



How are data collections
and vocabularies teaching AI
systems human stereotypes?

What are we talking about?

Idea and concepts

Digitalization of CH objects for machine ingestion may have started for **preservation** reasons, but it allowed **applying AI technology** in order to extract knowledge that can improve user experience and be a **valuable** resource for GLAM. Some use case are



Automatic
metadata annotation



Interaction with
minorities such as
visually impaired
citizens



New forms of
interaction with
users through
web-pages and app



Improving search
engine



Idea and concepts

But **risks** and **benefits** of using **AI** are two sides of the same coin

Why?

The terms “fairness” and “bias” are often used interchangeably to refer to whether different groups of people experience different performance from a AI model.



“Fairness”

“The terms “fairness” and “bias” are often used interchangeably to refer to whether different groups of people experience different performance from a machine learning model.”



“Bias”

We define bias here as data that is in some way not representative of the real world.

“Building Machine Learning Pipelines Automating Model Life Cycles with TensorFlow” Hannes Hapke and Catherine Nelson

Is your data fair enough?



Why is fairness **important**?

Just like **humans**, artificial intelligence can be **sexist and racist**

Princeton University study finds machine learning **copies human prejudices** when learning language

Using the popular GloVe algorithm, trained on around 840 billion words from the internet, three Princeton University academics have shown AI applications replicate the stereotypes shown in the human-generated data.

These prejudices related to both race and gender.

Fairness in GLAM

Case 1

Saint George on a Bike Project



Two people were classified by two different classes:
"Person" and "Monkey"



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"Person" and "Monkey"

Fairness in GLAM

Case 2 IconClass

📁 33C2 📁 lovers; courting, flirting

Search with these related keywords:

human being, lover, relationship

Add more detail:

- 33C21 · courting
- 33C22 · lovers' meeting
- 33C23 · couple of lovers
- 33C29 · the envious friends; criticizing bystanders ~ love couple
- 33C2(+0) · lovers; courting, flirting (+ variant)

Classification of “Love”
representation in IconClass

📁 33C6 📁 homosexual love

Search with these related keywords:

homosexual, human being, lesbianism, relationship

Add more detail:

- 33C61 · pederasty, sexual contact between man and boy
- 33C62 · sodomy, sexual contact between men
- 33CC6 · homosexual love - CC - homosexual love between women: lesbianism
- 33C6(+0) · homosexual love (+ variant)

Potentially Offensive grouping of
different art content



Homosexuality in Art

Kyiv art museum, an icon from St. Catherine's Monastery on Mt. Sinai in Israel. It shows two robed Christian saints. Between them is a traditional Roman 'pronubus' (a best man), overseeing a wedding. The pronubus is Christ. The married couple are both men. Image source: [medievaltumblr.com](https://www.medievaltumblr.com)

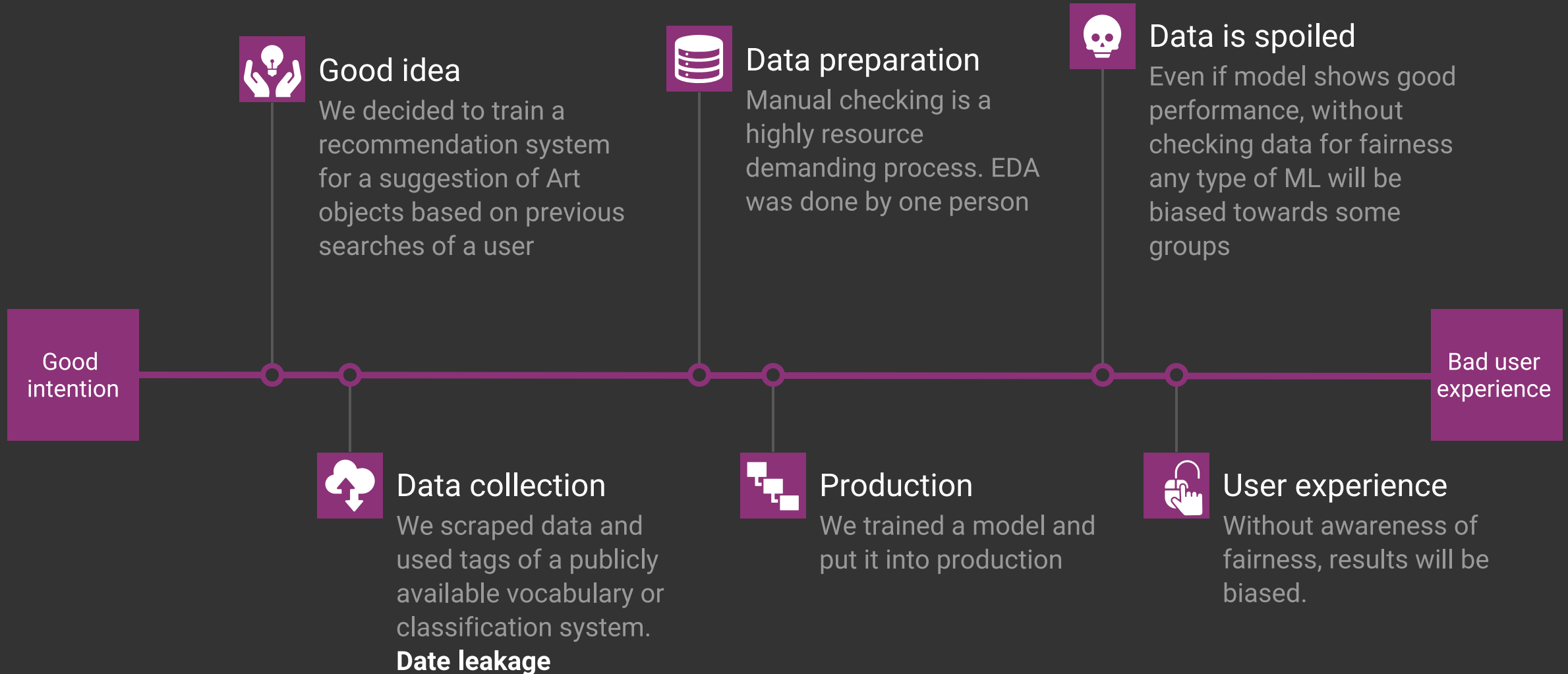
How can it happen?

A yellow sticky note is affixed to a light-colored, textured wall. From the bottom edge of the note, several thick, dark, viscous liquid drips are running down the wall, creating a stark contrast with the light background and the bright yellow of the note.

Data Leakage

Data leakage is a concept in AI when information from outside the training dataset is used to create the model. This additional information can allow the model to learn or know something that it otherwise would not know and in turn invalidate the estimated performance of the mode being constructed.

Pipeline of ML Project



A guide to machine learning (ML) fairness - Think with Google

Algorithms don't remember incidents of unfair bias. But customers do.



What can we do?

Several steps which helps you to avoid bad user experience



Be transparent.

Tell people how your algorithm makes decisions. Knowing how your product works — and how well it works across groups — will make people more comfortable using it.



Test, tune, and test again.

Inspect training datasets for bias using a fairness indicator, visualizer, or other tool. Even a widely used dataset might have flaws, so it's important to review it carefully. Teams should also continue monitoring algorithms after they are released.



Seek different points of view.

Hire people with diverse backgrounds and areas of expertise. Invite the public to share local knowledge. Collaborate with community groups and advocates. A wide range of input makes data more robust.



Ask questions.

Does your product use data such as race, skin color, religion, sexual orientation, socioeconomic status, income, country, location, health, language, or dialect?

Questions?

