



**IEEE International Conference on Multimedia and Expo**  
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# **MatchingGAN: Matching-Based Few-Shot Image Generation**

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# Catalog

- 1 Few-shot Learning
- 2 Few-shot Image Generation
- 3 Matching GAN for Few-shot Image Generation
- 4 Experiments



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Few-shot Learning

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Experiments

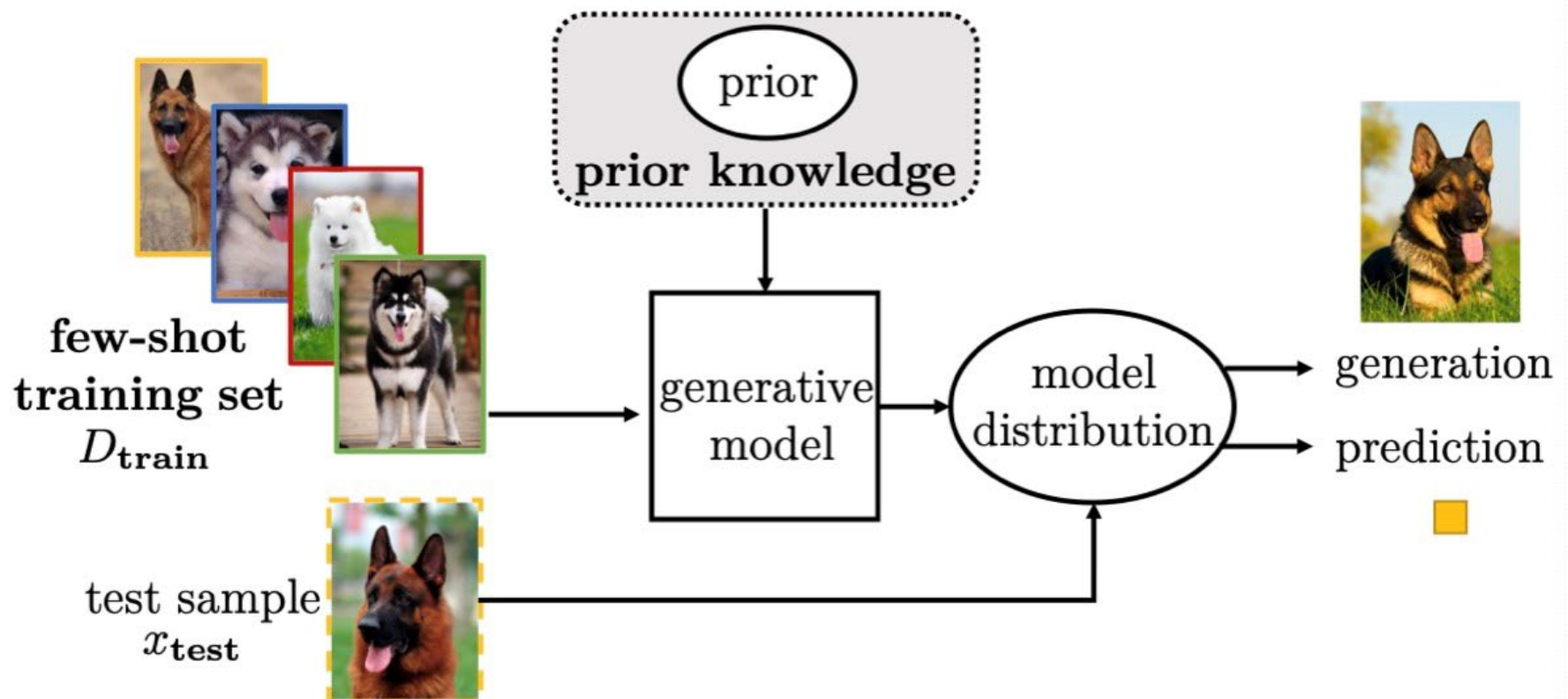
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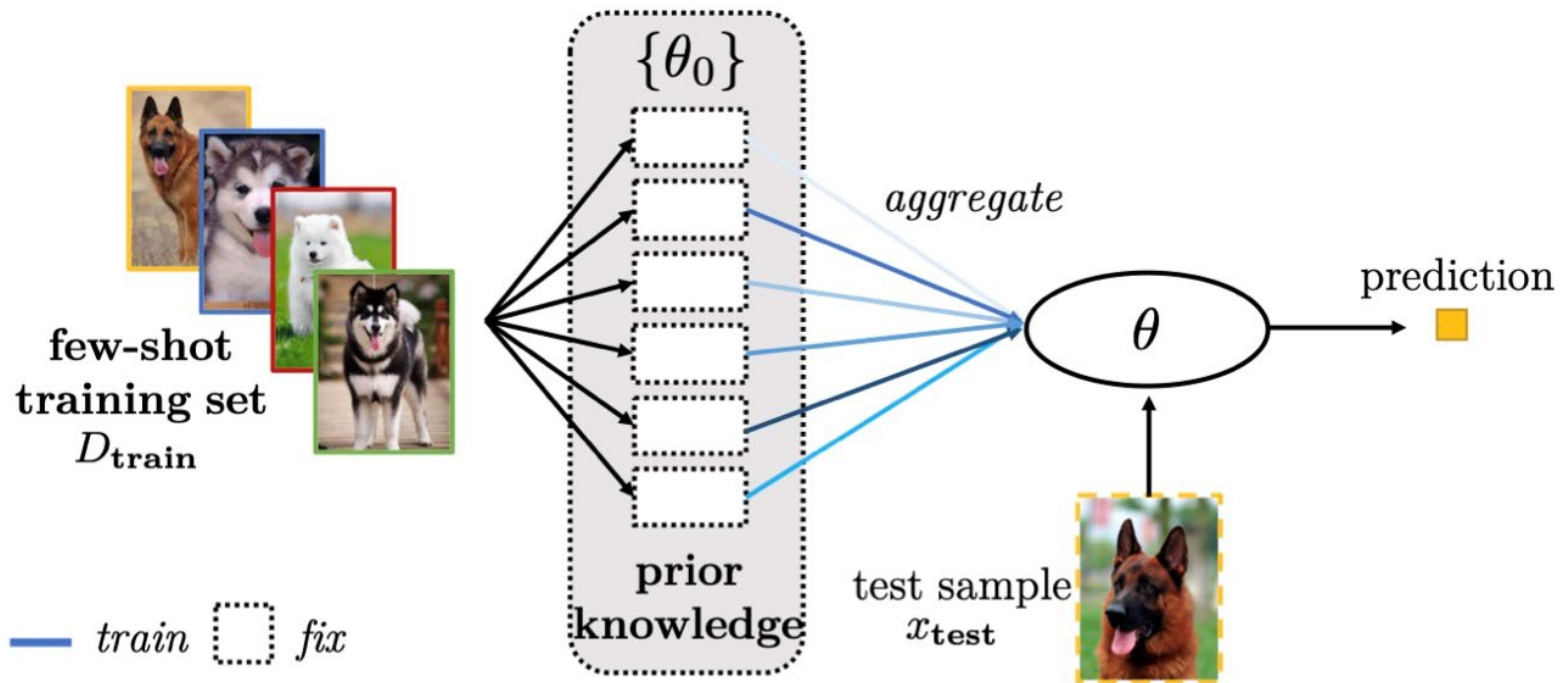
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# Few-shot Learning



# Metric-based Few-shot Learning



The model can be used at **testing** phase without **fine-tuning**

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# Few-shot Image Generation

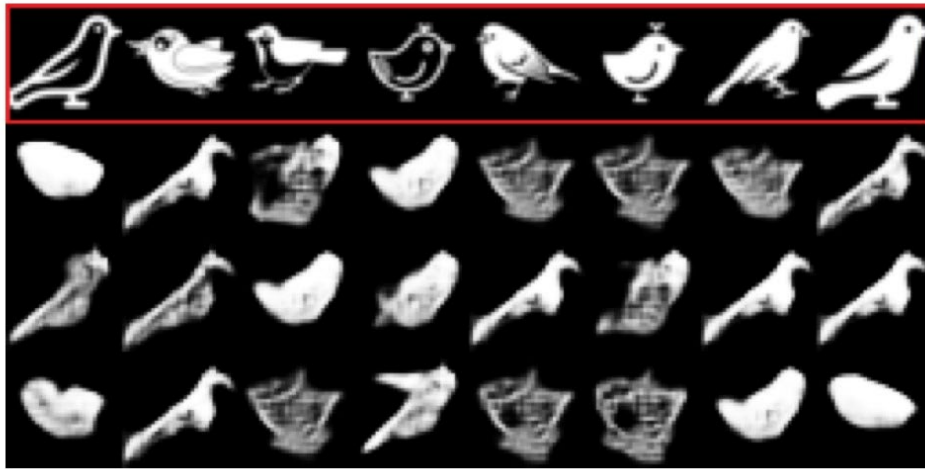


- **Extensive training** samples is expensive, difficulty in **quick adaptation**
- Few shot image generation can **augment training dataset**, facilitate **downstream tasks** like few-shot classification



# The Issues in Existing Few-shot Image Generation

- The quality of generated images is **poor**



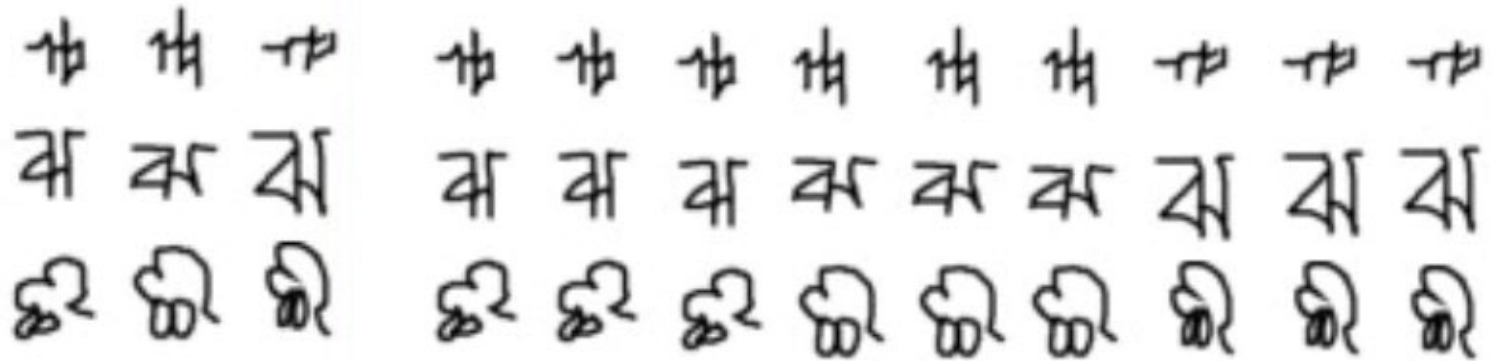
Generated images are **vague**



Generated images are **unreasonable**

# The Issues in Existing Few-shot Image Generation

- The **diversity** of generated images is **limited**



Conditional images



Generated images

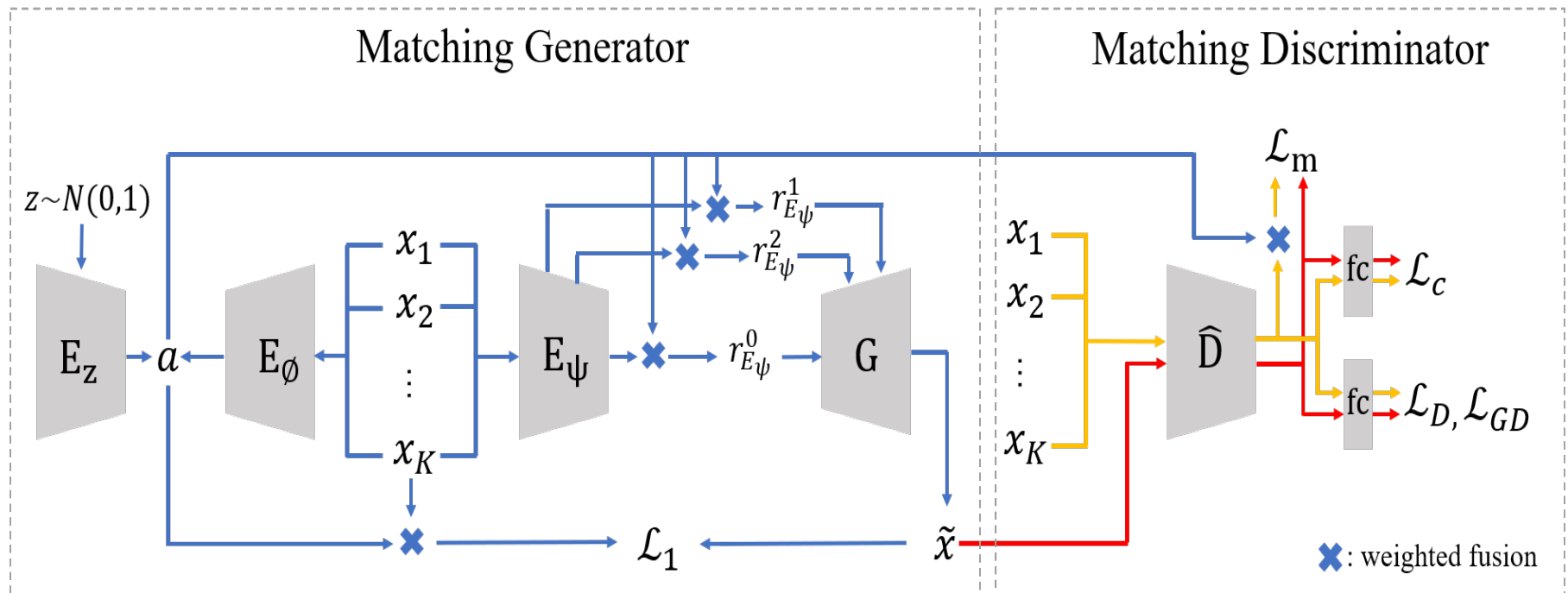
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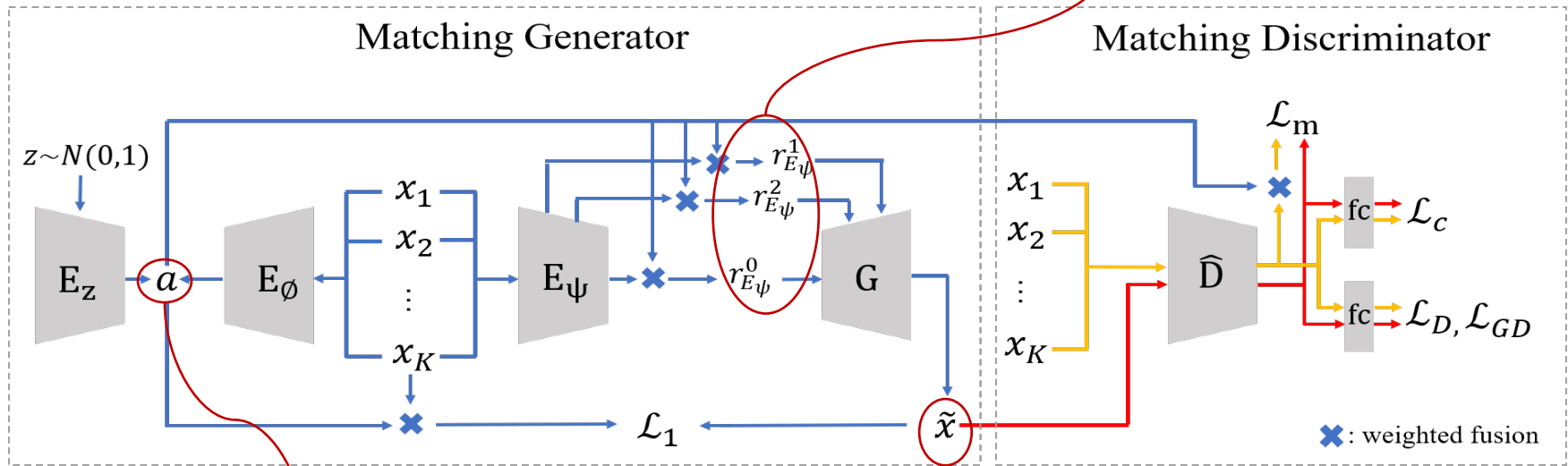


## Combining matching procedure with generative adversarial network



# Matching Procedure

$$\mathbf{r}_{E_\psi}^j = \sum_{i=1}^K a(E_z(\mathbf{z}), E_\phi(\mathbf{x}_i)) E_\psi^j(\mathbf{x}_i), \quad j = 0, \dots, L$$



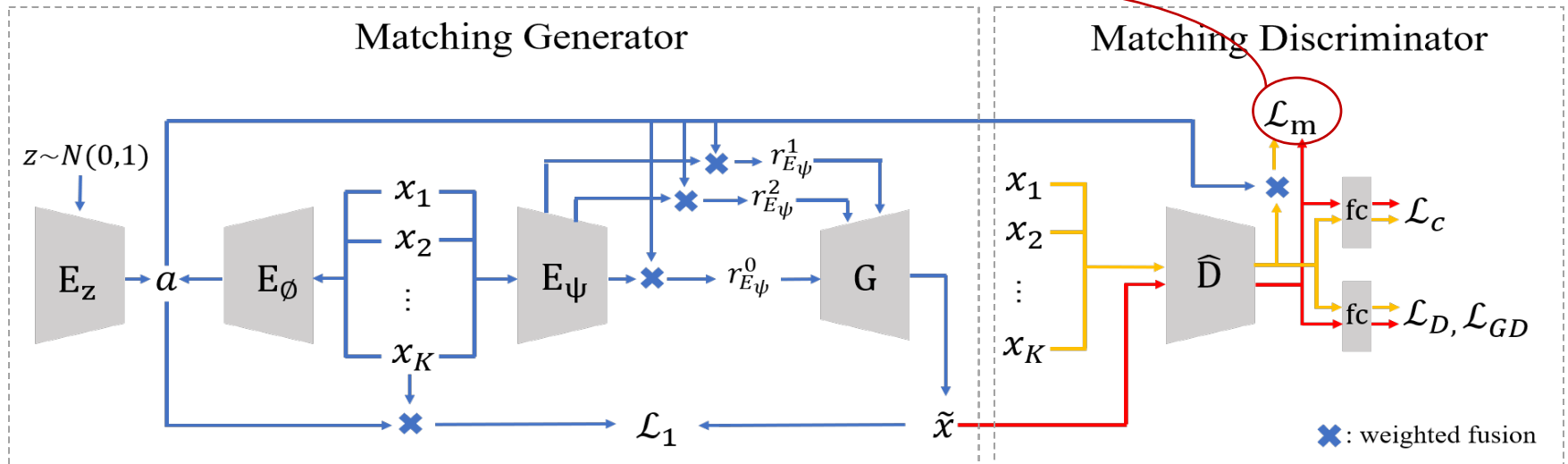
$$a(E_z(\mathbf{z}), E_\phi(\mathbf{x}_i)) = \frac{e^{\cos(E_z(\mathbf{z}), E_\phi(\mathbf{x}_i))}}{\sum_{i=1}^K e^{\cos(E_z(\mathbf{z}), E_\phi(\mathbf{x}_i))}}$$

$$\tilde{\mathbf{x}} = G(\mathbf{r}_{E_\psi}^0, \mathbf{r}_{E_\psi}^1, \dots, \mathbf{r}_{E_\psi}^L)$$

# Matching Procedure



$$\mathcal{L}_m = \left\| \sum_{i=1}^K a(E_z(z), E_\phi(x_i)) \hat{D}(x_i) - \hat{D}(\tilde{x}) \right\|_1$$

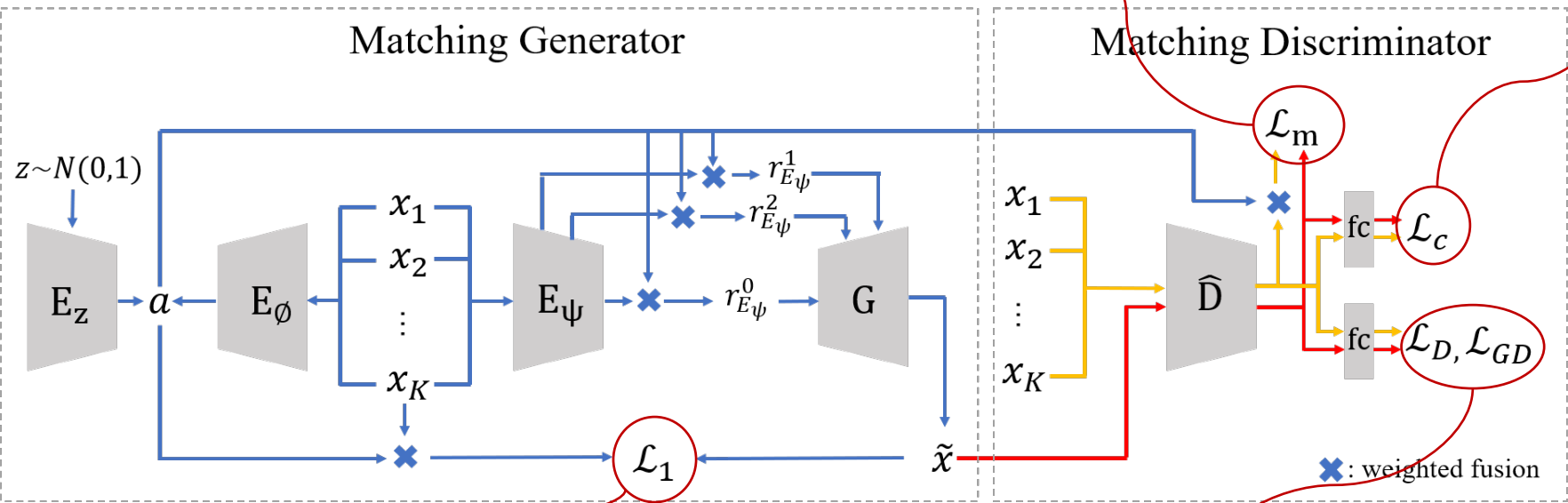


# Optimization



$$\mathcal{L}_m = \left\| \sum_{i=1}^K a(E_z(z), E_\phi(\mathbf{x}_i)) \hat{D}(\mathbf{x}_i) - \hat{D}(\tilde{\mathbf{x}}) \right\|_1$$

$$\mathcal{L}_c = -\log p(c(\mathbf{x})|\mathbf{x})$$



$$\mathcal{L}_1 = \sum_{i=1}^K a(E_z(z), E_\phi(\mathbf{x}_i)) \|\mathbf{x}_i - \tilde{\mathbf{x}}\|_1$$

$$\mathcal{L}_D = \mathbb{E}_{\tilde{\mathbf{x}}}[\max(0, 1 + D(\tilde{\mathbf{x}}))] + \mathbb{E}_{\mathbf{x}_i}[\max(0, 1 - D(\mathbf{x}_i))]$$

$$\mathcal{L}_{GD} = -\mathbb{E}_{\tilde{\mathbf{x}}}[D(\tilde{\mathbf{x}})]$$

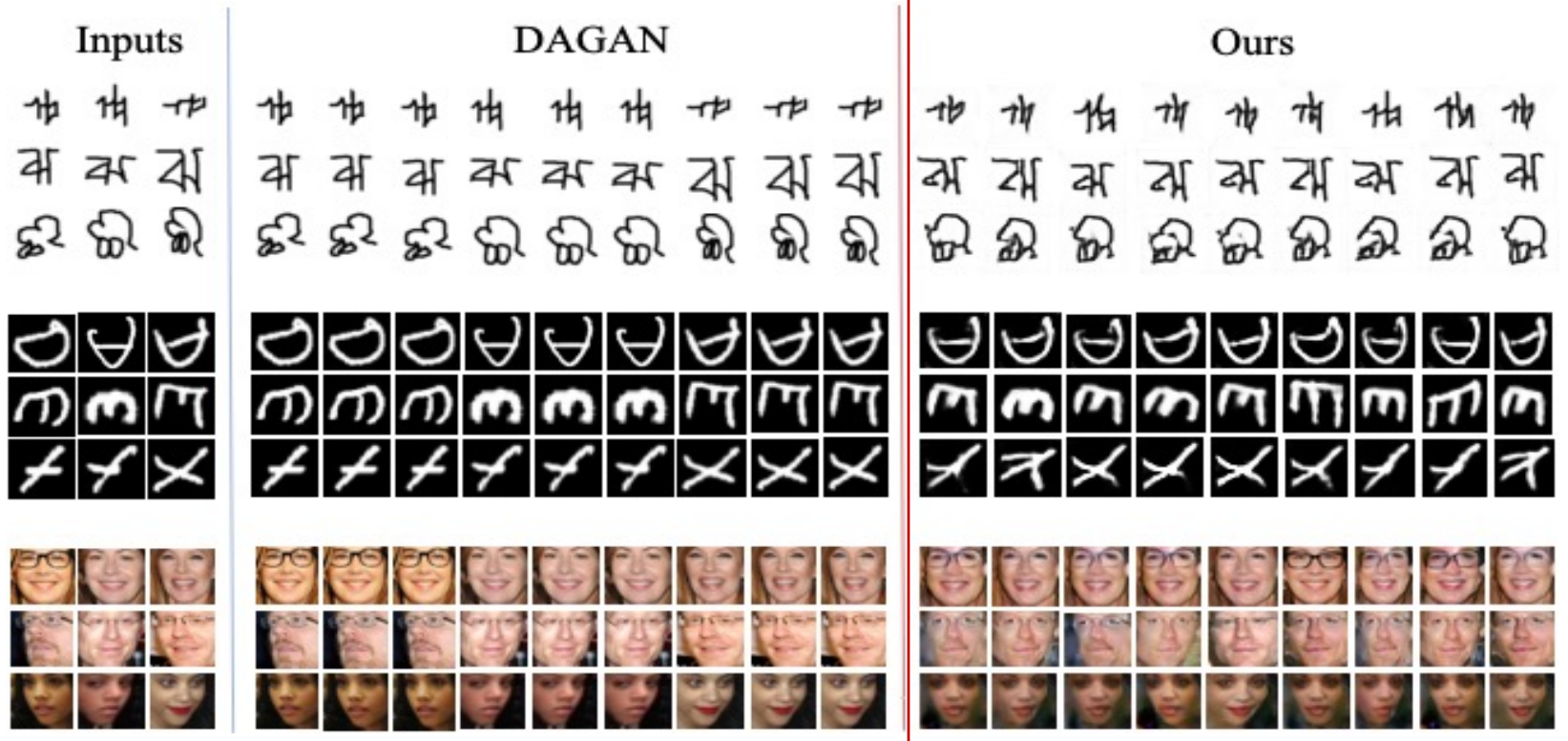
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# Visualization Results



Methods	FID (↓)	IS (↑)
FIGR [3]	154.21	5.19
GMN [4]	201.12	6.38
DAGAN [6]	121.43	4.12
Ours	108.56	8.32

# Classification in Low-data Setting



Method	Dataset	Accuracy		
		5	10	15
Standard	Omniglot	66.22	81.87	83.31
FIGR [3]	Omniglot	69.23	83.12	84.89
GMN [4]	Omniglot	67.74	84.19	85.12
DAGAN [6]	Omniglot	88.81	89.32	95.38
Ours	Omniglot	89.03	90.92	96.29
Standard	EMNIST	83.64	88.64	91.14
FIGR [3]	EMNIST	85.91	90.08	92.18
GMN [4]	EMNIST	84.56	91.21	92.09
DAGAN [6]	EMNIST	87.45	94.18	95.58
Ours	EMNIST	91.75	95.91	96.29
Standard	VGGFace	8.82	20.29	39.12
FIGR [3]	VGGFace	6.12	18.84	32.13
GMN [4]	VGGFace	5.23	15.61	35.48
DAGAN [6]	VGGFace	19.23	35.12	44.36
Ours	VGGFace	21.12	40.95	50.12

# Classification in Few-shot Setting



Methods	Dataset	5-way 5-shot	10-way 5-shot
MatchingNets [11]	Omniglot	98.70	98.91
MAML [20]	Omniglot	99.90	99.13
RelationNets [21]	Omniglot	99.80	99.22
MTL [22]	Omniglot	99.85	99.35
DN4 [23]	Omniglot	99.83	99.29
Ours	Omniglot	99.93	99.42
MatchingNets [11]	VGGFace	60.01	48.67
MAML [20]	VGGFace	61.09	47.89
RelationNets [21]	VGGFace	60.93	49.12
MTL [22]	VGGFace	63.67	51.94
DN4 [23]	VGGFace	62.89	51.58
Ours	VGGFace	65.12	53.21

# Ablation Study



setting	accuracy	FID ( $\downarrow$ )	IS ( $\uparrow$ )
$\lambda_r = 0.01$	35.62	112.16	7.89
$\lambda_r = 0.1$	40.95	108.56	8.32
$\lambda_r = 1$	33.89	107.16	9.17
$\lambda_r = 10$	30.12	106.12	11.04
$\lambda_m = 1$	40.95	108.56	8.32
$\lambda_m = 0$	28.98	111.4	7.56
matching coefficient	40.95	108.56	8.32
random coefficient	38.12	110.98	7.92
1 connection	38.67	113.21	7.09
2 connection	40.95	108.56	8.32
3 connection	34.12	106.12	9.14



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**Thanks for watching!**

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