Supplemental Materials for "Hard Example Generation by Texture Synthesis for Cross-domain Shape Similarity Learning"

Huan Fu[1*] **Shunming Li**[1*] **Rongfei Jia**[1] **Mingming Gong**[2]

Binqiang Zhao[1] **Dacheng Tao**[3]

[1]TaoXi Technology Department, Alibaba Group, China
[2]The University of Melbourne, Australia
[3]The University of Sydney, Australia

`{fuhuan.fh, shunming.lsm, rongfei.jrf, binqiang.zhao}@alibaba-inc.com`
`mingming.gong@unimelb.edu.au dacheng.tao@sydney.edu.au`

1 Network Architecture

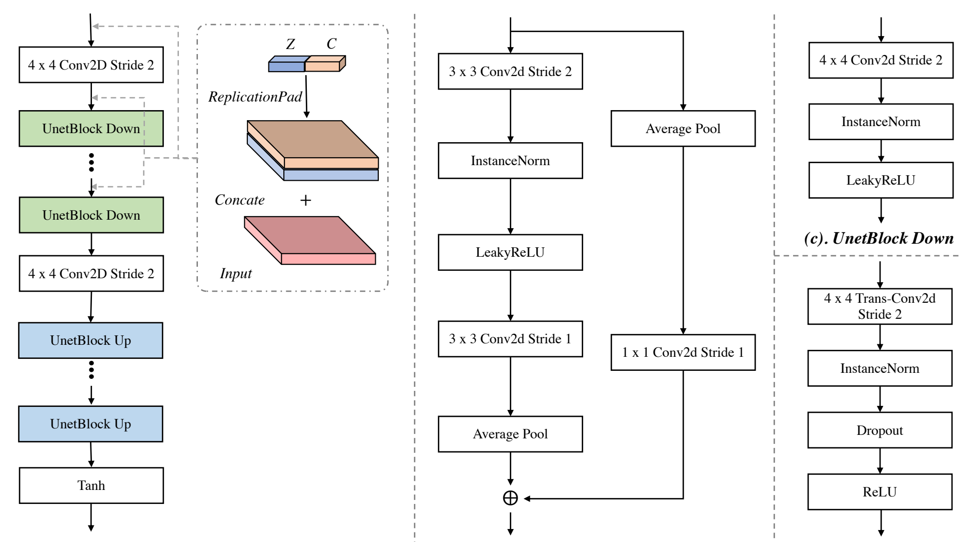

Figure 1: (a). Generator in Texture Synthesis Module (TSM). We show how to inject z and c into the generator, where z and c represents a latent code and a semantic latent code, respectively. Note that, for Stanford Cars and Comp Cars, c has been ignored since there is only one category in the two benchmarks. (b). ResBlock of the texture encoder in TSM. (c) The Unet downsampling block. (d) The Unet upsampling block. More details are reported in Table 1.

The network architectures for our geometry-focused multi-view metric learning framework are reported in Table 1 (TSM), Table 2 (AMV-ML), and Figure 1. For convenience, we use the following abbreviation: C_{in} = Input channel, C_{out} = Feature channel, K = Kernel size, S = Stride Size, Conv =

[*]Equal contribution.

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Convolutional layer, FC = Fully-connected layer, ResBlock = A residual block, ResNet34-Convi$_x$ = the ith convolutional block of ResNet34.

Table 1: The network architecture of our **Texture Synthesis Module (TSM)**. Here, C is the category number of the dataset.

Texture Synthesis Module (TSM)					
Encoder					
Index	Layer	C_{in}	C_{out}	K	S
1	Conv + InstanceNorm + LeakyReLU	3	64	4	2
2	ResBlock + InstanceNorm + LeakyReLU	64	64	3	1
3	ResBlock + InstanceNorm + LeakyReLU	64	128	3	1
4	ResBlock + InstanceNorm + LeakyReLU	128	192	3	1
5	ResBlock + InstanceNorm + LeakyReLU	192	256	3	1
6	ResBlock + LeakyReLU	256	256	3	1
7	Average Pool	-	-	8	8
8	Embedding $\mathcal{N}$ Linear 256 $\rightarrow$ 8	-	-	-	-
Generator					
1	Conv + LeakyReLU	3+4+8	64	4	2
2	UnetBlock Down	64+4+8	128	4	2
3	UnetBlock Down	128+4+8	256	4	2
4	UnetBlock Down	256+4+8	512	4	2
5	UnetBlock Down x4	512+4+8	512	4	2
6	Conv + ReLU	512	512	4	2
7	UnetBlock Up x 4	1024	512	4	2
13	UnetBlock Up	1024	256	4	2
14	UnetBlock Up	512	128	4	2
15	UnetBlock Up	256	64	4	2
16	UnetBlock Up + Tanh	128	3	4	2
Discriminator - 70x70					
1	Conv + LeakyReLU	3	64	4	2
2	Conv + InstanceNorm + LeakyReLU	64	128	4	2
3	Conv + InstanceNorm + LeakyReLU	128	256	4	2
4	Conv + InstanceNorm + LeakyReLU	256	512	4	1
5	Conv	512	1	4	1
5	Average Pool + FC	512	C	-	-
Discriminator - 140x140					
1	Average Pool	-	-	3	2
2	Conv + LeakyReLU	3	32	4	2
3	Conv + InstanceNorm + LeakyReLU	32	64	4	2
4	Conv + InstanceNorm + LeakyReLU	64	128	4	2
5	Conv + InstanceNorm + LeakyReLU	128	256	4	1
6	Conv	256	1	4	1
6	Average Pool + FC	512	C	-	-

2 Dataset Statistics

In Table 3, we report the statistics of the used datasets in our submission. For all the datasets, we train a single model instead of performing category-specific training. Note that, 3D-FUTURE here contains more fine-grained 3D CAD models. In contrast to other datasets, the 866 3D CAD models corresponding to the 5865 test images are totally unseen during the training procedure. In the evaluation stage, we use the full evaluation set (5548) as the 3D pool. Note that, Pix3D only provides a few 3D beds and sofas. Thus, our Top1@R is only slightly higher than previous methods on the bed and sofa categories.

Table 2: The network architecture of our **Attentive Multi-View Metric Learning (AMV-ML)**. For the Upernet decoder, see their public codes for more details.

Attentive Multi-View Metric Learning (AMV-ML)					
$Enc1$					
Index	Layer	C_{in}	C_{out}	K	S
1	Conv + BatchNorm + ReLU	3	64	7	2
2	MaxPool	-	-	3	2
3	ResNet34 - Conv2_x	64	64	3	-
$Enc2$ and $Enc3$					
1	ResNet34 - Conv3_x	64	128	3	-
2	ResNet34 - Conv4_x	128	256	3	-
3	ResNet34 - Conv5_x	256	512	3	-
UperNet					
1	Adaptive Average Pool	-	-	-	-
2	Conv + BatchNorm + ReLU	512	128	1	1
3	Conv + BatchNorm + ReLU	512+128	128	1	1
4	Feature Pyramid Network	-	-	-	-
5	Conv + BatchNorm + ReLU	512	128	3	1
6	Conv	128	1	1	1

Table 3: **Dataset Statistics.**

Dataset	**Category**	**Train Images**	**Train Models**	**Test Images**	**Test Models**	**Evaluation 3D Pool**
Pix3D	bed	198	19	196	-	19
	chair	1507	221	1387	-	221
	sofa	558	20	534	-	20
	table	384	62	354	-	62
	total	2647	322	2471	-	322
Stanford	car	8144	134	8041	-	134
Comp	car	3798	98	1898	-	98
3D-FUTURE	total	25913	4662	5865	886	5548 (4662 + 886)

3 Qualitative Results

We make qualitative comparisons with two widely studied retrieval solutions, including 2.5D-Sketch and Feature Adaptation (no-texture), on 3D-FUTURE. The results are shown in Figure 2. We can see that our method potentially focuses more on discovering the shape characteristics, thus achieve high-performing fine-grained retrieval. Note that, the other two methods are building on our proposed AMV-ML for fair comparisons, thus can also obtain reasonable retrieval results. More results are also shown in Figure 3.

We also report some challenging cases and failure cases in Figure 4. Firstly, we show three representative challenging cases on 3D-FUTURE, including partially occlusions, slight object incompletion, and unfavorable illumination. Our method can still capture acceptable retrieval sequences in these cases. However, our method can not handle some cases well, especially when the interested objects are heavily occluded, or the saliency objects are visually indistinguishable.

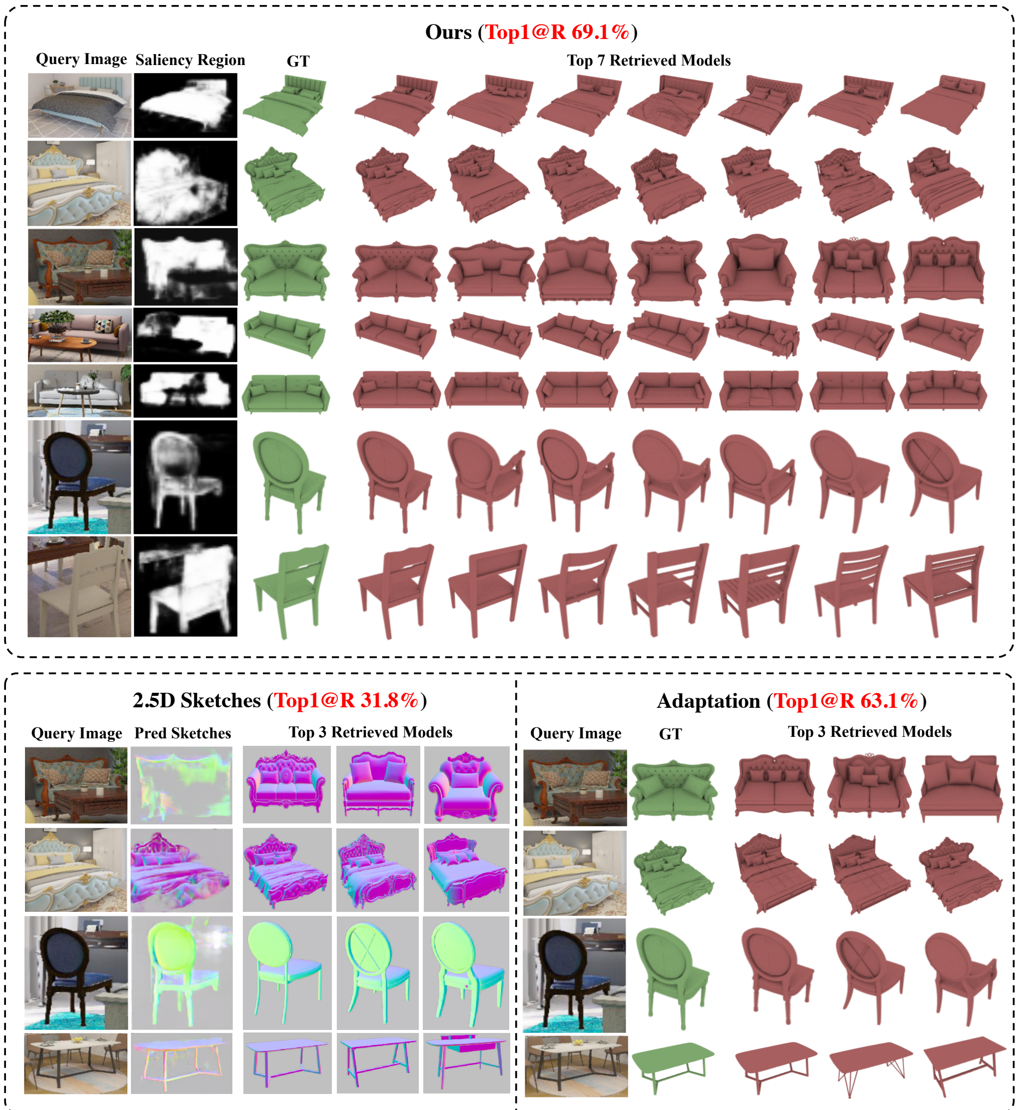
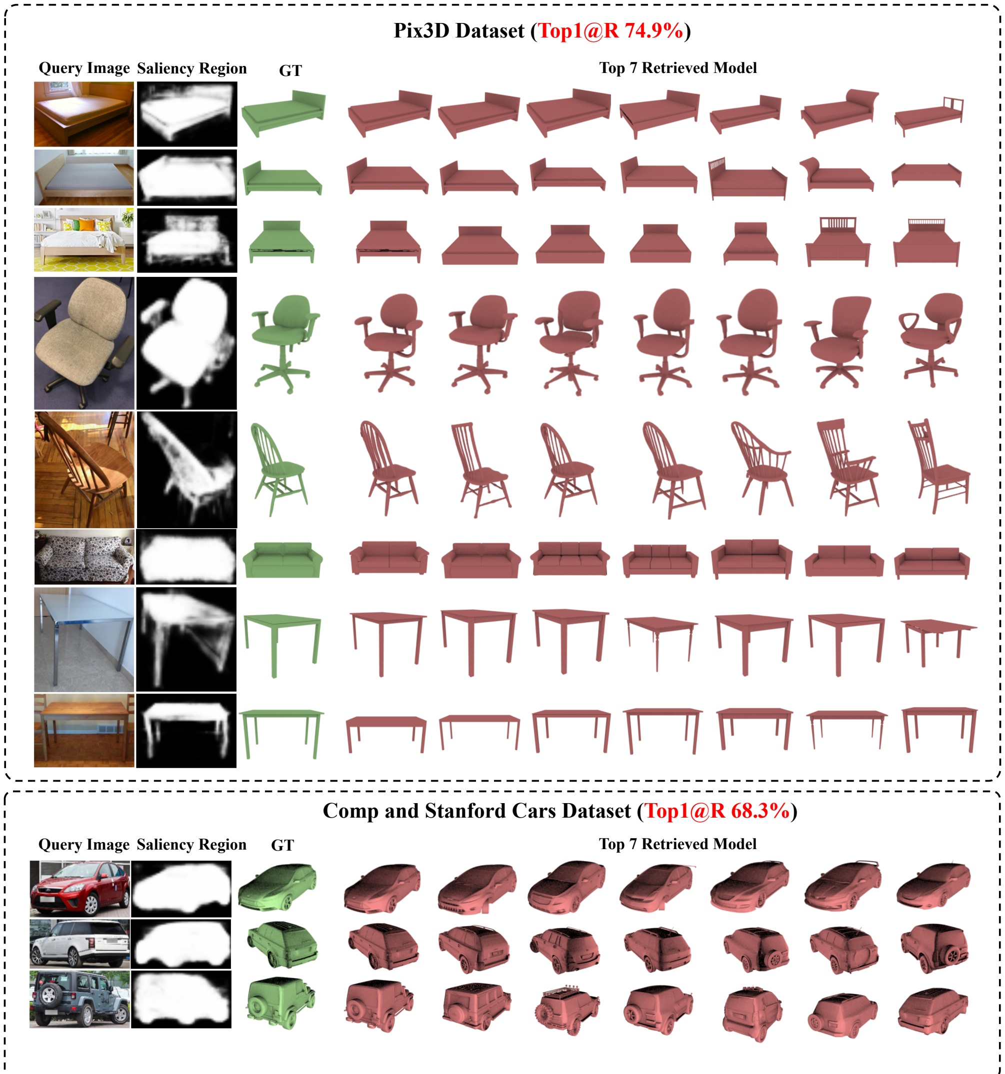


Figure 2: Qualitative comparisons with 2.5D-Sketch and Adaptation. For a fair comparison, all the experiments here are developed based on our AMV-ML in Sec. 2.2 in our submission. Benefiting from AMV-ML, all the compared methods here performs much better than SOTA methods.

Figure 3: **Qualitative Results on Other Public Benchmarks.**



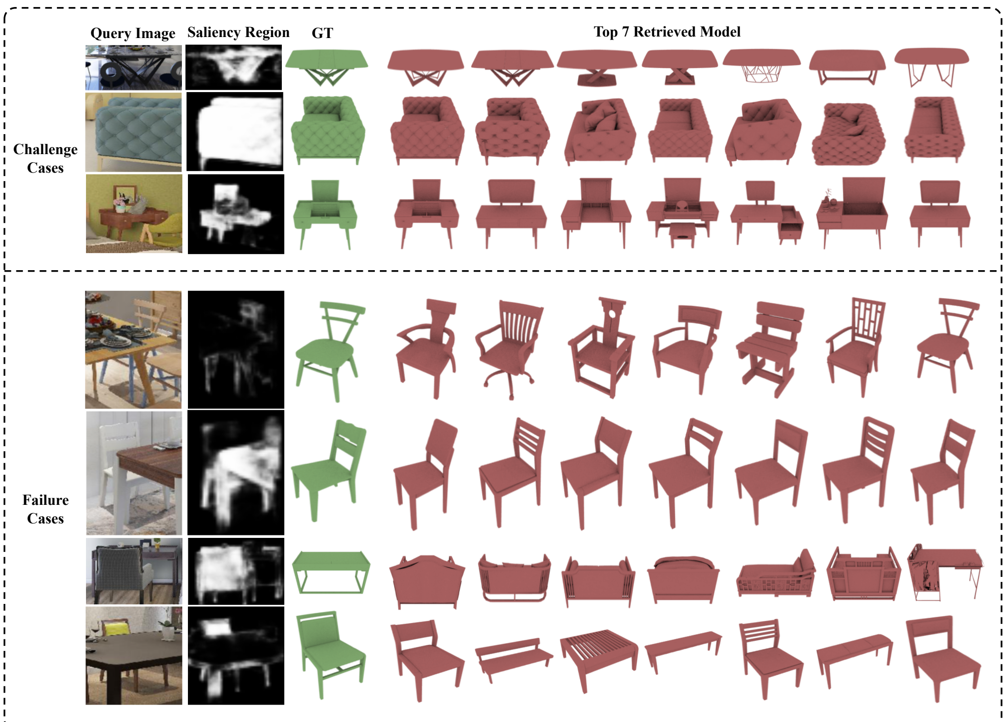


Figure 4: Some Challenging cases and Failure cases on 3D-FUTURE.