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#073374

AI Frontier (I) – On-site Rebar Inspection using Deep Learning and Digital Twin

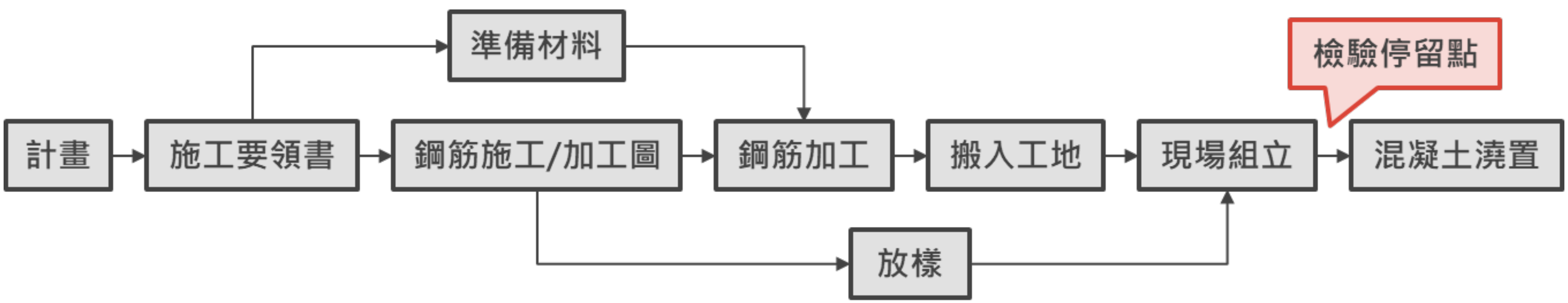
Learning Objectives

- Learn how we use deep learning to conduct rebar inspection.
- Learn the techniques we use to make the deep learning model perform better.

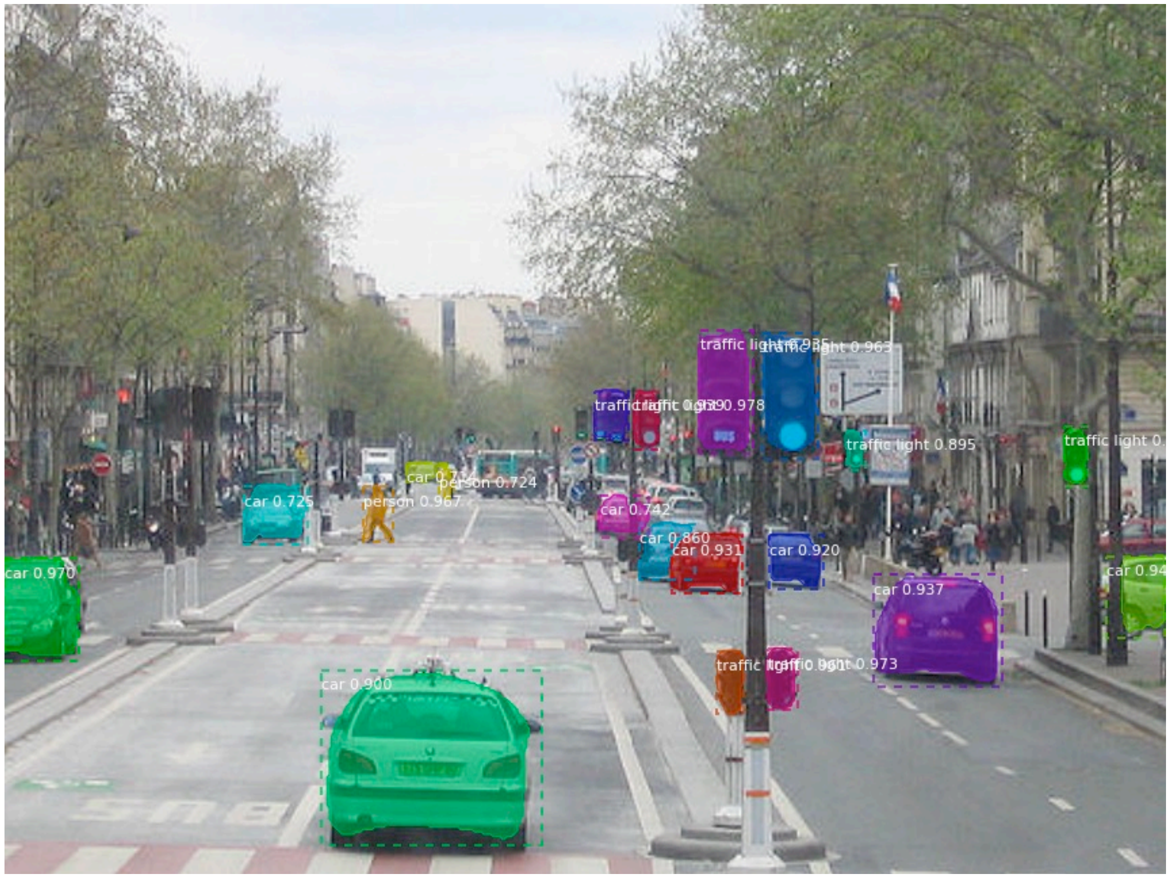
Rebar Inspection using Deep Learning

Rebar Project Construction Inspection Process

- **Current inspection method**
  - Tape measure
  - Construction drawing
  - Hard-copy record
- **Issues**
  - Large number of rebars
  - Difficult measurement
  - Timeliness

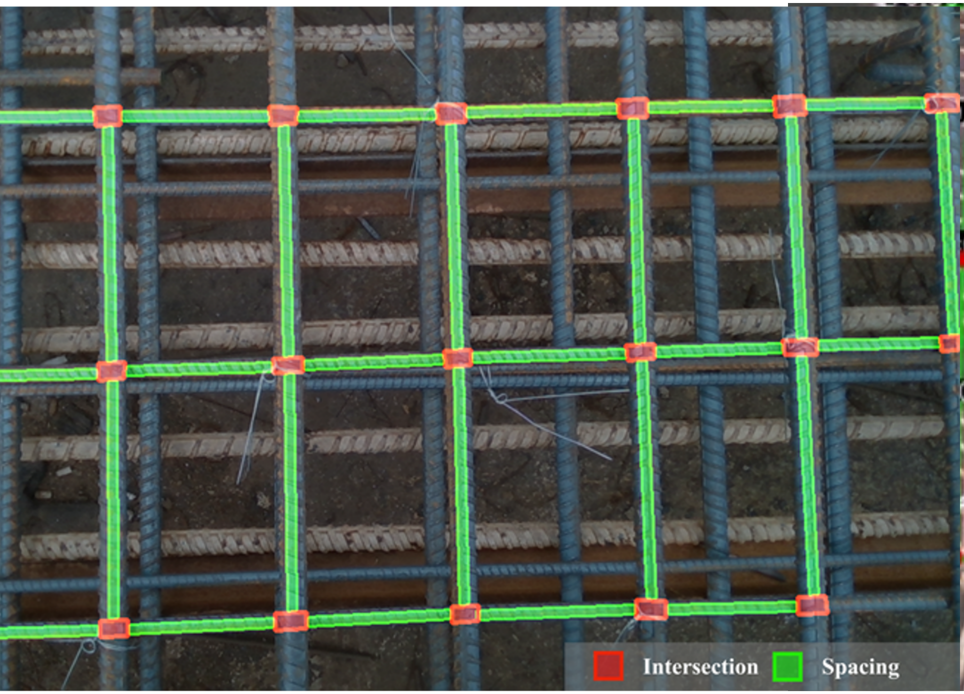


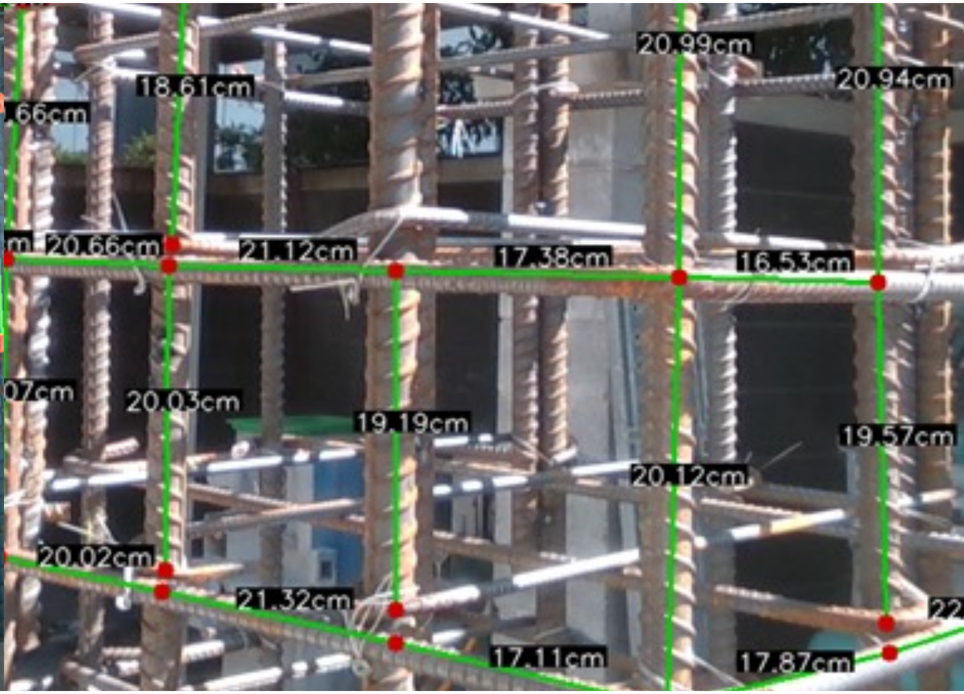
Instance Segmentation (Pixel Level Recognition) Mask R-CNN



Kaiming He et al. (2018). Mask R-CNN. axXiv:1703.06870

Instance Segmentation (Pixel Level Recognition) Mask R-CNN

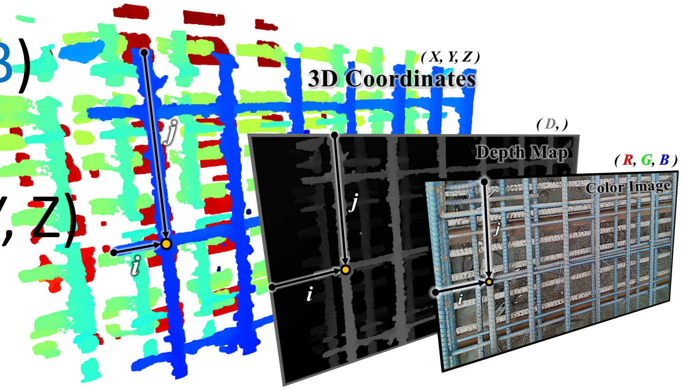


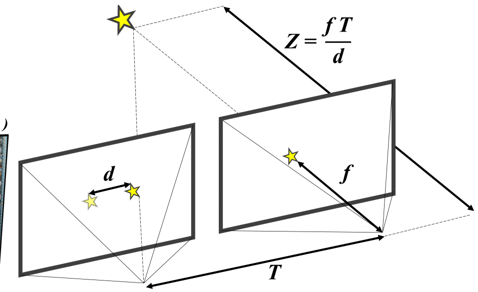


Kaiming He et al. (2018). Mask R-CNN. axXiv:1703.06870

Data Collection

- **RGB-D data**
  - Color image (R, G, B)
  - Depth map (D,)
  - 3D point cloud (X, Y, Z)

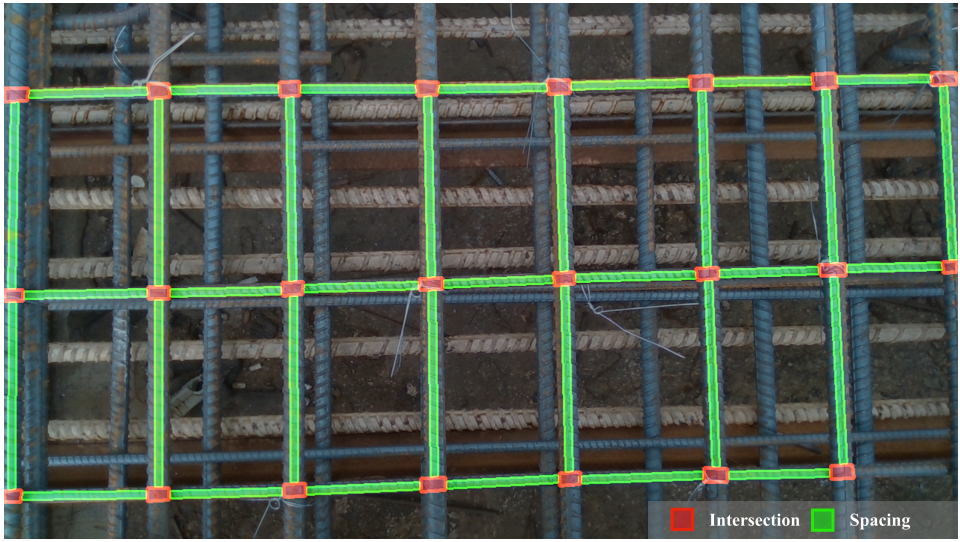




Collected Date	Rebar assembly	Training set	Testing set
2019/05/31	Precast U-girder	93	—
2019/07/10	Precast U-girder	81	—
2019/10/24	Precast U-girder	56	—
2021/04/07	Precast U-girder	—	85
2021/04/07	Continuous wall	—	40
Total		**230**	**125**

Rebar Dataset

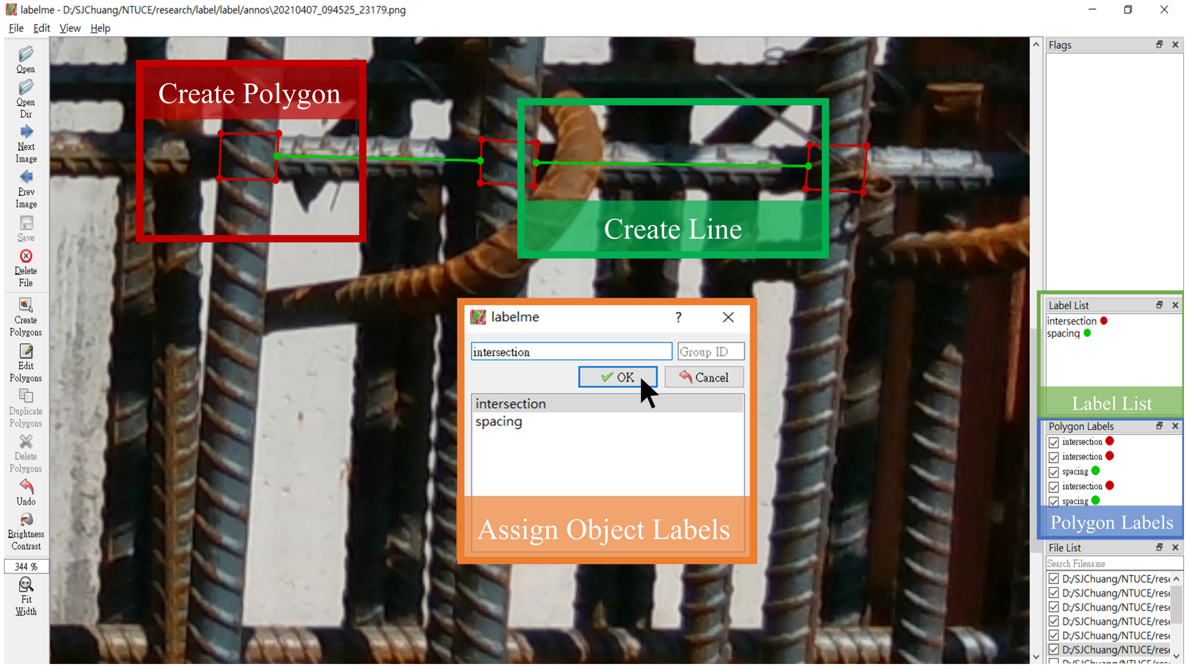
- **Features and class definitions**
  - Intersection
  - Spacing
- **Labeling configuration**
  - Intersection
    - Def: Overlap area of rebars
    - Shape: Polygon
    - Format: Boundary points
    - Goal: Reference point
  - Spacing
    - Def: Link between intersection
    - Shape: Line
    - Format: Two endpoints
    - Goal: Link prediction



Rebar Dataset

- **Labeling tool**

labelme



- **Saved format (.json)**

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"shapes": [
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    "label": "intersection",
    "points": [
      [504, 7], [501, 44], [532, 48],
[534, 8]
    ],
    "shape_type": "polygon"
  },
  {
    "label": "spacing",
    "points": [
      [924, 162], [924, 59]
    ],
    "shape_type": "line"
  }
]
```

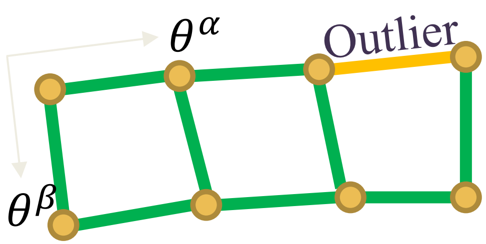
Deep Learning Models

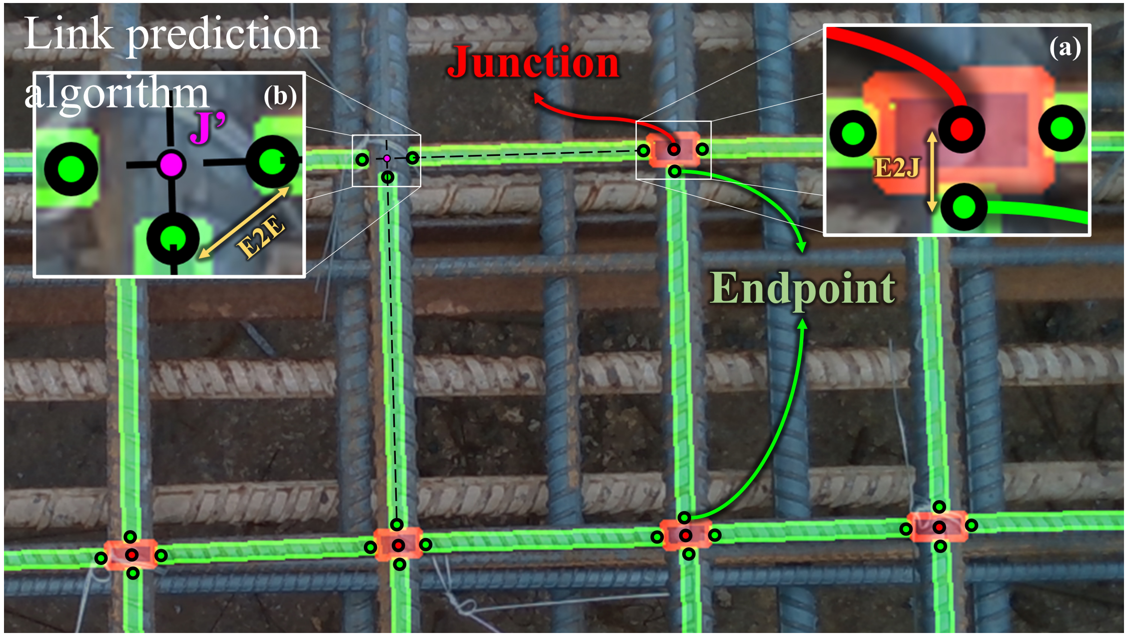
- **Dataset preparation**
  - 230 labeled data from Precast U-girder in 2019
  - Data splitting: Training [179], validation [22], testing [29]
  - Preprocessing: centroid point and line segment to polygon conversion
- **Loss**
  - $L = L_{cls} + L_{box} + L_{mask} + \lambda \, L_{keypoint}$
- **Performance metrics**
  - Average precision
    - Area under precision-recall curve
    - AP_{50}: AP at IoU = 0.50
    - AP: mean AP at IoU = 0.50 : 0.05 : 0.95
    - AP, AP_{50}, AP_{75}
  - Dice coefficient (DC)
    - DC_J: How accurate is the indexed point (*Junction*)
    - DC_L: How accurate are the paired points (*Link*)

Mask R-CNN config	Description
Framework	Detectron2 (FAIR)
Input format	RGB
Backbone	ResNet-101-FPN
Pretrained weights	MS COCO
Batch size	4
Iteration	30,000
Optimizer	SGD
Base learning rate	**0.0002**

Post Processing

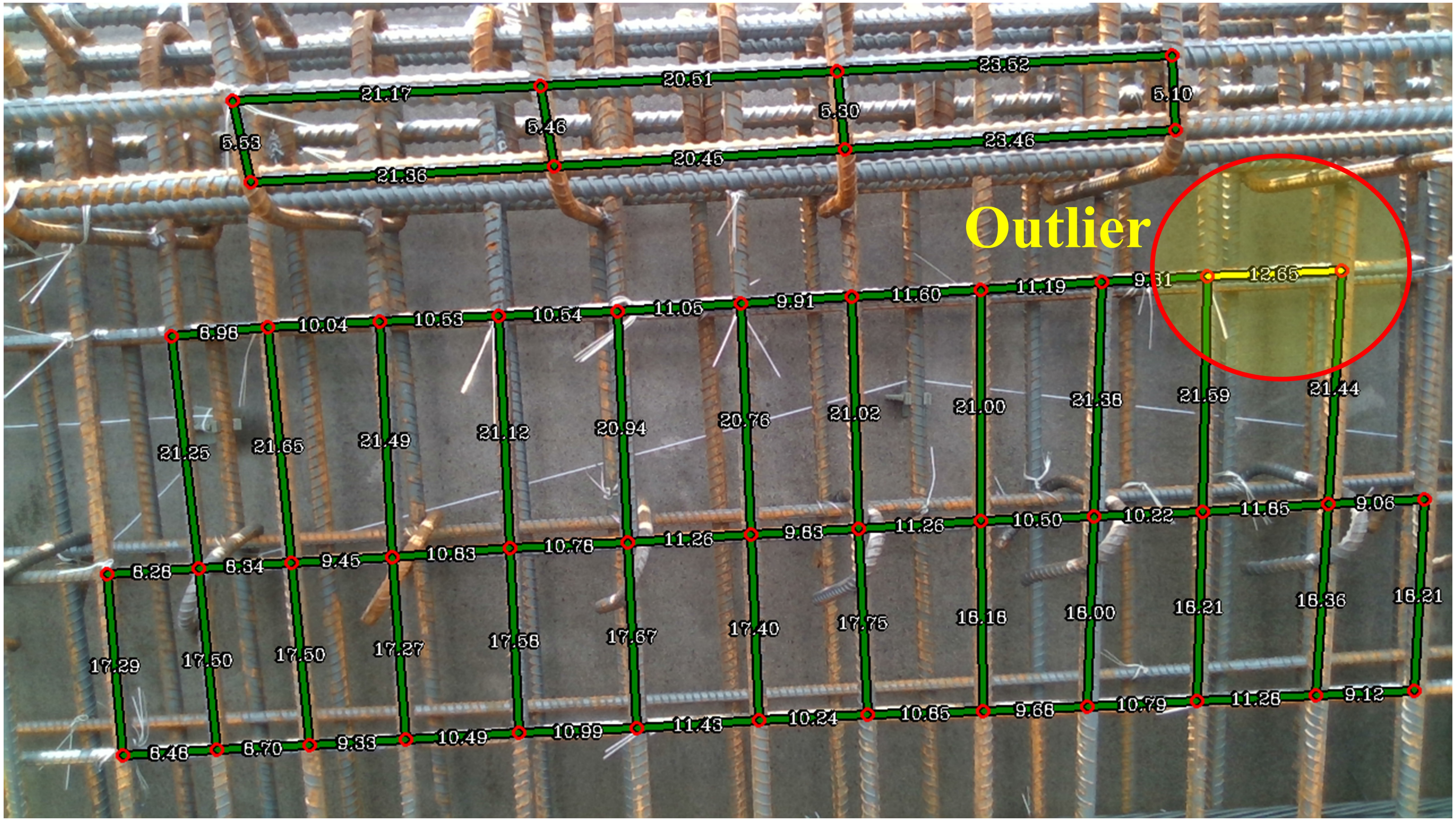
- **Link prediction**
  - $\delta_{E2J} = 30\ px$
  - $\delta_{E2E} = 50\ px$
- **Spacing measurement**
- **Visualization**
- **Active screening**





Rebar Spacing Measurements

Rebar Spacing Measurements



$$Absolute\ Error(AE) = |S_{pred} - S_{GT}|$$

$$Relative\ Error(RE) = \frac{|S_{pred} - S_{GT}|}{S_{GT}}$$

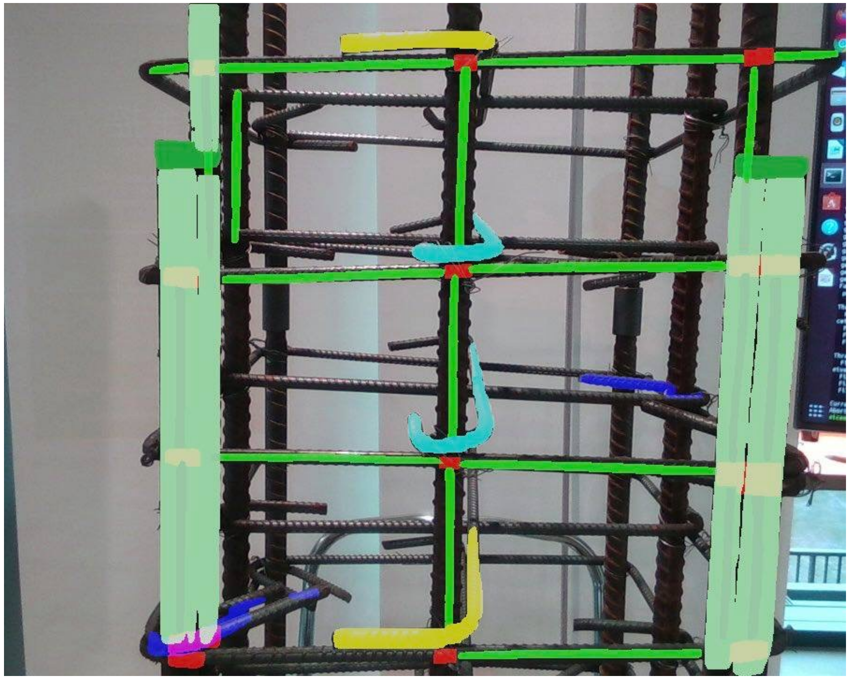
Detected spacings	AE (cm)	RE (%)
1368	0.166	1.388

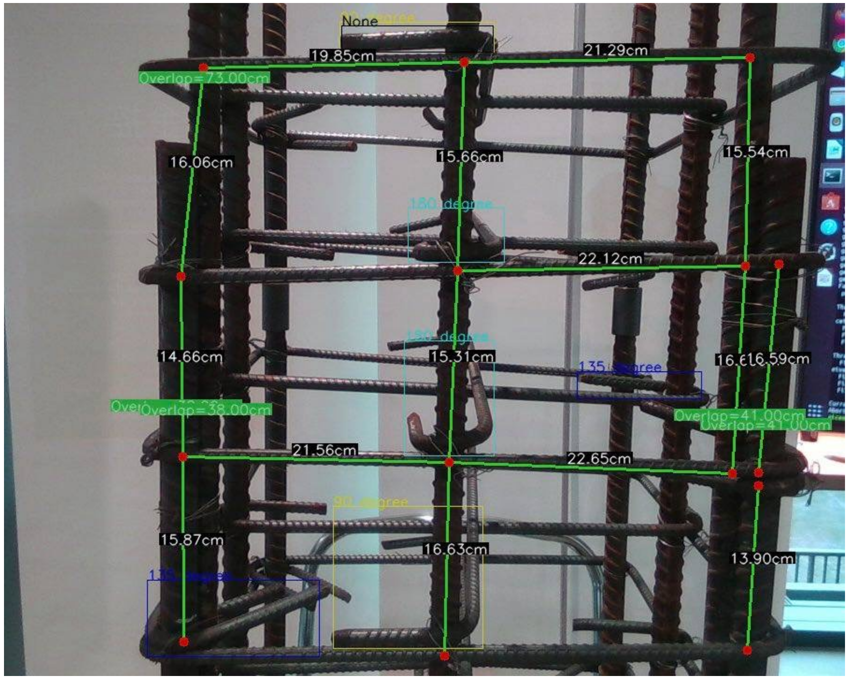
Mask R-CNN + Link Prediction Algorithm

Mask R-CNN 實例分割預測

空間自動量測與物件定位

以演算法獲取實例分割圖中的關鍵像素點或定界框後，索引三維點雲座標，即可計算空間距離，達成自動量測效果。





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Rebar Inspection using SSL, Active Learning & Domain Adaptation

Instance Segmentation

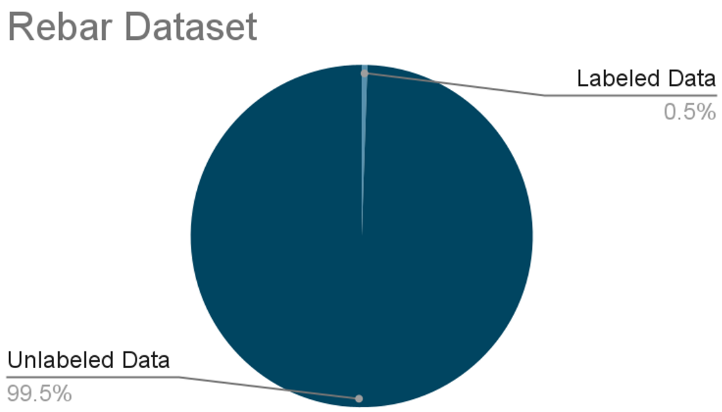
- **Levels of image recognition**
  - Object detection (bounding-box level)
  - Semantic segmentation (pixel-level segmentation)
  - Instance segmentation (instance-level segmentation)

- **Labeling issues**
  - Time-consuming & costly
  - Annotation by domain experts

Rebar Dataset

- Labeled data: 50 ~ 200 images per domain
  - Pixel-wise labels
  - Labor-selected samples that should represent the domain data well
  - **But** the trained model only works on old known domain
- Unlabeled data: 8,000 ~ 37,000 images per domain
  - Large amount of continuous & highly similar images per shoot
  - Easy to collect on new domains
  - **But** not usable in supervised learning

What a waste
not using them
in model training!

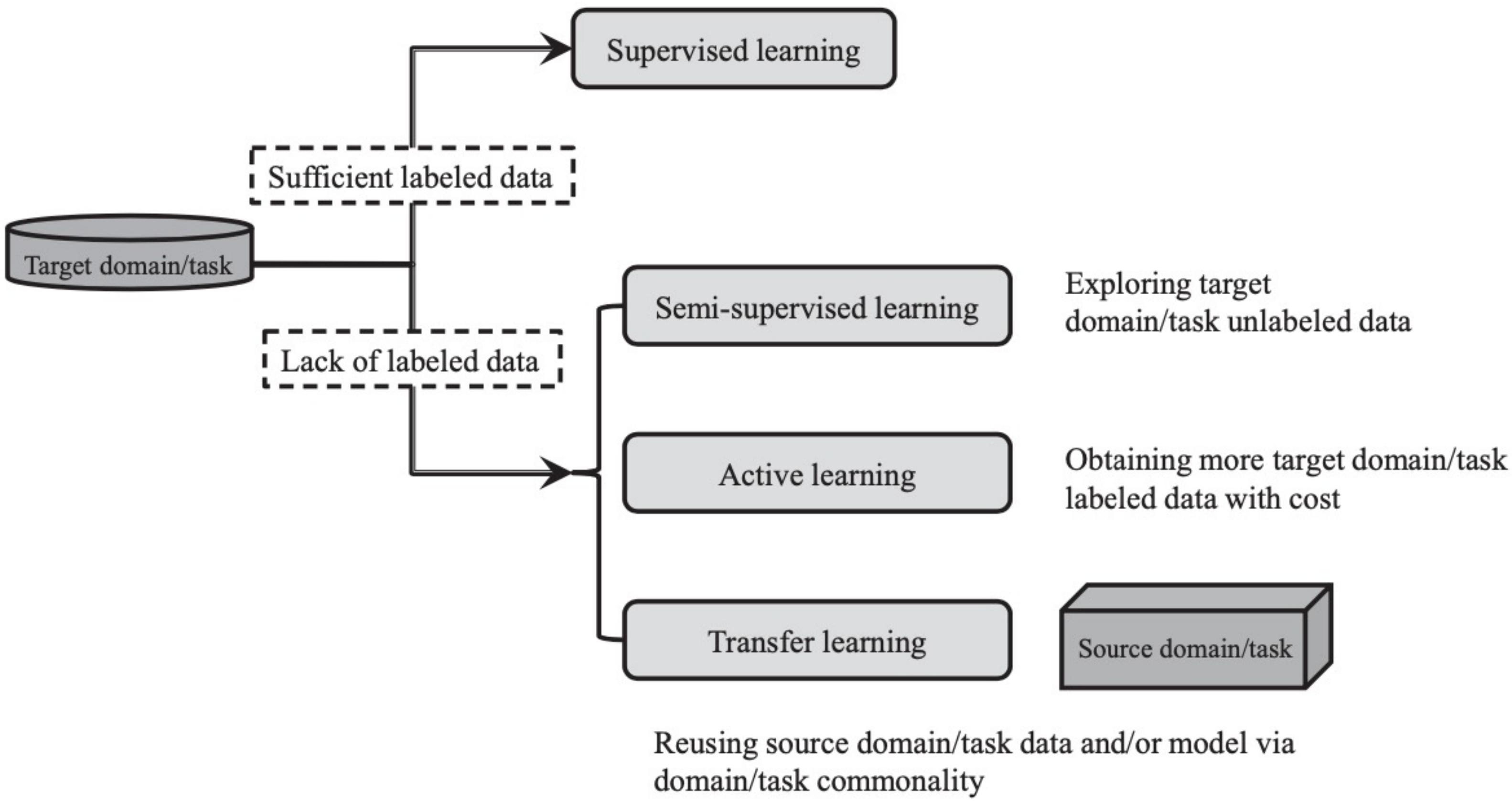


Rebar Dataset

The current deep model by **supervised training** only performs well on its trained domain due to domain variance.

Domain variance:

- rebar assembly
- collecting time
- shooting position



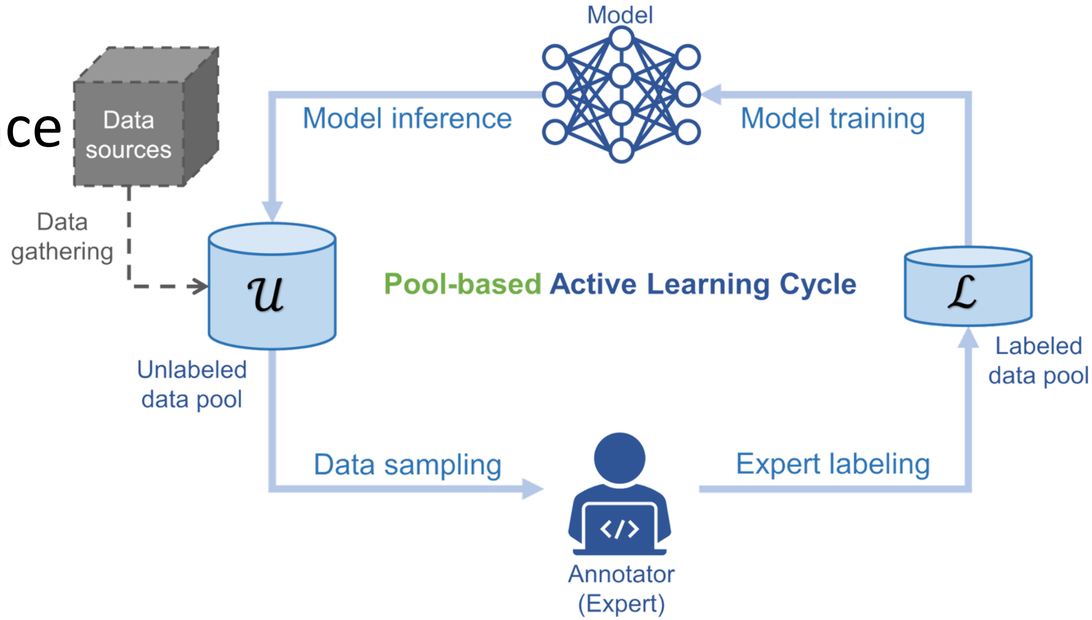
Yang et al., Transfer Learning, Cambridge University Press, 2020.

Active Learning

Small data for big performance

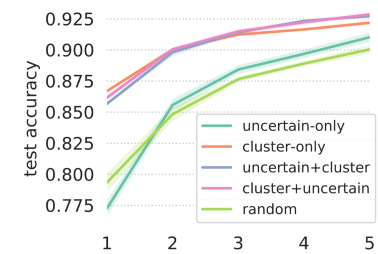
Active Learning

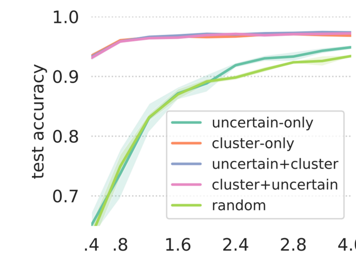
- **Definition**
  - A Subfield of machine learning.
  - A learning algorithm interactively query oracle to label new data with expected output.
  - Query learning, optimal experimental design.
- **Uncertainty sampling**
  - Query strategy
  - Least model confidence
- **Pool-based active learning cycle**
  - Data sampling
  - Expert labeling
  - Model training
  - Model inference



Active Learning

- **Active learning loop**
- **Active learning for object detection**
  - Entropy-based uncertainty measurement
    - Aggregation function (Sum, Average, Max)
  - Ensemble-based disagreement measurement
    - Consensus score
    - RoI matching
- **Active learning with clustering**





Algorithm 1 Active learning loop

$\mathcal{U}$: A set of unlabeled data $\{x^1, x^2, x^3, \dots\}$

$\mathcal{L}$: A set of labeled data $\{\langle x^a, y^a\rangle, \langle x^b, y^b\rangle, \langle x^c, y^c\rangle, \dots\}$

$\mathcal{B}$: Labeling budget

for i in $\mathcal{B}$ **do**

  Train a model $\mathcal{M}$ based on $\mathcal{L}$

  Select the most uncertain instance $x^* \in \mathcal{U}$ according to $\mathcal{M}$

  Query the oracle to obtain label y^*

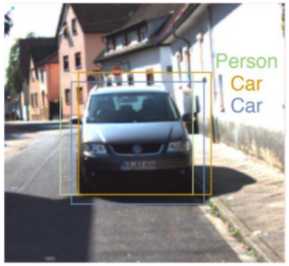
  Let $\mathcal{L} \leftarrow \mathcal{L} \cup \{\langle x^*, y^*\rangle\}$

  Let $\mathcal{U} \leftarrow \mathcal{U} \backslash \{x^*\}$

end for

IoU = 0.85

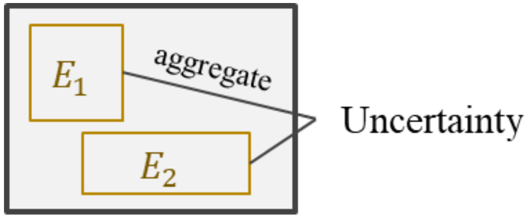
Consensus score = 1 – 0.85

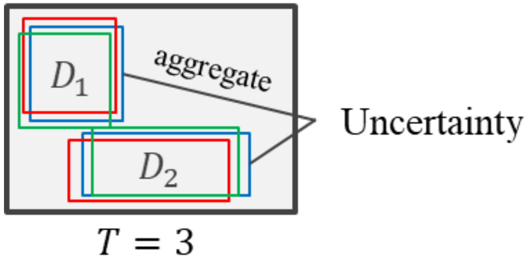


IoU = 0.85, $\mathcal{VR}$ = 1 – 2/3

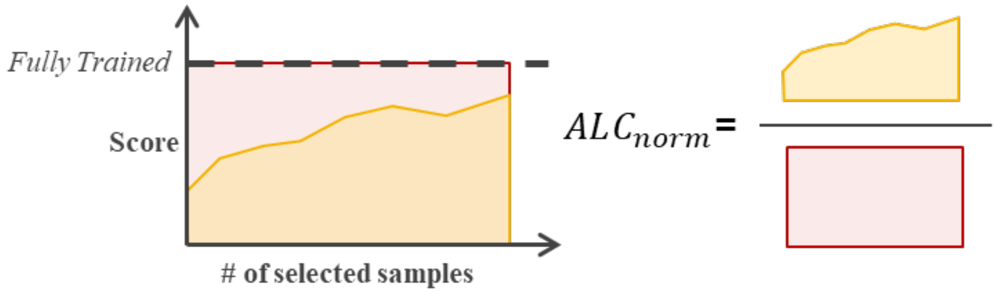
Consensus score $\mathcal{VR}$ = 1 – 0.561

Active Learning Algorithms

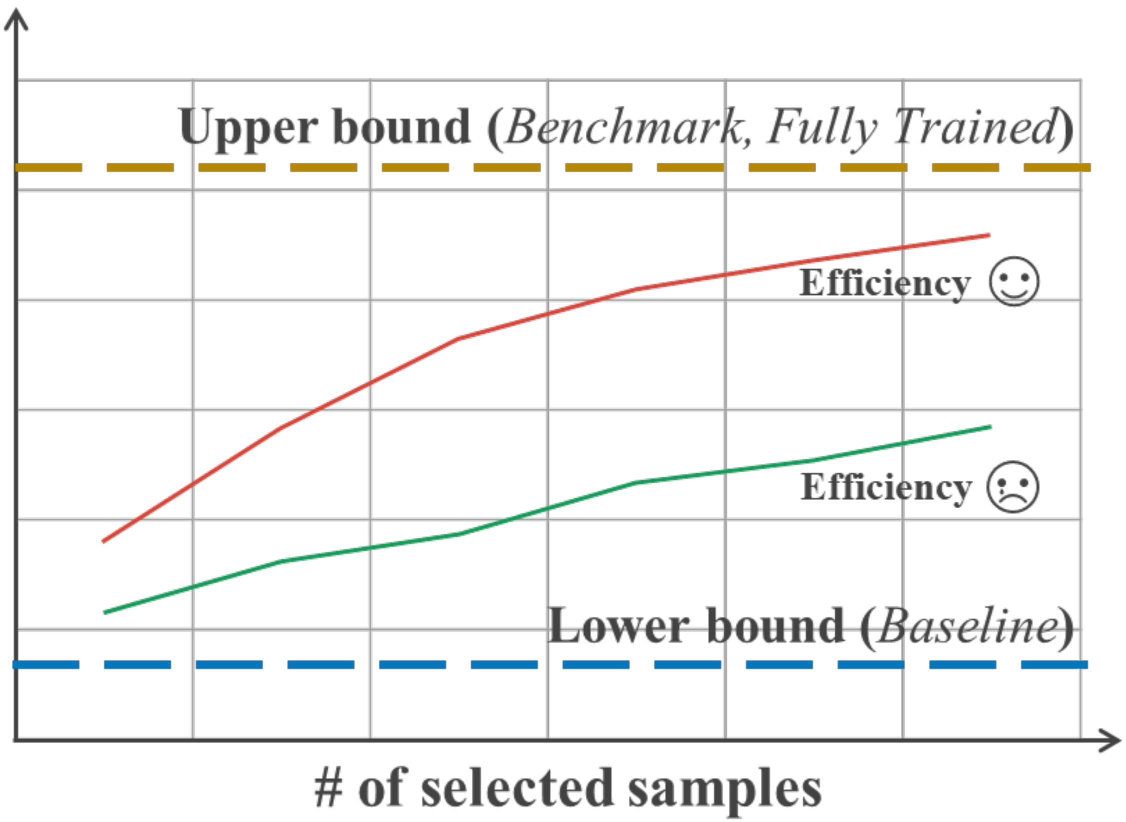


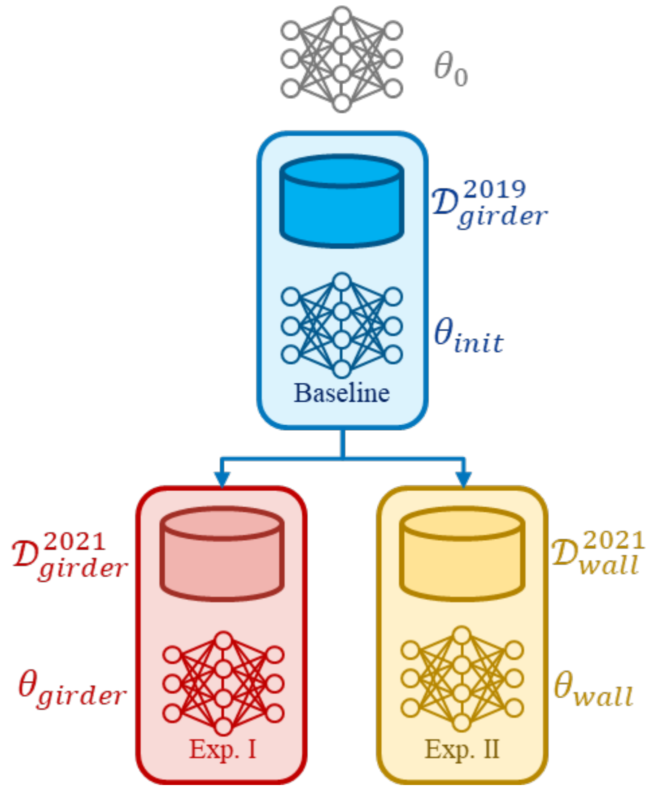


- **Uncertainty estimation**
  - Entropy of the probability distribution
    - Three aggregation functions ($\sum$, $\frac{1}{N}\sum$, $\max\limits_{E}$)
  - RoI matching method
    - Generate controversial predictions through MC dropout
    - Three disagreement measures ($E_{vote}, E_{consensus}, Div_{KL}$)
    - Aggregated by average
- **Performance metrics**
  - Normalized area under the learning curve ALC_{norm}



Active Learning Experiments

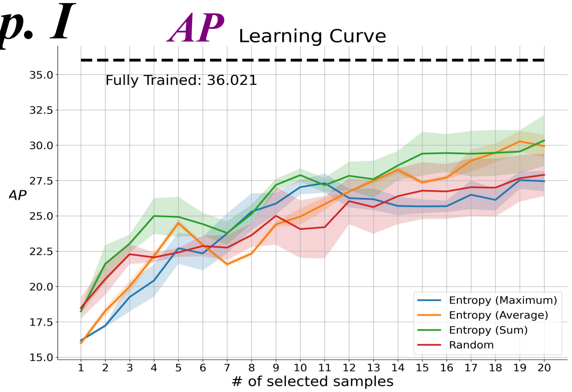


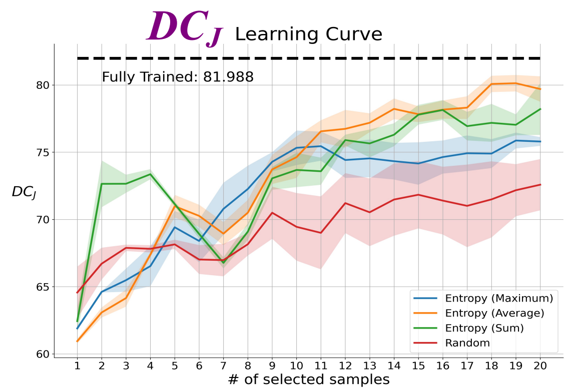


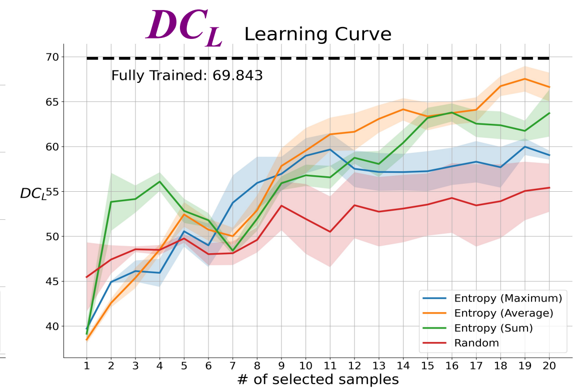
Active Learning Experiments (Entropy)

Sum, Average, Maximum, Random

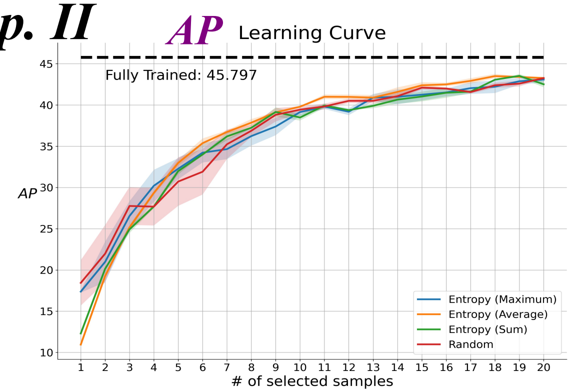
Exp. I

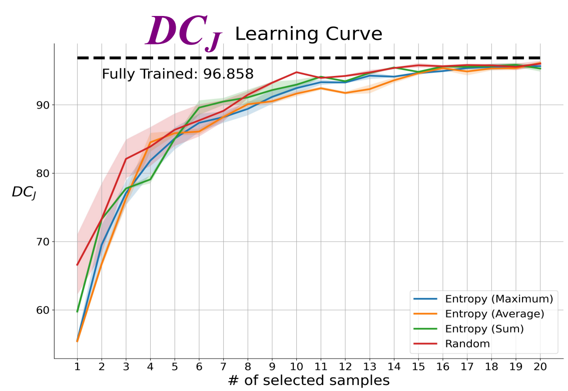


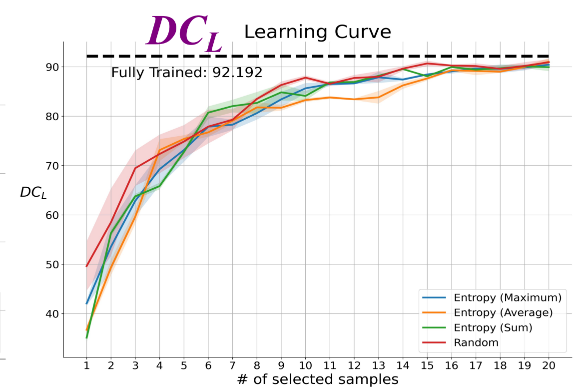




Exp. II





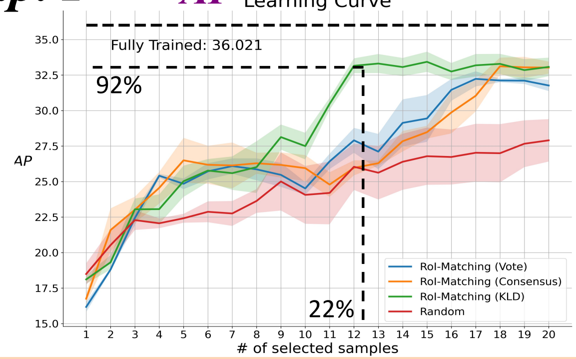


Active Learning Experiments (RoI Matching)

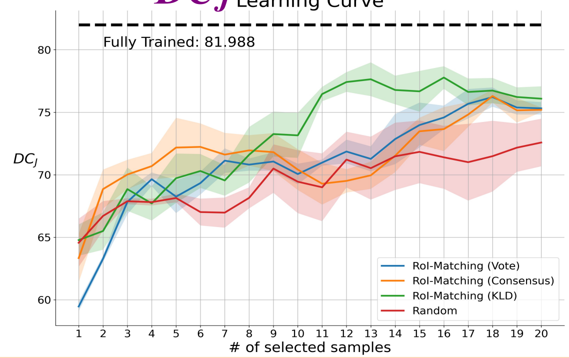
KL Divergence, Consensus Entropy, Vote Entropy, Random

Exp. I

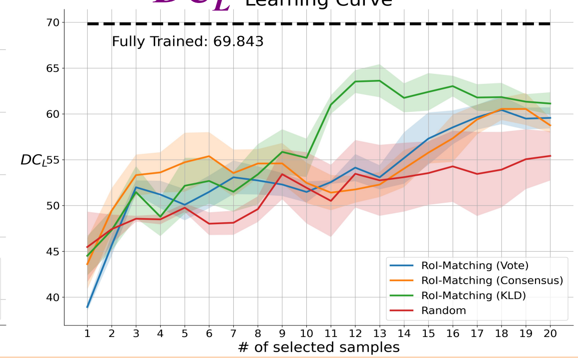
AP Learning Curve



DC_J Learning Curve

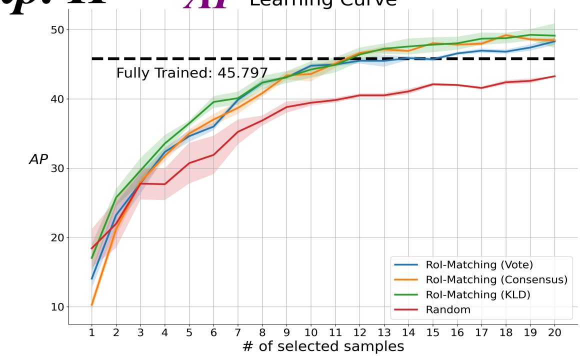


DC_L Learning Curve

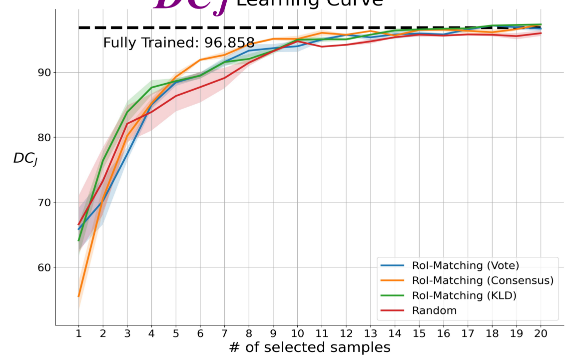


Exp. II

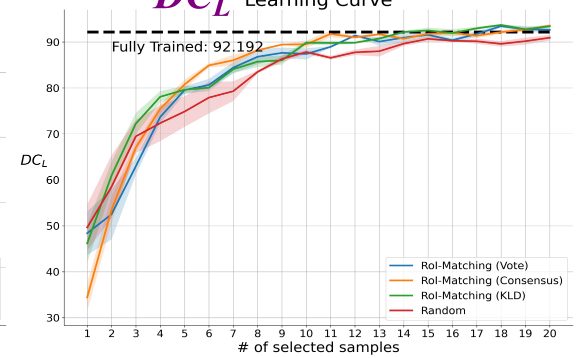
AP Learning Curve



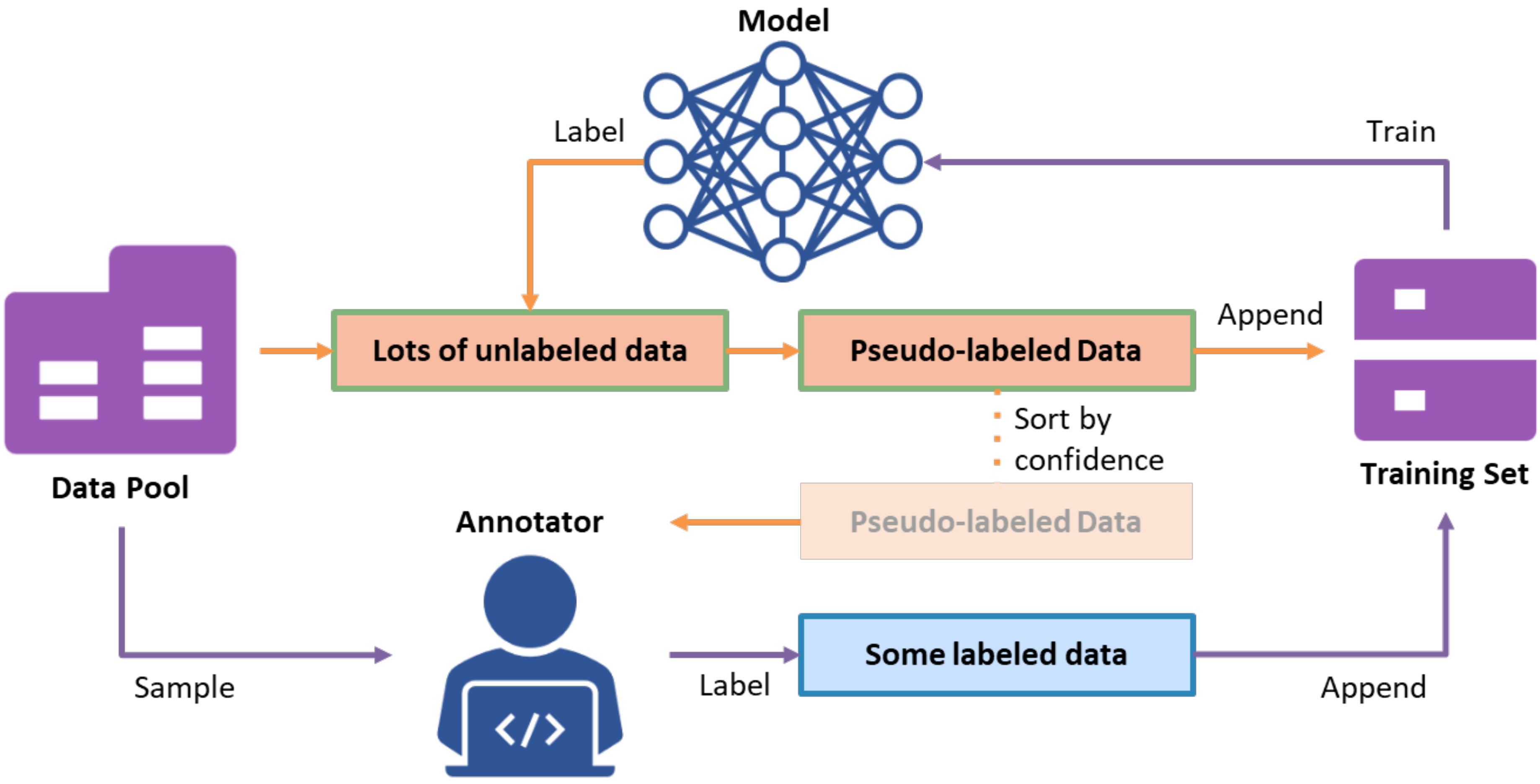
DC_J Learning Curve



DC_L Learning Curve



Active Learning + Pseudo Labeling

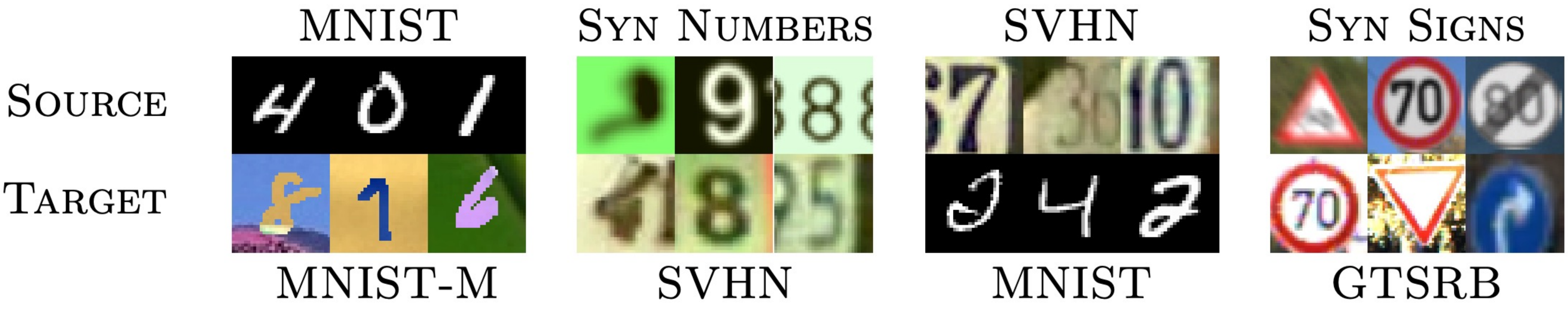


Domain Adaptation

TL will be the next driver of ML commercial success after supervised learning, Andrew Ng (2016 NIPS)

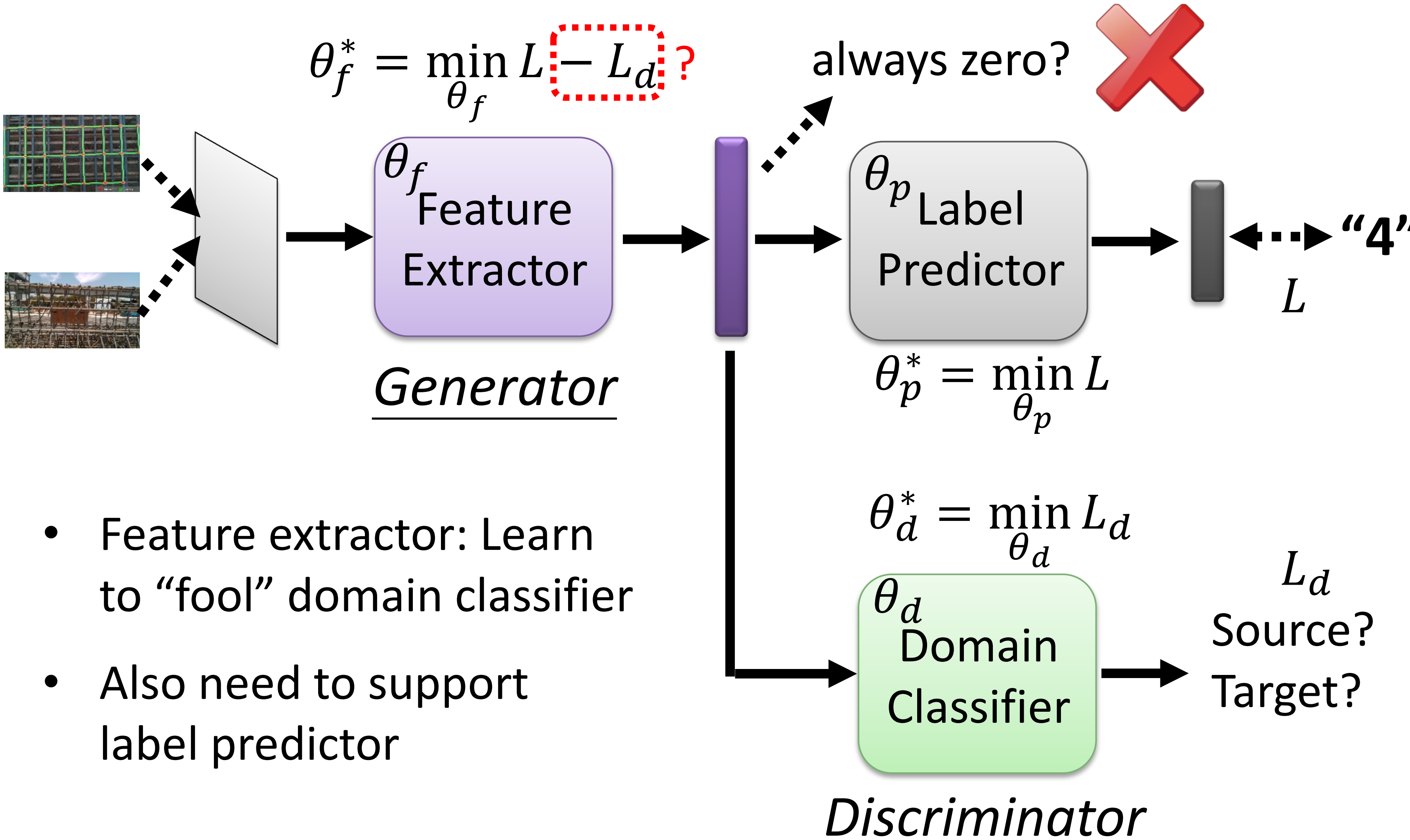
Domain Adaptation: A Subfield of Transfer Learning

Domain adaptation is a specific scenario where the label space remains same, yet the probabilities between source and target domains change $P(X_s) \neq P(X_t)$



Domain Advesarial Training

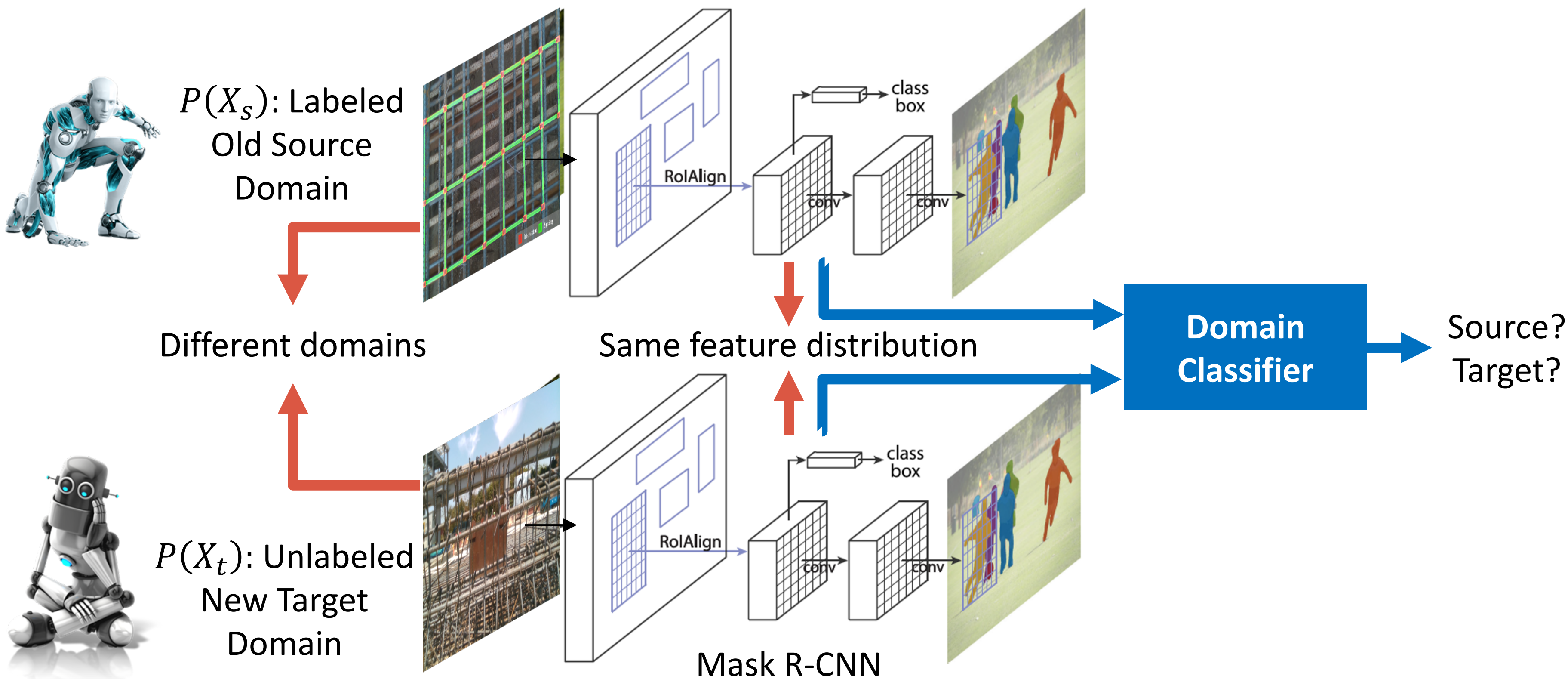
credit: Hung-Yi Lee, https://speech.ee.ntu.edu.tw/~hylee/ml/2021-spring.html



- Feature extractor: Learn to "fool" domain classifier
- Also need to support label predictor

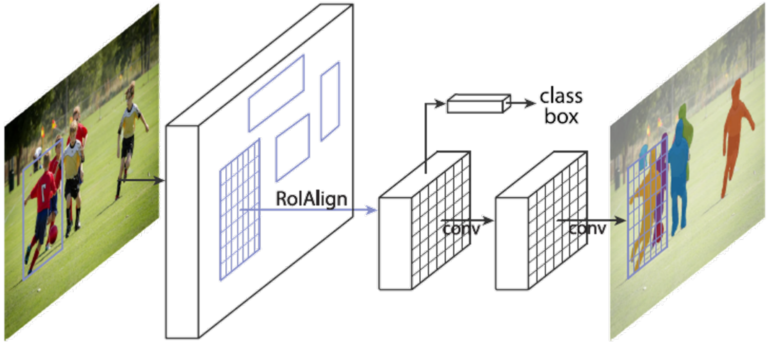
Domain Adaptation for Rebar Image Segmentation

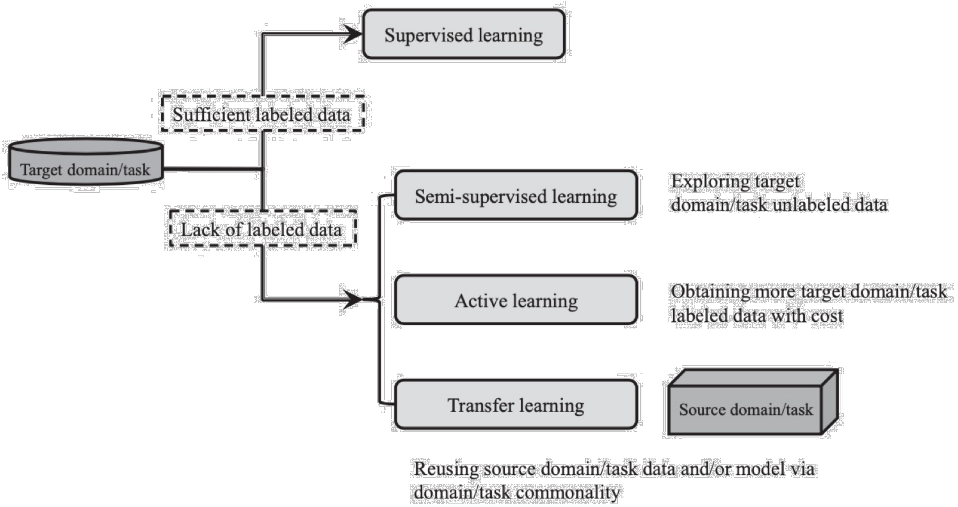
- **Domain variance** in rebar dataset:
  rebar assembly, collecting time, shooting position
- **Domain adversarial training:** reduce discrepancy between domains
  - **Domain classifier:** try to distinguish between source and target domain
  - **Feature extractor:** try to fool domain classifier while training model

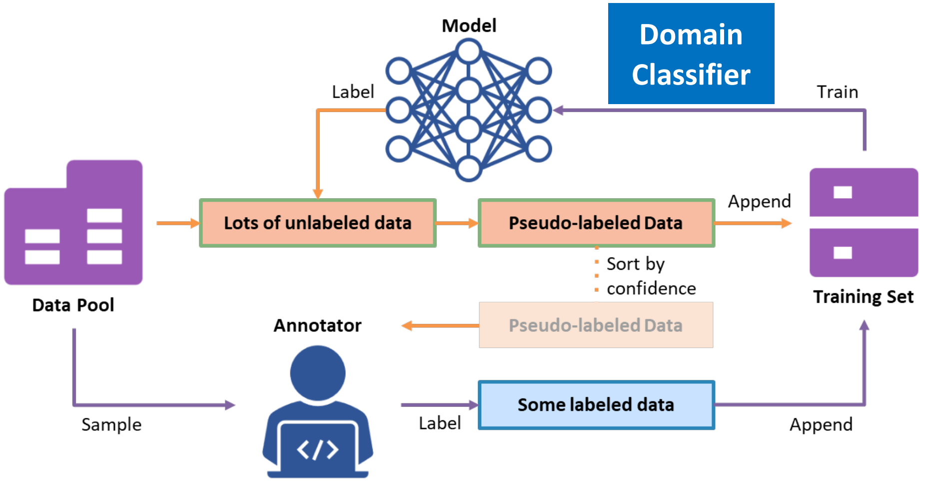


labelme

Summary







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Digital Twin