CartoonNet: Cartoon Parsing with Semantic Consistency and Structure Correlation

Jian-Jun Qiao
Southwest Jiaotong University
Chengdu, China
qjjai56@gmail.com

Meng-Yu Duan
Southwest Jiaotong University
Chengdu, China
duanmengyu369@gmail.com

Xiao Wu*
Southwest Jiaotong University
Chengdu, China
wuxiaohk@gmail.com

Yu-Pei Song
Southwest Jiaotong University
Chengdu, China
yupei-song@my.swjtu.edu.cn

Abstract

Cartoon parsing is an important task for cartoon-centric applications, which segments the body parts of cartoon images. Due to the complex appearances, abstract drawing styles, and irregular structures of cartoon characters, cartoon parsing remains a challenging task. In this paper, a novel approach, named CartoonNet, is proposed for cartoon parsing, in which semantic consistency and structure correlation are integrated to address the visual diversity and structural complexity for cartoon parsing. A memory-based semantic consistency module is designed to learn the diverse appearances exhibited by cartoon characters. The memory structure stores features of diverse samples and retrieves the samples related to new samples for consistency, which aims to improve the semantic reasoning capability of the network. A self-attention mechanism is employed to conduct consistency learning among diverse body parts belong to the retrieved samples and new samples. To capture the intricate structural information of cartoon images, a structure correlation module is proposed. Leveraging graph attention networks and a main body-aware mechanism, the proposed approach enables structural correlation, allowing it to parse cartoon images with complex structures. Experiments conducted on cartoon parsing and human parsing datasets demonstrate the effectiveness of the proposed method, which outperforms the state-of-the-art approaches for cartoon parsing and achieves competitive performance on human parsing.

CCS Concepts

• **Computing methodologies → Image segmentation**.

Keywords

Cartoon Parsing, Memory Structure, Graph Attention Network

*Corresponding author: Xiao Wu

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Figure 1: Cartoon parsing remains a challenging task due to the various styles, complex appearances and abstract structures of cartoon images. The diversity and complexity of cartoon images pose great difficulties for cartoon parsing.

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1 Introduction

Cartoon characters are an important part of culture and media with their diverse appearances and abstract structures. From human-like cartoon characters to animal-like cartoon images, cartoons exhibit a wide range of styles. The task of cartoon parsing, which aims to segment different parts of cartoon characters, holds substantial importance for various applications, including cartoon animation, content creation, virtual worlds, and more. Due to the inherent variations in cartoon appearances and lack of uniformity in cartoon structures, identifying diverse visual appearances and complex structures of cartoons is a challenging task.

Cartoon images have various, complex and abstract visual appearances and structures, as illustrated in Fig. 1. Unlike real-world humans, the styles of cartoon characters may vary depending on author or cultural background, which results in the diversity and complexity of cartoon images. For human-like cartoons, their appearances and structures are quite different. The properties of cartoons make the body parts such as limbs, hair and body of human-like cartoon characters abstract and complicate, which are not consistent to real-world humans. Animal-like cartoons are more complex due to diverse animal categories. For different animal species such as fish, mammals, reptiles, their visual appearances and body structures are different when presented in the form of cartoon image.

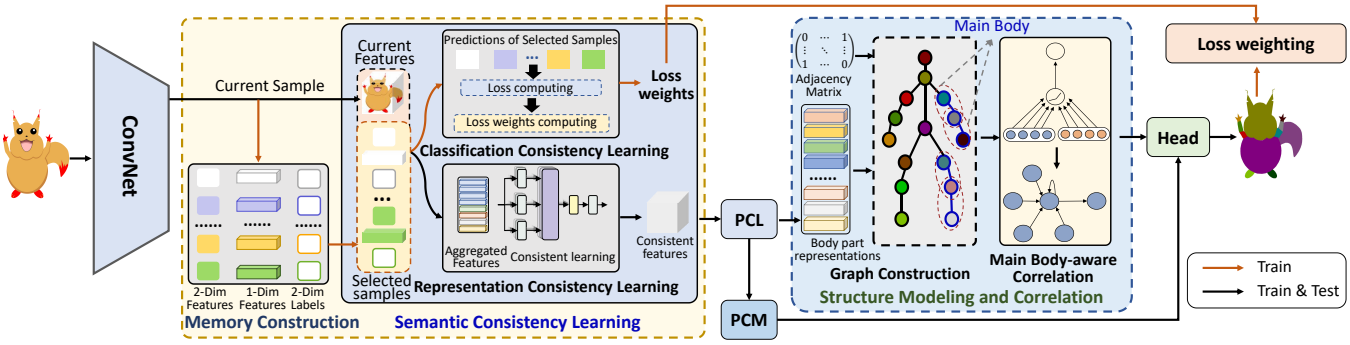

Figure 2: The framework of the proposed CartoonNet. It mainly consists of memory-based semantic consistency and main body-aware structure correlation. The memory-based semantic consistency utilizes a memory structure to achieve consistency learning across different samples. The main body-aware structure correlation focuses on correlation of body structures, modeling the structure of cartoons. PCL and PCM refers to pixel correlation learning and part correlation modeling [23], which are employed to solve the irregularities of cartoon images.

Therefore, cartoon parsing remains a challenging task for cartoon characters.

For image parsing, existing methods have primarily focused on human parsing and achieved significant progress. Previous human parsing methods have explored hierarchical structure learning [12, 34, 35, 43], pose estimation-guided learning [19, 41] and the integration of self-correction strategy [14]. However, due to the significant differences between real humans and cartoon images, these human parsing methods exhibit limited performance in cartoon parsing. With the development of cartoon related applications, the advanced deep learning methods [23, 32] have been applied to cartoon parsing. They employ multi-scale learning structures, and leverage pixel and part correlation to infer irregular cartoon structures. However, the diversity and complexity of cartoon images remains a challenge.

In this paper, CartoonNet is proposed to address the diversity and complexity of cartoon images in cartoon parsing. It augments cartoon parsing by designing a memory-based semantic consistency structure and a graph attention network-based structure correlation module. The framework is illustrated in Fig. 2. The semantic consistency module encodes and learns the diverse appearances displayed by cartoon characters. It designs a memory-based learning structure to conduct consistency learning of diverse body parts. The memory-based semantic consistency learns the visual differences of cartoon characters, which aims to alleviate the rich diversity of cartoon images and improve generalization ability. The structure correlation approach focuses on modeling and learning the intricate and irregular structures exhibited by cartoon characters. It leverages graph attention networks (GATs) [2, 11, 31] and a main body-aware mechanism to facilitate structural learning and correlation. By modeling the structural features of cartoon images across the main bodies, the method focuses on important parts of cartoon images to alleviate the structural complexity of cartoon parsing. Experiments conducted on cartoon parsing and human parsing datasets demonstrate the effectiveness of the proposed approach, which outperforms the state-of-the-art methods for cartoon parsing and achieves competitive results on human parsing. The contributions are summarized as follows:

- CartoonNet is proposed to address the challenges of visual diversity and structure complexity in cartoon images, which designs a memory-based semantic consistency module and a main body-aware structure correlation strategy for cartoon parsing.
- A memory-based learning structure is proposed to facilitate appearance learning, which captures the inconsistent appearances of different cartoon characters and utilizes self-attention mechanism to achieve semantic consistency among diverse body parts.
- A main body-aware structure correlation method is proposed to model the structural information of cartoon characters with complex structures, which employs the graph attention networks and a main body-aware mechanism to focus on the modeling complex structures..
- The proposed method achieves state-of-the-art performance on the cartoon parsing datasets, which demonstrates the effectiveness of CartoonNet.

2 Related Work

2.1 Human Parsing

Human parsing [5, 16, 29], the task of segmenting human body parts in images, has achieved significant progress. Previous human parsing methods develop approaches including hierarchical structure learning [12, 34, 35, 43], pose estimation-guided learning [19, 41], self-correction strategy [14], and so on, achieving satisfactory results on recognition of body parts of humans. However, applying human parsing methods to cartoon parsing presents challenges due to fundamental differences. Cartoons are known for their complexity, diverse styles, irregular lines, unique color schemes, and abstract representations, varying greatly based on creators and cultural contexts. Human parsing models [15, 18] are designed on real-world human images, making them unsuitable for cartoon parsing, where characters often have unconventional body proportions and articulations. Cartoon parsing necessitates dedicated research and specialized algorithms to address its unique characteristics, emphasizing accuracy and effectiveness in dealing with the diversity and complexity of cartoon images.

2.2 Cartoon Parsing

The task of cartoon parsing has gained increasing attention in recent years due to its relevance in various multimedia applications. Researchers have proposed several approaches to address the challenges posed by diverse and complex cartoon appearances

and structures. Early works in this domain primarily focused on rule-based methods and handcrafted feature extraction techniques. These approaches, while capable of capturing some aspects of cartoon images, often struggle with the diversity and complexity of cartoon imagery. The emergence of deep learning techniques, particularly the convolutional neural networks (CNNs) [1, 17, 25, 27], has significantly advanced the field of cartoon parsing. DFPNet [32] applies feature pyramid network to cartoon dog parsing, which alleviates the varied scales in cartoon parsing. However, it ignores the correlations of visual cues and structural features in cartoon characters. CPNet [23] recognizes the irregular cartoon structures and body parts with different semantics but have visually akin appearances, by introducing a pixel and part correlation learning structure. However, it ignores the semantic consistency of diverse cartoon images and structure correlation of complex cartoon characters. Although CNN-based methods demonstrate improved performance in recognizing cartoon characters, addressing the diversity and complexity of cartoon images remains a challenge.

2.3 Memory-Augmented Networks

Memory-augmented neural networks [36, 37] have shown promise in capturing and utilizing long-term dependencies in data. These networks [13, 24] employ an external memory structure that can be read from and written to, enabling the storage and retrieval of information over extended sequences. In the context of cartoon parsing, memory-augmented networks can offer a promising potential for encoding and learning the diverse appearances exhibited by cartoon characters. Despite the growing interest in memory-augmented networks, their potential for cartoon parsing remains unexplored. The ability to store appearance information and perform semantic consistency learning opens possibilities for addressing individual visual differences. Therefore, this paper proposes a novel approach applicable to cartoon parsing, with the aim of addressing the issue of significant sample diversity in cartoon parsing through a memory-based structure.

3 Cartoon Parsing

3.1 Framework

CartoonNet is proposed to address the problems of cartoon parsing, which are caused by visual diversities and structural complexities of cartoon characters. A two-fold strategy integrating appearance learning and structural modeling is introduced to capture features of diverse visual appearances and model complex structural representations. The framework is illustrated in Fig. 2. ConvNet [10] is employed to encode and extract features for cartoon images. The memory bank is adopted to store features of diverse samples with its three column structures. The stored features are matched to current images by measuring feature similarity, which aims to parse current samples by recalling previous experience. The previous experience are integrated to current samples by adopting self-attention mechanism, which achieves semantic consistency among diverse samples. To learn the correlation of complex body parts, a main body-aware structure correlation strategy is designed. It incorporates graph attention networks and a main body-aware mechanism to facilitate part correlation. The graph attention networks model the structural representations and capture relations among the body parts. The main body-aware mechanism learn important body parts that reflect the complex structural properties of the cartoon images.

3.2 Memory Bank Construction

Previous cartoon parsing methods only consider multi-scale learning, as well as pixel and part correlation among a single cartoon character [23, 32]. They have difficulties in identifying diverse cartoon images. Therefore, the first significant component of the approach is to encode and learn the visual appearances of diverse cartoon characters. A memory-based learning structure is proposed to address the problems caused by visual diversity, which aims to achieve semantic consistency among different semantic parts. The memory-based consistency learning includes two parts, representation consistency and classification consistency. The representation consistency is designed to conduct consistency learning on semantic parts from different cartoon characters at high-dimensional semantic feature level. The classification consistency is proposed to achieve consistency learning of semantic parts from various cartoon characters at the semantic recognition level, which leverages the constraint information.

Given a cartoon image X, $F \in \mathbb{R}^{C\times H\times W}$ is the encoded image features outputted by ConvNet. C denotes the number of channels. H and W refer to height and width of the feature maps, respectively. A memory structure with three columns is defined, where the first column stores the two-dimensional feature maps, the second column saves one-dimensional feature representations, and the third one retains labels. Specifically, F is fed into a decoder with three convolution layers [4] to obtain the two-dimensional feature maps $F_{mem} \in \mathbb{R}^{C_n\times H\times W}$, where C_n denotes the number of classes. F_{mem} is then stored in the first column of the memory structure. Additionally, the operation of information aggregation with global adaptive max pooling is performed on each feature map of F, which outputs a feature vector $F_v \in \mathbb{R}^{C\times 1\times 1}$. F_v is the representation of X and it is stored in the second column of the memory structure. The label $L \in \mathbb{R}^{H\times W}$ corresponding to X is stored in the third column of the memory structure, which aims to provide supervision for the semantic consistency learning. In the initial stage, all three columns of the memory structure are initialized as zeros. During the training process, image features of each iteration are stored in the memory structure. When the memory is full, the earliest stored features are deleted from memory to ensure that the memory structure have space for features of new iterations, which aims to continuously update the memory throughout the training process.

During each iteration, F not only gets stored in the memory structure but also undergoes further forward operations. A memory selection operation is performed to choose samples from the memory structure. These selected samples have some similarities to current sample and they are used to achieve semantic consistency, which aims to enhances the semantic reasoning of network for targets sharing similar characteristics. Specifically, when inputting a new sample, the network selects similar samples from the memory structure. By leveraging the knowledge acquired from these learned samples, the network accurately infers and identifies current sample. To achieve memory selection, during each training iteration, a similarity calculation is performed between current F^c_{mem} and the stored F^m_{mem} within the memory structure. This is done using the

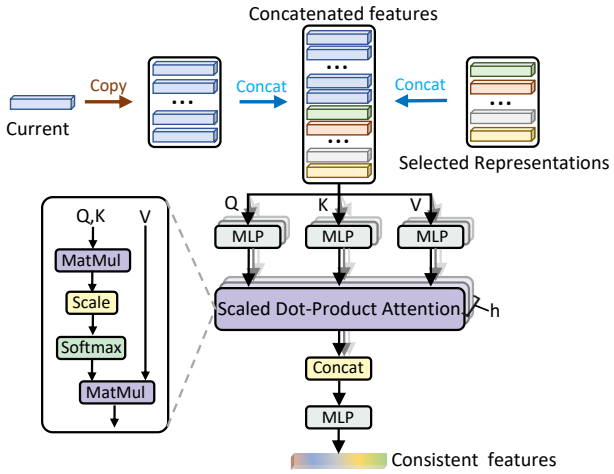

Figure 3: Memory-based representation consistency.

Euclidean distance, which retrieves n samples from the memory structure.

3.3 Representation Consistency Learning

The problem of inconsistent appearances among different cartoon images poses great challenges for cartoon parsing. To achieve consistency learning for the body parts that belong to the same class but from different samples, the network initially performs consistency learning at the representation level. This involves the integration and consistency of the feature representations of current sample and the feature representations of relevant samples retrieved from the memory structure, as can be seen in Fig. 3. The multi-head self-attention [30] is employed to achieve consistency learning among the semantic parts from different samples. It ensures that current sample and the samples stored in the memory structure are associated and consistent at the feature representation level.

Specifically, the current features F is mapped into 1-dimensional feature representation with a global adaptive max pooling operation, which is denoted as F_v^c. Through the memory selection, n feature representations $F_v^{m,n}$ that represents the retrieved samples are selected for the current sample. F_v^c is then duplicated n times and concatenated with $F_v^{m,n}$ to aggregate information. This is formulated as follows:

$$F_v^{cat} = Cat(Copy(Gap(F)), Selection(M)) \tag{1}$$

where F_v^{cat} is the concatenated features. $Gap(\cdot)$ denotes global adaptive max pooling operation. $Copy(\cdot)$ is the duplication operation. $Cat(\cdot)$ refers to concatenation operation. $Selection(\cdot)$ is the memory selection operation which retrieves the memory M for related samples. Subsequently, multi-perceptual (MLP) layers are used to create queries for the multi-head self-attention structure. It is formulated as,

$$Q = F_v^{cat} W^Q, K = F_v^{cat} W^K, V = F_v^{cat} W^V \tag{2}$$

where W^Q, W^K, and W^V are learnable weight matrices that project the input vectors F_v^{cat} into query Q, key K, and value V, respectively.

The multi-head attention mechanism calculates the output vectors F_v^{out} as a weighted sum of the input vectors F_v^{cat}, where the weights are determined by the attention scores. The attention scores

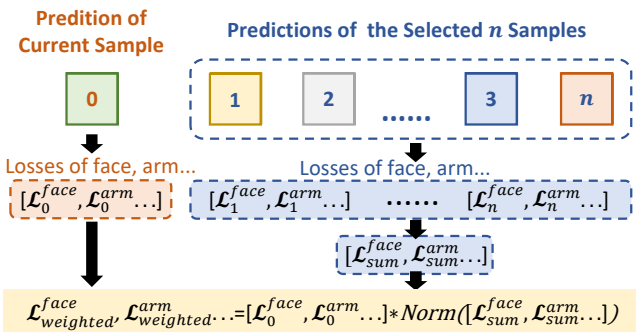

Figure 4: Memory-based classification consistency.

are calculated as,

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{3}$$

where dot products of the query Q with all keys K are computed and scaled by the scaling factor $\frac{1}{\sqrt{d_k}}$. d_k is the dimension of query. The softmax operation generates the attention scores. The dot products of the attention score and value V associate the representations of different samples.

The multi-head attention mechanism has h heads and it performs the attention calculation in parallel for each head. The outputs of the heads are then concatenated and projected back to the original dimension of F_v^{cat}, which is formulated as,

$$\text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V) \tag{4}$$

$$F_v^{out} = \text{MultiHead}(Q, K, V) = Cat(\text{head}_1, \ldots, \text{head}_h)W^O \tag{5}$$

where W_i^Q, W_i^K, W_i^V, and W^O are learnable weight matrices.

This allows the model to attend to different representations of the same input sequence when calculating the output vectors F_v^{out} which denotes the consistent features. F_v^{out} is fused to the original features F as,

$$F_{rc} = Cat(F, F \odot Sig(F_v^{out})) \tag{6}$$

where $Sig(\cdot)$ denotes sigmoid operation that aims to map the values of vectors into calibration weights. $\odot$ refers to element-wise multiplication.

3.4 Classification Consistency Learning

In addition to representation consistency, the proposed method also performs classification consistency between the current sample and the samples retrieved from the memory structure. This enables the network to consistently recognize semantic parts that share the same semantics but may exhibit variations in appearances.

With the memory selection, the network obtains encoded predictions $F_{mem}^{m,n}$ of the retrieved n samples, which are related to the encoded feature F of the current sample X. F is mapped to the category dimension for semantic prediction. The mapping process uses the decoder of DeepLabV3+ [4], which is widely used in parsing methods [14, 26]. It is formulated as,

$$F_{mem}^c = Decoder(F, F') \tag{7}$$

where F' denote the shallow features from ConvNet that provide spatial details for the deep features F.

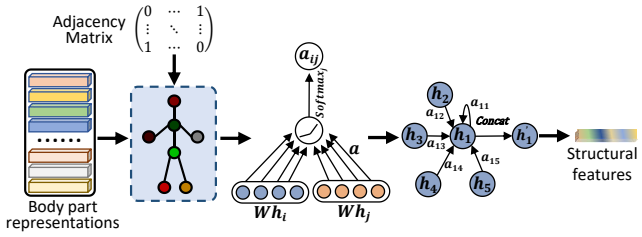

Figure 5: GAT-based structure correlation process.

To ensure that the network consistently recognizes the body parts that belong to the same class in F^c_{mem} and $F^{m,n}_{mem}$, the classification consistency is performed by calibrating the recognition results of F^c_{mem} using the recognition results of $F^{m,n}_{mem}$. As can be seen in Fig. 4, for each sample in $F^{m,n}_{mem}$, losses of each sample are calculated for each category such as face and arm, which outputs n loss values for the same category and they are summed for the corresponding category, aggregating the losses from different samples. Subsequently, all summed losses are normalized and mapped to weights. The weights are multiplied to the loss of each category in F^c_{mem}. Consequently, the recognition of each category in F^c_{mem} is calibrated by the corresponding category in $F^{m,n}_{mem}$, which achieves classification consistency learning. It is formulated as follows:

$$\mathcal{L}_{cls} = CE_{cls}(F^{m,n}_{mem}, L^n) \tag{8}$$

$$\mathcal{L}_{wts} = Norm(Sum_{cls}(\mathcal{L}_{cls})) \tag{9}$$

$$\mathcal{L}_{weighted} = CE_{cls}(F^c_{mem}, L) \odot \mathcal{L}_{wts} \tag{10}$$

where $CE_{cls}(\cdot)$ means modified cross entropy loss function which is used for loss computation of each classes. $Sum_{cls}(\cdot)$ denotes gather the losses of the same classes from the selected samples. $Norm(\cdot)$ refers to normalization on the summed losses of different categories. F^c_{mem} and $F^{m,n}_{mem}$ are predictions of the current sample and the retrieved samples, respectively. L and L^n are the corresponding labels, respectively.

3.5 Structure Correlation

In addition to appearance learning, structural learning is also crucial for cartoon parsing. Previous methods consider the correlation of different parts, but they overlook the learning of strongly related local limb structures. As illustrated in Fig. 6, some local limbs exhibit high correlations, such as the face, hair, and hat, which are strongly related. Similarly, the thighs, shins, and shoes, or the palms, upper arms, and forearms, are also strongly related. Therefore, this paper introduces the main body-aware recognition strategy, which focuses on structural modeling of strongly correlated limbs to enhance the parsing capability of complex structures.

Given F_{rc}, the output of representation consistency, pixel correlation learning (PCL) is performed to capture pixel correlation of the cartoon images [23]. After that, feature aggregation is performed using global average pooling along the channel dimension to obtain a one-dimensional feature representation. This one-dimensional feature representation is divided into n_c feature representations, which are treated as nodes of graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$. n_c represents the number of categories. $\mathcal{V}$ denotes the set of nodes that correspond to body parts of cartoon character. $\mathcal{E}$ refers to the set of edges that indicates the connection relations of adjacent body parts. For the construction of edge $\mathcal{E}$, the adjacency matrix that indicates the connections of semantic parts is computed to associate body parts, as can be seen in Fig. 5.

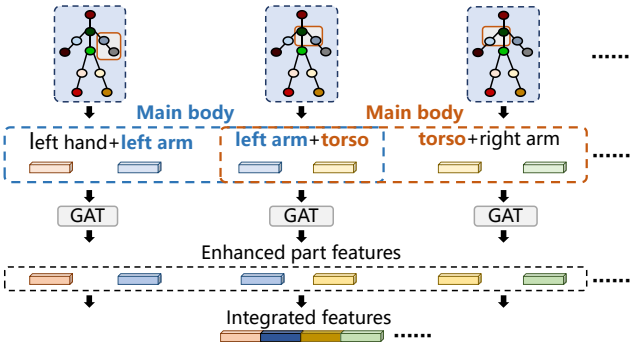

Figure 6: Main body-aware correlation.

GAT layers [31] are constructed to model the graph $\mathcal{G}$. Specifically, the network first computes the attention score a_{ij} between nodes i and j. For a node i in graph $\mathcal{G}$, the attention of its neighbor j is defined as,

$$a_{ij} = \text{LeakyReLU}(a^T Cat(Wh_i, Wh_j)) \tag{11}$$

where a is a learnable vector. h_i and h_j are the feature vectors of nodes i and j. LeakyReLU is the activation function used for nonlinearity. $Cat(\cdot)$ allows the model to consider the features of both node i and j. The features are transformed with weight matrix W, which learns the importance of different node pairs.

Softmax function is applied to the attention scores, normalizing them to form weights α_{ij}. The attention coefficient α_{ij} represents the importance of node j when updating the representation of node i. The coefficient from node j to node i is calculated as,

$$\alpha_{ij} = \frac{\exp(a_{ij})}{\sum_{k \in \mathcal{N}_i} \exp(a_{ik})} \tag{12}$$

where $\mathcal{N}_i$ is the set of neighbors of node i.

The new representation of node i, h'_i, is calculated as a weighted sum of the transformed features of its neighbors, with weights given by the attention coefficients α_{ij}. This allows each node to selectively attend to its neighbors, capturing the importance of different connections in the graph. It is formulated as,

$$h'_i = \sigma(\sum_{j \in \mathcal{N}_i} \alpha_{ij} W h_j) \tag{13}$$

where σ denotes to a nonlinearity operation [31].

The ultimately updated node representation h'_i is obtained by employing multi-head attention [30]. Specifically, S independent attention mechanisms perform the transformation described in Equation 13. Their features are then concatenated to produce the following feature representation as,

$$h'_i = Cat(\sigma(\sum_{j \in \mathcal{N}_i} \alpha^0_{ij} W^0 h_j), ..., \sigma(\sum_{j \in \mathcal{N}_i} \alpha^S_{ij} W^S h_j)) \tag{14}$$

where $\alpha^s_{ij}(s \in [0, 1, 2, ..., S])$ refers to the normalized attention coefficients computed by the k-th attention mechanism. W^S is the weight matrix of the corresponding input linear transformation.

Unlike the typical GAT, the GATs built are hierarchical, which are designed to model different structural levels. Firstly, a GAT layer is adopted to model the pre-constructed graph structure, updates all node data and returns the results. Subsequently, the subgraph

structures are built by merging strongly related nodes among the n_c nodes, and GAT is then applied to model the strongly related nodes and return the results. As can be seen in Fig. 6, the graph of the left hand, left arm and torso is treated as a main body graph because they are strongly connected through the left arm. By feeding the paired nodes associated with the left arm into GAT for learning, the structural information related to the left arm is emphasized. The network facilitates the recognition of specific regions by focusing on the main body structure. After that, the learning results of various main bodies are aggregated and the integrated results are combined with the initially modeled results from the global graph, producing the ultimate output. The output of the structure correlation is fused with the input features, resulting in a stronger structural feature representation that is used for more accurate structural modeling, which is formulated as,

$$h_i' = SC_{GATs}(Divide(Gap(PCL(F_{rc})))) \tag{15}$$

$$F_{rc-main} = Head(F_{rc} \oplus h_i', PCM(PCL(F_{rc}))) \tag{16}$$

where $SC_{GATs}(\cdot)$ denotes the structure correlation function based on GATs. $Divide(\cdot)$ is the operation dividing the one-dimensional feature representation into n_c nodes. $Head(\cdot)$ means a stacked module of concatenation and a convolution layer. $PCM(\cdot)$ denotes part correlation modeling [23].

3.6 Loss Functions

The objective function of this paper is composed of the proposed classification consistency loss, pixel correlation loss, part correlation loss, spatial loss and edge loss, which is formulated as,

$$\begin{aligned}\mathcal{L}_{obj} = \mathcal{L}_{cc} + CE(F^c_{mem}, L) + CE(F_{pcl}, L) + \\ CE(F_{rc-main}, L) + \mathcal{L}_{spatial} + \mathcal{L}_{edge}\end{aligned} \tag{17}$$

where $CE(\cdot)$ is the cross entropy loss function. $CE(F^c_{mem}, L)$ is adopted to predict segmentation results using features from the ConvNet. $CE(F_{pcl}, L)$ and $CE(F_{rc-main}, L)$ are used to learn pixel correlations and structure correlations [23]. F_{pcl} is obtained by using a convolution layer to map the output of PCL into predictions. $\mathcal{L}_{spatial}$ and $\mathcal{L}_{edge}$ are utilized to learn spatial information [20, 23, 28] and edge information [14, 26]. $\mathcal{L}_{cc}$ is the proposed classification consistency loss and it is defined as follows:

$$\begin{aligned}\mathcal{L}_{cc} = (CE_{cls}(F^c_{mem}, L) + CE_{cls}(F_{pcl}, L) + \\ CE_{cls}(F_{rc-main}, L)) \odot \mathcal{L}_{wts}\end{aligned} \tag{18}$$

4 Experiments

4.1 Datasets and Evaluation Metrics

CartoonSet. The CartoonSet dataset [23] comprises 2,229 cartoon images, which are divided into 1,530 images for training, 510 for testing, and 189 for validation. It includes diverse samples of drawings of children, illustrations with brief strokes, animated characters, and more. The various body parts such as face and neck of the cartoon images are annotated and categorized into 24 classes.

Cartoon dog. The Cartoon dog dataset [32] contains 965 images of cartoon dogs. It consists of 773 images for training and 192 images for testing. This dataset focuses on cartoon dog parsing, with eight distinct classes such as head and body for labeling.

LIP. LIP [8] is a human parsing dataset consisting of 50,462 single-person images. It is divided into 30,462 training images, 10,000 testing images, and an additional 10,000 images for validation. It provides annotations for 19 classes, which include categories such as face and right arm.

Evaluation Metrics. Following previous approaches [15, 22, 23, 32], the utilized evaluation metric is the Mean Intersection over Union (Mean IoU). Mean IoU computes the average intersection-to-union ratio between the predicted body parts and ground truth. Additionally, Mean Accuracy (Mean Acc.) is employed to calculate per-class accuracy and Pixel Accuracy (Pixel Acc.) is used to compute the accuracy of the correctly predicted pixels in each class.

4.2 Implementation Details

To implement the proposed approach, Stochastic Gradient Descent (SGD) is employed as the optimizer with a momentum of 0.9 and a weight decay of 5e-4. Following previous methods [3, 7, 21, 38, 39, 42], the "poly" learning rate strategy is utilized, which is defined as $lr = lr_{base} \times (1 - \frac{C_n}{T_n})^{power}$. lr and lr_{base} are the current learning rate and the base learning rate, respectively. $power = 0.9$. C_n and T_n represent the current iteration number and the total iteration number, respectively. As for data augmentation, random left-right flipping with a 0.5 probability and random scaling within the range of [0.25, 1.0] are applied.

To ensure a fair comparison on CartoonSet, CartoonNet is trained with a batch size of 8 and image size of 384×384. The number of training epochs is 150 and the learning rate for CartoonSet is set to 7e-3. For Cartoon dog dataset, CartoonNet uses a learning rate of 1e-3, and the training images are resized to 384×384. All methods adopt single-scale evaluation on CartoonSet and Cartoon dog dataset. As for LIP dataset, CartoonNet is trained with a learning rate of 7e-3, using training images resized to 473×473. The number of training epochs is 150. The multi-scale evaluation approach [14, 15] is employed for LIP dataset.

4.3 Comparison with the State-of-the-Art Approaches

To evaluate the performance of the proposed approach, it is compared with the state-of-the-art human parsing approach like SCHP [14] and cartoon parsing methods such as CPNet [23]. DeepLabV3+ [4], a model not specialized for cartoon parsing, demonstrates subpar performance in the domain of cartoon parsing. DFPNet [32] is dedicated to cartoon parsing and boost the performance by introducing a multi-scale learning mechanism. But it primarily focuses on scale variations, resulting in limited performance. Methods like HHP [35] and CNIF [34] employed GNN to model the strcuture information, which further improves the results. However, their hierarchical body structures are designed for real humans with consistent and regular structure. When segmenting the irregular and complex body structures of cartoon characters, their performances are limited [23]. CE2P [26] leverages global context information and edge details to improve the results. But it fails to account for the visual diversity and structural complexity of cartoon images, resulting in limited performance. CDGNet [15] uses class distributions as spatial constraints, outperforming most of the methods. But it ignores the structure modeling and learning. SCHP [14] achieves

Table 1: Comparison on the CartoonSet.

Method	Pixel Acc.	Mean Acc.	Mean IoU
DeepLabV3+ [4]	87.28	63.42	50.12
DFPNet [32]	88.21	65.33	51.71
HHP [35]	87.51	64.42	51.98
CE2P [26]	88.06	66.55	52.90
CNIF [34]	87.74	66.01	53.21
CDGNet [15]	88.11	67.98	53.99
SCHP [14]	88.63	69.36	55.44
CPNet [23]	89.42	69.90	57.02
CartoonNet (Ours)	**89.61**	**70.59**	**57.84**

Table 2: Comparison on the cartoon dog dataset.

Method	Pixel Acc.	Mean Acc.	Mean IoU
Mask R-CNN [9]	89.21	57.78	50.56
CE2P [26]	92.63	76.43	65.32
DFPNet [32]	93.50	79.40	68.39
SCHP [14]	94.05	81.15	71.22
CDGNet [15]	94.09	80.03	71.44
CPNet [23]	94.32	82.60	72.28
CartoonNet (Ours)	**94.64**	**84.01**	**74.05**

improved results using a self-correction strategy, which helps differentiate visually complex body parts, making it suitable for cartoon parsing. Nonetheless, it still faces challenges of addressing the diversity and complexity of cartoon characters. CPNet [23] significantly improves the performance of cartoon parsing by addressing the irregular structures encountered in cartoon parsing with its pixel and part correlation learning structure. However, CPNet [23] mainly focuses on single cartoon character, which makes it less effective for recognizing diverse cartoon characters. Compared to the previous methods, CartoonNet achieve the best results on CartoonSet. This is because CartoonNet addresses the challenges posed by diverse and complex cartoon characters. It makes comprehensive exploration of semantic consistency and structure correlation across diverse and complex cartoon images. The memory-based semantic consistency and main body-aware mechanism are effective to address the diversity and complex of cartoon images.

To further evaluate the performance of the proposed method, it is tested on the Cartoon dog dataset. Overall, the performance of previous human parsing methods are limted when tested on the Cartoon dog dataset. The limitations are caused by the differences between abstract cartoon images and real-world humans. Cartoon parsing method like CPNet [23] performs better because it accounts for some properties of cartoon images. But the diversity and complexity of cartoon images remain challenges, which limited the performance. Compared to previous methods, CartoonNet achieves the state-of-the-art performance on the Cartoon dog dataset, as listed in Table 2. The specific design of CartoonNet effectively alleviates the challenges posed by the diverse visual appearances and complex structures of cartoon characters. The results listed in Table 2 further demonstrate the effectiveness of the proposed method.

To verify the generalization ability of CartoonNet, it is tested on the human parsing dataset LIP. Table 3 illustrates the comparative results. Methods like DeepLabV3+ [4], OCR (ResNet101) [40], OCR (HRNetV2-W48) and HRNetV2 [33] are common semantic segmentation methods. Despite these methods have achieved outstanding performance on segmentation datasets such as Cityscapes [6], their performance on LIP is limited due to the lack of specific

Table 3: Comparison on the LIP dataset.

Method	Pixel Acc.	Mean Acc.	Mean IoU
DeepLabV3+ [4]	n/a	n/a	52.09
CE2P [26]	87.37	63.20	53.10
CorrPM [44]	87.68	67.21	55.33
OCR (ResNet101) [40]	n/a	n/a	55.60
HRNetV2 [33]	n/a	n/a	55.90
OCR (HRNetV2-W48) [40]	n/a	n/a	56.65
CPNet [23]	88.29	68.41	57.21
CNIF [34]	88.03	68.80	57.74
HHP [35]	**89.05**	70.58	59.25
SCHP [14]	n/a	n/a	59.36
CDGNet [15]	88.86	**71.49**	**60.30**
CartoonNet (Ours)	88.59	69.57	58.27

designs for human parsing. Compared to the common semantic segmentation approaches, the human parsing methods like SCHP [14] and CDGNet [15] achieve better performance. Their components such as GNN-based hierarchical structure learning module [34, 35], self-correction strategy and class distribution learning method [15] are designed for real-world humans and achieve good performance. Although the proposed CartoonNet is designed for cartoon parsing, it achieves competitive performance on LIP dataset. Compared to common semantic segmentation methods, the performance of CartoonNet on LIP dataset is unexpected, which surpasses OCR (HRNetV2-W48) [40] and HRNetV2 [33] by a large margin. CartoonNet outperforms the cartoon parsing method CPNet [23] significantly in terms of the performance on the LIP dataset, which proves its generalization ability. The performance of CartoonNet on LIP dataset demonstrates that the proposed semantic consistency and structure correlation are effective for human parsing as well and have good generalization ability.

4.4 Ablation Studies

To validate the effect of the proposed method, ablation studies are conducted and listed in table 4. The incorporation of representation consistency and classification consistency leads to a marked improvement in Mean IoU metric, as compared to the baseline approach. The performance is improved because the proposed memory-based consistency learning strategy facilitates the semantic consistency of the body parts that belong to the same class but from diverse cartoon images. When adopting the main body-aware structure correlation to address the complexity of cartoon images, the performance is further boosted. The integration of the memory-based consistency module and the main body-aware structure correlation achieves the best results, confirming that the proposed method is effective in addressing challenges posed by diverse appearances and complex structures of cartoon parsing. To further verify the effectiveness of the proposed modules, ablation studies on the Cartoon dog dataset are also conducted. As listed in table 5, compared to the baseline model, the proposed modules achieve significant performance improvements. CartoonNet with all proposed modules significantly improves the Mean IoU metric based on the baseline, which proves the effectiveness of the proposed approach.

To verify the effect of the memory structure, ablation studies of size of the memory structure and number of selected similar samples from the memory structure are conducted. As listed in the table 6, CartoonNet + M400 represents training CartoonNet with a

Figure 7: Visualization comparisons on the CartoonSet.

Table 4: Effect of the proposed modules on CartoonSet dataset.

Method	Pixel Acc.	Mean Acc.	Mean IoU
Baseline	89.19	68.91	56.12
Baseline + RC	89.33	70.24	57.11
Baseline + CC	89.51	69.71	57.08
Baseline + RC + CC	89.49	70.50	57.47
Baseline + Main	89.48	69.61	57.26
Baseline + RC + CC + Main	**89.61**	**70.59**	**57.84**

Table 5: Effect of the proposed modules on Cartoon Dog dataset.

Method	Pixel Acc.	Mean Acc.	Mean IoU
Baseline	94.09	82.22	72.13
Baseline + RC	94.47	83.05	73.24
Baseline + CC	94.37	81.91	73.09
Baseline + RC + CC	94.50	83.19	73.69
Baseline + Main	94.44	82.69	72.77
Baseline + RC + CC + Main	**94.64**	**84.01**	**74.05**

memory storage size of 400 samples. 1530 is the number of images of training set in the CartoonSet dataset. It can be observed from the table that the storage size of the memory structure has little impact on the accuracy. CartoonNet + N3 represents selecting three similar samples in each iteration, and the data in the table indicates that the best result is obtained when the number of the selected samples is 5.

4.5 Qualitative Evaluation

To qualitatively evaluate the proposed method, the visualization results of CartoonNet and the state-of-the-art approaches are illustrated in Fig. 7. For diverse cartoon characters, existing methods tend to make recognition errors when segmenting body parts that belong to the same class but exhibit significant visual and structural differences. For example, the head of the panda and the dog are quite different. As the state-of-the-art method among the previous methods, CPNet [23] has difficulties in recognizing diverse cartoon images as it primarily focuses on internal pixel and part correlation within a single cartoon character. The proposed method conducts semantic consistency learning across different cartoon characters, achieving better results with diverse cartoon images. Previous methods have suboptimal performance when the targets have intricate and irregular structures such as the hair of the girls, as they lack specialized recognition structures for the irregularities in cartoon characters. Among the previous methods, CPNet [23] performs better by considering the irregularities of cartoon characters. However, it still falls short in recognizing complex structures as it doesn't emphasize the main bodies. The proposed method introduces the main body-aware strategy, addressing the recognition issues related to complex structures.

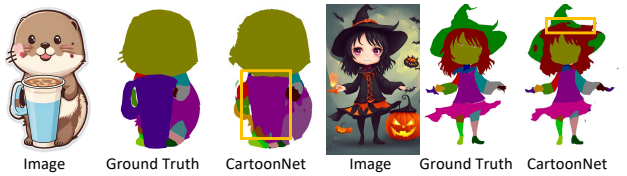

Figure 8: Visualization results of failure examples.

Table 6: Ablation studies of the memory size and the number of selected samples.

Method	Pixel Acc.	Mean Acc.	Mean IoU
CartoonNet + M400	**89.61**	70.59	**57.84**
CartoonNet + M800	89.51	70.48	57.45
CartoonNet + M1200	89.56	**70.94**	57.31
CartoonNet + M1530	89.41	70.45	57.67
CartoonNet + N3	89.49	70.04	57.15
CartoonNet + N5	**89.61**	70.59	**57.84**
CartoonNet + N7	89.67	**70.85**	57.47
CartoonNet + N9	89.51	69.64	57.40

Although CartoonNet achieves the state-of-the-art performance, it still faces some challenges. The failure examples are illustrated in Fig. 8. When the body of cartoon characters are significantly occluded by other objects such as cups, it is difficult for CartoonNet to correctly segment the cartoon image. In addition, if the adjacent body parts have similar appearances, for example, the black hat and black hair, then CartoonNet may make some error predictions.

5 Conclusion

In this paper, a cartoon parsing method named CartoonNet is proposed to address the challenges of diverse appearances and complex structures in cartoon characters. It primarily consists of a consistency learning strategy based on memory structure and a main body-aware structure correlation module. The memory-based consistency learning achieves semantic consistency among diverse cartoon characters, which explores deep relations of the body parts that have different appearances but belong to the same class. The main body-aware structure correlation enhances the recognition capability of complex structures by focusing on the core body parts. By combining the memory-based consistency learning with the main body-aware structure correlation strategy, the proposed method achieves state-of-the-art results in cartoon parsing.

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