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Emotions analysis of written text

Bureau d'étude - Understanding humans through technology

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Why NLP and why emotionally?

Natural language processing aims to understand natural language data.

Emotions are a key part of the communication process in humans. We usually get emotive elements from non-verbal aspects of speech such as facial expressions and voice tone, but most of the time we don't have access to those features. Hence, we would like to:

1. Make machines emotionally intelligent
2. Do so by only analysing written text

Emotionally intelligent systems may have applications such as:

- Analyse emotions of a large amount of people
- Automatic analysis of product reviews
- Improve responses of chatbots

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Valence, Arousal and Dominance

In order to perform a sentiment/emotions analysis we need to set a theoretical framework. Here we will work with the **VAD** model, which states that emotions and their intensities can be represented in the three dimensional space given by: valence, arousal and dominance [1].

1. **Valence** varies from unpleasant (negative) to pleasant (positive).
2. **Arousal** ranges from passive (low) to active (high), indicating how strongly human feels.
3. **Dominance** extends from submissive to dominant, which reflects the control ability of the human in a certain emotion.

Valence, Arousal and Dominance

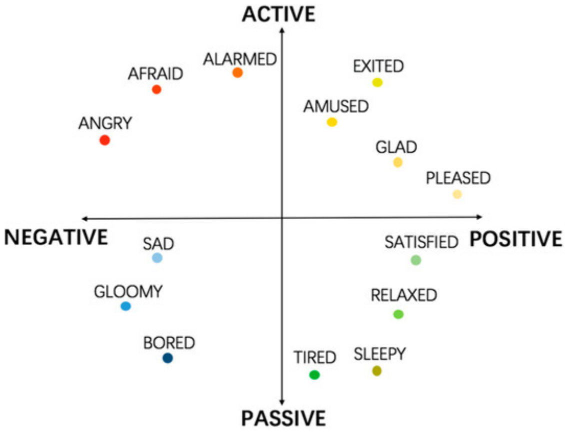

Figure: The emotional space spanned by the Valence-Arousal model [1]

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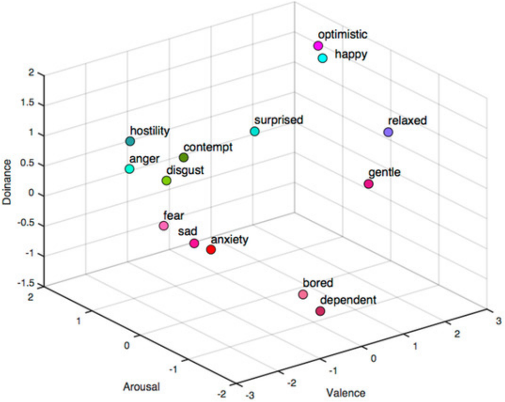
Valence, Arousal and Dominance



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Natural language processing

Lets say we want to analyse the following sentence in an automatic manner:

This class is boring!

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Natural language processing

Lets say we want to analyse the following sentence in an automatic manner:

This class is so boring!

Issues to be addressed:

- Sentences may have different lengths
- How can we make our algorithm catch the semantics
- And furthermore, its emotional value!

We'll try to answer the first two...

Recurrent neural networks

Neural networks provide us with an excellent tool for getting rid of the different length problem: **recurrent neural networks.** As its name suggests, this this architecture consists of a unit applying itself recurrently to each element of an input sequence (which in this case it will be our sentence!). More precisely, here we apply the simplest version (Elman network [2]):

$$h_t = \sigma_h(W_h x_t + U_h x_{t-1} + b_h)$$

$$y_t = \sigma_y(W_y h_t + b_y)$$

With x_t the input vector, h_t the hidden layer and y_t the output vector. W, U and b will be the parameters to learn and σ_h and σ_y will be activation functions, *tanh* in this case (hyperbolic tangent).

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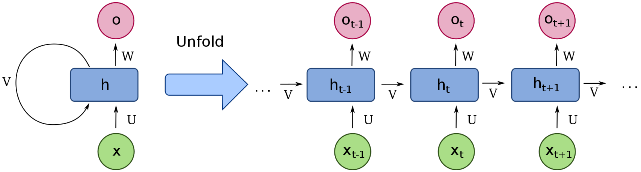

Figure: Visualisation of a recurrent neural network

Word embedded spaces

Now that we have our architecture we need to find a way of representing words. **Word embedded spaces** not only do that but they are also capable of seize the semantics. If we didn't have them we would need to work in a huge dimensional space as it's shown in the following example:

$$paris = \begin{pmatrix} 0 \\ \vdots \\ 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix} \Longrightarrow \begin{pmatrix} 0.28199 \\ -0.043577 \\ \vdots \\ -0.37809 \\ -0.11996 \end{pmatrix}$$

We pass from a dimension equal to the size of the vocabulary (around 400000) to a space of a much lower dimension (for instance 300).

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Practical work

Now we hope that we can model the emotional VAD values of our sentences with the elements shown before!

https://github.com/camilocarvajalreyes/BE-emotions-in-text

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Emotional models

The VAD emotional model is one among others such as:

- Ekman's six basic emotions

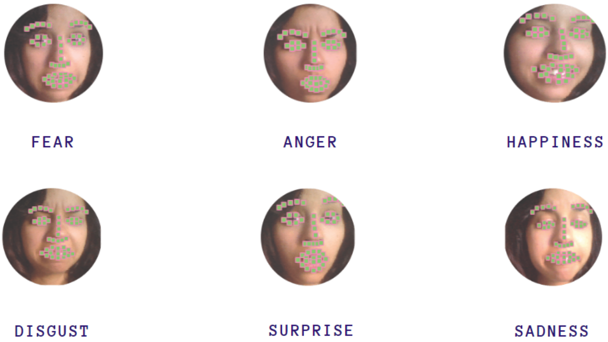

Figure: Ekman basic emotions [3]

Emotional models

The VAD emotional model is one among others such as:

- Ekman's six basic emotions
- Putchik's wheel of emotions

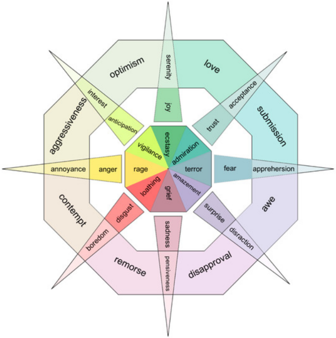

Figure: Plutchik's wheel of emotions [1]

Emotional models

The VAD emotional model is one among others such as:

- Ekman's six basic emotions
- Putchik's wheel of emotions

They are both discrete models. If we had a data base where the annotation corresponded to whether the emotion is present or not then we would have faced a **classification problem**. A difference in terms of architecture is that we would have needed to model the probability of belonging to a certain emotion for each sentence.
We could also have done that with the VAD information we got for each element.

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Valence = 2.06, Arrousal = 2.73, Dominance = 2.43
We would have got something between **boredom** and **dependency**... which makes a lot of sense!

Deep learning alternatives

We have used the simplest possible recurrent neural network. Other alternatives that we could have considerd instead:

- **Long short memory network (LSTM)** [4]

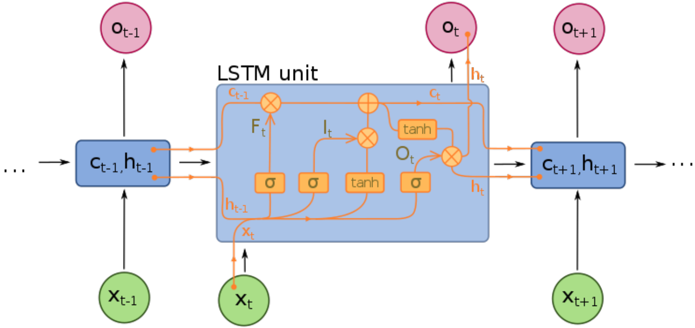

Figure: Architecture of a long short term memory network

Deep learning alternatives

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- Long short memory network (LSTM)
- Bidirectionality [5]

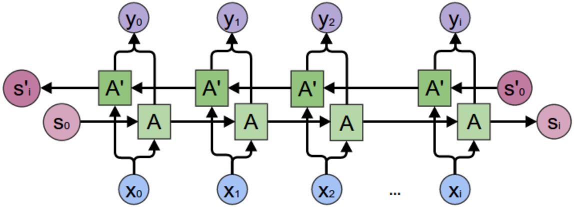

Figure: Standard form of a bidirectional RNN

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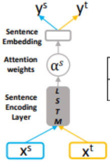
Deep learning alternatives

We have used the simplest possible recurrent neural network. Other alternatives that we could have considerd instead:

- Long short memory network (LSTM)
- Bidirectionality
- Attention [6]



a. Fully-Shared (FS)

Methods	When you dread going to work early ... but you always come back home happy ; smiling # goodday 😍	Prediction
Base	0.04 0.03 0.25 0.01 0.01 0.00 0.00 ... 0.03 0.02 0.03 0.01 0.02 0.03 0.28 0.03 0.09 0.02 0.02 0.03	joy, optimism

Figure: Attention in the context of a LSTM-fully shared transfer learning architecture and an example

Word embedded spaces (emotionally!)

Word embedded spaces also allow some margin for improvement. They get semantic information, but can they grasp the emotional value of words?

Some questions to be answered:

- How do we evaluate word embeddings in terms of emotions?
- If we find a better way of making them, should we build them from scratch or refine them?
- How do we fix the homonyms issue? (words may have multiple meanings...)
- How to capture non verbal aspects?

We are trying to answer those questions!

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