Cyber Psychosocial and Physical (CPP) Computation Based on Social Neuromechanism

-Joint research work by Fudan University and University of Novi Sad

By Professor Weihui Dai

Fudan University, China

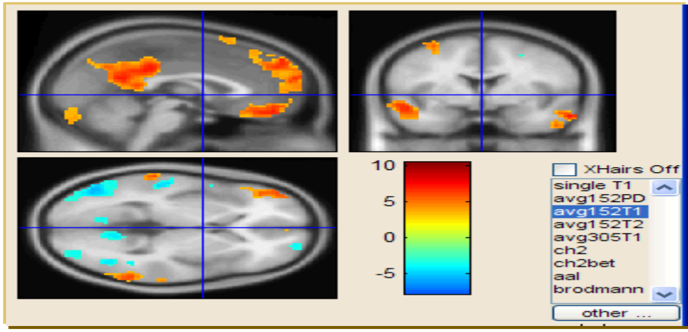
Agenda

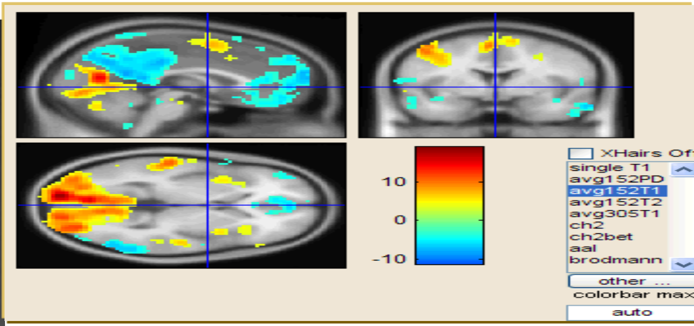
- Cultural Neurology and Social Neuroscience
- Neural Cognition and Affective Computing
- CPP (Cyber Psychosocial and Physical) Computation Method
- Application and Discussion

Cultural Neurology and Social Neuroscience




Differences in cognitive experience between the audience and an artist:





More activated functional areas in the brain and emotional activities for an artist.

Cultural Neurology and Social Neuroscience

Favorite style of people living in Shanghai, China

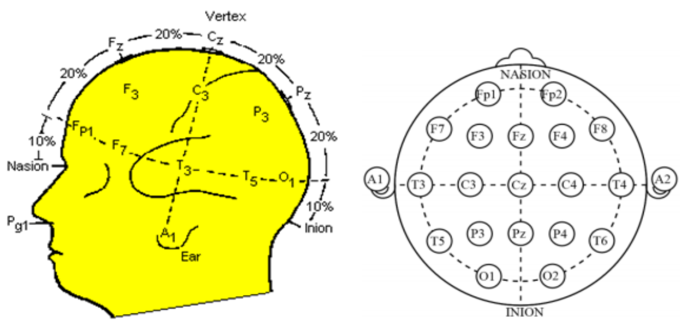
Attractive design:
fashionable shape and elegant appearance.

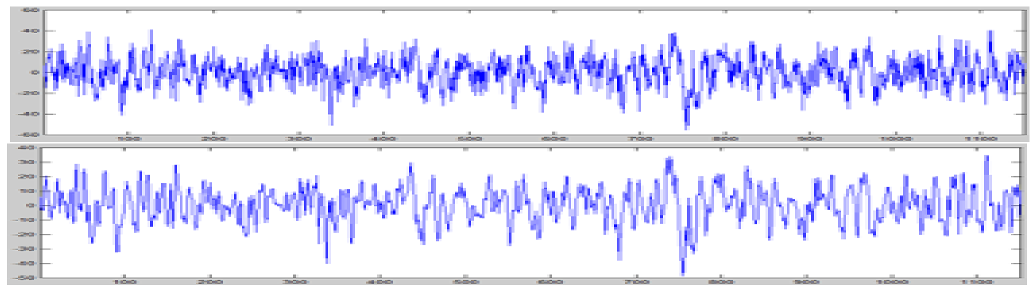
Favorite style of people living in Beijing, China

Attractive design:
Water, long-range perspective and red color.

Cultural Neurology and Social Neuroscience

Music emotional experiences analysis from EEG signals:





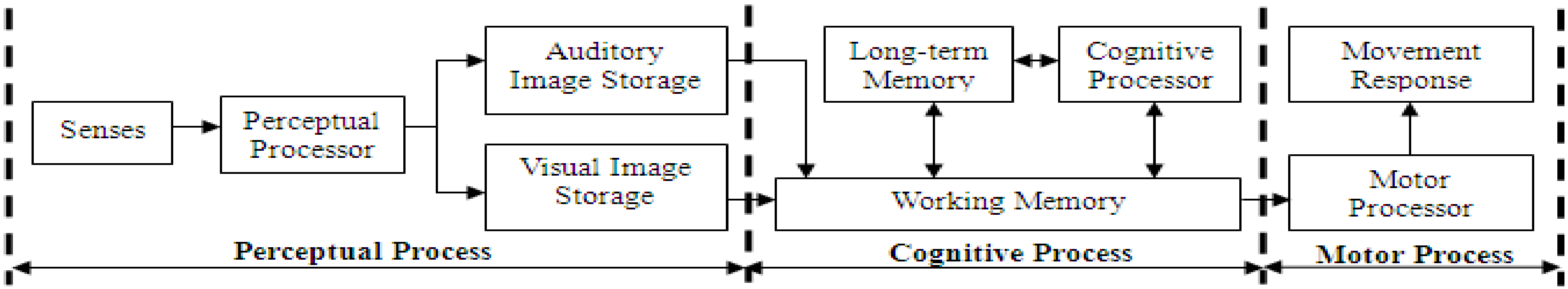
Results – nationality

Distance	Chinese			Serbian		
L2	C2	alpha	0.875406	C4	gamma	0.811331
	C8	theta	0.884013	C2	gamma	0.837271
	C4	gamma	0.885615	C8	gamma	0.838976
	C4	alpha	0.885948	C3	gamma	0.842635
	C5	theta	0.886371	C6	gamma	0.859906
DTW	C2	gamma	0.861348	C4	gamma	0.793518
	C4	gamma	0.86728	C2	gamma	0.810572
	C8	beta	0.871106	C8	gamma	0.818156
	C8	gamma	0.87167	C3	gamma	0.839903
	C7	gamma	0.877916	C6	gamma	0.842098
ERP	C4	gamma	0.769959	C4	gamma	0.716459
	C2	gamma	0.778723	C2	gamma	0.760053
	C5	gamma	0.802679	C3	gamma	0.775114
	C8	gamma	0.804224	C6	gamma	0.779021
	C7	gamma	0.807291	C8	gamma	0.780355

Significant differences in individual and genders, but no significant differences in nationalities.

There are some common music features which are independent of cultures and nationalities.

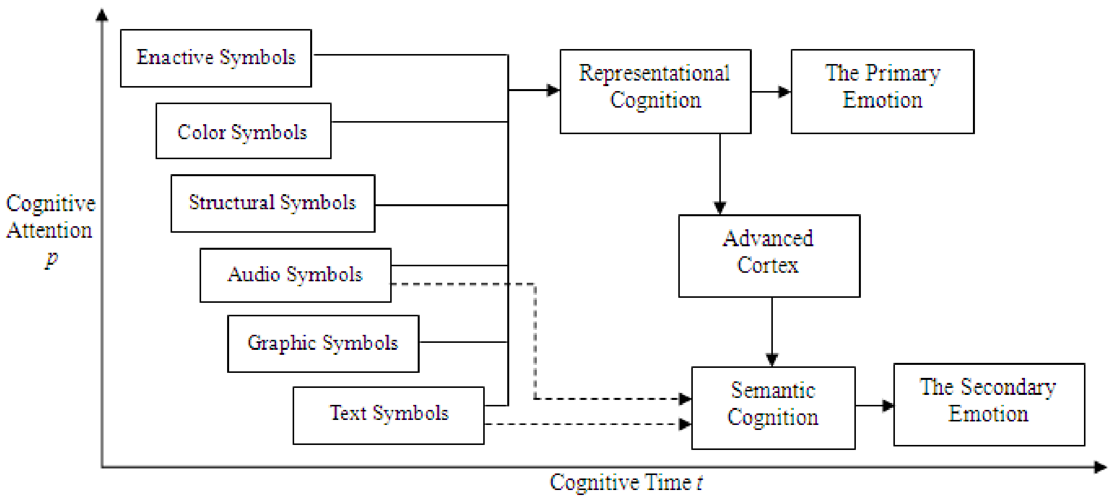
Cultural Neurology and Social Neuroscience



Information process in human processor model (S.K. Card, T. P. Moran, and A. Newell, 1986)

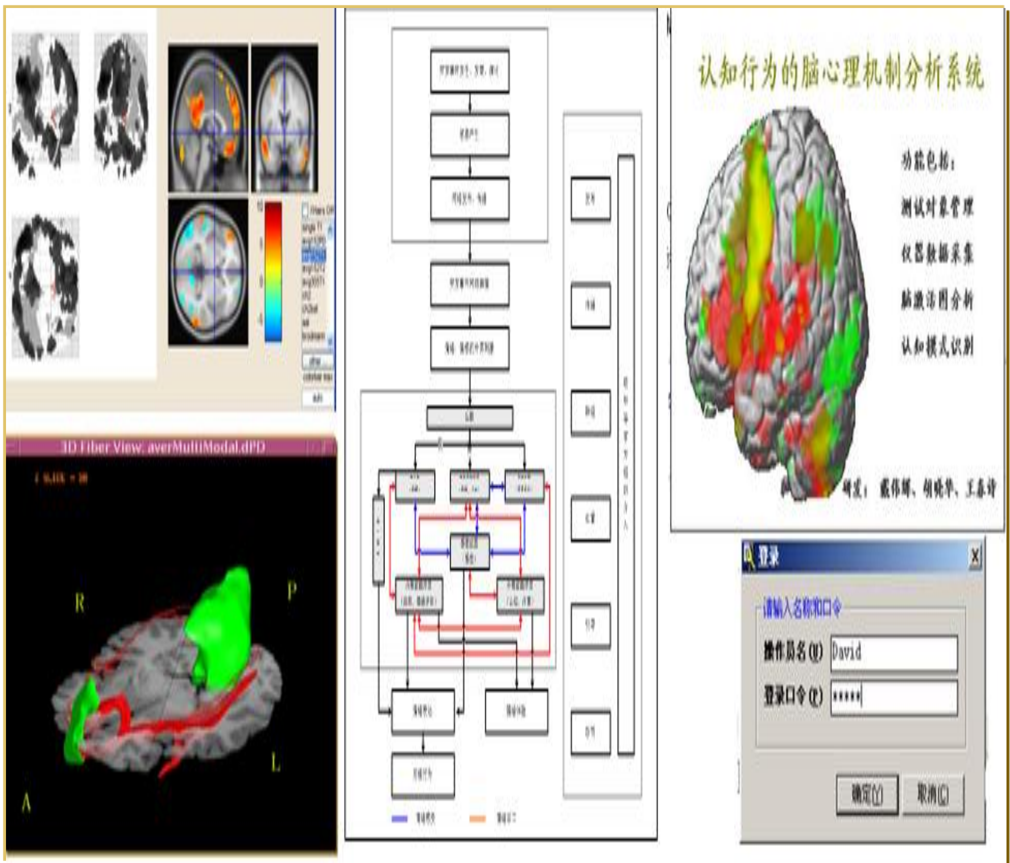
Time parameters in the Perceptual Process and Cognitive Process

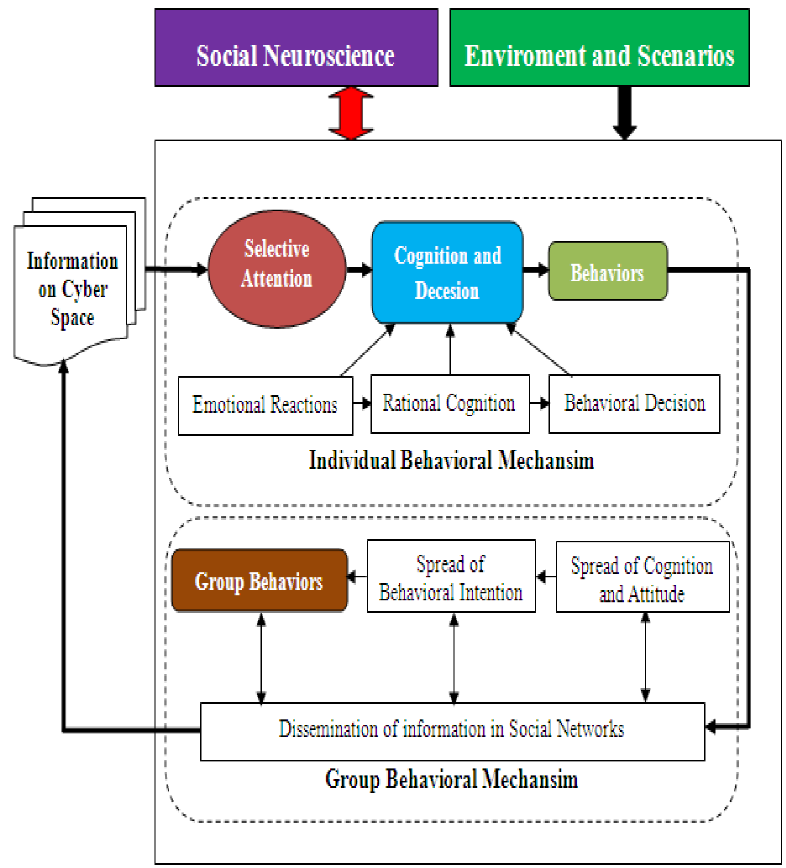
Parameter	Mean	Range
Decay half-life of visual image storage	200 ms	90–1000 ms
Decay half-life of auditory storage	1500 ms	90–3500 ms
Perceptual processor cycle time	100 ms	50–200 ms
Decay half-life of working memory	7 sec	5–226 sec
Cognitive processor cycle time	70 ms	25–170 ms



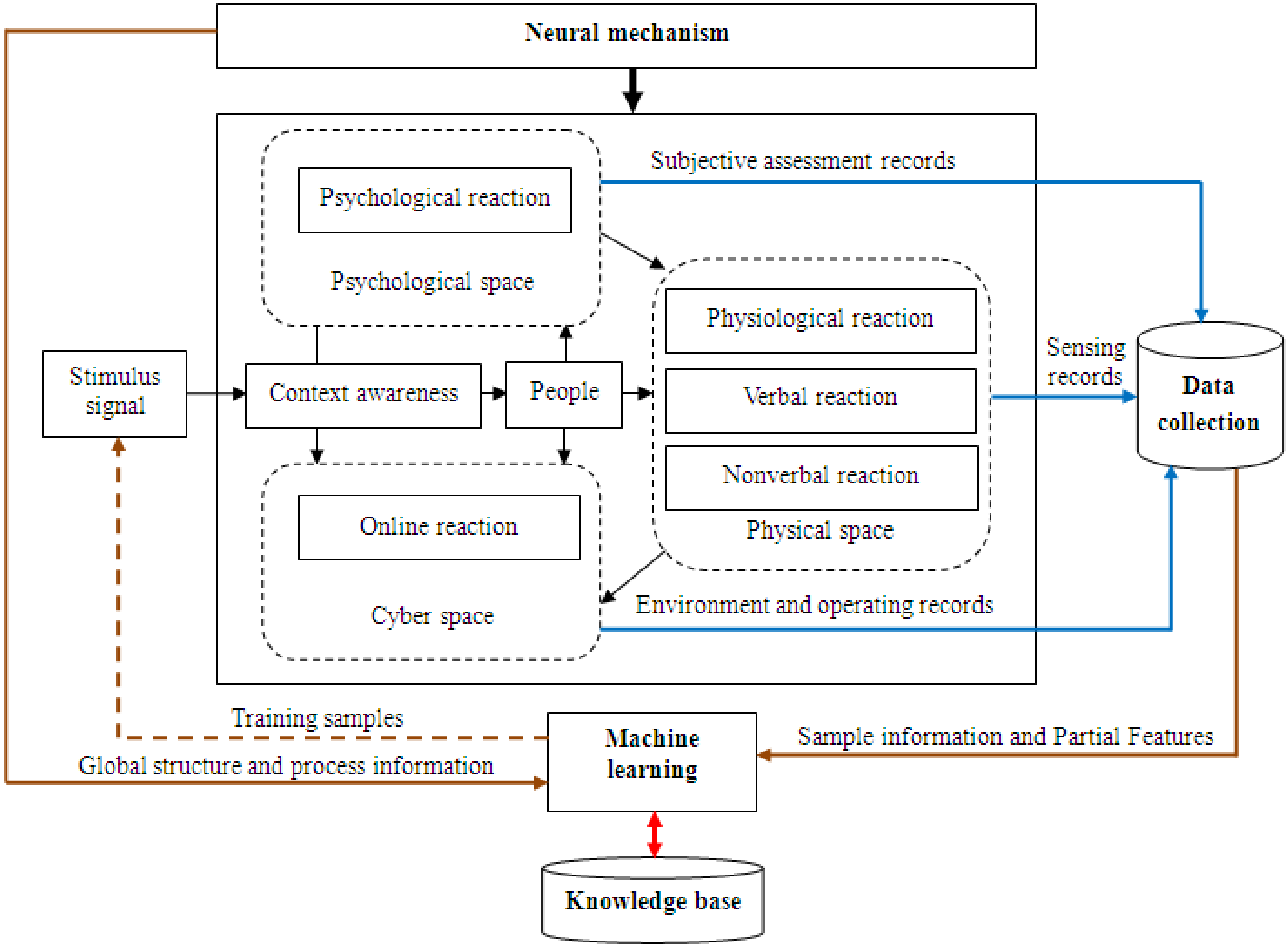
Social Neuromechanism

Social Neuroscience: J. T. Cacioppo and G. G. Berntson, “Social psychological contributions to the decade of the brain: doctrine of multilevel analysis,” *American Psychologist*, vol.47, pp.1019-1028, 1992.





Cyber Psychosocial and Physical Computation(CPP)



For example, if the task is to find the possible online actions based on psychological reactions, it can be described as a forward problem shown

$$R_{cyb}(t) = f(R_{psy}(t))$$

Reversely, estimation of the psychological states from the recoded data about environment information and operating actions can be described as an inverse problem shown

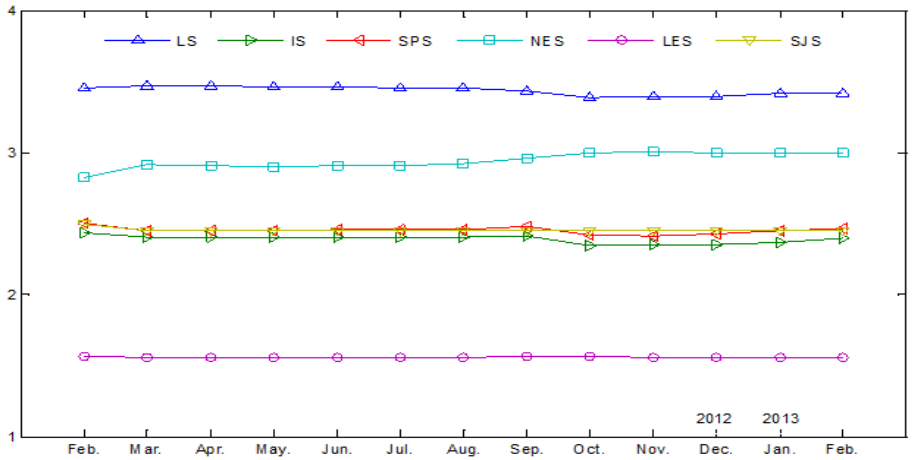
$$R_{psy}(t) = F(R_{cyb}(t))$$

Here, $F(\cdot)$ is the inverse operator of $f(\cdot)$

Cyber Psychosocial and Physical Computation(CPP)

In today's society, the sensing means and human-computer interfaces are becoming all-around and on-line. **This makes it more possible than ever before to study human's psychology and behaviors from the big data from cyber and physical spaces.**

A lot of researches have demonstrated that the cyber space is "an amplified forerunner of the real word" in social mood. So we can make a good judgment and timely grasp the emotional state of the real society in cyber space which is the well mapping of real social mood.



Based on the cyber psychosocial computation, the social satisfaction to the government's policies can be estimated at an accuracy rate of 84.5% compared with the real survey results.

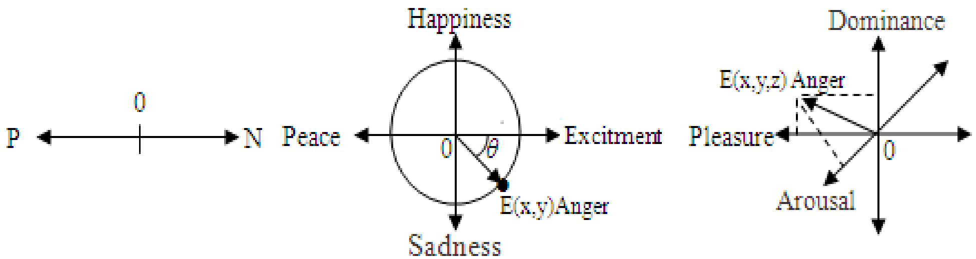
Computation in Psychological Space

In the psychological space, the reactions will bring subsequent activities and result in the changes of physiological variables which may be reported by subjective assessment and recorded in the data collection:

$$R_{psy}(t) = \{p_1(t), p_2(t), p_3(t), \cdots p_N(t)\}$$

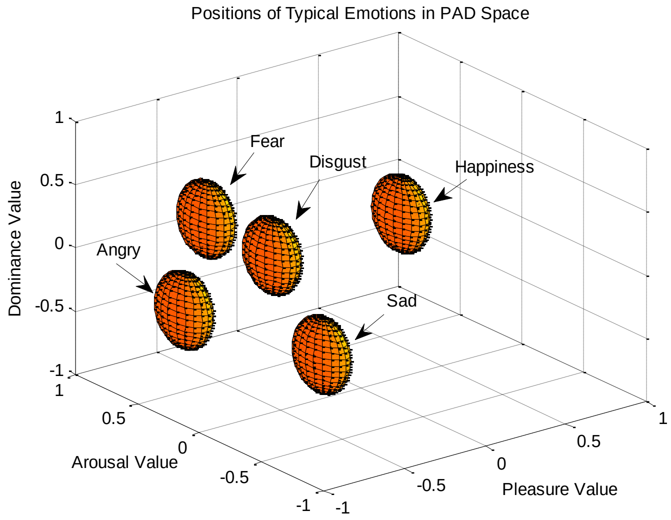
TABLE 1: Calibration for scoring records in psychological assessment

Variables	Scores										
Attention	0	1	2	3	4	5	6	7	8	9	10
Interest	0	1	2	3	4	5	6	7	8	9	10
Emotion	-5	-4	-3	-2	-1	0	1	2	3	4	5
Satisfaction	-5	-4	-3	-2	-1	0	1	2	3	4	5



1-D Coordinate 2-D Coordinate 3-D Coordinate

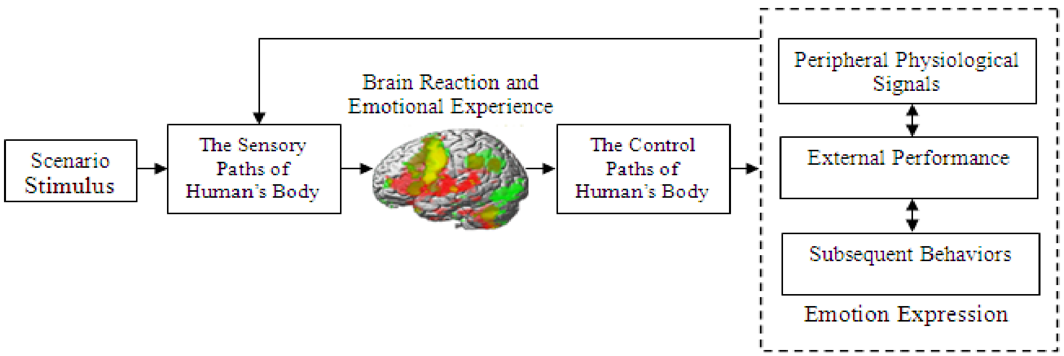
PAD model presented by A. Mehrabian in 1995

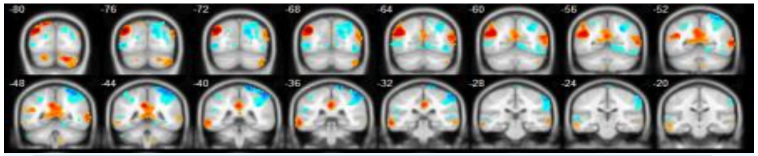


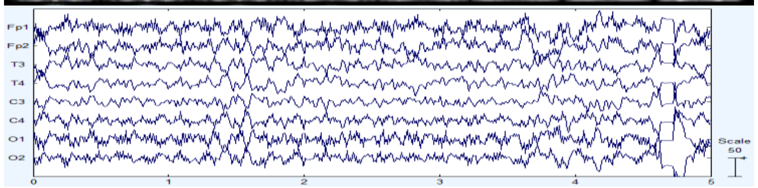
Computation in Physical Space

In the physical space, human's reactions exhibit on the variations of physiological signals (e.g. EEG, ECG, ERPs, respiration, skin temperature, etc.) and external performances (e.g. speeches, facial expressions, gestures, movements, subsequent behaviors, etc.) which can be divided into the verbal reactions and nonverbal reactions. Those reactions can be detected by sensing equipment and recorded in the data collection:

$$R_{phy}(t) = \{ph(t), vb(t), nbv(t)\}$$







Infrared pictures

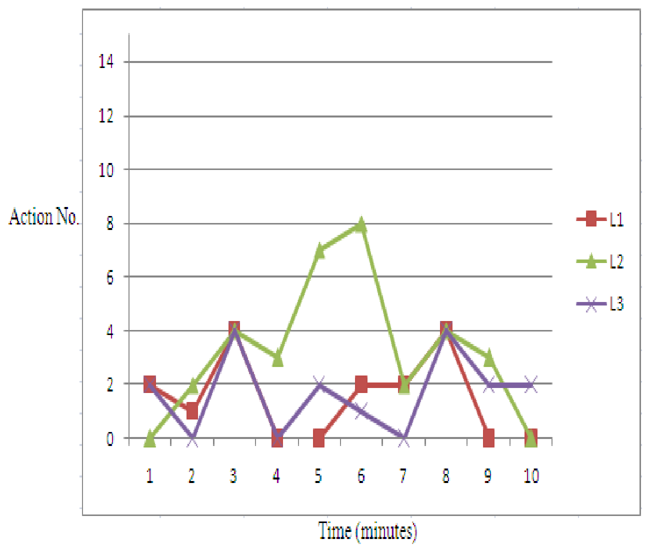
Computation in Cyber Space

In the cyber space, reactions are reflected on the actions such as the mouse movements and keyboard operations which are related to the current environment, for example, the layout and contents of a browsing web page. Therefore, the environment information and operating actions should be all recorded in the data collection by some online tracking and content analyzing tools :

$$R_{cyb}(t) = \{E(t), A(t)\}$$

TABLE 2: Basic actions and parameters of the learner's habitual behaviors in cyber space

No.	Actions	Parameters
0	No action	The object in screen center
1	Mouse: Click	on a botton or link, on other place
2	Mouse: Scroll	Speed, the object in screen center when stop scrolling
3	Mouse: Move	Speed, radius
4	Mouse: open a new page	null
5	Mouse: change a page	null
6	Mouse: close a page	null
7	Mouse: store a page	null
8	Keyboard: input	Number of characters
9	Keyboard: delete	Number of characters
10	Mouse and keyboard: retrieve information	Number of keywords
11	Mouse and keyboard: post information on BBS	Number of characters
12	Mouse and keyboard: send information to other people	Number of characters, number of recievers
13	Mouse and keyboard: chat with othet people	Number of characters, number of chated people
14	Streaming media: Voice communication	Acoustic fearture parameters
15	Streaming media: Video communication	Visual fearture parameters



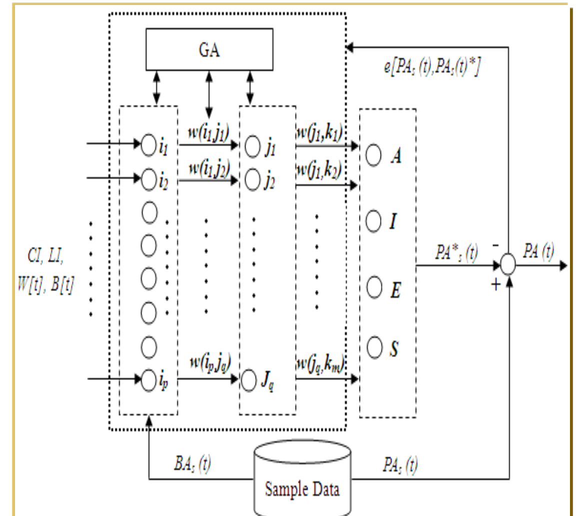
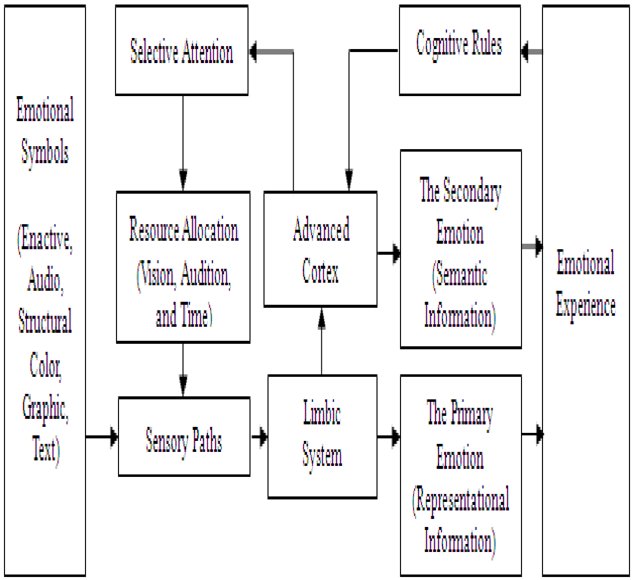
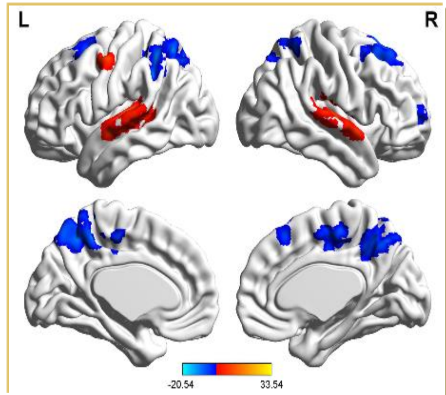
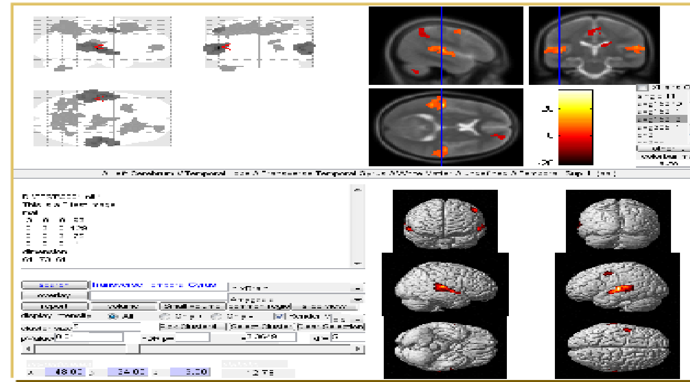


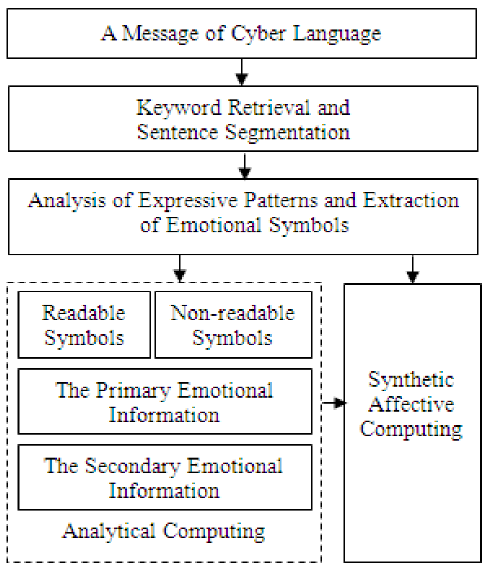
FIGURE 2: BP-GA neural network for CyberPsychological computation

Neural Cognition and Affective Computing on Cyber Language

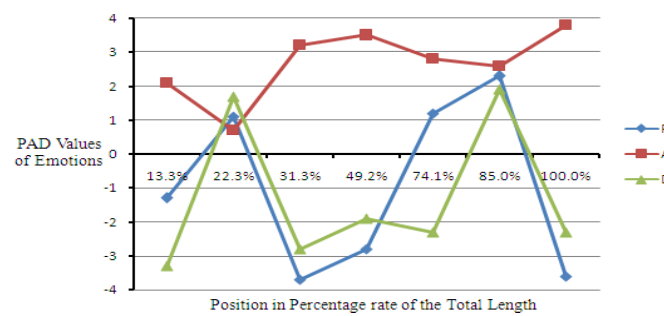








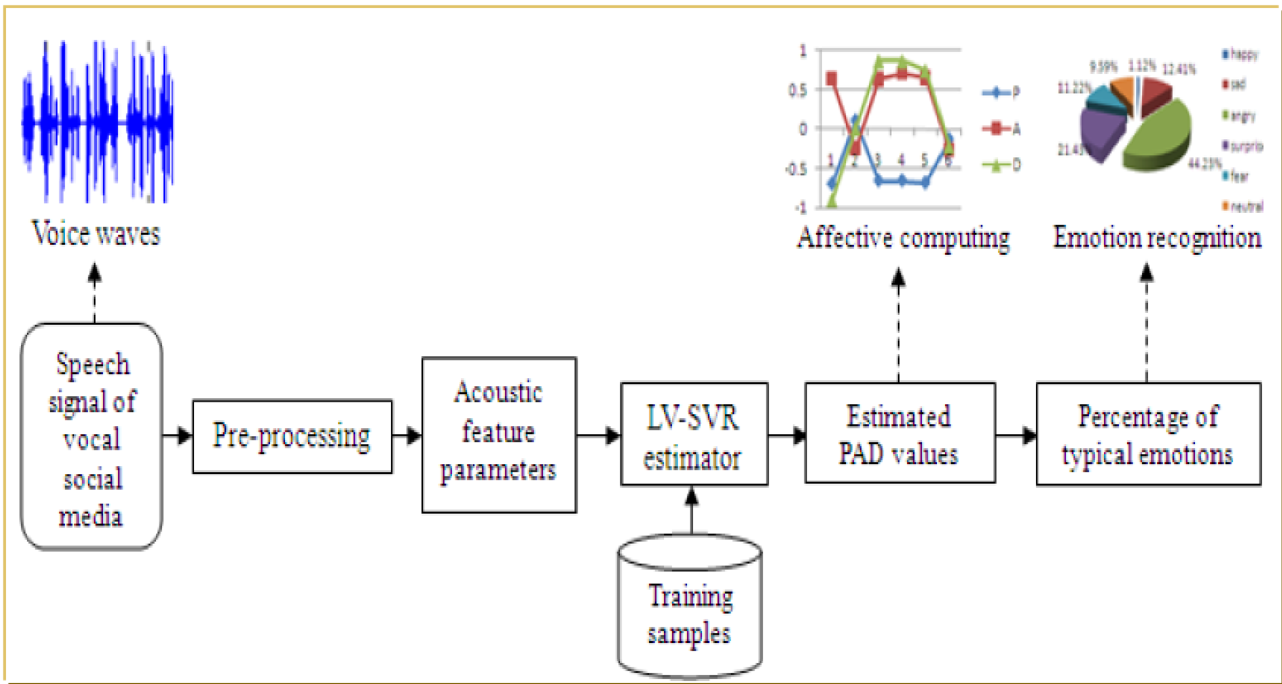
Functions of Connectors	Chinese	English	Spanish
Alternatives	①不是…就是.. ②即不是..也不是. ③或者 ④以及 ⑤和，与，并且 ⑥和…都	①either…or… ②neither…nor… ③or ④as well as ⑤and ⑥both…and….	①ni…ni… ②no…tampoco… ③y ④tambien ⑤y ⑥ambos…y…
Cause and Effect	①因此 ②所以 ③总之，因此 ④由于 ⑤基于，由于 ⑥因为	①therefore ②so ③as a result ④because of ⑤due to ⑥because	①por lo tanto ②así que ③por consiguiente ④por ⑤gracias a ⑥es que
Concession	①还未，仍然没有 ②但是，但 ③而，正当 ④相反地说,而是 ⑤可是，不过，然而 ⑥然而	①yet ②but ③while ④on the contrary ⑤however ⑥at the same time	①aún ②pero ③sino ④por el contrario ⑤sin embargo ⑥mientras
Conclusion/Summary	①总之 ②整体上，大体 ③简单地说，简言之 ④总结下就是说 ⑤总共，总计 ⑥概括下说	①in a word ②on the whole ③in brief ④to conclude ⑤in all ⑥to sum up	①en fin ②en general ③cortar el rollo ④para concluir ⑤en total ⑥resumir
Examples	①举例来说 ②在那个案例上 ③解释下，说明下 ④一方面地讲 ⑤打比方说，比如说 ⑥比如，譬如	①for example ②in that case ③to illustrate ④for one thing ⑤such as ⑥for instance	①por ejemplo ②en eso caso ③por ilustrar ④por una parte ⑤tal como ⑥entre ellos



Emotion Recognition and Affective Computing on Vocal Social Media

Vocal media has become a popular way of communication in today's social networks.

In the meantime of conveying semantic information, vocal message usually also contains abundant emotional information which has been the new focus of attention in the data-mining of social media analytics.



The emotion recognition and affective computing are based on the trained LV-SVR model as follows [47]:

Set $\{X_i, Z_i\}_{i=1}^{N}$ as the collection of the training samples, where the input $x_i \in R^n$ and the output $z_i \in R$, so the LS-SVR regression model in a high dimensional space can be described as:

$$z(x) = \omega^T \phi(x) + b \tag{4}$$

Here, ω^T is the vector of the weights, and $\phi(x)$ is the non-linear function for mapping the input x_i to that high dimensional space, b is the error constant. Therefore the estimation of $z(x)$ can be transformed into the following optimization problem:

$$\min J(\omega, e) = \frac{1}{2}\omega^T \omega + \frac{\gamma}{2}\sum_{i=1}^{N} e_i^2 \tag{5}$$

Subject to: $z(x_i) = \omega^T \phi(x_i) + b + e_i \quad i = 1,2,3,\cdots N$ (6)

Where, γ is the normalized constant, e_i is the error variable of x_i. Set the Lagrangian function as:

$$L(\omega, b, e, \alpha) = J(\omega, b, e) = \sum_{i=1}^{N} \alpha_i \{\omega^T \phi(x_i) + b - z_i + e_i\} \tag{7}$$

Where, α_i is the Lagrangian multiplier satisfying $\alpha_i \in R$. By solving extreme value point of $L(\omega, b, e, \alpha)$, we get the matrix of the linear equation:

$$\begin{bmatrix} 0 & -Z^T \\ Z & k(x, x_i) + \frac{1}{r} I \end{bmatrix} * \begin{bmatrix} b \\ \alpha_i \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \tag{8}$$

Where, $Z = (z_1, z_2, \cdots, z_n)$, $k(x, x_i)$ is the core function which must satisfy the Merce condition. Here, we choose RBF (Radical Basis Function) as the core function:

$$k(x, x_i) = \exp\left(-\frac{\|x - x_i\|^2}{2\sigma^2}\right) \tag{9}$$

Where, σ is the width of RBF, $i = 1,2,3,\cdots,N$. Calculating the Lagrangian multiplier α_i and the constant b, we get the LS-SVR estimation model:

$$f(x) = \sum_{i=1}^{N} \alpha_i k(x, x_i) + b \tag{10}$$

Combined with the Formula (9), we get the final LS-SVR model:

$$f(x) = \sum_{i=1}^{N} \alpha_i \left[\exp(-\|x - x_i\|^2 / 2\sigma^2)\right] + b \tag{11}$$

In the computation of LS-SVR model, the normalized constant γ and the width of RBF σ have major influence on the accuracy of estimated result. To avoid the fitting problem on the training sample, we adopt the cross validation method [45, 55] to choose the most suitable values of γ and σ in our method.

Emotion Recognition and Affective Computing on Vocal Social Media

The acoustic feature parameters require to be tested to show that they are only related to the vocal emotions and independent of the semantic information in a speech. This test is carried out with the CASIA, a widely used standard corpus for Chinese language test .

Based on the chosen parameters we apply our SVR model to estimate the PAD values of each emotional speech and convert the values into the most possible typical emotion state by Formula (12). Table 2 shows the test result of the recognition rates.

Table 2. Test result of recognition rates

Emotion type	Recognition rate
happy	81.32%
sad	85.27%
angry	87.72%
surprise	77.69%
fear	79.37%
neutral	83.23%
Average	82.43%

The test result shows that recognition rates of happy, sad, angry, surprise, fear, and neutral are 81.32%, 85.27%,87.72%, 77.69%, 79.37%, 83.23% respectively, and the average rate reaches 82.43%, which are higher than the existing results reported by the similar tests.

Table 4. Chats on Wechat and the estimated PAD values

Chat No.	Start time	End time	Speaker ID	Referred listeners' ID	Estimated PAD values by the LV-SRV model
1	00:00:00	00:00:07	NO.001	All	(-0.692, 0.617, 0.891)
2	00:00:11	00:00:29	NO.002	All	(-0.712, 0.721, 0.913)
3	00:00:33	00:00:39	NO.003	All	(-0.156, 0.525, -0.192)
4	00:00:42	00:00:56	NO.004	NO.003	(-0.101, -0.311, -0.114)
5	00:01:00	00:01:18	NO.005	All	(-0.697, 0.633, -0.907)
6	00:01:23	00:01:33	NO.003	All	(0.105, -0.251, 0.002)
7	00:01:45	00:02:02	NO.002	NO.003	(-0.655, 0.626, 0.866)
8	00:02:17	00:02:30	NO.006	All	(-0.803, 0.609, 0.798)
9	00:02:39	00:02:56	NO.007	All	(-0.653, 0.707, 0.863)
10	00:03:10	00:03:45	NO.003	All	(-0.682, 0.644, 0.743)
11	00:03:52	00:04:14	NO.004	All	(-0.131, -0.267, -0.225)
12	00:04:21	00:04:48	NO.004	NO.001	(0.102, -0.312, -0.123)
13	00:04:59	00:05:16	NO.008	All	(0.104, -0.261, -0.002)
14	00:05:26	00:05:46	NO.004	All	(0.111, -0.107, -0.211)
15	00:05:56	00:06:12	NO.003	All	(0.108, -0.119, -0.111)
...	...	...	...	...	...
52	00:35:11	00:35:27	NO.001	All	(0.107, -0.351, 0.022)

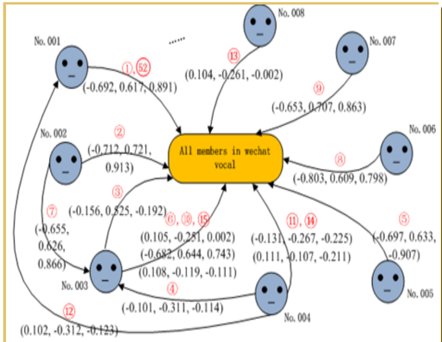


Fig.7. Dynamic process of emotion propagation in the group

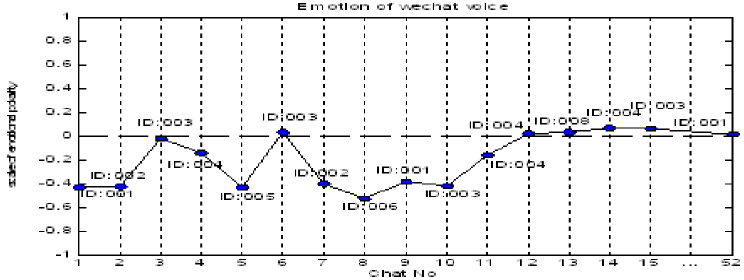


Fig.8. Dynamic process of emotion propagation in positive and negative coordinates

From Fig.8, we can find that this propagation started from No.001 with a strong negative emotion to this group, hereafter negatively enlarged by No.002, and finally stopped at No.001 in the nearly neutral emotion. In whole process, No.002 contributed the most negative emotions, No.004 acted as the most active participant, and No.003 had the most impacts on the group who looked like the opinion leader.

Machine Learning

We believe that machine learning can be the most prospective even the only way to accomplish the complex computation on human's psychology and behaviors in the ubiquitous environment.

However, in doing so, the research of machine learning needs to pay attention to the following new aspects which may be beyond the computer science and technology, and require the interdisciplinary ideas and methods:

(1) Comprehensive ability of context awareness in physical, cyber and psychological spaces as well as the information fusion processing which we called as CPP (CyberPsychological and Physical) computation;

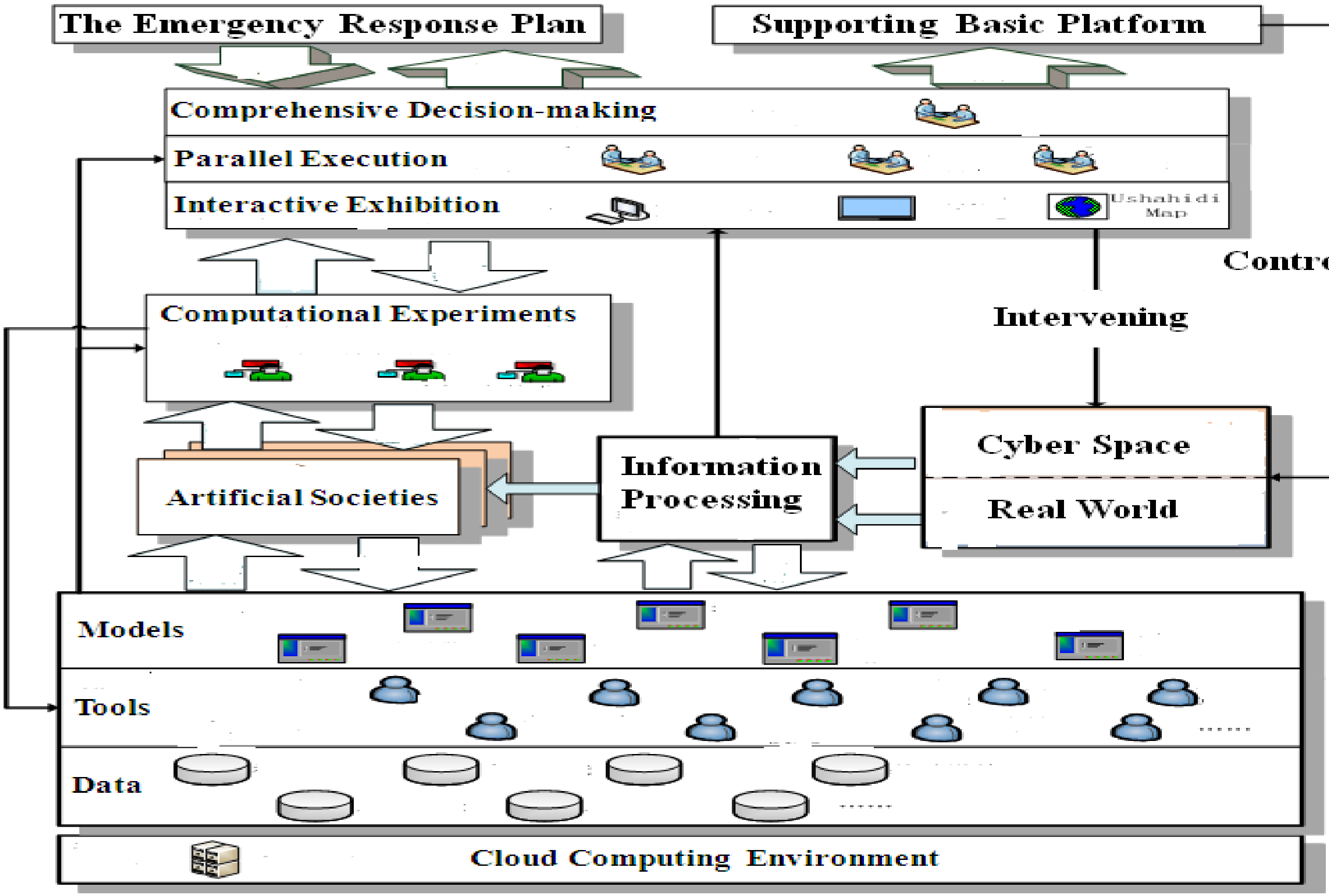
(2) Endowment with both rational intelligence and emotional intelligence of human beings in the learning process which called as smart learning;

(3) A systematic model such as neural mechanism which describes the dominant process of human's psychology and behaviors, and helps the machine to understand its globally structural features and therefore reduce the computational cost by learning from the limited samples of a big data set.

One barrier needs to be broken is **how to avoid the "curse of dimensionality" and ensure the generalization ability in the learning process.** Fortunately, the tentative path has been lighted owing to the efforts such as **D. Koller & N. Friedman' work on Probabilistic Graphical Models** and the **Compressive Sensing (CS) theory presented by E. Candès & E. Candès, etc**.

"predicting" the changes based on generalization ability and **"describing" the knowledge discovered from huge data** will be the big two tasks of machine learning in the future.

Simulation Platform Unconventional Emergency



TDF (Theory-Data-Feedback) Framework and Method

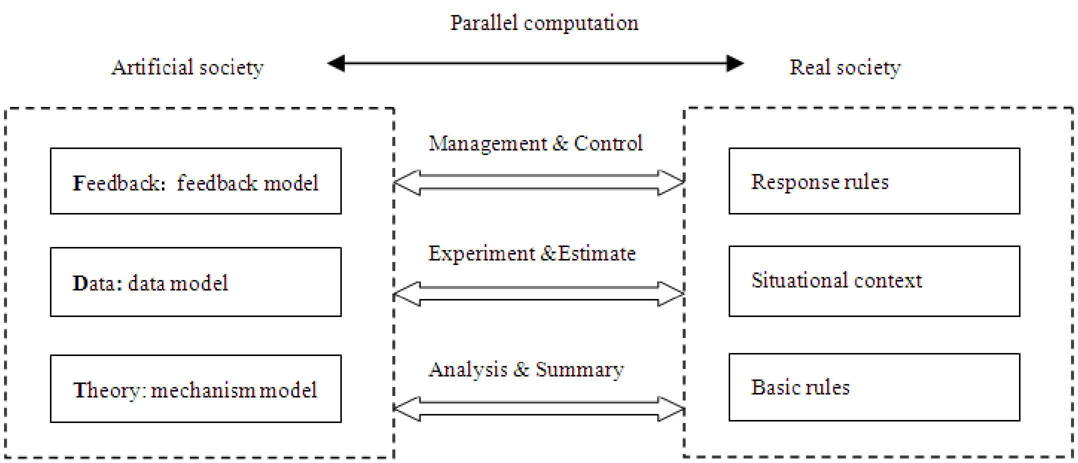
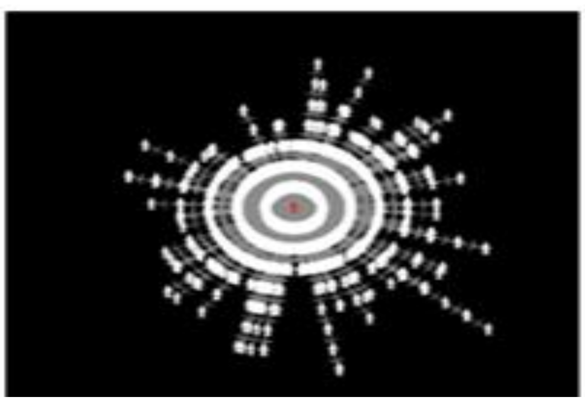
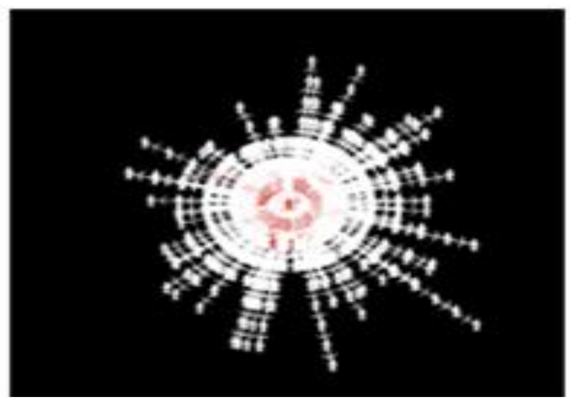
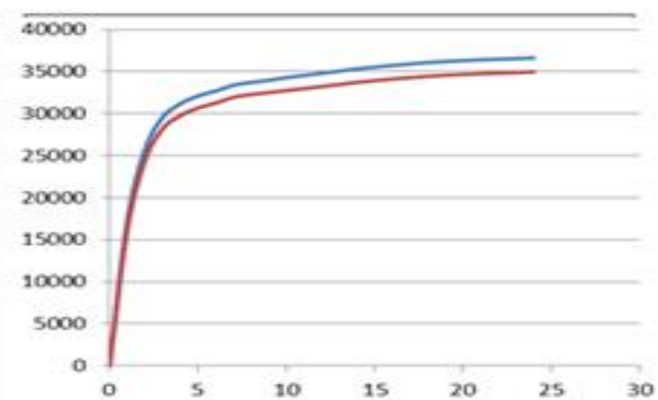


TABLE 1: Information dissemination on social networks

Time(hours)	Number of Information Dissemination	Time(hours)	Number of Information Dissemination
1	17107	13	261
2	8530	14	272
3	3896	15	204
4	1624	16	200
5	937	17	181
6	585	18	166
7	698	19	132
8	337	20	98
9	255	21	98
10	314	22	70
11	264	23	63
12	250	24	80







Application

Prediction of the Ebola outbreak in Beijing and Bird flu in China.

Table.3 The verification of infection probability

Infection probability (IP)	Reproductive number (R_0)	Doubling times (Dt)	Remark
0.005	1.7141	40	Failed
0.008	1.9107	27	Failed
0.01	2.2108	21	selected
0.02	3.1105	11	discard
0.05	4.7008	5	discard

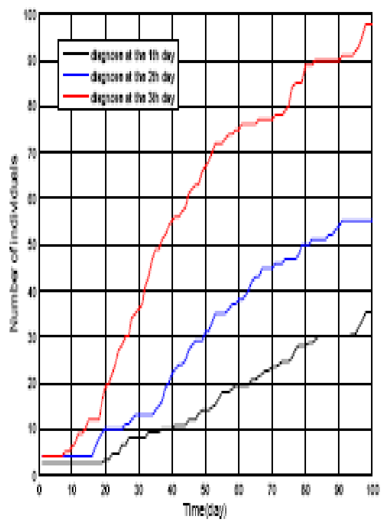


FIGURE 6: Total infection cases under different diagnose time

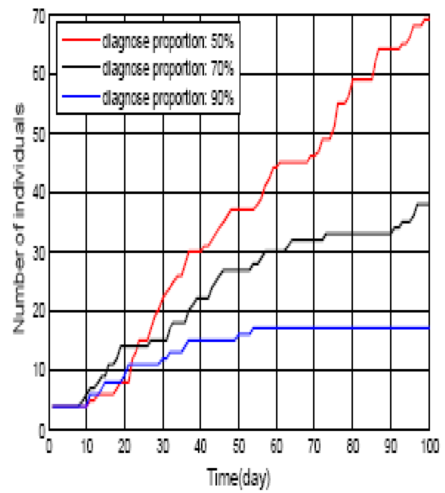
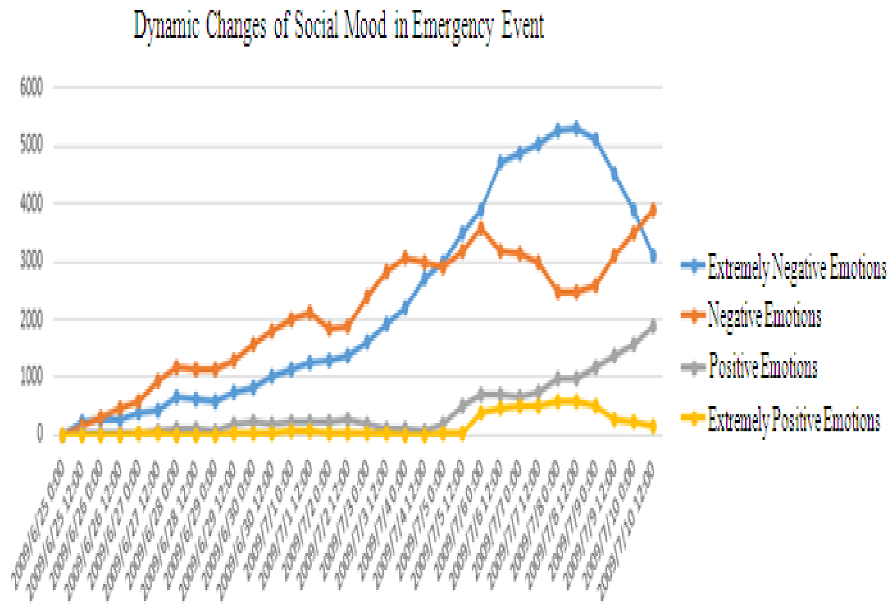


FIGURE 7: Total infections under different diagnose protection

The dynamic changes of social mood in a real emergency event which took place in Urumchi, China in 2009. It was produced by the CPP computation based on smart learning from the historical data of on-site records, survey and cyber information, and estimated



Thank you!