

Evidential Deep Learning for Open Set Action Recognition

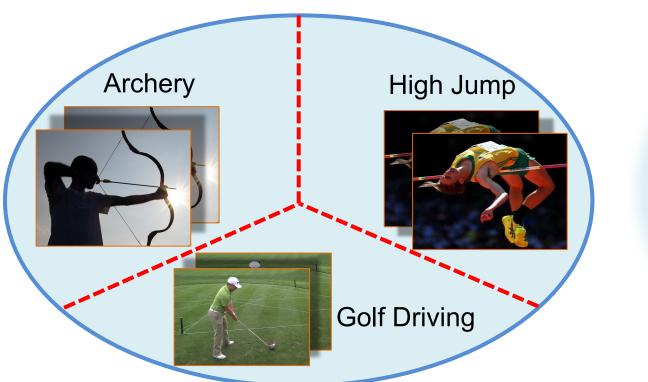
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Introduction

Open Set Action Recognition (OSAR) requests for: (1) action classification (2) reject the unknown.



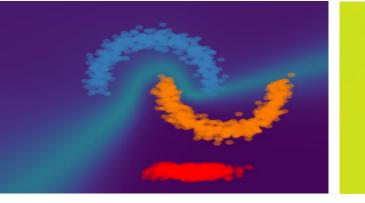


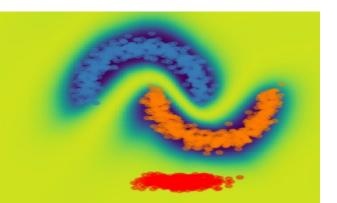
Closed Set Action Recognition

Open Set Action Recognition

Motivations:

- DNNs are over-confident in their predictions, and do not know that they don't know.
- DNNs tend to learn spurious correlation from static bias of video data without learning from the human actions.







over-confident

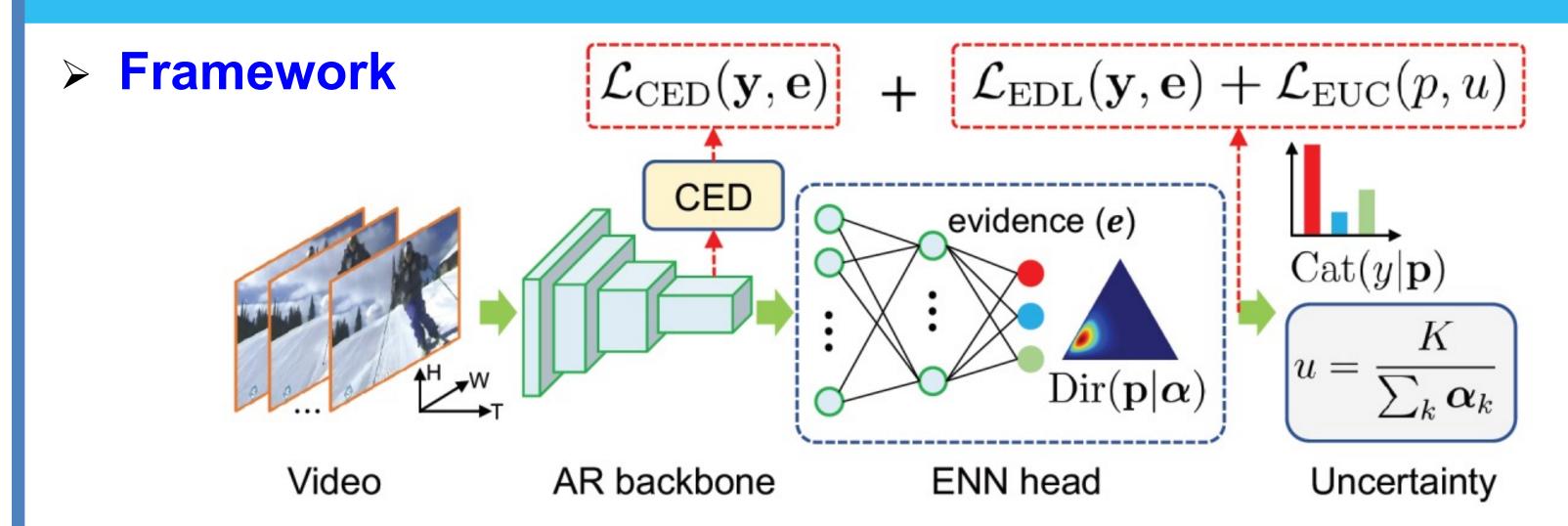
well-calibrated

surfing water

Contribution

- The first Evidential Deep Learning (EDL) method for video action recognition in an open world.
- DEAR: An open set action recognition model with principled and efficient uncertainty estimation.
- We further proposed **EUC** loss to mitigate overconfident predictions, and CED module to eliminate static bias in videos.

DEAR Model



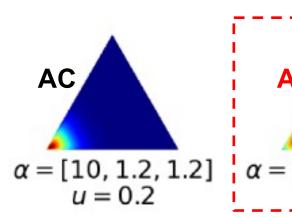
- > Evidential Deep Learning (EDL)
- EDL assumes a Dirichlet Prior on categorical probabilities, and the strength α of the Dirichlet posterior is learned by DNNs.

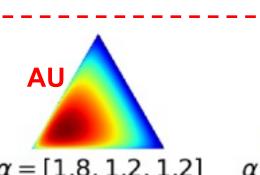
$$\mathcal{L}_{EDL}^{(i)}(\mathbf{y}^{(i)}, \mathbf{e}^{(i)}; \theta) = \sum_{k=1}^{K} \mathbf{y}_{k}^{(i)} \left(\log S^{(i)} - \log(\mathbf{e}_{k}^{(i)} + 1) \right)$$

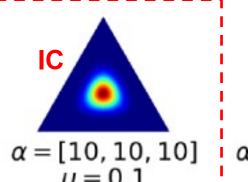
• Dirichlet strength (α) , Evidence (e), Belief (b), and uncertainty (u):

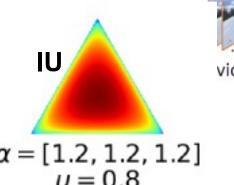
$$\alpha = e + 1$$
 $b = \frac{e}{\sum_{k} \alpha_{k}}$ $u = \frac{K}{\sum_{k} \alpha_{k}}$

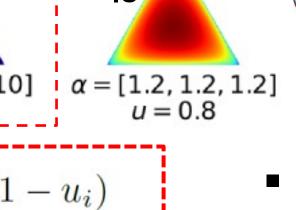
- > Evidential Uncertainty Calibration
- Be confident in accurate predictions, and uncertain about inaccurate ones.

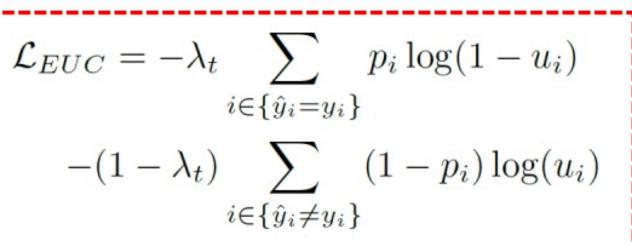






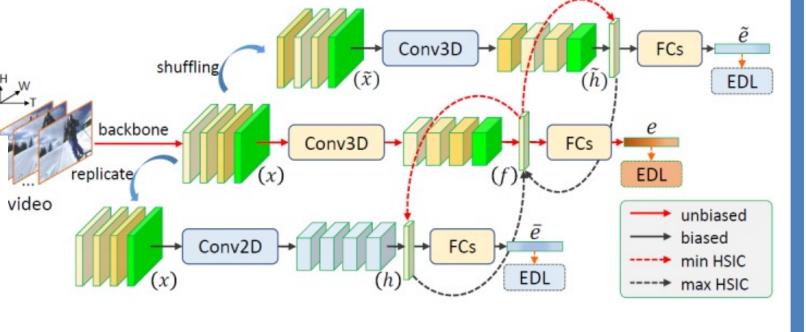






Here λ_t is exponentially increasing

Contrastive Evidence Debiasing

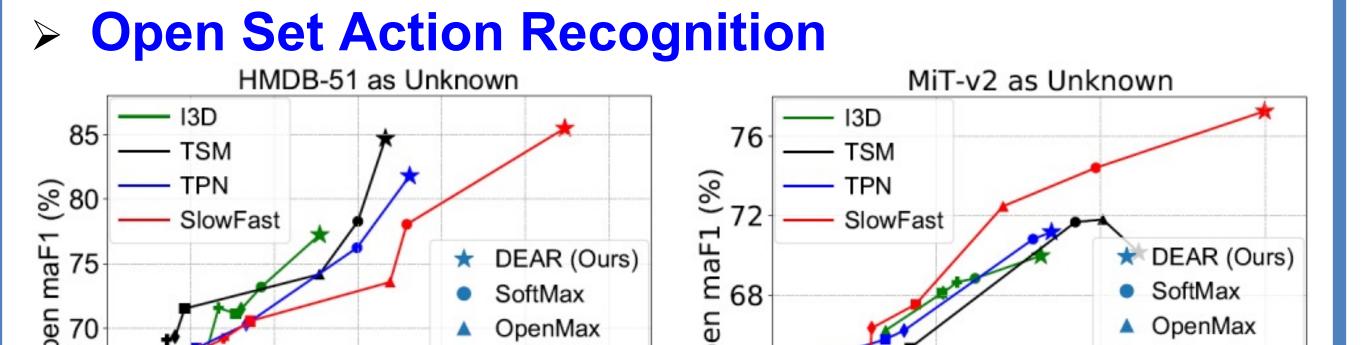


- Debias the evidential feature by two biased branches.
- Alternative optimization:

Here
$$\lambda_t$$
 is exponentially increasing w.r.t. training epoch t from 0.01 to 1.0.
$$\mathcal{L}(\theta_f, \phi_f) = \mathcal{L}_{EDL}(\mathbf{y}, \mathbf{e}; \theta_f, \phi_f) + \lambda \sum_{\mathbf{h} \in \Omega} \text{HSIC}(\mathbf{f}, \mathbf{h}; \theta_f),$$

$$\mathcal{L}(\theta_f, \phi_f) = \sum_{\mathbf{h} \in \Omega} \{\mathcal{L}_{EDL}(\mathbf{y}, \mathbf{e}_h; \theta_h, \phi_h) - \lambda \text{HSIC}(\mathbf{f}, \mathbf{h}; \theta_h)\}$$

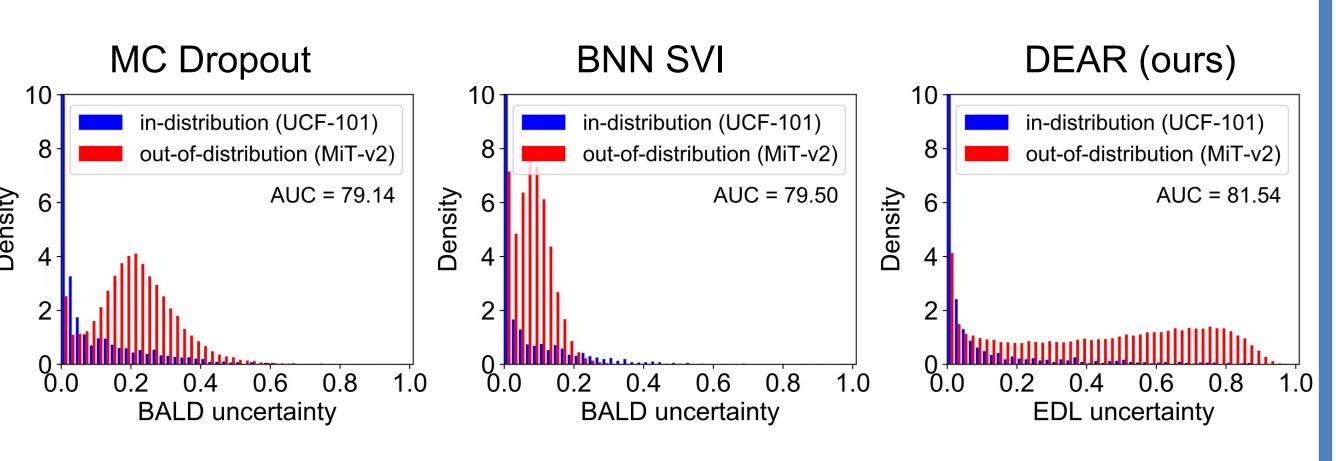
Experimental Results



DEAR method outperforms baselines by large margins.

MC Dropout

> Out-of-Distribution Detection



 DEAR could learn better uncertainty separation between I.D. and OOD human actions.

Open Resources







MC Dropou

BNN SVI

Open-Set AUC Score (%)

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