«Human-Centered Data Science»

Examining the Role of Data in Your Data Science Practice

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Lecture Overview

Recap & Motivation

Bias in Data Collection and Processing (Defining bias, overview on bias in the data science pipeline, discussing different types of bias and examples)

Break

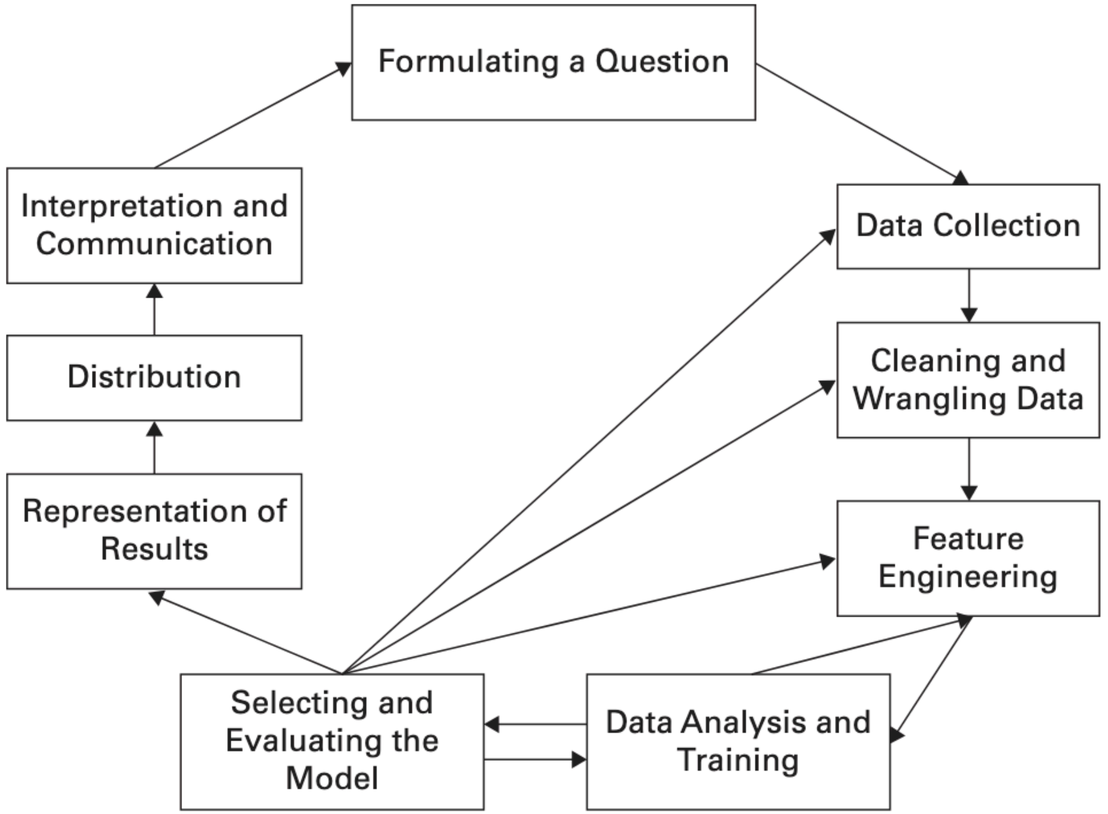
Approaches to Mitigate Bias (datasheets for datasets, structure of the datasheets for datasets, other approaches and example), documentation as reflexive practice)

Recap

Incorporating Principles in Your Data Science Practice

Principles

- Professional Responsibility
- Promotion of Human Values
- Fairness and Non-discrimination
- Human Control of Technology
- Safety and Security
- Transparency and Explainability
- Accountability
- Privacy

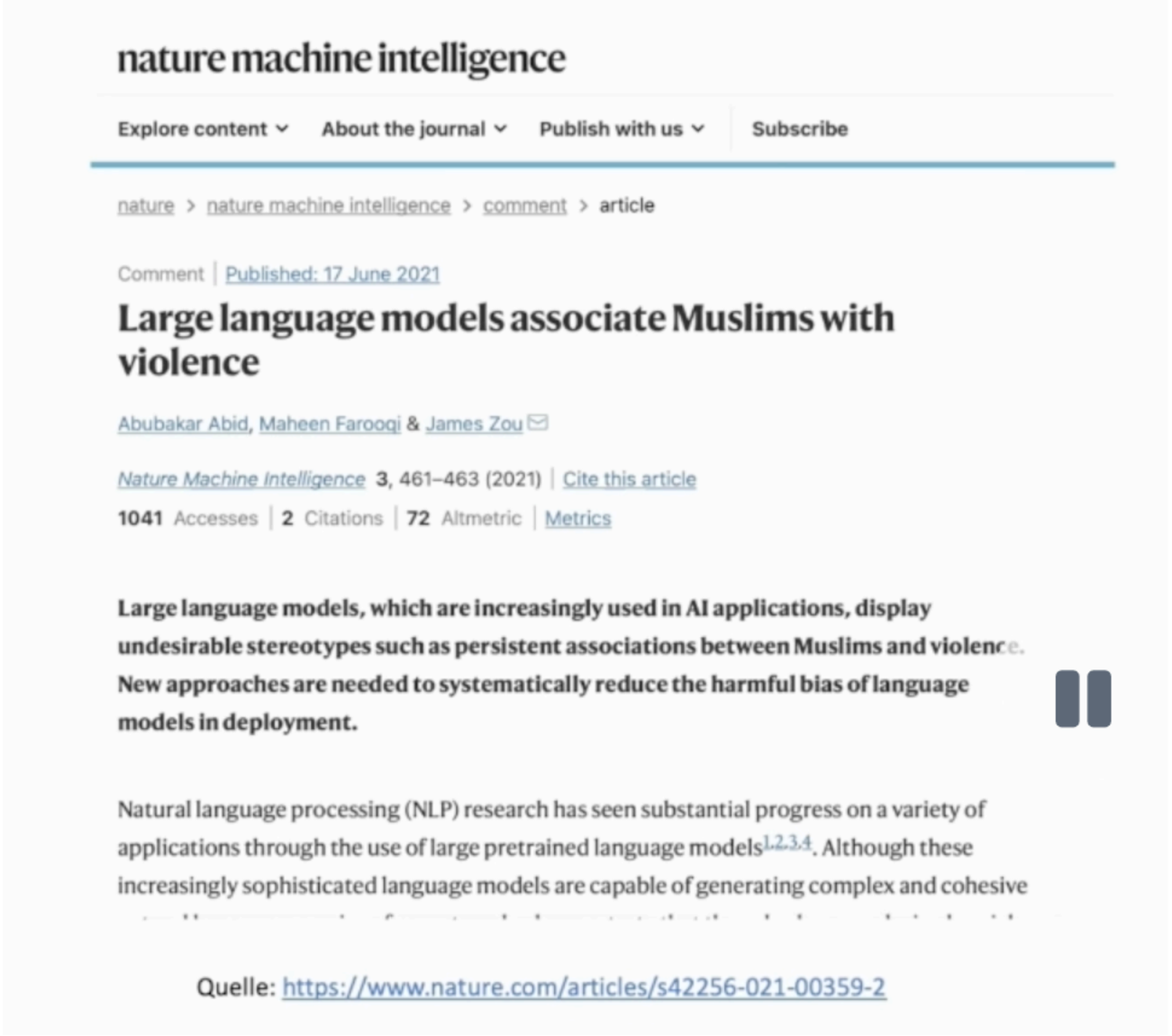


Motivation

Text Data


English
Turkish
Spanish
Detect language
English
Turkish
Spanish
Translate
She is a doctor.
He is a nurse.
31/5000
O bir doktor.
O bir hemşire.
English
Turkish
Spanish
Turkish - d
O bir doktor.
O bir hemşire
ENGLISCH – ERKANNT
DEUTSCH
ENGLISCH
FRANZÖSISCH
DEUTSCH
ENGLISCH
FRANZÖSISCH
doctor
ˈdäktər
6 / 5000
Übersetzungen sind geschlechtsspezifisch. WEITERE INFORMATIONEN
Ärztin (feminin)
Arzt (maskulin)

Language Model



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Comment | Published: 17 June 2021

Large language models associate Muslims with violence

Abubakar Abid, Maheen Farooqi & James Zou

Nature Machine Intelligence 3, 461–463 (2021) | Cite this article

1041 Accesses | 2 Citations | 72 Altmetric | Metrics

Large language models, which are increasingly used in AI applications, display undesirable stereotypes such as persistent associations between Muslims and violence. New approaches are needed to systematically reduce the harmful bias of language models in deployment.

Natural language processing (NLP) research has seen substantial progress on a variety of applications through the use of large pretrained language models[1,2,3,4]. Although these increasingly sophisticated language models are capable of generating complex and cohesive

Quelle: https://www.nature.com/articles/s42256-021-00359-2

Image Data


diri noir avec banan
@jackyalcine
Following
Google Photos, y'all [redacted]up. My friend's not a gorilla.
Skyscrapers
Airplanes
Cars
Bikes
Gorillas
Graduation
© Twitter – @jackyalcine

Public Employment Service Austria

AMS
Arbeitsmarktservice
Österreich

Photo by Amy Hirschi on Unsplash

High chances

Opportunities for integration within the next 7 months > 66%

Middle chances

Group on which resources are to be concentrated in the future

Low chances

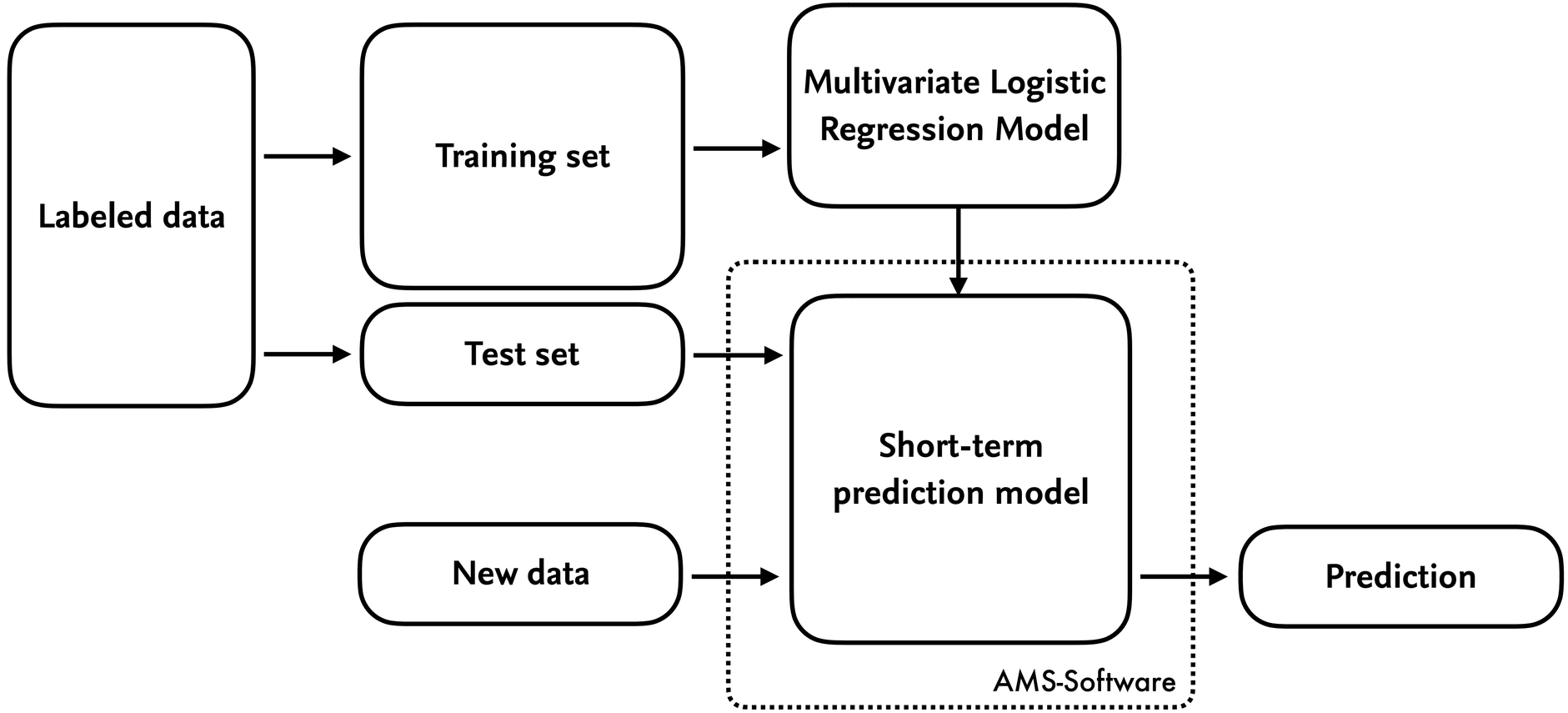
Opportunities for integration within the next 2 years < 25%

Possible Machine Learning (ML)-Pipeline

Repurposed data

» Self-reported data of job seekers upon registration with the AMS

» Social security data (e.g., gender)



Insights taken from
Allhutter, D., Cech, F., 0007, F. F., Grill, G., & Mager, A. (2020). Algorithmic Profiling of Job Seekers in Austria - How Austerity Politics Are Made Effective. Frontiers Big Data, 3, 326. http://doi.org/10.3389/fdata.2020.00005

Used Features

BE_INT

= f (0,10

– 0,14 x GENDER_FEMALE

– 0,13 x AGE-GROUP_30_49

– 0,70 x AGE-GROUP_50_PLUS

+ 0,16 x STATE_GROUP_EU

– 0,05 x STATE_GROUP_THIRD

+ 0,28 x EDUCATION_APPRENTICESHIP

+ 0,01 x EDUCATION_MATURA_PLUS

– 0,15 x CARE_TAKING

– 0,34 x LIVING_TYP_2

– 0,18 x LIVING_TYP_3

– 0,83 x LIVING_TYP_4

– 0,82 x LIVING_TYP_5

…

…

– 0,67 x IMPAIRED

+ 0,17 x OCCUPATION_PRODUCTION

– 0,74 x OCCUPATION_DAYS_LITTLE

+ 0,65 x FREQUENCY_CASE_1

+ 1,19 x FREQUENCY_CASE_2

+ 1,98 x FREQUENCY_CASE_3_PLUS

– 0,80 x CASE_LONG

– 0,57 x MN_PARTICIPATION_1

– 0,21 x MN_PARTICIPATION_2

– 0,43 x MN_PARTICIPATION_3)

Translated features from http://www.forschungsnetzwerk.at/downloadpub/arbeitsmarktchancen_methode_%20dokumentation.pdf

Kurzfristige Integrationschance

Dieser Rechner berechnet die kurzfristige Integrationschance für Arbeitssuchende wie hier beschrieben. Dieses Modell ist nur eines von 96 verschiedenen, die die Chancen von Arbeitssuchenden einschätzen sollen und bezieht sich nur auf die ersten sieben Monate nach Beginn der Arbeit des AMS.

Geschlecht

männlich | weiblich

Alter

unter 30 | 30-49 Jahre | 50 oder älter

Staatsangehörigkeit

Österreich | andere EU-Staaten | Drittstaaten

Ausbildung

höchstens Pflichtschule | Lehre oder berufsbildende mittlere Schule (BMS) | Matura oder höhere Ausbildung

Gesundheitliche Beeinträchtigung

Nein | Ja

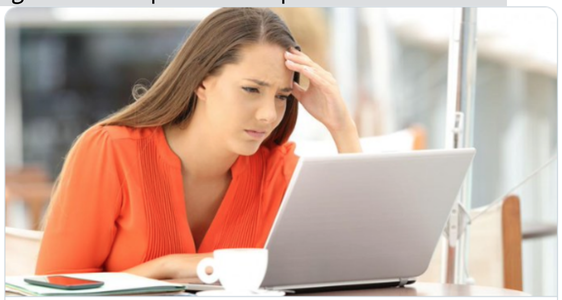
Betreuungspflichten

Nein | Ja

Animation taken from https://derstandard.at/2000089925698/Berechnen-Sie-Ihre-Jobchancen-so-wie-es-das-AMS-tun

Der AMS-Algorithmus ist ein „Paradebeispiel für Diskriminierung“

The AMS algorithm is a prime example of discrimination



Der AMS-Algorithmus ist ein „Paradebeispiel für Diskriminierung“
Ein Computerprogramm soll ab 2019 die Arbeitsmarktchancen von Arbeitslosen berechnen. Experten von der TU und WU Wien schlagen Alarm.
futurezone.at

Austria's employment agency is rolling out a sorting algorithm that gives lower points to women and the disabled, in the name of efficiency.

A textbook example of automated – and possibly illegal – discrimination.

Austria's employment agency rolls out discriminatory algorithm, sees no pro...
AMS, Austria's employment agency, is about to roll out a sorting algorithm that gives lower scores to women and to the disabled. It is very likely illegal under...

What does discrimination mean?

Bias in Data Collection and Processing

Bias in Computer Systems

BATYA FRIEDMAN
Colby College and The Mina Institute
and
HELEN NISSENBAUM
Princeton University

From an analysis of actual cases, three categories of bias in computer systems have been developed: preexisting, technical, and emergent. Preexisting bias has its roots in social institutions, practices, and attitudes. Technical bias arises from technical constraints or considerations. Emergent bias arises in a context of use. Although others have pointed to bias in particular computer systems and have noted the general problem, we know of no comparable work that examines this phenomenon comprehensively and which offers a framework for understanding and remedying it. We conclude by suggesting that freedom from bias should be counted among the select set of criteria—including reliability, accuracy, and efficiency—according to which the quality of systems in use in society should be judged.

Categories and Subject Descriptors: D.2.0 [**Software**]: Software Engineering; H.1.2 [**Information Systems**]: User/Machine Systems; K.4.0 [**Computers and Society**]: General

General Terms: Design, Human Factors

Additional Key Words and Phrases: Bias, computer ethics, computers and society, design methods, ethics, human values, standards, social computing, social impact, system design, universal design, values

Batya Friedman
University of Washington

Helen Nissenbaum
Cornell Tech University

Friedman, B., & Nissenbaum, H. (1996). Bias in computer systems. ACM Trans. Inf. Syst., 14(3), 330–347. http://doi.org/10.1145/230538.230561

> **The term bias refer to computer systems that systematically and unfairly discriminate against certain individuals or groups of individuals in favor of others, contains bias or is biased. A system discriminates unfairly if it denies an opportunity or a good or if it assigns an undesirable outcome to an individual or group of individuals on unreasonable or inappropriate grounds.**
>
> (Friedman & Nissenbaum 1996)

Systematic discrimination does not establish bias unless it is joined with an unfair outcome.

Unfair discrimination alone does not give rise to bias unless it occurs systematically.

Friedman, B., & Nissenbaum, H. (1996). Bias in computer systems. ACM Trans. Inf. Syst., 14(3), 330–347. http://doi.org/10.1145/230538.230561

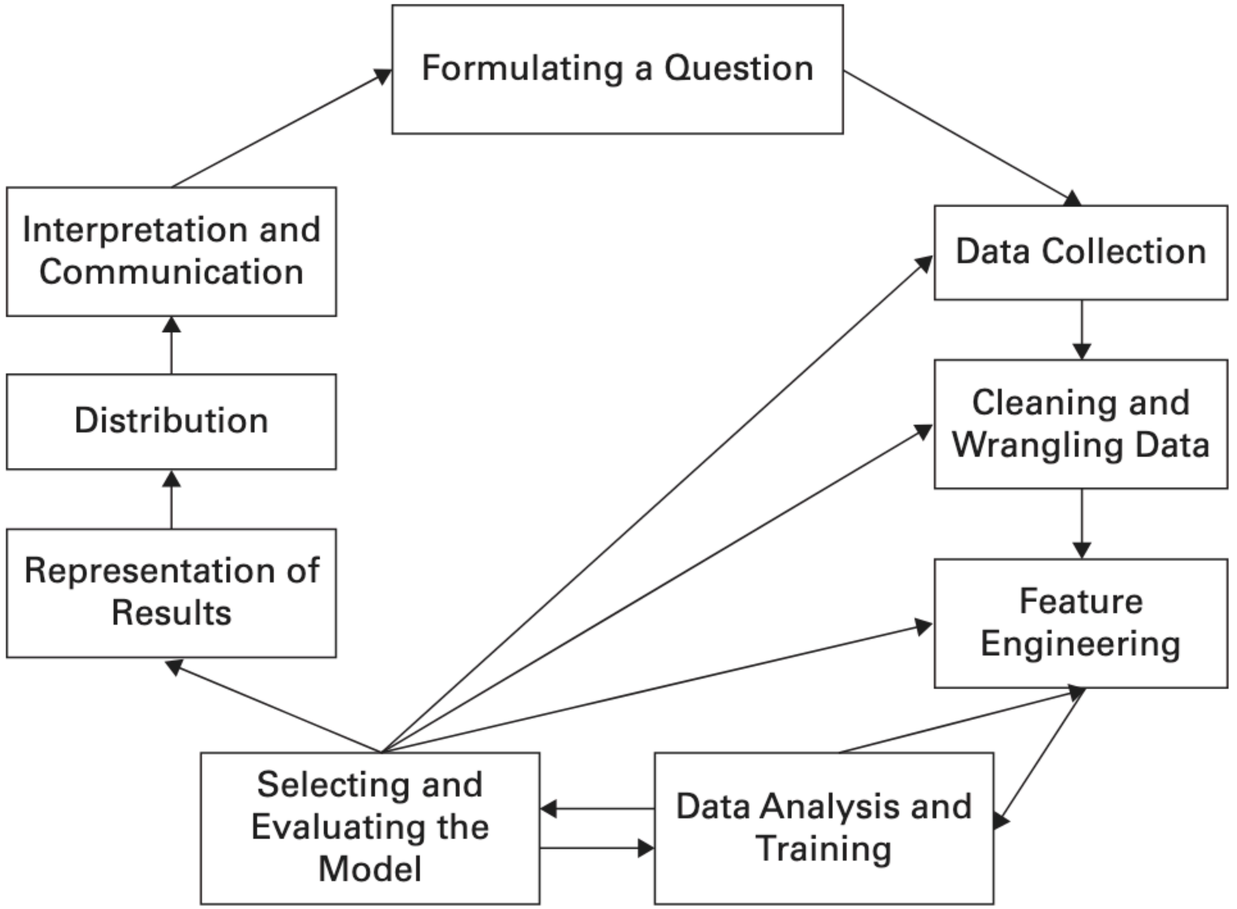
Types of Bias

Preexisting bias has its roots in social institutions, practices, and attitudes.

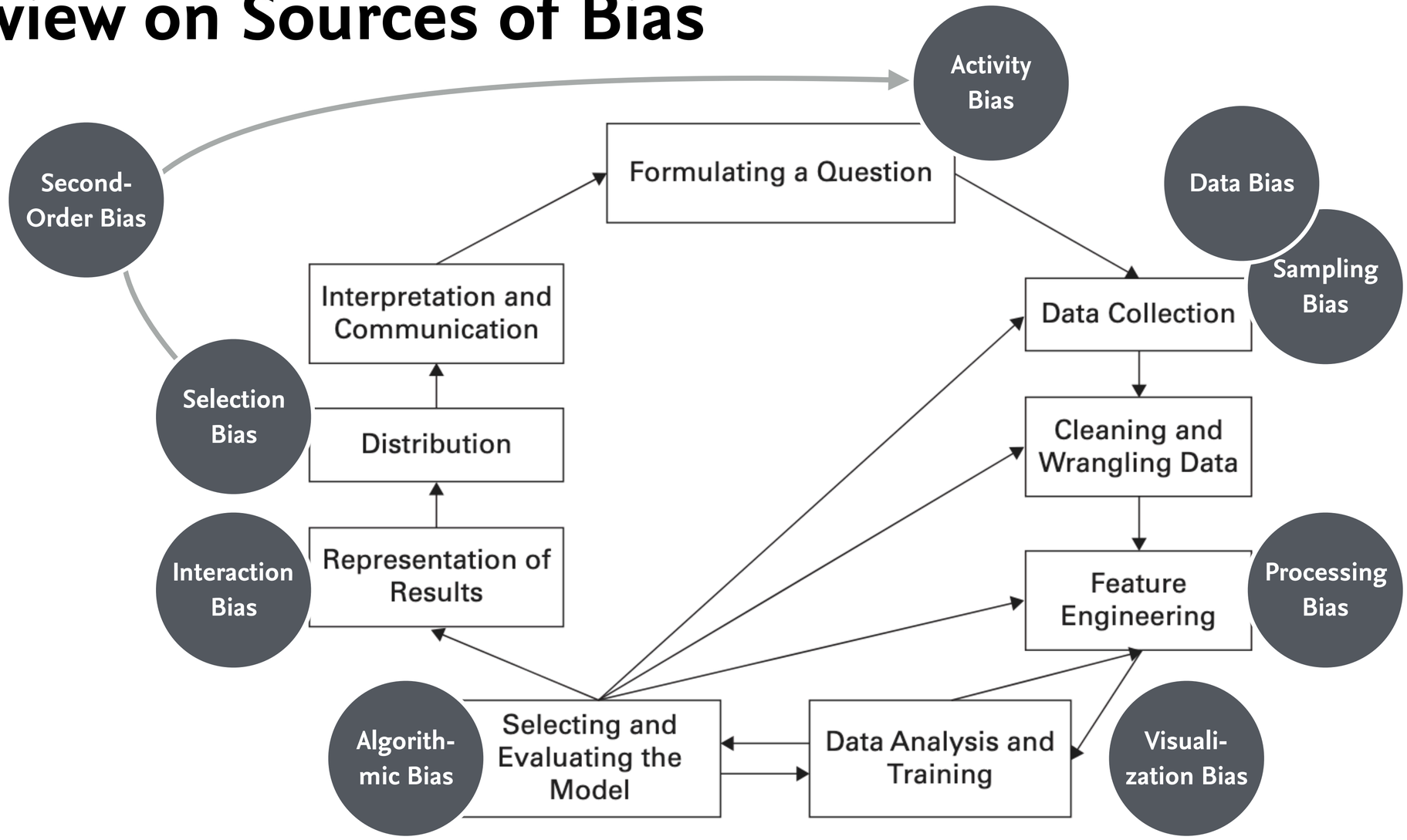
Technical bias arises from technical constraints or technical considerations.

Emergent bias arises in a context of use.

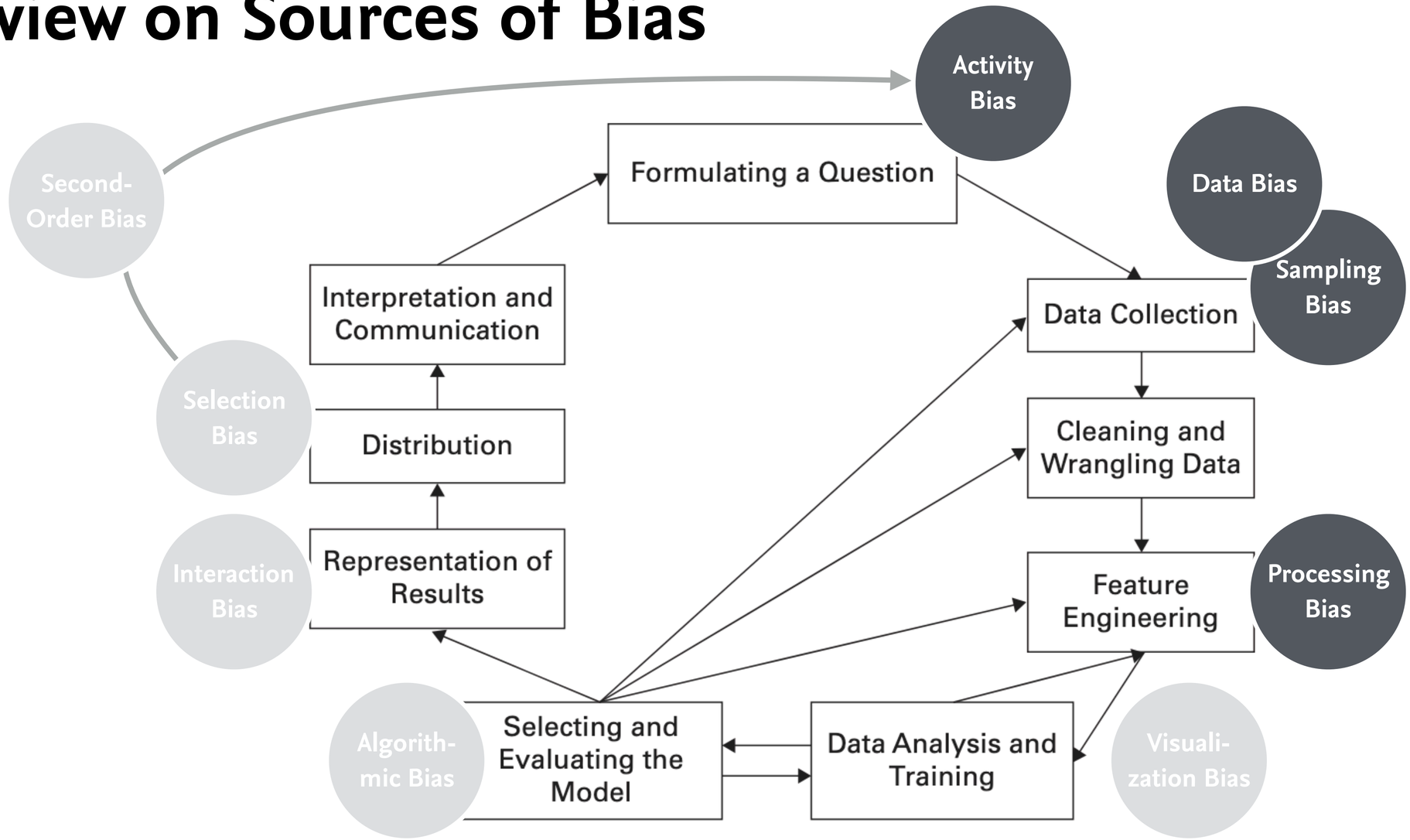
Data Science Pipeline



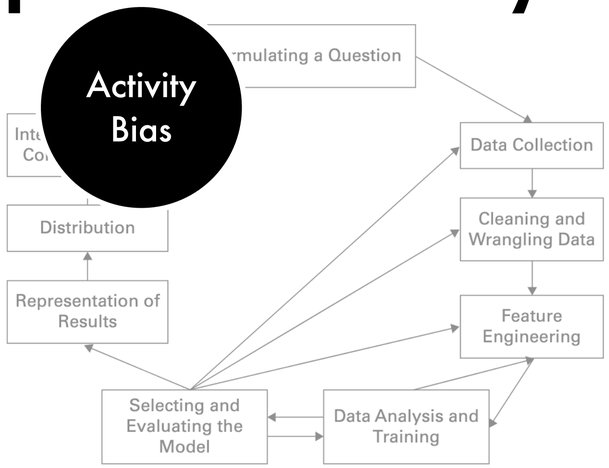
Overview on Sources of Bias



Overview on Sources of Bias



Types of Activity Bias



Population biases	Differences in demographics or other user characteristics between a population of users represented in a dataset or platform and a target population.
Behavioral biases	Differences in user behavior across platforms or contexts, or across users represented in different datasets.
Content production biases	Behavioral biases that are expressed as lexical, syntactic, semantic, and structural differences in the contents generated by users.
Temporal variations	Differences in populations or behaviors over time.

Olteanu, A., Castillo, C., Diaz, F., & Kiciman, E. (2019). Social data: Biases, methodological pitfalls, and ethical boundaries. Frontiers in Big Data, 2, 13. http://doi.org/10.3389/fdata.2019.00013

Example: Population Bias

	Gesamt			Geschlecht		Alter			
	2018	2019	2020	Frauen	Männer	14-29 J.	30-49 J.	50-69 J.	ab 70 J.
WhatsApp*	65	63	68	73	63	92	79	62	32
Facebook	19	21	14	15	13	24	19	10	1
Instagram	9	13	15	16	14	53	13	1	1
Snapchat	6	5	6	5	7	27	1	–	0
Twitter	1	2	2	1	4	4	3	2	1
Xing	1	1	1	1	1	0	2	0	–
LinkedIn**	–	1	1	0	2	2	2	1	–
Twitch**	–	1	1	0	2	3	1	–	–
TikTok**	–	1	2	2	1	7	1	0	–

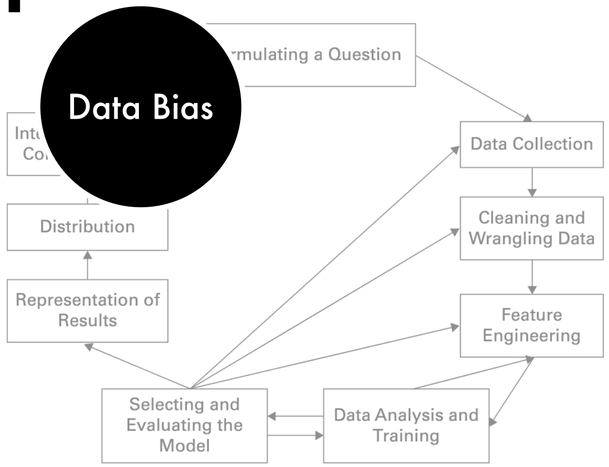
* WhatsApp 2018: Wert stammt aus dem Convergence Monitor.
** 2018 nicht erfasst.
Basis: Deutschspr. Bevölkerung ab 14 Jahren (2020: n=3003; 2019: n=2000; 2018: n=2009).

Quelle: ARD/ZDF-Onlinestudien 2018-2020.

Daily Use of Social Media in Germany

Natalie Beisch, Carmen Schäfer: Internetnutzung mit großer Dynamik: Medien, Kommunikation, Social Media. Ergebnisse der ARD/ZDF-Onlinestudie 2020 https://www.ard-zdf-onlinestudie.de/files/2020/0920_Beisch_Schaefer.pdf

Types of Data Bias



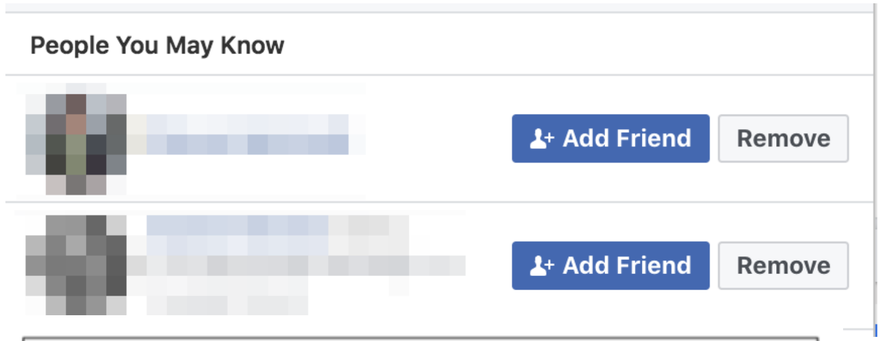
Functional biases	Biases that are a result of platform-specific mechanisms or affordances, that is, the possible actions within each system or environment.
Normative biases	Biases that are a result of written norms or expectations about unwritten norms describing acceptable patterns of behavior on a given platform.
External biases	Biases resulting from factors outside the social platform, including considerations of socioeconomic status, ideological/religious/ political leaning, education, social pressure, privacy concerns, topical interests, language, personality, and culture.
Non-individual agents	Interactions on social platforms that are not produced by individuals, but by accounts representing various types of organizations, or by automated agents.

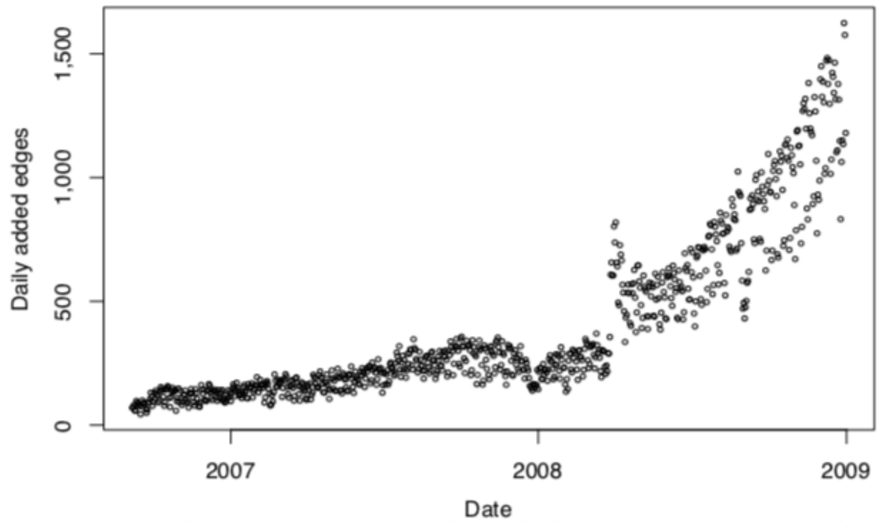
Olteanu, A., Castillo, C., Diaz, F., & Kiciman, E. (2019). Social data: Biases, methodological pitfalls, and ethical boundaries. Frontiers in Big Data, 2, 13. http://doi.org/10.3389/fdata.2019.00013

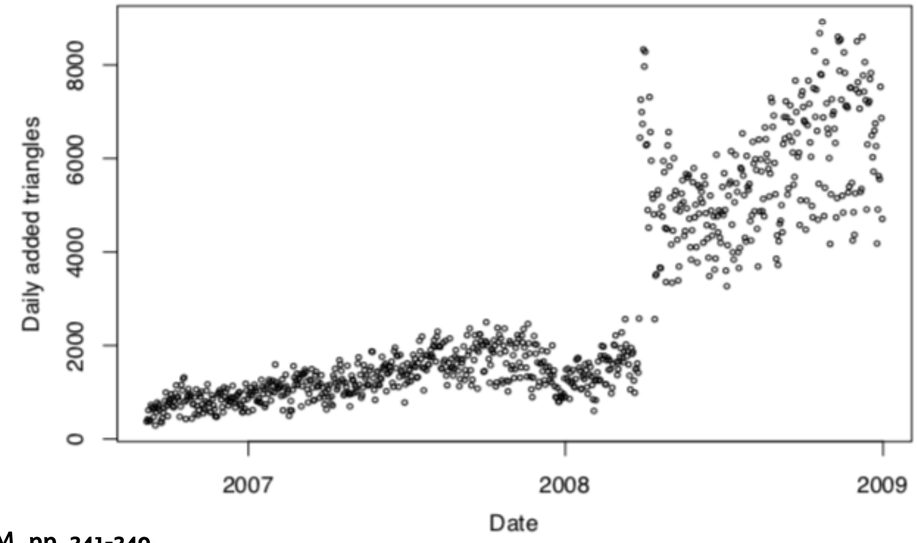
Example: Functional Biases

Reused dataset from Facebook New Orleans data through a manual crawl starting from a single user and using breadth-first search.

Facebook introduces “People You May Know” (PYMK) feature on March 26, 2008.

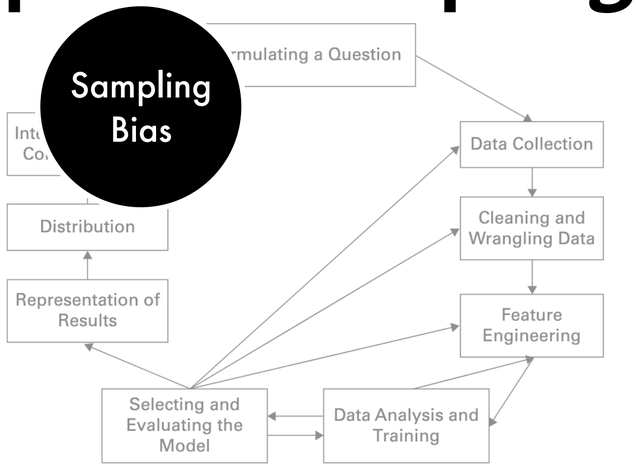






Malik, M. M., & Pfeffer, J. (2016, May). Identifying Platform Effects in Social Media Data. In ICWSM. pp. 241-249.

Types of Sampling Bias



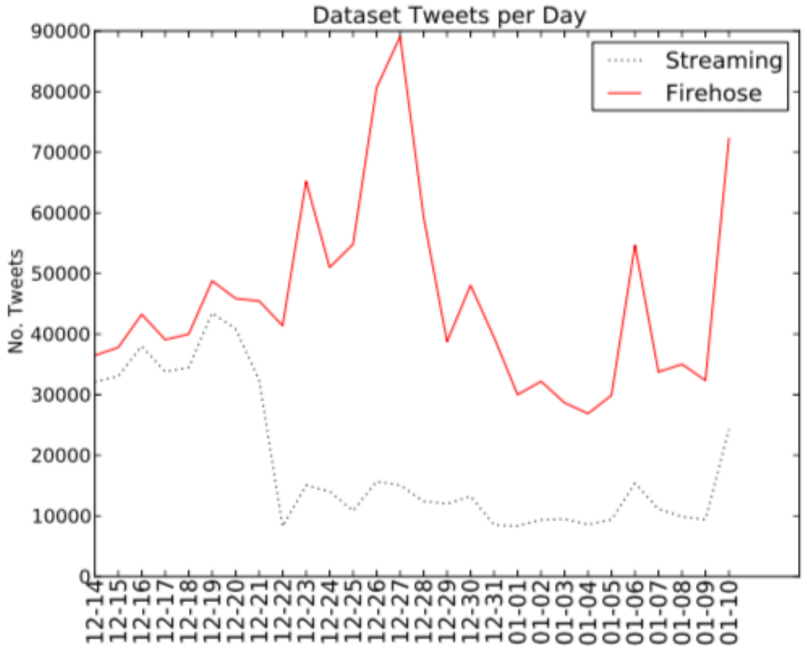
Data Acquisition	Data collection by third parties for example, by providing limited programmatic access. They sampling strategies are often opaque.
Data Querying	APIs have limited expressiveness regarding information needs and the choice of keywords in keyword-based queries shapes the resulting datasets.
Data Filtering	Outliers are sometimes relevant for data analysis and text filtering operations may bound certain analyses.

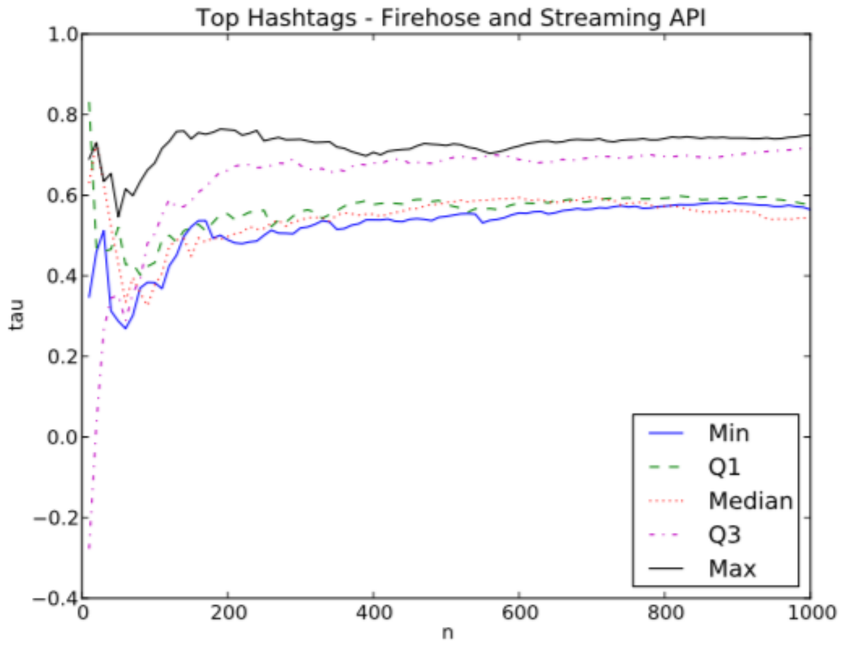
Olteanu, A., Castillo, C., Diaz, F., & Kiciman, E. (2019). Social data: Biases, methodological pitfalls, and ethical boundaries. Frontiers in Big Data, 2, 13. http://doi.org/10.3389/fdata.2019.00013

Example Data Acquisition: Is this sample good enough?

Keywords	Geoboxes	Users
#syria, #assad, #aleppovolcano, #alawite, #homs, #hama, #tartous, #idlib, #damascus, #daraa, #aleppo, #سوريا*, #houla	 (32.8, 35.9), (37.3, 42.3)	@SyrianRevo

* Arabic word for "Syria"

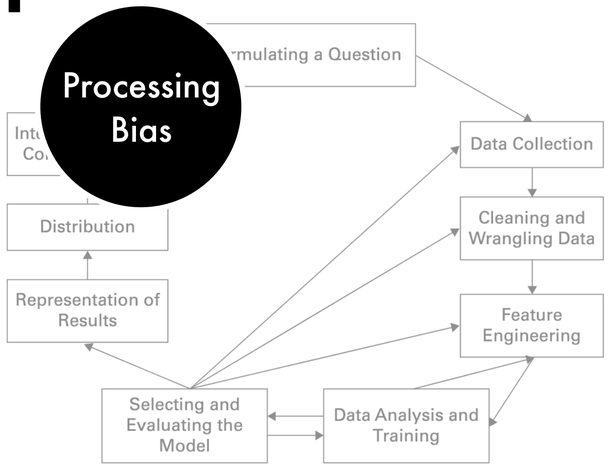




Kendall's τ is a statistic which measures the correlation of two ordered lists.

Morstatter, F., Pfeffer, J., Liu, H., & Carley, K. M. (2013). Is the sample good enough? Comparing data from twitter's streaming API with Twitter's firehose. In In ICWSM 2013. pp. 400-408.

Types of Data Processing Bias



Data Cleaning	Data representation choices and default values may introduce biases, the normalization of geographical references.
Data Enrichment	For example, manual annotation often yields subjective and noisy labels, or automatic annotation may introduce errors or bias.
Data Aggregation	For example, consider pre-processing heuristics that aggregate the data to make it more manageable at the cost of losing information.

Olteanu, A., Castillo, C., Diaz, F., & Kiciman, E. (2019). Social data: Biases, methodological pitfalls, and ethical boundaries. Frontiers in Big Data, 2, 13. http://doi.org/10.3389/fdata.2019.00013

Bias in Word Embeddings

A word embedding is trained on word co-occurrence in text corpora. It represents each word (or common phrase) as a d-dimensional word vector. Words with similar semantic meanings tend to have vectors that are close together.

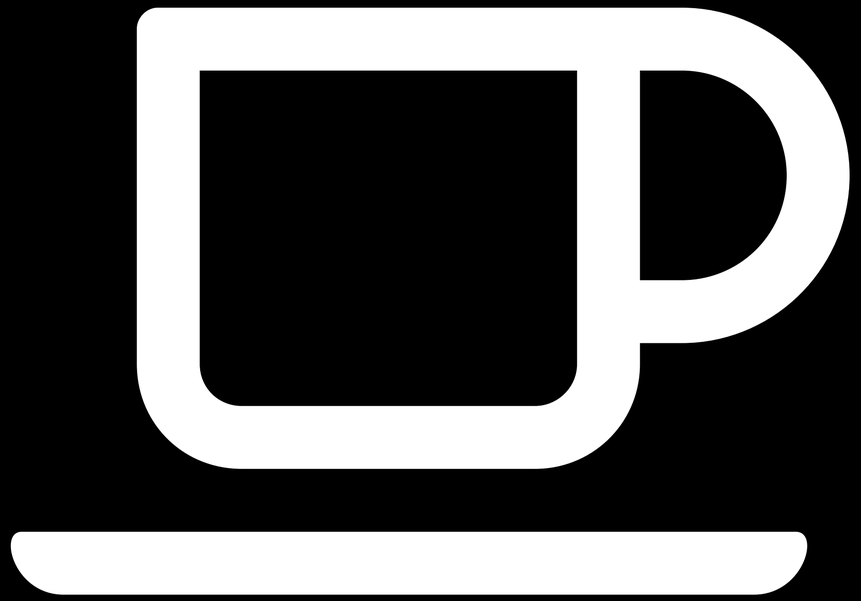
man:woman as **king:queen**

man:computer programmer as **woman:homemaker**

Father:doctor as **woman:nurse**

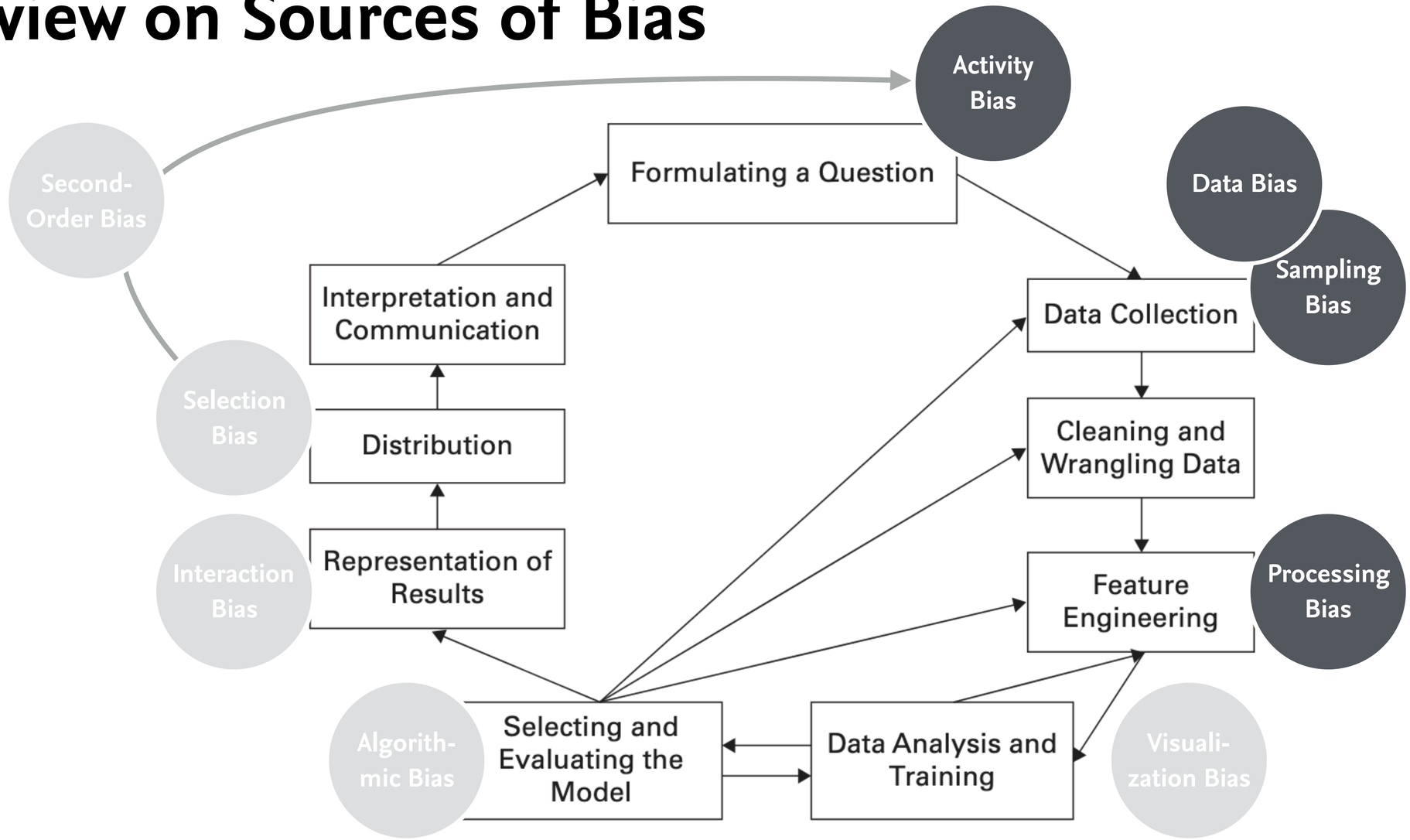
Extreme *she*	**Extreme *he***
1. homemaker	1. maestro
2. nurse	2. skipper
3. receptionist	3. protege
4. librarian	4. philosopher
5. socialite	5. captain
6. hairdresser	6. architect
7. nanny	7. financier
8. bookkeeper	8. warrior
9. stylist	9. broadcaster
10. housekeeper	10. magician

Bolukbasi, T., Chang, K.-W., Zou, J. Y., Saligrama, V., & Kalai, A. T. (2016). Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings. Advances in Neural Information Processing Systems, 29, 4349–4357.



5 minutes break

Overview on Sources of Bias



How to Mitigate Bias

General Considerations to Mitigate Bias

Reflect on your motivation Which problem needs to be solved by your data-driven software or what questions do you want to answer?

Understand the data origin What are the “circumstances” under which the data where created? How well do you understand the context of data collection? How much could you control the nature of the data set? What are your assumptions? What are platform-specific characteristics of your data? Can you quantify platform population mismatches?

Reconsider the collection process What mechanisms or procedures were used to collect the data? What was the sampling strategy? Who was involved in the data collection process? What was the timeframe?

Gebru, T., Morgenstern, J., Vecchione, B., Vaughan, J. W., Wallach, H., Daumé III, H., & Crawford, K. (2018). Datasheets for datasets. arXiv preprint arXiv:1803.09010.
Ruths, D., & Pfeffer, J. (2014). Social media for large studies of behavior. Science, 346(6213), 1063-1064.

Inspiration: Electronic Components

Sensirion Pressure sensor 1 pc(s) SDP610-025Pa -25 Pa up to 25 Pa (L x W x H) 29 x 18 x 27.05 mm

Primary Like Image

Item no.: 1313587

Manufacturer no.: 1-100759-02

EAN: 2050002956520

SENSIRION
THE SENSOR COMPANY

With the sensor out of the SDP600 series, launched one of the first digital dynamic Sensirion differential pressure sensor. The sensor has a digital I²C interface and measures even the smallest pressure differences (10 Pa) with highest sensitivity an...

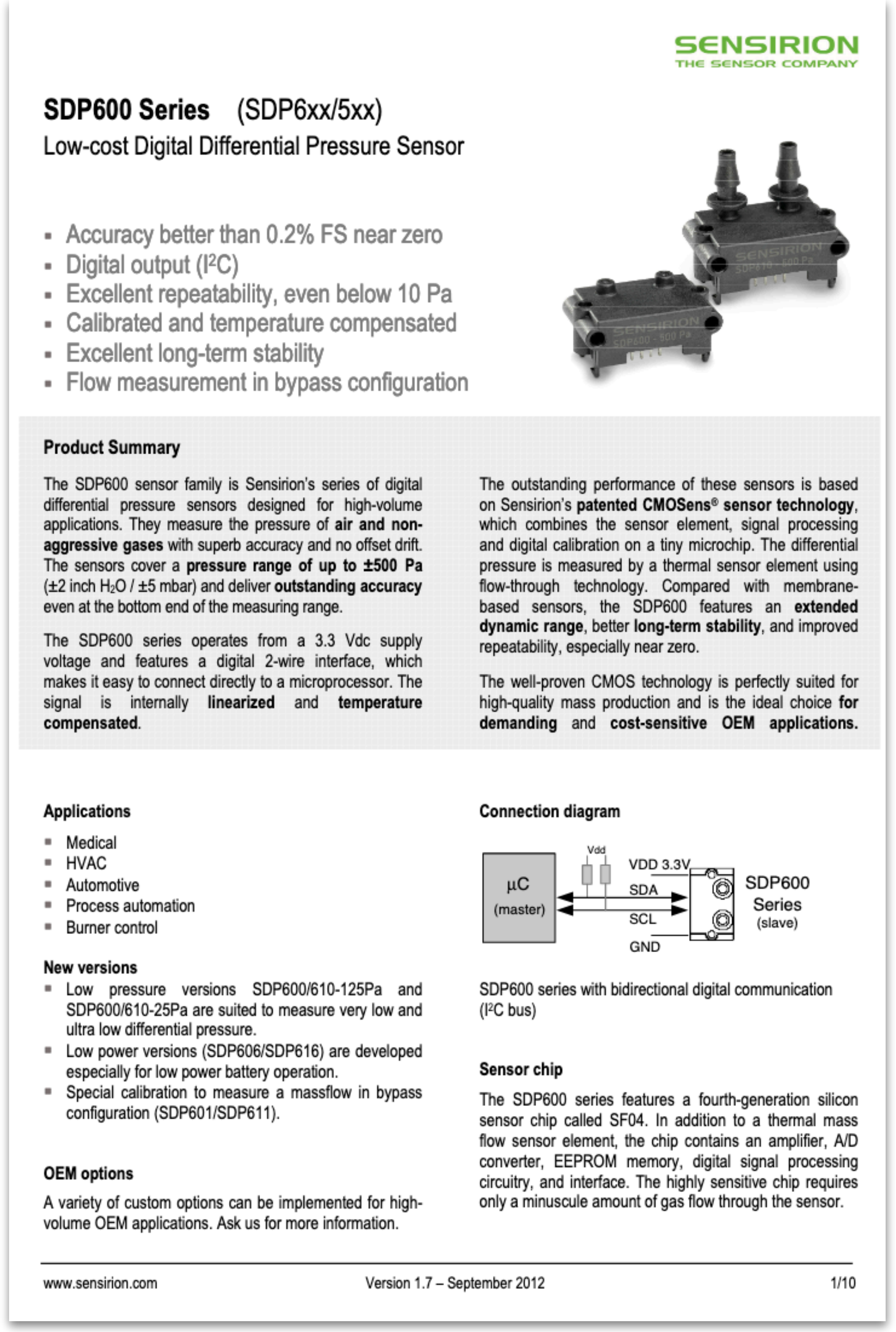
Full description

Guaranteed product originality

Documents & Downloads

Data sheets (1)

Datasheet 1313587 Sensirion Pressure sensor 1 pc(s) SDP610-025Pa -25 Pa up to 25 Pa (L x W x H) 29 x 18 x 27.05 mm
PDF



SENSIRION
THE SENSOR COMPANY

SDP600 Series (SDP6xx/5xx)
Low-cost Digital Differential Pressure Sensor

- Accuracy better than 0.2% FS near zero
- Digital output (I²C)
- Excellent repeatability, even below 10 Pa
- Calibrated and temperature compensated
- Excellent long-term stability
- Flow measurement in bypass configuration

Product Summary

The SDP600 sensor family is Sensirion's series of digital differential pressure sensors designed for high-volume applications. They measure the pressure of **air and non-aggressive gases** with superb accuracy and no offset drift. The sensors cover a **pressure range of up to ±500 Pa** (±2 inch H_2O / ±5 mbar) and deliver **outstanding accuracy** even at the bottom end of the measuring range.

The SDP600 series operates from a 3.3 Vdc supply voltage and features a digital 2-wire interface, which makes it easy to connect directly to a microprocessor. The signal is internally **linearized** and **temperature compensated**.

The outstanding performance of these sensors is based on Sensirion's **patented CMOSens® sensor technology**, which combines the sensor element, signal processing and digital calibration on a tiny microchip. The differential pressure is measured by a thermal sensor element using flow-through technology. Compared with membrane-based sensors, the SDP600 features an **extended dynamic range**, better **long-term stability**, and improved repeatability, especially near zero.

The well-proven CMOS technology is perfectly suited for high-quality mass production and is the ideal choice **for demanding** and **cost-sensitive OEM applications.**

Applications

- Medical
- HVAC
- Automotive
- Process automation
- Burner control

New versions

- Low pressure versions SDP600/610-125Pa and SDP600/610-25Pa are suited to measure very low and ultra low differential pressure.
- Low power versions (SDP606/SDP616) are developed especially for low power battery operation.
- Special calibration to measure a massflow in bypass configuration (SDP601/SDP611).

OEM options

A variety of custom options can be implemented for high-volume OEM applications. Ask us for more information.

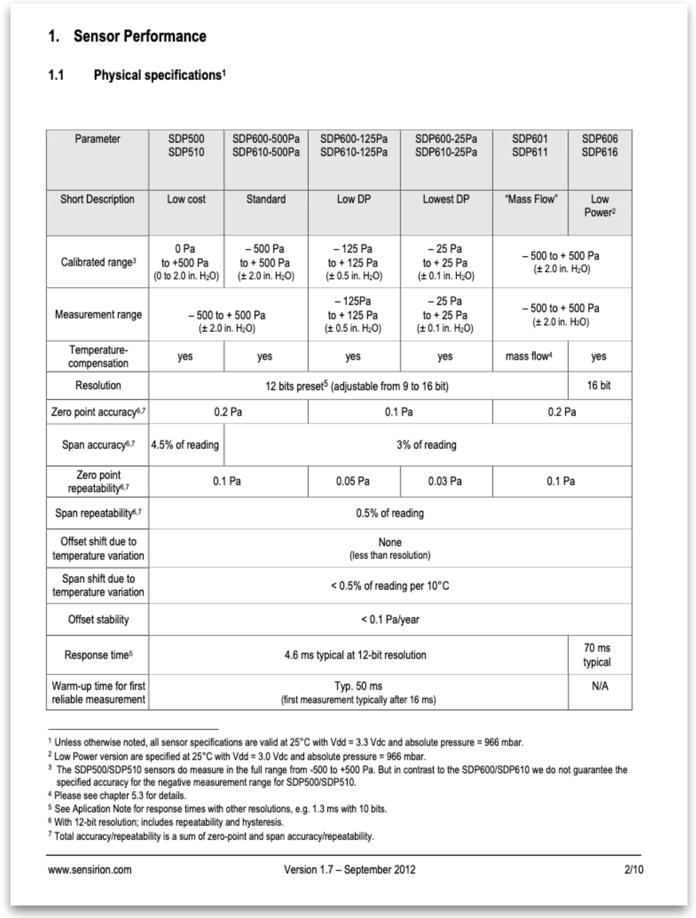
Connection diagram

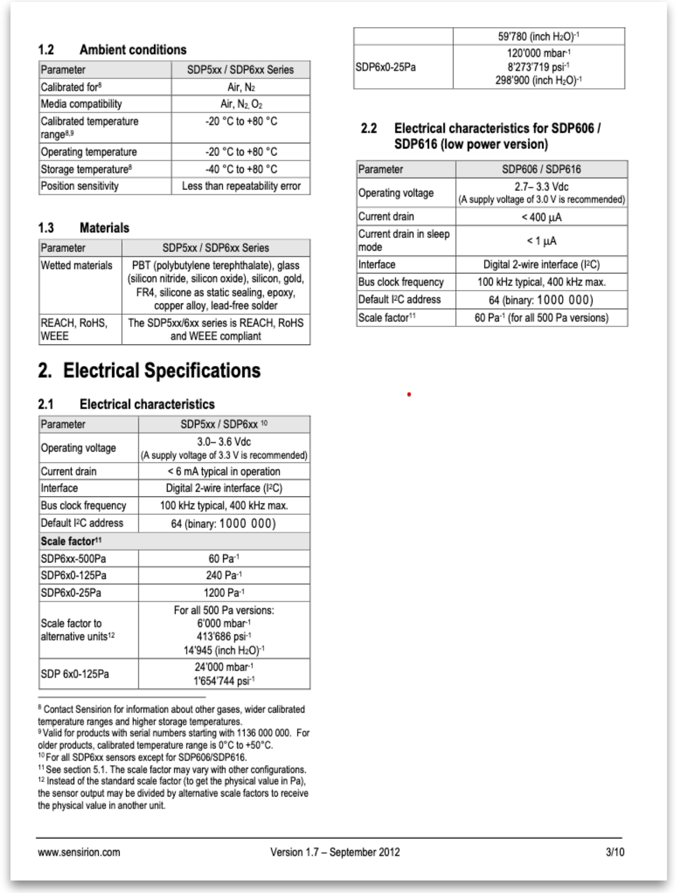
SDP600 series with bidirectional digital communication (I²C bus)

Sensor chip

The SDP600 series features a fourth-generation silicon sensor chip called SF04. In addition to a thermal mass flow sensor element, the chip contains an amplifier, A/D converter, EEPROM memory, digital signal processing circuitry, and interface. The highly sensitive chip requires only a minuscule amount of gas flow through the sensor.

www.sensirion.com Version 1.7 – September 2012 1/10





Screenshots taken from https://www.conrad.com/p/sensirion-pressure-sensor-1-pcs-sdp610-025pa-25-pa-up-to-25-pa-l-x-w-x-h-29-x-18-x-2705-mm-1313587

BY TIMNIT GEBRU, JAMIE MORGENSTERN,
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HANNA WALLACH, HAL DAUMÉ III, AND KATE CRAWFORD

Datasheets for Datasets

Objective of «Datasheets for Datasets»

For Dataset Creators Encouraging careful reflection on the process of creating, distributing, and maintaining a dataset, including any underlying assumptions, potential risks or harms, and implications of use.

For Dataset Consumers Ensuring that they (policy makers, consumer advocates, investigative journalists, individuals*) have the information they need to make informed decisions about using a dataset for their chosen tasks and avoid unintentional misuse.

(*) individuals whose data is included in datasets, and individuals who may be impacted by models

Timnit Gebru, Jamie Morgenstern, Briana Vecchione, Jennifer Wortman Vaughan, Hanna Wallach, Hal Daumé III, and Kate Crawford. 2021. Datasheets for datasets. Commun. ACM 64, 12 (December 2021), 86–92.

Sections of «Datasheets for Datasets»

- motivation
- composition
- collection process
- preprocessing/ cleaning/labeling
- uses
- distribution
- maintenance

Timnit Gebru, Jamie Morgenstern, Briana Vecchione, Jennifer Wortman Vaughan, Hanna Wallach, Hal Daumé III, and Kate Crawford. 2021. Datasheets for datasets. Commun. ACM 64, 12 (December 2021), 86–92.

Sections of «Datasheets for Datasets»

motivation	Describe the motivations for creating the dataset, including funding, any specific tasks the authors had in mind, and who the authors are.
composition	Describe the composition of the dataset, like what kinds of data are in it, how it was collected, whether labels are associated with the data, and whether the dataset contains sensitive information.
collection process	Describe the data collection process, like how the data was collected, where or who is was collected from, who was involved in the collection process, and, if people are involved, if consent was given for the data to be collected.
preprocessing/ cleaning/labeling	Whether the data was process or labelled and how it was done.
uses	The tasks the dataset is intended to be used for, how it has already been used, and limitations of use. Distribution: How the dataset will be distributed and to who, and any restrictions on distribution.
maintenance	Who and how the dataset will be maintained, and if and how others will be able to build on it.
distribution	Whether the dataset is distributed to third parties outside of the owner with what license by employing any restrictions.

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Example

Motivation

For what purpose was the dataset created? Was there a specific task in mind? Was there a specific gap that needed to be filled? Please provide a description.

The dataset was created to enable research on predicting sentiment polarity—i.e., given a piece of English text, predict whether it has a positive or negative affect—or stance—toward its topic. The dataset was created intentionally with that task in mind, focusing on movie reviews as a place where affect/sentiment is frequently expressed.[1]

Who created the dataset (e.g., which team, research group) and on behalf of which entity (e.g., company, institution, organization)?

The dataset was created by Bo Pang and Lillian Lee at Cornell University.

Who funded the creation of the dataset? If there is an associated grant, please provide the name of the grantor and the grant name and number.

Funding was provided from five distinct sources: the National Science Foundation, the Department of the Interior, the National Business Center, Cornell University, and the Sloan Foundation.

Any other comments?

None.

these are words that could be used to describe the emotions of john sayles' characters in his latest , limbo . but no , i use them to describe myself after sitting through his latest little exercise in indie egomania . i can forgive many things . but using some hackneyed , whacked-out , screwed-up * non * - ending on a movie is unforgivable . i walked a half-mile in the rain and sat through two hours of typical , plodding sayles melodrama to get cheated by a complete and total copout finale . does sayles think he's roger corman ?

Figure 1. An example "negative polarity" instance, taken from the file `neg/cv452_tok-18656.txt`.

exception that no more than 40 posts by a single author were included (see "Collection Process" below). No tests were run to determine representativeness.

What data does each instance consist of? "Raw" data (e.g., unprocessed text or images)or features? In either case, please provide a description.

Each instance consists of the text associated with the review, with obvious ratings information removed from that text (some errors were found and later fixed). The text was down-cased and HTML tags were removed. Boilerplate newsgroup header/footer text was removed. Some additional unspecified automatic filtering was done. Each instance also has an associated target value: a positive (+1) or negative (-1) sentiment polarity rating based on the number of stars that that review gave (details on the mapping from number of stars to polarity is given below in "Data Preprocessing").

Is there a label or target associated with each instance? If so, please provide a description.

The label is the positive/negative sentiment polarity rating derived from the star rating, as described above.

Is any information missing from individual instances? If so, please provide a description, explaining why this information is missing (e.g., because it was unavailable). This does not include intentionally removed information, but might include, e.g., redacted text.

Everything is included. No data is missing.

Are relationships between individual instances made explicit (e.g., users' movie ratings, social network links)? If so, please describe how these relationships are made explicit.

None explicitly, though the original newsgroup postings include poster name and email address, so some information (such as threads, replies, or posts by the same author) could be extracted if needed.

Are there recommended data splits (e.g., training, development/validation, testing)? If so, please provide a description of these splits, explaining the rationale behind them.

The instances come with a "cross-validation tag" to enable replication of cross-validation experiments; results are measured in classification accuracy.

Are there any errors, sources of noise, or redundancies in the dataset? If so, please provide a description.

See preprocessing below.

Is the dataset self-contained, or does it link to or otherwise rely on external resources (e.g., websites, tweets, other datasets)? If it links

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Other Approaches

To appear in Transactions of the ACL

Data Statements for Natural Language Processing: Toward Mitigating System Bias and Enabling Better Science

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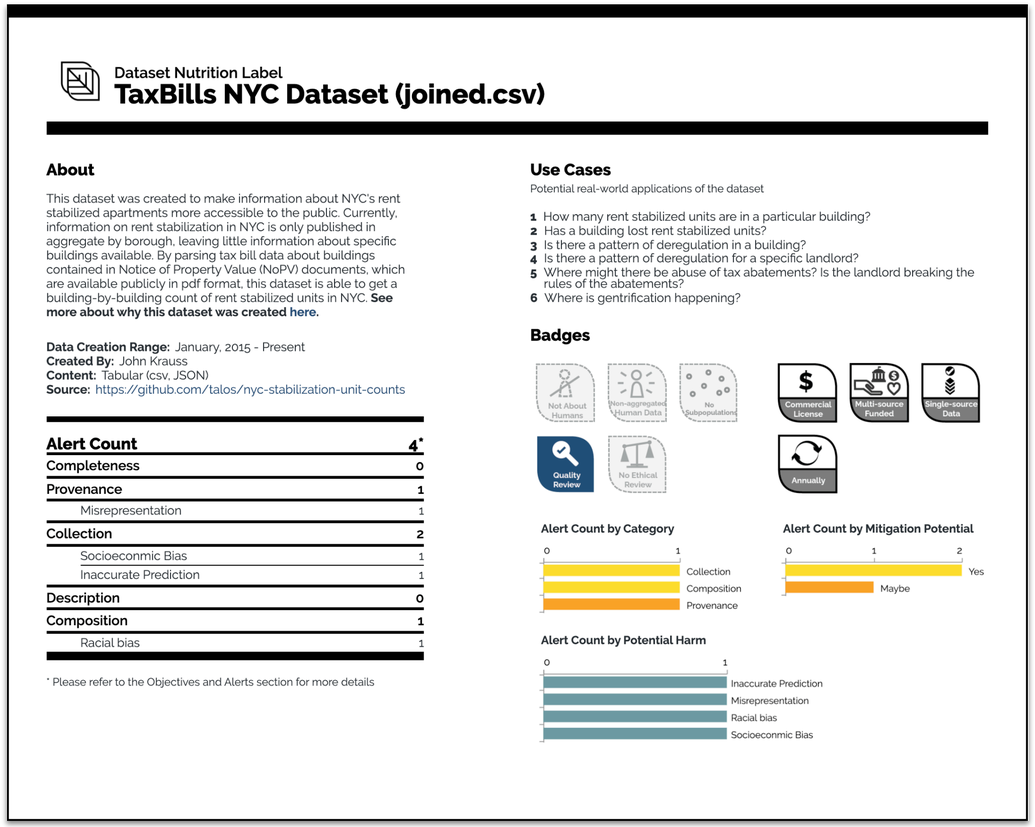
Abstract

In this paper, we propose *data statements* as a design solution and professional practice for natural language processing technologists, in both research and development — through the adoption and widespread use of data statements, the field can begin to address critical scientific and ethical issues that result from the use of data from certain populations in the development of technology for other populations. We present a form that data statements can take and explore the implications of adopting them as part of regular practice. We argue that data statements will help alleviate issues related to exclusion and bias in language technology; lead to better precision in claims about how NLP research can generalize and thus better engineering results; protect companies from public embarrassment; and ultimately lead to language technology that meets its users in their own preferred linguistic style and furthermore does not misrepresent them to others.

gramming jobs because of biases present in training text). There are both scientific and ethical reasons to be concerned. Scientifically, there is the issue of generalizability of results; ethically, the potential for significant real-world harms. While there is increasing interest in ethics in NLP,[1] there remains the open and urgent question of how we integrate ethical considerations into the everyday practice of our field. This question has no simple answer, but rather will require a constellation of multi-faceted solutions.

Toward that end, and drawing on value sensitive design (Friedman et al., 2006), this paper contributes one new professional practice — called *data statements* — which we argue will bring about improvements in engineering and scientific outcomes while also enabling more ethically responsive NLP technology. A data statement is a characterization of a dataset which provides context to allow developers and users to better understand how experimental results might generalize, how software might be appropriately deployed, and what biases might be reflected in systems built on the software. In developing this



Dataset Nutrition Label
TaxBills NYC Dataset (joined.csv)

About

This dataset was created to make information about NYC's rent stabilized apartments more accessible to the public. Currently, information on rent stabilization in NYC is only published in aggregate by borough, leaving little information about specific buildings available. By parsing tax bill data about buildings contained in Notice of Property Value (NoPV) documents, which are available publicly in pdf format, this dataset is able to get a building-by-building count of rent stabilized units in NYC. **See more about why this dataset was created here.**

Data Creation Range: January, 2015 - Present
Created By: John Krauss
Content: Tabular (csv, JSON)
Source: https://github.com/talos/nyc-stabilization-unit-counts

Alert Count	**4***
Completeness	**0**
Provenance	**1**
Misrepresentation	1
Collection	**2**
Socioeconmic Bias	1
Inaccurate Prediction	1
Description	**0**
Composition	**1**
Racial bias	1

* Please refer to the Objectives and Alerts section for more details

Use Cases

Potential real-world applications of the dataset

1 How many rent stabilized units are in a particular building?
2 Has a building lost rent stabilized units?
3 Is there a pattern of deregulation in a building?
4 Is there a pattern of deregulation for a specific landlord?
5 Where might there be abuse of tax abatements? Is the landlord breaking the rules of the abatements?
6 Where is gentrification happening?

Badges

Not About Humans · Non-aggregated Human Data · No Subpopulations · Commercial License · Multi-source Funded · Single-source Data · Quality Review · No Ethical Review · Annually

Alert Count by Category

0 1
Collection
Composition
Provenance

Alert Count by Mitigation Potential

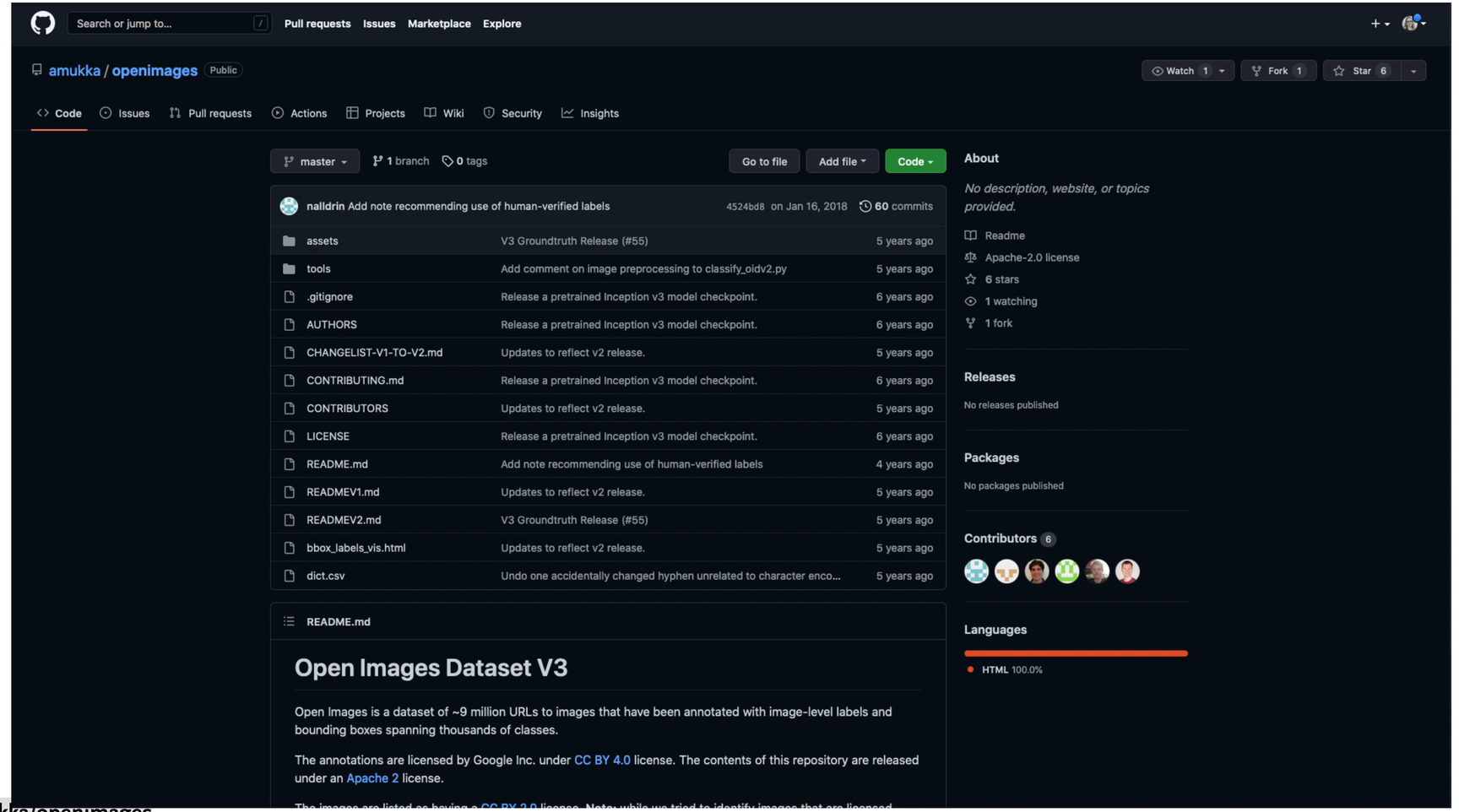
0 1 2
Yes
Maybe

Alert Count by Potential Harm

0 1
Inaccurate Prediction
Misrepresentation
Racial bias
Socioeconmic Bias

Bender, Emily M, und Batya Friedman. „Data Statements for NLP: Toward Mitigating System Bias and Enabling Better Science“ 2018.
Holland, Sarah, Ahmed Hosny, Sarah Newman, Joshua Joseph, and Kasia Chmielinski. 2018. “The Dataset Nutrition Label - a Framework to Drive Higher Data Quality Standards.” CoRR cs.DB (January).

Example: Open Images Dataset V3 (Data Fact Sheet)



https://github.com/amukka/openimages

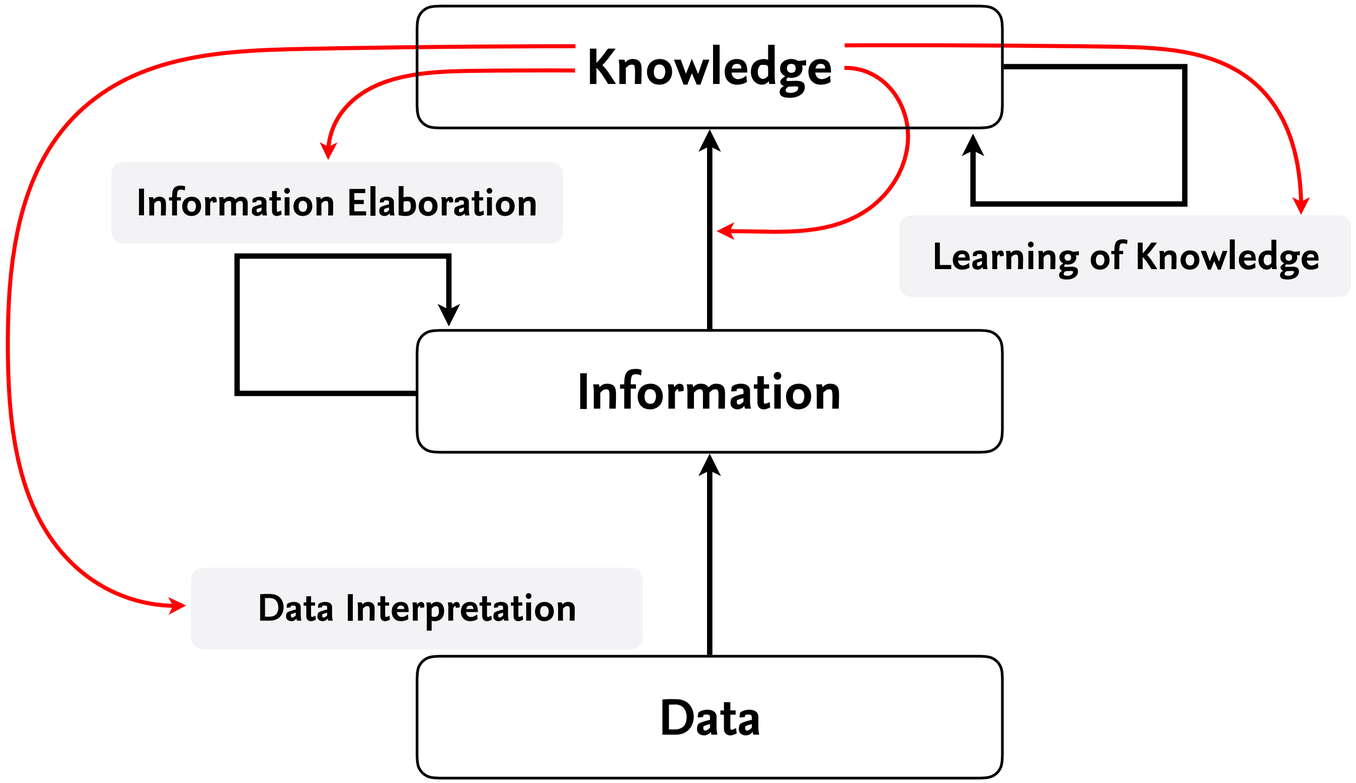
Krasin,I.etal. OpenImages:Apublicdatasetfor large-scale multi-label and multi-class image classification, 2017.

Documentation As Reflexive Practice

When Data Become Data

> **Rarely can a magic moment be established when things become data**
>
> Borgman, C. L. (2016). Big data, little data, no data: Scholarship in the networked world. MIT press. (p. 62)

What is Data?



Knowledge **Interpreted symbol structures**

» used to interpret data, elaborate on information, and learn

» used within decision steps

Information **Interpreted symbols and symbol structures**

» input to a decision step

» output from a decision step

Data **Observed, uninterpreted symbols**

» signs, character sequences, patterns

Aamodt, A., & Nygard, M. (1995). Different Roles and Mutual Dependencies of Data, Information, and Knowledge - An AI Perspective on their Integration. Data Knowledge Engineering, 16(3), 191–222.

What is the Origin of Data?

Situated knowledges emphasis on **disclosing the mechanisms for the production of data.** These mechanisms for data production include social, cultural, historical and material conditions.

Additionally, a reflection on your **own perspective** is necessary but also **on existing values**.

Data need Context

Reflexivity is a precondition for restoring context in data creation.

D'Ignazio, C., & Klein, L. F. (2020). Data feminism. MIT Press.
Haraway, D. (1988). Situated knowledges: The science question in feminism and the privilege of partial perspective. Feminist studies, 14(3), 575-599.

Documentation As Reflexive Practice

Documentation as reflexive practices should be seen as a **constitutive part** of data work.

Reflexive documentation could

- »**make** praxis-based and **situated decision-making explicit** and help preserve it in documentation
- »be especially useful to **improve traceability**
- »provide the context of dataset production could constitute a useful tool for **auditability**
- »become an additional supportive tool for data workers to contribute towards the **compliance with** existing **legal frameworks**

Miceli, Milagros, Tianling Yang, Laurens Naudts, Martin Schuessler, Diana Serbanescu, und Alex Hanna. „Documenting Computer Vision Datasets: An Invitation to Reflexive Data Practices“. In _Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency_, 161–72. FAccT '21. New York, NY, USA: Association for Computing Machinery, 2021.

Check your Insights

» What is bias and what are the prerequisites that bias emerges in data science workflows?

» Is it possible to completely avoid bias in data science?

» What are the types of bias and where does bias can occur in the data science workflow?

» What approaches do you know to mitigate bias? What is the basic idea that unites all these approaches?

» Why is it necessary to consider the context of data when working with data?

» What is meant by documentation as reflexive practice? What is the difference to the other approaches?

«Human-Centered Data Science»

Next Session: Digging Deeper into Approaches to Identify, Mitigate and Avoid Bias

Prof. Dr. Claudia Müller-Birn

Human-Centered Computing, Institute of Computer Science

Freie Universität Berlin

June 2, 2022