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Developing a quality level prediction framework with semi-supervised learning and ordinal classification for UV lamps

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Introduction

- **Applications of deep learning in manufacturing processes**
  - No need of handcrafted feature extraction
  - Frequent tasks: quality prediction, anomaly detection, prognostics and health management (PHM), etc.
  - Applications: molding, additive manufacturing, joining, machining, etc.

- **Limitations**
  - Require large-scale labeled data
    - Labels: faultiness, quality level, anomalous score, etc.
    - Generating annotations: high cost, time, and domain expertise
  - Relatively abundant **unlabeled** data

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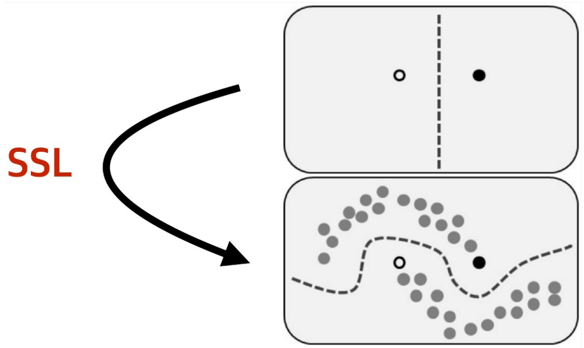
Introduction

- **Semi-supervised Learning (SSL)**
  - Train models with both labeled and unlabeled data
  - Enhanced performance compared to solely supervised learning

$$D_l = \{(x_i, y_i) : i \in (1, ..., B)\}$$

$$D_u = \{(x_j) : j \in (1, ..., \mu B)\}$$

- **Quality prediction with deep neural networks**
  - Predict quality levels (e.g., low, medium, high levels) of a product
  - Levels of quality with ordinality (c.f., classification, fault detection)



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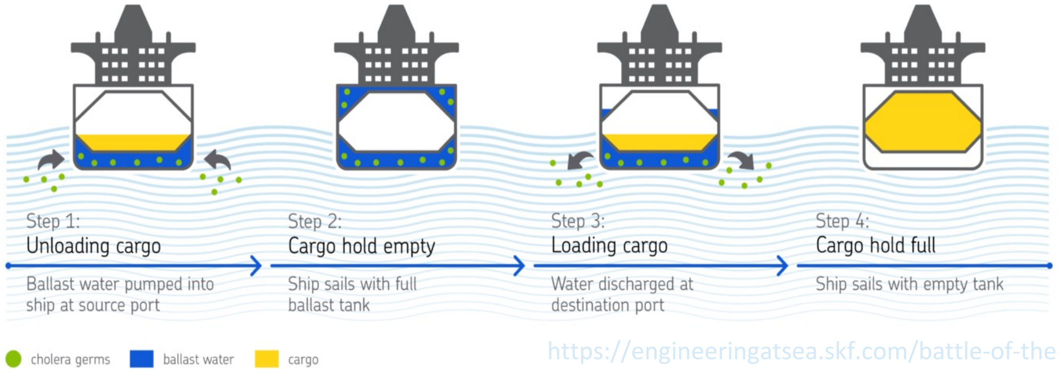
Introduction

- A case study with real-world data from a manufacturing process of **UV lamps**



https://engineeringatsea.skf.com/battle-of-the-ballast/

- An UV lamp is used for Ballast Water Treatment Systems.
- An UV lamp is an eco-friendly lamp for purifying ballast water.
- Expected useful life is associated with qualities
  - > 1000 hours for best quality products

- Abundant **unlabeled data**
- Difficulty in **product quality inspection**
- **More insightful analysis** required than conventional anomaly detection

"A quality level prediction framework with semi-supervised learning and ordinal classification for UV lamps is proposed"

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Related works

- Applications for solving real-world problems in a manufacturing domain
  - Deep neural networks
    - CNN-based fault diagnosis[1]
    - Sparse deep stacking network-based fault detection[2]
    - MLP-based fault classification[3]
  - Semi-supervised learning
    - SSL-based fault diagnosis[4]
    - SSL-based quality control[5]
    - CNN-based fault classification[6]

1.M. Zhao, M. Kang, B. Tang, and M. Pecht, ”Deep residual networks with dynamically weighted wavelet coefficients for fault diagnosis of planetary gearboxes,” IEEE Trans. Ind. Electron., vol. 65, no. 5, pp. 4290-4300, 2017.
2.C. Sun, M. Ma, Z. Zhao, and X. Chen, ”Sparse deep stacking network for fault diagnosis of motor,” IEEE Trans. Ind. Inform., vol. 14, no. 7, pp. 3261-3270, 2018.
3.M. Heydarzadeh, S. Kia, M. Nourani, H. Henao, and G. Capolino, ”Gear fault diagnosis using discrete wavelet transform and deep neural networks,” in Proc. 42nd Annu. Conf. IEEE Ind. Electron. Soc., 2016, pp. 1494-1500.
4.R. Razavi-Far et al., ”Information fusion and semi-supervised deep learning scheme for diagnosing gear faults in induction machine systems,” IEEE Trans. Ind. Electron., vol. 66, no. 8, pp. 6331-6342, 2018.
5.Y. Kong and D. Ni, ”A semi-supervised and incremental modeling framework for wafer map classification,” IEEE Trans. Semicond. Manuf., vol. 33, no. 1, pp. 62-71, 2020.
6.T. Ko and H. Kim, ”Fault classification in high-dimensional complex processes using semi-supervised deep convolutional generative models.” IEEE Trans. Ind. Inform., vol. 16, no. 4, pp. 2868-2877, 2019.
7.R. D´ıaz and A. Marathe, ”Soft labels for ordinal regression,” in Proc.IEEE/CVF Conf. Comput. Vis. Pattern Recognit., 2019, pp. 4738-4747.

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Related works

- Ordinal classification
  - Naïve approaches
    - Using standard regression or classification scheme
    - K-1 formulation
  - **Soft ordinal vector (SORD)**
    - Able to use conventional classification models
    - Semi-supervised learning approaches can be applied

1.M. Zhao, M. Kang, B. Tang, and M. Pecht, ”Deep residual networks with dynamically weighted wavelet coefficients for fault diagnosis of planetary gearboxes,” IEEE Trans. Ind. Electron., vol. 65, no. 5, pp. 4290-4300, 2017.
2.C. Sun, M. Ma, Z. Zhao, and X. Chen, ”Sparse deep stacking network for fault diagnosis of motor,” IEEE Trans. Ind. Inform., vol. 14, no. 7, pp. 3261-3270, 2018.
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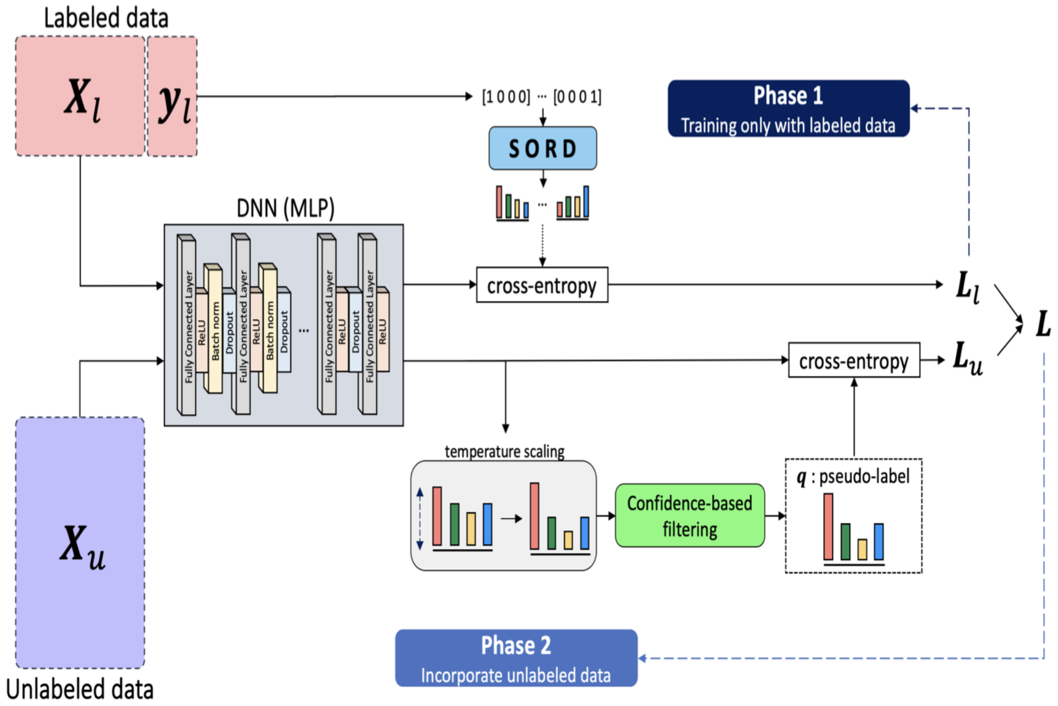
Proposed quality level prediction model



Step 1	Render original label vectors into **SORD** vectors
Step 2	Train the **DNN** prediction model on **labeled samples** with the rendered targets
Step 3	Generate **pseudo-labels** for X_u and compute prediction confidences using ordinal entropy
Step 4	Compute **unlabeled losses** only with highly confidently predicted unlabeled samples
Step 5	**Train the model** using both labeled and unlabeled losses

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Proposed quality level prediction model

Step 1

Render original label vectors into **SORD** vectors

- Utilize **SORD** as a method for taking **label ordinality** into the model training.
- Following the original SORD formulation with an L1-norm, as a distance function ϕ, the original target vectors are transformed into SORDs, where original targets $Y = \{y_1, y_2, y_3, \dots, y_{C-1}, y_C\}$.

$$r_i = \frac{e^{-\phi(y_t, y_i)}}{\sum_{c=1}^{C} e^{-\phi(y_t, y_c)}}. \ \forall y_i \in \mathcal{Y}$$

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Proposed quality level prediction model

Step 2

Train the **DNN** prediction model on **labeled samples** with the rendered targets

- Utilize the **standard DNN** type, known as a multi-layer perceptron (MLP) for the prediction model.
- Employ **temperature scaling** for mitigating the overconfidence issue of the DNN model on the final outputs of the prediction model.
- Temperature scaling uses a scalar parameter *T* for all classes in order to calibrate the model predictions.

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Proposed quality level prediction model

Step 3

Generate **pseudo-labels** for X_u and compute prediction confidences using ordinal entropy

- Generate pseudo-labels for unlabeled samples.
- In semi-supervised learning, self-training with entropy minimization is employed in this framework.
- **To reflect the inherent ordinality of the label**, the 'ordinal entropy' is proposed

$$H_{ord}(X) = \lambda H(X) + \sum_{j=1}^{k-1} h_j(X).$$

$$h_j(X) = -P(\textstyle\sum_{i=1}^{j} X_i) log P(\sum_{i=1}^{j} X_i) - P(\sum_{i=j+1}^{n} X_i) log(P \sum_{i=j+1}^{n} X_i)$$

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Proposed quality level prediction model

Step 4

Compute **unlabeled losses** only with highly confidently predicted unlabeled samples

Step 5

Train the model using both labeled and unlabeled losses

- During the training framework, the cross-entropy loss for **labeled samples L_l and** selected **unlabeled samples L_u** constitutes **total loss data.**

$$L = L_l + L_u$$

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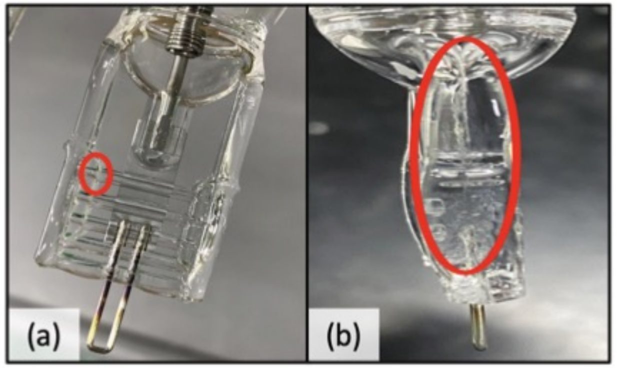
Experiments

Data: Real-world data collected during the **UV lamp manufacturing process**

- **The number of labeled instances**: 6,203
- **The number of unlabeled instances**: 27,492
- **Types of the faults**: 1) Cracks , 2) Sidelines
- **The labels** are divided into **4 classes**:
  0 for the item of the best quality without any faults,
  1 for the item with a single minor fault,
  2 for the item with middle-level faults,
  3 for the item with major faults that must be disposed



Types of the defects (a) cracks, (b) sidelines

Experimental setup:

- Kolmogorov–Smirnov (KS) test for labeled and unlabeled data
- dropout and batch-normalization
- with SGD and ADAM optimizer

Evaluation criteria:

- precision, recall, accuracy, F_1 score, and MAE

A description of data variable

Category	Variable	Unit	Description
Gas	Amount of oxygen	L/min	The amount of oxygen injected into the quartz tube
	Amount of hydrogen	L/min	The amount of hydrogen injected into the quartz tube
Burner	Burner speed	-	(no specific metric used)
	Burner rotation	Hz	The frequency rotation of the burner that heats up the quartz tube
Lamp	Distance of electrodes	mm	The measured distance between two electrodes placed at each end
Sealing	Upper thickness	mm	The measured thickness of the upper sealing part
	Lower thickness	mm	The measured thickness of the lower sealing part

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Results

Compare the performance of the prediction model

Algorithm	Metric					Unlabeled data usage
	Precision	Recall	Accuracy	F_1 score	MAE	
SVM	0.4952 ± 0.0212	0.4959 ± 0.0197	0.9745 ± 0.0029	0.4954 ± 0.0204	$\mathbf{0.0348} \pm 0.0059$	X
LR	0.5020 ± 0.0072	0.5210 ± 0.0501	0.9793 ± 0.0049	0.5032 ± 0.0012	0.0444 ± 0.0098	X
NB	0.5262 ± 0.0476	0.5087 ± 0.0015	0.7032 ± 0.0433	0.4771 ± 0.0092	0.7974 ± 0.1471	X
DT	0.5155 ± 0.0118	0.5153 ± 0.0105	0.9696 ± 0.0025	0.5150 ± 0.0105	0.0673 ± 0.0057	X
XGBoost	0.5196 ± 0.0194	0.5845 ± 0.0736	$\mathbf{0.9840} \pm 0.0014$	0.5299 ± 0.0300	0.0377 ± 0.0050	X
DNN w/o SORD	0.6124 ± 0.0108	0.5861 ± 0.0389	0.9826 ± 0.0029	0.5927 ± 0.0281	0.0351 ± 0.0039	X
DNN w/ SORD (**proposed**)	$\mathbf{0.6208} \pm 0.0394$	$\mathbf{0.6087} \pm 0.0472$	0.9825 ± 0.0027	$\mathbf{0.6133} \pm 0.0428$	0.0349 ± 0.0047	X

- The backbone model (DNN) outperforms with SORD-based rendering

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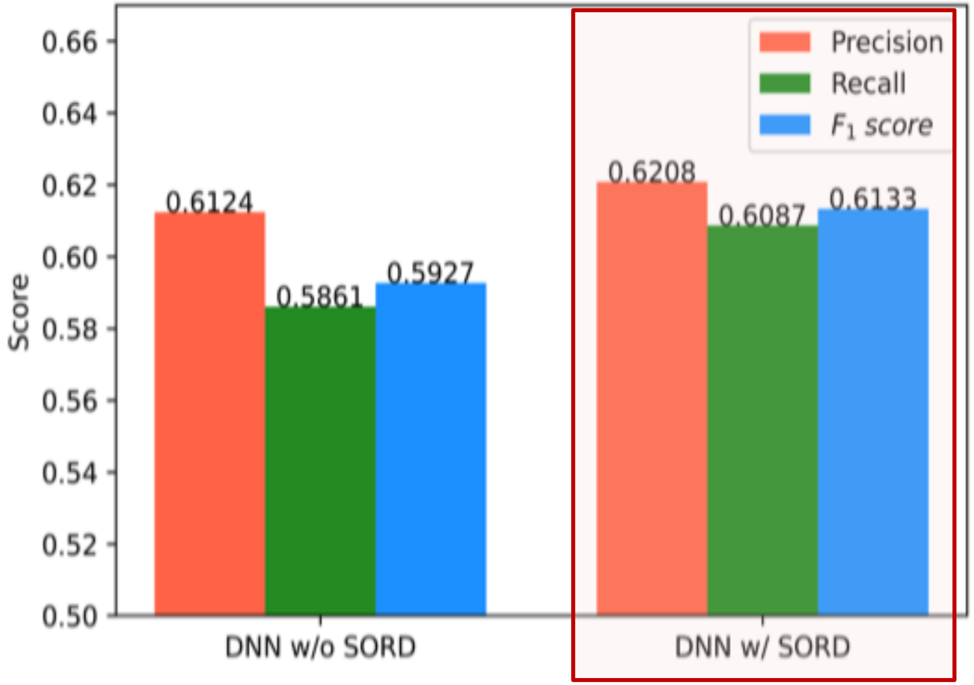
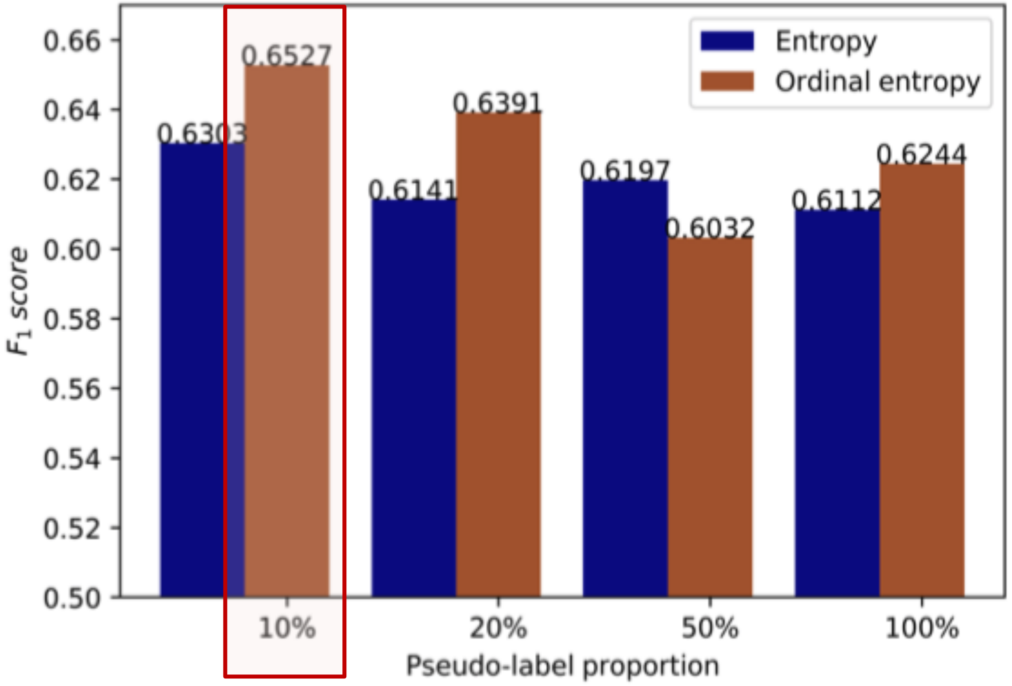
Results

Compare the performance to find best configuration of the framework

Effects of **SORD** prediction performances



F_1 score comparison of **confidence measures** used



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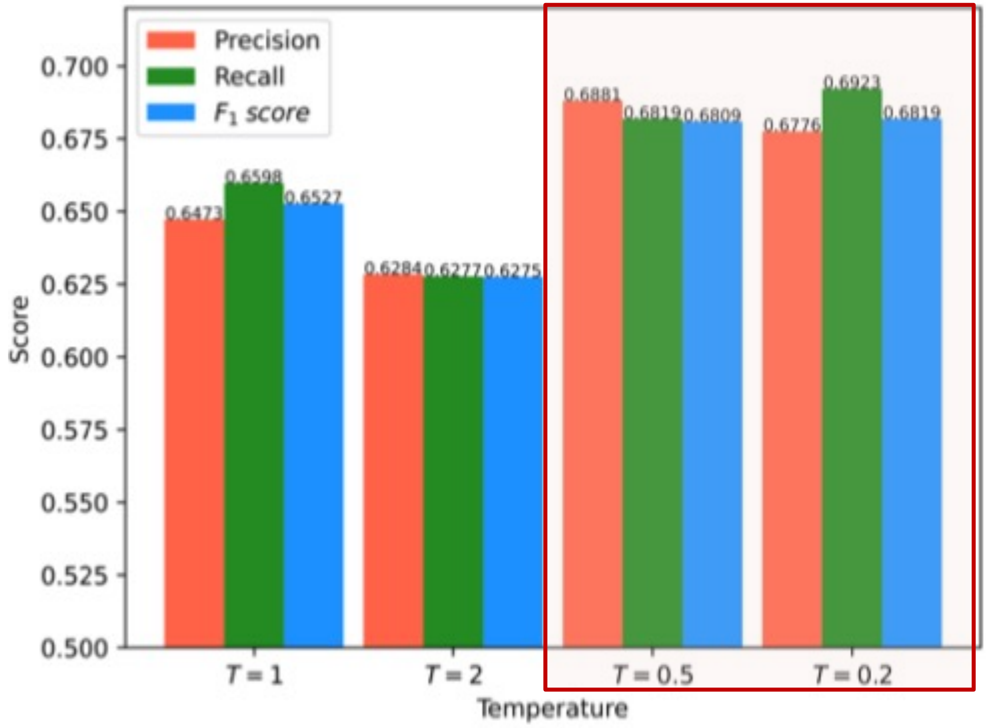
Results

Compare the performance to find best configuration of the framework

Effects of **temperature *T*** on prediction performances



- When **T=0.5,** it shows the highest **precision.**
- When **T=0.2,** it shows the most effective in terms of **recall.**

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Results

With **real-world data from the UV lamp manufacturing process**, various experiments have been conducted to find the **best configuration** of the framework with the proof as follows:

- Our backbone model (**DNN**) outperforms the conventional supervised machine learning algorithms.
- Given the improvement in performance with **SORD-based** rendering, it is efficacy to reflect inherent ordinality.
- The experiment conducted with unlabeled data shows better performance than supervised learning methods.
- When ***p*=10%** and **ordinal entropy** are used, it shows the best performance in semi-supervised learning.
- Through the diverse experiments based on *T*, it is represented that ***T*=0.5** has shown the best **precision** and ***T*=0.2** has shown to be the most effective in terms of **recall** and **F1 score**.

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Conclusions and future works

The contributions of this research

- Abundant **unlabeled data** are utilized in a SSL framework.
- The **ordinality of the labels** is taken into account via application of a label rendering method and a novel information measure for confidence computation.
- A variety of configurations of the proposed framework is validated with extensive experiments using **real-world manufacturing data**.

Future works

- Application of the proposed framework in other type of data
  - to **predict the lifespan** of UV lamps
- Manufacturing process parameter **optimization**

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Appendix

Compare the effects of temperature scaling on prediction performance

Temperature	Confidence measure	Metric				
		Precision	Recall	Accuracy	F_1 score	MAE
$T = 1$ (temperature removed)	ordinal entropy	0.6473 ± 0.0145	0.6598 ± 0.0148	$\mathbf{0.9855} \pm 0.0006$	0.6527 ± 0.0135	0.0323 ± 0.0011
$T = 2$	ordinal entropy	0.6284 ± 0.0010	0.6277 ± 0.0078	0.9852 ± 0.0005	0.6275 ± 0.0048	$\mathbf{0.0300} \pm 0.0005$
$T = 0.5$	ordinal entropy	$\mathbf{0.6881} \pm 0.0460$	0.6819 ± 0.0427	0.9825 ± 0.0024	0.6809 ± 0.0419	0.0346 ± 0.0023
$T = 0.2$	ordinal entropy	0.6776 ± 0.0422	$\mathbf{0.6923} \pm 0.0304$	0.9854 ± 0.0029	$\mathbf{0.6819} \pm 0.0346$	0.0302 ± 0.0054

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Appendix

Performance comparisons of ablation experiments of the proposed semi-supervised method

Pseudo-labels proportion	Confidence measure: Entropy	Confidence measure: Ordinal entropy **(proposed)**	Metric: Precision	Metric: Recall	Metric: Accuracy	Metric: F_1 score	Metric: MAE	Unlabeled data usage
$p = 10\%$	○	×	0.6390 (±0.0604)	0.6288 (±0.0759)	0.9853 (±0.0034)	0.6303 (±0.0707)	**0.0248** (±0.0027)	○
	×	○	**0.6473** (±0.0145)	**0.6598** (±0.0148)	**0.9855** (±0.0006)	**0.6527** (±0.0135)	0.0323 (±0.0011)	○
$p = 20\%$	○	×	0.6283 (±0.0373)	0.6048 (±0.0583)	0.9524 (±0.0705)	0.6141 (±0.0472)	0.0369 (±0.0082)	○
	×	○	0.6425 (±0.0231)	0.6421 (±0.0566)	0.9838 (±0.0041)	0.6391 (±0.0409)	0.0320 (±0.0069)	○
$p = 50\%$	○	×	0.6263 (±0.0048)	0.6177 (±0.0171)	0.9852 (±0.0009)	0.6197 (±0.0099)	0.0307 (±0.0008)	○
	×	○	0.6285 (±0.0304)	0.5950 (±0.0505)	0.9795 (±0.0047)	0.6032 (±0.0437)	0.0303 (±0.0152)	○
$p = 100\%$	○	×	0.6245 (±0.0183)	0.6120 (±0.0552)	0.9810 (±0.0046)	0.6112 (±0.0436)	0.0351 (±0.0062)	○
	×	○	0.6249 (±0.0212)	0.6250 (±0.0235)	0.9830 (±0.0012)	0.6244 (±0.0223)	0.0362 (±0.0021)	○

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