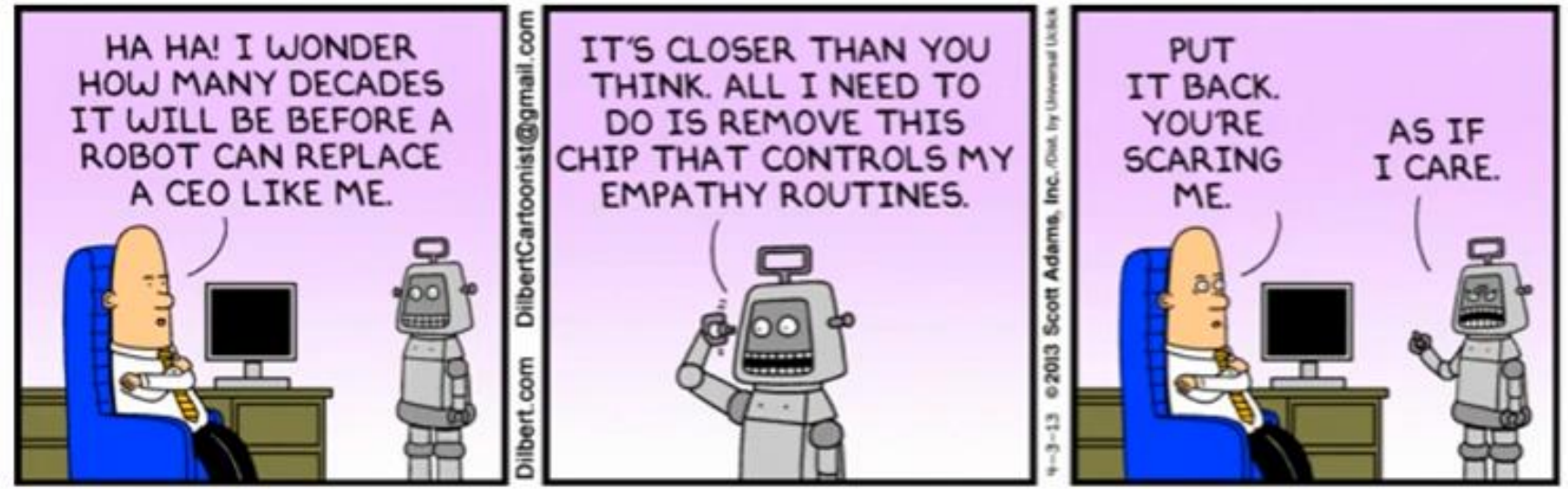
LnD Talk : Affective Computing In Modelling Human Emotions

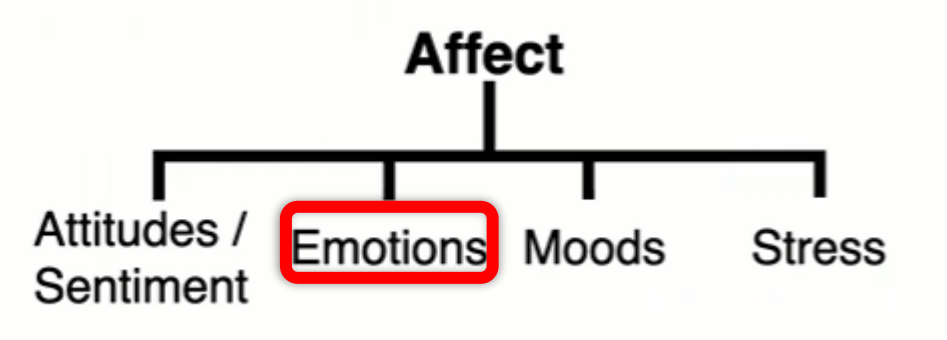
Comic strip from Dilbert…..

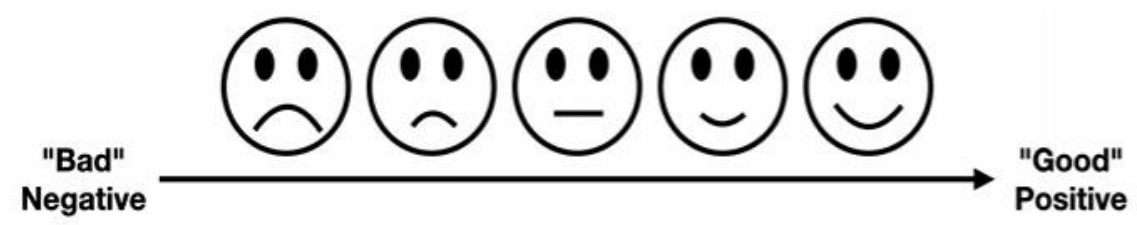


- **Humans are emotional**
- **Understanding expressions , inferring emotions has great potential in promoting development of humanoid robots and animated software agents.**

LnD Talk : Affective Computing In Modelling Human Emotions

Taxonomy of Affective States





Related Phenomena

- Personality
- Physical State
- Mental State

Initial Beginnings …

- Scientific studies in 1800s leaned on Darwin's theory of recognizing emotions from faces

'Chimpanzee disappointed and sulky"

"Head of snarling dog"

- Emotions evolved because of adaptive functions and

- Facial expressions that were observed in animals resembled / drew parallels with humans

1970s … The Era of Paul Ekman

- Emotion can be systematically studied through the Facial Action Units (AU) coding system scientifically.
- AUs are part of the 44 anatomically distinct muscular activities that activate when changes occur in an individual's facial expression
- Objective (physical changes that occur when muscles contract) versus Subjective (what is the person feeling?)
- Observable and Reliable versus Unobservable and To-Be-Inferred ?
- Empirical studies have proven high reliability and accuracy but time consuming as its manual
- Map FACS codes to emotions

Emotion	Example photo	Action units
Sadness		1+4+6+15+17

Emotion	AUs associated with Emotion
Angry	4, 5 and/or 7, 22, 23, 24
Fear	1, 2, 4, 5, 7, 20, 25 or 26
Surprise	1, 2, 5, 25 or 26

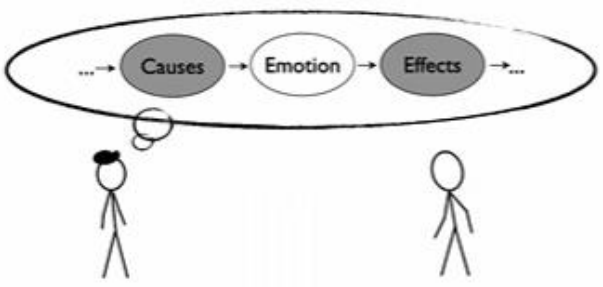
The Next Phase…..

- What is affective computing ? – A bunch of models that can be written as a series of computations.

- A formal representation that instantiates an abstract theory. Highly data driven.

1. Probabilistic Inference model based on causal theory reasoning

Imagine a simple model of the world of what causes emotions and what behaviors gets triggered by emotions. We can (infer) predict the probability of emotions given the cause and effect

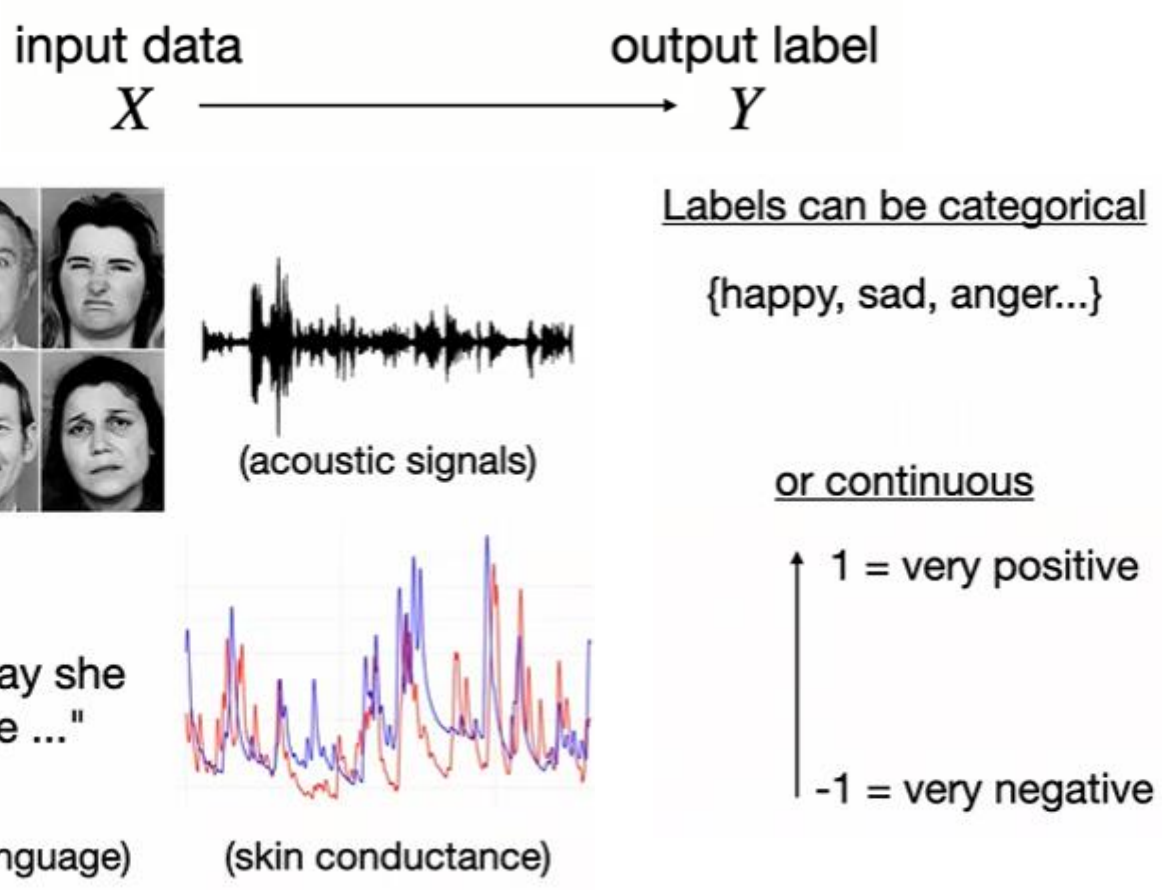


$$P(\text{emotion} \mid \text{cause, effect}) \xrightarrow{\text{Bayes' Rule}} \frac{P(\text{emotion} \mid \text{cause})P(\text{emotion} \mid \text{effect})}{P(\text{emotion})}$$

- **Multi-class causes and contingency formulation problem**

2 : Machine Learning –Automated Facial Analysis

- Involve Feature Extraction (extract facial landmarks and apply transformation before applying supervised algorithms to predict labels (emotions / gender / age) on the image.



- **Class Imbalance leads to bias problem**

3 : Deep Learning

- Deep Learning models– skip the step of feature engineering and model learns the relevant features by itself.

- High dimensional vectors that can encode a lot of information, need lots of data.

State of the Art Models :

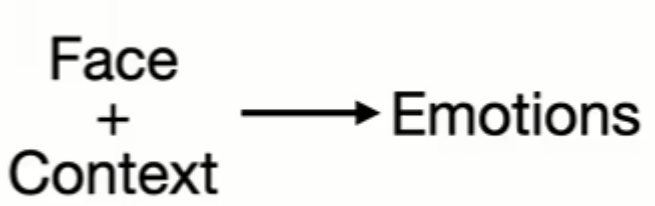
Computer Vision task > Images > Convolutions work very well with images (CNN over NN)

Natural Language task > Text > LSTMs and Transformers

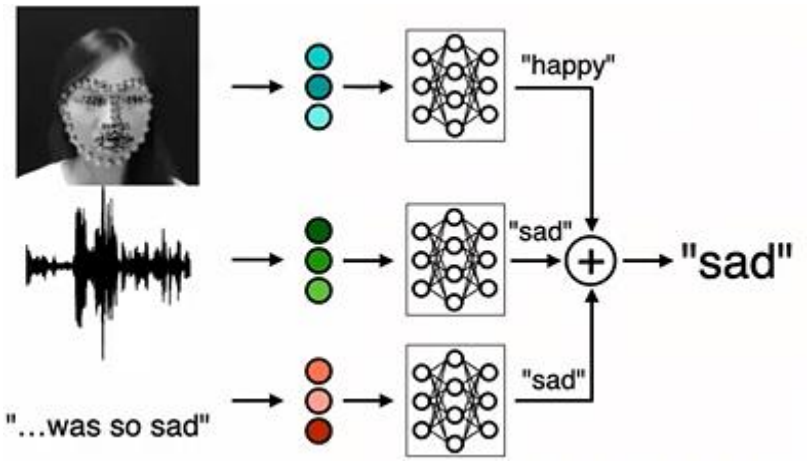
- **Emotions are latent**

- **Models howsoever accurate fail to contextualize and be interpretable**

- **Can we build a model to infer emotions based on proxy data?**



4 : Current Research….Multi- Modality and Decision Fusion Models



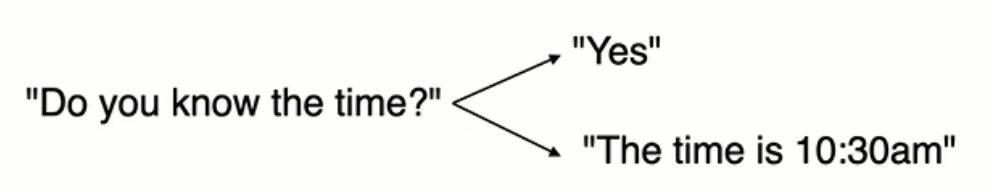
- Different modalities measure different components of emotions.
- New information can make the model do better in the sense of interpretability + accuracy

Conclusion….

- Emotions are challenging. Using the modality of natural language in text, we see it has different level of meanings…

- Semantics : What words literally mean

- Pragmatics : What humans mean when they use words



Interviewer: What is your biggest weakness?
A: I am excellent at understanding the semantics of a question, but I tend to ignore the pragmatics.
Interviewer: Can you give an example?
A: Yes, I could.