RankED: Addressing Imbalance and Uncertainty in Edge Detection Using Ranking-based Losses

Bedrettin Cetinkaya, Sinan Kalkan*, Emre Akbas*

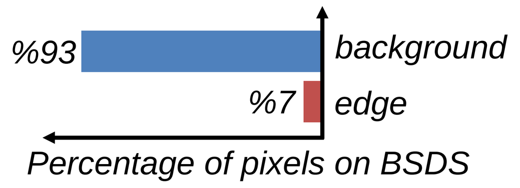
Dept. of Computer Eng. & METU ROMER Robotics Center, Middle East Technical University, Ankara, Turkey

**Equal contribution for senior authorship*

Introduction

Two Main Problems in Edge Detection:

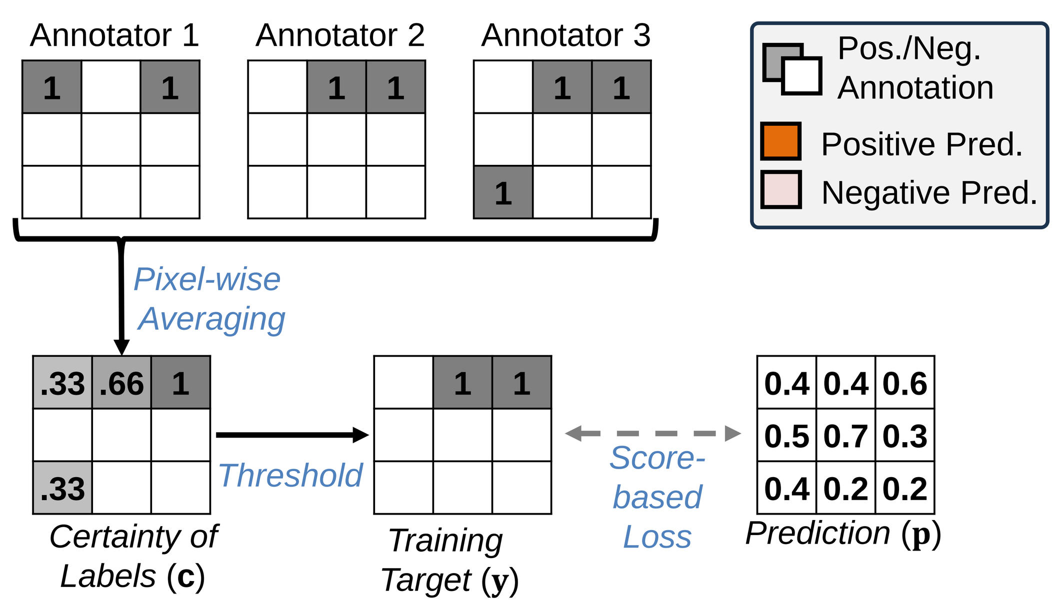
Problem (P1): Heavy imbalance between positive and negative classes.



Problem (P2): Label uncertainty due to multiple annotations.

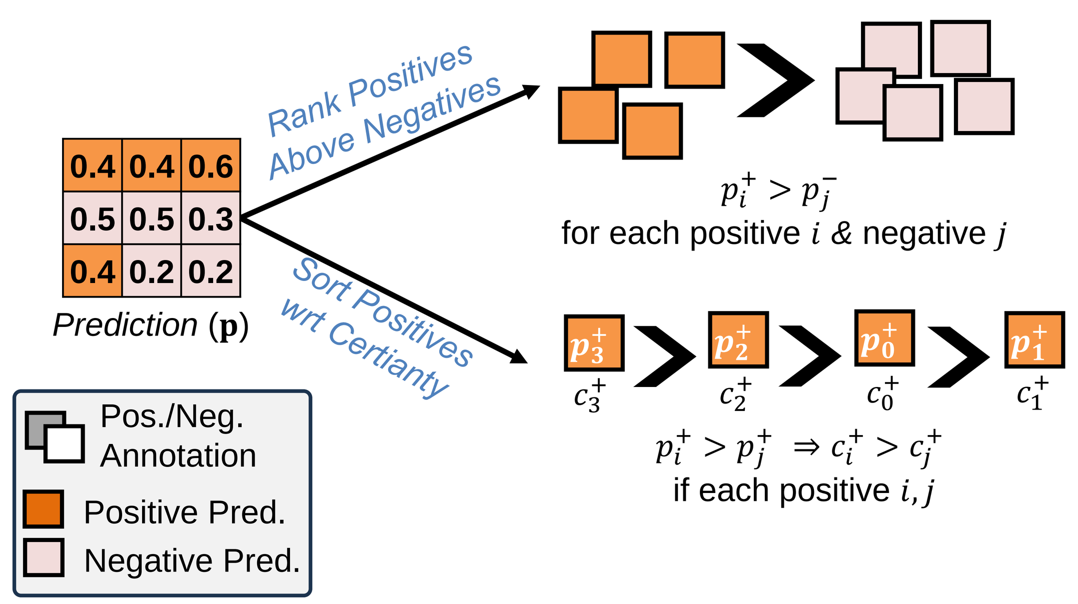
Existing Solutions:

For P1: Class-balanced Cross-Entropy.
For P2: Thresholding after pixel-wise averaging.



Our Ranking-based Edge Detection (RankED):

For P1: Rank positives above negatives.
For P2: Sort positives wrt. uncertainty.



RankED: Ranking-based Edge Detection

Ranking positives above negatives ($\mathcal{L}_{\text{Rank}}$):

$$\mathcal{L}_{\text{Rank}} = 1 - \text{AP} = 1 - \frac{1}{|\mathcal{P}|}\sum_{i\in\mathcal{P}} \frac{\text{rank}^+(i)}{\text{rank}(i)}$$

Rank Among Positives

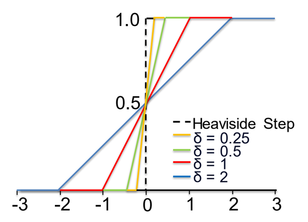
$$\text{rank}^+(i) = \sum_{j\in\mathcal{P}} \text{H}(x_{ij})$$

Rank Among All

$$\text{rank}(i) = \sum_{j\in\mathcal{P}\cup\mathcal{N}} \text{H}(x_{ij})$$

Interpolated Step:

$$\text{H}(x) = \begin{cases} 0, & x < -\delta \\ \frac{x}{2\delta} + 0.5, & -\delta \le x \le \delta \\ 1, & \delta < x \end{cases}$$



Score Differences:

$$x_{ij} = p_j - p_i$$

Sorting Positives wrt their Uncertainties($\mathcal{L}_{\text{Sort}}$):

$$\mathcal{L}_{\text{Sort}} = \frac{1}{|\mathcal{P}|}\sum_{i\in\mathcal{P}} \left(\ell_{\text{Sort}}(i) - \ell^*_{\text{Sort}}(i)\right)$$

Label Certainty for Pixel i (c_i):

$$c_i = \frac{1}{n}\sum_a CP(\hat{y}_i, \mathbf{y}^a, d)$$

i.e., avg. of label annotations in a *d*-vicinity

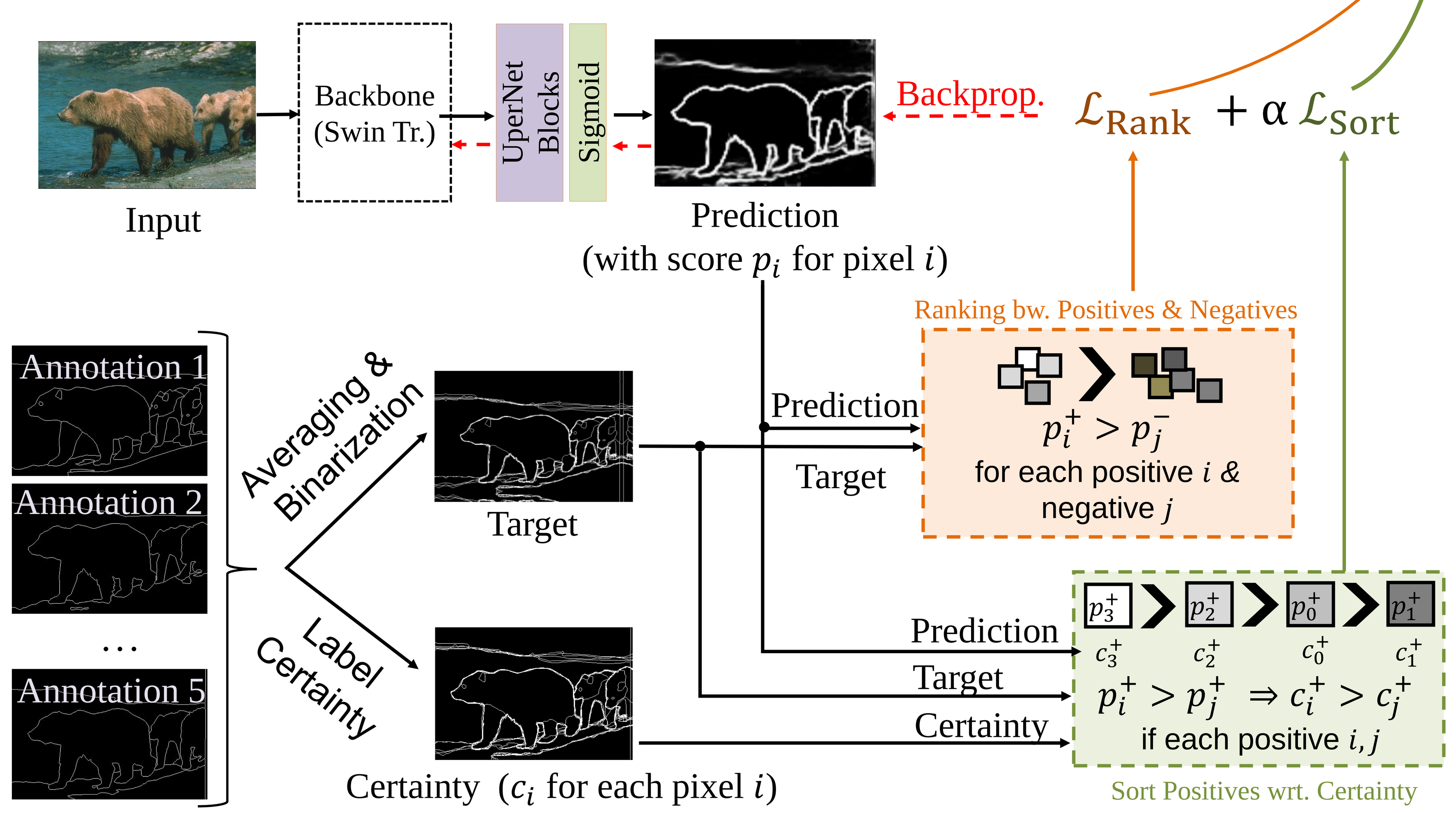
Sorting Error

$$\ell_{\text{Sort}}(i) = \frac{1}{\text{rank}^+(i)}\sum_{j\in\mathcal{P}} H(x_{ij})(1 - c_j)$$

Label Certainty

Target Sorting Error

$$\ell^*_{\text{Sort}}(i) = \frac{\sum_{j\in\mathcal{P}} \text{H}(x_{ij})[c_j \ge c_i](1 - c_j)}{\sum_{j\in\mathcal{P}} \text{H}(x_{ij})[c_j \ge c_i]}$$



Quantitative Results

Method	ODS	OIS	AP
PidiNet (ICCV' 21)	.733	.747	.715
EDTER (CVPR' 22)	.774	.789	.797
ACTD (Neurocomp.' 23)	.762	.774	-
RANKED (R)	**.780**	**.793**	**.826**

(a) NYUD

Method	ODS	OIS	AP
FCL-Net (NN' 22)	.807	.822	-
EDTER (CVPR' 22)	.824	.841	.880
UAED (CVPR' 23)	**.829**	**.847**	.892
ACTD (Neurocomp.' 23)	.817	.836	.839
RANKED (R)	.822	.838	.886
RANKED (R+S)	.824	.840	**.895**

(b) BSDS

Method	ODS	OIS	AP
PiDiNet (ICCV' 21)	.855	.860	-
FCL-Net (NN' 22)	.875	.880	-
EDTER (CVPR' 22)	.894	.900	.944
UAED (CVPR' 23)	.895	.902	.949
CHRNet (Pat. Rec.' 23)	.907	.922	-
ACTD (Neurocomp.' 23)	.890	.905	-
RANKED (R)	.951	.953	.962
RANKED (R+S)	**.962**	**.965**	**.973**

(c) Multicue (Edge)

Method	ODS	OIS	AP
PiDiNet (ICCV' 21)	.818	.830	-
FCL-Net (NN' 22)	.834	.840	-
EDTER (CVPR' 22)	.861	.870	.919
UAED (CVPR' 23)	.864	.872	.927
CHRNet (Pat. Rec.' 23)	.859	.863	-
ACTD (Neurocomp.' 23)	.852	.863	-
RANKED (R)	.954	.958	.992
RANKED (R+S)	**.963**	**.967**	**.995**

(d) Multicue (Boundary)

Comparison with Traditional Losses

Dataset	Loss	ODS	OIS	AP
NYUD	CE_{CB}	.775	.789	.802
	CE + DICE	.779	.791	.807
	RankED (R)	**.780**	**.793**	**.826**
BSDS	CE_{CB}	.820	.831	.871
	CE + DICE	.821	.836	.872
	RankED (R)	.822	.838	.886
	RankED (R + S)	**.824**	**.840**	**.895**

Visual Results

RGB

GT

RankED

Acknowledgement & References

Acknowledgments: *We gratefully acknowledge the computational resources provided by METU-ROMER, Center for Robotics and Artificial Intelligence, Middle East Technical University.*

References:

Kean Chen, Weiyao Lin, Jianguo Li, John See, Ji Wang, and Junni Zou. AP-loss for accurate one-stage object detection. PAMI 2020.

Kemal Oksuz, Baris Can Cam, Emre Akbas, and Sinan Kalkan. Rank & sort loss for object detection and instance segmentation. ICCV 2021.