Distilling Image Classifiers in Object Detectors

Research paper study and discussion

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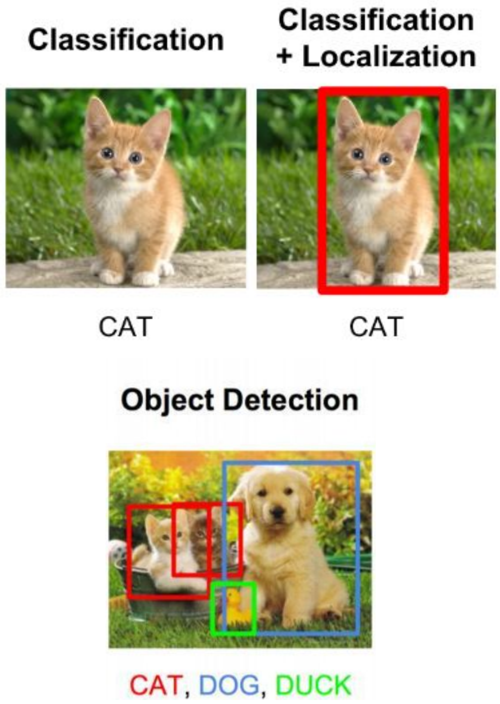
Agenda

1. Introduction
2. Model Concept
3. Experimental Result Analysis
4. Significance and Impact

Introduction

Object Detection

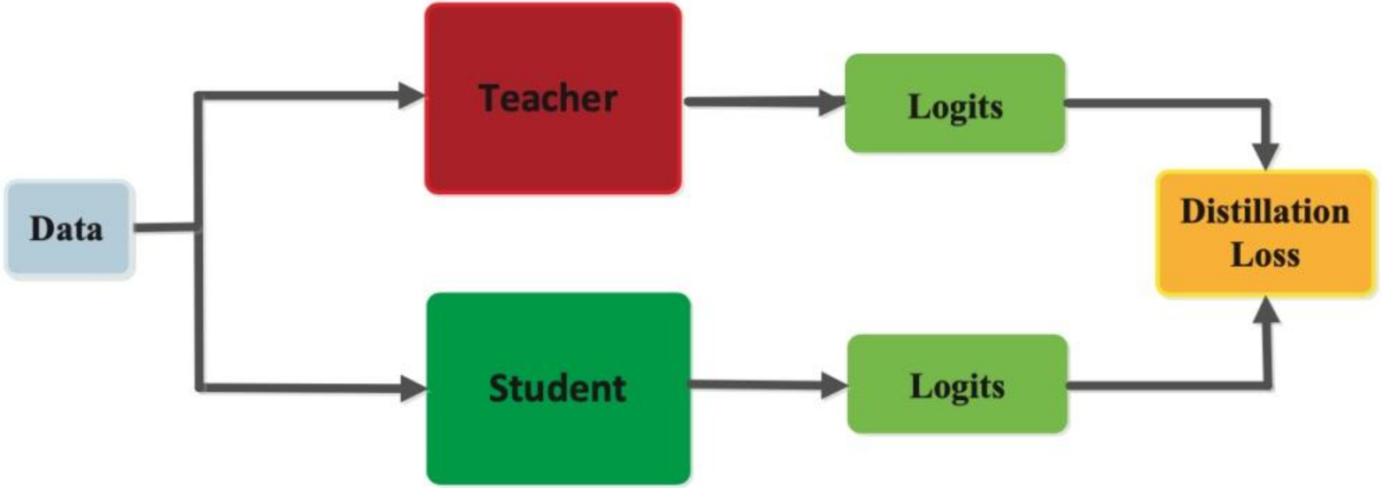


Challenges:
limited memory and computation power

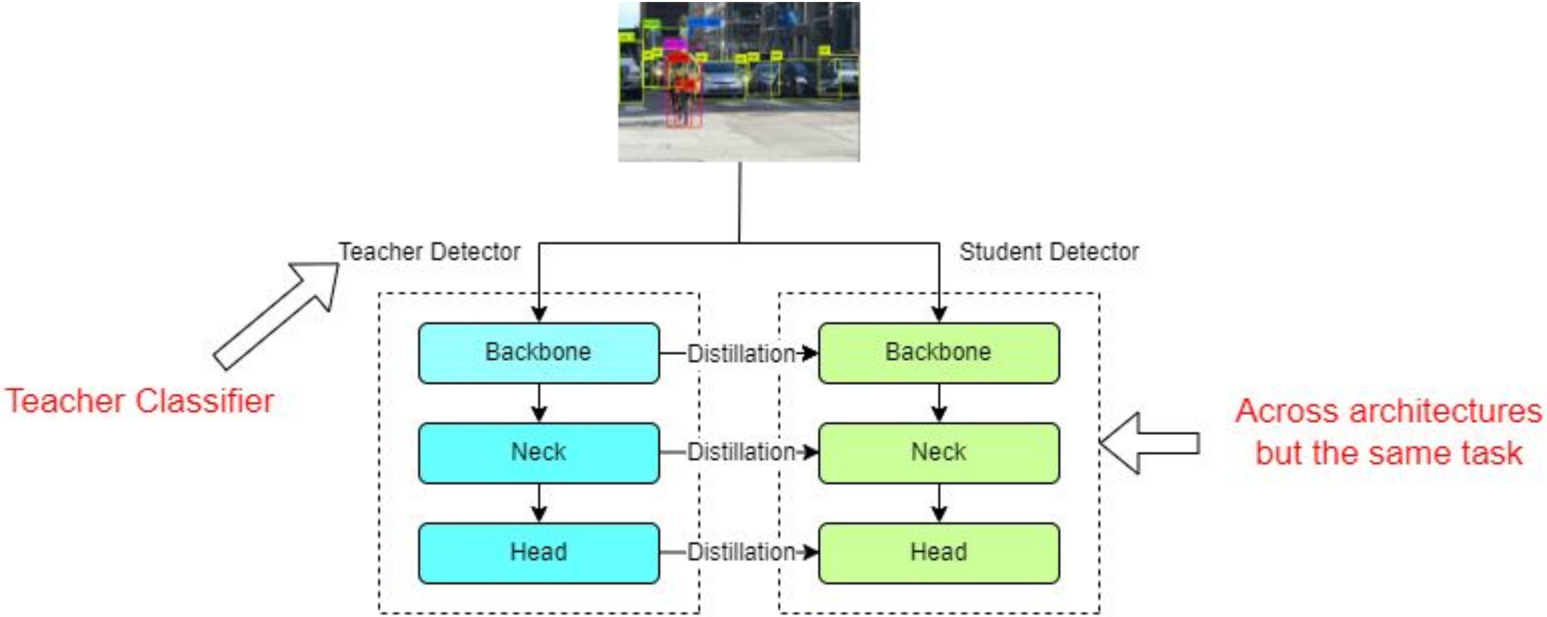
Existing methods:
pruning, quantization, knowledge distillation

This paper:
introduce a knowledge distillation approach for object detection

Knowledge Distillation



Limitation and Goal

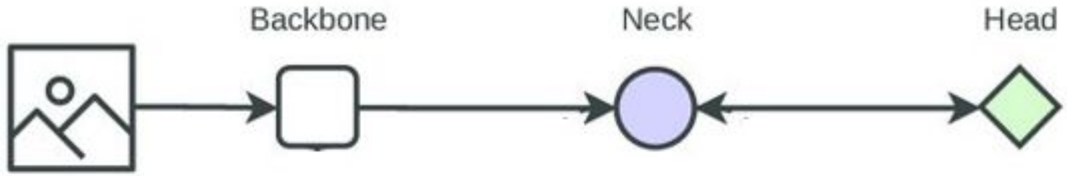


Detecoer-to-Detector Distillation

Model Concept

General Pipeline for a Detector

- Framework of a detector

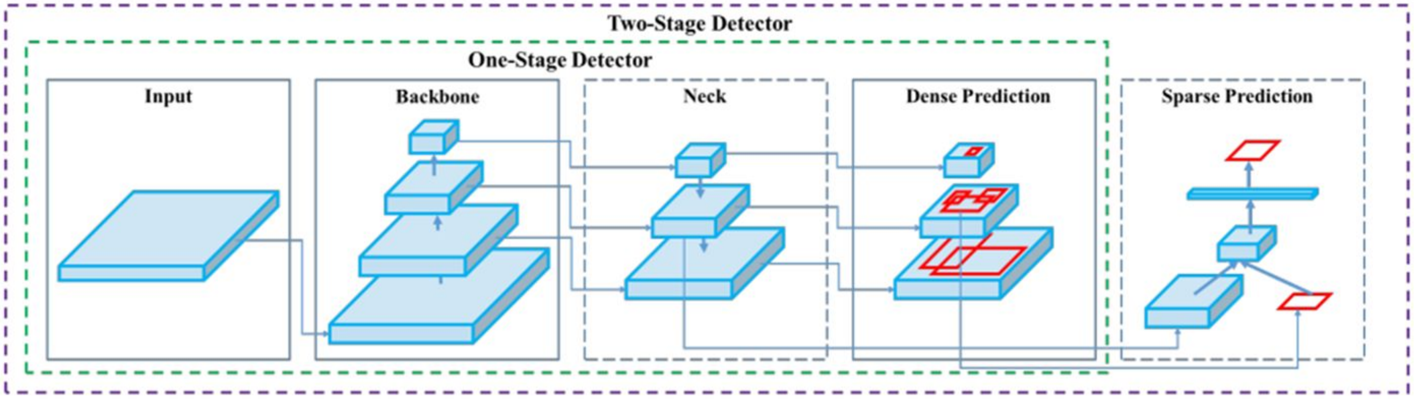


Extract features

Fuse features

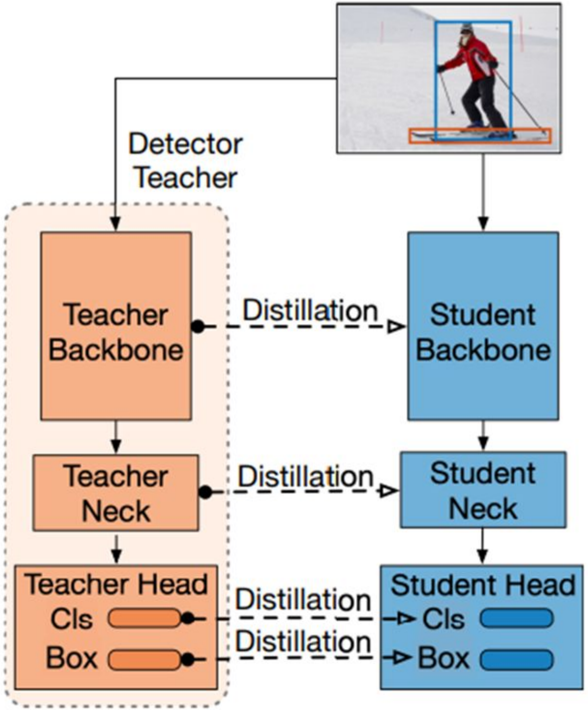
Predict class and bounding box

- Common object detector



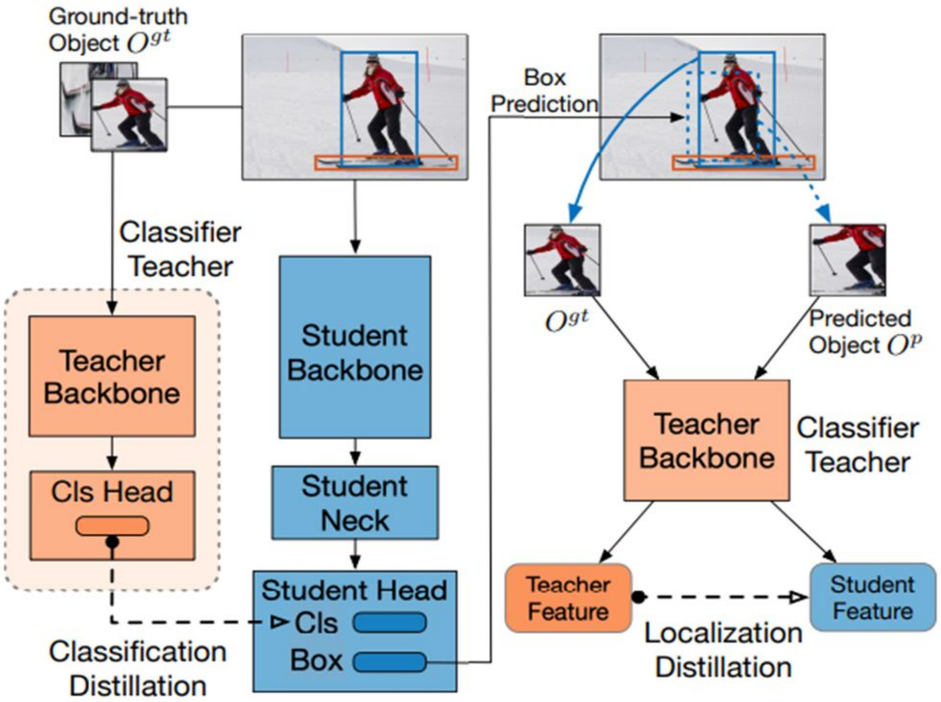
Knowledge Distillation: Detector-to-Detector

- The student and teacher follow the **same kind of detection framework**
- SOTA Method



Knowledge Distillation: Classifier-to-Detector

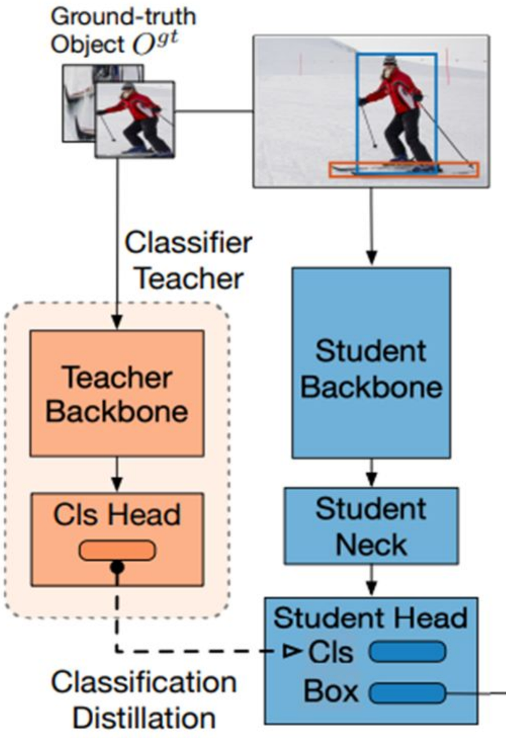
- Knowledge distillation **across tasks**
- From a image **classification teacher** to an **object detection student**



Knowledge Distillation: Classifier-to-Detector

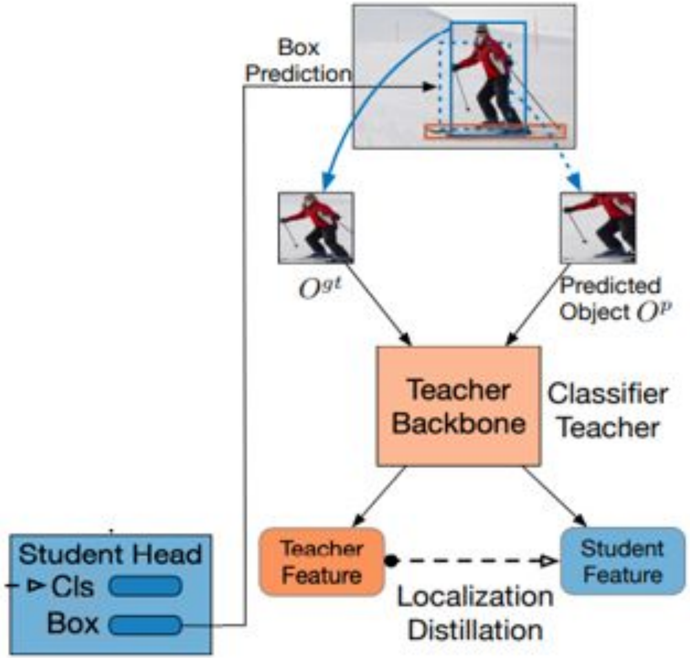
- The classification branch

A loss function defined by the class probabilities of the teacher and the student.



Knowledge Distillation: Classifier-to-Detector

- The localization branch



Feature level distillation strategy: Comparing the features within the predicted bounding box with those within the ground truth.

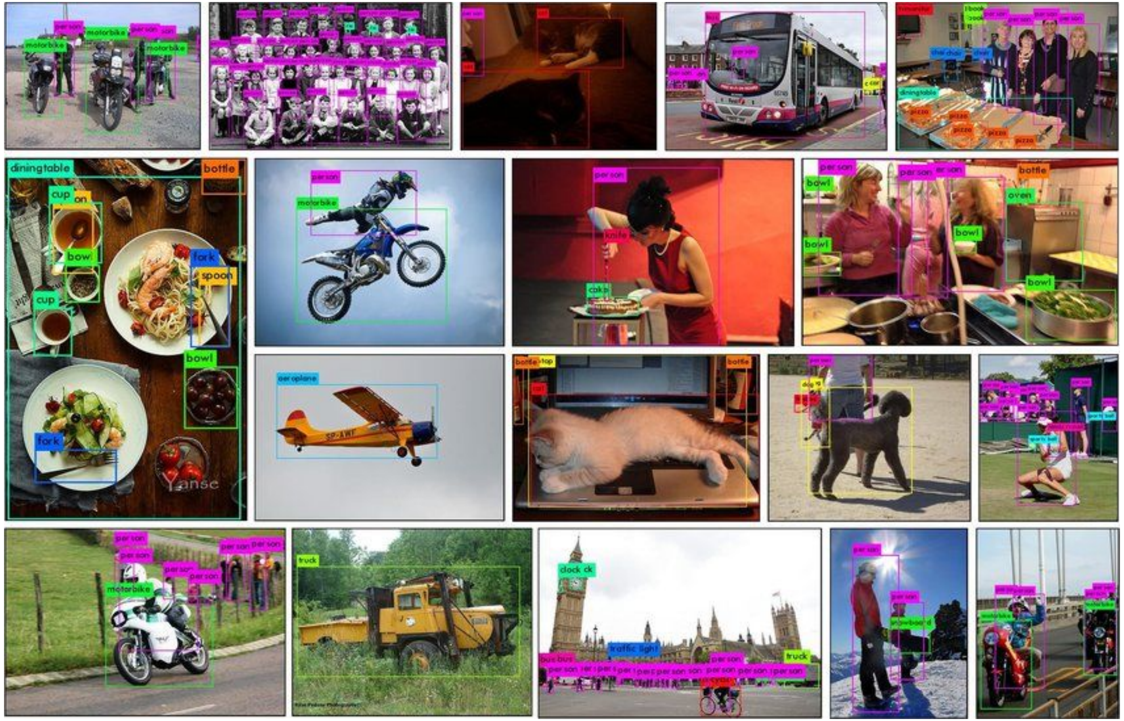
Experimental Result Analysis

Dataset

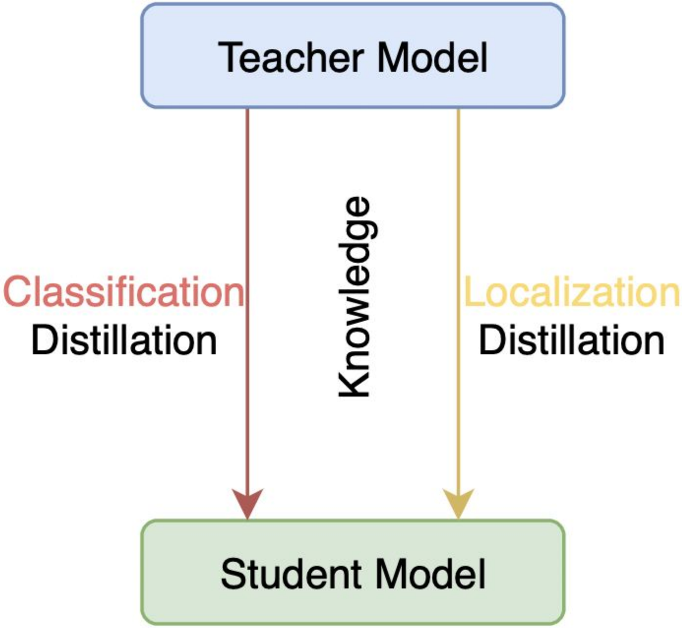
COCO
Common Objects in Context

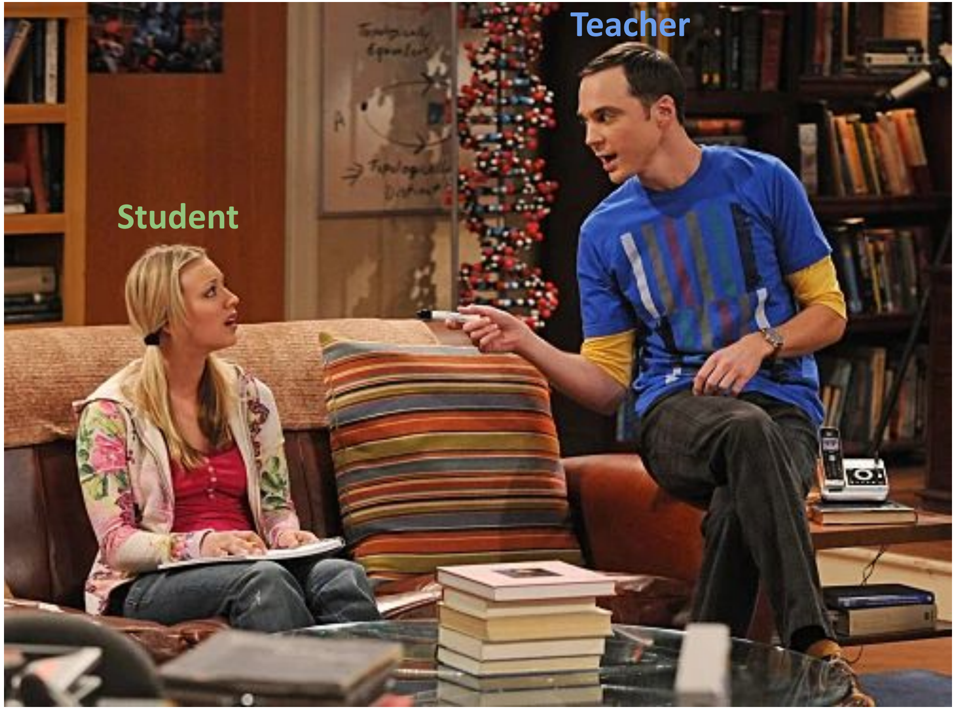
MS COCO 2017(Microsoft) Dataset

- 80 object classes
- 118k images for training
- 5k images for testing



Architecture



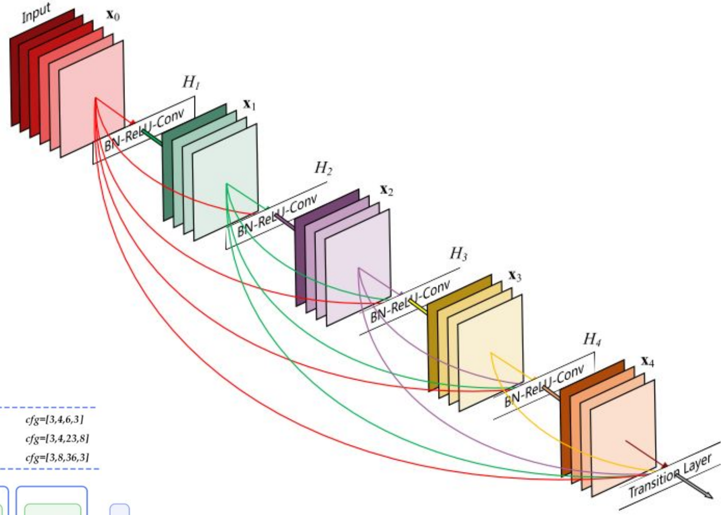


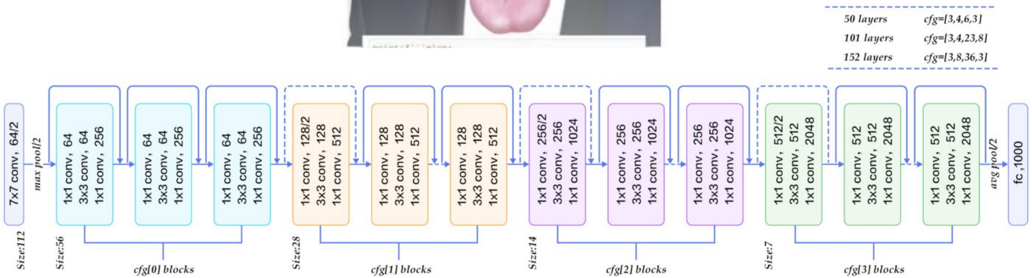
Overall Loss Function

$$\mathcal{L} = \mathcal{L}_{det} + \lambda_{kc}\mathcal{L}_{kd-cls} + \lambda_{kl}\mathcal{L}_{kd-loc}$$

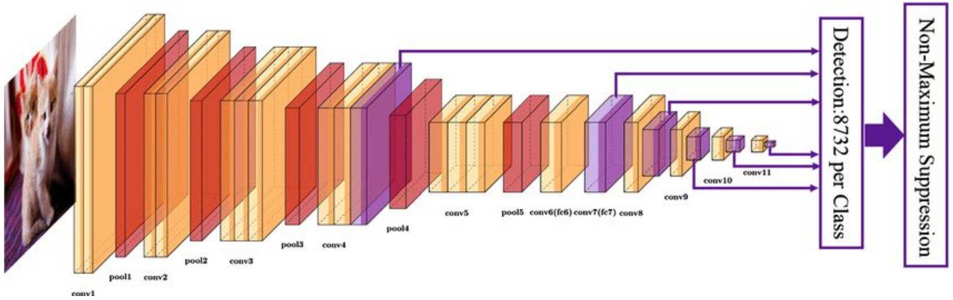
Teacher Model (Classification)

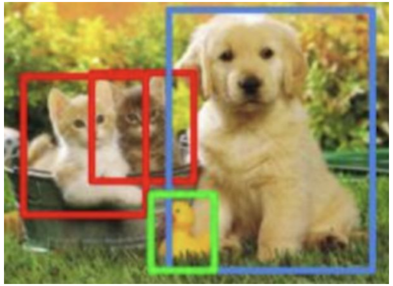
ResNet50
(50 Layers)

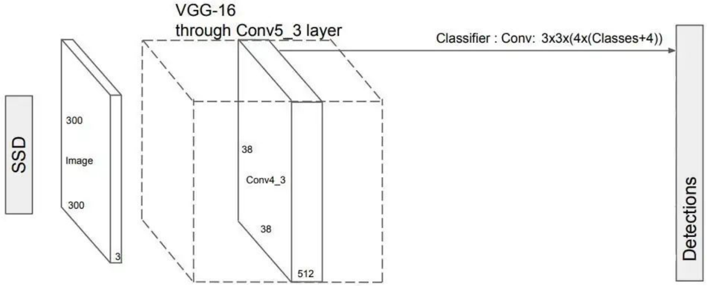




Student Model 1: SSD512(vgg16) (Detection)





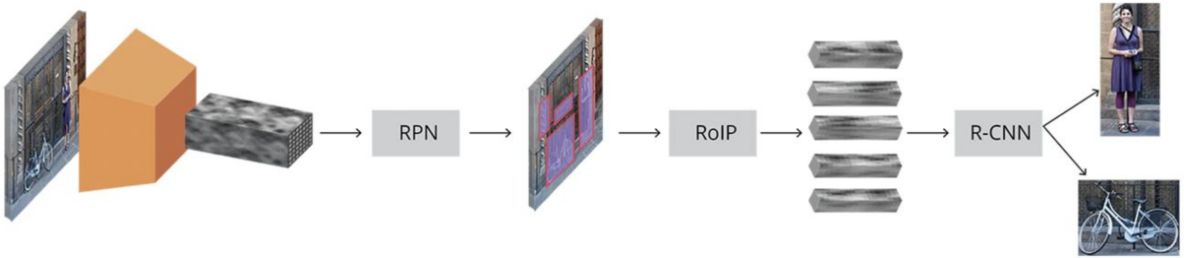


Single Shot Multibox Detector
with VGG16 as backbone

With Distillation:

- 2.7 mAP improvement

Student Model 2: Faster RCNN (Detection)



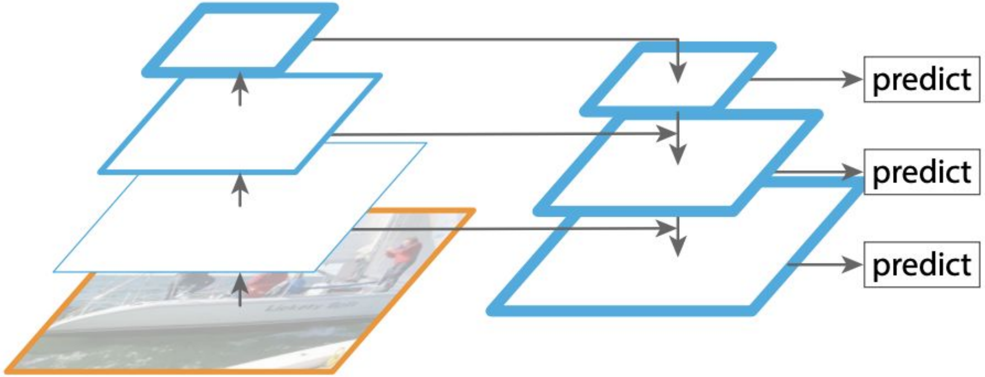
Complete Faster R-CNN architecture

With Distillation:

- 3.9 mAP improvement

Faster RCNN
(Quatered-ResNet50 Backbone)

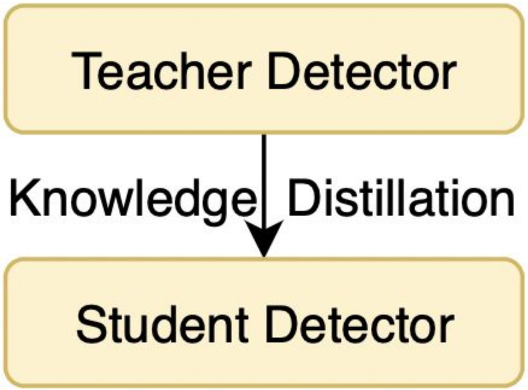
Student Model 3: RetinaNet (Detection)

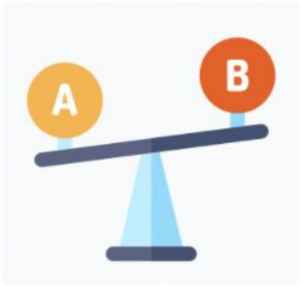


Only used in the comparison experiment

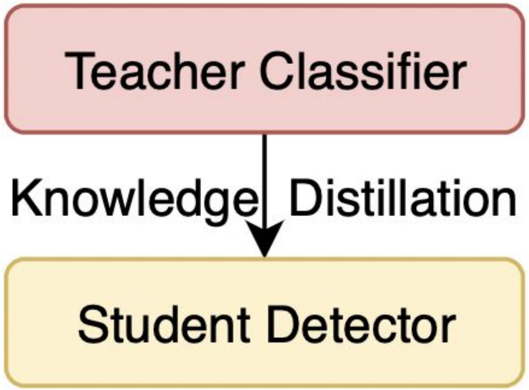
Comparison Experiment

<u>**SOTA**</u> Detector-Detector
Distillation Model: **FKD**

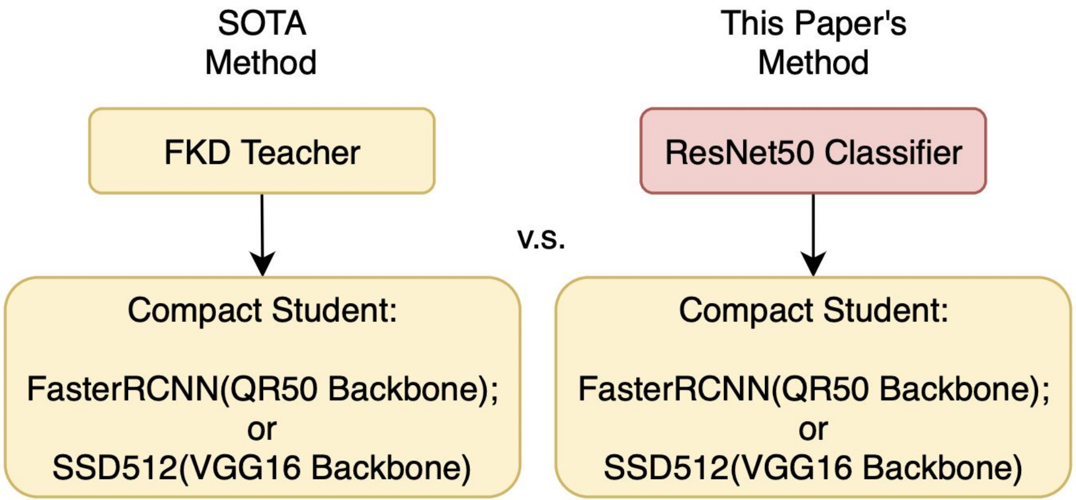




<u>**Novel**</u> Classifier-Detector
Distillation Model



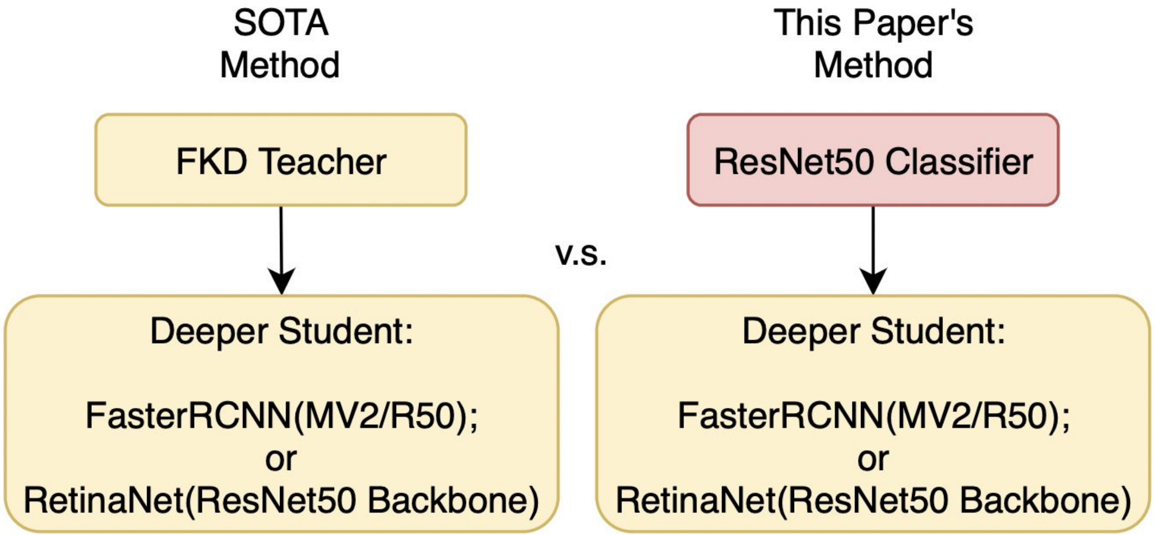
Comparison Using ***Compact*** Student Network



This Paper wins by:

- 1.1 mAP (FasterRCNN)
- 0.9 mAP (SSD512)

Comparison Using ***Deeper*** Student Network



- SOTA Method Wins
- The method of this paper performs better for compact networks

Combination Is Even Better

SOTA FKD + Classifier-Detector Distillation

Table 2: Comparison to detector-to-detector distillation methods on the COCO2017 validation set.

Method	mAP	AP_s	AP_m	AP_l
Faster RCNN-QR50	23.3	13.1	25.0	30.7
+ FKD [43]	26.1	14.6	27.3	35.0
+ Ours	27.2	15.2	29.3	36.2
+ Ours + FKD	**28.0**	**15.4**	**29.8**	**38.5**
SSD512-VGG16	29.4	11.7	34.1	44.9
+ FKD [43]	31.2	12.6	37.4	46.2
+ Ours	32.1	13.3	36.6	47.9
+ Ours + FKD	**32.6**	**13.5**	**37.6**	**48.3**
Faster RCNN-MV2	31.9	18.5	34.4	41.0
+ FKD [43]	33.9	18.3	36.3	45.4
+ Ours	32.7	**19.0**	35.0	42.9
+ Ours + FKD	**34.2**	18.5	**36.3**	**45.9**
Faster RCNN-R50	38.4	21.5	42.1	50.3
+ KD [5]	38.7	22.0	41.9	51.0
+ FGFI [39]	39.1	22.2	42.9	51.1
+ GID [8]	40.2	22.7	44.0	53.2
+ FKD [43]	41.5	23.5	45.0	55.3
+ Ours	38.8	22.5	42.5	50.8
+ Ours + FKD	**41.9**	**23.8**	**45.2**	**56.0**
RetinaNet-R50	37.4	20.0	40.7	49.7
+ FGFI [39]	38.6	21.4	42.5	51.5
+ GID [8]	39.1	22.8	43.1	52.3
+ FKD [43]	39.6	22.7	43.3	52.5
+ Ours	37.9	20.5	41.3	50.5
+ Ours +FKD	**40.7**	**23.1**	**44.7**	**53.8**

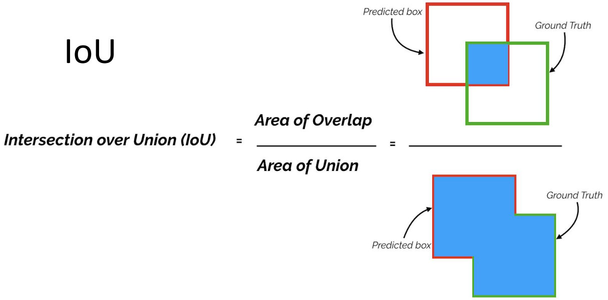
Ablation Study(Component Study)

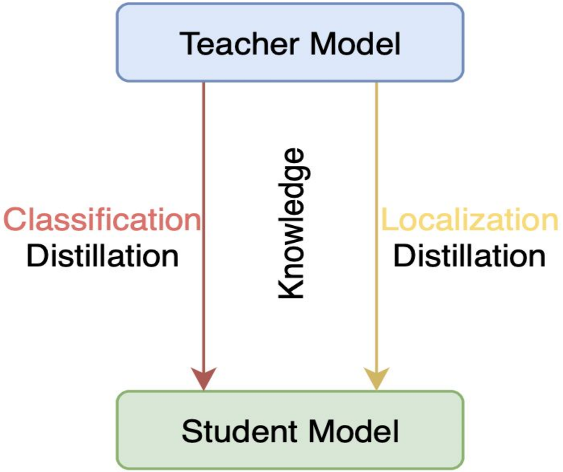
Observations:

- **Classification** distillation yields larger improvement for **smaller** IoU threshold
- **Localization** distillation yields larger improvement for **Larger** IoU threshold

Analysis:

- **Classification** distillation distills category info to student
- **Localization** distillation focuses on precise location





Significance and Impact

Novelty

Old	Detector-Detector Distillation
New	Classifier-Detector Distillation

This research showed:

- Using classification model as teacher in distillation
    - Works!
    - Performs better than baseline
- Improves the SOTA detector-detector distillation

Influenced Paper

1. Knowledge Distillation for 6D Pose Estimation by Keypoint Distribution Alignment

   Contributions:
   - Allowed compact compact network for 6D pose estimation running on embedded devices
   - Powered Robotics Research

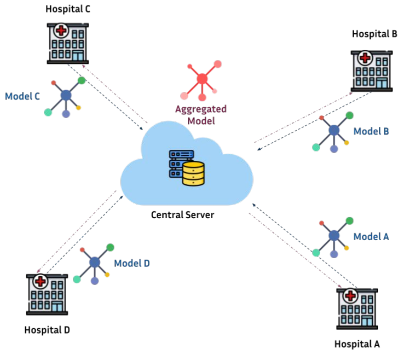
2. Task-Balanced Distillation for Object Detection

   Contributions:
   - Inspired research on task-balanced distillation

Broader Impact

1. Resource-constrained environments:
    a. Improve model performs in mobile devices
    b. Greatly reduced the Training resources

2. Further Research:
    a. Knowledge can be transferred not only across architectures, but also across tasks
    b. Provide new knowledge distillation techniques for federated learning



Q&A

Acknowledgement

- Guo, S., Alvarez, J. M., & Salzmann, M. (2021). Distilling Image Classifiers in Object Detectors. *Advances in Neural Information Processing Systems*, *34*, 1036-1047.

- Guo, S., Hu, Y., Alvarez, J. M., & Salzmann, M. (2022). Knowledge Distillation for 6D Pose Estimation by Keypoint Distribution Alignment. *arXiv preprint arXiv:2205.14971*.

- Tang, R., Liu, Z., Li, Y., Song, Y., Liu, H., Wang, Q., ... & Tan, J. (2022). Task-Balanced Distillation for Object Detection. *arXiv preprint arXiv:2208.03006*.

Thank You