EVE: Emotion Vector Encoding

Towards Learning Feature Representations for Emotion Embeddings

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DS 340: Final Project Presentation

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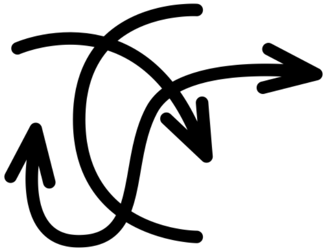
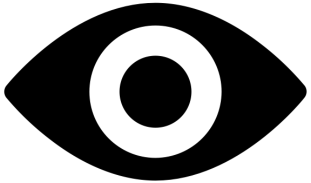
Introduction

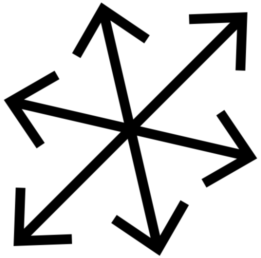
Problem: Current methods for learning feature representations for emotions have not been well studied or considered.



Complex



Subjective



Dynamic

Related Work

Machine Learning models fundamentally utilize the following two representations:

Discrete Emotions

Ekman's Theory of Emotions

Happy	Sad	Angry
Fear	Surprised	Neutral

26 Distinct Emotions Theory

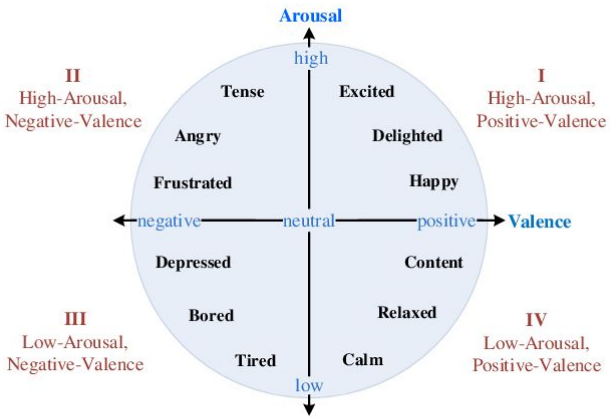
Peace	Affection	Esteem
Fatigue	Surprise	Sympathy
Pleasure	Yearning	Aversion

etc...

Typically encoded as one-hot vectors

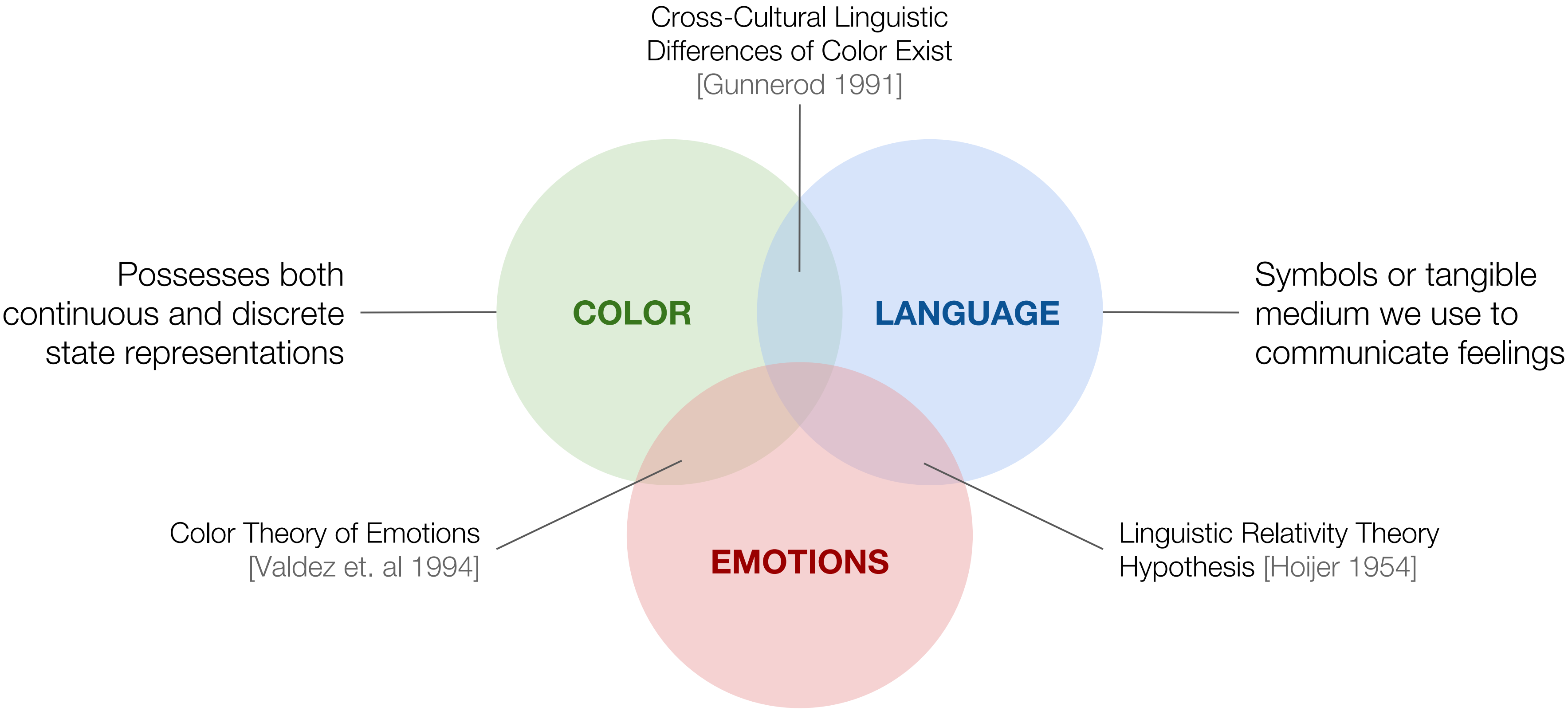
Continuous Emotions

Valence, Arousal, & Dominance Model (VAD)



Can we devise an alternative model between a discrete and continuous state?

Key Inspirations



EVE: Emotion Vector Encoding

We introduce a novel methodology and usage for representing **emotional states** as a ***distributed vector representation (Word Embedding)***.

Our modeling method presents the following advantages:

- Learns subtle semantic features of *emotions* and *qualia* quantitatively.
- Ability to encode a large corpus of emotional state representations.
- Allows for modeling of multi-linguistic corpus models.
- Allows for both interoperability and interpretability.
- Easy for humans to understand, and computers to compute on.
- Ability to be utilized in various Machine Learning tasks.

Kansei Information Processing

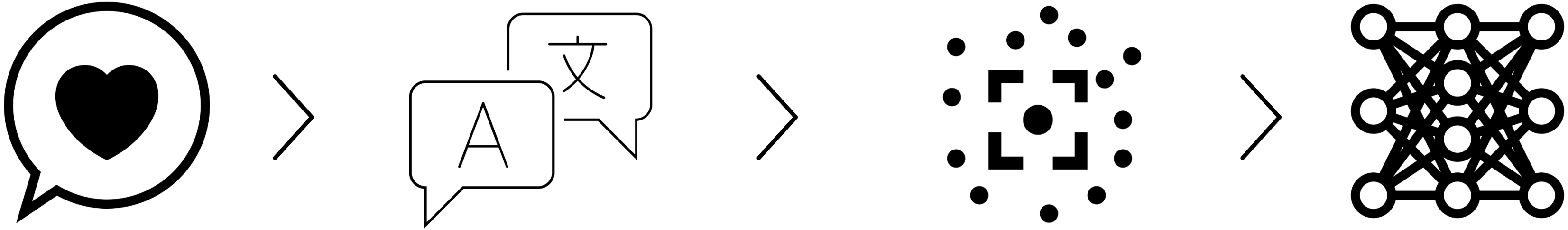
- EVE Methodology was inspired by Kansei Information Processing

- **Qualia** (感性 - Kansei): A relative placement of emotional states based on an individual threshold.

- Engineering methodology devised by Prof. Nagamichi during the 90s used to help design Mazda vehicles.

- A statistical framework which aimed to translate *qualitative psychological and emotional terms* to specific *quantitative parameters*.

The Kansei Methodology



Domain Choice › Semantic Spanning › Feature Space Spanning › Synthesis

Dataset

We used two different datasets for evaluating empirical performance under ***different semantic contexts***. We are only concerned about **labels**.

26 Discrete Emotions	3 Dimensional (VAD)
EMOTIC	**BoLD Dataset**
Static Images	Short Videos
23,788 Samples	26,146 Samples
Curated via AMT	Curated via AMT

EVE Encoding & Decoding Framework

We first need to define an **encoding** and **decoding framework** to convert between our distributed vector representation and the discrete and/or continuous representation (and vice-versa).

W = { ['happy', 'excited', 'surprised'],
['angry', 'disgusted', 'aversion', 'fear'],
… } → **M**

Given trained model M we can both encode and decode emotions:

New Set of Annotated Emotions → **M(X)** → **Encoded** Emotion Vector

Encoded Emotion Vector → **M'(X)** → **Decoded** Emotion Representation

Mean Vectorization Method

For proof-of-concept, we first attempted to encode the average VAD of the 26 emotions.

Assumption (Naive): Each emotion *occurs independently* from other emotions.

For emotions with *multiple emotions*, we decomposed them in the following manner:

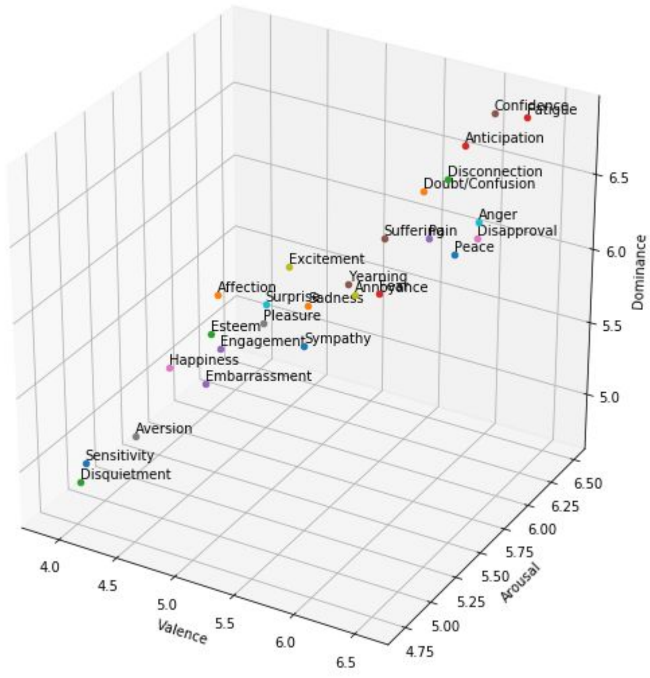
Original Data Pair

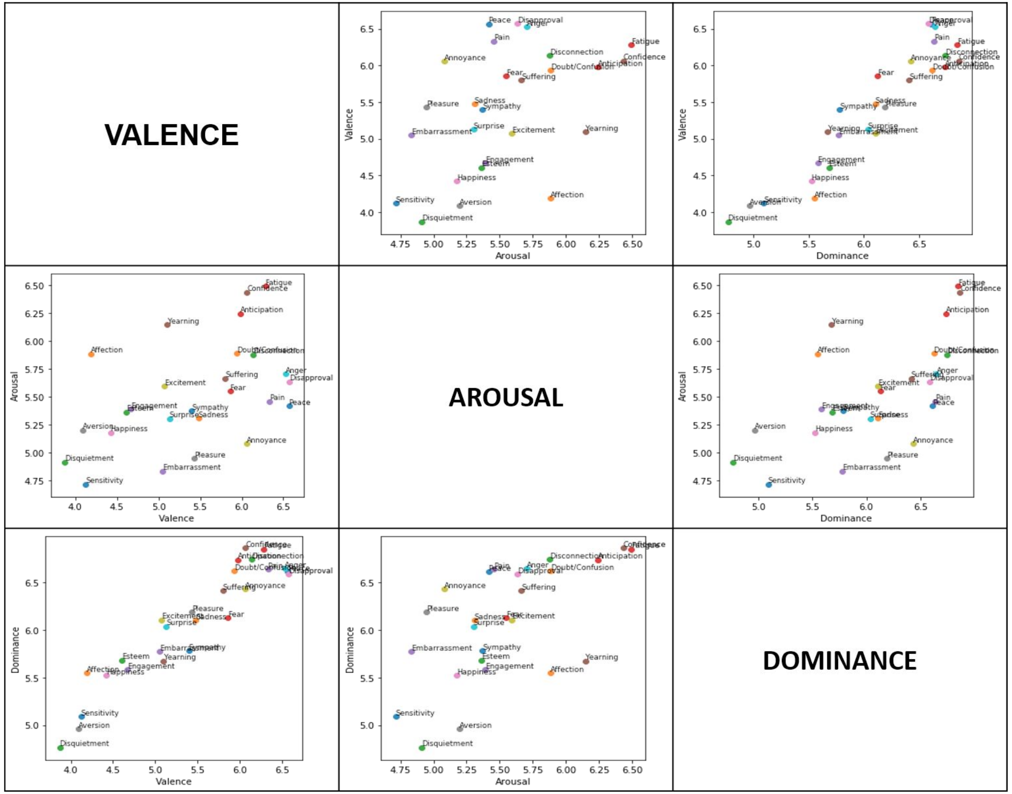
[0, 1, 0, 1, 1] [3, 5, 2]

[0, 1, 0, 0, 0] [3, 5, 2]

[0, 0, 0, 1, 0] [3, 5, 2]

[0, 0, 0, 0, 1] [3, 5, 2]


Confidence
Fatigue
Anticipation
Disconnection
Doubt/Confusion
Anger
Disapproval
Suffering
Pain
Peace
Excitement
Yearning
Annoyance
Fear
Affection
Surprise
Sadness
Pleasure
Esteem
Engagement
Sympathy
Happiness
Embarrassment
Aversion
Sensitivity
Disquietment
Valence
Arousal
Dominance


VALENCE
AROUSAL
DOMINANCE
Valence
Arousal
Dominance

Word Embedding Model

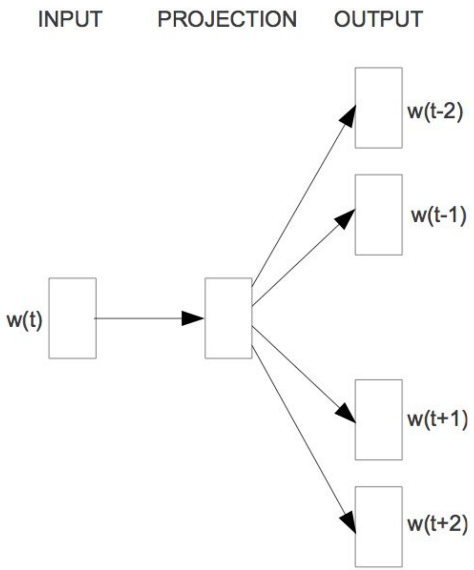
To learn semantic context, we build a two-layer neural network which aims to ***predict the co-occurring emotions*** given a single emotional state.

['happy', 'surprised', 'excited', 'joyful']

t-1 t t+1

Given the softmax probability: $p(w_O|w_I) = \frac{\exp {v'_{w_O}}^T v_{w_I}}{\sum_{w=1}^{W} \exp {v'_{w_O}}^T v_{w_I}}$

Maximize $\frac{1}{T} \sum_{t=1}^{T} \sum_{-c \leq j \leq c, j \neq 0} \log p(w_{t+j}|w_t)$



Hyperparameters

Vector Dimension: 150

Window Size: 2

Learning Rate: 0.025

Minimum Words: 2

Evaluation Task: K-NN Semantic Evaluation

Given a emotion word, we can empirically evaluate its semantic quality by looking at the top-k nearest neighbors defined by the *cosine similarity metric*.

Mean Vectorization Method

EMOTIC

Anger		**Pleasure**		**Excitement**	
Disapproval	(0.999964)	Embarrassment	(0.999774)	Sensitivity	(0.999898)
Pain	(0.999842)	Sadness	(0.999391)	Esteem	(0.999783)
Peace	(0.999730)	Disconnection	(0.999377)	Happiness	(0.999734)
Fear	(0.999477)	Annoyance	(0.999359)	Engagement	(0.999719)
Annoyance	(0.999467)	Pain	(0.999358)	Confidence	(0.999688)

BoLD

Anger		**Pleasure**		**Excitement**	
Aversion	(0.999189)	Affection	(0.999872)	Anticipation	(0.998858)
Disapproval	(0.997003)	Happiness	(0.999858)	Engagement	(0.998493)
Annoyance	(0.996613)	Esteem	(0.999110)	Esteem	(0.997461)
Suffering	(0.994039)	Peace	(0.998402)	Sympathy	(0.997130)
Disquietment	(0.991150)	Excitement	(0.994050)	Affection	(0.995656)

Evaluation Task: K-NN Semantic Evaluation

Given a emotion word, we can empirically evaluate its semantic quality by looking at the top-k nearest neighbors defined by the *cosine similarity metric*.

Word Embedding Model

EMOTIC

Anger		**Pleasure**		**Fear + Sadness**	
Aversion	(0.88505)	Esteem	(0.827299)	Fatigue	(0.895345)
Embarrassment	(0.85801)	Sympathy	(0.563033)	Pain	(0.894816)
Disapproval	(0.83252)	Anticipation	(0.542841)	Embarrassment	(0.888998)
Doubt/Confusion	(0.77493)	Confidence	(0.506502)	Sensitivity	(0.840702)
Disconnection	(0/71646)	Yearning	(0.500476)	Disapproval	(0.720077)

BoLD

Anger		**Pleasure**		**Fear+Sadness**	
Disconnection	(0.41355)	Esteem	(0.523179)	Pain	(0.520315)
Doubt/Confusion	(0.38539)	Peace	(0.487809)	Embarrassment	(0.518160)
Disquietment	(0.38140)	Happiness	(0.477360)	Yearning	(0.498758)
Fatigue	(0.37158)	Anticipation	(0.439886)	Fatigue	(0.493225)
Fear	(0.35472)	Affection	(0.430348)	Suffering	(0.481661)

Theory: EVE Models Personality

According to a work done by Revelle et. al (2008):
"Personality is the coherent patterning of affect, behavior, cognition, and desires (goals) over time and space."

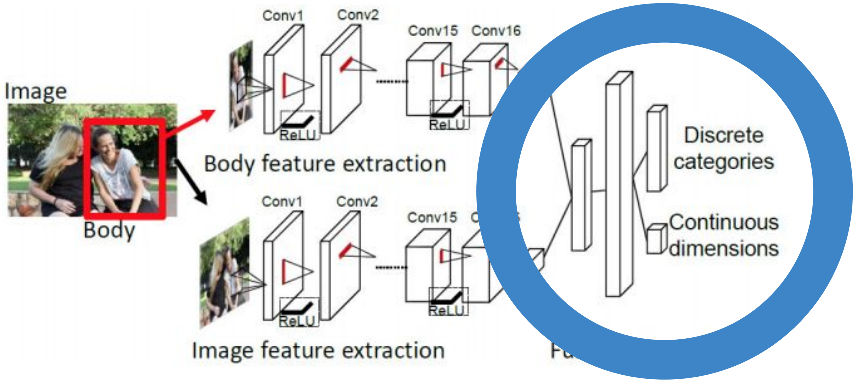
Or as an analogy... **Personality is to Emotion as Climate is to Weather**

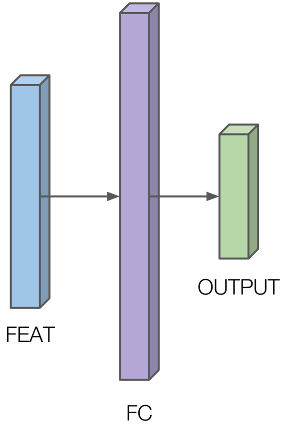
In other words:

A trained EVA Model for an individual's personality, composed of a collection of N set of emotion vectors geometrically positions over a sample of time, can model long-term emotional tendencies or <u>personalities</u>.

Applications: Discriminative Modeling

Reduce our optimization function as a single regression based output - and still obtain representations for both discrete and continuous values (using encoder and decoder).

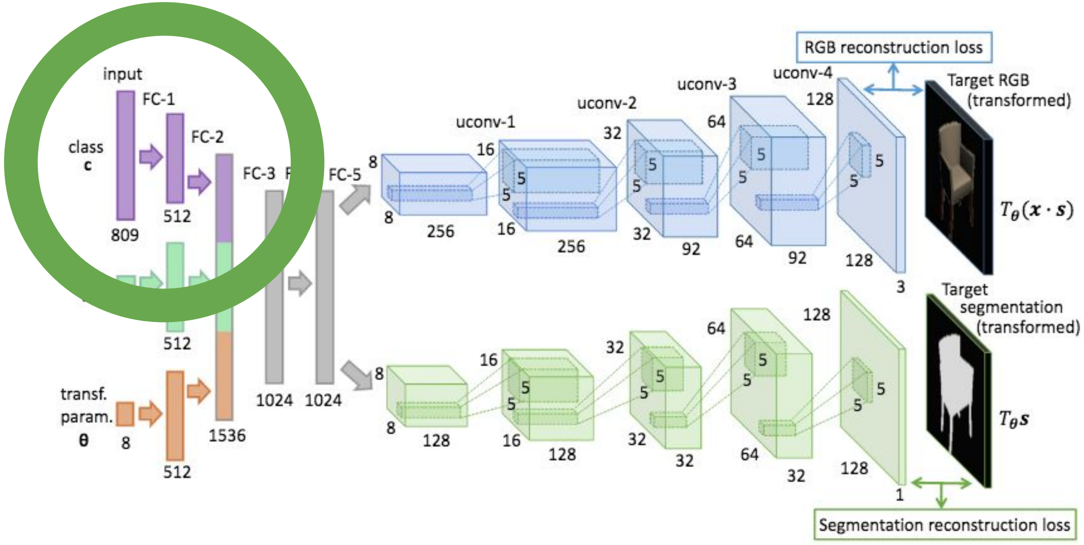


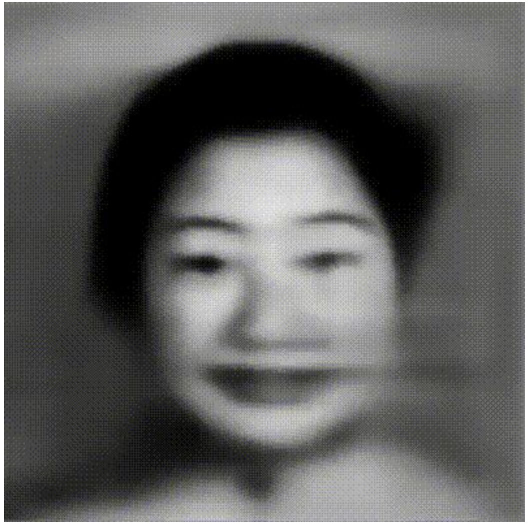


We trained a model on the EMOTIC CNN by changing the output representation based on the EVE Representation

Applications: Generative Modeling

Utilizing a distributed representation as a the latent class vectors can *improve interoperability* between various emotional states.





HAPPY → EXCITED → ANGRY → SAD

Conclusion

In this work our primary contributions include:

1. A novel framework for encoding and decoding embedded emotion representations.
2. A modeling methodology for emotion representation using distributed vector representations.
3. Various empirical experiments demonstrating the feasibility of this representation.
4. Demonstration of various applications of this representation in various affective computational tasks.

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