G-DetKD: Towards General Distillation Framework for Object Detectors via Contrastive and Semantic-guided Feature Imitation

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In this paper, we investigate the knowledge distillation (KD) strategy for object detection and propose an effective framework applicable to both homogeneous and heterogeneous student-teacher pairs. The conventional feature imitation paradigm introduces imitation masks to focus on informative foreground areas while excluding the background noises. However, we find that those methods fail to fully utilize the semantic information in all feature pyramid levels, which leads to inefficiency for knowledge distillation between FPN-based detectors. To this end, we propose a novel semantic-guided feature imitation technique, which automatically performs soft matching between feature pairs across all pyramid levels to provide the optimal guidance to the student. To push the envelop even further, we introduce contrastive distillation to effectively capture the information encoded in the relationship between different feature regions. Finally, we propose a generalized detection KD pipeline, which is capable of distilling both homogeneous and heterogeneous detector pairs. Our method consistently outperforms the existing detection KD techniques, and works when (1) components in the framework are used separately and in conjunction; (2) for both homogeneous and heterogeneous student-teacher pairs and (3) on multiple detection benchmarks. With a powerful X101-FasterRCNN-Instaboost detector as the teacher, R50-FasterRCNN reaches 44.0% AP, R50-RetinaNet reaches 43.1% AP and R50-FCOS reaches 43.1% AP on COCO dataset.

1. Introduction

Knowledge distillation (KD) is a training strategy aiming at transferring the learnt knowledge from a powerful, cumbersome model (teacher) to a more compact model (student). The seminal work [12] introduced the idea of KD and this technique has been proven to be effective on classification tasks by many subsequent works [38, 9, 27]. However, integrating the idea of KD into detection is nontrivial. The conventional paradigm of classification KD can not be directly applied to detection task since simply minimizing the KL divergence between the classification outputs fails to extract the spatial information from the teacher and only brings limited performance gain [31] to the student. In this work, we aim at developing a general KD framework which can efficiently extract the spatial information and is applicable to both homogeneous and heterogeneous student-teacher pairs.

It is acknowledged that feature map imitation with foreground attention mechanisms helps students learn better [2, 15, 31, 26]. Previous works propose different imitation masks to focus on the informative foreground regions while excluding the background noises. However, mask-based methods were first developed for outdated detectors, i.e., vanilla Faster-RCNN without FPN [24], which fail to extend to modern detectors equipped with FPN. Specifically, those methods perform direct one-to-one matching between pyramid levels of the student-teacher pair, which leads to two issues: (1) indiscriminately applying the same mask on all levels can introduce noise from unresponsive feature levels; (2) mask-based methods are not extendible to heterogeneous detector pairs since their feature levels may not be strictly aligned, e.g., FasterRCNN constructs the feature pyramid from \( P_2 \) to \( P_6 \), while RetinaNet uses \( P_3 \) to \( P_7 \).

To address the above issues, we propose a simple yet effective Semantic-Guided Feature Imitation (SGFI) approach based on object proposals. By analyzing the re-
spesive knowledge to help the student’s learning. Thus, we represent representations of different regions also encodes information corresponding to the same region, whereas the relation between feature imitation approaches by a large margin.

Optimal guidance. The proposed SGFI outperforms other methods: R50-FasterRCNN reaches 44.0% AP; while the effect on homogeneous students is also significant: R50- Retina reaches 43.3% AP and R50-FCOS reaches 43.1% AP. Our method generalizes surprisingly well for large detectors like CascadeRCNN with ResNeXt101-DCN as the backbone: boosting its AP from 46.0% to 50.5%. In addition, the generalization ability of our method is validated on multiple mainstream detection benchmarks, e.g., Pascal VOC [7] and BDD [36].

In summary, the contributions of this paper are threefold:

- We propose a novel semantic-guided feature imitation approach (SGFI) with a semantic-aware soft-matching mechanism.
- We propose contrastive knowledge distillation (CKD) to capture the information encoded in the relationship between teacher’s different feature regions.
- We make the first attempt to construct a general KD framework (G-DetKD) capable of distilling knowledge for both homogeneous and heterogeneous detectors pairs. Comprehensive experiments are conducted to show the significant performance boosts brought by our approach.

2. Related Works

Object Detection. Object detection is one of the fundamental problems in computer vision. State-of-the-art detection networks can be categorized into one-stage, two-stage and anchor-free detectors. One-stage detectors such as [22, 19, 23] perform object classification and bounding box regression directly on feature maps. On the other hand, two-stage detectors such as [24, 16] adopt a “coarse-to-fine” approach which uses a region proposal network (RPN) to separate foreground boxes from background and a RCNN head to refine the regression results and perform the final classification. [30, 6, 33] propose to directly predict location of objects rather than based on anchor priors, which opens a new era for object detection. Recent works also perform NAS on detection tasks, which searches for novel detectors automatically without human intervention [13, 32, 10, 34, 35].

Knowledge Distillation. KD was first proposed in [12]. Its effectiveness has been explored by many subsequent works [38, 9, 27, 25]. For object detection, [2] first proposes imitating multiple components in detection pipeline, e.g., backbone features, RPN and RCNN. Recent works demonstrate that foreground instances are more important in feature imitation. Various methods are proposed to help student model focus on foreground information, including multiple mask generating approaches [28, 26] and RoI extraction [15]. However, these methods are designed for detectors without FPN, which fail to extend to FPN-based detectors with multiple feature levels. This motivates us to design a new KD framework that is able to fully exploit teacher’s feature pyramid.

Contrastive Learning. Contrastive learning is a popular approach for self-supervised tasks [20, 11, 5]. The goal is to bring closer the representations of similar inputs and push away those of dissimilar ones, which naturally takes into account the relationship between contrastive pairs. Inspired by the recent work [28], which proposes a distilla-
tion method using a contrastive approach for classification, we propose to integrate the information encoded in the relationship between different object regions by introducing contrastive knowledge distillation for object detection.

3. Preliminary

We start by briefly reviewing previous works on KD for object detection. [2] conducted knowledge distillation on detector’s classification and localization predictions, which are formulated as: 

$$L_{cls} = -\frac{1}{N} \sum_{i=1}^{N} P_i \log P_s, \quad L_{reg} = -\frac{1}{N} \sum_{i=1}^{N} | reg_t^i - reg_s^i |, \quad \text{where } P_s, P_t \text{ and } reg_s, reg_t \text{ are the class scores and localization outputs of the student-teacher pair, respectively. However, simply distilling from the prediction outputs neglects the teacher’s spatial information.}

More recent works mainly focus on distilling knowledge from the feature maps, which encode spatial information that is crucial for detection. These methods propose different imitation masks I to form an attention mechanism for foreground features and filters away excessive background noises. The objective can be formulated as:

$$L_{feat} = \frac{1}{2N_p} \sum_{l=1}^{L} \sum_{i=1}^{W} \sum_{j=1}^{H} \sum_{c=1}^{C} I_{ij} \left( f_{adapt}^l \left( S^l \right)_{ijc} - T_{ijc}^l \right)^2$$

where L, W, H, C are feature levels, width, height and number of channels, respectively; S and T are student’s and teacher’s feature maps; I is the imitation mask; $f_{adapt}(\cdot)$ is an adaptation function mapping S and T to the same dimension, which is usually implemented as a 3x3 conv layer; $N_p$ is the total number of positive elements in the mask.

Various methods can differ in the definition of I. For example, FGFI [31] generates an imitation mask according to the near object anchor locations, while TADF [26] proposed to generate a soft mask using Gaussian function.

Those mask-based methods are originally proposed for detectors without FPN. To extend them for the FPN-based modern detectors, the masks are generated by the same rule for all feature levels, then features on the corresponding levels are matched for imitation. We argue this direct adaptation to modern detectors with feature pyramids is suboptimal due to the following reasons: (1) generally, in the design paradigm of FPN, each feature level is responsible for detecting objects of different scales. Thus, indiscriminately applying the same mask on all levels can introduce noise from unresponsive feature levels; (2) mask-based methods are not extendible to heterogeneous detector pairs since the their feature pyramid levels may not be strictly aligned, e.g., Faster-RCNN-FPN constructs the feature pyramid from P2 to P6, while RetinaNet-FPN uses P3 to P7. These weaknesses promote us to design a feature imitation mechanism that can automatically match the features of the student-teacher pair for imitation and eliminate the excessive noise, while also being extendible to heterogeneous detector pairs.

4. Methods

4.1. Semantic-Guided Feature Imitation (SGFI)

The aforementioned problem of mask-based methods can be partially solved via a straightforward approach which uses positive RoI features for imitation: instead of uniformly imitating foreground regions on all feature levels, RoI extraction operation selects foreground features based on object proposals in a fine-grained manner, which automatically matches the features from corresponding levels according to their scales. However, RoI extractor’s proposal assignment heuristics is purely based on the proposal scales, which is agnostic to the semantic relationship between features of the student-teacher pair.

Intuitively, a promising feature distillation approach needs to consider the semantics of features when constructing them into pairs for imitation. We reflect on the feature matching mechanism by looking into the characteristics of feature pyramids, which are visualized in Figure 2. We observe that for different detectors, given an object in the image, the corresponding region on the same feature level present various patterns, while the difference is more significant between heterogeneous detectors.

This phenomenon implies that the best matching feature for imitation may not be from the corresponding pyramid level, which is an issue that the purely scale-based heuristics fails to address. Thus, we are motivated to conduct feature matching based on their semantics instead of scales. In addition, the object region on nearby feature levels are activated in a similar manner, while the similarity diminishes as the distance between levels becomes greater. This implies that student features from other levels which carry similar semantics should also be involved during imitation to fully
exploat the potential of teacher’s representation power.

To this end, we propose a semantic-guided feature imitation (SGFI) scheme which performs soft matching between features of the student-teacher pair as illustrated in Figure 3. Specifically, given a proposal indexed by $i$, the teacher’s feature $T_i \in R^{H \times W \times C}$ is extracted from the heuristically assigned pyramid level (which is consistent with its training process). In contrast, the student’s features from all levels are extracted and mapped to the same dimension as $T_i$ using $f_{\text{adapt}}$ and is denoted as $S_i \in R^{L \times H \times W \times C}$, where $L$ is the number of pyramid levels. We first project $T_i$ and each $S_i^l (l = 1, ..., L)$ onto the same embedding space with $f_{\text{embed}} : R^{H \times W \times C} \rightarrow R^{C_{\text{key}}}$, then the level-wise weights $\alpha_l$ are calculated using the dot product between the embeddings followed by a softmax function, which is used to aggregate $S_i^l (l = 1, ..., L)$ to obtain $S_{agg}$. The final loss is the mean square error between $T_i$ and $S_{agg}$. The calculation of cross-level imitation loss can be formulated as:

$$K_{si} = f_{\text{embed}}(f_{\text{adapt}}(S_i)), \quad K_{ti} = f_{\text{embed}}(T_i)$$

$$\alpha_l = \text{softmax} \left( \frac{K_{si}^T K_{ti}}{\tau} \right)$$

$$S_{agg} = \sum_{l=1}^{L} \alpha_l^l \times f_{\text{adapt}}(S_i^l)$$

$$L_{\text{feat}} = \frac{1}{N} \sum_{i=1}^{N} (\text{MSE}(S_{agg}, T_i))$$

(1)

where $f_{\text{adapt}}$ is implemented as a convolutional layer; $f_{\text{embed}}$ is implemented as a lightweight network which consists of 2 convs with stride=2, each followed by ReLU; both networks for $f_{\text{adapt}}$ and $f_{\text{embed}}$ are excluded during inference; $N$ and $L$ are the number of proposals and the number of levels in the feature pyramid, respectively; $\text{MSE}$ is the mean square error; $\tau$ is a learnable temperature to control the sharpness of softmax logits.

Our proposed SGFI effectively addresses the misalignment between feature levels of student-teacher pairs, which can be easily extended to heterogeneous detector pairs.

4.2. Exploiting Region Relationship with Contrastive KD (CKD)

Feature imitation methods transfer teacher’s knowledge by maximizing the agreement between features of the same region. However, the structural information encoded in the relationship between different regions is ignored, which may also provide guidance to the student. To this end, we push the envelope further by integrating the region relationship into KD for detection. Inspired by the recent work [28], we propose to incorporate the idea of contrastive learning into our KD framework. The objective is to maximize the agreement between the representations of positive pairs while pushing away those of the negative pairs in the given metric space, which intrinsically captures the relationship between contrastive pairs.

Specifically, given a set $B$ consisting of $N$ RoI bounding boxes, i.e., $B = \{bbox_i\}_{i=1}^{N}$, their corresponding representations $\{r_i^s, r_i^t\}_{i=1}^{N}$ are drawn from the embeddings before the output layer. We form the contrastive pairs as follows: representations that correspond to the same box are constructed as positive pairs while those of different box are constructed as negatives, namely, $x_{pos} = \{r_i^s, r_i^t\}$, $x_{neg} = \{r_i^s, r_j^t\} (i \neq j)$. Our objective is recognizing the positive pair $x_{pos}$ from the set $S = \{x_{pos}, x_{neg}^1, x_{neg}^2, ..., x_{neg}^K\}$ that contains $K$ negative pairs, which is implemented in the form of InfoNCE loss [20]:

$$L_{\text{ckd}} = \frac{1}{N} \sum_{i=1}^{N} - \log \frac{g(r_i^s, r_i^t)}{\sum_{j=0}^{K} g(r_i^s, r_j^t)}$$

(2)

where $K$ is the number of negative samples; $N$ is the number of proposals in a batch; $g$ is the critic function that estimates the probability of $(r_i^s, r_i^t)$ being the positive pair, which is defined as:

$$g(r_i^s, r_i^t) = \exp \left( \frac{f_\theta(r_i^s) \cdot f_\theta(r_i^t)}{\|f_\theta(r_i^s)\| \cdot \|f_\theta(r_i^t)\|} \cdot \frac{1}{\gamma} \right)$$

where $f_\theta$ is a linear function to project the representation to a lower dimension, which is implemented as a fully connected layer whose parameters are shared between the student-teacher pair; $f_{\text{adapt}}(r_i^s)$ and $f_{\text{adapt}}(r_i^t)$ is the cosine similarity; $\gamma$ is a temperature hyper-parameter. Theoretically, minimizing $L_{\text{ckd}}$ is equivalent to maximizing the lower bound of the mutual information between $f_\theta(r_i^s)$ and $f_\theta(r_i^t)$ (Detailed proof can be found in previous work [20]):

$$MI(f_\theta(r_i^s), f_\theta(r_i^t)) \geq \log (K) - L_{\text{contrastive}}$$
**Memory Queue.** We implement a memory queue [11] to store the representations for constructing more negative pairs: a queue across multiple GPUs is maintained, and once the max size is reached, the oldest batch is dequeued when new batch arrives. Theoretically, the lower bound becomes tighter as $K$ increases, which implies that using more negative samples benefits representation learning. However, we observe that setting $K$ too large leads to performance degradation. To effect of $K$ is shown in the Appendix.

**Negative Sample Assignment Strategy.** Another key issue for contrastive KD in detection task is the mechanism to select negative samples. Specifically, the dilemma lies in the overlapping between region proposals: those proposal with large overlaps may contain similar semantics, thus pushing them away may cause instability during training. To address this issue, we use IoU to filter out the highly overlapping proposal boxes and exclude them from negative samples. We conduct an ablative study in the appendix to decide the optimal IoU threshold.

### 4.3. General Detection KD Framework (G-DetKD)

In some specific scenarios, only detectors with certain architectures can be deployed due to hardware constraints, which may cause the student to have a different architecture from the teacher. Thus, it is promising if knowledge distillation can be conducted between heterogeneous detector pairs. However, previous works only consider KD between homogeneous detectors pairs due to their lack of extensibility. Therefore, we are motivated to propose a general detection KD framework applicable for both homogeneous and heterogeneous student-teacher detector pairs.

#### 4.3.1 Homogeneous Detector Pairs

Homogenous detector pairs are strictly aligned in terms of network categories and feature representations, which facilitates the design of KD framework. Other than the previously introduced SGFI and CKD, we propose two additional techniques to further promote the framework’s effectiveness, namely, **class-aware localization KD** and **head transfer**. In particular, we study the case when the student and teacher are both two-stage detectors.

**Class-aware Localization KD.** A core component distinguishing detection KD from classification KD lies in how to effectively transfer teacher’s localization ability to student. Intuitively, simply imitating the four coordinates output by the teacher provides limited information as they are only “inaccurate targets”. This motivates us to incorporate teacher’s localization knowledge with the class “uncertainty”, i.e., utilizing all the class-wise localization predictions generated by the teacher. For illustration, when the detector captures only a part of an object, how the box should be shifted may depend on what class the object belongs to.

![Diagram of Semantic-Guided Feature Distillation and Contrastive Distillation for Heterogeneous Student Detectors](image)

Figure 4. Framework of semantic-guided feature distillation and contrastive distillation for heterogeneous student detectors. As shown in top of the picture, the proposals are sampled from bounding boxes predicted by the localization head, which are then used by SGFI (illustrated in Fig. 3) and CKD; the bottom part illustrates the CKD process: student’s classification features are constructed as contrastive pairs with teacher’s features. In the case of one-stage student, each feature is further decoupled for different box regions centered at the same pixel.

This idea requires both student and teacher to have localization predictions for each possible class, which is a common setting for two-stage detectors) We calculate the sum of regression values weighted by classification scores:

$$L_{reg} = \frac{1}{N} \sum_{i=0}^{N} \sum_{s=0}^{C} p_i \times (reg_s^t - reg_s^s)$$  \hspace{0.5cm} (3)$$

where $C$ is the number of classes; $p_i$ and $reg_s$ are the classification score and regression outputs of foreground class $i$; superscripts $s$ and $t$ represent student and teacher. This class-aware regression loss helps student acquire localization knowledge from teacher; the experiment is shown in Appendix.

**Head Transfer.** For homogeneous detector pairs, the student and the teacher have backbones with different capacities, while sharing the same head structure. This motivates a more straightforward knowledge transfer strategy for homogeneous detector pairs: directly copying the weights from the teacher’s head to the student. Our experiments demonstrate it helps accelerate students’ convergence and further improves the performance.

Overall, the loss function of our framework for homogeneous detectors can be formulated as: $L = L_{gt} + L_{feat} + L_{ckd} + L_{cls} + L_{reg}$, where $L_{gt}$ is the ground truth loss; $L_{feat}, L_{ckd}$ and $L_{reg}$ correspond to $1, 2$ and $3$, respectively; $L_{cls}$ is defined in Section 3.

#### 4.3.2 Heterogeneous Detector Pairs

Modern detectors have diversified into multiple families, such as one-stage, two-stage and anchor-free detectors.
Each family has its own merits and weaknesses. In particular, two-stage detectors often have higher performance, while being slower in inference speed. On the other hand, dense prediction detectors (e.g., one-stage and anchor-free detectors) are faster than two-stage counterparts while being less accurate, as they adopt fully convolutional network. In practice, it is a natural idea to use two-stage detectors as teacher to enhance detectors belonging to other families.

The difficulty in knowledge distillation between heterogeneous detector pairs lies in the following aspects: (1) the feature levels are not aligned, e.g., FasterRCNN constructs the feature pyramid from \( P2 \) to \( P6 \), while RetinaNet uses \( P3 \) to \( P7 \), which creates obstacle for feature distillation; (2) different loss function are used during training, causing their outputs to carry different meanings. E.g., two-stage detectors use cross entropy loss, and dense prediction detectors often adopt focal loss [17], which hinders distillation on the prediction outputs.

We first try to conduct KD on the prediction outputs of FasterRCNN teacher and RetinaNet student and find it bringing only limited gains, and the gains diminish when applied with other KD methods (the results are shown in Table 1). Next, we elaborate on how to extend our feature level distillation method to heterogeneous detectors.

The overview of our G-DetKD for heterogeneous detector pairs is shown in Figure 4. We use the student’s bounding box predictions to generate a set of RoIs, which are then applied to cross-level feature imitation and contrastive KD in the same way as described in Sections 4.1 and 4.2.

RoI Extraction. Analogous to the RPN head in two-stage detectors, we first match all the student’s predicted boxes with the ground truths and label those with IoUs greater than a threshold (set to be 0.5) as positive samples. Then the boxes are sampled with 1:3 ratio of positive to negative samples.

Semantic-guided Feature Imitation. As introduced in 4.1, our method eliminates the requirement for strict alignment between feature levels of the student-teacher pairs, thus is directly applicable to heterogeneous detector pairs.

Decoupling Representations for Contrastive KD. The typical bounding box head structures of dense prediction detector consists of separate multi-convolution classification and localization branches. As illustrated in Figure 4, given a set of the RoIs, the contrastive pairs are constructed using the features of the teacher’s last fully connected layer and the corresponding features from the last layer of student’s classification branch. For one-stage detectors, each representation encodes information of multiple anchors centered at the same location, which is decoupled for each anchor.

Overall, the loss function of our framework for heterogeneous detectors can be formulated as: \( L = L_{gt} + L_{feat} + L_{ckd} \), where \( L_{gt} \) is the ground truth loss; \( L_{feat} \) and \( L_{ckd} \) correspond to 1,2 and 3, respectively.

### 5. Experiments

#### Datasets.
We evaluate our knowledge distillation framework on various modern object detectors and popular benchmarks. Our main experiments are conducted on COCO dataset [18]. When compared with other popular algorithms, test-dev split is used and the performances are obtained by uploading the results to the COCO test server. Berkeley Deep Drive (BDD) [36] and PASCAL VOC (VOC) [7] are then used to validate the generalization capability of our method. The default evaluation metrics for each dataset is adopted.

**Implementation Detail.** We use cosine annealing learning rate schedule; the initial learning rate is set to 0.03. Training is conducted on 8 GPUs using synchronized SGD, batch size is 2 for each GPU. The shorter side of the input image is scaled to 800 pixels, the longer side is limited up to 1333 pixels. ‘1x’ (namely 12 epochs) and ‘2x+ms’ (namely 24 epochs with multi-scale training) training schedules are used. More details can be found in Appendix.

#### 5.1. Main Results

**Decoupling the effectiveness of each distillation component.** We first investigate the effectiveness of each distillation component for three types of student detectors. The experiment results are shown in Table 2, where use FasterRCNN-R50-FPN as teacher and all students have R18-FPN backbones. The result for FasterRCNN student demonstrates the effectiveness of our class-aware localization KD, which outperforms the naive localization KD approach by a large margin. In addition, contrastive KD is the most effective approach when used alone, which leads to 3.1% gain in \( AP \). On the other hand, for heterogeneous students, we can see our SGFI and Contrastive KD provide even higher performance gain compared to their results for homogeneous pairs. The combination achieving the highest performance gain is selected for other main experiments.

**Comparison with SOTA Detection KD Methods.** We compare our results for homogeneous pairs with previous works in Table 3, since those methods only consider distillation between homogeneous teacher-student pairs. The results show that our G-DetKD and CKD consistently out-

| Part                  | AP  |
|-----------------------|-----|
| Baseline R18          | 32.3|
| Cls pred              | 32.6\( \pm \)0.3 |
| Reg pred              | 32.7\( \pm \)0.4 |
| SGFI                  | 36.1\( \pm \)3.8 |
| SGFI+pred(cls+reg)    | 36.1\( \pm \)3.8 |

Table 1. Knowledge distillation between R18-RetinaNet student and R50-fasterRCNN teacher. The gain of prediction KD is negligible and diminishes when applied with our SGFI.
Table 2. Effectiveness of each KD component for different type of students. SGFI and CKD are our semantic-guided feature imitation and contrastive KD, respectively; Csl and CAReg are classification KD and our class-aware regression KD, respectively; HT is our head transfer technique.

| KD Method       | FasterRCNN[24] | Retina[17] | FCOS[30] |
|-----------------|----------------|------------|----------|
| Teacher R50-FPN | 39.9           | -          | -        |
| Student R18-FPN | 34.0           | 32.6       | 30.3     |
| SGFI            | 36.7+2.7       | 36.0+3.4   | 35.2+4.9 |
| CKD             | 37.1+3.1       | 35.8+3.2   | 34.9+4.6 |
| Pred (Cls+Reg)  | 36.4+2.4       | 33.1+0.5   | -        |
| Pred (Cls+CAReg)| 37.0+3.0       | -          | -        |
| HT              | 35.5+1.3       | -          | -        |
| SGFI+CKD        | 37.6+3.6       | 36.3+3.7   | 35.6+5.3 |
| SFGI+CKD+Pred+HT| 37.9+3.9       | -          | -        |

Table 3. Comparison between our KD methods with other approaches. The results show that our G-DetKD and CKD consistently outperforms others by a large margin.

| Method           | AP   | AP_S | AP_M | AP_L |
|------------------|------|------|------|------|
| Teacher R152-FPN | 41.5 | 24.1 | 45.8 | 54.0 |
| Student R50-FPN  | 37.4 | 21.8 | 41.0 | 47.8 |
| FGFI[31]         | 39.8+2.4 | 22.9 | 43.6 | 52.8 |
| TADF[26]         | 40.0+2.6 | 23.0 | 43.6 | 53.0 |
| CKD (Ours)       | 40.3+2.9 | 23.2 | 44.1 | 52.3 |
| G-DetKD (Ours)   | 41.0+3.6 | 23.7 | 45.0 | 53.7 |
| Teacher R50-FPN  | 37.4 | 21.8 | 41.0 | 47.8 |
| Student R50(1/4)-FPN | 29.4 | 16.3 | 31.7 | 39.0 |
| FGFI[31]         | 31.7+2.3 | 17.1 | 34.2 | 43.0 |
| CKD (Ours)       | 32.4+3.0 | 17.2 | 34.8 | 43.0 |
| G-DetKD (Ours)   | 33.7+4.3 | 18.1 | 36.6 | 44.5 |

Table 4. Our detection KD framework brings significant performance boosts for both homogeneous and heterogeneous detector pairs. All students use two-stage detectors as teachers. “Insta” means Instaboost [8]; “HTC” stands for Hybrid Task Cascade [3].

| Method           | backbone | AP   | AP_S | AP_M | AP_L |
|------------------|----------|------|------|------|------|
| RepPoints [33]   | R101-DCN | 45.0 | 66.1 | 49.0 |
| SAPF [40]        | R101     | 43.5 | 63.6 | 46.5 |
| ATSS [59]        | R101     | 43.6 | 62.1 | 47.4 |
| PAA [14]         | R101     | 44.8 | 63.3 | 48.7 |
| BorderDet [21]   | R101     | 45.4 | 64.1 | 48.8 |
| BorderDet [21]   | X101-64x4d-DCN | 47.2 | 66.1 | 51.0 |
| RetinaNet (Ours) | R101     | 44.8 | 64.2 | 48.3 |
| FCOS (Ours)      | R101     | 45.0 | 64.1 | 48.5 |
| FasterRCNN (Ours)| R101     | 45.6 | 65.9 | 49.9 |
| Cascade (Ours)   | X101-32x4d-DCN | 50.5 | 69.3 | 55.1 |

Table 5. Comparison of our G-DetKD with SOTA detector design approaches. Detectors in the four last rows are enhanced by our G-DetKD framework.

5.2. Ablation Study

Comparison of Feature Imitation Strategies. We evaluate different feature imitation strategies, including various mask-based methods, RoI feature imitation (RoIFI) and our SGFI, for both homogeneous and heterogeneous student-teacher pairs in Table 6. For homogeneous detectors, mask-based approaches show similar performances, which are outperformed by RoI-based imitation methods by a large margin. Our proposed SGFI beats the best mask-based approach by 1.1% AP. For heterogeneous detectors, the superiority of SGFI becomes more evident, which indicates that SGFI can well resolve the misalignment issue between feature levels of the student-teacher pairs.

Visualizing Pyramid Level Matching in SGFI. To investigate the feature’s matching pattern in SGFI, we visualize the distributions of the pyramid level difference between the student-teacher pair’s best matching features in Figure 5. Specifically, 500 images (consisting of around 50000 positive proposals) are fed into the trained student-teacher pair. For each proposal, we collect its corresponding teacher’s pyramid level and student’s best matching level to calcu-
Table 6. Comparison between different feature distillation techniques. As can be seen, our SGFI outperforms the other methods by a large margin. RoIFI stands for RoI feature imitation method.

![Figure 5](image-url) Distributions of the pyramid level difference between the student-teacher pair’s best matching features.

![Figure 6](image-url) Visualization of the difference between the student-teacher pair’s correlation matrices at the classification logits. The intensity of the color represents the magnitude.

Table 7. Our KD framework consistently boosts the performance given students and teachers with different capacities. The values in the parentheses indicate baseline APs.

Table 8. Generalization on VOC and BDD datasets. The value at the left of ↑ is the baseline AP while the value at the right is AP achieved with KD.

6. Conclusion

In this paper, we propose a semantic-guided feature imitation method and contrastive distillation for detectors, which helps the student better exploit the learnt knowledge from teacher’s feature pyramid. Furthermore, a general KD framework for detectors is proposed, which is applicable for both homogeneous and heterogeneous detector pairs.
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Supplementary Materials

A. Experiment Setups

Datasets and evaluation metrics. We evaluate our knowledge distillation framework on various modern object detectors and popular benchmarks. Our main experiments are conducted on COCO dataset [18]: we use train2017 split (115K images) to perform training and validate the result on minival split (5K images). When compared with other popular algorithms, test-dev split is used and the performances are obtained by uploading the results to the COCO test server. Berkeley Deep Drive (BDD) [36] and PASCAL VOC (VOC) [36] are then used to validate the generalization capability of our method: BDD is an autonomous driving dataset containing 10 object classes, 70K images for training and 10K for evaluation; for VOC, trainval07 split is used for training and test2007 split is used for testing. For experiments on COCO and BDD, mAP for IoU thresholds from 0.5 to 0.95 is used as the performance metric; while AP at IOU = 0.5 is used for VOC.

Additional Implementation details. Other than the settings mentioned in the main paper’s Main Results section, we provide the additional details as follows: weight decay is set to 0.0001, momentum is set to 0.9. For contrastive KD, $K = 80 \times 1024$ (1024 proposals per GPU for 8 GPUs) proposals are used to form the memory queue; When Transfer Head is applied, the weights of transferred RPN and RCNN are frozen throughout the training process. The checkpoints of all teacher models in following sections can be easily obtained from the MMDetection [4] official website. 1

B. Contrastive KD Implementation

In this section, we carefully analyze the influence of the important factors in our contrastive KD. As introduced in Section 4.2 of the main paper, the size of memory queue and the IoU threshold for assigning negative samples both play important roles in the performance of our contrastive KD (CKD). Thus, we conduct ablative experiments to find the optimal values for those hyper-parameters. For those experiments, R50-FasterRCNN is used as the teacher, while R18-FasterRCNN is used as the student. The training schedule is 1x.

Memory Queue. We implement a memory queue borrowing the idea from [11] to increase the number of negative samples. As given by the Proofs, a large queue size $K$ is theoretically beneficial for the training objective. However, we observe that a large $K$ does not necessarily lead to a better result. The optimal value for $K$ is around 80x1024. As a single GPU has 1024 proposal features per batch, 8x1024 proposal features can be directly obtained by gathering from all 8 GPUs, the additional negative samples are formed using representations from previous batches. In addition, we observe that the training becomes unstable and the loss often explodes when $K$ is too large. The experimental results are shown in Table 9.
Figure 7. Performance plots for different values of memory queue size and IoU threshold. The optimal IoU threshold is around 0.5, while the best memory queue size is 1024 × 80.

### Table 9. Performance of Contrastive KD with different memory sizes. The results show that the optimal memory size $K$ is around 1024*80.

| Memory Size | Student | AP       |
|-------------|---------|----------|
| 1024*8      | R18     | 36.8±2.8 |
| 1024*40     |         | 36.9±2.9 |
| 1024*80     | FasterRCNN | 37.1±3.1 |
| 1024*120    | (34.0)  | 37.0±3.0 |
| 1024*160    |         | 36.9±2.9 |

### Table 10. Performance of Contrastive KD with different IoU thresholds for negative assignment. The results show that the optimal IoU threshold is around 0.5.

| IoU Threshold | Student | AP       |
|---------------|---------|----------|
| 0.1           | R18     | 36.8±2.8 |
| 0.3           |         | 36.9±2.9 |
| **0.5**       | FasterRCNN | **37.1±3.1** |
| 0.7           | (34.0)  | 37.0±3.0 |
| 0.9           |         | 36.8±2.8 |
| 1.0           |         | 36.8±2.8 |

Threshold value is around 0.5.

The performance curves plotted by varying the values for memory queue size and IoU threshold are demonstrated in Figure 7.

### B.1. Projection Head

Recall that the critic function $g(r_s, r_t) = \exp \left( \frac{f_\theta(r_s) \cdot f_\theta(r_t)}{\|f_\theta(r_s)\| \cdot \|f_\theta(r_t)\|} \right)$ utilizes a projection head $f_\theta$ to map the representations to a lower dimension for both student and teacher. [5] claimed that using a nonlinear projection head improves the representation quality. However, this finding does not apply in our case. We observe that linear projection head outperforms its nonlinear counterpart. We assume this is because introducing nonlinearity into the projection further complicates the learning process. The experiments are shown in Table 11.

### B.2. Forming Contrastive Pairs for Heterogeneous Detectors

As elaborated in the main paper, when dense prediction detector is used as the student, the contrastive pairs are constructed using the representations of the teacher’s last fully connected layer and the corresponding features from the last layer of student’s classification branch. However, the representations from student’s localization branch may also be used for CKD. We compare the performance of different ways to construct contrastive pairs. The observation is that using student’s classification representations brings to the most gain. We assume this is because the effectiveness of CKD is reflected mostly on its classification ability. The results are shown in Table 12.

### Table 11. Comparison between nonlinear and linear projecting heads. Linear projection head outperforms its nonlinear counterpart for our CKD.

| Method   | Projection | AP      |
|----------|------------|---------|
| Baseline | N/A        | 34.0    |
| CKD      | nonlinear  | 36.7±2.7|
|          | **linear** | **37.1±3.1** |

### Table 12. Performance of Contrastive KD using representations from different branches of the student. The results show that using representation from student’s classification branch leads to the most performance gain. “combined” means summing up the corresponding representations from both heads for forming contrastive pairs.

| Branch      | Student | AP      |
|-------------|---------|---------|
| classification | R18     | 35.8±3.2|
| localization | RetinaNet | 34.3±1.7|
| combined     | (32.6)  | 35.1±2.5|

### Table 13. Comparison between class-agnostic and class-aware regression losses. 'N' means class-agnostic; 'Y' means class-aware. Class-agnostic loss only distills the regression outputs corresponding to the proposal’s ground truth class, while class-aware loss incorporates the uncertainty information by calculating the sum of all regression outputs weighted by their corresponding class confidence. The result shows a significant boost when applying our class-aware loss.

| Method | Class-aware | AP      |
|--------|-------------|---------|
| Baseline | N/A        | 34.0    |
| Regression | N          | 34.7±1.7|
|          | Y           | **35.7±1.7** |

C. Localization Distillation with Uncertainty

We show in Table 13 the superior performance of our proposed class-aware localization distillation (elaborated in Section 4.3.1 of the main paper) in contrast to the regular approach which adopts L1 loss. As can be seen, our CAReg outperforms the regular KD by a large margin.
| Model         | Student | Teacher | AP   |
|---------------|---------|---------|------|
| Faster-RCNN-C4| R18 (22.0) | R50 (34.8) | 29.1 |
|               | R50 (31.9) | R50 (34.8) | 34.7 |
|               | R101 (36.0) | R50 (34.8) | 36.8 |
| Faster-RCNN-Cascade | R18 (36.5) | R50 (43.0) | 40.4 |
|               | R50 (40.3) | R50 (43.0) | 42.5 |
|               | R101 (42.5) | R50 (43.0) | 43.3 |

Table 14. Our KD framework shows performance gains for students with different structures and capacities. The values in the parentheses indicate baseline APs.

D. Prediction Distillation for Heterogeneous Detectors

Knowledge distillation using the prediction outputs for heterogeneous detector pairs is not straightforward, since the loss functions used during training are usually different, which causes the outputs to carry different meanings. E.g., two-stage detectors use cross entropy loss, and dense prediction detectors often adopt focal loss [17]. We attempt to conduct KD on the prediction outputs of FasterRCNN teacher and RetinaNet student by converting the student’s outputs to make it have the same meaning as the teacher’s outputs. Specifically, we apply softmax function on the class dimension of student logits, the result is divided by its maximum on the class dimension. Then we extract only the values for object classes to obtain class predictions, which has the same dimension as the teacher’s prediction outputs. The conversion can be formulated by:

$$P_s = \frac{\text{softmax}(L_s)}{\text{max}(\text{softmax}(L_s))} [1, ..., C]$$

where $L_s \in \mathbb{R}^{N \times C+1}$ is the logits from the student detector, $N$ is the batch size and $C$ is the number of classes (excluding background); $\text{softmax}$ is the softmax function performed on the class dimension; max takes the maximum from the class dimension; $[1, ..., C]$ means take only the values for object classes.

The KD loss can be formulated as: $L_{cls} = \frac{1}{N} \sum^N P_t \log P_s$, where $P_s \in \mathbb{R}^{N \times C}$, $P_t \in \mathbb{R}^{N \times C}$ are the class scores of the student and the teacher, respectively.

E. Generalization Ability of G-DetKD

We conduct additional experiments to explore the generalization ability of our G-DetKD for various detector architectures with different capacities. The results in Table 14 shows our method consistently improves the student’s performances. Homogeneous detector pairs are used.

F. Proofs

In this section, we provide proofs for: (1) the optimal critic function $g^*(r_s,r_t)$ is proportional to the ratio between the joint distribution $p(f_a(r_s), f_a(r_t))$ and the product of marginal distributions $p(f_a(r_s)) p(f_a(r_t))$. i.e., $g^*(r_s,r_t) \propto \frac{p(f_a(r_s), f_a(r_t))}{p(f_a(r_s)) p(f_a(r_t))}$; (2) Minimizing our contrastive loss $L_{c_kd}$ has the effect of maximizing the lower bound on the mutual information (MI) between the teacher’s and student’s latent representations. Our proof follows the standard structure outlined in [29, 20].

F.1. Critic function

Mutual information is defined as the $KL$ divergence between the joint distribution and the product of marginal distribution of two random variables:

$$MI(X;Y) = D_{KL}(P_{XY}(x,y) || P_X(x) P_Y(y))$$

$$= \sum_{x,y} P_{XY}(x,y) \log \frac{P_{XY}(x,y)}{P_X(x) P_Y(y)}$$

$$= \mathbb{E}_{P_{XY}} \log \frac{P_{XY}(x,y)}{P_X(x) P_Y(y)}$$

Thus, the first step of our proof is that the optimal critic function $g^*(r_s,r_t)$ is proportional to the ratio between the joint distribution and the product of marginal distributions. Note that $g$ contains a learnable projection mapping $f_a$ and here we denote $g^*$ as the critic function with the optimal parameters $\theta^*$. We can consider the distribution of positive pairs as $p_{pos} = p(r_s,r_t)$ (the joint distribution) and the distribution of negative pairs as $p_{neg} = p(r_s)p(r_t)$ (the product of marginal distributions) Suppose the $\{r^i_s,r^i_t\}$ forms a positive sample pair (the representation of the same proposal feature), all other teacher’s representations $\{r^j_t\} (i \neq j)$ form negative pairs with $\{r^i_s,r^j_t\}$ (representations of different proposal features). Namely, $\{r^i_s,r^j_t\}$ is a sample from $p_{pos}$ while all other pairs $\{r^i_s,r^j_t\} (i \neq j)$ are samples from $p_{neg}$. We denote the optimal probability to be $p(pos = i)$. Thus, we can have the following equation:

$$p(pos = i) = \frac{p_{pos}(r^i_s,r^i_t) \prod_{n=0, n \neq i}^k p_{neg}(r_n^i, r_n^t)}{\sum_{j=0}^k p_{pos}(r^i_s, r^j_t) \prod_{n=0, n \neq j}^k p_{neg}(r_n^i, r_n^t)}$$

$$= \frac{p(r^i_s,r^i_t) \prod_{n=1, n \neq i}^k p(r_n^s)}{\sum_{j=0}^k p_{pos}(r^i_s, r^j_t) \prod_{n=0, n \neq j}^k p(r_n^i)}$$

$$= \frac{p(r^i_s,r^i_t)}{\sum_{j=0}^k p(r^i_s, r^j_t) p(r_n^i)}$$

$$= \frac{g^*(r^i_s,r^i_t)}{\sum_{j=0}^k g^*(r^i_s, r^j_t)}$$
We first plug in $p_{pos}$ and $p_{neg}$, then divide the nominator and denominator by $\prod_{n=1}^{k} p_{neg}(r_s^n, r_t^n)$ at the same time, which leads to the final form of the equation. Note that $g$ can be defined for either the original feature inputs $\{r_s, r_t\}$ or the latent representations $\{f_0(r_s), f_0(r_t)\}$. As the latent representations are used in practice, we will replace $\{r_s, r_t\}$ by $\{\gamma_s, \gamma_t\}$ in following proofs (we denote $f_0(r)$ as $\gamma$ for simplicity). We can see that according to the definition of our loss function, $g^*(r_s, r_t)$ is actually proportional to $p(\gamma_s, \gamma_t) p(\gamma_s) p(\gamma_t)$.

**F.2. Maximizing the lower bound of MI**

As derived from above, $g^*(r_s, r_t) \propto \frac{p(z_s, z_t)}{p(z_s) p(z_t)}$, we can then substitute the $g^*(r_s, r_t)$ in our loss function by $\frac{p(z_s, z_t)}{p(z_s) p(z_t)}$, then we have the following expression:

$$ L_{ckd}^{opt} = - \mathbb{E} \log \left[ \frac{g^*(r_s^i, r_t^i)}{\sum_{j}^{K} g^*(r_s^i, r_t^i)} \right] $$

$$ = - \mathbb{E} \log \left[ \frac{\frac{p(\gamma_s^i, \gamma_t^i)}{p(\gamma_s^i) p(\gamma_t^i)}}{\sum_{j}^{K} \frac{p(\gamma_s^j, \gamma_t^j)}{p(\gamma_s^j) p(\gamma_t^j)}} \right] $$

$$ = \mathbb{E} \log \left[ \frac{p(\gamma_s^i) p(\gamma_t^i)}{p(\gamma_s^i, \gamma_t^i)} \sum_{j \neq i}^{K} \frac{p(\gamma_s^j, \gamma_t^j)}{p(\gamma_s^j) p(\gamma_t^j)} + 1 \right] $$

$$ \approx \mathbb{E} \log \left[ \frac{p(\gamma_s^i) p(\gamma_t^i)}{p(\gamma_s^i, \gamma_t^i)} K + 1 \right] $$

$$ \geq \log (K) - \mathbb{E}_{p_{pos}} \log \left[ \frac{p(\gamma_s^i, \gamma_t^i)}{p(\gamma_s^i) p(\gamma_t^i)} \right] $$

$$ = \log (K) - \mathbb{E}_{p_{pos}} \log \left[ \frac{p(\gamma_s^i) p(\gamma_t^i)}{p(\gamma_s^i) p(\gamma_t^i)} \right] $$

$$ = \log (K) - MI (f_0(r_s); f_0(r_t)) $$

As can be seen, minimizing $L_{ckd}$ can be interpreted as maximizing the mutual information between $\{z_s, z_t\}$. We can notice in the equation that larger $K$ leads to a tighter lower bound, thus it is theoretically beneficial to set $K$ to be a very large number. However, we experimentally find that it is not true for our contrastive KD in object detection. The experiments are shown in previous section.