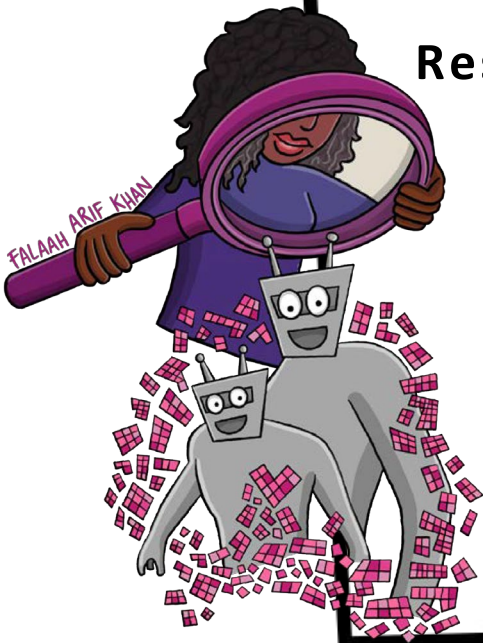




Follow the data!

Responsible AI starts with responsible data
management



Julia Stoyanovich
New York University
stoyanovich@nyu.edu



NYU Center for Responsible AI



How it started

October 2015

Le Monde

Plaidoyer pour une analyse « responsable » des données

Face aux risques d'atteinte à la vie privée, les chercheurs en informatique Serge Abiteboul et Julia Stoyanovich plaident pour une collecte et une analyse des données impartiales, transparentes et accessibles à tous.

Publié le 06 octobre 2015 à 15h41, modifié le 19 octobre 2015 à 16h16 | ⌚ Lecture 5 min.



Serge Abiteboul
and Julia
Stoyanovich

NOVEMBER 20,
2015

DATA, RESPONSIBLY

≡ Big Data

(This blog post is an extended version of an October 12, 2015 Le Monde op-ed article (in French)) Our society is increasingly relying on algorithms in all aspects of its operation. We trust algorithms not only to help carry out routine tasks, such as accounting and automatic manufacturing, but also to make decisions on our [...]

Read more →

November 2015

Association For
Computing Machinery



ACM SIGMOD Blog

r/ai center
for
responsible
ai

How it started

July 2016



Data, Responsibly

Organizers

Serge Abiteboul (ENS – Cachan, FR)

Gerome Miklau (University of Massachusetts – Amherst, US)

Julia Stoyanovich (Drexel Univ. – Philadelphia, US)

Gerhard Weikum (MPI für Informatik – Saarbrücken, DE)



How it started

Int. No. 1696

August 2017

By Council Member Vacca

A Local Law to amend the administrative code of the city of New York, in relation to automated processing of data for the purposes of targeting services, penalties, or policing to persons

Be it enacted by the Council as follows:

1 Section 1. Section 23-502 of the administrative code of the city of New York is amended
2 to add a new subdivision g to read as follows:

3 g. Each agency that uses, for the purposes of targeting services to persons, imposing
4 penalties upon persons or policing, an algorithm or any other method of automated processing
5 system of data shall:

6 1. Publish on such agency's website, the source code of such system; and

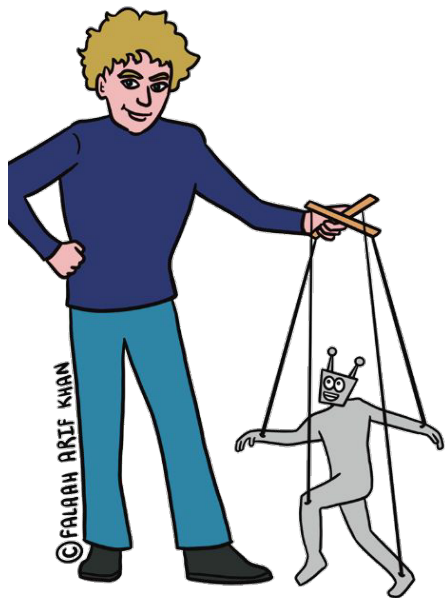
7 2. Permit a user to (i) submit data into such system for self-testing and (ii) receive the
8 results of having such data processed by such system.

9 § 2. This local law takes effect 120 days after it becomes law.

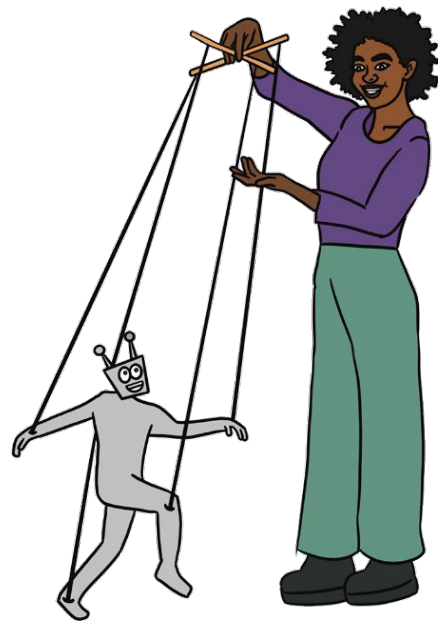
MAJ
LS# 10948
8/16/17 2:13 PM

October 2017





Policy





<https://science.house.gov/2025/4/deepseek-a-deep-dive>



Testimony of Dr. Julia Stoyanovich

Associate Professor of Computer Science & Engineering and of Data Science,
Director of the Center for Responsible AI at New York University

DeepSeek: A Deep Dive

Hearing of the Committee on Science, Space and Technology of the U.S.
House of Representatives, Research and Technology Subcommittee

April 8, 2025

Note: ChatGPT 4o was used for stylistic purposes when drafting this testimony.

Thank you for the opportunity to testify today, on the topic of national security and technological implications of DeepSeek—a family of AI models developed in the People's Republic of China.

Launched on January 10, 2025, the DeepSeek AI assistant quickly rose to the top of the U.S. Apple App Store, as American consumers embraced it over competitors like *ChatGPT*.¹ The *DeepSeek-V3* and *DeepSeek-R1* models are now readily accessible to developers and researchers on Microsoft's Azure AI Foundry² and GitHub³.

DeepSeek's large language models (LLMs) perform comparably to leading U.S.-based models while requiring significantly fewer resources—including hardware, power, and data annotation labor—to build.⁴ And while LLM technology was already available to American consumers, developers, and researchers, DeepSeek's models introduced high-performing, cost-effective alternatives. Their release has acted as a catalyst for the U.S. AI industry—intensifying competition, prompting exploration of more efficient methods, and encouraging greater openness. By showing that advanced models can be built with relatively modest resources, DeepSeek has helped shift the U.S. AI landscape toward more accessible and collaborative innovation.



SIPRI and UNODA launch joint initiative on responsible innovation in AI for peace and security

3 April 2023



This month SIPRI and the United Nations Office for Disarmament Affairs (UNODA) launched a three-year joint initiative on responsible innovation in artificial intelligence (AI) for peace and security. The initiative, which is funded by a decision of the Council of the European Union ([Council Decision \(CFSP\) 2022/2269 of 18 November 2022](#)), aims to support greater engagement from the civilian AI community in mitigating the risks that the misuse of civilian AI technology can pose to international peace and security.



Government
of Canada

Gouvernement
du Canada

 CAN/ASC - EN 301 549:2024 - Accessibility requirements for ICT products and services (EN 301 549:2021, IDT)

CAN/ASC - EN 301 549:2024 - Accessibility requirements for ICT products and services (EN 301 549:2021, IDT)

Areas of focus

There are common areas where people with disabilities may experience barriers to accessibility in information and communication technology products and services. These include, but are not limited to:

- websites
- software
- electronic devices
- mobile apps

The technical committee on Accessibility Requirements for Information and Communication Technology Products and Services worked towards the adoption of the European harmonized standard "EN 301 549, Accessibility requirements for ICT products and services" in its entirety. The adoption of this standard as a National Standard of Canada in May 2024 represents a fundamental step in accessible Canadian procurement advancement.

This standard is a National Standard of Canada.

- This standard provides key requirements and best practices to help government departments and federally regulated entities as they continue their journey to improve accessibility in this priority area.
- The final standard was published on May 31, 2024.

[Read the standard](#)

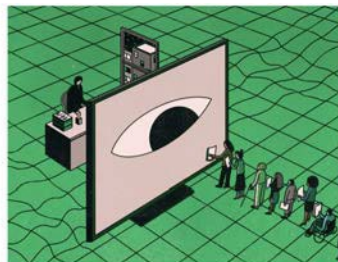
We Need Laws to Take On Racism and Sexism in Hiring Technology

Artificial intelligence used to evaluate job candidates must not become a tool that exacerbates discrimination.

March 17, 2021

By Alexandra Reeve Givens, Hilke Schellmann and Julia Stoyanovich

Ms. Givens is the chief executive of the Center for Democracy & Technology. Ms. Schellman



Liik Fing

THE WALL STREET JOURNAL.

BUSINESS | JOURNAL REPORTS: LEADERSHIP

Hiring and AI: Let Job Candidates Know Why They Were Rejected

As more companies use artificial intelligence in their hiring decisions, here's one way to make the system more transparent

By Julia Stoyanovich

Updated Sept. 22, 2021 11:00 am ET



Labels that explain a hiring process that uses AI could allow job seekers to opt out if they object to the
The New York Times Account IGES

A Hiring Law Blazes a Path for A.I. Regulation

New York City's pioneering, focused approach sets rules on how companies use the technology in work force decisions.

Statement of Julia Stoyanovich

Associate Professor of Computer Science & Engineering and of Data Science,
Director of the Center for Responsible AI at New York University

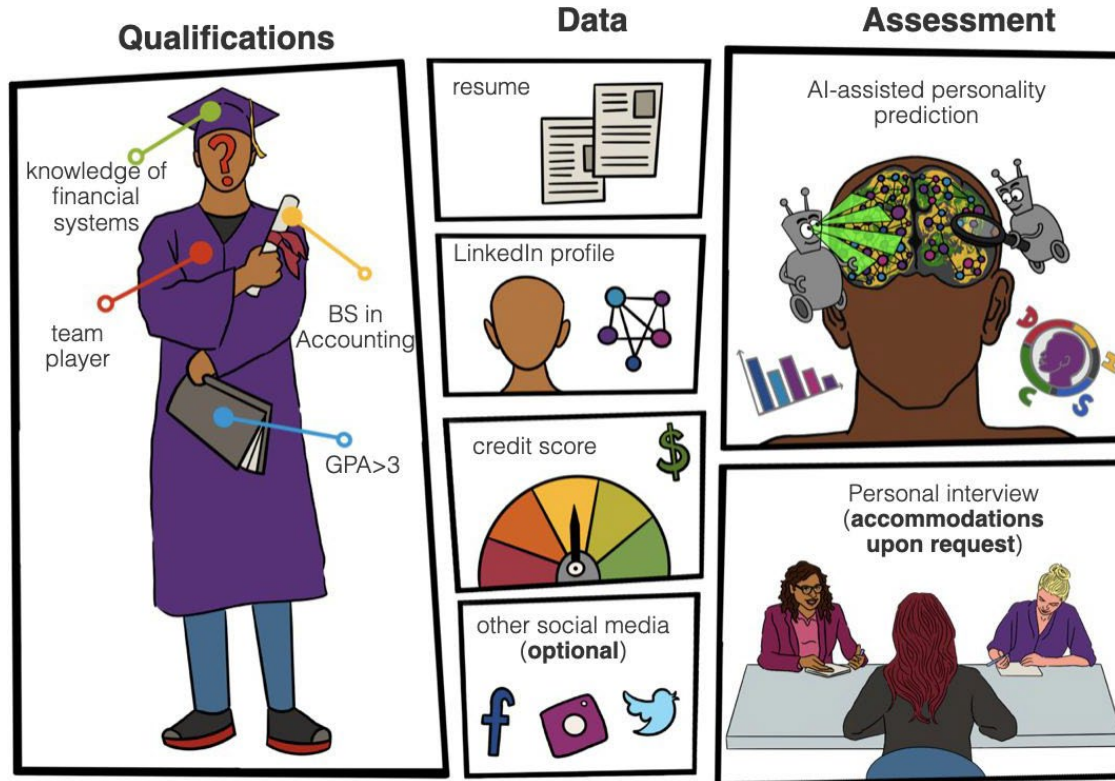
U.S. Senate AI Insight Forum: High Impact AI

November 1, 2023

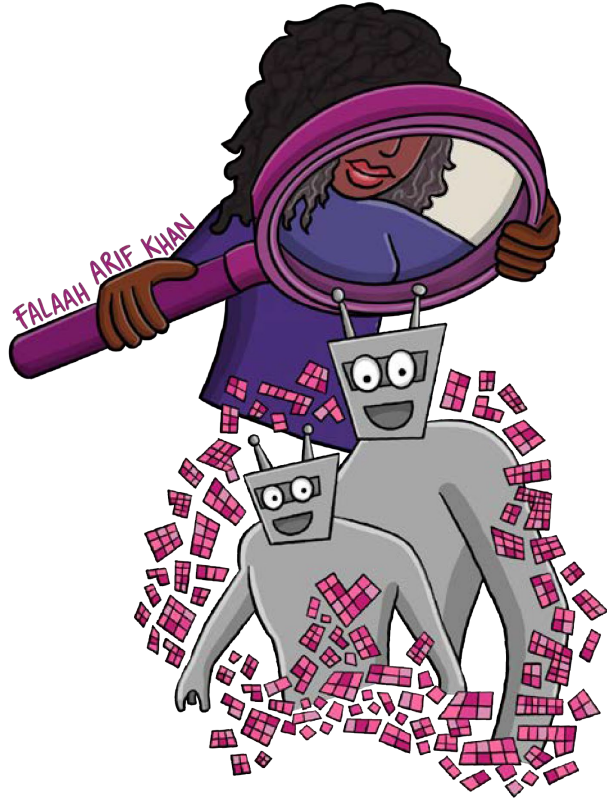
Leader Schumer, Senators Rounds, Heinrich, and Young, thank you for inviting me to participate in this important forum! I am an associate professor of Computer Science & Engineering and of Data Science, and the founding Director of the Center for Responsible AI at New York University. My academic research is focused on AI and data engineering systems, and on how to incorporate legal requirements and ethical norms into the way these systems are designed, developed and used.¹ I teach responsible AI to students², practitioners in industry and government³, and members of the public⁴. And I have been deeply involved in AI governance and regulation in New York City⁵, New York State⁶, and elsewhere, since 2017.



“Nutritional labels” for job postings



Responsible AI is about ...



... exposing the knobs
of responsibility to
people

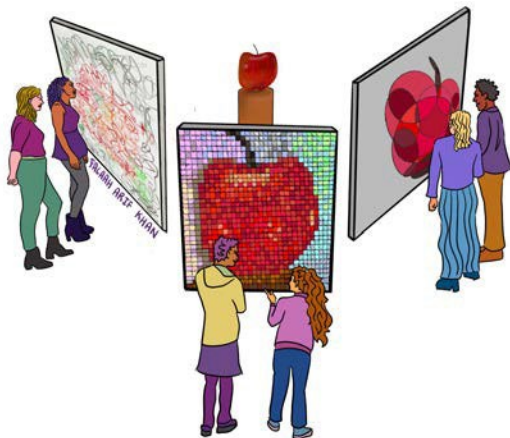




Research



Data-centric AI & responsible data management



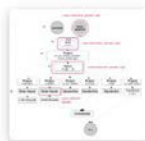
Automated Data Cleaning Can Hurt Fairness in Machine Learning-based Decision Making

Shubha Guha, Falaah Arif Khan, Julia Stoyanovich, and Sebastian Schelter

In Proceedings of the 39th International Conference on Data Engineering, ICDE 2023

[CITE](#)

[PDF](#)



Fairness-Aware Instrumentation of Preprocessing Pipelines for Machine Learning

Ke Yang, Biao Huang, Julia Stoyanovich, and Sebastian Schelter

In Proceedings of the Workshop on Human-In-the-Loop Data Analytics, HILDA at SIGMOD 2020

[CITE](#)

[PDF](#)



Taming Technical Bias in Machine Learning Pipelines

Sebastian Schelter, and Julia Stoyanovich

IEEE Data Eng. Bull. 2020

[CITE](#)

[PDF](#)



Responsible Data Management

Julia Stoyanovich, Serge Abiteboul, Bill Howe, H. V. Jagadish, and Sebastian Schelter

Communications of the ACM 2022

[CITE](#)

[PDF](#)



Developing data capability with non-profit organisations using participatory methods

Anthony McCosker, Xiaofang Yao, Kath Albury, Alexia Maddox, Jane Farmer, and Julia Stoyanovich

Big Data & Society 2022

[CITE](#)

[PDF](#)

RAI for Ukraine

Responsible
AI Research for
Ukrainian
Scholars

Launched in June 2022



<http://r-ai.co/ukraine>

Data-centric AI & responsible data management



[Stoyanovich, Abiteboul, Howe, Jagadish, Schelter; *Comm. ACM* 2022]

Data-centric AI & responsible data management

contributed articles



DOI:10.1145/3487217

Perspectives on the role and responsibility of the data-management research community in designing, developing, using, and overseeing automated decision systems.

BY JULIA STOYANOVICH, SERGE ABITEBOUL, BILL HOWE, H.V. JAGADISH, AND SEBASTIAN SCHELTER

Responsible Data Management

INCORPORATING ETHICS and legal compliance into data-driven algorithmic systems has been attracting significant attention from the computing research community, most notably under the umbrella of fair^a and interpretable^b machine learning. While important, much of this work has been limited in scope to the “last mile” of data analysis and has disregarded both the *system’s design, development, and use life cycle* (What are we automating and why? Is the system working as intended? Are there any unforeseen consequences post-deployment?) and the *data life cycle* (Where did the data come from? How long is it valid and appropriate?). In this article, we argue two points. First, the decisions we make during data collection and preparation profoundly impact the robustness, fairness, and interpretability of the systems we build. Second, our responsibility for the operation of these systems does not stop when they are deployed.

Example: Automated hiring systems. To make our discussion concrete, consider the use of predictive analytics in hiring. Automated hiring systems are seeing ever broader use and are as varied as the hiring practices themselves, ranging from resume screeners that claim to identify promising applicants^c to video and voice analysis tools that facilitate the interview process^d and game-based assessments that promise to surface personality traits indicative of future success^e. Bogen and Biele^f describe the hiring process from the employer’s point of view as a series of decisions that forms a funnel, with stages corresponding to

^a <https://www.acmlife.com/>
^b <https://www.interpretable.com/>
^c <https://www.gematrix.ai/>



The Cambridge Report on Database Research

Anastasia Ailamaki, Samuel Madden, Daniel Abadi, Gustavo Alonso, Sihem Amer-Yahia, Magdalena Balazinska, Philip A. Bernstein, Peter Boncz, Michael Cafarella, Surajit Chaudhuri, Susan Davidson, David DeWitt, Yanlei Diao, Xin Luna Dong, Michael Franklin, Juliana Freire, Johannes Gehrke, Alon Halevy, Joseph M. Hellerstein, Mark D. Hill, Stratos Idreos, Yannis Ioannidis, Christoph Koch, Donal Kossman, Tim Kraska, Arun Kumar, Guoliang Li, Volker Markl, René Miller, C. Mohan, Thomas Neumann, Beng Chin Ooi, Fatma Özcan, Aditya Parameswaran, Ippokratis Pandis, Iqbal P. Patel, Andrew Pavlo, Danica Porobic, Viktor Sanca, Michael Stonebraker, Julia Stoyanovich, Dan Suciu, Wang-Chiew Tan, Shiv Venkataraman, Matei Zaharia, and Stanley B. Zdonik

1 Introduction

On October 19–20, 2023, the authors of this report convened in Cambridge, MA, to discuss the state of the database research field¹, its recent accomplishments and ongoing challenges, and future directions for research and community engagement. This gathering continues a long-standing tradition in the database community, dating back to the late 1980s, in which researchers meet roughly every five years to produce a forward-looking report [1–9].

This report summarizes the key takeaways from our discussions. We begin with a retrospective on the community’s academic, open-source, and commercial successes over the past five years. We then turn to future opportunities, with a focus on core data systems—particularly in the context of cloud computing and emerging hardware—as well as on the growing impact of data science, data governance, and generative AI.

This document is not intended as an exhaustive survey of all technical challenges or industry innovations in the field. Rather, it reflects the perspectives of senior community members on the most pressing challenges and promising opportunities ahead.

2 Evolution Over The Past Five Years

The past five years have continued to see important advances in the database and data systems landscape, particularly around new hardware, cloud-based data systems, and the continued adoption of statistical techniques, ML, and AI in both core data systems architecture and components.

The rise of Large Language Models (LLMs) has significantly shaped the collective consciousness of both computer science and society in recent years. While LLM-related technologies are still evolving and have yet to reach their full potential, they offer a promising solution to many complex data challenges, particularly those involving natural language and unstructured data. Already, LLMs have unlocked new possibilities for understanding human intentions and needs,

paving the way for more intuitive, natural language-based querying and analysis interfaces. They have also demonstrated the capacity to comprehend data, including unstructured formats such as video and text, and to ground structured data in broader general knowledge. Additionally, LLMs are capable of synthesizing complex, multi-step data transformation programs. Fully realized, these technologies promise to revolutionize the ability of data systems to understand users, data, and programs. This has already prompted researchers to reconsider traditional database interactions, broadening the scope to incorporate unstructured data and natural language into conventional database systems. We explore these LLM-related opportunities in greater detail in Section 3.2 below.

2.1 Research Successes

In this section, we briefly review some of the key areas of progress in the community in the past few years.

2.1.1 Core Data Systems. In reaction to the low-level MapReduce-style tools of the previous decade of Big Data, database research and products make great strides toward usability and rich functionality of databases at massive scales. In particular, cloud-native architectures have matured significantly, and the industry has widely adopted the concept of disaggregated storage and compute, enabling a high degree of scalability and flexibility.

The hardware landscape continues to evolve rapidly to cater to resource-hungry AI, opening up new challenges and opportunities for data systems. The database community has made strides in leveraging improved hardware capabilities, such as NVMe SSDs, GPUs, DPUs, and specialized AI accelerators such as PGAs and ASICs. For example, research on NVMe SSDs has led to the development of new storage engines that can fully utilize their high IOPS and low latency, often redesigning traditional data structures such as B-trees to minimize random accesses. Work on persistent memory has resulted in novel index structures that provide crash consistency without the overhead of traditional

¹Formally defined as the community of researchers publishing in ACM SIGMOD, VLDB, and related conferences, journals, and workshops.

arXiv:2504.11259v1 [cs.DB] 15 Apr 2025

Grounding: Bias in computer systems

Pre-existing: independent of the technical system, has origins in society

Technical: introduced or exacerbated by the properties of the technical system

Emergent: arises due to the context of use



[Friedman & Nissenbaum, 1996]

Example: Taming **technical** bias

Goal: design a model to predict appropriate level of compensation for job applicants

Problem: accuracy is lower for applicants who have more experience on the job - a **fairness concern**

demographics			

employment	

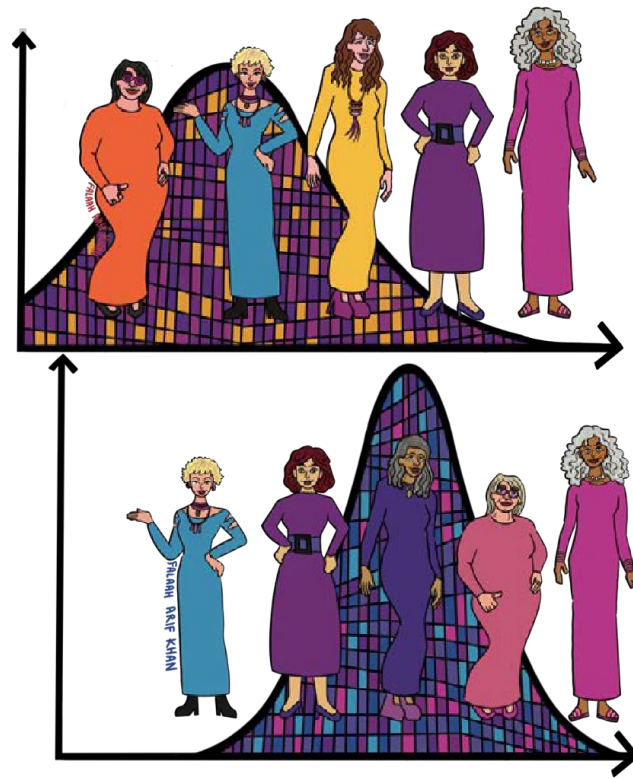


Missing values imputation

are values **missing at random** (e.g., *gender, age, years of experience, disability status* on job applications)?

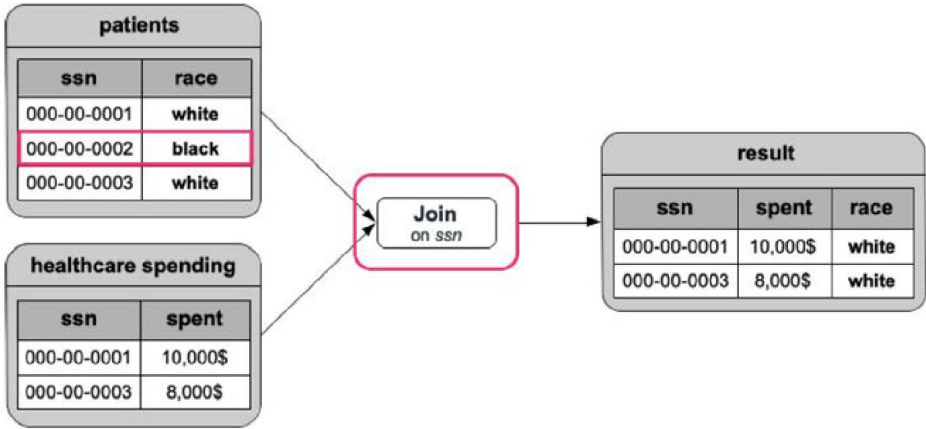
are we ever interpolating **rare categories** (e.g., *Native American*)

are **all categories** represented (e.g., *non-binary gender*)?



Data filtering

operations like **selection** and **join**, can arbitrarily change demographic group proportions



age_group	county
60	CountyA
60	CountyA
20	CountyA
60	CountyB
20	CountyB
20	CountyB

50% vs 50%



age_group	county
60	CountyA
60	CountyA
20	CountyA

66% vs 33%

Data distribution debugging

Potential issues in preprocessing pipeline:

- 1 Join might change proportions of groups in data
- 2 Column 'age_group' projected out, but required for fairness
- 3 Selection might change proportions of groups in data
- 4 Imputation might change proportions of groups in data
- 5 'race' as a feature might be illegal!
- 6 Embedding vectors may not be available for rare names!

Python script for preprocessing, written exclusively with native pandas and sklearn constructs

```
# load input data sources, join to single table
patients = pandas.read_csv(...)
histories = pandas.read_csv(...)
data = pandas.merge([patients, histories], on=['ssn'])

# compute mean complications per age group, append as column
complications = data.groupby('age_group')
    .agg(mean_complications=('complications', 'mean'))
data = data.merge(complications, on=['age_group'])

# Target variable: people with frequent complications
data['label'] = data['complications'] >
    1.2 * data['mean_complications']

# Project data to subset of attributes, filter by counties
data = data[['smoker', 'last_name', 'county',
    'num_children', 'race', 'income', 'label']]
data = data[data['county'].isin(counties_of_interest)]

# Define a nested feature encoding pipeline for the data
impute_and_encode = sklearn.Pipeline([
    (sklearn.SimpleImputer(strategy='most_frequent')),
    (sklearn.OneHotEncoder())])
featurisation = sklearn.ColumnTransformer(transformers=[
    (impute_and_encode, ['smoker', 'county', 'race']),
    (Word2VecTransformer(), 'last_name')
    (sklearn.StandardScaler(), ['num_children', 'income'])])

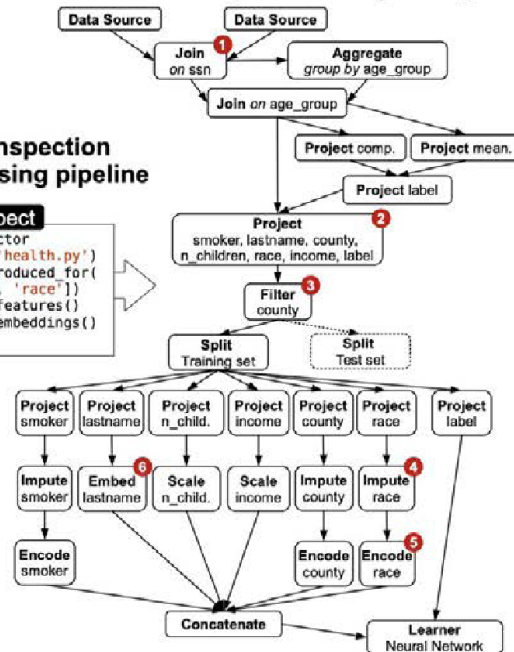
# Define the training pipeline for the model
neural_net = sklearn.KerasClassifier(build_fn=create_model())
pipeline = sklearn.Pipeline([
    ('features', featurisation),
    ('learning_algorithm', neural_net)])

# Train-test split, model training and evaluation
train_data, test_data = train_test_split(data)
model = pipeline.fit(train_data, train_data.label)
print(model.score(test_data, test_data.label))
```

Declarative inspection of preprocessing pipeline

```
mlinspect
PipelineInspector
.on_pipeline('health.py')
.no_bias_introduced_for([
    'age_group', 'race'])
.no_illegal_features()
.no_missing_embeddings()
.verify()
```

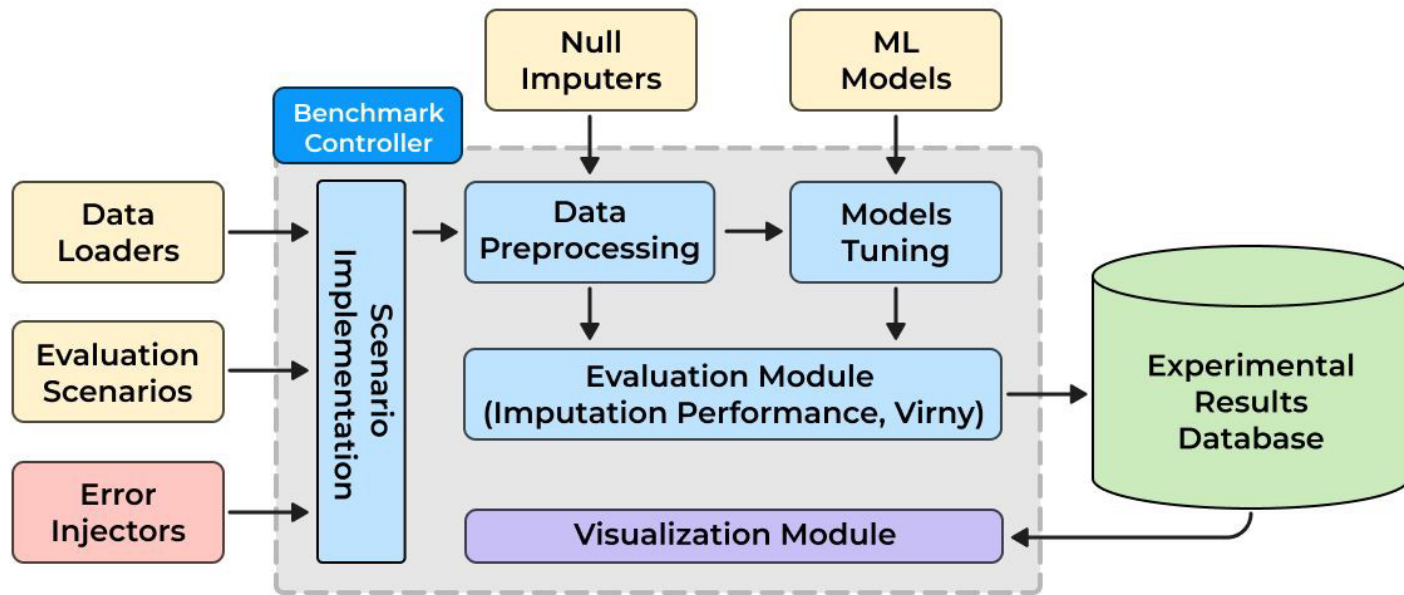
Corresponding dataflow DAG for instrumentation, extracted by *mlinspect*



[Grafberger, Stoyanovich & Schelter; *CIDR 2021 & SIGMOD 2021*]

[Grafberger, Groth, Stoyanovich & Schelter; *VLDBJ 2022*]

Shades-of-NULL: A missing value imputation benchmark



Shades-of-NULL: Evaluation scenarios



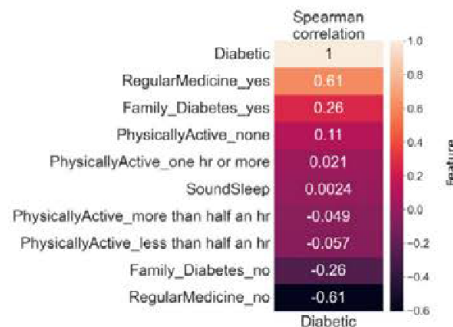
Scenario	Train			Test		
	MCAR	MAR	MNAR	MCAR	MAR	MNAR
S1	✓			✓		
S2		✓			✓	
S3			✓			✓
S4	✓				✓	
S5	✓					✓
S6		✓		✓		
S7		✓				✓
S8			✓	✓		
S9			✓		✓	
S10	✓	✓	✓	✓	✓	✓

- **Missingness:** MCAR, MAR, MNAR
- Missingness as a form of **bias**
- **Mixed** missingness
- **Missingness** shift
- Socially-salient evaluation scenarios

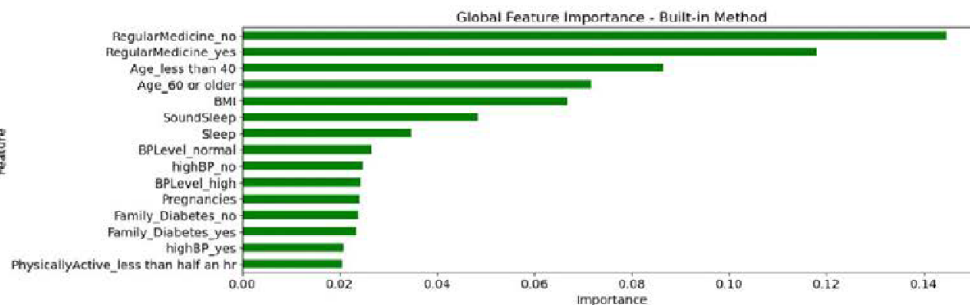
Shades-of-NULL: Missingness in context



Mechanism	Missing Column (\mathcal{F}^m)	Conditional Column (I)	$\Pr(\mathcal{F}^m I \text{ is dis})$	$\Pr(\mathcal{F}^m I \text{ is priv})$
MCAR	SoundSleep, Family_Diabetes, PhysicallyActive, RegularMedicine	N/A	0.3	0.3
MAR	Family_Diabetes, RegularMedicine, PhysicallyActive, SoundSleep	Sex	0.2 (female)	0.1 (male)
		Age	0.2 (≥ 40)	0.1 (< 40)
MNAR	Family_Diabetes	Family_Diabetes	0.25 (yes)	0.05 (no)
	RegularMedicine	RegularMedicine	0.2 (yes)	0.1 (no)
	PhysicallyActive	PhysicallyActive	0.25 (none, $< \frac{1}{2}$ hour)	0.05 ($> \frac{1}{2}$ hour, > 1 hour)
	SoundSleep	SoundSleep	0.2 (< 5)	0.1 (≥ 5)

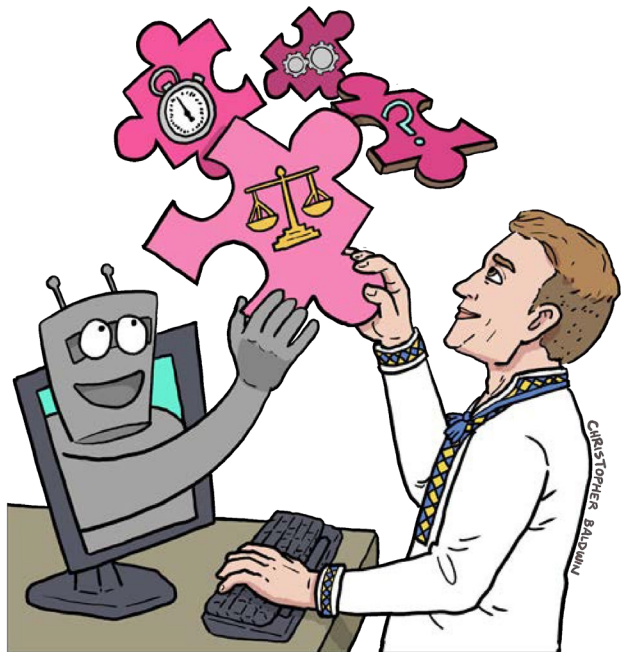


(a) Correlation with label



(b) Feature importance

Virny: Responsible model selection



Responsible Model Selection with Virny and VirnyView

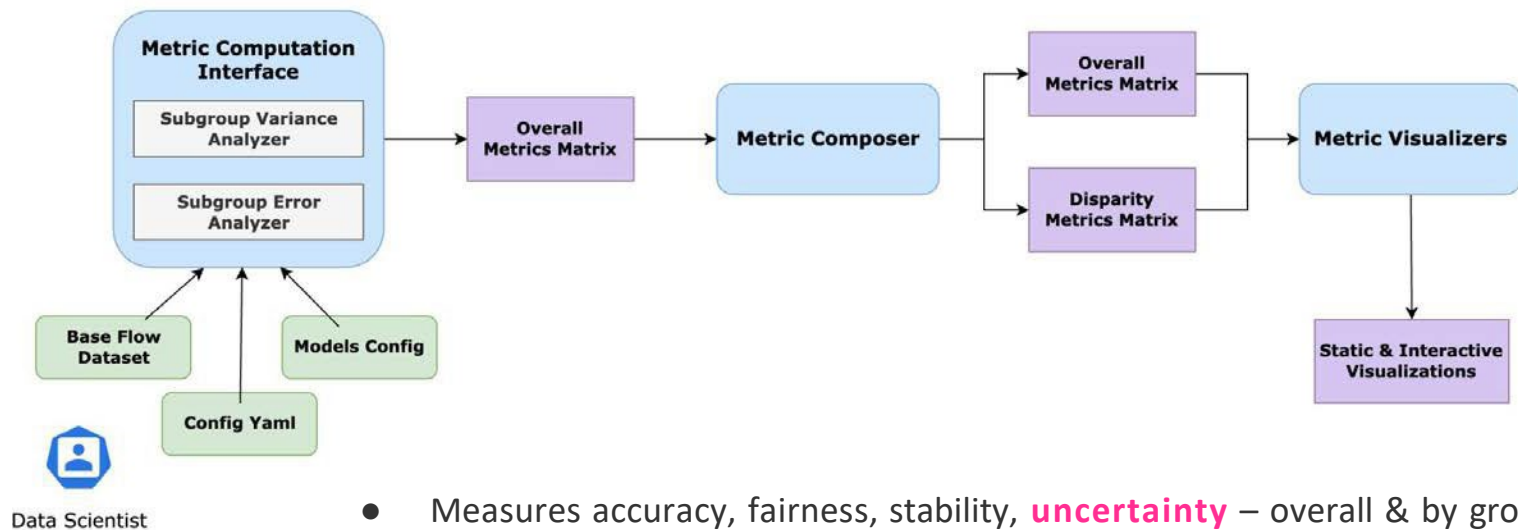
Denys Herasymuk, Falaah Arif Khan, and Julia Stoyanovich

*In Companion of the International Conference on Management of Data,
SIGMOD/PODS, Santiago, Chile 2024*

[CITE](#)[PDF](#)[GITHUB](#)

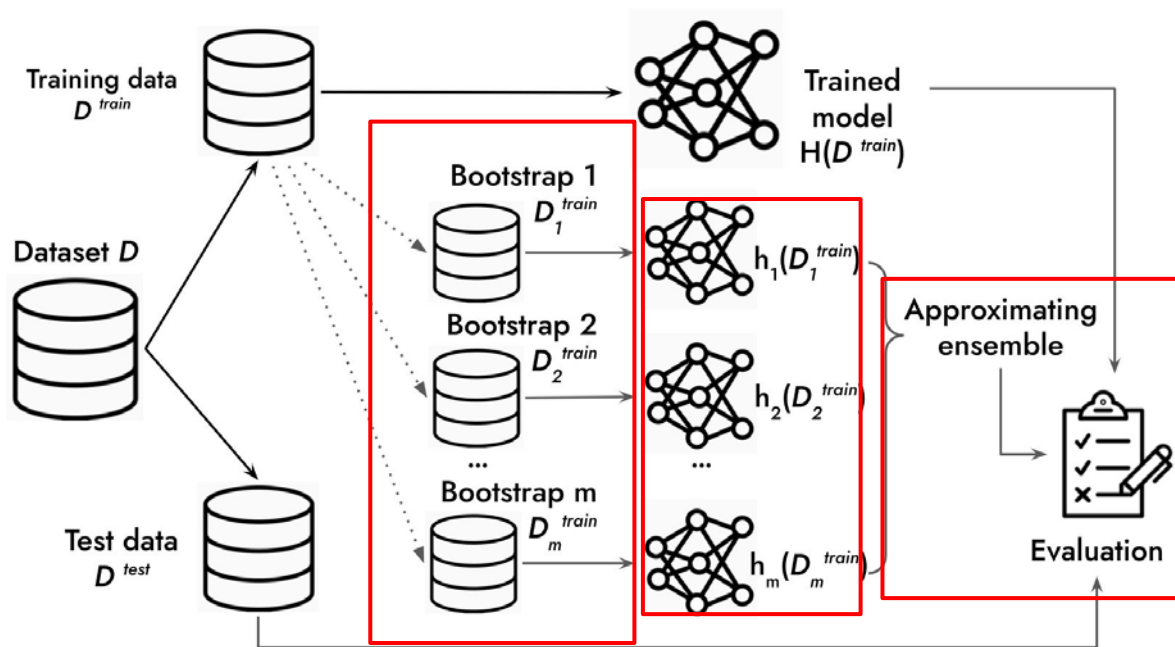
[Herasymuk, Arif Khan, Stoyanovich; *SIGMOD* 2024]

Virny: Responsible model selection



- Measures accuracy, fairness, stability, **uncertainty** – overall & by group
- Supports **multiple sensitive attributes** and their intersections
- Offers **diverse metric computation interfaces** for in-depth profiling of model performance

Virny: Measuring arbitrariness & uncertainty



Virny: Model selection



Bar Chart for Model Selection

Select input arguments to create a bar chart for model selection. Default values display the lowest and greatest limits of constraints.

Group Name for Disparity Metrics

SEX&RACIP

Overall Constraint (C1)

Accuracy

Min value

0.81

Max value

1.0

Disparity Constraint (C2)

Equalized_Odds_FNR

Min value

-0.08

Max value

0.08

Overall Constraint (C3)

Label_Stability

Min value

0.87

Max value

1.0

Disparity Constraint (C4)

Label_Stability_Ratio

Min value

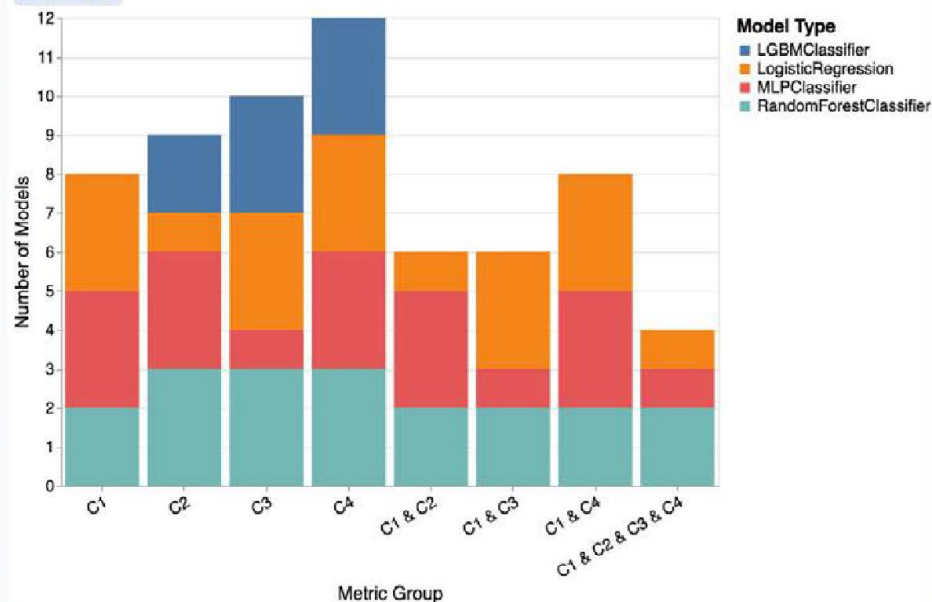
0.9

Max value

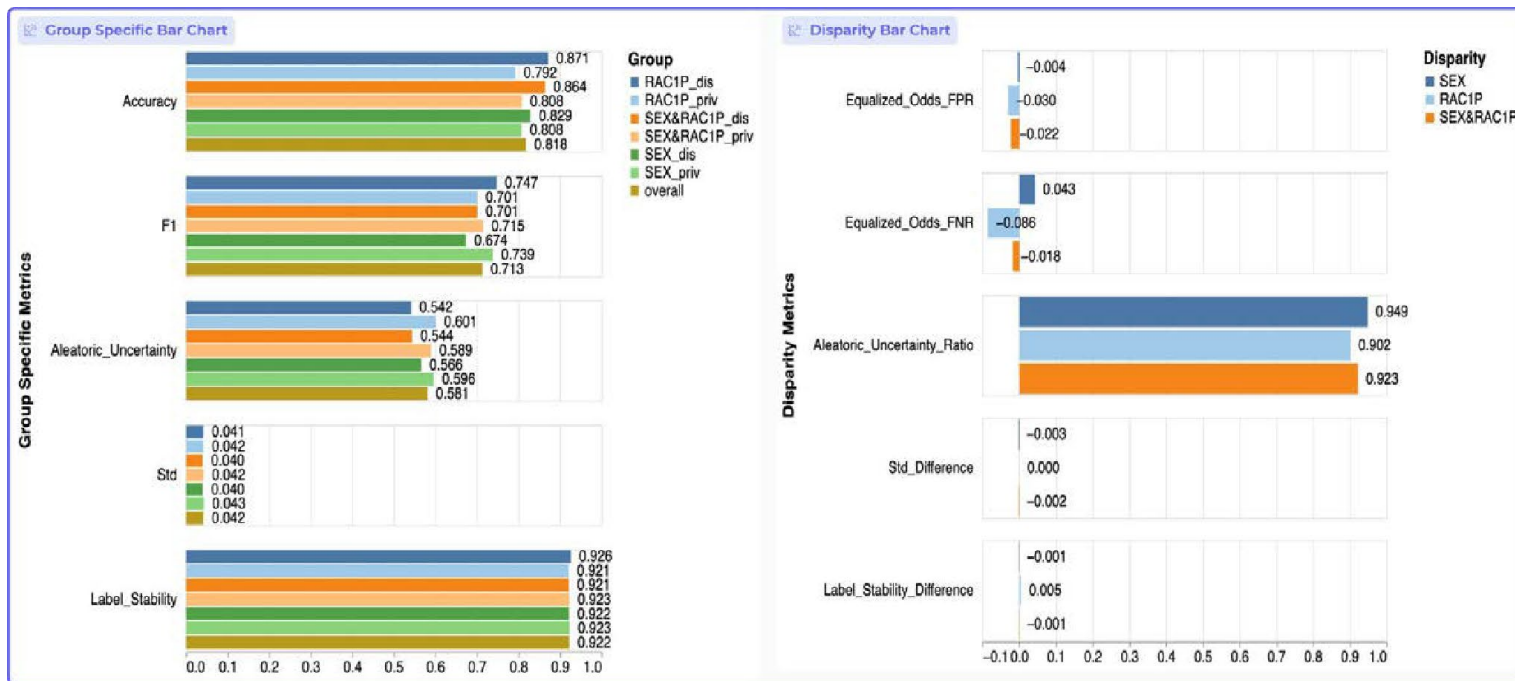
1.1

Submit

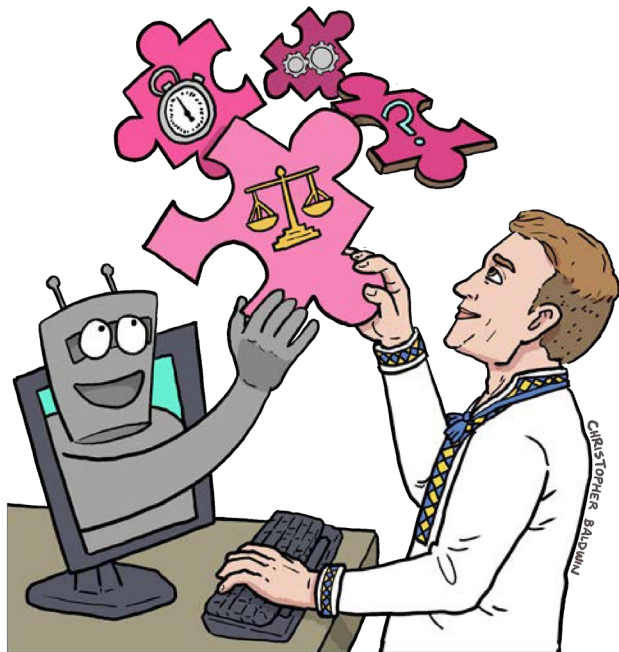
Bar Chart



Virny: Model nutritional label



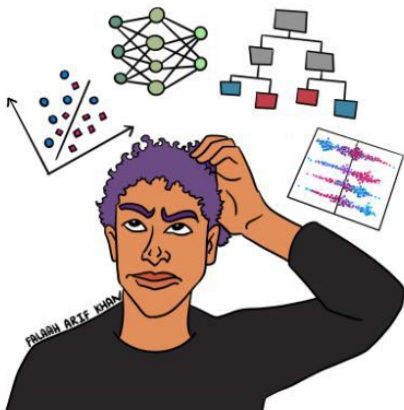
Virny: ongoing work



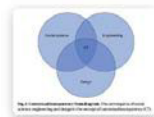
- **Speed up** responsible model selection - **VirnyFlow**
- Integrate multiple of model performance objectives into **hyperparameter optimization** - **VirnyFlow**
- **Assess** the impact of **ML lifecycle stages** on different aspects of model performance - **Shades-of-NULL**



Transparency & explainability



It's Just Not That Simple: An Empirical Study of the Accuracy-Explainability Trade-off in Machine Learning for Public Policy
Andrew Bell, Ian Solano-Kamaiko, Oded Nov, and Julia Stoyanovich
In Proceedings of the 5th Annual ACM Conference on Fairness, Accountability, and Transparency, FAccT 2022

[CITE](#)[PDF](#)

Introducing contextual transparency for automated decision systems
Mona Sloane, Ian Solano-Kamaiko, Jun Yuan, Aritra Dasgupta, and Julia Stoyanovich
Nature Machine Intelligence 2023

[CITE](#)[PDF](#)

Think About the Stakeholders First! Towards an Algorithmic Transparency Playbook for Regulatory Compliance
Andrew Bell, Oded Nov, and Julia Stoyanovich
Data & Policy 2023

[CITE](#)[PDF](#)

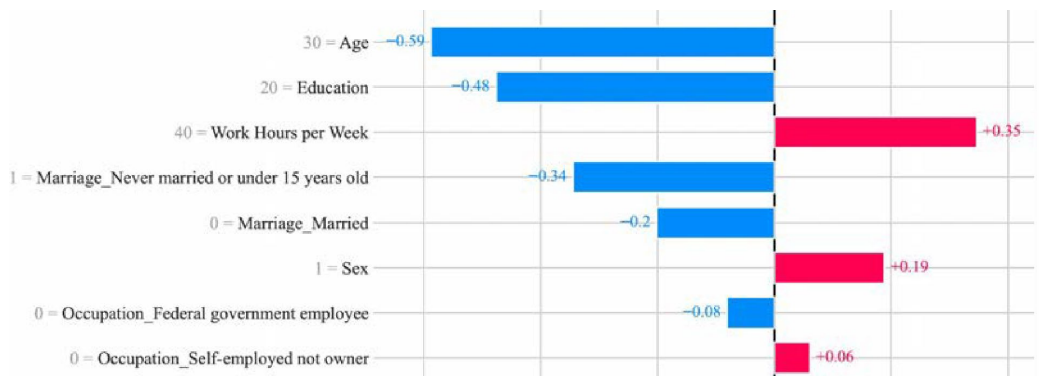
The Imperative of Interpretable Machines
Julia Stoyanovich, Jay J. Van Bavel, and Tessa V. West
Nature Machine Intelligence 2020

[CITE](#)

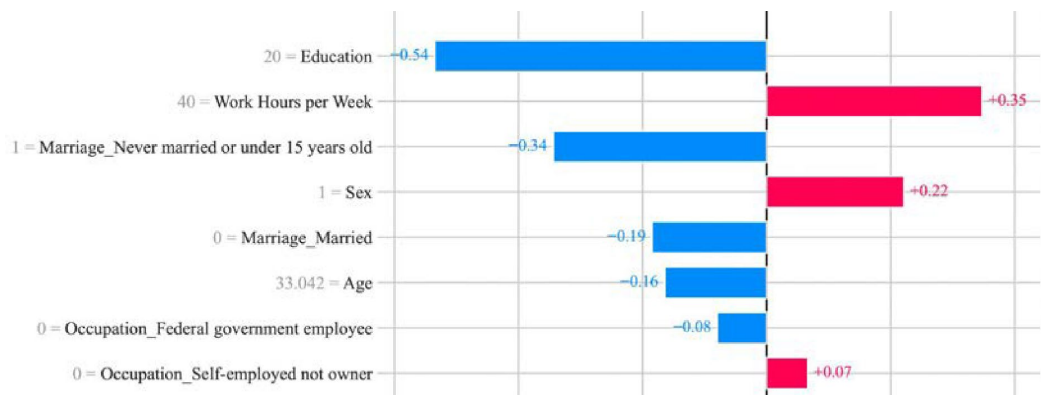
Nutritional Labels for Data and Models
Julia Stoyanovich, and Bill Howe
IEEE Data Eng. Bull. 2019

[CITE](#)[PDF](#)

SHAP attack!



continuous age value: most important feature (-0.59)



bucketized age (12 equi-width intervals) value: low importance (-0.16)

ShaRP: Explaining ranked outcomes

name	gpa	sat	essay	f	g
Bob	4	5	5	4.6	5
Cal	4	5	5	4.6	5
Dia	5	4	4	4.4	4
Eli	4	5	3	4.2	3
Fay	5	4	3	4.2	3
Kat	5	4	2	4.0	2
Leo	4	4	3	3.8	3
Osi	3	3	3	3.0	3

(a)

$r_{\mathcal{D},f}$
Bob
Cal
Dia
Eli
Fay
Kat
Leo
Osi

(b)

$r_{\mathcal{D},g}$
Bob
Cal
Dia
Eli
Fay
Leo
Osi
Kat

(c)

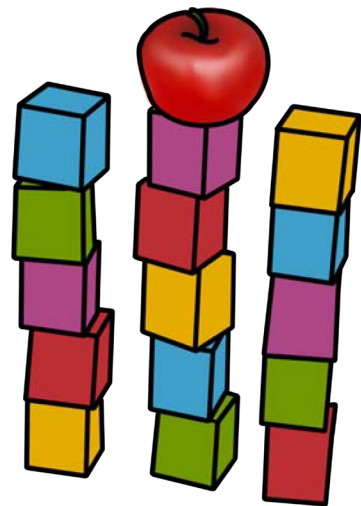





Figure 1: (a) Dataset \mathcal{D} of college applicants, scored on gpa , sat , and $essay$. (b) Ranking $r_{\mathcal{D},f}$ of \mathcal{D} on $f = 0.4 \times gpa + 0.4 \times sat + 0.2 \times essay$; the highlighted top-4 candidates will be interviewed and potentially admitted. (c) Ranking $r_{\mathcal{D},g}$ on $g = 1.0 \times essay$; the top-4 coincides with that of $r_{\mathcal{D},f}$, signifying that $essay$ has the highest importance for f , despite carrying the lowest weight in the scoring function.

Example: CSRankings

CSRankings: Computer Science Rankings

CSRankings is a metrics-based ranking of top computer science institutions around the world. **Click on a triangle (▶)** to expand areas or institutions. **Click on a name** to go to a faculty member's home page. **Click on a chart icon** (the  after a name or institution) to see the distribution of their publication areas as a . **Click on a Google Scholar icon** () to see publications, and **click on the DBLP logo** () to go to a DBLP entry. *Applying to grad school? Read this first.* For info on grad stipends, check out [CSStipendRankings.org](https://cstipendrankings.org). Do you find CSRankings useful? [Sponsor CSRankings on GitHub](#).

Rank institutions in by publications from to

$$f = \sqrt[27]{(AC_{AI}^5 + 1)(AC_{Sys}^{12} + 1)(AC_{Th}^3 + 1)(AC_{Int}^7 + 1)}$$

All Areas ☐ ☒

AI ☐ ☒

- ▶ Artificial intelligence ☒
- ▶ Computer vision ☒
- ▶ Machine learning ☒
- ▶ Natural language processing ☒
- ▶ The Web & information retrieval ☒

Systems ☐ ☒

- ▶ Computer architecture ☒
- ▶ Computer networks ☒
- ▶ Computer security ☒
- ▶ Databases ☒
- ▶ Design automation ☒
- ▶ Embedded & real-time systems ☒
- ▶ High-performance computing ☒
- ▶ Mobile computing ☒
- ▶ Measurement & perf. analysis ☒
- ▶ Operating systems ☒
- ▶ Programming languages ☒
- ▶ Software engineering ☒

Theory ☐ ☒

- ▶ Algorithms & complexity ☒
- ▶ Cryptography ☒
- ▶ Logic & verification ☒

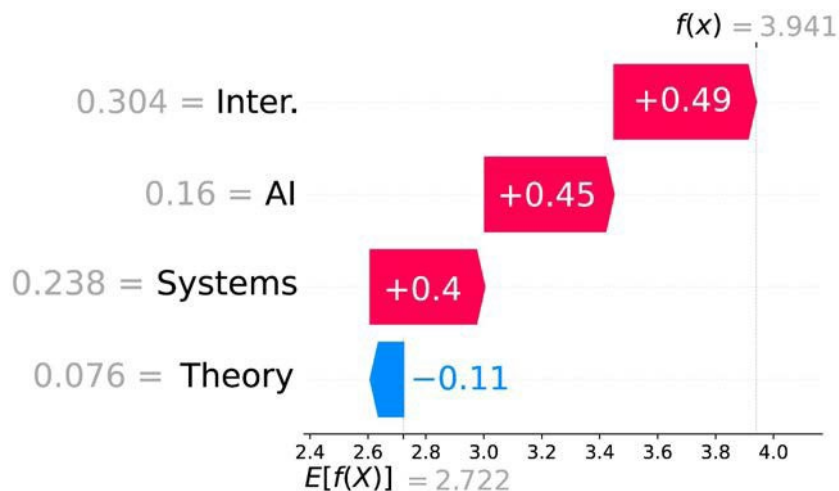
Interdisciplinary Areas ☐ ☒

- ▶ Comp. bio & bioinformatics ☒
- ▶ Computer graphics ☒
- ▶ Computer science education ☒
- ▶ Economics & computation ☒
- ▶ Human-computer interaction ☒
- ▶ Robotics ☒
- ▶ Visualization ☒

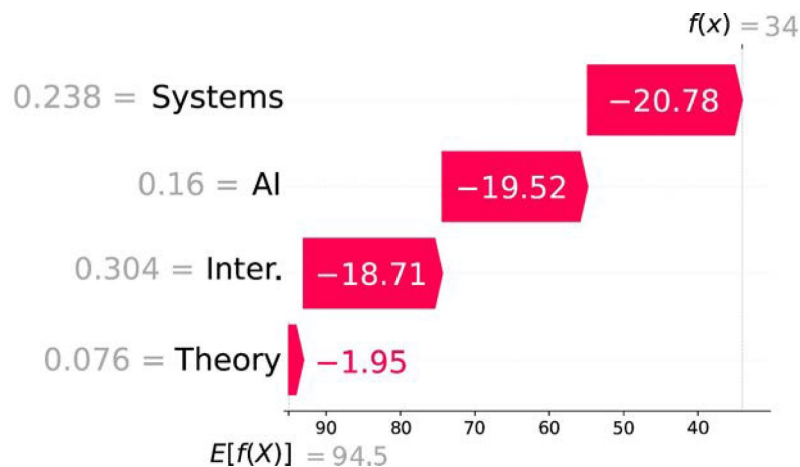
Feature contributions to score vs. rank



Texas A&M, **score** quantity of interest: *Interdisciplinary* is most important

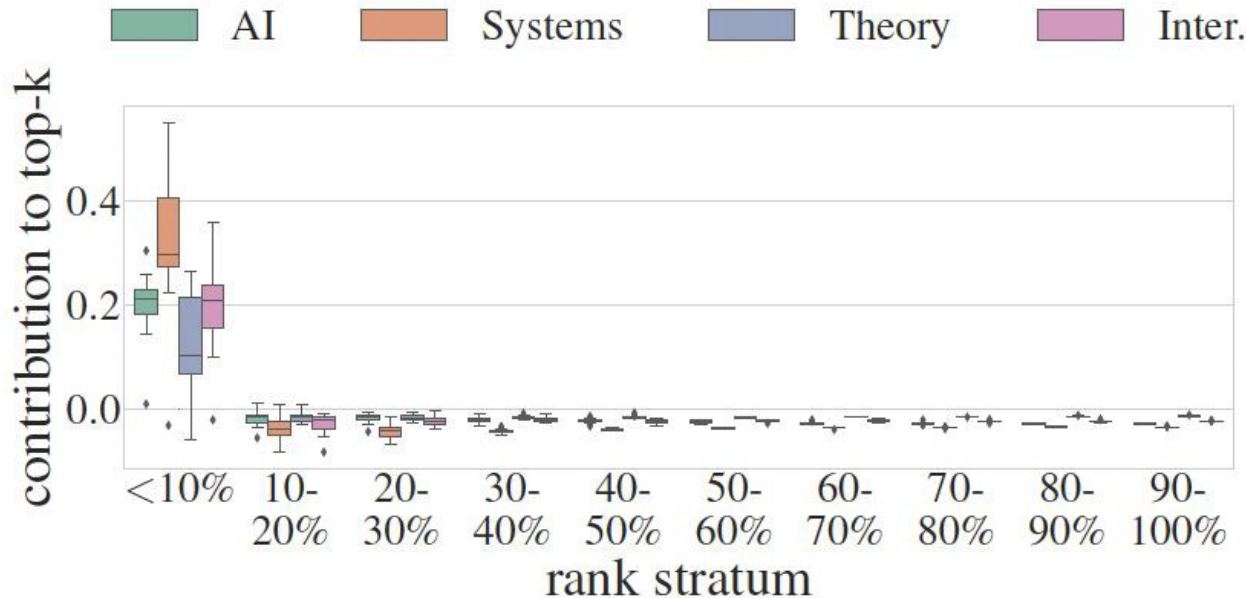


Texas A&M, **rank** quantity of interest: *Systems* is most important



[Pliatsika, Fonseca, Akhynko, Shevchenko, Stoyanovich; *arXiv* 2024]

Feature contributions to the top-20



(a) Feature contribution to the top- k QoI, for $k = 10\%$. Systems is the most important feature, followed by Interdisciplinary and AI.

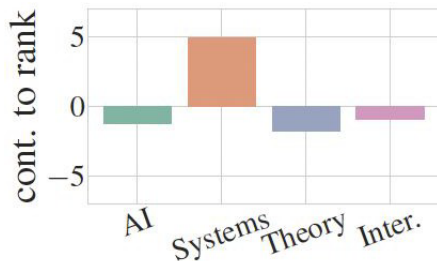
[Pliatsika, Fonseca, Akhynko, Shevchenko, Stoyanovich; *arXiv* 2024]

Feature contributions: Pairwise outcomes

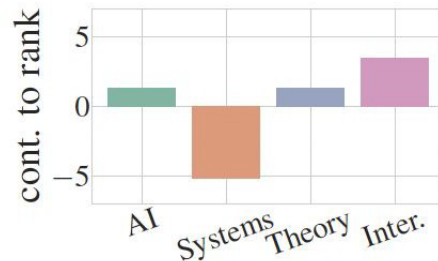


Institution	AI	Systems	Theory	Inter.	Rank
Georgia Tech	28.5	7.8	6.9	10.2	5
Stanford	36.7	5.4	13.3	11.5	6
UMich	30.4	9.0	9.3	5.9	7

(b) Feature values and rank of three highly ranked departments: Georgia Tech, Stanford, and UMich.

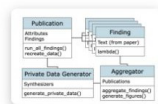


(c) Pairwise method using the rank QoI: Georgia Tech ranks higher than Stanford because of its relative strength in Systems.



(d) Pairwise method using the rank QoI: Stanford ranks higher than UMich despite Stanford's relative weakness in Systems.

Privacy & data protection



Epistemic Parity: Reproducibility as an Evaluation Metric for Differential Privacy

Lucas Rosenblatt, Bernease Herman, Anastasia Holovenko, Wonkwon Lee, Joshua R. Loftus, Elizabeth Mckinnie, Taras Rumezhak, Andrii Stadnik, Bill Howe, and Julia Stoyanovich

Proc. VLDB Endow. 2023

[CITE](#)[PDF](#)[GITHUB](#)

The Many Facets of Data Equity

H.V. Jagadish, Julia Stoyanovich, and Bill Howe

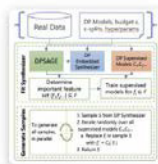
ACM Journal of Data and Information Quality 2023

[CITE](#)[PDF](#)

Personal Data for Personal Use: Vision or Reality?

Xin Luna Dong, Bo Li, Julia Stoyanovich, Anthony Kum Hoe Tung, Gerhard Weikum, Alon Y. Halevy, and Wang-Chiew Tan

In Companion of the 2023 International Conference on Management of Data, SIGMOD/PODS 2023, Seattle, WA, USA, June 18-23, 2023 2023

[CITE](#)[PDF](#)

Spending Privacy Budget Fairly and Wisely

Lucas Rosenblatt, Joshua Allen, and Julia Stoyanovich

Theory and Practice of Differential Privacy (@ICML) 2022

[CITE](#)[PDF](#)

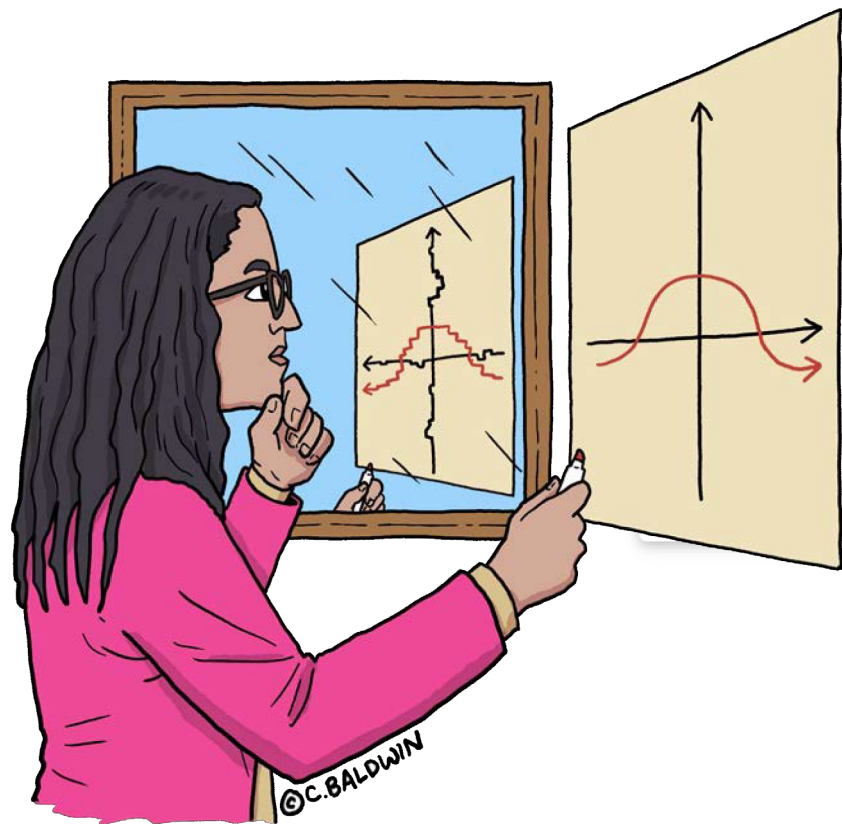
Transparency, Fairness, Data Protection, Neutrality: Data Management Challenges in the Face of New Regulation

Serge Abiteboul, and Julia Stoyanovich

ACM Journal of Data and Information Quality 2019

[CITE](#)[PDF](#)

Epistemic parity



Epistemic Parity: Reproducibility as an Evaluation Metric for Differential Privacy

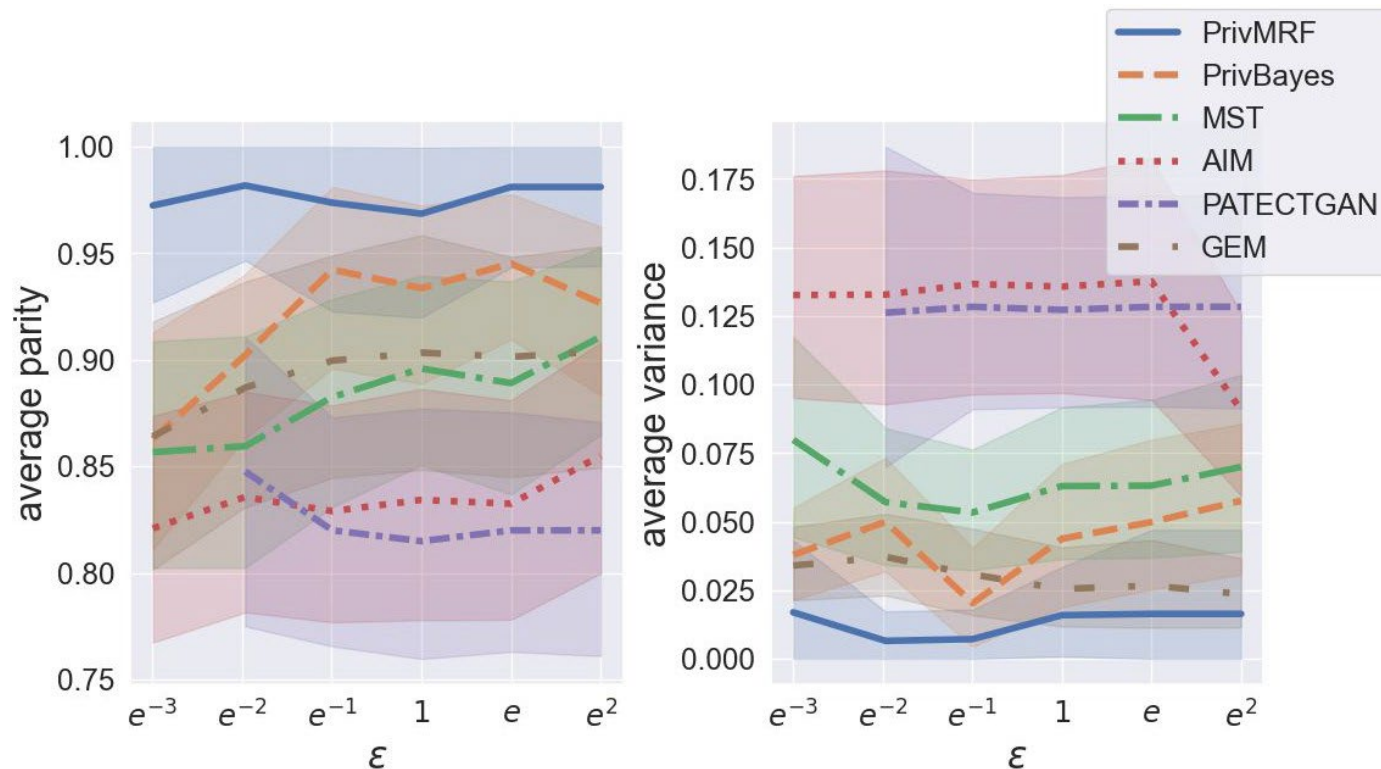
Lucas Rosenblatt, Bernease Herman, Anastasia Holovenko, Wonkwon Lee, Joshua R. Loftus, Elizabeth Mckinnie, Taras Rumezhak, Andrii Stadnik, Bill Howe, and Julia Stoyanovich

Proc. VLDB Endow. 2023

[CITE](#)[PDF](#)[GITHUB](#)

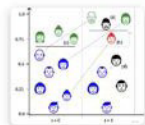


Epistemic parity: Results



[Rosenblatt et al., VLDB 2023]

Algorithmic fairness



Setting the Right Expectations: Algorithmic Recourse Over Time

João Fonseca, Andrew Bell, Carlo Abrate, Francesco Bonchi, and Julia Stoyanovich

In Proceedings of the 3rd ACM Conference on Equity and Access in Algorithms, Mechanisms, and Optimization, EAAMO 2023, Boston, MA, USA, 30 October 2023 - 1 November 2023 2023

[CITE](#)[PDF](#)

Fairness in Ranking: From Values to Technical Choices and Back

Julia Stoyanovich, Meike Zehlike, and Ke Yang

In Companion of the 2023 International Conference on Management of Data, SIGMOD/PODS 2023, Seattle, WA, USA, June 18-23, 2023 2023

[CITE](#)[PDF](#)

Counterfactuals for the Future

Lucius E. J. Bynum, Joshua R. Loftus, and Julia Stoyanovich

In Proceedings of the AAAI Conference on Artificial Intelligence 2023

[CITE](#)[PDF](#)

Towards Substantive Conceptions of Algorithmic Fairness: Normative Guidance from Equal Opportunity Doctrines

Falaah Arif Khan, Eleni Manis, and Julia Stoyanovich

In Equity and Access in Algorithms, Mechanisms, and Optimization, EAAMO 2022, Arlington, VA, USA, October 6-9, 2022 2022

[CITE](#)[PDF](#)

Query Refinement for Diversity Constraint Satisfaction

Jinyang Li, Yuval Moskovitch, Julia Stoyanovich, and H. V. Jagadish

Proc. VLDB Endow. 2023

[CITE](#)[PDF](#)

Fairness as equality of opportunity (EO): The principles

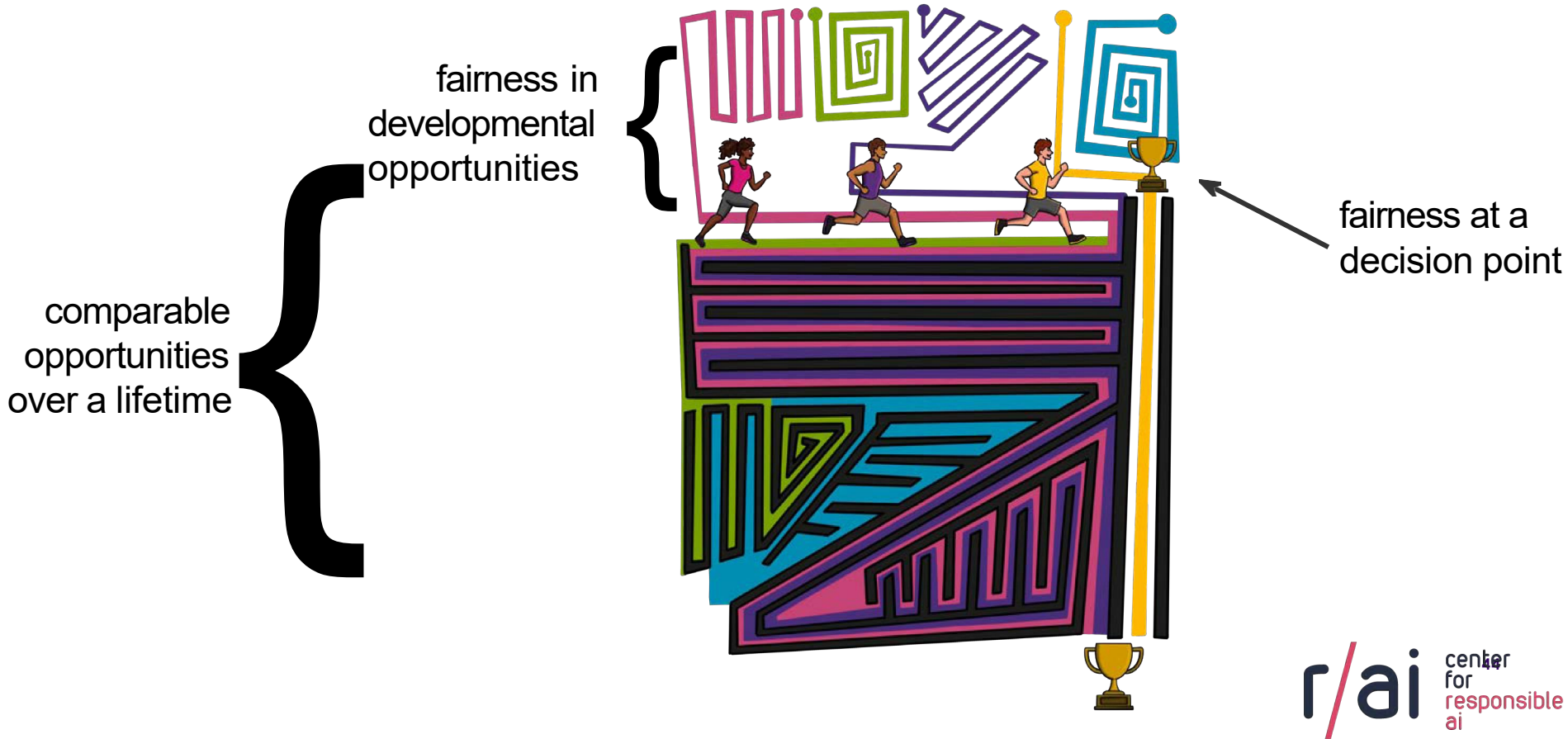
fair contests (non-discrimination)



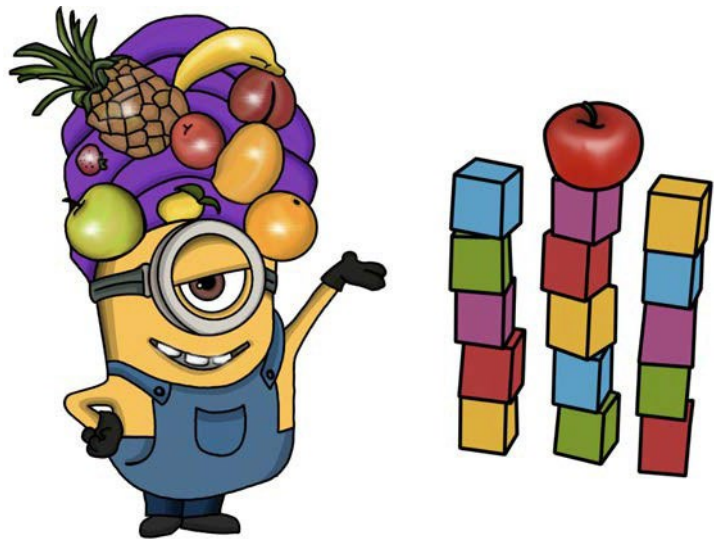
fair life chances (leveling the playing field)



Fairness as equality of opportunity (EO): The domains



Fairness in ranking



Fairness in Ranking: From Values to Technical Choices and Back

Julia Stoyanovich, Meike Zehlike, and Ke Yang

In Companion of the 2023 International Conference on Management of Data, SIGMOD/PODS 2023, Seattle, WA, USA, June 18-23, 2023

[CITE](#)[PDF](#)

Fairness in Ranking, Part I: Score-Based Ranking

Meike Zehlike, Ke Yang, and Julia Stoyanovich

ACM Computing Surveys 2023

[CITE](#)[PDF](#)

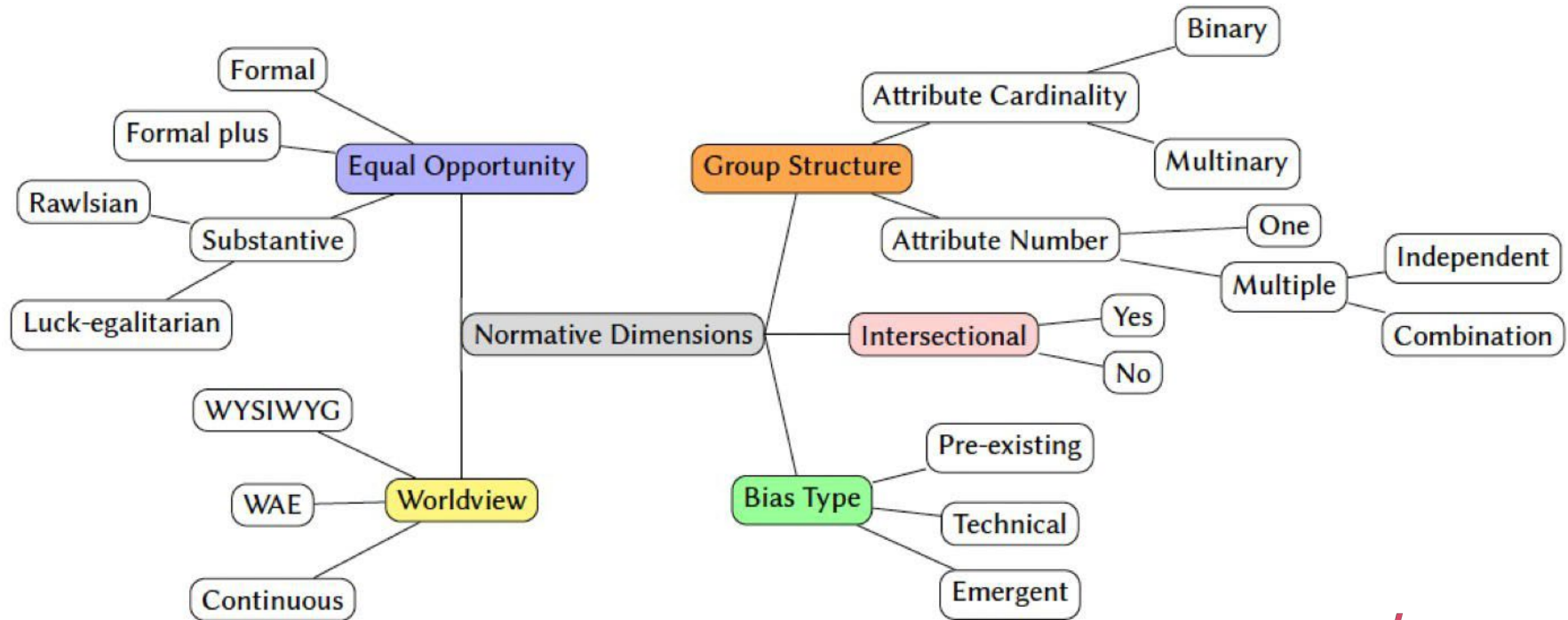
Fairness in Ranking, Part II: Learning-to-Rank and Recommender Systems

Meike Zehlike, Ke Yang, and Julia Stoyanovich

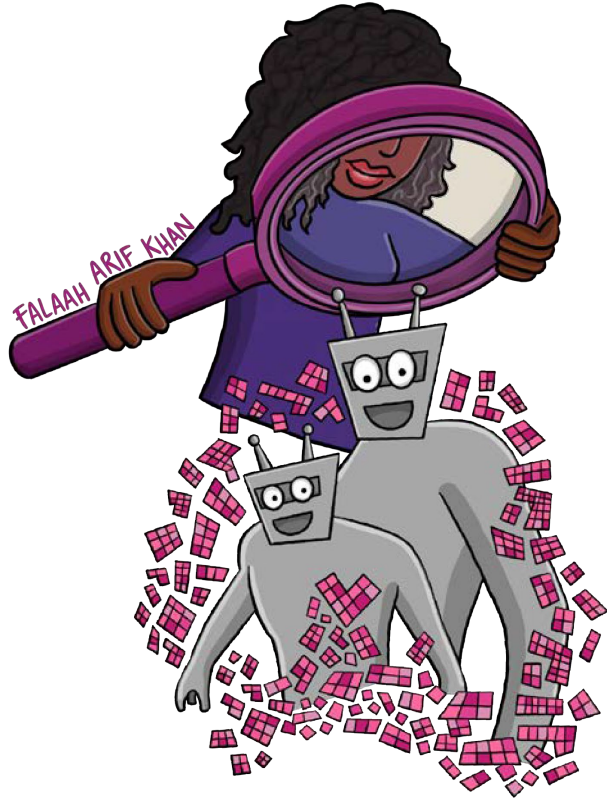
ACM Computing Surveys 2023

[CITE](#)[PDF](#)

Classification of fair ranking methods



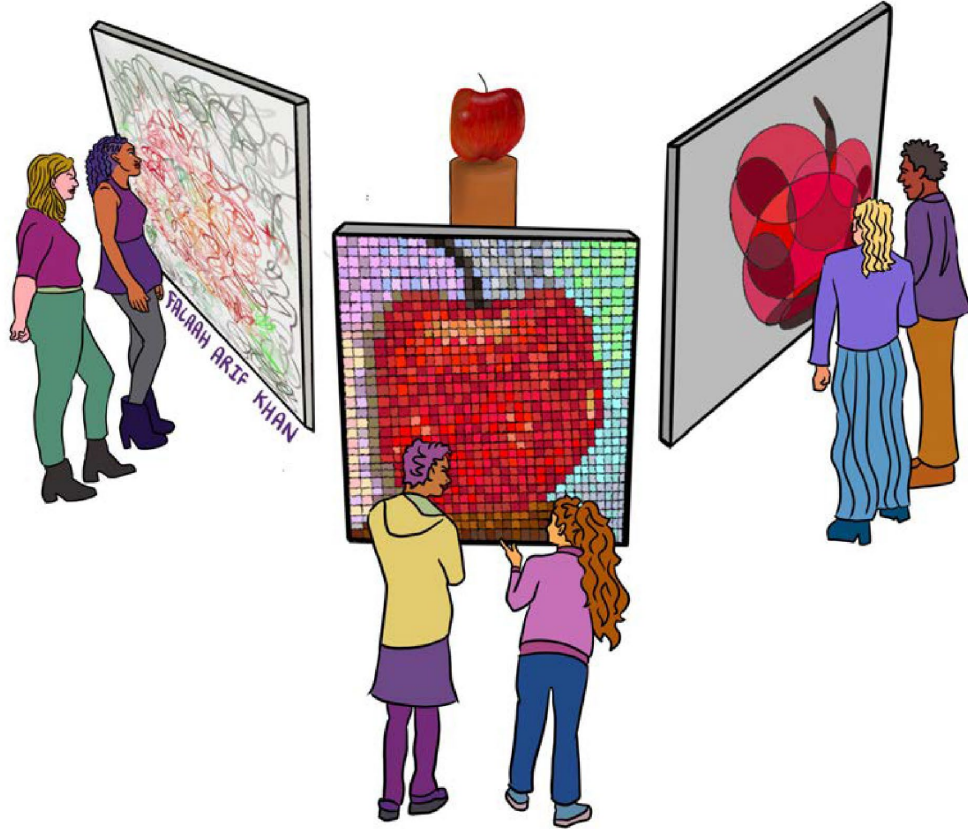
Responsible AI is about ...



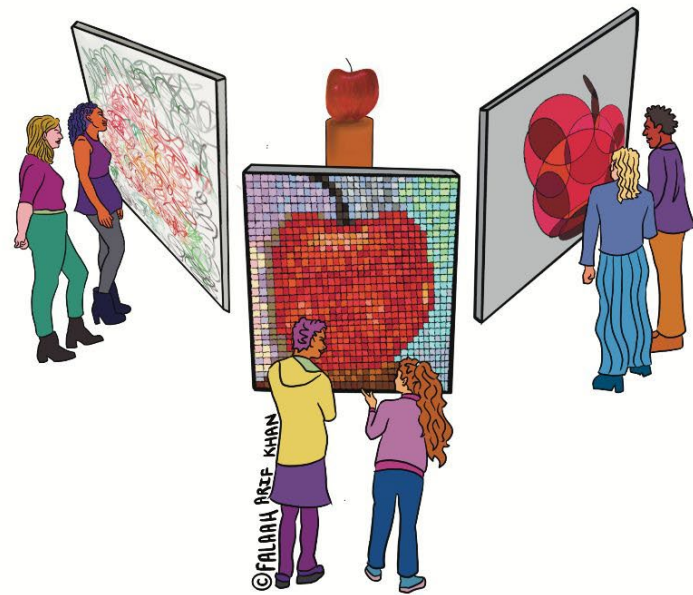
... exposing the knobs
of responsibility to
people



We need (responsible) AI education & training for everyone!



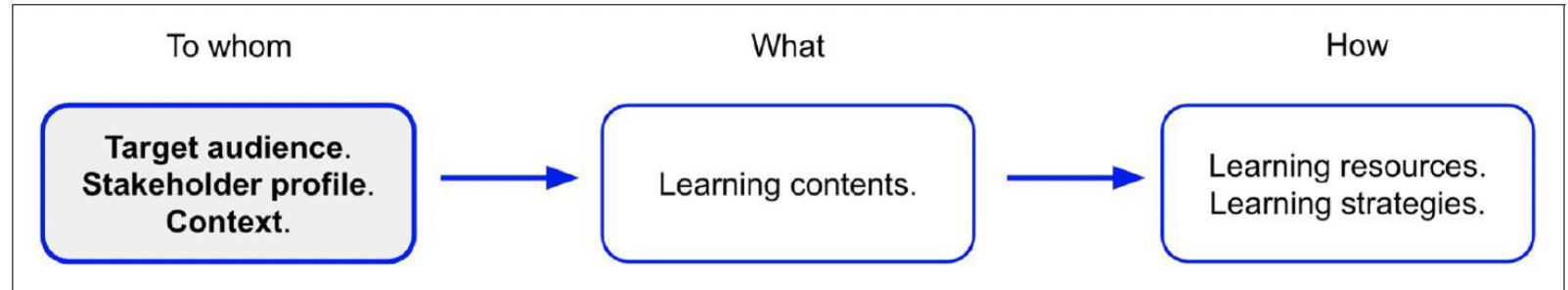
Education & Training



Responsible AI literacy: A stakeholder-first approach

Daniel Domínguez Figaredo¹  and Julia Stoyanovich² 

Big Data & Society
July–December: 1–15
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DOI: 10.1177/20539517231219958
journals.sagepub.com/home/bds



Education & training: students (since 2019)

Audience: undergraduate and graduate students in data science, computer science

Prerequisites: introduction to data science or computer science (not machine learning!)

Challenge: reconcile technical training with interdisciplinary ethical concerns

Bonus: uses many of the technical tools I'll discuss today, all course materials are open

Responsible Data Science: Charting New Pedagogical Territory

NYU Center for Data Science Feb 17, 2020 · 4 min read



In response to the dearth of scholarship surrounding responsible data science (RDS), NYU CDS faculty are paving the way with a course dedicated to RDS and the publication of their pedagogical methodology.



<http://r-ai.co/education>

[Lewis and Stoyanovich; *IJAIED* 2022]

Practitioner training

NYU CENTER FOR RESPONSIBLE AI PRESENTS

WHAT IS RESPONSIBLE AI & HOW DOES IT APPLY TO YOUR WORK AT META?

Responsible AI is the science and the practice of making the design, development, and use of AI socially sustainable. In this workshop, the **NYU Center for Responsible AI** will give an overview of the discipline, and will present and extensively discuss concrete Meta-relevant case studies on ad targeting, content ranking, machine translation, algorithmic hiring, and more. We will take deep dives into algorithmic fairness, transparency and interpretability, and privacy and data protection, while keeping the conversation relevant to your work at Meta. No prior knowledge of responsible AI concepts or techniques is required, or even expected, for participation. Whether you are a responsible AI aficionado or a skeptic, and whether or not your role at Meta is technical — this workshop is for you!

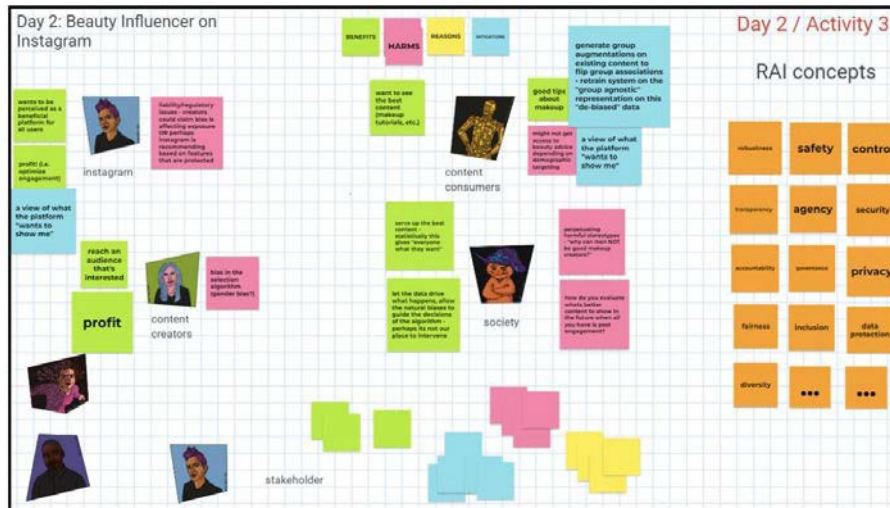
This workshop will consist of two 120-minute sessions. When signing up for the workshop, you commit to attending both sessions and participating in the discussion. Note that the NYU team is conducting an educational research study in conjunction with the workshop, to learn more about effective ways to teach responsible AI concepts and techniques to industry practitioners. They welcome your participation in the workshop even if you do not wish to participate in the research study. You will have an opportunity to find out more about the research and opt into the study at the start of the workshop.



The workshop will be presented by **Dr. Julia Stoyanovich**, Institute Associate Professor of Computer Science and Engineering, Associate Professor of Data Science, and Director of the Center for Responsible AI at NYU. Please reach out to her at stoyanovich@nyu.edu if you have any questions about the workshop.

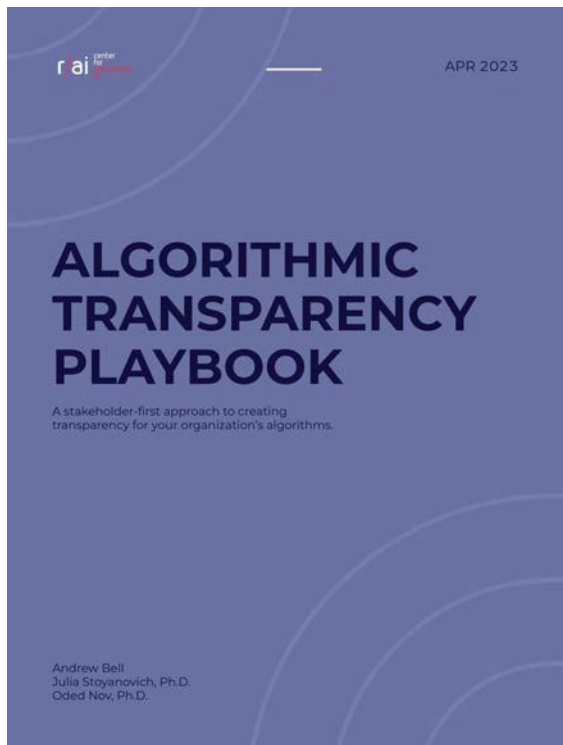
NYU Center for Responsible AI aims to make responsible AI synonymous with AI. We engage in basic and applied research, participate in technology policy & regulation efforts, and teach responsible AI to data science students, practitioners, and members of the public. For more information, visit <https://airesponsibly.com>.

r/ai
center for responsible ai



[Stoyanovich, de Paula, Lewis, Zheng; EAAI 2025]

Practitioner training



[Bell and Stoyanovich, *EAAI* 2025]

NYU CENTER FOR RESPONSIBLE AI PRESENTS

THE ALGORITHMIC TRANSPARENCY WORKSHOP

Join us for a workshop on algorithmic transparency from the NYU Center for Responsible AI!

Date: December 12, 2023 (Tuesday) from 12:00 pm - 2:00 pm

Venue: NYU Tandon Future Labs (7th floor, 370 Jay Street, Brooklyn, NY 11201)

Free lunch for participants will be served beginning at 11:30 am.

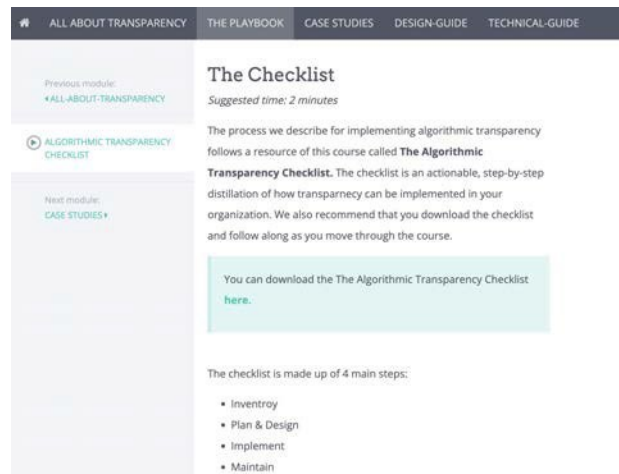


Please RSVP here

As more organizations use AI and algorithmic systems, there is a need for practitioners, industry leaders, managers, and executives to take part in making AI responsible. In this workshop, we'll provide you with an overview of [algorithmic transparency](#), along with a playbook detailing how to influence change and implement transparency into your organization's systems.

In this workshop, we'll look at:

- What is algorithmic transparency?
- What are the available tools, techniques, & methods for making algorithms more understandable for humans
- Play-by-plays for implementing transparency into your organization's algorithmic systems
- Case studies and examples of transparency



Course Instructors

The workshop will be co-taught by **Andrew Bell**, fellow at the NYU Center for Responsible AI (RAI) and **Julia Stoyanovich**, Director of NYU RAI.



Andrew Bell

Andrew Bell is a Computer Science Ph.D. Candidate being co-advised by Prof. Julia Stoyanovich and Dr. Oded Nov. He is a recipient of the National Science Foundation Graduate Research Fellowship (NSF GRFP). His research interests lie at the intersection of machine learning and public policy and are more narrowly focused on the fairness and explainability of algorithmic decision systems. In Spring 2023, Andrew was a visiting research fellow at the Center for AI (CENTAI) in Turin, Italy.



Julia Stoyanovich

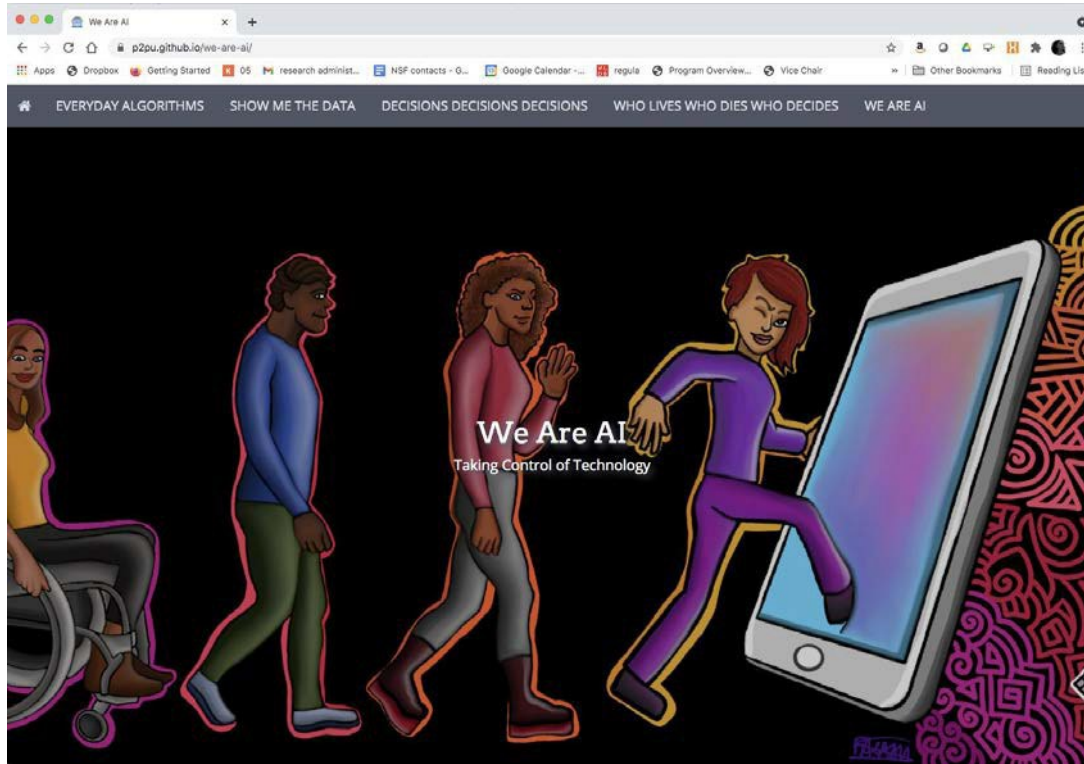
Dr. Julia Stoyanovich is Associate Professor of Computer Science & Engineering and of Data Science, and Director of the Center for Responsible AI at NYU. Her goal is to make "responsible AI" synonymous with "AI". Julia has co-authored over 100 academic publications, and has written for the New York Times, the Wall Street Journal and Le Monde. She engages in technology policy, has been teaching responsible AI to students, practitioners and the public, and has co-authored comic books on this topic. She received her Ph.D. in Computer Science from Columbia University.

About the NYU Center for Responsible AI

The NYU Center for Responsible AI aims to make responsible AI synonymous with AI. The center, which is made up of over 15 researchers across a broad range of fields, conducts interdisciplinary research, engages in AI policy and regulation, and aims to teach different audiences about AI and its social impact. More information can be found at <https://airesponsibility.net/>

rai
center
for
responsible
ai

We are AI: Taking control of technology

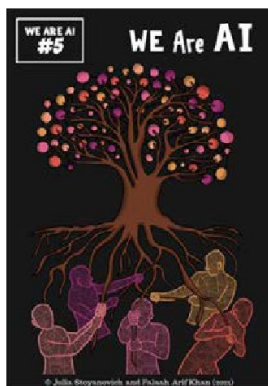
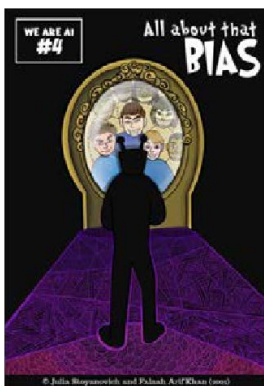
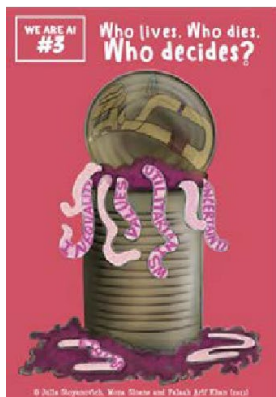


[Stoyanovich, Lewis, Corbett, et al., *EAAI* 2025]



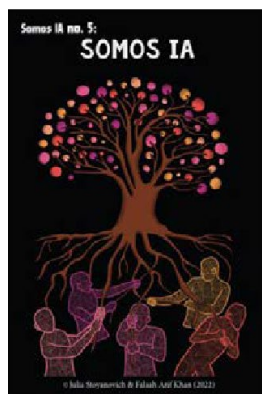
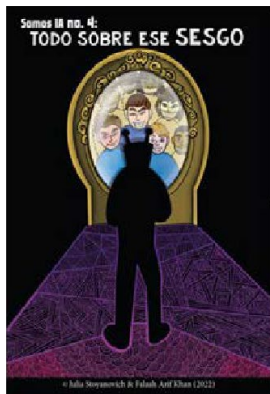
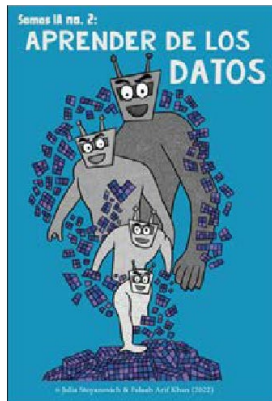
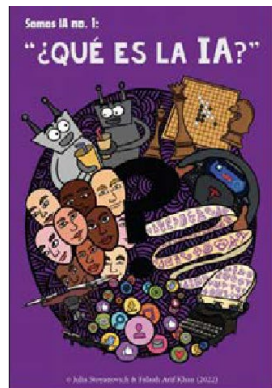
<http://r-ai.co/We-are-AI>

We are AI comics



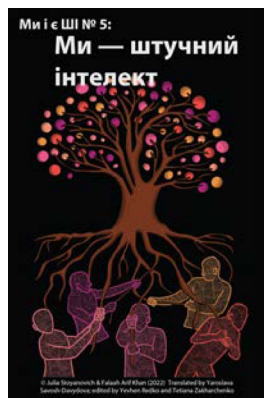
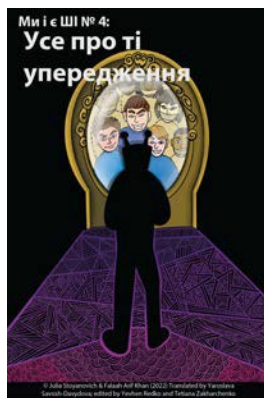
<http://r-ai.co/comics>

We are AI comics / Spanish



<http://r-ai.co/comics>

We are AI comics / Ukrainian



<http://r-ai.co/comics>



2023

ALL ABOARD! MAKING AI EDUCATION ACCESSIBLE

Authors:

Falaah Arif Khan, Lucius Bynum, Amy Hurst, Lucas Rosenblatt,
Meghana Shanbhogue, Mona Sloane, Julia Stoyanovich



<http://r-ai.co/AllAboard>

The poster features a dark background with a perspective view of a road. In the center, a figure in a red dress hangs from a swing. To the left and right, other figures hang from swings, including one in a police uniform. At the top, a silhouette of a person pushing a stroller is visible. The title 'ALICE IN ALGORITHMIA' is written in large, white, bold letters across the top.

ALICE IN ALGORITHMIA

STORY BY JULIA STOYANOVICH AND ALEX BUDOVSKY

ANIMATION BY ALEX BUDOVSKY

MUSIC BY ALEX DREYSHNER

VOICE BY SAVA SARKISOV

CREATIVE CONSULTANT OLEG SARKISOV

r/ai center
for
responsible
ai

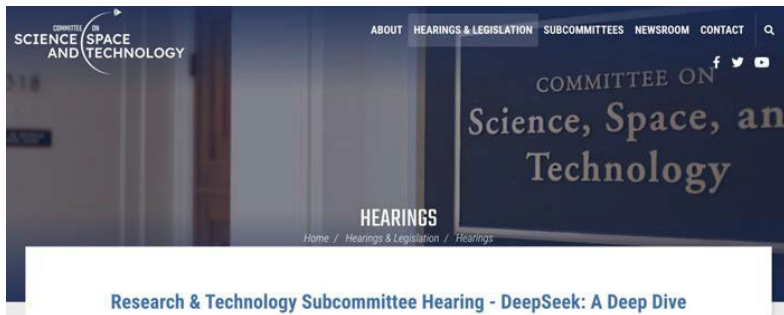
 **NYU | TANDON**



<http://r-ai.co/alice>

r/ai center
for
responsible
ai

Looking ahead: A responsible AI “Sputnik” moment



- Robust trustworthy AI cyberinfrastructure - **the NAIRR**
- Responsible data engineering tools and primitives across the lifecycle
- Data protection tools, primitives, guardrails



<https://science.house.gov/2025/4/deepseek-a-deep-dive>

Looking ahead: A responsible AI “Sputnik” moment

Correspondence

Promoting transparency in AI for biomedical and behavioral research

Recent advancements in artificial intelligence (AI) in healthcare have highlighted the need for transparency, including explainability, interpretability, and accountability across the AI lifecycle¹. Transparency ensures stakeholders can make informed decisions about data and model reuse, fostering trust and fairness while aligning with regulatory frameworks. However, the concept of transparency lacks a clear definition for both biomedical research and clinical care, resulting in inconsistent practices.

This Correspondence focuses on transparency within the realm of AI-driven biomedical and behavioral research. Although the effect of AI on clinical care is crucial, this discussion centers on its implications for research, addressing gaps in data reuse, model generalization and fairness. The National Institutes of Health (NIH) Office of Data Science Strategy (ODSS) convened a workshop that brought together leading experts in AI, healthcare, and ethics to examine transparency in this context². The workshop findings highlight practical solutions tailored to research contexts, addressing documentation standards, patient and community co-design, and oversight mechanisms to achieve equitable outcomes.

Transparency in AI extends beyond technical documentation to include ethical and societal dimensions. We define transparency as a multidimensional construct comprising three pillars: clarity of processes, stakeholder engagement, and accountability mechanisms. Clarity of processes includes documenting model development, training data sources, and decision-making pathways. Stakeholder engagement, such as actively involving patients and communities in the co-design of models and tools, ensures that AI is aligned with societal values. Finally, researchers need to establish oversight frameworks for ethical AI deployment. This approach enables transparency to address specific challenges in biomedical research ensuring ethical use and reuse practices.

Transparency empowers patient and community engagement by enabling active involvement in AI decision-making processes

across the AI lifecycle, including these perspectives in AI governance ensures that research outputs align with ethical standards, fostering trust and accountability between developers, researchers and the communities that they serve. Seeking input on data sovereignty and benefit sharing further strengthens transparency and ethical decision-making across the healthcare ecosystem. Transparency should extend to educating stakeholders about the impacts of AI on healthcare, incorporating principles such as data sovereignty and benefit sharing. These strategies support the development of patient-centered AI by ensuring alignment with societal values, fostering trust, and promoting active participation in decision-making processes.

Although co-design is not a new concept, the integration of patients and communities in AI development introduces unique challenges. For example, AI systems often involve complex processes and technical methodologies that may alienate non-technical stakeholders. To address this, it is important to simplify technical challenges through educational resources tailored for diverse audiences. Governance structures are needed to ensure meaningful input from underrepresented communities, and it is essential to establish feedback loops to evaluate the long-term impacts of community involvement. This requires ensuring patient-centered AI development, ensuring ethical alignment and fostering trust.

A comprehensive training framework for researchers and clinicians is essential to understand AI's capabilities, limitations and societal impacts³. With AI becoming more prevalent and sophisticated, there is an increasing need to educate researchers and practitioners on both the capabilities and limitations of AI technologies. Furthermore, it is important to understand how AI interacts with human decision-making in research and clinical practice. Developing a living compendium of ethical challenges and best practices can guide future work in responsible AI⁴.

Comprehensive documentation standards, such as model cards and data sheets are crucial for ethical AI practices⁵. Workshop findings propose augmenting existing

tools to further transparency. Establishing metadata registries for datasets and models can track provenance, consent and lifecycle information, ensuring that AI tools are used ethically and effectively. This registry would serve as a centralized record of datasets and models, including their provenance, tracking their origin, data ownership, consent and any modifications. This requires refining existing metadata standards, creating lifecycle-centric methodologies, and integrating semi-automated documentation tools. A registry of proxy variables would also be integral components of the AI lifecycle metadata. Proxy variables are stand-in measures used to represent underlying factors or characteristics that are difficult to measure directly, such as socioeconomic status or access to healthcare. Equally important are harm identification databases that track adverse outcomes linked to AI tools to guide future improvements. These databases may also identify known biases and potential harms from AI data use. These resources will provide a foundation for ethical AI development and help mitigate unintended consequences in healthcare AI applications.

Improving the effectiveness, safety and inclusivity of AI in research and practice requires a distributed accountability framework in which all stakeholders contribute to the responsible design, development and oversight of AI technologies. Building institutional capacities in education, training, public engagement and standardization is essential to support these efforts. Institutions should prioritize the development of specialized curricula and certification programs tailored to ethics, transparency and bias mitigation. These programs should target diverse stakeholders, including researchers, clinicians and administrators, to ensure a shared understanding of responsible AI practices. Public engagement initiatives must foster open dialogue between the scientific community and society, addressing concerns about AI's impact and building trust.

Expanding Institutional Review Boards (IRBs) to include AI expertise is crucial to address transparency, bias and ethical concerns. Expanding IRBs to include AI expertise is crucial to address transparency, bias and ethical concerns. Expanding IRBs to include AI expertise is crucial to address transparency, bias and ethical concerns.

nature medicine

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U.S. Department of Health and Human Services (HHS)
National Institutes of Health (NIH)
Office of the Director (OD)
Division of Program Coordination, Planning, and Strategic Initiatives (DPCPSI)
Office of Data Science Strategy (ODSS)

Report from the Community Workshop Toward an Ethical Framework for Artificial Intelligence in Biomedical and Behavioral Research: Transparency for Data and Model Reuse

Authors

Workshop Co-Chairs Dr. Tina Hernandez-Boussard, Dr. Aaron Lee, Prof. Julia Stoyanovich;
Workshop Breakout Leads Drs. Ansu Chatterjee, Caroline Chung, Maia Hightower, Sajid Hussain, H.V. Jagodish, Jayashree Kalpathy-Cramer, Vincent Liu, Courtney Lyles, Shazia Siddique, Eric Stahlberg, and Colin Washley

January 31 – February 2, 2024
Rockledge II, 6701 Rockledge Drive
Bethesda, MD
& Virtual

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Community-Informed Policies and Best-Practices for the National Artificial Intelligence Research Resource (NAIRR)

Workshop Report

July 29–31, 2024
New York University
New York, NY

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What need education and practitioner training on RAI

It's more expensive to do things right (i.e., responsibly) than to do them somehow. **Small and medium-sized businesses that develop and/or use AI need support, training, tools, data, compute, infrastructure.**

NYU CENTER FOR RESPONSIBLE AI PRESENTS

WHAT IS RESPONSIBLE AI & HOW DOES IT APPLY TO YOUR WORK AT META?

Responsible AI is the science and the practice of making the design, development, and use of AI socially sustainable. In this workshop, the NYU Center for Responsible AI will give an overview of the discipline, and will present and extensively discuss concrete Meta-relevant case studies on ad targeting, content ranking, machine translation, algorithmic hiring, and more. We will take deep dives into algorithmic fairness, transparency and interpretability, and privacy and data protection, while keeping the conversation relevant to your work at Meta. No prior knowledge of responsible AI concepts or techniques is required, or even researched for participation. Whether you are a responsible AI advocate or a skeptic, or whether or not your role at Meta is technical — this workshop is for you!

This workshop will consist of two 120-minute sessions. When signing up for the workshop, you commit to attending both sessions and participating in the discussion. Note that the NYU team is conducting an educational research study in conjunction with the workshop, to learn more about effective ways to teach responsible AI concepts and techniques to industry practitioners. They welcome your participation in the workshop even if you do not wish to participate in the research study. You will have an opportunity to find out more about the research and opt into this study at the start of the workshop.

The workshop will be presented by **Dr. Julia Stoyanovich**, Institute Associate Professor of Computer Science and Engineering, Associate Professor of Data Science, and Director of the Center for Responsible AI at NYU. Please reach out to her at stoyanovich@nyu.edu if you have any questions about the workshop.

NYU Center for Responsible AI aims to make responsible AI synonymous with AI. We engage in basic and applied research, participate in technology policy & regulation efforts, and teach responsible AI to data science students, practitioners, and members of the public. For more information, visit <https://theresponsibleai.com>

r/ai

APR 2023

ALGORITHMIC TRANSPARENCY PLAYBOOK

A stakeholder-first approach to creating transparency for your organization's algorithms

Andrew Ball
Julia Stoyanovich, Ph.D.
Oded Nov, Ph.D.

ALL ABOUT TRANSPARENCY THE PLAYBOOK CASE STUDIES DESIGN GUIDE TECHNICAL GUIDE

The Checklist

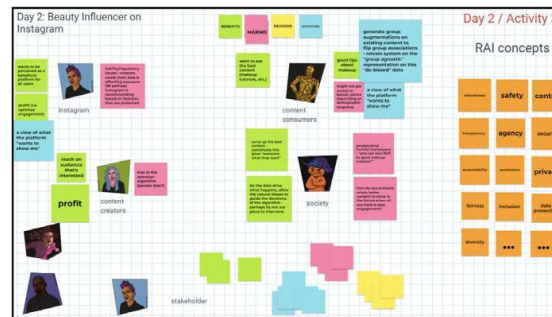
Suggested time: 2 minutes

The process we describe for implementing algorithmic transparency follows a resource of this course called **The Algorithmic Transparency Checklist**. The checklist is an actionable, step-by-step distillation of how transparency can be implemented in your organization. We also recommend that you download the checklist and follow along as you move through the course.

You can download **The Algorithmic Transparency Checklist** here.

The checklist is made up of 4 main steps:

- Inventory
- Plan & Design
- Implement
- Maintain



NYU CENTER FOR RESPONSIBLE AI PRESENTS THE ALGORITHMIC TRANSPARENCY WORKSHOP

Join us for a workshop on algorithmic transparency from the NYU Center for Responsible AI!
Date: December 12, 2023 (Tuesday) from 12:00 pm - 2:00 pm
Venue: NYU London Future Labs (7th floor, 370-Jay Street, Brooklyn, NY 11201)

Please reach out to stoyanovich@nyu.edu if you have any questions.

As more organizations use AI and algorithmic systems, there is a need for practitioners, industry leaders, managers, and executives to take part in making AI responsible. In this workshop, we'll provide you with an overview of **algorithmic transparency**, along with a playbook detailing how to influence change and implement transparency into your organization's systems.

In this workshop, we'll look at:

- What is algorithmic transparency?
- What are the available tools, techniques, & methods for making algorithms more understandable for humans?
- Play-by-plays for implementing transparency into your organization's algorithmic systems.
- Case studies and examples of transparency.

Course Instructors

The workshop will be co-taught by **Andrew Ball**, fellow at the NYU Center for Responsible AI (PhD) and **Julia Stoyanovich**, Director (PhD) RAI.



Andrew Ball

Andrew Ball is a Computer Science Ph.D. candidate being co-advised by Prof. Julia Stoyanovich and Dr. Oded Nov. He is a recipient of the National Science Foundation Graduate Research Fellowship (NSF GRFP). His research interests lie at the intersection of machine learning and public policy and are more narrowly focused on the fairness and explainability of algorithmic decision systems. In Spring 2023, Andrew was a visiting research fellow at the Center for AI (CDOT) in Turin, Italy.



Julia Stoyanovich

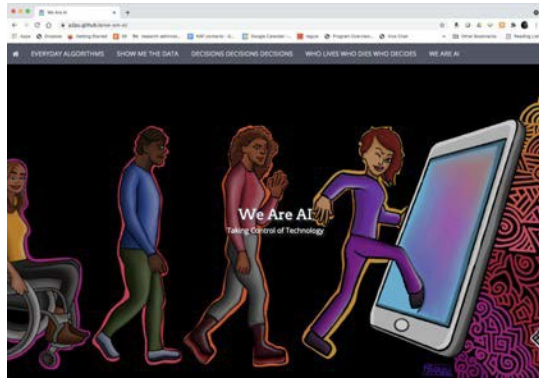
Dr. Julia Stoyanovich is Associate Professor of Computer Science & Engineering and of Data Science, and Director of the Center for Responsible AI at NYU. Her goal is to make "responsible" synonymous with "AI". Julia has co-authored over 100 academic publications, and has written for the New York Times, the Wall Street Journal and Le Monde. She engages in technology policy, has been teaching responsible AI to students, practitioners and the public, and has co-authored some books on this topic. She received her Ph.D. in Computer Science from Columbia University.

About the NYU Center for Responsible AI

The NYU Center for Responsible AI aims to make responsible AI synonymous with AI. The center, which is made up of over 15 researchers across a broad range of fields, conducts interdisciplinary research, engages in AI policy and regulation, and aims to reach different audiences about AI and its social impact. More information can be found at <https://theresponsibleai.com>

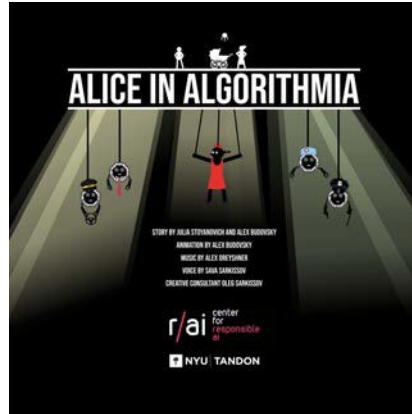
What need AI literacy for everyone!

Many of us are passionate about AI literacy, and have invested time and effort into pilot projects.
And now, we need to scale up and scale out.



2023
**ALL ABOARD!
MAKING AI EDUCATION
ACCESSIBLE**

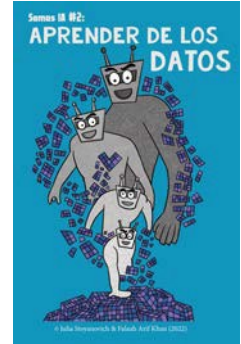
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Meghana Shanbhogue, Mona Sloane, Julia Stoyanovich



Responsible AI literacy: A stakeholder-first approach
Daniel Dominguez, and Julia Stoyanovich
Big Data and Society 2023

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Thank you!



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