

# Creation and Evaluation of a Self-Learning Course for Data Hazard Labels

Bachelor Thesis

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# Introduction

- **Creation of a self learning course using LiaScript**
- **Aimed at university students**
- **Intersection between ethics and data science**
- **Course can be used as supplementary material for lectures**

# Data Hazards



**Created and maintained by the Data Hazard Project**

**Goal: Create a tool to help initiate ethics discussion on data science**

**Data hazard labels:**

- **Similar to real Hazard labels**
- **Currently 11 labels for data science and 5 for synthetic biology**
- **Can be assigned to any projects using data science**
- **Not strict true or false**
- **Multiple labels can apply**

# Data Hazards



Generic Data Hazard



Reinforces Existing Biases



Automates Decisionmaking

**Not present:**

- **High Environmental Cost**
- **Risk to privacy**
- **Lacks Informed Consent**
- **Difficult to understand**



Ranks or Classifies People



Danger of Misuse



May cause Harm

# Current Prototype

## Data Hazard Labels

### Reinforces Existing Biases

Definition

Examples

Prevention of Bias

Videos

Quiz

### Ranks or classifies people

Definition

Examples

Prevention of improper ranking  
and classification

Videos

Quiz

### Automates decision making

Definition

Examples

Precautions for automated  
decision making

## Definition



This label indicates that data, algorithms, or software could lead to unfair treatment of individuals or certain groups. There are various reasons why this hazard might arise.

One source of bias can be the input data itself. If the data used contains biases and these are not corrected, the bias will be perpetuated. For example, if historical data reflects societal biases, algorithms trained on this data will likely replicate those biases.

Additionally, the design of an algorithm can introduce bias. If an algorithm gives more importance to certain characteristics, it might favor some individuals or groups over others. This can happen even if the intention is not to discriminate.

Societal biases can also infiltrate data and algorithms, reflecting and reinforcing existing stereotypes. These biases are often unintentional and unwanted, but if left unaddressed, they can have negative and unforeseen consequences. It is crucial to recognize and mitigate these biases to ensure fairness and equity in the use of data and technology.



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## Examples

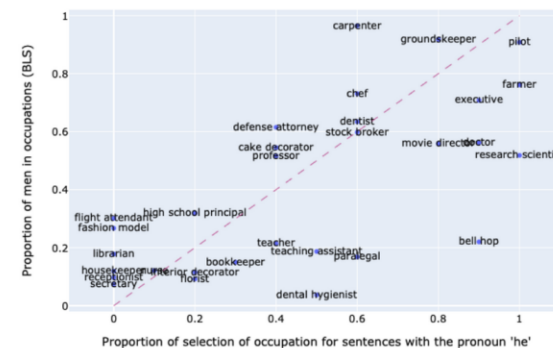
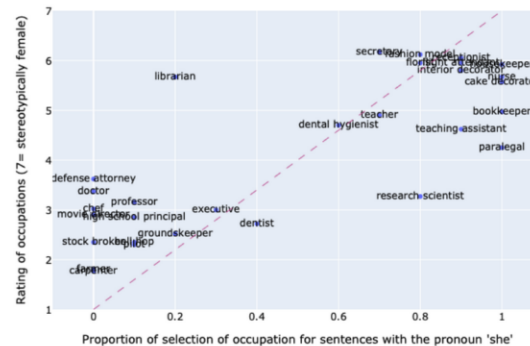
### Input data

An algorithm that uses historic employment data that comes to the conclusion that men are more suited to managerial position, as historically men were favoured or even the only allowed candidates for such positions.

### Societal Bias

Natural Language processing data can reinforce sexist biases due to a bias in training data. This could mean that a model evaluates certain jobs such as secretary or caretaker as intrinsically linked to women.

Such cases were [studied](#) and both natural and large language models were found perpetuate stereotypes. Since these models are used more, great care should be taken when working with such cases and active measures taken to prevent the spread of such stereotyping. Such cases prove furthermore that



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## Videos

Documentary: Coded Bias (<https://www.imdb.com/title/tt11394170/>)



[Die Schwachstelle von KI – wir Menschen | ZDF Magazin Royale \(10.09.2021\) 11:22-12:22](#)



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## Quiz

Test your knowledge! (Multiple Choices can be true)

Which of the following is a potential source of bias in algorithms?

- ☐ The length of the input data
- ☐ The speed of the algorithm
- ☐ The cost of the data analysis
- ☐ The design of the algorithm

Check



What is a key strategy to minimize the risk of having bias in data, software, or algorithms?

- ☐ Increasing the speed of data processing
- ☐ Analyzing the input data carefully for societal factors
- ☐ Using more comprehensive data collection methods
- ☐ Reducing the number of variables in the data

Check



Which is an example of societal bias in natural language processing data?

- ☐ A model that links certain jobs to specific genders

# Current Prototype

Q Search

Videos

Quiz

## Danger of misuse

Definition

Examples

Prevention of misuse

Videos

Quiz

## May cause direct harm

Definition

Examples

Prevention of harm

Videos

Quiz

## Generic Data Hazard

[How to apply data hazard labels?](#)

Sources and additional reading



### How to apply data hazard labels?

The application of data hazard labels is not meant as an apply and be done with it concept. The labels are meant to open up discussion and help with reflection on responsible ethical use and potential consequences of data science. Ethics in data science is a complex topic so there is no need for a group to come to a definitive conclusion on which labels do or do not apply.

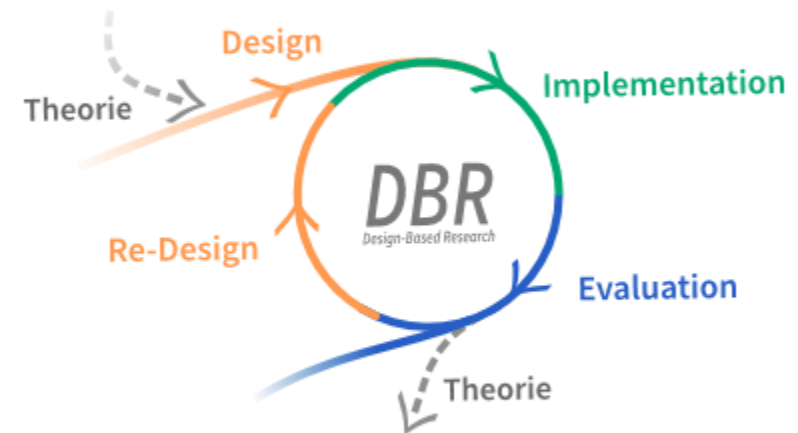
The labels also allow external people to participate in discussions on the ethical impact a technology or algorithm might have which can be tough to get into otherwise. Researchers working in data science might not have the necessary training or knowledge to be able to consider all these possible cases, which is why the data hazard project was started in the first place.

So if you are working on a project using data science, take a minute to think which labels could apply to your project and encourage others to do the same to get a well rounded perspective on the possible outcomes!



# Evaluation and Interviews

- Next step is interviews
- Interviewing experts from relevant fields
- Getting a feedback on design and content
- Use feedback to improve learning course



# Questions

Thank you for your attention!

# Quellen

- The data hazard project (<https://datahazards.com/index.html>)
- Design based research icon ([https://commons.wikimedia.org/wiki/File:DBR\\_german\\_colour.svg](https://commons.wikimedia.org/wiki/File:DBR_german_colour.svg))