SIGIR 5 Papers

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Sentiment Analysis of Peer Review Texts for Scholarly Papers

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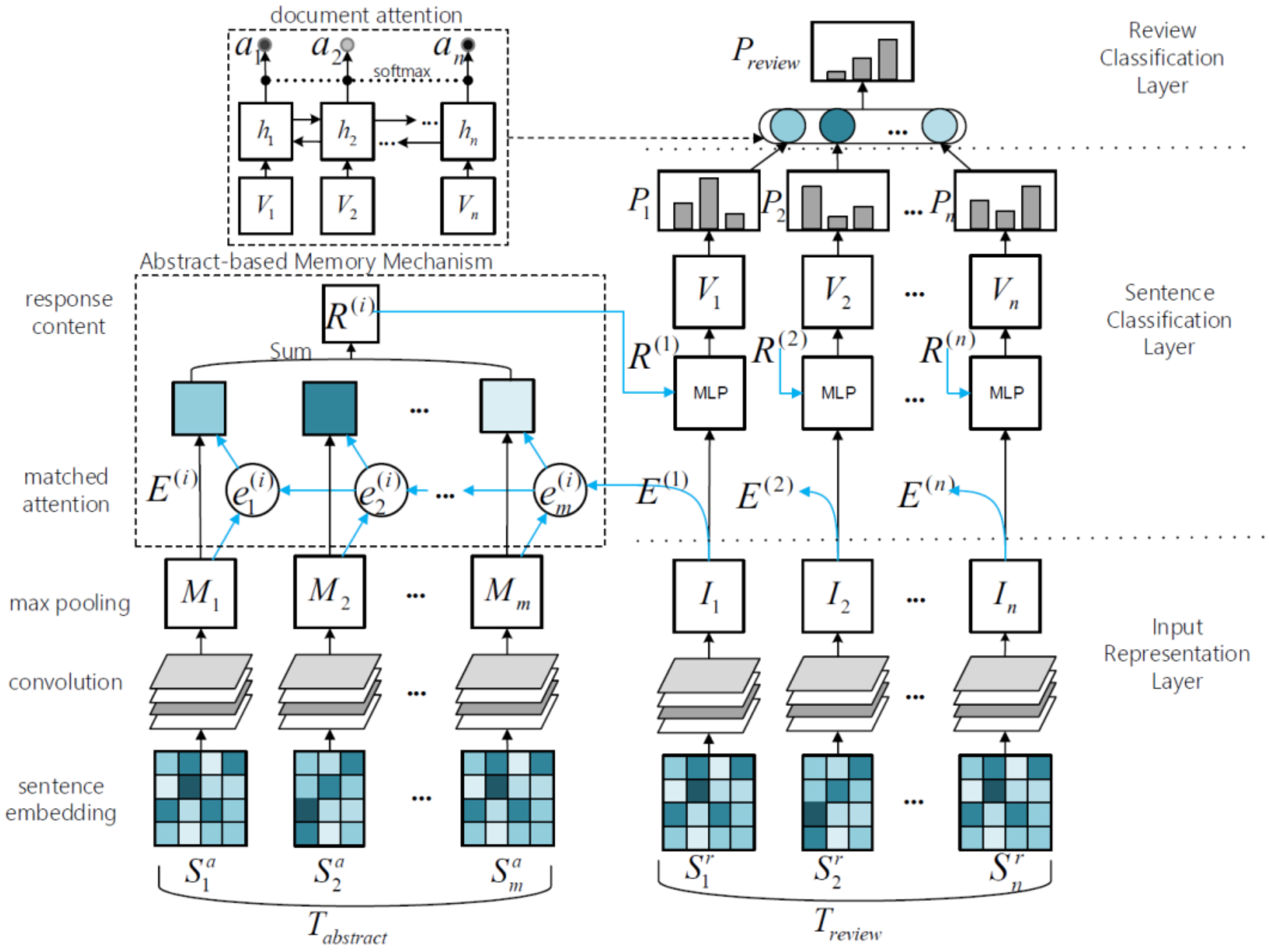
Manifold-Ranking Based Topic-Focused Multi-Document Summarization. X Wan, J Yang, J Xiao IJCAI 7, 2903-2908	223	2007
Single Document Keyphrase Extraction Using Neighborhood Knowledge. X Wan, J Xiao AAAI 8, 855-860	219	2008

Motivation

- Whether the review texts and the recommendation scores are consistent with each other or not
- Help the chair to write a comprehensive meta-review
- Be convenient for authors to further improve their paper

- There is very few researches
- Long
- Mixture of non-opinionated and opinionated texts.
- Mixture of pros and cons.

Model



- Memory

$$e_t' = LSTM(\hat{h}_{t-1}, \boldsymbol{M}_t), (\hat{h}_0 = \boldsymbol{I}_i, t = 1, ..., m)$$

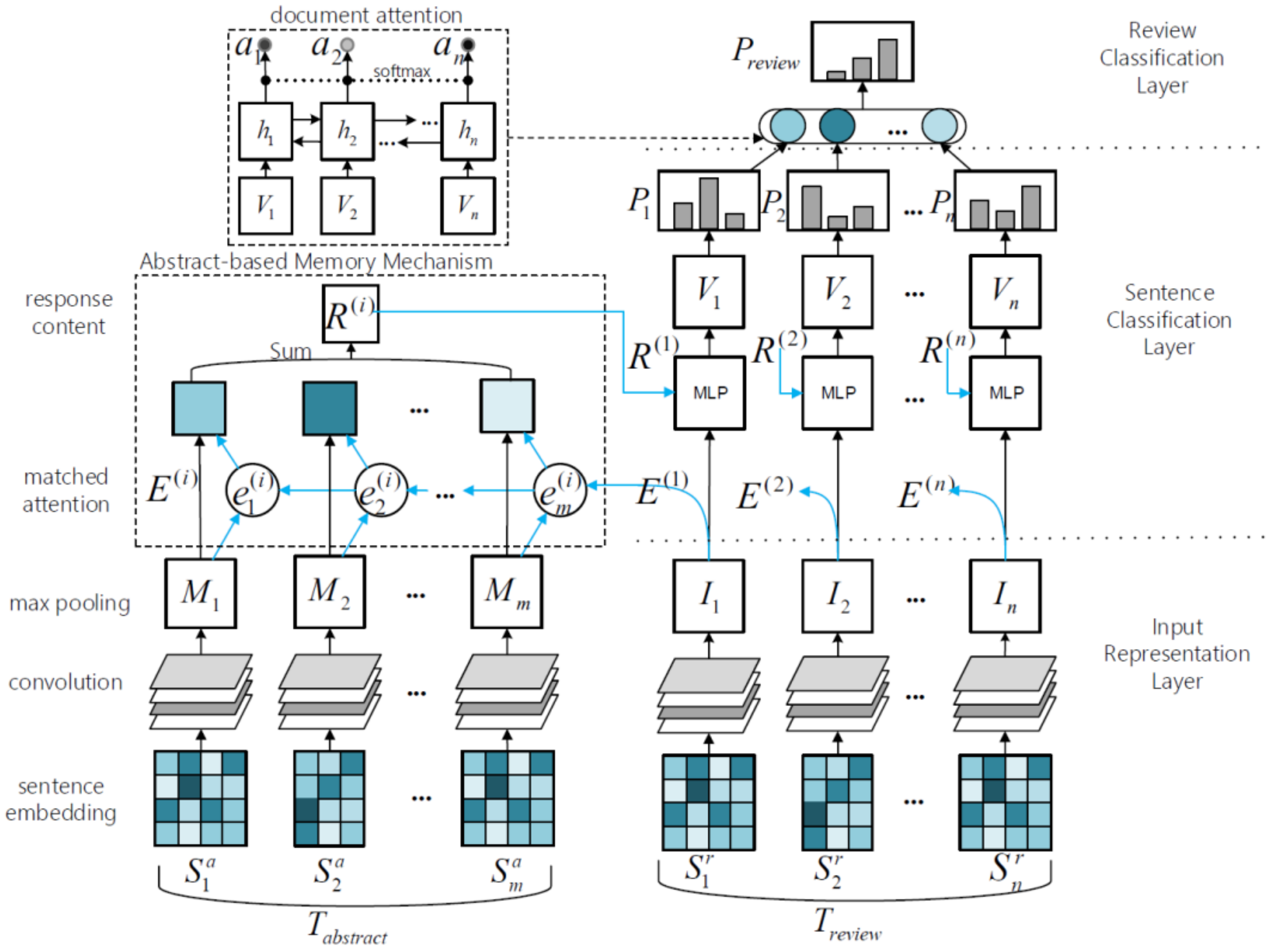
$$e_t^{(i)} = \frac{exp(e_t')}{\sum_j exp(e_j')}$$

$$\boldsymbol{E}^{(i)} = [e_t^{(i)}]_{t=1}^{m}$$

$$\boldsymbol{R}^{(i)} = \sum_{t=1}^{m} e_t^{(i)} \boldsymbol{M}_t$$

$$\boldsymbol{V}_i = f_{mlp}(\boldsymbol{I}_i || \boldsymbol{R}^{(i)}; \theta_{mlp}).$$

Model



- Review classifier

$$\boldsymbol{P_i} = softmax(\boldsymbol{W_p} \cdot \boldsymbol{V_i} + \boldsymbol{b_p}),$$

$$\boldsymbol{P_i} = [p_i^1, \ldots, p_i^C]$$

$$\overrightarrow{h_i} = \overrightarrow{LSTM}(\boldsymbol{V_i})$$

$$\overleftarrow{h_i} = \overleftarrow{LSTM}(\boldsymbol{V_i})$$

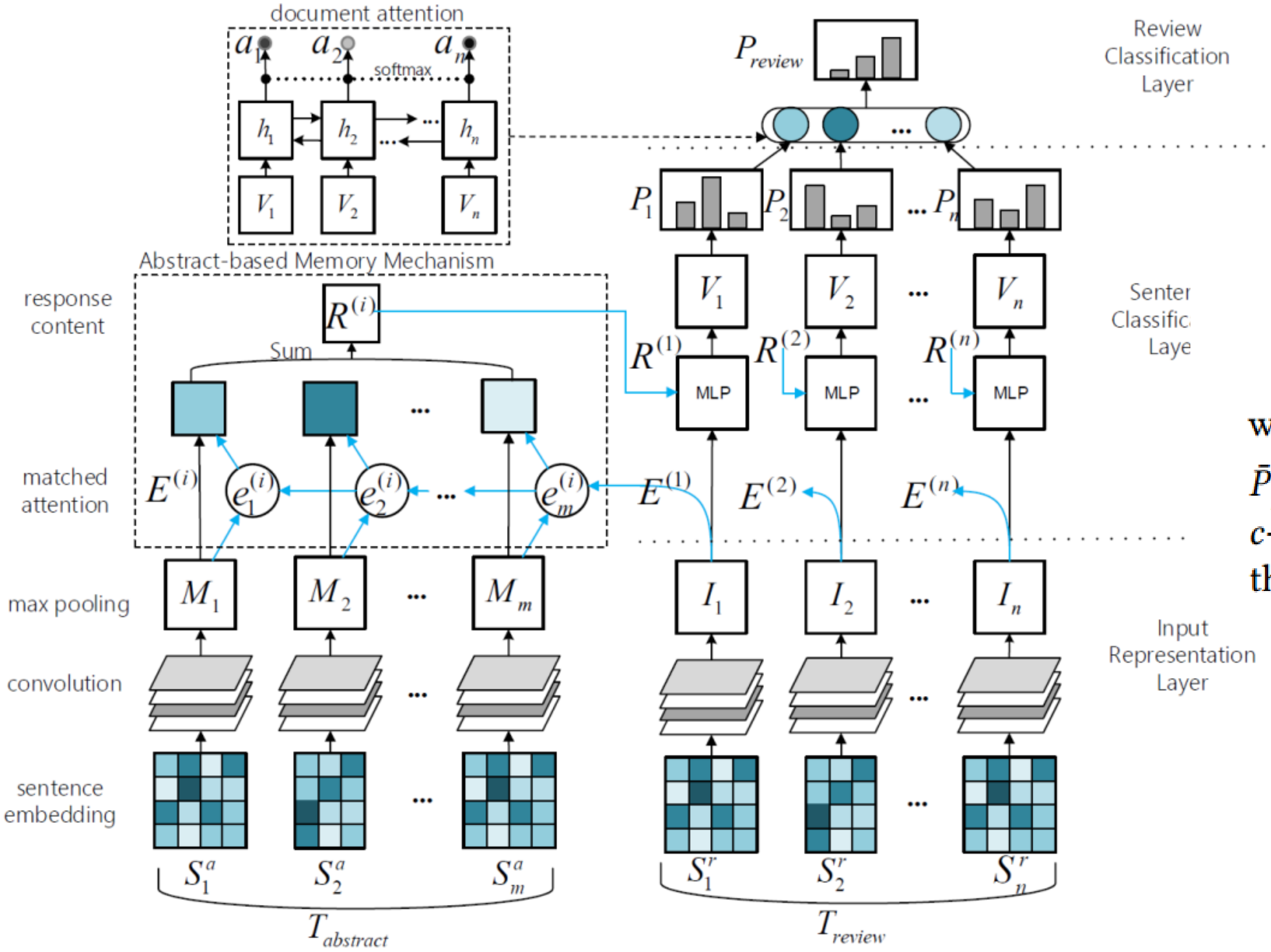
$$h_i = \overrightarrow{h_i} || \overleftarrow{h_i}$$

$$h_i' = tanh(\boldsymbol{W_a} \cdot h_i + \boldsymbol{b_a})$$

$$a_i = \frac{exp(h_i')}{\sum_j exp(h_j')}$$

$$P_{review}^{(c)} = \sum_i a_i P_i^{(c)}, c \in [1, C]$$

Model



- Objective Function

the categorical cross-entropy loss

$$L(\theta) = \sum_{T_{review}} \sum_{c=1}^{C} -P_{review}^{(c)} \log(\bar{P}_{review}^{(c)}) \quad (17)$$

where T_{review} is the review text in the training data, $P_{review}^{(c)}$ and $\bar{P}_{review}^{(c)}$ are the true and predicted probabilities of belonging to the c-th class, respectively. We use Adam [21] with minibatch to learn the model parameter θ.

Experiment

- ICLR, NIPS workshops, ICML workshops on the OpenReview website(https://openreview.net/)
- Only ICLR 2017 and ICLR 2018 provided both peer reviews and the corresponding overall recommendation scores for each submission
- K-fold cross validation(k=10)
- Google’s 300-dimensional word vectors

Result

This paper presents low-rank bilinear pooling that uses Hadamard product. The paper implements · · ·

· · · · · ·

I like the insights about low-rank bilinear pooling using Hadamard product presented in the paper. *However, it could not be justified that low-rank bilinear pooling leads to better performance than compact bilinear pooling. It does lead to reduction in number of parameters but it is justification of why low-rank bilinear pooling is better than other forms of pooling.*

Prediction: Accept

Summary:

[+0.19] I like the insights about low-rank bilinear pooling leads· · ·
[+0.12] The paper presents new insights into element-wise · · ·
[+0.06] The paper presents a new model for the task of VQA · · ·
[+· · ·] · · ·
[- 0.12] it could not be experimentally verified that low-rank · · ·
[- 0.11] I would like the authors to provide experimental · · ·
[- 0.05] It is not very clear from reading the paper.
[-· · ·] · · ·

Methods	ICLR-2017	ICLR-2018
SVM(Uni)	70.14% (+/- 4.37%)	71.02% (+/- 3.81%)
SVM(Uni&Bi)	71.56% (+/- 2.52%)	73.23%(+/- 5.29%)
SVM(Uni&Bi&Senti)	74.23% (+/- 3.21%)	75.24% (+/- 2.36%)
CNN	68.93% (+/- 5.24%)	73.31% (+/- 2.70%)
LSTM	65.24% (+/- 4.21%)	69.25% (+/- 3.82%)
CNN+Bi-LSTM	74.35% (+/- 3.51%)	76.21% (+/- 4.08%)
CNN+Bi-LSTM+Att	75.64% (+/- 3.42%)	77.85% (+/- 3.72%)
MIL	75.02% (+/- 2.85%)	76.57% (+/- 2.31%)
MILAM	**78.24% (+/- 4.92%)**	**80.32% (+/- 5.43%)**

A Co-Memory Network for Multimodal Sentiment Analysis

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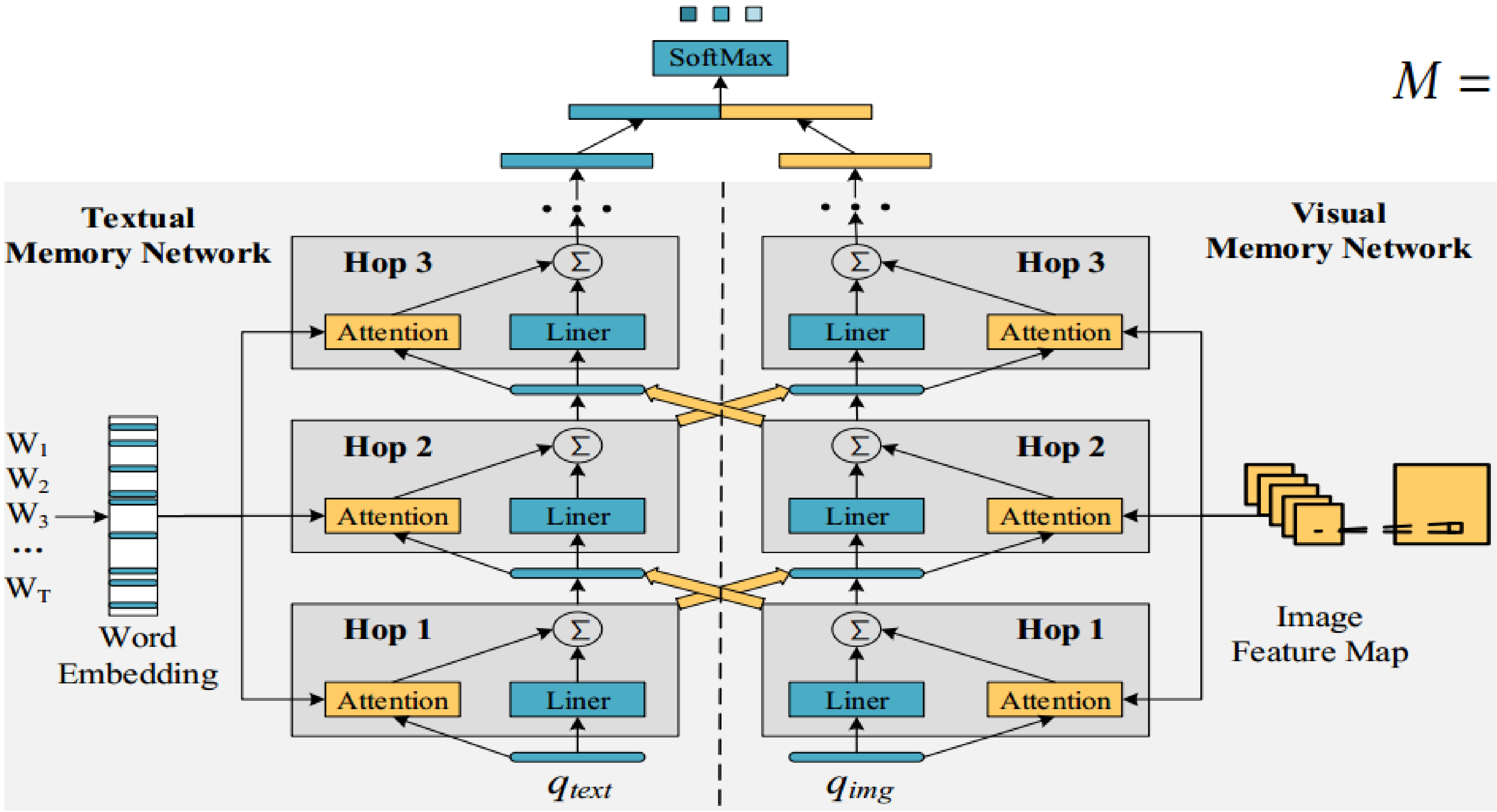
Motivation

- As visual and textual information in multimodal data can mutually **reinforce and complement** each other in analyzing the sentiment of people, previous research all ignores this mutual influence between image and text.

Model



- Image Feature：

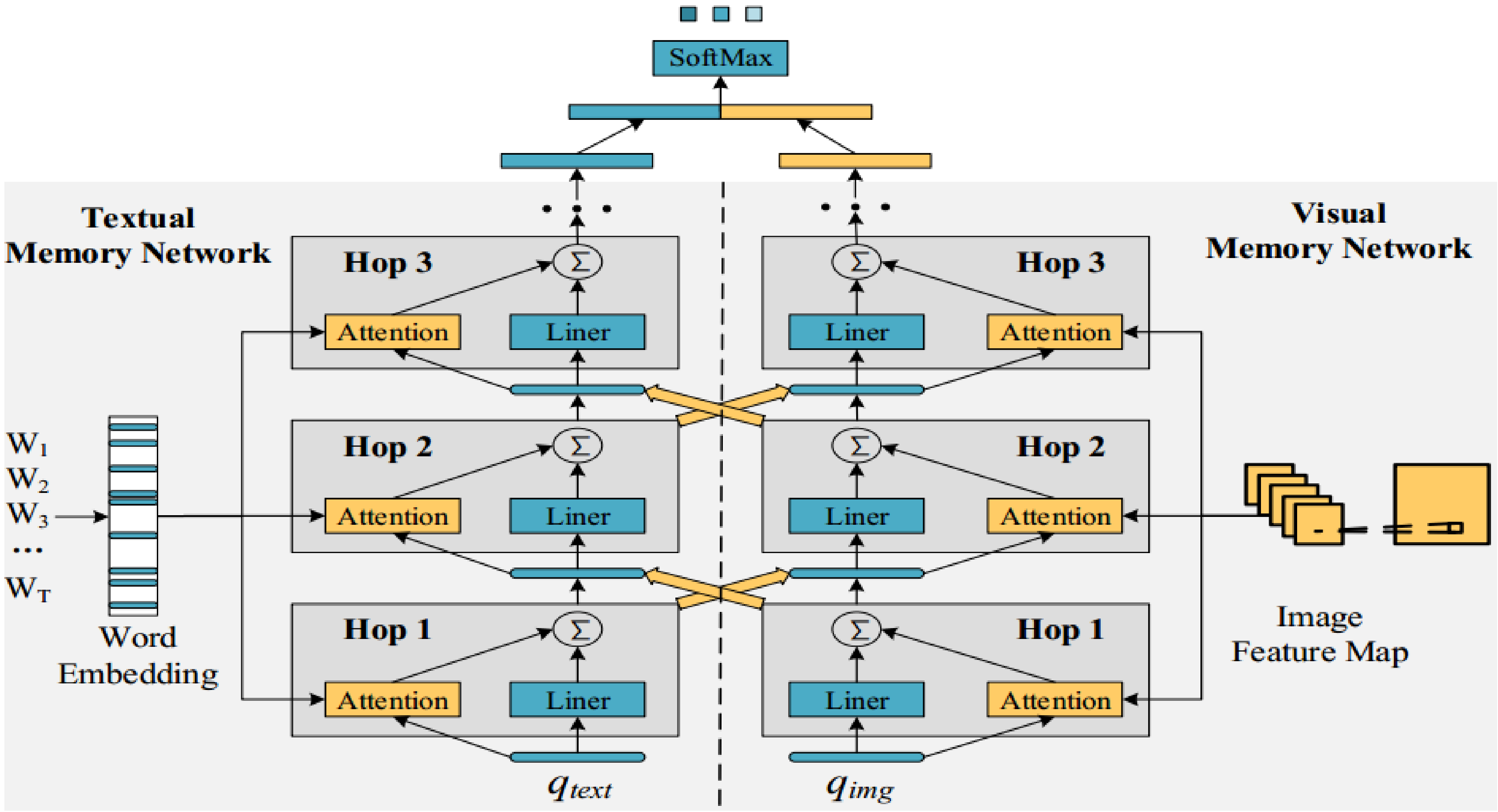
$$M = \{m_1, m_2, \ldots, m_L\}, m_i \in \mathbb{R}^{D_{img}}$$

$$h_i^1 = tanh(w_{img}^1 m_i + b_{img}^1)$$

$$\alpha_i^1 = \frac{exp({h_i^1}^T q_{img})}{\sum_{j=1}^{L} exp({h_j^1}^T q_{img})}$$

$$v_{img}^1 = \sum_{i=1}^{L} \alpha_i^1 m_i$$

Model



- Text Feature：

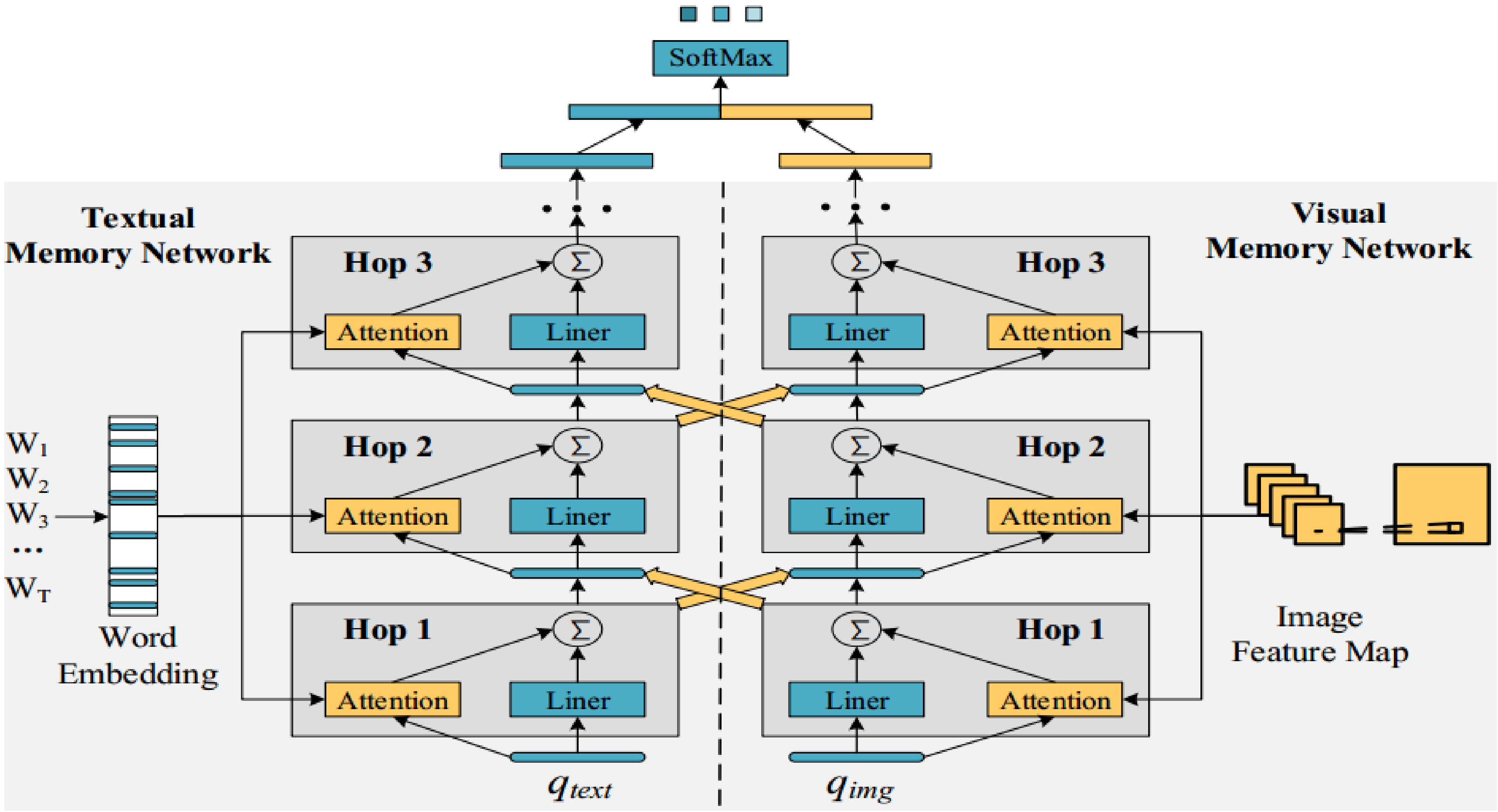
$$X = \{x_1, x_2, \dots, x_T\}, x_t \in \mathbb{R}^{D_{text}}$$

$$g_t^1 = tanh(w_{text}^1 x_t + b_{text}^1)$$

$$\beta_t^1 = \frac{exp({g_t^1}^T q_{text})}{\sum_{r=1}^T exp({g_r^1}^T q_{text})}$$

$$v_{text}^1 = \sum_{t=1}^T \beta_t^1 x_t$$

Model



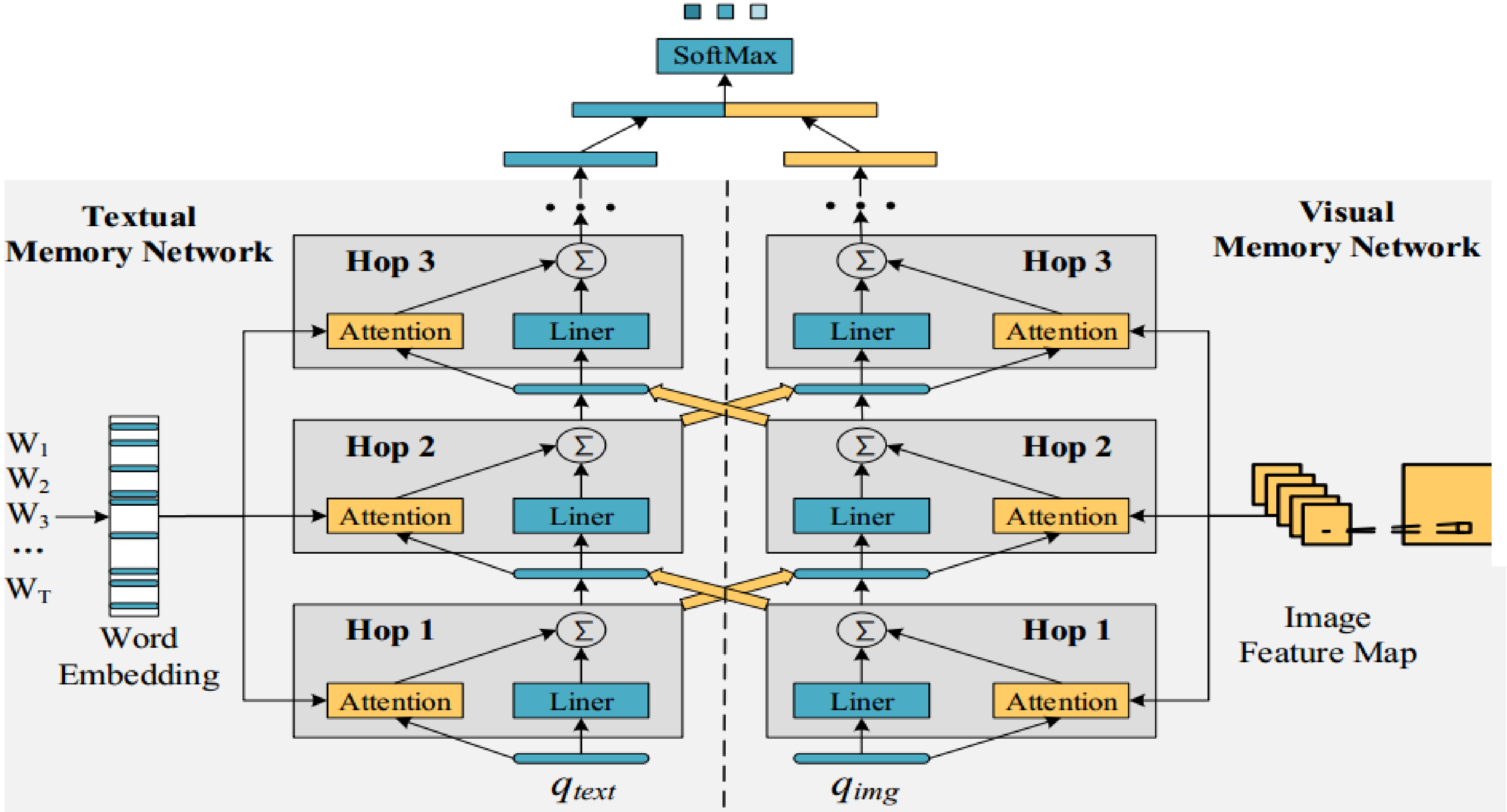
- Co-Memory Network:
- 1. Text-guided Visual Memory Network (TgVMN):

$$h_i^2 = tanh(w_{img}^2[m_i, v_{text}^1] + b_{img}^2)$$

$$\alpha_i^2 = \frac{exp(h_i^2)}{\sum_{j=1}^{L} exp(h_j^2)}$$

$$v_{img}^2 = \sum_{i=1}^{L} \alpha_i^2 m_i$$

Model



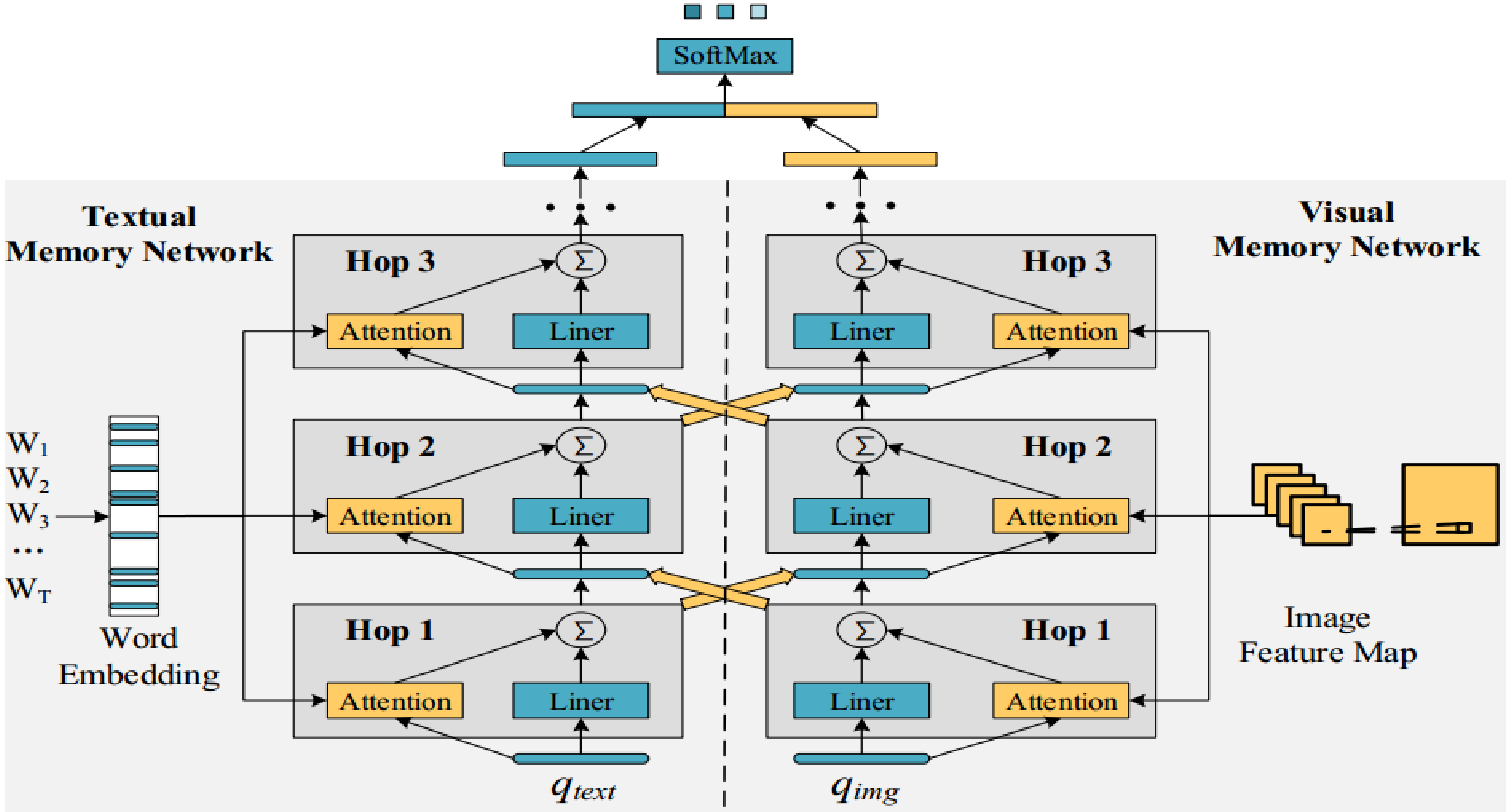
- 2. Image-guided Textual Memory Network (IgTMN):

$$g_t^2 = tanh(w_{text}^2[x_t, v_{img}^1] + b_{text}^2)$$

$$\beta_t^2 = \frac{exp(g_t^2)}{\sum_{r=1}^{T} exp(g_r^2)}$$

$$v_{text}^2 = \sum_{t=1}^{T} \beta_t^2 x_t$$

Model



- Stacked Co-Memory Network：

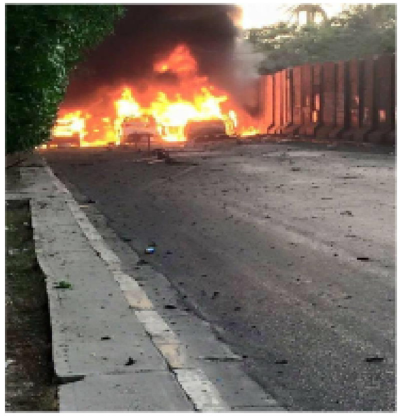
$$v_{text}^{k} = IgTMN([x_t, v_{img}^{k-1}])$$
$$v_{img}^{k} = TgVMN([m_i, v_{text}^{k-1}])$$

- Sentiment Classification：

$$y = Softmax(w_s[v_{text}^{K}, v_{img}^{K}] + b_s)$$

Experiment

Method	MVSA-Single		MVSA-Multi	
	Acc	*F1*	*Acc*	*F1*
SentiBank+SentiStrength	52.05	50.08	65.62	55.36
CBOW+DA+LR	63.86	63.52	64.22	63.73
CNN-Multi	61.20	58.37	66.39	64.19
DNN-LR	61.42	61.03	67.86	66.33
HSAN	66.83	66.9	68.16	67.76
MultiSentiNet	69.84	69.63	68.86	68.11
MN-Hop1	64.31	63.12	67.16	66.48
MN-Hop2	64.84	63.96	67.32	66.57
MN-Hop2+text2img	65.19	64.37	67.80	67.01
MN-Hop2+img2text	68.07	65.19	67.92	67.16
CoMN-Hop2	70.07	68.03	68.68	68.06
CoMN-Hop3	69.62	65.95	69.39	68.57
CoMN-Hop4	69.18	68.29	**69.92**	**69.83**
CoMN-Hop5	69.40	69.71	69.68	69.31
CoMN-Hop6	**70.51**	**70.01**	68.92	68.83



RT @IraqiSecurity: Car bomb in Aden Sq, Kadhimiyah, N. #Baghdad. Initial reports suggest at least 5 martyrs & 22 wounded. #ShiaGenocide httбн

RT @IraqiSecurity: Car bomb in Aden Sq, Kadhimiyah, N. #Baghdad. Initial reports suggest at least 5 martyrs & 22 wounded. #ShiaGenocide httбн

Convolution-based Memory Network for Aspect-based Sentiment Analysis

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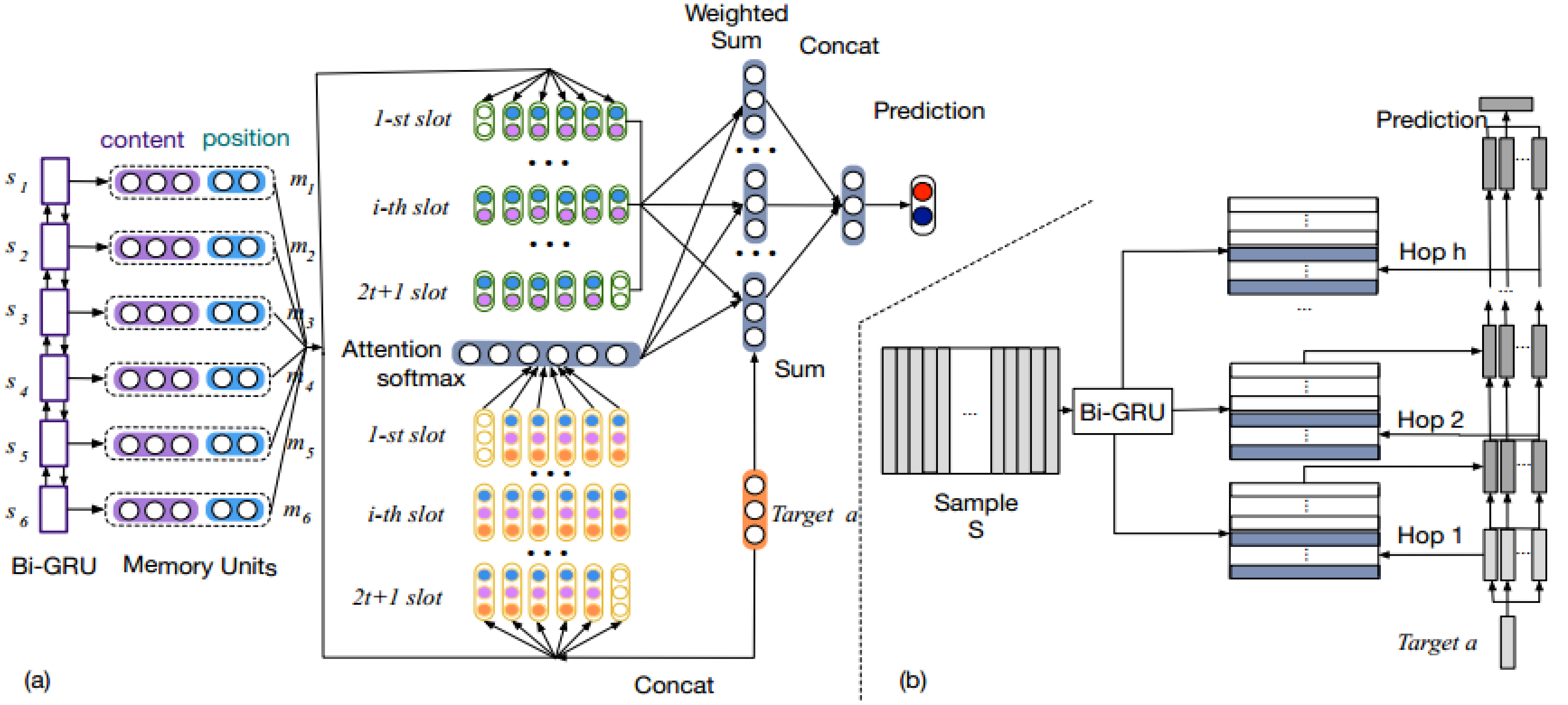
TITLE	CITED BY	YEAR
Interpreting tf-idf term weights as making relevance decisions HC Wu, RWP Luk, KF Wong, KL Kwok ACM Transactions on Information Systems (TOIS) 26 (3), 13	478	2008
Component-based software engineering: technologies, development frameworks, and quality assurance schemes X Cai, MR Lyu, KF Wong, R Ko Software Engineering Conference, 2000. APSEC 2000. Proceedings. Seventh Asia ...	215	2000
Extractive summarization using supervised and semi-supervised learning KF Wong, M Wu, W Li Proceedings of the 22nd International Conference on Computational ...	148	2008
A genetic algorithm-based clustering approach for database partitioning CH Cheng, WK Lee, KF Wong IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and ...	130	2002

Motivation

- Ordinary memory networks only capture word-level information and lack the capacity for modeling complicated expressions which consist of multiple words

Model



- Pre-processing：

$$M = \{m_1, m_2, \ldots, m_n\}$$

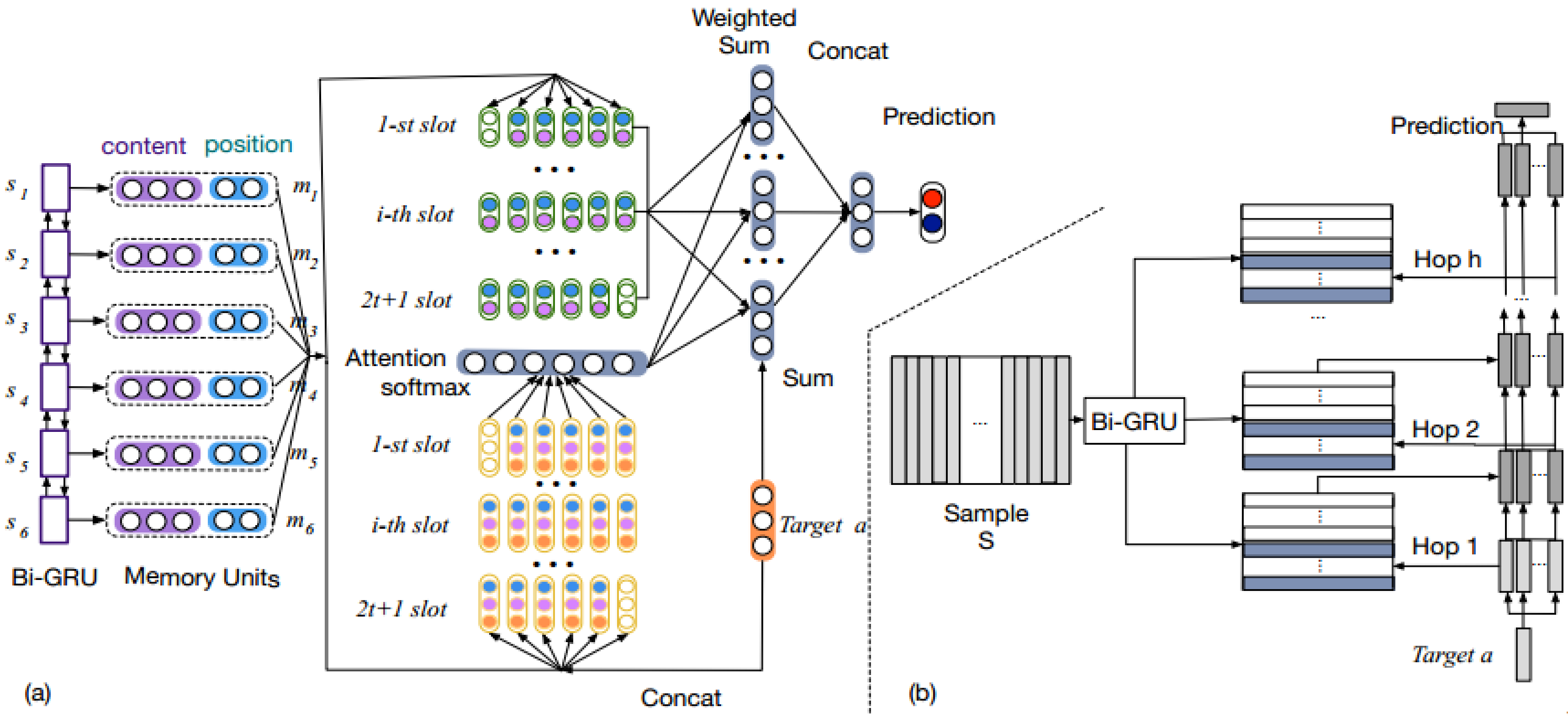
- Attention：

$$g_i = w^T \left(\sum_{j=i-t}^{i+t} (m_j \oplus T) \right)$$

$$\alpha_i = \frac{\exp(g_i)}{\sum_{i'} \exp(g_{i'})}$$

$$o_j = T + \sum_{i=1}^{n} \alpha_i \cdot m_{i+j} \qquad (j = -t, \ldots, 0, \ldots, t)$$

Model



- Multi-hop：

$$g_i = w^T(\sum_{j=i-t}^{i+t}(m_j \oplus o_{j-i}^{h-1}))$$

- Prediction：

$$o = o_{-t} \oplus o_{-t+1} \ldots o_t$$

$$\hat{o} = softmax(W_m \cdot o)$$

- Objective function:

$$L = \sum_{(x,y)\in D} \sum_{c\in C} y^c log f^c(x;\theta)$$

Experiment

Table 1: Experimental performance

Method	Laptop		Restaurant		Tweet	
	ACC	Macro-F1	ACC	Macro-F1	ACC	Macro-F1
SVM	0.7049	NA	0.8016	NA	0.6340	0.6330
TD-LSTM	0.7183	0.6843	0.7800	0.6673	0.6662	0.6401
MemNet	0.7033	0.6409	0.7816	0.6583	0.6850	0.6691
RAM	0.7449	0.7135	**0.8023**	**0.7080**	0.6936	0.6730
Conv-Memnet	**0.7637**	**0.7210**	0.7826	0.6838	**0.7211**	**0.7080**

No. of Hops	Laptop	Restaurant	Tweet
Hop 1	0.6775	0.6689	0.6735
Hop 2	0.7000	0.6752	0.6767
Hop 3	**0.7210**	**0.6838**	**0.7080**
Hop 4	0.6869	0.6741	0.6948
Hop 5	0.6694	0.6406	0.6795
Hop 6	0.6655	0.6226	0.6631

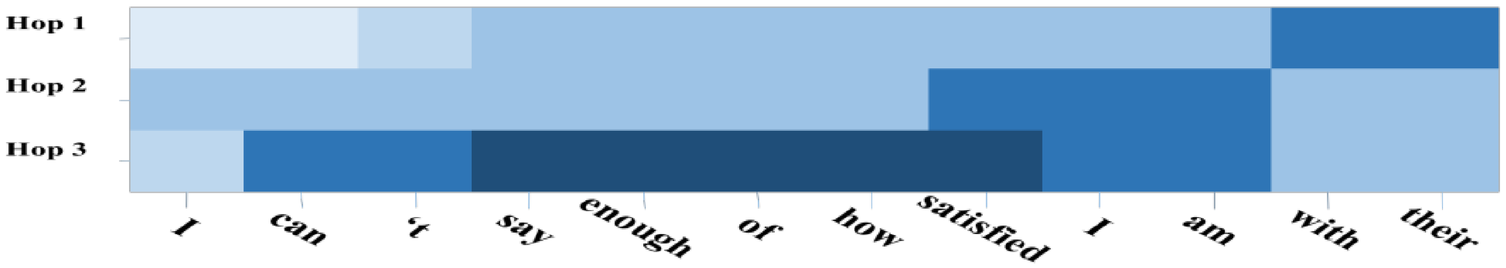


Figure 2: The changes in each hop of attention

SAAN: A Sentiment-Aware Attention Network for Sentiment Analysis

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Motivation

- make full use of the prior sentiment knowledge (e.g., sentiment lexicon, negation words, intensity words)

Word-level correlation modeling

- Pre-processing:

$$x^c = [x_1^c, x_2^c, \ldots x_i^c, \ldots, x_n^c]$$

$$x^s = [x_1^s, x_2^s, \ldots, x_j^s, \ldots, x_m^s]$$

$$R = (x^c)^T \cdot x^s \in \mathbb{R}^{n \times m} \quad (1)$$

where each element $R_{i,j}$ refers to the correlation between the i-th word x_i^c in the context and j-th word x_j^s in the sentiment resource words.

- Attention: $\phi = softmax(\frac{\sum_{h=1}^{m} R[:,h]}{m})$ $\quad \varphi = softmax(\frac{\sum_{k=1}^{n} R[k,:]}{n})$

$$\mathbf{v}^{\phi} = \sum_{i=1}^{n} \phi_i \mathbf{x}_i^c. \qquad \mathbf{v}^{\varphi} = \sum_{i=1}^{m} \varphi_i \mathbf{x}_i^s$$

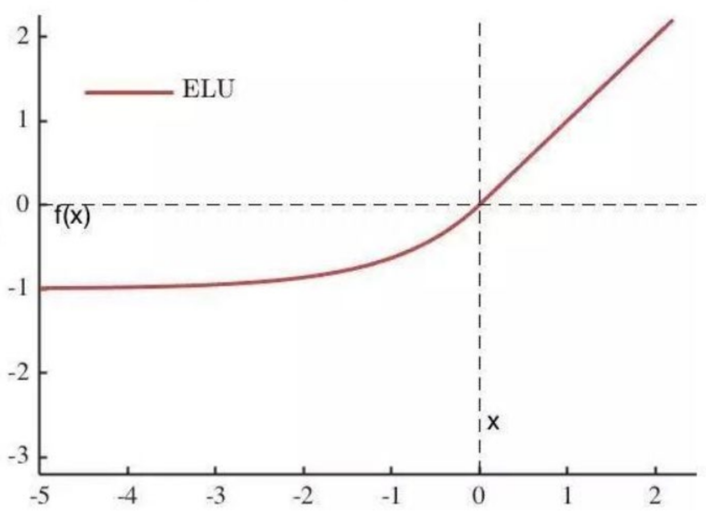
Word-level correlation modeling

- Enhanced representation:

$$E^c = \tilde{f}_{semantics}(x^c + \mathbf{e_n} \otimes \mathbf{v}^{\boldsymbol{\phi}}) \quad (2)$$

$$\tilde{f}_{semantics}(x) = \begin{cases} x & x > 0 \\ \xi(exp(x) - 1) & x \leq 0, \xi > 0 \end{cases} \quad (3)$$

$$E^s = \tilde{f}_{semantics}(x^s + \mathbf{e_m} \otimes \mathbf{v}^{\boldsymbol{\varphi}}) \quad (4)$$



Phrase-Level Correlation Modeling

- CNN

$$P^c = P^c_{\ell_1} \oplus P^c_{\ell_2} \cdots \oplus P^c_{\ell_q} \tag{5}$$

$$P^s = P^s_{\ell_1} \oplus P^s_{\ell_2} \cdots \oplus P^s_{\ell_q} \tag{6}$$

$$P^c_{\ell_i} = \gamma(E^c * W^{\ell_i} + b) \in \mathbb{R}^{(n-\ell_i+1)\times k} \tag{7}$$

$$P^s_{\ell_i} = \gamma(E^s * W^{\ell_i} + b) \in \mathbb{R}^{(m-\ell_i+1)\times k}, i = 1, 2, ..., q \tag{8}$$

- Attention

$$S = P^s \odot \{(P^c)^T softmax(P^c(P^s)^T)\}$$

$$\bar{s} = \frac{\sum_{j=1}^{m} S[:, j]}{m}$$

Final Model

- Sentence-level Semantic Modeling

$$\rho = Q^T tanh(\tilde{U}(P^c + e_n \otimes \bar{s}))$$

$$B = \frac{exp(\rho)}{\sum_{i=1}^{n} exp(\rho)}$$

$$\tilde{\mathbf{o}} = flatten(BP^s)$$

- Sentence Classifer

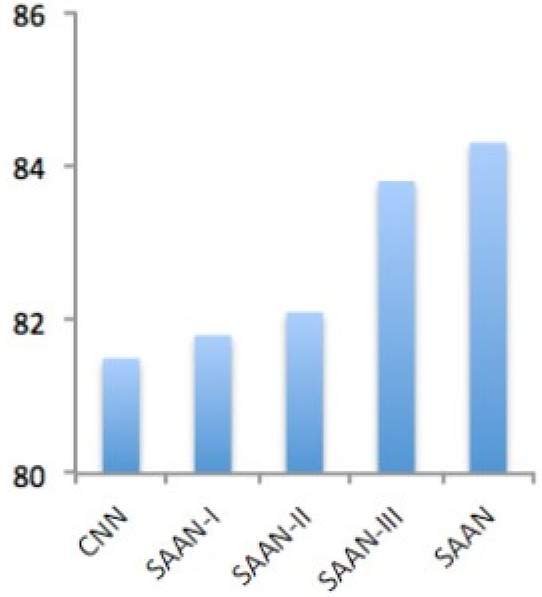
$$\hat{y} = \frac{exp(U_o^T \tilde{\mathbf{o}} + b_o)}{\sum_{k=1}^{C} exp(U_o^T \tilde{\mathbf{o}} + b_o)}$$

- Loss function

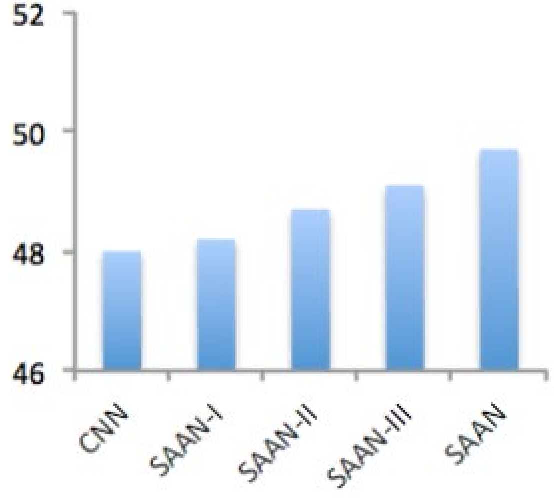
$$L(\hat{y}, y) = -\sum_{i=1}^{N} \sum_{j=1}^{C} y_i^j log(\hat{y}_i^j) + \lambda(\sum_{\theta \in \Theta} \theta^2)$$

Experiment

Methods	MR	SST(sent.-level)
RNTN [10]	75.9%	45.7%
LSTM [2]	77.4%	45.6%
BiLSTM	79.3%	46.5%
Tree-LSTM [11]	80.7%	48.1%
CNN [4]	81.5%	48.0%
NSCL [12]	82.9%	47.1%
LR-LSTM [8]	81.5%	48.3%
LR-Bi-LSTM [8]	82.1%	48.6%
Self-attention [6]	82.5%*	48.7%*
SAAN (our model)	**84.3%**	**49.7%**



(a) MR



(b) SST

Measuring Influence on Instagram: a Network-oblivious Approach

Noam Segev, Noam Avigdor, Eytan Avigdor

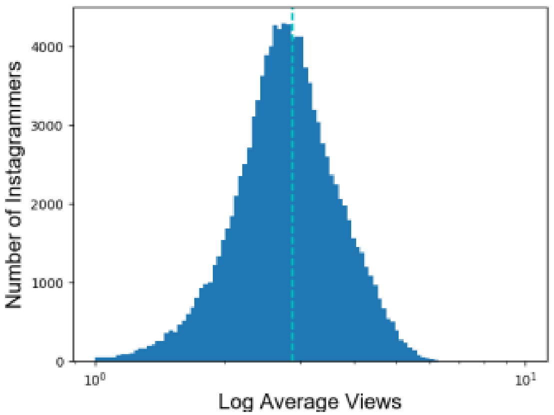
Motivation

- Graphs information are not always available, and building them for Instagram users require a great deal of resources, e.g., crawling time and computing costs.
- Infer the underlying network structure using the user activity logs
- Instagram content, however, is “pulled”

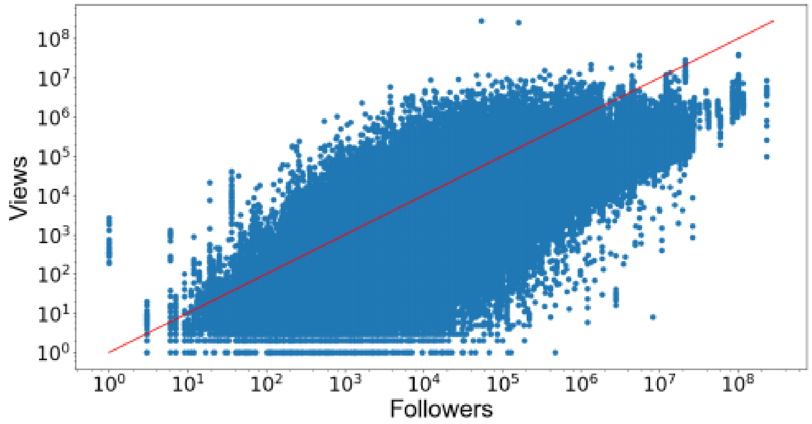
Method

- Collected feature
  - $likes_c$ - Number of likes awarded to post c.
  - $comments_c$ - Number of comments given to post c.
  - v_c - Number of Instagrammers who watched part of the video.

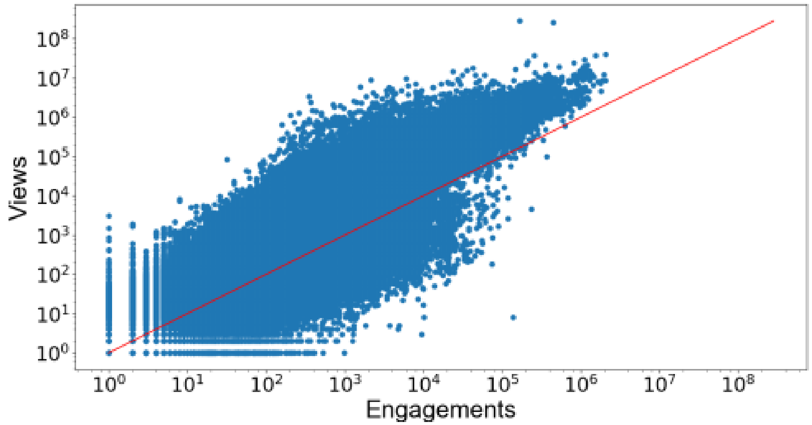
- Instagram statistics



(a) Views Histogram



(b) Views per Followers



(c) Views per Likes

Method

- Features controlled

$likes$ - The average number of user post likes.
$comments$ - The average number of comments per user post.
$followers$ - The users audience size.
$\sqrt{likes \cdot followers}$ - Geometric mean of likes and followers, taken as neither statistic is an exact representation of influence.
$\frac{followers}{post}$ - Used to suggest odd behavior as same level influencers should have similar ratios.
$\frac{comments}{likes}$ - Another odd behavior indicator as bought engagements tend to effect likes more than comments.

$focus$ - The difference and ratio between most and least engaged post, these features were designed to test the variance and stability of a user engagement level.

Model

- Regression model

  Ridge Regression(RR)

  Random Forests(RF)

- Tricks

  K-means

$$f\left(x\right)=\frac{x}{\ln x}$$

Experiment

	Regression		Multi-Regression	
	R^2	r_s	R^2	r_s
full Ridge Regression	**0.725**	0.848	**0.727**	0.821
full Random Forest	0.626	**0.869**	0.621	**0.861**
minimal Ridge Regression	0.723	0.818	0.727	0.818
minimal Random Forest	0.616	0.864	0.611	0.859
Followers Baseline	0.211	0.757	0.204	0.725
Likes Baseline	0.666	0.859	0.654	0.853

Thanks!