# Cross-Modal Hierarchical Modelling for Fine-Grained Sketch Based Image Retrieval







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# All categories

# **Category level SBIR**





## **Fine-grained SBIR**



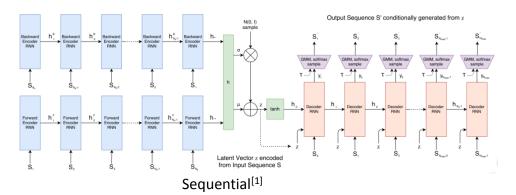


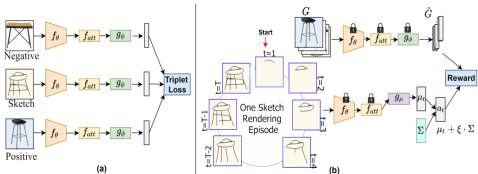




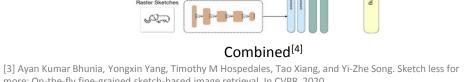


#### **Explored traits in sketches**



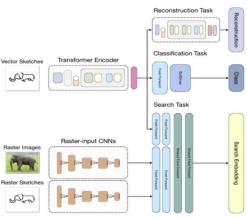


Stroke-wise<sup>[3]</sup>



Sequential data input organize his trains in it. O I don't like how thin the metal is. O It dents as easy as a cola can. If it were made better, it would be worth the money. O Save your money on this. AU: atomic unit Goal-driven abstraction 0-0 0-0-0 0--0 Goal - category (parade) Goal - category (owl/rabbit) Goal - sentiment (negative) 0-0 0--0--0 0-0 Goal - attribute (humans Goal - attribute (eyes/tail) Goal - category (toys) Videos

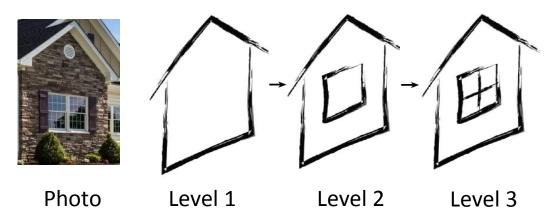
#### Abstract<sup>[2]</sup>



- [1] David Ha and Douglas Eck. A neural representation of sketch drawings. In ICLR, 2018.
- [2] Umar Riaz Muhammad, Yongxin Yang, Timothy Hospedales, Tao Xiang, and Yi-Zhe Song. Goal-driven sequential data abstraction. In ICCV, 2019.
- more: On-the-fly fine-grained sketch-based image retrieval. In CVPR, 2020
- [4] Leo Sampaio, Ferraz Ribeiro, Tu Bui, John Collomosse, and Moacir Ponti. Sketchformer:Transformer-based representation for sketched structure. In CVPR, 2020

#### **Motivation:**

- Extent of details being sketched can vary from coarse to fine.
- Sketches are **hierarchical** in terms of extent of detail sketched.
- Capturing hierarchical cross-modal correspondence between a sketch and its matching photo would therefore improve retrieval accuracy.



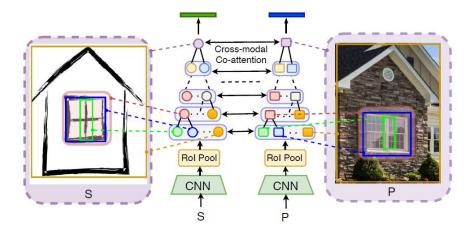
No matter the extent of detail drawn, we can fetch the right match!

### Why Challenging?

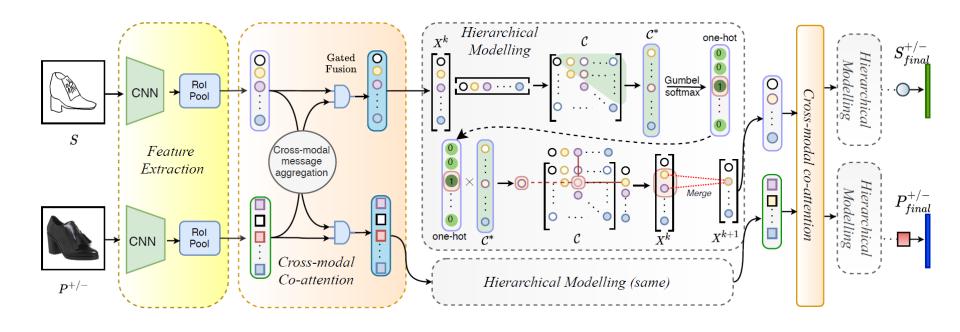
- Absence of predefined composition rules between sketch strokes.
- Unexplored cross-modal interaction between sketches and photos.

#### **Contributions:**

- End-to-end trainable framework that enables the **discovery of the underlying hierarchy** in a sketch.
- Cross-modal co-attention module to facilitate cross-modal hierarchy construction.
- Unique perspective of utilising hierarchies for FG-SBIR.



#### **Overall Framework**



#### **Cross-modal Co-attention module**

**Aim**: Enrich sketch representation with knowledge from its corresponding photo and vice-versa.

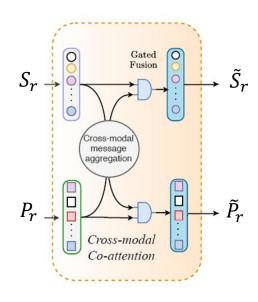
#### Method:

Calculate a stroke-region affinity matrix

$$\mathbf{A} = (S_r. W_{\psi}^S).(P_r. W_{\psi}^P)^T; \mathbf{A} \in \mathbb{R}^{N_S \times N_P}$$

Using co-attention, accumulate information to be fused.

$$\mathbf{A}_P^* = \operatorname{softmax}\left(\frac{\mathbf{A}}{\sqrt{d_h}}\right); \quad P_r^S = \mathbf{A}_P^*.P_r, \quad P_r^S \in \mathbb{R}^{N_S \times d}$$



Adaptively fuse the aggregated information onto its respective branch via a gating mechanism.

$$G^{S} = \operatorname{sigmoid}([S_{r}, P_{r}^{S}] . W_{G}^{S}), \qquad W_{G}^{S} \in \mathbb{R}^{2d \times d}$$

$$\tilde{S}_{r} = \mathbb{E}_{S}(G^{S} \odot (S_{r} \oplus P_{r}^{S})) \oplus S_{r}, \qquad \tilde{S}_{r} \in \mathbb{R}^{N_{S} \times d}$$

$$\tilde{S}_r = \mathbb{E}_S(G^S \odot (S_r \oplus P_r^S)) \oplus S_r, \qquad \tilde{S}_r \in \mathbb{R}^{N_S \times d}$$

#### **Hierarchical Modelling**

Formulate intra-regional compatibility matrix

$$\mathbf{C} = (X^k . W_{\phi}^C) . (X^k . W_{\phi}^C)^T, \mathbf{C} \in \mathbb{R}^{N^k \times N^k}$$

$$\mathbf{C}^* = \text{flatten}(\mathsf{UpTri}(\mathbf{C}))$$

Modeling discrete decision via Gumbel-softmax [1] distribution

$$q_i = \frac{\exp\left(\frac{\log \pi_i + g_i}{\tau}\right)}{\sum_{i=1}^{H^k} \exp\left(\frac{\log \pi_j + g_j}{\tau}\right)} \qquad q^{ST} = \left(q_1^{ST}, q_2^{ST}, \dots q_{H^k}^{ST}\right); \quad q_i^{ST} = 1_{[i=argmax_j(q_j)]}$$

Fusion: 
$$\hat{x}_{a,b} = \text{ReLU}(W_{\phi}^F . [x_a, x_b])$$
,  $W_{\phi}^F \in \mathbb{R}^{d \times 2d}$ 

Updation: 
$$X^{k+1} := X^k - \{x_a, x_b\} + \{\hat{x}_{a,b}\}; x_a, x_b \in X^k$$

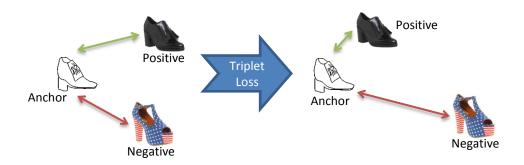
one-hot

Hierarchical

Modelling

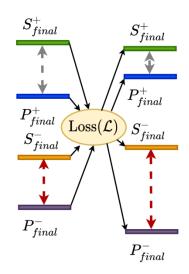
### **Learning Objective**

**Triplet Loss:** 
$$\mathcal{L}_{\theta}(s, p^+, p^-) = \max\{0, \Delta + D(f_{\theta}(s), f_{\theta}(p^+)) - D(f_{\theta}(s), f_{\theta}(p^-))\}^{[1]}$$



#### **Our formulation:**

$$\mathcal{L}\left(S_{final}^{+}, S_{final}^{-}, P_{final}^{+}, P_{final}^{-}\right) = \max\left\{0, \Delta + D\left(S_{final}^{+}, P_{final}^{-}\right) - D\left(S_{final}^{-}, P_{final}^{-}\right)\right\}$$



#### **Experiments**

- Datasets: QMUL-Shoe-V2, QMUL-Chair-V2, SWIRE
- Evaluation Metric:
  - top-1 accuracy (acc@1), top-10 accuracy (acc@10)
- Competitors:
  - Contemporary state-of-the-arts:
    - Triplet-SN [1]
    - Triplet-Attn-SN [2]
    - SWIRE [3]
  - Baselines:
    - B-Siamese: Siamese triplet network with Inception V3 backbone.
    - B-Gated-Siamese: Network involving paired embedding by employing a matching gate [4].
    - B-Localised-Coattn: Framework with paired embedding having interaction between local photo-sketch sub-regions, without hierarchy.
    - B-Graph-Hierarchy: A framework modelling a graph-based method inspired by DIFFPOOL [5].
  - Other contemporary SBIR pipelines:
    - SketchFormer-variant: Based on Sketch-former architecture [6].
    - SketchBERT-variant: Based on Sketch-BERT architecture [7].
- [1] Qian Yu, Feng Liu, Yi-Zhe Song, Tao Xiang, Timothy M Hospedales, and Chen-Change Loy. Sketch me that shoe. In CVPR, 2016.
- [2] Jifei Song, Qian Yu, Yi-Zhe Song, Tao Xiang, and Timothy M Hospedales. Deep spatial-semantic attention for fine-grained sketch-based image retrieval. In ICCV, 2017.
- [3] Forrest Huang, John F Canny, and Jeffrey Nichols. Swire: Sketch-based user interface retrieval. In CHI, 2019.
- [4] Rahul Rama Varior, Mrinal Haloi, and GangWang. Gated siamese convolutional neural network architecture for human re-identification. In ECCV, 2016
- [5] Zhitao Ying, Jiaxuan You, Christopher Morris, Xiang Ren, Will Hamilton, and Jure Leskovec. Hierarchical graph representation learning with differentiable pooling. In NeurIPS, 2018
- [6] Leo Sampaio Ferraz Ribeiro, Tu Bui, John Collomosse, and Moacir Ponti. Sketchformer: Transformer-based representation for sketched structure. In CVPR, 2020.
- [7] Hangyu Lin, Yanwei Fu, Yu-Gang Jiang, and Xiangyang Xue. Sketch-bert: Learning sketch bidirectional encoder representation from transformers by self-supervised learning of sketch gestalt. In CVPR, 2020

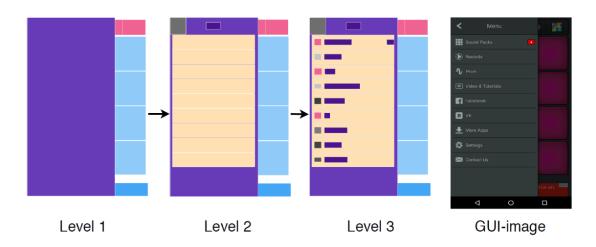
# **Performance Analysis**

Methods		Chair-V2		Shoe-V2		SWIRE	
	Tetrious	acc.@1	acc.@10	acc.@1	acc.@10	acc.@1	acc.@10
State-of-the-arts	Triplet-SN	45.65	84.24	28.71	71.56	-	-
	Triplet-Attn-SN	56.54	88.15	31.74	74.78	-	-
	SWIRE	-	-	-	-	15.90	60.90
Baselines	B-Siamese	49.54	85.98	30.96	72.54	54.21	82.15
	<b>B-Gated-Siamese</b>	53.08	86.34	32.65	74.24	62.12	85.65
	<b>B-Localised-Coattn</b>	55.24	88.21	33.21	77.83	65.48	88.65
	B-Graph-Hierarchy	58.22	89.97	34.05	79.54	66.18	89.32
Others	SketchBERT-Variant	13.54	54.78	8.15	48.23	-	-
	SketchFormer-Variant	32.54	84.82	26.21	65.34	-	-
	Proposed	62.45	90.71	36.27	80.65	67.23	90.11

#### **Ablation Study**

#### Is hierarchy useful for FG-SBIR?

- Design elements in GUIs have a hierarchy defined by **containment**.
- Larger rectangular boxes encompass smaller ones (buttons) within.
- If hierarchy is at all useful, it should be **most helpful** in sketch based GUI image retrieval task, as there exists a pre-defined rule here.



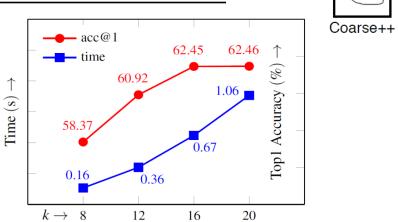
Layout order in a GUI

#### **Further Analysis**

Table 2: Ablative Study (acc.@1)

	<u> </u>		
Methods	Chair-V2	Shoe-V2	SWIRE
Explicit Hierarchy	-	-	71.54
w/o Localised-Coattn	51.85	31.82	60.32
w/o Hierarchy	55.24	33.21	65.48
Sketch-coarse	47.64	31.83	51.26
Sketch-coarse++	42.33	24.11	45.33
Proposed	62.45	36.27	67.23

Table 3: Retrieval performance on varying extent of detail (Acc@10)						
		ChairV2	ShoeV2			
B-Siamese	Sketch-coarse	75.32	62.68			
	Sketch-coarse++	65.31	54.32			
	Full sketch	85.98	72.54			
	Sketch-coarse	87.58	77.23			
Proposed Method	Sketch-coarse++	85.64	75.91			
	Full sketch	90.71	80.65			



Full

Coarse

Study on impact of number of regions chosen for feature extraction in image branch

#### **Qualitative Results**



QMUL Shoe-V2 Dataset

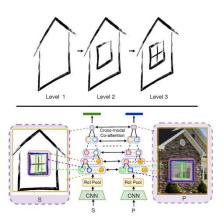
#### **Qualitative Results (contd.)**



**SWIRE Dataset** 



#### http://sketchx.ai



https://aneeshan95.github.io/Cross-modal\_Hierarchy\_FGSBIR