Lecture 13:

Word embedding and sentiment analysis

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Agenda

- Recap
- Word2Vec
- Sentiment analysis
- Affect states
  - Emotion
  - Personality traits

Zhizheng | Cai Xukun

`cosine_similarity(` [-0.4, 0.8, 0.5, -0.2, 0.3] `,` [-0.3, 0.2, 0.3, -0.4, 0.9] `) = 0.66`

Zhizheng | Michelle Yeoh

`cosine_similarity(` [-0.4, 0.8, 0.5, -0.2, 0.3] `,` [-0.5, -0.4, -0.2, 0.7, -0.1] `) = -0.37`

Embedding representations

Dense Matrix

1	2	31	2	9	7	34	22	11	5
11	92	4	3	2	2	3	3	2	1
3	9	13	8	21	17	4	2	1	4
8	32	1	2	34	18	7	78	10	7
9	22	3	9	8	71	12	22	17	3
13	21	21	9	2	47	1	81	21	9
21	12	53	12	91	24	81	8	91	2
61	8	33	82	19	87	16	3	1	55
54	4	78	24	18	11	4	2	99	5
13	22	32	42	9	15	9	22	1	21

Sparse Matrix

1	.	3	.	9	.	3	.	.	.
11	.	4	.	.	.	.	.	2	1
.	.	1	.	.	.	4	.	1	.
8	.	.	.	3	1	.	.	.	.
.	.	.	9	.	.	1	.	17	.
13	21	.	9	2	47	1	81	21	9
.	.	.	.	.	.	.	.	.	.
.	.	.	.	19	8	16	.	.	55
54	4	.	.	.	11	.	.	.	.
.	.	2	.	.	.	.	22	.	21

Sparse versus dense vectors

TF-IDF (or PMI) vectors are

- **long** (length |V|= 20,000 to 50,000)
- **sparse** (most elements are zero)

Alternative: learn vectors which are

- **short** (length 50-1000)
- **dense** (most elements are non-zero)

Sparse versus dense vectors

- Why dense vectors?
  - Short vectors may be easier to use as features in machine learning (fewer weights to tune)
  - Dense vectors may generalize better than explicit counts
  - Dense vectors may do better at capturing synonymy:
    - car and automobile are synonyms; but are distinct dimensions
    - a word with car as a neighbor and a word with automobile as a neighbor should be similar, but aren't
- In practice, they work better

Static embedding: one fixed embedding for each word in the vocabulary

Dynamic embedding: the vector for each word is different in different contexts

Word2vec

Popular embedding method

Very fast to train

Idea: **predict** rather than **count**

Word2vec provides various options. We'll do:

skip-gram with negative sampling (SGNS)

Skip-gram with negative samples

```
... lemon,  a [tablespoon of apricot jam,     a] pinch ...
               c1          c2     w     c3        c4
```

positive examples +

w	c_{pos}
apricot	tablespoon
apricot	of
apricot	jam
apricot	a

negative examples -

w	c_{neg}	w	c_{neg}
apricot	aardvark	apricot	seven
apricot	my	apricot	forever
apricot	where	apricot	dear
apricot	coaxial	apricot	if

Word2vec

Instead of **counting** how often each word *w* occurs near "*apricot*"

- Train a classifier on a binary **prediction** task:
  - Is *w* likely to show up near "*apricot*"?

We don't actually care about this task

- But we'll take the learned classifier weights as the word embeddings

Big idea: **self-supervision**:

- A word c that occurs near apricot in the corpus cats as the gold "correct answer" for supervised learning
- No need for human labels
- Bengio et al. (2003); Collobert et al. (2011)

Approach: predict if candidate word *c* is a "neighbor"

1. Treat the target word *t* and a neighboring context word *c* as **positive examples**.
2. Randomly sample other words in the lexicon to get negative examples
3. Use logistic regression to train a classifier to distinguish those two cases
4. Use the learned weights as the embeddings

Skip-Gram Training Data

Assume a +/- 2 word window, given training sentence:

…lemon, a [tablespoon of apricot jam, a] pinch…

c1 c2 c3 c4

[target]

Skip-Gram Classifier

(assuming a +/- 2 word window)

…lemon, a [tablespoon of apricot jam, a] pinch…

c1 c2 [target] c3 c4

Goal: train a classifier that is given a candidate (**w**ord, **c**ontext) pair

(apricot, jam)

(apricot, aardvark)

…

And assigns each pair a probability:

$P(+|w, c)$

$P(-|w, c) = 1 - P(+|w, c)$

Sentiment analysis

+	*...zany characters and richly applied satire, and some great plot twists*
−	*It was pathetic. The worst part about it was the boxing scenes...*
+	*...awesome caramel sauce and sweet toasty almonds. I love this place!*
−	*...awful pizza and ridiculously overpriced...*

Positive or negative movie review?

+ *...zany characters and richly applied satire, and some great plot twists*

− *It was pathetic. The worst part about it was the boxing scenes...*

+ *...awesome caramel sauce and sweet toasty almonds. I love this place!*

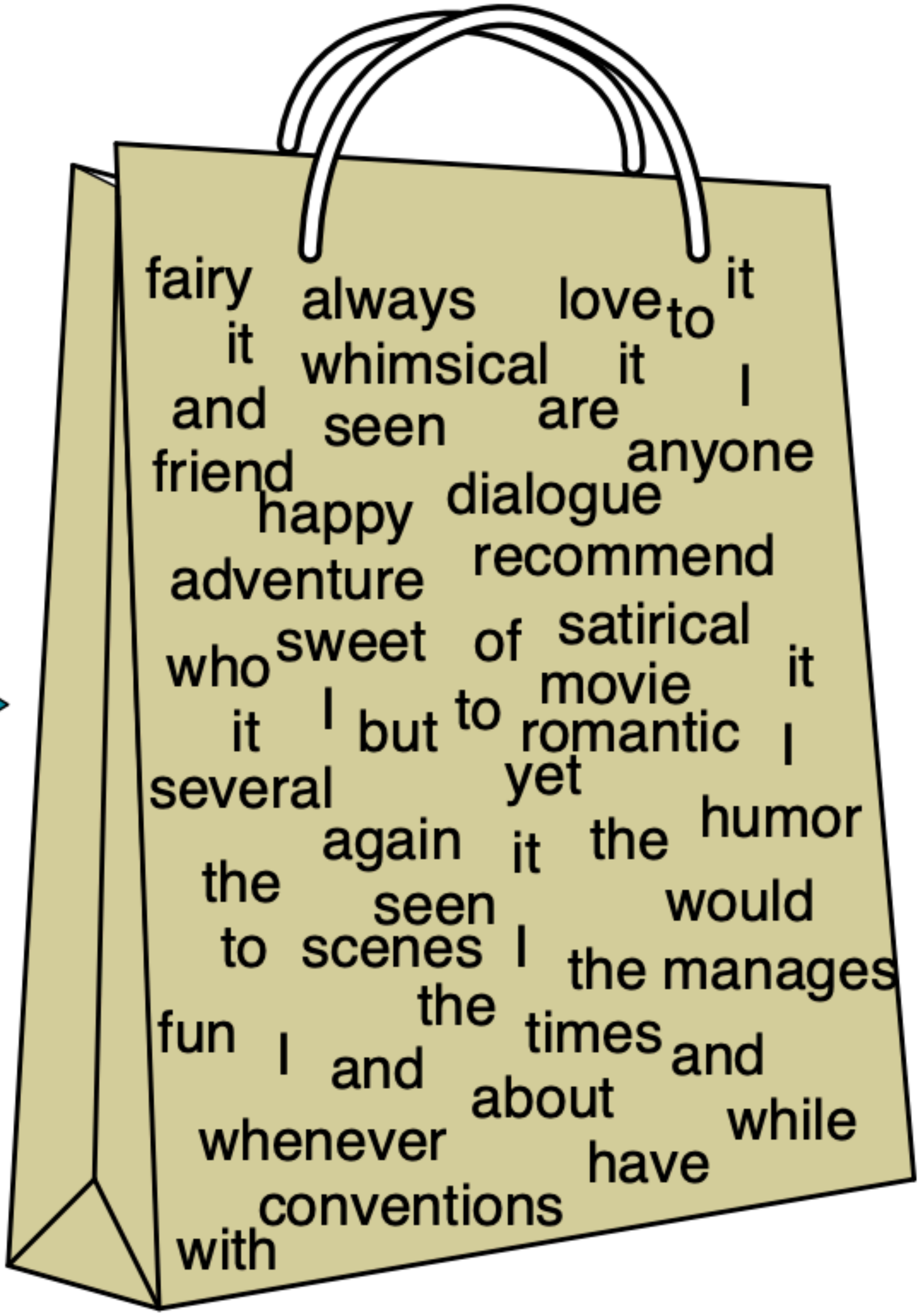
− *...awful pizza and ridiculously overpriced...*

Positive or negative movie review?

- \+ *...zany characters and **richly** applied satire, and some **great** plot twists*
- – *It was **pathetic**. The **worst** part about it was the boxing scenes...*
- \+ *...**awesome** caramel sauce and sweet toasty almonds. I **love** this place!*
- – *...**awful** pizza and **ridiculously** overpriced...*

THE UNITED STATES
QUARTER DOLLAR
LIBERTY
IN GOD WE TRUST
ONE DIME
E PLURIBUS UNUM
WASHINGTON
Treasurer of the United States.
ONE DOLLAR

I love this movie! It's sweet, but with satirical humor. The dialogue is great and the adventure scenes are fun... It manages to be whimsical and romantic while laughing at the conventions of the fairy tale genre. I would recommend it to just about anyone. I've seen it several times, and I'm always happy to see it again whenever I have a friend who hasn't seen it yet!



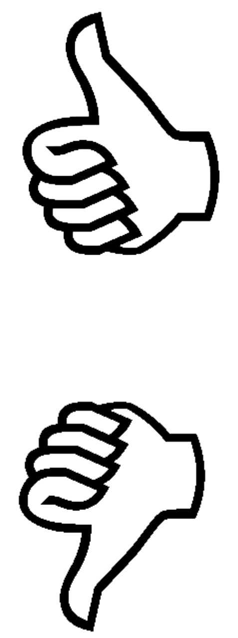
it	6
I	5
the	4
to	3
and	3
seen	2
yet	1
would	1
whimsical	1
times	1
sweet	1
satirical	1
adventure	1
genre	1
fairy	1
humor	1
have	1
great	1
…	…

Vector representation

$\mathcal{F}($

seen	2
sweet	1
whimsical	1
recommend	1
happy	1
...	...

$) = c$



Data sources

- Hand labeling
- kaggle.com
- Internet

起昵称回廊亭屎 2023-03

3月11日晚观影下楼有感

看完电影十一点半，商场关了，从五楼下
面的竖状金属反射材质使得视觉上有了额
说是日落黄昏时火炬似的黄色晚霞，是晚
(展开)

△ 56 ▽ 1 11回应

小苗 2023-03-07 18:08:0

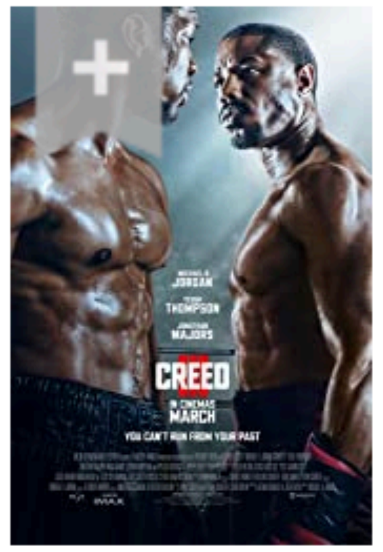
他为什么不死，你为什么而活

| 这篇影评可能有剧透

周末的时候，参加了一个兴趣社团的聚餐，
姑娘。餐厅很吵，餐桌很长，大多数时间，
了，但是我清楚的记得，小姑娘聊到，她
(展开)

△ 13 ▽ 1 0回应

Scream VI (2023)
1 (▲ 18)
★ 7.3



Creed III (2023)
2 (▲ 3)
★ 7.3

Everything Everywhere All at Once (2022)
3 (▲ 3)
★ 7.9

Cocaine Bear (2023)
4 (▼ 3)
★ 6.3

The Whale (2022)
5 (▼ 1)
★ 7.8

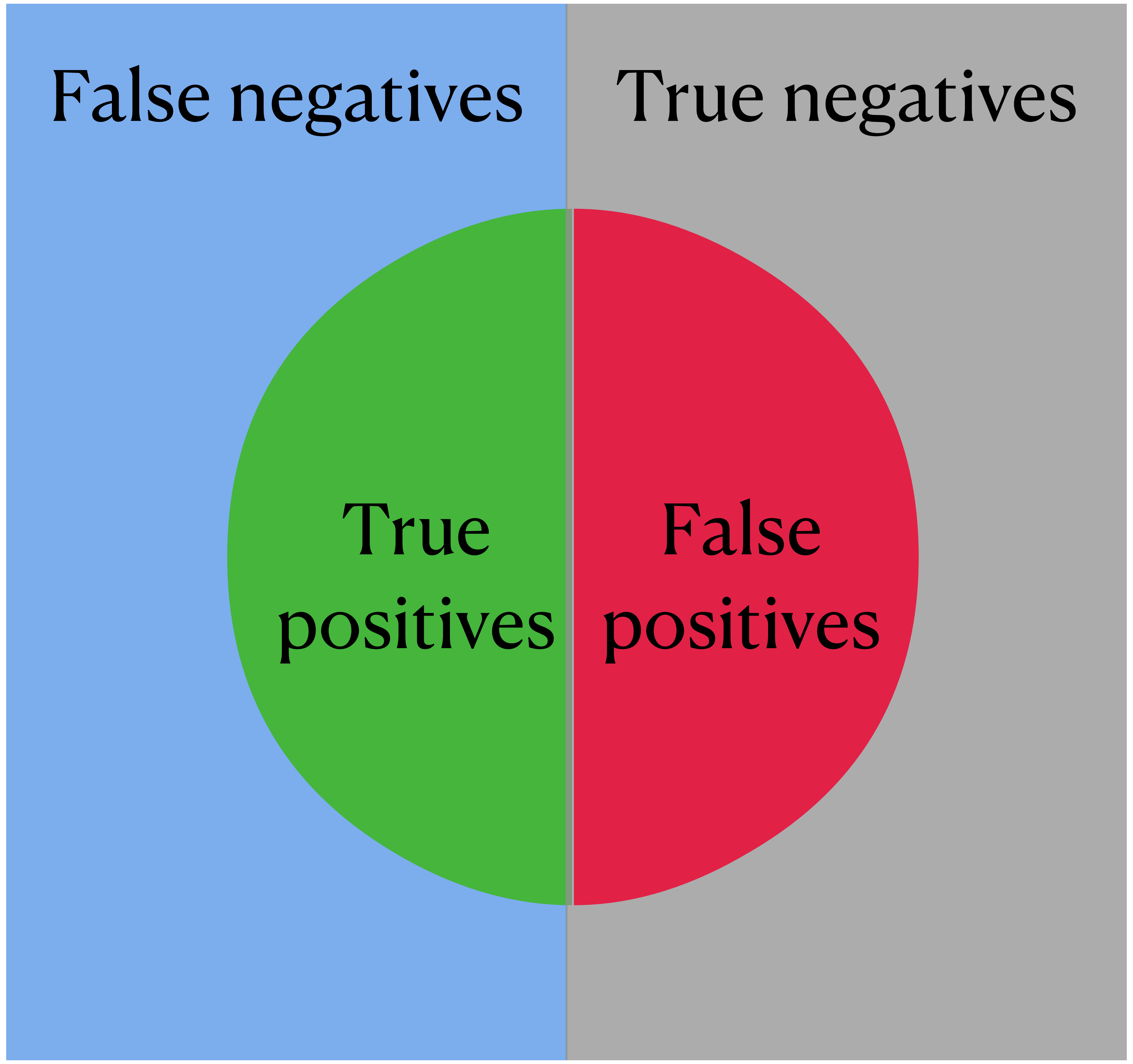
Ghosted (2023)
6 (▲ 2,371)

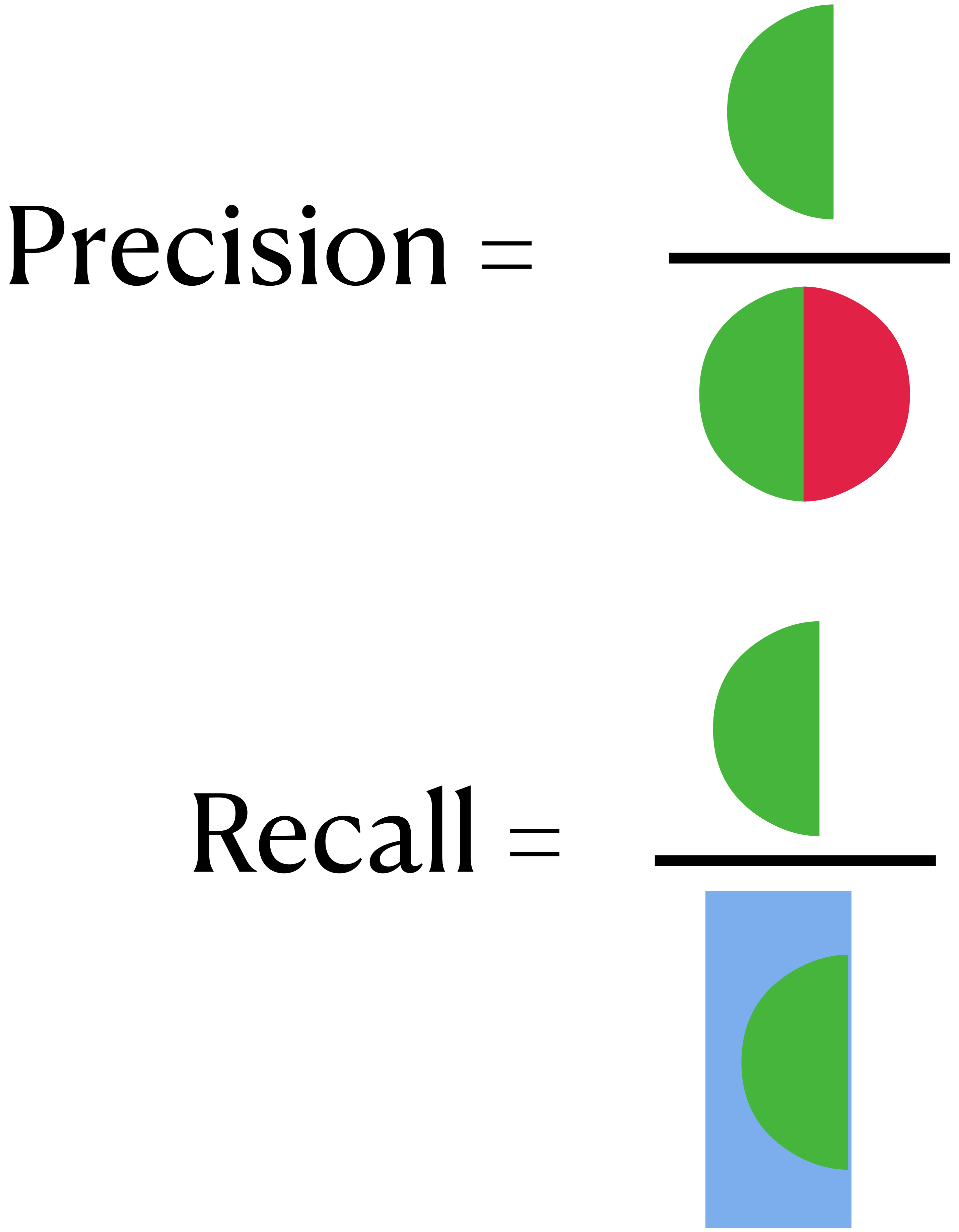
Teenage Mutant Ninja Turtles: Mutant Mayhem (2023)
7 (▲ 1,401)

65 (2023)
8 (▲ 29)
★ 5.7

Evaluation metrics

- Precision and recall





Evaluation metrics

- *F*-score
  - The harmonic mean of precision and recall
  - F_1 gives equal importance to precision and recall

$$F_1 = \frac{2}{\mathrm{recall}^{-1} + \mathrm{precision}^{-1}} = 2\frac{\mathrm{precision} \cdot \mathrm{recall}}{\mathrm{precision} + \mathrm{recall}}$$

- Accuracy
  - Binary classification $\mathrm{Accuracy} = \dfrac{TP + TN}{TP + TN + FP + FN}$
  - Multi-class classification $\mathrm{Accuracy} = \dfrac{\text{Correct classifications}}{\text{All classification}}$

TP = True positive; FP = False positive; TN = True negative; FN = False negative

Scherer Typology of Affective States

Emotion: brief organically synchronized … evaluation of a major event

- *angry, sad, joyful, fearful, ashamed, proud, elated*

Mood: diffuse non-caused low-intensity long-duration change in subjective feeling

- *cheerful, gloomy, irritable, listless, depressed, buoyant*

Interpersonal stances: affective stance toward another person in a specific interaction

- *friendly, flirtatious, distant, cold, warm, supportive, contemptuous*

Attitudes: enduring, affectively colored beliefs, dispositions towards objects or persons

- *liking, loving, hating, valuing, desiring*

Personality traits: stable personality dispositions and typical behavior tendencies

- *nervous, anxious, reckless, morose, hostile, jealous*

Sentiment

Attitudes: enduring, affectively colored beliefs, dispositions towards objects or persons

- *liking, loving, hating, valuing, desiring*

Emotion

- One of the most important affective classes
- A relatively brief episode of response to the evaluation of an external or internal event as being of major significance
- Detecting emotion has the potential to improve a number of language processing tasks
  - Tutoring systems
  - Emotions in reviews or customer responses
  - Emotion can play a role in medical NLP tasks like helping diagnose depression or suicidal intent

Two families of theories of emotion

- Atomic basic emotions
  - A finite list of 6 or 8, from which others are generated

- Dimensions of emotion
  - Valence (positive negative)
  - Arousal (strong, weak)
  - Control

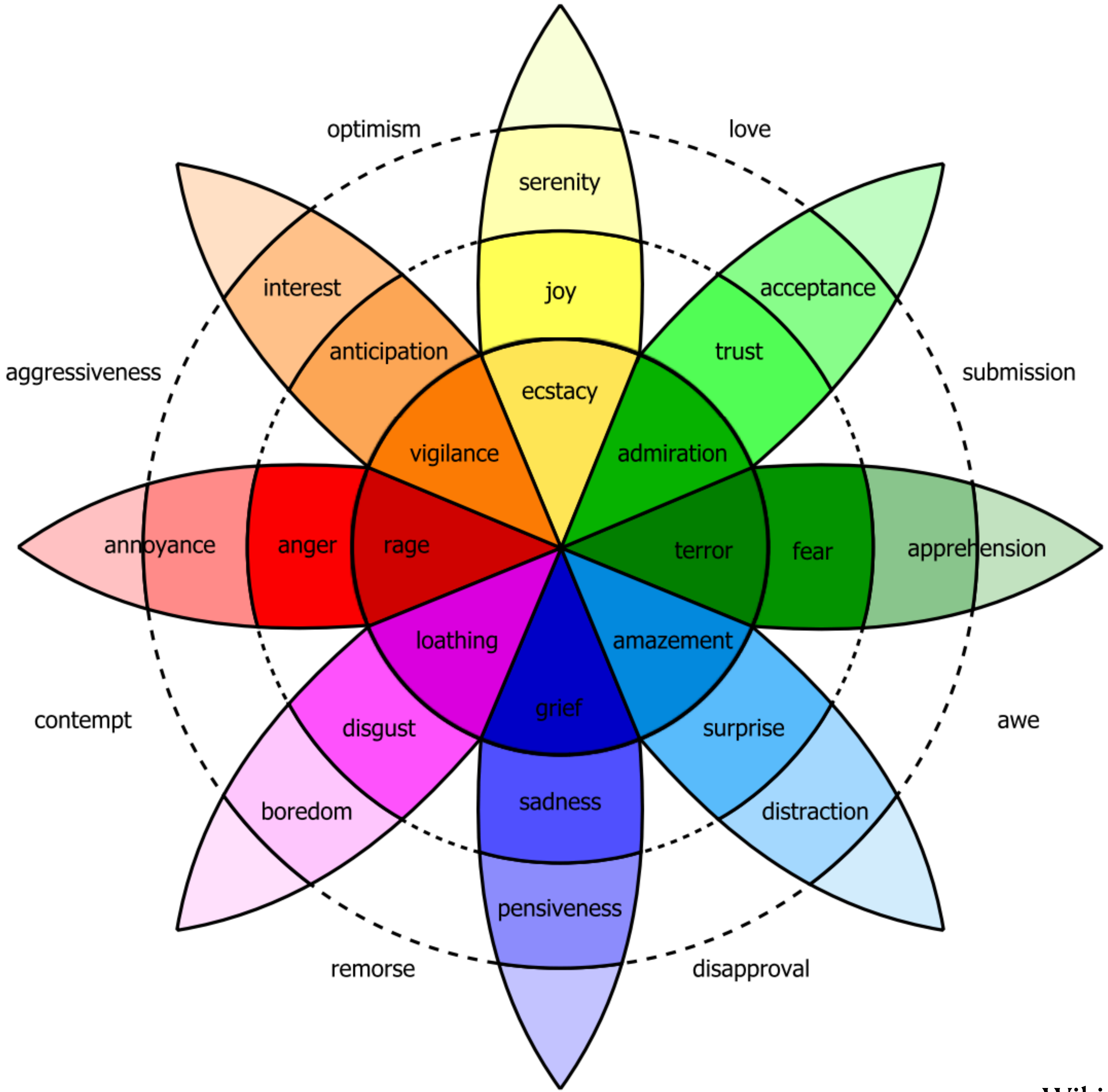
Ekman’s 6 basic emotions

Surprise
Happiness
anger
fear
disgust
sadness

Ekman & Matsumoto 1989

Plutchik's wheel of emotion

- 8 basic emotions
- four opposing pairs
  - joy - sadness
  - anger - fear
  - trust - disgust
  - anticipation - surprise



Wikipedia

Alternative: spatial model

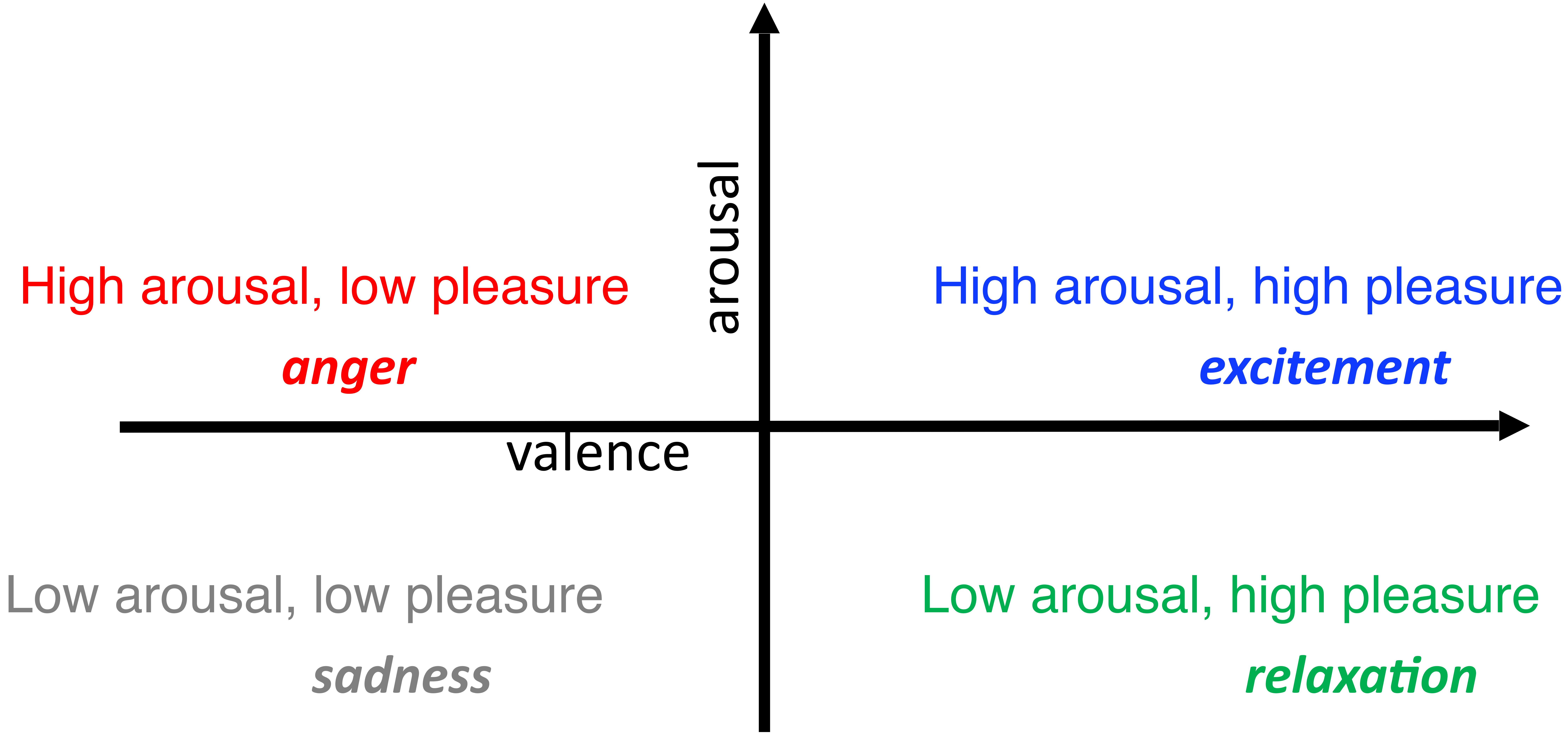
An emotion is a point in 2- or 3-dimensional space

valence: the pleasantness of the stimulus

arousal: the intensity of emotion provoked by the stimulus

(sometimes) **dominance**: the degree of control exerted by the stimulus

Valence/Arousal Dimensions




Sentiment
Emotion
Positive
Negative
laughing
Well
Sad
Shocked
Angry
Happy

NRC Word-Emotion Association Lexicon

Mohammad and Turney 2011

```
amazingly   anger   0
amazingly   anticipation 0
amazingly   disgust 0
amazingly   fear    0
amazingly   joy         1
amazingly   sadness 0
amazingly   surprise    1
amazingly   trust     0
amazingly   negative    0
amazingly   positive    1
```

More examples

Word	anger	anticipation	disgust	fear	joy	sadness	surprise	trust	positive	negative
reward	0	1	0	0	1	0	1	1	1	0
worry	0	1	0	1	0	1	0	0	0	1
tenderness	0	0	0	0	1	0	0	0	1	0
sweetheart	0	1	0	0	1	1	0	1	1	0
suddenly	0	0	0	0	0	0	1	0	0	0
thirst	0	1	0	0	0	1	1	0	0	0
garbage	0	0	1	0	0	0	0	0	0	1

NRC Emotion/Affect Intensity Lexicon (Mohammad, 2018b)

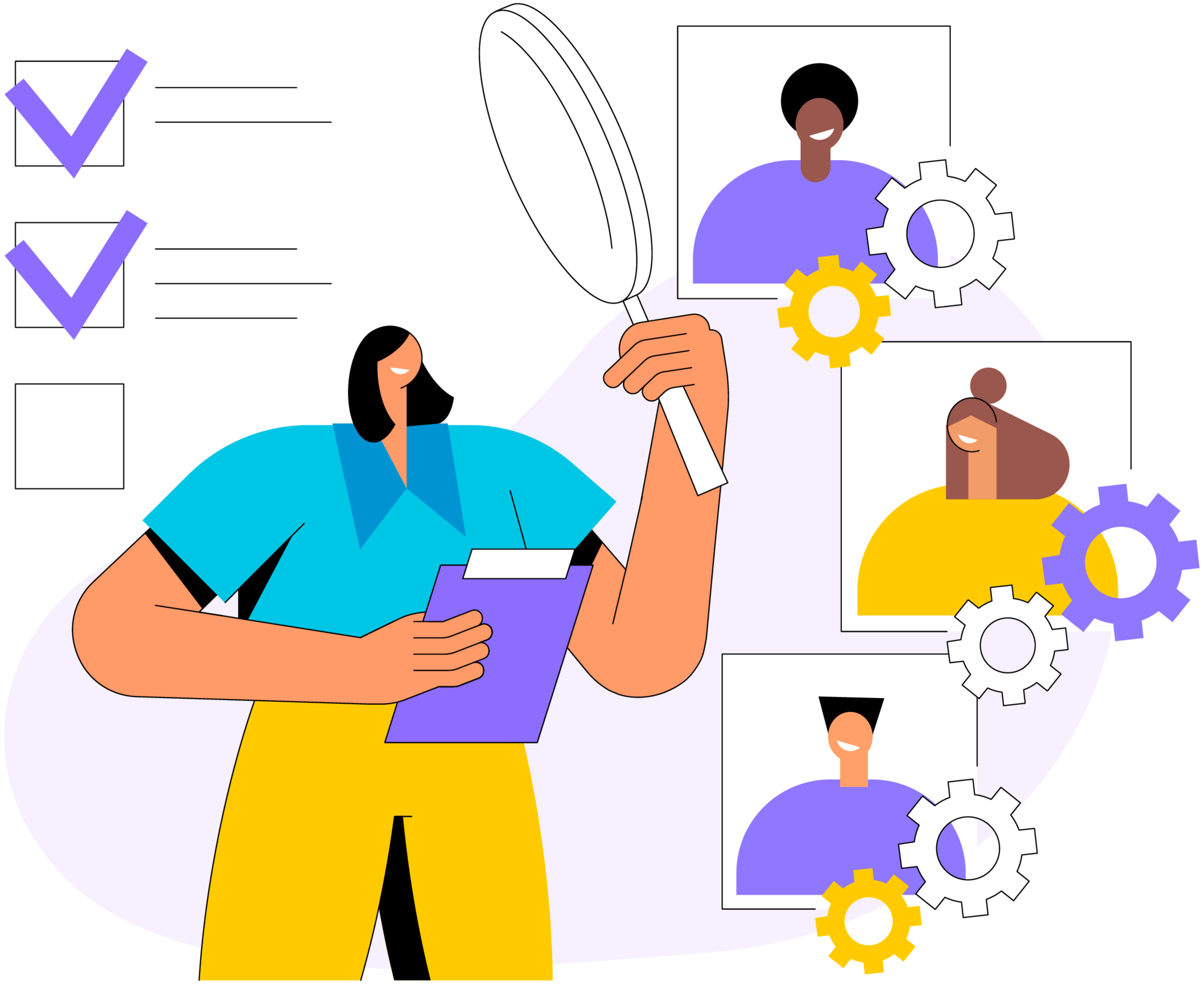
Anger		Fear		Joy		Sadness	
outraged	0.964	horror	0.923	superb	0.864	sad	0.844
violence	0.742	anguish	0.703	cheered	0.773	guilt	0.750
coup	0.578	pestilence	0.625	rainbow	0.531	unkind	0.547
oust	0.484	stressed	0.531	gesture	0.387	difficulties	0.421
suspicious	0.484	failing	0.531	warms	0.391	beggar	0.422
nurture	0.059	confident	0.094	hardship	.031	sing	0.017

Ekman’s 6 basic emotions: spoken version

Surprise
Happiness
anger
fear
disgust
sadness

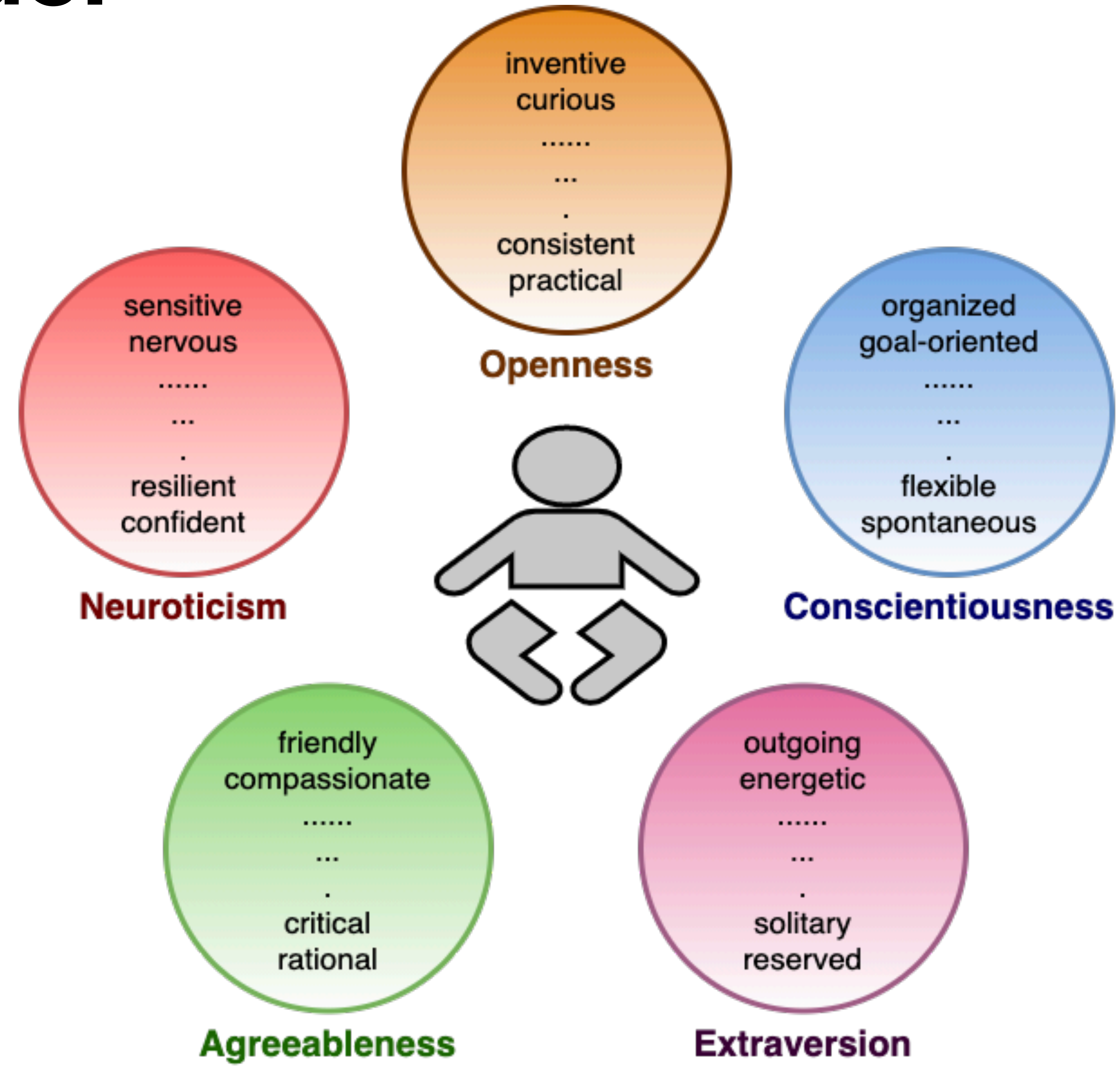
Ekman & Matsumoto 1989

Personality traits

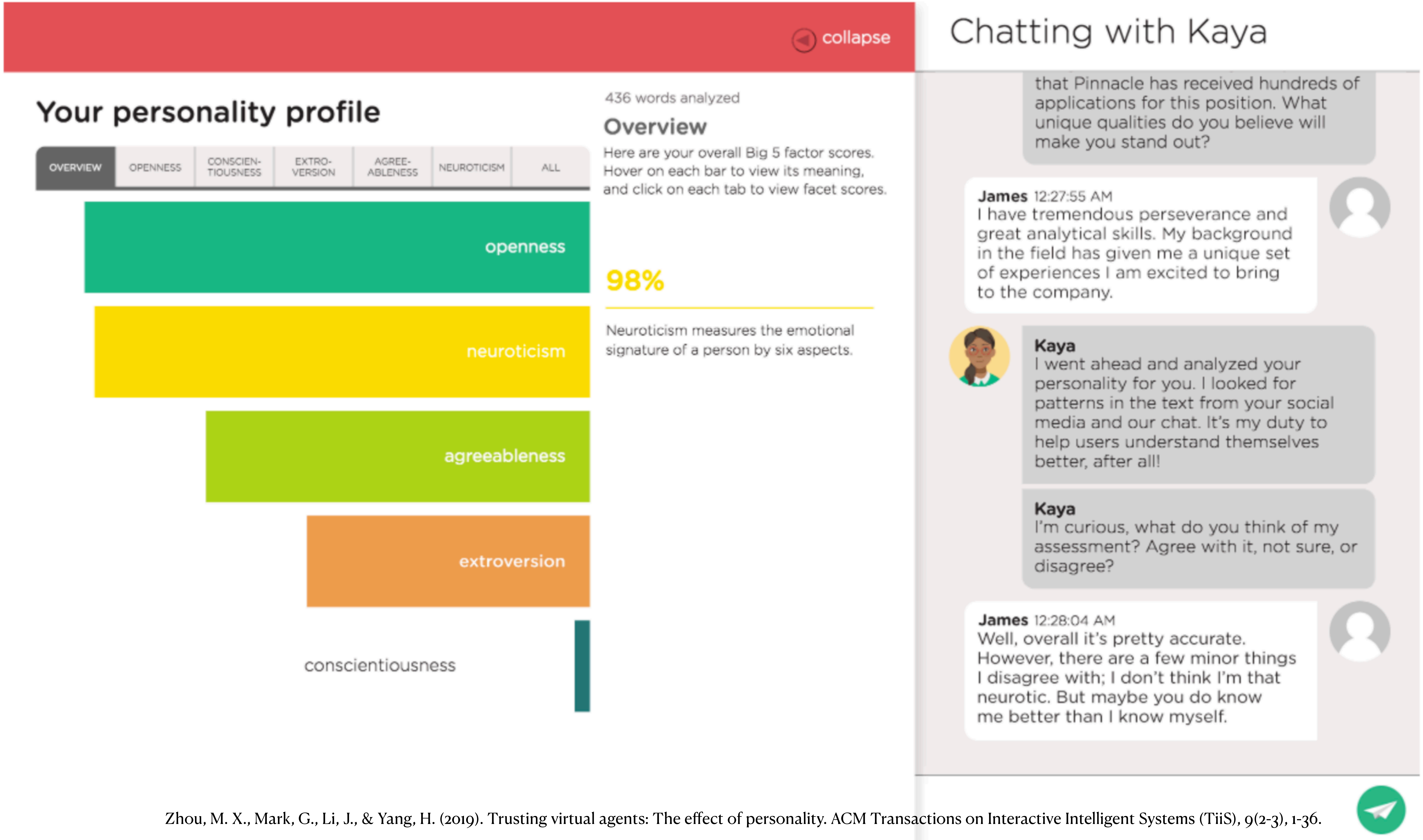


Five-Factor Model

- Openness(开放型)
- Conscientiousness（责任心）
- Extraversion（外向型）
- Agreeableness（宜人性）
- Neuroticism(神经质)



Virtual agents for interviewing



Zhou, M. X., Mark, G., Li, J., & Yang, H. (2019). Trusting virtual agents: The effect of personality. ACM Transactions on Interactive Intelligent Systems (TiiS), 9(2-3), 1-36.

	Kaya	Albert
Image Profile (Static)		
Personality	Gregarious, Cheerful, Warm, Agreeable, Humorous; Like a friend	Reserved, Calm, Assertive, Rational, Careful; Like a counselor
Effective Inquiring	Affective strategy [36]; Positive politeness [12] **Example**: "*You are so knowledgeable, would you mind telling me more about...*"	Cognitive strategy [36]; Negative politeness [12] **Example**: "*I'm sorry to keep you longer, would you mind telling me more about...*"
Effective Influencing	Empathy, Comfort, Frankness, Cooperation, Agreement [11] **Example**: "*I can certainly understand your point and agree with you that ...*"	Reassurance, Commitment, Forgiveness [11] **Example**: "*It is important to answer this question but no need to overthink...*"
Small Talk	Personable [9] **Example**: "*I love to chat with my online friends in my spare time, what do you do in your spare time?*"	Minimal chitchatting **Example**: "*Life is not just about work, what do you do in your spare time?*"
Linguistic Style	Questions, suggestions, affective expressions [9, 36, 104] **Examples**: "*Thank you so much for your input!*" "Could you say a bit more?"	Assertions, projective statements, terse expressions [36, 72, 104] **Examples**: "*Thanks.*" "Please tell me more."

Zhou, M. X., Mark, G., Li, J., & Yang, H. (2019). Trusting virtual agents: The effect of personality. ACM Transactions on Interactive Intelligent Systems (TiiS), 9(2-3), 1-36.

Summary

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Readings

- Chapter 4: Naive Bayes and Sentiment Classification
  - https://web.stanford.edu/~jurafsky/slp3/4.pdf
- Chapter 25: Lexicons for Sentiment, Affect, and Connotation
  - https://web.stanford.edu/~jurafsky/slp3/25.pdf