Pearls from Pebbles: Improved Confidence Functions for Auto-labeling

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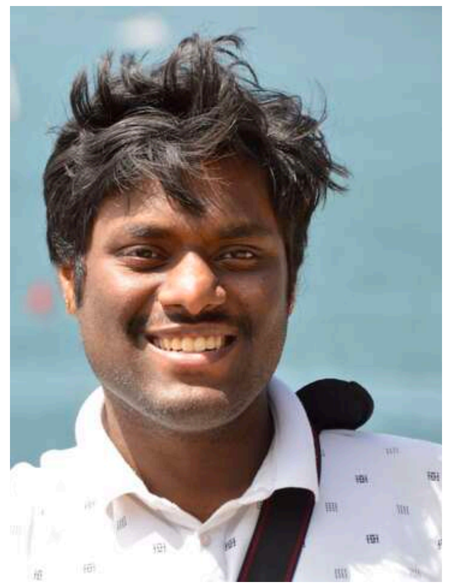
Harit Vishwakarma
CS Ph.D. Candidate

Advisors
Prof. Fred Sala
Prof. Ramya Korlakai Vinayak

NEURAL INFORMATION PROCESSING SYSTEMS

WISCONSIN
UNIVERSITY OF WISCONSIN–MADISON

Yi (Reid) Chen
ECE Ph.D. Student



Srinath Namburi
CS Masters -> GE

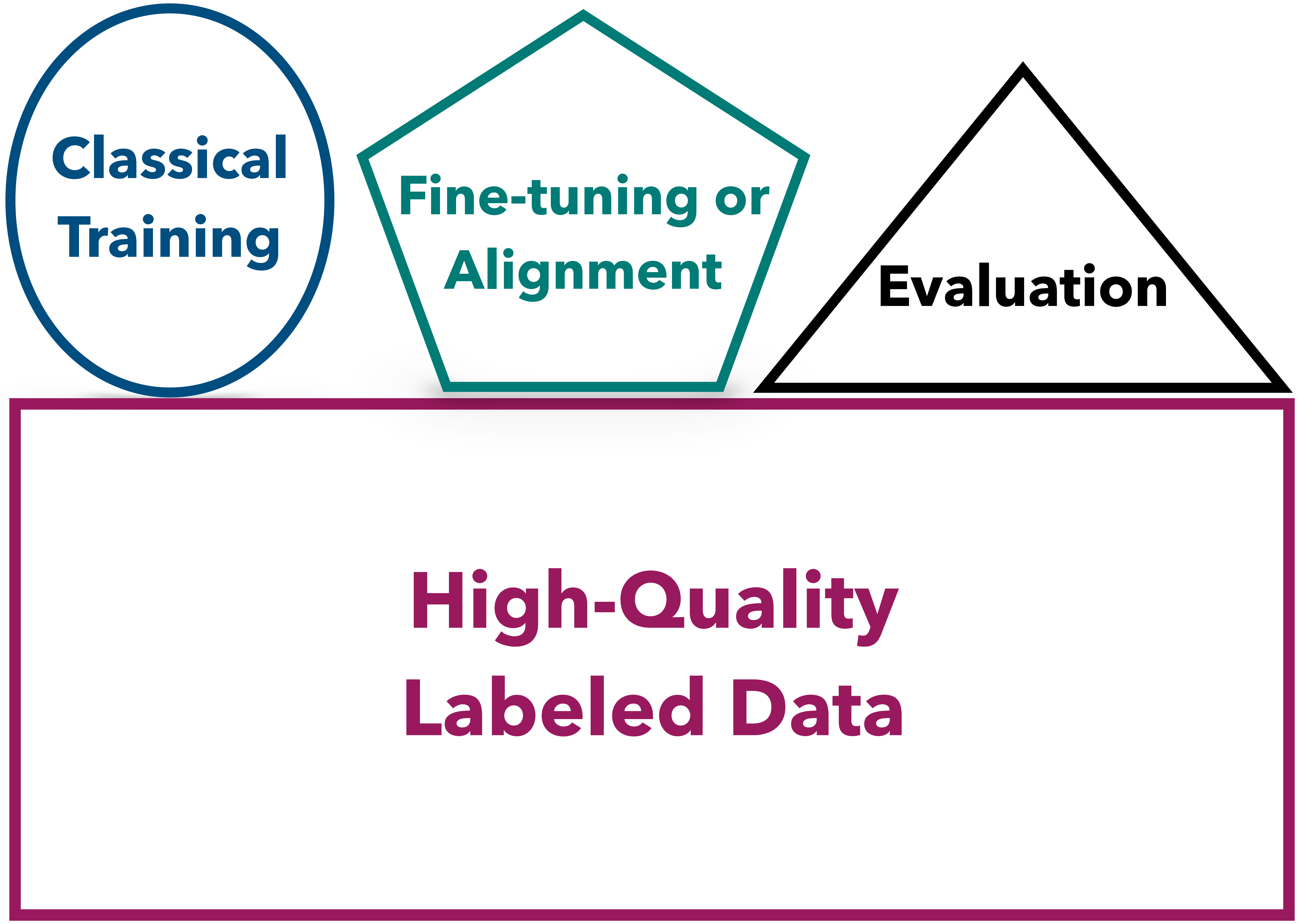
Sui Jiet Tay
CS UG -> NYU

Prof. Fred Sala
CS

Prof. Ramya K. Vinayak
ECE + CS, Stats

Labeled Data Bottleneck

Need for high-quality labeled data is perpetual

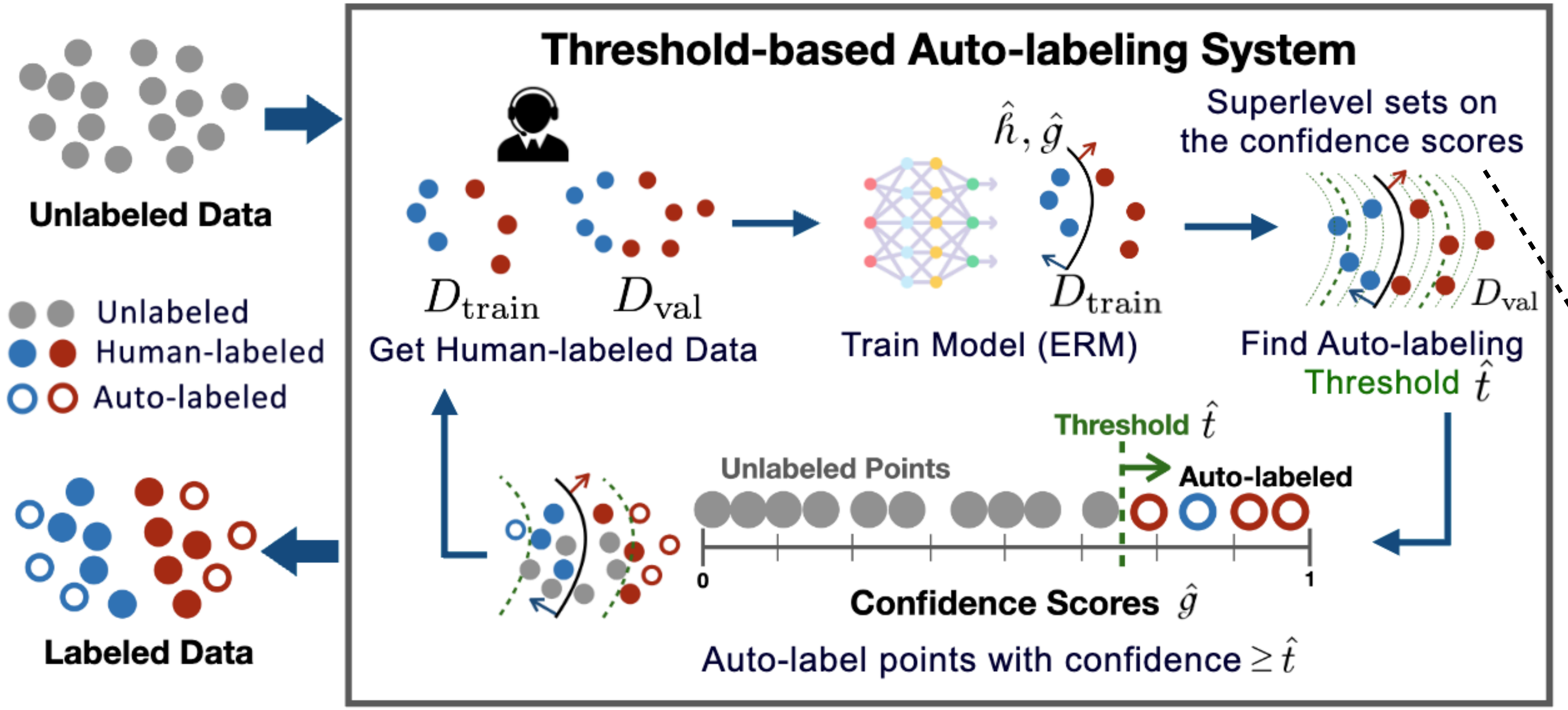


Collecting it is Costly, Time Consuming & Laborious.

A Promising Solution: Threshold-based Auto-labeling (TBAL)

Commercial technique getting used in practice (e.g. Amazon Sagemaker Groundtruth)

Auto-labels points on which model's **confidence scores** are above a **threshold**



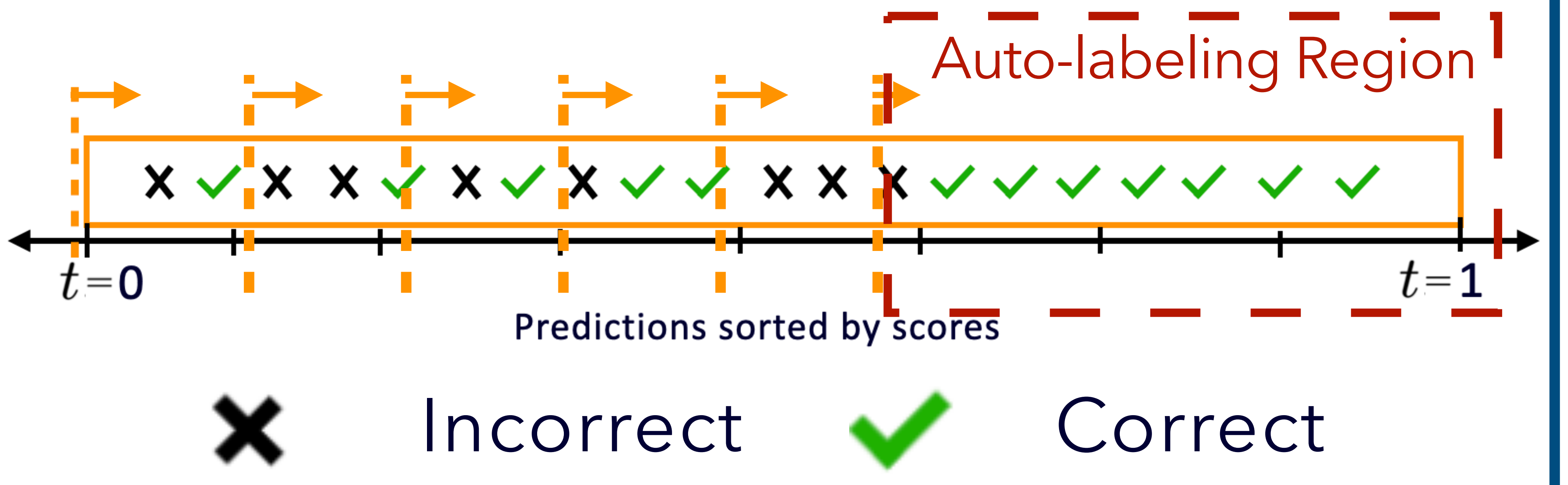
Standard Procedure

Model: Neural Nets

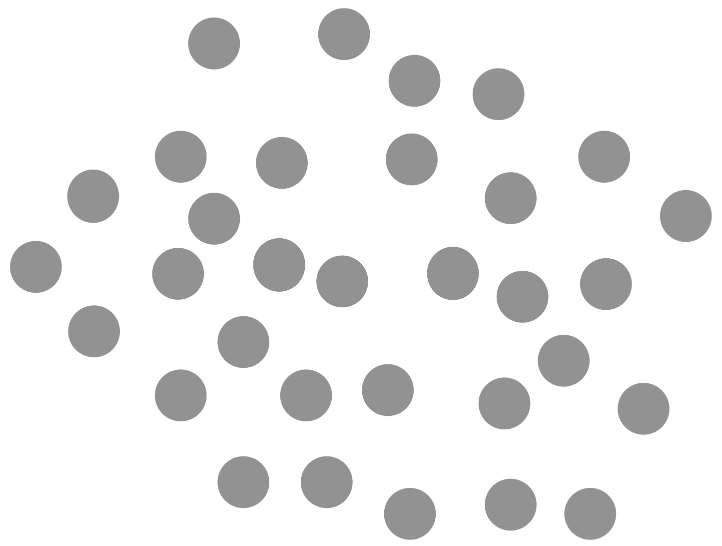
Training: Min. Cross Entropy with SGD

Scores (g): Softmax Outputs

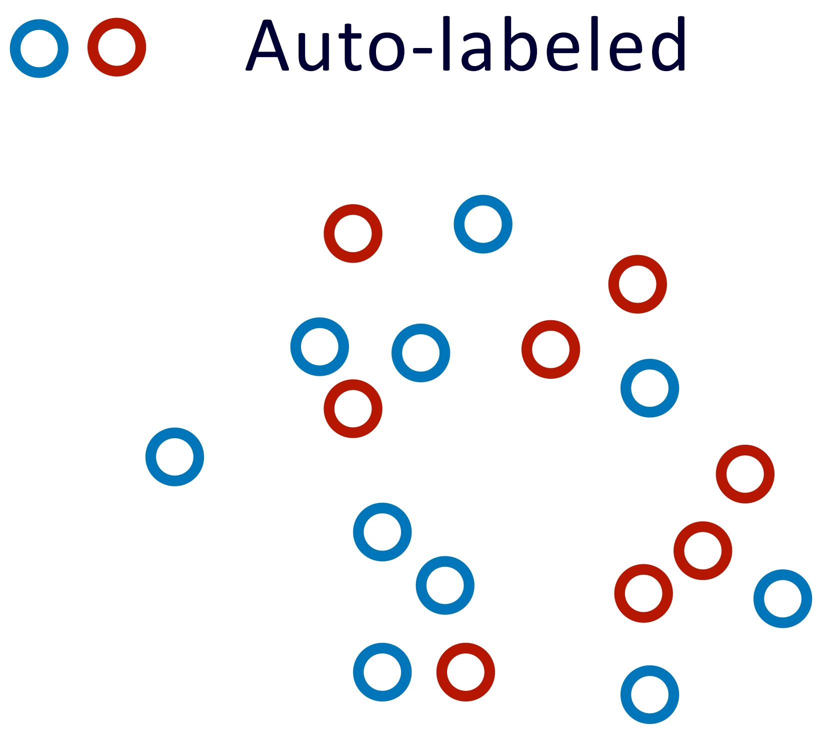
Use **scores** and **validation data** to find threshold



Quality and Quantity of Auto-labeled Data

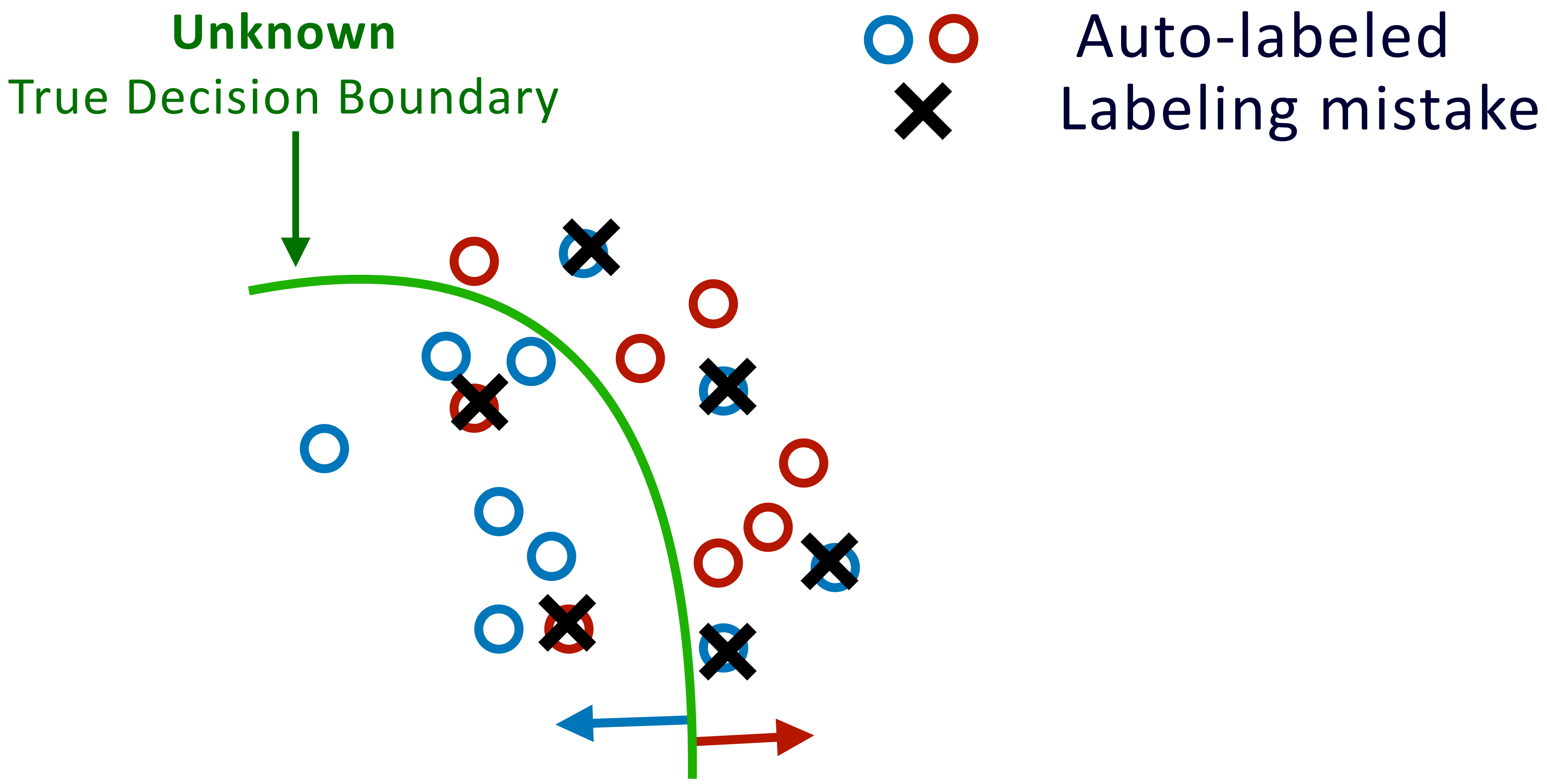


N Number of **unlabeled** points



A Set of **auto-labeled** points

N_a Number of auto-labeled points



M_a Number of labeling mistakes

Quantity

Auto-labeling Coverage

$$\hat{\mathcal{P}} = \frac{N_a}{N}$$

Good Stuff
maximize this

Quality

Auto-labeling Error

$$\widehat{\mathcal{E}} = \frac{M_a}{N_a}$$

Bad Stuff
minimize this

There are Trade-offs between Coverage and Error

Need to guarantee $\leq \epsilon_a$

Factors Affecting TBAL Performance

Assume human labels are always correct (no noise).

1. Amount of validation data used for threshold estimation.

   Less val. data $\implies$ High variance in threshold estimation $\implies$ low coverage or high error.

   Promises and Pitfalls of Threshold-based Auto-labeling, **V**LSV, NeurIPS' 23 (spotlight).

2. Confidence scores on which threshold is estimated.

   Poor/overconfident scores $\implies$ low coverage or high error.

   Pearls from Pebbles: Improved Confidence Functions for Auto-labeling, **V**CTNSV, NeurIPS' 24

3. More factors: noise, class proportions, querying strategies, model training etc.

   Future…

Standard training procedure and softmax scores can be bad for auto-labeling

Prone to the overconfidence problem

High scores even for incorrect predictions

Deep Neural Networks are Easily Fooled:
High Confidence Predictions for Unrecognizable Images

Anh Nguyen
University of Wyoming
anguyen8@uwyo.edu

Jason Yosinski
Cornell University
yosinski@cs.cornell.edu

Jeff Clune
University of Wyoming
jeffclune@uwyo.edu

Don't Just Blame Over-parametrization for Over-confidence:
Theoretical Analysis of Calibration in Binary Classification

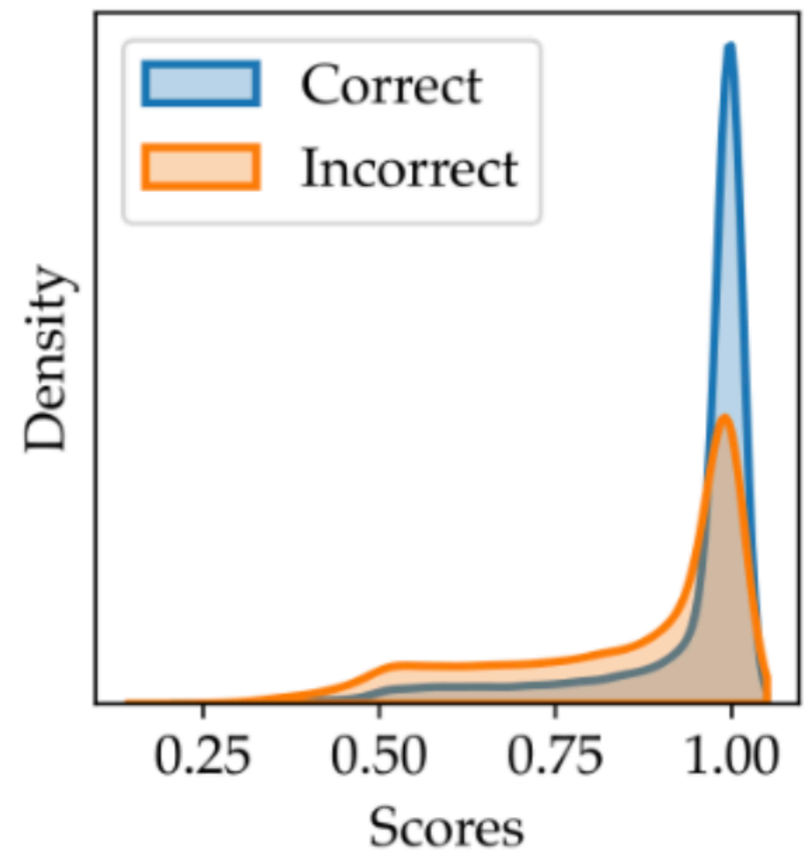
Yu Bai [1] **Song Mei** [2] **Huan Wang** [1] **Caiming Xiong** [1]

Szegedy et al. 2014; Nguyen et al. 2015; Hendricks & Gimpel 2017; Guo et al. 2017; Hein et al. 2018, Bai et al. 2021

Experiment

Run 1 round of TBAL

Data	CIFAR-10
Model	CNN model (5.8 M parameters)
Training data	4000 points drawn randomly
Validation data	1000 points drawn randomly
Error Tolerance	5%



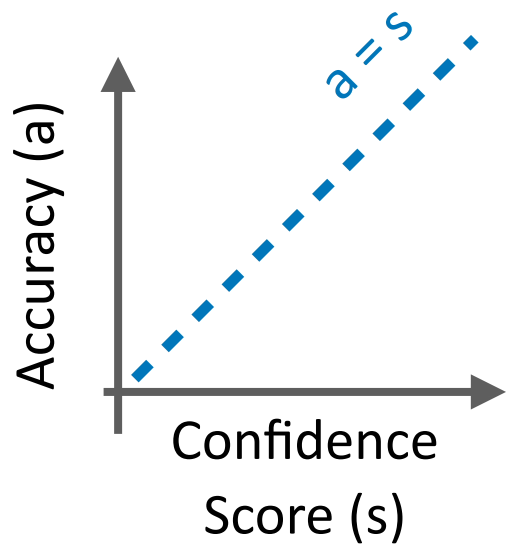
Kernel Density Estimate(KDE) of scores on the remaining unlabeled data

Test Accuracy	55%
Coverage	2.9%
Auto-labeling Error	10.1%

Ad-hoc Methods to Reduce Overconfidence may not help either

Calibration

Points where score is t, the accuracy on those points should be t



On Calibration of Modern Neural Networks

Chuan Guo [*1] Geoff Pleiss [*1] Yu Sun [*1] Kilian Q. Weinberger [1]

Verified Uncertainty Calibration

Ananya Kumar, Percy Liang, Tengyu Ma

TOP-LABEL CALIBRATION AND MULTICLASS-TO-BINARY REDUCTIONS

Chirag Gupta & Aaditya Ramdas

Cut your Losses with Squentropy

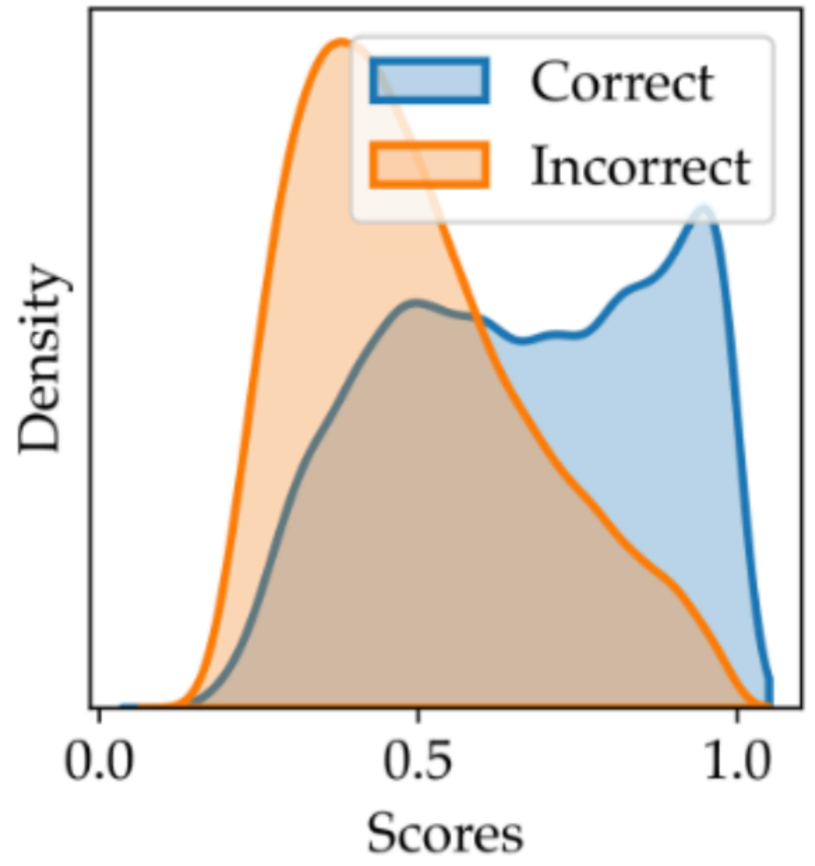
Like Hui [1 2] Mikhail Belkin [2 1] Stephen Wright [3]

Platt 1999; Zadrozny & Elkan, 2001; 2002; Guo et al. 2017; Kumar et al. 2019; Corbiére et al. (2019); Kull et al. 2019, Mukhoti et al. 2020; Gupta & Ramdas 2021; Moon et al. 2020; Zhu et al. 2022; Hui et al. 2023

Experiment

Run 1 round of TBAL + **Temperature Scaling**

Data	CIFAR-10
Model	CNN model (5.8 M parameters)
Training data	4000 points drawn randomly
Validation data	1000 points drawn randomly
Error Tolerance	5%



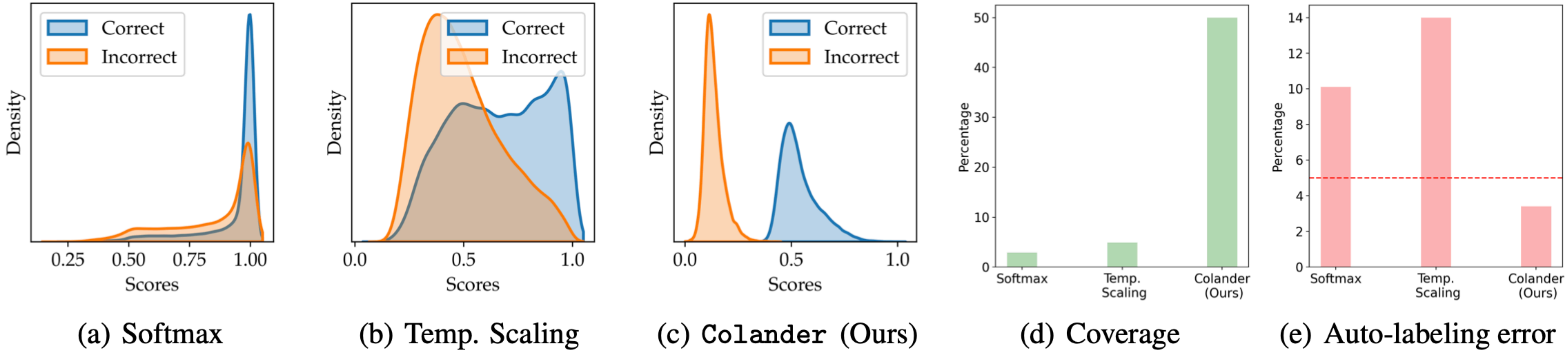
Kernel Density Estimate(KDE) of scores on the remaining unlabeled data

Test Accuracy	55%
Coverage	4.9%
Auto-labeling Error	14.1%

What are the right choices of scores and how do we get them?

We propose Colander, a principled method to learn confidence scores tailored for TBAL.

Colander boosts coverage significantly



Data	CIFAR-10
Model	CNN model (5.8 M parameters)
Training data	4000 points drawn randomly
Validation data	1000 points drawn randomly
Error Tolerance	5%

Run 1 round of TBAL +
Temperature Scaling or **Colander**

How does Colander work?

The Optimal Confidence Functions for TBAL

In any round, given the classifier h

We want to find function g that can,

a) Give maximum coverage

b) Ensure auto-labeling error $\leq \epsilon_a$

$\hat{y} := h(\mathbf{x})$

confidence function $g : \mathcal{X} \to \Delta^k$

Depends on h

but drop it for convenience

Hypothetically, if we know true distribution and labels,

Coverage $\mathcal{P}(g, \mathbf{t} \mid h) := \mathbb{P}_{\mathbf{x}}\big(g(\mathbf{x})[\hat{y}] \geq \mathbf{t}[\hat{y}]\big),$

Auto-labeling Error $\mathcal{E}(g, \mathbf{t} \mid h) := \mathbb{P}_{\mathbf{x}}\big(y \neq \hat{y} \mid g(\mathbf{x})[\hat{y}] \geq \mathbf{t}[\hat{y}]\big).$

$$\underset{g \in \mathcal{G}, \mathbf{t} \in T^k}{\arg\max} \quad \mathcal{P}(g, \mathbf{t} \mid h) \ \text{ s.t. } \ \mathcal{E}(g, \mathbf{t} \mid h) \leq \epsilon_a. \qquad \textbf{(P1)}$$

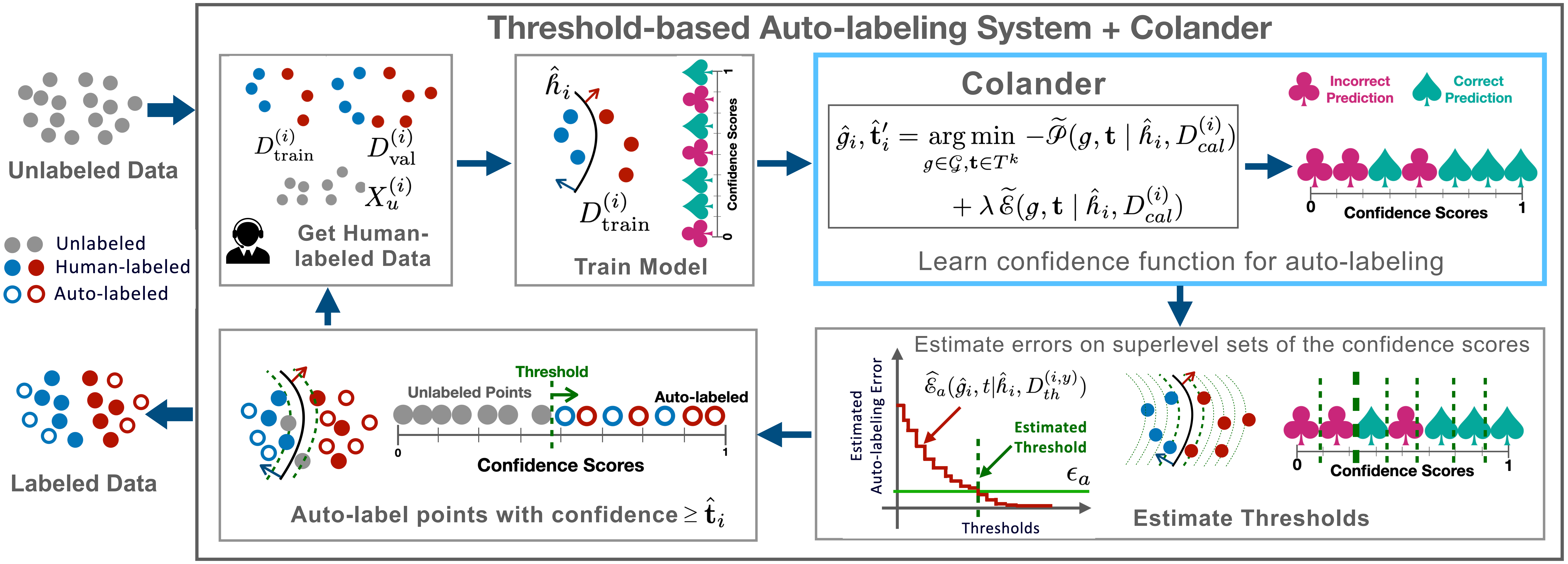
$$g^\star \quad \mathbf{t}^\star$$

Practical Version

Estimate using part of validation data

Use smooth surrogates
and solve using SGD.

Updated workflow of TBAL



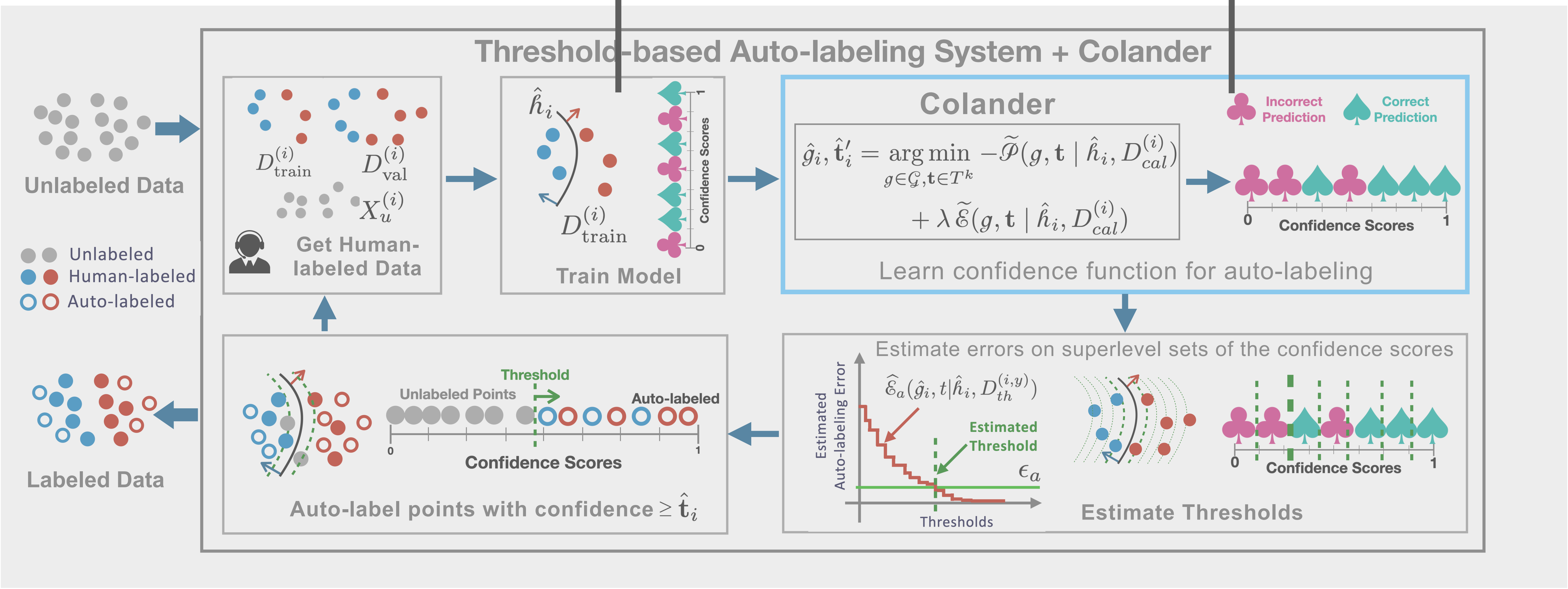
Experiments Setup and Results

Train-time

1. Vanilla
2. CRL (Moon et al. 2020)
3. FMFP (Zhu et al. 2022)
4. Squentropy (Hui et al. 2023)

Post-hoc

1. Colander (Ours)
2. Temperature Scaling (Guo et al. 2017)
3. Histogram Binning (Gupta & Ramdas, 2021)
4. Scaling Binning (Kumar et al. 2019)
5. Dirichlet (Kull et al. 2019)



Cross product, resulting in 20 methods.

With Colander, TBAL achieves significantly high coverage while respecting the error constraint.

	20 Newsgroups		Tiny-ImageNet	
	Err (↓)	Cov (↑)	Err (↓)	Cov (↑)
Softmax	4.6±0.4	52.0±1.2	7.8±0.3	36.2±0.8
TS	8.3±0.6	66.6±1.4	13.3±0.1	44.9±1.0
Dirichlet	7.8±0.6	64.0±1.3	14.1±0.3	42.5±0.7
SB	7.8±0.7	63.0±2.9	13.0±0.5	45.2±2.0
Top-HB	8.2±0.8	66.5±2.2	13.7±0.1	45.9±1.4
AdaTS	7.4±0.6	64.7±2.6	14.0±0.3	46.1±0.7
Ours	**3.3±0.8**	**82.9±0.4**	**0.6±0.2**	**66.5±0.7**

Results with Squentropy Train-time Method

(See paper for full results)

Thank You

Paper

Poster

Wed 11

4:30 - 6:30 PM

\end{talk}