Decoding emotional content from GIFs using MEG data

by

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Eidesstattliche Erklärung

Hiermit erkläre ich, Vera Klütz, die vorliegende Arbeit *Decoding emotional content from GIFs using MEG data* selbständig verfasst zu haben und keine anderen Quellen oder Hilfsmittel als die angegebenen verwendet zu haben.

Mannheim, den 21.8.2024

Vera Klütz, 991846

Affirmation Statement

I, Vera Klütz, hereby certify that the work presented here is, to the best of my knowledge and belief, original and the result of my own investigations, except as acknowledged, and has not been submitted, either in part or whole, for a degree at this or any other university.

Mannheim, August 21, 2024

Vera Klütz, 991846

Abstract

1 page This is going to be great! Keep on reading!

Acknowledgements

less than 1 page Thank you everyone!

Contents

List of Figures

List of Tables

1 Introduction

ca 40 pages for whole thesis
3-4 pages
Motivation to do this project,
background
aim of the project
shortly say which methods are being used
(Structure of this thesis?)

1.1 Section One

Hello. This is a citation: (Engel, Maye, Kurthen, & König, 2013).

1.2 Section Two

Hello. This is a table (ref. Table 1.1).

Table 1.1: LMM Regression Results Overview

Model:	MixedLM	Dependent Variable:	Gaze
No. Observations:	1400	Method:	REML
No. Groups:	10	Scale:	1.0
Min. group size:	90	Log-Likelihood:	-1700.0
Max. group size:	130	Converged:	Yes
Mean group size:	120		

hjkhj gjgh

2 Current State of Research

15 pages

Literature overview and stand der Forschung
theoretical concepts and models
conceptual framework
'Something like: In order to assess the current state of research for this task, it has to be divided into three subtasks. For each of one of them, major choices have to be made in order to successfully

2.1 Measuring Emotions

In order to be able to decode emotional content it has to be stated what 'emotional' means. Since the adjective links to the broader concept of 'emotions', the question arises what emotions are and how to measure them for this task.

Ekman and Cordaro define that "Emotions are discrete, automatic responses to events, forming a family of related states with at least 12 characteristics" (Ekman & Cordaro, 2011). This definition highlights the automatic nature of emotional responses as well as the connectedness between those emotional states. However, it is debatable which characteristics fully describe the different states and how many core emotions there are. Vytal and Hamann conducted a meta-analysis and "identified consistent neural correlates for five basic emotions: fear, anger, disgust, sadness, and happiness" (Vytal & Hamann, 2010, p.3). It is important to note that this meta-analysis does not divide emotions based on philosophical conclusion or by observing facial expressions, but by looking at neural correlates. For this thesis, being able to measure emotions is a necessary premise and neural activity is a measurable physiology. Still, the continuous neural activity has to be mapped to discrete emotions, as Ekman and Cordaro already pointed out above.

Another way to describe an emotion, which is easier to standardize between people and less dependent on the usage of the same linguistic terms, is by using the valence and arousal model. According to Colibazzi et al., "Emotions are linear combinations of valence and arousal" (Colibazzi et al., 2010). This means that an emotion can be assessed by its position on these two scales, with valence ranging from 'negative' to 'positive' and arousal diverging from 'calming' to 'exciting' (Kensinger, 2004).

Elicit emotions? chromatic map? Verarbeitung von Emotionen im Gehirn elektrische SIgnale mit magnetischen Feldern von MEG messbar

- Scherer
- Valence Arousal Wund is the first one - e.g., Lang, Greenwald, Brad- ley, & Hamm, 1993; Mehrabian & Russell, 1974; Russell, 1980) Hello

2.2 Data Preprocessing

Hello

2.3 machine learning model, classifier,.. selection

For the scope of this thesis, several Gigabytes of data have been collected. AI is a useful tool for interpreting such data, especially for detecting common patterns and features which would be difficult to identify for a human. Haenlein and Kaplan (2019) define AI as the ability of a system to accurately interpret outside data, learn from it, and apply that learning to accomplish particular tasks and goals through adaptable change. Whereas first AI attempts rely on explicit representation of knowledge, machine learning, which is a subpart of AI, uses computational methods rather than preset formulas to teach machines to learn from their past experiences (Shaveta, 2023). AI can also generally be described as a system for advanced problem solving (Janiesch, Zschech, & Heinrich, 2021), and ML is a branch of AI that relieves the user of the need to explicit their knowledge into machine-interpretable rules (Janiesch et al., 2021). Instead, ML is able to automatically improve with experience (Mitchell, 1997) and is therefore nowadays seen as the core of AI (Mukhamediev et al., 2022).

Machine Learning itself can be divided into three different subparts, which can be seen in Figure 1, namely Supervised Learning, Unsupervised Learning, and Reinforcement Learning. The first one requires training data that contains not only the input variable, but also the labeled target variable (Janiesch et al., 2021), so the 'solution' to the task the machine learning algorithm is trying to solve. This allows the algorithm to learn and update its own parameters, until it is able to correctly predict unseen data (Janiesch et al., 2021). The second category that can be seen in Figure 1 is called Unsupervised Learning, because here the labels are missing, and therefore an external way of 'supervision' is not included (James et al., 2023). Here, the goal is to find structural information (Janiesch et al., 2021). For example, in the clustering technique the algorithm is looking for common properties in groups of elements, or for the dimensionality reduction technique a high-dimensional space is projected into a lower one (Janiesch et al., 2021). In contrast, in a reinforcement learning system the machine learning model learns how to achieve the goal on its own by maximizing a reward through trial and error (Janiesch et al., 2021). Therefore, its current state has to be described, a goal has to be specified, a list of actions that are permissible have to be provided, as well as the environmental constraints that apply to their outcomes (Janiesch et al., 2021).

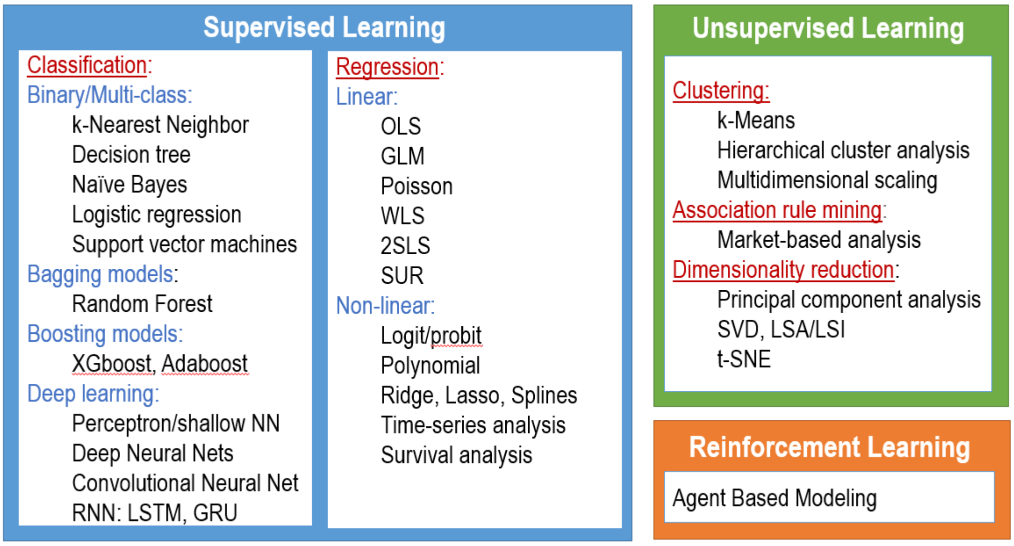

Figure 1: Machine Learning overview (Krumnack, 2022)

For the scope of this thesis, supervised learning is the most relevant. Labeled target variables exist which helps to form clear criteria for model optimization and the labels allow for a straight forward evaluation of the algorithm.

In the field of supervised learning, there are two major fields of problems, namely classification problems and regression problems, as shown on Figure 1. For the first one, categorical values are predicted, for example the category 'happy' or 'sad', for regression numerical values are predicted, for example someones height or age (Janiesch et al., 2021). For each of those two problems there are different classifiers to choose from, as depicted on Figure 1. Despite its name, one common classification method is called 'Logistic Regression'. It estimates class probabilities for binary classes with the logistic function, which ensures that the calculated class probability stays between 0 and 1 (James et al., 2023). The logistic function can be seen in Figure 2 along with the formula for calculating the probability for the target variable Y to belong to a class, given the input variable X.

If more than two classes are part of the paradigm, then multinomial logistic regression can be used to overcome the binary capacities of logistic regression.

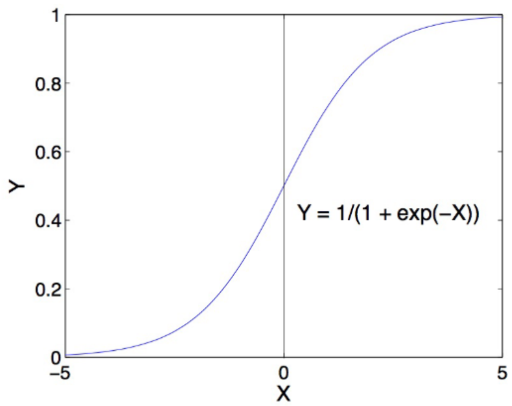

Figure 2: Logistic function (Mitchell, 1997, p.8)

Therefore, one class is serving as a baseline, which class is chosen does not influence the prediction but only the coefficient estimates of the mathematical model (James et al., 2023). Another way to implement multinomial logistic regression is to use softmax coding. Here, all classes are treated symmetrically instead of choosing a baseline class (James et al., 2023).

Another classifier type which falls into the category of binary/multi-class classifiers as shown in Figure 1 are support vector machines. They rely on the notion of a single hyperplane being able to divide the space of data points into two subparts. A hyperplane is always one dimension smaller than the actual data space, so in a 2D space a hyperplane is just 1D, and therefore a line (James et al., 2023). In a 3D space it would be a plane dividing the space into two parts. The idea is illustrated in Figure 3.

Of course, the figure just shows one out of many possible hyperplanes for this space, it could be rotated or shifted a bit and would still be correct. The optimal hyperplane position can be calculated by different factors, for example S.381

However, all of those hyperplanes would lead to a linear decision boundary (James et al., 2023).

classifier choice:

logistic regression see figure 1 random forest

lazy learner eager learner

classifier evaluation Therefore, the dataset will be split into a training and testing dataset, validation cross validation (validation) evaluation: accuracy f1score metric, fals e positive matrix?

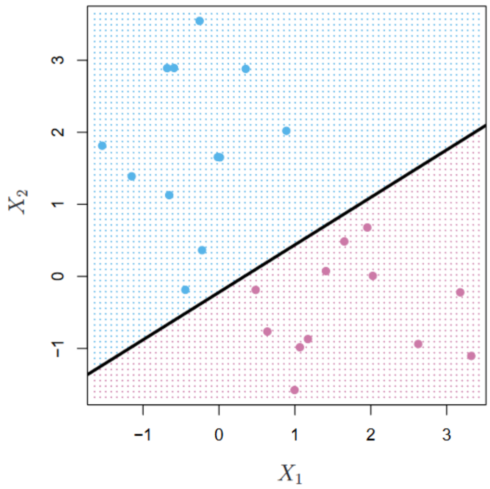

Figure 3: A black hyperplane is visualizing a decision rule that divides a grid into a blue and a red area. Each data point inside this area will be assigned to the corresponding class. (James et al., 2023, p.370)

2.4 Feature Selection

Hello

3 Methodology

5-10 pages

Description of Methods:

preprocessing

state/ explain data getting procedure, high arousal, different valences

Machine learning, ´classification vs regression, linear regression

3.1 Section One

Hello

3.2 Section Two

Hello

4 Results

5-20 pages

4.1 Section One

Hello

4.2 Section Two

Hello

5 Discussion

5-10 pages
Interpretation of Results
Answering the Forschungsfrage if applicable
bring it back to the literature/theoretical background
implications for further research

Conclusion/Fazit at the end? 3-4 pages
-¿ leave it out at it is the same as above!?!
summary of most important findings
critical refelction

5.1 Section One

Hello

5.2 Section Two

Hello

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A Appendix One

This is the first appendix

Hello

B Appendix Two

This is the second appendix

Hello