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Affective rating ranking based on face images in arousal-valence dimensional space

Key words: Ordinal ranking; Dimensional affect recognition; Valence; Arousal; Facial image processing

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Motivations

1. Affect recognition involves multiple scientific disciplines, which has huge research and application value.

2. A small number of discrete emotion categories are not enough to reflect the complexity of affective states, thus the use of the dimensional description of affect is advocated.

3. In dimensional affect recognition, commonly used classification and regression methods do not use the ordinal property of dimensional affective annotations.

4. An affective rating ranking framework is proposed to use the ordinal property appropriately and improve the performance.

Contributions

1. This is the first paper proposing the ordinal ranking approach to predict affect ratings based on face images in the arousal-valence space.

2. We conduct exhaustive experiments to compare the performance of our ranking method with different cost-sensitive settings and empirically find the most suitable settings for affect rating ranking in arousal and valence dimensions.

Methods

1. Transform continuous affective annotations to form discrete and finite affective ratings.

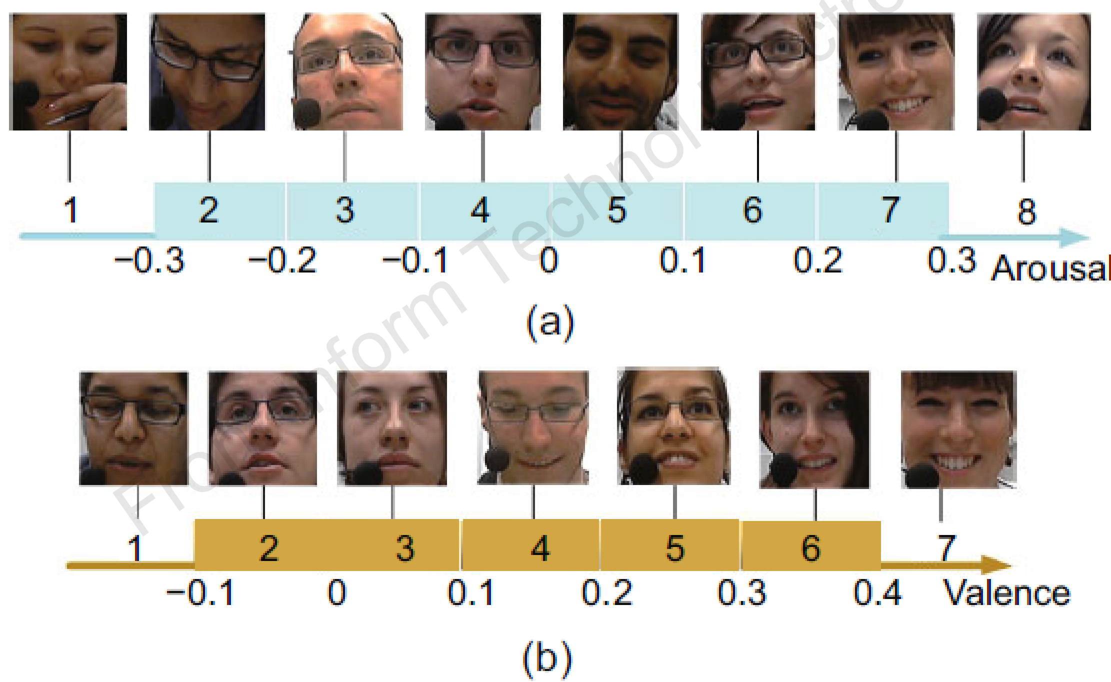

Fig. 3 Presentation of discretized affective ratings and some corresponding face images of the AVEC 2015 benchmarking database in arousal (a) and valence (b)

Methods

2. Train a series of cost-sensitive binary classifiers for affective rating ranking.

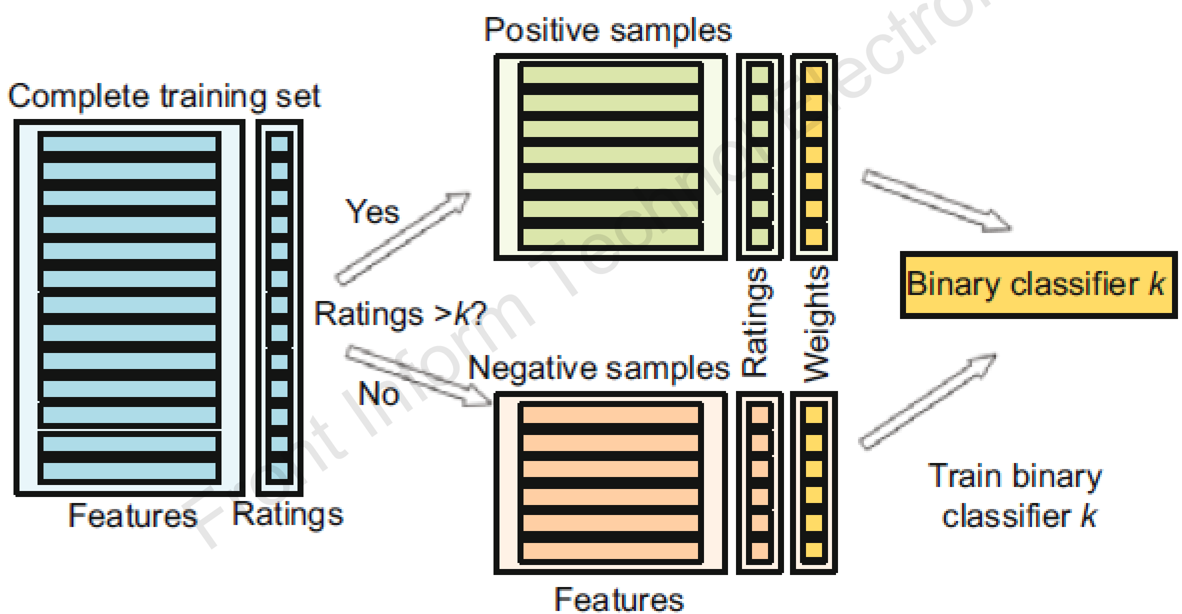

Fig. 2 Training process of the k^{th} cost-sensitive binary classifier

Methods

3. Aggregate binary decision results of all binary classifiers for affective rating inference.

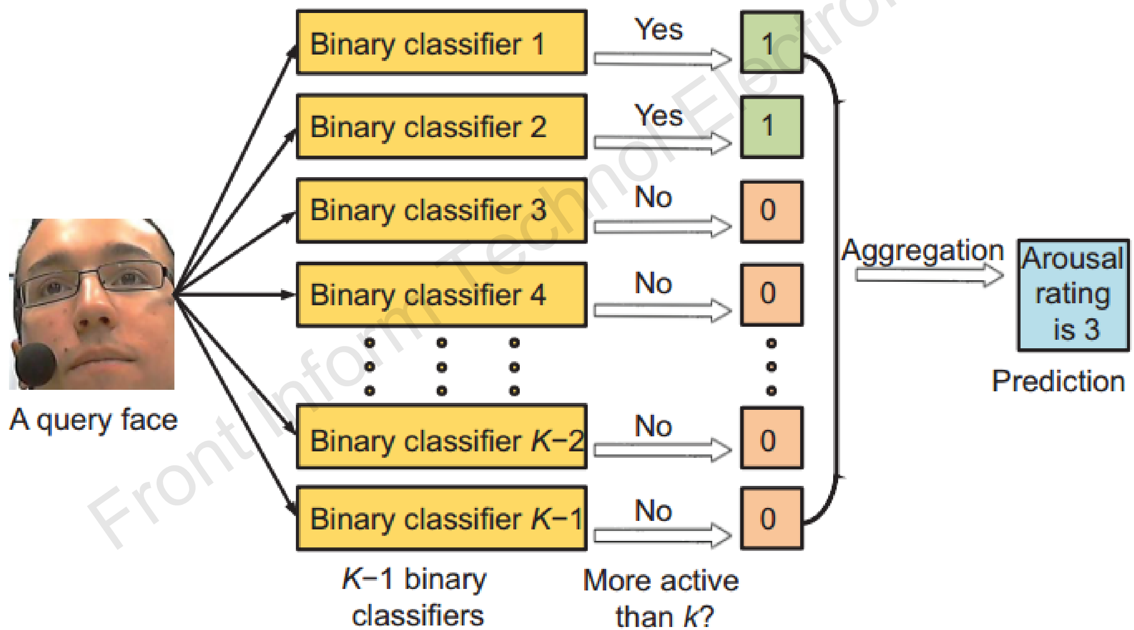

Fig. 1 Illustration of our affective rating ranking framework for arousal rating estimation of a given sample

Major results

1. Our ranking method can produce better results compared with other methods in 2 datasets.

Table 3 CS-1 and MAE comparison in arousal in the AVEC 2015 benchmarking database

Learning method	Feature type	CS-1 (%)	MAE
Epsilon-SVR	LGBP	29.42	1.9011
C-SVC	LGBP	38.44	2.2211
ARR-SVM	LGBP	42.11	1.8559
Epsilon-SVR	ST	31.07	1.7922
C-SVC	ST	39.29	2.3596
ARR-SVM	ST	**50.83**	**1.7507**
C-CNN	–	44.58	1.9469
R-DBLSTM	ST	32.27	1.7653

Bold numbers denote the best results. CS-1: cumulative score calculated by Eq. (3) when $L=1$; MAE: mean absolute error

Table 4 CS-1 and MAE comparison in valence in the AVEC 2015 benchmarking database

Learning method	Feature type	CS-1 (%)	MAE
Epsilon-SVR	LGBP	39.91	1.5362
C-SVC	LGBP	58.74	1.5048
ARR-SVM	LGBP	65.89	1.3387
Epsilon-SVR	ST	43.47	1.3840
C-SVC	ST	**66.45**	1.3854
ARR-SVM	ST	63.84	**1.3286**
C-CNN	–	54.88	1.6687
R-DBLSTM	ST	47.60	1.3483

Bold numbers denote the best results. CS-1: cumulative score calculated by Eq. (3) when $L=1$; MAE: mean absolute error

Major results

Table 5 CS-1 and MAE comparison in arousal in the subset of the SEMAINE database

Learning method	Feature type	CS-1 (%)	MAE
Epsilon-SVR	LGBP	28.93	1.8084
C-SVC	LGBP	29.11	2.7851
ARR-SVM	LGBP	45.79	1.8660
Epsilon-SVR	ST	26.21	1.8576
C-SVC	ST	44.60	2.0549
ARR-SVM	ST	45.23	1.7197
C-CNN	–	**53.30**	**1.5828**
R-DBLSTM	ST	29.45	1.6413

Bold numbers denote the best results. CS-1: cumulative score calculated by Eq. (3) when $L=1$; MAE: mean absolute error

Table 6 CS-1 and MAE comparison in valence in the subset of the SEMAINE database

Learning method	Feature type	CS-1 (%)	MAE
Epsilon-SVR	LGBP	35.38	**1.7214**
C-SVC	LGBP	42.65	2.3794
ARR-SVM	LGBP	**46.25**	2.0434
Epsilon-SVR	ST	20.98	2.1378
C-SVC	ST	42.88	2.1558
ARR-SVM	ST	44.18	1.9989
C-CNN	–	45.16	2.2341
R-DBLSTM	ST	34.77	1.8238

Bold numbers denote the best results. CS-1: cumulative score calculated by Eq. (3) when $L=1$; MAE: mean absolute error

Major results

2. Exhaustive experiments are conducted to find the most suitable cost-sensitive settings in arousal and valence empirically.

Table 7 Accuracy, CS-1, and MAE comparison of ARR-SVM when using different cost-sensitive settings and features in arousal

Cost	Feature type	Accuracy (%)	CS-1 (%)	MAE
No cost	LGBP	14.64	41.63	1.9023
CS-1	LGBP	14.73	41.55	1.9052
CS-2	LGBP	14.76	**42.12**	1.8835
CS-3	LGBP	14.50	41.40	1.9063
CSMAE1	LGBP	14.51	41.84	1.8870
CSMAE2	LGBP	14.45	41.65	1.8876
CSMAE3	LGBP	15.30	41.97	**1.8434**
Absolute	LGBP	**15.33**	42.11	1.8559
No cost	ST	17.57	49.10	1.7806
CS-1	ST	16.43	45.92	1.8160
CS-2	ST	16.75	48.24	1.7821
CS-3	ST	16.62	48.59	1.7938
CSMAE1	ST	16.83	49.03	1.8133
CSMAE2	ST	16.61	47.77	1.8158
CSMAE3	ST	16.98	48.48	1.7513
Absolute	ST	**17.75**	**50.83**	**1.7507**

No cost: no cost used for data reweighting; MAE: mean absolute error; CS-n: cost generated by Eq. (5) when $L=n$ (n=1, 2, 3); CSMAEn: cost generated by Eq. (6) when $L=n$ (n=1, 2, 3); Absolute: cost generated by Eq. (4). Bold numbers denote the best results

Table 8 Accuracy, CS-1, and MAE comparison of ARR-SVM when using different cost-sensitive settings and features in valence

Cost	Feature type	Accuracy (%)	CS-1 (%)	MAE
No cost	LGBP	22.93	65.91	1.3426
CS-1	LGBP	**24.22**	64.34	1.3969
CS-2	LGBP	23.88	64.56	1.3776
CS-3	LGBP	23.44	**65.98**	1.3402
CSMAE1	LGBP	23.66	63.38	1.4077
CSMAE2	LGBP	23.88	64.31	1.3785
CSMAE3	LGBP	23.91	65.89	**1.3387**
Absolute	LGBP	22.13	60.05	1.4607
No cost	ST	23.01	62.69	1.4035
CS-1	ST	23.72	64.08	1.3426
CS-2	ST	23.58	62.64	1.3528
CS-3	ST	23.60	**64.26**	1.3320
CSMAE1	ST	22.73	62.11	1.3642
CSMAE2	ST	23.88	62.49	1.3510
CSMAE3	ST	**24.96**	63.84	**1.3286**
Absolute	ST	23.96	63.24	1.3473

No cost: no cost used for data reweighting; MAE: mean absolute error; CS-n: cost generated by Eq. (5) when $L=n$ (n=1, 2, 3); CSMAEn: cost generated by Eq. (6) when $L=n$ (n=1, 2, 3); Absolute: cost generated by Eq. (4). Bold numbers denote the best results

Conclusions

1. In this paper, we proposed an ordinal ranking framework to solve the affect recognition problem in the arousal-valence space. It appropriately uses the ordinal property of dimensional affective annotations.

2. Experiment results demonstrated the effectiveness of our ranking method in both arousal and valence dimensions and the ordinal property of the annotations is important to use to enhance recognition performance.