Open Set Recognition

발표자 : 백승호

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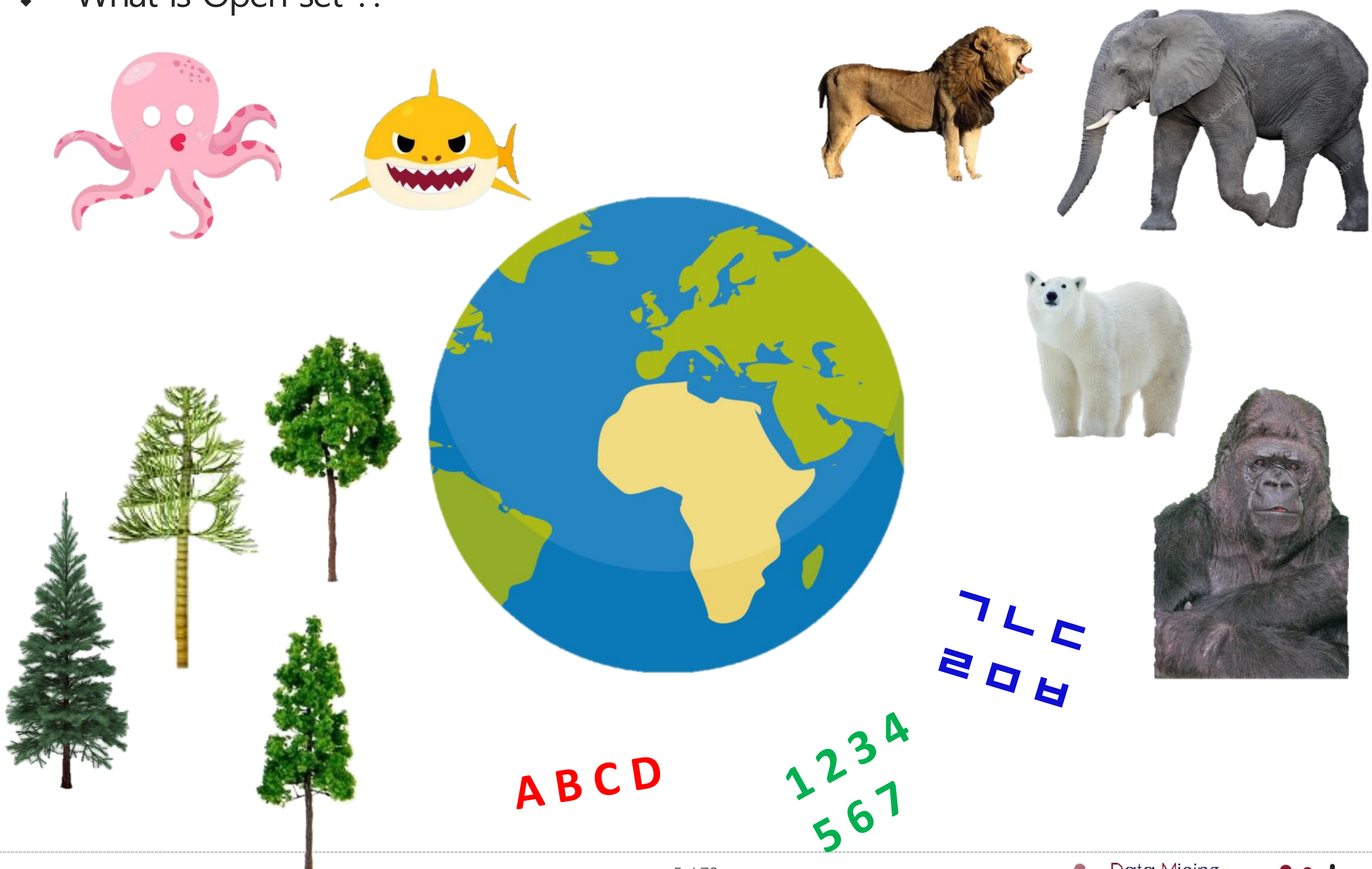
1. Introduction

Introduction

❖ What is Open set ??

Introduction

❖ What is Open set ??



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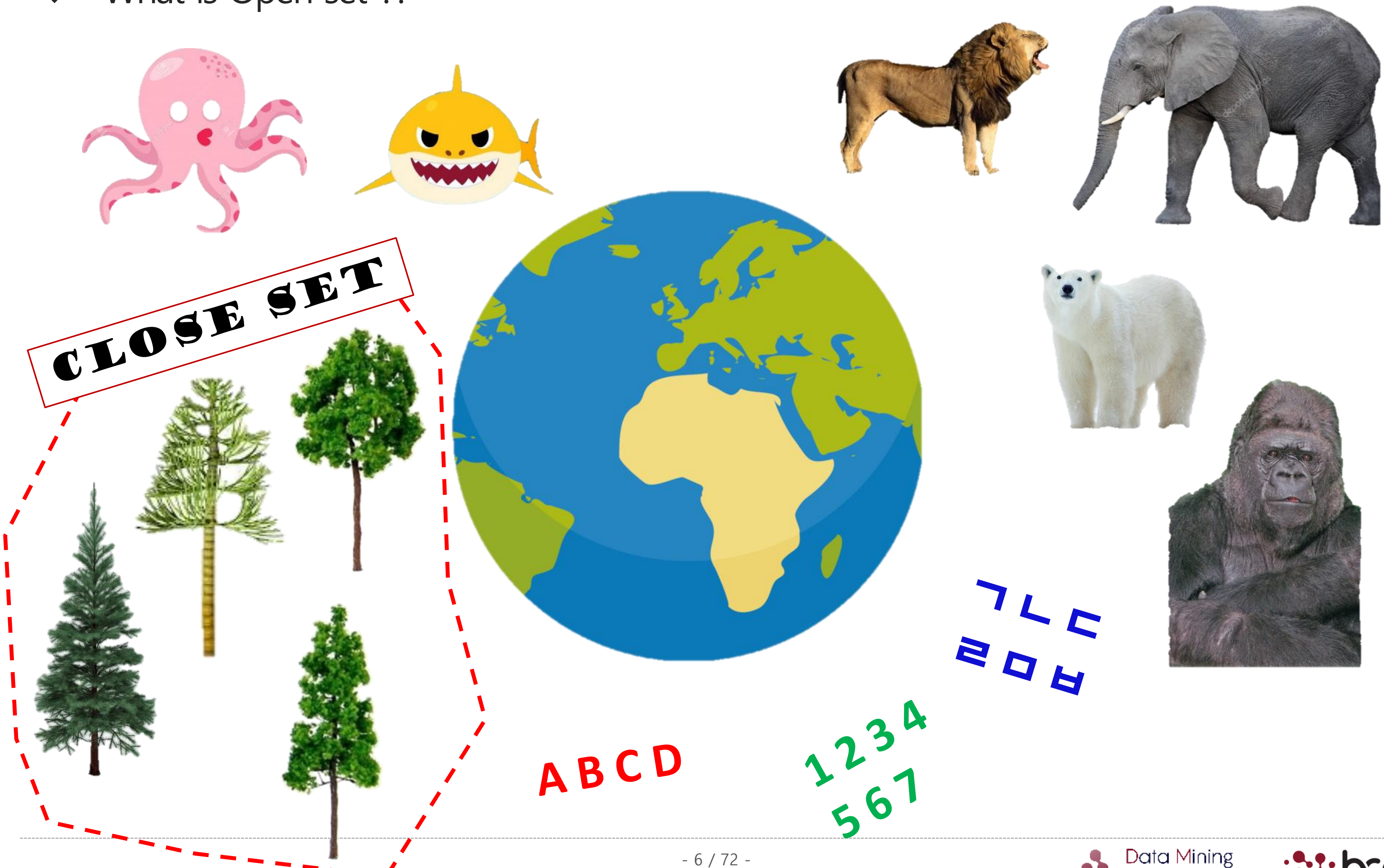

Introduction

❖ What is Open set ??

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English

Math

Art

Science

Introduction

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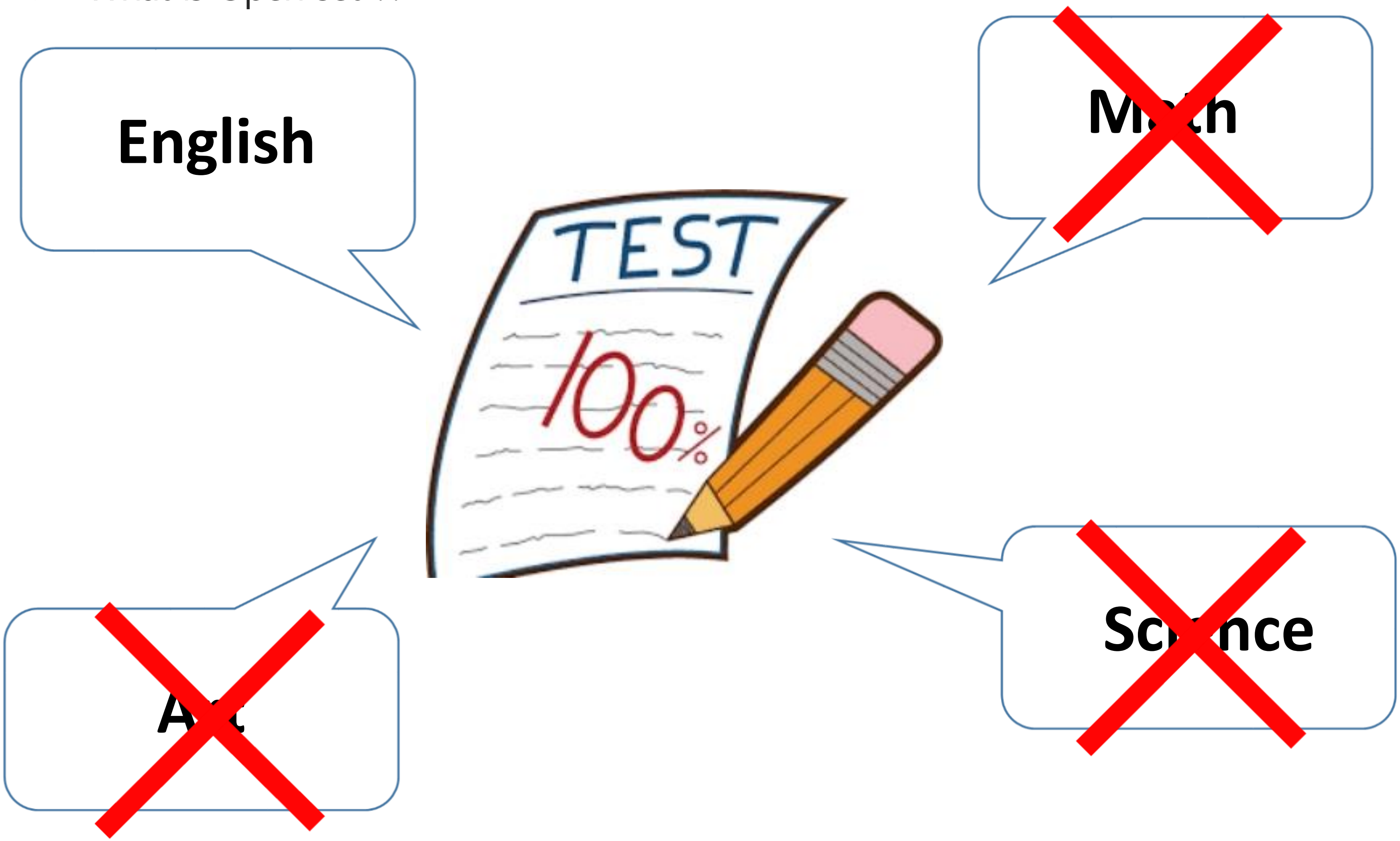

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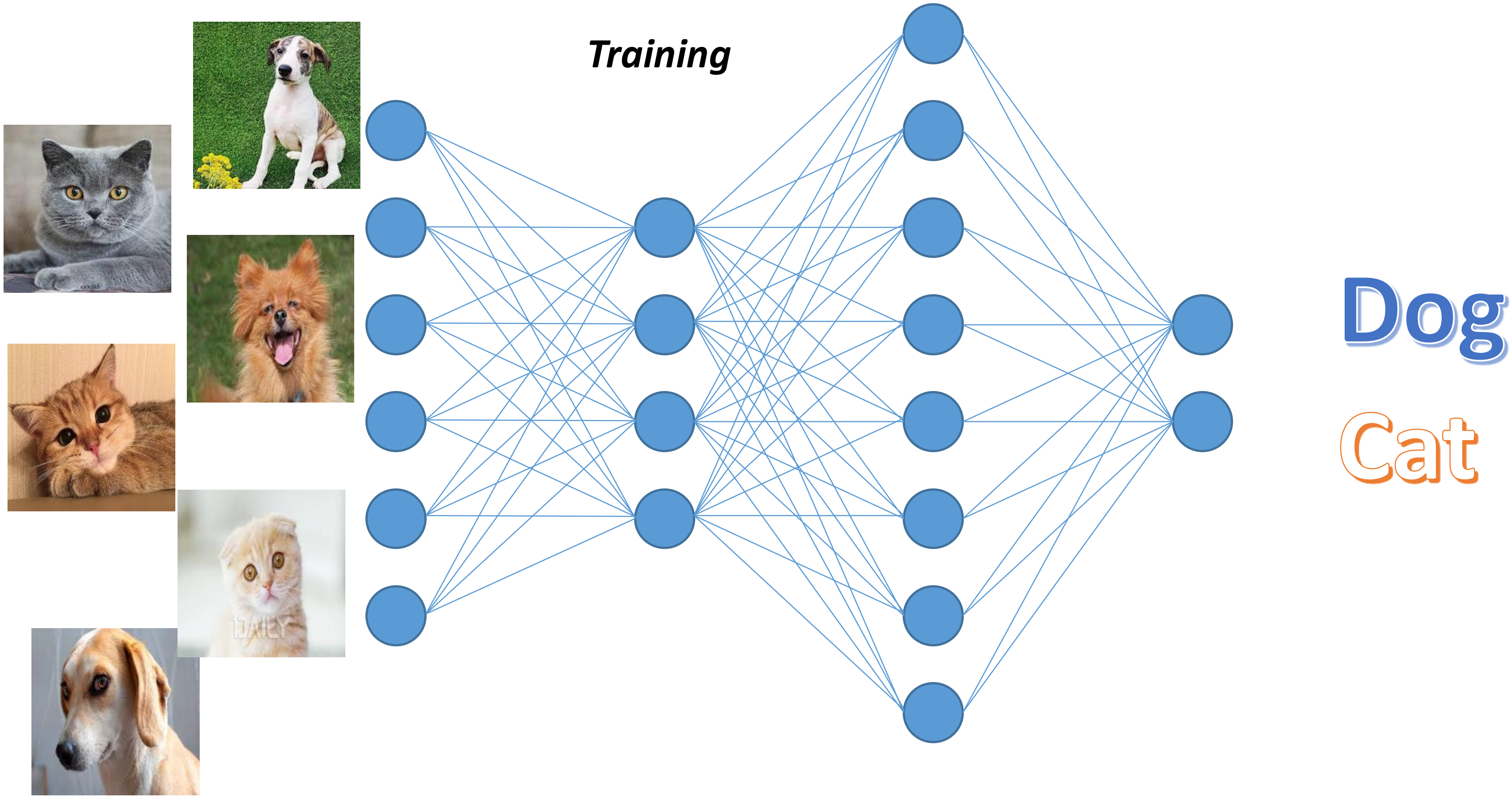

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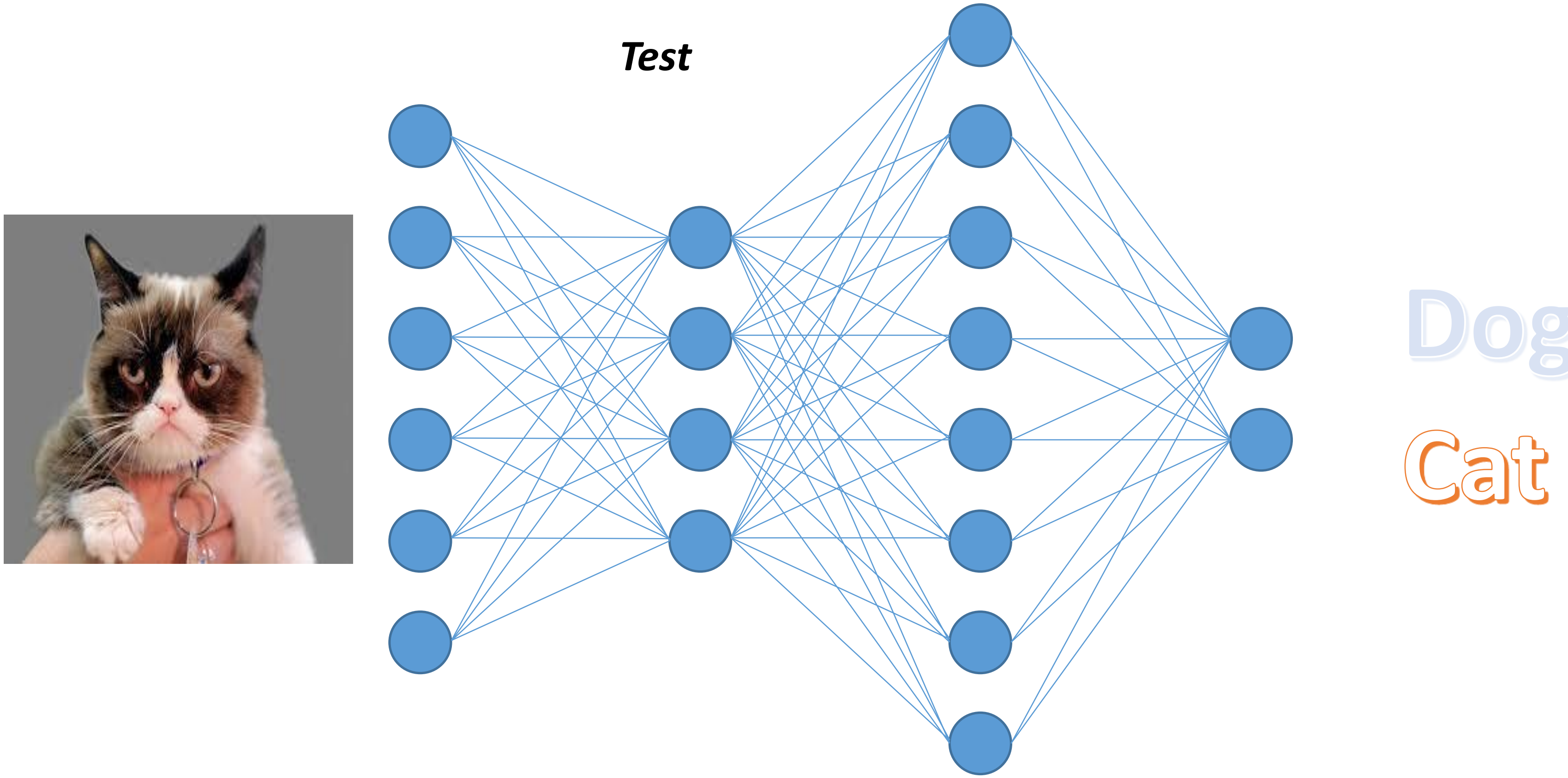

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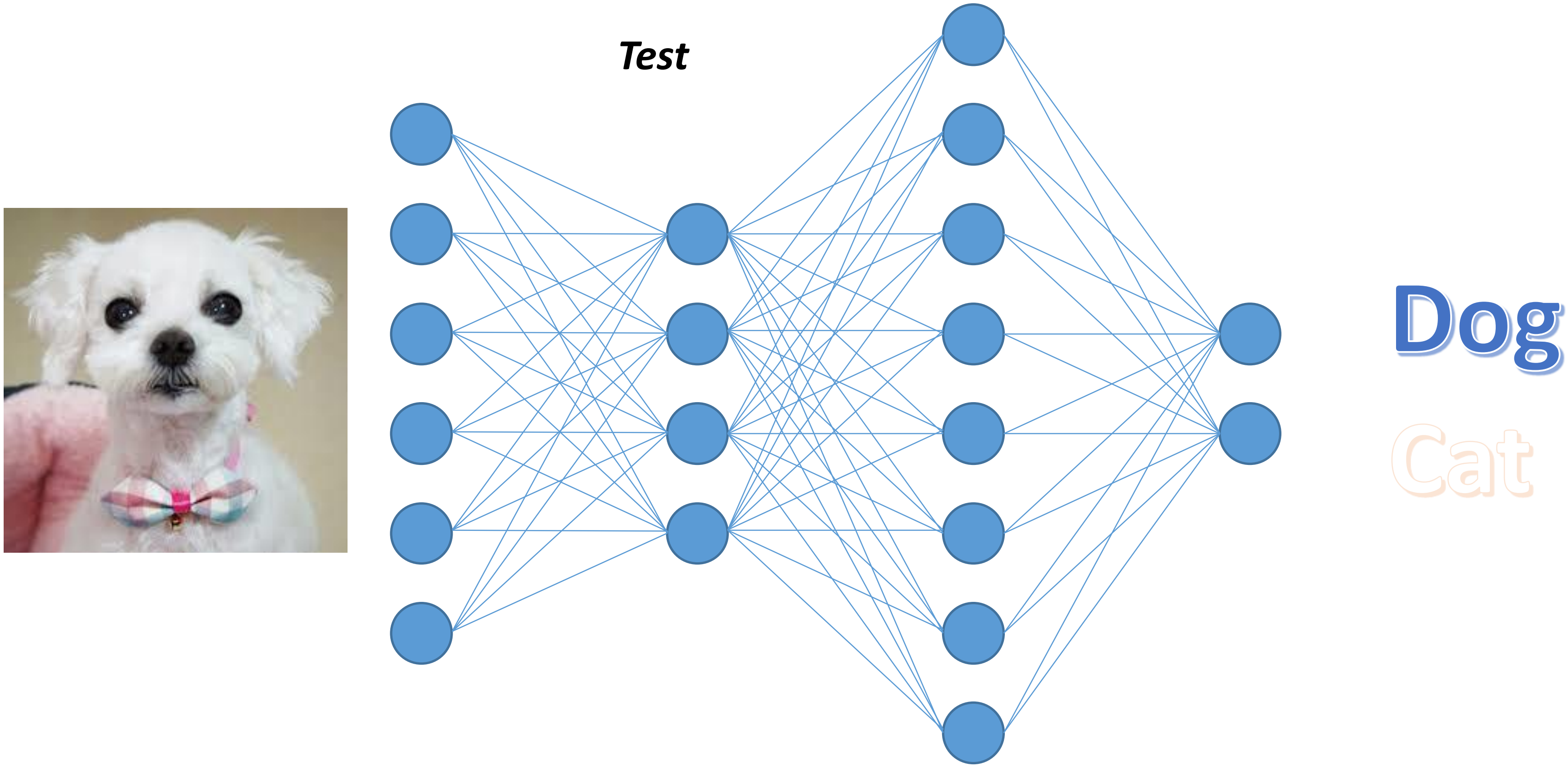

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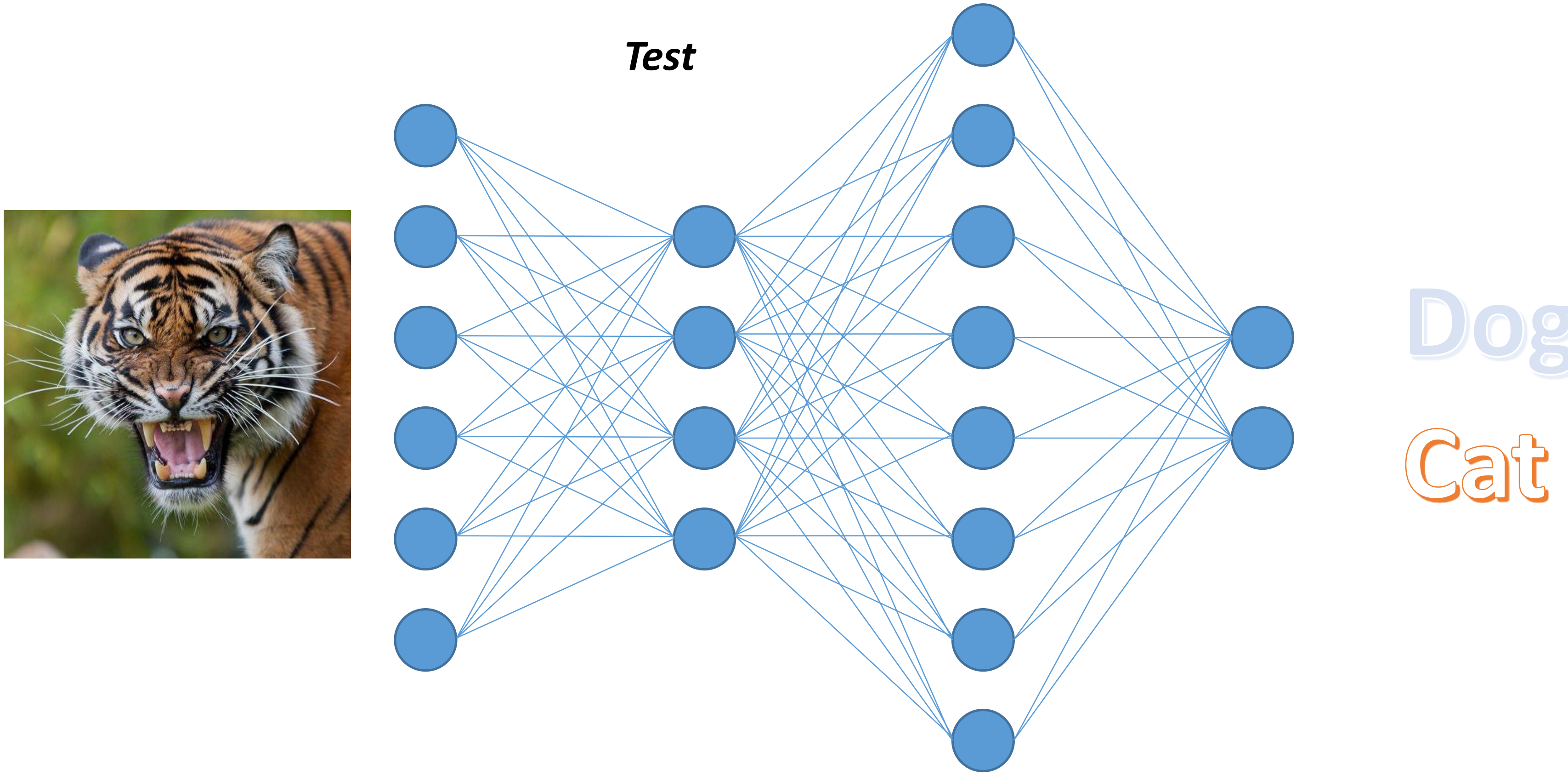

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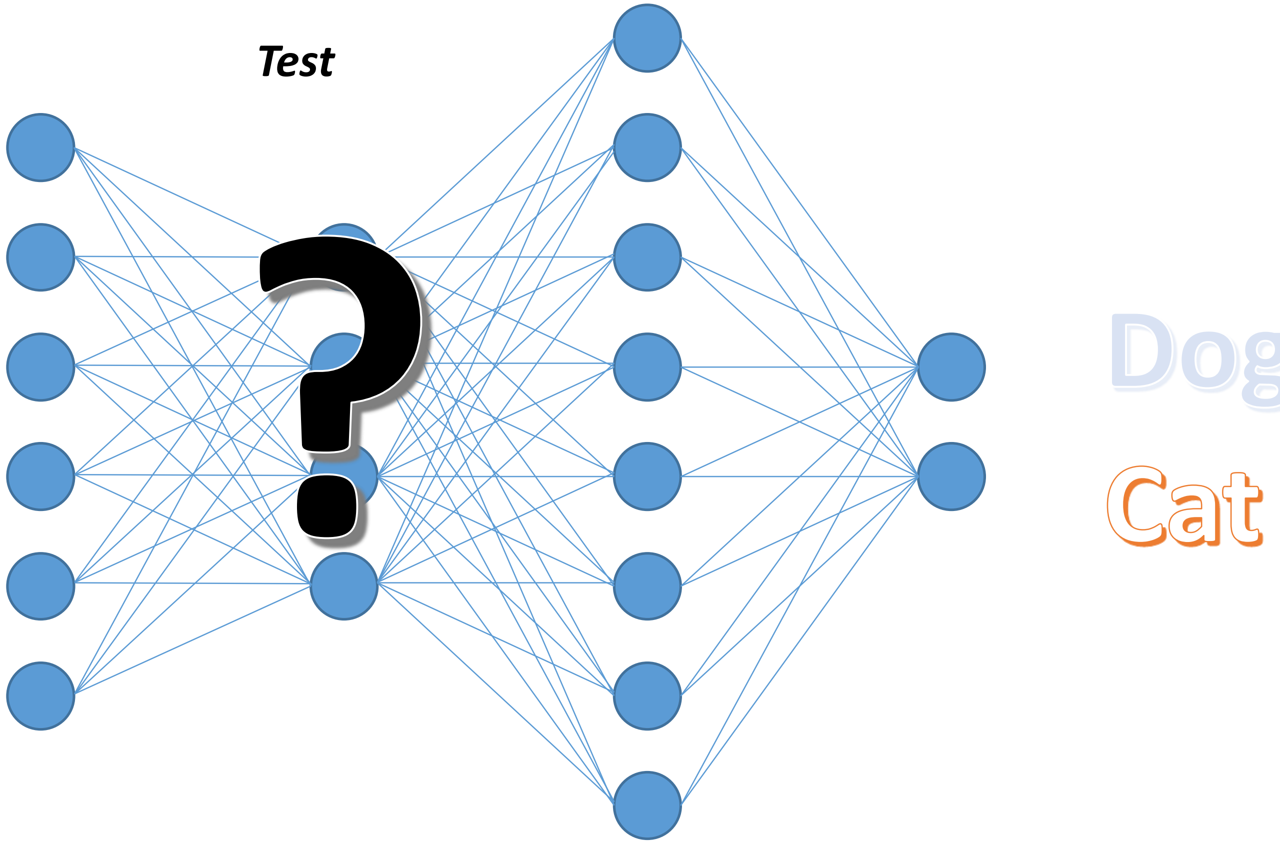


Introduction

Recent Advances in Open Set Recognition: A Survey

Chuanxing Geng, Sheng-Jun Huang and Songcan Chen

***Abstract*—In real-world recognition/classification tasks, limited by various objective factors, it is usually difficult to collect training samples to exhaust all classes when training a recognizer or classifier. A more realistic scenario is open set recognition (OSR), where incomplete knowledge of the world exists at training time, and unknown classes can be submitted to an algorithm during testing, requiring the classifiers to not only accurately classify the seen classes, but also effectively deal with the unseen ones. This paper provides a comprehensive survey of existing open set recognition techniques covering various aspects ranging from related definitions, representations of models, datasets, evaluation criteria, and algorithm comparisons. Furthermore, we briefly analyze the relationships between OSR and its related tasks including zero-shot, one-shot (few-shot) recognition/learning techniques, classification with reject option, and so forth. Additionally, we also overview the open world recognition which can be seen as a natural extension of OSR. Importantly, we highlight the limitations of existing approaches and point out some promising subsequent research directions in this field.**

***Index Terms*—Open set recognition/classification, open world recognition, zero-short learning, one-shot learning.**

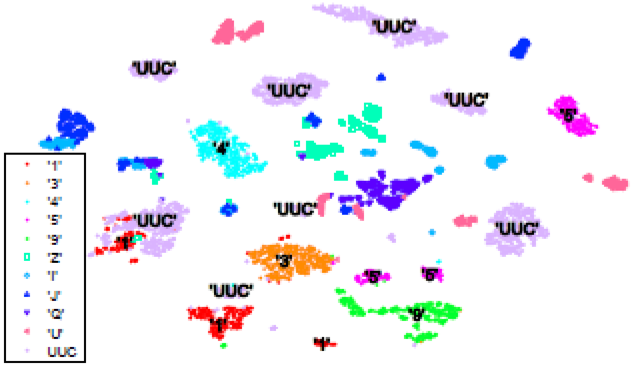


Fig. 1. An example of visualizing KKCs, KUCs, and UUCs from the real data distribution using t-SNE. Here, '1','3','4','5','9' are randomly selected from PENDIGITS as KKCs, while the remaining classes in it as UUCs. 'Z','I','J','Q','U' are randomly selected from LETTER as KUCs.

as negative samples for other KKCs), and even have the corresponding side-information like semantic/attribute information, etc.;

2) *known unknown classes* (KUCs), i.e., labeled nega-

2. Recent Advances in Open Set Recognition

Recent Advances in Open Set Recognition

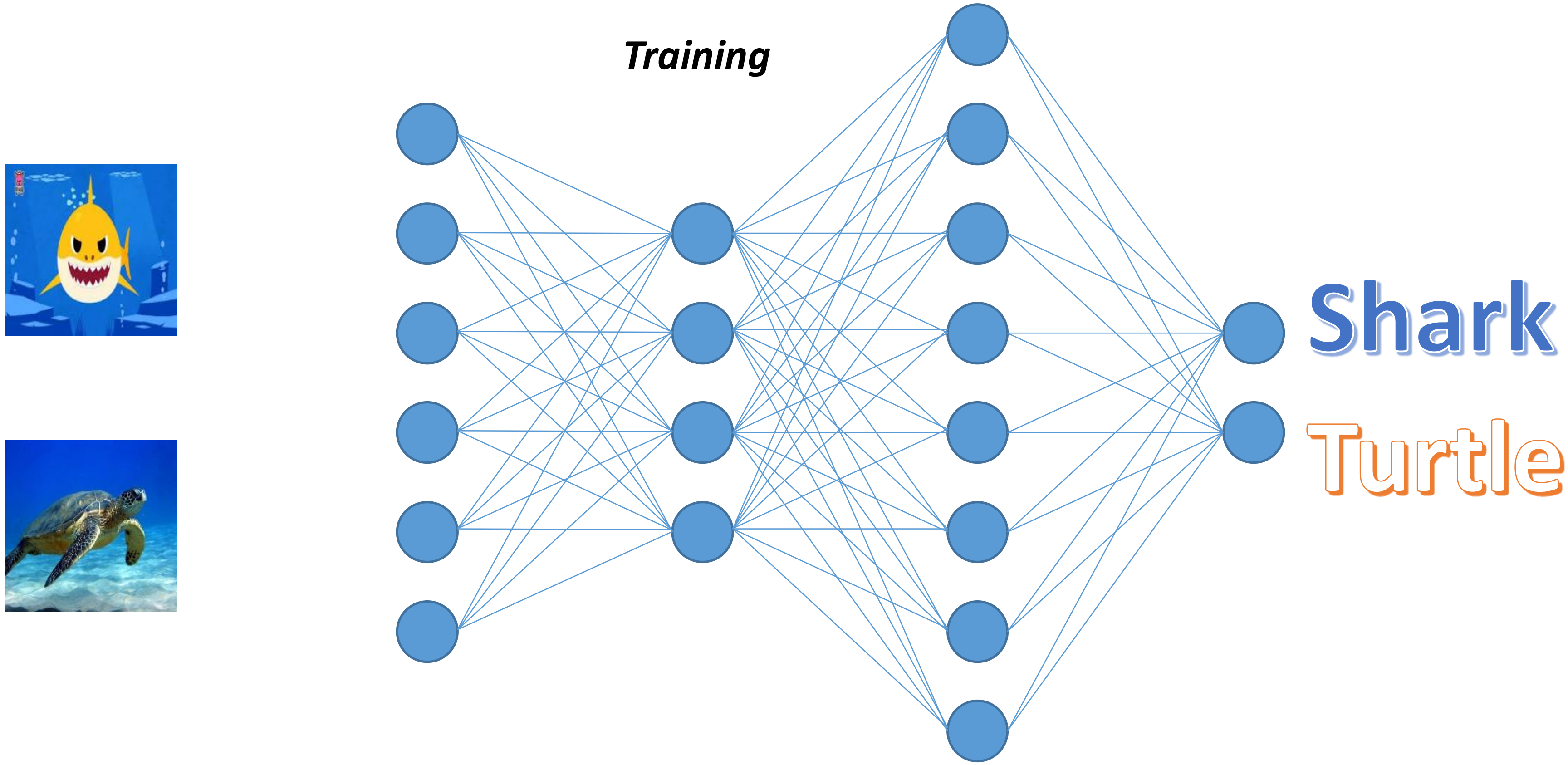
❖ Kind of Class

Knowledge of Domain (Understanding) ↑ High / ↓ Low	Knowns	Unknowns
Knowns	***Knowns Knowns*** (KKC) Data 有 Label 有	***Knowns Unknowns*** (KUC) Data 有 Label 無
Unknowns	***Unknowns Knowns*** (UKC) Data 無 Label 有	***Unknowns Unknowns*** (UUC) Data 無 Label 有

High ← Knowledge of State (Data available) → Low

Recent Advances in Open Set Recognition

❖ Example : Scuba-diving in Ocean



Recent Advances in Open Set Recognition

❖ Example : Scuba-diving in Ocean

Knowledge of State (Data available): *High* ↑ … ↓ *Low*

	Knowns	*Unknowns*
Knowns	***Knowns Knowns*** (KKC)  a el 	***Knowns Unknowns*** (KUC) Data 有 Label 無
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High ← Knowledge of Domain (Understanding) → *Low*

Recent Advances in Open Set Recognition

❖ Example : Scuba-diving in Ocean

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Knowledge of State (Data available): *High* ↑ … ↓ *Low*

	Knowns	*Unknowns*
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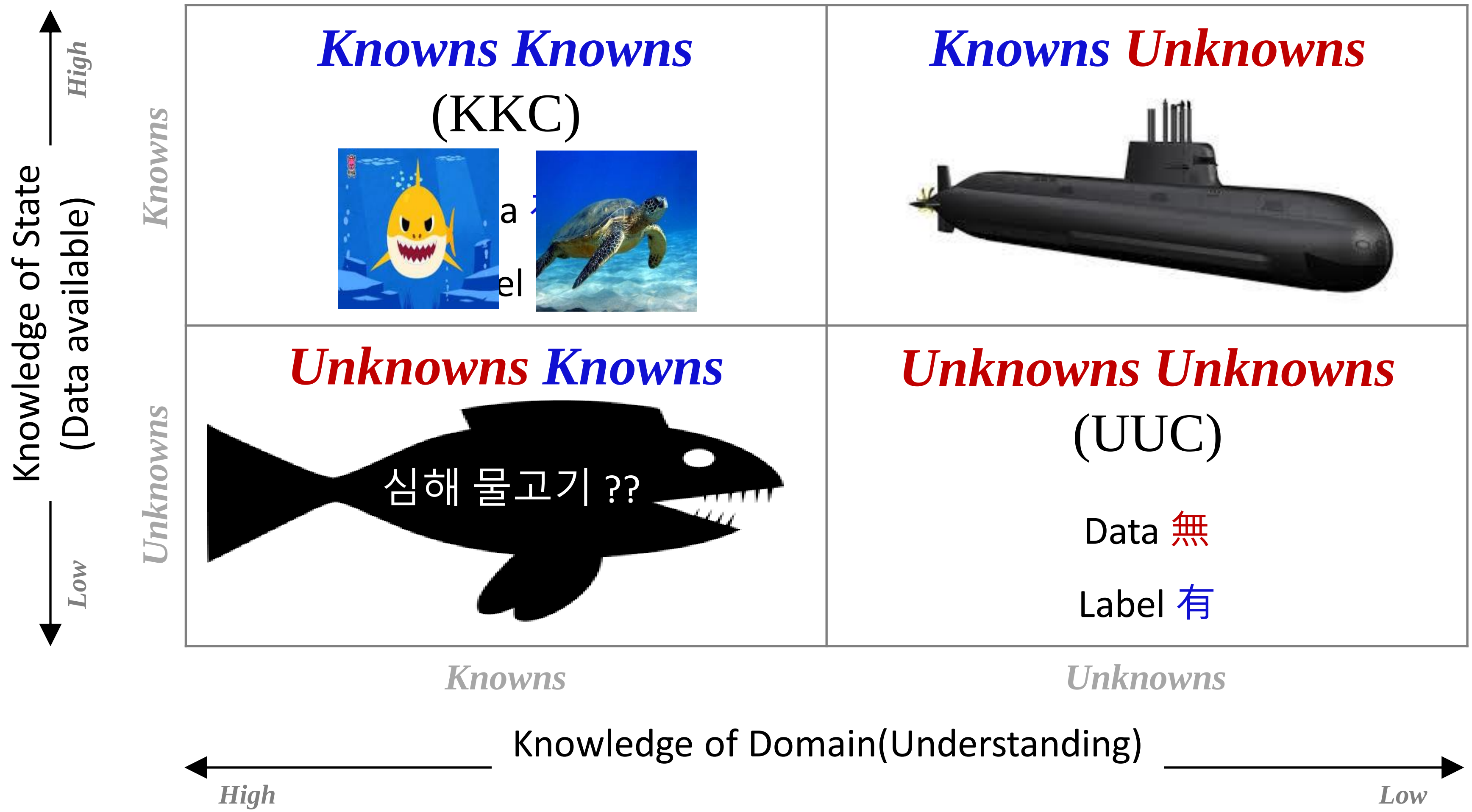

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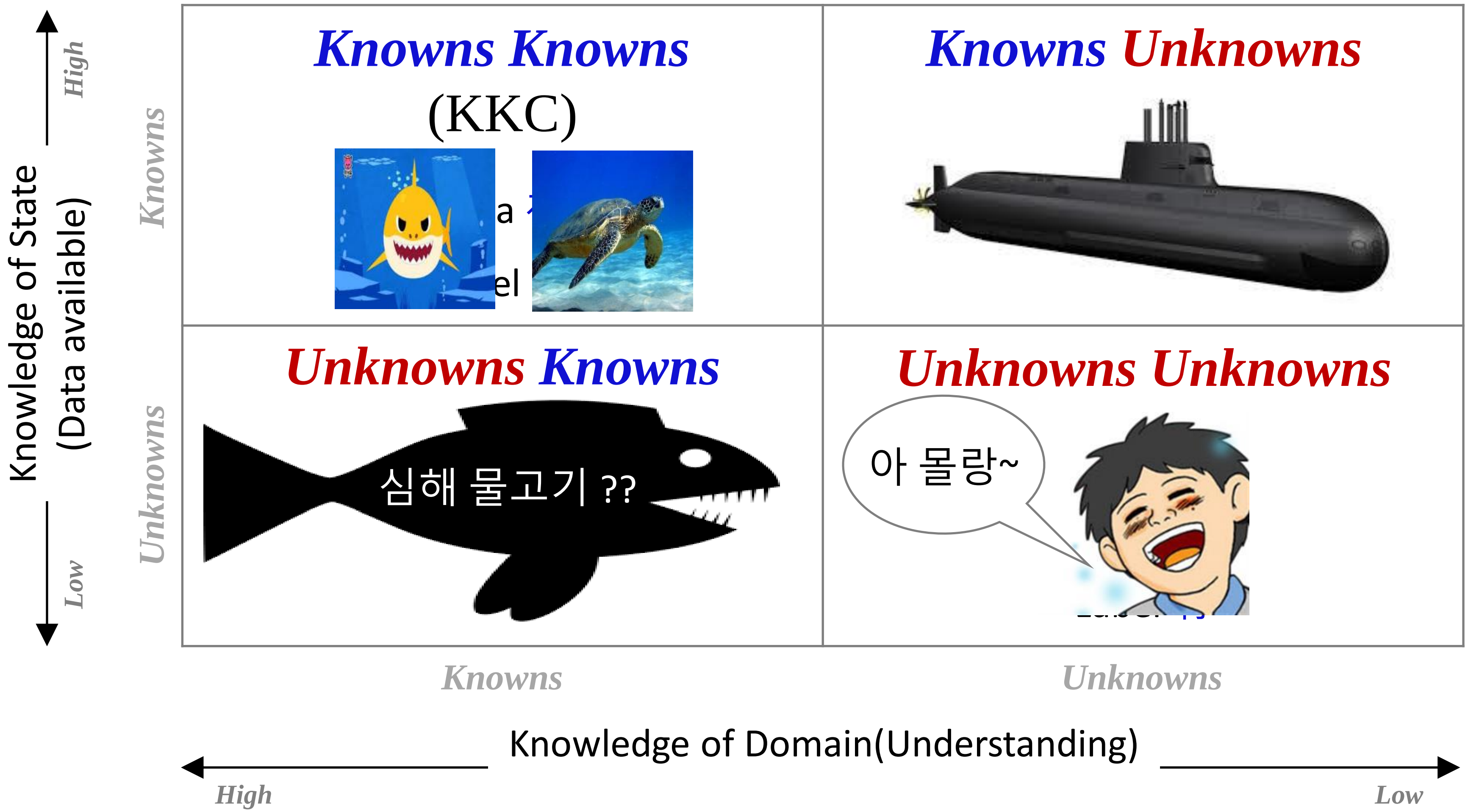

Recent Advances in Open Set Recognition

❖ Various Open Set Recognition Methods

Task \ Setting	Training	Testing	Goal
Traditional classification	KKC	KKC	Classifying KKC
Classification with Reject Option	KKC	KKC	Classifying KKC & rejecting samples of low confidence
One-class Classification (Anomaly Detection)	KKC & few or none outliers from KUCs	KKC & few or none outliers	Detecting outliers
One-shot Learning (Few-shot Learning)	KKC & a limited number of UKCs' samples	UKC	Identifying UKC
Zero-shot Learning	KKC & semantic-information	KKC & UKC	Identifying KKC & UKC
Open Set Recognition	KKC	KKC & UKC	Identifying KKC & rejecting UKC

Recent Advances in Open Set Recognition

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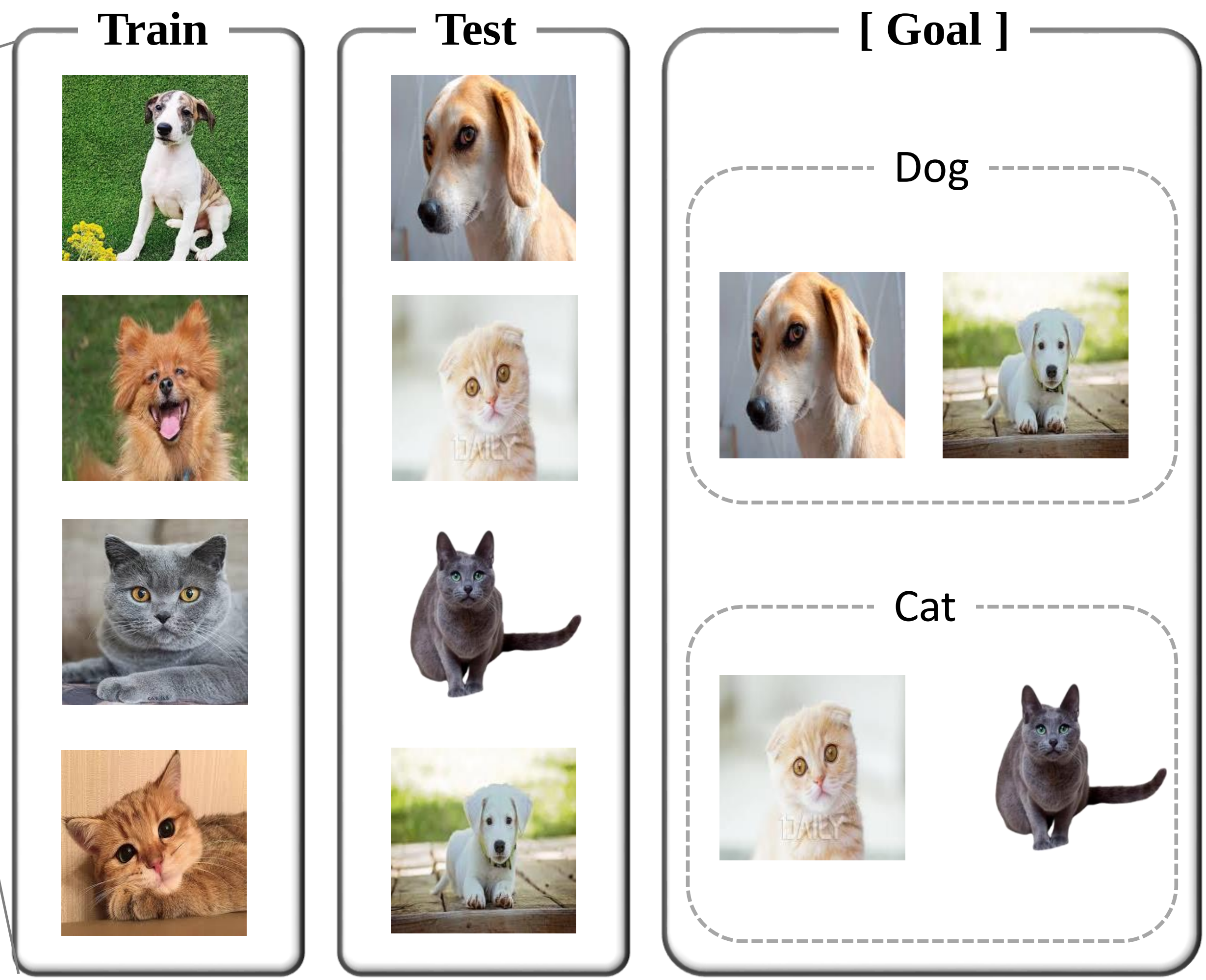

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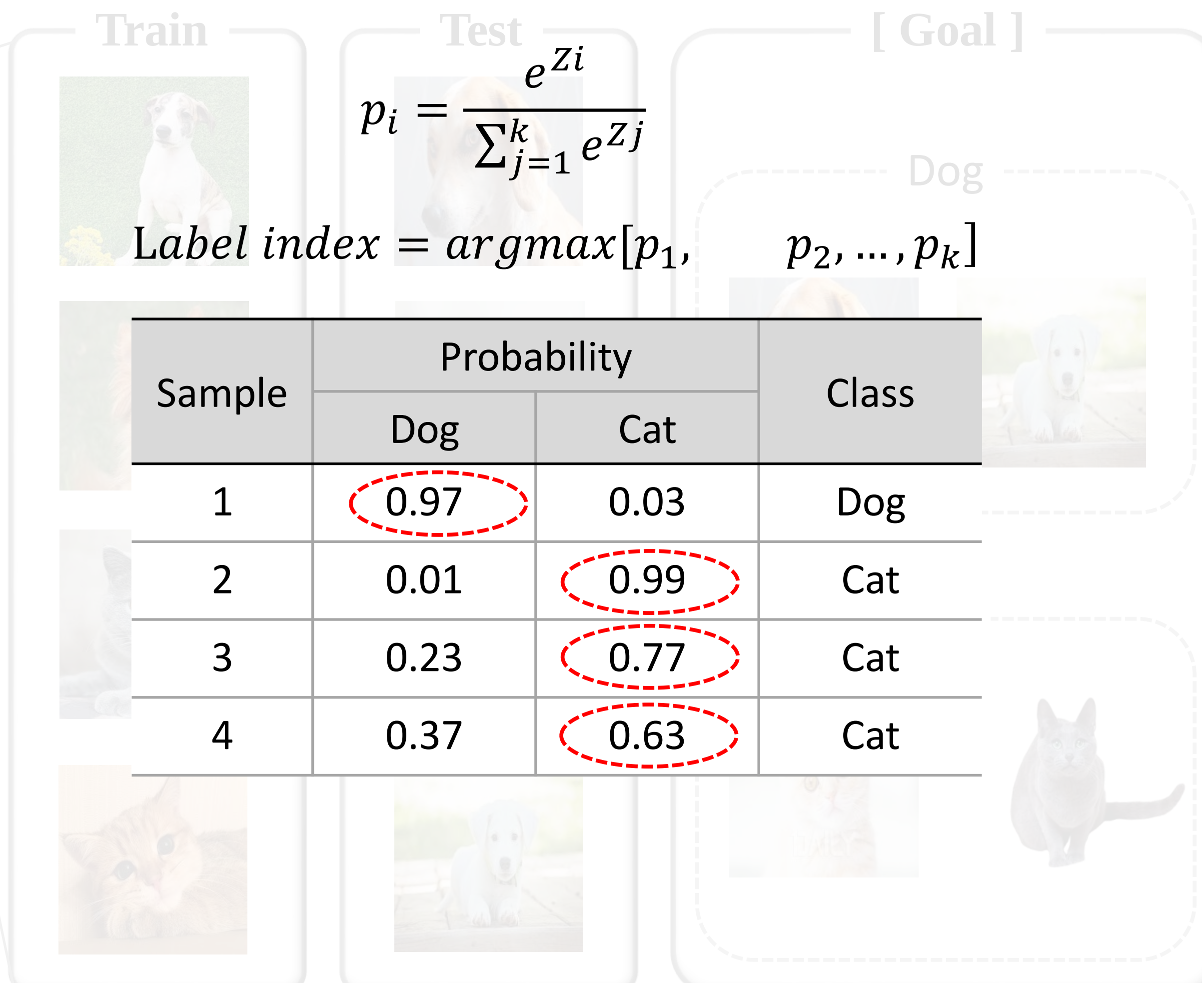

$$p_i = \frac{e^{Zi}}{\sum_{j=1}^{k} e^{Zj}}$$

$$Label\ index = argmax[p_1, \quad p_2, \ldots, p_k]$$

Sample	Probability		Class
	Dog	Cat	
1	0.97	0.03	Dog
2	0.01	0.99	Cat
3	0.23	0.77	Cat
4	0.37	0.63	Cat

Recent Advances in Open Set Recognition

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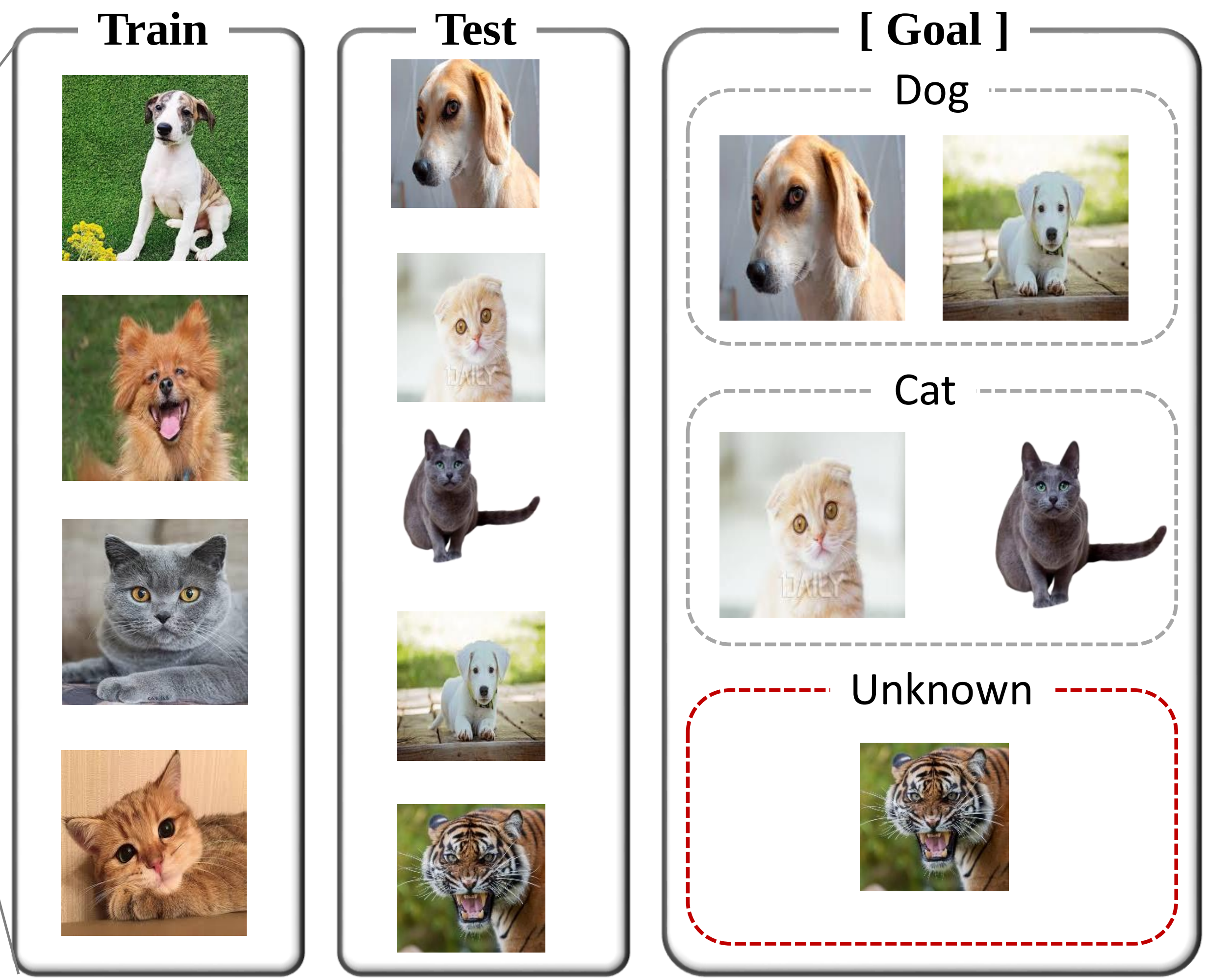

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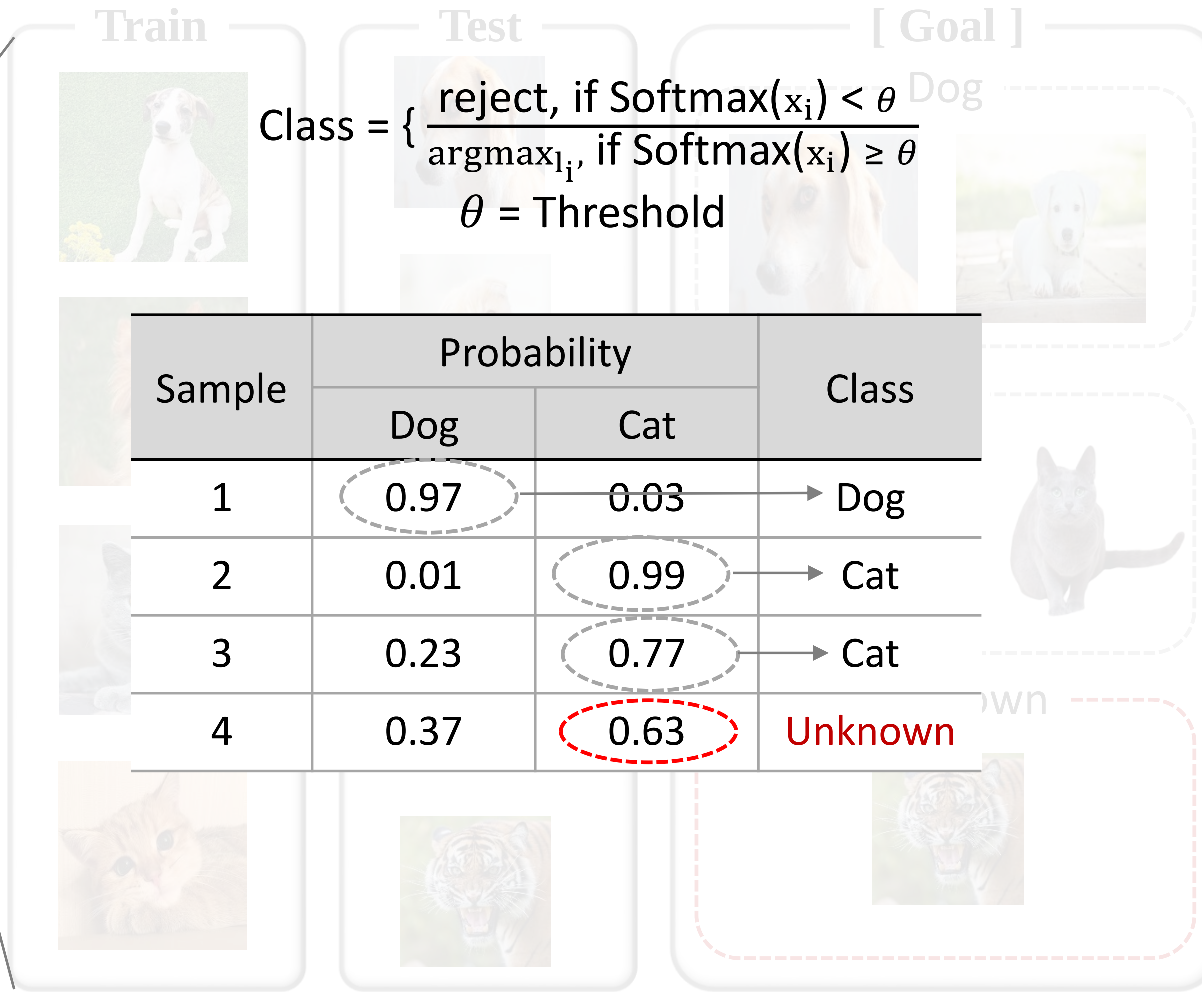

$$\text{Class} = \begin{cases} \text{reject, if Softmax}(x_i) < \theta \\ \operatorname{argmax} l_i, \text{ if Softmax}(x_i) \geq \theta \end{cases}$$

θ = Threshold

Sample	Probability		Class
	Dog	Cat	
1	0.97	0.03	Dog
2	0.01	0.99	Cat
3	0.23	0.77	Cat
4	0.37	0.63	Unknown

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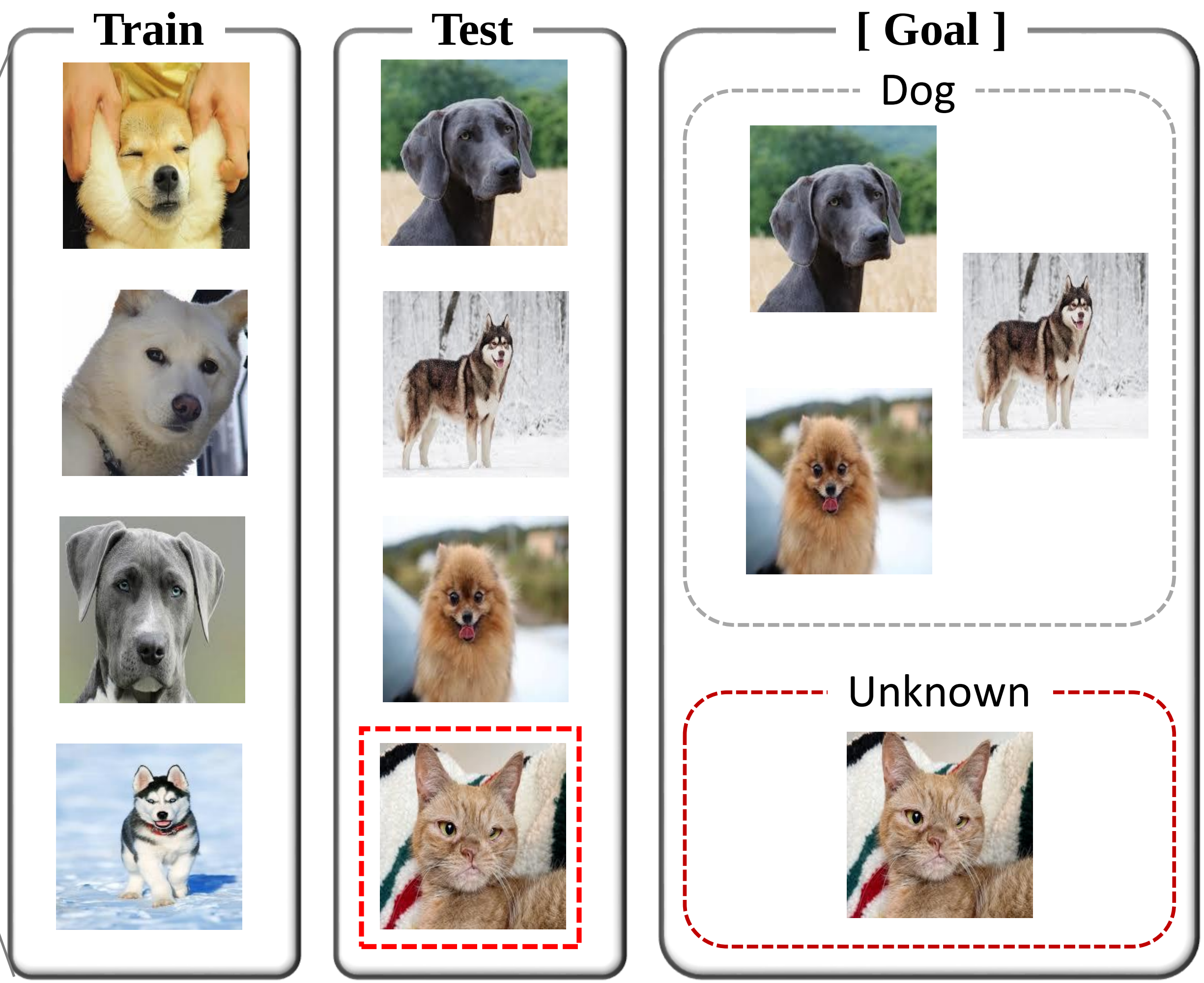

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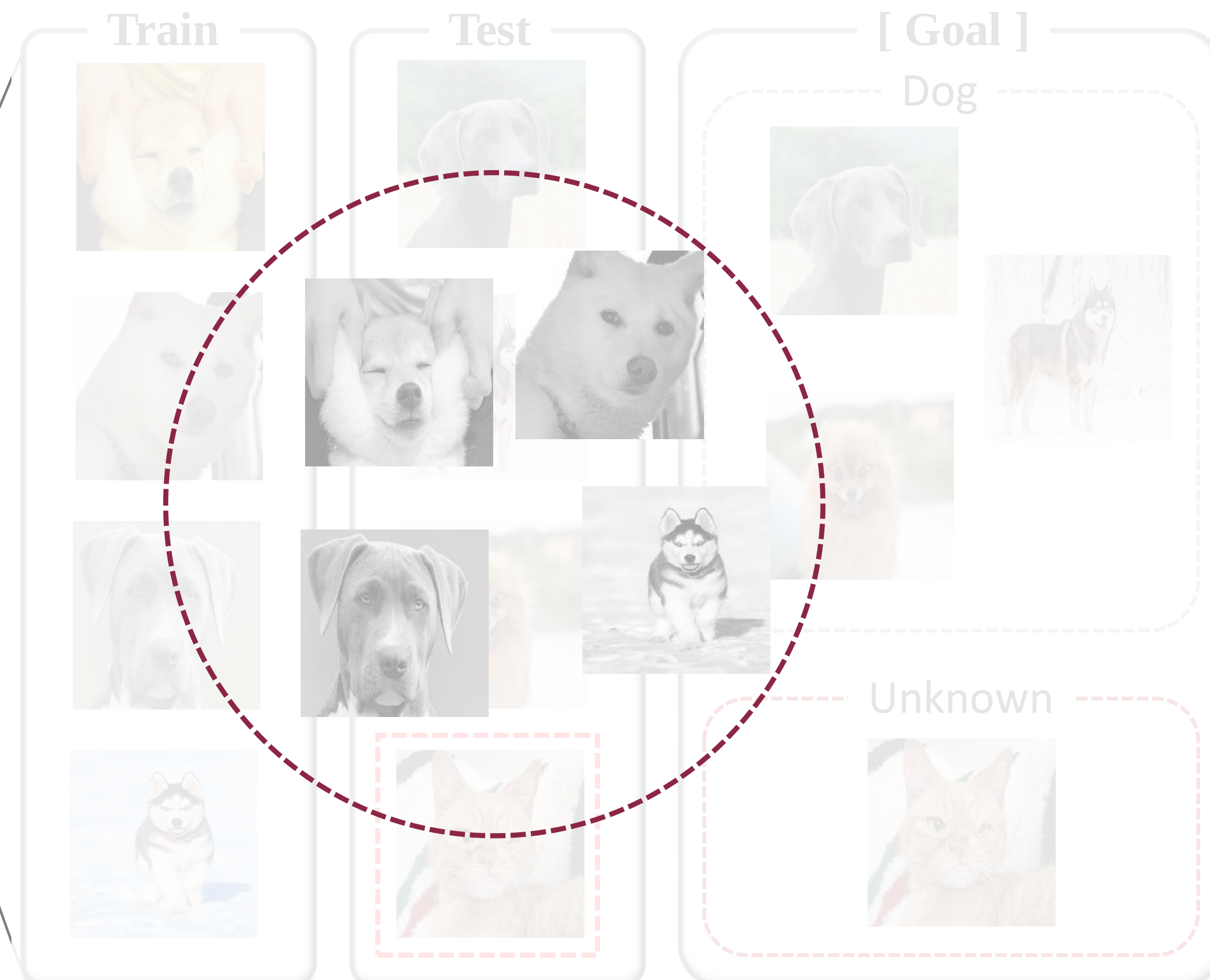

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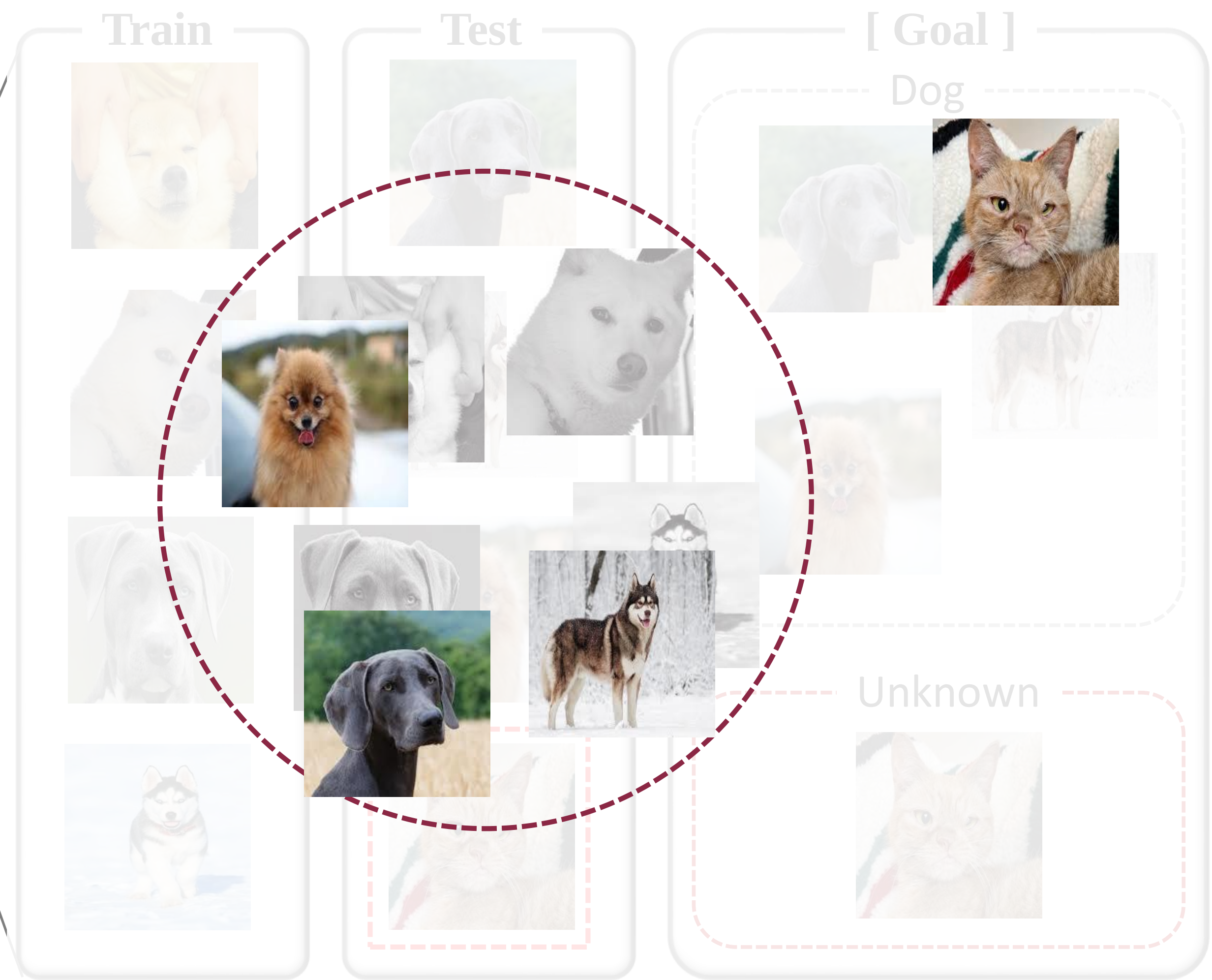

Data Mining Quality Analytics

Recent Advances in Open Set Recognition

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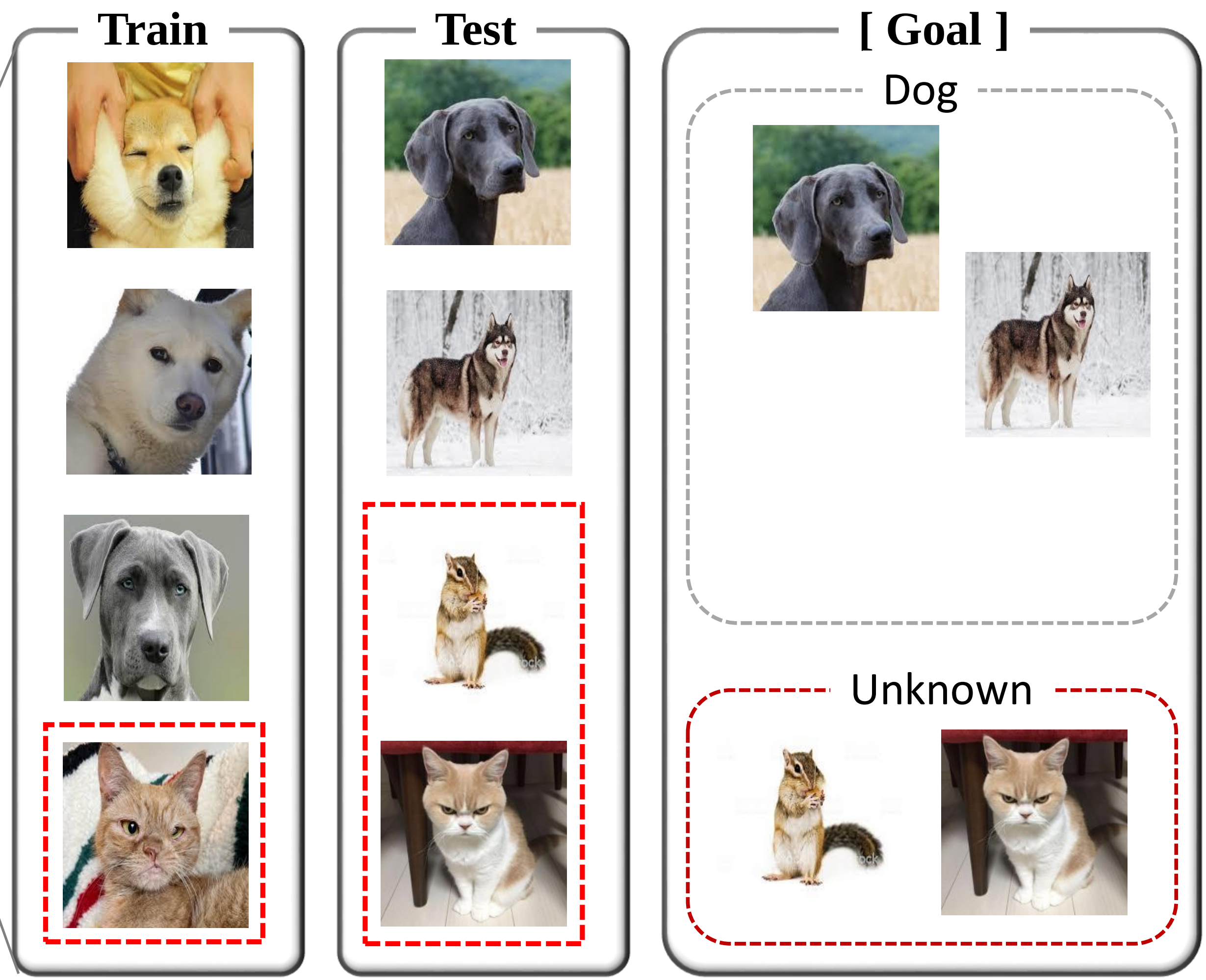

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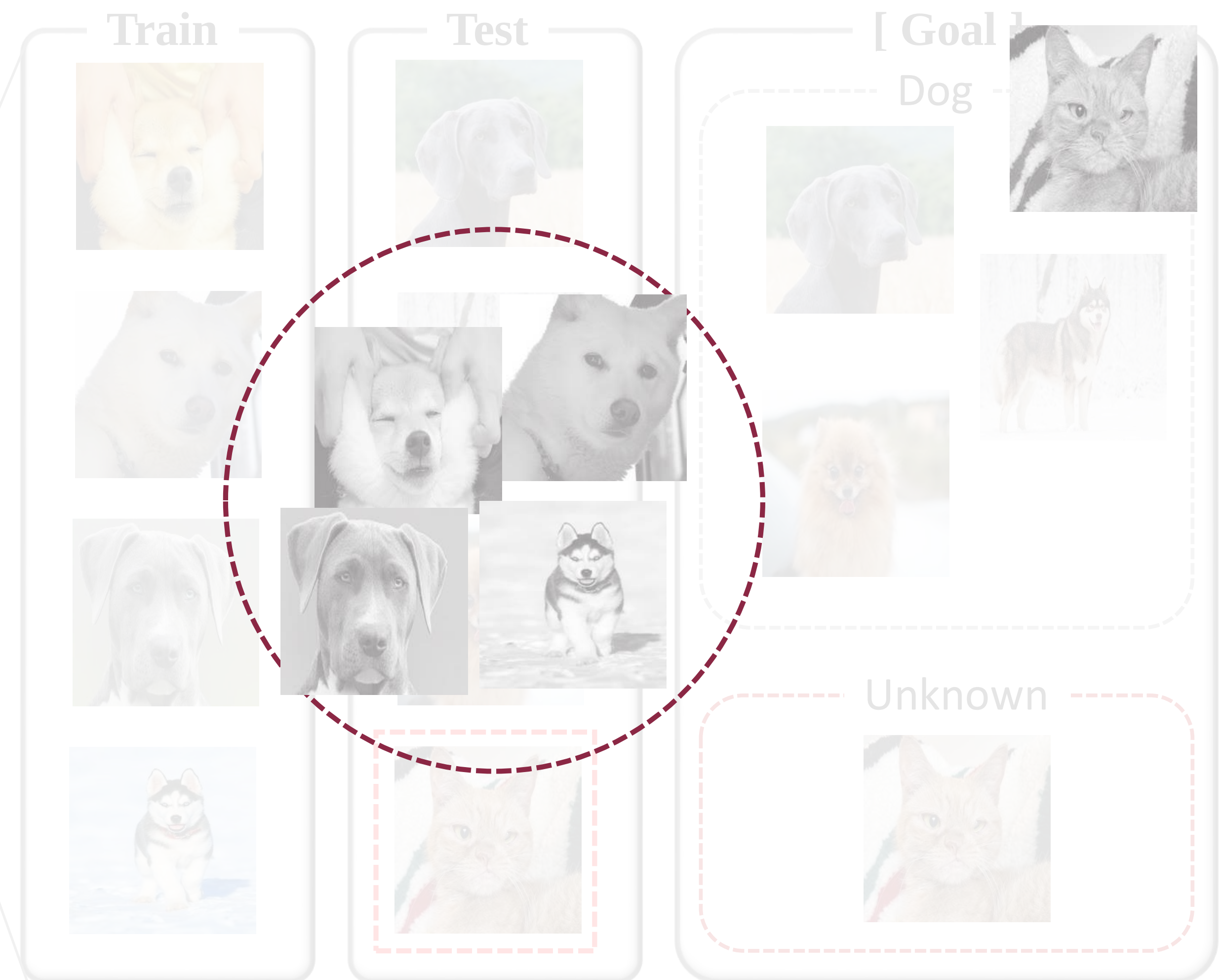

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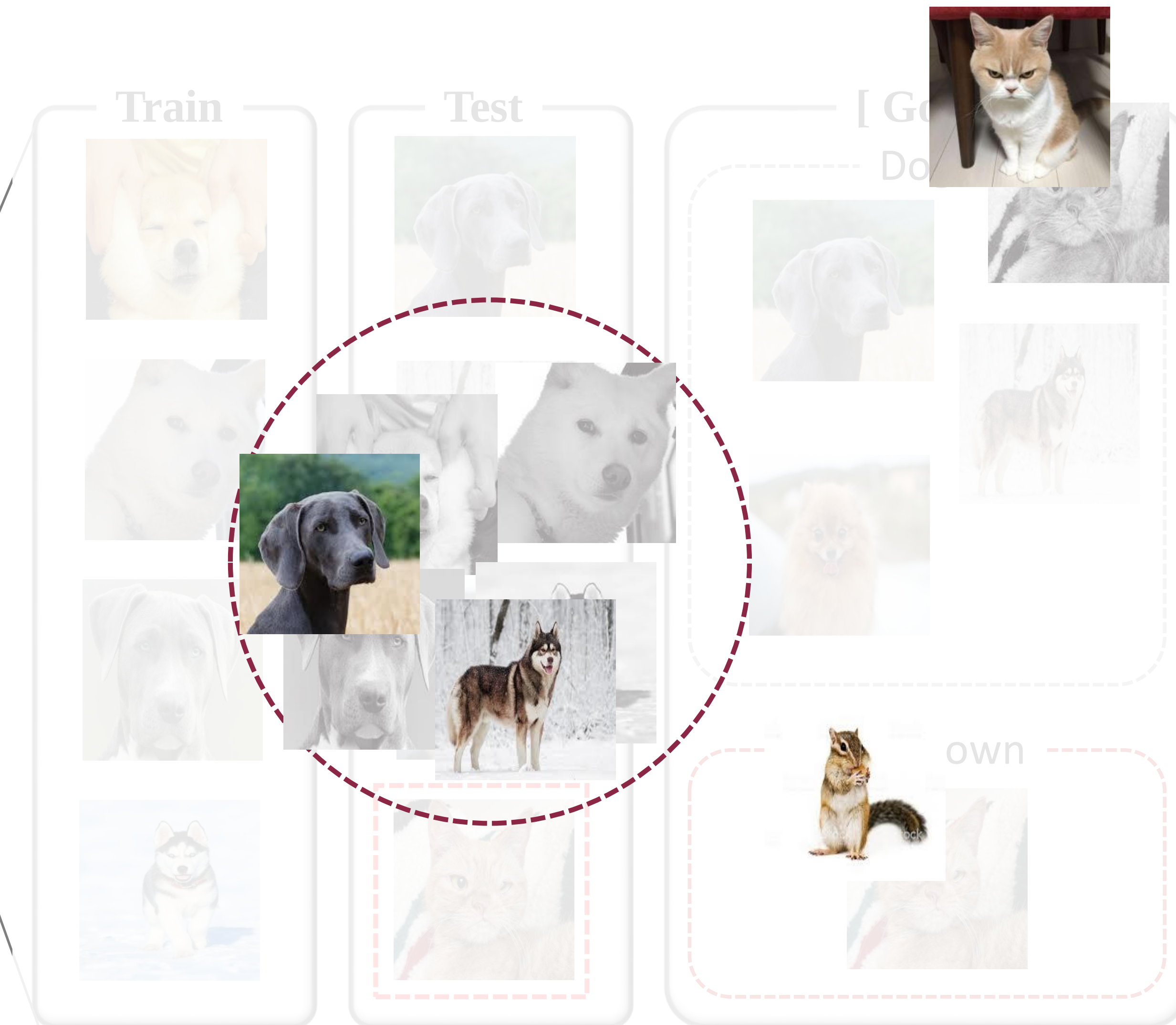

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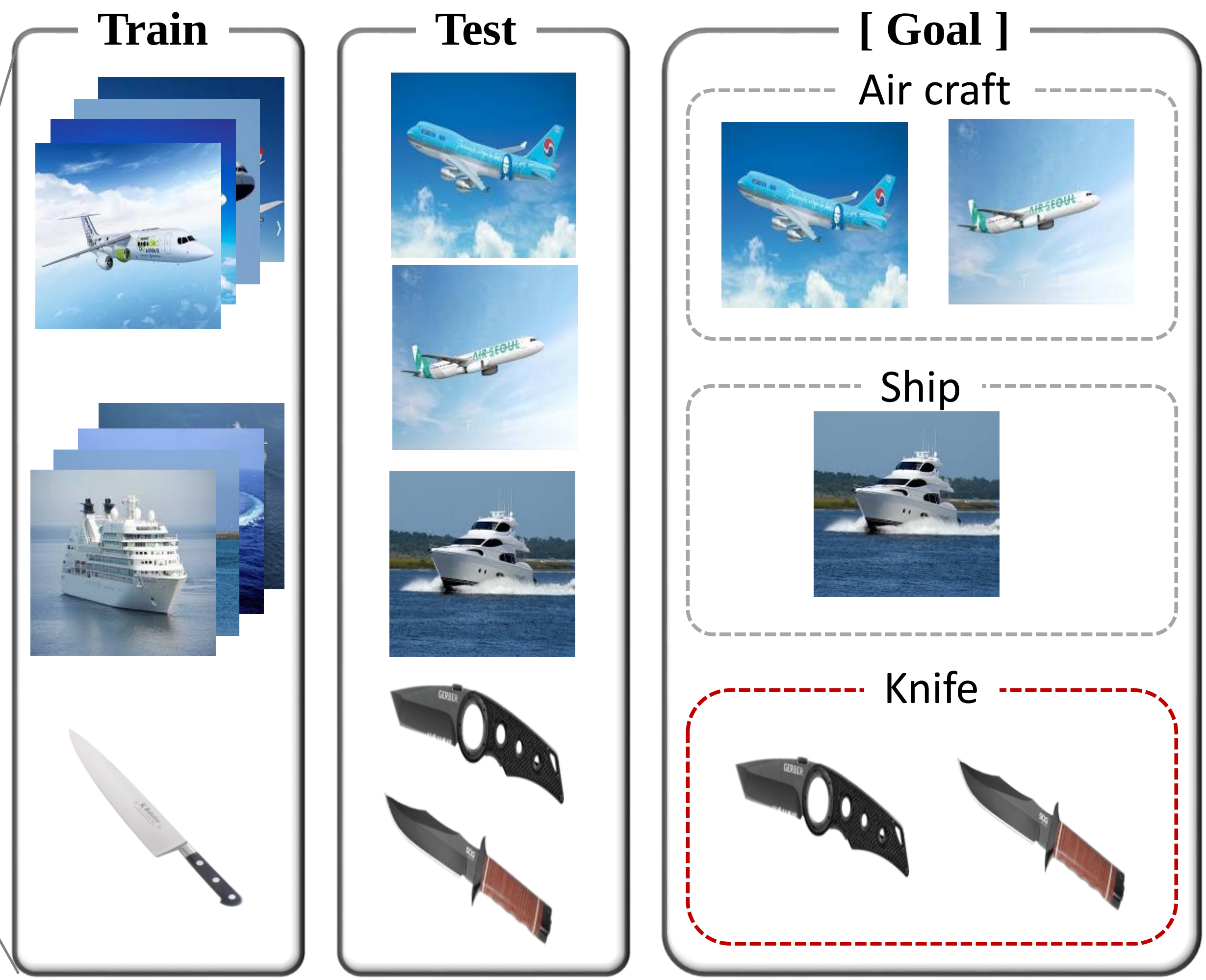

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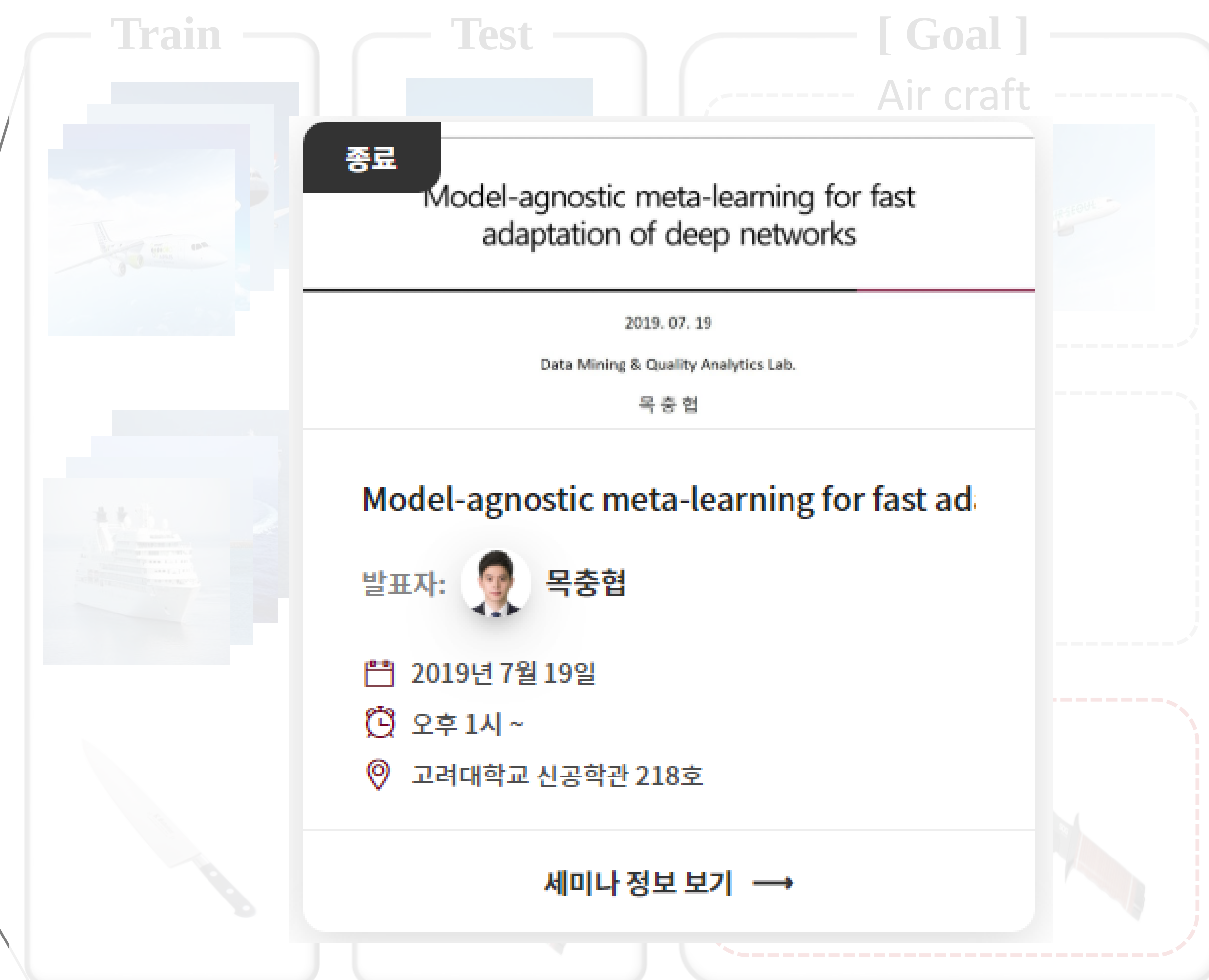

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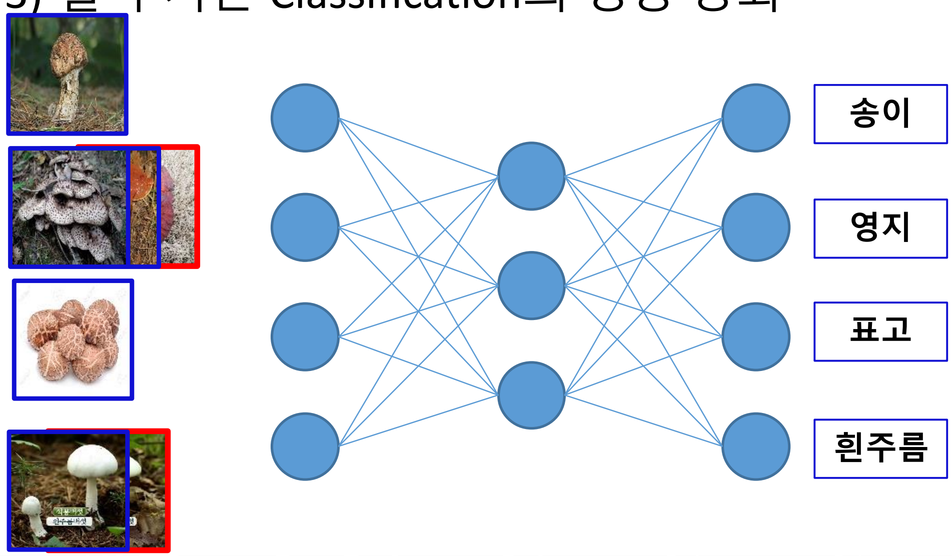
[Why Zero Shot ?]

1) AI 전성 시대 & Data 홍수의 시대
   (너무 많은 Class가 필요)

2) 일부 Class에 대한 Label은 전문가만이 가능

3) 결국 기존 Classification의 성능 강화



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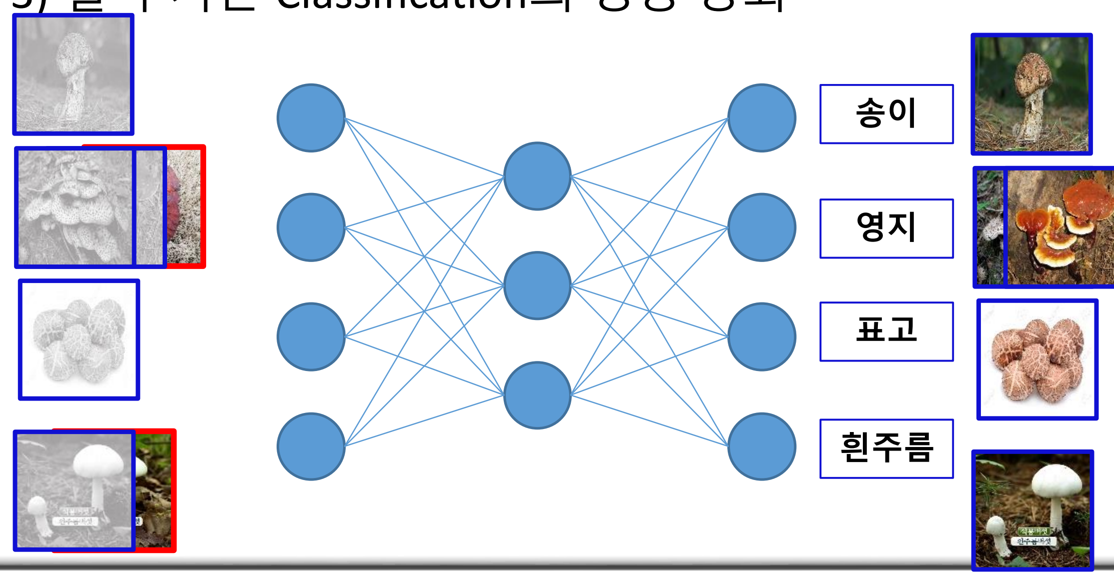

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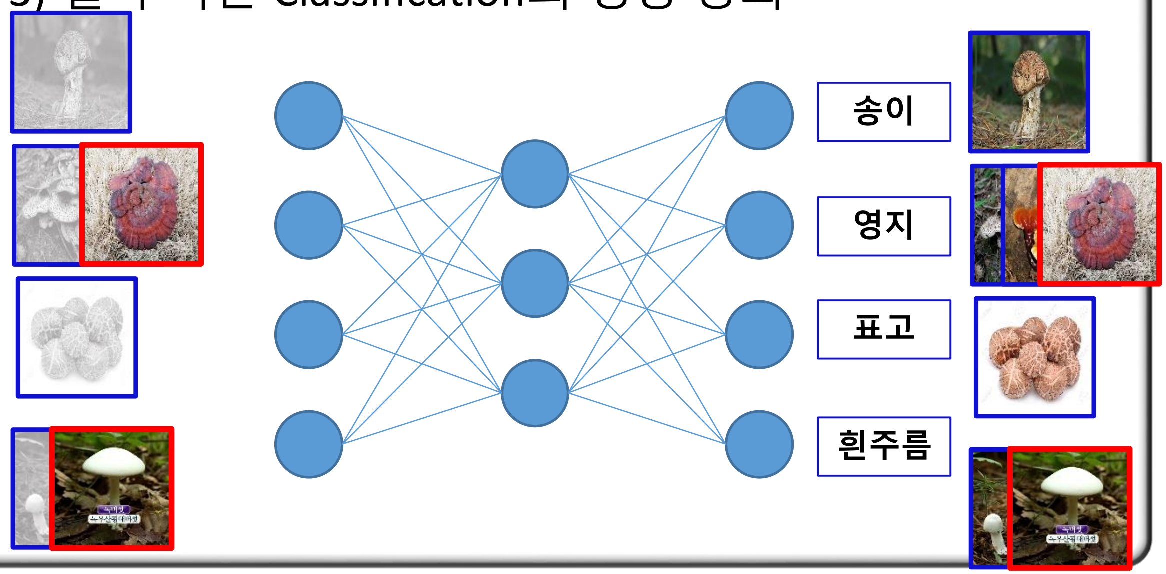

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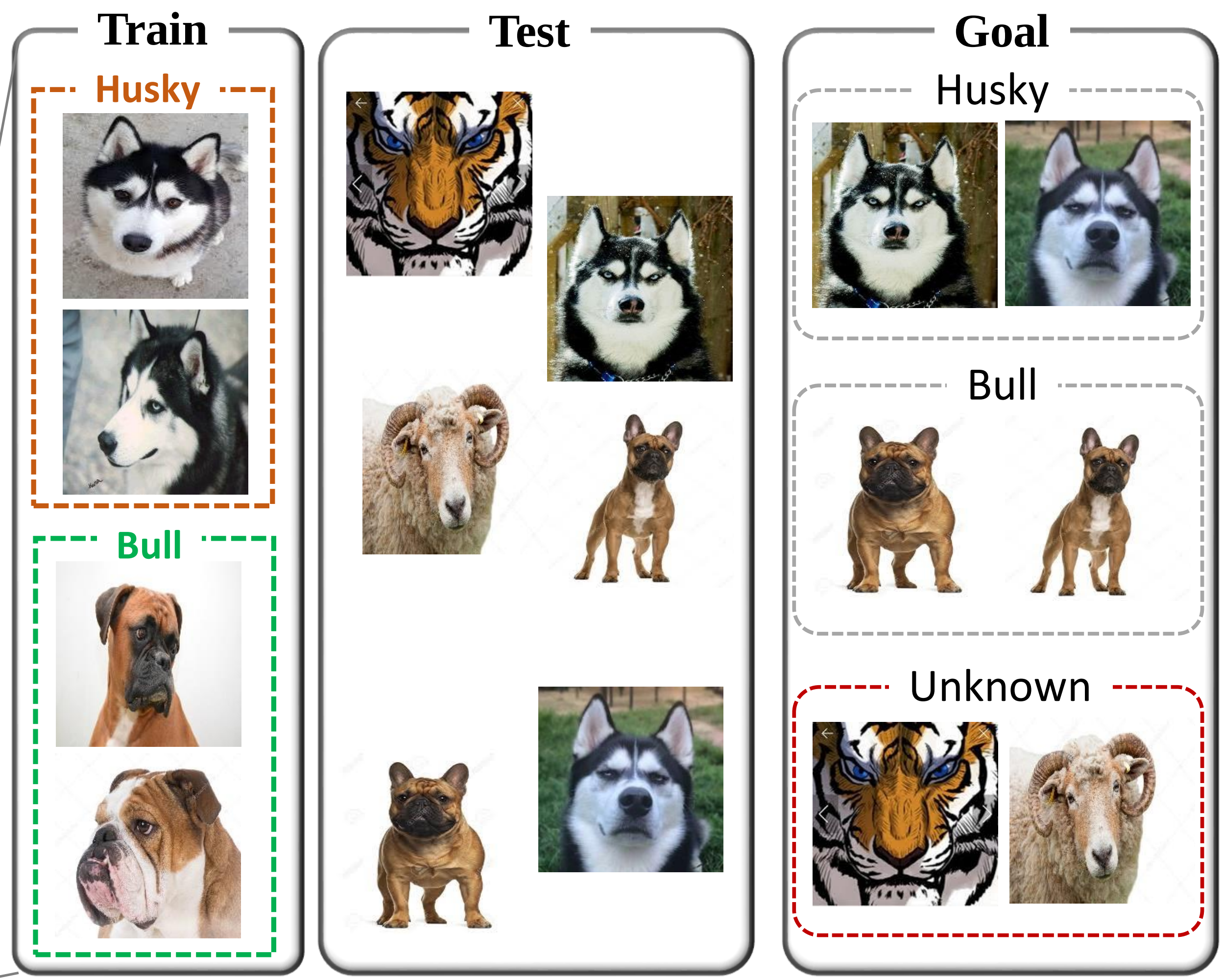

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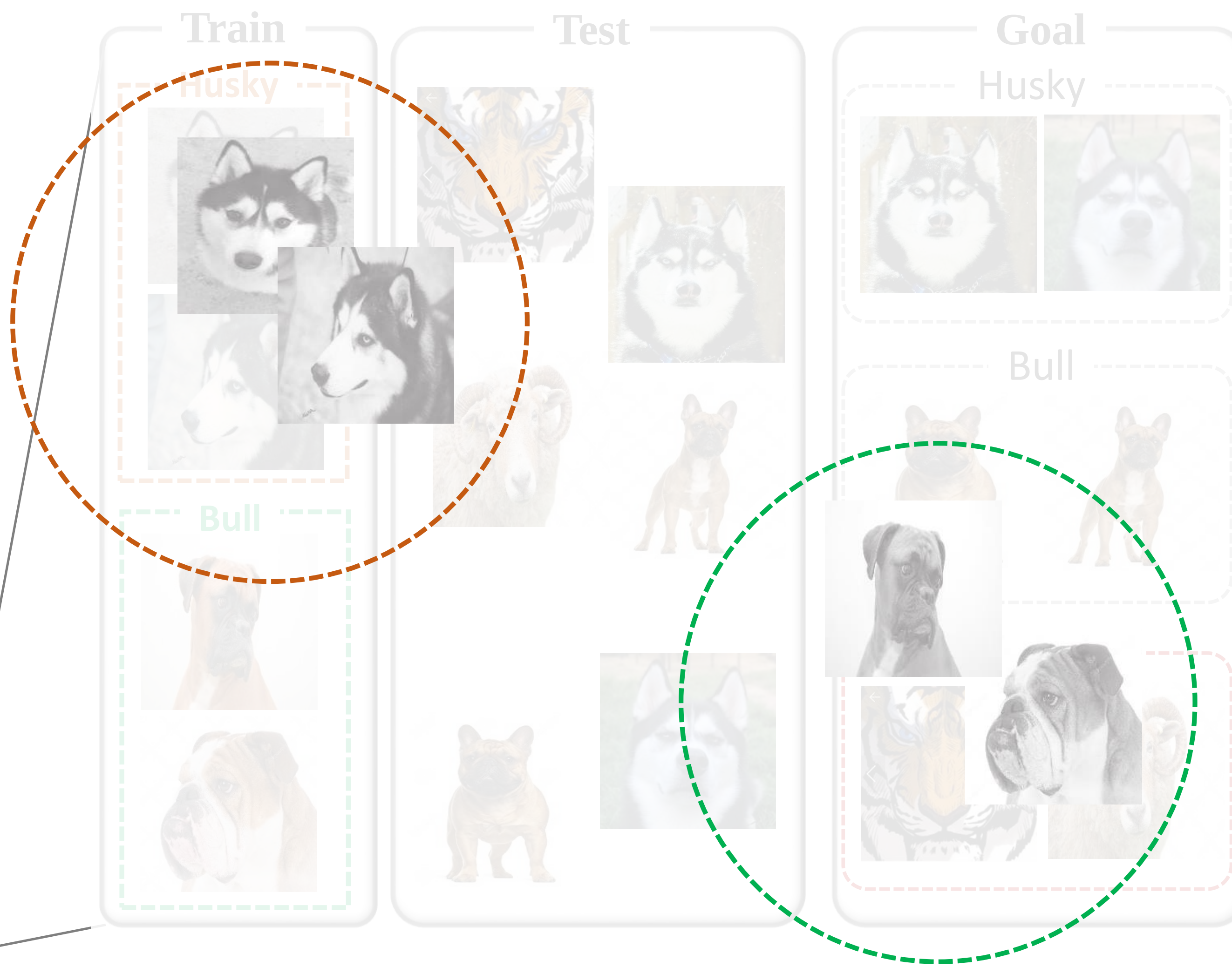

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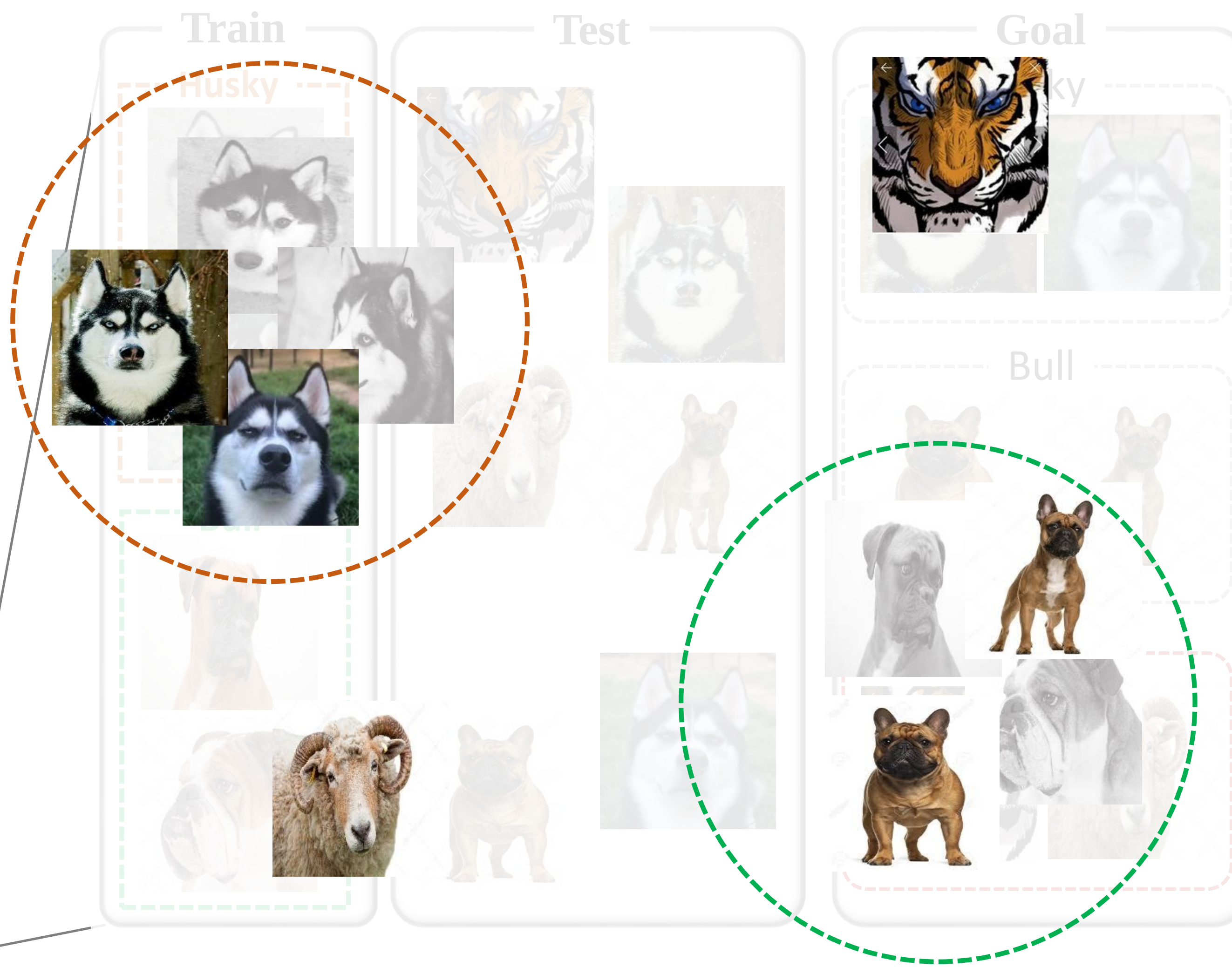

Recent Advances in Open Set Recognition

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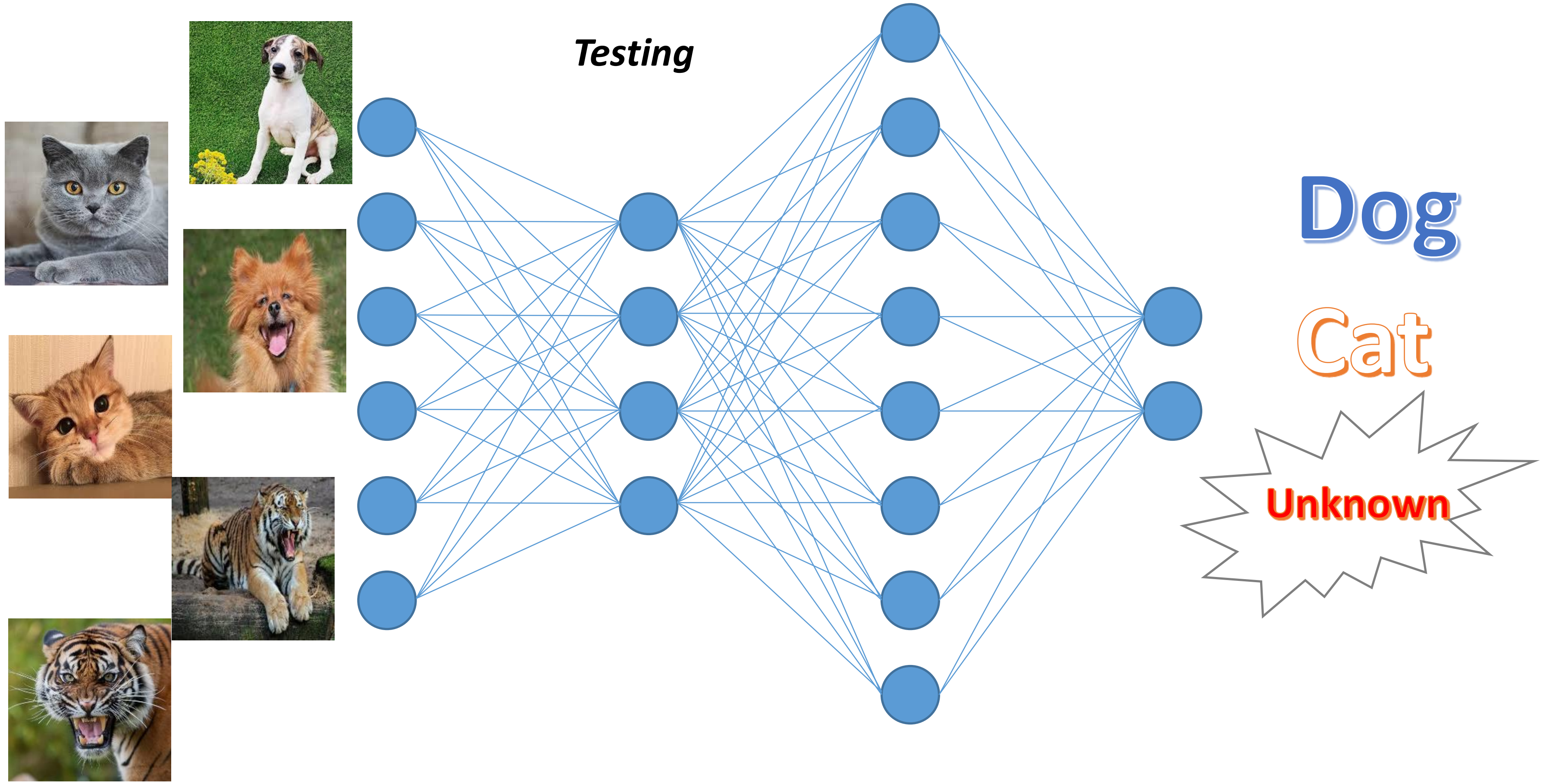

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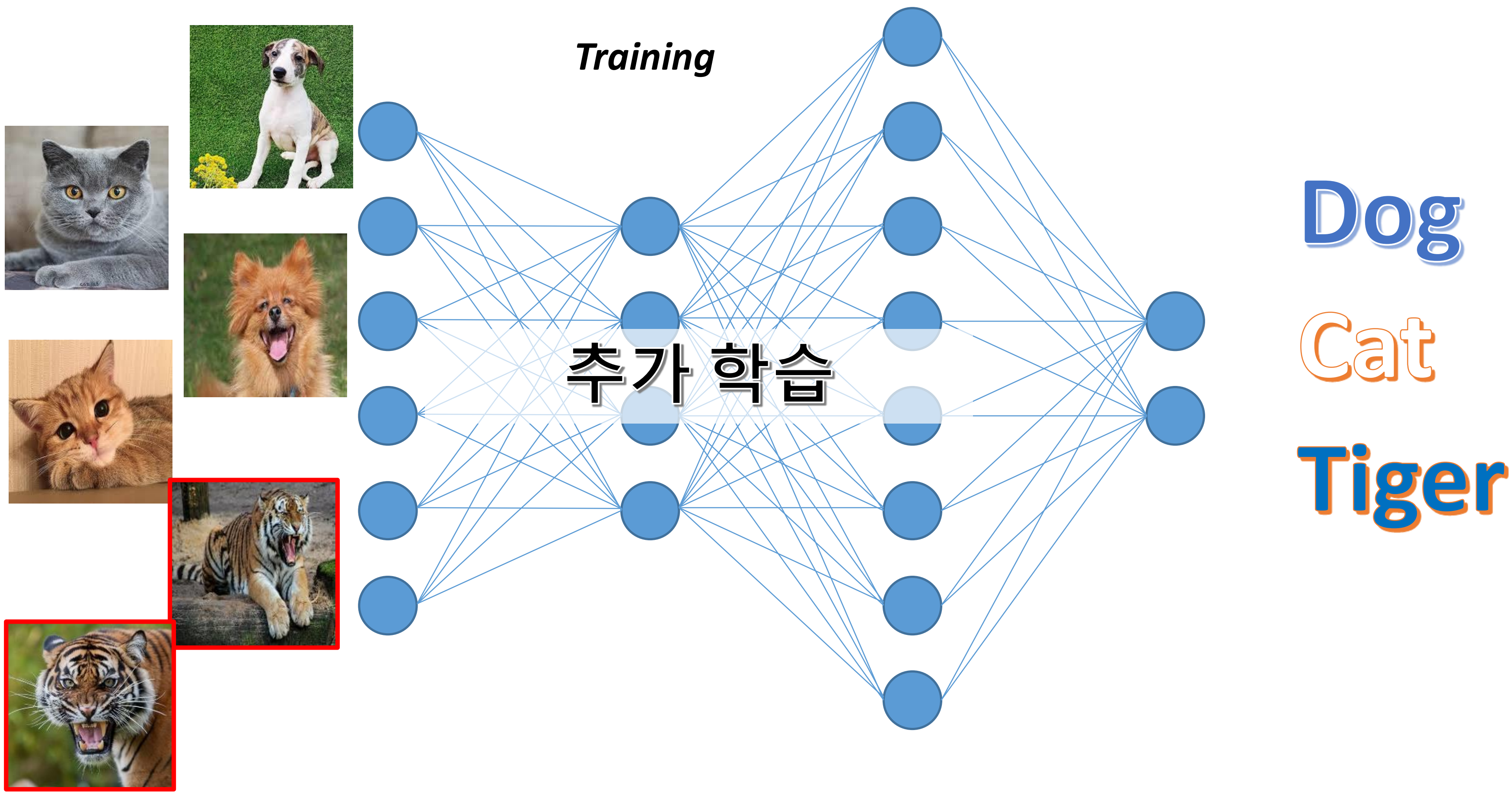


3. What I do in DMQA ?

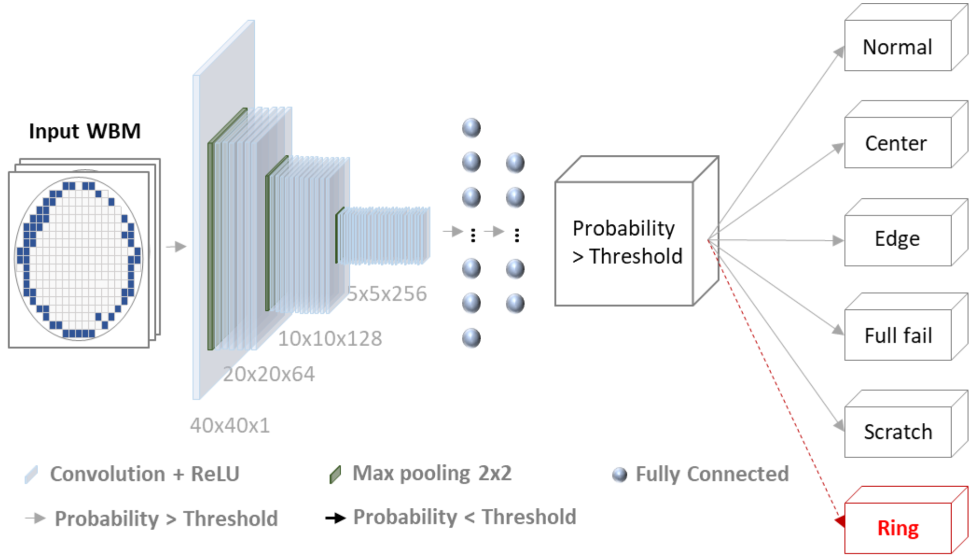
What I do in DMQA ?

❖ Wafer Bin MAP (WBM) Classification

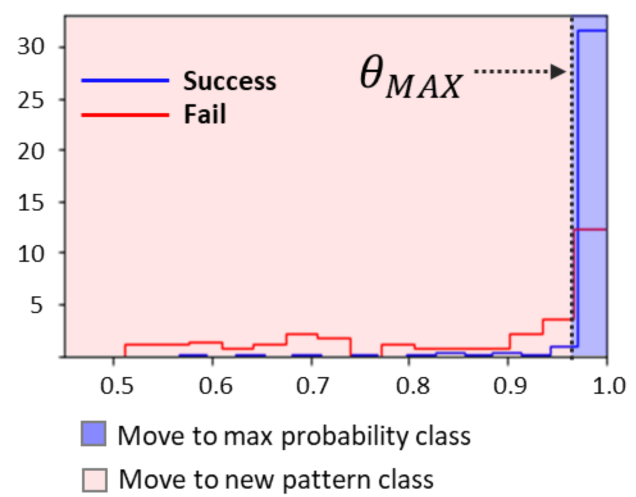
➢ Center / Edge / Loc etc 기존의 Pattern을 잘 분류 하자!!

But!! 새로운 Pattern이 나온다면?

[Structure]



[How to find θ]



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Original Classification

True label \ Predict label	Normal	Center	Edge	Full fail	Scratch	Ring (New)
Normal	225	0	9	0	0	0
Center	5	78	5	1	0	0
Edge	16	4	272	4	0	0
Full fail	1	1	3	20	1	0
Scratch	0	3	2	1	5	0
Ring (New)	0	2	0	15	68	0

Proposed Classification (by max)

True label \ Predict label	Normal	Center	Edge	Full fail	Scratch	Ring (New)
Normal	199	0	4	0	0	31
Center	3	69	1	0	0	16
Edge	4	2	256	1	0	33
Full fail	0	1	1	16	0	8
Scratch	0	1	0	1	3	6
Ring (New)	0	0	0	2	36	47

Proposed Classification (by stdev)

True label \ Predict label	Normal	Center	Edge	Full fail	Scratch	Ring (New)
Normal	205	0	7	0	0	22
Center	3	73	2	0	0	11
Edge	5	2	260	1	0	28
Full fail	0	1	1	17	0	7
Scratch	0	2	0	1	4	4
Ring (New)	0	0	0	3	43	39

□ Number of samples found a new pattern　□ The number of samples that require reclassification

What I do in DMQA ?

❖ Wafer Bin MAP (WBM) Classification

성 과	한계점
1) 신규 불량 패턴 등장 인식 가능 2) 잘못된 분류의 감소 (후속 처리 품질 위험 감소)	1) 지정된 범주의 이중 불량 발생 탐지 불가 2) 신규 불량 패턴의 종류를 고려하지 않고 모두 신규 패턴(1 Class)으로 분류 (2개 이상의 신규 패턴 등장 ??)

4. DOC : Deep Open Classification of Text Documents

Data Mining Quality Analytics

DOC : Deep Open Classification of Text Documents

DOC: Deep Open Classification of Text Documents

Lei Shu, Hu Xu, Bing Liu
Department of Computer Science
University of Illinois at Chicago
{lshu3, hxu48, liub}@uic.edu

Abstract

Traditional supervised learning makes the *closed-world* assumption that the classes appeared in the test data must have appeared in training. This also applies to text learning or text classification. As learning is used increasingly in dynamic open environments where some new/test documents may not belong to any of the training classes, identifying these novel documents during classification presents an important problem. This problem is called *open-world classification* or *open classification*. This paper proposes a novel deep learning based approach. It outperforms existing state-of-the-art techniques dramatically.

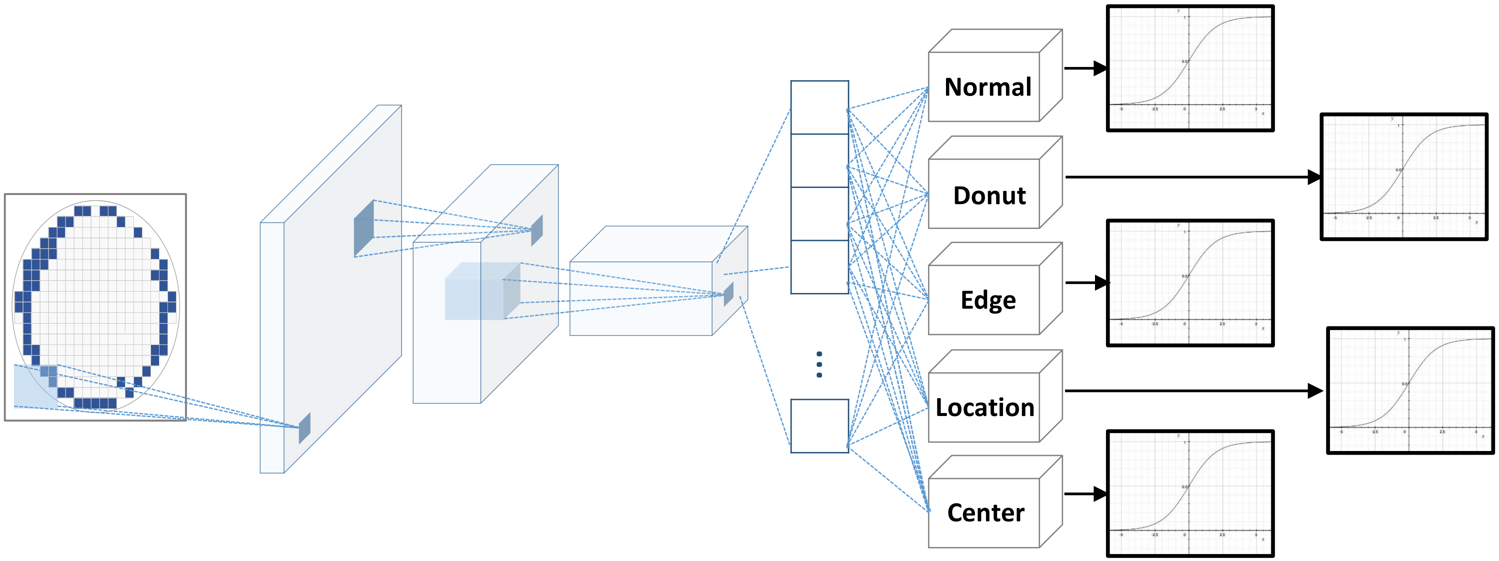
not know. This paper proposes a novel technique to solve this problem.

Problem Definition: Given the training data $D = \{(\mathrm{x}_1, y_1), (\mathrm{x}_2, y_2), \ldots, (\mathrm{x}_n, y_n)\}$, where x_i is the i-th document, and $y_i \in \{l_1, l_2, \ldots, l_m\} = \mathcal{Y}$ is x_i's class label, we want to build a model $f(\mathrm{x})$ that can classify each test instance x to one of the m training or *seen* classes in $\mathcal{Y}$ or reject it to indicate that it does not belong to any of the m training or seen classes, i.e., *unseen*. In other words, we want to build a $(m+1)$-class classifier $f(\mathrm{x})$ with the classes $\mathcal{C} = \{l_1, l_2, \ldots, l_m, \textit{rejection}\}$.

There are some prior approaches for open classification. One-class SVM (Schölkopf et al., 2001; Tax and Duin, 2004) is the earliest approach. However, as no negative training data is used, one-class classifiers work poorly. Fei and Liu (2016)

DOC : Deep Open Classification

❖ DOC : Structure

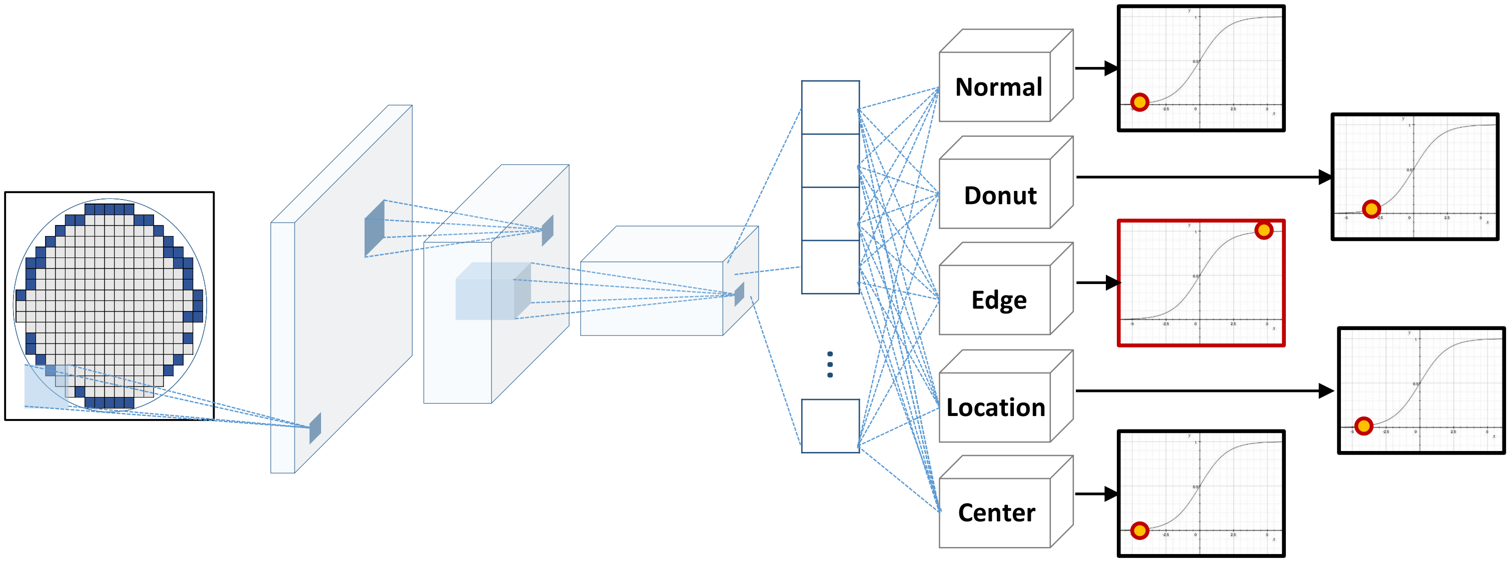


➢ 각 Class 별로 Sigmoid를 최종 활성화 함수로 갖는다.
(고전적인 Multi-task 분류기는 Softmax 사용)

➢ 각 범주별 확률을 따로 계산

DOC : Deep Open Classification

❖ DOC : Example



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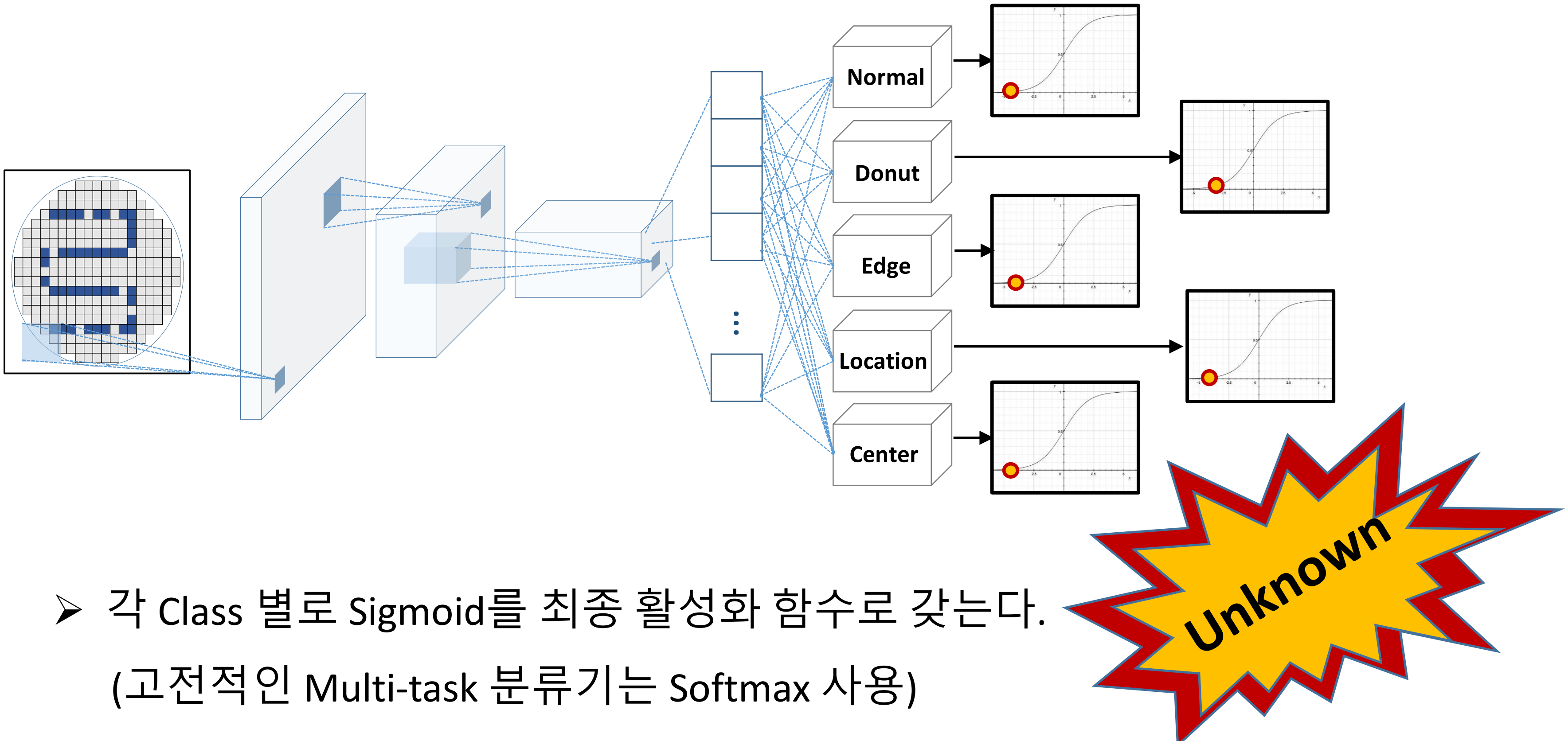

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DOC : Deep Open Classification

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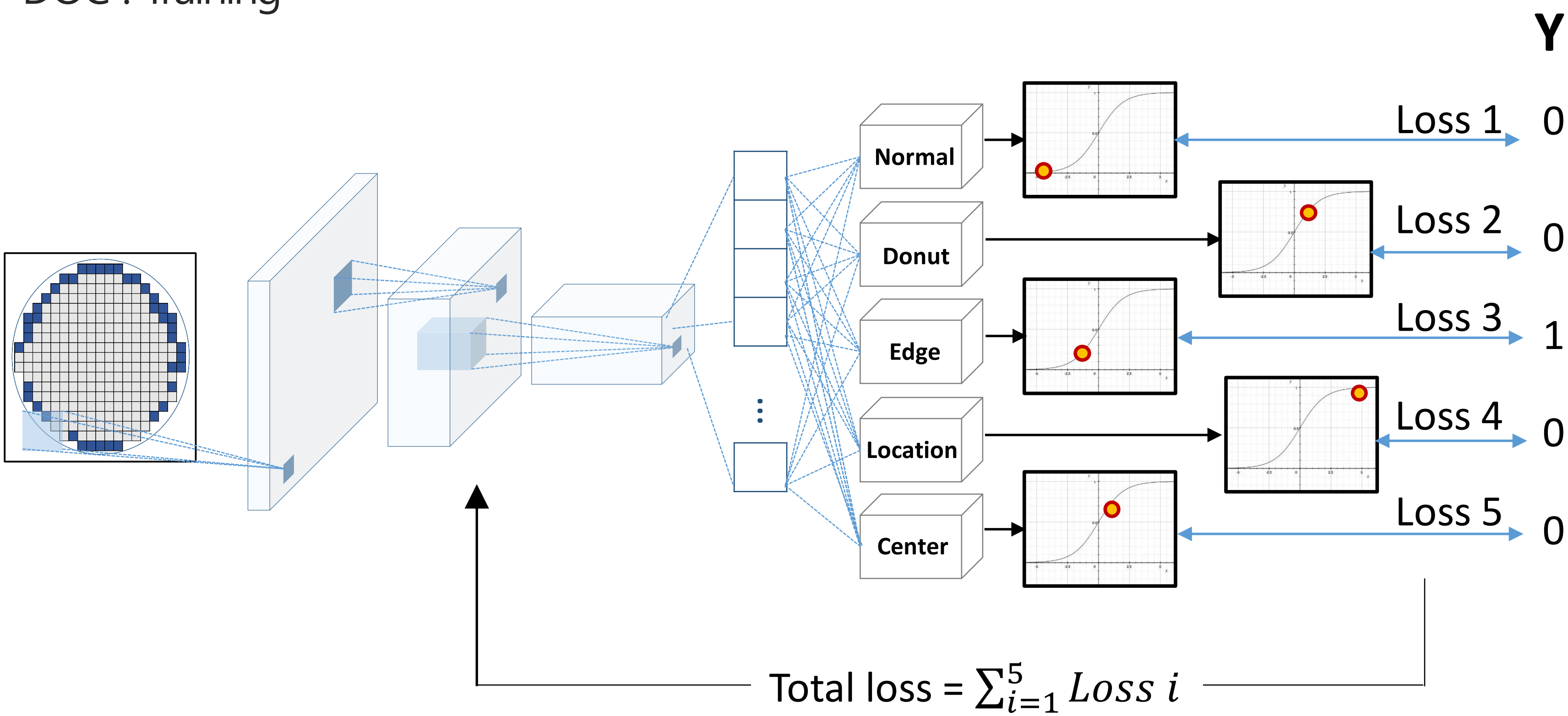
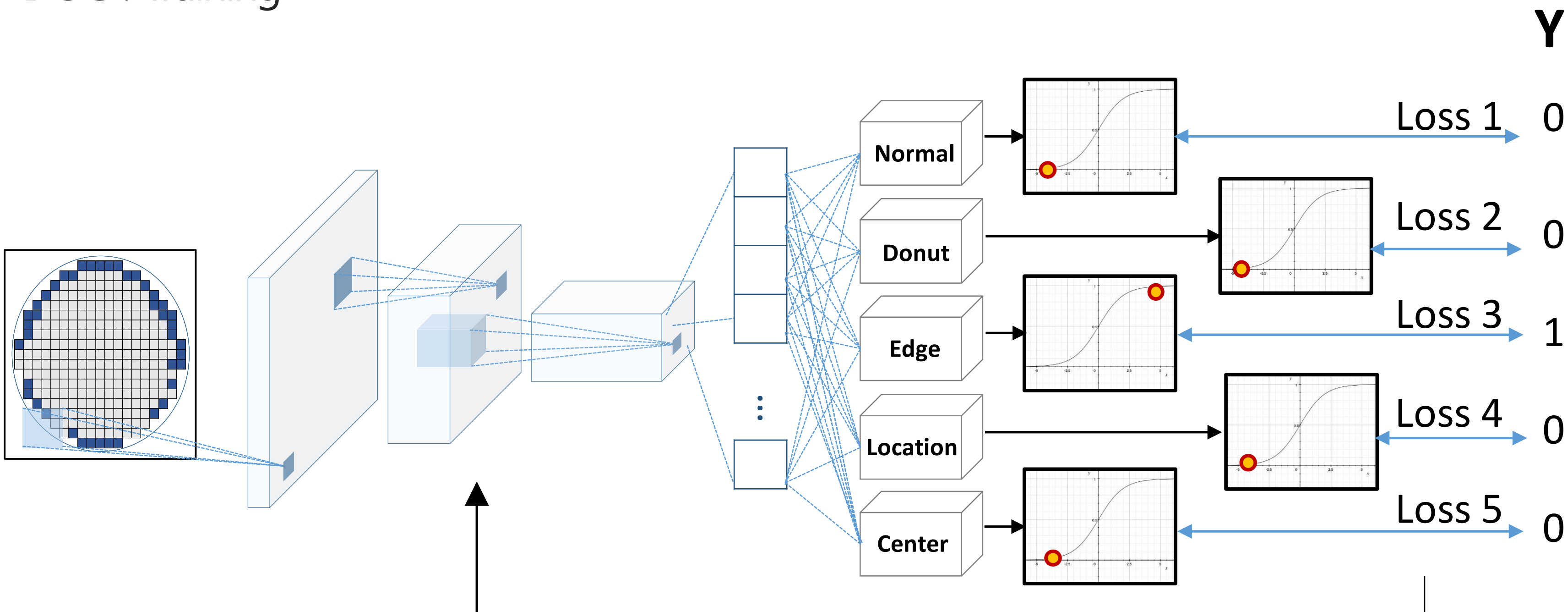


DOC : Deep Open Classification

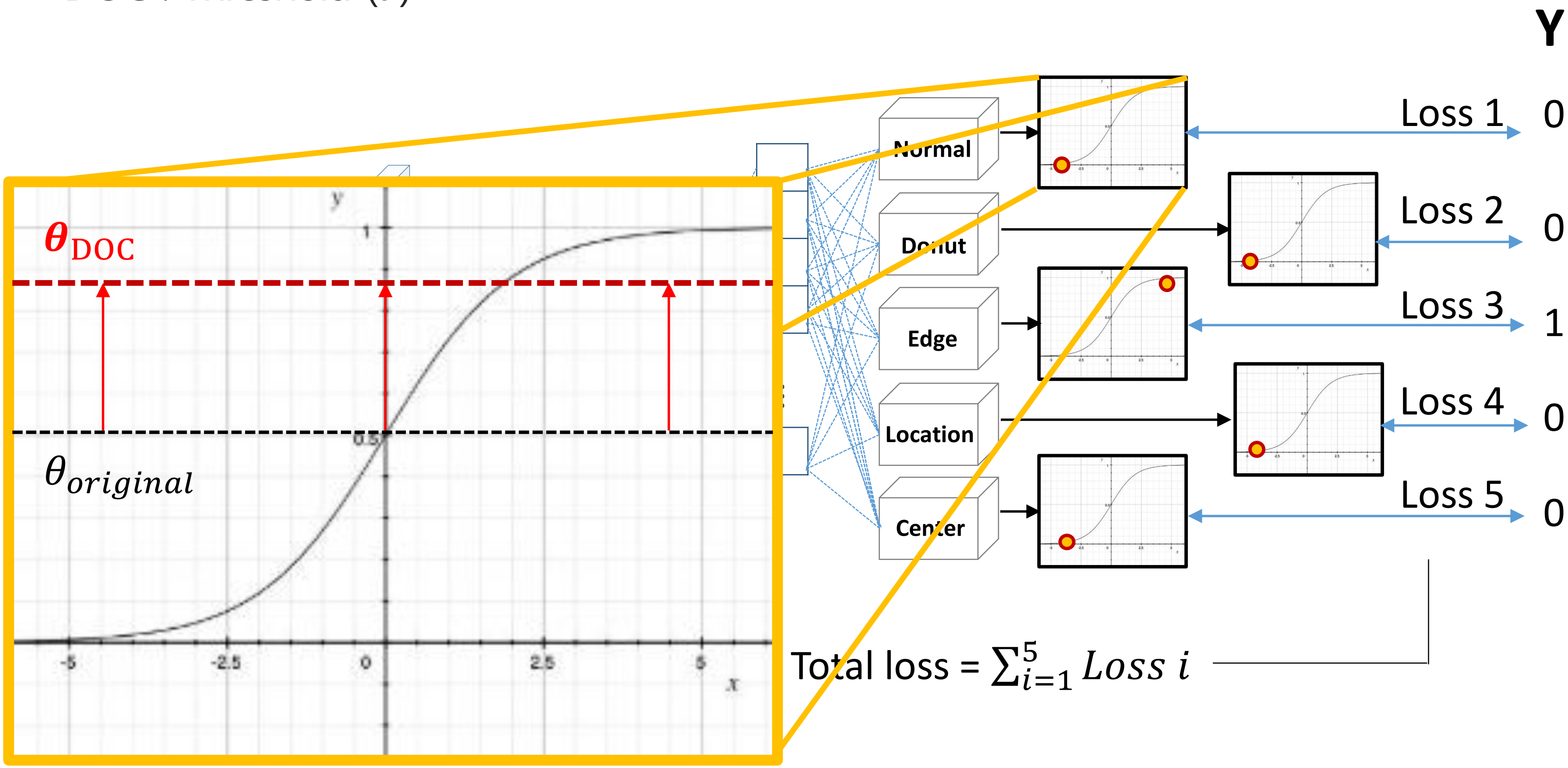
❖ DOC : Training



Total loss = $\sum_{i=1}^{5} Loss\ i$

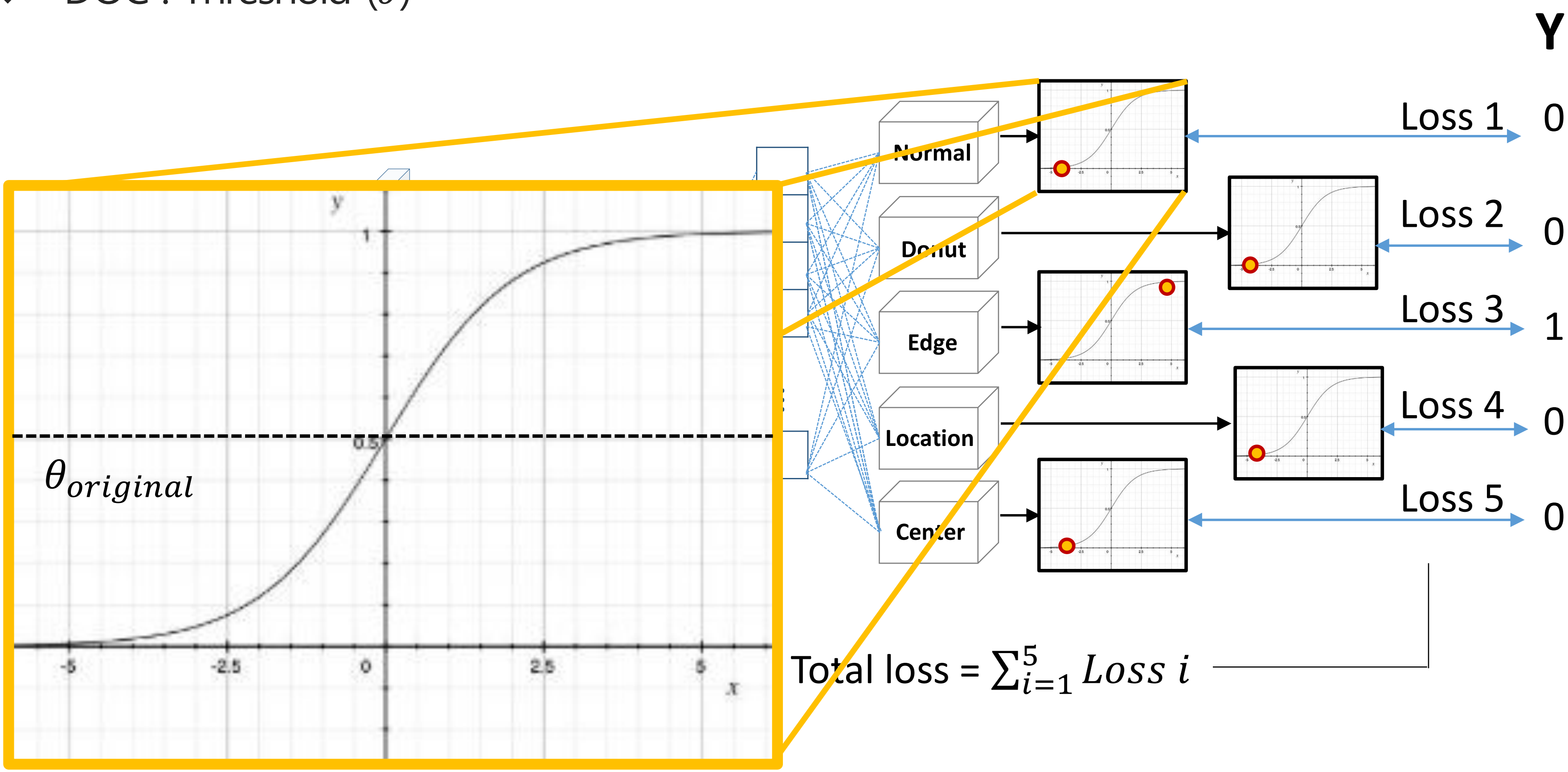
DOC : Deep Open Classification

❖ DOC : Threshold (θ)



DOC : Deep Open Classification

❖ DOC : Threshold (θ)



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2. Estimate the standard deviation σ_i using both the existing points and the created points.
3. In statistics, if a value/point is a certain number (α) of standard deviations away from the mean, it is considered an outlier. We thus set the probability threshold $t_i = \max(0.5, 1 - \alpha\sigma_i)$. The commonly used number for α is 3, which also works well in our experiments.

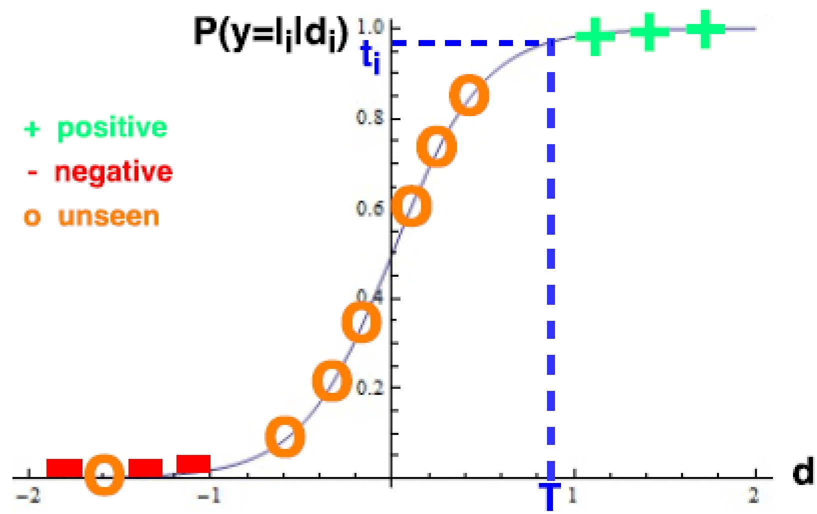

Figure 2: Open space risk of sigmoid function and desired decision boundary $d_i = T$ and probability threshold t_i.

DOC : Deep Open Classification

1) Class i의 예측 확률 $p(y = l_i | x_j, y_j = l_i)$이 가우시안 분포의 절반을 따른다고 가정

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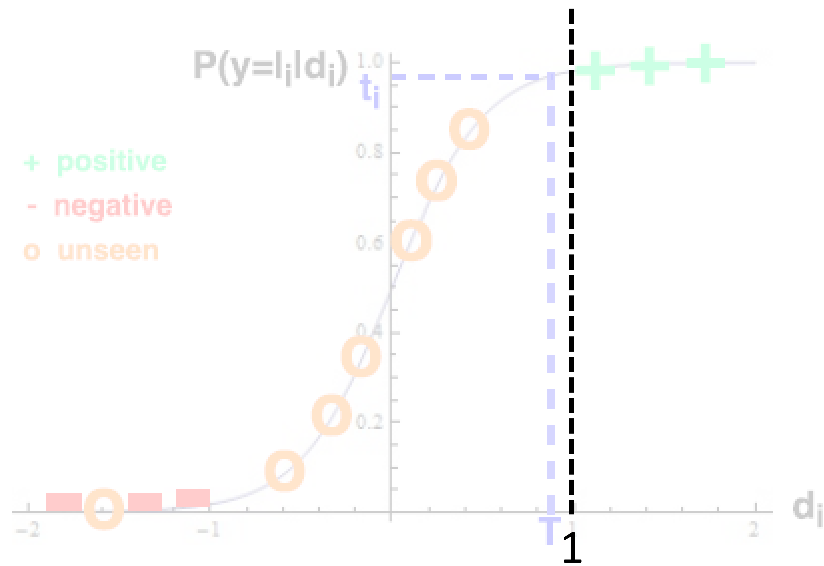

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평균 “1”에 미러링 된 점을 만든다

$mirrored\ point = 1 + (1 - p(y = l_i|x_j, y_j{=}l_i))$

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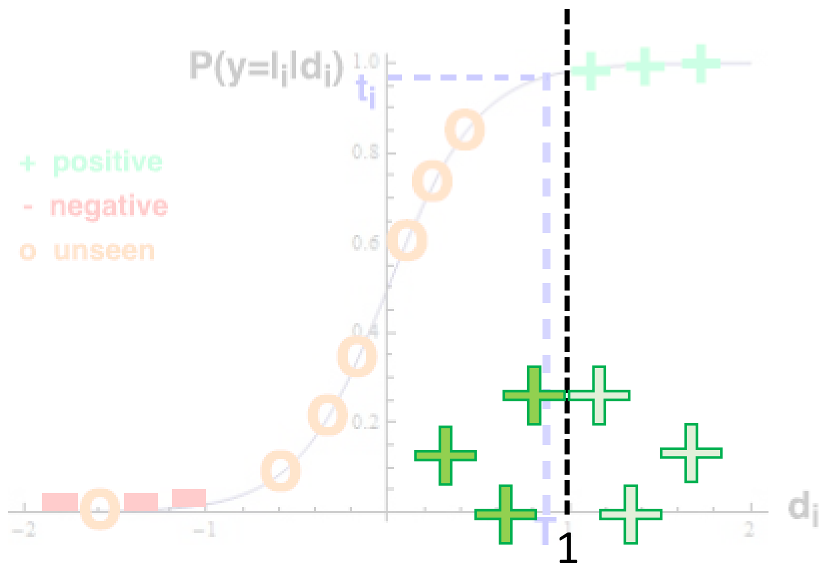

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Data Mining Quality Analytics

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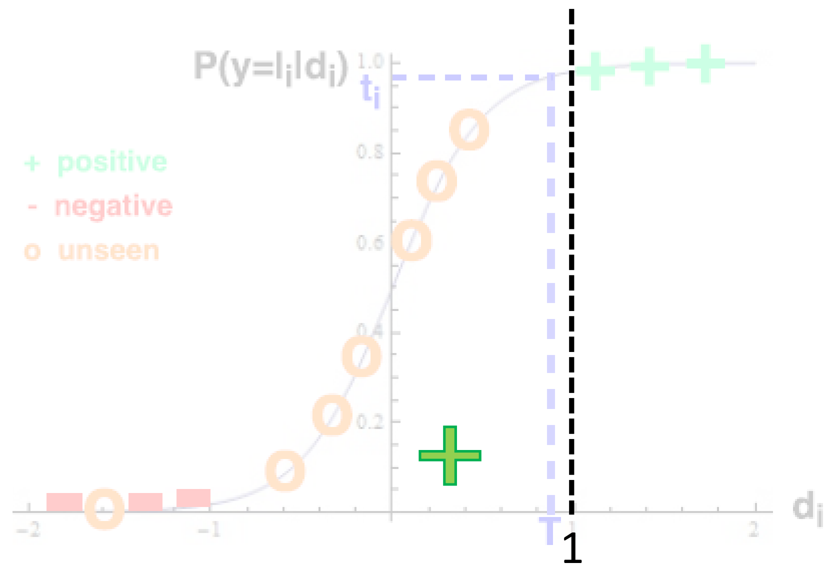

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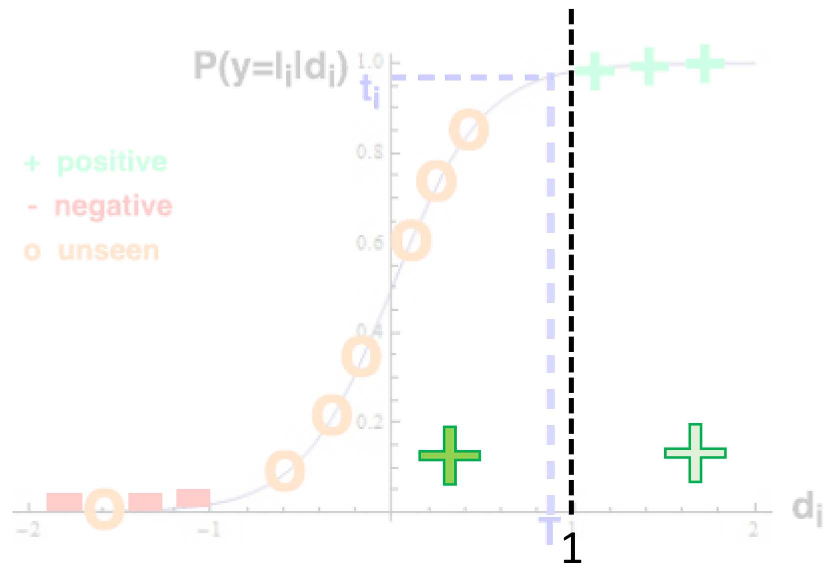

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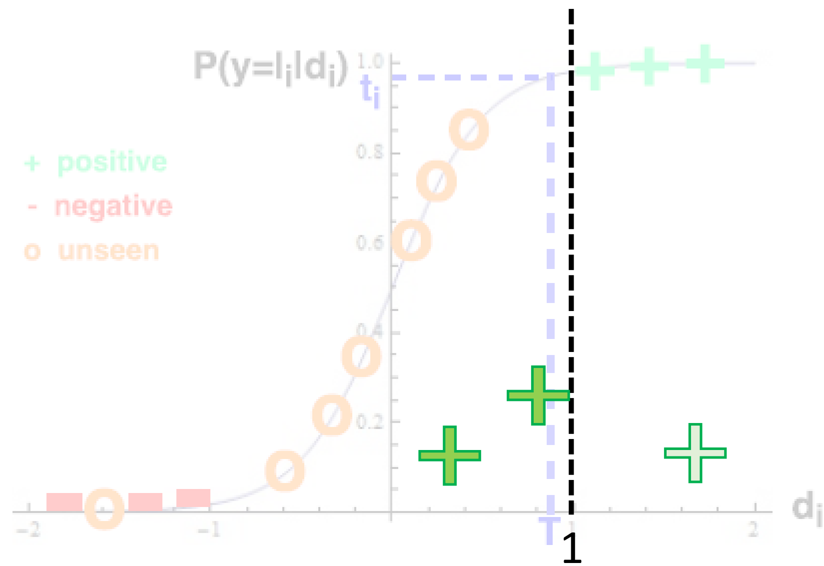

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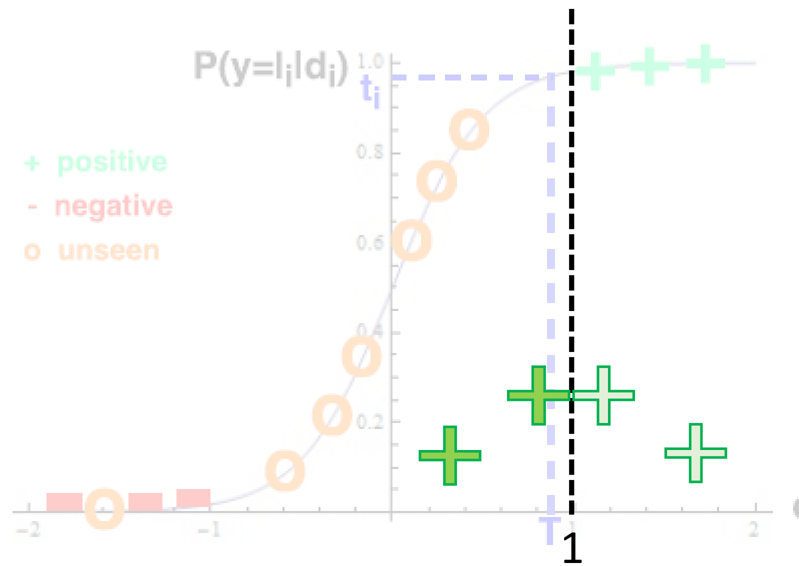

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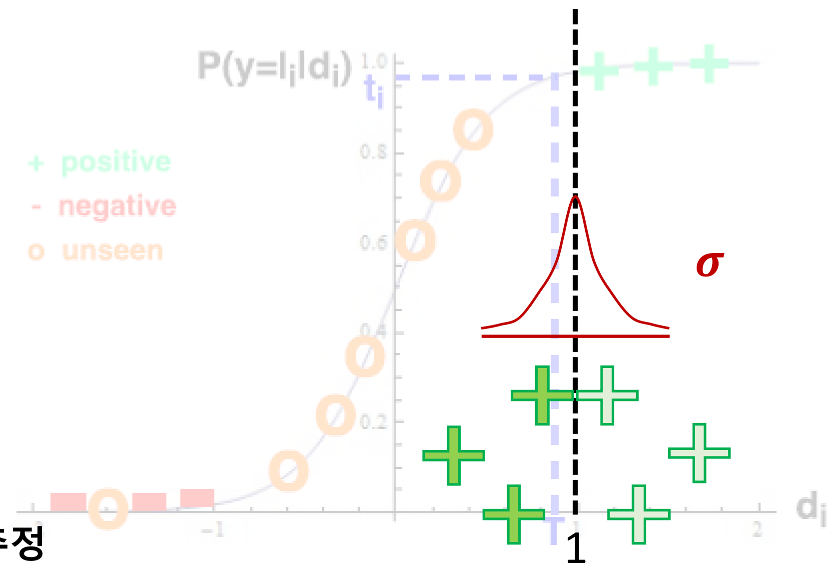

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$$\theta_{DOC}(t_i) = max(0.5\,, 1 - \alpha \cdot \sigma_i)$$

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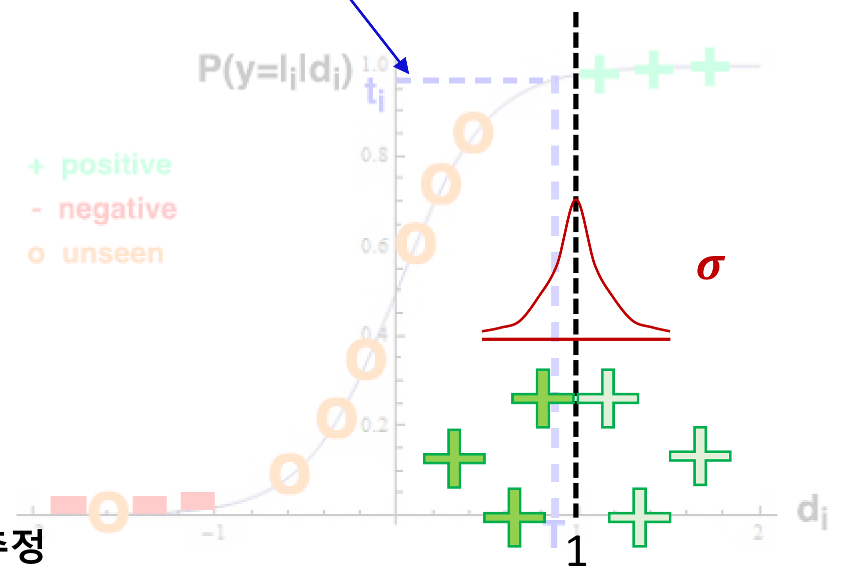
α는 일반적으로 3을 사용



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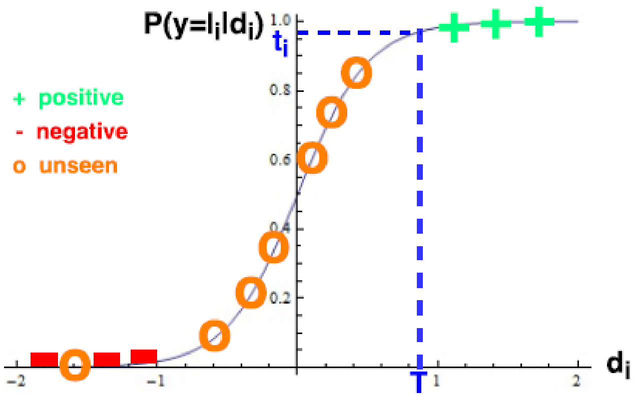
Data Mining Quality Analytics

DOC : Deep Open Classification

❖ DOC : Threshold (θ)



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✓ 일반적인 Sigmoid func.의 임계값은 0.5이다

✓ Train에 참가하지 않은 Unseen 표본에 대한 확률을 고려 必

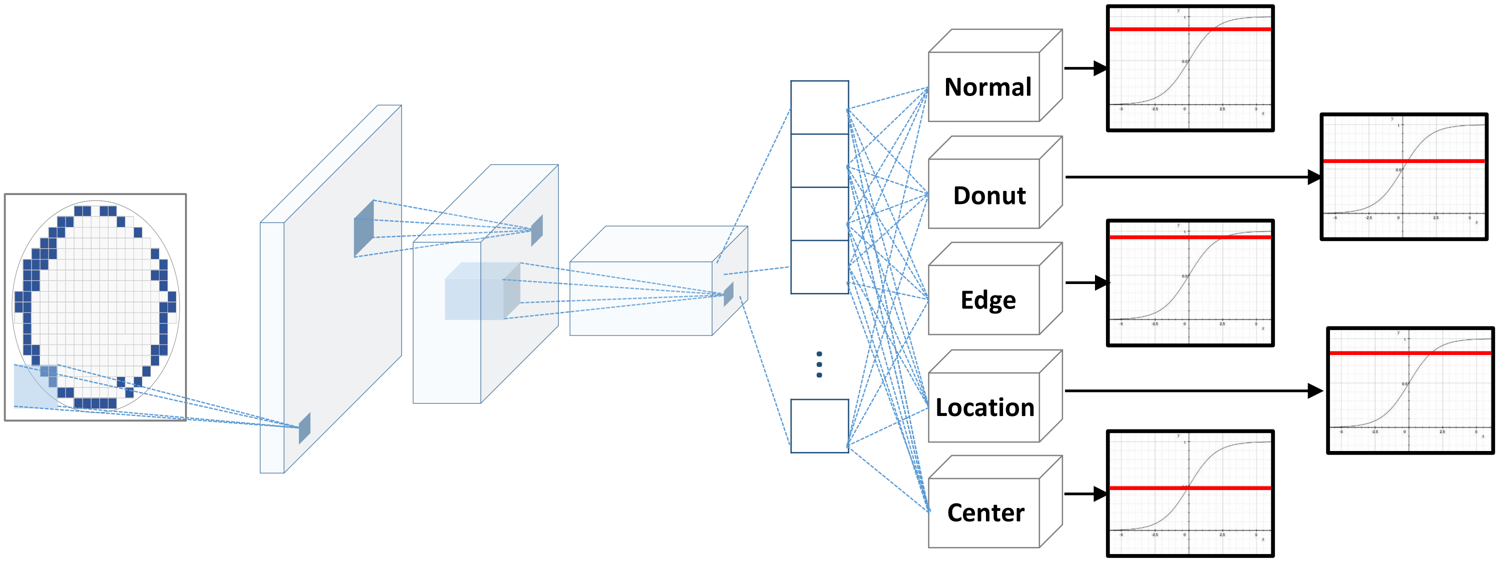
✓ DOC는 잠재적인 Unseen 표본에 대한 확률을 고려 하여 임계값을 재설정

✓ 각 임계값은 Class 별로 차등 적용

Data Mining Quality Analytics

DOC : Deep Open Classification

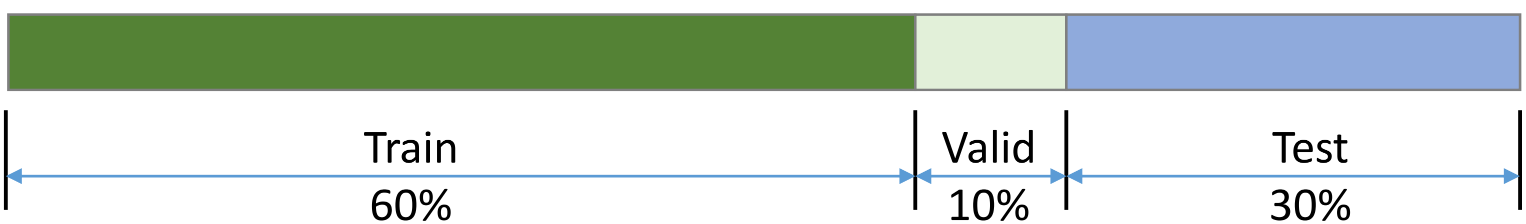
❖ DOC : Example



DOC : Deep Open Classification

❖ DOC : Test

	Data-set 1	Data-set 2
DOCU.	News	Review
Class	20	50
# of Samples (in 1 class)	1000	1000



DOC : Deep Open Classification

❖ DOC : Test

Table 1: Macro-F_1 scores for 20 newsgroups

% of seen classes	25%	50%	75%	100%
cbsSVM	59.3	70.1	72.0	85.2
OpenMax	35.7	59.9	76.2	91.9
DOC ($t = 0.5$)	75.9	84.0	87.4	92.6
DOC	82.3	85.2	86.2	92.6

Table 2: Macro-F_1 scores for 50-class reviews

% of seen classes	25%	50%	75%	100%
cbsSVM	55.7	61.5	58.6	63.4
OpenMax	41.6	57.0	64.2	69.2
DOC ($t = 0.5$)	51.1	63.6	66.2	69.8
DOC	61.2	64.8	66.6	69.8

- **Unknown을 많이 가지고 있더라도 성능 저하가 적다**
- **DOC가 DOC($t = 0.5$) 보다 성능이 높다**

5. Conclusion

Conclusion

❖ Conclusion

① Open set 에 대한 개념 및 Open set을 풀어내기 위한 DATA의 종류를 학습

② Data의 종류별 활용 가능 Open set 해결 기법에 대해

③ Multi-class Open set 문제에 강력한 DOC 기법을 이해함

④ 기존 Softmax 대신 Multi-task를 이용한 기법이 흥미로웠으며

⑤ 각 범주별 임계값을 따로 적용할 수 있음이 인상 깊음

⑥ 단, 임계값 설정에 대해서는 여러 다른 아이디어가 있을 수 있음

❖ 향후 계획

① 현재 진행 중인 WBM 분류 연구에 DOC 적용

② 기존 모델 vs 기타 Multi-tasking 모델과 비교

③ Class별 파라미터를 따로 하는 병렬 구조 대비 정확도 비교

감사합니다.