BiMaCoSR: Binary One-Step Diffusion Model Leveraging Flexible Matrix Compression for Real Super-Resolution

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Introduction

Motivation

- **Diffusion Models** excel in Real-World SR tasks but face high costs.
- One-Step Distillation **(OSD)** significantly reduce the computation cost but with performance loss.
- Binarization reduces computation extremely with severe performance degradation.
- We propose **BiMaCoSR,** a binarization method for one-step distillation model in SR.

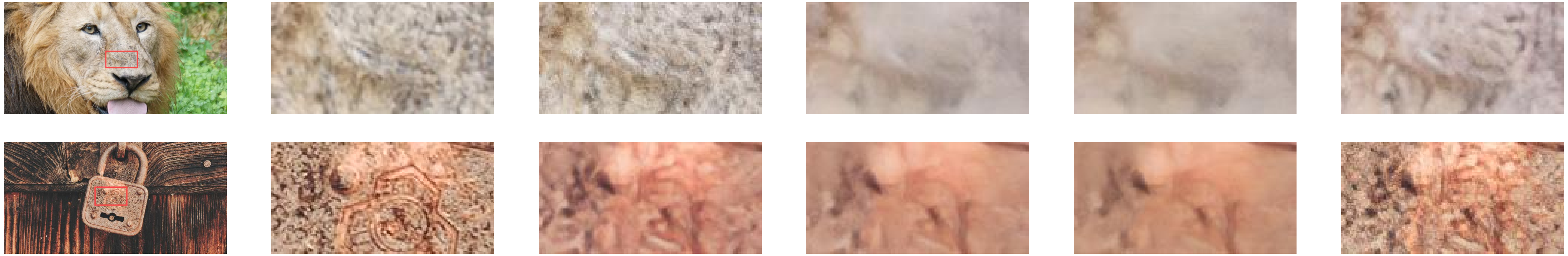
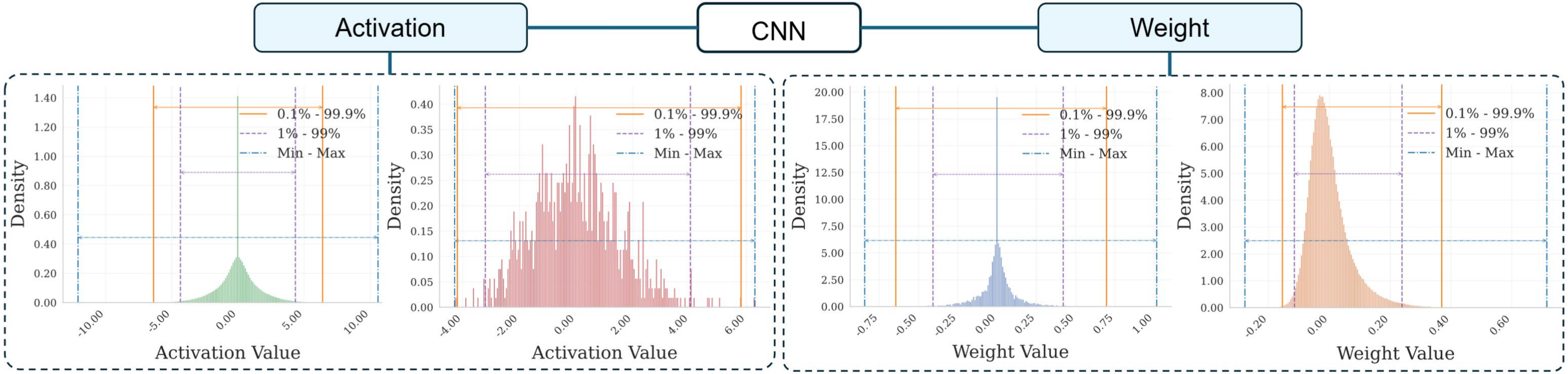


Image HR SinSR (FP) XNOR ReSTE BiMaCoSR

Observation



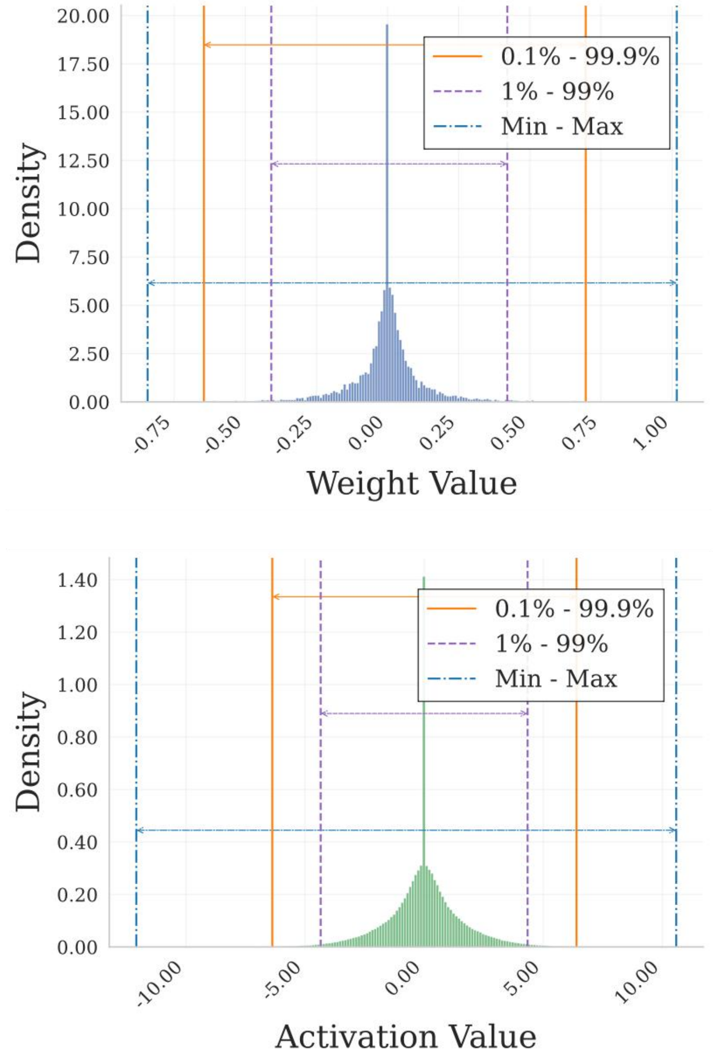
(a) convolutional layer (b) FC layer (c) convolutional layer (d) FC layer

Distribution

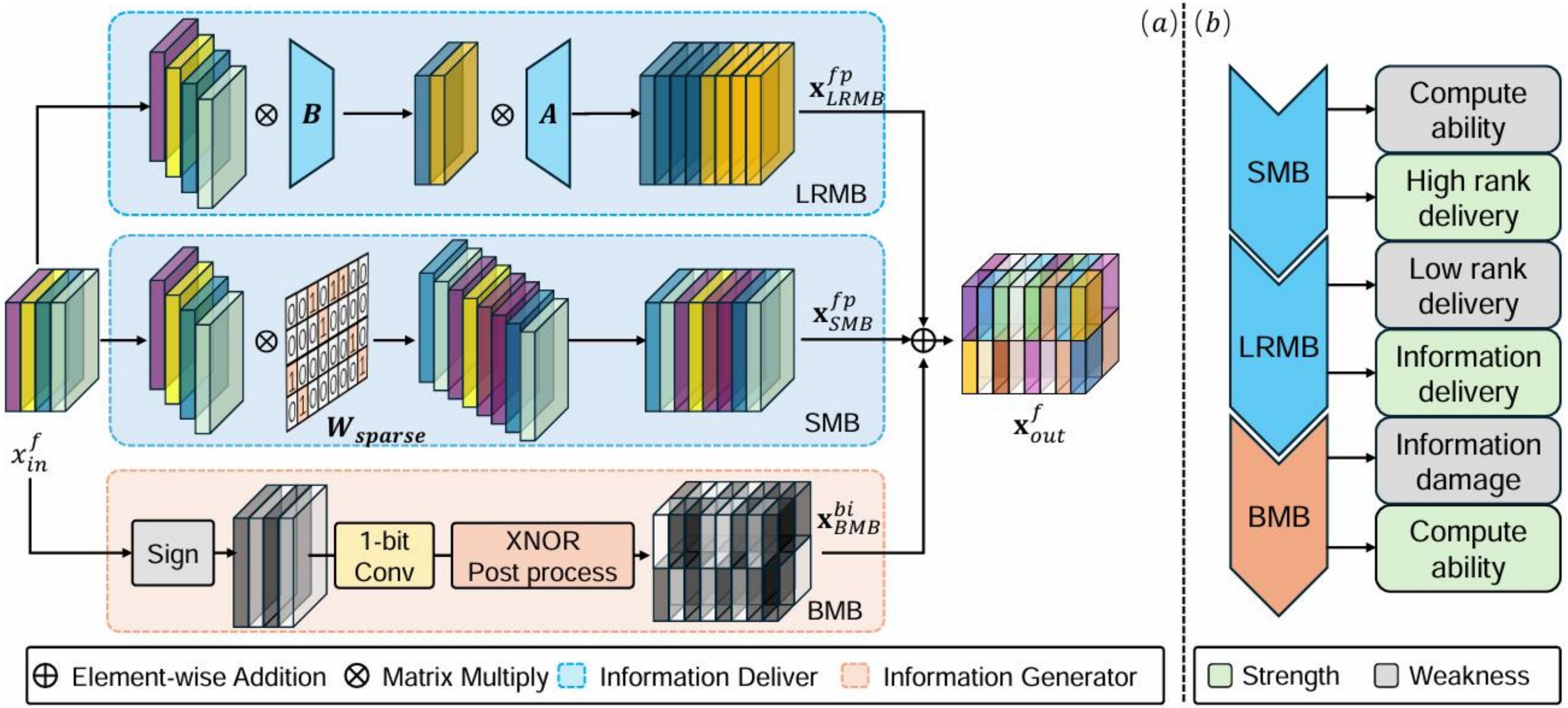
- The distribution of activation and weights of all layers obeys the normal distribution.
- The function of the distribution can be divided into three parts:
  - The extreme values (big values);
  - The majority values (around zero);
  - The body values (between big values and zero).

Observation

- We can set different percentile range to obtain different bound for quantization parameters.
- The majority values are around zero. They are response for the low-frequency information of the figure, i.e., the overall color blocks.
- The outliers are rare but extremely big. They are response for the hard local textures.
- Between these two kinds of values, there are around than 1% values that also contributes the details and textures but the simple one.
- Therefore, we need to keep all these values to maintain the performance of Diffusion model.



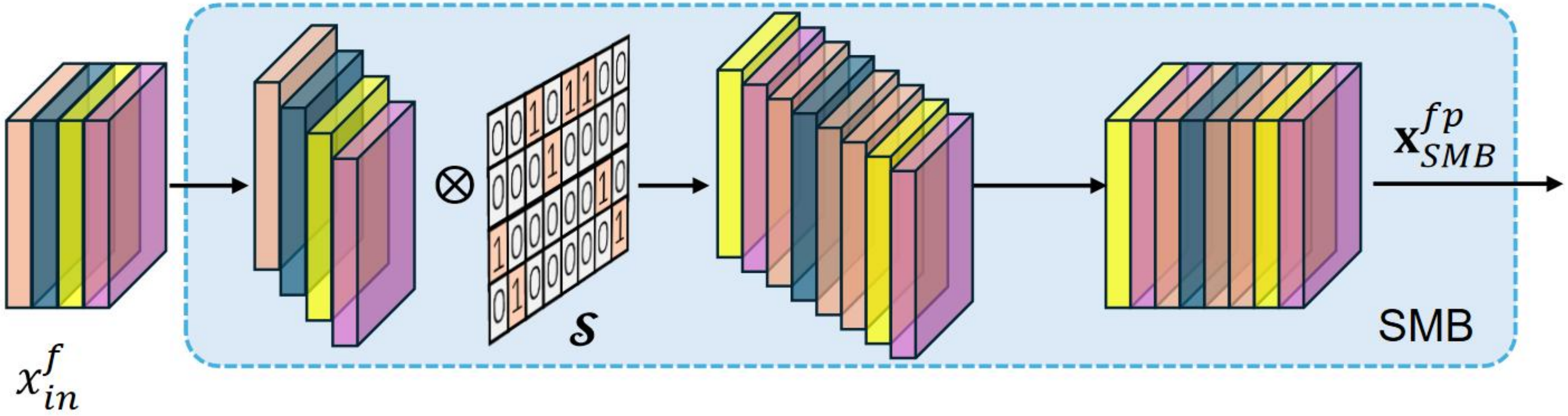
Method-Overview



Overall

- **The overall pipeline of our proposed BiMaCoSR.**
- The whole pipeline can be divided into three parts: LRMB, SMB, and BMB.

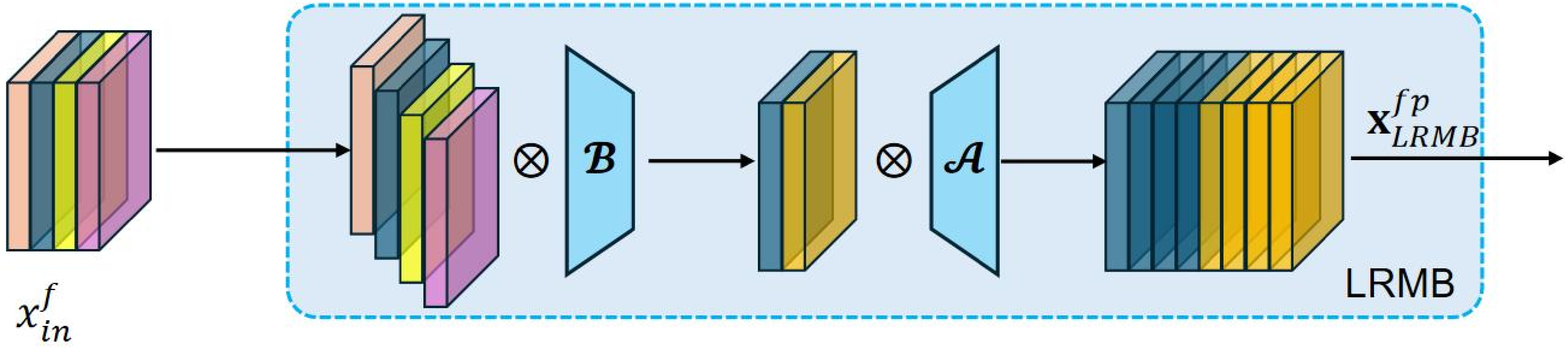
Method-SMB



SMB

- **We leverage Sparse Matrix to absorb the extreme values**.
- Given a $m * n$ matrix, the top $2 * max(m, n)$ values will be absorbed into the sparse matrix to provide high frequence information.
- Each element is stored with COO structure, where the element is stored with a triple, i.e., $(x, y, value)$.
- There are many mature algorithm to calculate the production in $\mathcal{O}(n^2)$.

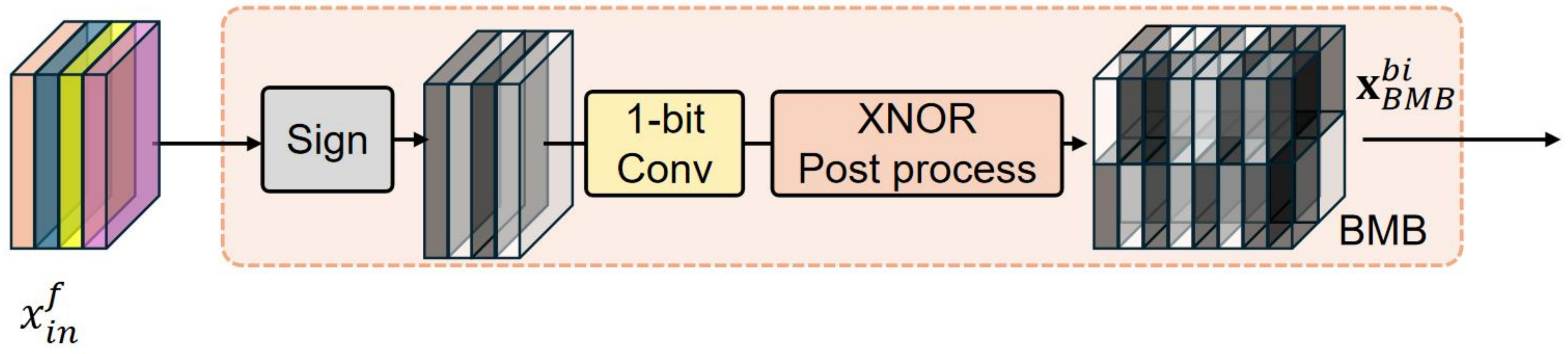
Method-LRMB



LRMB

- **We leverage Low-Rank Matrix to absorb the majority values**.
- Given a $m * n$ matrix, we can leverage SVD to obtain a low-rank approximation.
- $W = U\Sigma V^T = Udiag\{\sigma_1, \sigma_2, ..., \sigma_n\}V^T \approx Udiag\{\sigma_1, \sigma_2, ..., \sigma_r, 0, ..., 0\}V^T = B_{m*r}A_{r*n}$.
- The time complexity of matrix production is $\mathcal{O}(n^2 r)$.

Method-BMB



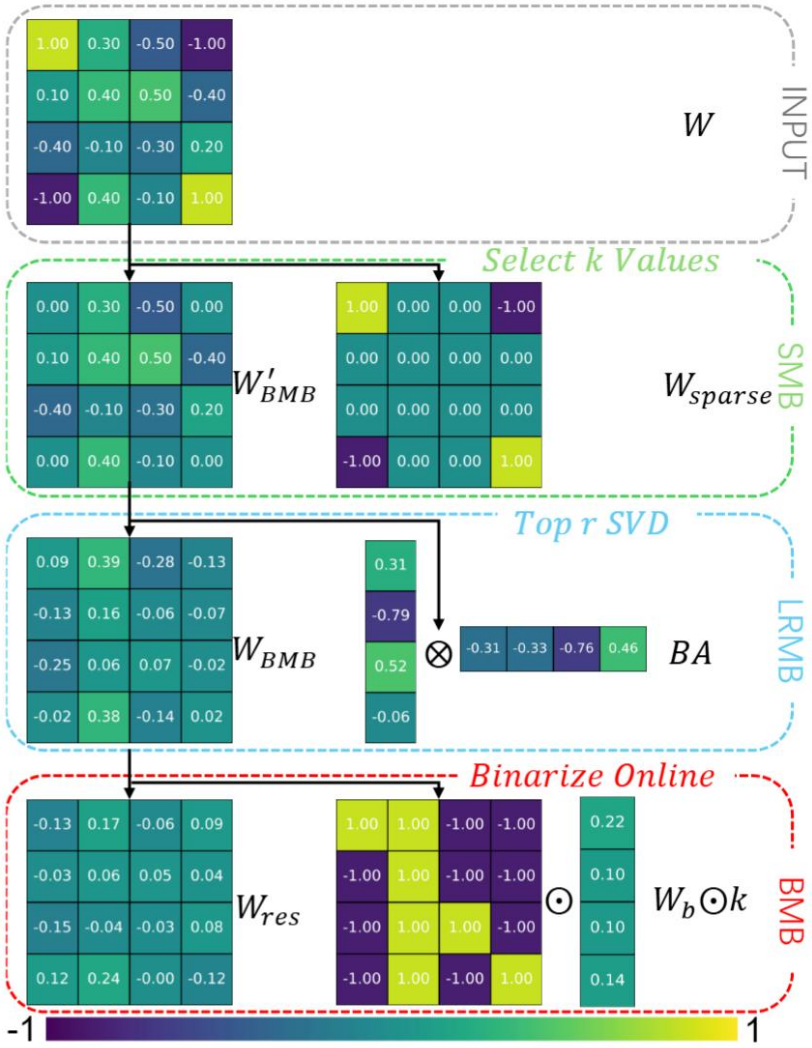
BMB

- **We leverage Binarized Matrix to absorb the most high-frequence values**.
- $X_b = Sign(X), W_b = Sign(W)$
- $X_{BMB} = BitCount(XNOR(X_b, W_b)) \odot (\mathcal{A} \otimes k)$

Method-Initialization

Initialization

- **We first initialize the Sparse Matrix Branch (SMB) with the top k values.**
- After substracting the top k values, we initialize the Low-Rank Matrix Branch (LRMB) with singular value decomposition.
- After further substracting LRMB, we finally initialize the Binarized Matrix Branch with the remaining weights.



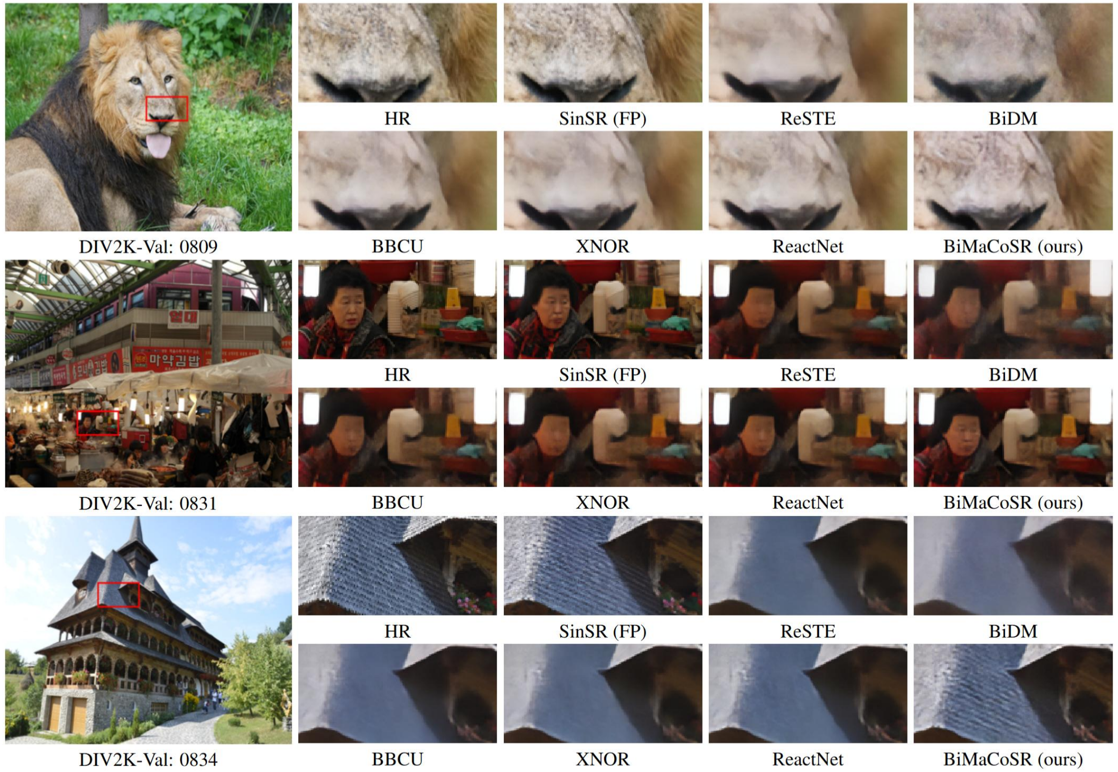
Experiments

Datasets	Methods	Bits (W/A)	PSNR ↑	SSIM ↑	LPIPS ↓	MUSIQ ↑	MANIQA ↑	DISTS ↓	FID ↓	NIQE ↓	CLIP-IQA+ ↑
RealSR	SinSR	32/32	26.51	0.7380	0.3635	57.87	0.5139	0.2193	56.36	5.826	0.5736
	ResShift	32/32	25.45	0.7243	0.3731	56.23	0.5005	0.2344	58.14	7.353	0.5708
	XNOR	1/1	26.48	0.7434	0.3968	43.56	0.3732	0.2609	105.72	6.014	0.4380
	ReActNet	1/1	26.60	0.7530	0.3834	44.18	0.3829	0.2551	109.36	6.306	0.4361
	BBCU	1/1	26.43	0.7488	0.3902	43.70	0.3792	0.2575	108.32	6.058	0.4298
	ReSTE	1/1	26.26	0.7408	0.4184	41.04	0.3677	0.2719	113.86	6.174	0.4083
	BiDM	1/1	25.07	0.7036	0.5042	35.60	0.3517	0.3226	115.23	6.759	0.3935
	BiMaCoSR	1/1	26.84	0.7698	0.3375	49.01	0.4034	0.2183	86.09	5.856	0.4800
DRealSR	SinSR	32/32	27.89	0.7332	0.4499	30.81	0.4519	0.2209	16.56	5.789	0.6052
	ResShift	32/32	26.64	0.7298	0.4478	31.09	0.4345	0.2337	18.12	6.959	0.5795
	XNOR	1/1	29.03	0.8319	0.3712	26.19	0.3560	0.2447	29.88	6.229	0.4449
	ReActNet	1/1	29.34	0.8431	0.3571	26.83	0.3618	0.2411	30.18	6.561	0.4380
	BBCU	1/1	29.00	0.8385	0.3643	26.37	0.3594	0.2433	30.94	6.337	0.4383
	ReSTE	1/1	28.91	0.8353	0.3899	25.12	0.3509	0.2641	33.64	6.459	0.4131
	BiDM	1/1	27.40	0.7942	0.4849	23.38	0.3529	0.3118	37.83	6.753	0.4307
	BiMaCoSR	1/1	29.33	0.8393	0.3400	29.38	0.3802	0.2278	22.31	6.150	0.4867
DIV2K-Val	SinSR	32/32	27.75	0.7694	0.1903	64.62	0.5336	0.1029	6.27	4.308	0.6147
	ResShift	32/32	27.18	0.7667	0.1775	65.04	0.5548	0.1016	7.54	5.121	0.6280
	XNOR	1/1	26.44	0.7185	0.3727	49.10	0.3972	0.2204	55.77	5.320	0.4584
	ReActNet	1/1	26.49	0.7260	0.3602	50.29	0.4078	0.2111	52.32	5.366	0.4726
	BBCU	1/1	26.39	0.7221	0.3660	50.09	0.4035	0.2148	53.22	5.263	0.4653
	ReSTE	1/1	26.07	0.7125	0.3916	46.95	0.3907	0.2295	61.52	5.399	0.4328
	BiDM	1/1	24.29	0.6725	0.4370	40.15	0.3747	0.2916	62.28	6.090	0.4112
	BiMaCoSR	1/1	27.35	0.7547	0.2999	53.38	0.4337	0.1806	27.99	4.987	0.5176

Quantitative

- **Best performance:** Achieves the best results among quantization methods for SR.
- More results can be found in the main paper.

Experiments



Visual

- Our method restores clearer images with more texture details.
- The gap between the quant model and the FP model is small.
- Quantization alleviates overfitting and in some condition, quantized model has better performance compared with FP model.

	ResShift	SinSR	ReActNet	BBCU	ReSTE	BiDM	XNOR	Ours
Inference Step	15	1	1	1	1	1	1	1
FLOPs (G)	753.45	50.23	5.83	5.83	5.83	11.60	5.83	1.83
# Total Param (M)	118.59	118.59	4.95	4.95	4.95	18.69	4.95	4.98
PSNR/LPIPS	25.45/0.3731	26.51/0.3635	26.60/0.3834	26.43/0.3902	26.26/0.4184	25.07/0.5042	26.48/0.3968	26.84/0.3375

Compression

- Small complexity.
- High performance.

Experiments

Branch	PSNR ↑	SSIM ↑	LPIPS ↓	MANIQA ↑	FID ↓	CLIP-IQA+ ↑	FLOPs (G)	Param (M)
BMB	26.41	0.7408	0.4141	0.3704	110.15	0.4325	0.78	3.69
+LRMB	26.95	0.7718	0.3400	0.3937	88.72	0.4663	1.83	4.98
+LRMB+SMB	26.84	0.7698	0.3375	0.4034	86.09	0.4800	1.83	4.98

(a) Break down ablation.

Loss	PSNR ↑	SSIM ↑	LPIPS ↓	CLIP-IQA+ ↑
Distill loss	26.83	0.7698	0.3375	0.4800
SinSR loss	26.37	0.7466	0.4029	0.4273

(b) Ablation study on losses.

Initialization	PSNR ↑	SSIM ↑	LPIPS ↓	CLIP-IQA+ ↑
Zero + Random	26.88	0.7660	0.3497	0.4674
SVD	26.84	0.7698	0.3375	0.4800

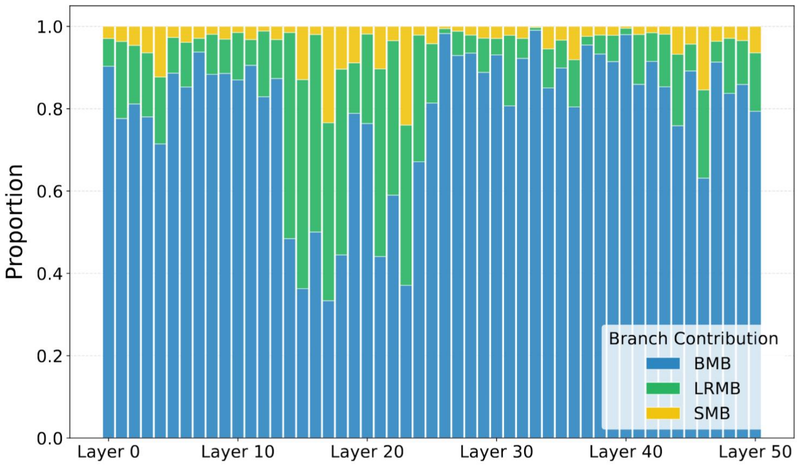
(c) Ablation study on LRMB initialization.

Rank	PSNR ↑	SSIM ↑	LPIPS ↓	CLIP-IQA+ ↑	FLOPs (G)	Param (M)
4	26.29	0.7383	0.4197	0.4411	1.31	4.37
8	26.84	0.7698	0.3375	0.4800	1.83	4.98
12	26.97	0.7695	0.3400	0.4766	2.32	5.60
16	26.72	0.7625	0.3442	0.4971	2.83	6.21

(d) Ablation study on the rank of LRMB.

Initialization	PSNR ↑	SSIM ↑	LPIPS ↓	CLIP-IQA+ ↑
Zero initial	26.72	0.7628	0.3561	0.4639
Uni-shortcut	25.69	0.7113	0.5105	0.4008
Sparse skip	26.84	0.7698	0.3375	0.4800

(e) Ablation study on SMB initialization.



Ablation

- All branches are useful and the parameter overhead is minor.
- Simplified loss lead to higher performance.
- The initialization method is efficient and effectivitive.

Frequence

- BMB provide the most high frequence information.
- The other two branchs also contribute to the high frequence.

Conclusion

Contribution

We propose **BiMaCoSR**, a binarized one-step distillation model for image SR.

- **LRMB & SMB:** Two light-weight branches to compensate the binarized branch.
- **Initialization:** Tri-stage residual initialization brings robust performance.
- **Performance:** Outperforms SOTA PTQ methods for SR.

Poster

- Time: XXX

  XXX

Project

Thanks