A Multi-head Self-relation Network for Scene Text Recognition

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Outline

Introduction

- Natural scene images usually contain a large amount of rich and valuable text information, which can be found on documents, road signs, billboards and other objects.
- The scene text recognition aims to retrieve all text strings from scene text images.

Figure: Some examples for scene text image

Introduction

- It is a high-level and complicated task that translate between two different forms of information: Computer vision and Natural Language Processing.
- Extracting a meaningful text representation has become a challenge due to the complex environment in the irregular scene text recognition task such as uneven illumination, positional changes and so on.

Related Work

- Most existing methods only encode text in the image as a one-dimensional(1-D) sequence of features and ignore the complicated spatial layout of scene text.
- Recently, several works take Graph Convolutional Networks (GCN) to update the node state according to the input related nodes by learning a parametric function, which is shared among all nodes

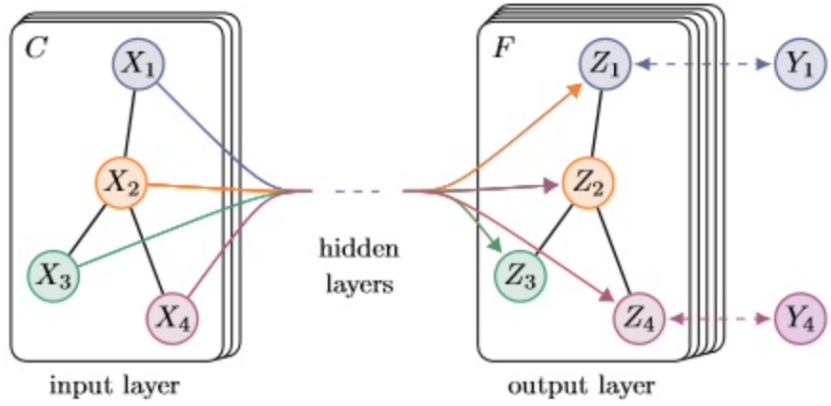


Figure: Graph Convolutional Network

Methods

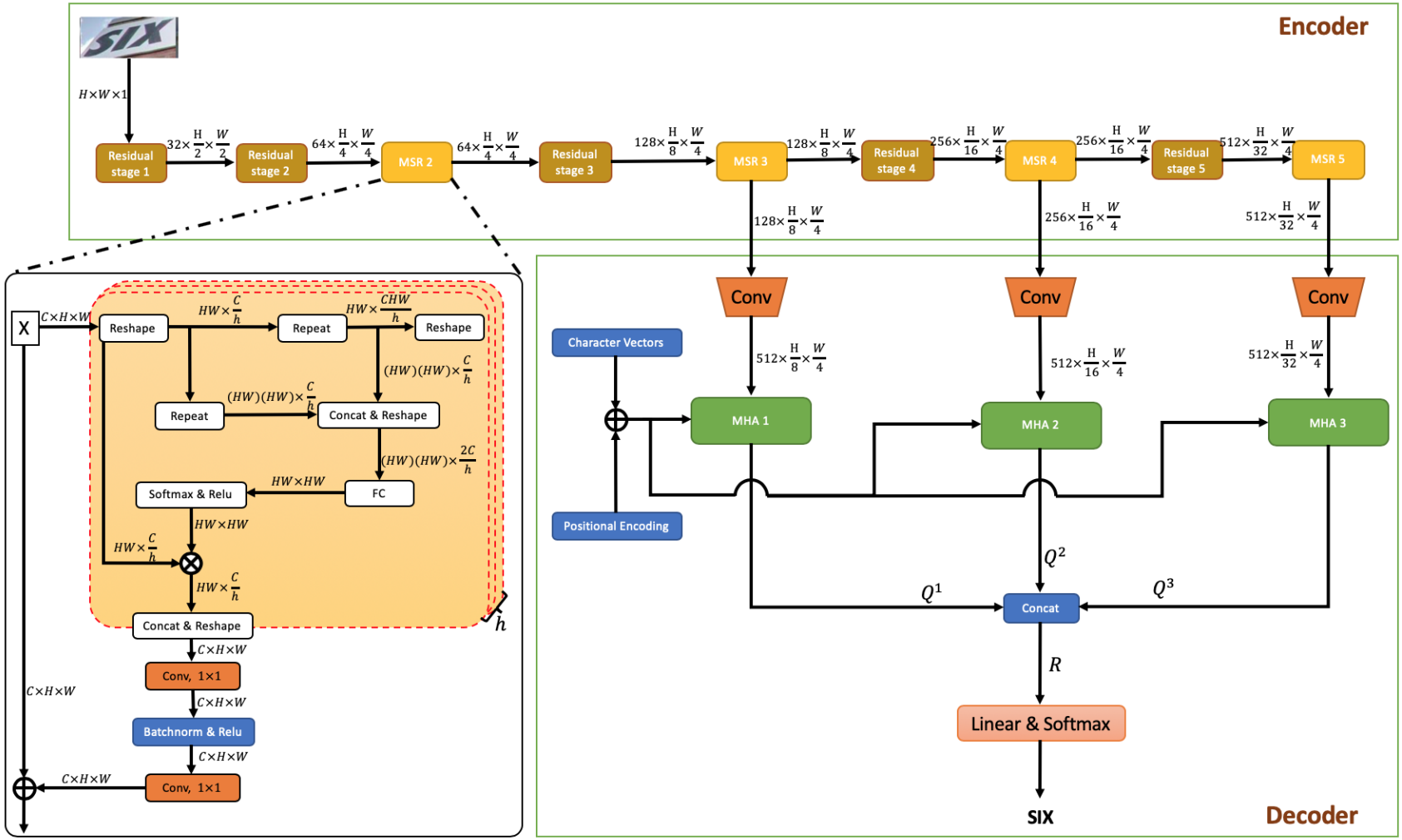


Figure: The overall framework of our proposed recognition network.

Methods

Multi-head Self-relation Layer

Algorithm: Multi-head Self-relation Layer

Input: Visual feature vectors generated by a convolutional layer

1: Transform the visual feature vectors $X = \{x_1, x_{2,} \cdots\cdots, x_i, \cdots\cdots, x_n\}$ into higher-level features $E = \{e_1, e_{2,} \cdots\cdots, e_i, \cdots\cdots, e_n\}$ by a learnable weight W.

2: Get the relation coefficient between each vector.

3: **for** head = 1: head numbers **do**:

4: **for** i = 1: n **do** :

5: $z_{ij} = gConcat(e_i, e_j)$

6: $\alpha_{ij} = \frac{exp(LeakyReLU(z_{ij}))}{\sum_{m=1}^{n} exp(LeakyReLU(z_{im}))}$

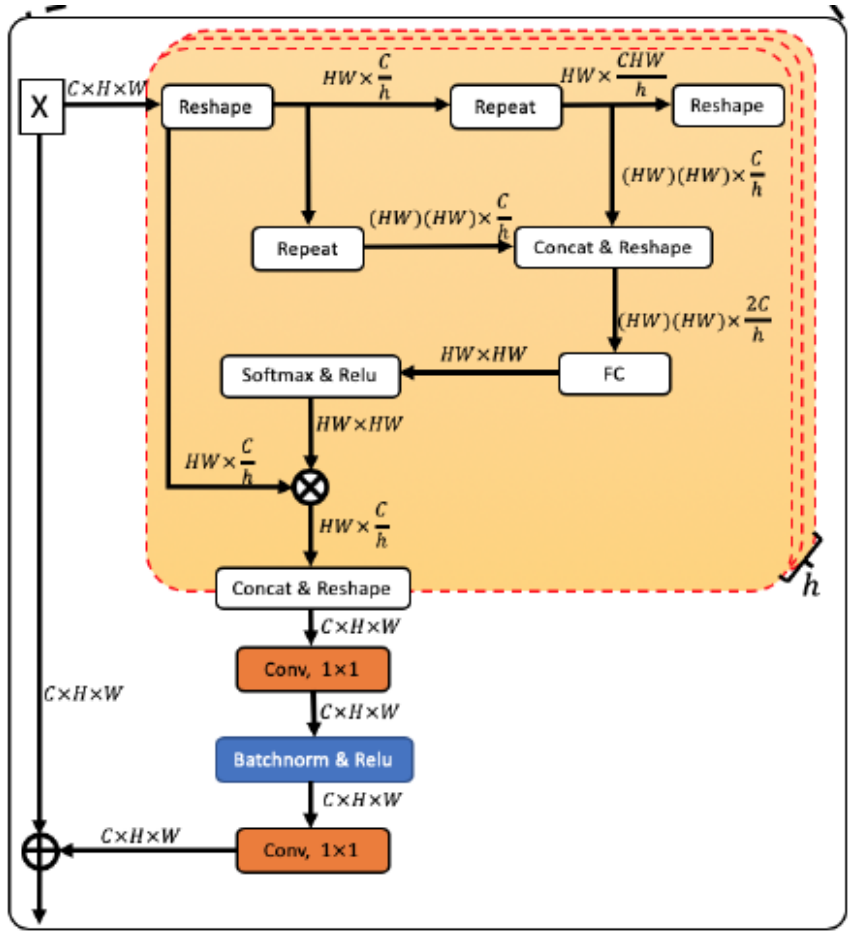
7: $h_i = \sum_{j=1}^{n} \alpha_{ij} e_j$

8: **end for**

9: **end for**

10: Then all the heads' features are concatenated resulting in $t_i = Concat(h_i^1, \cdots\cdots, h_i^{nh})$. #nh means head numbers

11 : **Output**: $y_i = x_i + W1ReLU(BN(W2t_i))$



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Performance analysis

TABLE I
UNDER THE DIFFERENT NUMBERS OF SELF-RELATION HEADS OUR NETWORK RECOGNITION ACCURACY, THE TRAINING DATASET IS SYSTH90K. THE MSRN CONTAINS MSR2, MSR3, MSR4, AND MSR5. THE DECODER INCLUDES MHA1, MHA2, MHA3.

Head number	IIIT5K	SVT	IC03	IC13	CUTE80	IC15	SVTP
1	79.4	78.5	88.5	89.2	56.9	63.8	67.8
4	79.2	81.6	92.2	90.8	**64.2**	67.0	72.8
8	**82.1**	**82.4**	**92.8**	**91.6**	63.9	**68.6**	**73.3**
16	79.4	81.3	88.4	88.3	56.6	64.9	71.1

Table I shows that when the head number is 8, the recognition network gets the best performance.

TABLE II
COMPARISON OF DIFFERENT MSRN SETTINGS. ✓ IN THE COLUMN NAMED MSRi MEANS THE NETWORK CONTAINS THE i-TH MSR LAYER, THE TRAINING DATASET IS SYSTH90K, THE HEAD NUMBER IS 8. THE DECODER INCLUDES MHA1, MHA2, MHA3.

MSR2	MSR3	MSR4	MSR5	IIIT5K	SVT	IC03	IC13	CUTE80	IC15	SVTP
			✓	80.3	80.4	89.5	89.3	59.0	65.9	72.5
		✓	✓	**82.3**	**82.4**	90.9	89.9	63.5	66.4	72.0
✓		✓	✓	81.5	80.1	**93.4**	91.5	**63.9**	67.0	73.0
	✓	✓	✓	79.1	79.2	90.1	89.1	59.2	65.1	69.5
✓	✓	✓	✓	82.1	**82.4**	92.8	**91.6**	**63.9**	**68.6**	**73.3**

Table II shows that when we use MSR2, MSR3, MSR4, and MSR5, the performance is best.

Performance analysis

TABLE III
COMPARE THE PERFORMANCE UNDER DIFFERENT DECODER SETTINGS. ✓ IN THE COLUMN NAMED MHAi MEANS THE DECODER CONTAINS THE i-TH MHAi BLOCK. THE TRAINING DATASET IS SYSTH90K, THE MSRN CONTAINS MSR2, MSR3, MSR4 AND MSR5. THE HEAD NUMBER IS 8.

MHA1	MHA2	MHA3	IIIT5K	SVT	IC03	IC13	CUTE80	IC15	SVTP
		✓	80.5	79.5	89.9	88.8	59.4	63.7	71.2
	✓	✓	80.1	77.9	88.8	88.0	59.0	62.9	65.7
✓		✓	81.8	81.5	90.1	90.5	64.2	67.1	72.3
✓	✓	✓	**82.1**	**82.4**	**92.8**	**91.6**	**63.9**	**68.6**	**73.3**

As shown in Table III, when the decoder includes MHA1, MHA2, and MHA3, our model gets the best recognition accuracy.

TABLE IV
COMPARE WITH OTHER METHODS, ALL SCORES ARE IN LEXION-FREE MODE. 90K MEANS SYNTH90K DATASET ST MEANS SYNTHTEXT DATASET, 'STADD' MEANS SYNTHADD DATASET. ST$^+$ MEANS INCLUDING CHARACTER-LEVEL ANNOTATIONS OR USING ADDITIONAL DATASETS.

Method	Convnet,Data	Regular datasets				Irregular datasets		
		IIIT5K	SVT	IC03	IC13	CUTE80	IC15	SVTP
Shi et al.	VGG,90K	78.2	80.8	89.4	86.7	-	-	-
*Shi et al.	VGG,90K	81.9	81.9	90.1	88.6	-	59.2	71.8
Lee et al.	VGG,90K	78.4	80.7	88.7	90.0	-	-	-
Jaderberg et al.	VGG,90K	-	80.7	93.1	90.8	-	-	-
Wang et al.	-,90k	80.8	81.5	91.2	-	-	-	-
Cheng et al.	ResNet, 90k+ST$^+$	87.4	85.9	94.2	93.3	-	70.6	-
Cheng et al.	-, 90k+ST$^+$	87.0	82.8	91.5	-	76.8	68.2	73.0
Shi et al.	ResNet,90k+ST$^+$	**93.4**	**93.6**	94.5	91.8	79.5	76.1	78.5
Luo et al.	-,90k+ST	91.2	88.3	95.0	92.4	77.4	68.8	76.1
Zhan et al.	ResNet,90k+ST	93.3	90.2	-	91.3	**83.3**	76.9	79.6
Li et al.	ResNet,90k+ST$^+$	91.5	84.5	-	91.0	**83.3**	69.2	76.4
MSRN(ours)	ResNet,90k+ST$^+$	91.9	89.7	**95.1**	**95.2**	79.5	**78.1**	**81.8**

From Table IV we can also learn that the performance of our method improves more on irregular datasets than that on regular datasets.

Conclusions

- In this paper, we propose a novel multi-head self-relation network, which can extract the relationship between each feature map cell.
- In our recognition network, a feature map is treated as a graph and each cell is treated as a node of the graph, then a correlation matrix is learnt to guide the nodes states updating.
- The performance of our recognition network shows that the MSRN is effective.

Thank you!