Sentiment Analysis of Fashion Related Posts in Social Media

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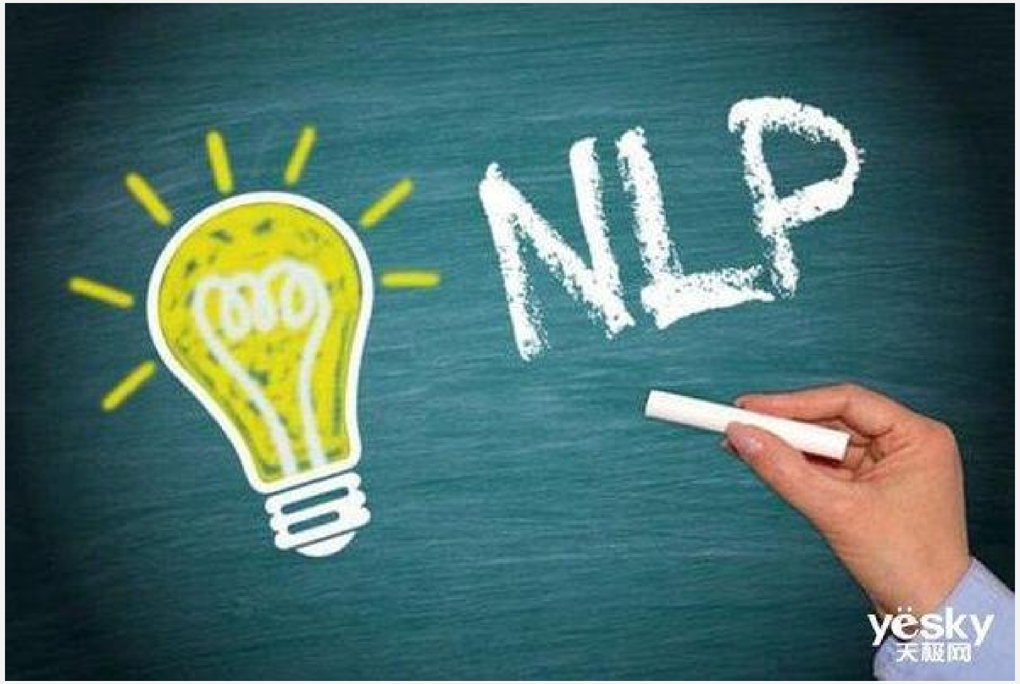
Reported by Jia Wang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Introduction

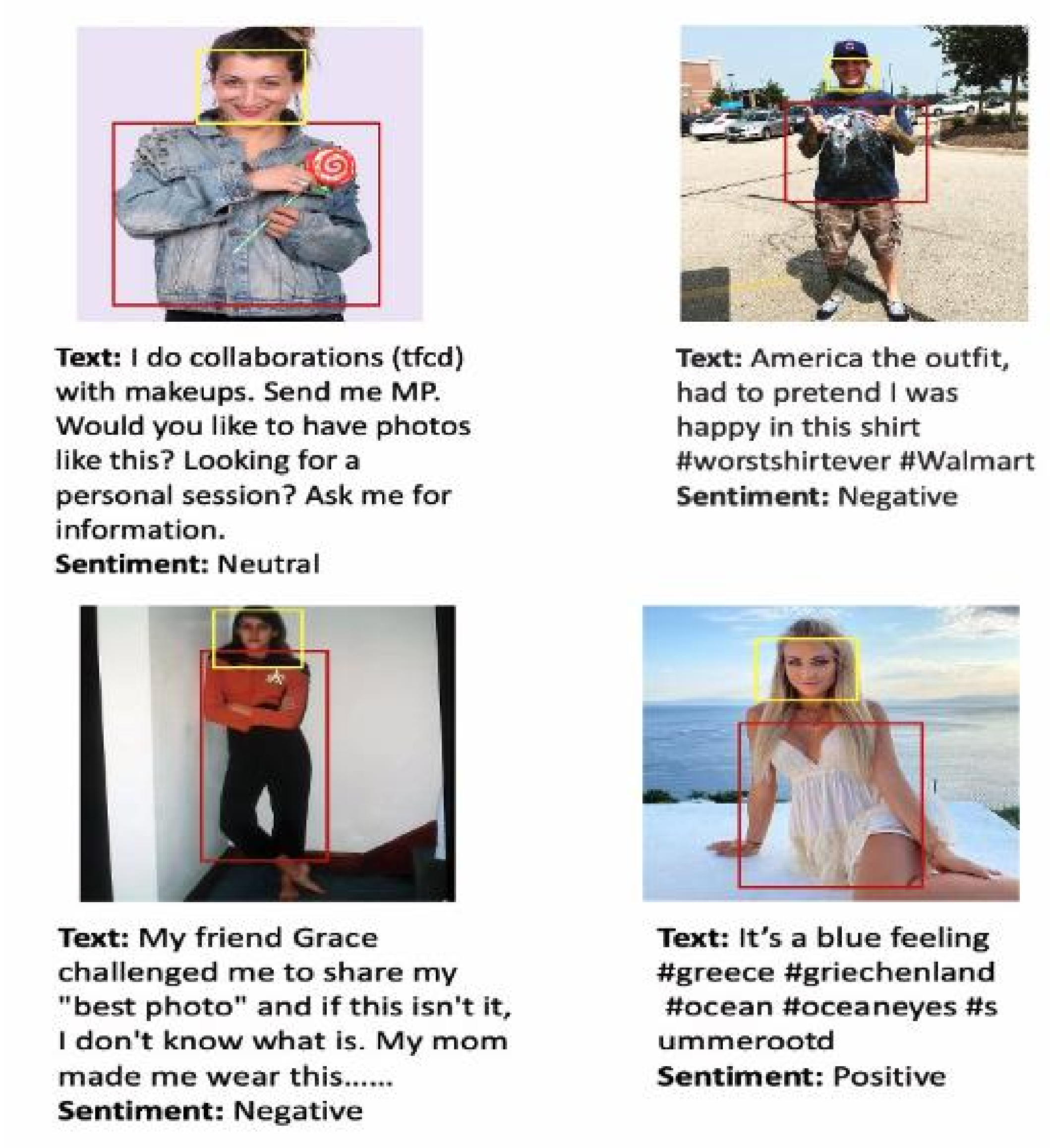


Figure 1: Some examples of our Instagram fashion sentiment analysis dataset. The red box is the fashion items box and the yellow one is the face detection box.

Introduction

In conclusion, the main contributions of this work are as follows:

• Our model detects the user sentiment polarity from fashion related posts in social media. A novel framework has been developed, which jointly exploits information from images,post texts, and fashion attributes.

• The mutual relationship between the fashion attributes extracted from post images and the post texts is captured via a mutual attention mechanism.

• We collect a large-scale dataset of over 12k fashion relatedsocial media posts, each includes an image and the corresponding post texts. Extensive experiments are conducted on two datasets to demonstrate the effectiveness of our model.

Approach

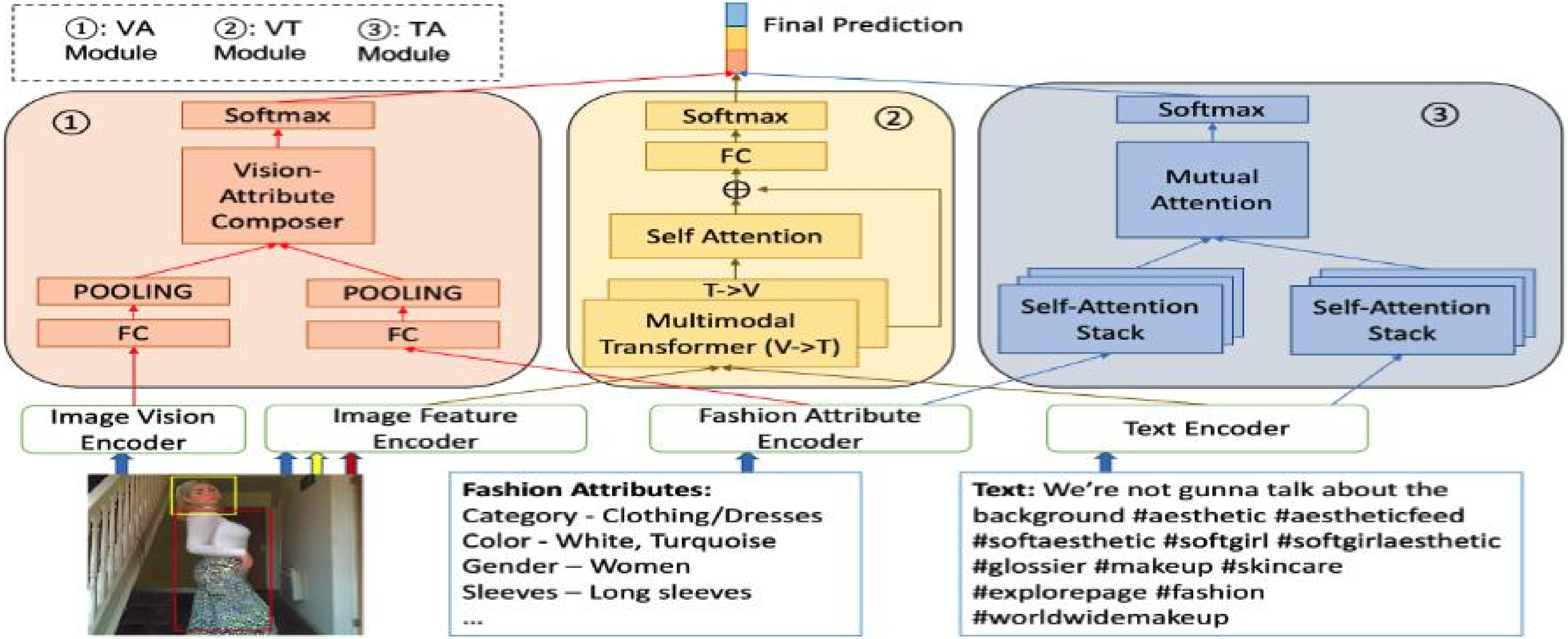
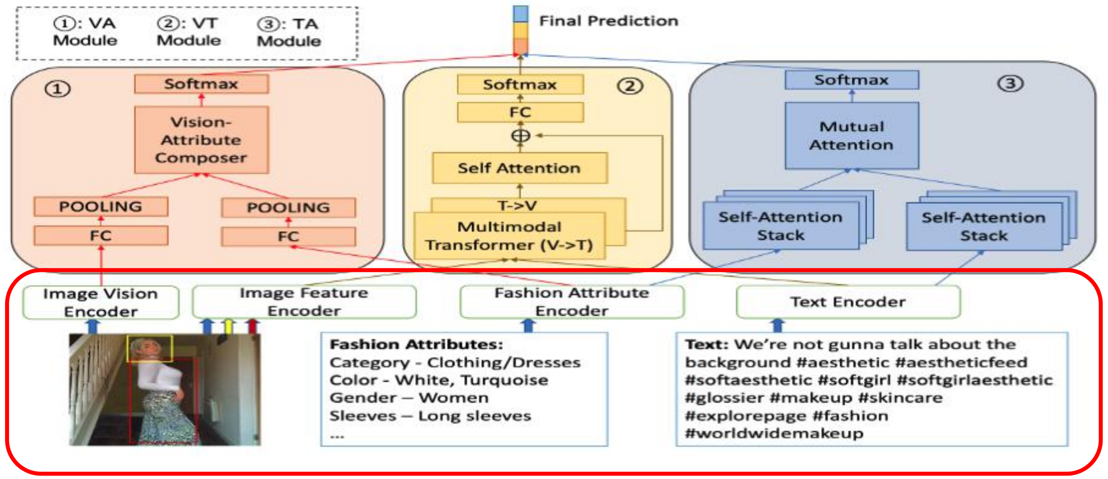


Figure 2: The overall structure of our framework. It consists of a fashion-aware vision composition module (VA module), a fashion-aware text composition module (TA module), and a vision text composition module (VT module). The input is an image annotated with face and fashion item boxes, the corresponding post texts, and the extracted fashion attributes.

Approach

Preprocessing and Basic Encoding



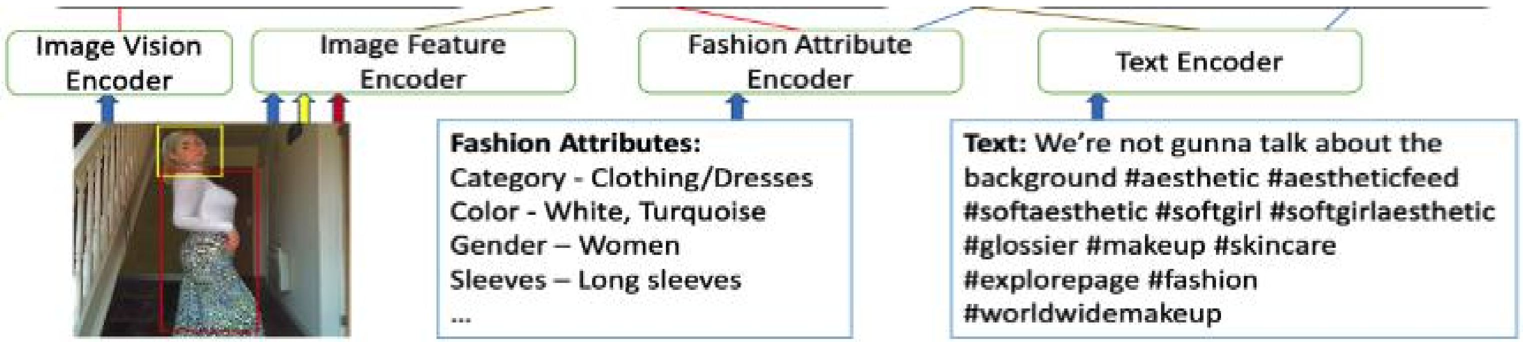


Image Vision Encoder(ResNet)

$$v_i = ImgEnc(p_i) \in \mathbb{R}^{d_p}$$

Image Feature Encoder

MTCNN (Multi-task Cascaded Convolutional Networks)

YOLOv3、ResNet

$$v_i' = ImgFtEnc(p_i) \in \mathbb{R}^{l_v \times d_p}.$$

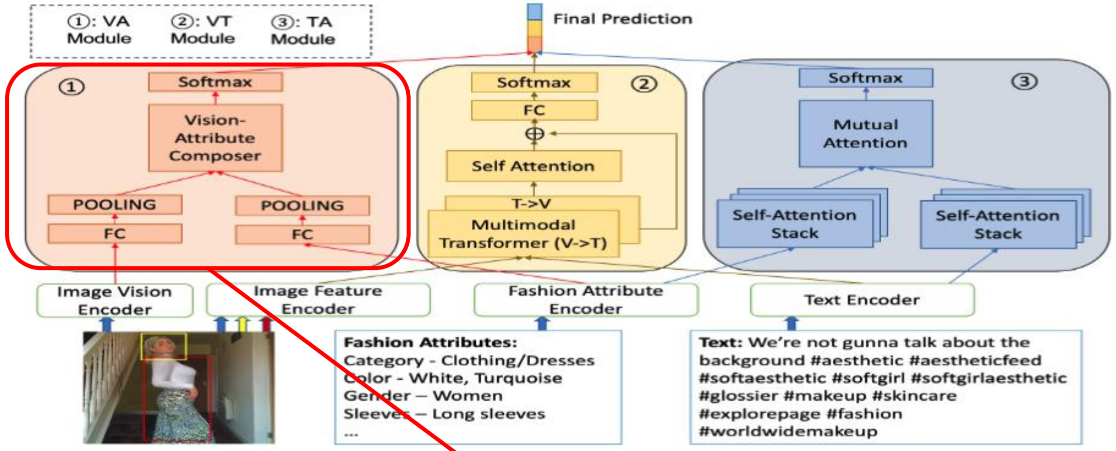
Text Encoder（Glove）

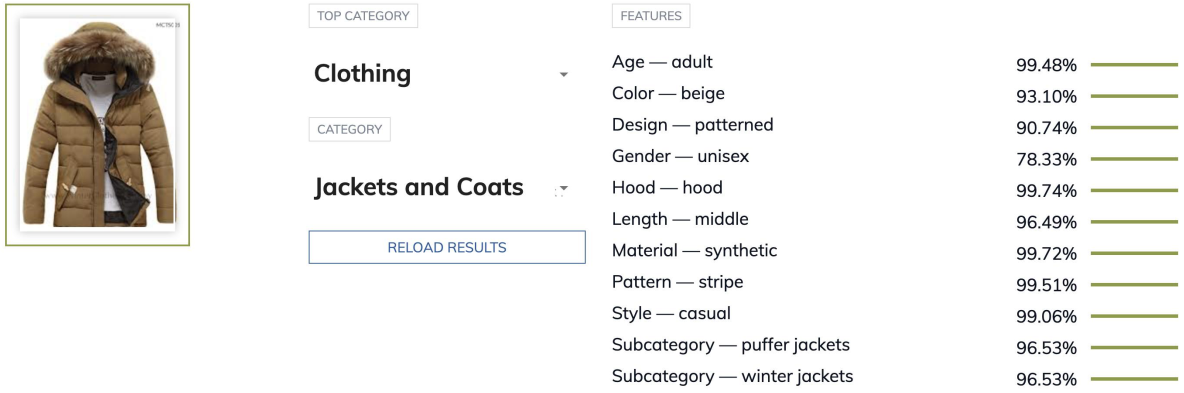
$$e_i = TxtEnc(t_i) \in \mathbb{R}^{l_t \times d_t}$$

Approach

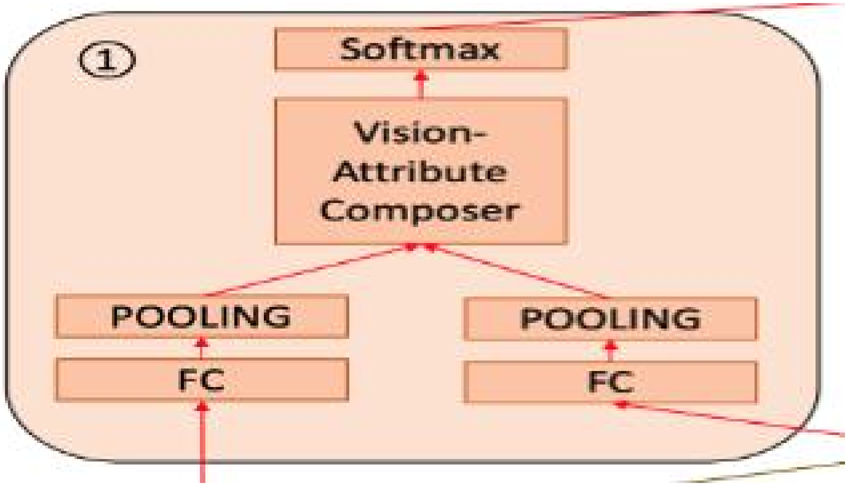
Fashion-Aware Vision Composition Module

（使用Ximilar4提供的时尚标签工具从图片中提取时尚属性）





$$f_i = AttrEnc(a_i) \in \mathbb{R}^{l_a \times d_t}$$



$$c_i = ComposeAE(FC(POOLING(v_i)), FC(POOLING(f_i))) \quad (1)$$

where the composed representation $c_i \in \mathbb{R}^d$.

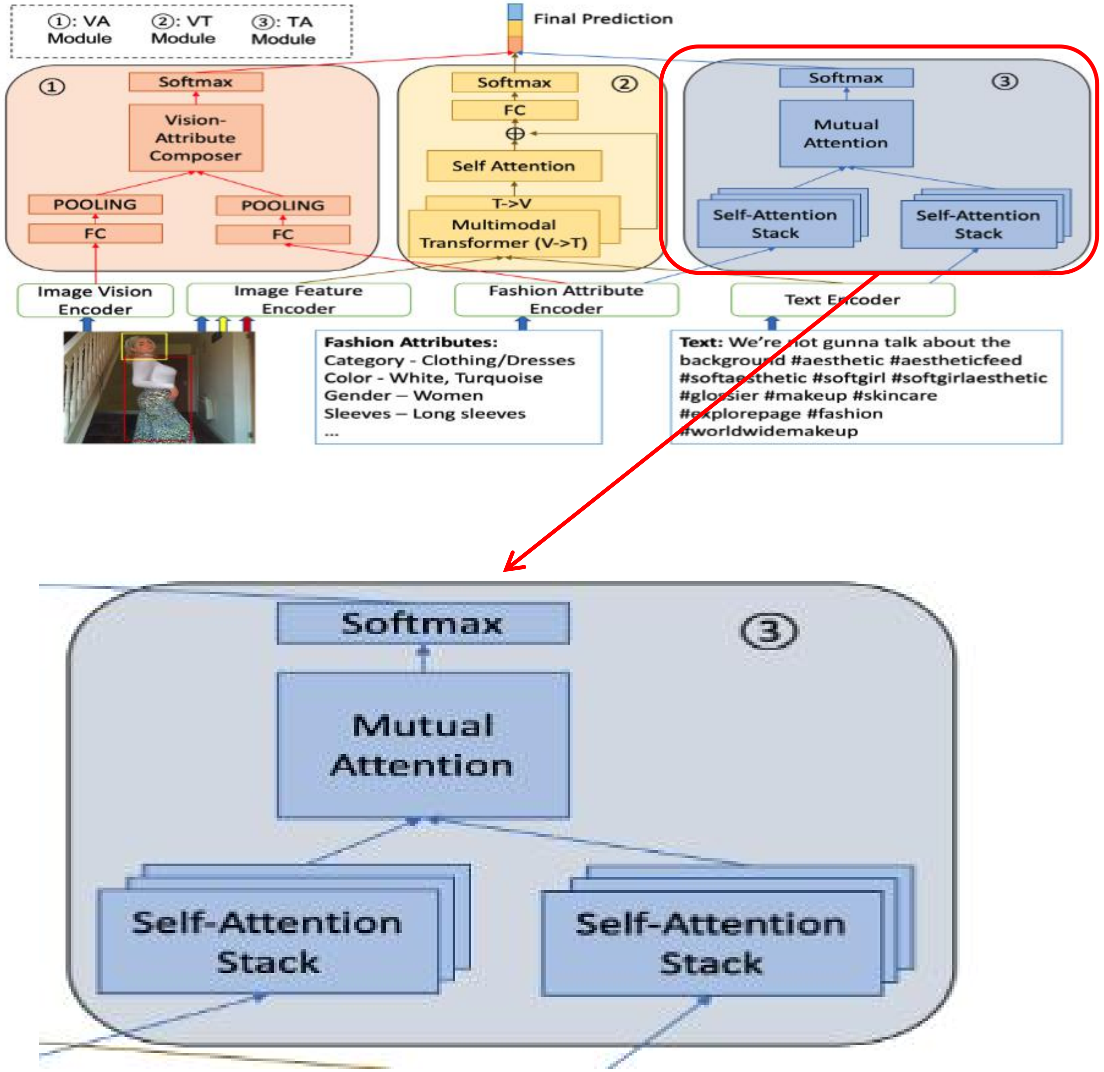
$$V_{final}^{[1]} = softmax(c_i) \in \mathbb{R}^{d_c} \quad (2)$$

where d_c is the number of label categories.

Compositional Learning of Image-Text Query for Image Retrieval (IEEE WACV 2021)

Approach

Fashion-Aware Text Composition Module

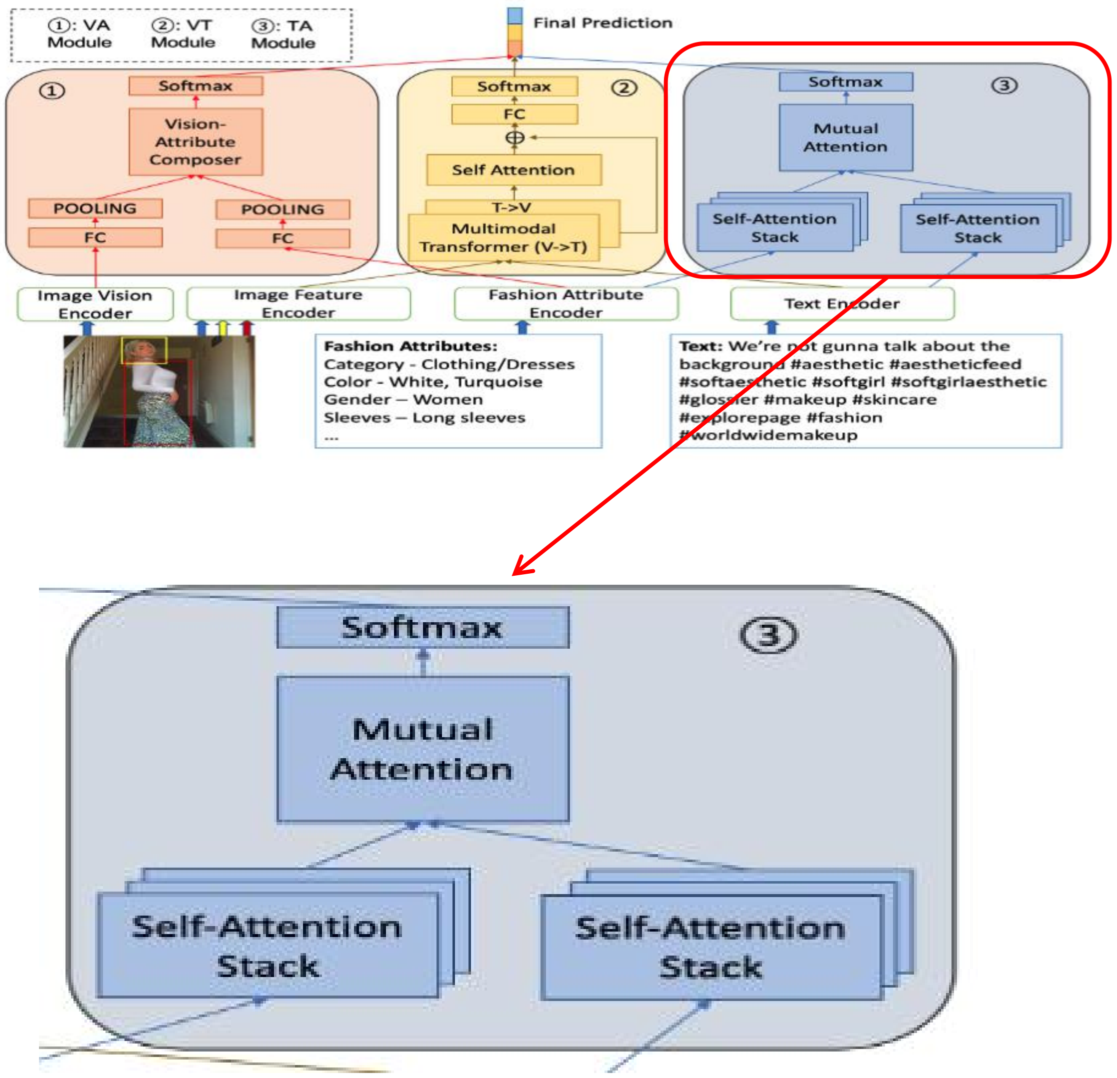


$$x_i = SAtt(e_i) = Avg(MHAtt(Q, K, V = e_{i,j})_{j=1}^{D}) \in \mathbb{R}^{l_t \times d_t} \tag{3}$$

$$y_i = SAtt(f_i) = Avg(MHAtt(Q, K, V = f_{i,j})_{j=1}^{D}) \in \mathbb{R}^{l_a \times d_t} \tag{4}$$

where D is the number of attention blocks in the self attention stack. $e_{i,j}$ is the text encoding output of the j-th attention block, which also serves as the input of the $j+1$-th block. $MHAtt$ denotes the multi-head attention mechanism. Note that the initial vector $e_{i,0}$ equals to the text embedding e_i, and $f_{i,0}$ equals to the attribute embedding result f_i.

Fashion-Aware Text Composition Module



Attribute-to-Text Attention.

$$\alpha_{mn} = softmax(g(W_1^T[x_{im}; y_{in}] + b_1))_n \tag{5}$$

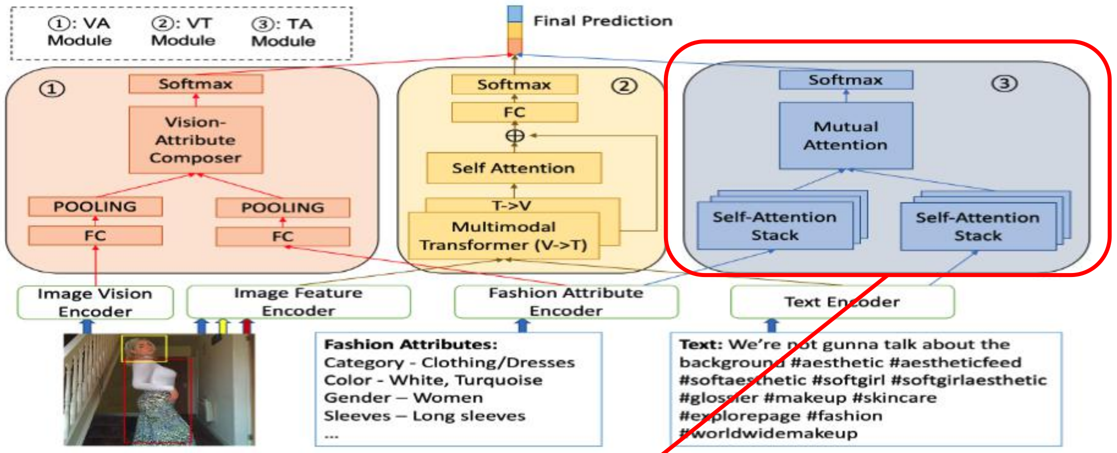
where α_{mn} is the attention weight between the m-th text feature and the n-th fashion attribute feature. $g(\cdot)$ is an non-linear activation function. $softmax(\cdot)_n$ denotes the softmax function is performed along n dimensions.

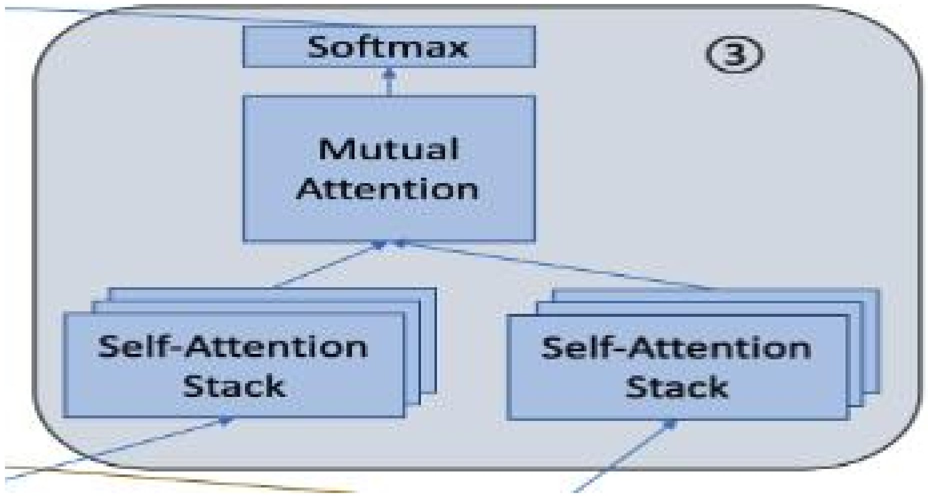
$$x_i^j = \sum_{k=1}^{l_t} \alpha_{jk} x_{ik} \tag{6}$$

$$S(x, a_j) = h(x_i^j, y_{ij}) \tag{7}$$

where $h(\cdot)$ denotes the inner product, y_{ij} is the j-th fashion attribute in the vector.

Fashion-Aware Text Composition Module





Text-to-Attribute Attention

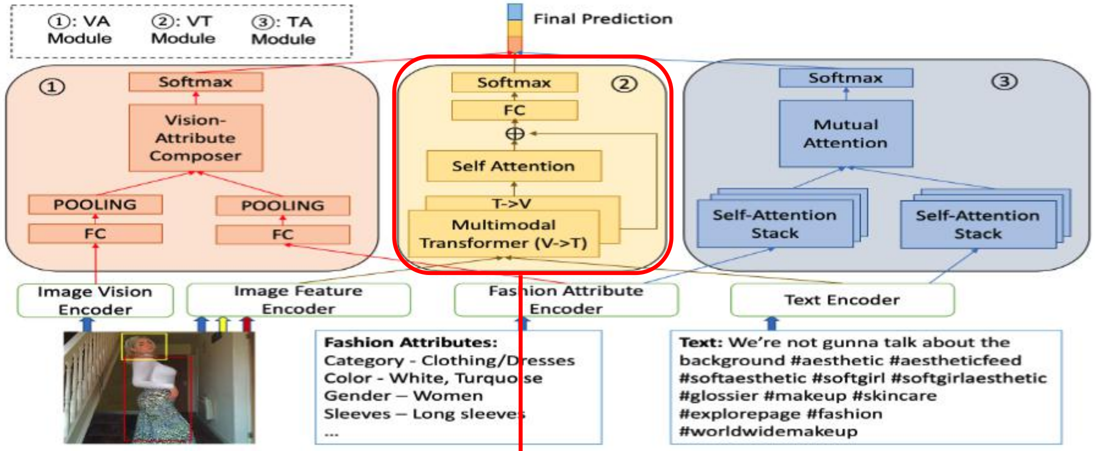
$$\beta a_m = softmax(g(W_2^T[\bar{x_i}; y_{im}] + b_2))_m \quad (8)$$

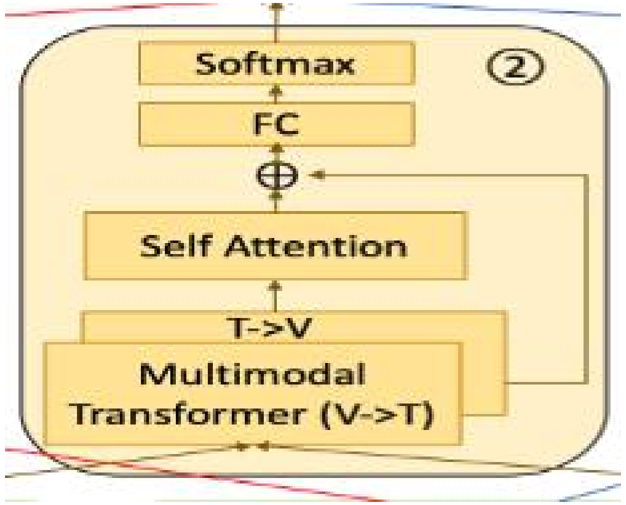
where βa_m is the weight between the m-th fashion attribute and the text representation. $\bar{x_i}$ is calculated by averagely pooling all the feature vectors in x_i. The final partial prediction vector is the weighted sum of the correlation vectors obtained in the last step followed by a fully connected layer with a softmax function.

$$Y^{[2]}_{final} = softmax(FC(\sum_{a_k \in \{a_e, a_s, \dots\}} \beta a_k S(x, a_k))) \quad (9)$$

Approach

Vision Text Composition Module





$$X_{t\to v} = MHAtt(Q = W_Q v_i', K = W_K e_i, V = W_V e_i) \quad (10)$$

$$\hat{Y}^{[i]}_{t\to v} = MHAtt(LN(Y^{[i-1]}_{t\to v}), LN(Y^{[0]}_t)) + LN(Y^{[i-1]}_{t\to v}) \quad (11)$$

$$Y^{[i]}_{t\to v} = f_\theta(LN(\hat{Y}^{[i]}_{t\to v})) + LN(\hat{Y}^{[i]}_{t\to v}) \quad (12)$$

where LN is the layer normalization function, and $Y_t^{[0]}$ is the text feature. $Y^{[0]}_{t\to v}$ is initialized as $X_{t\to v}$. f_θ is a positionwise feed-forward sublayer parametrized by θ.

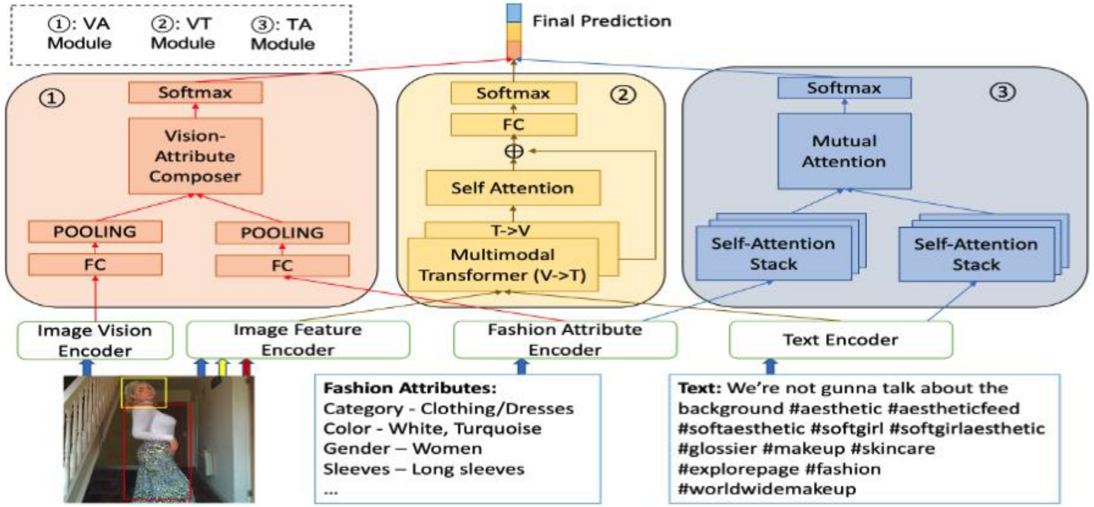
$$Y_{t,v} = [Y^{[L]}_{t\to v}; Y^{[L]}_{v\to t}] \quad (13)$$

$$Y^{[3]}_{final} = softmax(FC(SAtt(FC(Y_{t,v})) + Y_{t,v})) \quad (14)$$

where $SAtt$ denotes the self-attention stack. FC is the fully connected layer. L is the number of attention blocks in the stack.

Approach

Partial Prediction Score Combination and Training



$$Y_{final} = w_1 Y_{final}^{[1]} + w_2 Y_{final}^{[2]} + w_3 Y_{final}^{[3]} \tag{15}$$

where w_1, w_2, w_3 are the weights we would like to optimize. During training, we use the softmax cross entropy as the loss function.

Experiments

hashtag	Positive	Negative	Neutral	Total
#fashion	2489	739	1608	4836
#instagood	977	22	413	1412
#ootd	381	120	180	681
#tbt	187	89	111	387
#stupidshirt	59	143	121	323
Total	4387	2727	4947	12061

Table 1: Detailed information of the top 5 hashtags in our dataset.

Experiments

Type	Model	TWMMS1 Acc	TWMMS1 Precision	TWMMS1 Recall	TWMMS1 F1	Our Dataset Acc	Our Dataset Precision	Our Dataset Recall	Our Dataset F1
Unimodal	Text-Only	28.93	17.78	17.50	16.15	57.96±0.66	59.92±1.43	57.28±1.20	56.80±1.06
	Image-Only	15.25	8.55	7.87	8.62	47.04±1.11	46.84±0.76	46.38±0.50	44.58±0.21
	Attribute-Only	6.42	1.12	2.02	1.21	43.95±1.66	39.75±0.44	38.49±0.64	34.94±0.58
Multimodal (2 Modalities)	Early Fusion	31.31	22.66	21.53	19.18	59.68±1.26	62.41±1.41	59.96±1.70	58.91±1.66
	Late Fusion	32.85	23.48	20.61	19.98	60.30±1.06	63.09±2.39	60.76±1.56	60.02±1.63
	TIRG	29.33	18.08	18.16	18.98	62.60±1.49	64.21±1.06	64.95±1.12	63.07±1.16
	ComposeAE	34.45	18.97	19.67	19.99	62.01±0.51	64.31±0.87	62.60±0.85	61.48±0.71
	ViLBERT	36.77	25.68	24.93	22.12	66.25±0.63	66.06±0.56	66.51±0.51	66.23±0.19
	ViLBERT CC	35.78	25.70	24.85	22.26	66.38±0.99	66.13±0.21	67.73±0.20	66.47±0.41
	A2T	11.63	5.87	6.33	5.78	63.18±0.83	66.16±1.62	63.27±1.22	62.55±1.07
	T2A	8.36	2.86	3.42	2.90	62.94±0.83	64.61±0.20	64.89±0.37	63.17±0.40
Multimodal (3 Modalities)	M^3H-Att	29.27	17.16	17.88	16.16	58.08±2.21	59.85±2.51	58.36±2.41	56.86±2.29
	Ours	37.60	26.82	26.13	24.20	67.58±0.83	68.09±0.76	67.13±0.76	67.56±0.77

Table 2: Experimental results on two datasets

Experiments

Model	Acc	Precision	Recall	F1
VA module	48.26	47.94	48.18	46.71
TA module	63.93	65.72	63.69	62.83
VT module	66.58	66.41	67.96	66.67
w/o VA	67.09	67.94	67.15	66.70
w/o TA	66.07	66.45	65.92	66.18
w/o VT	64.93	66.68	62.98	64.28

Table 3: Ablation study of our proposed model

Experiments

Figure 3: Case study of different methods

Experiments

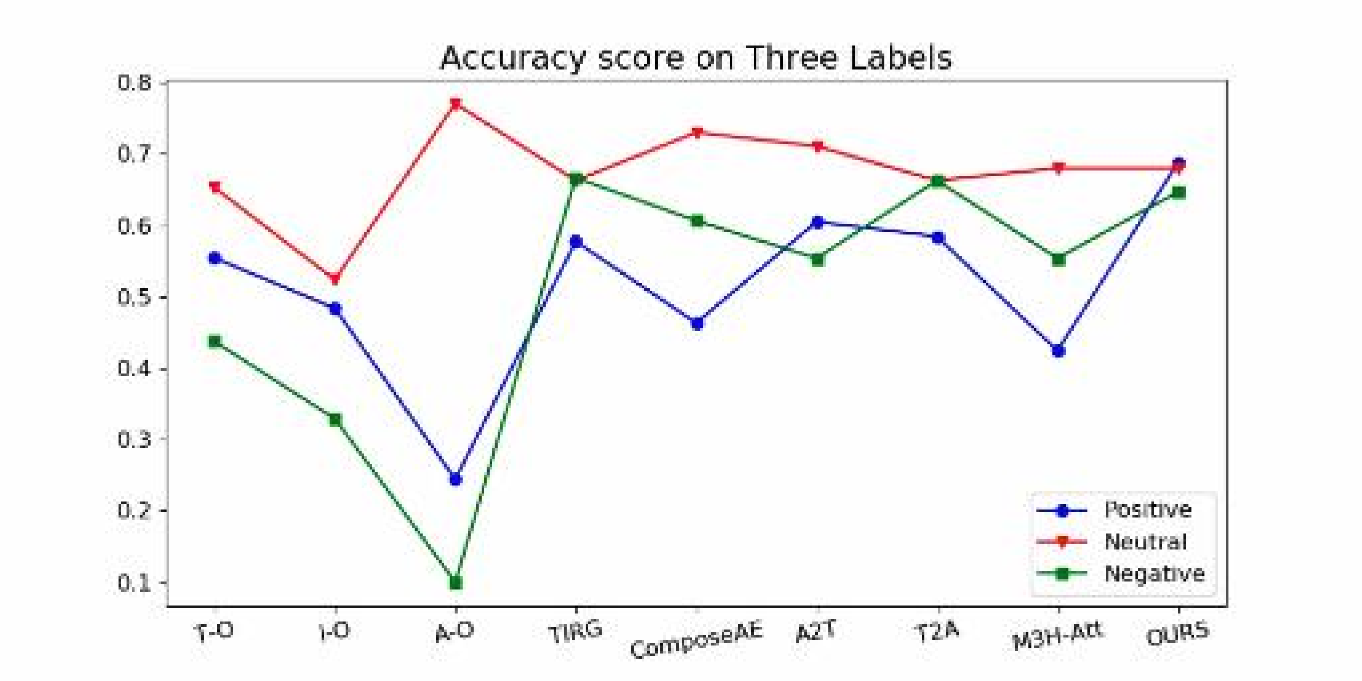


Figure 4: Accuracy score of different methods on three sentiment categories. T-O, A-O, I-O denote the three unimodal methods respectively.

Thanks！