RIFE: Real-Time Intermediate Flow Estimation for Video Frame Interpolation

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Abstract

We propose RIFE, a Real-time Intermediate Flow Estimation algorithm for Video Frame Interpolation (VFI). Most existing methods first estimate the bi-directional optical flows and then linearly combine them to approximate intermediate flows, leading to artifacts on motion boundaries. RIFE uses a neural network named IFNet that can directly estimate the intermediate flows from images. With the more precise flows and our simplified fusion process, RIFE can improve interpolation quality and have much better speed. Based on our proposed leakage distillation loss, RIFE can be trained in an end-to-end fashion. Experiments demonstrate that our method is significantly faster than existing VFI methods and can achieve state-of-the-art performance on public benchmarks. The code is available at https://github.com/hzwer/arXiv2020-RIFE.

1. Introduction

Video Frame Interpolation (VFI) aims to synthesize intermediate frames between two consecutive frames of a video and is widely used to improve the frame rate and enhance visual quality. VFI also supports various applications like slow-motion generation, video compression [31], and training data generation for video motion deblurring [4]. Moreover, VFI algorithms running on high-resolution videos (e.g., 720p, and 1080p) with real-time speed have many more potential applications, such as playing a higher frame rate video on the client’s player, providing video editing services for users with limited computing resources.

VFI is challenging due to the complex, large non-linear motions and illumination changes in the real world. Flow-based VFI algorithms have recently offered a framework to address these challenges and achieved impressive results [17, 22, 35, 2]. Common approaches for these methods involve two steps: 1) warping the input frames according to approximated optical flows and 2) fusing and refining the warped frames using a bunch of Convolutional Neural Networks (CNNs).

According to the way of warping frames, flow-based VFI algorithms can be classified into forward warping based methods and backward warping based methods. Backward warping is more widely used because forward warping lacks unified and efficient implementation and suffers from conflicts when multiple source pixels are mapped to the same location, which leads to overlapped pixels and holes.

Given the input frames $I_0, I_1$, backward warping based methods need to approximate the intermediate flows $F_{t \rightarrow 0}, F_{t \rightarrow 1}$ from the perspective of the frame $I_t$ that we are expected to synthesize. Common practice [17, 34, 2] first computes bi-directional flows from pre-trained off-the-shelf optical flow models, then linearly combines them. This combination, however, will fail on motion boundaries, as there will be different objects in the two frames. Consequently, previous VFI methods share two major drawbacks:

1) To solve the artifacts brought by the linear combination of optical flows, previous methods usually need to approximate various representations, e.g., image depth [2], intermediate flow refinement [17]. Coupled with the large complexity in the bi-directional flow estimation,
Given two input frames \( I_0, I_1 \), we directly feed them into our extremely efficient IFNet to get the intermediate flows \( F_{t \rightarrow 0}, F_{t \rightarrow 1} \). Then the fusion process takes the warped frames \( \hat{I}_{0 \rightarrow t}, \hat{I}_{1 \rightarrow t} \), intermediate flows \( F_{t \rightarrow 0}, F_{t \rightarrow 1} \) and the input frames \( I_0, I_1 \) as input. Inside the fusion process, a FusionMap and Residual is firstly estimated, then the warped frames are linearly combined according to the FusionMap, and added with the Residual to get reconstructed intermediate frame \( \hat{I}_t \).

none of these methods can achieve real-time speed.

2) Having no direct supervision for the approximated intermediate flows: The intermediate flow estimation process and later refine process is trained with only the final reconstruction loss. There is no other supervision explicitly designed for the flow estimation process, making the whole system hard to converge.

We first develop a specialized and efficient intermediate flow network named IFNet to directly estimate the intermediate flows. IFNet adopts a coarse-to-fine strategy with progressively increased resolutions: it iteratively updates a flow field via successive IFBlocks. Conceptually, according to the iteratively updated flow fields, we move corresponding pixels from two input frames to the same location in a latent intermediate frame. Unlike most previous optical flow models, IFNet does not contain expensive operators like cost volume or pyramid feature warping and simply uses ResNet block [11] as building blocks. This intentional and simple design can benefit from the out-of-the-box efficient implementation of ResNet blocks.

Employing strong intermediate supervision is also found to be important. In fact, when training the IFNet end-to-end with later fusion process using the final reconstruction loss, our method produces worse results than previous methods that used complex pipelines and pre-trained flow models in the intermediate flow estimation process. The picture changes dramatically after we proposed much more advanced supervision to our intermediate flow model, named leakage distillation loss. This novel loss employs an overpowered teacher with access to the intermediate frames during training.

Combining these designs, our algorithm can achieve excellent results when trained from scratch. We illustrate the speed and accuracy trade-off compared with other methods in Figure 1.

In summary, our contributions are three-fold:

- We design a novel and efficient IFNet to simplify the flow-based VFI methods. IFNet can be trained from scratch and directly approximate the intermediate flows given two input frames.
- We provide effective supervision for the IFNet by proposing an adapted census loss function and a novel leakage distillation loss function, which leads to a more stable convergence and large performance improvement.
- Our proposed RIFE is the first flow-based and real-time VFI algorithm that can process 720p videos at 30FPS. Experiments show that RIFE can achieve impressive performance on public benchmarks.

2. Related Work

We provide a brief overview of the optical flow estimation task, which is the core of most VFI methods. Then, we will review several most related flow-based VFI methods, and cover some inspiring flow-free methods.

2.1. Optical Flow

Optical flow estimation is a long-standing vision task that aims to estimate the per-pixel motion. It provides a useful representation that can be used in lots of downstream tasks like video alignment [5], video editing [33], and video analysis [36]. Since the milestone work of FlowNet [9] based on U-net autoencoder [27], architectures for optical flow model have evolved for several years, yielding
more accurate results while being more efficient, such as FlowNet2 [15], PWCNet [29] and LiteFlowNet [14]. These methods typically adopt an iterative refinement approach and often involve operators like cost volume, pyramidal features, and backward feature warping. Recently Teed et al. [30] introduce RAFT, which iteratively updates a flow field through a recurrent unit and achieves a big breakthrough in optical flow estimation. These methods usually use synthetic datasets [9, 15] to perform supervised learning because of the difficulty of optical flow labeling.

Another important direction in this area is unsupervised optical flow estimation learning because of the abundance of video data. Unsupervised methods try to use diverse real data to train an optical flow model that does not suffer from the mismatch between its training data and its test data. The general idea behind all the unsupervised optical flow is that we can use the accurate optical flow between two consecutive images to warp one image to reconstruct the other image’s non-occlusion area. These methods use many constraints such as the smoothness assumption of flow fields [21, 18].

2.2. Video Frame Interpolation

Jiang et al. [17] propose the first successful flow-based VFI algorithm named SuperSlomo. It uses the linear combination of the two bi-directional flows estimated by the off-the-shelf optical flow network as an initial approximation of the intermediate flows. Then refine them and predict visibility maps that encode occlusion information. SuperSlomo backward warps the input frames according to refined flow fields and linearly fuse them with the visibility maps to get final results. The whole system is trained with a reconstruction loss in an end-to-end fashion. Later improvements on flow-based VFI algorithms mainly focus on two major components: better flow estimation, better refinement, and fusion of the warped frames. Xu et al. [34] exploit four consecutive frames to get the intermediate flow estimation, then fuse the warped frames the same as SuperSlomo. Bao et al. [2] improve the flow estimation using a depth-aware flow projection layer, which estimates the intermediate flow as a weighted combination of bidirectional flow using a depth map computed by an off-the-shelf depth estimator, then utilize an adaptive warping layer and frame synthesis network to get the final results.

Along with flow-based methods, flow-free methods have also achieved remarkable progress in recent years. Niklaus et al. [25, 22] formulate VFI as a spatially-adaptive convolution whose convolution kernel is generated using a convolution network given the input frames. Choi et al. [8] propose an efficient flow-free, fully convolution method named CAIN, which employs the PixelShuffle operator and channel attention to implicitly capture the motion information. Our proposed RIFE achieves comparable results with state-of-the-art flow-based methods while enjoys the same level of efficiency with the fastest flow-free method.

3. Method

In this section, we first provide an overview of our proposed RIFE. We then describe the efficient design of the major components in RIFE in section 3.2, elaborate on our proposed leakage distillation loss in section 3.3, and explain the training details in section 3.4.

3.1. Pipeline Overview

We illustrate the overview of our proposed RIFE in Figure 2. Given a pair of consecutive RGB frames, \(I_0, I_1\), our goal is to synthesize an intermediate frame \(\hat{I}_t\) at time \(t \in (0, 1)\). Previous intermediate flow estimation methods use a bad assumption to directly reverse optical flows [17], which may cause artifacts on motion boundaries, depicted in Figure 3. Our proposed algorithm directly estimate the intermediate flow \(F_{t \rightarrow 0}\) by feeding input frames into IFNet. Then we get \(F_{t \rightarrow 1}\) using a linear motion assumption:

\[
F_{t \rightarrow 1} = \frac{1 - t}{t} F_{t \rightarrow 0}. \tag{1}
\]

Note the difference from bi-directional optical flow estimation with the target frame reference. Second, we can get two coarse results \(\hat{I}_{0 \rightarrow t}, \hat{I}_{1 \rightarrow t}\) by backward warping the input frames. To remove the artifacts in the warped frames, we feed the input frames, the approximated flow, and warped frames into the fusion process with an encoder-decoder like FusionNet to generate the interpolated frame.

3.2. Efficient Architecture Design

There are two major components in RIFE: (1) Efficient intermediate flow estimation with the IFNet. (2) Fusion process of the warped frames using a FusionNet. We describe the details of these components in this subsection.

**IFNet.** We illustrate the detailed architecture of IFNet in Figure 4. The role of our IFNet is to directly and efficiently predict \(F_{t \rightarrow 0}\) given two consecutive input frames \(I_0, I_1\).
To handle the large motion encountered in intermediate flow estimation, we employ a coarse-to-fine strategy with gradually increasing resolutions. Specifically, we first compute a rough prediction of the flow on low resolutions, which is believed to capture large motions easier, then iteratively refine the flow fields with gradually increasing resolutions. Following this design, our IFNet has a stacked hourglass structure, where a flow field is iteratively refined via downsampling and upsampling operators.

\[
F_{t=0}^i = F_{t=0}^{i-1} + g_i(F_{t=0}^{i-1}, \hat{F}_{0 \to t}, \hat{F}_{1 \to t}), \quad (2)
\]

where \(F_{t=0}^{i-1}\) denotes the current estimation of the intermediate flow, \(\hat{F}_{0 \to t}\) and \(\hat{F}_{1 \to t}\) denote the warped input frames using previous approximated flow, and \(g_i\) represents the \(i\)th IFBlock. We use a total of 3 IFBlocks, and each has a resolution parameter, \(K_i\). To keep our design simple, each IFBlock has a feed-forward structure consisting of a downsampling operator, 6 ResNet blocks, and an up-sampling operator.

In Figure 5, we provide visual results of our IFNet and compare them with the linearly combined bi-directional optical flow generated by a pre-trained LiteFlowNet [14]. Our IFNet produces clear and sharp motion boundaries, while linearly combined bi-directional optical flow suffers from overlapped pixels and blurring on motion boundaries.

Fusion process. With the estimated intermediate flows \(F_{t=0}, F_{t=1}\), we can get the coarse reconstruction \(\hat{I}_{0 \to t}, \hat{I}_{1 \to t}\) by performing backward warping on input frames. To reduce the severe artifacts in the warped frames, we perform a refine and fusion process formulated as:

\[
\hat{I}_t = M \odot \hat{I}_{0 \to t} + (1 - M) \odot \hat{I}_{1 \to t} + \Delta, \quad (3)
\]

where \(M\) is a soft fusion map used to fuse the two warped frames, \(\Delta\) is the reconstruction residual term used to refine the details in images, \(\odot\) is an element-wise multiplier, and \(0 \leq M, \Delta \leq 1\).

Following previous work [17, 2, 23], the fusion process includes a context extractor and a FusionNet with an encoder-decoder architecture similar to U-Net. The context extractor and encoder part of the FusionNet have similar architectures, consisting of 4 ResNet blocks with stride as 2. The decoder part in the FusionNet has four transpose convolution layers. We use the sigmoid function to restrict the
outputs of FusionNet.

First, we use the context extractor to extract pyramid contextual features from raw inputs separately. We denote the pyramid contextual feature as \(C_0 = \{C_0^1, C_0^2, C_0^3, C_0^4\}\) and \(C_1 = \{C_1^1, C_1^2, C_1^3, C_1^4\}\). We perform backward warping on these features using estimated intermediate flows to produce aligned pyramid features, \(C_{0\rightarrow t}\) and \(C_{1\rightarrow t}\). Then we feed the warped frames and intermediate flows to the FusionNet to produce the fusion map \(M\) and the reconstruction residual \(\Delta\), and the output of each block in the encoder part of the FusionNet is concatenated with the corresponding aligned pyramid features before fed into the next block.

Except for the layer that outputs the optical flow residuals, the fusion map, and the reconstruction residual, we use PReLU [10] as the activation function. We use Batch Normalization [16] in IFNet, which is common used to accelerate the convergence. We select a variant of ResNet block named SE-ResNet block [13], which can slightly improve the performance.

### 3.3. Leakage Distillation for IFNet

Directly approximating the intermediate flow is hard because of no access to the intermediate image and the lack of supervision. To address this problem, during training, we add a leakage distillation loss to our IFNet in which the target is the prediction of an overpowered teacher network who has access to the intermediate frame. Specifically, we feed \(\{I_0, I_t^{GT}\}\) to a pre-trained optical flow estimation network to get the intermediate flow prediction \(F_{t\rightarrow 0}\) and \(F_{t\rightarrow 1}\). And the leakage distillation loss \(L_{\text{dis}}\) is defined as follows:

\[
L_{\text{dis}} = ||F_{t\rightarrow 0} - F_{t\rightarrow 0}^{\text{Leak}}||_1 + ||F_{t\rightarrow 1} - F_{t\rightarrow 1}^{\text{Leak}}||_1. \tag{4}
\]

Our IFNet produces the final flow estimation using an iteratively update procedure, following previous work [30], we apply the leakage distillation loss over the full sequence of predictions.

Our distillation scheme is different from those in semi-supervised learning algorithms [7, 32], where a pre-trained model is used to infer the label of unlabeled data because, with the access of the target intermediate frame \(I_t^{GT}\), our teacher model has a different view of video clip with the student. Conceptually, the overpowered teacher causes a leakage [19] where our flow estimator can have access to the information of the target intermediate frame during training, and in the experiments section, we show that this kind of data (target) leakage is beneficial to the training of our whole system.

### 3.4. Implement Details

#### Supervision.

Given a pair of consecutive frames, \(I_0, I_1\), our training loss \(L\) is a linear combination of the reconstruction loss \(L_{\text{rec}}\), census loss \([21]\) \(L_{\text{cen}}\) and leakage distillation loss \(L_{\text{dis}}\) as defined in section 3.3:

\[
L = L_{\text{rec}} + \lambda_c L_{\text{cen}} + \lambda_d L_{\text{dis}}, \tag{5}
\]

where we set \(\lambda_c = 1\) and \(\lambda_d = 0.01\).

The reconstruction loss \(L_{\text{rec}}\) models the reconstruction quality of the intermediate frame. We denote the synthesized frame by \(\hat{I}_t\) and the ground-truth frame by \(I_t^{GT}\). The reconstruction loss has the formulation of:

\[
L_{\text{rec}} = \sum_x \rho \left( \hat{I}_t(x) - I_t^{GT}(x) \right), \tag{6}
\]

where \(\rho(x) = \sqrt{x^2 + \epsilon^2}\) is the Charbonnier penalty function [6]. We set the constant \(\epsilon\) to \(10^{-6}\).

As the brightness constancy constraint is often violated in realistic situations, census loss is widely used in unsupervised optical flow estimation [18] methods to address the illumination changes. We adopt the census loss in our framework to robustly handle the illumination changes between consecutive frames. The census loss is defined as the soft Hamming distance on census-transformed [37] image patches. We optimize the census loss between census-transformed \(\hat{I}_t\) and \(I_t^{GT}\) with the width of patches as 9.

#### Training dataset.

We use the Vimeo90K dataset [35] to train our model. The Vimeo90K dataset has 51,312 triplets for training, where each triplet contains three consecutive video frames with a resolution of 256 × 448. We train our network to predict the middle frame (i.e., \(t = 0.5\)) of each triplet. We randomly augment the training data by horizontal and vertical flipping and reversing the triplet’s temporal order during training.

#### Training strategy.

We train our system from scratch on the Vimeo90K training set. A LiteFlowNet [14] pre-trained on the FlyingChairs [9] dataset is used as the overpowered teacher in the leakage distillation.

Our model is optimized by AdamW [20] with weight decay \(10^{-5}\) for 300 epochs on the Vimeo90K training set. The training is based on 224 × 224 patches and uses a batch size of 64. We gradually reduce the learning rate from \(5 \times 10^{-4}\) to 0 using cosine annealing during the whole training process. Our pipeline is implemented in PyTorch. We train RIFE on four NVIDIA TITAN X (Pascal) GPUs, which takes about 15 hours to converge. The preprocess needs 2 hours in one GPU, and different models can use the same preprocess results.

### 4. Experiments

In this section, we conduct several experiments to validate our method. We first introduce the benchmarks for evaluation. Then we provide variants of our models with
Figure 6: **Qualitative comparison on Vimeo90K testing set.** We cut out the moving objects according to the green boxes and zoom in the results. While other methods cause various artifacts, our method produces best effects on the moving objects.

Table 2: **Quantitative comparisons on the UCF101, Vimeo90K, Middlebury OTHER set, and HD benchmarks.** The numbers in red and blue represent the best and second-best performance. We report the interpolation runtime for a single 640 × 480 video frame. The following works are sorted by publication time.

| Method         | # Parameters (Million) | Runtime (ms) | UCF101 [28] | Vimeo90K [35] | Middlebury [1] | HD [3] |
|----------------|------------------------|--------------|-------------|---------------|----------------|-------|
| TOFlow [35]    | 1.1                    | 430          | 34.58       | 0.967         | 33.73          | 0.968 | 2.15 | 29.37 |
| SepConv-\(L_1\) [24] | 21.6                  | 200          | 34.78       | 0.967         | 33.79          | 0.970 | 2.27 | 30.87 |
| MEMC-Net [3]   | 70.3                   | 121          | 35.01       | 0.968         | 34.40          | 0.970 | 2.12 | 31.60 |
| DAIN [2]       | 24.0                   | 125          | 35.00       | 0.968         | 34.71          | 0.976 | 2.04 | 31.64 |
| CAIN [8]       | 42.8                   | 32*          | 34.91       | 0.969         | 34.65          | 0.973 | 2.28 | 30.70*|
| SoftSplat [23] | 7.7                    | 135          | 35.39       | 0.970         | 36.10          | 0.980 | -   | -     |
| BMBC [26]      | 11.0                   | 770          | 35.15       | 0.969         | 35.01          | 0.976 | -   | -     |
| RIFE (Ours)    | 10.4                   | 21           | 35.14       | 0.969         | 35.69          | 0.978 | 2.05 | 32.04 |
| RIFE-Large (Ours) | 22.9               | 90           | 35.33       | 0.970         | 36.24          | 0.981 | 1.98 | 32.18 |

*: use officially released models to produce results
different computational costs to meet different needs in section 4.2. We compare our models with representative state-of-the-art methods, both quantitatively and visually, in section 4.3. An ablation study in section 4.4 is carried out to analyze our design of IFNet and the proposed leakage distillation loss. Finally, we show the capability of generating multiple frames using our models in section 4.5.

### 4.1. Benchmarks and Evaluation Metrics

We evaluate our model on four benchmarks, including Middlebury [1], UCF101 [28], Vimeo90K [35] and HD [3] benchmark. Following previous work, we train our models on the Vimeo90K training dataset and directly test it on all these benchmarks.

**Middlebury.** The Middlebury benchmark is widely used to evaluate VFI methods. The image resolution in this dataset is around 640 × 480. There are two sets of Middlebury benchmark. We report the average interpolation error (IE) of the OTHER set.

**Vimeo90K.** There are 3,782 triplets in the Vimeo90K testing set [35]. The image resolution in this dataset is 448 × 256.

**UCF101.** The UCF101 dataset [28] contains videos with a large variety of human actions. There are 379 triplets with a resolution of 256 × 256.

**HD.** Bao et al. [3] collect 11 high-resolution videos for
Table 3: Increase model complexity by adjusting model size parameters. C denotes the multiplier for the number of channels, and F denotes the resolution multiplier. 2F represents removing the first downsampling layer of IFNet and the first one of FusionNet. The parameter setting of RIFE-Large is 1.5C2F.

| Scale Setting | RIFE  | 1.5C  | 2F  | RIFE-Large |
|---------------|-------|-------|-----|------------|
| UCF101 PSNR   | 35.14 | 35.26 | 35.32 | 35.33      |
| Vimeo90K PSNR | 35.69 | 35.88 | 36.08 | 36.24      |
| Middlebury IE | 2.03  | 2.03  | 1.99 | 1.98       |
| HD PSNR       | 32.04 | 32.13 | 31.96 | 32.18      |
| # Parameters* | 10.4M | 22.9M | 10.4M | 22.9M      |
| Runtime*      | 36ms  | 65ms  | 126ms | 196ms      |
| Complexity*   | 83G   | 185G  | 322G  | 724G       |

*: measure the whole algorithm on 720p videos.

4.2. Model Scaling

We provide several models with different computation cost and performance to meet different needs by model scaling. We introduce two hyper-parameters following [12]: width multiplier and resolution multiplier. Upon our base model RIFE, we apply a width multiplier on the number of channels uniformly at each layer. Choosing the width multiplier to 1.5 produces a model named RIFE-1.5C. Meanwhile, we can remove a downsampling layer from the headers of IFNet and FusionNet, which doubles the feature map’s width and height that produces a model named RIFE-2F. Together, we can combine these two modifications to produce a model named RIFE-Large (1.5C2F). The performance and runtime of these models is reported in Table 3 and depicted in Figure 1. We confirm that our model design is flexible, and increasing model capacity can effectively improve model performance.

4.3. Comparisons with Previous Methods

We compare RIFE with representative state-of-the-art models including

- **Backward warping based methods**: TOFlow [35], MEMC-Net [3], DAIN [2], BMBC [26].
- **Forward warping based methods**: SoftSplat [23].
- **Flow-free methods**: SepConv [25], CAIN [8].

We report the performance metric on benchmarks mentioned above and running speed measured on an NVIDIA TITAN X (Pascal) GPU with an input resolution of 640 × 480 in Table 2. Our base model RIFE runs considerably faster than all compared methods with comparable performance. A larger version of our model, namely RIFE-Large, runs 30% faster than the previous state-of-the-art method SoftSplat [23] with better performance on several benchmarks. We provide a visual comparison on video clips with large motions from the Vimeo90K testing set. We show the results in Figure 6, where SepConv-L1 and DAIN produce ghosting artifacts, and CAIN causes missing-parts artifacts in the shovel. Overall, our method can produce more reliable results.

4.4. Ablation Study

**Ablation on the design of IFNet.** To validate the effectiveness of the coarse-to-fine procedure with gradually increasing resolution, we perform a small ablation study on IFNet. We construct three models with the same architecture with our IFNet except for the combination of resolution parameters for each IFBlock. We compare the performance and runtime of these models and Table 4.

**Ablation on the loss functions.** We perform an ablation study to analyze the contributions of the proposed leakage distillation loss function and the adopted census loss function. We list the results of training our models under different loss function settings in Table 5. We confirm that
Figure 7: Interpolating multiple frames on the Vimeo90K testing dataset by applying RIFE recursively. We cut out the moving objects according to the green boxes and zoom in the results. RIFE provides smooth and continuous motions.

4.5. Generating Multiple Frames

To interpolate multiple intermediate frames at different time $t \in (0, 1)$, we can apply RIFE recursively. Specifically, given any two consecutive input frames $I_0, I_1$, we apply RIFE once to get intermediate frame $\hat{I}_{0.5}$ at $t = 0.5$, then we feed $I_0$ and $\hat{I}_{0.5}$ to get $\hat{I}_{0.25}$, and we can repeat this process recursively to get the $8 \times, 16 \times$ results.

To demonstrate this ability, we provide the visual results for $2 \times, 4 \times, 8 \times$ settings on images with large motions from the Vimeo90K testing set in Figure 7. We observe that RIFE successfully produces smooth and continuous motions.

5. Conclusion

In this paper, we develop an efficient and flexible algorithm for VFI, named RIFE. Unlike common flow-based VFI methods, RIFE produces the intermediate flows using an efficient CNN. With the more precise flows and our simplified fusion process, RIFE can effectively process videos of different resolutions, successfully interpolate multiple frames between two input frames, and surpass existing methods on public benchmarks.
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