



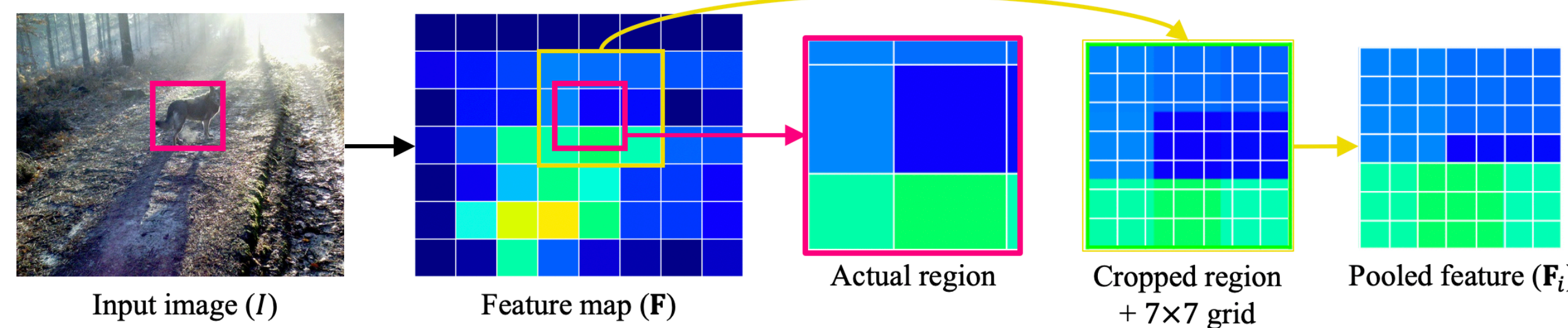
Summary

Problem: poor performance of a proposal-based detector using feature-level super-resolution on small objects

Cause: absence of direct supervision from target features

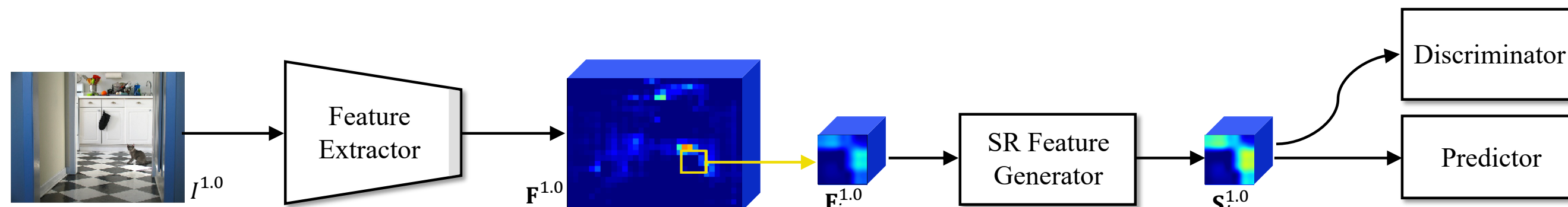
Solution: novel approach to "properly" extract target features as direct supervision

Difficulty of Detecting Small objects

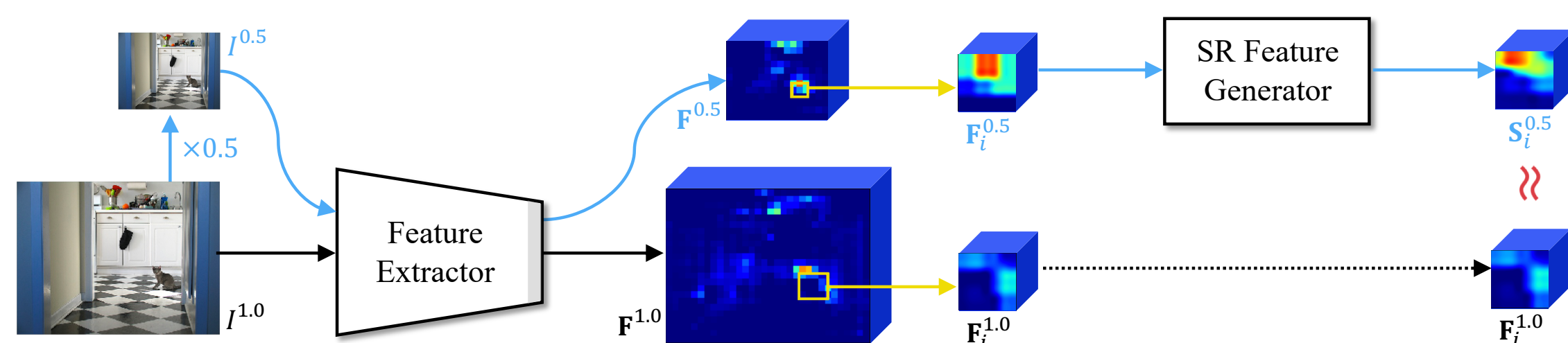


- 1. RoI pooled features do not contain detailed information due to its size
2. In the process of RoI pooling, internal positions are distorted
Then? Super-resolve features as large objects!

Methods to Generate Super-Resolution



- Step 1. Generate super-resolution features (Si^1.0) from an original image
1. To be similar to high-resolution features of a large object (Discriminator)
2. So that a class and box offsets of the small object are correctly predicted (Predictor)
-> But without supervision, training of the super-resolution feature generator can be unstable

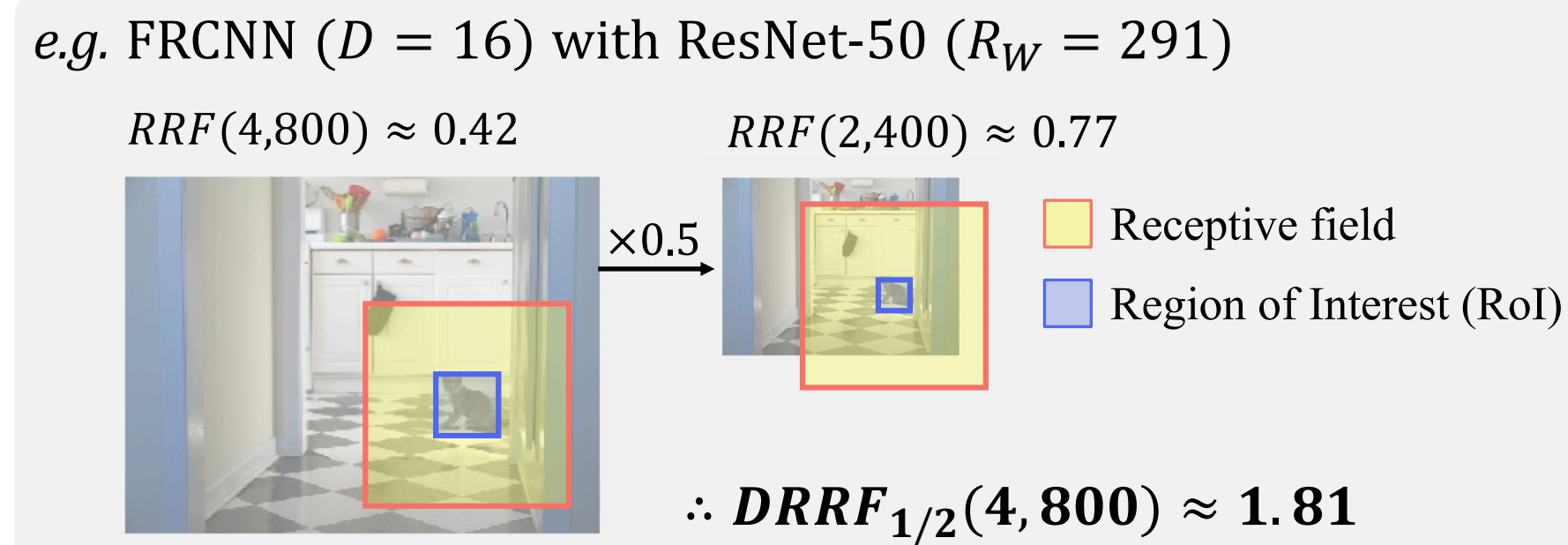
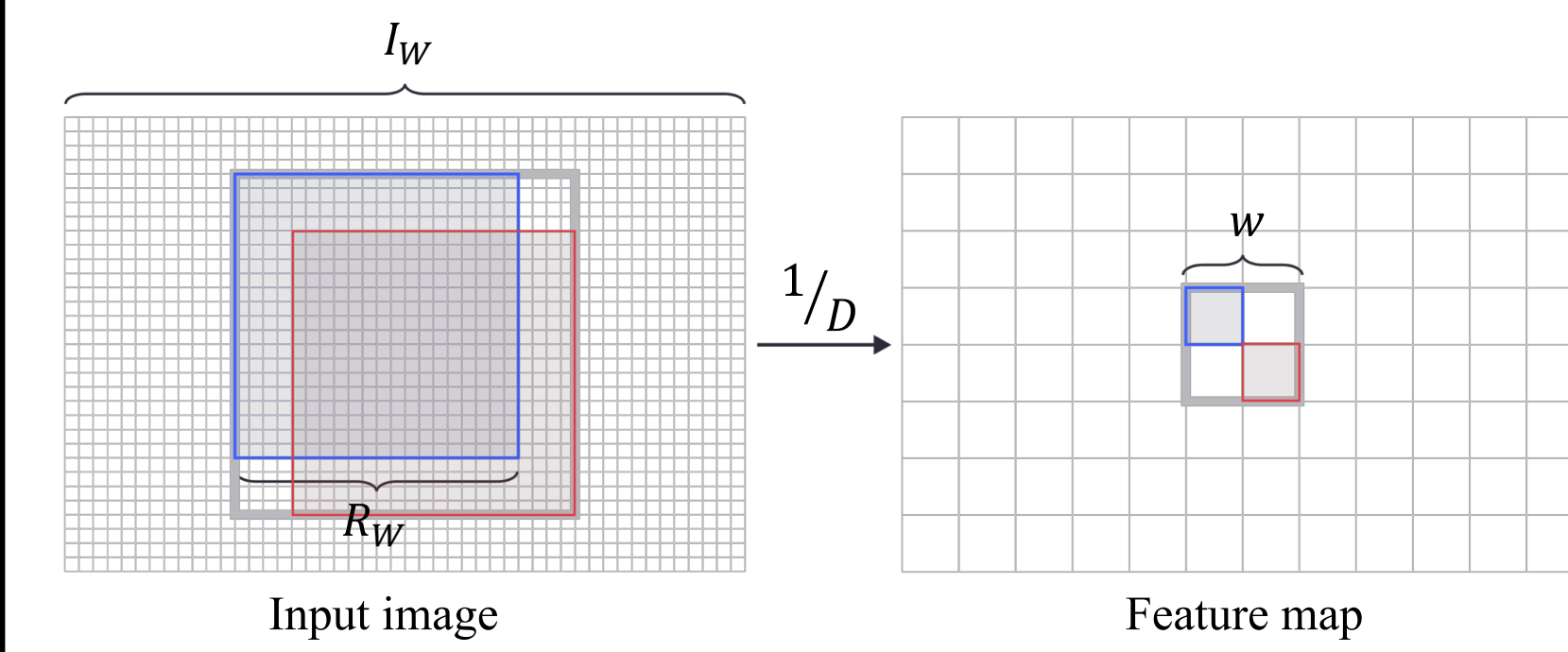


- Step 2. Generate super-resolution features (Si^0.5) from a downsampled image
3. To be similar to the corresponding naive targets (Fi^1.0)
-> Even with naive supervision, it is hard to imitate target features due to high disparity between input (Fi^0.5) and target features (Fi^1.0)

References

[1] Zhe Zhu, et al. Traffic-Sign Detection and Classification in the Wild. In CVPR, 2016.
[2] Jianan Li, et al. Perceptual Generative Adversarial Networks for Small Object Detection. In CVPR, 2017.
[3] Zhenwen Liang, et al. Small Object Detection Using Deep Feature Pyramid Networks. In Pacific Rim Conference on Multimedia, 2018.
[4] Zibo Meng, et al. Detecting Small Signs from Large Images. In IRI, 2017.

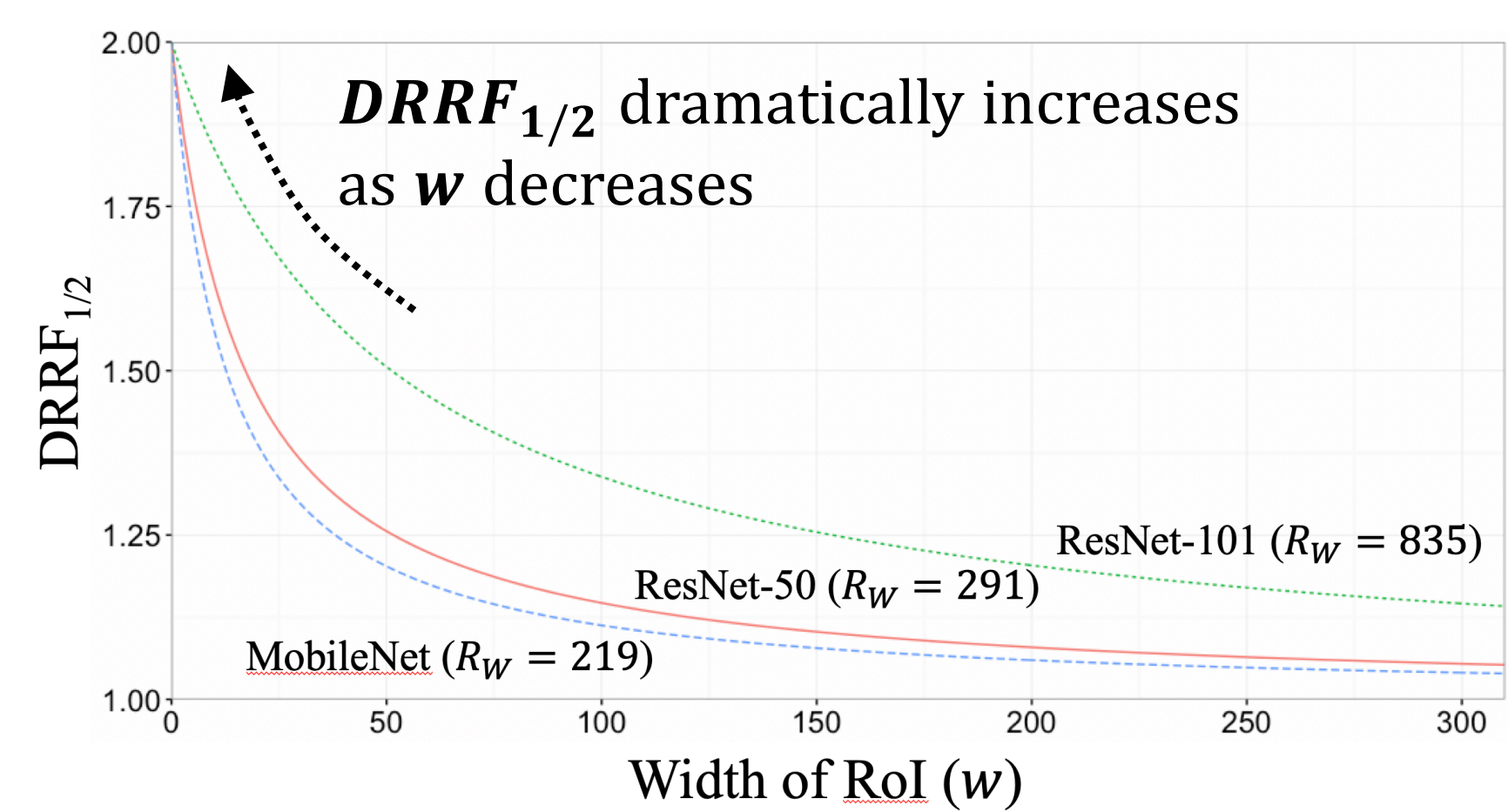
Mismatch of Relative Receptive Fields



- ARF: Absolute Receptive Field ARF(w) = RW + (w - 1) * D
RRF: Relative Receptive Field RRF(w, IW) = (RW + (w - 1) * D) / IW
DRRF: Discrepancy in RRF of the RoIs between the original and downsampled images

DRRF1/2(w, IW) = RRF(w/2, IW/2) / RRF(w, IW) = 2 - w / (c + w) where c = RW / D - 1

-> RRF of the RoI from the downsampled image is around 1.81 times larger than that from the original image

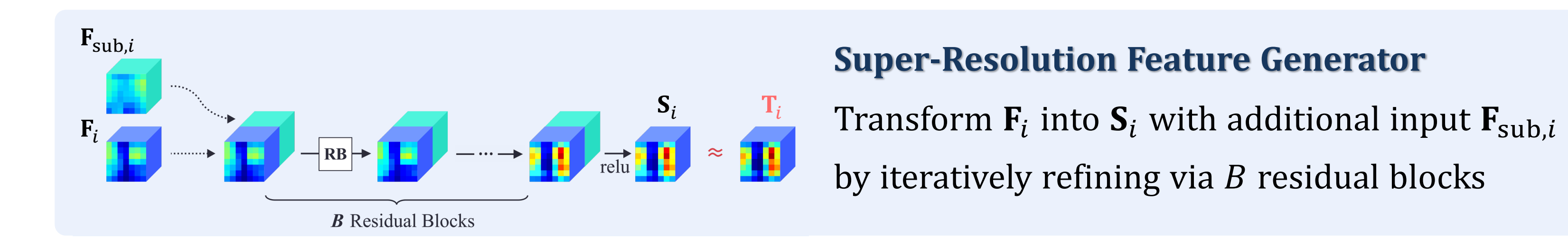
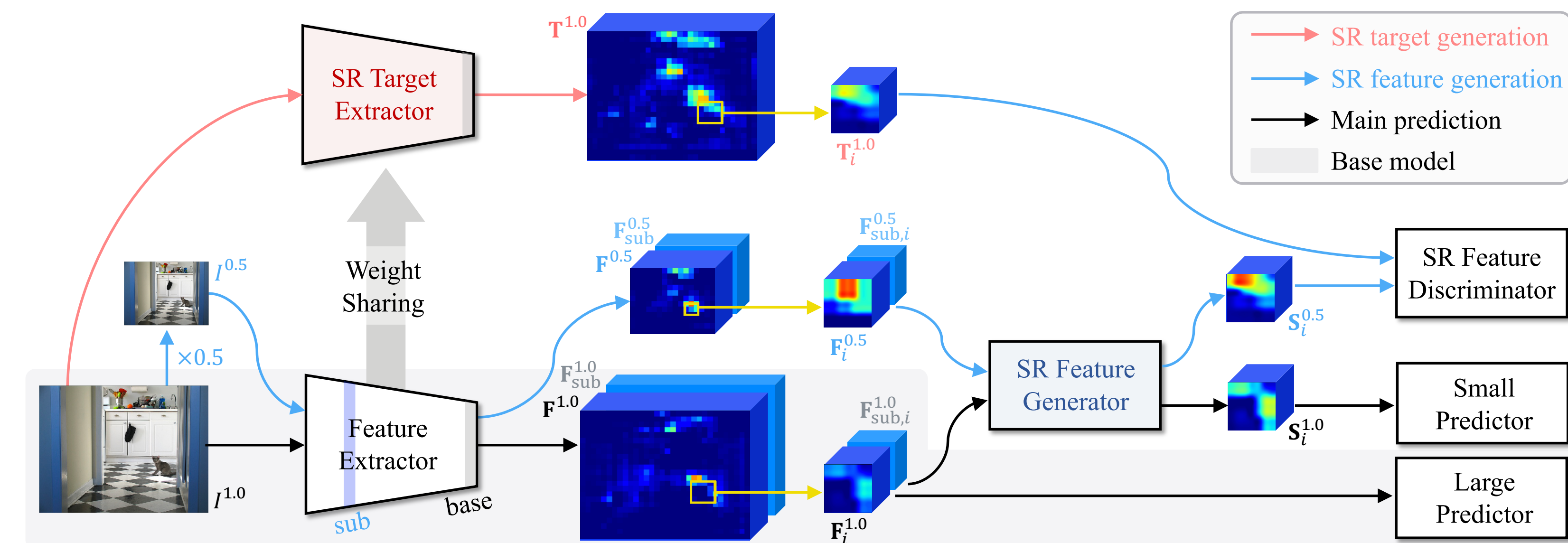
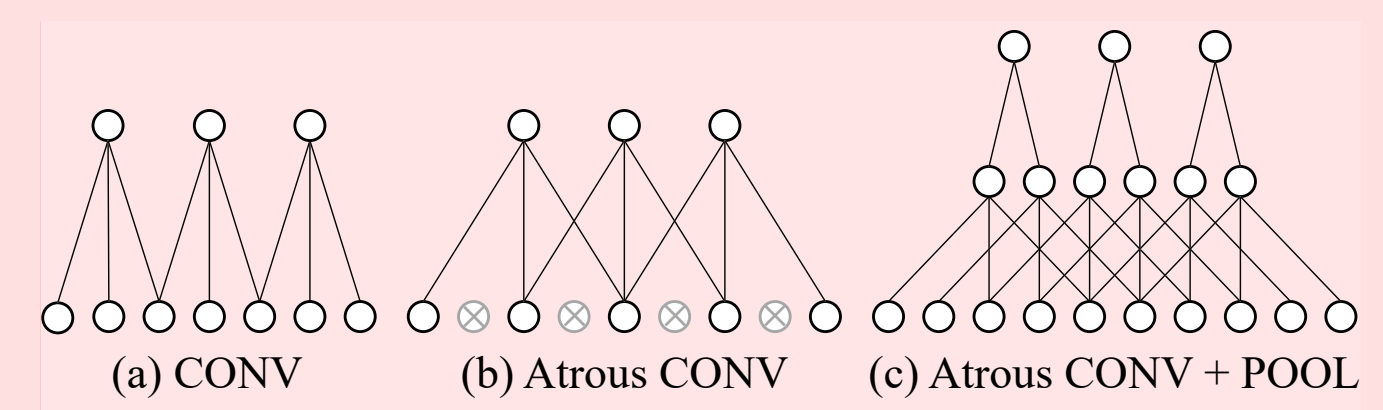


Our Approach

Super-Resolution Target Extractor

Replace every layer that increases relative field of feature extractor with a layer that doubles it (k: kernel size, s: stride, r: dilation rate)

- k x k POOL (k > 1) -> 2k x 2k POOL to use the same weights
k x k CONV (k > 1, s = 1) -> k x k Atrous CONV (r = 2, s = 1) not to skip every other pixel
k x k CONV (k > 1, s = 2) -> k x k Atrous CONV (r = 2, s = 1) + 2 x 2 POOL (s = 2)



Quantitative Results

Tsinghua-Tencent 100K

1. Results on different backbones (input: 1600x1600)

Table with columns: Model, Small (Rec, Acc, F1), Medium (Rec, Acc, F1), Large (Rec, Acc, F1), Overall (Rec, Acc, F1). Rows include MobileNet, ResNet-50, and ResNet-101 with and without 'Ours'.

- Consistent improvement over the base models regardless of the backbones
Performance (F1) improvement: small > medium > large

2. Comparison with SOTA models (input: 2048x2048)

Table comparing 'Ours' with SOTA models like Zhu et al., Perceptual GAN, Liang et al., and SOS-CNN across Small, Medium, Large, and Overall metrics.

3. Comparison of super-resolution methods

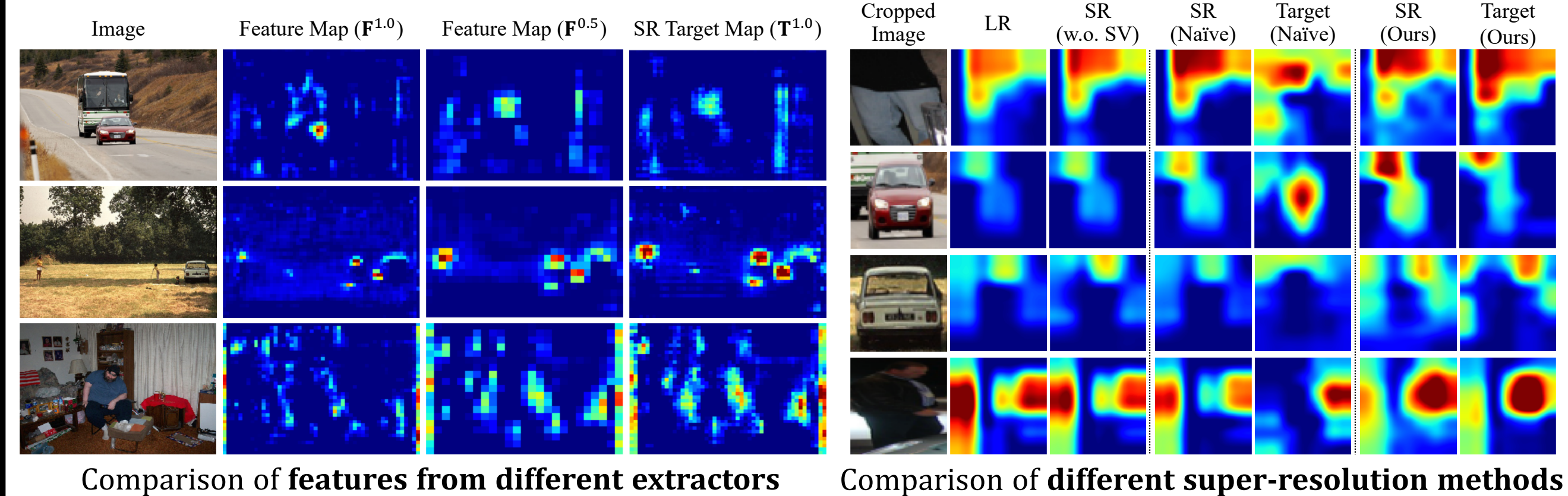
Table comparing 'Ours' with Base model (ResNet-50), SR (w.o. supervision), SR (Naive supervision), and SR (Ours) across Small, Medium, Large, and Overall metrics.

PASCAL VOC & MS COCO

Table comparing 'Ours' with other models on PASCAL VOC and MS COCO datasets across AP-S, AP-M, AP-L, AP-S:95, AP-75, and AP-L metrics.

Qualitative Results

Visualization of Features



Detection results on Tsinghua-Tencent 100K (G: TP, R: FP, B: FN)

