

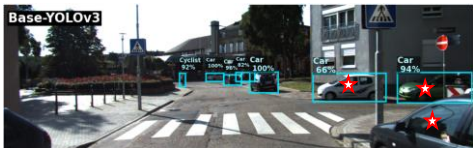
BEA: Revisiting anchor-based object detection DNN using Budding Ensemble Architecture

Qutub Syed Sha^{1,2}, Neslihan Kose¹, Rafael Rosales¹, Michael Paulitsch¹, Korbinian Hagn¹, Florian Geissler¹, Yang Peng¹, Gereon Hinz², Alois Knoll²

1. Intel Labs, Munich Germany, 2. Technical University of Munich, Munich Germany

Motivation

Deterministic object detection models and ensembles struggle with confidence score calibration and objects on corner.

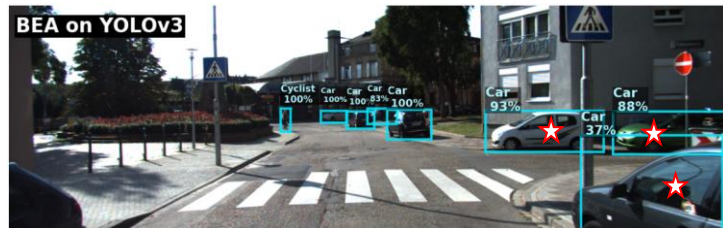


★ Example objects to compare base and BEA model performance

Contributions

- **Budding Ensemble Architecture (BEA)** outperforms state of the art models in terms of accuracy.
- **AP50-based retention curves** are introduced to measure the quality of calibration for object detection models.
- **Novel Tandem loss function** is introduced to the BEA model which increases the overall accuracy by ~6% and OOD detection at least by ~300%.

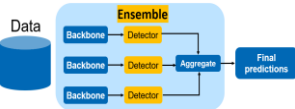
BEA results



The BEA shows better out-of-distribution image detection than the vanilla and ensemble models.

BEA method

"Budding Ensemble Architecture" uses a common backbone to feed an ensemble of detectors trained with our novel tandem loss function.

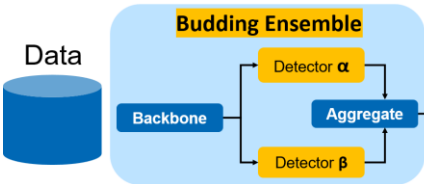


Tandem loss function

$$\mathcal{L}_{\text{tandem}} = \mathcal{L}_{\text{tq}} + \mathcal{L}_{\text{ta}} \quad \mathcal{L}_{\text{tq}}(\hat{\phi}) = \sum_{i=1}^{S^2} \sum_{j=1}^B \mathbb{1}_{ij}^{\text{noobj}} \frac{2}{\sqrt{(\hat{\phi}_i^\alpha - \hat{\phi}_j^\beta)^2}}$$

$$\mathcal{L}_{\text{bea}} = \mathcal{L}_{\text{conv}} + \mathcal{L}_{\text{tandem}}$$

$$\mathcal{L}_{\text{ta}}(\hat{\phi}) = \sum_{i=1}^{S^2} \sum_{j=1}^B \mathbb{1}_{ij}^{\text{obj}} \frac{\sqrt{(\hat{\phi}_i^\alpha - \hat{\phi}_j^\beta)^2}}{2}$$



$\mathcal{L}_{\text{tq}}(\hat{\phi})$ Tandem quelling loss

$\mathcal{L}_{\text{ta}}(\hat{\phi})$ Tandem aiding loss

$\mathcal{L}_{\text{conv}}$ Existing conventional loss function of the model

BEA applied to Validation dataset

BEA applied to shifted dataset

Kitti Image



BDD100k Image



NON-OOD

OOD

OOD

Models (input size 416 × 416)	mAP _{raw} (%) ↑	AP50 ↑		UE (%) ↓	AP50-based Retention curve AUC (%) ↑	Out-of-distribution detection (OOD) AUC-ROC (%) †		
		AP50 _{raw}	AP50 _{rand}			CityPersons	BDD100k	COCO
						U _{near-out}	U _{near-out}	U _{far-out}
Base-YOLOv3	51.72	87.4	78.2	11.96	53.1	35*	40.16*	20.21
YOLOv3 3 Ensemble	54.58	89	82.94	9.23	58.7	28.79*	32.44*	20.5*
YOLOv3 5 Ensemble	55.1	89.27	82.97	9.03	59.3	28.6*	12.19*	10.21*
BEA-YOLOv3	54.83 ± 0.28	89.3 ± 0.28	85.79 ± 0.13	4.55 ± 0.02	73.9 ± 1.1	98.75 ± 2.3	86.71 ± 1.7	97.33 ± 0.9