Computational Models to Emotion Analysis in Text

Yulan He

Aston University / University of Warwick, UK

Outline

- Emotion representations

- Multi-emotion detection from text
  - Relevant emotion ranking using support vector machines (Zhou, Yang and He, NAACL 2018)
  - Interpretable neural network for relevant emotion ranking (Yang, Zhou and He, EMNLP 2018)

- Emotion cause extraction from text
  - Memory-network based approach (Gui et al., ENMLP 2017)

Emotion Representations

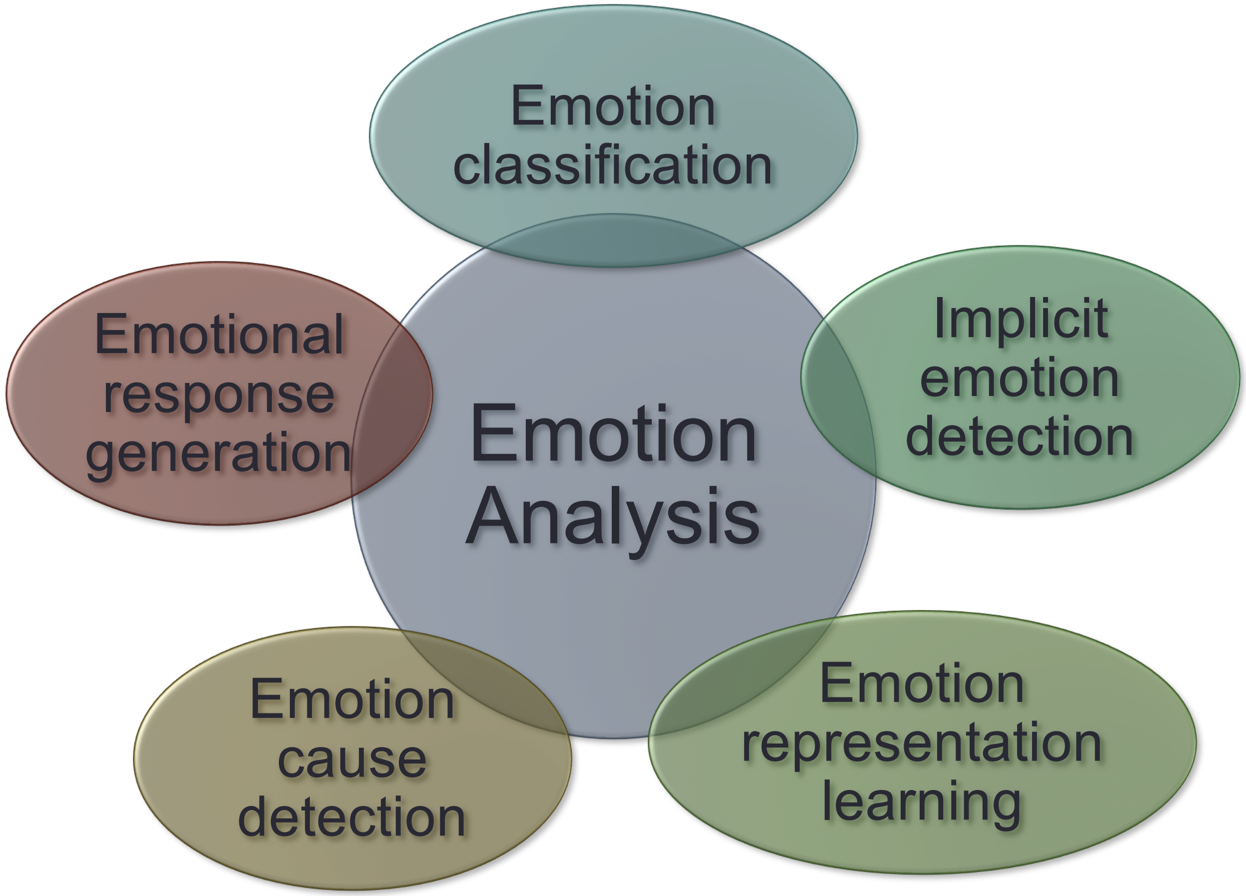
Emotion Representations

- Sentiment
  - Positive, negative, neutral

- Multi-category emotion representations

- Multi-dimensional emotion representations

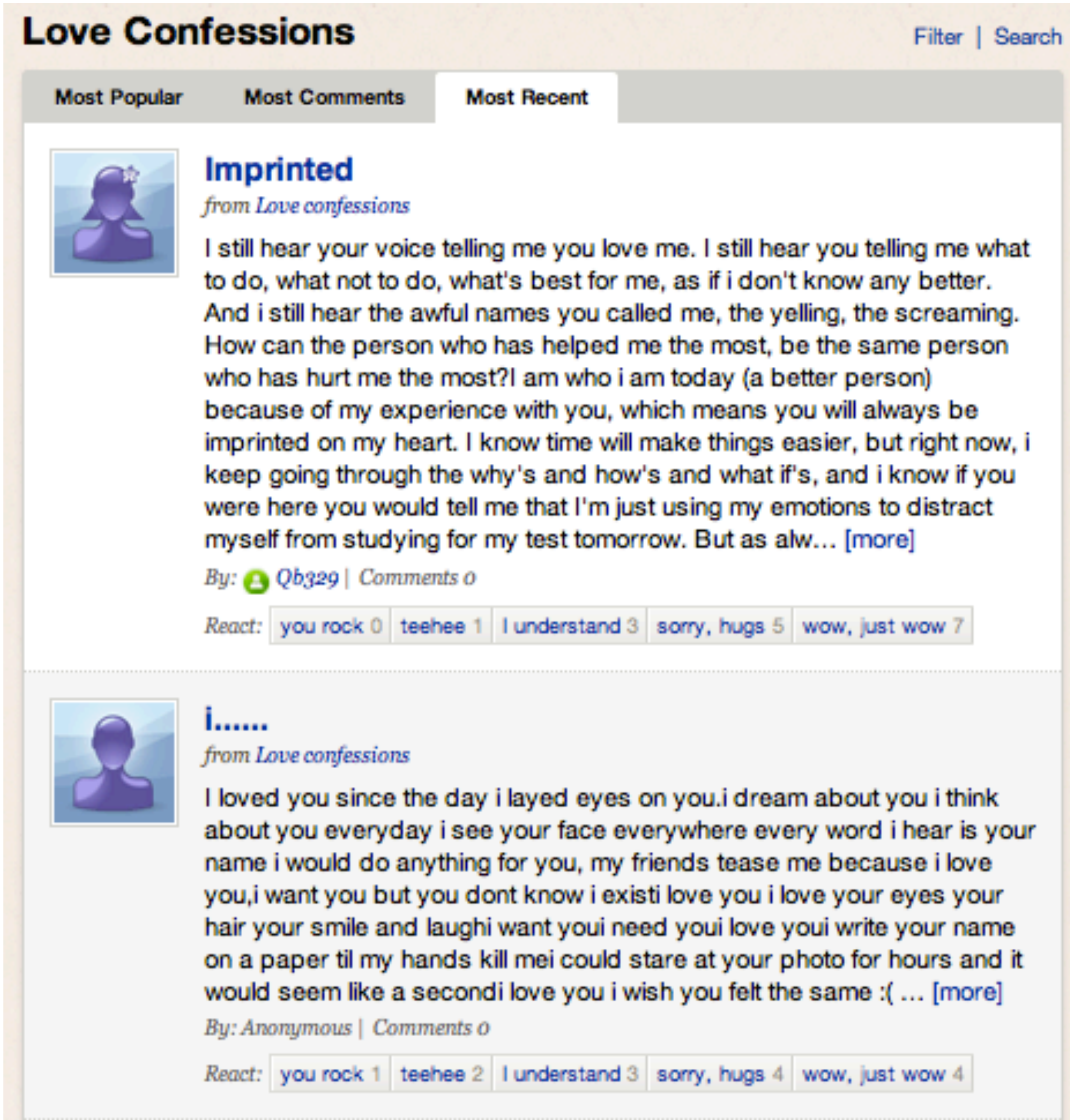
Emotion Analysis Tasks



Multi-Emotion Detection

Experience Project

Experience Project...



Love Confessions

Filter | Search

Most Popular | Most Comments | Most Recent

Imprinted

from Love confessions

I still hear your voice telling me you love me. I still hear you telling me what to do, what not to do, what's best for me, as if i don't know any better. And i still hear the awful names you called me, the yelling, the screaming. How can the person who has helped me the most, be the same person who has hurt me the most?I am who i am today (a better person) because of my experience with you, which means you will always be imprinted on my heart. I know time will make things easier, but right now, i keep going through the why's and how's and what if's, and i know if you were here you would tell me that I'm just using my emotions to distract myself from studying for my test tomorrow. But as alw... [more]

By: Qb329 | *Comments 0*

React: you rock 0 | teehee 1 | I understand 3 | sorry, hugs 5 | wow, just wow 7

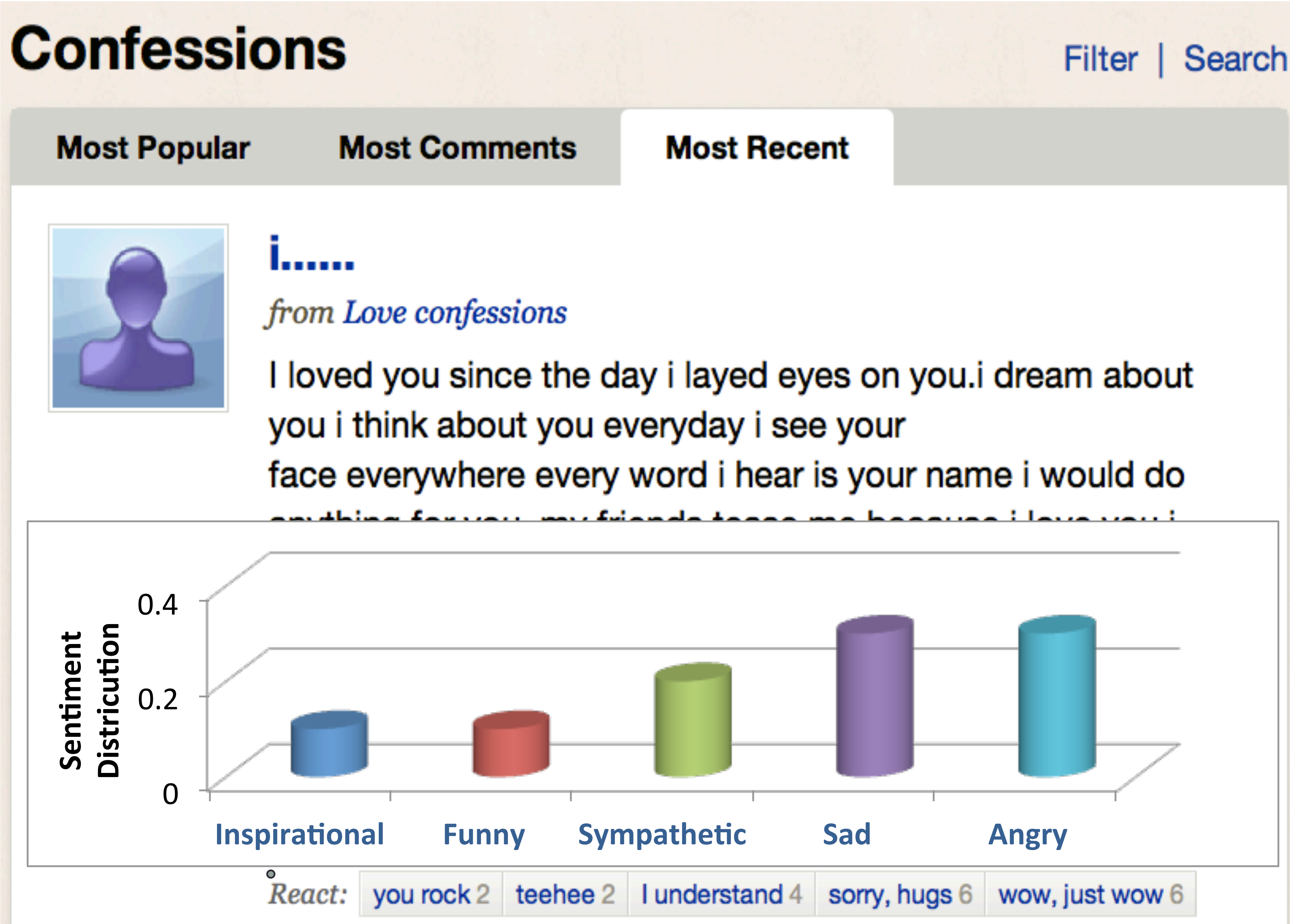
i......

from Love confessions

I loved you since the day i layed eyes on you.i dream about you i think about you everyday i see your face everywhere every word i hear is your name i would do anything for you, my friends tease me because i love you,i want you but you dont know i existi love you i love your eyes your hair your smile and laughi want youi need youi love youi write your name on a paper til my hands kill mei could stare at your photo for hours and it would seem like a secondi love you i wish you felt the same :(... [more]

By: Anonymous | *Comments 0*

React: you rock 1 | teehee 2 | I understand 3 | sorry, hugs 4 | wow, just wow 4


Confessions
Filter | Search
Most Popular
Most Comments
Most Recent
i......
from Love confessions
I loved you since the day i layed eyes on you.i dream about you i think about you everyday i see your
face everywhere every word i hear is your name i would do
Sentiment Districution
0.4
0.2
0
Inspirational
Funny
Sympathetic
Sad
Angry
React:
you rock 2
teehee 2
I understand 4
sorry, hugs 6
wow, just wow 6

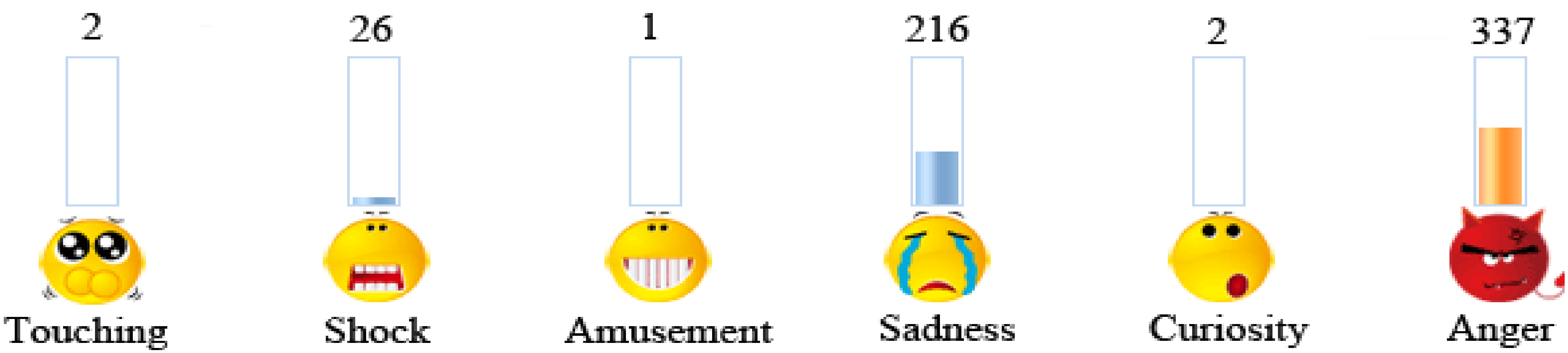
Sina News

2-year-old baby found abandoned in garbage heap by his runaway mother and drug-taking father

Recently, a netizen seek help for a 2-year-old baby who is alone at home unattended and starving because of his runaway mother and drug-taking father. According to the published pictures, the baby lives in a messy home with garbage everywhere. ……

妈妈出走爸爸吸毒 2岁娃无人管活在恶臭垃圾堆

近日网友发求助称因母亲离家出走父亲长期吸毒精神不正常，留下2岁的小“臭蛋”独自在家无人照料甚至连吃的都没有。在发布的图片中, 小“臭蛋”居住的家里凌乱不堪垃圾地。……



- Readers expressed different emotions with the majority showed “Sadness” and “Anger”
- Emotions receiving very few votes could be considered as *irrelevant ones*

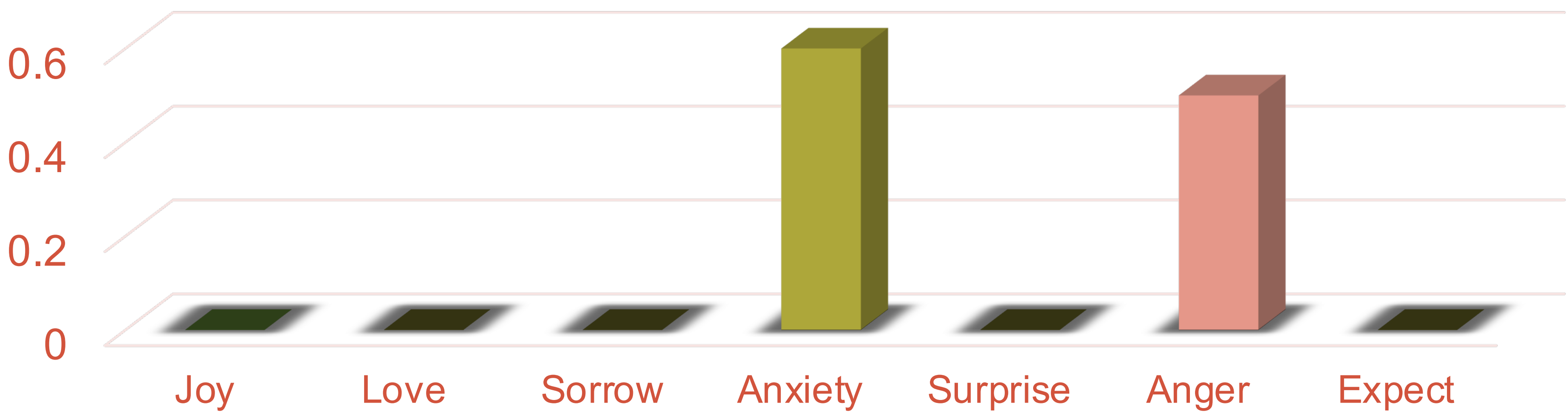
Chinese Blogs

My Daughter Experienced Injustice at School

Yesterday afternoon, my daughter came back from her school and told me that she had an important issue to discuss with me. “The dinner ladies at school always gave me much smaller portions of food compared to other kids. Do they have race discrimination?”

女儿在学校遭遇不平

昨天下午，女儿一进门就对我说，妈妈，我有重要的事跟你说:“每次管饭菜的人给我的饭菜总是比别人的少很多，她们是不是种族歧视啊?”...



Related Work

- Lexicon-based approaches
  - Emotional dictionaries constructed from training corpora of news articles were used to predict the readers' emotion of a new articles (Lei et al., 2014; Rao et al., 2012)
  - Use linguistic templates to predict reader's emotions (Chang et al., 2015)
  - Non-negative matrix factorisation with constraints derived from an emotion lexicon (Wang and Pal, 2015)

- Learning-based approaches
  - Variant of Latent Dirichlet Allocation (LDA) (Bao et al., 2012, He 2012)
  - A joint model to co-train a polarity classifier and an emotion classifier (Gao et al., 2013)
  - A Multi-task Gaussian-process based classification (Beck et al., 2014)
  - Logistic regression model with emotion dependency (Quan et al., 2015)
  - Emotion distribution learning (Zhou et al., 2016)

Emotion Ranking Framework (Zhou, Yang and He, NAACL 2018)

- Assuming a set of T emotions $E = \{e_1, e_2, \dots, e_T\}$ and a set of n instances $X = \{x_1, x_2, \dots, x_n\}$

- Each instance $x_i \in \mathbb{R}^d$ is associated with a ranked list of its relevant emotions $R_i \subseteq E$ and also a list of irrelevant emotions $\overline{R}_i \subseteq E - R_i$

- **Relevant emotion ranking** aims to learn a score function $\boldsymbol{g}(x_i) = [g_1(x_1), \dots, g_T(x_i)]$ assigning a score $g_t(x_i)$ to each emotion $e_t, t \in \{1, \dots, T\}$
  - Learn a threshold $g_\Theta(x_i)$ in order to differentiate between relevant and irrelevant emotions
  - Rank relevant emotions

Emotion Loss Function

- Assuming g are linear models, i.e.,

$$g_t(x_i) = w_t^T \times x_i, t \in \{1, 2, \dots, T\} \cup \{\Theta\}$$

  where Θ denotes the threshold

- The loss function for the instance x_i is defined as:

$$L(x_i, R_i, \prec, g) = \sum_{e_t \in R_i \cup \{\Theta\}} \sum_{e_s \in \prec e_t} \frac{1}{norm_{t,s}} l_{t,s}$$

  - where e_t refers to the emotion belonging to the relevant emotion set R_i or the threshold Θ of instance x_i
  - e_s refers to the emotion which is less relevant than e_t

Emotion Loss Function...

- (e_s, e_t) represents 4 types of emotion pairs:
  - (relevant, relevant)
  - (relevant, irrelevant)
  - (relevant, threshold)
  - (irrelevant, threshold)
- The normalisation term is used to balance the 4 types of emotion pairs to avoid dominated terms by their respective set size
- $l_{t,s}$ is a modified 0–1 loss:

$$l_{t,s} = \begin{cases} 1, g_t(x_i) < g_s(x_i) \\ \frac{1}{2}, g_t(x_i) > g_s(x_i) \\ 0, \text{otherwise} \end{cases}$$

Emotion Loss Function…

- But $l_{t,s}$ is non-convex and difficult to optimise, hence, a hinge loss function is used instead:

$$L(x_i, R_i, \prec, g) = \sum_{e_t \in R_i \cup \{\Theta\}} \sum_{e_s \in \prec e_t} \frac{1}{norm_{t,s}} (1 + g_s(x_i) - g_t(x_i))_+$$

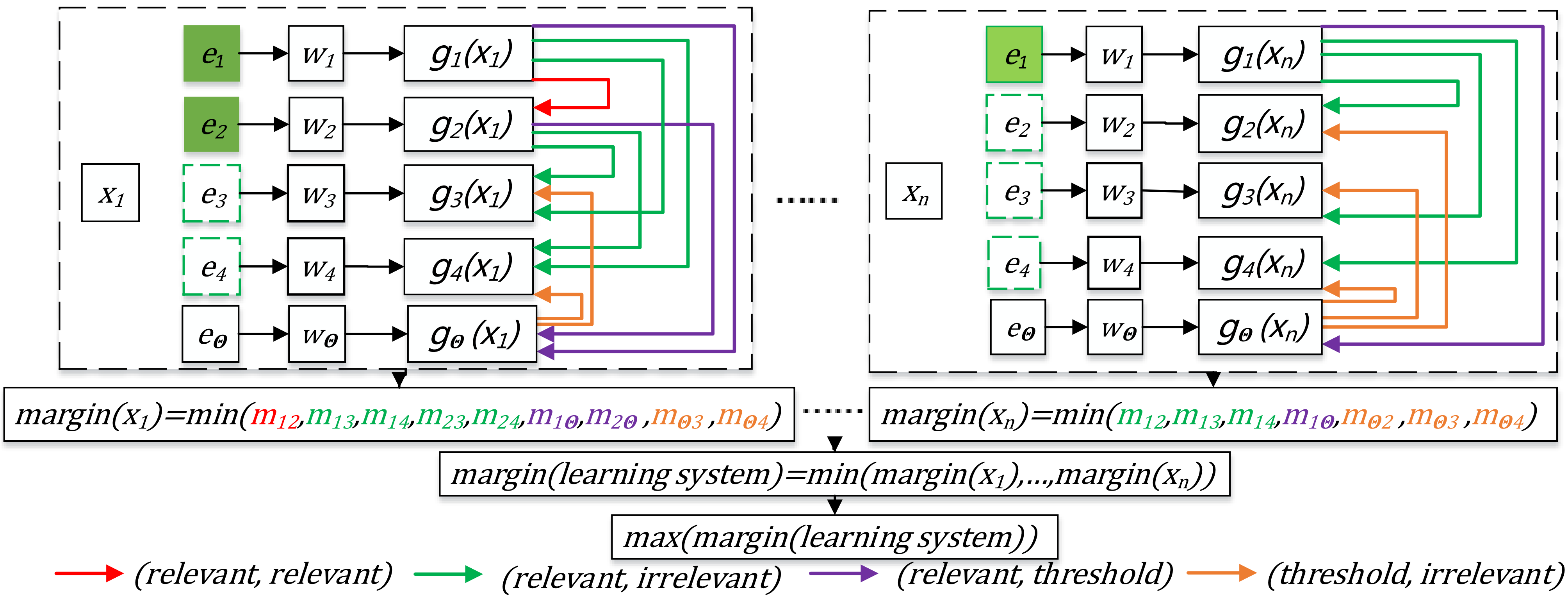
where $(u)_+ = \max\{0, u\}$

- We also want to take into account the relationships between emotions, e.g.,
  - “joy” and “love” often co-occur, but “joy” and “anger” rarely co-exist

- The final loss function:

$$L(x_i, R_i, \prec, g) = \sum_{e_t \in R_i \cup \{\Theta\}} \sum_{e_s \in \prec e_t} \frac{1}{norm_{t,s}} (1 + g_s(x_i) - g_t(x_i) + \omega_{ts}(w_t - w_s))_+$$

Various Margins

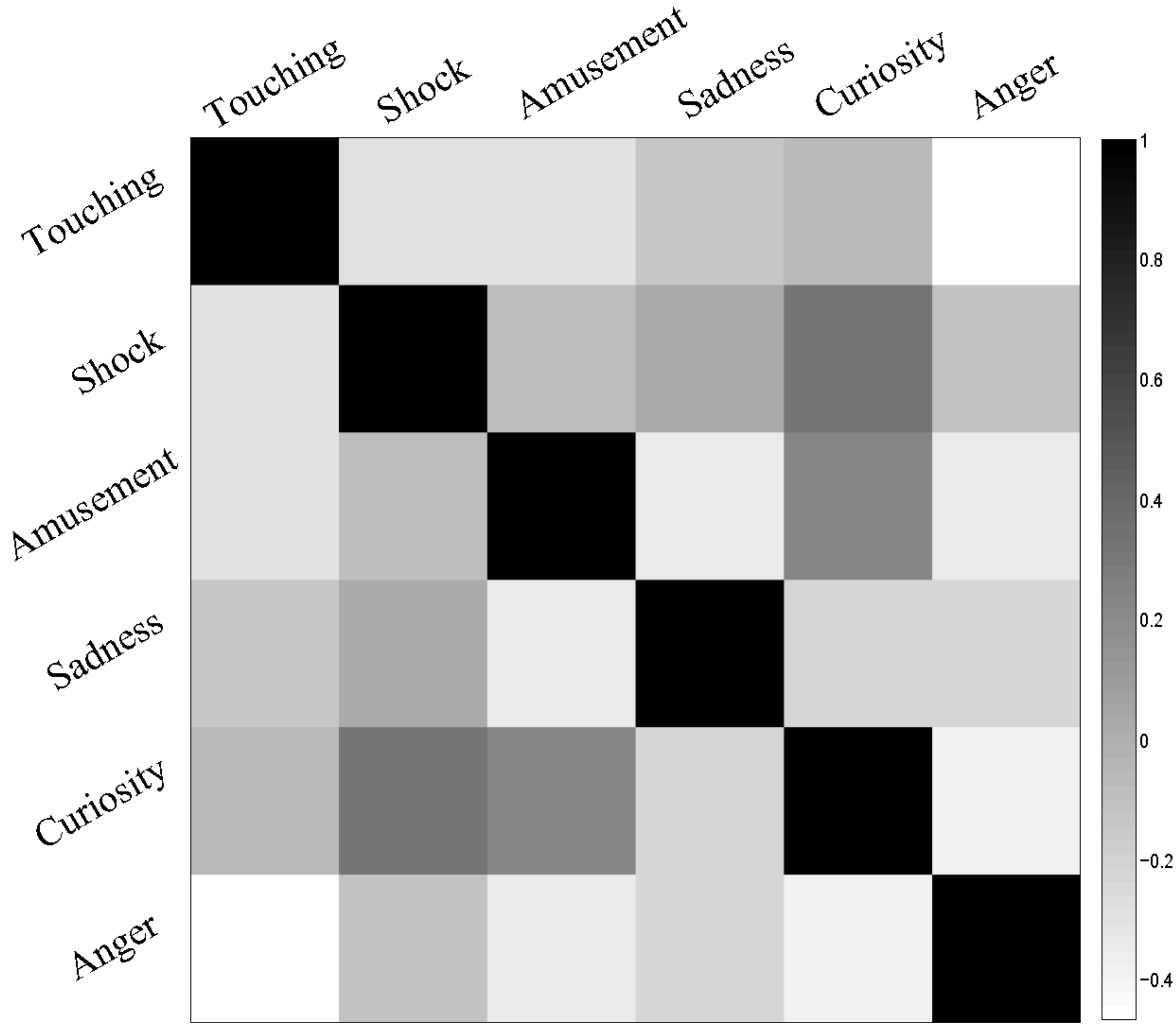


Datasets

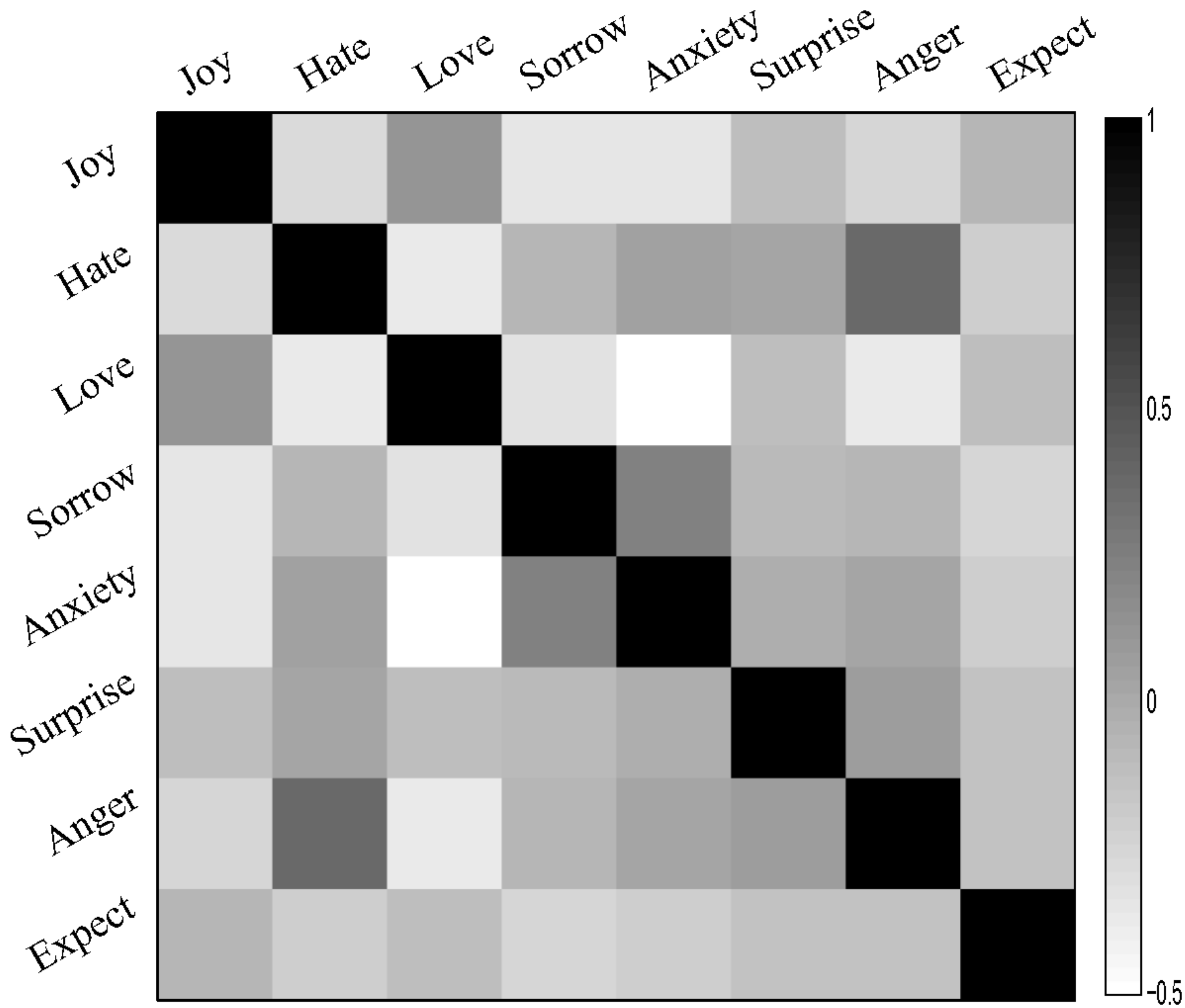
- Sina Social News – 5,586 news articles published between January 2014 and July 2016. Each news articles comes with readers' votes of their emotions.
- Ren-CECps corpus – 34,719 sentences selected from blogs in Chinese. Each sentence was annotated with eight basic emotions together with intensity from writer's perspective.

Sina Social News		Ren-CECps Corpus	
Category	**#Votes**	**Category**	**#Scores**
Touching	694,006	Joy	1,349.6
Shock	572,651	Hate	6,103.9
Amusement	869,464	Love	2,911.1
Sadness	837,431	Sorrow	2,042.5
Curiosity	212,559	Surprise	3,873.9
Anger	1,109,315	Anger	7,832.1
		Anxiety	5,006.4
		Expect	610.4
Total	4,295,426	**Total**	29,729.9

Emotion Relationships - Sina News



Emotion Relationships – Blogs



Evaluation Criteria

Name	Definition
PRO Loss	$\frac{1}{n}\sum_{i=1}^{n} \sum_{e_t \in R_i \cup \{\Theta\}} \sum_{e_s \in \prec(e_t)} \frac{1}{norm_{t,s}} l_{t,s}$ $l_{t,s}$ is a modified 0-1 error; $norm_{t,s}$ is the set size of label pair (t, s)
Hamming Loss	$\frac{1}{nT}\sum_{i=1}^{n} \lvert \hat{R}_i \triangle R_i \rvert$
Ranking Loss	$\frac{1}{n}\sum_{i=1}^{n} (\sum_{(e_t,e_s)\in R_i \times \overline{R_i}} \delta[g_t(x_i) < g_s(x_i)])/(\lvert R_i\rvert \times \lvert\overline{R_i}\rvert)$ where δ is the indicator function.
One Error	$\frac{1}{n}\sum_{i=1}^{n} \delta[\operatorname{argmax}_{\mathbf{e_t}} g_t(x_i) \notin R_i]$
Average Precision	$\frac{1}{n}\sum_{i=1}^{n} \frac{1}{\lvert R_i\rvert} \times$ $(\sum_{t: e_t \in R_i} \lvert\{e_s \in R_i \mid g_s(x_i) > g_t(x_i)\}\rvert)/(\lvert\{e_s \mid g_s(x_i) > g_t(x_i)\}\rvert)$
Coverage	$\frac{1}{n}\sum_{i=1}^{n} \max_{t: e_t \in R_i} \lvert\{e_s \mid g_s(x_i) > g_t(x_i)\}\rvert$
Subset Accuracy	$\frac{1}{n}\sum_{i=1}^{n} \delta[\hat{R}_i = R_i]$
$F1_{exam}$	$\frac{1}{n}\sum_{i=1}^{n} 2\lvert R_i \cap \hat{R}_i\rvert/(\lvert R_i\rvert + \lvert\hat{R}_i\rvert)$
MicroF1	$F1(\sum_{t=1}^{T} TP_t, \sum_{t=1}^{T} FP_t, \sum_{t=1}^{T} TN_t, \sum_{t=1}^{T} FN_t)$
MacroF1	$\frac{1}{T}\sum_{t=1}^{T} F1(TP_t, FP_t, TN_t, FN_t)$

Baselines

- Emotion Distribution Learning (EDL) (Zhou et al., 2016) learns a mapping function from texts to their emotion distributions based on label distribution learning.

- EmoDetect (Wang and Pal, 2015) outputs the emotion distribution based on a dimensionality reduction method using non-negative matrix factorization

Results – Sina News

Datasets	Evaluation Criterion	Methods			
		RER	RERc	EDL	EmoDetect
News	PRO loss(↓)	0.1992	**0.1913**	0.2596	0.2465
	Hamming Loss(↓)	0.2318	**0.2277**	0.2671	0.2696
	Ranking Loss(↓)	0.1477	**0.1405**	0.1689	0.1769
	One-error(↓)	0.1579	**0.1562**	0.2115	0.1903
	Average Precision(↑)	0.8775	**0.8789**	0.8028	0.7865
	Coverage(↓)	2.1398	**2.1316**	2.1595	2.2348
	Subset Accuracy(↓)	0.1899	**0.1822**	0.2026	0.2243
	$F1_{exam}$(↑)	0.7062	**0.7143**	0.6503	0.6469
	MicroF1(↑)	0.7086	**0.7171**	0.6346	0.6375
	MacroF1(↑)	0.6244	**0.6291**	0.5641	0.5767

Results - Blogs

Datasets	Evaluation Criterion	Methods			
		RER	RERc	EDL	EmoDetect
Blogs	PRO loss(↓)	0.2354	**0.2321**	0.2739	0.2912
	Hamming Loss(↓)	0.2054	**0.2014**	0.2102	0.2202
	Ranking Loss(↓)	0.2137	**0.2102**	0.2589	0.2781
	One-error(↓)	0.4556	**0.4550**	0.5227	0.5352
	Average Precision(↑)	0.6749	**0.6803**	0.6411	0.5663
	Coverage(↓)	2.1269	**2.1268**	2.1699	2.8956
	Subset Accuracy(↓)	**0.1663**	**0.1663**	0.2116	0.2321
	$F1_{exam}$(↑)	0.5080	**0.5114**	0.4606	0.4650
	MicroF1(↑)	0.5093	**0.5116**	0.4620	0.4552
	MacroF1(↑)	0.4102	**0.4161**	0.3923	0.3622

Emotion Words

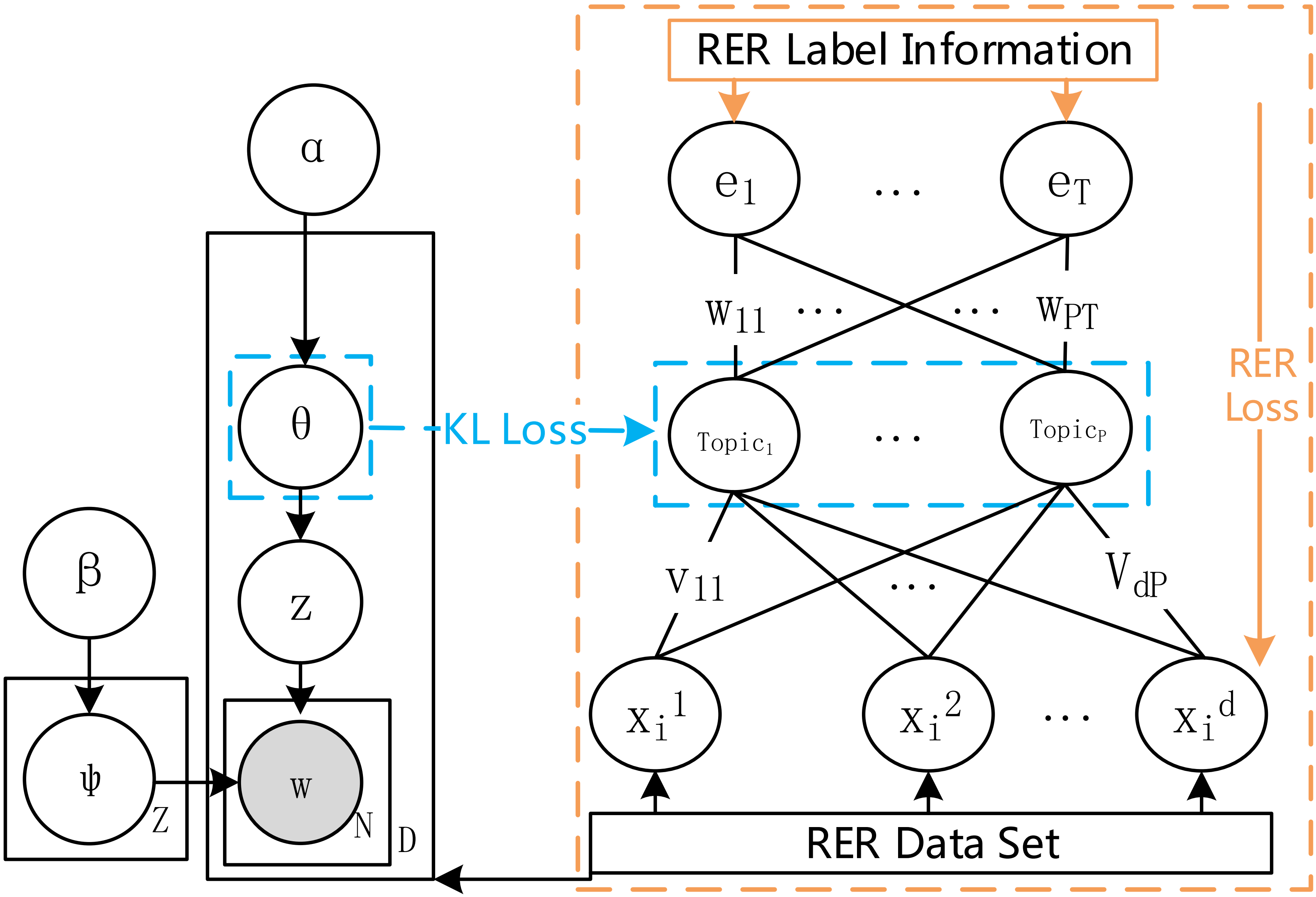
Anger	Anxiety	Expect	Hate
生气(angry)	害怕(fear)	祝福(blessing)	讨厌(hate)
愤怒(rage)	失去(lose)	幸福(happy)	虚伪(hypocrisy)
抱怨(complain)	孤独(lonely)	美好(fine)	炒作(hype)
批评(criticize)	压力(pressure)	梦想(dream)	无耻(shameless)
利益(interest)	现实(reality)	自由(freedom)	手段(means)
歧视(discriminate)	陌生(strange)	渴望(long for)	愚蠢(silly)
制止(stop)	心灵(heart)	希望(hope)	浪费(waste)
指责(accuse)	痛苦(pain)	学习(learn）	背后(behind)
懊恼(annoy)	想象(imagine)	信念(faith)	肮脏(dirty)
无耻(shameless)	伤害(hurt)	家里(home)	欺骗(lie)
Joy	**Love**	**Sorrow**	**Surprised**
快乐(happy)	美丽(beautiful)	孤独(lonely)	好奇(curious)
高兴(joyful)	爱情(love)	眼泪(tears)	惊讶(surprise)
朋友(friend)	朋友(friend)	爱情(love)	震惊(shock)
感动(touching)	幸福(happiness)	寂寞(solitude)	惊奇(wonder)
心情(mood)	孩子(child)	痛苦(pain)	惊人(amazing)
温暖(warm)	生命(life)	感情(feeling)	意外(accident)
享受(enjoy)	阳光(sunshine)	伤害(hurt)	惊吓(fright)
兴奋(excited)	温暖(warmth)	失去(lose)	惊呼(scream)
收获(harvest)	思念(miss)	思念(miss)	不经意(accidently)
微笑(smile)	可爱(lovely)	生活(life)	诧异(amazed)

Interpretable Neural Network for Emotion Ranking

Goal

- Emotions might be evoked by hidden topics
  - Unveil the topical information to understand how the emotions are evoked.
- A novel interpretable neural network approach for relevant emotion ranking
  - The neural network is initialized to make the hidden layer approximate the behavior of topic models.
  - A novel error function is defined to optimize the whole neural network for relevant emotion ranking.

Interpretable Neural Network for Relevant Emotion Ranking (INN-RER) (Yang, Zhou and He, EMNLP 2018)



Learning Process

- INN-RER initialisation
  - The first two layers of the network are initialized based on the output of the topic model
  - Minimizing the Kullback-Leibler (KL) divergence between the topic distribution produced by the topic model and the approximated distribution learned by the first two layers of the NN
- INN-RER learning
  - The whole network is learnt and fine-tuned based on the novel loss function

INN-RER Initialisation

Algorithm 1 Algorithm of INN-RER Initialization.

Input: x_i^q: Term frequency of text x_i; θ_{x_i}: Topic distribution of text x_i

Output: $\Delta v, \Delta \alpha$: gradient approximation of initialization procedure

Initialize $\Delta v, \Delta \alpha$ as random values
for each text $x_i \in G$ **do**
    for each iteration **do**
        for $q = 1, ..., d, h = 1, ..., P$ **do**
            $\Delta v_{qh} \leftarrow \Delta v_{qh} + \eta_{init} \cdot (\theta_h - f_h(\rho_h | v_{qh}, \alpha_h)) \cdot x_i^q + \lambda \cdot \Delta v_{qh}$
        end for
        for $h = 1, ..., P$ **do**
            $\Delta \alpha_h \leftarrow \Delta \alpha_h + \eta_{init} \cdot (\theta_h - f_h(\rho_h | v_{qh}, \alpha_h)) + \lambda \cdot \Delta \alpha_h$
        end for
    end for
end for

INN-RER learning

Error function

$$= \sum_{i=1}^{n} \sum_{e_t \in R_i} \sum_{e_s \in \prec e_t} \frac{1}{norm_{t,s}} [\exp(-(g_t(x_i) - g_s(x_i))) + \omega_{ts}(g_t(x_i) - g_s(x_i))^2]$$

- where e_s, e_t are two emotion labels, $e_s \in \prec e_t$ denote that e_s is less relevant than e_t
- $g_t(x_i) - g_s(x_i)$ measures the difference between two emotion outputs, e_t and e_s, of a given text input x_i
- The negation of the difference is to penalise the ith error term more severely if the score of e_t is much smaller than that of e_s
- ω_{ts} is the relationship between emotion e_t and e_s, calculated by Pearson correlation coefficient

INN-RER learning...

Algorithm 2 Algorithm of INN-RER Learning.

Input: x_i: Term frequency of text x_i; $\Delta v, \Delta \alpha$: Parameters after initialization; L: emotion labels

Output: A predictable neural network INN-RER.

1: Initialize INN-RER network parameters from Algorithm 1
2: **for** each text $x_i \in G$ **do**
3:     **for** each iteration **do**
4:         Forward compute output of INN-RER's score function g given x_i.
5:         Backward compute the gradient according to g and L based on the relevant emotion loss function with learning rate of η_{learn} and penalty term λ.
6:     **end for**
7: **end for**

Datasets

- Sina Social News (News) – 5,586 news articles, each with readers' votes of their emotions.
- Ren-CECps corpus (Blogs) – 34,719 sentences selected from blogs with each annotated with eight basic emotions together with intensity from writer's perspective.
- SemEval - 1,250 news headlines with each headline manually scored in a fine-grained valence scale of 0 to 100 across 6 emotions

Sina Social News		Ren-CECps Corpus		SemEval	
Category	**#Votes**	**Category**	**#Scores**	**Category**	**#Scores**
Touching	694,006	Joy	1,349.6	Anger	12,042
Shock	572,651	Hate	6,103.9	Disgust	7,634
Amusement	869,464	Love	2,911.1	Fear	20,306
Sadness	837,431	Sorrow	2,042.5	Joy	23,613
Curiosity	212,559	Surprise	3,873.9	Sad	24,039
Anger	1,109,315	Anger	7,832.1	Surprise	21,495
		Anxiety	5,006.4		
		Expect	610.4		
Total	4,295,426	**Total**	29,729.9	**Total**	109,129

Experimental Setup

- For long text such as News and Blogs, Latent Dirichlet Allocation (Blei et al., 2003) is employed for generating topic distributions.

- For short texts in Semeval, bi-term topic model (BTM) (Cheng et al., 2014) was used
  - BTM is a variant of LDA which models the generation of bi-terms in the whole corpus to alleviate the problem of sparsity.

- The topic number is set to 60 empirically.

- For each method, 10-fold cross validation is conducted.

Baselines

- **Topic-model based**
  - Multi-label supervised topic model (MSTM) and Sentiment latent topic model (SLTM) (Rao et al., 2014b) – variants of supervised topic models
    - MSTM first generates a set of topics from words, and then samples emotions from each topic.
    - SLTM generates topics directly from emotions.
  - Affective topic model (ATM) (Rao et al., 2014a) employs the exponential distribution to generate ratings for each emotion.

- **Discriminative approaches**
  - Emotion Distribution Learning (EDL) (Zhou et al., 2016) learns a mapping function from texts to their emotion distributions based on label distribution learning.
  - EmoDetect (Wang and Pal, 2015) outputs the emotion distribution based on a dimensionality reduction method using non-negative matrix factorization
  - RER (Zhou et al., 2018) predicts multiple emotions and their rankings from text based on relevant emotion ranking using support vector machines.

Emotion Ranking Results - News

Category	Method	Criteria								
		PL(↓)	HL(↓)	RL(↓)	OE(↓)	AP(↑)	Cov(↓)	F1(↑)	MiF1(↑)	MaF1(↑)
Topic model	**MSTM**	0.3343	0.4065	0.3097	0.2123	0.6677	3.3202	0.5666	0.5853	0.5044
	SLTM	0.3205	0.3639	0.2753	0.2008	0.7326	2.9863	0.6095	0.6429	0.4899
	ATM	0.3192	0.3743	0.2507	0.1947	0.7490	2.9369	0.6127	0.6412	0.4885
Discriminative	EDL	0.2348	0.2510	0.1616	0.2243	0.8372	2.1940	0.6260	0.6454	0.5703
	EmoDetect	0.2157	0.2575	0.1538	0.1627	0.8605	2.1761	0.6697	0.6739	0.5359
	RER	0.2142	0.2498	0.1491	0.1513	0.8633	2.1989	0.6820	0.6919	0.6198
Our model	**INN-RER(-t)**	0.1998	0.2420	0.1393	0.1456	0.8715	2.1377	**0.7116**	0.7137	0.6242
	INN-RER	**0.1973**	**0.2312**	**0.1353**	**0.1331**	**0.8764**	**2.1339**	0.7108	**0.7161**	**0.6282**

Emotion Ranking Results - Blogs

Category	Method	Criteria								
		PL(↓)	HL(↓)	RL(↓)	OE(↓)	AP(↑)	Cov(↓)	F1(↑)	MiF1(↑)	MaF1(↑)
Topic model	MSTM	0.3567	0.4171	0.3030	0.4761	0.6046	3.7005	0.5236	0.4978	0.4758
	SLTM	0.3148	0.3769	0.2397	0.4598	0.6547	**3.2513**	0.5757	0.5865	0.5283
	ATM	0.3493	0.3890	0.2885	0.4385	0.6278	3.4278	0.5105	0.5260	0.5026
Discriminative	EDL	0.3385	0.3916	0.2550	0.4206	0.6962	4.2491	0.5060	0.5396	0.4131
	EmoDetect	0.3115	0.3848	0.2123	0.2880	0.7617	4.1650	0.5340	0.5492	0.4387
	RER	0.3007	0.3657	0.2043	0.2728	0.7746	4.1638	0.5957	0.6084	**0.5342**
Our model	**INN-RER(-t)**	0.2868	0.3268	0.1993	0.2695	0.7706	3.9653	0.6132	0.6165	0.5069
	INN-RER	**0.2829**	**0.3209**	**0.1924**	**0.2626**	**0.7784**	3.9418	**0.6187**	**0.6225**	0.5133

Emotion Ranking Results - SemEval

Category	Method	Criteria								
		PL(↓)	HL(↓)	RL(↓)	OE(↓)	AP(↑)	Cov(↓)	F1(↑)	MiF1(↑)	MaF1(↑)
Topic model	MSTM	0.3524	0.3835	0.2796	0.3698	0.7653	3.1986	0.6962	0.7133	0.5854
	SLTM	0.3155	0.3253	0.2370	0.3150	0.8052	2.9589	0.7056	0.7378	0.5889
	ATM	0.3138	0.3276	0.2389	0.3767	0.8302	2.8976	0.7039	**0.7402**	0.5244
Discriminative	EDL	0.4130	0.4291	0.3401	0.3875	0.7345	3.3433	0.4002	0.4136	0.3813
	EmoDetect	0.3176	0.3167	0.2411	0.2208	0.8241	3.0439	0.6275	0.6245	0.5385
	RER	**0.2907**	0.3028	0.2389	0.2120	**0.8302**	2.9963	0.6839	0.6898	**0.6283**
Our model	**INN-RER(-t)**	0.3303	0.3056	0.2331	0.2388	0.8364	2.8773	0.7019	0.7118	0.5973
	INN-RER	0.3194	**0.3005**	**0.2302**	**0.2261**	**0.8379**	**2.8632**	**0.7081**	0.7156	0.6023

Top Topic Words under Each Emotion – News

Touching		Anger		Amusement	
Topic 1	Topic 2	Topic 1	Topic 2	Topic 1	Topic 2
救人(save)	教师(teacher)	歹徒(ruffian)	犯罪(sin)	男女(men and women)	网上(network)
照顾(take care of)	辛苦(hard)	强行(force)	嫌疑人(suspect)	宾馆(hotel)	醉酒(drunkenness)
身亡(sacrifice)	落水(fall into water)	猥亵(obscenity)	徒刑(imprisonment)	服务(service)	检察院(procuratorate)
治疗(cure)	年轻(youth)	女童(girl)	打人(beat)	照片(photo)	违法(illegal)
生命(life)	病情(state of an illness)	杀害(murder)	殴打(hit)	报警(call the police)	罚款(penalty)
老人(older)	坚持(persist)	造成(cause)	工地(construction site)	鉴定(authenticate)	调查(investigate)
感谢(grateful)	群众(public)	派出所(police station)	交警(traffic police)	诈骗(defraud)	违规(get out of line)
医院(hospital)	车祸(traffic accident)	作案(commit a crime)	采访(interview)	网络(internet)	现金(cash)
感动(moved)	感动(touching)	死亡(death)	曝光(exposure)	离婚(divorce)	警官(police officer)
Sadness		**Curiosity**		**Shock**	
Topic 1	Topic 2	Topic 1	Topic 2	Topic 1	Topic 2
失踪(disappear)	车祸(car accident)	家长(parents)	监控(monitoring)	抢劫(rob)	菜刀(kitchen knife)
不幸(misfortune)	小偷(thief)	中国(China)	妇女(women)	尸体(corpse)	脖子(neck)
去世(pass away)	公安(public security)	婚姻(marriage)	春节(spring festival)	紧急(emergency)	重症(sever illness)
杀害(murder)	围观(watch)	健康(health)	医院(hospital)	现场(scene)	地铁(subway)
犯罪(crime)	鉴定(identify)	女子(women)	怀孕(pregnancy)	安全(security)	新闻(news)
遭到(suffer)	道歉(apologize)	年轻(young)	早上(morning)	治疗(cure)	竟然(unexpectedly)
公安局(Public Security Bureau)	激动(excite)	结婚(marry up)	抢救(rescue)	生命(life)	银行(bank)
出事(have an accident)	执法(enforce the law)	男性(men)	无效(in vain)	检查(examine)	赔偿(compensate)
媒体(media)	派出所(police station)	现金(money)	喜欢(like)	家属(family member)	消费(consume)

Top Topic Words under Each Emotion – Blogs

Joy	Hate	Love	Sorrow
花儿(flower)	孤独(lonely)	学习(study)	角落(corner)
新年(ney year)	面对(face with)	比赛(competition)	希望(hope)
宝贝(baby)	无情(heartless)	开心(happy)	天堂(heaven)
享受(enjoy)	重新(again)	感觉(feeling)	寂寞(lonely)
快乐(happy)	情绪(emotion)	心境(mood)	地震(earthquake)
祝福(wish)	失去(lose)	充满(full of)	使命(mission)
宝宝(baby)	脾气(temper)	文化(culture)	男朋友(boyfriend)
开心(joyful)	痛苦(pain)	作品(production)	离开(leave)
微笑(smile)	完全(entirely)	丰富(rich)	无奈(helpless)
Anxiety	**Surprise**	**Anger**	**Expect**
房子(house)	彩虹(rainbow)	离开(leave)	希望(hope)
婚姻(marriage)	北海道(Hokkaido)	离婚(divorce)	责任(responsible)
老公(husband)	忽然(sudden)	无奈(helpless)	女性(women)
错误(error)	记忆(memory)	法律(law)	奥运会(Olympic)
心情(mood)	礼物(gift)	银行(bank)	幸福(happiness)
陌生(strange)	奇迹(miracle)	道德(morality)	行为(action)
家里(family)	据说(reputedly)	情感(emotion)	努力(strive)
上班(on duty)	好奇(curious)	悲伤(sorrow)	以后(later)
城市(city)	季节(season)	自己(self)	精彩(splendid)

Top Topic Words under Each Emotion – SemEval

Joy	Anger	Sad	Disgust	Fear	Surprise
home	kill	flu	sex	kill	sue
heart	attack	cancer	immigr	danger	korea
game	violenc	terror	scandal	iran	blast
youtub	terror	danger	porn	dead	north
movie	stop	health	charg	state	fight
friend	fire	kill	insist	fear	war
sleep	blast	flood	women	terror	nuclear
miss	death	crash	held	global	shoot
award	condemn	end	girl	attack	protest

Emotion Cause Extraction

Motivation

Emotion cause　　　　　　　　Emotion expression

I lost my phone yesterday, and I am very sad now.

Emotion expression　　　　　　　　Emotion cause

I am so so sad to hear that U.S. will quit the Paris Climate Agreement.

Detecting the cause of emotion is essential to social media analysis and many commercial applications.

Related Work

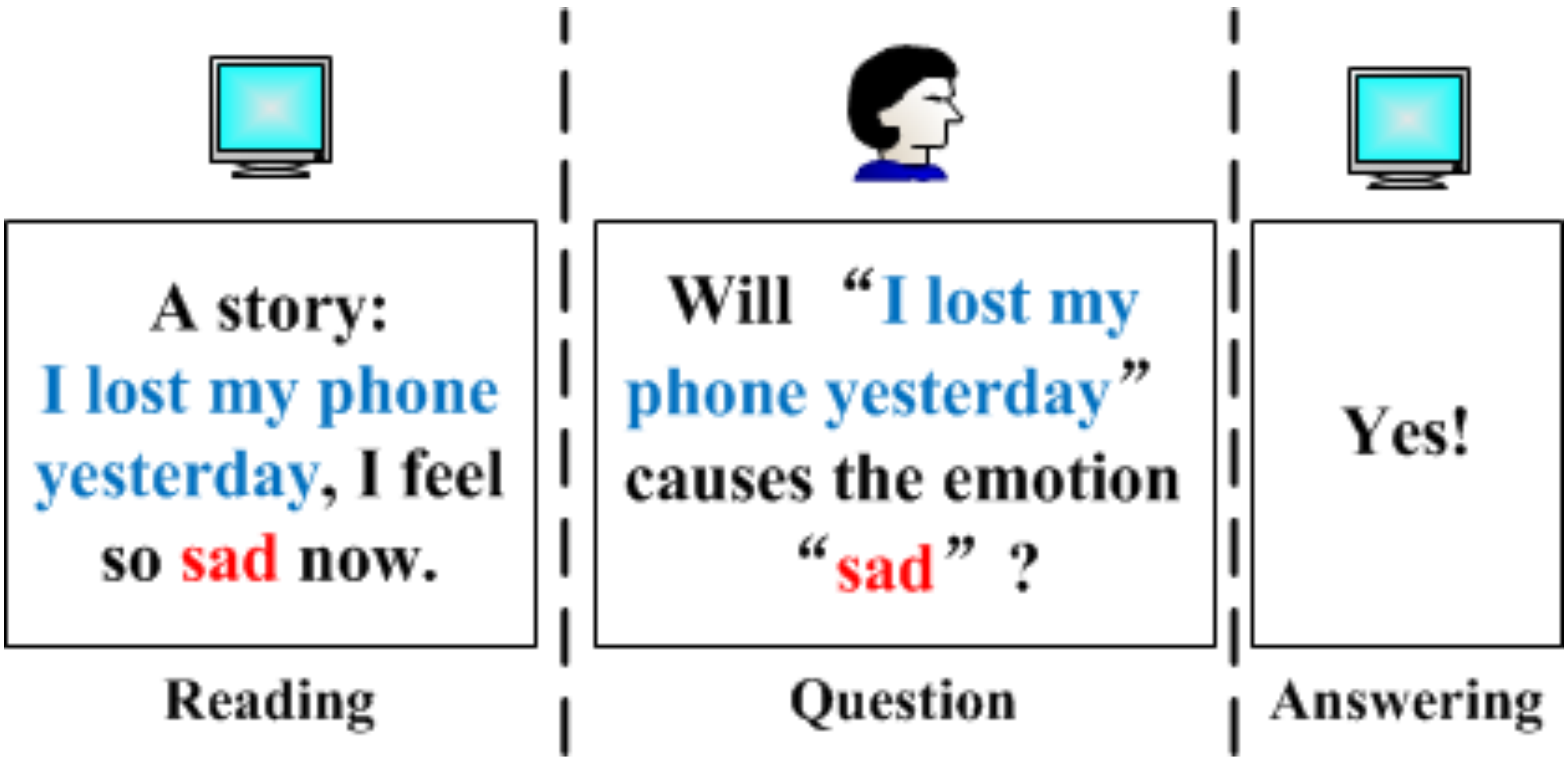
- Rule-based approaches:
  - Rule-based Emotion Cause (Lee et al., 2010)
  - Extended the rule-based approach by utilising the patterns and rules related to cause expression (Gui et al., 2014; Li and Xu, 2014)
  - OCC-model based Emotion Cause Detection(Gao et al., 2015)
  - Low coverage

- Learning-based approaches:
  - CRF-based Emotion Cause Detection (Ghazi et al., 2015)
    - requires emotion cause and emotion keywords to be in the same sentence
  - Multi-kernel based approach (Gui et al. 2016)
    - Convert emotion cause detection to tree classification task
    - Two variants of Tree-Kernel SVMs were used
    - Heavily depends on accurate dependency trees and cannot extract phrase-level emotion causes.

Frame Emotion Cause Detection as QA
(Gui et al., EMNLP 2017)

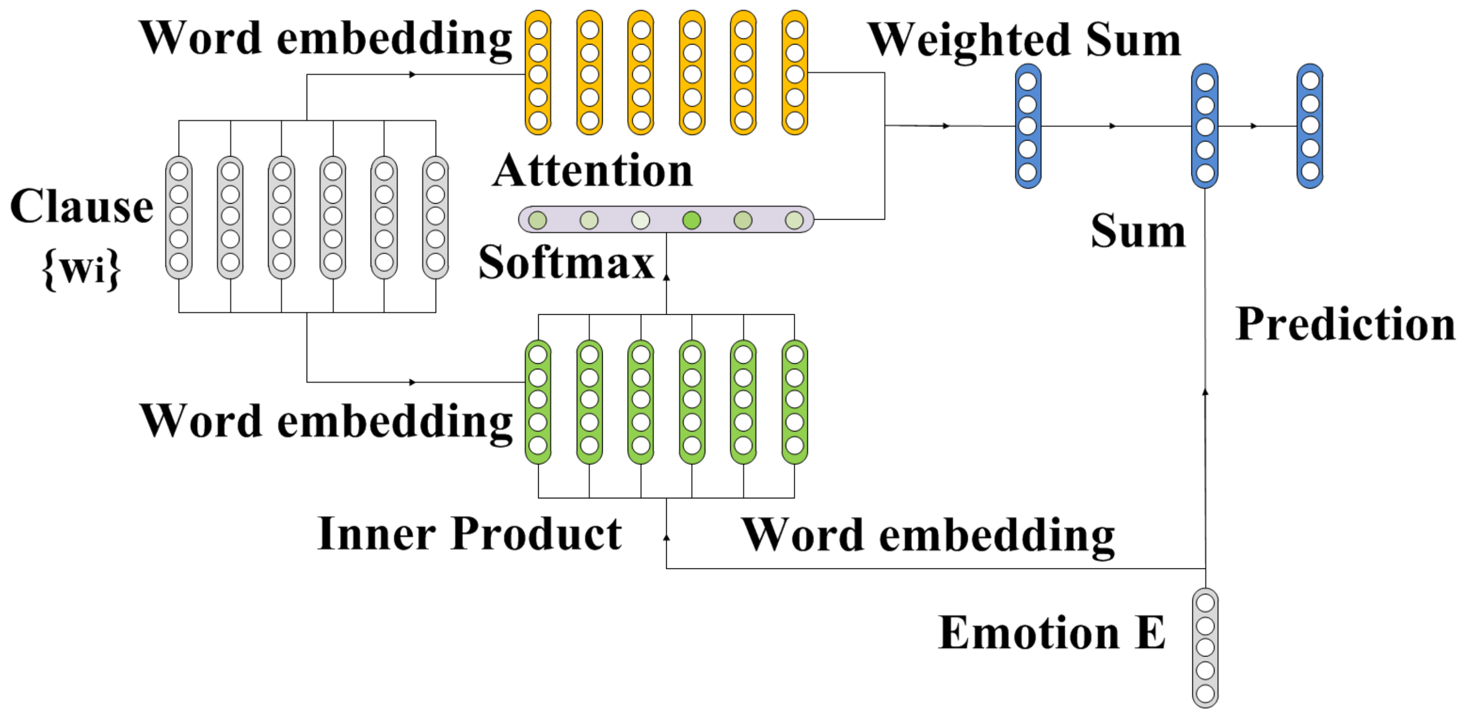
Emotion Cause Detection is analogue to Question Answering:

- Emotional Text as **Reading Text**
- Emotional words as **Question**
- Emotion cause as **Answer**



Memory Network (Memnet)

To model the process of question answering, the Memory Networks (Sukhbaatar et al. 2015) is used as the base model

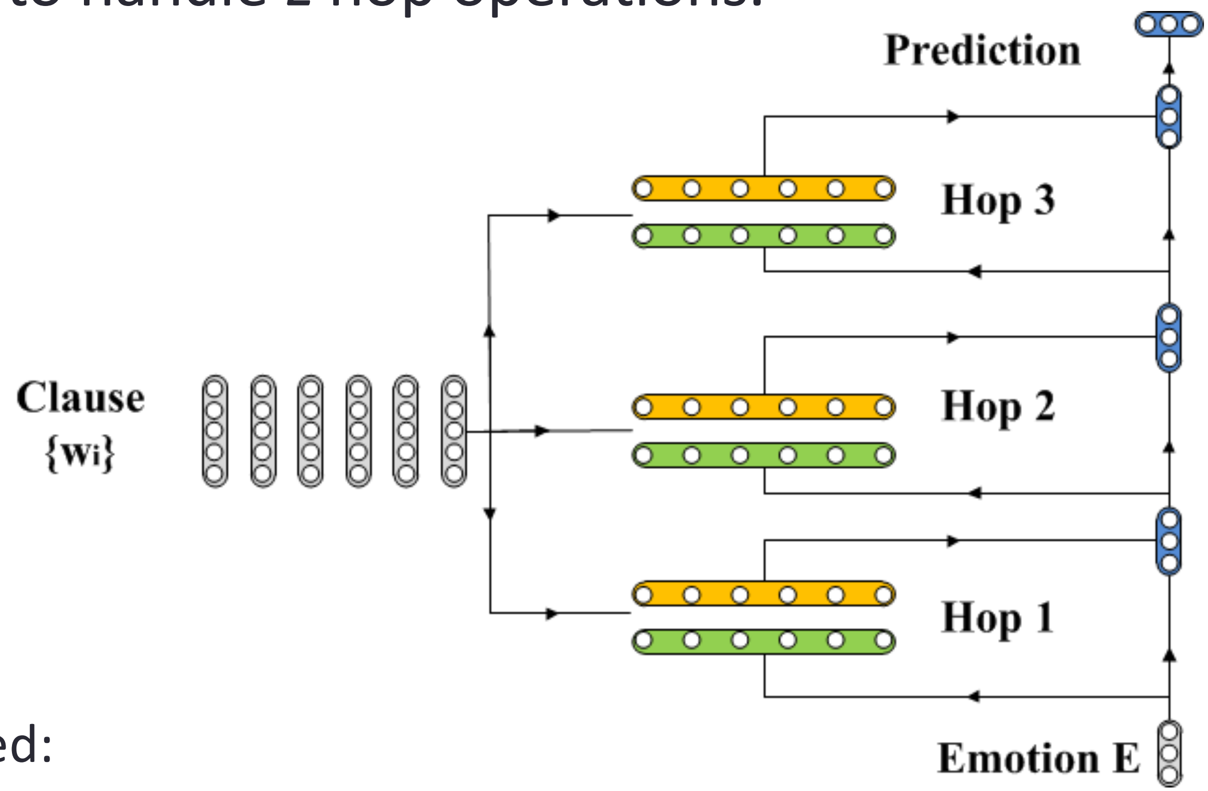


The memory network can better model the relation between an emotion word and its emotion causes in complex sentence structures.

Since a memory network models the emotion cause at a fine-grained level, each word has a corresponding weight to measure its importance in this task.

Memory Network (Memnet)

The basic model can be extended to deep architecture consisting of multiple layers to handle *L* hop operations.

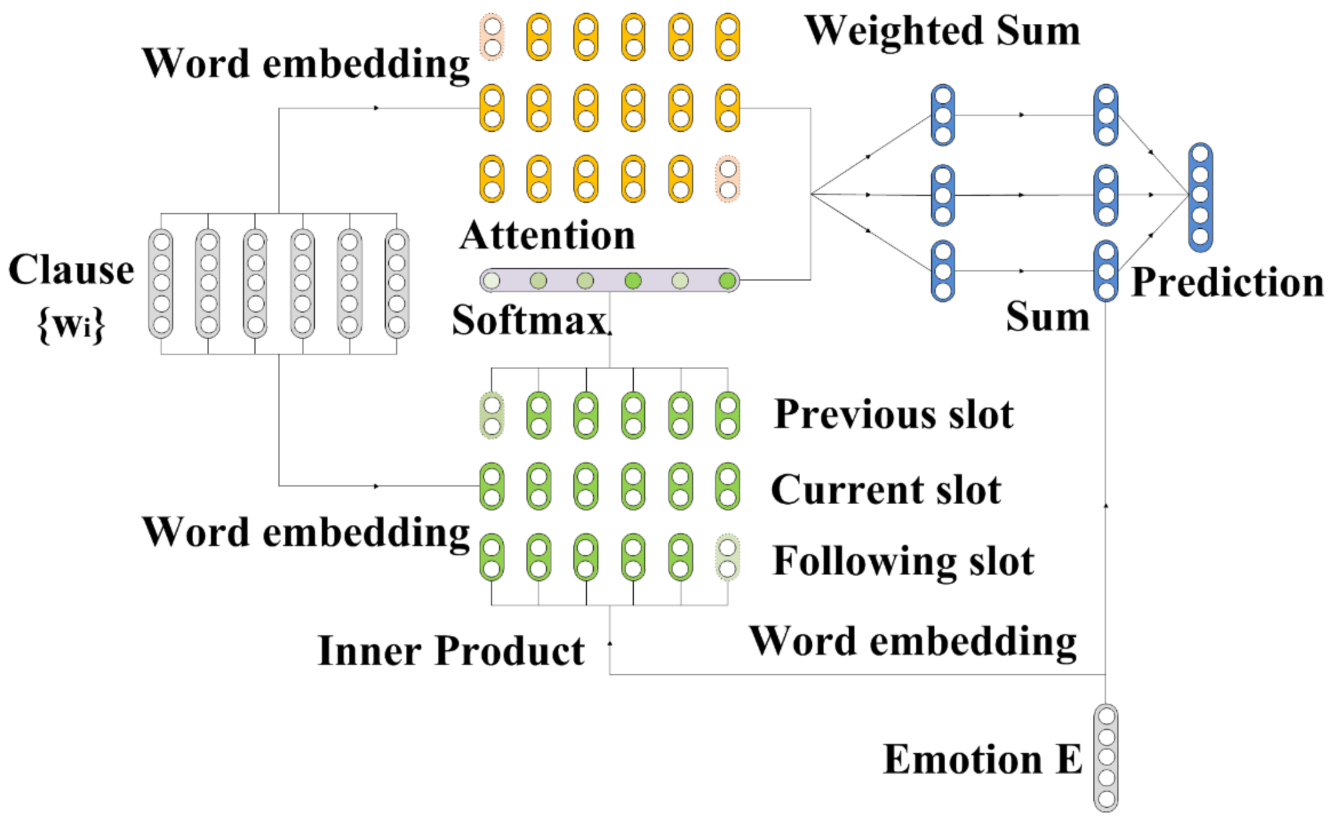


The network is stacked:

- For hop *i*, the query is the prediction vector of the previous hop and the prediction vector is fed into next hop;
- The output vector is at the top of the network. It is a softmax function on the prediction vector from hop L.

Problem: Does not capture the sequential information in context which is important in emotion cause extraction.

Convolutional Memory Network (Conv-Memnet)

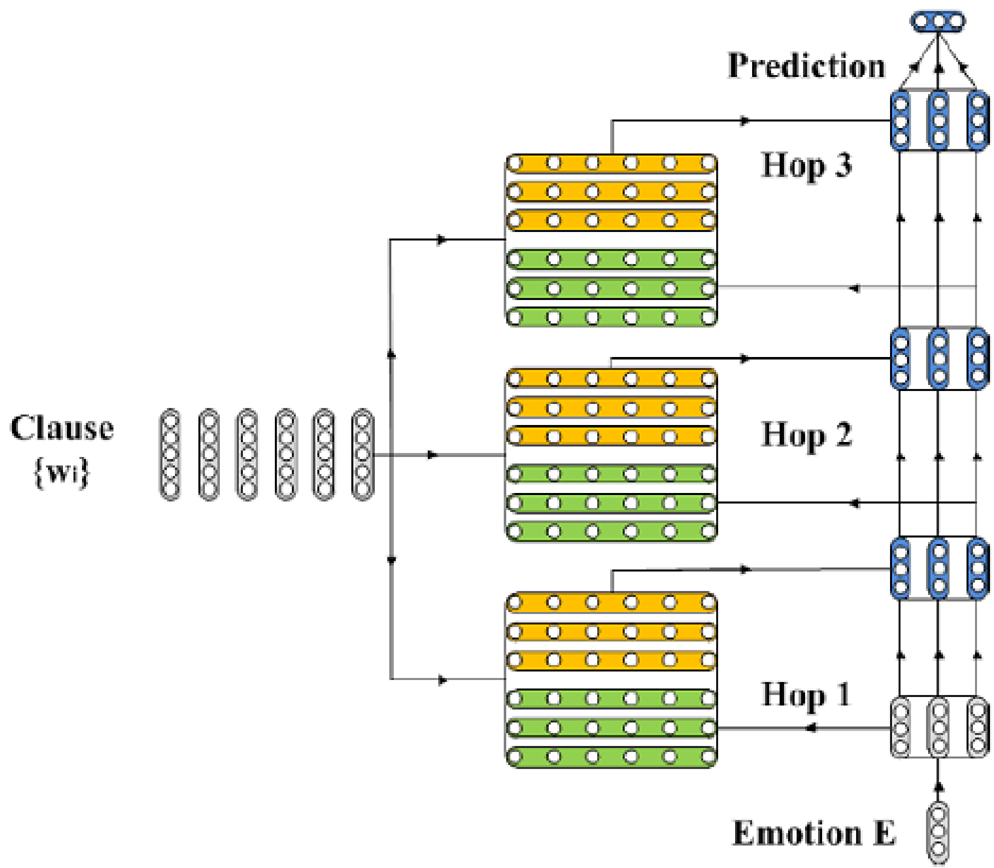


To capture context information for clauses, a new architecture contains more memory slot to model the context with a convolutional operation.

We set the size of the convolutional kernel to 3. That is, the weight of word considers both the previous word and the following word by a convolutional operation

$$m'_i = \sum_{j=1}^{3} e_{i-2+j} \cdot E$$

Convolutional Memory Network (Conv-Memnet)



- For the *first layer*, the query is an embedding of the emotion word
- In the *next layer*, there are three input queries. Since the previous layer has three outputs, we need to re-define the weights
- In the *last layer*, the three prediction vectors generate the final answer.

Experimental Setup

- A simplified Chinese emotion cause corpus (Gui et al., 2016)
  - The corpus contains 2,105 documents from SINA city news.
  - Each document has only one emotion label and one or more emotion causes.

Item	Number
Documents	2,105
Clauses	11,799
Emotion Causes	2,167
Documents with 1 emotion	2,046
Documents with 2 emotions	56
Documents with 3 emotions	3

Table 1: Details of the dataset.

$$P = \frac{\sum_{\text{correct causes}} 1}{\sum_{\text{proposed causes}} 1},$$

$$R = \frac{\sum_{\text{correct causes}} 1}{\sum_{\text{annotated causes}} 1},$$

$$F = \frac{2 \times P \times R}{P + R}.$$

Baselines

- RB (Rule based method): The rule-based method (Lee et al., 2010)
- CB (Common-sense based method): Chinese Emotion Cognition Lexicon (Xu et al., 2013) as the common-sense knowledge base
- RB+CB+ML (Machine learning method trained from rule-based features and facts from a common-sense knowledge base): (Chen et al., 2010)
- SVM: A SVM classifier using the unigram, bigram and trigram features
- Word2vec: A SVM classifier using word representations learned by Word2vec (Mikolov et al., 2013) as features
- CNN: The convolutional neural network for sentence classification (Kim, 2014)
- Multi-kernel: A multi-kernel based method (Gui et al., 2016)

Results

Method	Precision	Recall	F1
RB	***0.6747***	0.4287	0.5243
CB	0.2672	***0.7130***	0.3887
RB+CB+ML	0.5921	0.5307	0.5597
CNN	0.6215	0.5944	0.6076
Multi-Kernel	0.6588	0.6927	***0.6752***
Memnet	0.5922	0.6354	0.6131
ConvMS-Memnet	***0.7076***	***0.6838***	***0.6955***

Results...

Method	Precision	Recall	F1
RB	***0.6747***	0.4287	0.5243
CB	0.2672	***0.7130***	0.3887
RB+CB+ML	0.5921	0.5307	0.5597
CNN	0.6215	0.5944	0.6076
Multi-Kernel	0.6588	0.6927	***0.6752***
Memnet	0.5922	0.6354	0.6131
ConvMS-Memnet	***0.7076***	***0.6838***	***0.6955***

The rule based RB gives fairly high precision but with low recall.

Results…

Method	Precision	Recall	F1
RB	***0.6747***	0.4287	0.5243
CB	0.2672	***0.7130***	0.3887
RB+CB+ML	0.5921	0.5307	0.5597
CNN	0.6215	0.5944	0.6076
Multi-Kernel	0.6588	0.6927	***0.6752***
Memnet	0.5922	0.6354	0.6131
ConvMS-Memnet	***0.7076***	***0.6838***	***0.6955***

The common-sense based method, achieves the highest recall. Yet, its precision is the worst.

Results...

Method	Precision	Recall	F1
RB	***0.6747***	0.4287	0.5243
CB	0.2672	***0.7130***	0.3887
RB+CB+ML	0.5921	0.5307	0.5597
CNN	0.6215	0.5944	0.6076
Multi-Kernel	0.6588	0.6927	***0.6752***
Memnet	0.5922	0.6354	0.6131
ConvMS-Memnet	***0.7076***	***0.6838***	***0.6955***

The multi-kernel method gives the best results among the baselines because it considers context information in a structured way.

The syntactic structure information is important for the emotion cause extraction.

Results…

Method	Precision	Recall	F1
RB	***0.6747***	0.4287	0.5243
CB	0.2672	***0.7130***	0.3887
RB+CB+ML	0.5921	0.5307	0.5597
CNN	0.6215	0.5944	0.6076
Multi-Kernel	0.6588	0.6927	***0.6752***
Memnet	0.5922	0.6354	0.6131
ConvMS-Memnet	***0.7076***	***0.6838***	***0.6955***

Applying CNN or Memnet directly for emotion cause extraction outperforms all the baselines except the multi-kernel method.

Results...

Method	Precision	Recall	F1
RB	***0.6747***	0.4287	0.5243
CB	0.2672	***0.7130***	0.3887
RB+CB+ML	0.5921	0.5307	0.5597
CNN	0.6215	0.5944	0.6076
Multi-Kernel	0.6588	0.6927	***0.6752***
Memnet	0.5922	0.6354	0.6131
ConvMS-Memnet	***0.7076***	***0.6838***	***0.6955***

ConvMS-Memnet outperforms the previous best-performing method, multi-kernel, by 3.01% in F-measure.

It shows that by effectively capturing context information, ConvMS-Memnet identifies the emotion cause better.

Results – No. of Hops

Method	Precision	Recall	F-1
HOP 1	0.6597	0.6444	0.6520
HOP 2	0.6877	0.6718	0.6796
HOP 3	***0.7076***	***0.6838***	***0.6955***
HOP 4	0.6882	0.6722	0.6801
HOP 5	0.6763	0.6606	0.6683
HOP 6	0.6664	0.6509	0.6585
HOP 7	0.6483	0.6333	0.6407
HOP 8	0.6261	0.6116	0.6187
HOP 9	0.6161	0.6109	0.6089

Hop 3 gives the best results.

Further increasing the number of hops results in the decreased performance due to overfitting.

Word-Level Attention Weights

- Word-level attention weights in different hops of memory network training：

The family's insistence makes people more touched.

previous slot	**current slot**	following slot	**Hop 1**	**Hop 2**	**Hop 3**	**Hop 4**	**Hop 5**
家人/family	的/'s	坚持/insisting	0.1298	0.3165	0.1781	0.2947	0.1472
的/'s	坚持/insistence	更/more	0.1706	0.2619	**0.7346**	**0.6412**	**0.8373**
坚持/insisting	更/more	让/makes	**0.5090**	**0.3070**	0.0720	0.0553	0.0145
更/more	让/makes	人/people	0.0327	0.0139	0.0001	0.0001	0.0000
让/makes	人/people	感动/touched	0.1579	0.0965	0.0145	0.0080	0.0008

- In the first two hops, the highest attention weights centered on the word "more".
- From the third hop onwards, the highest attention weight moves to the word "insistence"
- The model is effective in identifying the most important keyword related to the emotion cause.

Results – Word Level

- To evaluate the quality of keywords extracted by memory networks, a **new metric** is defined on the keyword level for emotion cause extraction.
  - The **keyword** is defined as the *word having the highest attention weight* in the identified clause.
  - If the keywords extracted by our algorithm is located within the boundary of annotation, it is treated as correct.

Method	P	R	F
Memnet	0.5688	0.5588	0.5635
ConvMS-Memnet	**0.6250**	**0.6140**	**0.6195**

Comparison of word level emotion cause extraction.

Results – Training Epochs

45天，对于失去儿子的他们是多么的漫 长，宝贝回家了，这个春节是多么幸福。

(45 days, it is long time for the parents who lost their baby. If the baby comes back home, they would be so happy this Spring Festival.)

Clause	5 Epochs	10 Epochs	15 Epochs	20 Epochs
45 Days	0.0018	0.0002	0.0000	0.0000
it is ... baby	0.3546	0.6778	0.5457	0.3254
If the ... back home	**0.7627**	**0.7946**	**0.8092**	**0.9626**
they ... Spring Festival	0.2060	0.0217	0.0004	0.0006

- The table shows the probability of each clause containing an emotion cause in different training epochs.
- The model is able to detect the correct clause with only 5 epochs.
- With the increasing number of training epochs, the probability associated with the correct clause increases further while the probabilities of incorrect clauses decrease generally.

Limitations

- The model has a difficulty in dealing with complex sentence structures, e.g.,
  - Sentences contain long distance dependency relations, such as negations or emotion transitions

- The answer generated from the model is simply “yes” or “no”
  - This is partly due to the small size of the annotated corpus which makes it difficult to train a model that can output answers in full sentences.

Conclusions

- Multi-emotion detection from text framed as an emotion ranking problem
  - Relevant emotion ranking using support vector machines
  - Interpretable neural network for relevant emotion ranking
- Emotion cause extraction from text
  - Memory-network based approach

Acknowledgements

Deyu Zhou
Southeast University

Yang Yang
Southeast University

Lin Gui
Aston University /
University of Warwick

Ruifeng Xu
Harbin Institute of Technology

References

- S. Bao, S. Xu, L. Zhang, R. Yan, Z. Su, D. Han, and Y. Yu. 2012. Mining social emotions from affective text. *IEEE Transactions on Knowledge and Data Engineering* (TKDE), 24(9):1658–1670.
- K. Gao, H. Xu, and J. Wang. 2015. A rule-based approach to emotion cause detection for Chinese micro-blogs. *Expert Systems with Applications*, 42(9):4517–4528.
- D. Ghazi, Diana Inkpen, and Stan Szpakowicz. 2015. *Detecting emotion stimuli in emotion-bearing sentences*. In *Computational Linguistics and Intelligent Text Processing* (CICLing), pages 152–165.
- L. Gui, J. Hu, Y. He, R. Xu, Q. Lu and J. Du. 2017. A Question Answering Approach for Emotion Cause Extraction. *The 14th International Conference on Empirical Methods on Natural Language Processing* (EMNLP), Copenhagen, Denmark.
- L. Gui, D. Wu, R. Xu, Q. Lu, and Y. Zhou. 2016. Event-driven emotion cause extraction with corpus construction. *The 13th International Conference on Empirical Methods on Natural Language Processing* EMNLP, pages 1639–1649.
- L. Gui, L. Yuan, R. Xu, B. Liu, Q. Lu, and Y. Zhou. 2014. Emotion cause detection with linguistic construction in chinese weibo text. In *Natural Language Processing and Chinese Computing* (NLPCC), pages 457–464. Springer.

References…

- S.Y.M. Lee, Y. Chen, and C.-R. Huang. 2010. A text-driven rule-based system for emotion cause detection. In *Proceedings of the NAACL HLT Workshop on Computational Approaches to Analysis and Generation of Emotion in Text*, pages 45–53.
- W. Li and H. Xu. 2014. Text-based emotion classification using emotion cause extraction. *Expert Systems with Applications*, 41(4):1742–1749.
- J. Lei, Y. Rao, Q. Li, X. Quan, and W. Liu. 2014. Towards building a social emotion detection system for online news. *Future Generation Computer Systems*, 37:438–448.
- X. Quan, Q. Wang, Y. Zhang, L. Si, and W. Liu. 2015. Latent discriminative models for social emotion detection with emotional dependency. *ACM Transactions on Information Systems* (TOIS) , 34(1):2.
- Y. Rao, Q. Li, W. Liu, Q. Wu, and X. Quan. 2014a. Affective topic model for social emotion detection. *Neural Netw*, 58(5):29–37.
- Y. Rao. 2016. Contextual sentiment topic model for adaptive social emotion classification. *IEEE Intelligent Systems*, 31(1):41–47.
- Y. Rao, Q. Li, X. Mao, and W. Liu. 2014b. Sentiment topic models for social emotion mining. *Information Sciences*, 266(5):90–100.

References...

- Y. Wang and A. Pal. 2015. Detecting emotions in social media: A constrained optimization approach. In *Proceedings of the 24th International Joint Conference on Artificial Intelligence* (IJCAI).
- Y. Yang, D. Zhou and Y. He. 2018. An Interpretable Neural Network with Topical Information for Relevant Emotion Ranking, *The 15th International Conference on Empirical Methods on Natural Language Processing* (EMNLP), Brussel, Belgium.
- D. Zhou, X. Zhang, Y. Zhou, Q. Zhao, and X. Geng. 2016. Emotion distribution learning from texts. *The 13th International Conference on Empirical Methods in Natural Language Processing* (EMNLP), pages 638–647.
- D. Zhou, Y. Yang and Y. He. 2018. Relevant Emotion Ranking from Text Constraint with Emotion Relationships, *The 16th Annual Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies* (NAACL-HLT), New Orleans, Louisiana, USA.

Questions?

y.he@cantab.net