Predicting and Eliciting Addressee's Emotion in Online Dialogue

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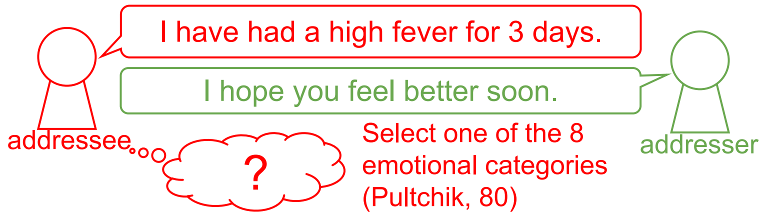
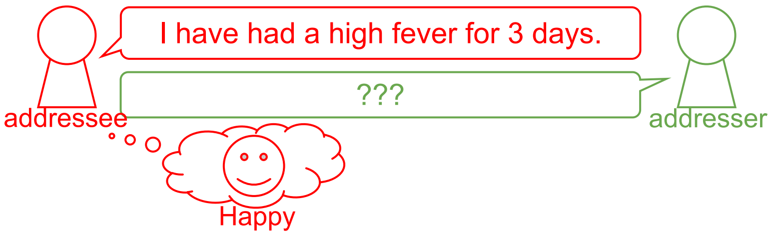
Background and task proposal

NLP research on *addressee' emotion* in dialogue is scarce, while there exist a tremendous amount of efforts on exploring addresser's emotion (Ayadi et al., 2011).

Task1: Predicting addressee's emotion



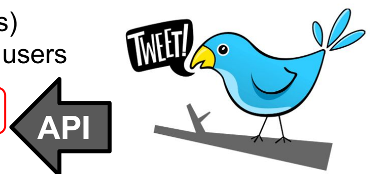
Task2: Generating response to elicit emotion



Emotion-tagged dialogue corpus

Mining emotional dialogues from twitter

Dialogue = tweets (utterances) interchangeably done by two users



Use Twitter API to get tweets (utterances)

Use **clue expressions** to label *addresser's emotion*

- 8 emotinal categories (Plutchik, 1980)
- 10,658,617 emotional utterances
- annotation accuracy: > 93 - 99% (kappa: 0.85)

Prediction of addressee's emotion

One-versus-the-rest classifier

PA-I (implemented in opal) is used to train 8 binary classifiers for 8 emotional categories

Dialogue-specific features

Use word n-grams (n=1-3) and the addressers' emotions estimated from their utterances

Extract features not only from the response but also from the previous utterance by the addressee

Gold standard data for evaluation

5 students choose 10 utterances per each emotion as goal emotion to respond (5 * 10 * 8 = 400)

For the chosen 400 utterances, 3 (out of 5) students make a response (400 * 3 = 1200)

1099 utterance-response pairs after double check

Features	PREC	REC	F_1
Response	0.542	0.492	0.497
Response/Utterance	**0.588**	**0.563**	**0.567**

correct emotion \ predicted emotion	ANGER	ANTICIPA.	DISGUST	FEAR	JOY	SADNESS	SURPRISE	TRUST	total
ANGER	**69**	0	<u>26</u>	20	0	8	2	1	126
ANTICIPA.	1	**86**	11	7	<u>13</u>	0	6	11	135
DISGUST	<u>25</u>	1	**68**	18	2	8	7	4	133
FEAR	3	0	<u>22</u>	**101**	1	5	9	2	143
JOY	1	<u>28</u>	9	4	**85**	1	7	9	144
SADNESS	6	3	<u>25</u>	14	5	**77**	5	2	137
SURPRISE	7	10	9	<u>32</u>	5	7	**59**	6	135
TRUST	3	12	10	<u>24</u>	7	9	6	**75**	146
total	115	140	180	220	118	115	101	110	1099

* Mostly confused emotion <u>underlined</u>

Eliciting addresee's emotion

SMT-based response generation (Ritter et al., 2011)

GIZA++ (Och and Ney, 2003) and Moses (Kohen et. al., 2007) are used

Train models for each emotion category by using the emotion-tagged corpus

Model interpolation for handling data-sparsity

Use general model, which is trained from the entire utterances in the corpus

Combine the general model with emotion-specific one (Sennrich, 2012)

Automatic and subjective evalution

	BLEU	Human
Baseline	0.64	147 (74)
Proposed	**1.05**	**157 (92)**

Automatic evaluation by BLEU (Papineni et al., 2002)

Subjective evaluation by 2 humans: #responses regarded as correct by either (both) of the human judges

Generation examples (goal emotion is JOY)

Input	写真コンクールで優秀賞とったーーーー！2 月7 日表彰式！ (I wooooon the outstanding award at the pho to competition! The ceremony is on Feb. 7!)
Baseline	残念ながら1日目だけですのー(Sorry to say, only the first day.)
Proposed	金賞受賞おめでとう！！！おめでとうなのー (Congratulations on winning the gold prize!!! Congrats.)