University of Twente

Master Thesis

Trust in automated decision making

How user's trust and perceived understanding is influenced by the quality of automatically generated explanations

Author:
Andrea Papenmeier

Supervisors:
Dr. Christin Seifert
Dr. Gwenn Englebienne

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Abstract

Contents

1 Introduction

State of the world
The big BUT
— Xerox experiment [32]
Therefore, we did
The key findings are
The contributions of this work are
In HCI, the purpose of empirical contributions is to reveal formerly unknown insights about human behavior in relation to information or technology.

2 Background

—Catchy first sentence.
Machine learning aims to infer generally valid relationships from a finite set of training data and apply those learned relations to new data [11] [23]. While some problems can be solved by manually encoding explicit rules, others require a different approach as explicit decision-making does not deliver highly accurate results [5]. Determining a student's grade in a multiple choice test can be solved by explicitly encoding mathematical rules, yet deciding whether the tonality of a text is positive or negative needs more than a simple rule set to function accurately [27]. The datasets needed to train machine learning models are often large and represented in a high-dimensional feature space, which makes it impossible for a human to carry out the learning task like a machine can. However, machines can be used to extend the cognitive capabilities of humans when working together on those learning tasks. [41] describes the fruitful collaboration between human and machine as *augmented intelligence*, pointing at the positive aspect of machine learning support.
—Narrowing topic to decision-making and discriminative algorithms and define "decision" as output from ML systems

2.1 Interpretability in AI

Humans cooperating with machines need to understand the principles of the method that is employed - a property referred to as *transparency* [23]. *Opacity*, the direct opposite of transparency [25], is a major problem for augmented intelligence. Although opacity can be used voluntarily as a means to self-protection and censorship, it also arises involuntarily due to missing technical expertise and failed human intuition and cognitive abilities [5].
On the application-side of machine learning systems, the question of transparency brings up the notion of *interpretability*. Interpretability refers to how well a "typical classifier generated by a learning algorithm" can be understood [23], as compared to the theoretical principle of the method. That is, an interpretable machine learning system is either inherently interpretable, meaning that its operations and result patterns can be understood by a human [4] [41], or it is capable of generating descriptions understandable to humans [13]. It is also possible to equip a system retrospectively with interpretability by adding a proxy model capable of mirroring the original system's behaviour while being comprehensible for humans [15]. Using an interpretable system as a human means being enabled to make inferences about underlying data [41].
[15] assigns ten desired dimensions to interpretable machine learning systems:

- *Scope*: Global interpretability (understanding the model and operations) and local interpretability (understanding what brought about a single decision)
- *Timing*: Time scope available in the application use case for a target user to understand

- *Prior knowledge*: Level of expertise of target user
- *Dimensionality*: Size of the model and the data
- *Accuracy*: Target accuracy of the system while maintaining interpretability
- *Fidelity*: Accuracy of explanation vs. accuracy of model
- *Fairness*: Robustness against automated discrimination and ethically challenging biases in data
- *Privacy*: Protection of sensible and personal data
- *Monotonicity*: Level of monotonicity in relations of input and output (human intuition is largely monotonic)
- *Usability*: Efficiency, effectiveness, and joy of use

In the context of interpretability for machine learning systems, the terms *understandability*, *comprehensibility*, *explainability*, and *justification* are often mentioned in literature. In this paper, we adopt the definition of [35]. *Understandability*, *accuracy* of the explanation, and *efficiency* of the explanation together form *interpretability*. *Explainability* is a synonym of *comprehensibility* [45], which is also synonymic to *understandability* [3] and therefore an aspect of interpretability, showing the reasons for the system's behaviour [13]. Figure 1 gives an overview over these terms. Finally, *justification* refers to the evidence for why a decision is correct, which does not necessarily include the underlying reasons and causes [4].

If the human cognition is augmented by a machine learning system, talking

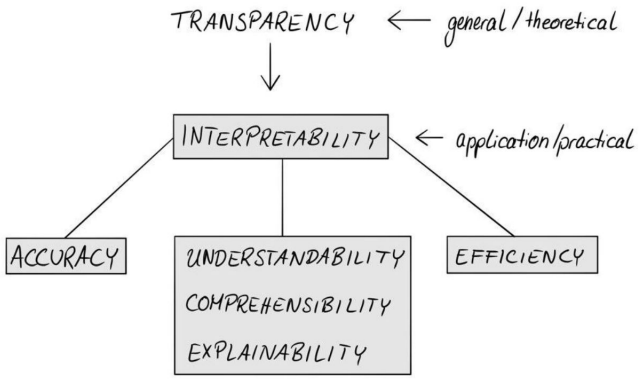

Figure 1: Relation of terms connected to interpretability

about interpretability should also include discussing the interpretability of the human in the loop. [25] argues that human behaviour is often mistakenly identified as interpretable because humans can explain their actions and beliefs. Yet

the actual operations of the human brain remain opaque, which contradicts the concept of interpretability [25]. If human interpretability is taken as a point of reference for the discussion of algorithmic interpretability, [25]'s argument should be taken into account. Human interpretability, however, is not the focus of this paper and will therefore not be discussed in more detail here.

2.2 Need for Explainability in AI

A subfield of artificial intelligence research revolves solely around the explainability of intelligent systems: *xAI*, explainable artificial intelligence, for the purpose of enabling communication with agents about their reasoning [18]. xAI systems face a trade-off challenge: Their explanation has to be complete and interpretable at the same time [13]. The attention span and cognitive abilities of humans therefore become an important factor to consider in the design of a xAI systemm [24]. Furthermore, the goal of explaining the system is twofold: create actual knowledge and convince the user that the knowledge is sound and complete. Actual understanding and perceived understanding however do not always go hand in hand: Persuasive systems can convince the user without creating actual transparency [13]. The persuasiveness of an explanation is uncoupled from the actual information content of an explanation [4] and needs to be taken into account in user studies. As users can only report on their perception of the explanation, an objective measure to evaluate the fidelity of an explanation is needed. High-fidelity (also called descriptive) explanations are faithful, in that they represent truthful information about the underlying machine learning model [19]. Persuasive explanations, on the opposite, are less faithful to the underlying model, yet open up possibilities for abstraction, simplification, analogies, and other stylistic devices for communication. [19] notes a dilemma in explanation fidelity: "This freedom permits explanations better tailored to human cognitive function, making them more functionally interpretable", but "descriptive explanations best satisfy the ethical goal of transparency". The xAI practitioner therefore needs to consider a tradeoff between fidelity and interpretability.
Besides low-fidelity persuasiveness, badly designed explanations likewise "provide an understanding that is at best incomplete and at worst false reassurance" [5]. Therefore, not only possible explanations for white box (inherently interpretable) and black box (inherently non-interpretable) systems need to be examined, but also the (visual) design and communication of explanations [15]. In recent years, machine learning algorithms employed in the wild show a trend towards increasing accuracy but also increasing complexity. In general, the higher the accuracy and complexity, the lower the explainability [33] [6] in machine learning. However, users do not necessarily perceive systems with simple explanations as more understandable [1]. The authors of the user study in [1] hypothesise that users detect missing information in simple explanations, which in turn leads to the perception of incomprehensibility. [40] examined user preferences in more detail and concluded that users overall preferred more soundness

and completeness over simplicity, as well as global explanations over local explanations.
Humans involved in the explanation process are not only users, but also domain experts and engineers during the design and training phase. As explanations are user-dependent (not monolithic) [31], the design and evaluation of explanation needs to be conducted in reference to the target users. Including experts in the modelling and training process is not only a way to integrate expert knowledge that is otherwise difficult to model, but can also increase user trust [41]. [26] call the situation where a human expert works alongside the machine learning system to improve it "mixed initiative guidance".

2.2.1 Explanation Goals

Machine learning systems are able to achieve high accuracy on classification tasks, for example in information retrieval, data mining, speech recognition, and computer graphics [26]. Explainability is a means to ensure that machine learning systems are not only right in a high number of cases, but right for the right reasons [31]. High accuracy does not necessarily mean that correct generalisations were learned from the dataset or that no biases were present in the data.
The need for interpretability is dependent on the role of the explanation user and the severity of the consequences of the classification result and possible errors. Since explanations are not monolithic, i.e. have to be adapted to the target user's level of expertise, preferences for explanation types, and cognitive capabilities, the need for interpretability is also dependent on the targeted audience. Furthermore, different users can have different data access rights and have different goals to achieve in their interaction with the system [42]. While an engineer could be interested in technical details, a bank employee assessing loan credibility could be interested in similar cases and relevant characteristics of a single decision case. [33] separates a general need for interpretability into three categories:

- **no need** for interpretability if no consequences arise from faulty decisions
- interpretability is **beneficial** if consequences for individuals arise from faulty decisions
- interpretability is **critical** if serious consequences arise from faulty decisions

The three classes of interpretability needs give an overview about possible consequences, yet are too general to serve as guideline for practitioners. More details about decisive factors are needed.
For users of an automatic decision system, having insights into the system functioning and decision process increases trust [31] [10] [4] [7] [42], even in critical decisions such as medical diagnosis [1]. The level of trust should be in relation to the soundness and completeness of an explanation. Having too much or too

little trust in a system can hinder fruitful interaction between the user and the system [31] [33] [40] [32]. Other positive effects on users are satisfaction and acceptance [4] [7] [42] as well as the ability to predict the system's performance correctly [4].
Explanations also help engineers and experts to design, debug, and improve an automatic decision system [31]. Explanations facilitate the identification of unintuitive, systematic errors [13] [32] in the design and redundantise time-consuming trial-and-error procedures for parameter optimisation [26]. Unethical biases in training data leading to automated discrimination [10] can be identified and examined via explanations [13] [33] [32]. Ultimately, the early identification of errors avoids costly errors in high-risk domains [10] [3] [40] and ensures human safety in safety-critical tasks [13] [33].
Besides helping users and engineers, explanations also serve general goals of protection, conformity, and knowledge management. Criminals or hackers that aim to disturb the system or take advantage of it can make imperceptible changes to the input data or model at hidden levels. Having a system capable of explaining its behaviour and inner structure helps to identify unwanted alterations [13]. With the European General Data Prodection Regulation (GDPR) put into place in 2018, a debate on a *right to explanation* started, which will be discussed in the following section. Although the specific implications of the right to explanation remain unclear, it should still be noted that designing interpretability follows up on that regulation [14] [13] [3]. Finally, the most general goal of implementing explanations for automatic decision systems is the opening and accessibility of a knowledge source [3] [33]. The relations derived by a machine learner (stored in the model) can deliver relevant knowledge about the data at hand.

2.2.2 Regulations and Accountability

The General Data Protection Regulation (GDPR) is a European law dealing with the processing of personal data within the European Economic Area (EEA, includes also all countries of the EU). The law holds for all companies within the EEA, companies with subsidiaries in the EEA, and any company processing personal data of a citizen of the EEA. In this context, "processing" does not only relate to automatic systems but also spans to manual processing of personal data [14]. The GDPR defines personal data as data relating to an identifiable natural person, i.e. data that can be used to identify a person [REF TO LAW TEXT]. Names, location data, or personal identification numbers are all examples of personal data that falls under the GDPR. [14] identifies two consequences of the GDPR: the legal right to non-discrimination, and a right to explanation.
Algorithmic decisions must not be based on sensitive, personal data (GDPR article 22 paragraph 4) that are nowadays used to identify groups of people with similar characteristics, such as ethnicity, religion, gender, disability, sexuality, and more [10]. Sensitive information can, however, correlate with non-sensitive

data. Real-life data almost always reflects a society's structures and biases - explicitly through sensitive information, or implicitly via dependent information. As the task of classification means separating single instances into groups based on the available data, the biases are recovered in the model [14]. A guarantee non-discrimination is therefore difficult to achieve. The GDPR does not specify whether only sensitive data or also correlated variables have to be considered when following the law. [14] identifies both interpretations as possible.
While article 13 of the GDPR specifies a right to obtain information about one's personal information and the processing of that personal information, it assures "meaningful information about the logic involved" in profiling without further defining meaningfulness. Based on the ambiguity of "meaningful", several interpretations exist, ranging from denial of the "right to explanation" [43] to a positive interpretation [36]. In summary, precedents are needed to clarify the boundaries of the law.
Besides legal regulations, ethical considerations also play a role in augmented intelligence. Accountability is the ethical value of acknowledging responsibility for decisions and actions towards another party [2]. It is an inherent factor in human-human interaction; artificial intelligence employed to interact with humans or collaborate with humans in augmented intelligence settings therefore bring about the challenge of "computational accountability" [2]. It is important to note that accountability is not a general issue in the digital world: For something to be held accountable of its own decisions or actions, it needs to act autonomously v. In order to determine autonomy of an algorithm and work towards accountability, [10] suggests to disclose the following information for machine learning systems:

- *Human involvement*: who controls the algorithm, who designed it etc., leading to control through social pressure
- *Data statistics*: accuracy, completeness, uncertainty, representativeness, labelling & collection process, preprocessing of data
- *Model*: input, weights, parameters, hidden information
- *Inferencing*: covariance matrix to estimate risk, prevention measures for known errors, confidence score
- *Algorithmic presence*: visibility, filtering, reach of algorithm

[2] argues that causality is a necessary prerequisite for accountability. Machine learning algorithms often learn statistical relations between input features, which at best leads to probabilistic causality, but not certainly to deterministic causality. Whether an automatic decision system itself can be held accountable for its decisions is therefore debatable.

2.2.3 Application Areas

Artificial intelligence and machine learning algorithms are nowadays employed in a variety of areas. As described in 2.2.1, the need for interpretability depends

on the potential consequences of the decisions made by an automatic system. [5] summarises the application area as all systems with "socially consequential mechanisms of classification and ranking", pointing in particular to the consequences for humans. A similar view is expressed in [30] and [32], while [15] restricts the application areas in need for interpretability to those that process sensitive, i.e. personal data. In more detail, the following areas in need of interpretable intelligent systems are mentioned in literature:

- *Societal safety*: criminal justice [52] [19], terrorism detection [24]
- *Processing sensitive data*: banking, e.g. loans [52] [6] [19] [33] [36], medicine & health data [52] [3] [1] [15] [19] [16] [24], insurances [3] [33] [36], navigation [1]
- *Physical safety*: autonomous robotics [3] [15]
- *Knowledge*: education [16], knowledge discovery in research [3]
- *Economy*: manufacturing [16], individual performance monitoring [1], economic situation analysis [1], marketing [6] [33] [36]

But not only systems treating personal data or interacting directly with humans profit from interpretability- [41] suggest all machine learning based support systems as suitable candidates for interpretability. Machine learning is already employed in IT-services such as spam detection and search engines [5] [11], as well as in recommender systems [13] [33].
In the past, several machine learning systems have failed due to undetected systematic errors or automated discrimination. [15] lists incidents with machine learning systems, ranging from discrimination in the job application procedure and faulty target identification in automated weapons due to training data biases, to high differences in mortgage decisions by banks.
An interesting case is the American COMPAS system for automated crime prediction. The system predicted a significantly higher relapse rate for black convicts than for whites, which is assumed to result from human bias in the training data [15]. The argument of human bias is often used to object the perceived impartiality of computer systems, and other examples of discrimination of ethnic minorities exist [15], yet [38] counter-argues that differences found in the data set possibly reflect actual differences existing in the real world - which would shift the discussion about auto-discrimination to the field of ethics. Furthermore, the goal of profiling and classification is to separate a data set into groups [14]; discrimination is therefore "at some level inherent to profiling" [8].
In a study of 600.000 advertisements delivered by Google, [8] found a bias against women. Advertisements of higher-paid jobs were more often shown to men than they were to women. Google's targeted advertisements make use of profiling, i.e. delivering content to users depending on their gender, age, income, location, and other characteristics. In the study, the researchers did not have access to the algorithm and can therefore not determine whether the bias was introduced with the data set, the model, or simply by conforming to the advertisement

client's requirement for profiling.
Besides biased training data, systematic modelling errors can account for failures of machine learning systems. Google Flue Trends predicted the amount of humans infected with flue based on the received search queries, leading to large overestimates of actual flue cases [31]. [37] investigated the work of different research groups on the same data set, finding that the main reason for variance in results originates from the composition of the group. Compared to the group composition, the choice of classifier accounted for minor variance. They therefore concluded that the human bias in machine learning systems is the main factor influencing the results.
Deciding whether an automatic decision system meets legal and ethical standards requires knowledge about the system. In the case of Google's targeted advertisements, it is impossible to determine if the algorithm is discriminating women on purpose due to advertiser's requirements, or if the system has internal flaws that lead to unfair treatment. With the GDPR, judging the fairness of an automatic system is not only a concern of the company using machine learning techniques, but also the right of any data subject in the training set and the application.

2.3 Explanations

In the previous sections, we used "explanations" as a generic term. In this section, the concept of an explanation is described in more detail.
In general, an explanation is one or more reasons or justification for an action or belief [31]. Humans need explanations to build up knowledge about events, evaluate events, and ultimately to take control of the course of events.
When being confronted with a new event, artifact, or information in general, humans start building internal models. These mental models are not necessarily truthful nor complete, but represent an individual's interpretation about the event. Explanations are a tool to build and refine the inner knowledge model [28].
Explanations also help to assess events that are happening: We are able to compare methods or events with each other, justify the outcome of an event, and assign responsibility and guilt for past events [28] [22]. Explanations also serve to persuade someone of a belief [28], and can lead to appreciation through understanding [22].
Having understood what brings a certain event about, humans can use their knowledge model to predict the consequences of (similar) events in the future [28]. For an engineer working on a machine learning system, understanding underlying principles and consequences of the system's behaviour is a necessary step in designing a system that is "right for the right reasons" [31]. Similarly, the knowledge model can serve to prevent unwanted states or events, restore wanted states, and reproduce observed states or events [22].

2.3.1 Human-Human Explanations

Humans build mental models of the world, an inner, mental representation of events or elements. It might be noteworthy to point out the difference between the inner knowledge model and an explanation. The mental model is a subjective set of relations resulting from an individual's thought process. An explanation, however, is the interpretation of such relations [22]. Both the mental model and an explanation do not have to be truthful to the real world. We do not need to have complete, holistic mental models in order to use an artifact, but a *functional* model is needed to tell us how to use and make use of it, while a *structural* model stores information about the composition and how it is built [24].
Explanations are a cognitive and social process: The challenge of explaining includes finding a complete but compressed explanation, and transferring the explanation from the explainer to the explainee [28]. In its purest sense, "complete" means an explanation that uncovers all relevant causes [28], which is rarely the case in the real world.
[22] summarises four aspects of explanations:

- *Causal pattern content*: an explanation can reveal information about a common cause with several effects, a common effect brought about by several causes, a linear chain of events influencing each other chronologically, or causes that relate to the inner state of living things (homeostatics), e.g. intent
- *Explanatory stance*: refers to the mechanics, the design, and intention [28]. Atypical explanatory stances can lead to distorted understanding.
- *Explanatory domain*: different fields have different preferences of explanation stances
- *Social-emotional content*: can alter acceptance threshold and influence recipient's perception of explained event

What constitutes a good explanation? [22] describes good explanations as being non-circular, showing coherence, and having a high relevance for the recipient. Circularity are causal chains where an effect is given as cause to itself (with zero or more causal steps in between). Explanations can, but do not have to, explain causal relations [22]. Especially in the case of machine learning algorithms, the learned model shows correlation, not causation. Explanations for statistical models therefore cannot draw on typical causal explanations as found in human-human communication [REF NEEDED]. The probabilistic interpretation of causality comes closest to the patterns learned in statistical models: If an even A caused an event B, then the occurrence of A increases the probability of B occurring. Statistical facts are not satisfactory elements of an explanation, unless explaining the event of observing a fact [28]. Arguably, this holds true for statistical learning. Coherence refers to the systemacity of explanation elements: good explanations do not hold contradicting elements, but elements that

influence each other [22]. Finally, relevance is driven by the level of detail given in the explanation. The sender has to adapt the explanation to the recipient's prior knowledge level and cognitive ability to understand the explanation [28], which can mean to generalise and to omit information - [22] calls this adaptation process the "common informational grounding". The act of explaining also includes a broader grounding of shared beliefs and meanings of events and the world [28]. The "compression problem" poses a major challenge in constructing explanations for humans. Humans tend to not comprise all possible causes and aspects of the high-dimensional real world in an explanation, suggesting that there are compression strategies (on the sender's side) and coping strategies (on the recipient's side) in place [22].
[28] notes that besides presenting likely causes, and coherence, a good explanation is simple and general. The latter two characteristics refer to the agreement widely accepted in science that a simple theory (or, in this case, an explanation) is favoured over a more complicated theory if both explain an equal set of events or states.
[24] defines a good explanation as sound, complete, but not overwhelming. While soundness refers to the level of truthfulness, completeness describes the level of disclosure [24]. In order to avoid overwhelming the explainee, the informational grounding process takes place, i.e. a common understanding of related elements and an adaptation of the explanation's detailedness to the explainee's knowledge level. In general, the more diverse the given evidence, the higher the recipient's acceptance of the explanation [22].
Explainees' cultural background is known to influence their preference for an explanation type - explaining foremost the mechanics, the design, or the intention of an event or artifact. Although different explanation types are preferred in different cultures, all explanation types can be understood by all cultures in general [22].

mindlessness and explanations [32]

Explanation Types associations between antecedent and consequent, contrast and differences, causal mechanisms [10]
material cause, formal / categorical cause, efficient cause, final cause [28]

2.3.2 AI-Human Explanations

Focus:
[10]:

- feature-level: feature influence, intersection of actual & expected contribution per feature
- sample-level: explanation vector, linguistic explanation for textual data using BOW, subtext as justification for class (trained independently), caption generation

- model-level: rule extraction, prototypes & criticism samples representing model, proxy model (inherently interpretable) with comparable accuracy (NOTE: supposedly meant decision generation, not simple accuracy)

single focus: feature-based explanation best for recommender systems (as compared to similar previous decisions and similar neighbor decisions) [10]
[4]:

- understanding and reassurance (right for the right reasons)
- diagnosis (of errors, inacceptable performance or behaviour)
- refinement (improving robustness and performance)

[6]:

- representation of data & features
- processing of data (operations)
- explanation generation (within model)

[28]:

- computational / operations level
- representational level
- hardware level

[8]:

- learning algorithm behaviour
- model parameters
- model itself
- representation

[15]:

- within algorithm, directly based on model
- feature-based
- secondary, add-on explanation system separate from learning algorithm
- representation

[14]:

- inner workings for transparency
- post-hoc prediction visualisation, e.g. heat maps

[16]:

- dataset / features
- optimizer / learning algorithm
- model
- prediction / result
- evaluator

Explanation selection: it is not possible to show every case, parameter, feature importance to the user, therefore a selection of exemplary cases needs to be made [24]. Global explanation can originate from a set of representative cases [24].

2.3.3 When to explain?

[15] stresses that different explainability needs call for different timings of the explanation. Showing the explanation **before** a classification or generation task is useful for justifying the next step or explaining the plan. **During** a task, information about the operations and features can help identifying errors for correction and foster trust. Explaining the results of a task **after** the process is useful for reporting and knowledge discovery.

2.3.4 Explanation Systems

For models that are not inherently interpretable, the explanation can only be an approximation and cannot be complete (definition of non interpretable) [28]. There can be approximations for the computation / operations detecting properties and categorisations, and approximations of the decision behaviour [28].

counterfactual explanation [12] with fact & foil
[4] for overview over solutions for understanding, diagnosis, refinement
[6] for overview of solutions for explaining features, operations, generative explanations
[16] for solutions for dataset, optimizer, model, predictor and evaluator
[14] for set of programs (MYCIN, NEOMYCIN, CENTAUR, EES) that try to model explanations alongside with system
[19] presenting the L2X system
[24] Explanation software: LIME, ELUCIDEBUG

For feature-based models, [19] suggests salience map masks on input features, comparable cases (input and output) as reference (or very dissimilar cases as counterfactuals), and mutual information analysis per feature. For the latter, they use the Kullback-Leibler divergence to calculate the mutual information of two vectors: Learning to explain (L2X).

Inherently interpretable / transparent models:

- decision trees (graphical representation), rules (textual representation), linear models (feature magnitude and sign) [3]
- shallow rule-based models, decision lists, decision trees, feature selection, compositional generative models [10]
- decision trees, Naive Bayes, Rule-Learners [71]

[REF NEEDED] add-on and post-hoc systems might be good as explaining, but this fact in itself does not guarantee a sound, i.e. truthful, explanation, "however plausible they appear" [31].

[15] suggests to develop a new class of learning algorithms that have an inherent "explainability hyperparameter" to achieve high accuracy AND high explainability.

[36] argues that most high-dimensional real-world application data is "concentrated on or near a lower-dimensional manifold" [36], dimension reduction techniques like PCA or other feature selection algorithms can therefore be used to overcome the curse of dimensionality.

explanations for texts: [7] solution to recent development in text mining, where texts are represented in a high-dimensional vector space (e.g. fasttext, word2vec) and classified with neural nets. Compared to BOW/SVM, the W2V/CCN they used yields equally good results, because the CNN is better at identifying characteristic words.
[19] designed a system that uses deep neural networks for classification and mutual information for getting the input feature importance (in their case, single words).

Relevant words: A word is relevant to the text if removing it from the texts and classifying again results in a decrease of the classification score across all texts [56] take the opposite approach by eliminating irrelevant words, which leaves the relevant ones but show that this method does not work for neural classifiers

2.3.5 Explanation Evaluation

[6]:

- application grounded: true context, true task, users
- human-grounded: usability tests, human performance tests
- functionally grounded: no users, proxy

[8] evaluation of model interpretability:

- heuristics: number of rules, number of nodes, minimum description length (model parameters)

- generics: ability to select features, ability to produce class-typical data points, ability to provide information about decision boundaries
- specifics: user testing / perception (BUT: evaluation of visuals and perceived model rather than actual model), e.g. by measuring accuracy of prediction, answer time, answer confidence, understanding of model

[15] rather combination than only a single one:

- algorithm performance score
- user performance score
- user satisfaction score

2.4 Trust in AI

[25] notes that there exists no precise definition of trust in the field of computer science

[TRUST 02] examined the concept of trust in close relationships and define it as the willingness to put oneself at a risk and believing that the other will be benevolent. They grouped aspects of interpersonal trust into a model with three components: faith, dependability, predictability [TRUST 02].
Placed in agent, not a characteristic inherent to an agent [TRUST 02]
Trust is a subjective experience rather than objectively measurable [TRUST 05] [23].
dynamic: evolves as relationship matures [TRUST 02]
attribution of characteristics, e.g. dependability (repeated confirmation in risky situations), reliability (consistency or recurrent behaviour) [TRUST 02]
inappropriate trust can be harmful [17]
Trust as experience, trustworthiness is the characteristic and in case of computer programs consists of factors such as security, privacy, dependability, usability, correctness [TRUST 05] [TRUST 06]. Trust relates to the assurance that a system performs as expected [TRUST 05].
Trust in a system can be misused: e-crime with negative side effects, e.g. data misuse [TRUST 05].

2.4.1 Gaining User Trust

Trust factors: appeal, competence (privacy, security, functionality), transparency, duration (relationship, affiliation), reputation [23]
Concerning algorithms, users can put global trust into the system, which means trusting the model itself. Trust can also be assigned locally, into an individual decision. [24]
Trust dimensions of web systems: target (the entity being evaluated), representation (encoding of trust via social warranty, certificates, etc.), method (security), management (the entity putting trust into the system), computation

(evaluation metric), purpose [25]
For classification: expectation mismatch leads to direct decrease in trust [30], strength of decrease depends on the type of mismatch. Data-related mismatch weights less strongly than logic-driven mismatch. [30]
[31] argues that trust in machine learning algorithms also depends on the characteristics of misclassified cases. He points out that an automatic system can be considered trustworthy if it behaves exactly like humans, i.e. it misclassifies the same data points as a human and is correct on those cases that a human would also correctly classify [31].

2.4.2 Trust Evaluation

[23]: using experts to assign a weighted label to each element on a website or GUI and calculating a score

-1 irritant

1 chaotic

2 assuring

3 motivating

0 not present

But user study showed that experts find it problematic to assign discrete trust values. The advantage of this approach, however, is that it is possible to compare multiple websites [23].
user study with closed and open questions [24]:

- Do you trust this algorithm to work well in the real world?
- Why do you trust this algorithm to work well in the real world?
- How do you think the algorithm distinguished between the two classes?
- How certain are you of the correctness of your explanation?

[TRUST 02] develops a trust scale with 26 items, each belonging to one of the three trust factors (faith, dependability, predictability).
[TRUST 01] describes online trust (websites) as developing from external factors (website's reputation, navigational architecture, user's prior experience) as well as perceived factors (credibility, ease of use, risk)
"willingness to accept a computer-generated recommendation is considered a proxy measure of trust" [38]

2.4.3 Perceived Understanding

Perceived understanding important for trust (rather than actual understanding):
"Findings show that the transparent version was perceived as more understandable and perceived understanding correlated with perceived competence, trust and acceptance of the system. Future research is necessary to evaluate the effects of transparency on trust in and acceptance of user-adaptive systems" [59]
Most questionnaires use factual statements to investigate perceived understanding. Participants rate the statements according to their confidence of understanding [UND 03] [UND 07] or directly their subjective understanding [UND 01] [UND 02] [UND 04] [UND 05]

2.5 Summary

Summary

- summary
- systems
- evaluation of explanations and of trust

Hypotheses

3 Method

Intro

3.1 Use Case Scenario

definition of offensive language [34]
hate speech detection systems

4 Implementation

Intro

4.1 Dataset Selection

Few datasets with offensive language texts are publicly available. Table 3 presents an overview of four available datasets, their sizes and class balances. While the dataset of SwissText has the most fine-grained labelling of its data

Corpus	**Size**	**Classes**	
Davidson[1]	25,000	hate speech	6%
		offensive	77%
		neither	17%
Imperium[2]	3,947	neutral	73%
		insulting	27%
Analytics Vidhya[3]	31,962	hate speech	7%
		no hate speech	93%
SwissText[4]	159,570	toxic	10%
		severe_toxic	1%
		obscene	5%
		threat	0.3%
		insult	5%
		hate speech	1%
		neither	72.7%

Table 1: Publicly available datasets for offensive language texts

points, details on how the labels were assigned (i.e. number of annotators, inter-annotator agreement score, definition of the classes) are not available. The same holds for the datasets of Analytics Vidhya and Imperium.
In contrast, Davidson's datasets comes with a description of how the data points were collected, how the classes are defined, and uses at least three annotators per text. Furthermore, Davidson's dataset contains the most data points labelled as offensive: roughly 20750 Tweets fall into this category, while the Analytics Vidhya dataset contains 2240 hate speech texts, SwissText 1600, and Imperium 1000.
Throughout the literature, different definitions of hate speech and offensive language are given. For using a dataset in a user study with the scenario of a social media administrator, the definition of the label has to be clear. We therefore chose to work with the dataset of Davidson et al., as it offers the most detailed description of its labels and how the labels were obtained.

4.2 Dataset Construction

The original dataset was collected by Davidson et al. [9] for their research on defining and differentiating hate speech from offensive language. They con-

structed a dataset with offensive Tweets and hate speech by conducting a keyword search on Twitter, using keywords registered in the hatebase dictionary[5]. The timelines of Twitter users identified with the keyword search were scraped, resulting in a dataset of over 8 million Tweets. They selected 25 000 Tweets at random and had at least 3 annotators from Figure Eight[6] (formerly Crowd Flower) who labelled each Tweet as containing hate speech, offensive language, or neither. They reached an inter-annotator agreement of 0.92 [9]. The dataset is publicly available on GitHub[7].
The biggest class in the dataset are the offensive language Tweets (77%), while non-offensive Tweets represent 17%, and hate speech 6% of the dataset.
For our research, we are only interested in offensive and not offensive Tweets. We therefore excluded Tweets labelled as hate speech for the further construction of our dataset. We produced a balanced dataset by selecting only Tweets with the maximum inter-annotator agreement from each of the two remaining classes, and randomly drew Tweets from the bigger class (offensive Tweets) until the size of the subset was equal to the size of the smaller class (non-offensive Tweets). Table 4 presents statistical information about the resulting dataset.

	Not Offensive Class	**Offensive Class**
Size (absolute)	4,162	4,162
Size (relative)	50.00%	50.00%
Total words	58,288	61,504
Unique words	6,437	9,855
Average words per Tweet	14.00	14.78

Table 2: Statistical characteristics of the constructed dataset

4.3 Dataset Preprocessing

Tweets exhibit some special characteristics. First, the maximum length of a single Tweet is 140 characters. Twitter doubled the length in November 2017, yet the dataset was collected before this data and therefore contains only Tweets of 140 characters or shorter. Twitter users found creative ways to make use of the 140 characters given, leading to the usage of short URLs instead of original URLs [46], intentional reductions of words (e.g. “nite” instead of “night”) [46], abbreviations [16], emojis [12] [44] and smilies [39] [20].
Furthermore, social media content can be unstructured, with word creations that are non in standard dictionaries, like slang words [16] [44], intentional repetitions [46] [17] [29] [34] (e.g. “hhheeeey”), contractions of words [39] [17], and spelling mistakes. Although those new word formations do not appear in the dictionary, they are “intuitive and popular in social media” [21].

[5] https://www.hatebase.org
[6] https://www.figure-eight.com
[7] https://github.com/t-davidson/hate-speech-and-offensive-language

On Twitter, it is custom to mention other users within a Tweet by adding "@"+username [46] [29] [44] [34], retweeting (i.e. answering to) a Tweet [46] [17], and summarizing a Tweet's topic with "#"+topic [46] [44].
Other problems in text mining are the handling of stop words [46] [12] [16], language detection [46], punctuation [12] [17] [29], negation [44], and case folding [12] [16] [34].
Researchers have developed different strategies for preprocessing Tweets. One possible approach is to simply remove URLs, username, hashtags, emoticons, stop words, or punctuation [46] [12] [17] [29] [16] [44]. A reason to eliminate those tokens can be that they assumably do not hold information relevant to the classification goal [17]. Words that only exist for syntactic reasons (this concerns primarily stop words) can be omitted when focussing on sentiment or other semantic characteristics [12]. Mentions of other users are likewise not informative for sentiment analysis and are often removed from the texts [46] [44]. Depending on the dataset size, normalising the texts strongly by removing punctuation and emojis, as well as lowercasing the texts, can decrease the vocabulary size [12]. Especially on Twitter with its restricted text size, users tend to use shortened URLs. Short URLs have a concise, but often cryptic form, and redirect to the website with the original, long URL. While website links can encode some information on a topic, this information is lost when using a shortened URL. Removing the shortened URLs without replacement can be a step in preprocessing Tweets [46].
Rather than removing tokens, they can also be replaced by a signifier token, e.g. a complete link by "<<<hyperlink>>>" [20]. In Tweets, such signifier tokens are used for mentions of usernames [39] [20] [34], URLs [39] [20] [34], smilies [20] or negations [39]. Using signifier tokens eliminates some information, i.e. which user was mentioned or which website was linked, but retains the information that a mention or link exists. Tokens can also be grouped by using signifier tokens, i.e. tokens with similar content are summarised with a single token. [20] uses this technique to group smilies with similar sentiment and Twitter usernames related to the same company.
Case folding is often addressed by converting Tweets to lower case [12] [20] [16].

The following preprocessing steps are taken in chronological order:

1. Conversion of all texts to lower cases
2. Replacement of URLs by a dummy URL ("URL")
3. Replacement of referenced user names and handles by a dummy handle ("USERNAME")
4. This dataset encodes emojis in unicode decimal codes, e.g. "😀" for a grinning face. In order to keep the information contained in emojis, each emoji is replaced by its textual description (upper cased and without whitespaces to ensure unity for tokenizing)[8].

[8] https://www.quackit.com/character_sets/emoji/

5. Resolving contractions such as “we’re” or “don’t” by replacing contractions with their long version[9].
6. This dataset uses a few signifiers such as “english translation” to mark a Tweet that has been translated to English, or “rt” to mark a Retweet (i.e. a response to a previous Tweet). Since those information have been added retrospectively, we discard them here and delete the signifiers from the texts.
7. Replacement of all characters that are non-alphabetic and not a hashtag by a whitespace
8. Replacement of more than one subsequent whitespace by a single whitespace
9. Tokenization on whitespaces

After training the classifiers, the URL and username tokens are replaced by a more readable version (“http://website.com/website” and “@username”, respectively) to make it easier for participants of the user study to envision themselves in the scenario of a social media administrator reading real-world Tweets. Replacing the tokens by their original URLs and usernames would give the participants more information than the classifiers had; we therefore chose to use a dummy URL and username.

Following the preprocessing steps, the following Tweet is processed from its original form:

```
"@WBUR: A smuggler explains how he helped fighters along the

"Jihadi Highway": http://t.co/UX4anxeAwd"
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into a cleaned version:

```
@username a smuggler explains how he helped fighters along the

jihadi highway http://website.com/website
```

4.4 Classifier

Intro

Good System L2X

[9] https://en.wikipedia.org/wiki/Wikipedia:List_of_English_contractions

Medium System Logistic Regression with binary (1 / -1) coefficients

Bad System Inverse L2X

4.5 Explanations

Intro

Good System L2X mutual information

Medium System randomly choosing k words from the words with positive (offensive) or negative (not offensive) class

Bad System Inverse good system

4.6 Graphical User Interface

asdasdasd

4.7 Subset Sampling

For evaluating the different system-explanation conditions, users have to experience the system. However, it is not feasible to present them with the complete testeset, since it has a size of 1665 Tweets. Consequently, a subset of Tweets needs to be drawn from the testset, with a size that a human observer can understand and process within the time frame of a user study.
We furthermore aim to find 10 suitable subsets and assign participants randomly to one of the subsets, in order to reduce possible side effects from biases specific to single Tweets.
There are several requirements for the subsamples, originating from the conflict of reducing the sample for a human observer, yet still yielding a good representation of the testset and classifier:

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We set the subsample size to 15 Tweets, which is enough to show accuracies to the first decimal place, yet assumably not too much to process for an observer in a user study.

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5.8 Explanation Evaluation

6 User Study: Trust Evaluation

Intro

6.1 Method

Intro

Participants

- amount, mean age, SD age
- recruitment method
- exclusion criteria
- compensation for participation

Apparatus A paragraph about the experiment setup (physically), system requirements and technology used. For example the pixel dimensions of screenshots.

Procedure

- tasks / survey items
- ordering of tasks

Design & Analysis One paragraph for experiment design (statistically).

One paragraph for statistical analysis.

- data points per participant and in total
- statistical test
- corrections / disqualifications

6.2 Results

Intro

asdasdasd

7 Discussion

8 Conclusion

asd

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