Weakly Supervised Object Detection, Localization, and instance segmentation

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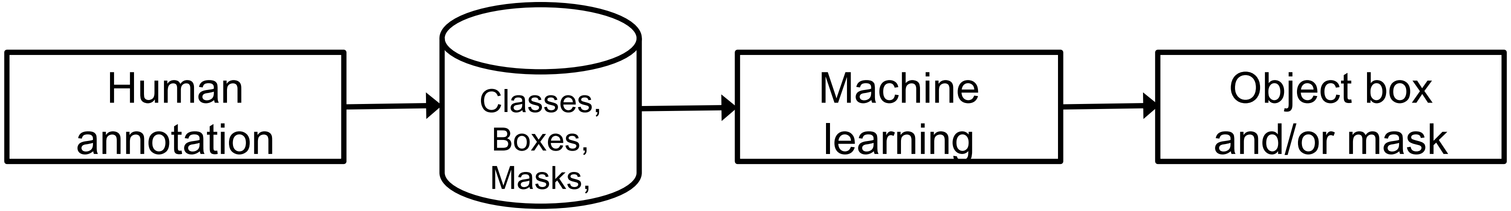
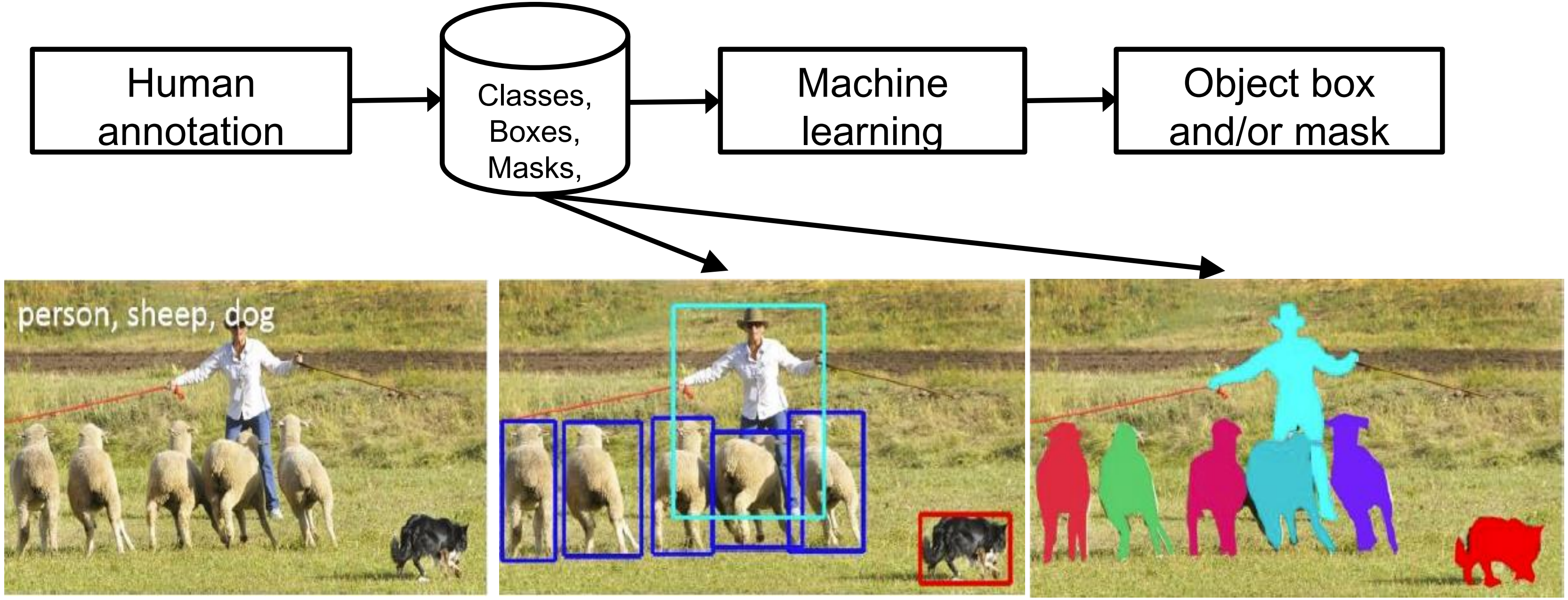
Problem

Supervised **object detection** and **instance segmentation** pipeline



Problem

Supervised **object detection** and **instance segmentation** pipeline



Bounding box annotation

Mask annotation

Problem

20k+ class $\xrightarrow{100/c}$ 2M instances $\xrightarrow{5min/I}$ **19 years /person**

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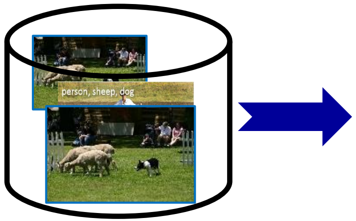
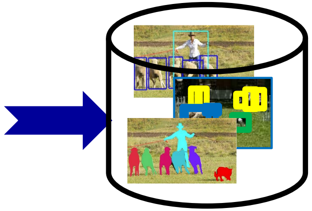
Problem

Imagery databases



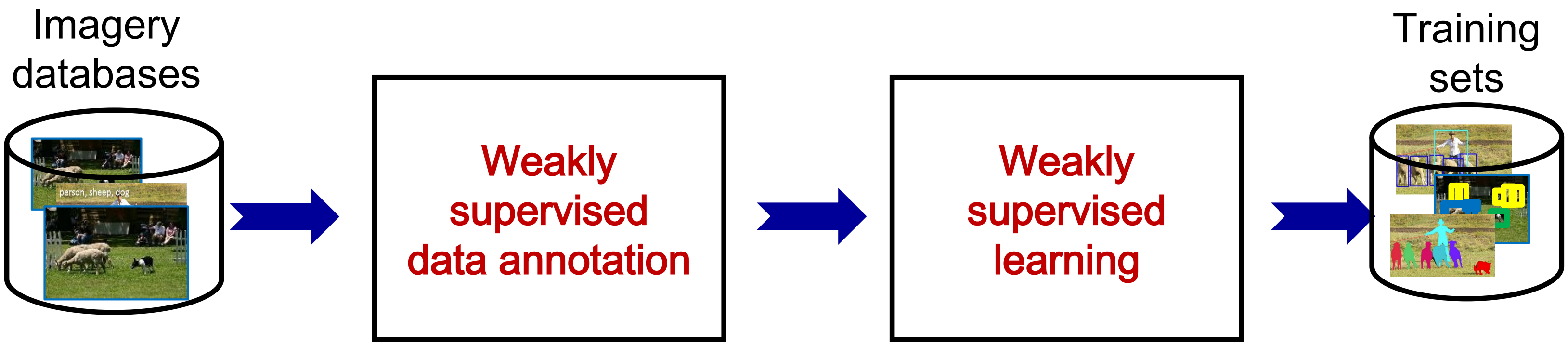
Training sets



Solutions

Data annotation is **expensive**

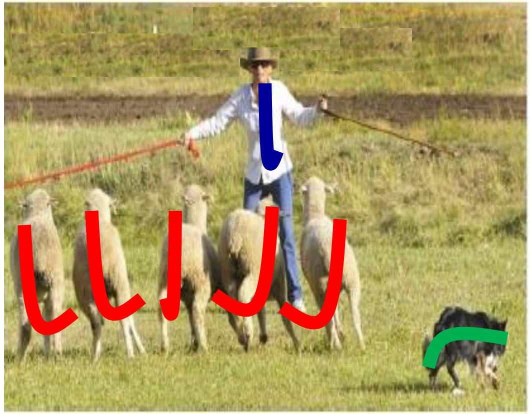
Solutions



Data annotation is **efficient and low-cost**

Solutions

Weakly Supervised Annotations



Scribes

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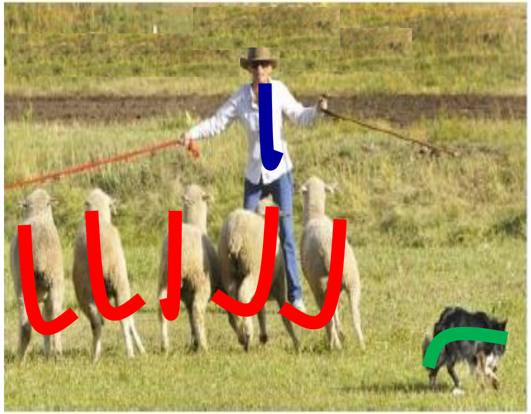
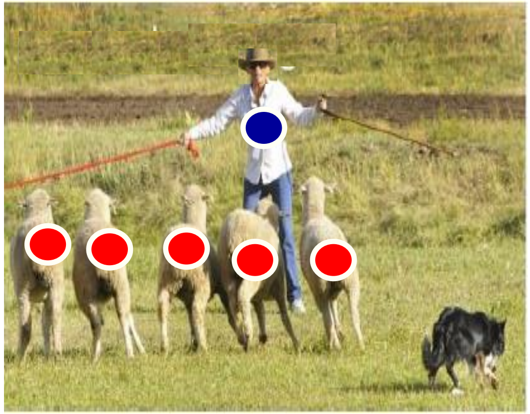
Solutions

Weakly Supervised Annotations



Scribes



Point

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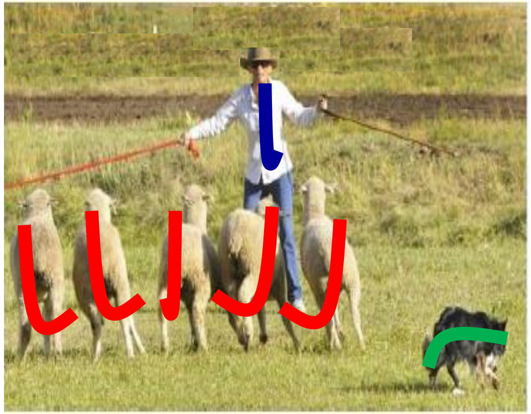
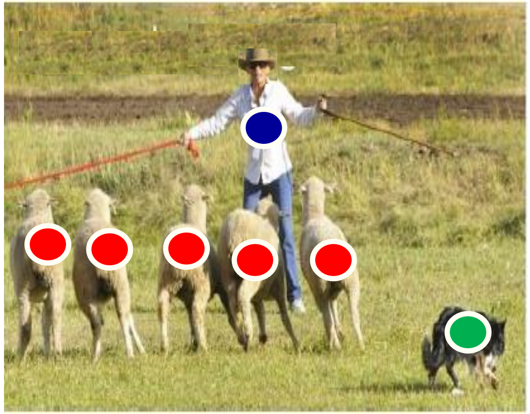
Solutions

Weakly Supervised Annotations



Scribes



Point

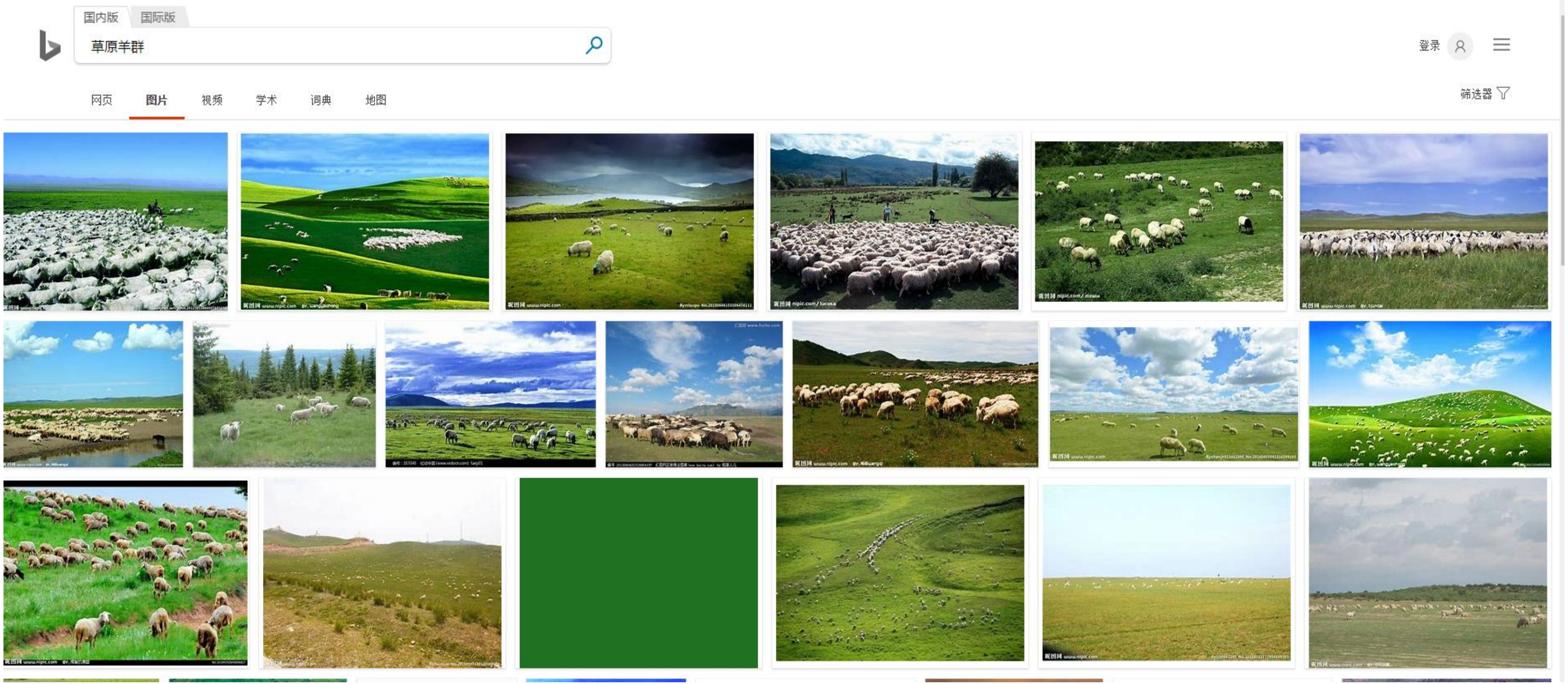
Image-level labels

The most efficient one

Copy from UIUC Yunchao's Slides

Solutions

Weakly labeled imagery is widely available on the Web



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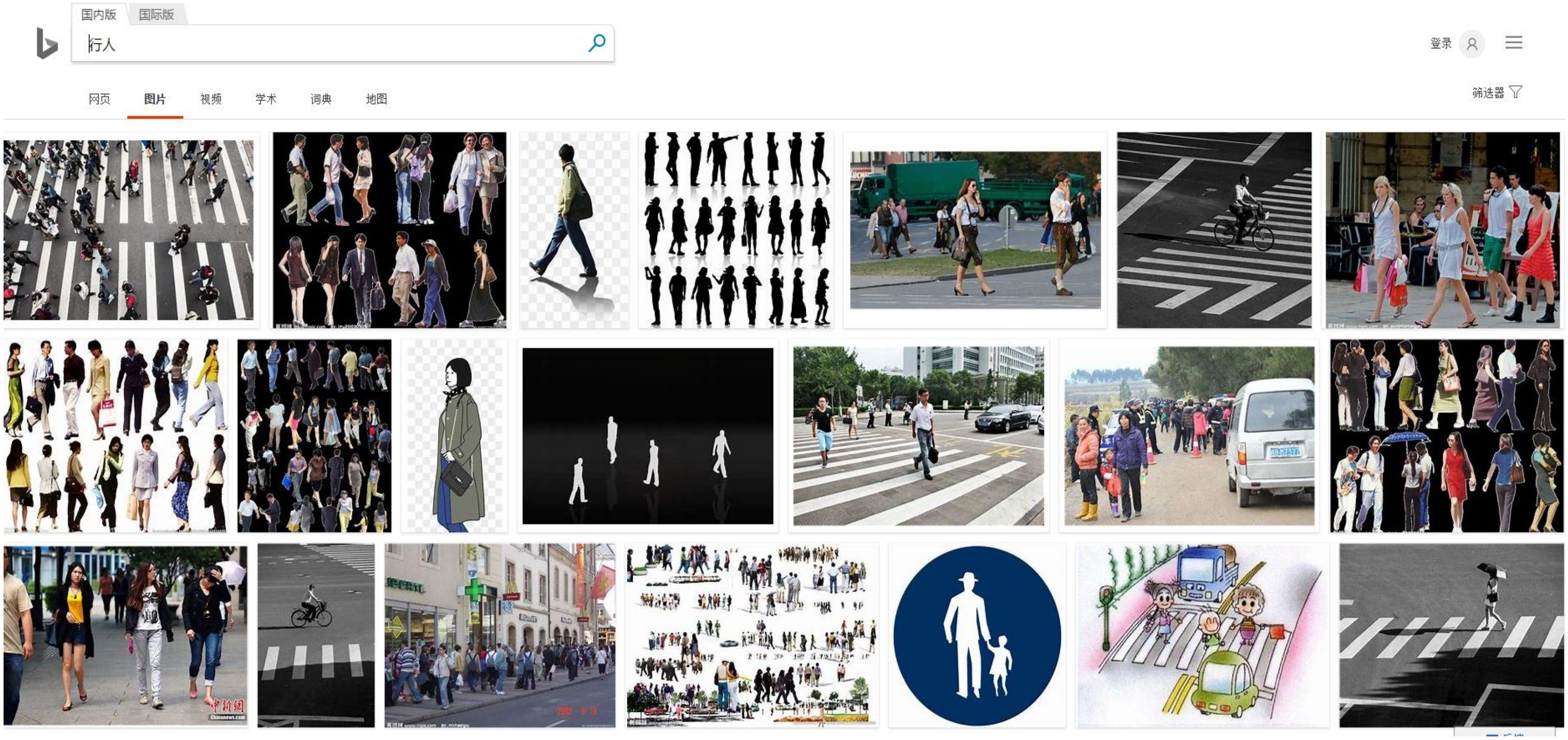


Solutions

Imagery databases

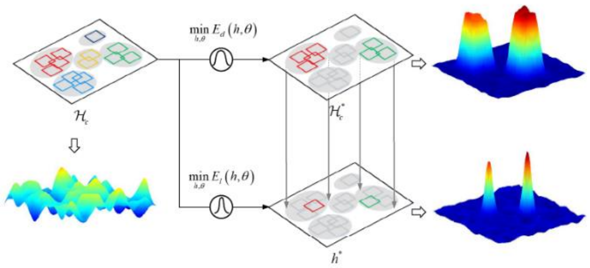
Weakly supervised data annotation

Weakly supervised learning

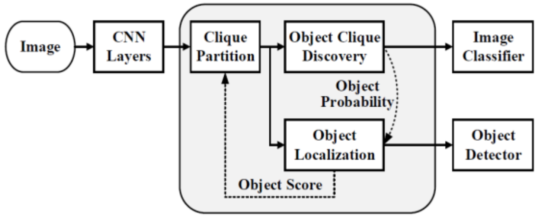
Training sets

Data annotation is efficient and low-cost

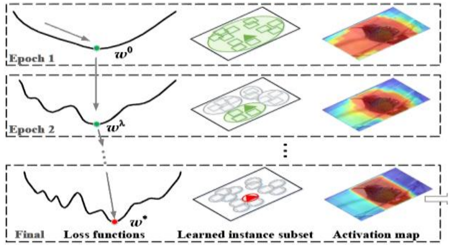
Our works



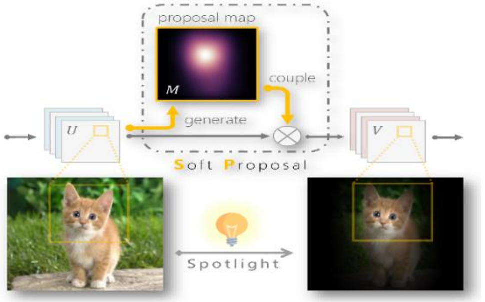
MELM
CVPR18: Min-entropy Latent Model (WSOD)



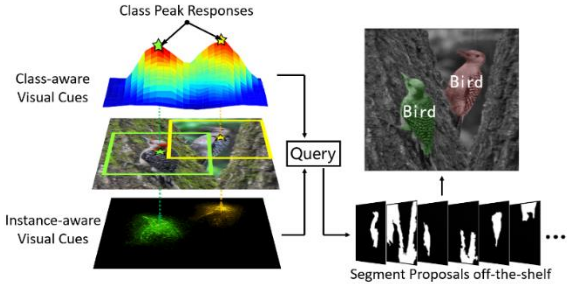
MELM+Recurrent Learning
PAMI2019: Recurrent Learning (WSOD)



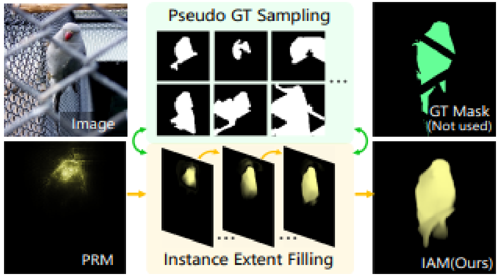
CMIL: Continuation Multiple Instance Learning
CVPR19 (WSOD)



SPN
ICCV17: Soft Proposal Network (WSOL)

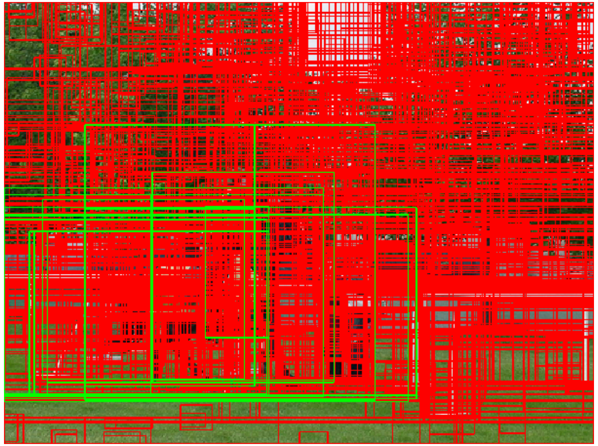


PRM
CVPR18: Peak Response Mapping (WSIS)



IAM
CVPR19: Instance Activation Map (WSIS)

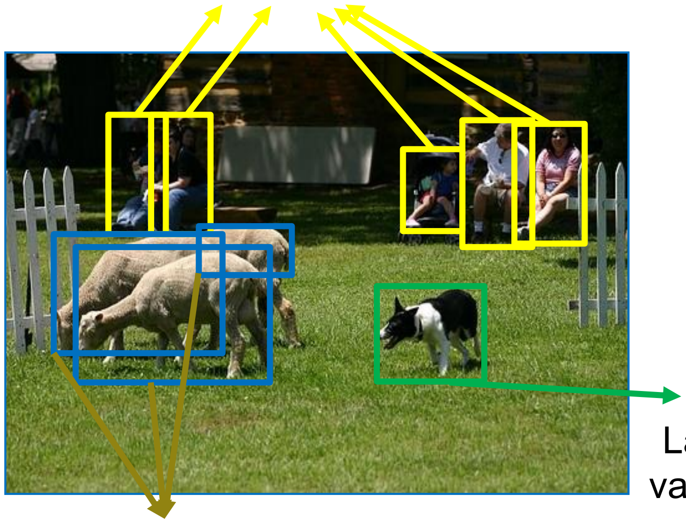
Our works-Challenge analysis



Latent variable learning

Multiple Instance learning

Latent variable h



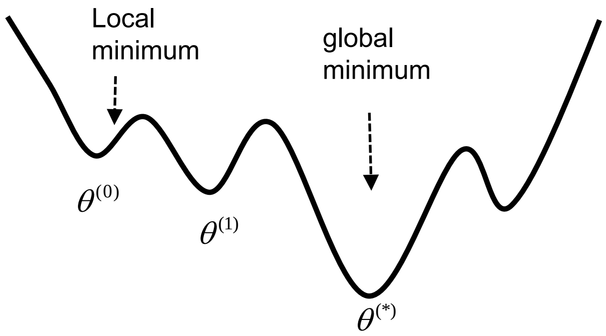
Latent variable

Latent variable

$$L(\Theta) = \frac{1}{2} \| \Theta \|^2 + \lambda \sum_i \max(0, 1 - y_i f(x_i, h_i))$$

$$f(x, h) = \max_h \Theta \cdot \Phi(x, h)$$

Our works-Challenge analysis



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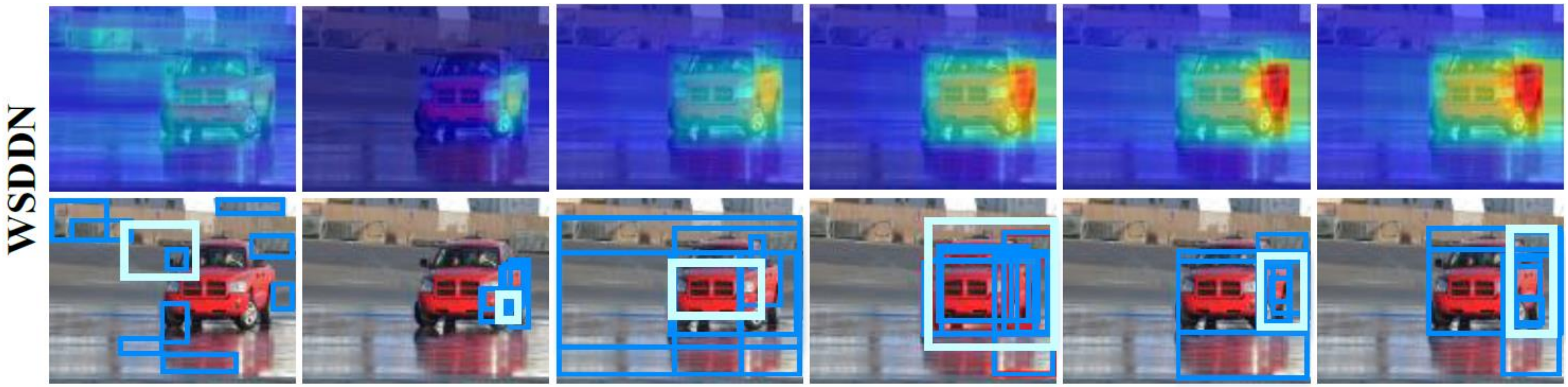
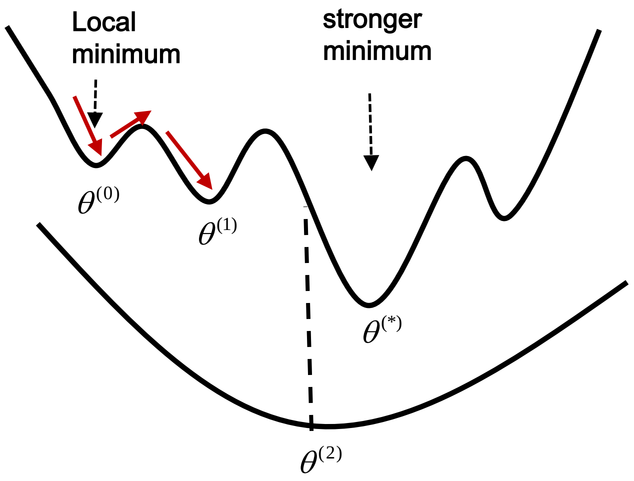
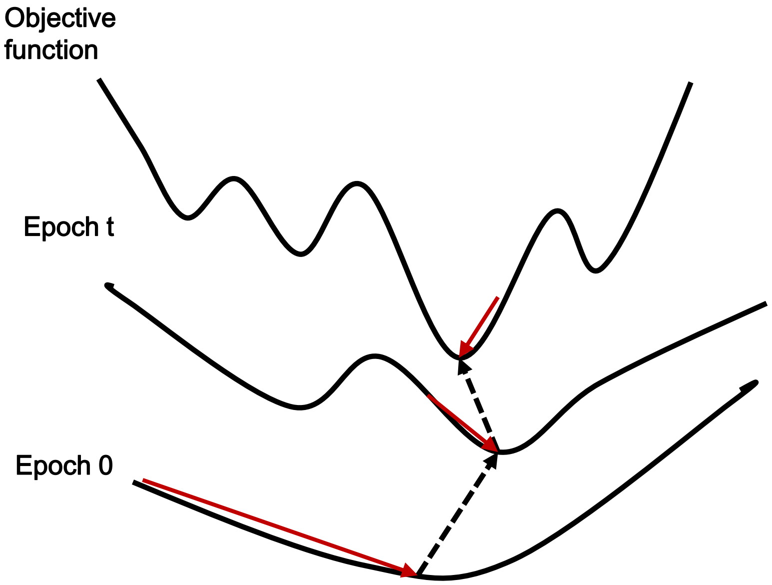


Our works-Methodology

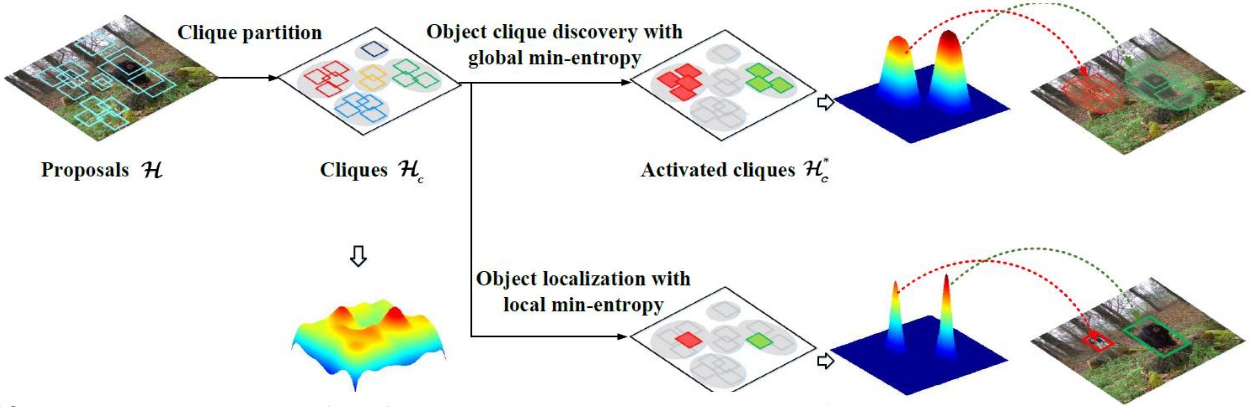


Convex Regularization



Continuation Optimization

Our works-Min-entropy latent model



$$\{h^*, \theta^*\} = \arg\min_{h,\theta} E_{(\mathcal{X},\mathcal{Y})}(h,\theta)$$
$$= \arg\min_{h,\theta} E_{(\mathcal{X},\mathcal{Y})}(\mathcal{H}_c,\theta) + \lambda E_{(\mathcal{X},\mathcal{Y},\mathcal{H}_c)}(h,\theta)$$

Object discovery

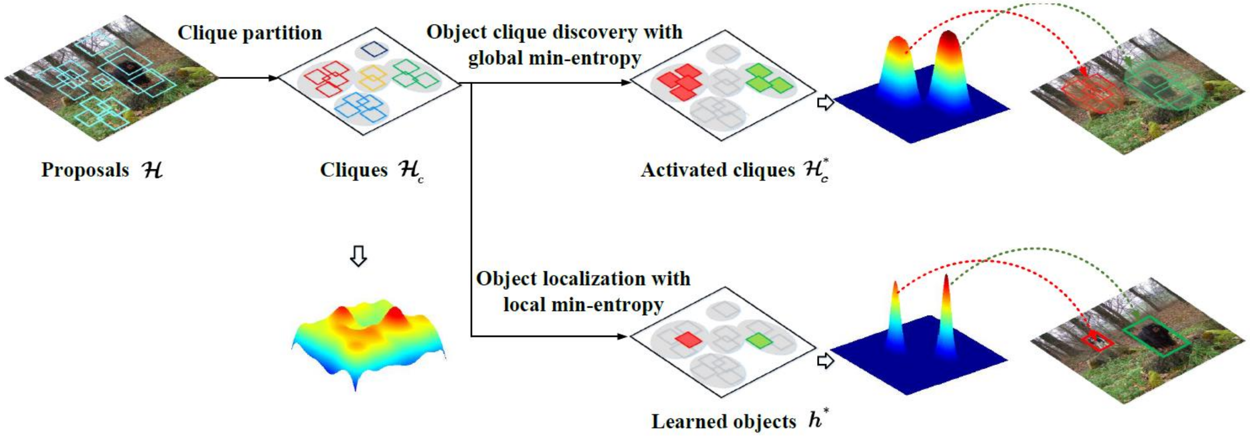
$$E_{(\mathcal{X},\mathcal{Y})}(\mathcal{H}_c,\theta) = -\log \sum w_{\mathcal{H}_c} p(y,\mathcal{H}_c;\theta)$$
$$L_{(\mathcal{X},\mathcal{Y})}(\mathcal{H}_c,\theta) = yE_{(\mathcal{X},\mathcal{Y})}(\mathcal{H}_c,\theta) - (1-y)\sum_h \log(1-p(y,h;\theta))$$

Object localizatio
n

$$h^* = \arg\min_{h\in\mathcal{H}_c^*} E_{(\mathcal{X},\mathcal{Y},\mathcal{H}_c^*)}(h,\theta)$$
$$E_{(\mathcal{X},\mathcal{Y},\mathcal{H}_c)}(h,\theta) = -\sum_{h\in\Omega_{h^*}} w_h p(y,h;\theta)\log p(y,h;\theta)$$
$$L_{(\mathcal{X},\mathcal{Y},\mathcal{H}_c)}(h,\theta) = E_{(\mathcal{X},\mathcal{Y},\mathcal{H}_c^*)}(h,\theta).$$

F. Wan, P. Wei, Z. Han, J. Jiao, Q. Ye, “Min-entropy Latent Model for Weakly Supervised object Detection,” IEEE CVPR2018

Our works-Min-entropy latent model

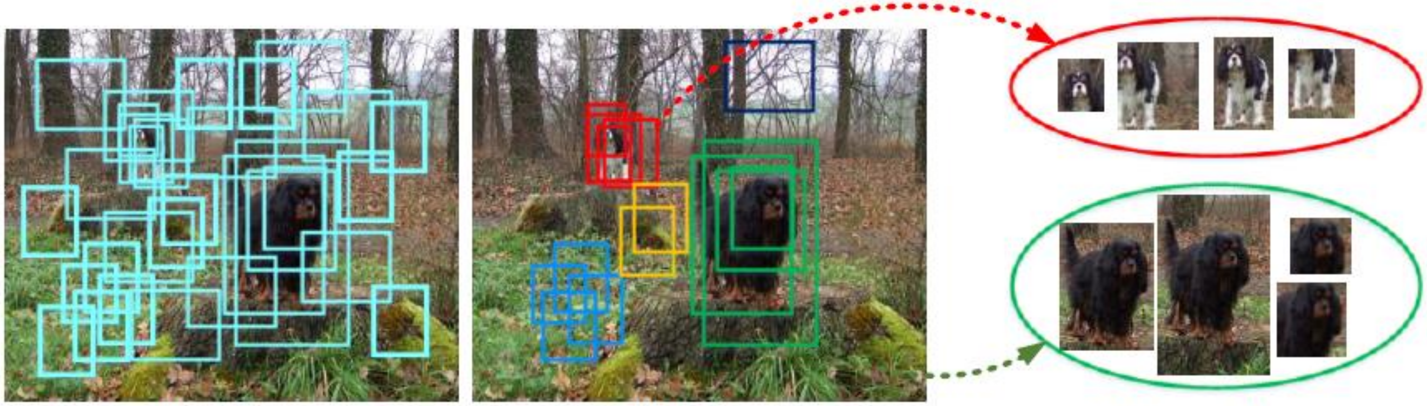


(1) Instance (object and object part) are collected with a clique partition module;

(2) Object clique discovery with a global min-entropy model;

(3) Object localization with a local min-entropy model

Our works-Min-entropy latent model

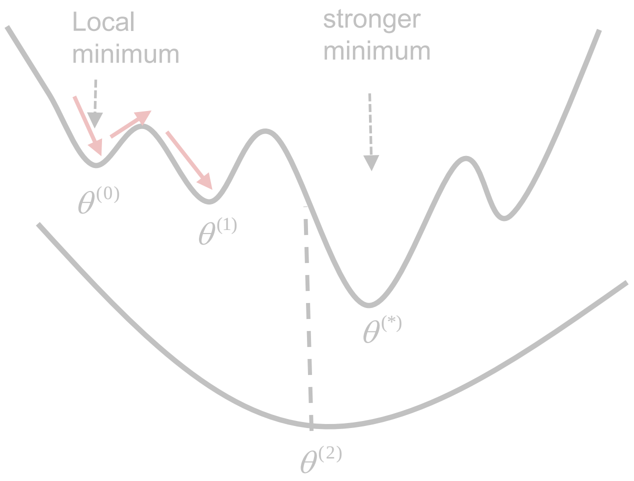


Proposals Cliques Object Cliques

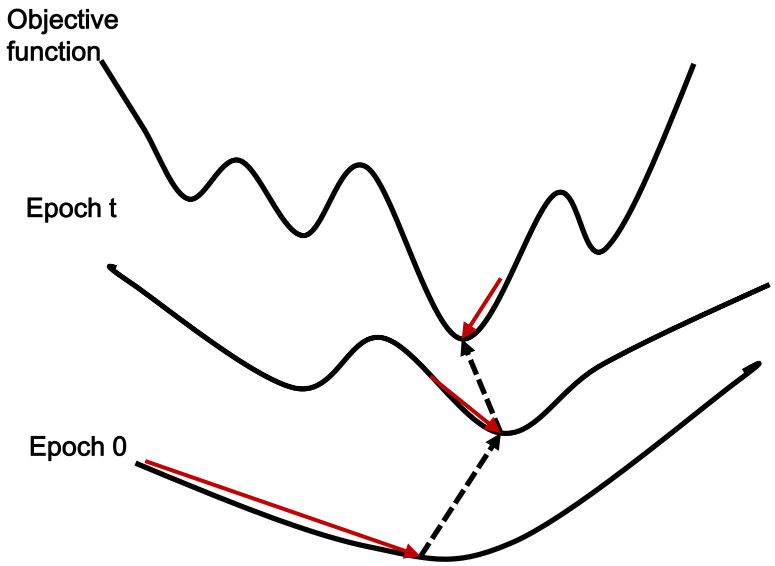
Clique partition:

$$\begin{cases} \bigcup\limits_{c=1}^{C} \mathcal{H}_c = \tilde{\mathcal{H}} \\ \forall c \neq c',\ \mathcal{H}_c \cup \mathcal{H}_{c'} = \emptyset \end{cases}$$

Our works-Methodology

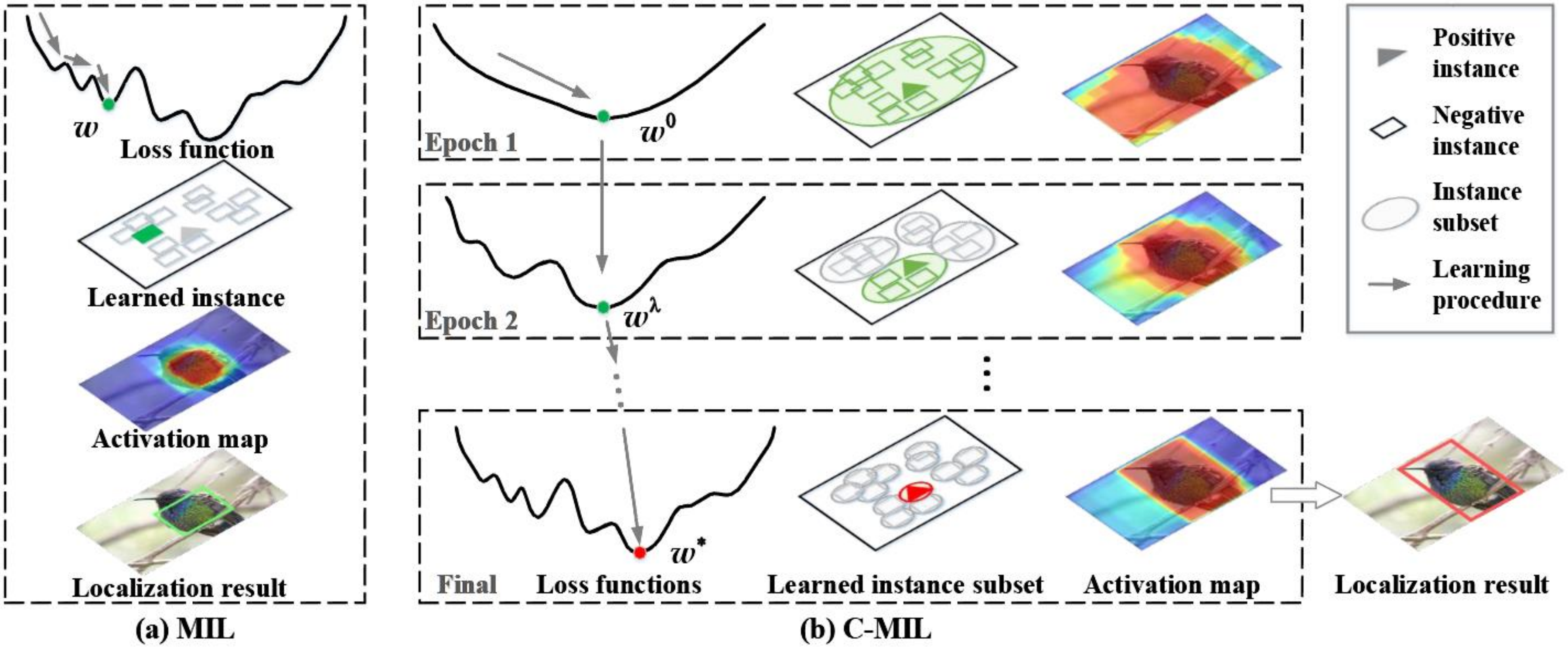


Convex Regularization



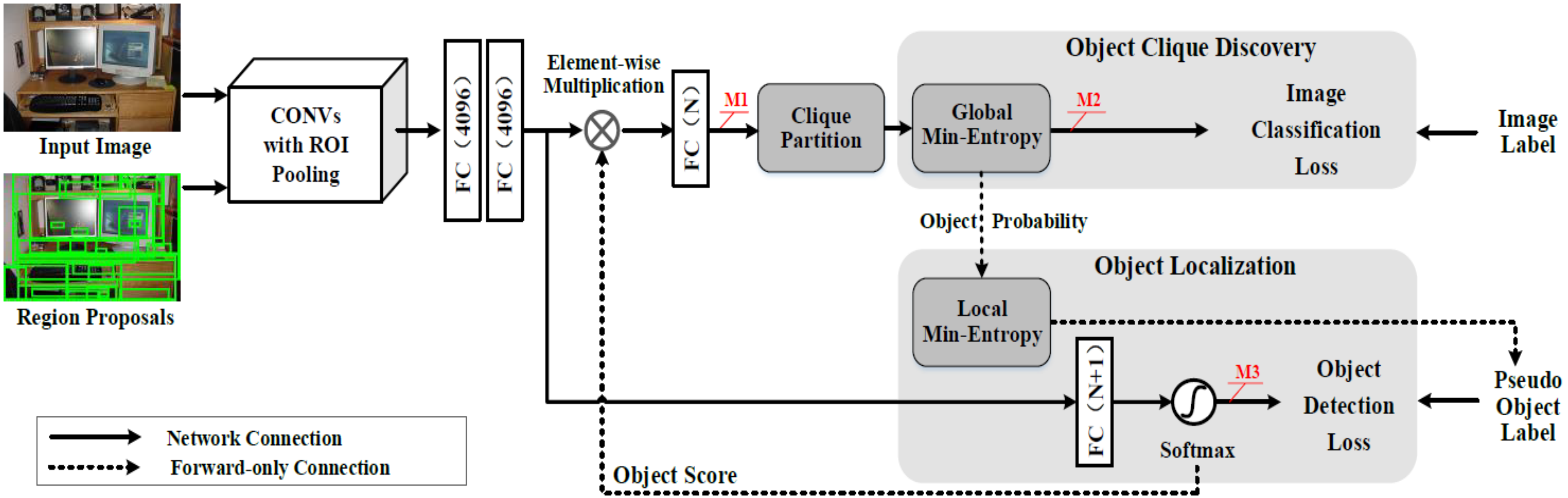
Continuation Optimization

Our works-Continuation Multiple Instance Learning

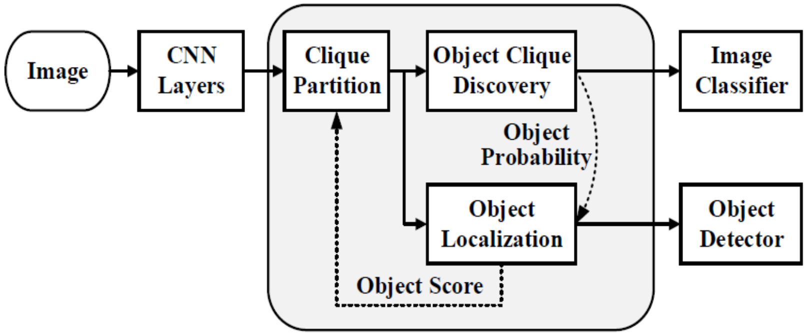


F. Wan, C. Liu, J. Jiao, Q. Ye, "**CMIL:** Continuation Multiple Instance Learning for Weakly Supervised object Detection (CVPR2019)

Our works-Min-entropy latent model

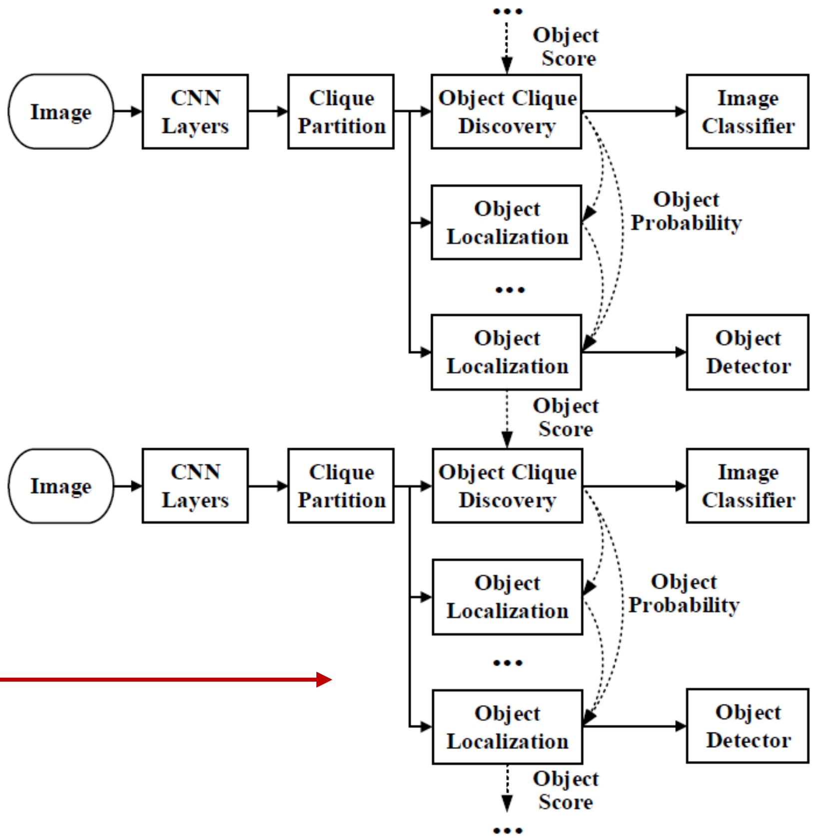


Our works-Recurrent Learning



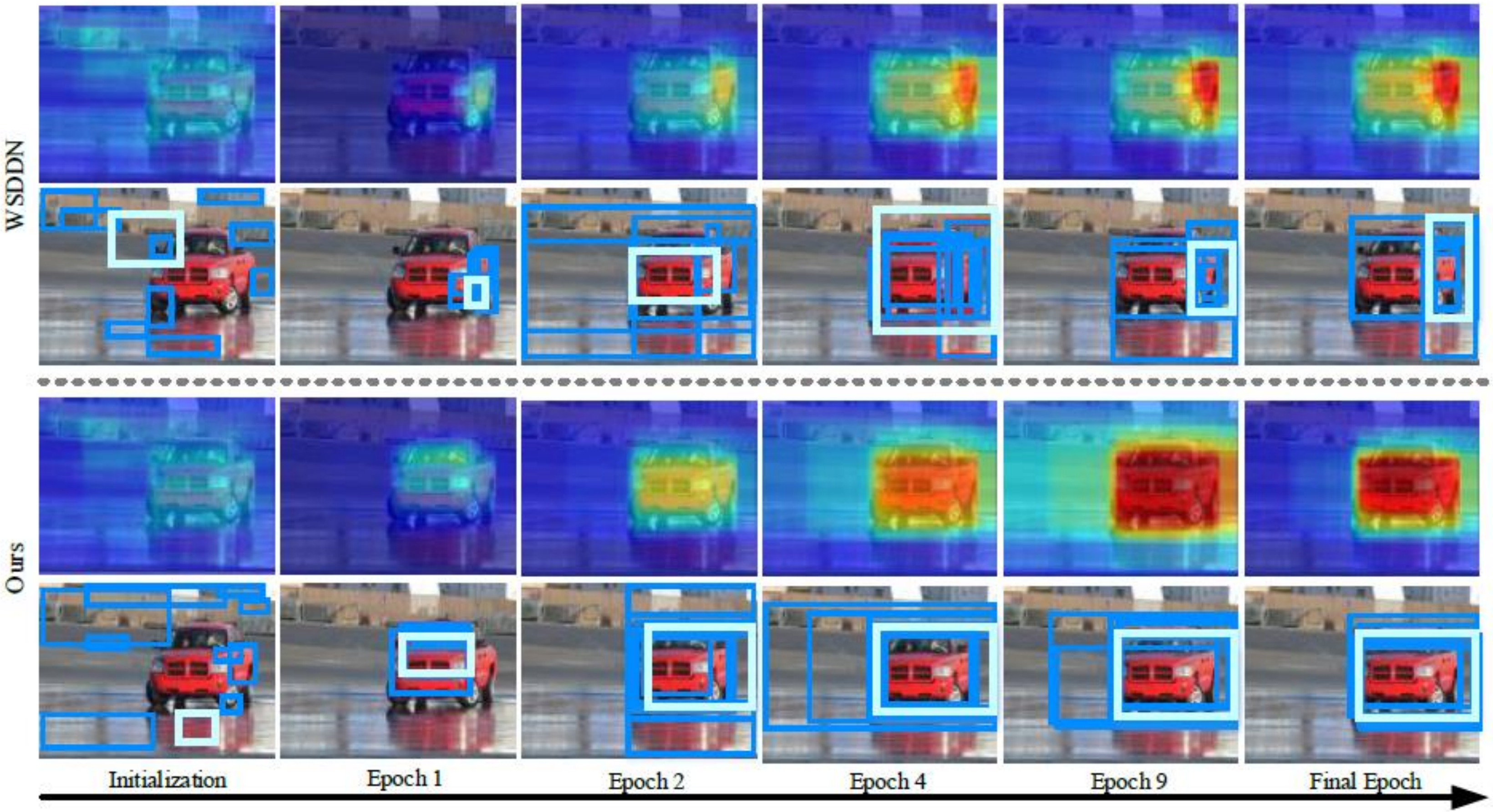
Recurrent Learning

Accumulated Recurrent Learning

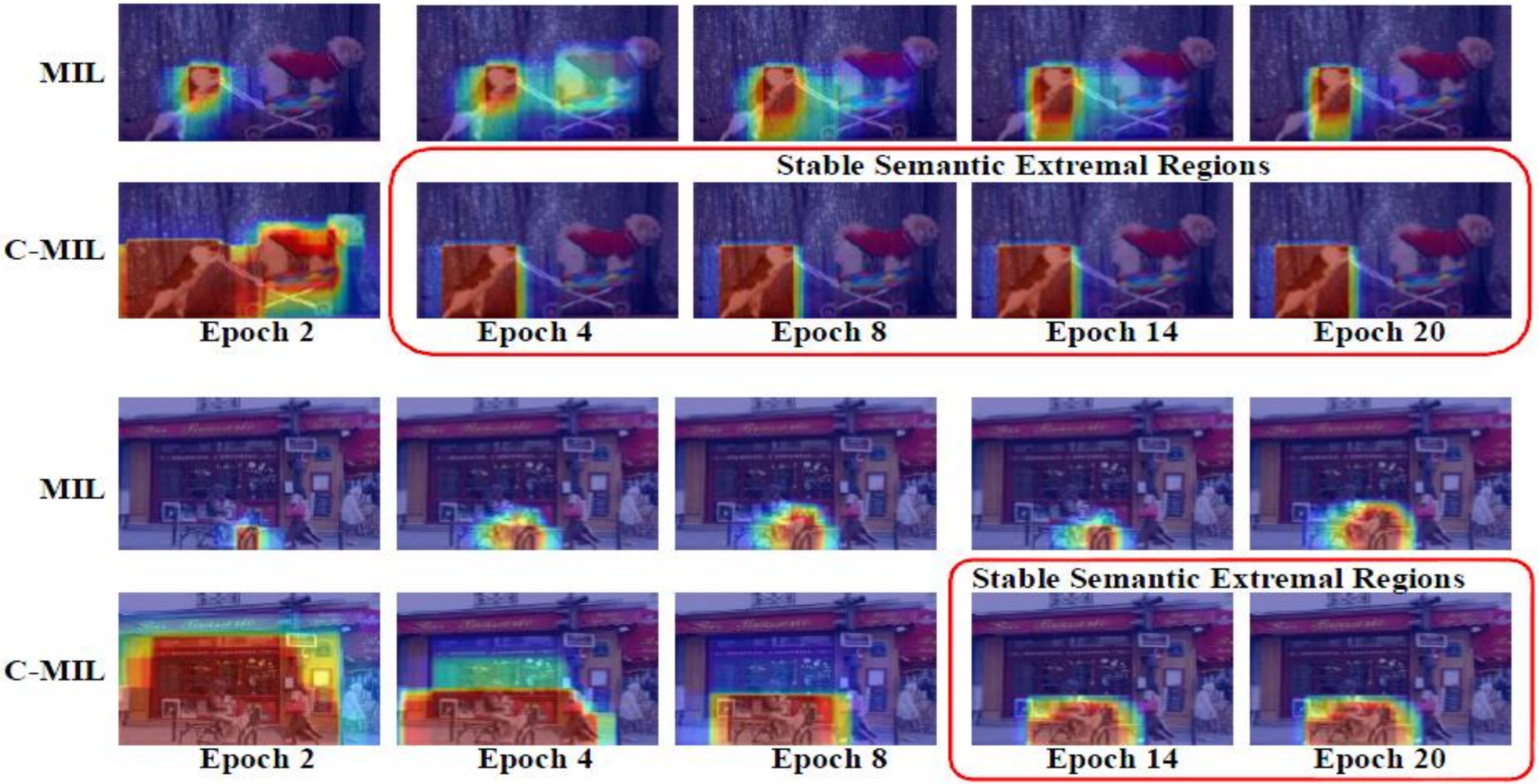


F. Wan, P. Wei, Z. Han, J. Jiao, Q. Ye, "Min-entropy Latent Model for Weakly Supervised object Detection," IEEE Transactions on Pattern Analysis and Machine Intelligence (**PAMI**), DOI:10.1109/TPAMI.2019.2898858.

Our works-Results

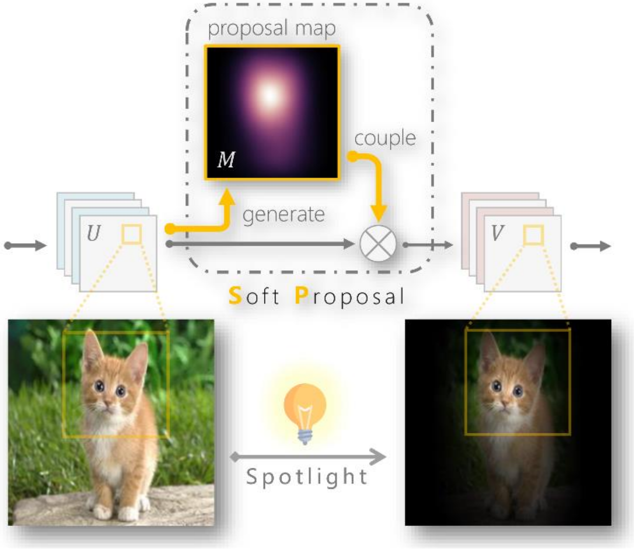


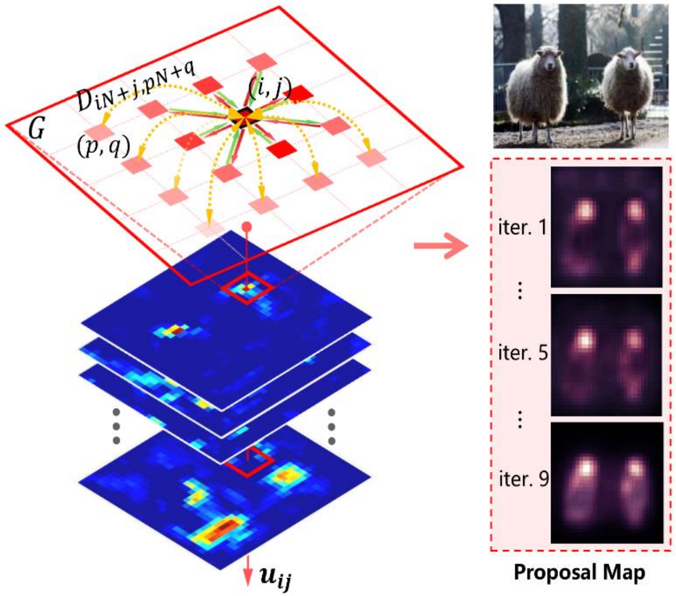
Our works-Results



SSER: Semantic Stable Extremal Region

Our works-Soft Proposal Network

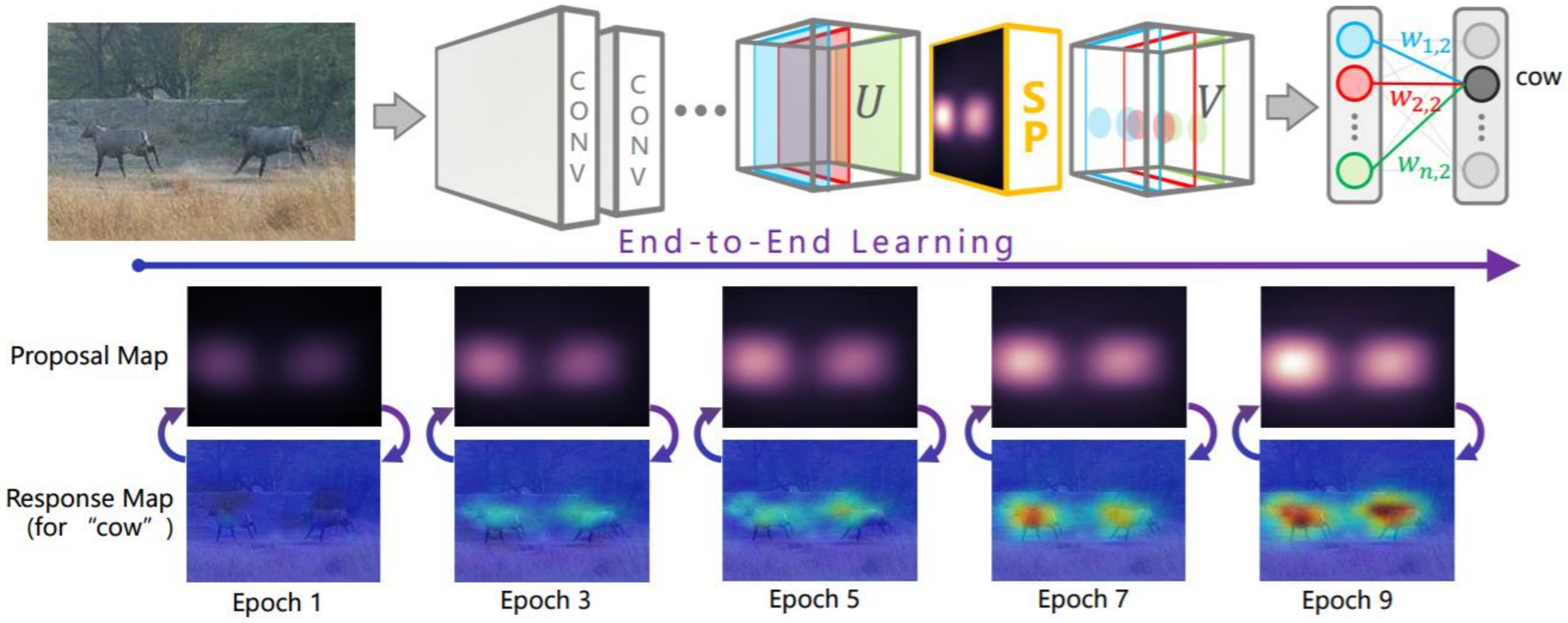




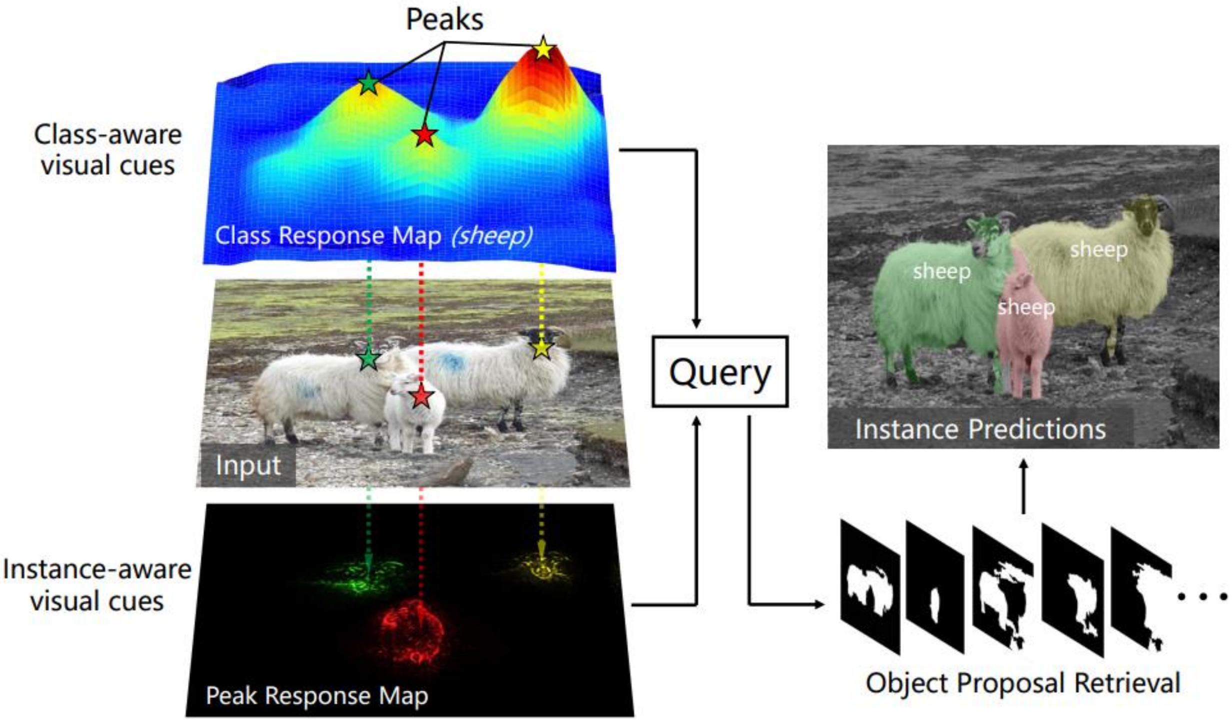
$$M \leftarrow D \times M. \qquad M \leftarrow D(U^l(W^l)) \times M. \qquad W^l = W^l + \Delta W(M)$$

Y. Zhu, Y. Zhou, Q. Ye, Q. Qiu, and J. Jiao, "Soft Proposal Network for Weakly Supervised Object Localization," in Proc. of IEEE Int. Conf. on Computer Vision (**ICCV**), 201

Our works-Soft Proposal Network

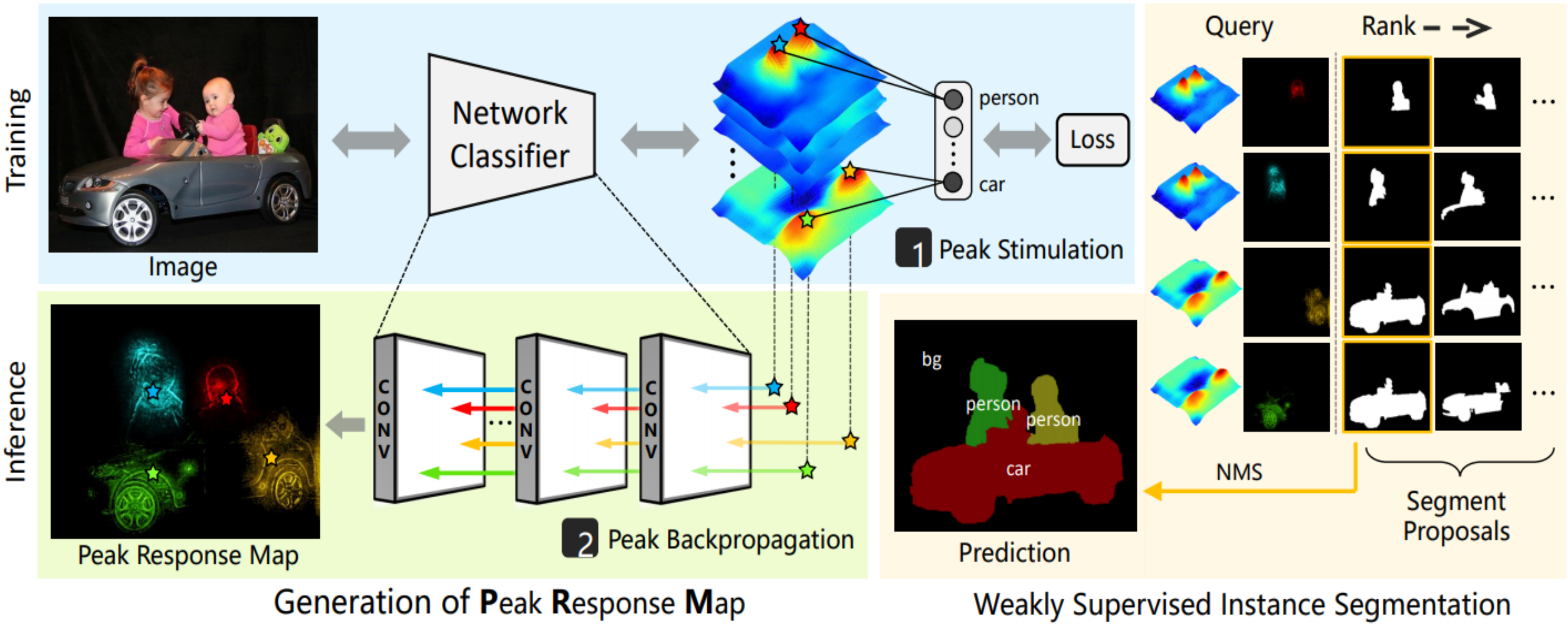


Our works-Peak Response Mapping

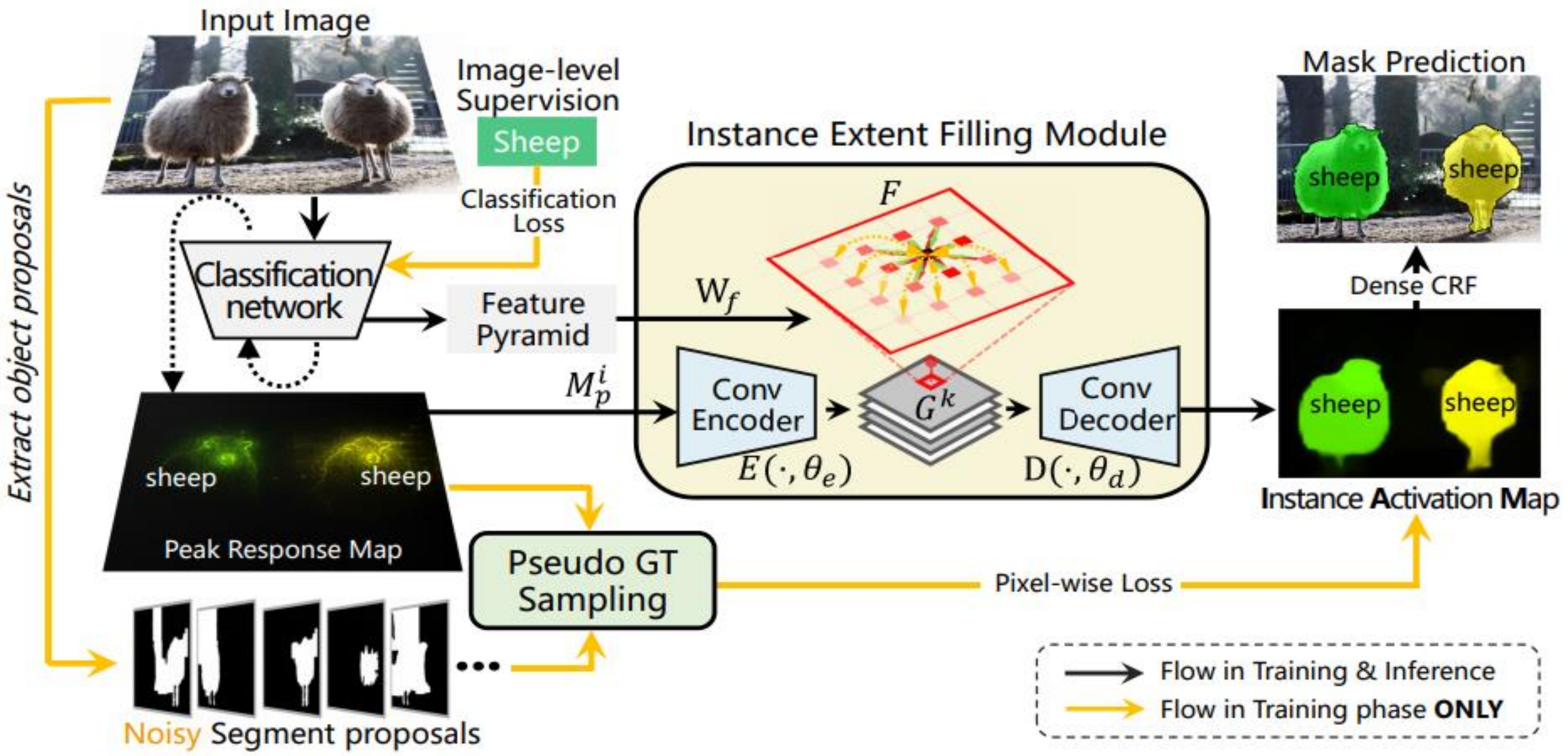


Y. Zhou, Y. Zhu, Q. Ye, Q. Qiu, J. Jiao, "Weakly Supervised Instance Segmentation using Class Peak Response, IEEE CVPR 2018 (**Spotlight**).

Our works-Peak Response Mapping

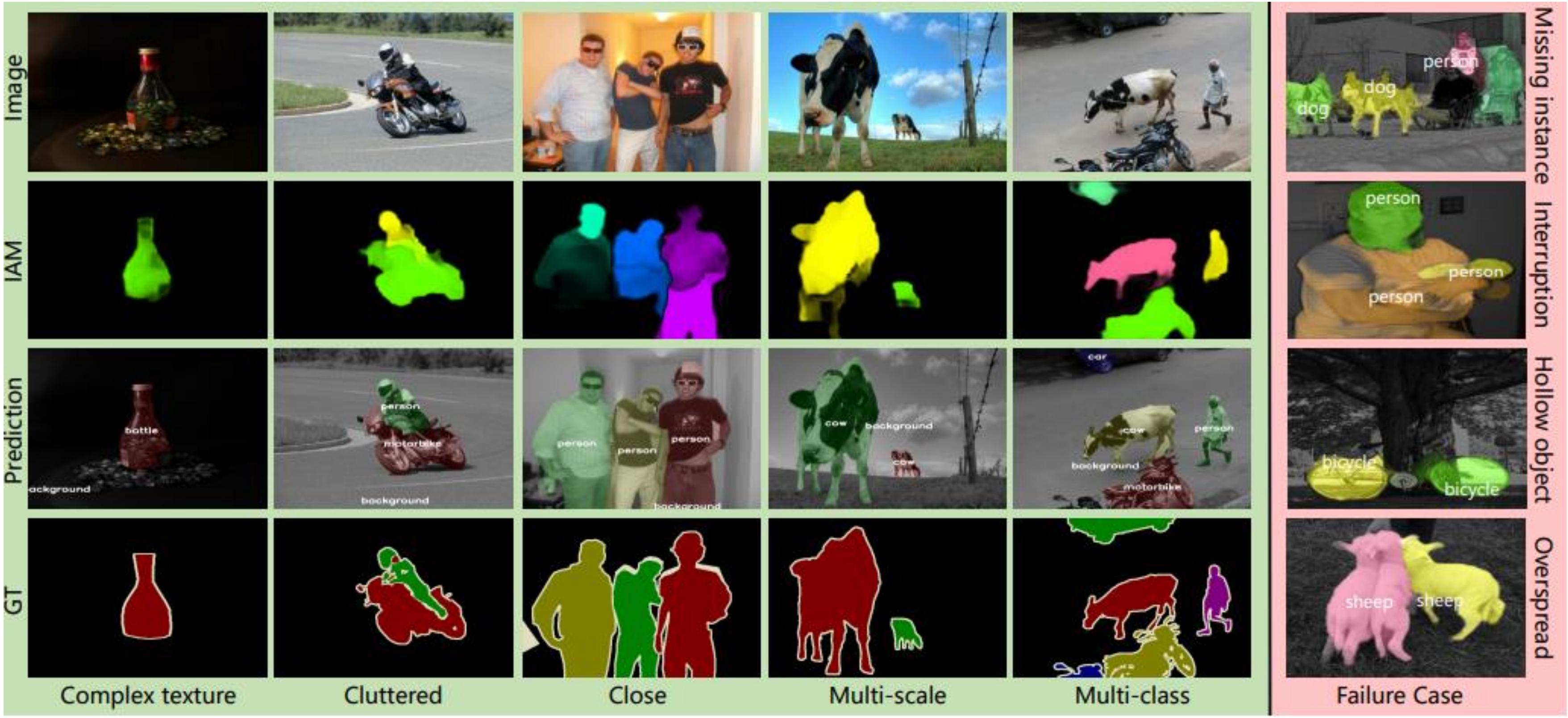


Our works-learning Instance Activation Maps



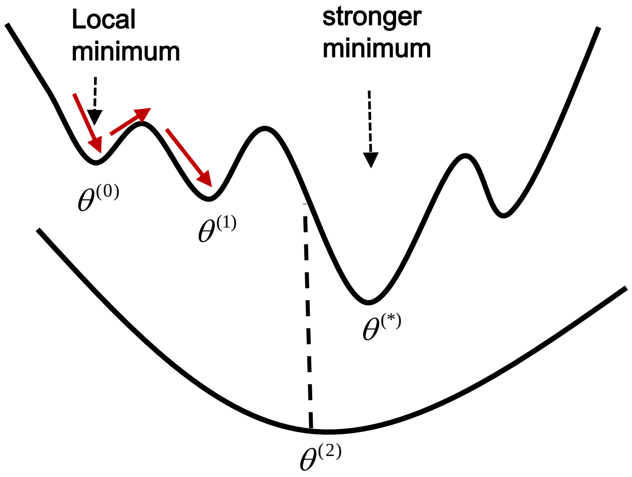
Y. Zhu, Y. Zhou, H. Xu, Q. Ye., D. Doermann, J. Jiao, "Learning Instance Activation Maps for Weakly Supervised Instance Segmentation," IEEE CVPR 2019.

Our works-learning Instance Activation Maps

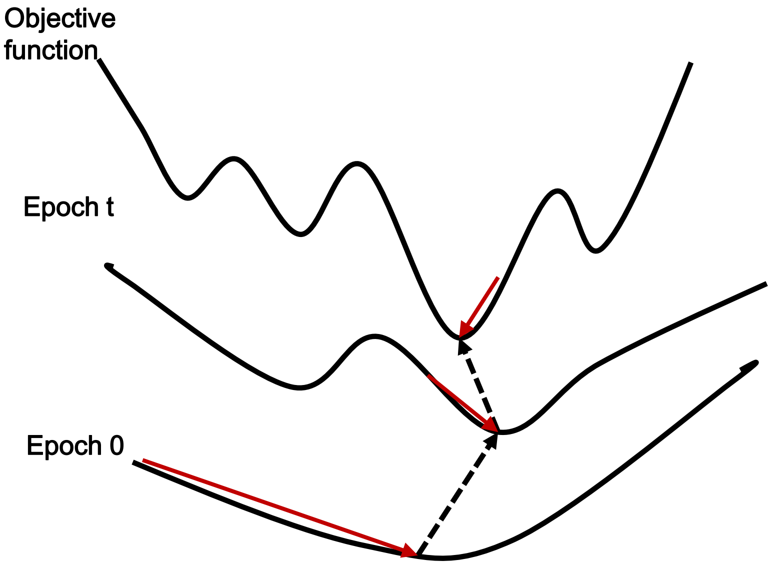


The future

Beyond regularization and continuation optimization



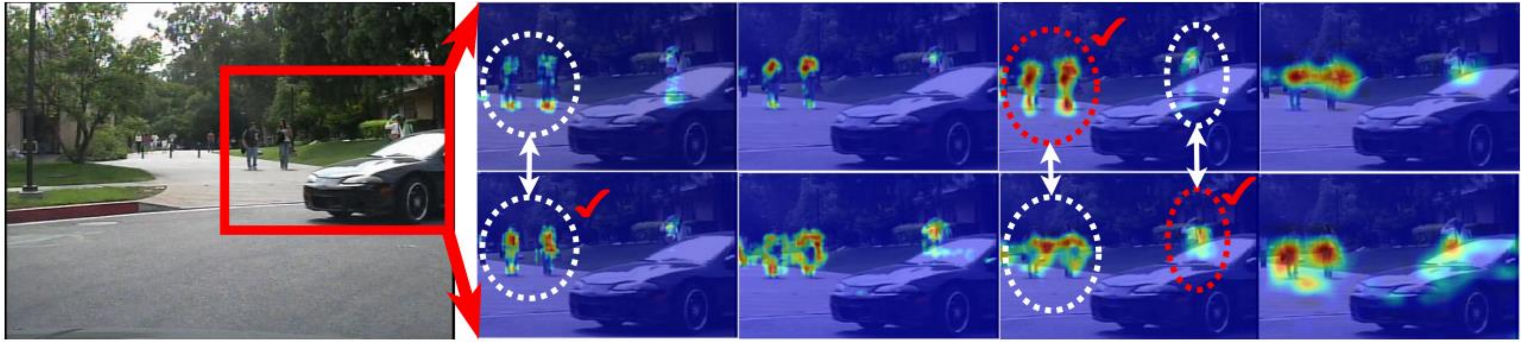
Convex Regularization



Continuation Optimization

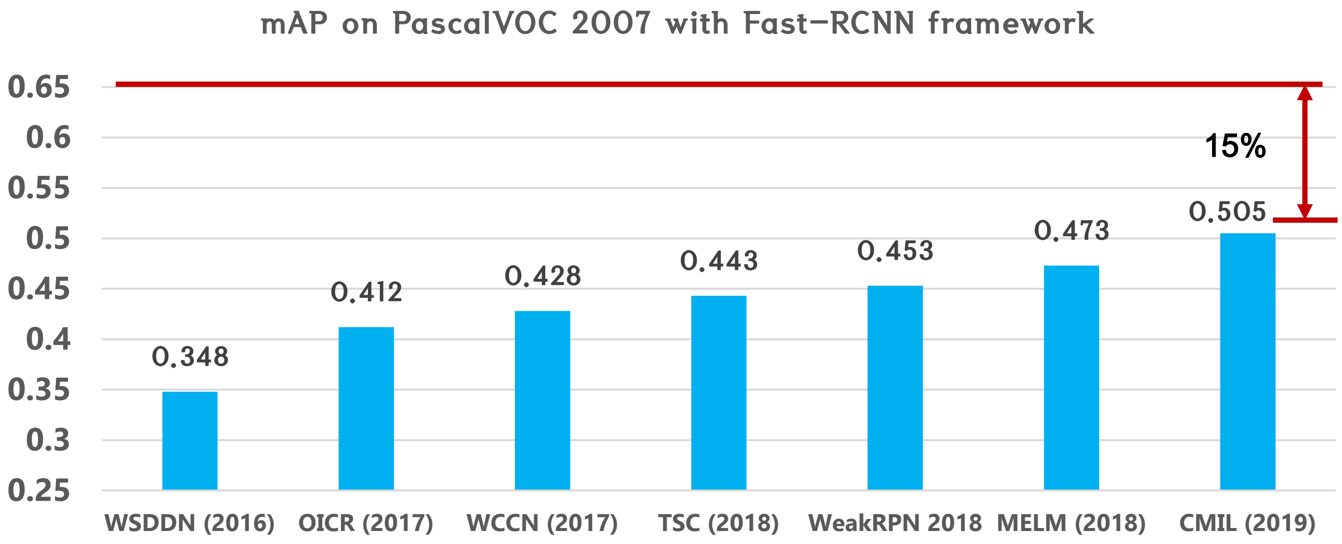
The future

Beyond weakly supervised detection and segmentation



The future

Fill the gap of supervised and weakly supervised methods



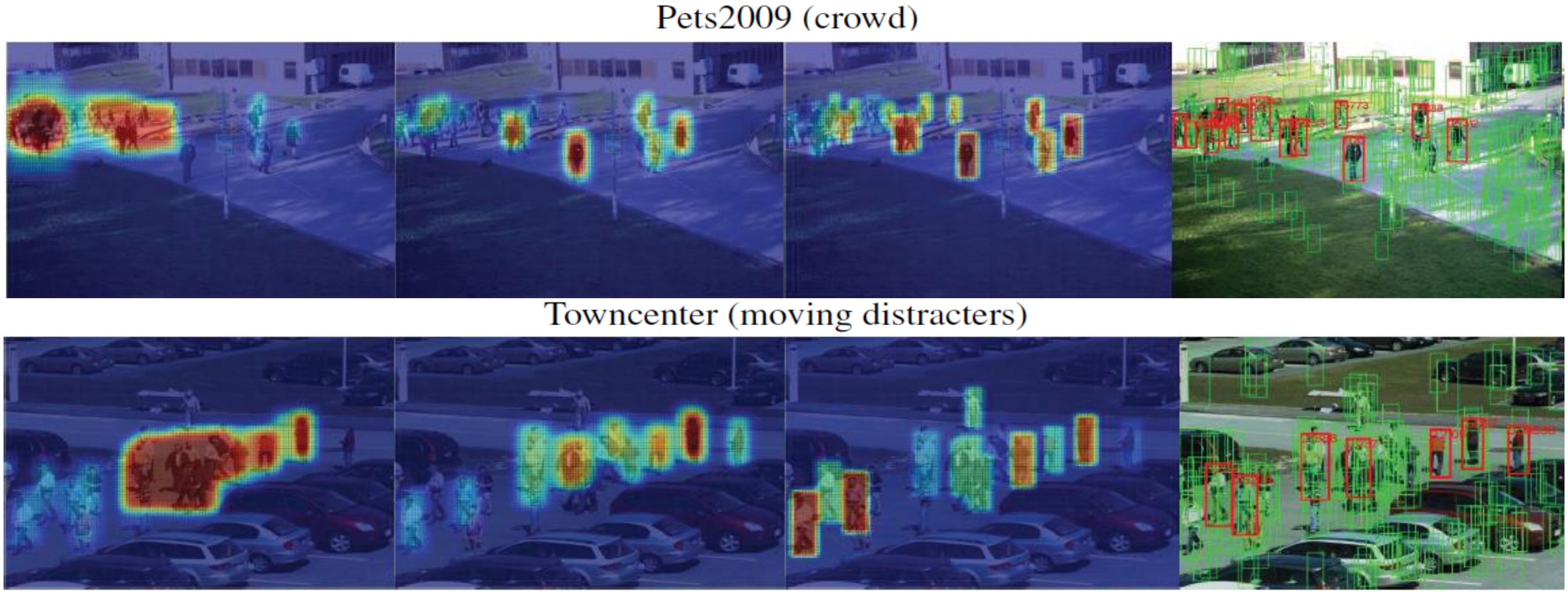
The future

Weakly supervised detection meets X

X= Few-shot Active Learning | Online Feedback | Temporal

The future

X= Few-shot Active Learning | Online Feedback | Temporal



Q. Ye, Z. Zhang, Q. Qiu, B. Zhang, J. Chen, and G. Sapiro, "Self-learning Scene-specific Pedestrian Detectors using a Progressive Latent Model," IEEE **CVPR**, 2017

Ref.

[1] F. Wan, P. Wei, Z. Han, J. Jiao, Q. Ye, “Min-entropy Latent Model for Weakly Supervised object Detection,” IEEE Trans. PAMI, DOI:10.1109/TPAMI.2019.2898858. **(MELM+Recurrent Learning)**

[2] F. Wan, C. Liu, J. Jiao, Q. Ye, “CMIL: Continuation Multiple Instance Learning for Weakly Supervised object Detection (CVPR2019) **(C-MIL)**

[3] Y. Zhu, Y. Zhou, H. Xu, Q. Ye., D. Doermann, J. Jiao, “Learning Instance Activation Maps for Weakly Supervised Instance Segmentation,” IEEE CVPR 2019. **(IAM)**

[4] P. Tang, X. Wang, S. Bai, W. Shen, X. Bai, W. Liu, and A. L. Yuille, “Pcl: Proposal cluster learning for weakly supervised object detection,” IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI), 2018. **(PCL)**

[5] Y. Zhou, Y. Zhu, Q. Ye, Q. Qiu, J. Jiao, “Weakly Supervised Instance Segmentation using Class Peak Response,” in Proc. of IEEE Int. Conf. on Computer Vision and Pattern Recognition (CVPR), 2018 (Spotlight). **(PRM)**

[6] F. Wan, P. Wei, Z. Han, J. Jiao, Q. Ye, “Min-entropy Latent Model for Weakly Supervised object Detection,” in Proc. of IEEE Int. Conf. on Computer Vision and Pattern Recognition (CVPR), 2018: 1297-1306. **(MELM)**

[7] Y. Zhu, Y. Zhou, Q. Ye, Q. Qiu, and J. Jiao, "Soft Proposal Network for Weakly Supervised Object Localization," in Proc. of IEEE Int. Conf. on Computer Vision (ICCV), 2017. **(SPN)**

[8] Q. Ye, Z. Zhang, Q. Qiu, B. Zhang, J. Chen, and G. Sapiro, "Self-learning Scene-specific Pedestrian Detectors using a Progressive Latent Model," IEEE CVPR, 2017 **(Self-Learning)**

[9] B. Hakan and V. Andrea, “Weakly supervised deep detection networks,” in Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit. (CVPR), 2016, pp. 2846–2854. **(WSDDN)**

[10] B. Zhou, A. Khosla, A. Lapedriza, A. Oliva, and A. Torralba, “Learning deep features for discriminative localization,” in Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit. (CVPR), 2016, pp.2921–2929. **(CAM)**

Thank!

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