Continual Machine Learning

Summer 2024

Teacher

Dr. Martin Mundt,

Research Group on Open World Lifelong Learning

Time

Every Friday 14:25 - 16:05 CEST

Course Homepage

http://owll-lab.com/teaching/cl_lecture_24

https://www.youtube.com/playlist?list=PLm6QXeaB-XkA5-lVBB-h7XeYzFzgSh6sk

Week 7: Ordering, Curricula & Difficulty

Recall: sequence was imposed

What about the order in which we learn? If we have the choice, which data or even tasks should we start with/include next?

What if some data sequence is harder to learn?

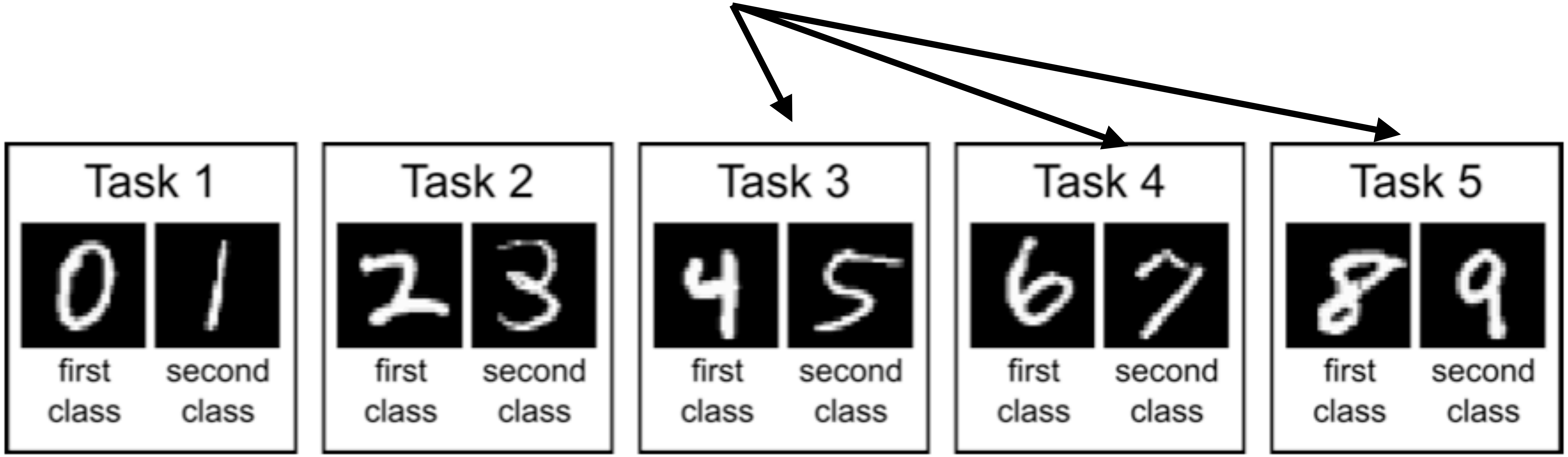


Figure 1: Schematic of split MNIST task protocol.

van de Ven & Tolias, “Three scenarios for continual learning”, arXiv:1904.07734, 2019

Curriculum learning

Curriculum Learning

Curriculum learning: a definition

Definition 1: Original Curriculum Learning [6]. A curriculum is a sequence of training criteria over T training steps: $\mathcal{C} = \langle Q_1, \ldots, Q_t, \ldots, Q_T \rangle$. Each criterion Q_t is a reweighting of the target training distribution $P(z)$:

$$Q_t(z) \propto W_t(z)P(z) \quad \forall \text{example } z \in \text{training set } D, \qquad (1)$$

such that the following three conditions are satisfied:

1) The entropy of distributions gradually increases, i.e., $H(Q_t) < H(Q_{t+1})$.
2) The weight for any example increases, i.e., $W_t(z) \leq W_{t+1}(z) \quad \forall z \in D$.
3) $Q_T(z) = P(z)$.

From Wang et al, “A Survey on Curriculum Learning”, TPAMI 2021, based on original definition by Bengio et al, “Curriculum Learning”, ICML 2009

Curriculum Learning

Curriculum learning: the more intuitive definition (with a little bit of a tautology)

Definition 3: Generalized Curriculum Learning. Discarding the definition of Q_t (Eq. $\boxed{1}$) and its three conditions in Definition 1, a curriculum is a sequence of training criteria over T training steps. Each criterion Q_t includes the design for all the elements in training a machine learning model, e.g., data/tasks, model capacity, learning objective, etc. Curriculum learning is the strategy that trains a model with such a curriculum.

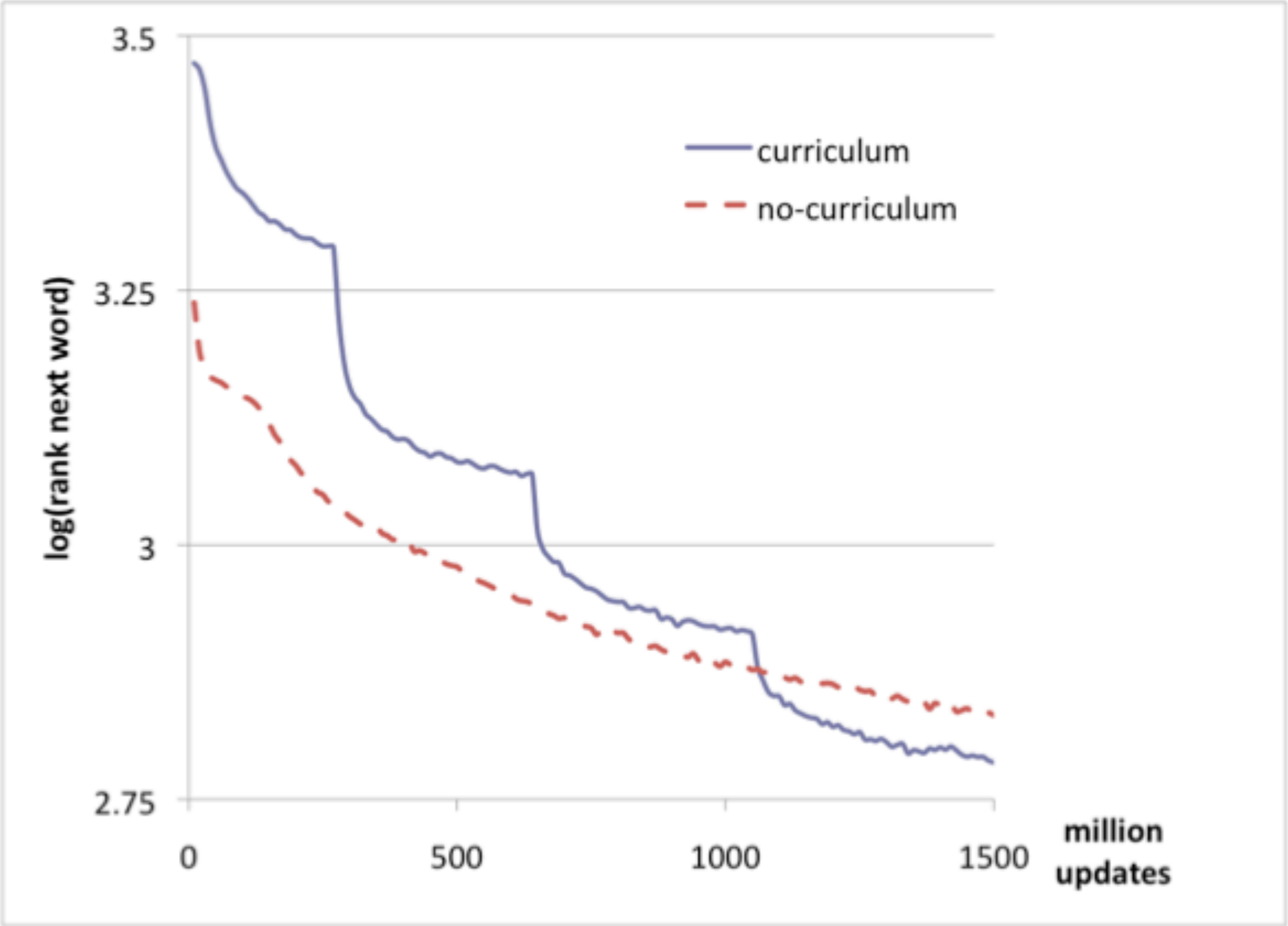
From Wang et al, “A Survey on Curriculum Learning”, TPAMI 2021, based on original definition by Bengio et al, “Curriculum Learning”, ICML 2009

Recall L1: a motivating example

Example: Ranking language model trained with vs without curriculum on Wikipedia

“Error” is log of the rank of the next word (within 20k-word vocabulary).

1. The curriculum-trained model skips examples with words outside of 5k most frequent words
2. Then skips examples outside 10k most frequent words and so on



Bengio et al, “Curriculum Learning”, ICML 2009

What are central questions in curriculum learning?

Curriculum learning

Two key challenges:

Scoring function (difficulty measurer):

Any function that provides us with an estimate of the difficulty of the instances in our dataset(s).

Pacing function (training scheduler):

(sometimes also called competence, as we'll see later)

The function that tells us how to interleave samples into the training process over time.

Curriculum learning

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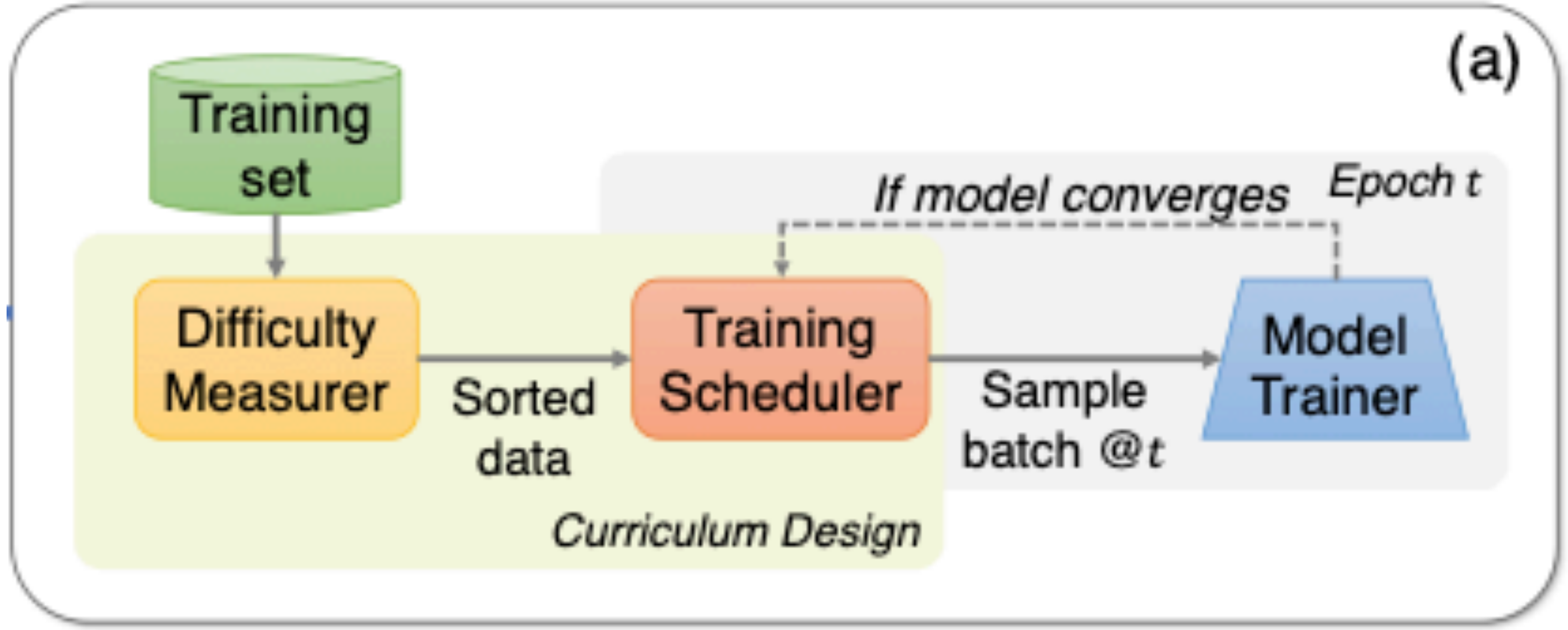
Algorithm 1 Curriculum learning method

Input: *pacing function* g_ϑ, *scoring function* f, data $\mathbb{X}$.
Output: sequence of mini-batches $\left[\mathbb{B}_1', ..., \mathbb{B}_M'\right]$.
sort $\mathbb{X}$ according to f, in ascending order
$result \leftarrow []$
for all $i = 1, ..., M$ **do**
  $size \leftarrow g_\vartheta(i)$
  $\mathbb{X}_i' \leftarrow \mathbb{X}\left[1, ..., size\right]$
  uniformly sample $\mathbb{B}_i'$ from $\mathbb{X}'$
  append $\mathbb{B}_i'$ to $result$
end for
return $result$

Algorithm from Hacohen & Weinshall, "On the power of curriculum learning in deep networks", ICML 2019

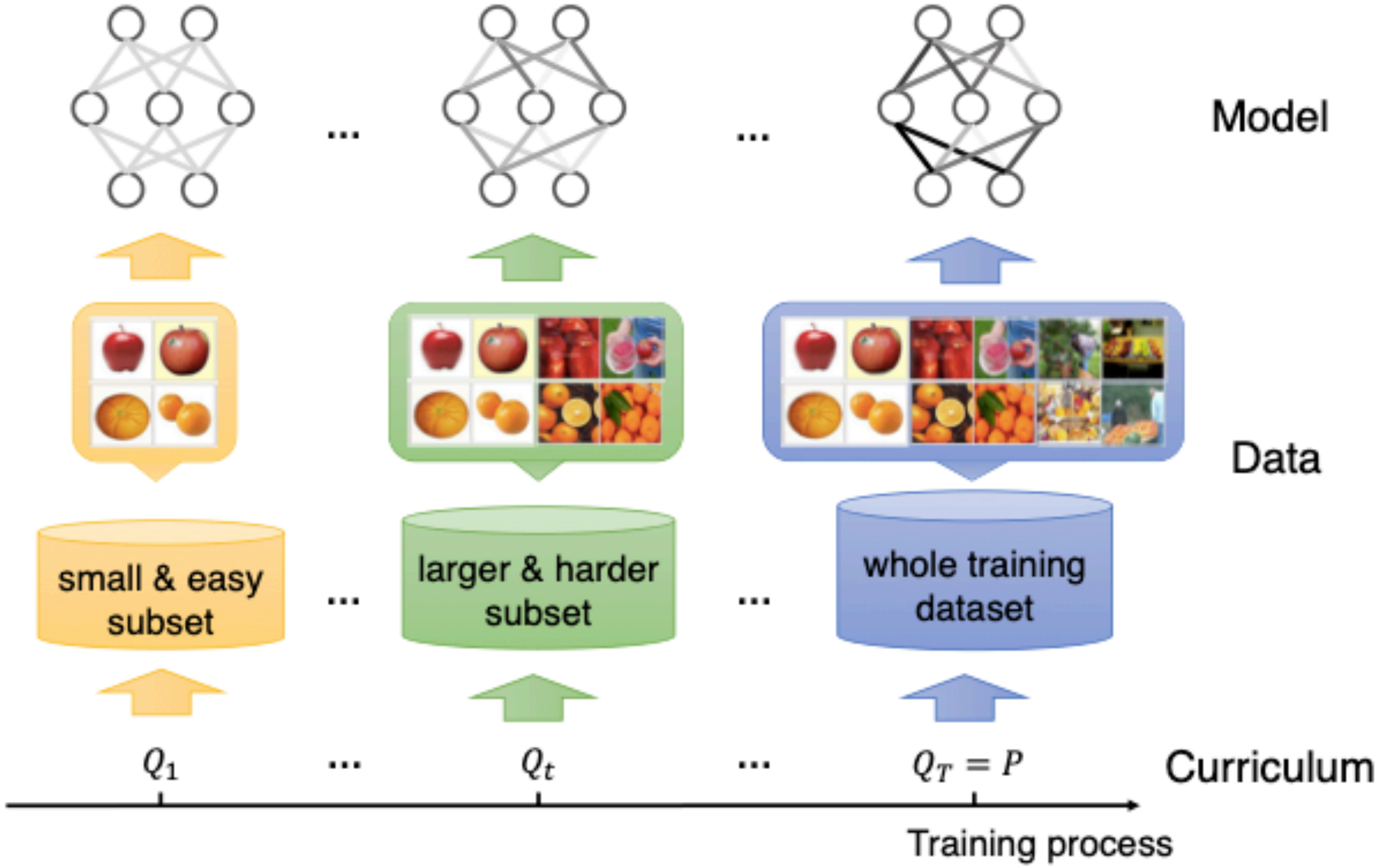
Curriculum learning

Let's start by considering a pre-defined curriculum, inspired by learning from "textbook style" content



Wang et al, "A Survey on Curriculum Learning", TPAMI 2021

Defining difficulty



If we want to define the curriculum up-front, according to prior knowledge, then:

what is an “**easy**” & what is a “**harder**” subset/dataset?

Wang et al, “A Survey on Curriculum Learning”, TPAMI 2021

Can you think of ways to define “difficulty”?

How to define difficulty

TABLE 2
Common types of predefined Difficulty Measurer. The "+" in ∝Easy means the higher the measured value, the easier the data example, and the "-" has the opposite meaning.

Difficulty Measurer*	Angle	Data Type	∝Easy
Sentence length [86], [107]	Complexity	Text	-
Number of objects [122]	Complexity	Images	-
# conj. [50], #phrases [113]	Complexity	Text	-
Parse tree depth [113]	Complexity	Text	-
Nesting of operations [131]	Complexity	Programs	-
Shape variability [6]	Diversity	Images	-
Word rarity [50], [86]	Diversity	Text	-
POS entropy [113]	Diversity	Text	-
Mahalanobis distance [14]	Diversity	Tabular	-
Cluster density [11], [31]	Noise	Images	+
Data source [10]	Noise	Images	/
SNR / SND [7], [89]	Noise	Audio	-
Grammaticality [66]	Domain	Text	+
Prototypicality [113]	Domain	Text	+
Medical based [44]	Domain	X-ray film	/
Retrieval based [18], [82]	Domain	Retrieval	/
Intensity [30] / Severity [111]	Intensity	Images	+
Image difficulty score [106], [114]	Annotation	Images	-
Norm of word vector [68]	Multiple	Text	-

Wang et al, "A Survey on Curriculum Learning", TPAMI 2021

Is difficulty task & model specific?

How to define difficulty

We have already seen that specific tasks allow for specific definitions of difficulty

Example: natural language translation (sentence length)

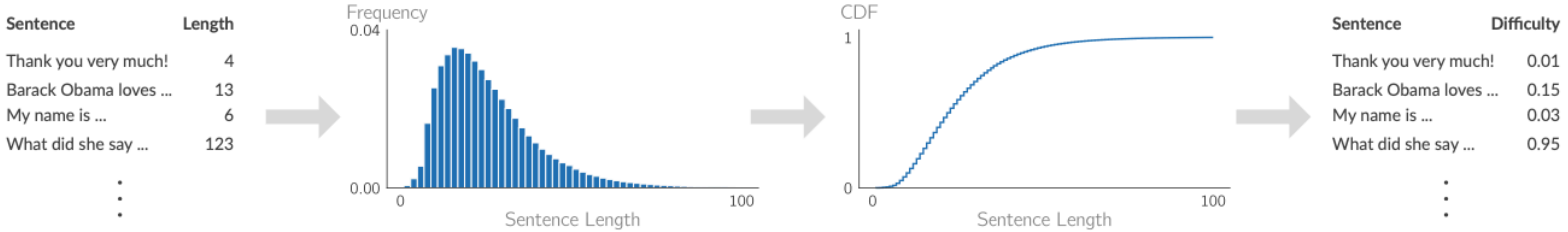


Figure 2: Example visualization of the preprocessing sequence used in the proposed algorithm. The histogram shown is that of sentence lengths from the WMT-16 En→De dataset used in our experiments. Here sentence lengths represent an example difficulty scoring function, *d*. "CDF" stands for the empirical "cumulative density function" obtained from the histogram on the left plot.

Platanios et al, "Competence based curriculum learning for neural machine translation", NAACL-HIT 2019

What is difficulty for a task?

We have already seen that specific tasks allow for specific definitions of difficulty

Example: image segmentation (entropy/clutter)

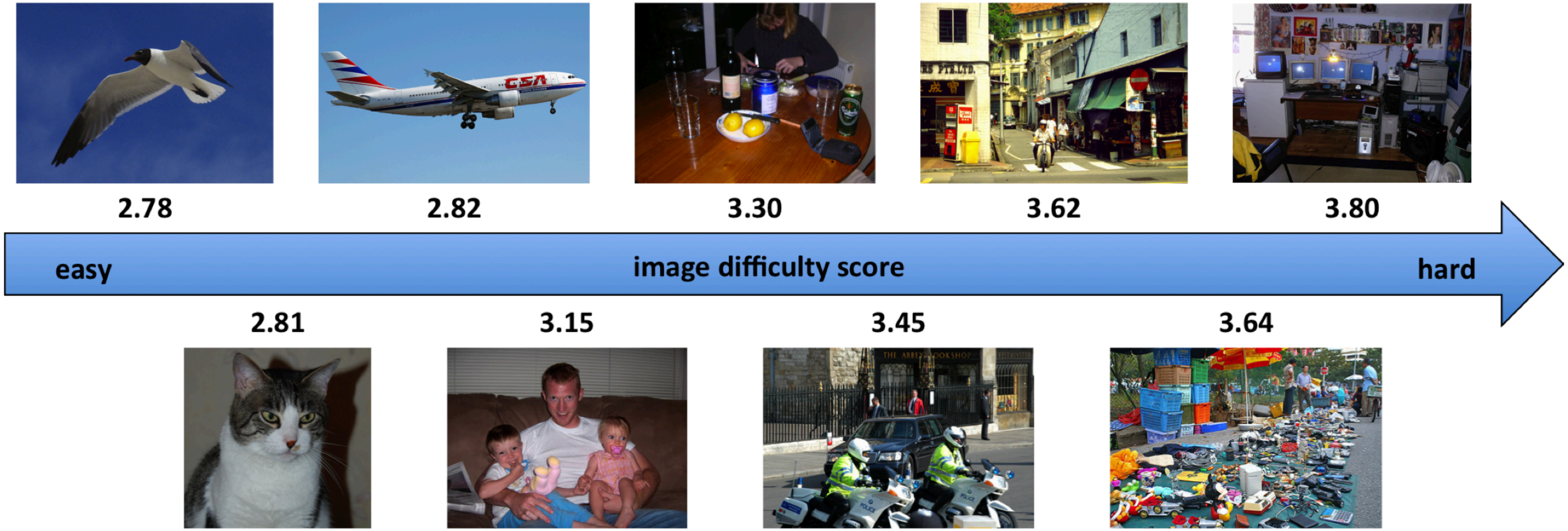


Figure 1. Images with difficulty scores predicted by our system in increasing order of their difficulty.

Ionescu et al, “How hard can it be? Estimating the difficulty of visual search in an image”, CVPR 2016

What is difficulty for a task?

There are various dimensions to difficulty, not just (basic) data statistics.

Especially if we think about factors that relate to what humans may find difficult

Compositional factors:

Size

"A sail boat on the ocean."

Location

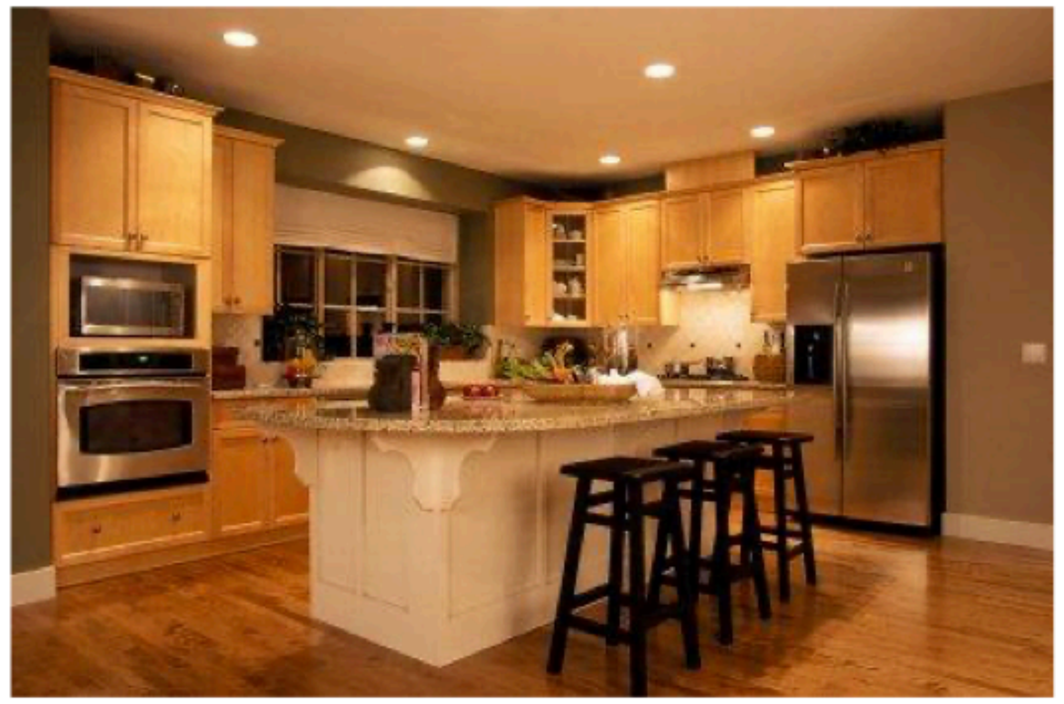
"Two men standing on beach."

Semantic factors:

Object Type

"Girl in the street"

Scene Type & Depiction Strength



"kitchen in house"

Context factors:

Unusual object-scene Pair

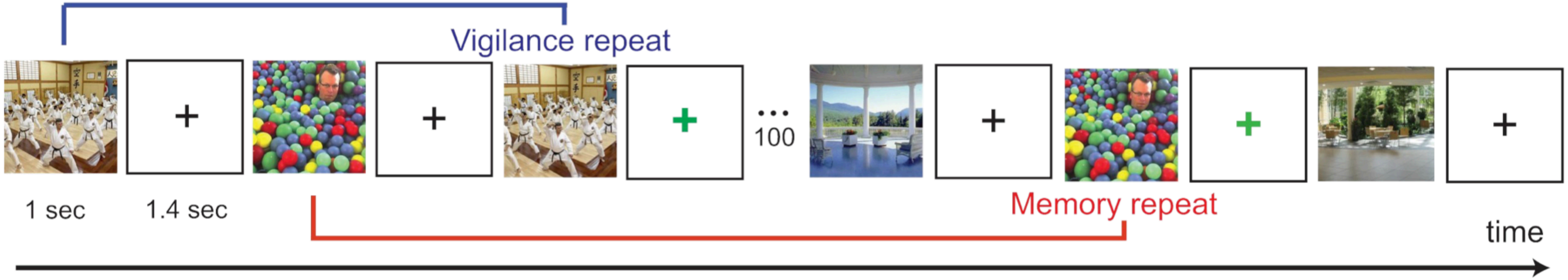
"A tree in water and a boy with a beard"

Berg et al, "Understanding and predicting importance in images", CVPR 2012

What is difficult for ML models?

But what is difficult for ML models & is this related to human perception?

Example: human memorability & image statistics



	Object Counts	Object Areas	Multiscale Object Areas	Object Label Presences	Labeled Object Counts	Labeled Object Areas	Labeled Multiscale Object Areas	Scene Category	Objects and Scenes	Other Humans
Top 20	68%	67%	73%	84%	82%	84%	84%	81%	85%	86%
Top 100	68%	68%	73%	79%	79%	82%	82%	78%	82%	84%
Bottom 100	67%	64%	64%	57%	57%	56%	56%	57%	55%	47%
Bottom 20	67%	63%	65%	55%	54%	53%	52%	55%	53%	40%
ρ	0.05	0.05	0.20	0.43	0.44	0.47	0.48	0.37	0.50	0.75

Table 1. Comparison of predicted versus measured memorabilities.

Isola et al, "What makes an image memorable", CVPR 2011

What is difficult for ML models?

But what is difficult for ML models & is this related to human perception?

Example: human response times

Collecting response times. We collected ground-truth difficulty annotations by human evaluators using the following protocol: (i) we ask each annotator a question of the type "Is there an {*object class*} in the next image?", where {*object class*} is one of the 20 classes included in the PASCAL VOC 2012; (ii) we show the image to the annotator; (iii) we record the time spent by the annotator to answer the question by "Yes" or "No". Finally, we use this response time to estimate the visual search difficulty.

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	Image property	Kendall τ
(i)	number of objects	0.32
(ii)	mean area covered by objects	-0.28
(iii)	non-centeredness	0.29
(iv)	number of different classes	0.33
(v)	number of truncated objects	0.22
(vi)	number of occluded objects	0.26
(vii)	number of difficult objects	0.20

Ionescu et al, "How hard can it be? Estimating the difficulty of visual search in an image", CVPR 2016

What is difficult for ML models?

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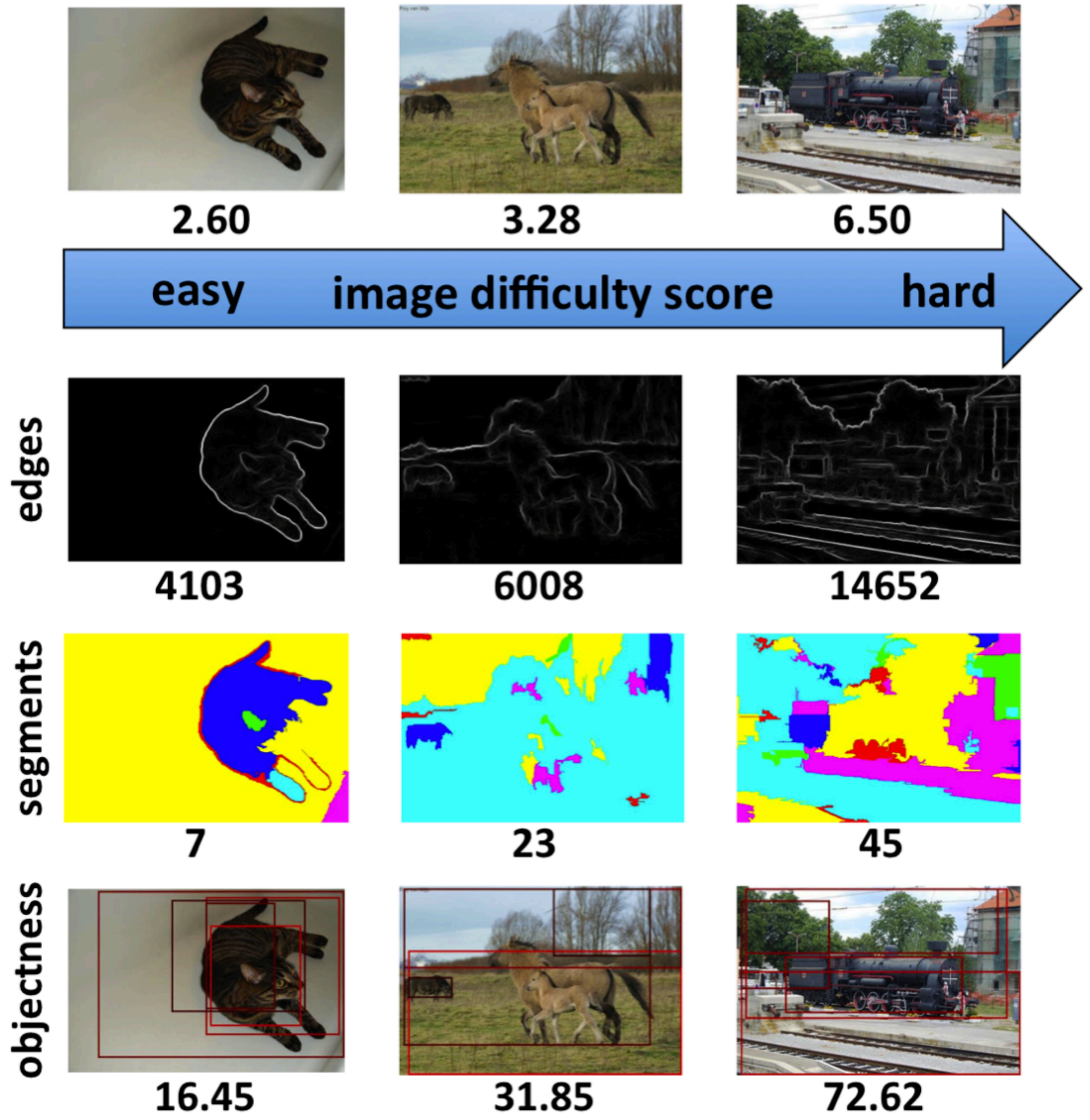
Human difficulty & model difficulty are not necessarily the same

Various factors come into play in ML models: a regression example



Model	MSE	Kendall τ
Random scores	0.458	0.002
Image area	-	0.052
Image file size	-	0.106
Objectness [1, 2]	-	0.238
Edge strengths [13]	-	0.240
Number of segments [16]	-	0.271
Combination with ν-SVR	0.264	0.299
VGG-f + KRR	0.259	0.345
VGG-f + ν-SVR	0.236	0.440
VGG-f + pyramid + ν-SVR	0.234	0.458
VGG-f + pyramid + flip + ν-SVR	0.233	0.459
VGG-vd + ν-SVR	0.235	0.442
VGG-vd + pyramid + ν-SVR	0.232	0.467
VGG-vd + pyramid + flip + ν-SVR	0.231	0.468
VGG-f + VGG-vd + pyramid + flip + ν-SVR	**0.231**	**0.472**

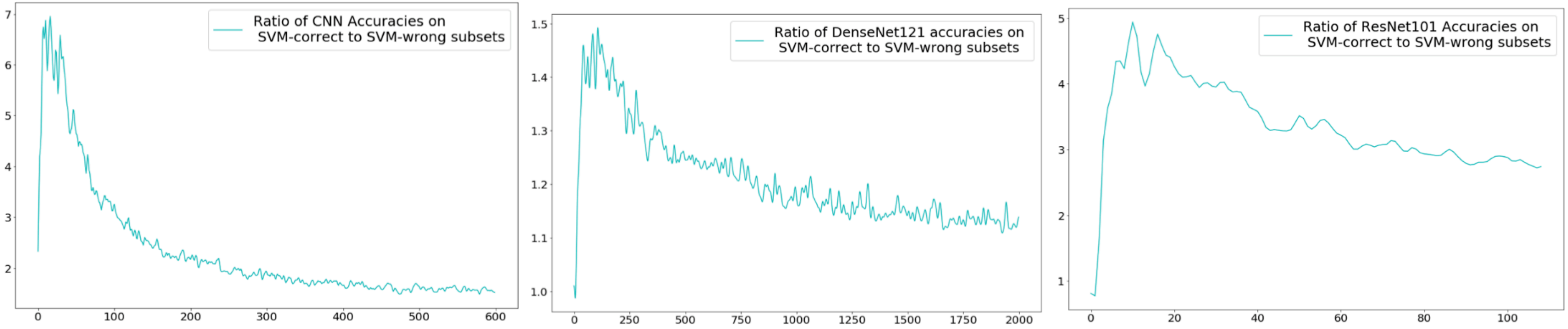
Ionescu et al, “How hard can it be? Estimating the difficulty of visual search in an image”, CVPR 2016

What is difficult for ML models?

Various factors come into play in ML models

Example: shallow embeddable examples seem to be learned first

A deep network in comparison to a SVM (random forest also in the paper)



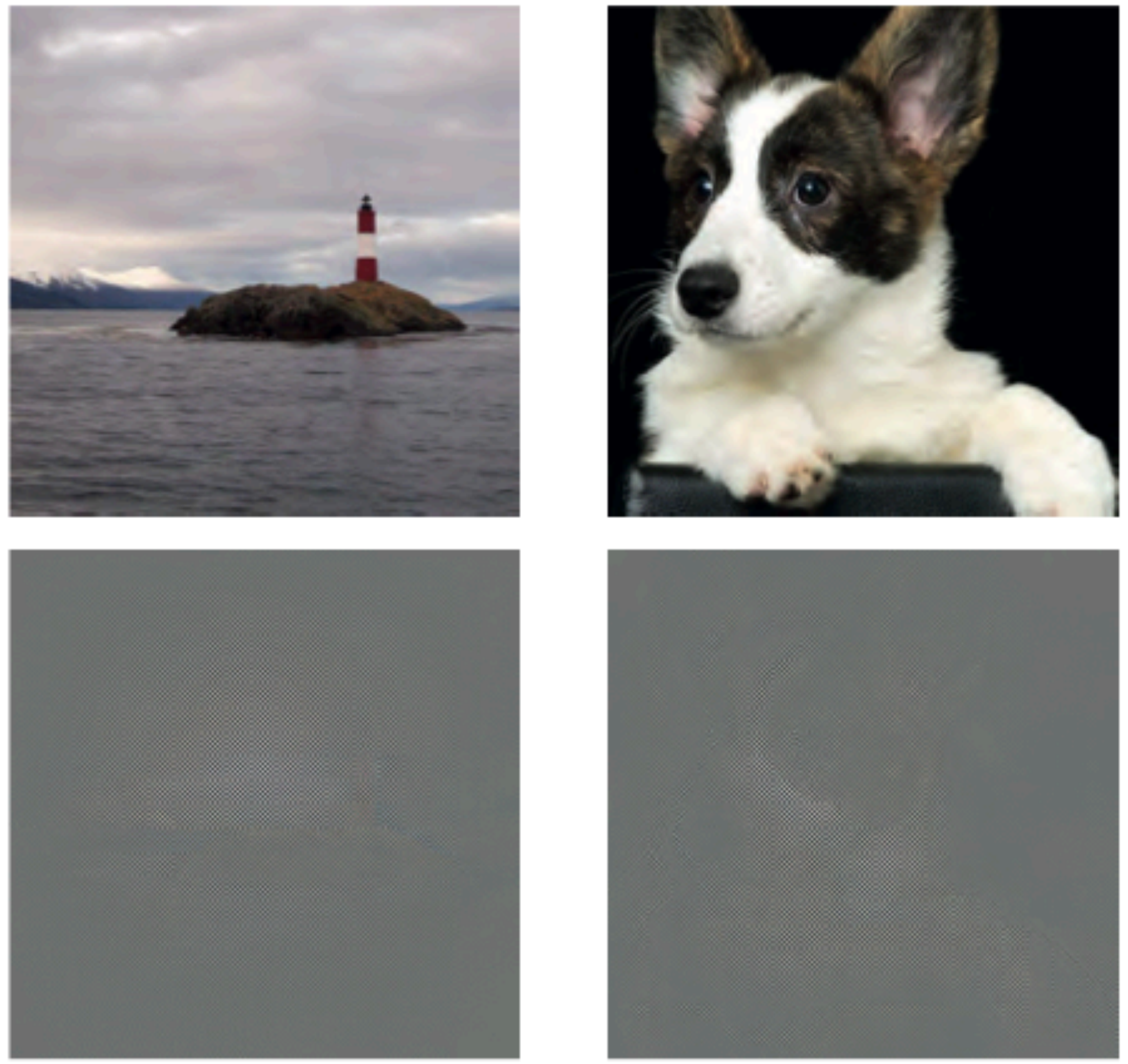
Ratio of Accuracies $\mathtt{R}^{\mathtt{i}}$ plotted against i with $\mathcal{M}$ being a Support Vector Machine.

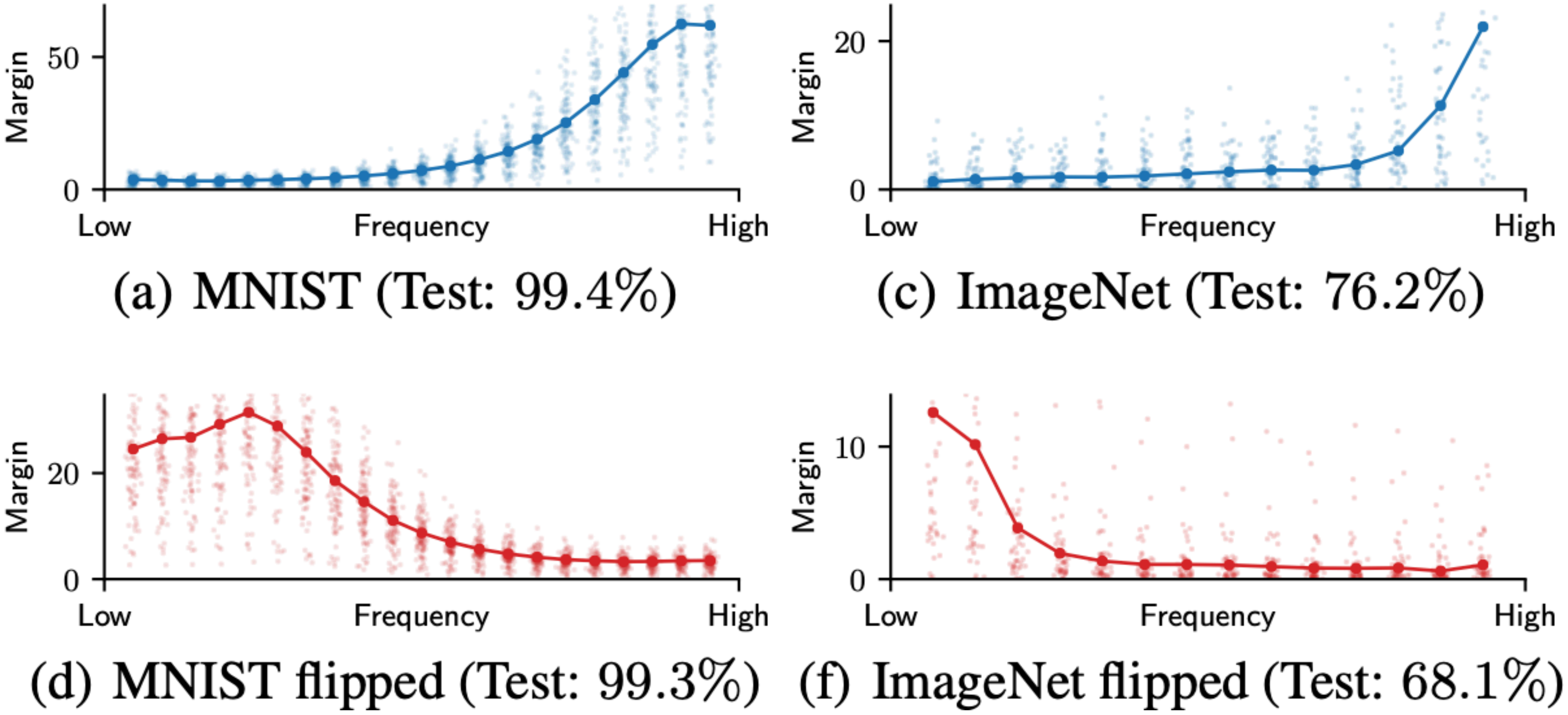
Mangalam & Prabhu, “Do deep neural networks learn shallow learnable examples first?”, ICML 2019 workshop on identifying and understanding deep learning phenomena

What is difficult for ML models?

Various factors come into play in ML models

Example: invariance to certain discriminative factors (e.g. frequencies) may exist



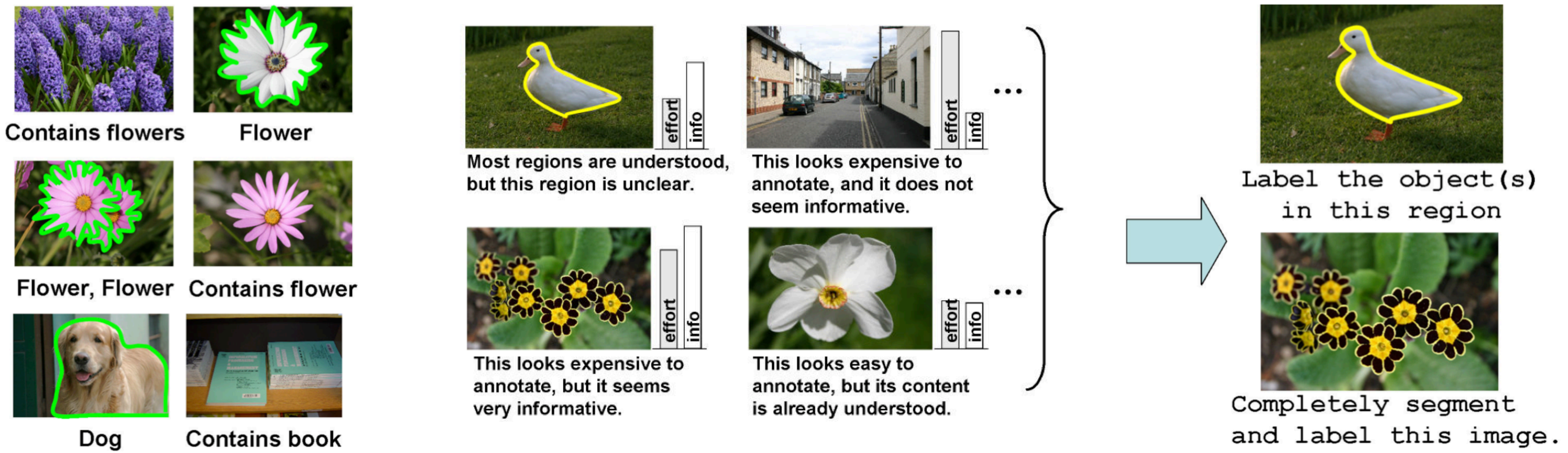


Ortiz-Jimenéz et al, “Hold me tight! Influence of discriminative features on deep network boundaries”, NeurIPS 2020

Beyond curriculum learning

Assessing difficulty of data instances is interesting beyond curriculum learning

Example: estimating the difficulty with respect to annotation cost



(a) Labeled (and partially labeled) examples to build models

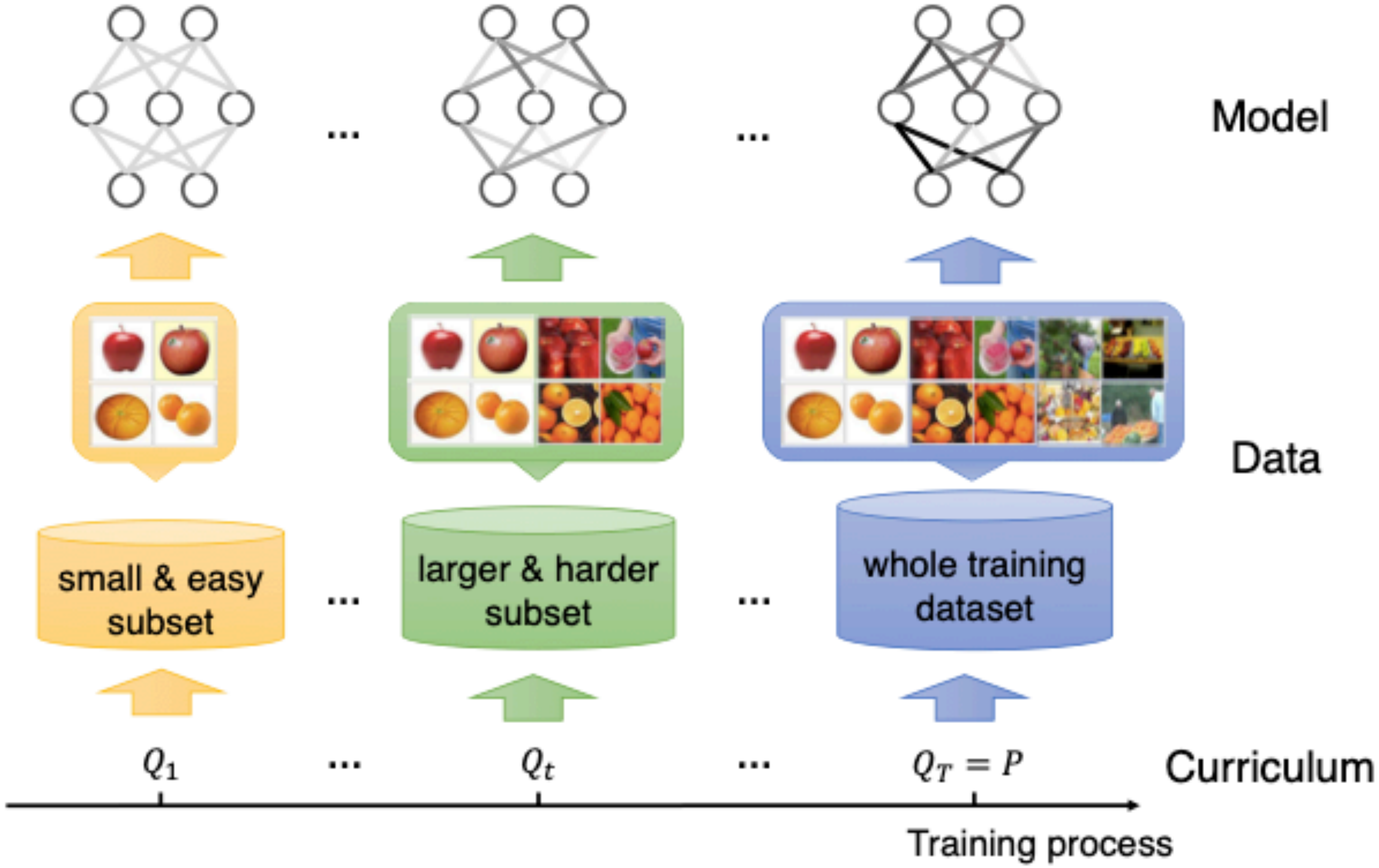
(b) Unlabeled and partially labeled examples to survey

(c) Actively chosen queries sent to annotators

Vijayanarasimhan & Grauman, "What's It Going to Cost You?: Predicting Effort vs. Informativeness for Multi-Label Image Annotations", CVPR 2009

Pacing: how to schedule the training

Scheduling training



Wang et al, “A Survey on Curriculum Learning”, TPAMI 2021

If we want to define the curriculum up-front, according to prior knowledge, then:

When do we introduce more difficult examples?

Pacing functions

Various options & heuristics are conceivable

Algorithm 1 One-Pass Curriculum

procedure OP-CURRICULUM(M,$\mathcal{D}$, $\mathcal{C}$)
  $\mathcal{D}' = \text{sort}(\mathcal{D}, \mathcal{C})$
  $\{\mathcal{D}^1, \mathcal{D}^2, ..., \mathcal{D}^k\} = \mathcal{D}'$ where $\mathcal{C}(d_a) < \mathcal{C}(d_b)$ $d_a \in D^i$, $d_b \in D^j, \forall i < j$
  for $s = 1...k$ **do**
    while not converged for p epochs **do**
      train(M, $\mathcal{D}^s$)
    end while
  end for
end procedure

Algorithm from Cirik et al, “Visualizing and understanding curriculum learning for long short-term memory networks”, arXiv, 2016
Based on the procedure described in Bengio et al, “Curriculum Learning”, ICML 2009

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Based on the procedure described in Bengio et al, “Curriculum Learning”, ICML 2009

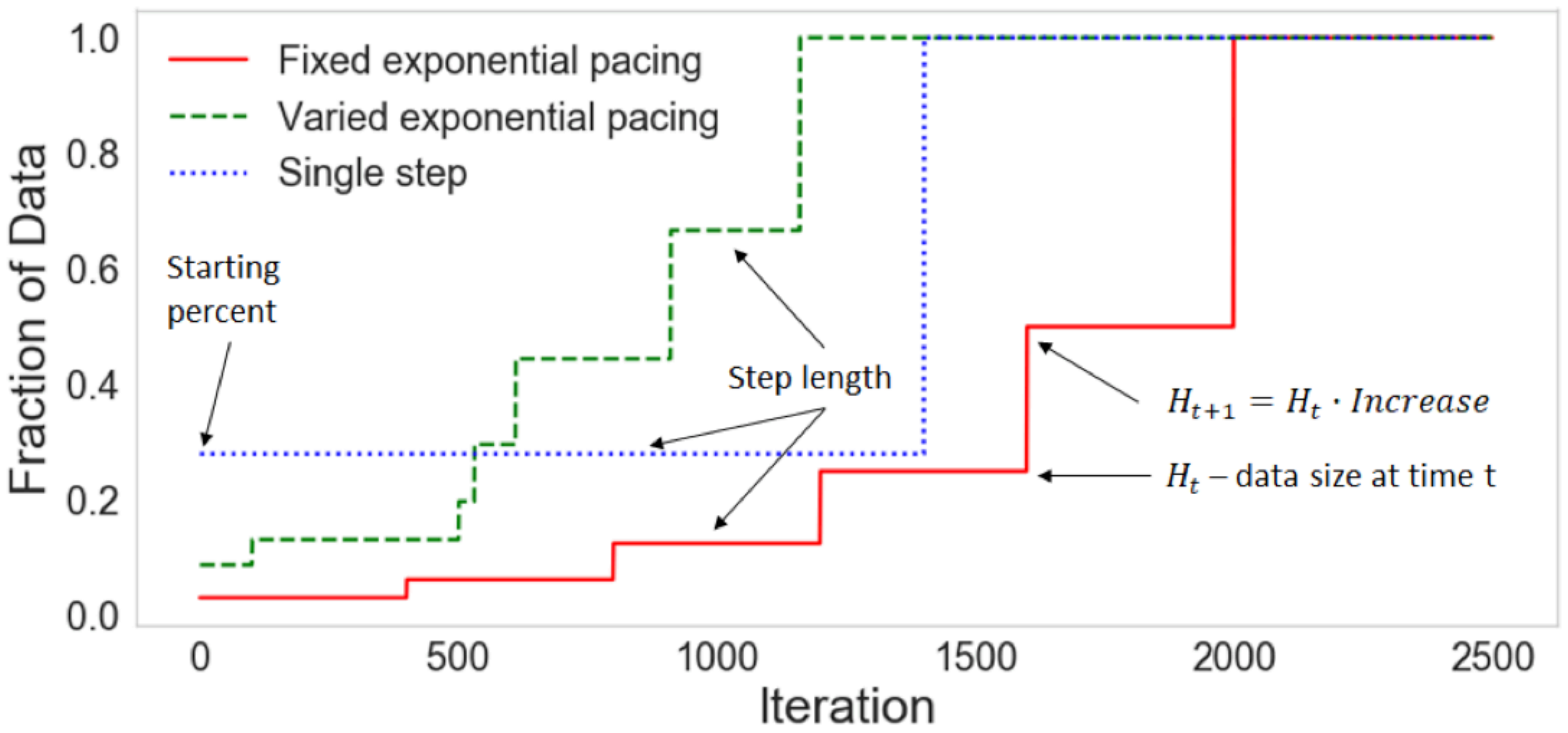
Algorithm 2 Baby Steps Curriculum

procedure BS-CURRICULUM(M,$\mathcal{D}$, $\mathcal{C}$)
    $\mathcal{D}' = \text{sort}(\mathcal{D}, \mathcal{C})$
    $\{\mathcal{D}^1, \mathcal{D}^2, ..., \mathcal{D}^k\} = \mathcal{D}'$ where $\mathcal{C}(d_a) < \mathcal{C}(d_b)$ $d_a \in D^i$, $d_b \in D^j, \forall i < j$
    $\mathcal{D}^{train} = \emptyset$
    for $s = 1...k$ **do**
        $\mathcal{D}^{train} = \mathcal{D}^{train} \cup \mathcal{D}^s$
        while not converged for p epochs **do**
            train(M, $\mathcal{D}^{train}$)
        end while
    end for
end procedure

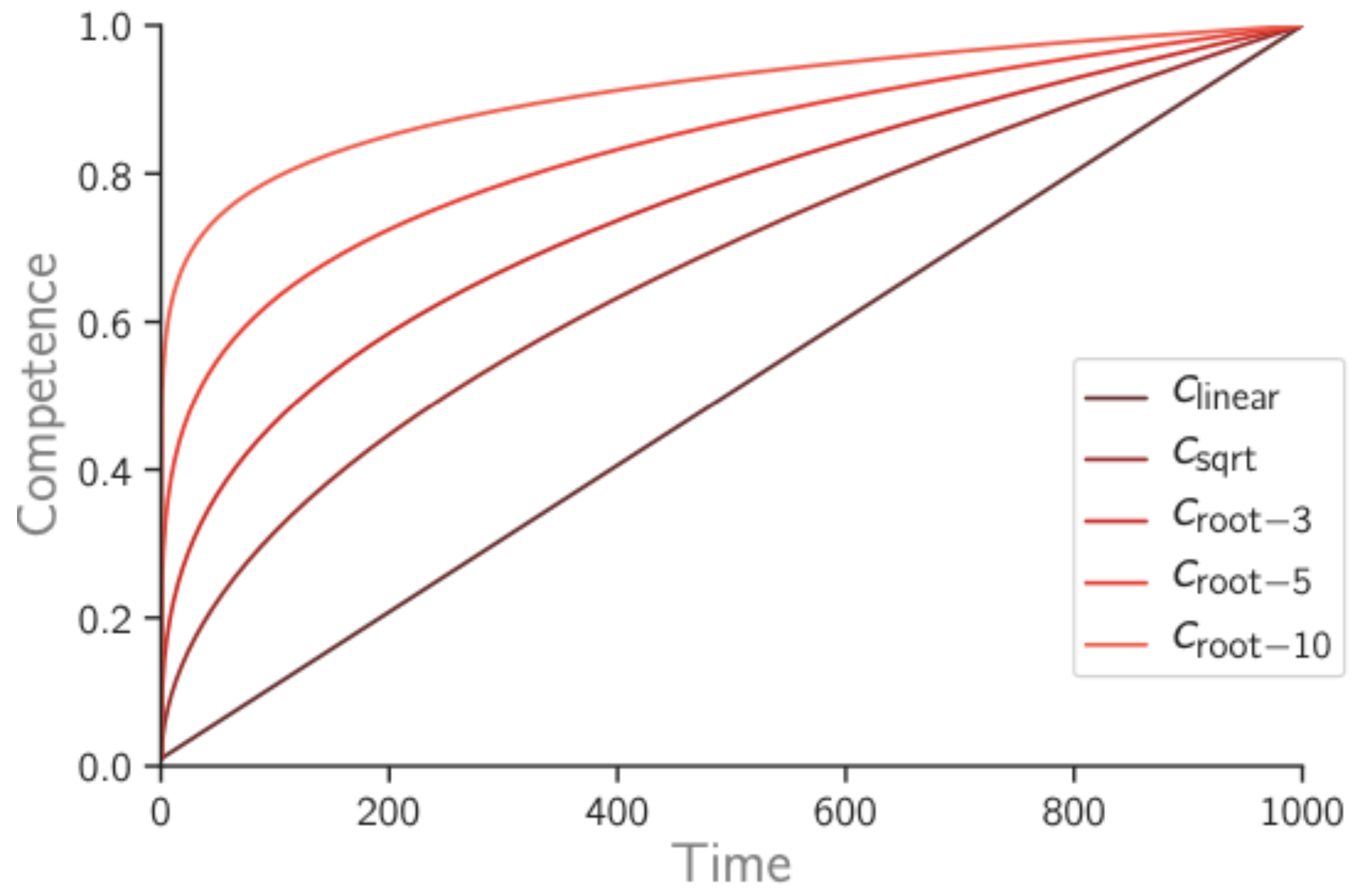
Algorithm from Cirik et al, “Visualizing and understanding curriculum learning for long short-term memory networks”, arXiv, 2016
Based on the procedure described in Spitkovsky et al, “From baby steps to leapfrogs: how less is more in unsupervised dependency parsing”, NAACL-HLT, 2010

Pacing functions

Various options & heuristics are conceivable



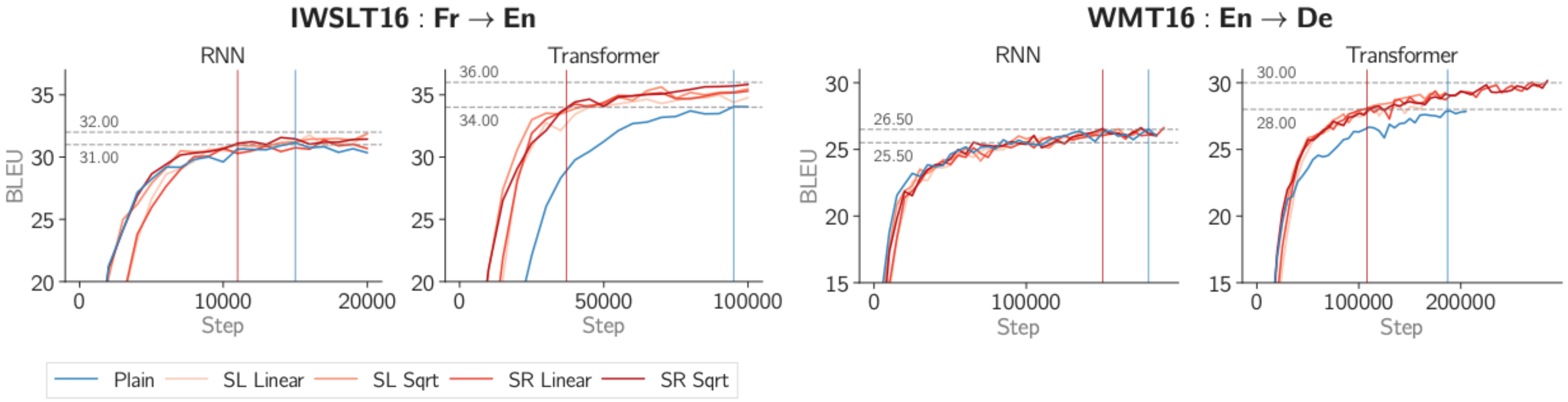
Hacohen & Weinshall, “On the power of curriculum learning in deep networks”, ICML 2019



Platanios et al, “Competence based curriculum learning for neural machine translation”, NAACL-HLT 2019

Pacing functions

It's not straightforward to choose, especially due to model/task dependency



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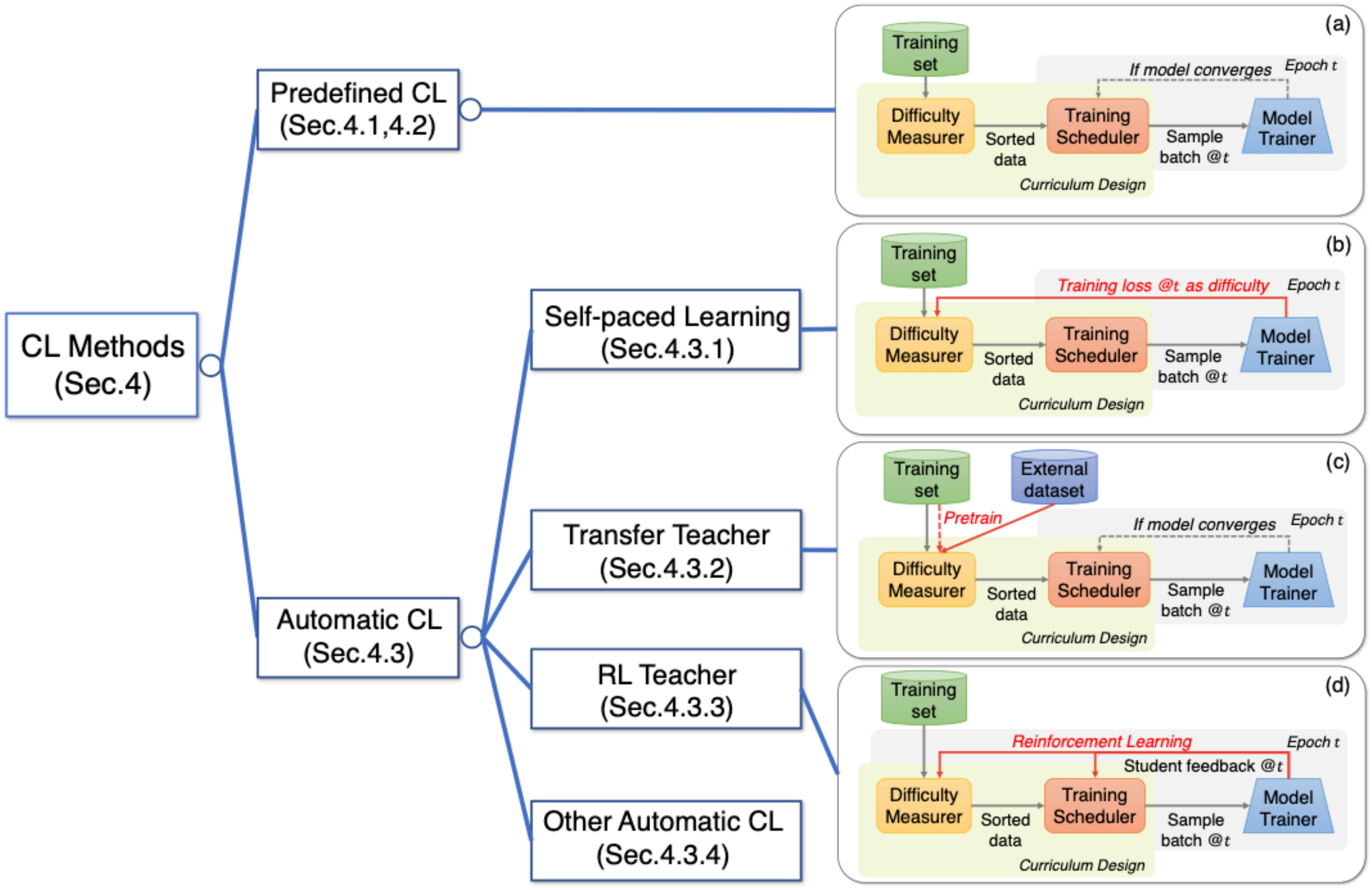
Moving away from a pre-defined curriculum

Beyond pre-defined curricula



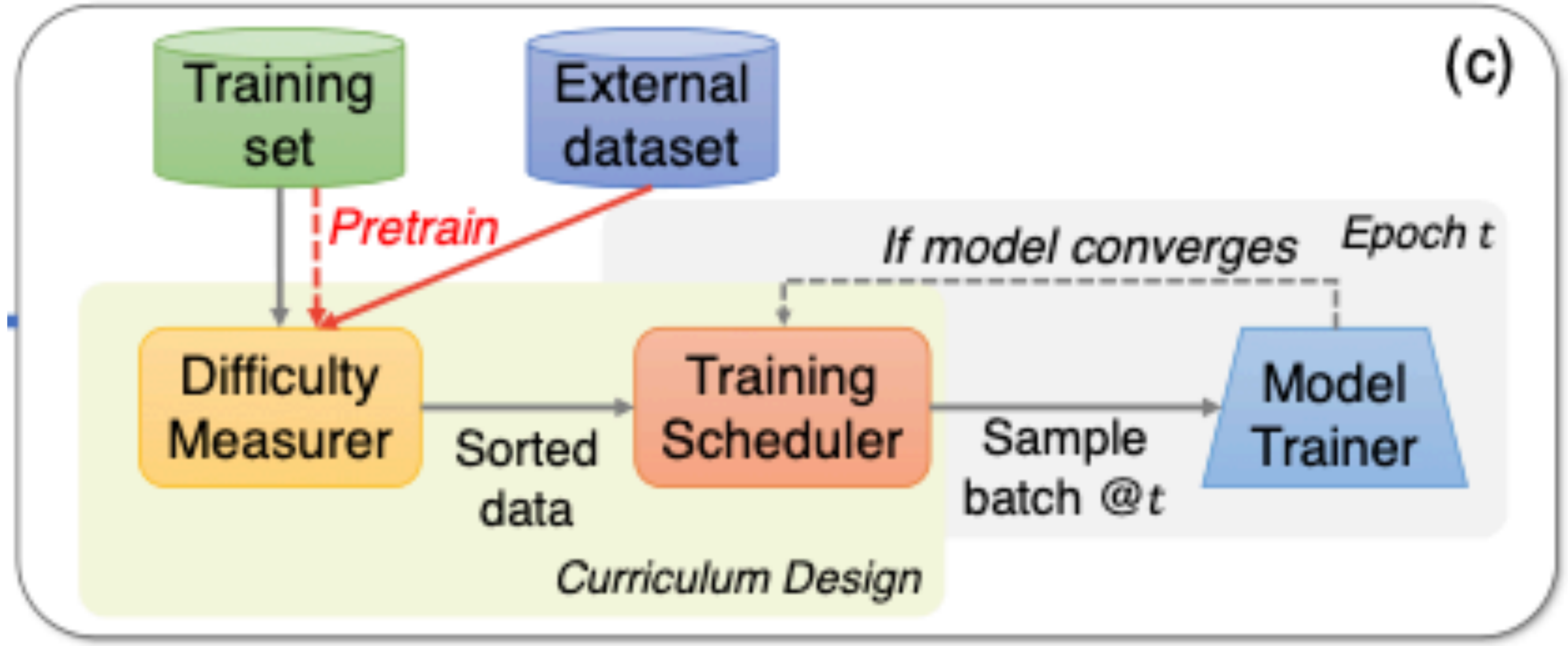
What we just talked about

What we'll consider next

Wang et al, "A Survey on Curriculum Learning", TPAMI 2021

Transfer-teacher curricula

Instead of defining the curriculum ourselves, we could use a pre-trained teacher model (based on a different related dataset) based difficulty measure



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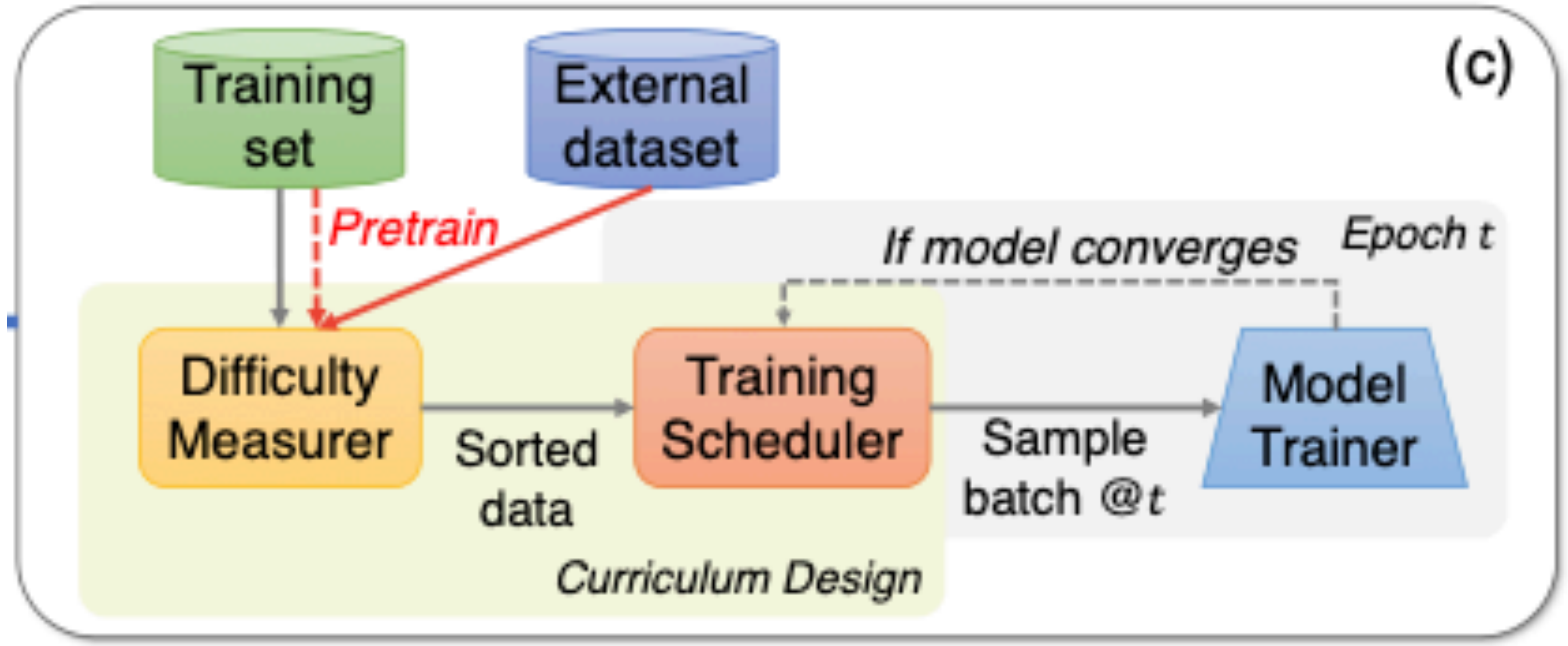


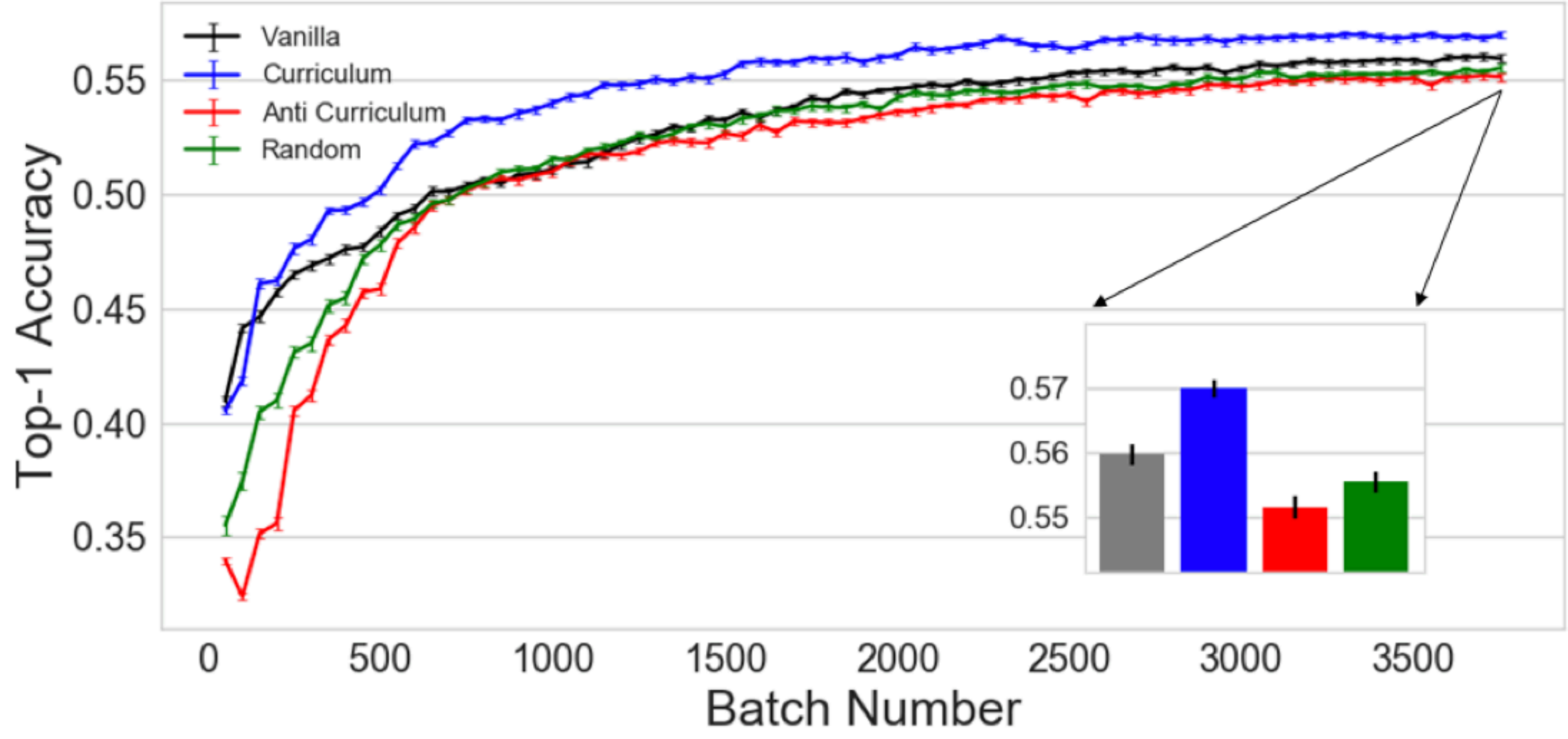


Figure 2. Results in **case 1**, with Inception-based *transfer scoring function* and *fixed exponential pacing function*.

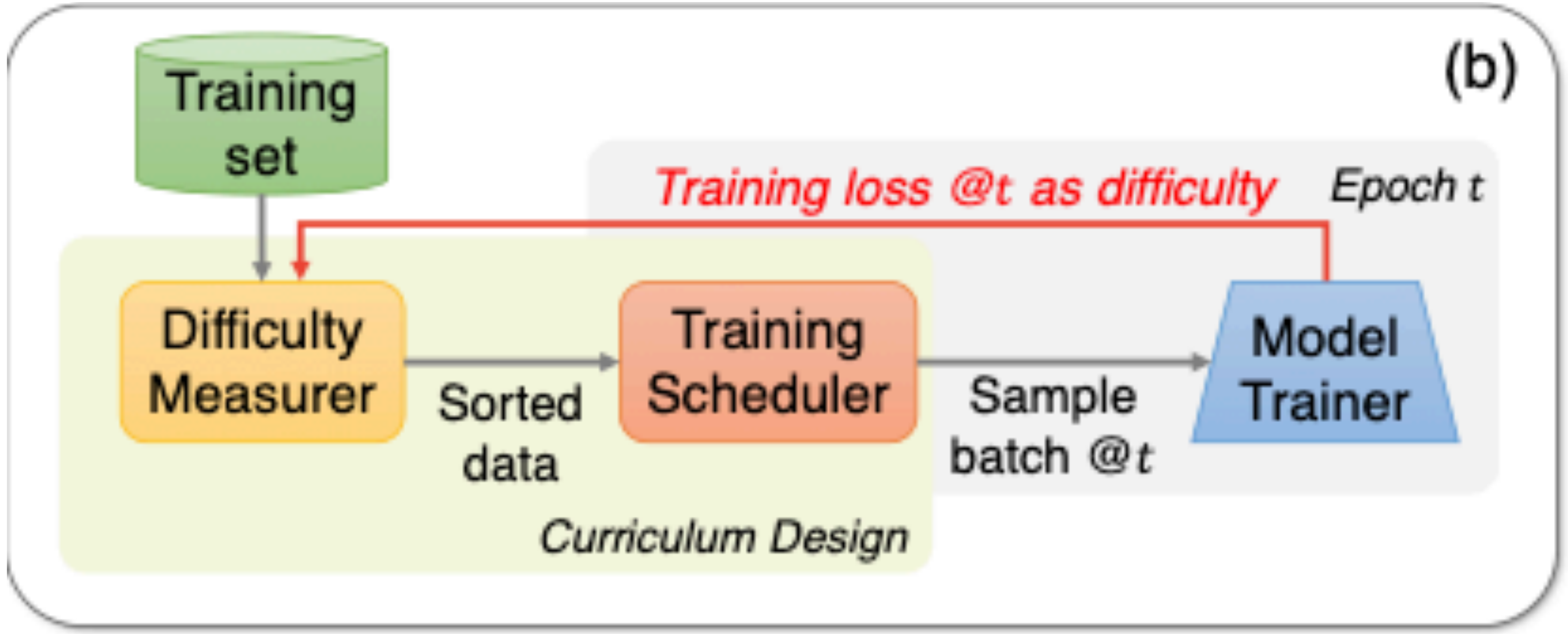
Wang et al, “A Survey on Curriculum Learning”, TPAMI 2021

Hacohen & Weinshall, “On the power of curriculum learning in deep networks”, ICML 2019

From pre-defined to self-paced

Using a teacher is still a form of pre-defined curriculum however, what if we want to have an adaptive measure of difficulty, based on our current model?

Moving away from a pre-defined curriculum towards model "competence"



Wang et al, "A Survey on Curriculum Learning", TPAMI 2021

From pre-defined to self-paced

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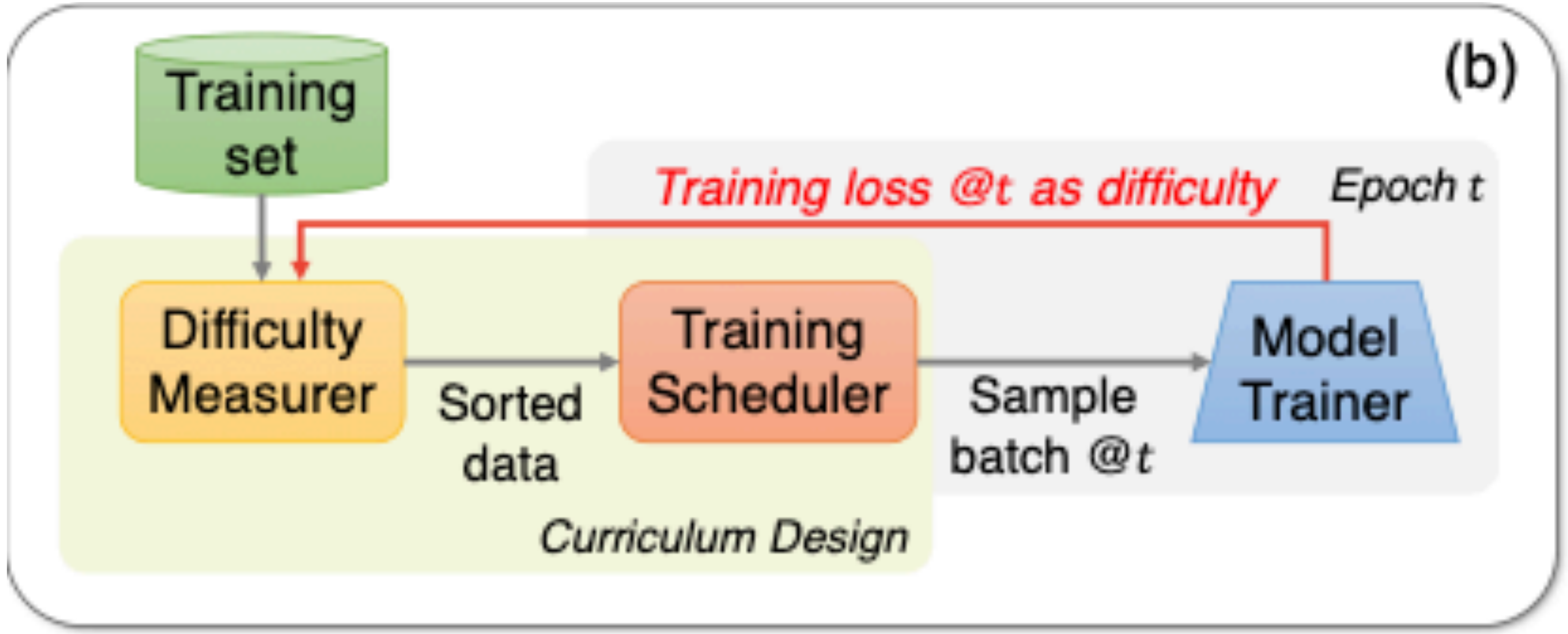
Often this is called self-paced learning

We now rely on the model's current hypothesis at each point in time to assign difficulty to the training instances, rather than ranking according to the target hypothesis.



Wang et al, "A Survey on Curriculum Learning", TPAMI 2021

Self-paced & self-taught

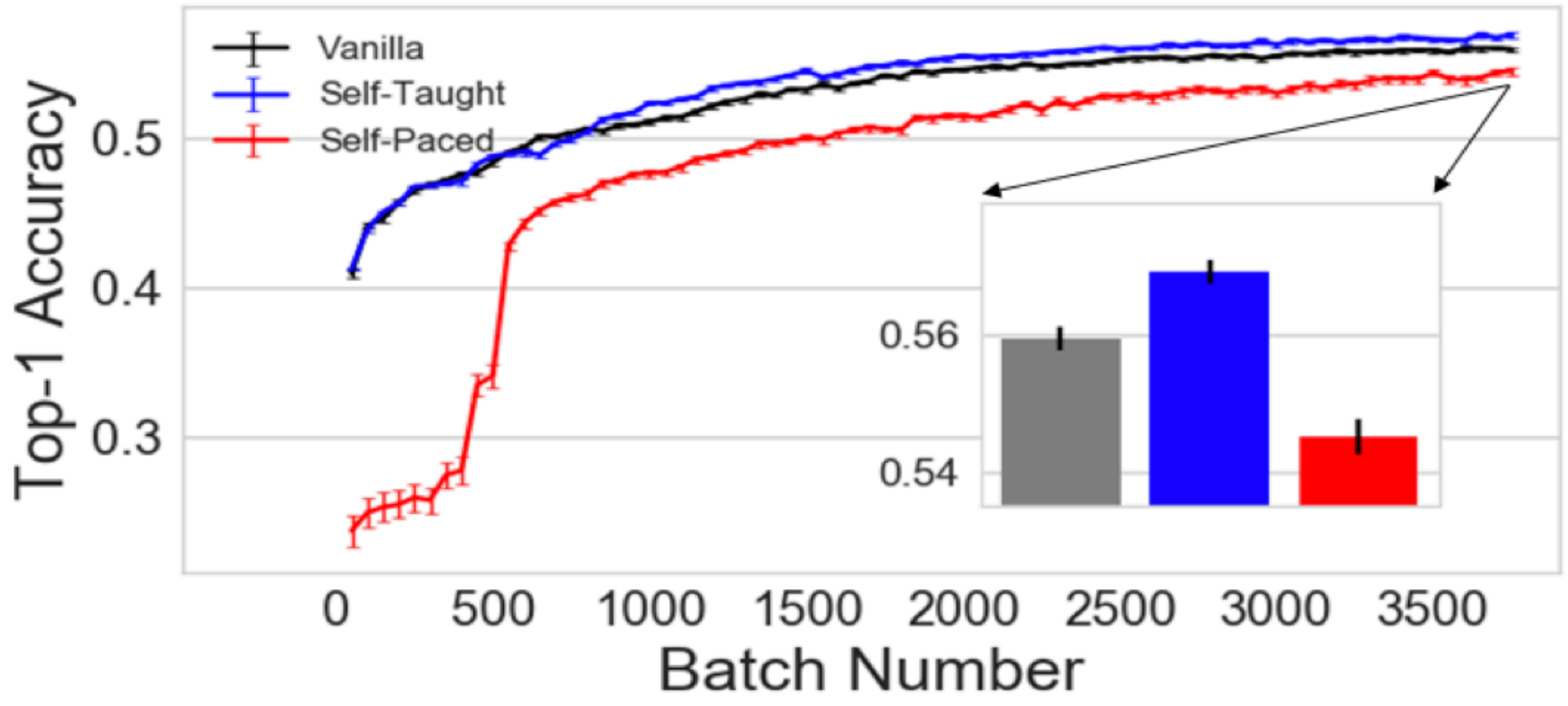
Somewhat related to what we've already seen

Self-paced learning:

Measure the difficulty of an instance according to current loss/predictions etc. (related to the ideas in *active learning*)

Self-taught learning:

Train a model fully, measure each instance according to final model, assign difficulty score and start over with curriculum -> repeat (related to the ideas in *boosting*)



Hacohen & Weinshall, "On the power of curriculum learning in deep networks", ICML 2019

Does intrinsic ordering/pacing exist?

If we can use the loss of a model as a measure of difficulty, does this perhaps mean that models “intrinsically order” examples during regular training to some degree as well?

Intrinsic ordering & pacing?

An experiment: let's train multiple models & check how similar representations are

Why is this interesting?

Recall that we typically use mini-batches + stochastic gradient descent,

where data is shuffled differently in every "epoch"

Intrinsic ordering & pacing?

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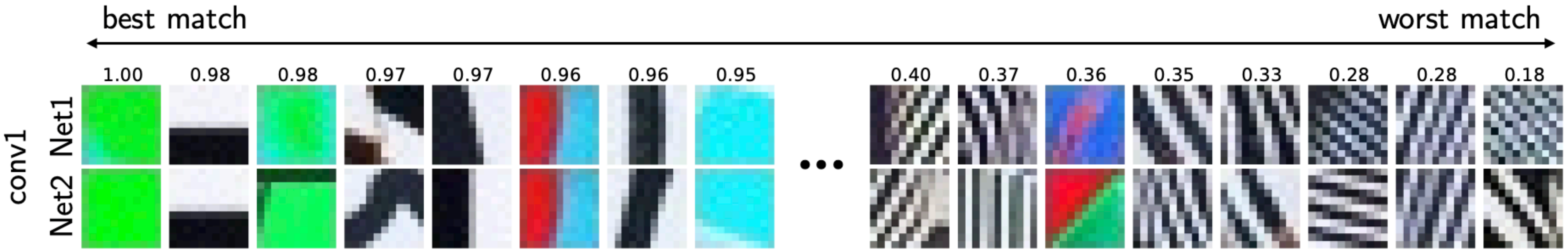
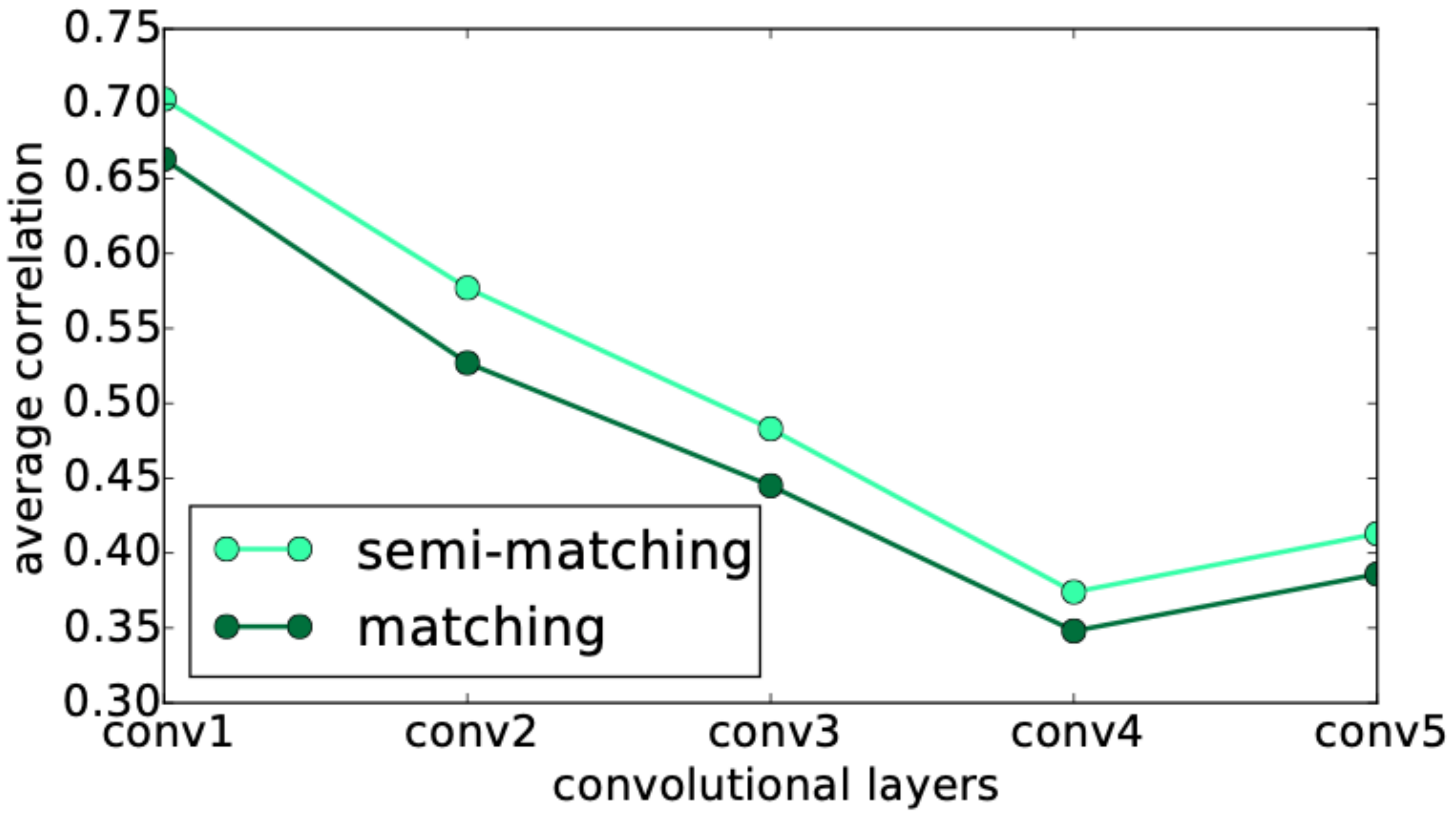


Li & Yosinski et al, "Convergent learning: do different neural networks learn the same representations", ICLR 2016

Intrinsic ordering & pacing?

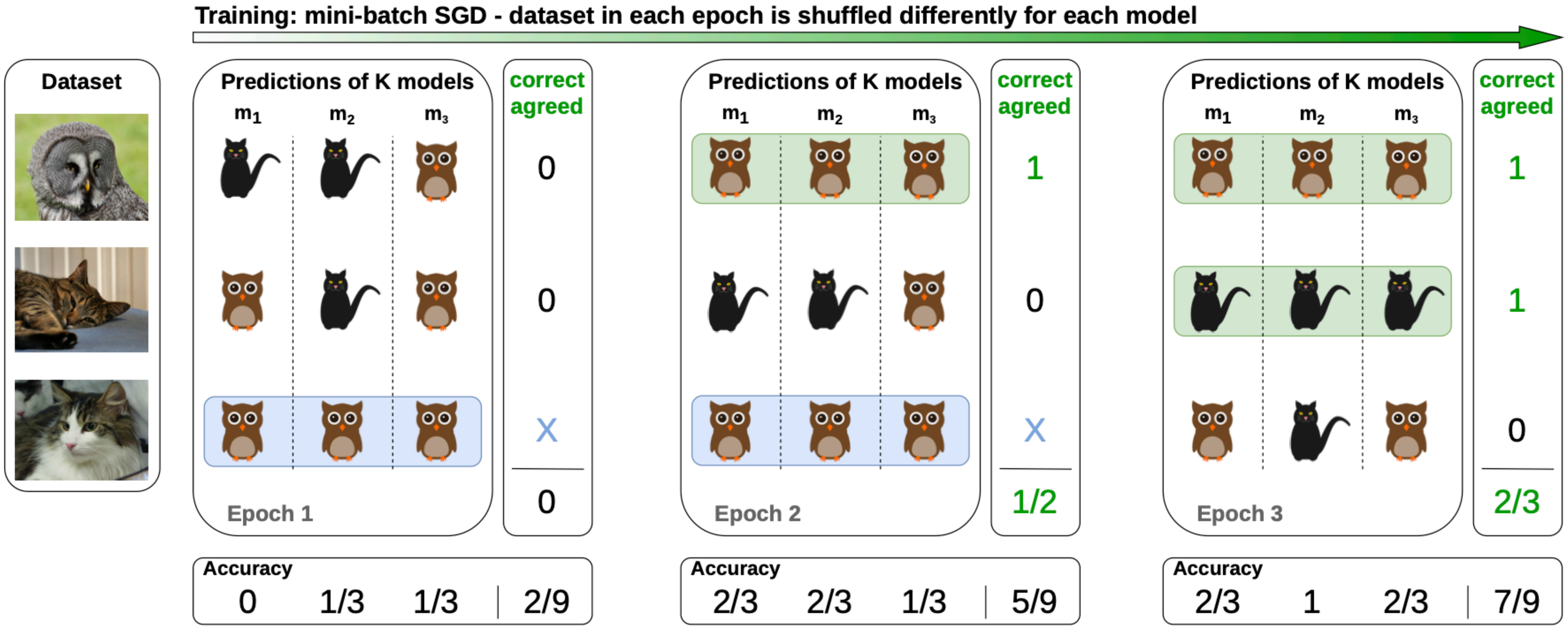
If we try to do a bi-partite matching of the representations in each neural network layer of different networks, there seem to exist strong correlations, especially in early, “generic” features



Li & Yosinski et al, “Convergent learning: do different neural networks learn the same representations”, ICLR 2016

Intrinsic ordering & pacing?

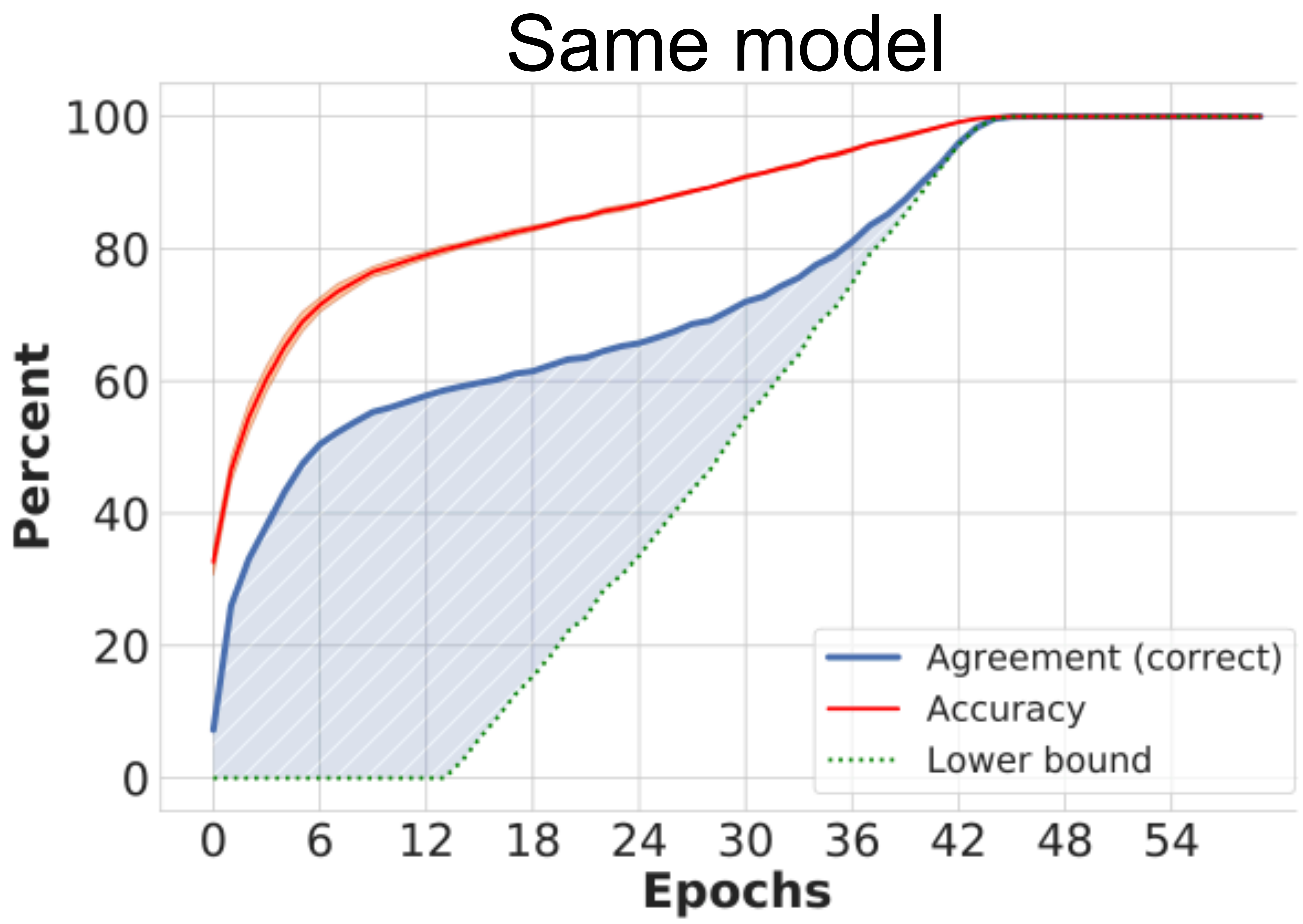
A step further: let's train multiple models & check how much they agree on instances

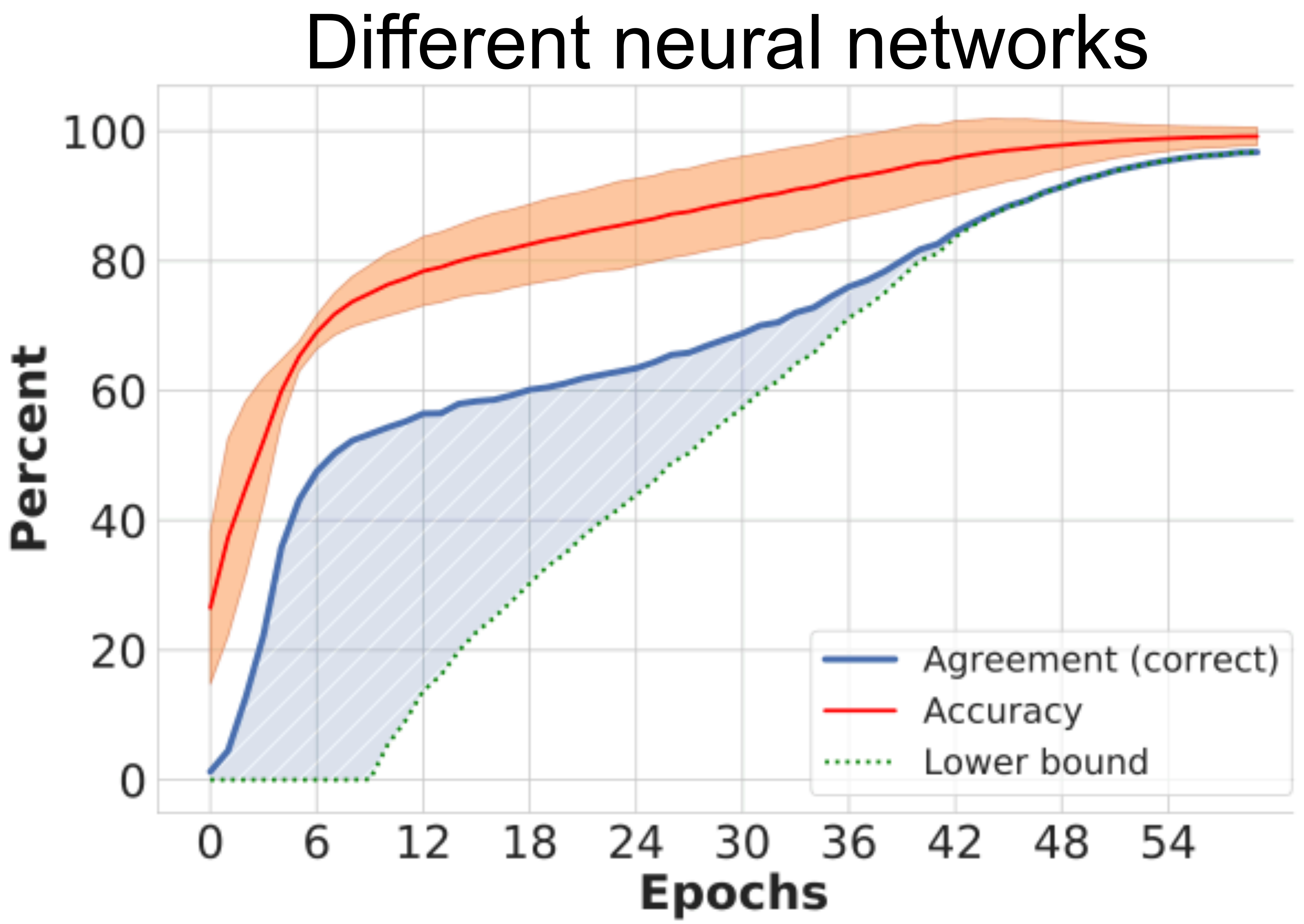


Pliushch et al, "When Deep Classifiers Agree: Analyzing correlations between learning order and image statistics", ECCV 2022
As a reproduction & extension to the earlier Hacohen et al, "Let's agree to agree: neural networks share classification order on on real datasets", ICML 2020

Intrinsic ordering & pacing?

Different neural networks seem to classify the same instances correctly at similar points in training: they "agree to agree"



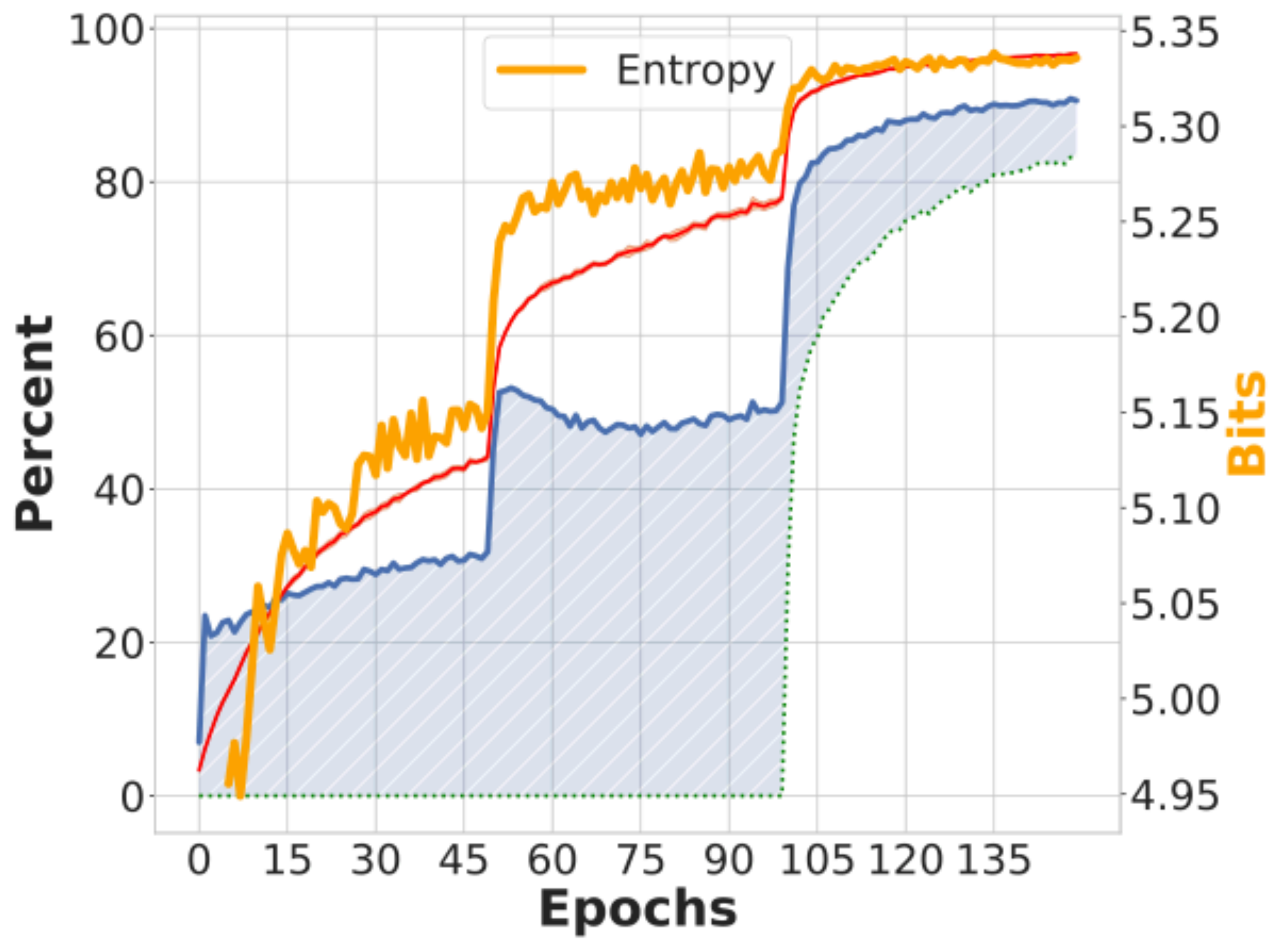


Pliushch et al, "When Deep Classifiers Agree: Analyzing correlations between learning order and image statistics", ECCV 2022
As a reproduction & extension to the earlier Hacohen et al, "Let's agree to agree: neural networks share classification order on on real datasets", ICML 2020

An outlook to closing the circle

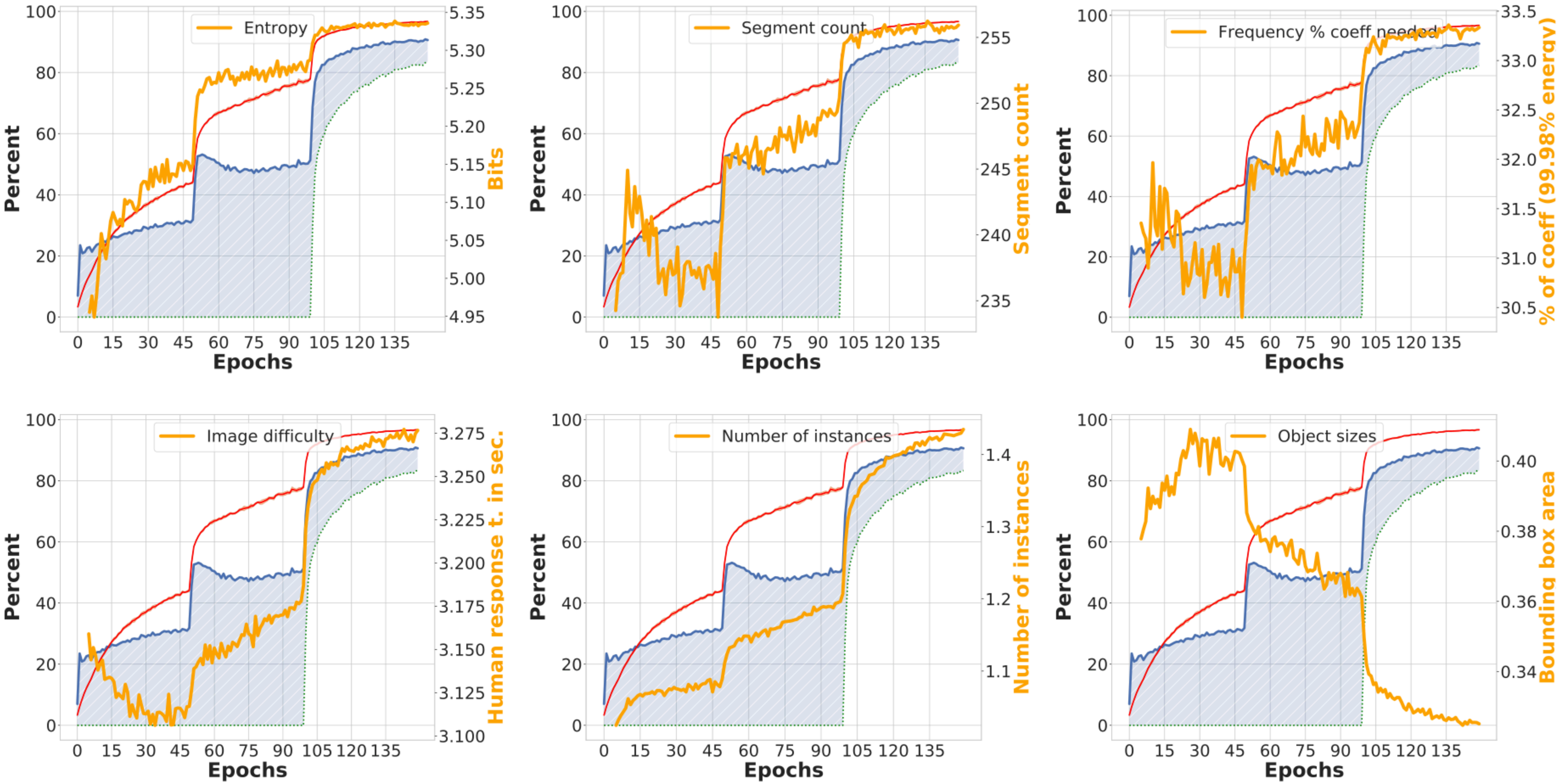
Could such inherent agreement be related to our notions of difficulty?

NN training, order & difficulty



Pliushch et al, “When Deep Classifiers Agree: Analyzing correlations between learning order and image statistics”, ECCV 2022

NN training, order & difficulty

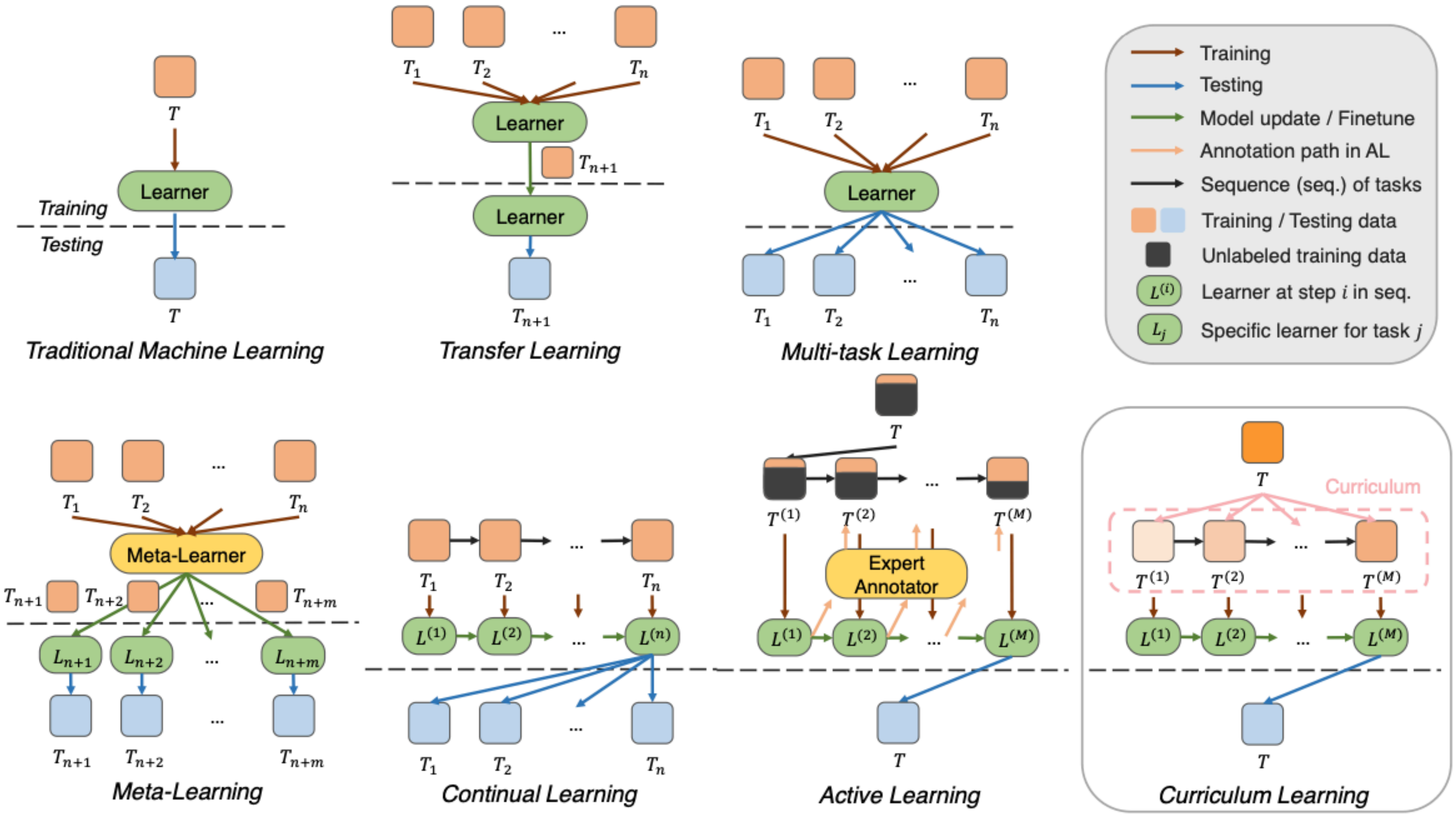


Pliushch et al, “When Deep Classifiers Agree: Analyzing correlations between learning order and image statistics”, ECCV 2022

As always: a disclaimer
there’s much we don’t yet know

And a final note =)

It's about set-up & evaluation



Wang et al, "A Survey on Curriculum Learning", TPAMI 2021