경험공유회: AI 비전공자로 AI 논문쓰기

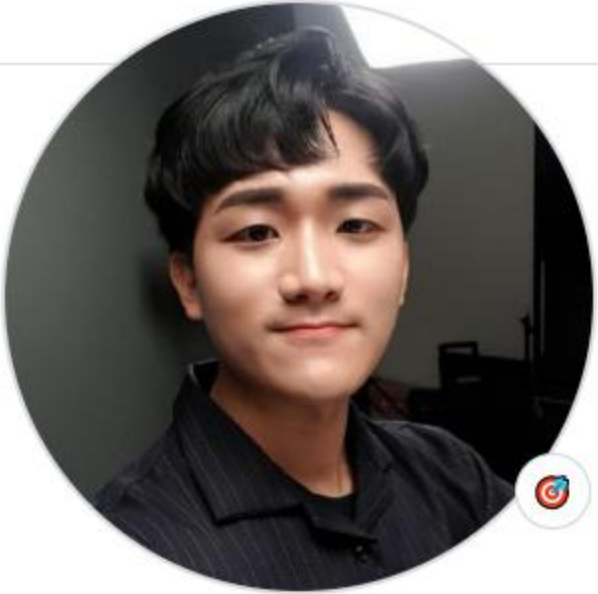
거꾸로 학습하며 배운 AI

조상현 (OGQ GYN)

OGQ GYN

모두의연구소

1. 소개



Sanghyun Jo
shjo-april

Deep Learning Research Engineer

Work experience

[Researcher]

✓ OGQ GYN – Research Engineer (17.07 ~ Present)
  1. 국내 최초 영상 보안 지능형CCTV 성능 인증 획득 (방화/쓰러짐, 날씨 환경 적용)
  2. 드론 실종자 수색 관련 영상 분석 AI 모델 개발 (경찰청)
  3. 수도시설 지능형 안전관리시스템 개발 (한국수자원공사)
  4. 다중 언어 지원하는 Tagging AI 모델 개발 (네이버, 연합뉴스, 아프리카TV)
  5. Quantization 기반 경량화 AI 개발 (아이닉스)

[Lecturer]

✓ Developers or MS/PhD Students – Tutoring (18.06 ~ Present)
✓ NEXTPAGE – Lecturer (18.10 ~ 20.09)
✓ EasyDeep – Lecturer & VOD (20.11 ~ 21.02)

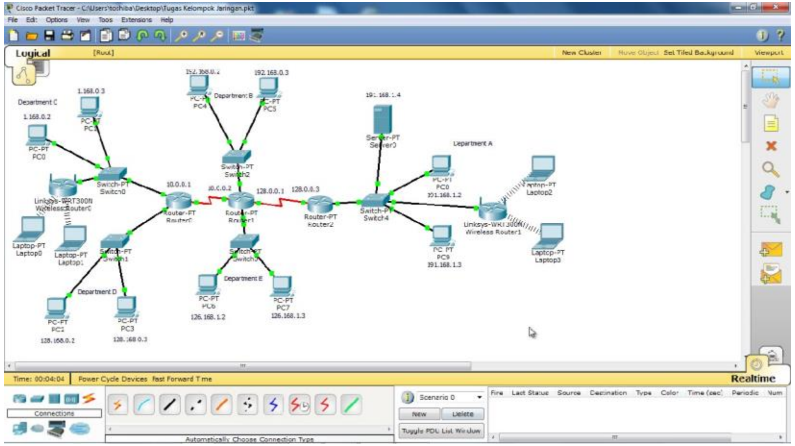
[Reviewer] – ICIP 2022, IEEE TCSVT 2022, ICML 2022

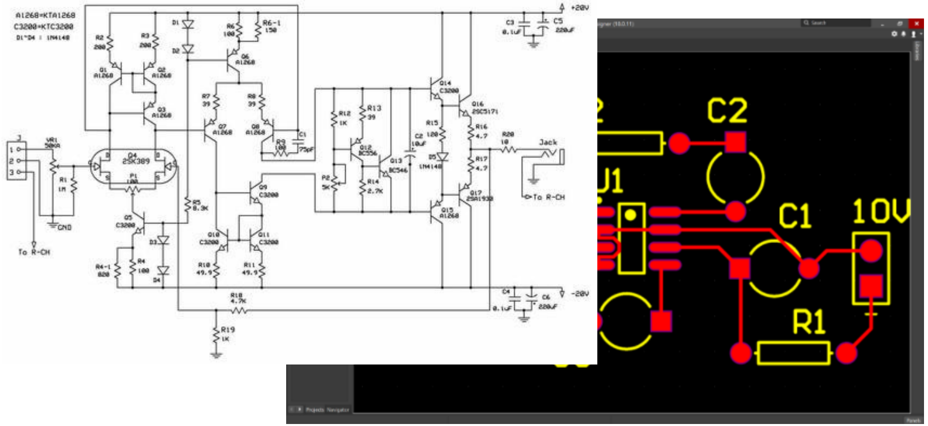
Papers

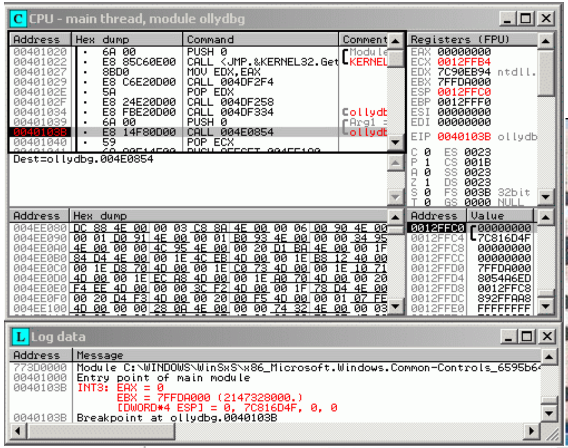
✓ **Puzzle-CAM: Improved localization via matching partial and full features**
(Git stars: 150, Citations: 34, ICIP 2021)

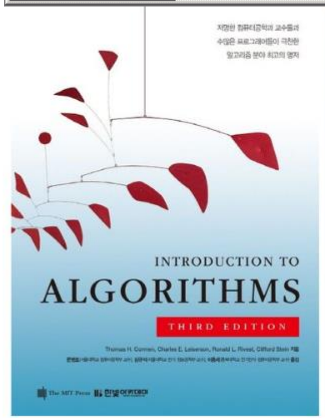
✓ **RecurSeed and EdgePredictMix: Single-stage learning is sufficient for Weakly-Supervised Semantic Segmentation**
(Git stars: 31, Citations: 1, Under Review, SOTA)

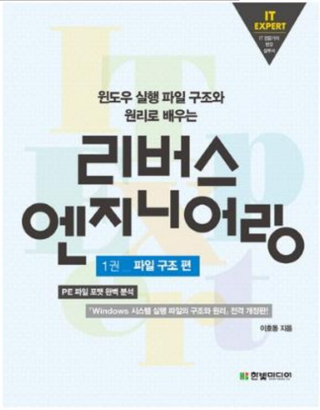
2. 성장 과정 - 입사 전 (15.03 ~ 17.06)

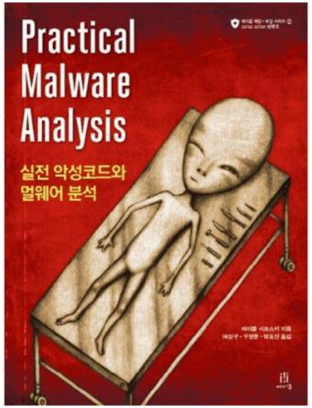












https://resources.altium.com/p/pcb-routing

2. 성장 과정 - 입사 후 (17.07 ~ Present)

Pinned

Customize your pins

PuzzleCAM Public

[ICIP2021] Puzzle-CAM: Improved localization via matching partial and full features.

Python ☆ 150 43

RecurSeed_and_EdgePredictMix Public

[Under Review] RecurSeed and EdgePredictMix: Single-stage learning is sufficient for Weakly-Supervised Semantic Segmentation

Python ☆ 31 3

Tensorflow_RetinaFace Public

[Re-implementation] RetinaFace: Single-stage Dense Face Localisation in the Wild

Python ☆ 26 11

Tensorflow_Improving_Pairwise_Ranking_for_Multi-label_Image_Classification Public

[Re-implementation] Improving Pairwise Ranking for Multi-label Image Classification (CVPR2017)

Python ☆ 17 4

Tensorflow_GIoU Public

[Re-implementation] Generalized Intersection Over Union: A Metric and a Loss for Bounding Box Regression (CVPR2019)

Python ☆ 13 2

Tensorflow_FixMatch Public

[Re-implementation] FixMatch: Simplifying Semi-Supervised Learning with Consistency and Confidence

Python ☆ 14 4

704 contributions in the last year

Contribution settings ▾ 2D 3D

Contributions

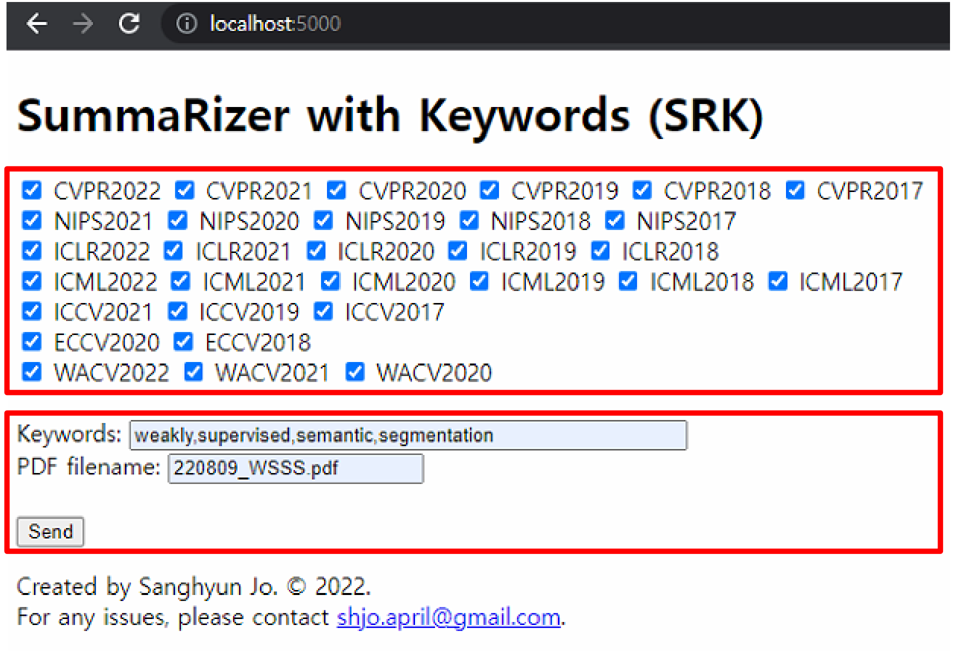
704	10
Total	Best day
Nov 21 → Nov 22	Jan 18

Average: 1.92 / day

Streaks

17 days	8 days
Longest	Current
Sep 13 → Sep 29	Nov 14 → Nov 21

2. 성장 과정 - 입사 후 (17.07 ~ Present)



2. 성장 과정 - 입사 후 (17.07 ~ Present)

Writing: 매 주 1회 이메일 작성 (Business)

Q1. What's your thought about the potential with the logistics business in line with reflecting this comment?

- The growth rate of the logistics business will significantly decrease. The most governments have decided to mitigate the regulation of Covid-19 to protect existing companies from the pressure of inflation, causing a critical damage to the delivery industry. Moreover, the war occurred by Russia has accelerated the negative effect globally. For example, Amazon announced the revocation of contract and the sublease to offset the current headwind. As a result, numerous incidents explicitly explain why the logistics business has the low potential.

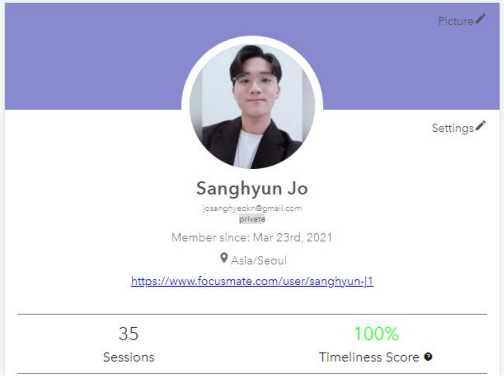
Q2. There are the puts and takes to lay groundwork for a new business. What if our company decides to jump in, which segment we need to lean into?

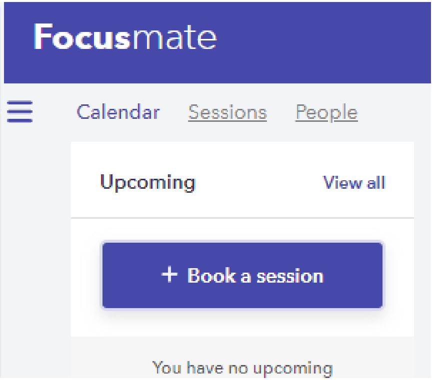
- Our company has to lean into B2B logistics revenue stream with Korean Conglomerates Manufacturing. The conglomerates already laid the groundwork for manufacturing. Therefore, our company not only conducts opportunities to experiment with the superiority of a new business but also minimizes the barrier to entry a new business by leveraging existing manufacturing infrastructures.

Q3. If we decided to avoid business risk in the logistics and invest in the logistics company by equity investment method investment, which domestic logistics company would be a promising option?

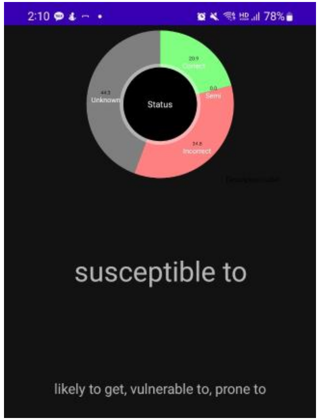
- To my knowledge, CJ Express is the most promising option to avoid business a risk in the logistics. Samsung SDS relies on the logistics BPO as shown in the first figure. By contrast, a category of the revenue in CJ Express includes global, CL, construction, and delivery. The diversification of the revenue is factored into minimizing a risk due to an unstable market.

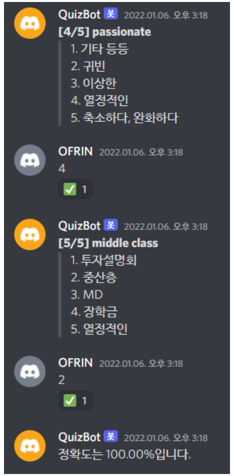
Speaking: Focusmate



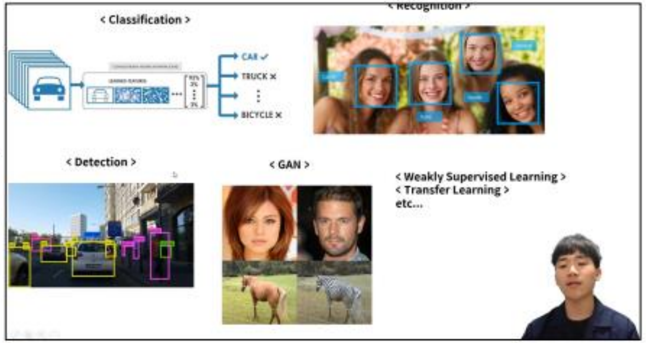


Words





2. 성장 과정 - 입사 후 (17.07 ~ Present)



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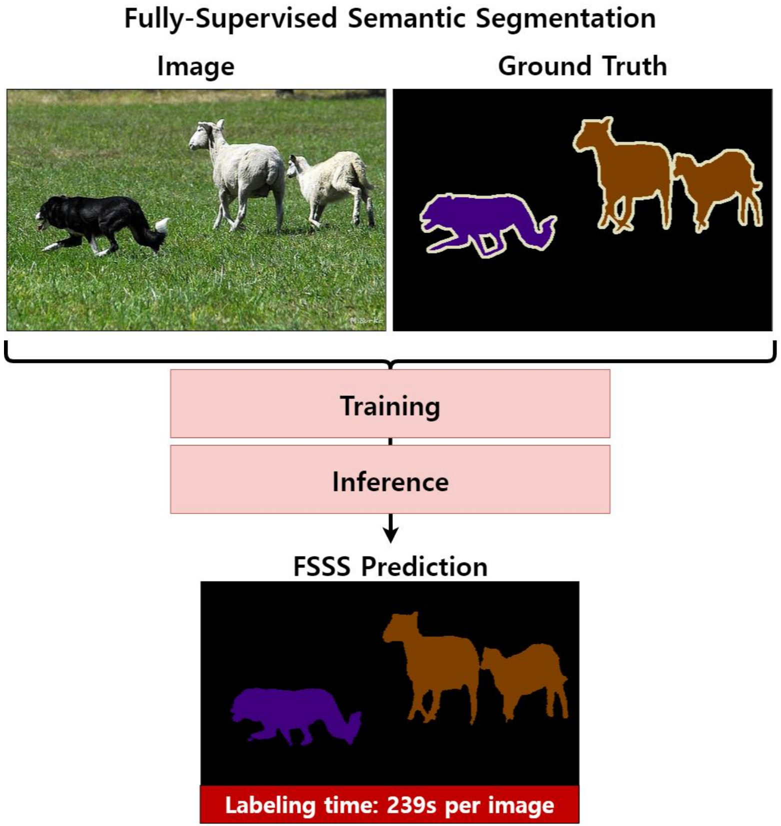
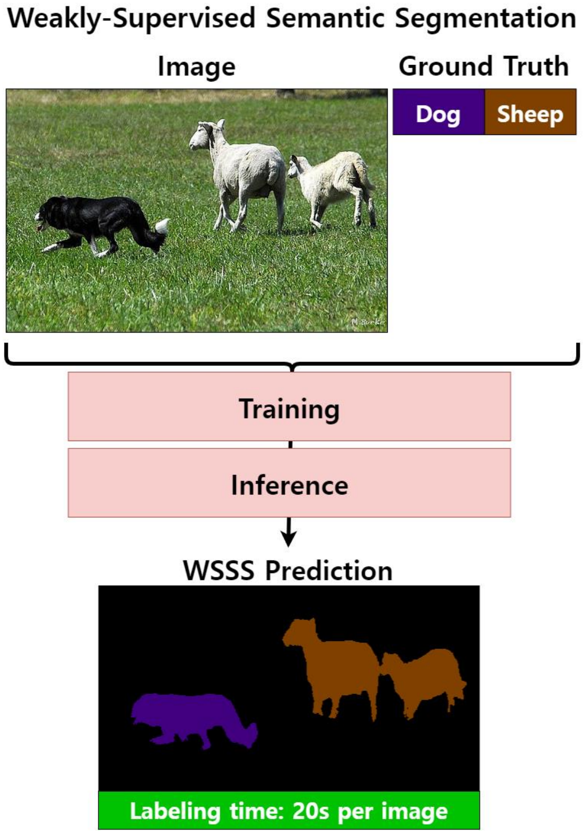
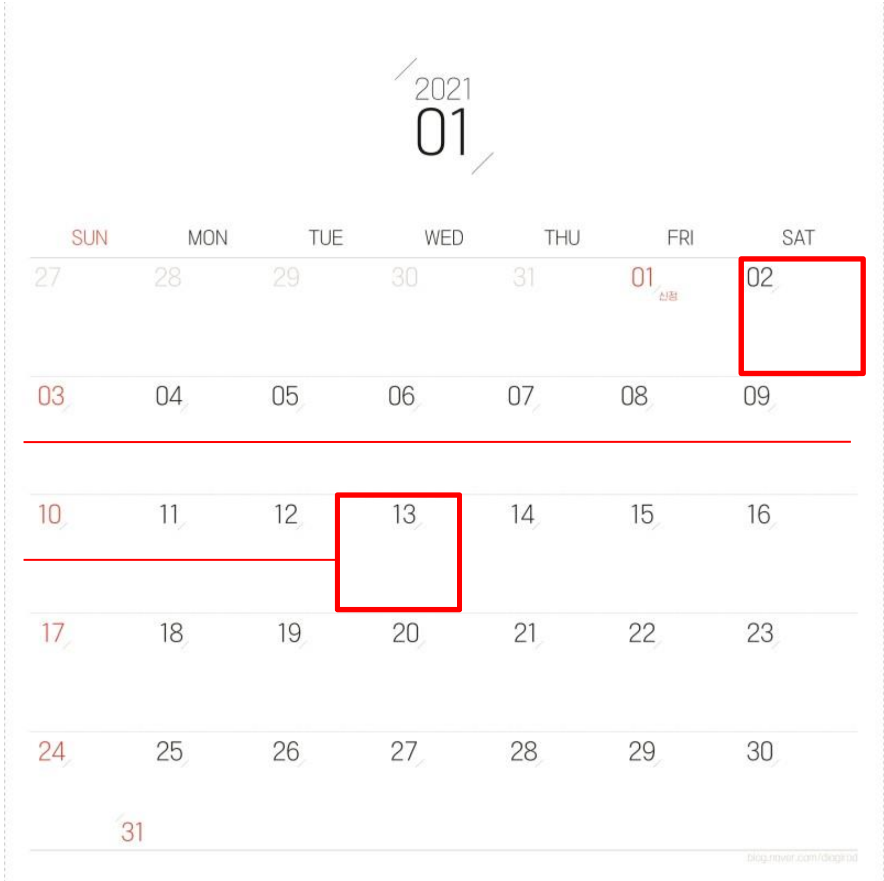
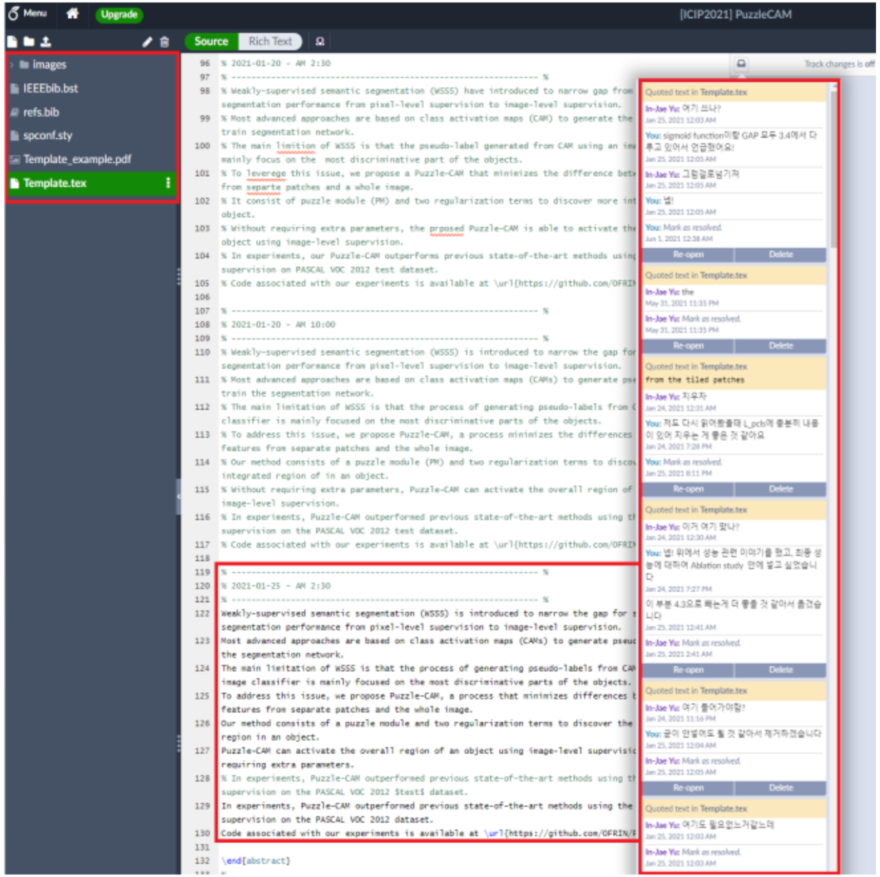




3. 논문 – Puzzle-CAM (20.12 ~ 21.01)





3. 논문 – Puzzle-CAM (20.12 ~ 21.01)

E-mail: shjo.april@gynetworks.com	**Affiliation:** GYNetworks
Name: Sanghyun Jo	**URL:** https://github.com/OFRIN
Default Category: eess.IV	**Country:** Korea (South)
Groups: eess and cs	**Career Status:** Other

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Identifier	Type	Title	Status	Actions	Expires
START NEW SUBMISSION	Would you like to replace or take another action on one of your previously-announced articles? Use the link icons under "Articles You Own" instead.				

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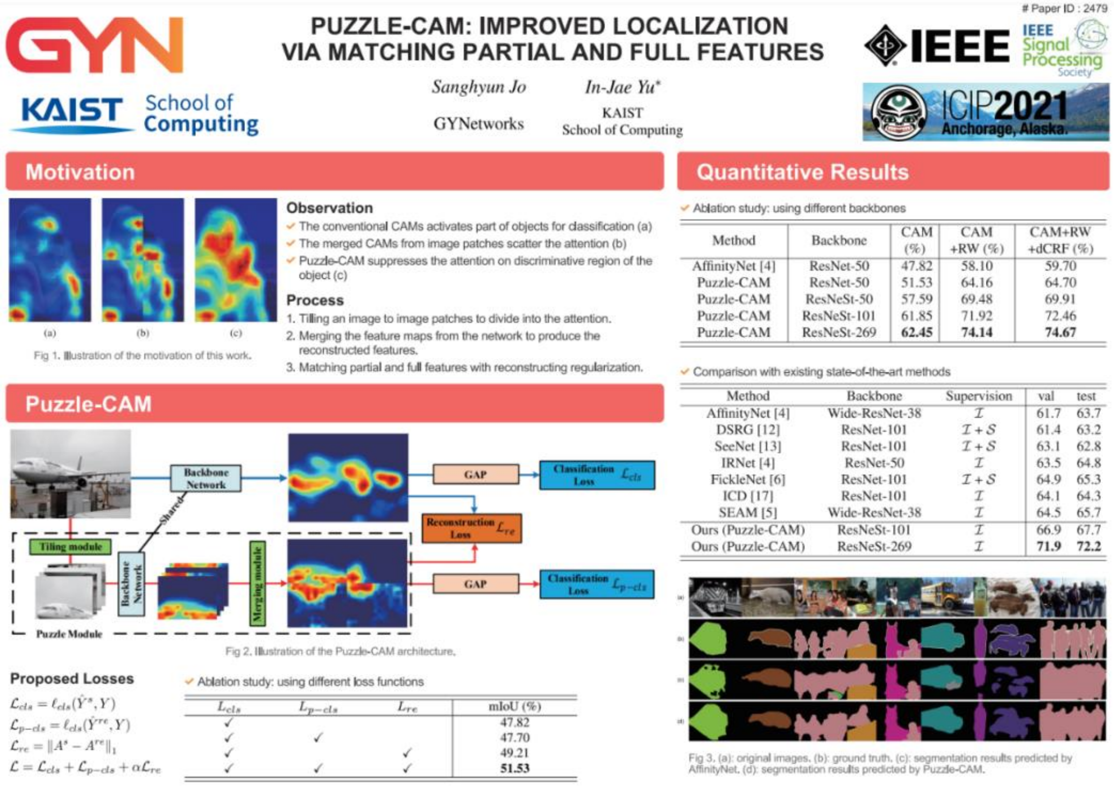
Identifier	Primary Category	Title	Actions	Author
2204.06754	cs.CV	RecurSeed and CertainMix for Weakly Supervised Semantic Segmentation		Y
2101.11253	cs.CV	Puzzle-CAM: Improved localization via matching partial and full features		Y

3. 논문 – Puzzle-CAM (20.12 ~ 21.01)



Paper ID : 2479

GYN

KAIST School of Computing

PUZZLE-CAM: IMPROVED LOCALIZATION VIA MATCHING PARTIAL AND FULL FEATURES

Sanghyun Jo — GYNetworks

In-Jae Yu* — KAIST School of Computing

IEEE Signal Processing Society

ICIP2021 Anchorage, Alaska.

Motivation

(a) (b) (c)

Fig 1. Illustration of the motivation of this work.

Observation

- The conventional CAMs activates part of objects for classification (a)
- The merged CAMs from image patches scatter the attention (b)
- Puzzle-CAM suppresses the attention on discriminative region of the object (c)

Process

1. Tiling an image to image patches to divide into the attention.
2. Merging the feature maps from the network to produce the reconstructed features.
3. Matching partial and full features with reconstructing regularization.

Puzzle-CAM

Backbone Network

Shared

GAP

Classification Loss $\mathcal{L}_{cls}$

Reconstruction Loss $\mathcal{L}_{re}$

Tiling module

Backbone Network

Merging module

GAP

Classification Loss $\mathcal{L}_{p-cls}$

Puzzle Module

Fig 2. Illustration of the Puzzle-CAM architecture.

Proposed Losses

$\mathcal{L}_{cls} = \ell_{cls}(\hat{Y}^s, Y)$

$\mathcal{L}_{p-cls} = \ell_{cls}(\hat{Y}^{re}, Y)$

$\mathcal{L}_{re} = \|A^s - A^{re}\|_1$

$\mathcal{L} = \mathcal{L}_{cls} + \mathcal{L}_{p-cls} + \alpha\mathcal{L}_{re}$

- Ablation study: using different loss functions

$\mathcal{L}_{cls}$	$\mathcal{L}_{p-cls}$	$\mathcal{L}_{re}$	mIoU (%)
✓			47.82
✓	✓		47.70
✓		✓	49.21
✓	✓	✓	**51.53**

Quantitative Results

- Ablation study: using different backbones

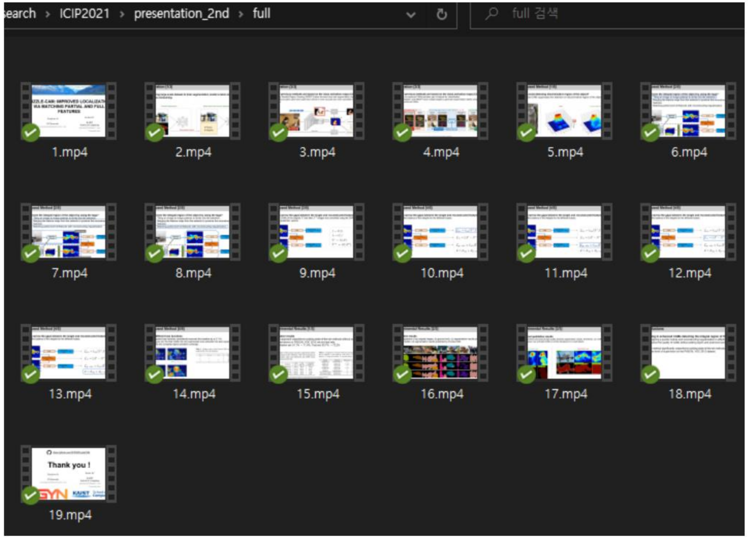
Method	Backbone	CAM (%)	CAM +RW (%)	CAM+RW +dCRF (%)
AffinityNet [4]	ResNet-50	47.82	58.10	59.70
Puzzle-CAM	ResNet-50	51.53	64.16	64.70
Puzzle-CAM	ResNeSt-50	57.59	69.48	69.91
Puzzle-CAM	ResNeSt-101	61.85	71.92	72.46
Puzzle-CAM	ResNeSt-269	**62.45**	**74.14**	**74.67**

- Comparison with existing state-of-the-art methods

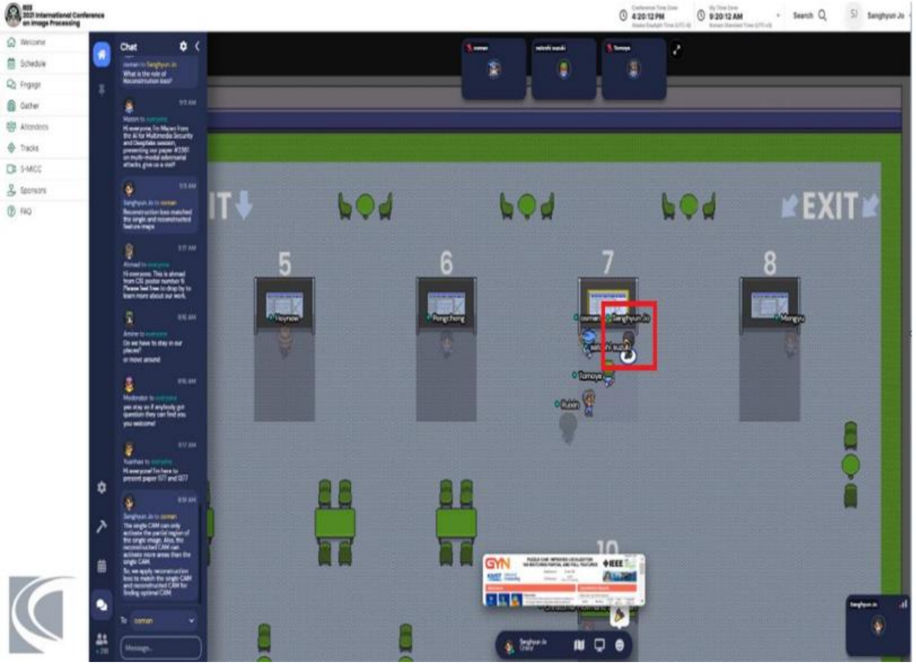
Method	Backbone	Supervision	val	test
AffinityNet [4]	Wide-ResNet-38	$\mathcal{I}$	61.7	63.7
DSRG [12]	ResNet-101	$\mathcal{I}+\mathcal{S}$	61.4	63.2
SeeNet [13]	ResNet-101	$\mathcal{I}+\mathcal{S}$	63.1	62.8
IRNet [4]	ResNet-50	$\mathcal{I}$	63.5	64.8
FickleNet [6]	ResNet-101	$\mathcal{I}+\mathcal{S}$	64.9	65.3
ICD [17]	ResNet-101	$\mathcal{I}$	64.1	64.3
SEAM [5]	Wide-ResNet-38	$\mathcal{I}$	64.5	65.7
Ours (Puzzle-CAM)	ResNeSt-101	$\mathcal{I}$	66.9	67.7
Ours (Puzzle-CAM)	ResNeSt-269	$\mathcal{I}$	**71.9**	**72.2**

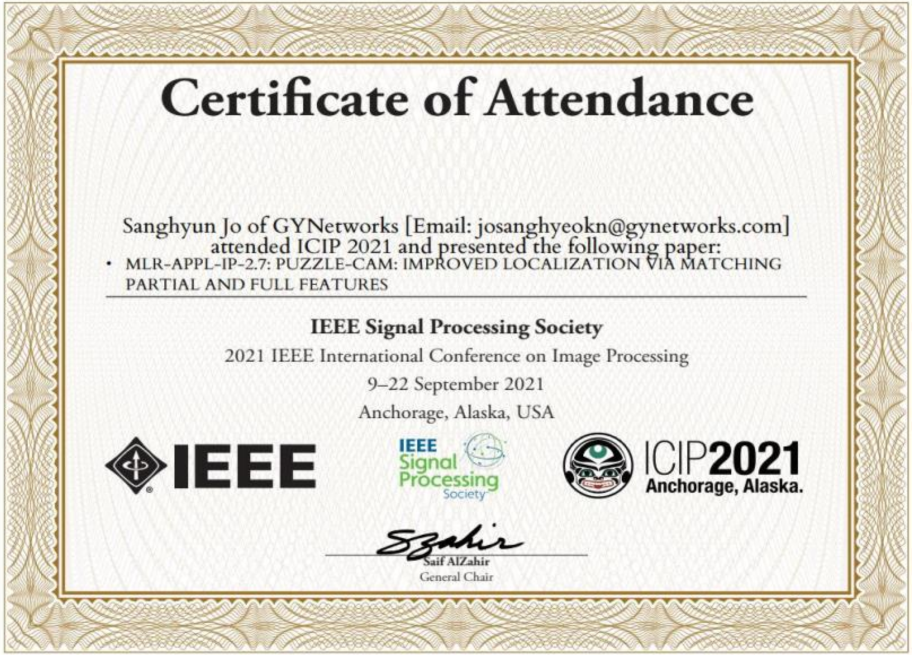
(a) (b) (c) (d)

Fig 3. (a): original images. (b): ground truth. (c): segmentation results predicted by AffinityNet. (d): segmentation results predicted by Puzzle-CAM.



3. 논문 – Puzzle-CAM (20.12 ~ 21.01)




Certificate of Attendance

Sanghyun Jo of GYNetworks [Email: josanghyeokn@gynetworks.com] attended ICIP 2021 and presented the following paper:

- MLR-APPL-IP-2.7: PUZZLE-CAM: IMPROVED LOCALIZATION VIA MATCHING PARTIAL AND FULL FEATURES

IEEE Signal Processing Society

2021 IEEE International Conference on Image Processing

9–22 September 2021

Anchorage, Alaska, USA

IEEE

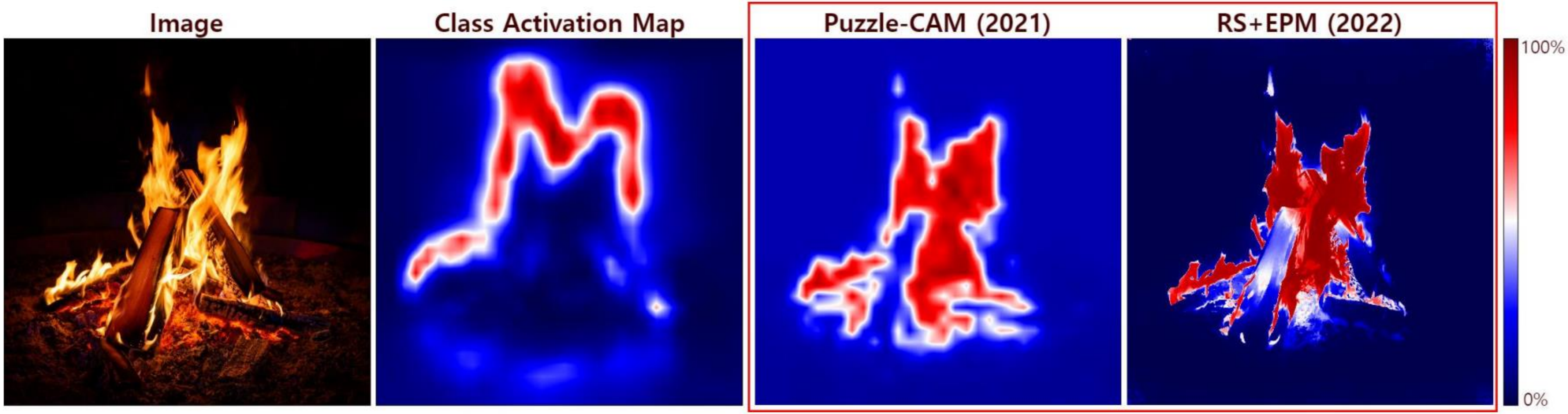
IEEE Signal Processing Society

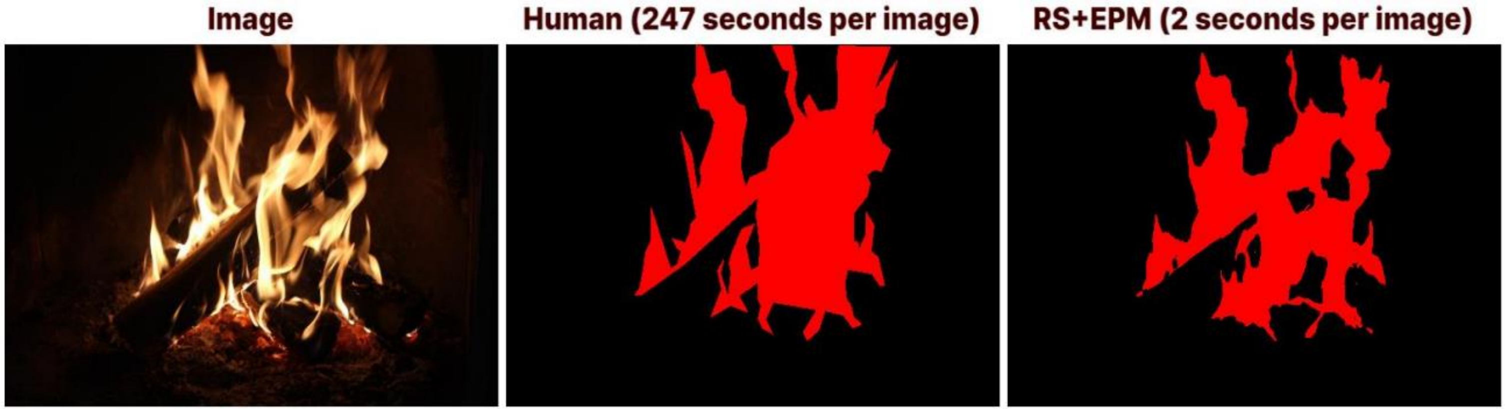
ICIP2021 Anchorage, Alaska.

Saif AlZahir

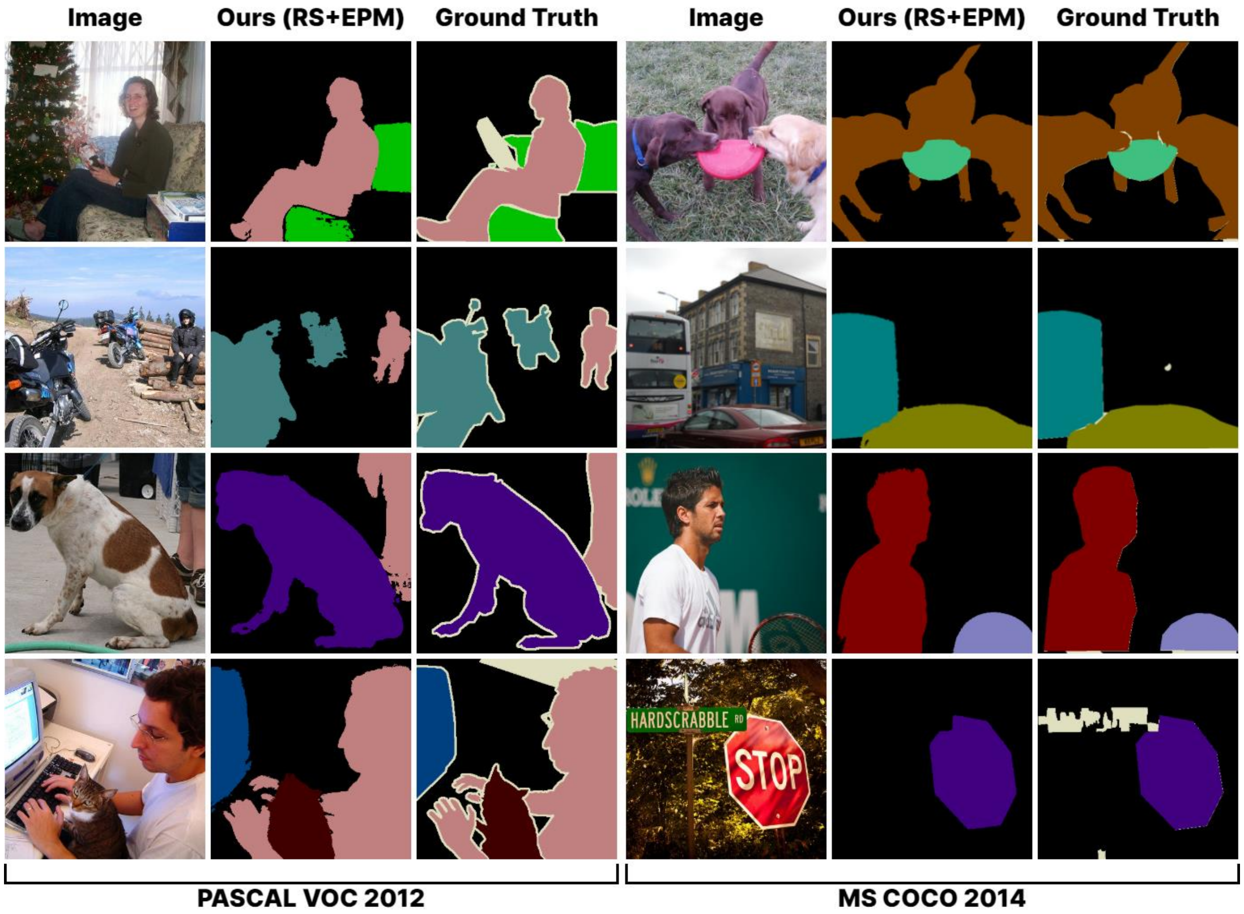
General Chair

3. 논문 – RS+EPM (21.11 ~ Present)





3. 논문 – RS+EPM (21.11 ~ Present)



3. 논문 – RS+EPM (21.11 ~ Present)

Table 2: Performance comparison of WSSS methods in terms of mIoU (%) on PASCAL VOC 2012 and COCO 2014. * and † indicate the backbone of VGG-16 and ResNet-50, respectively. Sup., supervision; $\mathcal{I}$, image-level class labels; $\mathcal{S}$, the saliency supervision; $\mathcal{D}$, the external dataset.

Method	Backbone	Sup.	VOC *val*	VOC *test*	COCO *val*
Single stage:					
EM ICCV'15 [17]	VGG16	$\mathcal{I}$	38.2	39.6	-
RRM AAAI'20 [19]	WR38	$\mathcal{I}$	62.6	62.9	-
SSSS CVPR'20 [20]	WR38	$\mathcal{I}$	62.7	64.3	-
AFA CVPR'22 [43]	MiT-B1	$\mathcal{I}$	66.0	66.3	38.9
Ours (single-stage, RS)	R50	$\mathcal{I}$	66.5	67.9	40.0
Ours (single-stage, RS+EPM)	R50	$\mathcal{I}$	**69.5**	**70.6**	**42.2**
PSA CVPR'18 [5]	WR38	$\mathcal{I}$	61.7	63.7	-
IRNet CVPR'19 [31]	R50	$\mathcal{I}$	63.5	64.8	-
SEAM CVPR'20 [29]	WR38	$\mathcal{I}$	64.5	65.7	31.9
AdvCAM CVPR'21 [7]	R101	$\mathcal{I}$	68.1	68.0	-
CSE ICCV'21 [54]	WR38	$\mathcal{I}$	68.4	68.2	36.4
CPN ICCV'21 [30]	WR38	$\mathcal{I}$	67.8	68.5	-
RIB NIPS'21 [32]	R101	$\mathcal{I}$	68.3	68.6	43.8
ReCAM CVPR'22 [55]	R101	$\mathcal{I}$	68.5	68.4	-
ADEHE CVPR'22 [41]	R101	$\mathcal{I}$	68.6	68.9	-
AMR AAAI'22 [56]	R101	$\mathcal{I}$	68.8	69.1	-
URN AAAI'22 [57]	R101	$\mathcal{I}$	69.5	69.7	40.7
SIPE CVPR'22 [13]	R101	$\mathcal{I}$	68.8	69.7	40.6
AMN CVPR'22 [36]	R101	$\mathcal{I}$	69.5	69.6	44.7
MCTformer CVPR'22 [39]	WR38	$\mathcal{I}$	71.9	71.6	42.0
SANCE CVPR'22 [42]	R101	$\mathcal{I}$	70.9	72.2	44.7†
Ours (multi-stage, RS)	R101	$\mathcal{I}$	72.8	72.8	45.8
Ours (multi-stage, RS+EPM)	R101	$\mathcal{I}$	**74.4**	**73.6**	**46.4**

3. 논문 – RS+EPM (21.11 ~ Present)

Computer Vision

Weakly-Supervised Semantic Segmentation

84 papers with code • 3 benchmarks • 5 datasets

The semantic segmentation task is to assign a label from a label set to each pixel in an image. In the case of fully supervised setting, the dataset consists of images and their corresponding pixel-level class-specific annotations (expensive pixel-level annotations). However, in the weakly-supervised setting, the dataset consists of images and corresponding annotations that are relatively easy to obtain, such as tags/labels of objects present in the image.

(Image credit: Weakly-Supervised Semantic Segmentation Network with Deep Seeded Region Growing)

Benchmarks

Add a Result

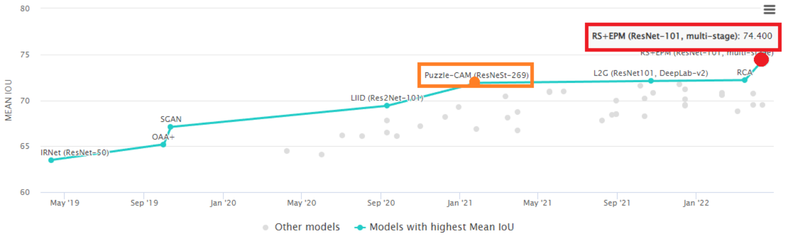
These leaderboards are used to track progress in Weakly-Supervised Semantic Segmentation

Trend	Dataset	Best Model	Paper	Code	Compare
	PASCAL VOC 2012 val	RS+EPM (ResNet-101, multi-stage)			See all
	PASCAL VOC 2012 test	RS+EPM (ResNet-101, multi-stage)			See all
	COCO 2014 val	RS+EPM (ResNet-101, multi-stage)			See all

Weakly-Supervised Semantic Segmentation on PASCAL VOC 2012 val

Leaderboard Dataset

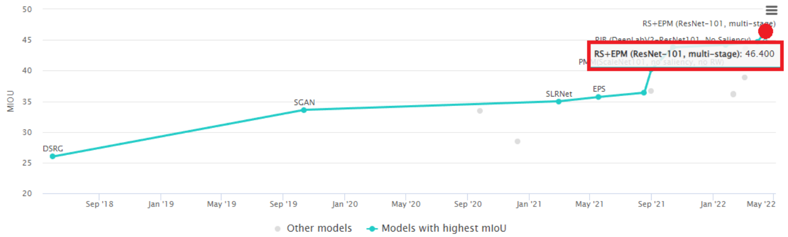
View Mean IoU by Date for All models



Weakly-Supervised Semantic Segmentation on COCO 2014 val

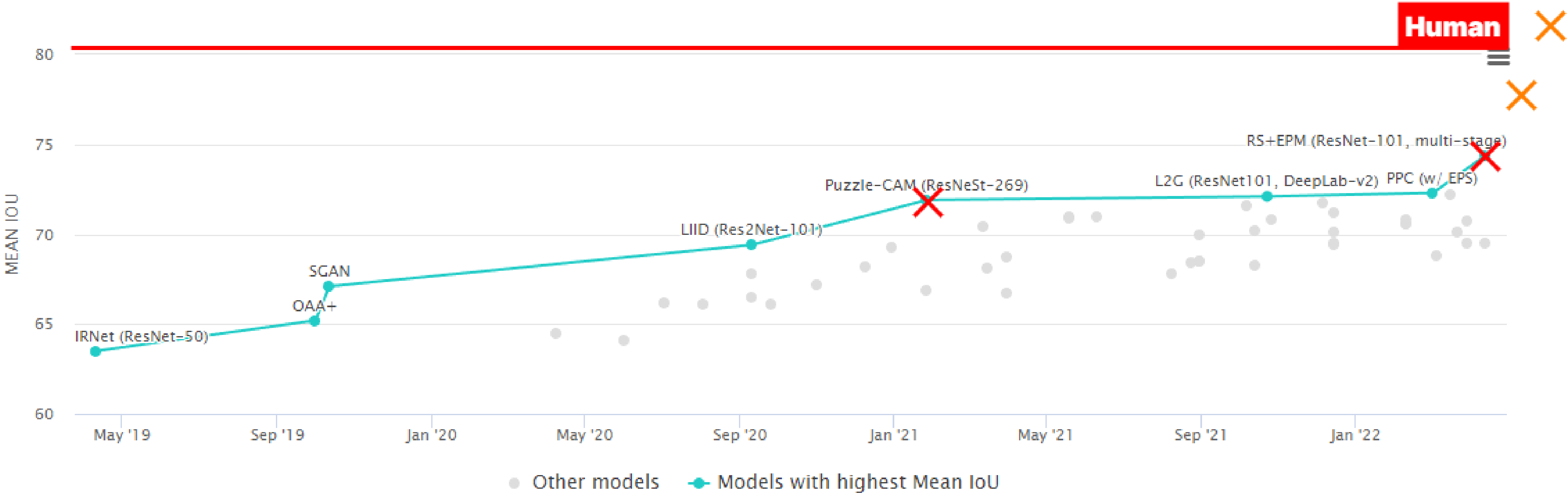
Leaderboard Dataset

View mIoU by Date for All models



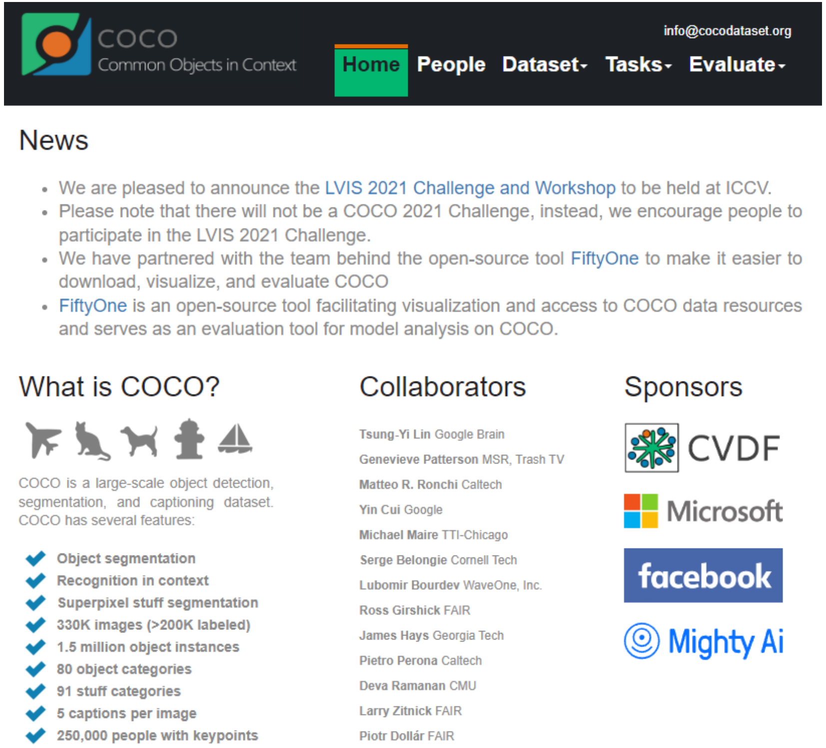
https://paperswithcode.com/task/weakly-supervised-semantic-segmentation

3. 논문 – RS+EPM (21.11 ~ Present)



1. Content Generation (Image/Video/Audio)

✓ DALLE-2, Stable Diffusion (CVPR 2022), Novel AI



http://host.robots.ox.ac.uk/pascal/VOC/voc2012/

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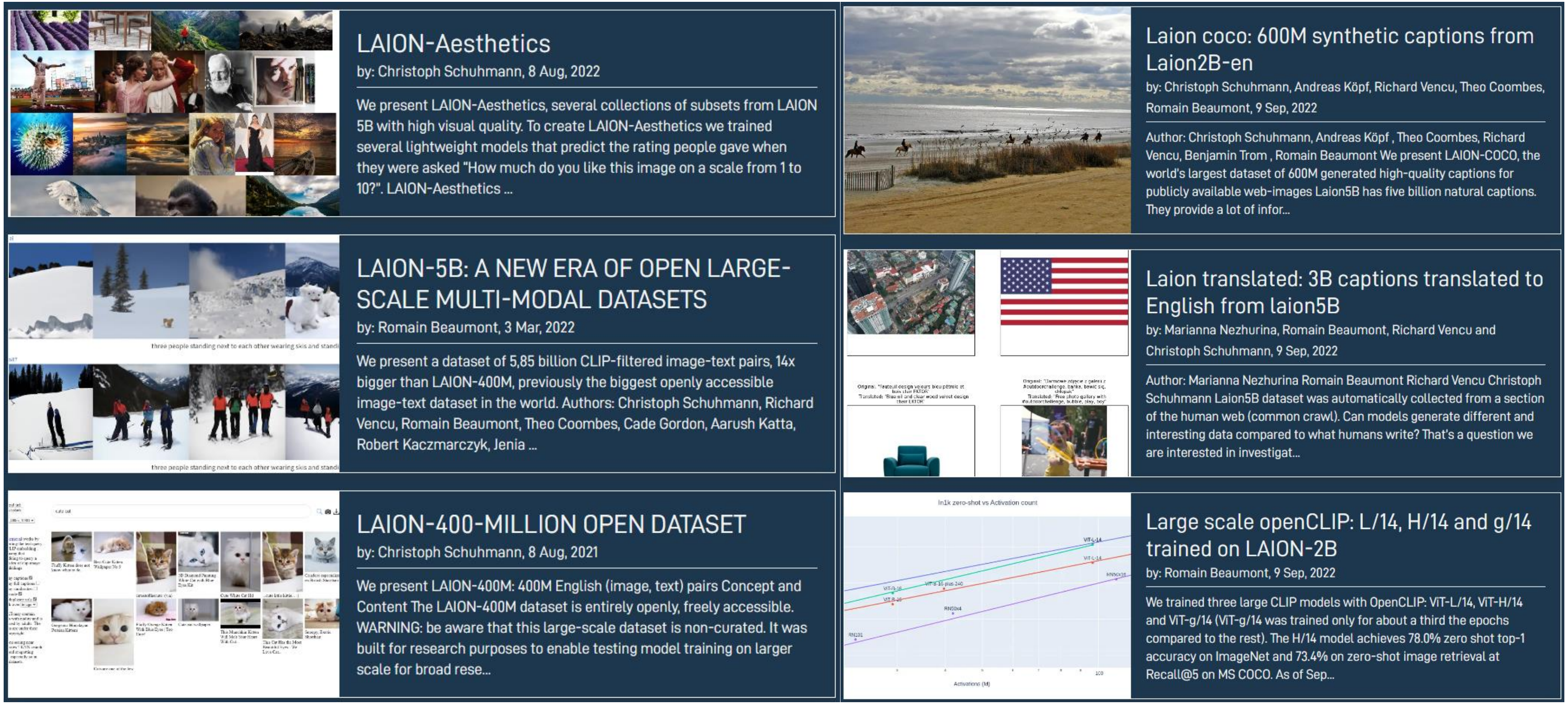


4. AI 발전 방향 예측

1. Content Generation (Image/Video/Audio)

✓ DALLE-2, Stable Diffusion (CVPR 2022), Novel AI

https://github.com/kakaobrain/coyo-dataset

4. AI 발전 방향 예측

1. Content Generation (Image/Video/Audio)

✓ DALLE-2, Stable Diffusion (CVPR 2022), Novel AI

https://cdm.link/2022/08/stable-diffusion-the-slick-generative-ai-tool-just-launched-and-went-live-on-github/

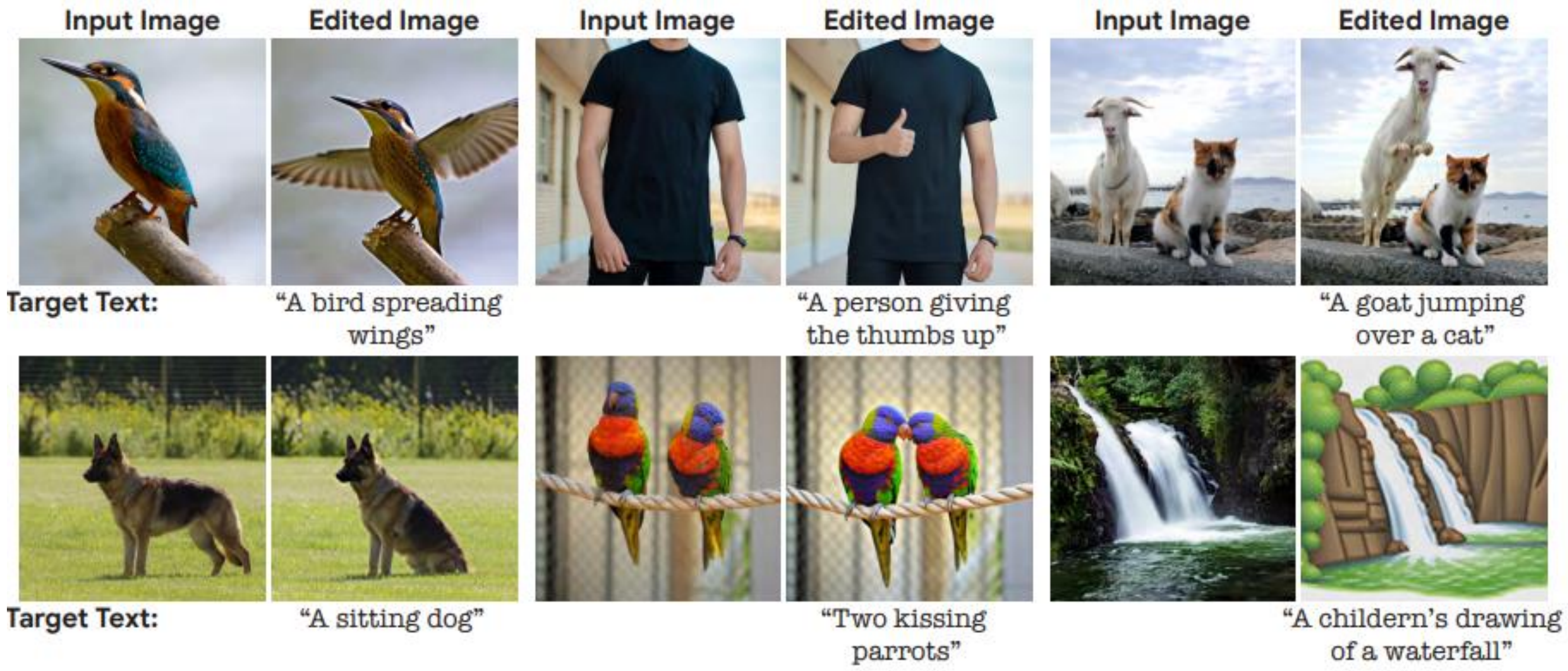
4. AI 발전 방향 예측

1. Content Generation (Image/Video/Audio)

✓ DALLE-2, Stable Diffusion (CVPR 2022), Novel AI

1. Content Generation (Image/Video/Audio)

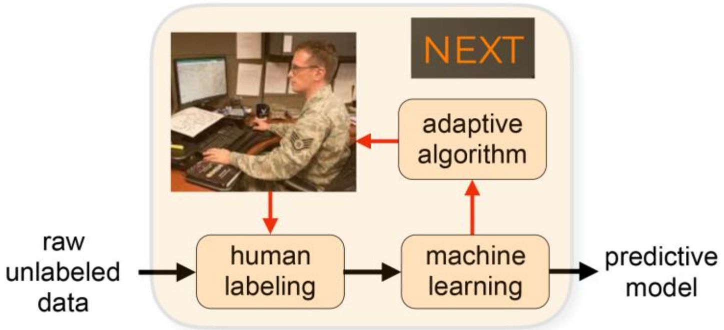
✓ DALLE-2, Stable Diffusion (CVPR 2022), Imagen, Novel AI



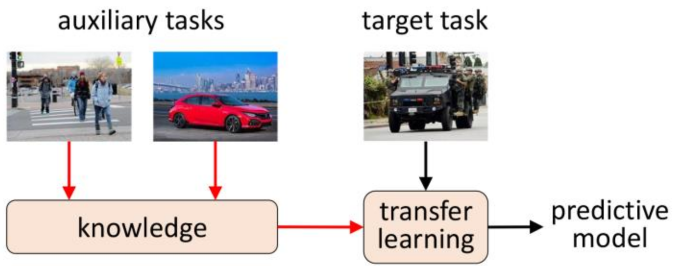
https://arxiv.org/pdf/2210.09276.pdf

4. AI 발전 방향 예측

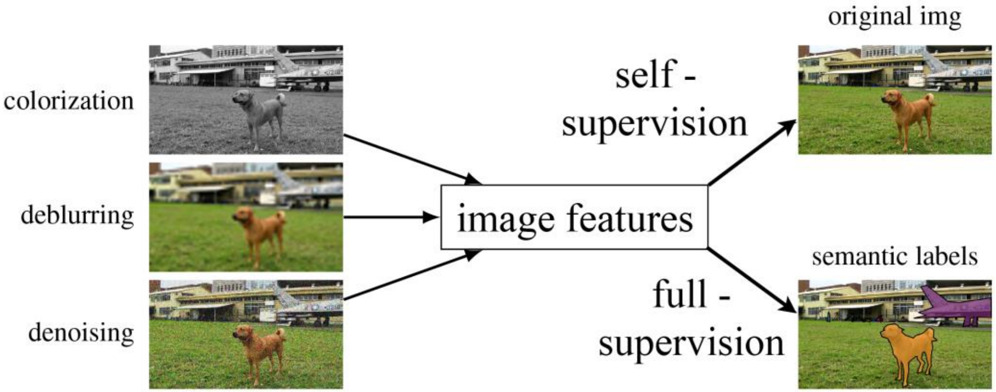
2. Data-efficient Training



(a) Active Learning



(b) Transfer Learning

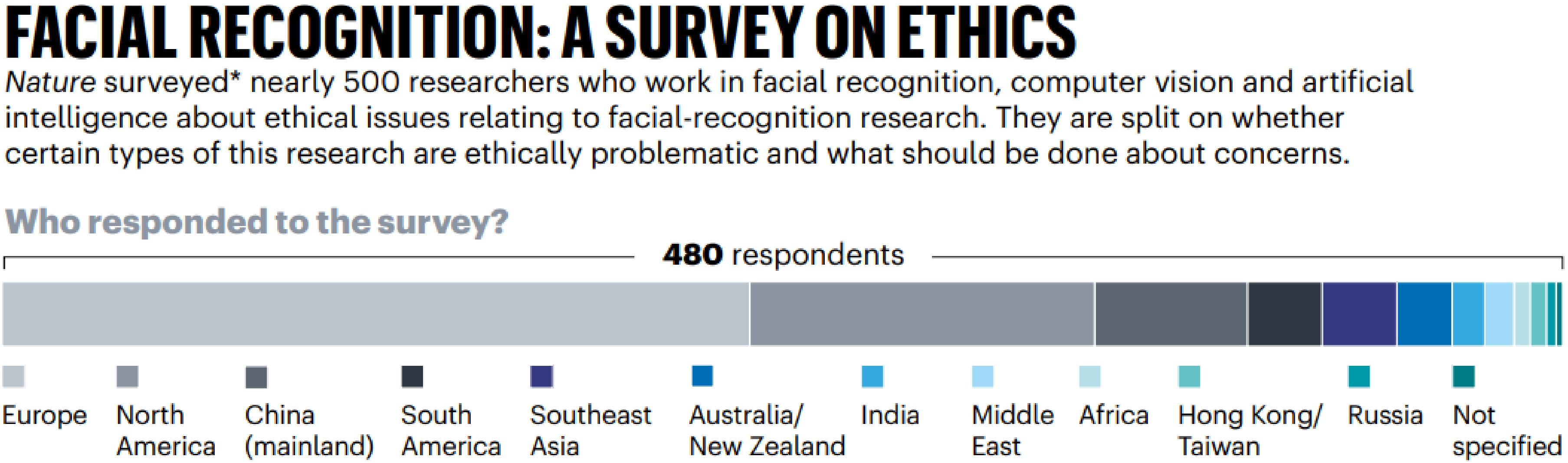


(c) Self-supervised Learning

https://madlab.ml.wisc.edu/research/thrust-1-data-efficient-ml/

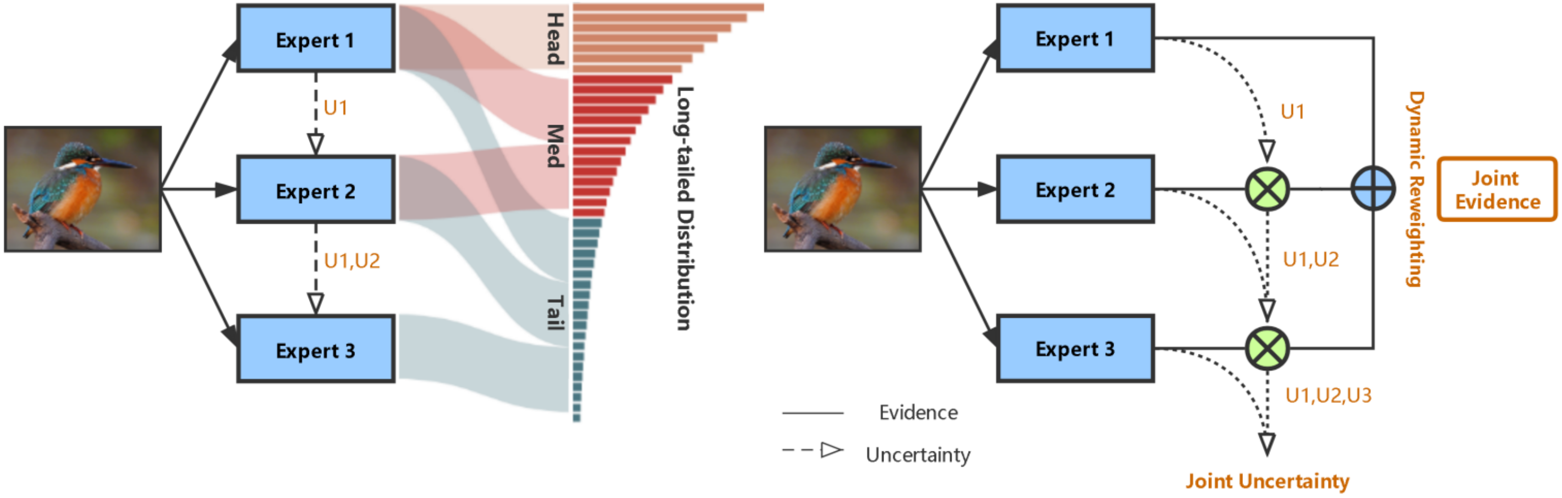
4. AI 발전 방향 예측

3. Ethical Issues



https://www.nature.com/articles/d41586-020-03187-3

3. Ethical Issues



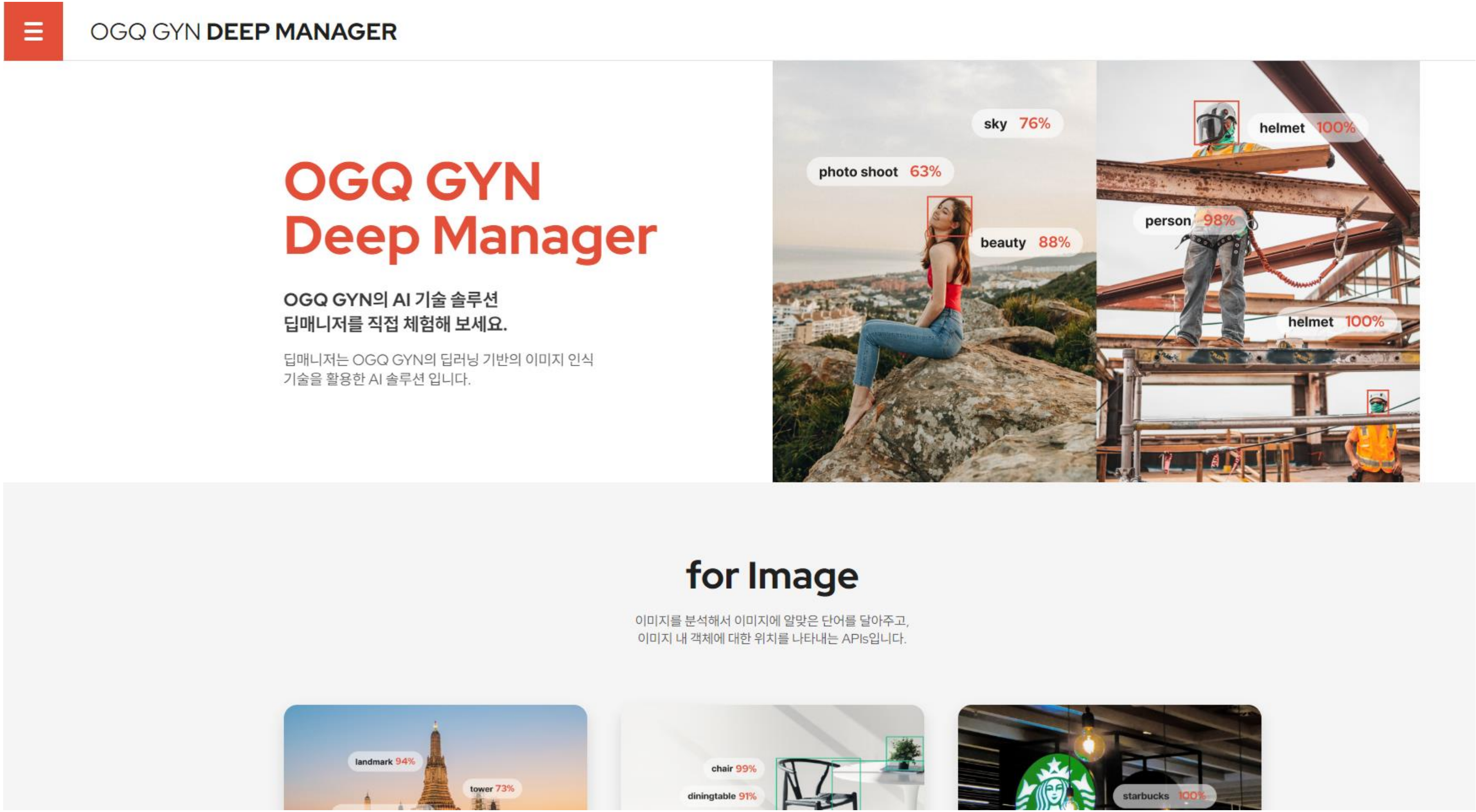
(a) Training

(b) Testing

Figure 1. Overview of the proposed Trustworthy Long-Tailed Classification (TLC). U1, U2 and U3 are the uncertainties of expert 1, 2 and 3 respectively. In training (a), we provide an example of collaborating in different class groups for multiple experts. TLC dynamically assigns averagely more experts to the samples in tail classes than those in head classes. This assignment is achieved automatically by identifying hard samples with uncertainty. In testing (b), the joint uncertainty is formed with the Dempster's rule, and the joint evidence is obtained by uncertainty-based dynamic reweighting.

https://openaccess.thecvf.com/content/CVPR2022/papers/Li_Trustworthy_Long-Tailed_Classification_CVPR_2022_paper.pdf

5. 채용



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Deep Manager
OGQ GYN의 AI 기술 솔루션
딥매니저를 직접 체험해 보세요.
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