IEEE Conference on Computer Vision and Pattern Recognition
CVPR JUNE 14-19 2020

# Closed-loop Matters: Dual Regression Networks for Single Image Super-Resolution

Yong Guo*, Jian Chen*, Jingdong Wang*, Qi Chen, Jiezhang Cao, Zeshuai Deng, Yanwu Xu†, Mingkui Tan†

## Background and Motivation

**Limitations** of existing super-resolution methods:

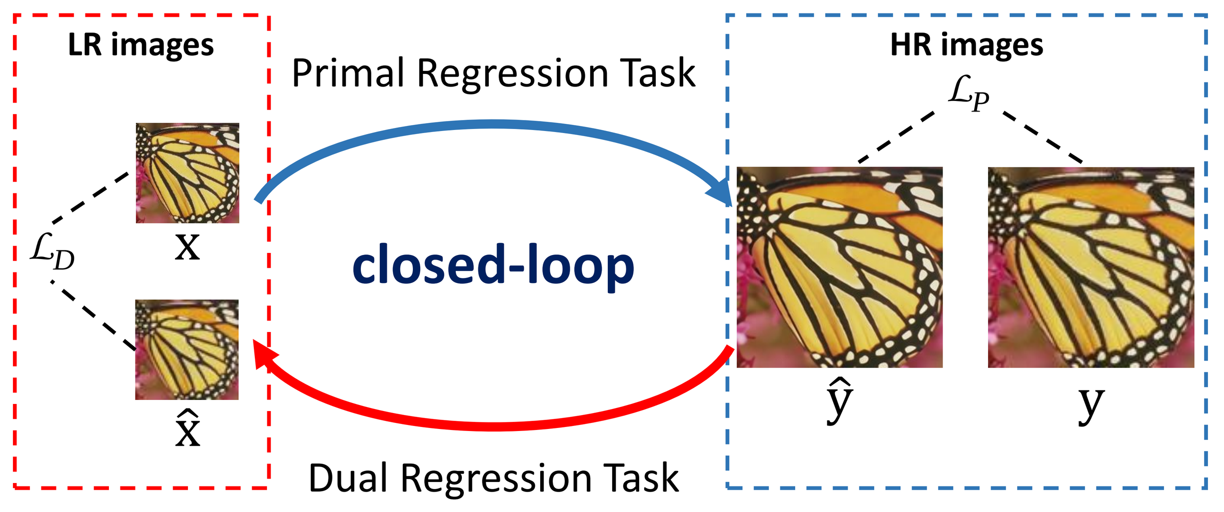
- The space of the possible functions that map LR to HR images is **extremely large**, since there exist **infinitely many** HR images that can be downscaled to obtain the same LR image.
- It is hard to obtain a promising SR model when **the paired data are unavailable**.

## Contributions

- We propose a novel and theoretically guaranteed **dual regression scheme** that can reduce the possible function space to enhance the performance of SR models.
- With the dual regression scheme, deep models can be **easily adapted** to unpaired real-world data, *e.g.*, raw video frames from YouTube.
- Extensive experiments demonstrate the **effectiveness** of the proposed dual regression scheme on both the SR tasks with **paired** training data and **unpaired real-world** data.

## Dual Regression Scheme

The dual regression scheme contains a **primal regression task** for super-resolution and a **dual regression task** to project super-resolved images back to LR images.




The primal and dual regression tasks form a **closed-loop** to reduce the space of possible mapping function, which helps to achieve **more accurate** SR predictions.

## Training Method for Paired Data

**Training Method:** Given paired data, the model is trained by minimizing Eqn. (1) under the learning scheme of supervised SR methods.

**Training Loss:**

$$\sum_{i=1}^{N} \underbrace{\mathcal{L}_P\Big(P(\mathbf{x}_i), \mathbf{y}_i\Big)}_{\text{primal regression loss}} + \lambda \underbrace{\mathcal{L}_D\Big(D(P(\mathbf{x}_i)), \mathbf{x}_i\Big)}_{\text{dual regression loss}}, \qquad (1)$$

- $N$ is the number of paired samples, $\mathbf{x}_i$ and $\mathbf{y}_i$ denote the i-th pair of low- and high-resolution images.
- $\mathcal{L}_P$ and $\mathcal{L}_D$ denote the loss function ($\ell_1$-norm) for the primal and dual regression tasks.

## Training Method for Unpaired Data

**Training Method:** As shown in Algorithm 1, the model is trained by minimizing Eqn. (2) when given both paired and unpaired data.

**Training Loss:**

$$\sum_{i=1}^{M+N} \mathbf{1}_{\mathcal{S}_P}(\mathbf{x}_i)\mathcal{L}_P\Big(P(\mathbf{x}_i), \mathbf{y}_i\Big) + \lambda \mathcal{L}_D\Big(D(P(\mathbf{x}_i)), \mathbf{x}_i\Big), \qquad (2)$$

- $M$ and $N$ donate the number of unpaired LR samples $\mathcal{S}_U$ and paired synthetic samples $\mathcal{S}_P$, respectively.
- $\mathbf{1}_{\mathcal{S}_P}(\mathbf{x}_i)$ is an indicator function that equals 1 when $\mathbf{x}_i \in \mathcal{S}_P$, and otherwise the function equals 0.

**Algorithm 1:** Adaptation Algorithm on Unpaired Data.

```
Input: Unpaired real-world data: S_U;
       Paired synthetic data: S_P;
       Batch sizes for S_U and S_P: m and n;
       Indicator function: 1_{S_P}(·).
Load the pretrained models P and D.
while not convergent do
    Sample unlabeled data {x_i}_{i=1}^m from S_U;
    Sample labeled data {(x_i, y_i)}_{i=m+1}^{m+n} from S_P;
    // Update the primal model
    Update P by minimizing the objective:
        sum_{i=1}^{m+n} 1_{S_P}(x_i) L_P(P(x_i), y_i) + λ L_D(D(P(x_i)), x_i)
    // Update the dual model
    Update D by minimizing the objective:
        sum_{i=1}^{m+n} λ L_D(D(P(x_i)), x_i)
end
```

## Theoretical Analysis

**Theorem 1.** *Let $\mathcal{L}_P(P(\mathbf{x}), \mathbf{y}) + \lambda \mathcal{L}_D(D(P(\mathbf{x})), \mathbf{x})$ be a mapping from $\mathcal{X} \times \mathcal{Y}$ to $[0, C]$ with the upper bound $C$, and the function space $\mathcal{H}_{dual}$ be infinite. Then, for any error $\delta > 0$, with probability at least $1-\delta$, the generalization error $E(P, D)$ (i.e., expected loss) satisfies for all $(P, D) \in \mathcal{H}_{dual}$:*

$$E(P, D) \leq \hat{E}(P, D) + 2\hat{R}_Z^{DL}(\mathcal{H}_{dual}) + 3C\sqrt{\frac{1}{2N}\log\left(\frac{1}{\delta}\right)},$$

*where $N$ is the number of samples, $\hat{E}(P, D)$ is empirical loss and $\hat{R}_Z^{DL}$ is the empirical Rademacher complexity of dual learning. Let $\mathcal{B}(P, D)$ be the generalization bound of the dual regression SR, i.e. $\mathcal{B}(P, D) = 2\hat{R}_Z^{DL}(\mathcal{H}_{dual}) + 3C\sqrt{\frac{1}{2N}\log\left(\frac{1}{\delta}\right)}$, we have*

$$\mathcal{B}(P, D) \leq \mathcal{B}(P),$$

*where $\mathcal{B}(P)$, $P \in \mathcal{H}$ is the generalization bound of the supervised learning w.r.t. the Rademacher complexity $\hat{R}_Z^{SL}(\mathcal{H})$.*

Theorem 1 proves that the dual regression scheme has a **smaller generalization bound** than traditional SR methods.

## Results of Quantitative Comparison

- **Comparison results on SR tasks with paired data**

| Algorithms | Scale | #Params (M) | Set5 PSNR / SSIM | Set14 PSNR / SSIM | BSDS100 PSNR / SSIM | Urban100 PSNR / SSIM | Manga109 PSNR / SSIM |
|---|---|---|---|---|---|---|---|
| Bicubic | 4 | - | 28.42 / 0.810 | 26.10 / 0.702 | 25.96 / 0.667 | 23.15 / 0.657 | 24.92 / 0.789 |
| ESPCN [36] | | - | 29.21 / 0.851 | 26.40 / 0.744 | 25.50 / 0.696 | 24.02 / 0.726 | 23.55 / 0.795 |
| SRResNet [26] | | 1.6 | 32.05 / 0.891 | 28.49 / 0.782 | 27.61 / 0.736 | 26.09 / 0.783 | 30.70 / 0.908 |
| SRGAN [26] | | 1.6 | 29.46 / 0.838 | 26.60 / 0.718 | 25.74 / 0.666 | 24.50 / 0.736 | 27.79 / 0.856 |
| LapSRN [25] | | 0.9 | 31.54 / 0.885 | 28.09 / 0.770 | 27.31 / 0.727 | 25.21 / 0.756 | 29.09 / 0.890 |
| SRDenseNet [38] | | 2.0 | 32.02 / 0.893 | 28.50 / 0.778 | 27.53 / 0.733 | 26.05 / 0.781 | 29.49 / 0.899 |
| EDSR [28] | | 43.1 | 32.48 / 0.898 | 28.81 / 0.787 | 27.72 / 0.742 | 26.64 / 0.803 | 31.03 / 0.915 |
| DBPN [17] | | 10.4 | 32.42 / 0.897 | 28.75 / 0.786 | 27.67 / 0.739 | 26.38 / 0.794 | 30.90 / 0.913 |
| RCAN [53] | | 15.6 | 32.63 / 0.900 | 28.85 / 0.788 | 27.74 / 0.743 | 26.74 / 0.806 | 31.19 / 0.917 |
| SAN [9] | | 15.9 | 32.64 / 0.900 | 28.92 / 0.788 | 27.79 / 0.743 | 26.79 / 0.806 | 31.18 / 0.916 |
| RRDB [40] | | 16.7 | 32.73 / 0.901 | 28.97 / 0.790 | **27.83 / 0.745** | 27.02 / **0.815** | 31.64 / 0.919 |
| DRN-S | | 4.8 | 32.68 / 0.901 | 28.93 / 0.790 | 27.78 / 0.744 | 26.84 / 0.807 | 31.52 / 0.919 |
| DRN-L | | 9.8 | **32.74 / 0.902** | **28.98 / 0.792** | **27.83 / 0.745** | **27.03** / 0.813 | **31.73 / 0.922** |
| Bicubic | 8 | - | 24.39 / 0.657 | 23.19 / 0.568 | 23.67 / 0.547 | 20.74 / 0.515 | 21.47 / 0.649 |
| ESPCN [36] | | - | 25.02 / 0.697 | 23.45 / 0.598 | 23.92 / 0.574 | 21.20 / 0.554 | 22.04 / 0.683 |
| SRResNet [26] | | 1.7 | 26.62 / 0.756 | 24.55 / 0.624 | 24.65 / 0.587 | 22.05 / 0.589 | 23.88 / 0.748 |
| SRGAN [26] | | 1.7 | 23.04 / 0.626 | 21.57 / 0.495 | 21.78 / 0.442 | 19.64 / 0.468 | 20.42 / 0.625 |
| LapSRN [25] | | 1.3 | 26.14 / 0.737 | 24.35 / 0.620 | 24.54 / 0.585 | 21.81 / 0.580 | 23.39 / 0.734 |
| SRDenseNet [38] | | 2.3 | 25.99 / 0.704 | 24.23 / 0.581 | 24.45 / 0.530 | 21.67 / 0.562 | 23.09 / 0.712 |
| EDSR [28] | | 45.5 | 27.03 / 0.774 | 25.05 / 0.641 | 24.80 / 0.595 | 22.55 / 0.618 | 24.54 / 0.775 |
| DBPN [17] | | 23.2 | 27.25 / 0.786 | 25.14 / 0.649 | 24.90 / 0.602 | 22.72 / 0.631 | 25.14 / 0.798 |
| RCAN [53] | | 15.7 | 27.31 / 0.787 | 25.23 / 0.651 | 24.96 / 0.605 | 22.97 / 0.643 | 25.23 / 0.802 |
| SAN [9] | | 16.0 | 27.22 / 0.782 | 25.14 / 0.647 | 24.88 / 0.601 | 22.70 / 0.631 | 24.85 / 0.790 |
| DRN-S | | 5.4 | 27.41 / 0.790 | 25.25 / 0.652 | 24.98 / 0.605 | 22.96 / 0.641 | 25.30 / 0.805 |
| DRN-L | | 10.0 | **27.43 / 0.792** | **25.28 / 0.653** | **25.00 / 0.606** | **22.99 / 0.644** | **25.33 / 0.806** |

- **Comparison results on 8× SR tasks with unpaired synthetic data**

| Algorithms | Degradation | Set5 PSNR / SSIM | Set14 PSNR / SSIM | BSDS100 PSNR / SSIM | Urban100 PSNR / SSIM | Manga109 PSNR / SSIM |
|---|---|---|---|---|---|---|
| Nearest | Nearest | 21.22 / 0.560 | 20.11 / 0.485 | 20.64 / 0.471 | 17.76 / 0.454 | 18.51 / 0.594 |
| EDSR [28] | | 19.56 / 0.580 | 18.24 / 0.498 | 18.53 / 0.479 | 15.68 / 0.435 | 17.22 / 0.598 |
| DBPN [17] | | 18.80 / 0.541 | 17.36 / 0.461 | 17.94 / 0.456 | 15.07 / 0.400 | 16.67 / 0.550 |
| RCAN [53] | | 18.33 / 0.534 | 17.11 / 0.436 | 17.67 / 0.444 | 14.73 / 0.380 | 16.25 / 0.525 |
| CinCGAN [46] | | 21.76 / 0.648 | 20.64 / 0.552 | 20.89 / 0.528 | 18.21 / 0.505 | 18.86 / **0.638** |
| DRN-Adapt | | **23.00 / 0.715** | **21.52 / 0.561** | **21.98 / 0.539** | **19.07 / 0.518** | **19.83** / 0.613 |
| EDSR [28] | BD | 23.54 / 0.702 | 22.13 / 0.594 | 22.71 / 0.567 | 19.70 / 0.551 | 20.64 / 0.700 |
| DBPN [17] | | 23.05 / 0.693 | 21.65 / 0.586 | 22.50 / 0.565 | 19.28 / 0.538 | 20.16 / 0.689 |
| RCAN [53] | | 22.23 / 0.678 | 21.01 / 0.567 | 21.85 / 0.552 | 18.36 / 0.509 | 19.34 / 0.659 |
| CinCGAN [46] | | 23.39 / 0.682 | 22.14 / 0.581 | 22.73 / 0.554 | 20.36 / 0.538 | 20.29 / 0.670 |
| DRN-Adapt | | **24.62 / 0.719** | **23.07 / 0.612** | **23.59 / 0.583** | **20.57 / 0.591** | **21.52 / 0.714** |

## Results of Visualization Comparison

- **Visualization comparison results on paired data**

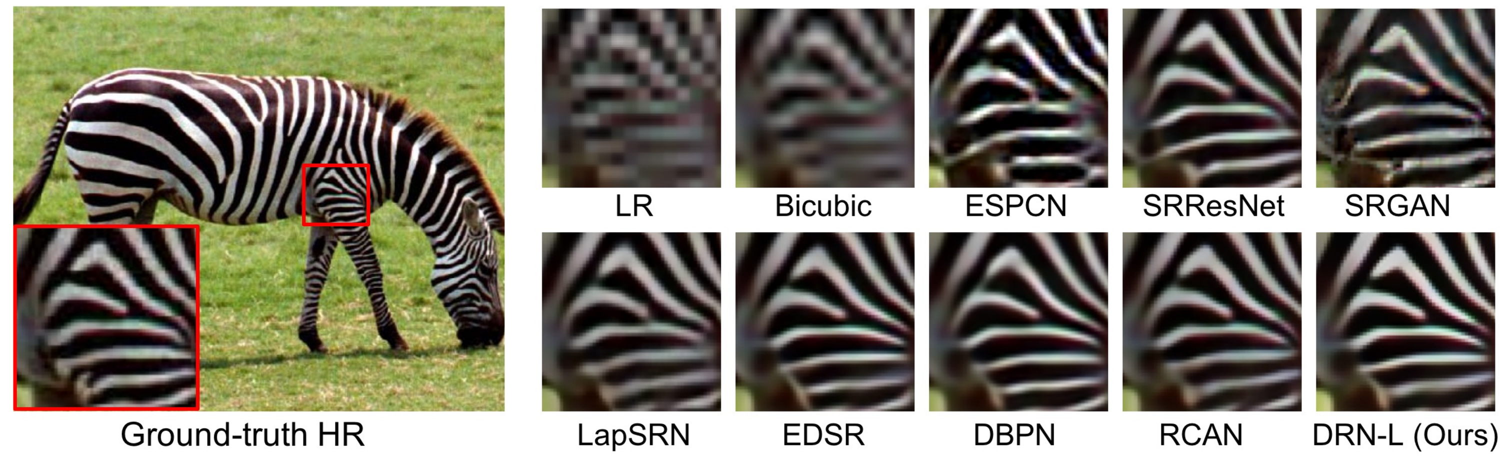



**Figure 1:** Visualization comparison on 4× SR with pair data.

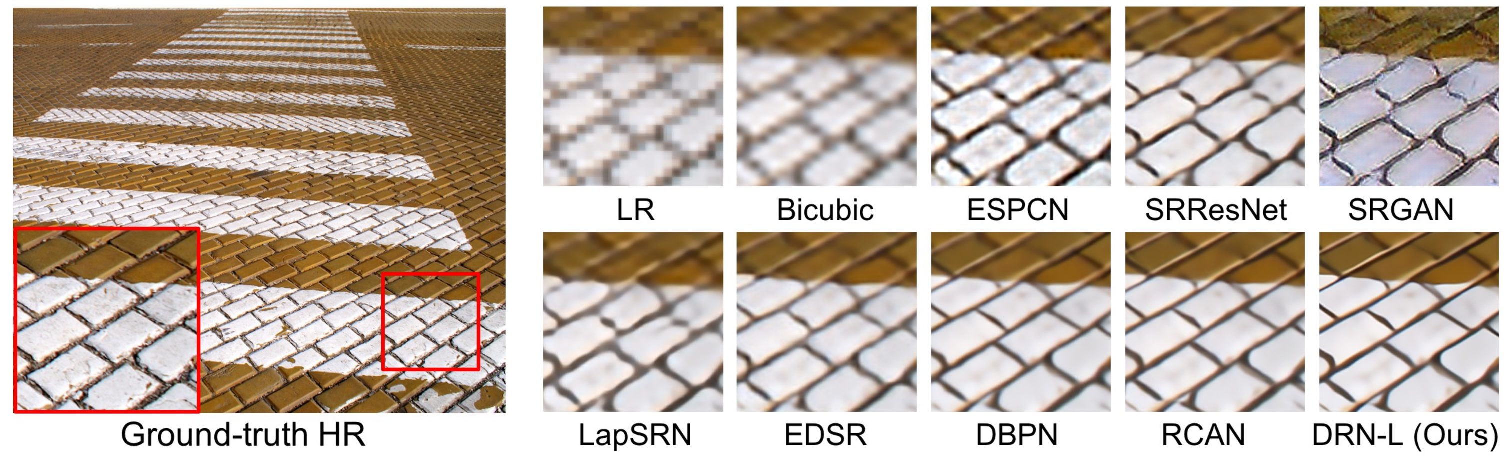



**Figure 2:** Visualization comparison on 8× SR with pair data.

- **Visualization comparison results on unpaired real-world data**


**Figure 3:** Visualization comparison on 8× SR with unpair real world data.

## Contact Information and Code

- Email: mingkuitan@scut.edu.cn
- Code: https://github.com/guoyongcs/DRN