Enhance Sketch Recognition's Explainability via Semantic Component-Level Parsing

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Abstract

Free-hand sketches are appealing for humans as a universal tool to depict the visual world. Humans can recognize varied sketches of a category easily by identifying the concurrence and layout of the intrinsic semantic components of the category, since humans draw free-hand sketches based a common consensus that which types of semantic components constitute each sketch category. For example, an airplane should at least have a fuselage and wings. Based on this analysis, a semantic component-level memory module is constructed and embedded in the proposed structured sketch recognition network in this paper. The memory keys representing semantic components of each sketch category can be self-learned and enhance the recognition network's explainability. Our proposed networks can deal with different situations of sketch recognition, i.e., with or without semantic components labels of strokes. Experiments on the SPG and SketchIME datasets demonstrate the memory module's flexibility and the recognition network's explainability. The code and data are available at https://github.com/GuangmingZhu/SketchESC.

Introduction

Free-hand sketch is a universal tool to depict the visual world, and it is not bound by age, race, language, geography, or national boundaries. Sketch images are highly sparse, abstract and lack of background. Sketch can be regarded as an expression of the human brain's internal representation of the visual world (Xu et al. 2022). Humans can recognize sketches and identify the intrinsic semantic components easily, even sketches of the same category drawn by different persons may be very different in appearance.

Sketch can be represented as an image in the static pixel space, as a time series in the dynamic stroke coordinate space, or as a graph in the geometric graph space. This results in various Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Graph Neural Network (GNN) based methods for sketch recognition (Zhang et al. 2019; Xu et al. 2022). These methods usually take image- or Scalable Vector Graphics (SVG)- format data as input, and predict the category label for a given sketch sample. However, there is lacking of work on interpreting the reason of giving such predictions.

Explainable artificial intelligence (XAI) has become a hot research topic to explain models' decision (Ramaswamy et al. 2020; Shitole et al. 2021; Garau et al. 2022). Visualizing the activation maps of deep neural networks is widely used in computer vision. However, sketch images composed of stroke lines without textures, are different from natural images. This means that the existing XAI methods cannot be applied directly in the sketch research field. A first look at explainability for human sketches was achieved by SketchXAI using the counterfactual explanation (Qu et al. 2023). The stroke location inversion module in SketchXAI offers an explainability angle to sketch in terms of asking a network how well it can recover stroke locations of an unseen sketch. Liu et al. developed an image classifier explanation model using the counterfactual maps, in which the counterfactual map generator module is used to identify the critical structures for the specific category (Liu et al. 2023).

Counterfactual explanation (CE), as a post-hoc explainability method, aims to identify what are the minimal input changes for a model to make a different visual decision (Van Looveren and Klaise 2021). SketchXAI (Qu et al. 2023) used CE to relocate reshuffled strokes to construct a sketch given a category, while Liu et al. designed a counterfactual map generator to discover the stroke-level principal components for a specific category (Liu et al. 2023). The above two methods try to explain the question of "*why the sketch is classified as X*" by providing positive and negative semantic explanation evidences. However, we believe that *the concurrence and layout of the intrinsic semantic components of a category can be a crucial evidence to explain the question from another perspective*. For example, taking into consideration the common knowledge that an airplane should at least have a fuselage and wings, if a sketch is composed of strokes which can be semantically grouped into a fuselage and wings, it probably is an airplane. As to the analysis above, we propose to enhance sketch recognition's explainability via semantic component-level parsing.

Specifically, a Semantic Component-level Memory (SCM) module is constructed, whose memory keys represent the semantic components of different sketch categories. The SCM module is embedded in a Structured Sketch Recognition (SSR) network, and evolves the stroke features based on the similarity with the learnable features of memory keys. The fused stroke-level or component-level

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features are fed into a Transformer to achieve a high recognition performance under the supervision on segmentation (if available) or compositionality (i.e., which types of semantic components constitute each sketch category). For the dataset with the category labels and the semantic component labels of strokes, the supervision on the component-level parsing in the SCM module and on the semantic segmentation results of the Transformer can be used to achieve a precise and explainable recognition performance. For the dataset only with category labels, the supervision on the compositionality can be used in the proposed SSR network to enhance the recognition network's explainability. This flexibility makes the proposed SCM module and SSR network applicable on sketch recognition and segmentation tasks and achieve better and explainable performance.

The main contribution can be summarized as follows.

- A semantic component-level memory module is constructed, which can learn and store memory keys representing semantic components, and do explainable parsing from strokes to components.
- A structured sketch recognition network is proposed, which has hierarchical and explainable abilities, from stroke-level embedding, component-level parsing to sketch-level recognition.
- The proposed network is explainable and flexibility to deal with the sketch recognition situations with or without semantic component labels of strokes, and can achieve remarkable performance on the public datasets.

Related Work

Sketch Recognition

Sketches are generally represented as pixel-level rasterized images or ordered sequences of point coordinates. Typically, CNNs (Yu et al. 2017; Prabhu et al. 2018), RNNs (Sarvadevabhatla and Kundu 2016; Ha and Eck 2017), or CNN-RNN architectures (Xu et al. 2018; Li et al. 2020) were constructed for sketch recognition. Recently, the trend from Euclidean (CNN, RNN based) to topological analysis (GNN based) has emerged in sketch recognition. A sketch can also be represented as the sparsely connected graphs in the topological space. Therefore, GNN based models were proposed to model sketch's local and global topological stroke structures (Xu, Joshi, and Bresson 2021). There is no consensus on which representation style is better than the other, as each has its own merits based on the application scenarios. Rasterized images ignore the sketching orders and are better for offline recognition. Sequence-based representation can be used to continuously predict the labels using accumulated sketch strokes online, and can be used in more interactive real-time applications. Graph-based representation is flexible to encode local and global geometric sketch structures, and can be used for sketch grouping or segmentation. However, no matter which representation style is used, visual explanation is rarely studied for sketch recognition.

Visual Explanation

Various activation map visualization techniques, such as the Grad-CAM series methods(Selvaraju et al. 2017; Chattopadhay et al. 2018; Omeiza et al. 2019), have been widely researched to interpret the classifier's decision-making rationale. These methods highlight the essential regions, but the explainability on sketch recognition is better to explore strokes' effects on recognition, therefore they are not suitable for sketch researches. Contrasted to these pixel-level methods, patch-level methods tried to use representative patches to explain the classifier's prediction (Chen et al. 2019; Zhang et al. 2018; Ge et al. 2021). However, considering the surrounding or overlapping between strokes of a sketch in the spatial layout, patches can not always represent individual semantic components. Besides, explanation via visualization is hard to understand for non-expert users.

Counterfactual explanation methods (Van Looveren and Klaise 2021; Miller 2019) supplied alternative approaches to identify what are the minimal input changes for a model to make a different visual decision. SketchXAI(Qu et al. 2023) used CE to relocate reshuffled strokes to construct a sketch given a category, while Liu et al. designed a counterfactual map generator to discover the stroke-level principal components for a specific category (Liu et al. 2023). These methods contribute the first exploration on sketch recognition's explainability in the stroke-level.

Humans draw free-hand sketches based a common consensus that which types of semantic components constitute each sketch category. Strokes of a sketch can be considered as abstract representation of the object's shape, component, or attributes. Therefore, since humans perceive the visual world by parsing objects' shape, components and attributes hierarchically and structurally, why cannot sketch recognition networks enhance their explainability by identifying the semantic components that strokes constitute. Alanize et al. constructed a Primitive-Matching Network (PMN) to learn interpretable abstracts of a sketch through simple primitives (Alaniz et al. 2022). Zhu et al. proposed a simultaneous sketch recognition and segmentation (SketchRecSeg) network which parses the semantic components at the same time when recognizing a sketch (Zhu et al. 2023). However, PMN (Alaniz et al. 2022) only fulfills the matching between strokes and primitives. SketchRecSeg (Zhu et al. 2023) uses a two-stream architecture, but its segmentation stream cannot enhance its recognition stream's explainability.

Methodology

We aim to construct a Structured Sketch Recognition (SSR) network which does Stroke-Level Embedding on each stroke, implements Component-Level Parsing, and fulfills explainable Sketch-Level Recognition, as shown in Fig. 1. For the data with category labels and the semantic component labels of each stroke (i.e., the scenario ① in Fig. 1), *sketches can be recognized and semantically segmented simultaneously*. For the data only with category labels and the prior knowledge about the intrinsic semantic components of each category (i.e., the scenario ② in Fig. 1), *sketches can be recognized with the auxiliary constraint that which types of semantic components constitute each sketch category*. Both two scenarios result in sketch recognition results with the auxiliary information about which types of semantic components constitute each sketch sample. This enhances the

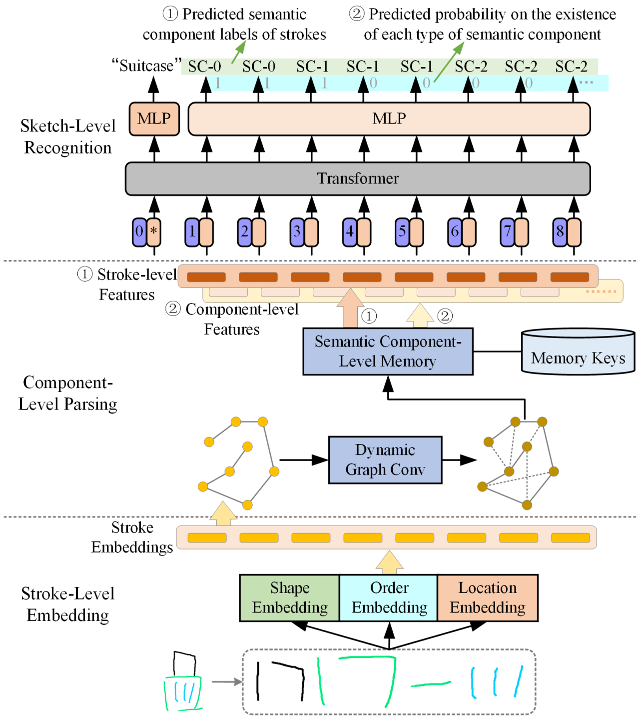


Figure 1: Overview of the proposed Structured Sketch Recognition network. The ① indicates the scenario that the Semantic Component-Level Memory module feeds the fused stroke-level features into Transformer for sketch recognition and segmentation. The ② indicates the scenario that the fused component-level features are fed into Transformer for sketch recognition and the probability prediction on the existence of each type of semantic component.

sketch recognition network's explainability.

Stroke-Level Embedding

Formally, each sketch can be represented as an ordered sequence of strokes, denoted as $\{s_1, s_2, \cdots, s_i, \cdots, s_N\}$. Stroke s_i consists of k points, $\{s_{i,1}, s_{i,2}, \cdots, s_{i,k-1}, s_{i,k}\}$, and each point contains a two-dimensional coordinate value and a two-dimensional binary pen state (Ha and Eck 2018). Three descriptors are learned to identify three inherent properties of each sketch, i.e., shape sh_i, stroke order o_i and location l_i, as in SketchXAI (Qu et al. 2023). The location of stroke s_i is defined as the coordinate of the first point $s_{i,1}$. Specifically, a bidirectional Long Short-Term Memory (LSTM) is used for the shape embedding to extract shape information sh_i of each stroke, a learnable embedding is used for the order embedding o_i, and one linear layer is used for the location embedding l_i. These three kinds of embeddings are summed as the stroke embeddings.

Component-Level Parsing

When a sketch is represented as a sparsely connected graph, the graph nodes generally denote the stroke points, as in SketchGNN (Yang et al. 2021) and MultiGraph Transformer (Xu, Joshi, and Bresson 2021). In this study, stroke points have been aggregated in the stroke-level embedding stage, therefore a stroke-level graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ can be constructed. $\mathcal{V}$ denotes the graph node set, in which each node represents a stroke. $\mathcal{E}$ denotes edges that connect adjacent strokes in sketching order.

Dynamic Graph Convolution The above stroke-level embedding does not involve inter-stroke feature fusion. However, the semantic meaning of a stroke does not only depend on its shape and location, but also depends on the context of strokes. Inter-stroke fusion is necessary to learn which strokes constitute a semantic component. A two-layer dynamic graph convolution (Yang et al. 2021) unit is used in our network. The same graph convolution operation as in EdgeConv (Wang et al. 2019) is adopted. In order to enlarge the receptive field, $\mathcal{E}$ is updated layer-by-layer using the Dilated k-NN (Li et al. 2019). The motivation of updating $\mathcal{E}$ is to explore the feature fusion between strokes which belong to the same semantic component but are not adjacent in sketching order. The dilation ratios in the two layers are 1 and 2, respectively. A residual connection exists in each graph convolution layer to sum the input and output features.

Semantic Component-Level Memory Memory augmented neural networks utilize external memory to explicitly access the experiences (Khasahmadi et al. 2019). A Semantic Component-level Memory (SCM) module can store the feature representation of semantic components, so that a similarity metric can be implemented to associate strokes with the semantic components to which they belong. In such case, strokes belonging to the same semantic component can be fused further to get the component-level features. Explainable similarity metrics ensure the explainability of the semantic component-level parsing, and the category classifier can do explainable inference, i.e., “*The sketch is recognized as X because it is composed of the semantic components which constitute X*”.

Specifically, the SCM module consists of a multi-head array of memory keys. Each semantic component is represented by a multi-head key in SCM. Given the stroke feature q_i outputted by the dynamic graph convolution module, we use Eq. (1) as a kernel to measure the normalized similarity between the stroke feature q_i and the key k_j of SCM as[1]:

$$C_{i,j} = \frac{(\varepsilon + \|q_i - k_j\|^2/\tau)^{-\frac{\tau+1}{2}}}{\sum_{j'} (\varepsilon + \|q_i - k_{j'}\|^2/\tau)^{-\frac{\tau+1}{2}}}, \tag{1}$$

where $C_{i,j}$ is the normalized score between the stroke feature q_i and the memory key k_j (representing the j-th type of semantic component), τ is the degree of freedom, and ε is a bias value which is much smaller than the average of $\|q_i - k_j\|^2/\tau$. *Memory keys are learnable parameters and learned automatically during the network training process.*

A Max-pooling operation is implemented to select the most similar head from the multi-head key of each semantic component for each stroke. For simplicity, we use $C_{i,j}$ to represent the similarity between the stroke q_i and its most

[1]The head index of multi-head keys is omitted for simplicity

similar head key k_j of the j-th type of semantic component in the following description, and use $\mathbf{K} \in \mathcal{R}^{K\times d}$ to represent the set of the most similar head key of each semantic component for one stroke, where K is the component type count. A Softmax operation is further implemented along the j-dimension of $\{C_{i,j}\}$ to obtain the normalized assignment matrix $\mathbf{C} \in \mathcal{R}^{N\times K}$, where N is the stroke count.

Feature Fusion. Two feature fusion strategies are designed. One is the stroke-level feature fusion, i.e., *enhancing the stroke features by memory keys*, denoted as

$$\mathbf{F}_s \in \mathcal{R}^{N\times d} = (1-max_j(\mathbf{C}))\circ\mathbf{Q}+max_j(\mathbf{C})\circ\mathbf{C}*\mathbf{K}. \quad (2)$$

The enhanced features $\mathbf{F}_s$ are further fed into Transformer for sketch recognition and segmentation. The other is the component-level feature fusion, i.e., *generating component features by fusing stroke features and memory keys*,

$$\mathbf{F}_c \in \mathcal{R}^{K\times d} = (1-max_j(\mathbf{C}))\circ\mathbf{C}^\top*\mathbf{Q}+max_j(\mathbf{C})\circ\mathbf{K}. \quad (3)$$

The component features $\mathbf{F}_c$ can be fed into Transformer for sketch recognition along with the prediction on the existence of each type of semantic component. In Eqs. (2) and (3), $\mathbf{Q} \in \mathcal{R}^{N\times d}$ is the stroke features outputted by the dynamic graph convolution module, $\circ$ is the broadcasting multiply operation, and $*$ is the matrix multiplication operation. The balance ratio $max_j(\mathbf{C})$ means that if a stroke can be assigned to a semantic component with a high confidence, the key feature of the semantic component is more representative and better used for sketch recognition.

Supervision on SCM. The keys in MemGNN are learned without extra supervision (Khasahmadi et al. 2019). We believe that it is better to ensure keys' distinguishability, since keys represent different types of semantic components. Therefore, a linear classifier and a *Cross-Entropy* (*CE*) loss are implemented in the SCM module as

$$\mathcal{L}1 = CE(f_{w1}(k_j), j). \quad (4)$$

If the semantic component label of each stroke is available, a supervision on the assignment matrix $\mathbf{C}$ can be implemented by a *balanced Binary Cross-Entropy* (*bBCE*) loss as

$$\begin{aligned}\mathcal{L}2 &= bBCE(\mathbf{C}, \mathbf{C}^{gt}) \\ &= \gamma_n \sum C^{gt}_{i,j}C_{i,j} + \gamma_p \sum (1-C^{gt}_{i,j})(1-C_{i,j}),\end{aligned} \quad (5)$$

where the (i, j)-th value $C^{gt}_{i,j}$ in $\mathbf{C}^{gt} \in \mathcal{R}^{N\times K}$ is 1 when the i-th stroke belongs to the j-th type of semantic component, otherwise the value is 0. The γ_n and γ_p denote the ratio of 0 and 1 in $\mathbf{C}^{gt}$, respectively. The balance ratio γ_n and γ_p prevent the $\mathbf{C}$ from being learned as all-zero, since only one of K elements in each row of $\mathbf{C}^{gt}$ is 1.

Sketch-Level Recognition

The Transformer architecture in ViT (Dosovitskiy et al. 2020) is used for sketch-level recognition. When taking the fused stroke-level features $\mathbf{F}_s$ as input, the Transformer outputs the category label and the semantic component label of each stroke. The classification ($\mathcal{L}4$) and stroke-level semantic segmentation ($\mathcal{L}5$) losses can be denoted as

$$\mathcal{L}3 = \underbrace{CE(f_{w2}(\mathbf{F}_s), y_c)}_{\mathcal{L}4} + \lambda_s \underbrace{CE(f_{w3}(\mathbf{F}_s), \mathbf{y}_s)}_{\mathcal{L}5}, \quad (6)$$

where y_c is the ground-truth category label and $\mathbf{y}_s$ is the ground-truth semantic component label of strokes.

When taking the fused component-level features $\mathbf{F}_c$ as input, the Transformer outputs the category label and the prediction probability on the existence of each semantic component in the sketch sample. The classification ($\mathcal{L}4$) and compositionality prediction ($\mathcal{L}6$) losses can be denoted as

$$\mathcal{L}3 = \underbrace{CE(f_{w2}(\mathbf{F}_s), y_c)}_{\mathcal{L}4} + \lambda_c \underbrace{bBCE(f_{w4}(\mathbf{F}_c), \mathbf{y}_e)}_{\mathcal{L}6}, \quad (7)$$

where $\mathbf{y}_e$ indicates the existence or not of each type of semantic component. $\mathbf{y}^j_e = 1$ when the sketch sample should contain the j-th type of semantic component, otherwise $\mathbf{y}^j_e = 0$. The component-level features $\mathbf{F}_c$ has fixed K feature vectors, no matter how many strokes are contained in the sketch sample. Therefore, $\mathbf{y}_e$ is sparse, and a balanced binary cross-entropy loss is used (denoted as $\mathcal{L}6$).

Losses

The overall loss can be calculated as

$$\mathcal{L} = \lambda_1\mathcal{L}1 + \lambda_2\mathcal{L}2 + \mathcal{L}3. \quad (8)$$

$\mathcal{L}1$ ensures the distinguishability of the memory keys in SCM, and it does not need the semantic component labels of keys or strokes.

$\mathcal{L}2$ works only when the dataset has the semantic component labels of strokes. If not, the memory keys are learned without the direct supervision on the assignment matrix $\mathbf{C}$.

$\mathcal{L}3$ in Eq. (6) works for sketch recognition and segmentation. If the semantic component labels of strokes are unavailable but the prior information about which types of semantic components constitute each sketch category is known, $\mathcal{L}3$ in Eq. (7) can help the Transformer achieve a better and explainable recognition performance.

Experiments

Datasets

The SPG dataset (Li et al. 2018) and SketchIME dataset (Zhu et al. 2023) are used to verify the advantages of the proposed network. SPG was originally constructed for sketch perceptual grouping, and the same 20 categories as in SketchGNN (Yang et al. 2021) are used for evaluation. An average of 600 samples per category are used for training, while 100 samples for testing. Total 87 types of semantic components are defined according to the original labels in SPG to support our researches. SketchIME is a systematic dataset comprising 374 specialized sketch categories. Total 139 types of semantic components are defined. This study selects 56K samples which have category labels and semantic component labels of strokes from the released 209K samples. An average of 100 samples per sketch category are used for training, while 50 samples for testing.

Available Labels	SCMFeat	w/ $\mathcal{L}2$	w/ $\mathcal{L}5$	w/ $\mathcal{L}6$	Acc@1	C-Metric
C-Labels Only	$\mathbf{F}_s$ as Eq. (2)				88.48	-
	$\mathbf{F}_s = \mathbf{C} * \mathbf{K}$				91.41	-
	$\mathbf{F}_s = \mathbf{Q}$				91.01	-
C-Labels and Prior Info	$\mathbf{F}_c$ as Eq. (3)				92.02	-
	$\mathbf{F}_c = \mathbf{C}^\top * \mathbf{Q}$				90.71	-
	$\mathbf{F}_c$ as Eq. (3)			✓	94.04	-
	$\mathbf{F}_c = \mathbf{C}^\top * \mathbf{Q}$			✓	94.55	-
C-Labels and SC-Labels	$\mathbf{F}_s$ as Eq. (2)	✓	✓		95.81	**90.12**
	$\mathbf{F}_s = \mathbf{C} * \mathbf{K}$	✓	✓		<u>96.62</u>	<u>89.69</u>
	$\mathbf{F}_s = \mathbf{Q}$	✓	✓		**96.67**	89.42

Table 1: The performance on the SPG dataset. "SCMFeat" denotes which kinds of features are fed into Transformer by the SCM module. "C-Labels" means the category labels, and "SC-Labels" denotes the semantic component labels of strokes. "Prior Info" represents the prior information about which types of semantic components constitute each sketch category. The losses $\mathcal{L}1$ and $\mathcal{L}4$ are always used, but $\mathcal{L}2$, $\mathcal{L}5$ and $\mathcal{L}6$ may not be used when different labels are available.

Evaluation Metrics

The Top-1 accuracy (Acc@1) is used as the evaluation metric for sketch recognition. SketchSegNet (Wu et al. 2018) and SketchGNN (Yang et al. 2021) used point-based accuracy and component-based accuracy for sketch segmentation. Since the proposed SSR network does predictions on strokes for semantic segmentation directly, only the component-based accuracy (C-Metric) which indicates the percentage of the correctly predicted strokes is used as the evaluation metric for segmentation.

Network Details

In the stroke-level embedding module, a bidirectional LSTM layer takes a sequence of 4-dimensional stroke points as input and outputs a 768-dimensional shape embedding, a linear layer transforms a two-dimensional coordinate into a 768-dimensional location embedding, and the 768-dimensional order embedding is learned by PyTorch's nn.Embedding function. In the dynamic graph convolution module, the number of neurons in each convolution layer is all 768. The same Transformer as ViT-Base (Dosovitskiy et al. 2020) is used for sketch-level recognition.

Training Details

The learning rate is initialized to 3×10^{-4} with a batch size of 128. The Adam optimizer is used. Total 200 epochs are implemented for each training. The τ in Eq. (1) is set to 1. The λ_1 and λ_2 in Eq. (8) are set to 1 and 20, respectively. The λ_s in Eq. (6) and the λ_c in Eq. (7) are set to 10 empirically. The SSR network is trained from scratch, except the Transformer module initialized with the pretrained ViT-Base model from HuggingFace [2]. Our network is implemented by Pytorch and trained on a single NVIDIA GTX 3090.

Ablation Study

As aforementioned, the proposed SCM module and SSR network can deal with different cases with or without semantic component labels of strokes. As illustrated in Table 1, three cases which use different features and losses are evaluated.

[2]https://huggingface.co/

Firstly, when the category labels and semantic component labels of strokes are available, the supervision on the assignment matrix $\mathbf{C}$ (i.e., "w/ $\mathcal{L}2$") and on the prediction of the semantic component labels of each stroke (i.e., "w/ $\mathcal{L}5$") can be used. The multi-rows of the case "C-Labels and SC-Labels" in Table 1 illustrate the evaluation results. No matter which kinds features outputted by the SCM module are fed into Transformer for recognition and segmentation, excellent performances are achieved compared with the cases without semantic component labels of strokes. "$\mathbf{F}_s = \mathbf{Q}$" means that the stroke features learned by the dynamic graph convolution module are fed into Transformer, while "$\mathbf{F}_c = \mathbf{C} * \mathbf{K}$" means that the transformed memory keys are fed into Transformer. Both the two cases have achieve comparable performance. This means the learned memory keys can represent the semantic components effectively, although the memory keys are not calculated from the stroke features directly. "$\mathbf{F}_s = \mathbf{Q}$" does not mean the SCM module is excluded from the learning process, $\mathbf{Q}$ is still partially updated according to the gradient propagation from the supervision on the assignment matrix $\mathbf{C}$.

Secondly, when the semantic component labels of strokes are unavailable but the prior information about which types of semantic components constitute each sketch category is known, the prior information still can be used to enhance recognition's performance. The multi-rows of the case "C-Labels and Prior Info" in Table 1 illustrate the evaluation results. In such case, the supervision on the existence of each type of semantic component given a sketch can be used (i.e., "w/ $\mathcal{L}6$"). The stroke features cannot be fed into Transformer directly, since Transformer cannot be supervised on the semantic component prediction for strokes. Therefore, the component-level features transformed from the stroke features based on the assignment matrix $\mathbf{C}$ are fed into Transformer. The four rows show that using the supervision can improve recognition performance significantly (92.02% vs. 94.04% and 90.71% vs. 94.55%). It also makes the recognition explainable, since Transformer can tell which types of semantic components are contained in each sketch sample, although it does not know to which type of semantic component each stroke belong.

Networks	Acc@1	C-Metric
ViT (Dosovitskiy et al. 2020)	76.21	-
BiGRU (Chung et al. 2014)	79.10	-
ResNet18 (Xu et al. 2022)	80.66	-
MGT (Xu, Joshi, and Bresson 2021)	91.05	-
SketchSegNet (Wu et al. 2018)	-	45.46
SketchGNN (Yang et al. 2021)	-	87.86
SketchRecSeg (Zhu et al. 2023)	**97.47**	**91.65**
SSR($\mathbf{F}_s$ as Eq. (2))	95.81	<u>90.12</u>
SSR($\mathbf{F}_s = \mathbf{C} * \mathbf{K}$)	96.62	89.69
SSR($\mathbf{F}_s = \mathbf{Q}$)	<u>96.67</u>	89.42

Table 2: Comparison with state-of-the-art methods on the SPG dataset. The proposed SSR network using all the losses in Eq. (6) and Eq. (8).

Thirdly, when neither the semantic component labels of strokes nor the prior information are available, the proposed network can still be used as a typical recognition network, as illustrated in the case of “C-Labels Only” in Table 1. Both the fused stroke-level features $\mathbf{F}_s$ (i.e., see the three rows of the case of “C-Labels Only”) and the fused component-level features $\mathbf{F}_s$ (i.e., see the top two rows of the case of “C-Labels and Prior Info”) can be fed into Transformer which only does the prediction of category labels. It is unsurprising that the performances are not so good, since the memory keys are hard to learn without any extra supervision.

In conclusion, it is expected that more supervision can result in better performance, and the proposed method gives a flexible and explainable architecture to deal with sketch recognition with different auxiliary information.

Comparison with State-of-The-Art

Table 2 gives the comparison results with the state-of-the-art methods on the SPG dataset. The proposed SSR network outperforms all the methods except SketchRecSeg (Zhu et al. 2023). This is because SketchRecSeg is a two-stream network which takes both image- and SVG-format data as input, but the proposed SSR network only uses the SVG-format data. Besides, SketchSegNet (Wu et al. 2018), SketchGNN (Yang et al. 2021) and SketchRecSeg (Zhu et al. 2023) all construct stroke point-level graphs and predict point-level segmentation labels. The proposed SSR network uses a hierarchical and structural architecture, stroke-level graphs are constructed and stroke-level predictions are performed. Furthermore, the proposed SSR network can fulfill simultaneous recognition and segmentation with the one-stream architecture, while SketchRecSeg (Zhu et al. 2023) employs a two-stream architecture for recognition and segmentation, respectively. These factors demonstrate the superiority of the proposed SSR network.

Table 3 gives the comparison results on the selected SketchIME dataset which has 374 categories and 139 types of semantic components. The proposed SSR network still obtains the superior performance. This exactly demonstrates the applicability on large-scale datasets.

Networks	Acc@1	C-Metric
ViT (Dosovitskiy et al. 2020)	22.02	-
ResNet18 (Xu et al. 2022)	89.01	-
MGT (Xu, Joshi, and Bresson 2021)	70.31	-
SketchSegNet (Wu et al. 2018)	-	61.78
SketchGNN (Yang et al. 2021)	-	94.01
SSR($\mathbf{F}_s$ as Eq. (2))	<u>89.88</u>	<u>94.59</u>
SSR($\mathbf{F}_s = \mathbf{C} * \mathbf{K}$)	87.92	94.43
SSR($\mathbf{F}_s = \mathbf{Q}$)	**91.48**	**94.91**

Table 3: Comparison with state-of-the-art methods on the SketchIME dataset. The proposed SSR network using all the losses in Eq. (6) and Eq. (8).

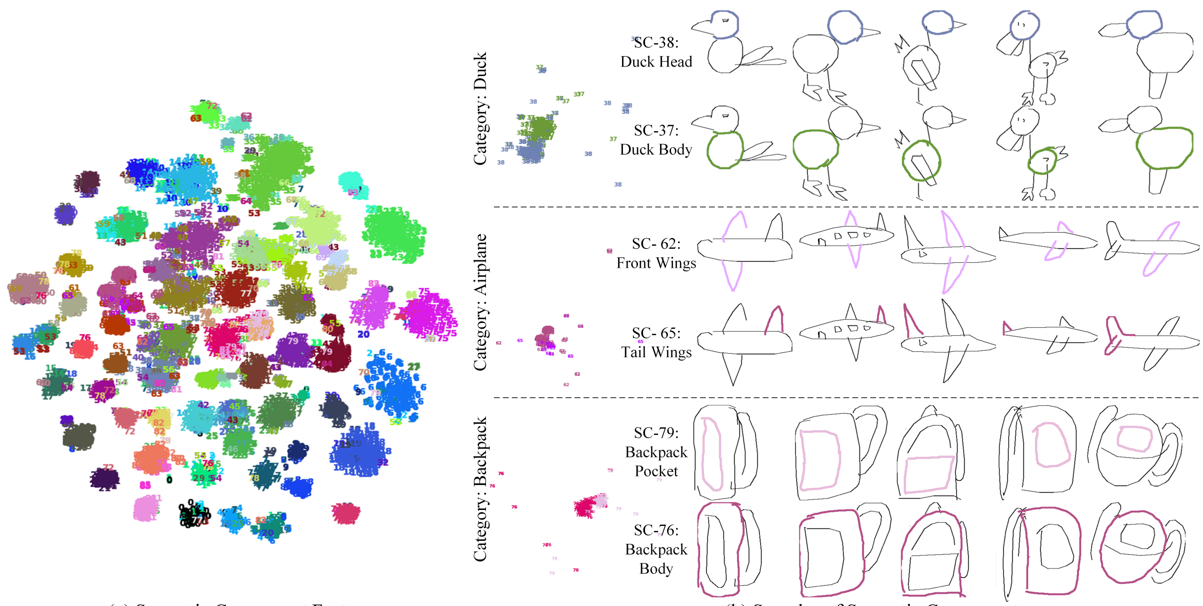
Visualization

Figure 2 gives the visualization of semantic component features using t-SNE (Van der Maaten and Hinton 2008) and some sketch samples. It can be concluded from the feature visualization in Fig. 2(a) that, the classification supervision on the memory keys of SCM ensures the distinguishability of the keys, and the SCM module further enhances the distinguishability of the strokes in the feature space. The memory mechanism can store the features of semantic components using multi-head arrays, and outperforms the mechanisms using classifiers to recognize the strokes' label directly or using Conditional Random Field (CRF) based methods (Yuan and Ji 2020) to learn strokes' clustering relationship. Figure 2(b) gives some sketch examples which have indistinguishable semantic components in the stroke feature space but are recognizable when considering the concurrence and layout of the semantic components. The proposed SSR network uses the SCM module to evolve stroke features in an explainable way, and uses Transformer to recognize the category label and the semantic component labels of strokes (or probabilities on the existence of each type of semantic component). This ensures the explainability of sketch recognition via semantic component-level parsing.

Figure 3 displays the recognition and segmentation results of some wrongly recognized sketch samples. It can be seen from Fig. 3 that these sketches are wrongly recognized because their strokes are wrongly resolved. Eqs. (2) and (3) show that the features fed into Transformer by the SCM module are calculated based on the stroke features outputted by the dynamic graph convolution module in an explainable way. Therefore, Transformer's prediction can be mapped into original strokes. This exactly demonstrates the explainability of our sketch recognition network.

Discussion

Activation map visualization techniques are not suitable for sketch recognition's explainability in the stroke-level. Counterfactual explanation based methods supply an alternative way, but SketchXAI (Qu et al. 2023) only uses CE to explore the deserved layout of strokes of a sketch, and Liu et al. use CE to discover the stroke-level principal components for a specific category (Liu et al. 2023). They just partially answer the question of “*why the sketch is classified as X*”. This



(a) Semantic Component Features (b) Samples of Semantic Components

Figure 2: Visualization of semantic component features using t-SNE and some sketch samples. Fig. 2(a) shows the feature visualization of the 87 types of semantic components in SPG. Fig. 2(b) shows some sketch examples whose parts of semantic components are indistinguishable in the feature space, but our SSR network can do recognition and segmentation correctly.

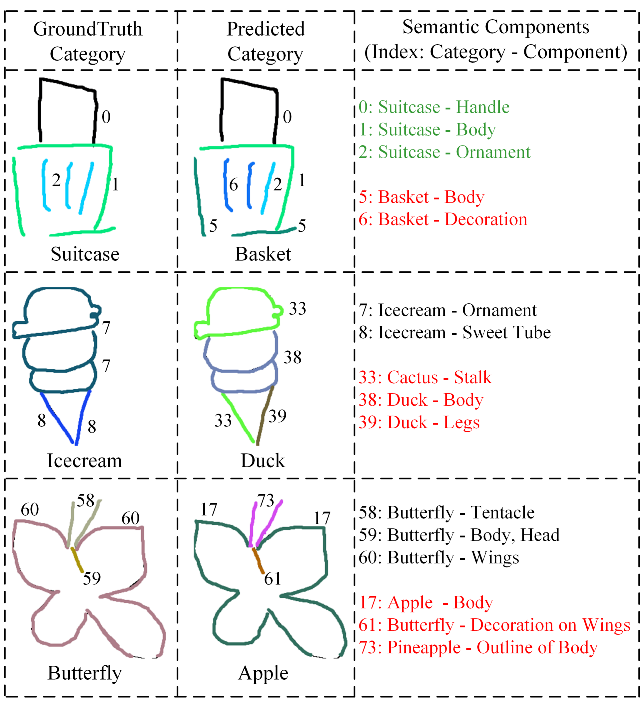


Figure 3: Examples of wrongly-recognized sketches. The numbers around the strokes are the groundtruth or predicted type indexes of semantic components.

study answers the question from a perspective of semantic component-level parsing. Humans generally describe an object using sentences about its components and attributes. *If a consensus can be reached that a sketch is represented structurally by some types of semantic components and their layout, we can easily find the superiority of our proposed network because the stroke-level embedding module can encode the layout of strokes, and the SCM and Transformer modules have abilities to resolve the semantic components.* The proposed SSR network gains sketch recognition's explainability in a more understandable and explainable way.

Conclusion

Deep learning based sketch recognition networks have achieved remarkable performance that even beats humans. However, humans can explain "*why the sketch is classified as X*" easily, while sketch recognition networks are lacking of interpretable reasons of predictions. This study tries to explore sketch recognition's explainability via semantic component-level parsing. A semantic component-level memory module is constructed, which can learn and store features of semantic components in multi-head arrays, and parse the strokes in the component-level. A structured sketch recognition network is proposed. The network gives the explanation "*The sketch is recognized as X because it is composed of the semantic components which constitute X*".

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