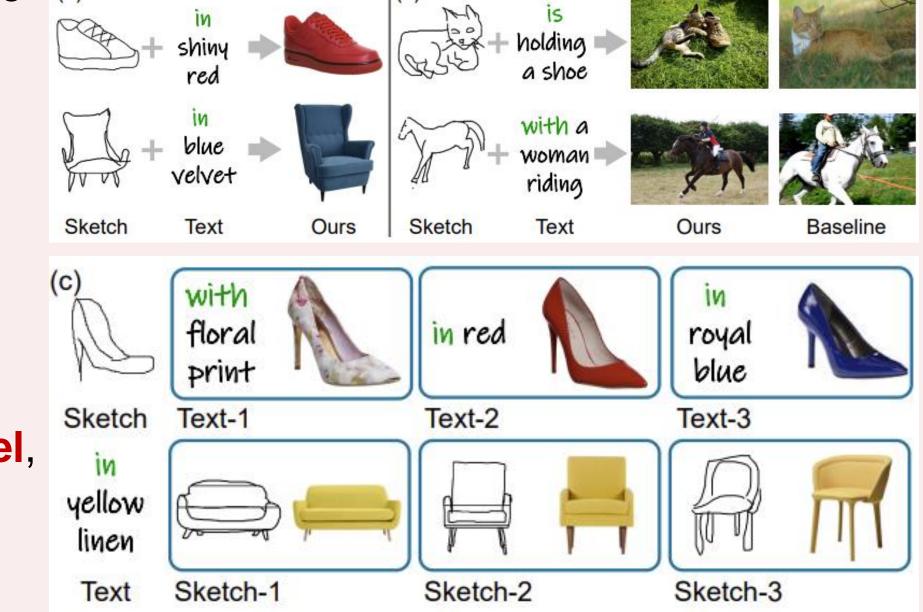
## Got 2 Minutes? Start here 4 Summary

- Addresses the challenge (a) of fine-grained image retrieval by leveraging the synergy between freehand sketches and text captions.
- Effectively combining sketches and text using pre-trained CLIP model, eliminating the need for extensive fine-grained textual descriptions.



> Unlocks novel applications like object-sketch-based scene retrieval, domain attribute transfer, & sketch+text-based fine-grained generation.

#### **Problems**

- Existing sketch+text-based retrieval methods have predominantly focused on scene-level or category retrieval.
- Existing fine-grained sketch-photo datasets lack paired fine-grained textual description.
- > Textual caption generation via SoTA captioners often results in noisy and inaccurate description in case of abstract freehand sketches.

### Solutions

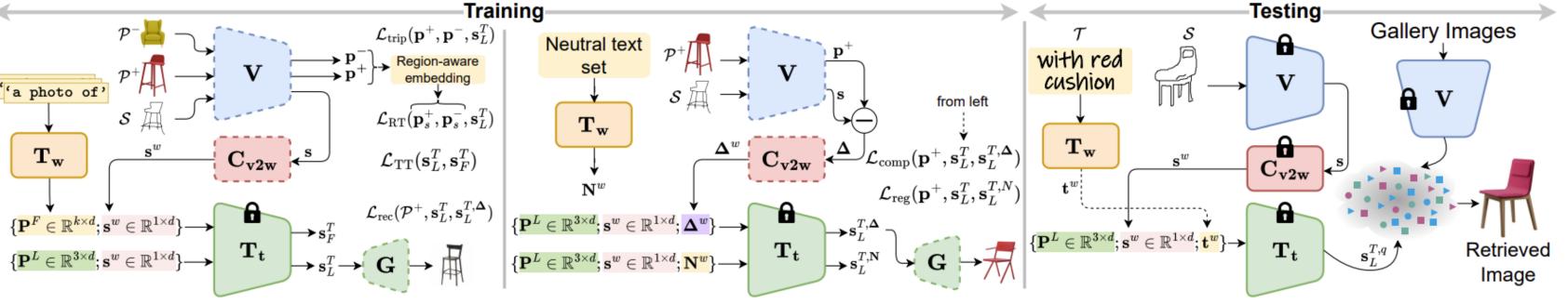
- > We convert input sketches into fine-grained textual equivalents, referred to as a "pseudo-word token". This token, when combined with text input, forms a fine-grained textual query that seamlessly integrates both sketch and text features.
- > We hypothesise that the fine-grained description embedded in a photo (P) can be approximated by that of a sketch (S) plus text (T), leading to T = P - S. This relationship illustrates how the absence of T can be approximated by the difference signal between P and S.
- We enforce fine-grained matching between composed query and paired photo embedding via region-aware triplet loss and an auxiliary generative loss.

# You'll Never Walk Alone: A Sketch and Text Duet for Fine-Grained Image Retrieval

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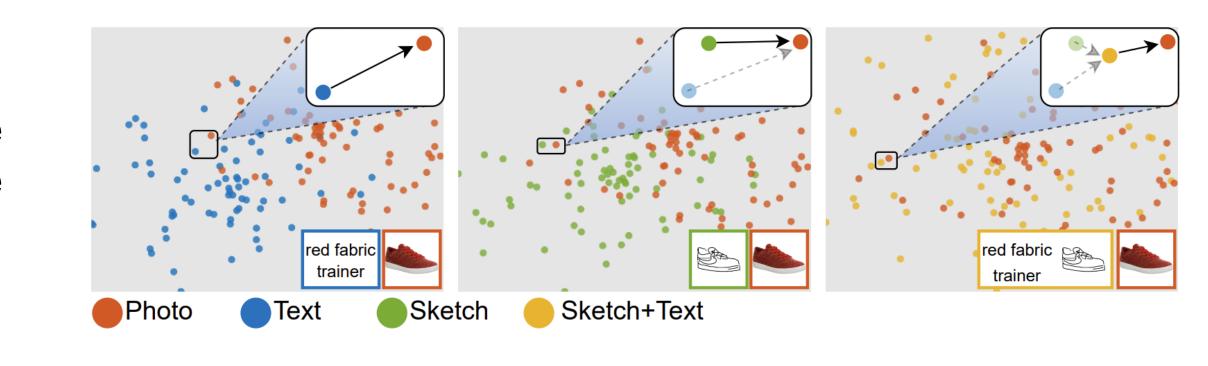
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<sup>2</sup>iFlyTek-Surrey Joint Research Centre on Artificial Intelligence



## **Proposed Model**

- > Salient Components
  - 1. Novel compositionality constraint to imitate the missing textual description.
  - 2. Neutral text to preserve the grammatical structure of CLIP's input text-space.
  - 3. Generalisable continuous prompt-learning over handcrafted textual prompts.
  - 4. Fine-grained matching via region aware triplet loss and auxiliary generative loss.
- > While our method does not rely on paired textual captions during training, users can provide optional captions during inference.
- $\triangleright$  We compute the sketch-photo difference signal embedding  $\Delta^w$ , which could be considered as a pseudo word token imitating the difference between sketch and photo, which ideally would be substituted with real query text during inference.
- $\triangleright$  Although  $\Delta^w$  enforces compositionality, this mere numeric signal does not exist in CLIP's input text manifold and might break its grammatical syntax.
- $\succ$  To restrict the adverse effect of  $\Delta^w$ , we regularise the training via a "neutral-text" set containing a list of 3-5 word generic description of a freehand sketch.
- We impose a text-totext generalisation loss that enforces the learned prompts to be similar to a set of handcrafted language prompts.



> Finally to maintain fine-grained appearance features, we use a UNet generator to enforce generator guidance.







### **Experiments & Results**

