Affective Computing in 2018

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Affective Computing

Emotion is the driving force of user's sentiments…

Charles Darwin:

- Emotion serves as a purpose for humans in aiding their survival during the evolution.[1]

Emotion stimulates the mind 3000 times quicker than rational thought!

[1] Charles Darwin. *The Expression of Emotions in Man and Animals*. John Murray, 1872.

Affective Computing

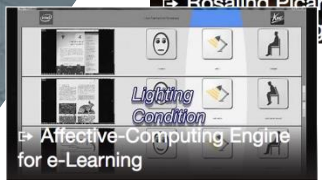
- **First raised emotion in machine**: **Minsky, M. 1986. The society of mind.**
- **Give a rough definition of affective computing**: **Picard, R. W. 1997, Affective computing**

Affective Computing in many aspects: facial expression recognition & synthesis, emotional speech recognition & synthesis, sentimental analysis in NLP...

Outline


AMA应用

ttention Meter应用

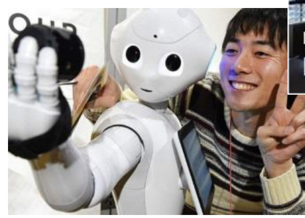


Affective computing (for engine

The study and development of **systems and devices** that can **recognize, interpret, process, simulate and mediate** human affects.


情感计算硬件设备开发


汉森机器人


情感计算机器人

Picard 情感计算组

微软小冰

清華大學 Tsinghua University

A Question for All of Us....

What will be the next mile stone of Affective Computing?

Today, let us start with
Big Data in Social Networks...

A Trillion Dollar Opportunity

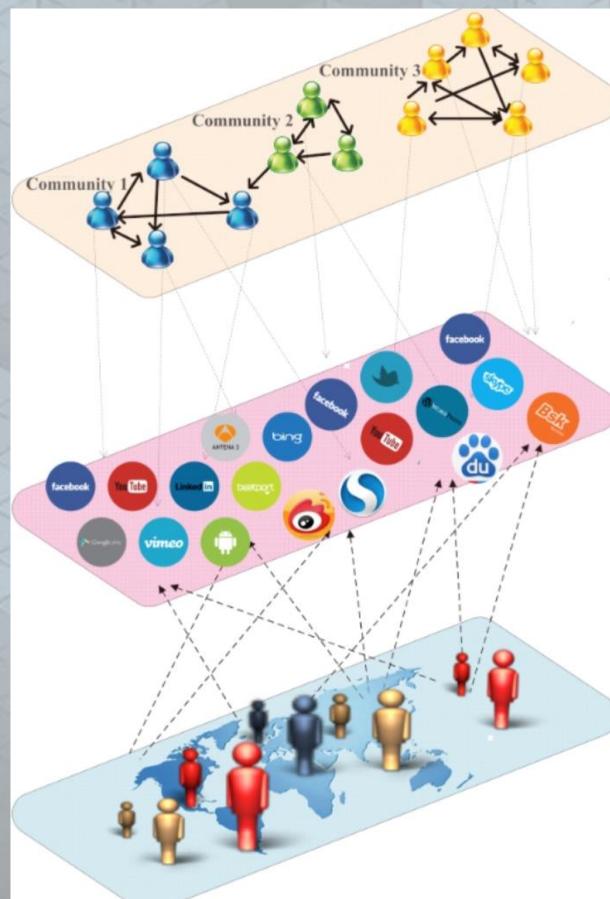
Social networks already become a bridge to connect our daily **physical** life and the **virtual** web space

On2Off **[1]**

[1] Online to Offline is trillion dollar business
http://techcrunch.com/2010/08/07/why-online2offline-commerce-is-a-trillion-dollar-opportunity/

A Trillion Dollar Opportunity for Affective Computing?

- **Social Big Data + Affective Computing**
  - **from “管窥一斑” to “俯瞰芸芸众生”**



Still Challenges

Q1: How to capture the intrinsic relationships between social data and the emotional impact, and scale up the model to large networks?

Keywords in 2018: Multimodalities; Weakly Supervised; Deep Learning; Multitask; Attention;

Q2: Are there any other social factor that may affect the analyzing/prediction results?

Keywords in 2018: Social Structure

Q3: How the affective computing benefits the social good?

Keywords in 2018: Mental Health Computing

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Outline

PART 1

Inferring Emotion from Social Media Data

Multimodalities
&
Methodologies

PART 2

Social Factors

PART 3

Go beyond affective computing

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Inferring Users' Emotions For Human-Mobile Voice Dialogue Applications

- Voice dialogue applications (VDAs) are gaining popularity worldwide.
  - *Siri, Cortana, Google Now, Sogou Voice Assistant…*
  - 57% of people worldwide having VDAs use it at least once a day.
- At present, VDAs mainly generate responses by *text-based* natural language processing (NLP) techniques.
- *The acoustic information of users' queries*
  - *`Why do you come here?'*
- *Query attributes*
  - Topical dependency
  - Geographical dependency

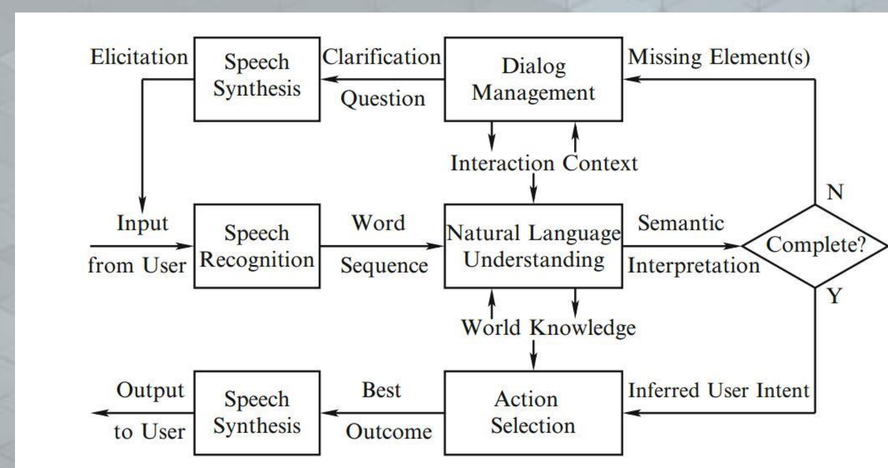
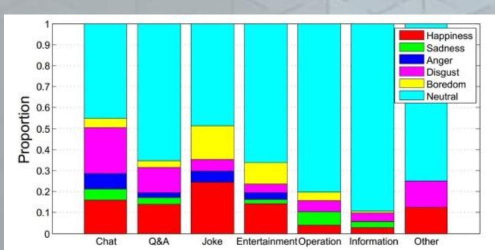
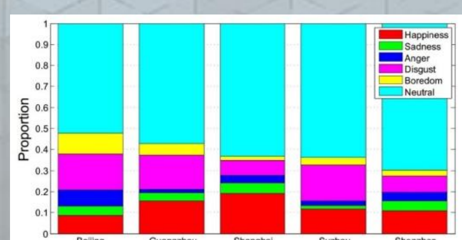


Fig. 1.1 Overview of "intelligent personal assistant" interaction model





Inferring Users' Emotions For Human-Mobile Voice Dialogue Applications

- *Hybrid Emotion Inference Model (HEIM)*
  - a Latent Dirichlet Allocation (LDA) to extract text features
  - a Long Short-Term Memory (LSTM) to model the acoustic features
  - a Recurrent Autoencoder Guided by Query Attributes (RAGQA) to incorporates other emotion-related query attributes to pre-train LSTM

Table 1. The F1-Measure of inferring emotions in VDAs.

Method	Happiness	Sadness	Anger	Disgust	Boredom	Neutral	Average
NB	0.4000	0.3617	0.2619	0.2514	0.2740	0.6548	0.3673
KNN	0.4693	0.3220	0.3947	0.2967	0.2132	0.7191	0.4025
SVM	0.4410	0.2625	0.4199	0.2787	0.1968	**0.7419**	0.3901
DSNN	0.4219	0.3238	0.4594	0.3412	0.2446	0.7111	0.4170
HEIM	**0.9715**	**0.9635**	**0.8905**	**0.5463**	**0.5170**	0.6226	**0.7519**

Inferring Emotion from Conversational Voice Data: A Semi-supervised Multi-path Generative Neural Network Approach. AAAI'18

Multimodal Sentiment Analysis to Explore the Structure of Emotions

Anthony Hu (University of Oxford); Seth Flaxman (Imperial College London), KDD 2018

Motivation: The goal is different than the standard sentiment analysis goal of predicting whether a sentence expresses positive or negative sentiment; instead, this paper aims to infer the latent emotional state of the user.

Contribution: The paper proposes a novel approach to multimodal sentiment analysis using deep neural networks combining visual analysis and natural language processing.

- The paper focuses on predicting the emotion word tags attached by users to their Tumblr posts, treating these as "self-reported emotions."
- The proposed multimodal model combining both text and image features outperforms separate models based solely on either images or text.

Multimodal Sentiment Analysis to Explore the Structure of Emotions

Table 1: Summary statistics for the Tumblr dataset, with posts from January 2011 to September 2017.

Tumblr data

Posts	Text filtered	Text & image filtered
1,009,534	578,699	256,897

Emotion	Posts	Text filtered	Text & image filtered
Happy	189,841	62%	29%
Calm	139,911	37%	29%
Sad	124,900	53%	15%
Scared	104,161	65%	20%
Bored	101,856	54%	29%
Angry	100,033	60%	21%
Annoyed	72,993	78%	10%
Love	66,146	61%	39%
Excited	37,240	58%	41%
Surprised	18,322	47%	32%
Optimistic	16,111	64%	36%
Amazed	10,367	61%	35%
Ashamed	10,066	63%	22%
Disgusted	9,178	69%	17%
Pensive	8,409	57%	34%

4.3.1 Architecture. Deep Sentiment builds on the models we have seen before as shown in Figure 4.

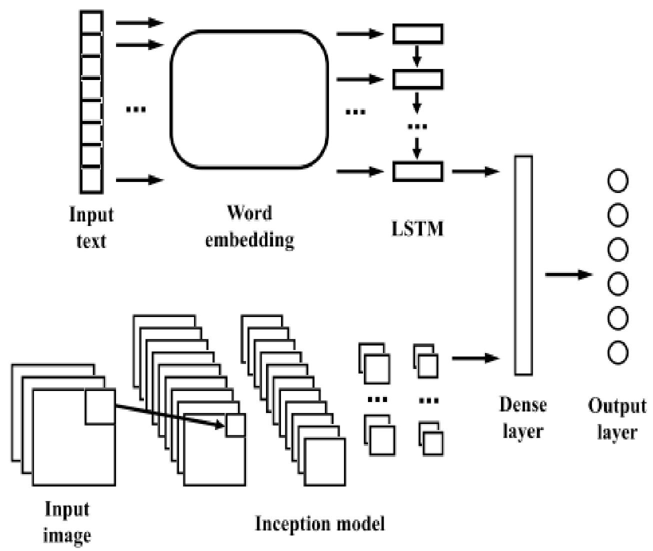


Figure 4: The Deep Sentiment structure. On the one hand, the input image, resized to (224,224,3) is fed into the Inception network and outputs a vector of size 256. On the other hand, the text is projected into a high-dimensional space that subsequently goes through an LSTM layer with 1024 units. The two modalities are then concatenated and fed into a dense layer. The final softmax output layer give the probability distribution over the emotional state of the user.

Multimodal Sentiment Analysis to Explore the Structure of Emotions

Table 3: Top 10 words for each emotion, ordered by the relative frequency of the emotion being used as a tag on Tumbl

Emotion	Top words
Happy	healthy, loving, enjoy, wonderful, warm, happiness, smile, lovely, cute, proud
Calm	quiet, situation, peace, mood, towards, warm, slowly, stay, sleep, rain
Sad	horrible, sorry, crying, hurts, tears, cried, lonely, memories, worst, pain
Scared	terrified, scary, panic, nervous, fear, afraid, horrible, woke, happening, worried
Bored	asleep, tired, kinda, busy, stuck, constantly, lonely, sat, listening, depression
Angry	anger, fear, panic, annoying, hate, mad, upset, anxiety, scares, stupid
Annoyed	pissed, ashamed, angry, nervous, speak, surprised, tired, worried, ignore, phone
Love	soul, dreams, happiness, kiss, sex, beauty, women, feelings, god, relationships
Excited	tonight, hopefully, watching, nervous, surprised, expect, tomorrow, amazing, hoping, happen
Surprised	birthday, cried, thank, yesterday, told, sorry, amazing, sweet, friend, message
Optimistic	positive, expect, surprised, healthy, grow, realize, clearly, hopefully, calm, peace
Amazed	surprised, excited, amazing, woke, realized, awesome, happening, ashamed, yeah, happened
Ashamed	totally, honestly, sorry, absolutely, freaking, honest, completely, stupid, seriously, am
Disgusted	ashamed, totally, angry, hate, stupid, annoyed, horrible, scares, freaking, absolutely
Pensive	mood, wrote, quiet, view, sadness, thoughts, calm, words, sad, kissed

Methodologies

Key Word: Weakly Supervised

- Weakly Supervised Induction of Affective Events by Optimizing Semantic Consistency, AAAI 2018

Key Word: Deep Learning

- Sentiment Analysis via Deep Hybrid Textual-Crowd Learning Model, AAAI 2018
- Cross-Lingual Propagation for Deep Sentiment Analysis, AAAI 2018
- SenHint: A Joint Framework for Aspect-level Sentiment Analysis by Deep Neural Networks and Linguistic Hints, WWW 2018

Key Word: Multitask Learning

- Cognition-Cognizant Sentiment Analysis With Multitask Subjectivity Summarization Based on Annotators' Gaze Behavior , AAAI 2018
- Text Emotion Distribution Learning via Multi-Task Convolutional Neural Network, IJCAI 2018

Methodologies

Key Word: Attention

- Hierarchical Attention Transfer Network for Cross-Domain Sentiment Classification , AAAI 2018
- Targeted Aspect-Based Sentiment Analysis via Embedding Commonsense Knowledge into an Attentive LSTM , AAAI 2018
- Improving Review Representations With User Attention and Product Attention for Sentiment Classification , AAAI 2018
- Aspect Sentiment Classification with both Word-level and Clause-level Attention Networks, IJCAI 2018
- Content Attention Model for Aspect Based Sentiment Analysis, WWW 2018
- LAAN: A Linguistic-Aware Attention Network for Sentiment Analysis, WWW 2018
- Cold-Start Aware User and Product Attention for Sentiment Classification, ACL 2018
- Recurrent Attention Network on Memory for Aspect Sentiment Analysis, EMNLP17
- A Cognition Based Attention Model for Sentiment Analysis, EMNLP17

Outline

PART 1

Inferring Emotion from Social Media Data

PART 2

Bring Social Factors in Modeling

From Individual Attributes to Social Structures

PART 3

Go beyond affective computing

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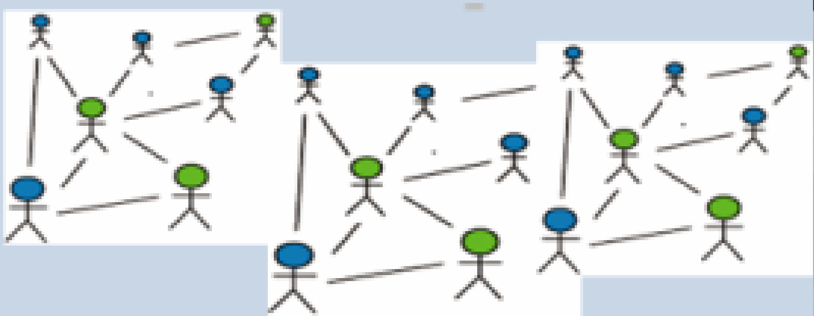
Uploaded time	the Unix time stamp value when image was up-loaded
Owner ID	the ID of the image owner

Social features



Social Factors

Classical Theory:

- **Homophily**: individuals to choose friends with similar tastes and preferences.
- **Confounding effects**: connected individuals to be exposed to the same external simuli.
- **Simultaneity**: connected individuals to behave similarly at approximately the same time.

S.Aral,etc, Identifying Influential and Susceptible Members of Social Networks, Science, 2012

Bring Social Theoris in…

- Temporal correlation（ACM MM'12）
  - Emotion evolves as time goes by.
- User Demographics（ICME'15, IEEE T-MM 17）
  - Gender, marital status, occupation
- Social Role（AAAI'16）
  - Opinion leader, structural hole spanner, ordinary users
- Social influence (AAAI'14,IEEE T-AC 2015)
  - The interaction among friends
- Group Homophily(IJCAI'16'17,T-KDE,ICME'18)
  - Similar tastes and preferences
- …….

Visit https://hcsi.cs.tsinghua.edu.cn/jiajia to find more detailed information

When Sentiment Analysis Meets Social Network: A Holistic User Behavior Modeling in Opinionated Data, KDD18

Lin Gong (University of Virginia); Hongning Wang (University of Virginia)

Motivation: User modeling is critical for understanding user intents, while it is also challenging as user intents are so diverse and not directly observable. Most existing works exploit specific types of behavior signals for user modeling, e.g., opinionated data or network structure; but the dependency among different types of user-generated data is neglected.

Contribution: Focuses on self-consistence across multiple modalities of user-generated data to model user intents.

- **A probabilistic generative model** is developed to integrate two companion learning tasks of opinionated content modeling and social network structure modeling for users.
- Individual users are modeled as a mixture over the instances of paired learning tasks to realize their behavior heterogeneity, and the tasks are clustered by sharing a global prior distribution to capture the homogeneity among users.

When Sentiment Analysis Meets Social Network: A Holistic User Behavior Modeling in Opinionated Data, KDD18

Table 1: Personalized sentiment classification results.

Models	Amazon		Yelp	
	Neg F1	Pos F1	Neg F1	Pos F1
Base	0.6300	0.8858	0.8141	0.9385
MT-SVM	**0.6929***	**0.8992***	0.8633	0.9591
MTLinAdapt+kMeans	0.6224	0.8390	0.8453	0.9336
cLinAdapt	0.6842	0.8752	0.8574	0.9527
cLinAdapt+HDP	0.6846	0.8868	0.8556	0.9566
GBSSL	0.6179	0.8847	0.8303	0.9529
HUB	0.6905	0.8934	**0.8647***	**0.9595***

*: p-value<0.05 under Wilcoxon signed-rank test.

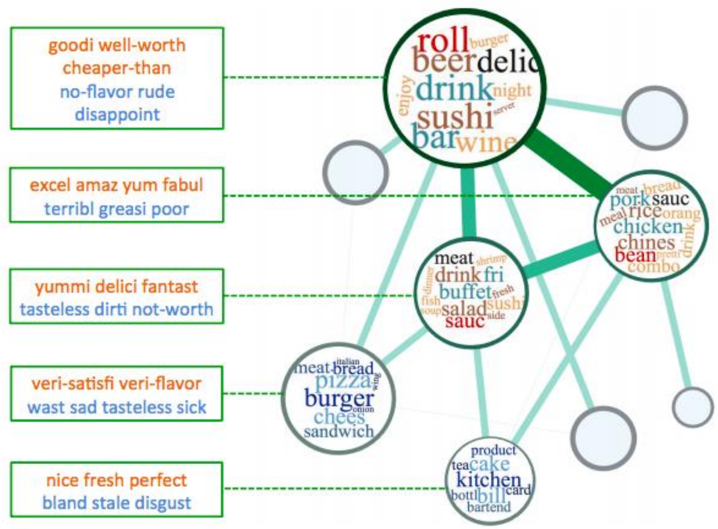


Figure 3: The identified behavior patterns among a subset of collective identities on Yelp dataset.

Table 2: Collaborative filtering results on Amazon and Yelp.

Models	Amazon		Yelp	
	NDCG	MAP	NDCG	MAP
Average	0.7813	0.6573	0.6606	0.4700
MT-SVM	0.7982	0.6798	0.7519	0.5847
cLinAdapt	0.7926	0.6725	0.7548	0.5898
cLinAdapt+HDP	0.7956	0.6766	0.7598	0.5989
SVD++	0.5502	0.3853	0.5731	0.3880
FM	0.4874	0.3110	0.4057	0.1979
HUB	**0.7993**	**0.6816**	**0.7685**	**0.6082**

Table 3: Friend recommendation results on Yelp.

Train Size	BoW		SVM		HUB	
	NDCG	MAP	NDCG	MAP	NDCG	MAP
4000	1.0003	1.0230	1.0314	1.3130	**1.1017**	**1.8779**
6000	1.0002	1.0419	1.0128	0.9222	**1.1137**	**1.5928**
8000	1.0010	1.0887	1.0602	1.4194	**1.1428**	**2.6532**

Outline

PART 1

Inferring Emotion from Social Media Data

PART 2

Bring Social Factors in Modeling

PART 3

Go beyond affective computing

Mental Health Computing

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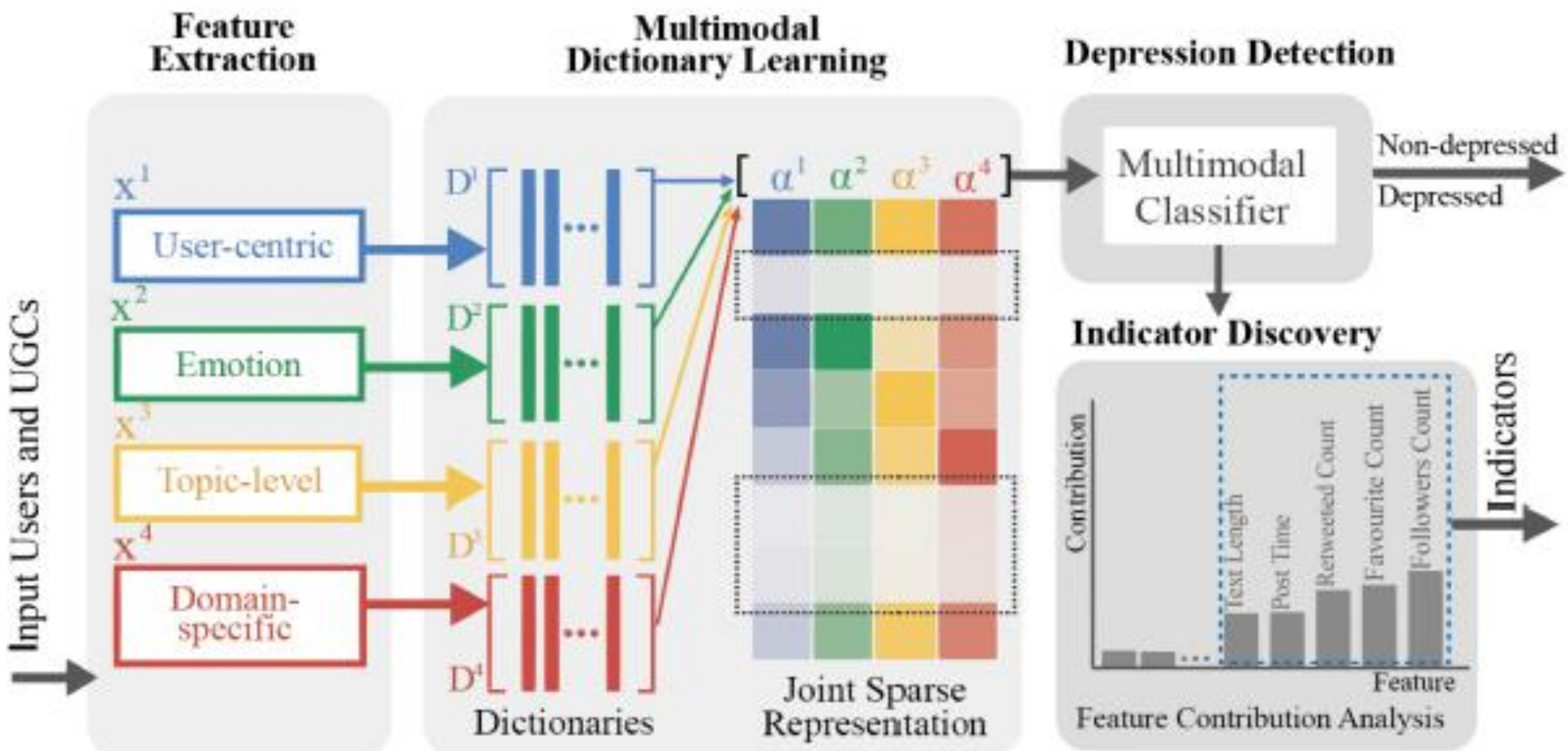
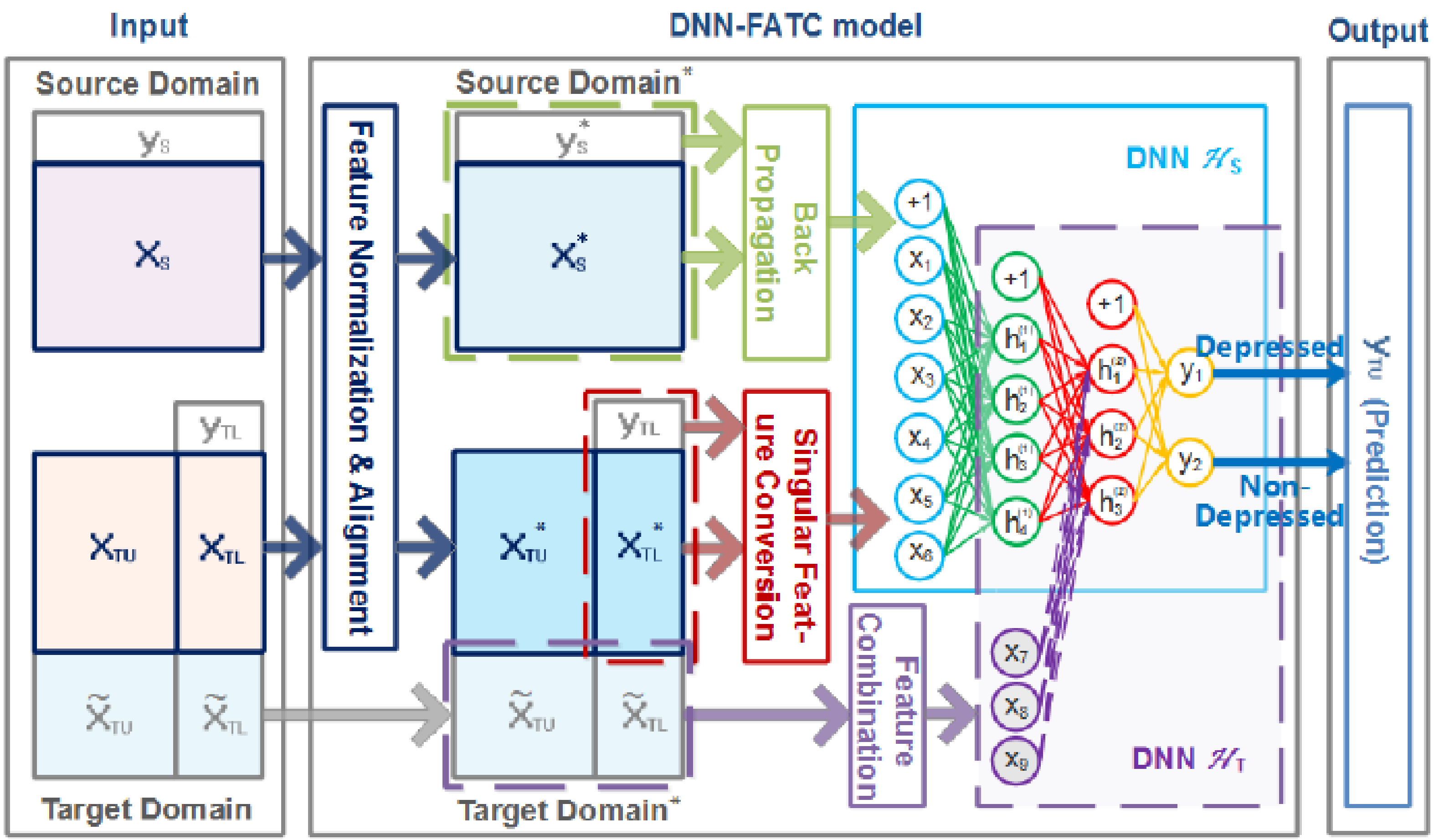
Depression Detection via Harvesting Social Media



Beyond Offline Indicators:
Enhance the Depression Criteria via Harvesting Social Media

Depression Detection via Harvesting Social Media: A Multimodal Dictionary Learning Solution, IJCAI 2017.

Cross-domain Depression Detection



Cross-domain Depression Detection via Harvesting Social Media. IJCAI'18.

Conclusion

PART 1

Inferring Emotion from Big Social Data

PART 2

Bring Social Factors in Modeling

PART 3

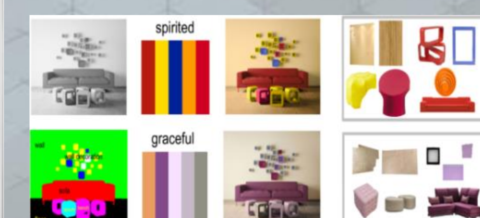
Go beyond affective computing

Conclusion: Experience instead of task

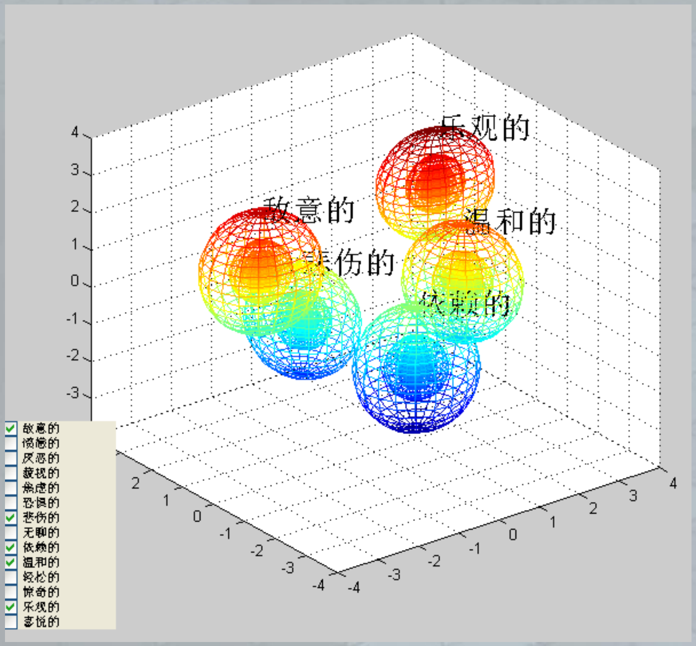
- **Combine social psychology with computational models**
- Apply technologies to "social good"
    - Uncover psychology stress
    - Find "gene" to be happy
    - Develop human-computer interaction mechanism
- Enable the affective interaction

Affective Computing in Dialog System (IJCAI'18 & ACL'18)

Cross-Domain Sentimental Analysis (ACL18 & EMNLP17)



Discussion: How to Describe the Complex Affective Semantics Dimensions or Categories?



Dimensional PAD Model

In Multimedia Area:
AVEC 2018 uses Dimensional Labels

	平均数			标准差		
	P	A	D	P	A	D
喜悦	2.77	1.21	1.42	1.31	1.30	1.42
乐观	2.48	1.05	1.75	1.31	1.20	1.43
轻松	2.19	-0.66	1.05	1.35	1.36	1.29
惊奇	1.72	1.71	0.22	1.44	1.41	1.57
温和	1.57	-0.79	0.38	1.16	1.29	1.51
依赖	0.39	-0.81	-1.48	1.31	1.20	1.73
无聊	-0.53	-1.25	-0.84	1.02	1.17	1.38
悲伤	-0.89	0.17	-0.70	1.09	1.00	1.45
恐惧	-0.93	1.30	-0.64	1.21	0.92	0.95
焦虑	-0.95	0.32	-0.63	1.10	0.70	1.42
藐视	-1.58	0.32	1.02	1.35	1.11	1.50
厌恶	-1.80	0.40	0.67	1.20	1.07	1.49
愤懑	-1.98	1.10	0.60	1.29	1.16	1.61
敌意	-2.08	1.00	1.12	1.31	1.12	1.58

中科院心理所，2006

For NLP: Moving from Category Method to Dimensional Method?

Question?