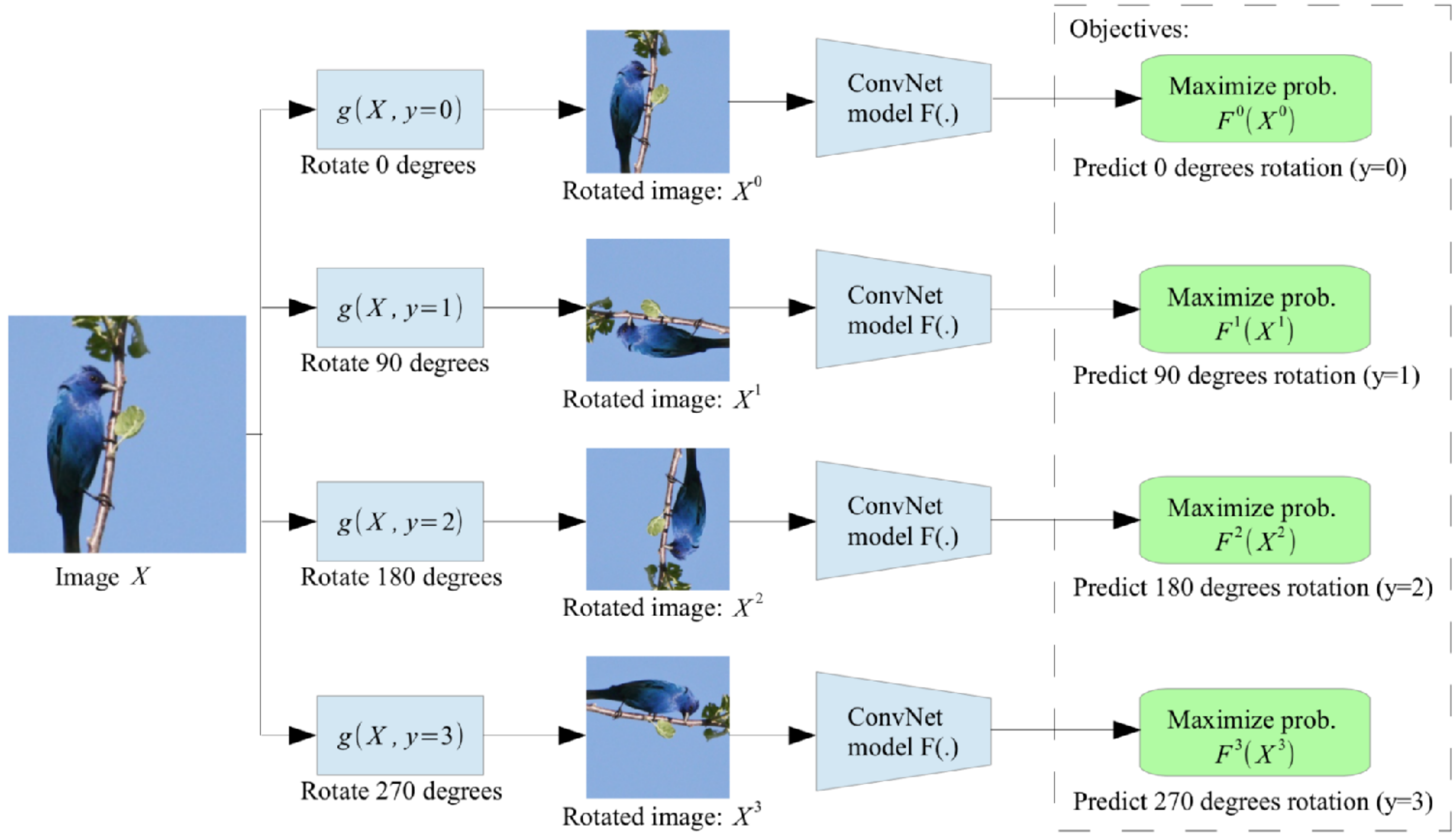
[Gidaris et al. 2018]

Rotation



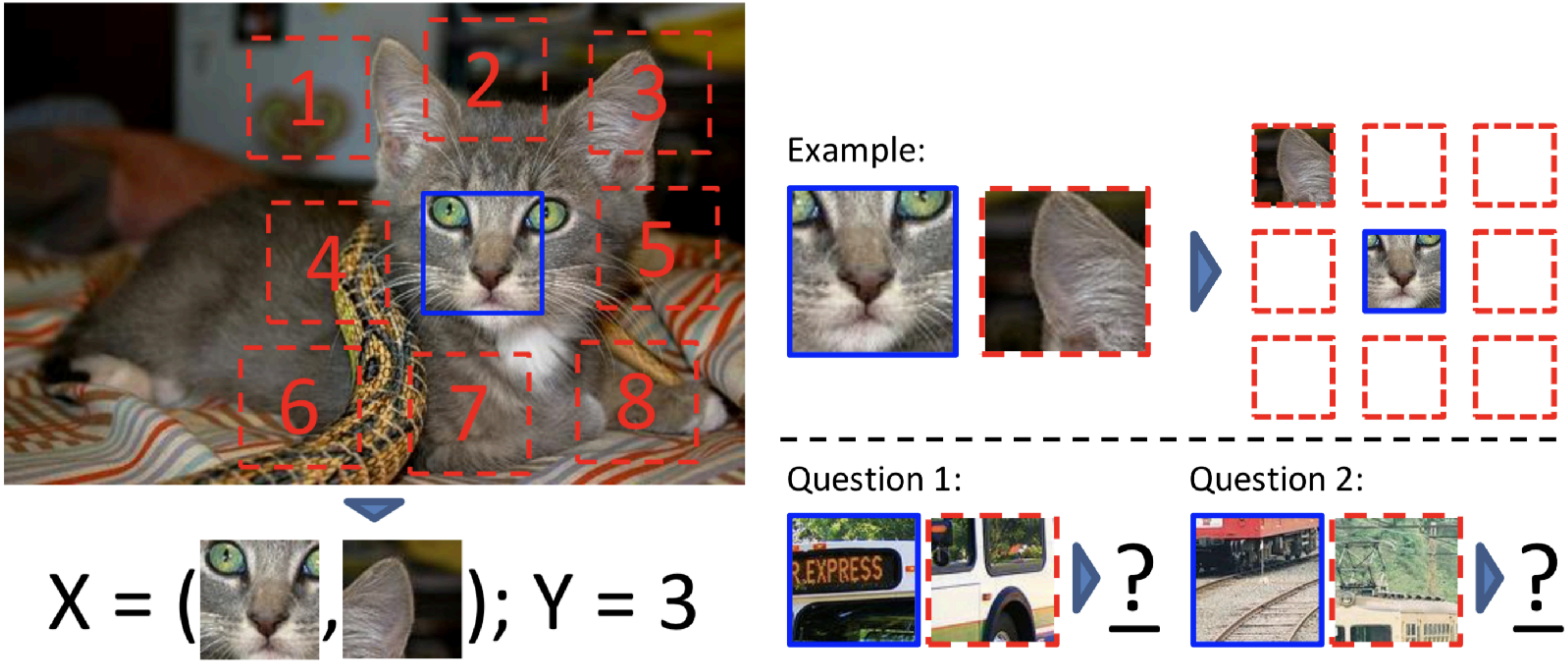
Gidaris et al. 2018

Rotation



Gidaris et al. 2018

Patches



[Doersch et al., 2015]

Summary

- Basic steps to build an ML system
- Open-world machine learning
- Industry-scale machine learning

Thank you!