


Zero-shot Synthesis with Group-Supervised Learning

ICLR 2021

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Agenda

- Motivation 
 - Visual Cognition: Human --> Machines
- Problem Statement and Approach
- Experiments
 - Qualitative results
 - Quantitative results

“Envision” a *novel* visual object

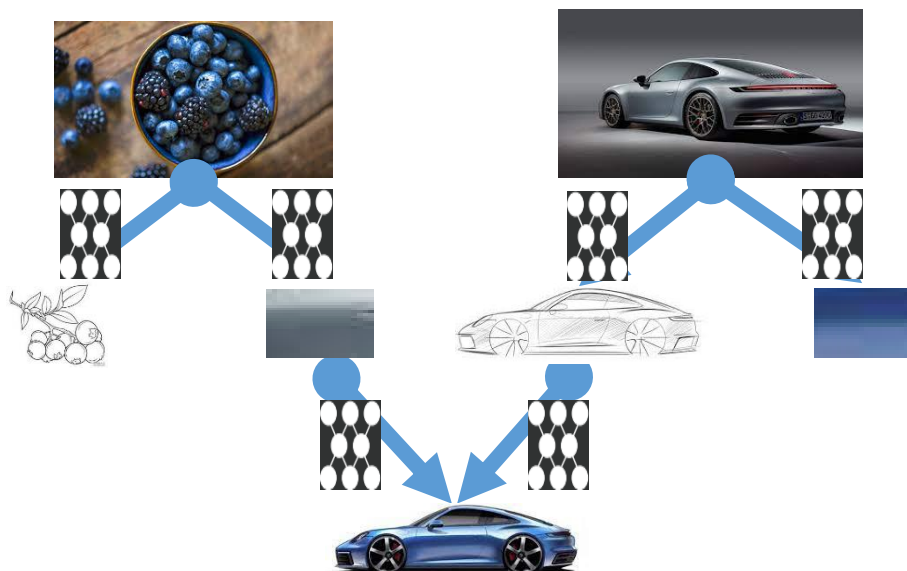


Group-Supervised
Learning

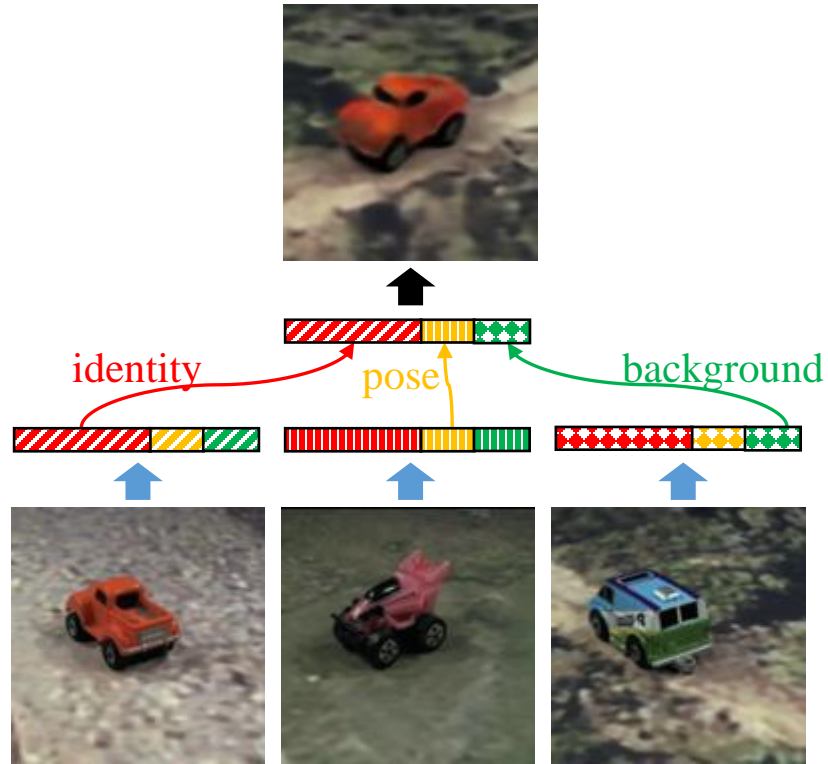
Zero-shot synthesis



Knowledge
Factorization[1]



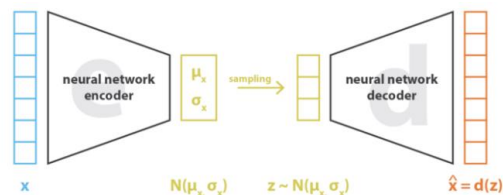
Controllable
Disentangled
Representation Learning



Group-Supervised learning (GSL) allows us to **decompose** inputs into a **disentangled representation** with **swappable** components, that can be **recombined** to synthesize new samples.

Controllable Disentangled Representation Learning

Unsupervised



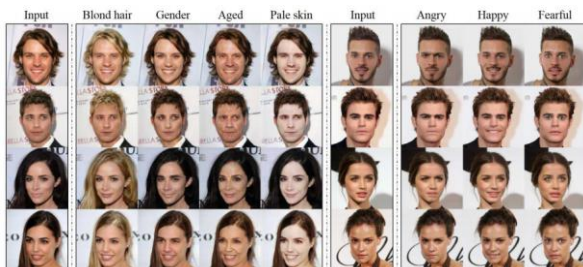
$$\text{loss} = ||x - \hat{x}||^2 + \text{KL}[N(\mu_x, \sigma_x), N(0, I)] = ||x - d(z)||^2 + \text{KL}[N(\mu_x, \sigma_x), N(0, I)]$$



VAE DP Kingma, et al. 2016

☹️ Controllable

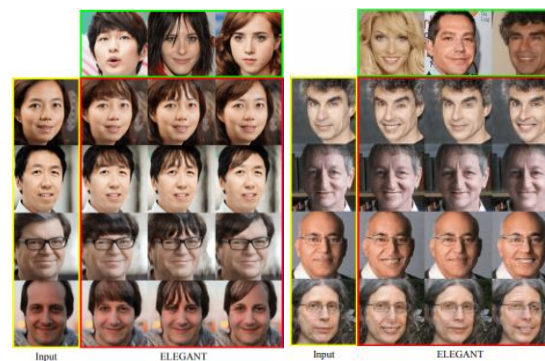
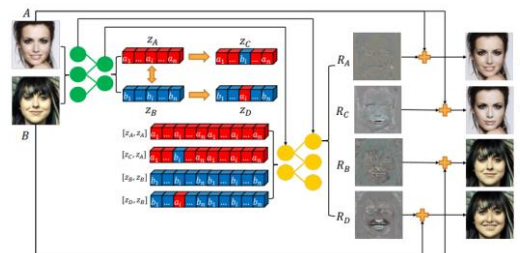
Supervised



StarGAN Choi, Yunjey, et al. 2018

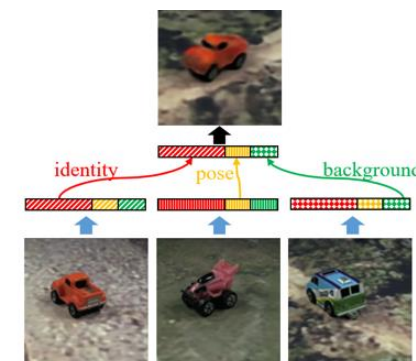
😊 Controllable
 ☹️ Global semantical consistency
 ☹️ Easy implement and training

Supervised



ELEGANT Xiao, T. et al. 2018


Supervised



Group-Supervised Learning (Ours)

😊 Controllable
 😊 Global semantical consistency
 😊 Easy implement and training

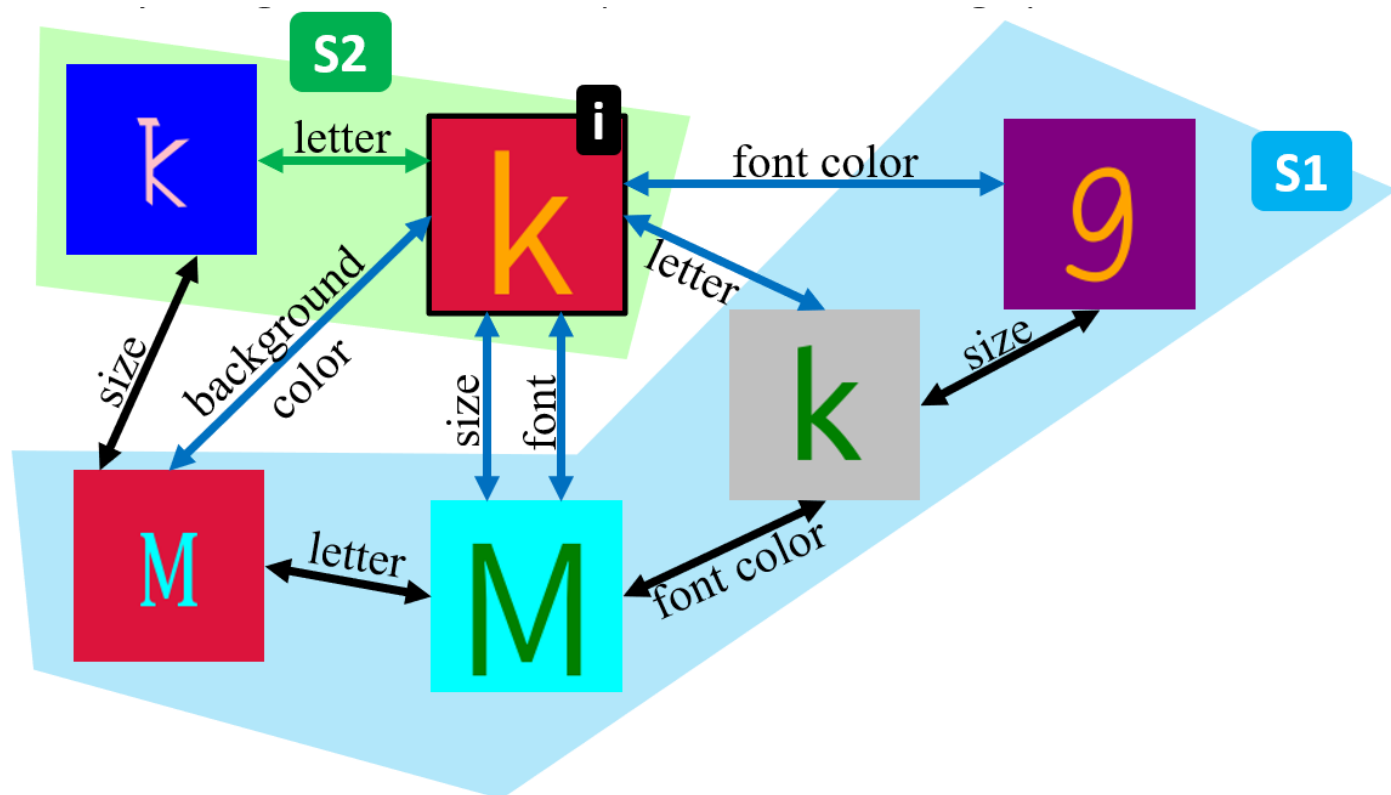
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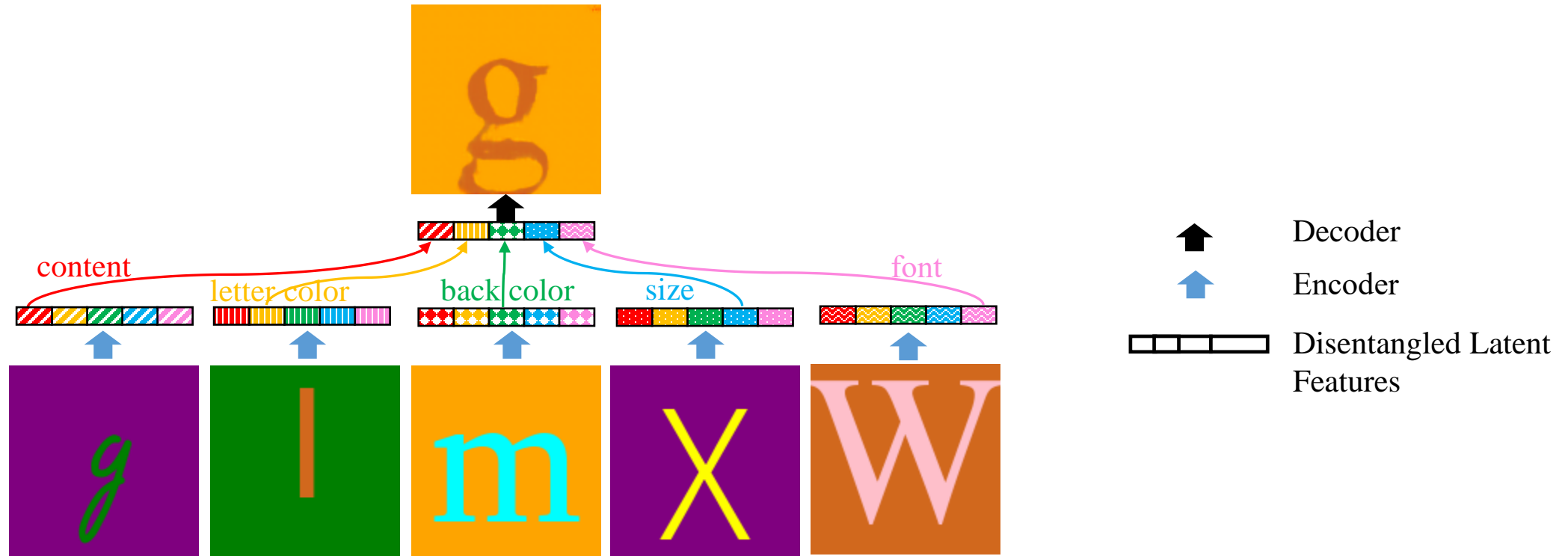
Given: Dataset --> Multi-graph



Letter : A
Size : large
Font color : red
Background color : orange
Font : Abadi

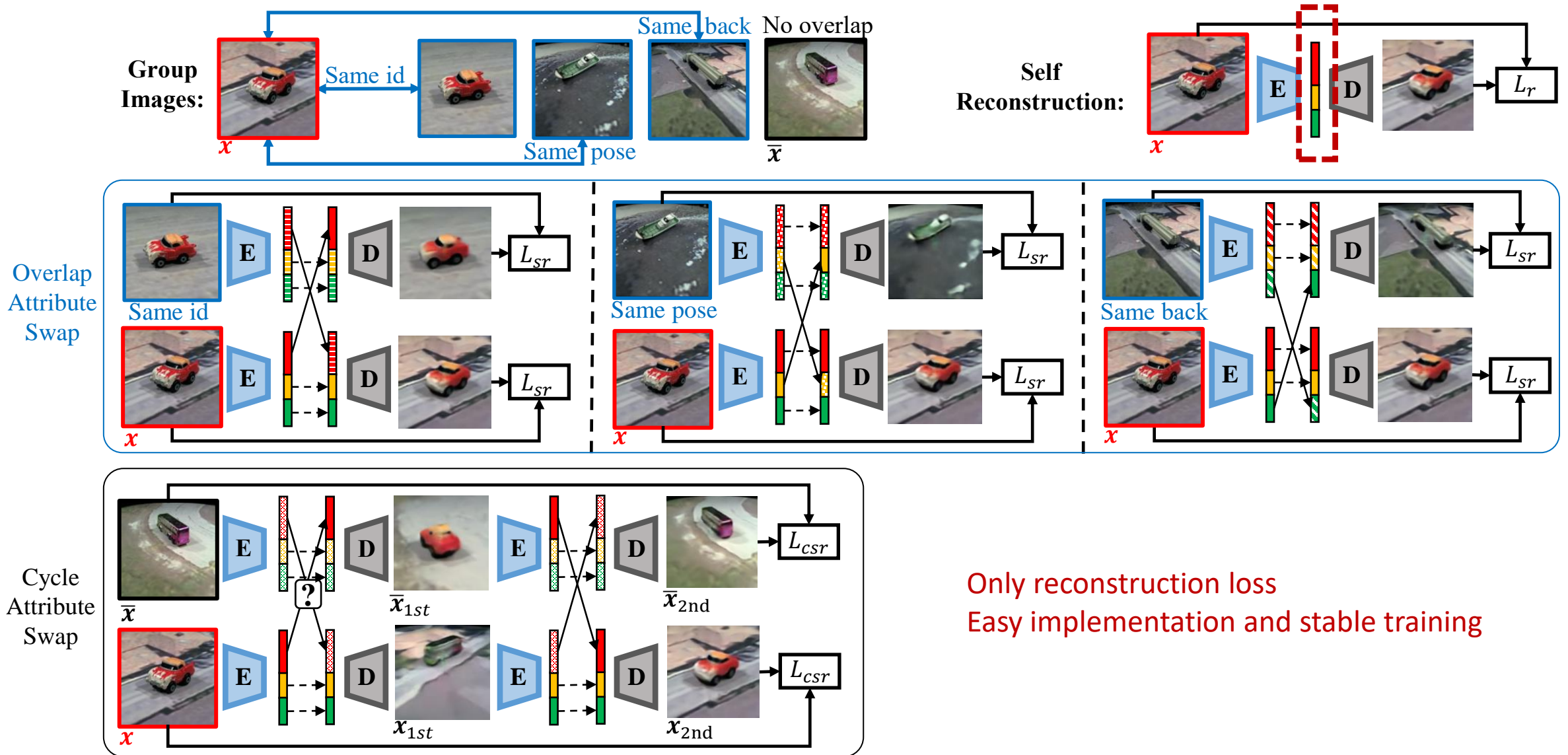


Goal: **Controllable** Synthesis by Disentangle Representation Learning




Group-Supervised Learning

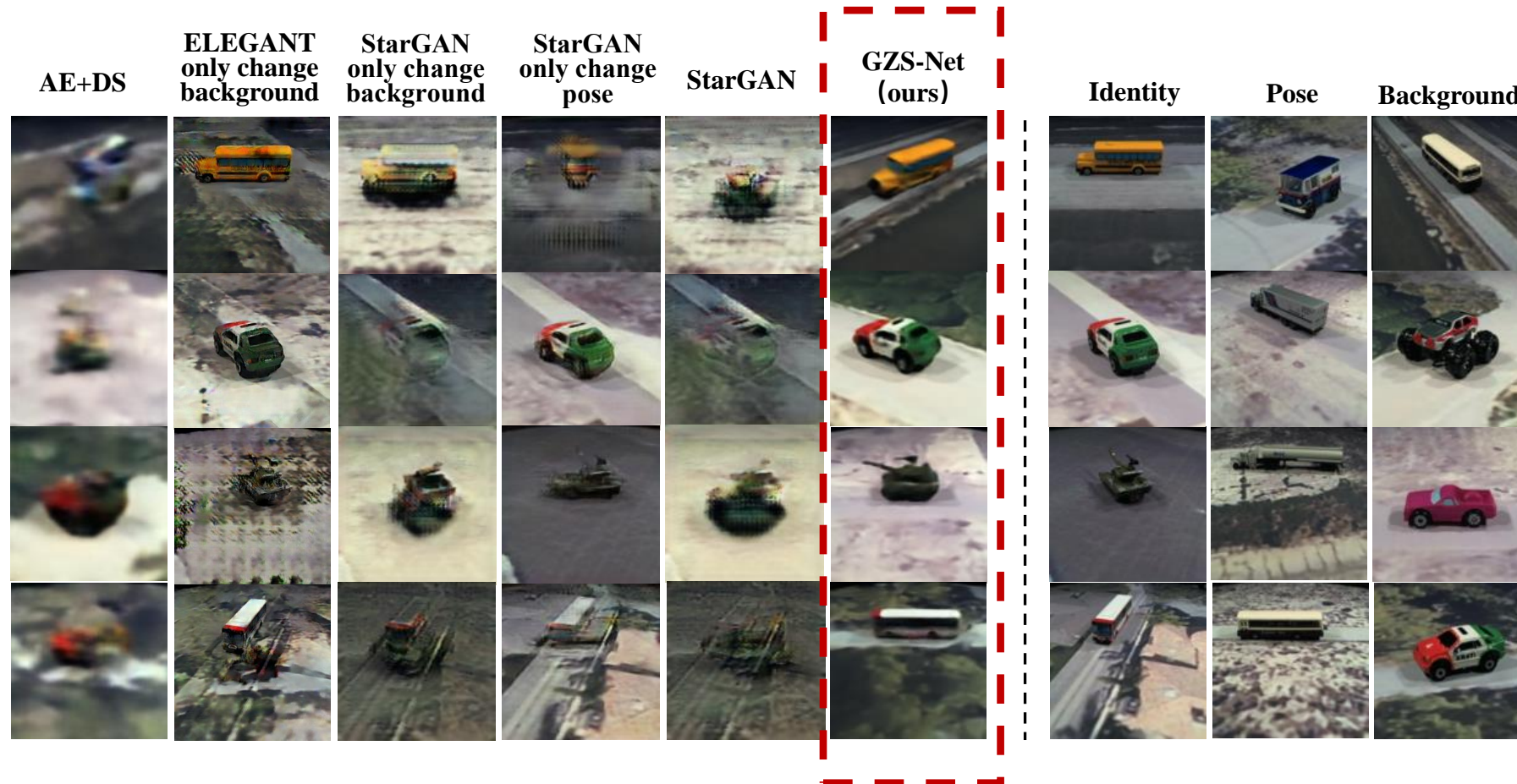
Controllable Disentanglement: (1) Predefine partition (2) Mine the similarity by **attribute swap**.



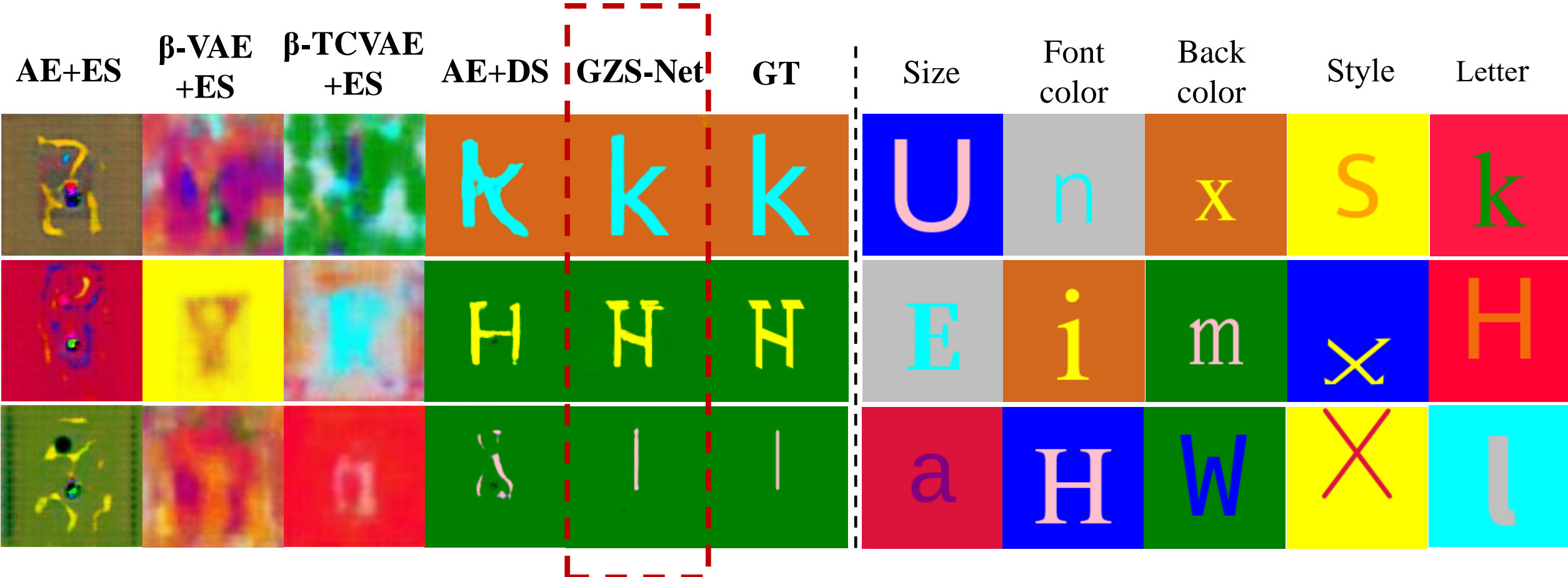
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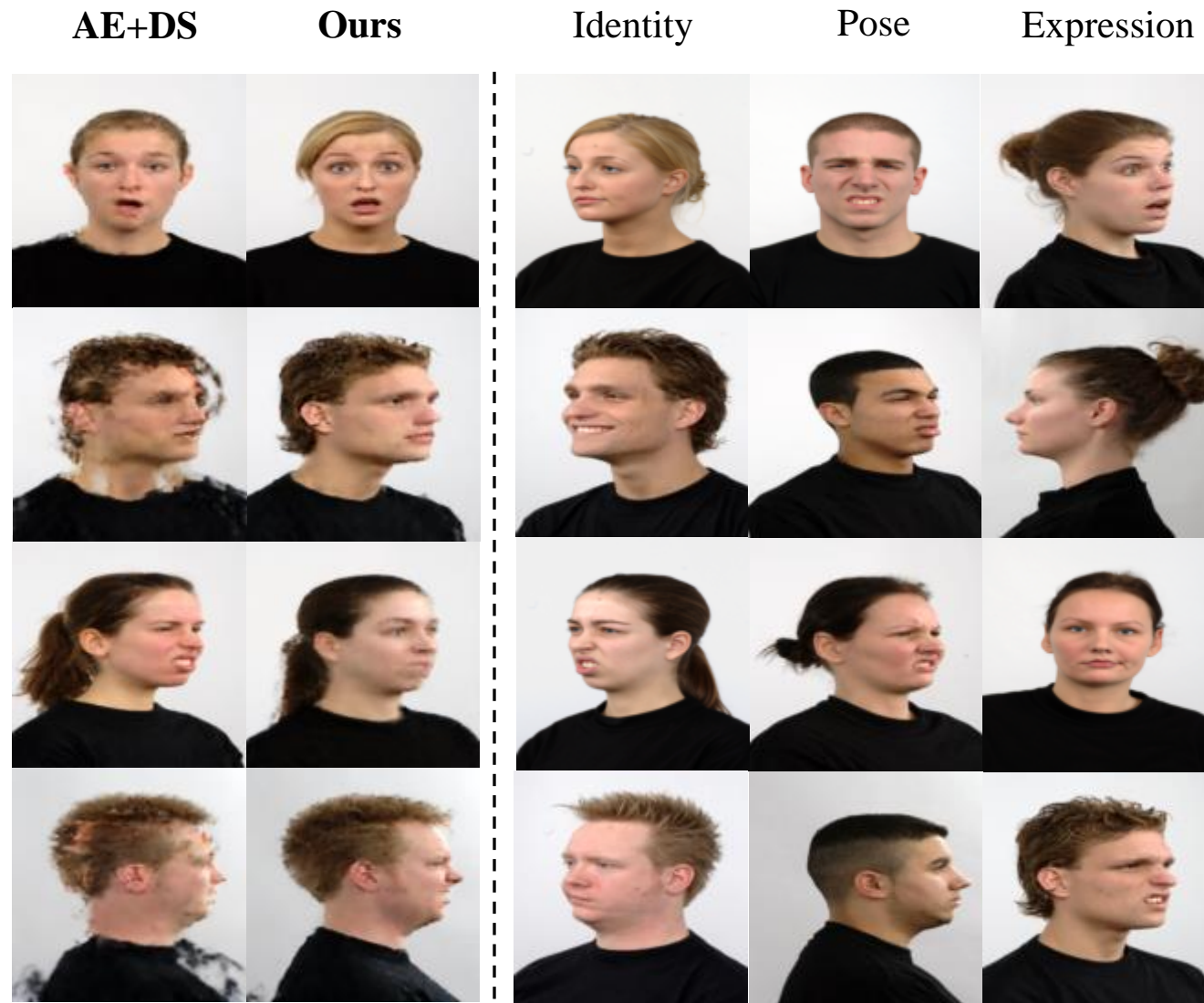
Qualitative Results 1 --- iLab-20M [1]



Qualitative Results 2 --- Fonts



Qualitative Results 3 --- RaFD [1]

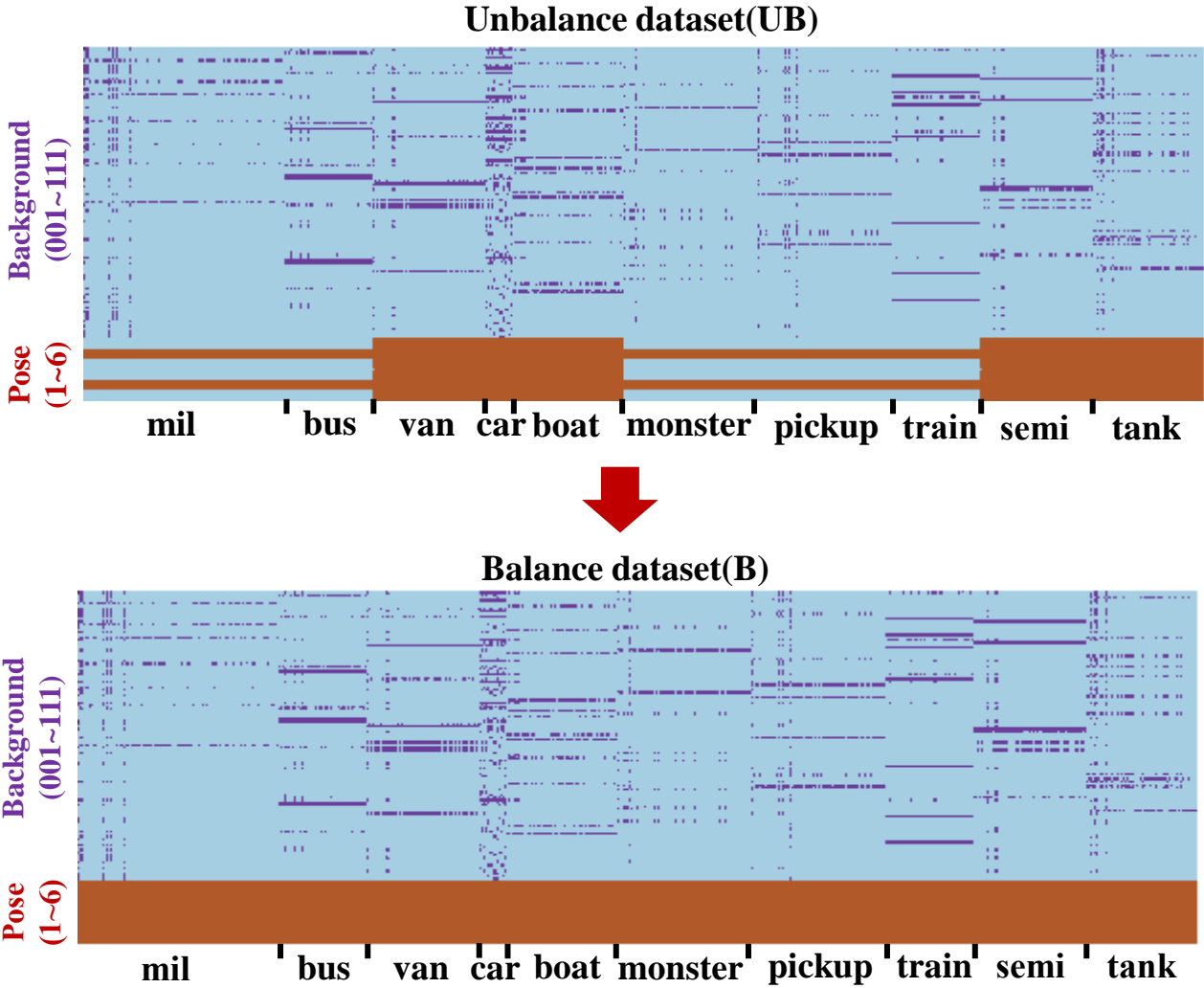


Quantitative Results 1 --- Disentanglement analysis

Table 1: Disentangled representation analysis. Diagonals are bolded.

	GZS-Net					Auto-encoder					AE + DS					β -VAE + ES					β -TCVAE + ES				
$\mathcal{A} (\mathcal{A})$	<u>C</u>	<u>S</u>	<u>FC</u>	<u>BC</u>	<u>St</u>	<u>C</u>	<u>S</u>	<u>FC</u>	<u>BC</u>	<u>St</u>	<u>C</u>	<u>S</u>	<u>FC</u>	<u>BC</u>	<u>St</u>	<u>C</u>	<u>S</u>	<u>FC</u>	<u>BC</u>	<u>St</u>	<u>C</u>	<u>S</u>	<u>FC</u>	<u>BC</u>	<u>St</u>
<u>C</u> ontent (52)	.99	.92	.11	.13	.30	.48	.60	.71	.92	.06	.99	.72	.22	.20	.25	.02	.35	.11	.19	.01	.1	.39	.13	.11	.01
<u>S</u> ize (3)	.78	1.0	.11	.15	.36	.45	.61	.77	.96	.07	.54	1.0	.19	.23	.25	.02	.38	.29	.11	.01	.02	.47	.18	.19	.01
<u>F</u> ont <u>C</u> olor (10)	.70	.88	1.0	.16	.23	.48	.60	.67	.95	.06	.19	.64	1.0	.66	.20	.02	.33	.42	.11	.01	.02	.35	.21	.13	.01
<u>B</u> ack <u>C</u> olor (10)	.53	.78	.21	1.0	.15	.53	.63	.64	.93	.08	.32	.65	.29	1.0	.25	.02	.34	.11	.86	.01	.03	.40	.24	.75	.01
<u>S</u> tyle (100)	.70	.93	.12	.12	.63	.49	.60	.70	.94	.06	.38	.29	.20	.20	.65	.02	.33	.10	.11	.02	.02	.33	.10	.08	.01

Quantitative Results 2 --- Data Augmentation

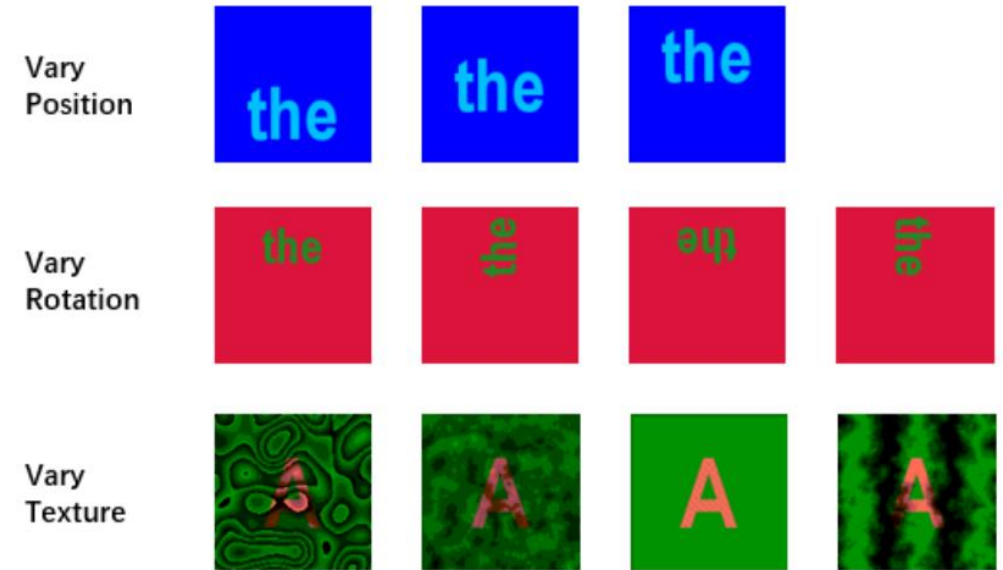


Dataset	UB	B	S-B	A-UB	Test
Source	real	real	GZS-Net synthesized	Traditional augmented	real
Numbe	25149	37417	37395	37395	37469
Overall Accuracy on Test	56.5	64.4	63.5	56.6	

Font dataset



Primary motivation : allows fast testing and idea iteration, on disentangled representation learning and zero-shot synthesis.



Group-Supervise Learning

Paper: <https://arxiv.org/pdf/2009.06586.pdf>

Code: <https://github.com/gyhandy/Group-Supervised-Learning>

Website:

