

Ethical Aspects of Data

Fairness, Bias, Mitigation

Frederic Precioso

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(MAASAI, Joint Research Group INRIA-CNRS-UniCA)

frederic.precioso@univ-cotedazur.fr

Overview

- **Context**
- Definition & Taxonomy
- Bias in ML
- Ethics In AI is not only about fairness

CONTEXT



Biases in Data

Biases in Data

Selection Bias: Selection does not reflect a random sample



CREDIT

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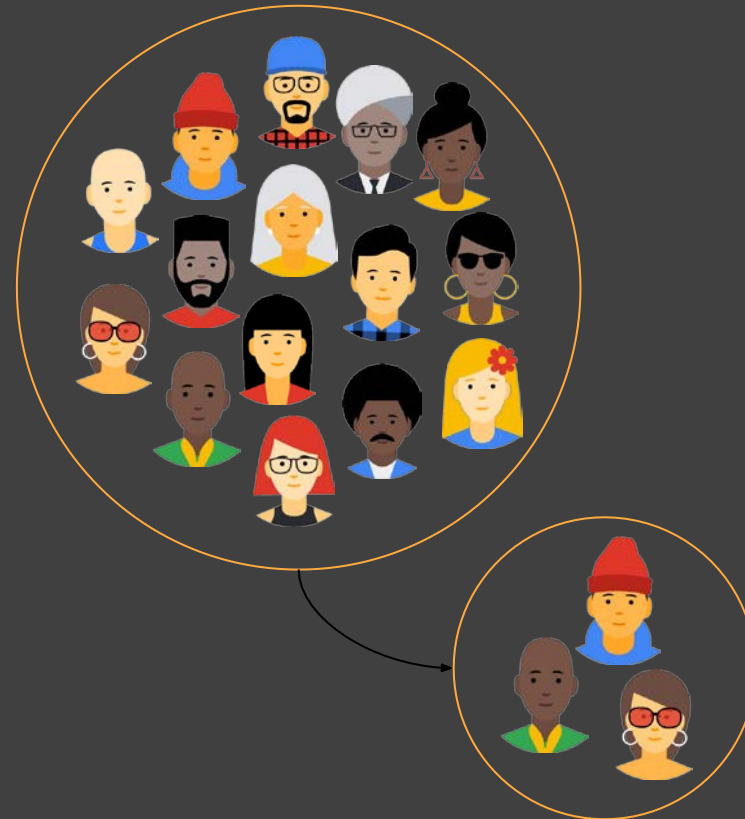
Biases in Data

Out-group homogeneity bias: Tendency to see outgroup members as more alike than ingroup members



Biases in Data → Biased Data Representation

It's possible that you have an appropriate amount of data for every group you can think of but that some groups are represented less positively than others.



Biases in Data → Biased Labels

Annotations in your dataset will reflect the worldviews of your annotators.



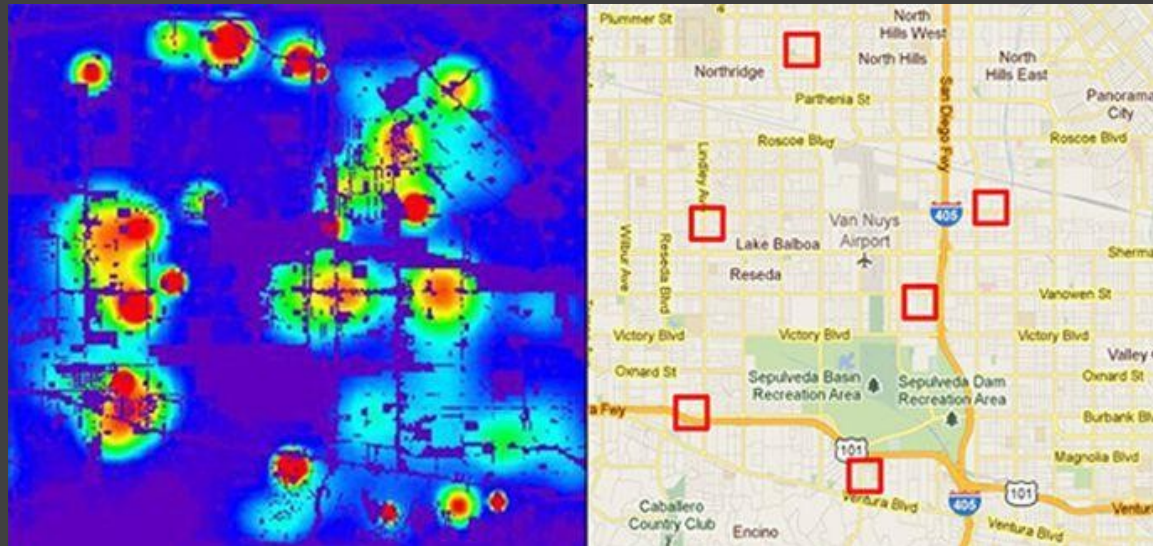
<https://ai.googleblog.com/2018/09/introducing-inclusive-images-competition.html>



Predicting Future Criminal Behavior

Predicting Policing

- Algorithms identify potential crime hot-spots
- Based on where crime is previously reported, not where it is known to have occurred
- Predicts future events from past



CREDIT

[Smithsonian, Artificial Intelligence Is Now Used to Predict Crime. But Is It Biased? 2018](#)

Predicting Sentencing

- Prater (who is white) rated **low risk** after shoplifting, despite two armed robberies; one attempted armed robbery.
- Borden (who is black) rated **high risk** after she and a friend took (but returned before police arrived) a bike and scooter sitting outside.
- Two years later, Borden has not been charged with any new crimes. Prater serving 8-year prison term for grand theft.

CREDIT

[ProPublica. Northpointe: Risk in Criminal Sentencing. 2016.](#)

Predicting Criminality

Israeli startup, [Faception](#)

*“Faception is first-to-technology and first-to-market with proprietary computer vision and machine learning technology for profiling people and **revealing their personality based only on their facial image.**”*

Offering specialized engines for recognizing “High IQ”, “White-Collar Offender”, “Pedophile”, and “Terrorist” from a face image.

Main clients are in homeland security and public safety.

Predicting Criminality

[“Automated Inference on Criminality using Face Images”](#) Wu and Zhang, 2016.
arXiv

1,856 closely cropped images of faces;
Includes “wanted suspect” ID pictures
from specific regions.

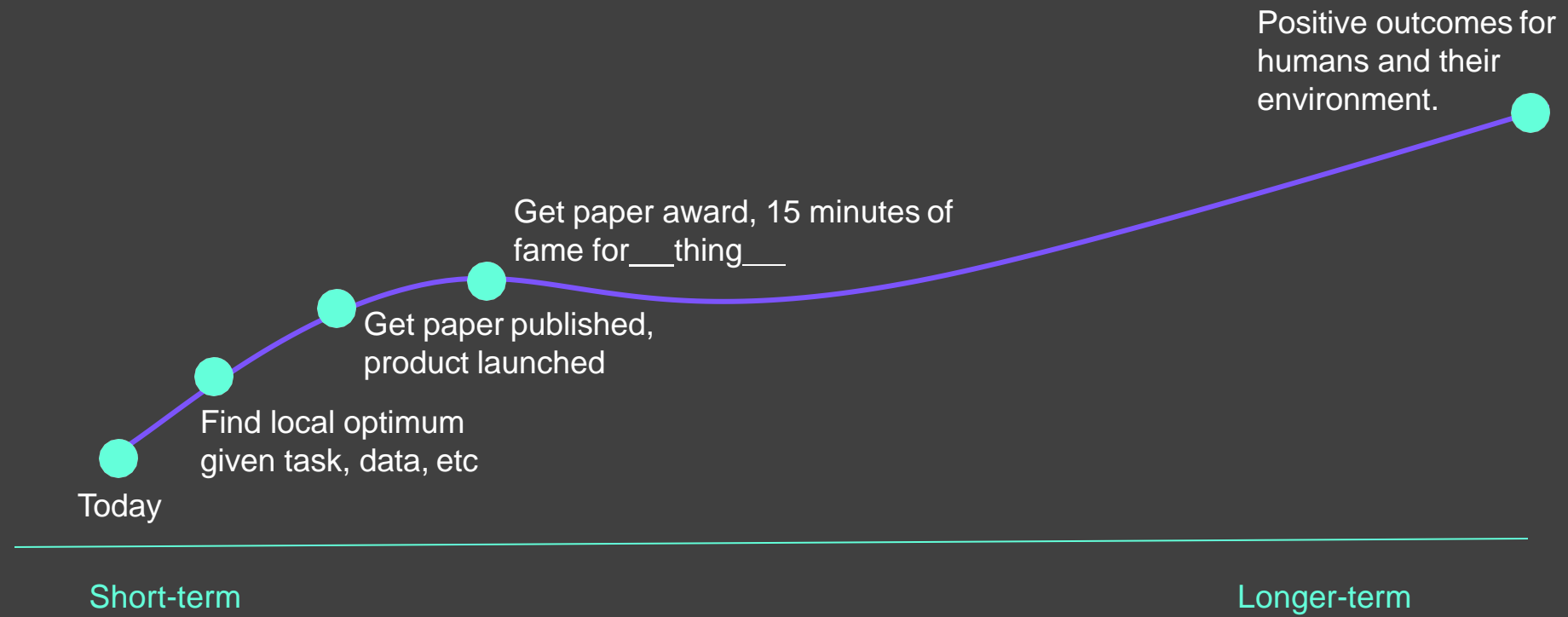
*“[...] angle θ from nose tip to two
mouth corners is on average 19.6%
smaller for criminals than for
non-criminals ...”*



See our longer piece on Medium, [“Physiognomy’s New Clothes”](#)



It's up to **us** to influence how AI
evolves.



Overview

- Context
- **Definition & Taxonomy**
- Bias in ML
- Ethics In AI is not only about fairness

DEFINITIONS & TAXONOMY

Early taxonomy - 1996

Pre-existing Bias

Roots in

- Social institutions
- Social attitudes
- Social practices

Technical Bias

Arising from

- Technical constraints
- Technical considerations

Emergent

From changing

- Societal knowledge
- Population
- Cultural values

Early taxonomy - 1996

Pre-existing bias:

Pre-existing bias can enter a system either through the **explicit** and **conscious efforts** of **individuals** or **institutions**, or **implicitly** and **unconsciously**, even **in spite of the best of intentions**.

1.1 Individual Bias that originates from individuals who have significant input in to the design of the system, such as the client commissioning the design or the system designer (e.g., a client embeds personal racial biases into the specifications for loan approval software).

1.2 Societal Bias that originates from society at large, such as from organizations (e.g., industry), institutions (e.g., legal systems), or culture at large (e.g., gender biases present in the larger society that lead to the development of educational software that overall appeals more to boys than girls).

Early taxonomy - 1996

Technical bias:

Technical bias arises from technical constraints or technical considerations.

2.1 Computer Tools, from a limitation of the computer technology including hardware, software, and peripherals

e.g., in a database for matching organ donors with potential transplant recipients certain individuals retrieved and displayed on initial screens are favored systematically for a match over individuals displayed on later screens.

2.2 Decontextualized Algorithms, from the use of an algorithm that fails to treat all groups fairly under all significant conditions

e.g., a scheduling algorithm for airplanes take-off relies on the alphabetic airline listing to rank order flights ready within a given period of time.

2.3 Random Number Generation, from imperfections in pseudo random number generation or in the misuse of pseudo random numbers

e.g., an imperfection in a random-number generator used to select recipients for a scarce drug leads systematically to favoring individuals toward the end of the database.

2.4 Formalization of Human Constructs, from attempts to make human constructs such as discourse, judgments, or intuitions amenable to computers: when we quantify the qualitative, discretize the continuous, or formalize the nonformal

e.g., a legal expert system advises defendants on whether or not to plea bargain by assuming that law can be spelled out in an unambiguous manner that is not subject to human and humane interpretations in context.

Early taxonomy - 1996

Emergent Bias:

Emergent bias arises in a context of use with real users. This bias typically emerges some time after a design is completed, as a result of changing societal knowledge, population, or cultural values. User interfaces are likely to be particularly prone to emergent bias because interfaces by design seek to reflect the capacities, character, and habits of prospective users. Thus, a shift in context of use may well create difficulties for a new set of users.

3.1 New Societal Knowledge, from the emergence of new knowledge in society that cannot be or is not incorporated into the system design

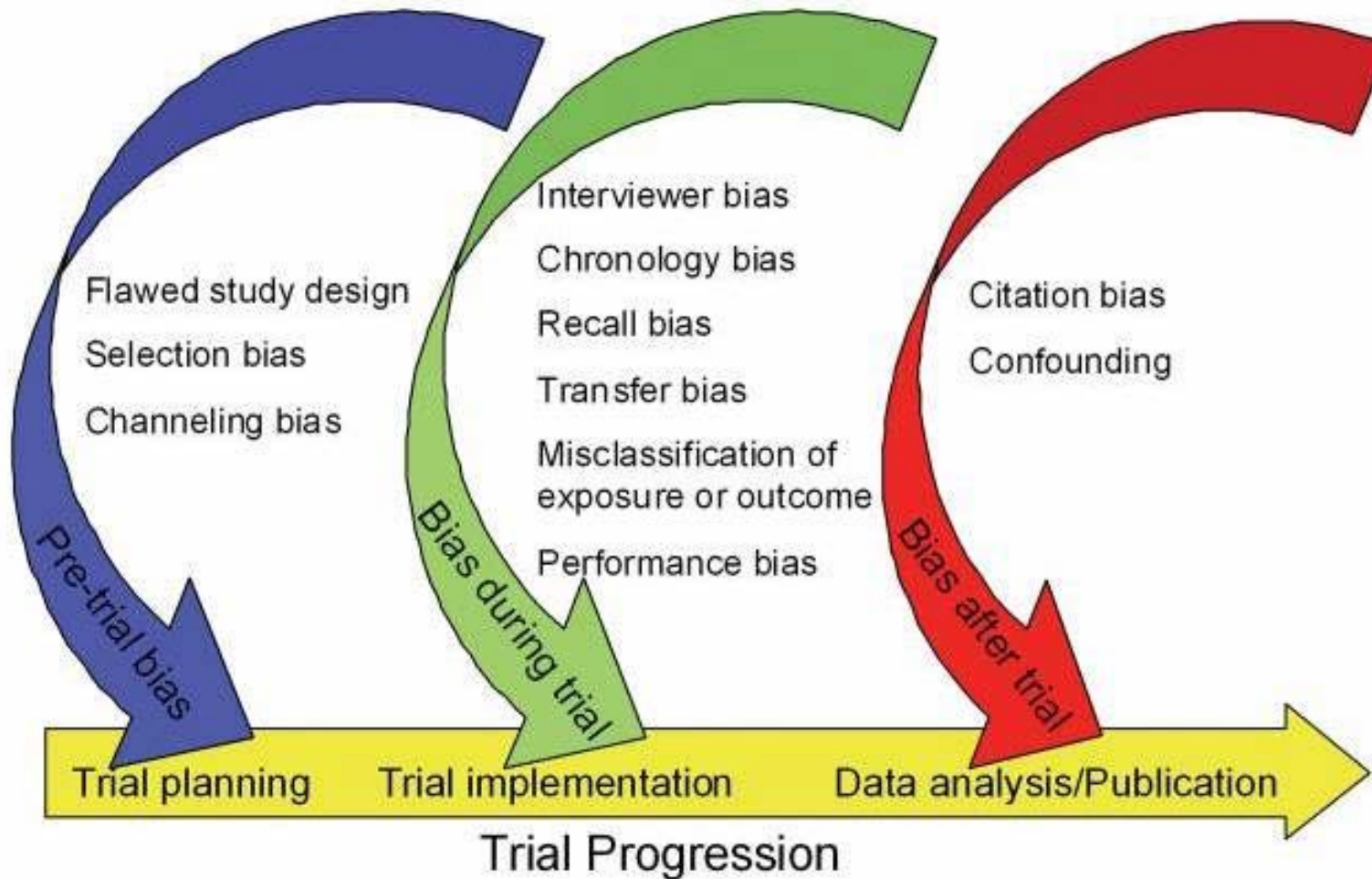
e.g., a medical expert system for AIDS patients has no mechanism for incorporating cutting-edge medical discoveries that affect how individuals with certain symptoms should be treated.

3.2 Mismatch between Users and System Design, when the population using the system differs on some significant dimension from the population assumed as users in the design.

3.2.1 Different Expertise, when the system is used by a population with a different knowledge base from that assumed in the design
e.g., an ATM with an interface that makes extensive use of written instructions—“place the card, magnetic tape side down, in the slot to your left”—is installed in a neighborhood with primarily a nonliterate population.

3.2.2 Different Values, when the system is used by a population with different values than those assumed in the design
e.g., educational software to teach mathematics concepts is embedded in a game situation that rewards individualistic and competitive strategies but is used by students with a cultural background that largely eschews competition and instead promotes cooperative endeavors.

Major Biases in Clinical Research - 2010





Major Biases in Clinical Research - 2010

Type of Bias	How to Avoid
Pre-trial bias	
Flawed study design	<ul style="list-style-type: none"> Clearly define risk and outcome, preferably with objective or validated methods. Standardize and blind data collection.
Selection bias	<ul style="list-style-type: none"> Select patients using rigorous criteria to avoid confounding results. Patients should originate from the same general population. Well designed, prospective studies help to avoid selection bias as outcome is unknown at time of enrollment.
Channeling bias	<ul style="list-style-type: none"> Assign patients to study cohorts using rigorous criteria.
Bias after trial	
Citation bias	<ul style="list-style-type: none"> Register trial with an accepted clinical trials registry. Check registries for similar unpublished or in-progress trials prior to publication.
Confounding	<ul style="list-style-type: none"> Known confounders can be controlled with study design (case control design or randomization) or during data analysis (regression). Unknown confounders can only be controlled with randomization.

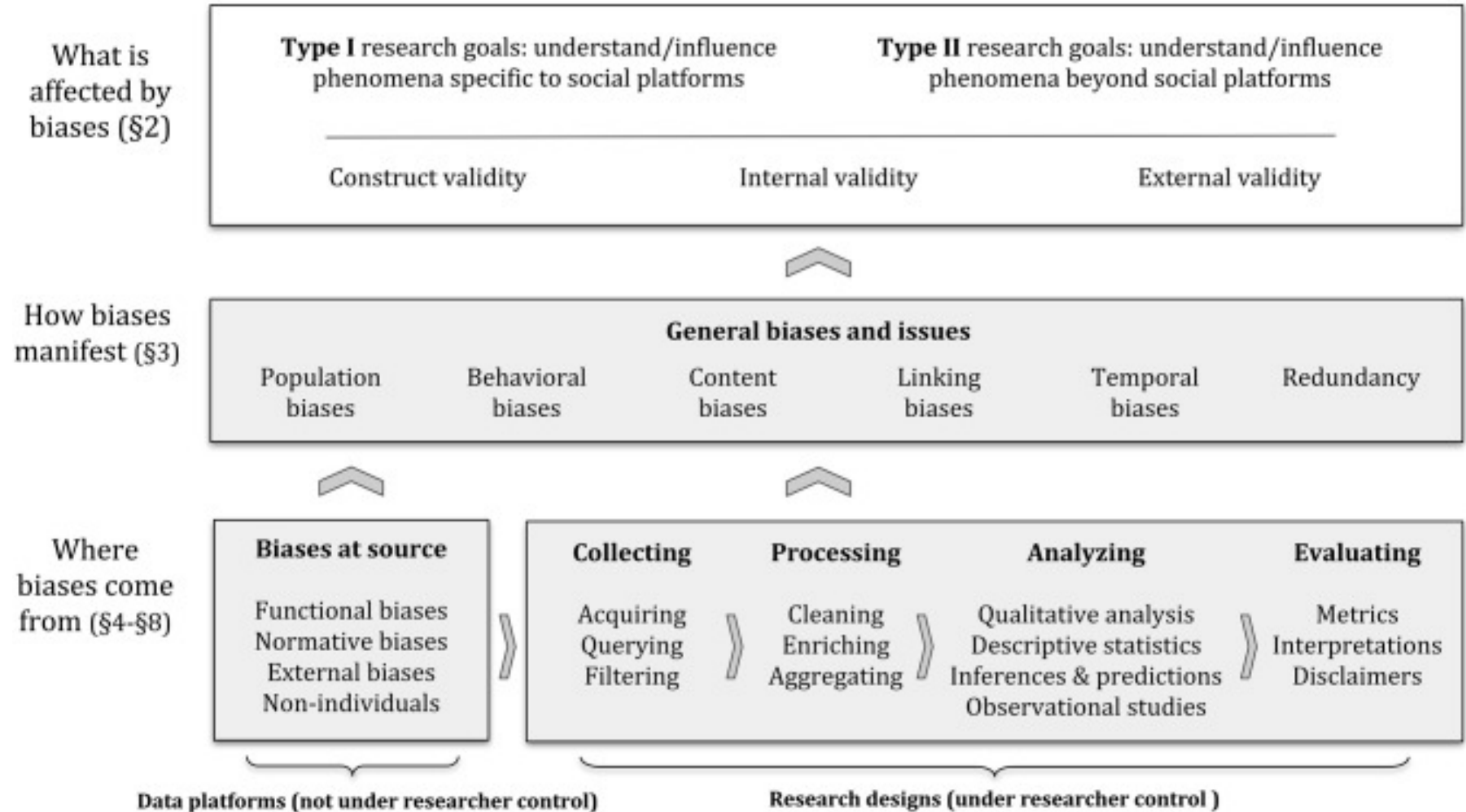


Major Biases in Clinical Research - 2010

Type of Bias	How to Avoid
Bias during trial	
Interviewer bias	<ul style="list-style-type: none"> • Standardize interviewer's interaction with patient. Blind interviewer to exposure status.
Chronology bias	<ul style="list-style-type: none"> • Prospective studies can eliminate chronology bias. Avoid using historic controls (confounding by secular trends).
Recall bias	<ul style="list-style-type: none"> • Use objective data sources whenever possible. When using subjective data sources, corroborate with medical record. <p>Conduct prospective studies because outcome is unknown at time of patient enrollment.</p>
Transfer bias	<ul style="list-style-type: none"> • Carefully design plan for lost-to-followup patients prior to the study.
Exposure Misclassification	<ul style="list-style-type: none"> • Clearly define exposure prior to study. Avoid using proxies of exposure.
Outcome Misclassification	<ul style="list-style-type: none"> • Use objective diagnostic studies or validated measures as primary outcome.



Bias in social data - 2019





Many different biases!

Population Bias	Representation Bias	Selection Bias	Self-Selection Bias
Behavioral Bias	Measurement Bias	Coverage Bias	Omitted Variable Bias
Content Production Bias	Evaluation Bias	Participation Bias	Cause-Effect Bias
Linking Bias	Aggregation Bias	Group Attribution Bias	Observer Bias
Temporal Bias	Simpson's Paradox	Implicit Bias	Funding Bias
Sampling Bias	Longitudinal Data	Confirmation Bias	
Popularity Bias	Fallacy	Experimenter's Bias	
Algorithmic Bias	Emergent Bias	Presentation Bias	
User Interaction Bias	Reporting Bias	Ranking Bias	
Historical Bias	Automation Bias	Social Bias	



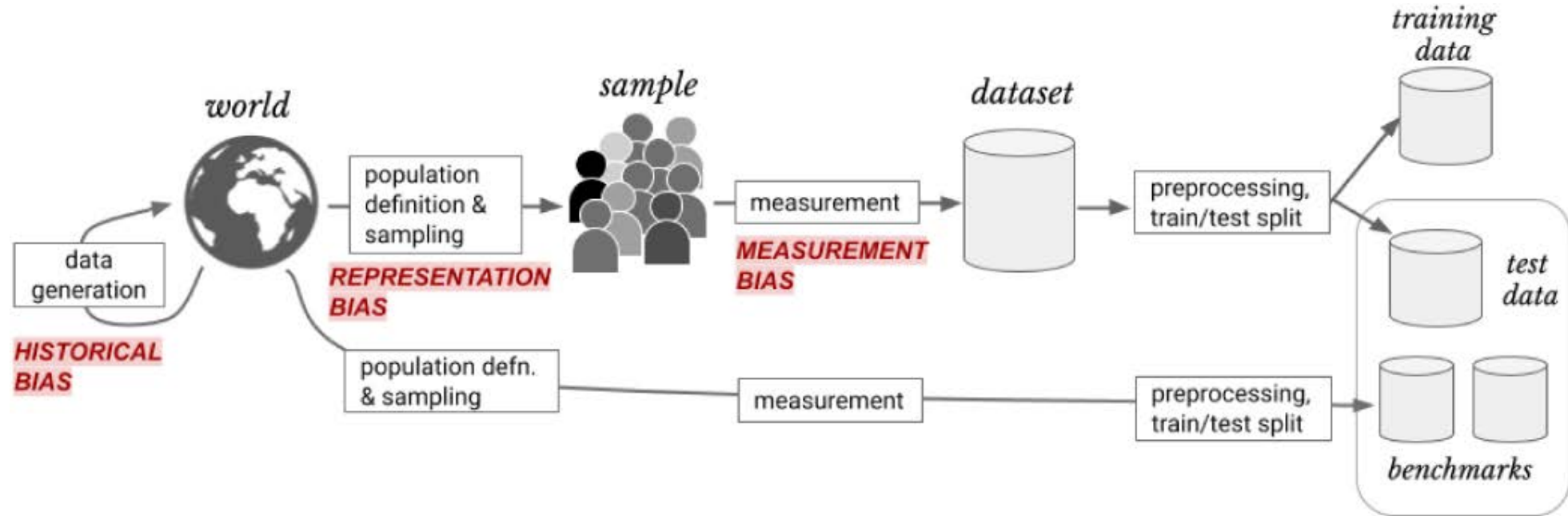
Overview

- Context
- Definition & Taxonomy
- **Bias in ML**
 - Different forms of Biases
 - Bias Metrics
 - Mitigation
- Ethics In AI is not only about fairness

BIAS IN ML

Different forms of Biases

Bias in ML pipeline - 2021



(a) Data Generation



Historical bias

- **Historical bias arises even if data is perfectly measured and sampled, if the world *as it is* or *was* leads to a model that produces harmful outcomes.** Such a system, even if it reflects the world accurately, can still inflict harm on a population. Considerations of historical bias often involve evaluating the representational harm (such as reinforcing a stereotype) to a particular group.
- *Examples:*
 - *5% of Fortune 500 CEO's are women. What should image search for CEO return?*
 - *How does Google change search algorithm? Should Google change algorithm? Who makes this decision?*

<https://www.google.com/search?q=teacher>

Search in June 2016



<https://www.google.com/search?q=teacher>

Search in January 2017



<https://www.google.com/search?q=teacher>

Search in February 2019



Editorial: Teachers deserve more pay ...
doblenews.scuc.txed.net



Teacher pay is disrupting class. Here's ...
usatoday.com



Diverse, but America's Teachers ...
takepart.com



Teachers of Tomorrow to Fill Teacher ...
thejournal.com



Loan Forgiveness Programs for Teachers ...
blog.ed.gov



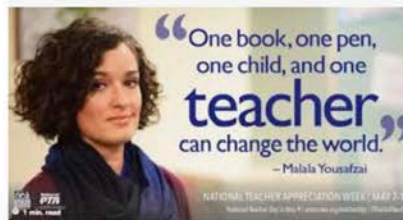
How Do Teachers Feel (Now) About the ...
ewa.org



Avoid Getting Sick ...
self.com



Too many teachers in the US are ...
ideas.ted.com



<https://www.google.com/search?q=teacher>

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New Teachers: How to Develop 'The Look ...
edutopia.org



Keeping Your Teachers Motivated ...
chalk.com



The best and worst states for teachers
usatoday.com



Avoid Getting Sick ...
self.com



Teaching: A Calling vs. Profession - I ...
nyack.edu



How to Become a Math Teacher: Salary ...
education.cu-portland.edu



Qualities Every Teacher Needs
careeraddict.com



Editorial: Teachers deserve more pay ...
dobienews.scuc.txed.net



<https://www.google.com/search?q=professor>

Search in June 2016



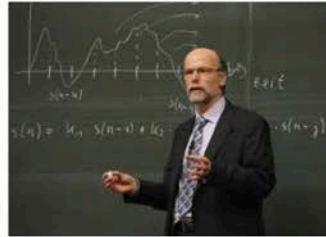
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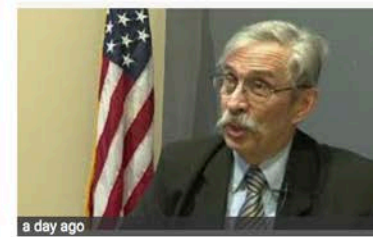
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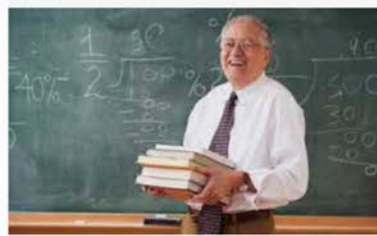
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professor awarded Guggenheim Fellowsh...
news.illinois.edu



Local professor talks 2020 democratic ...
abc12.com



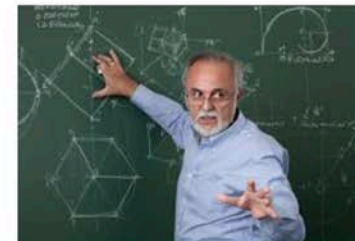
Nabs Posh Office in Hop Broom Closet
sites.dartmouth.edu



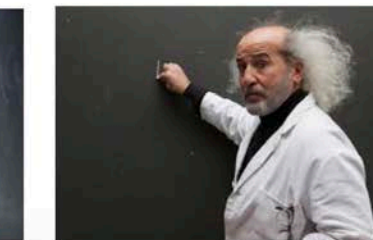
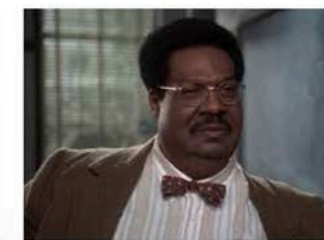
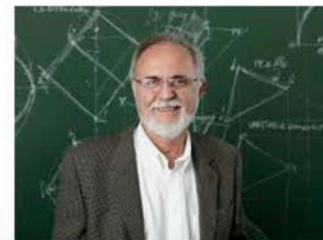
How to Pick the Best Professors | Fastweb
fastweb.com



Professor - Wikipedia
en.wikipedia.org

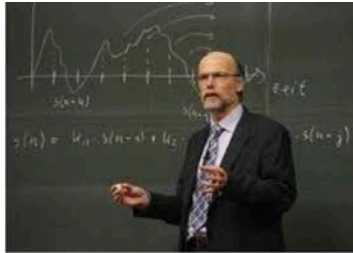


Professor Profiles - Reflector Magazine
reflectorgsu.com

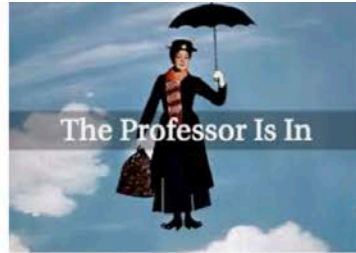


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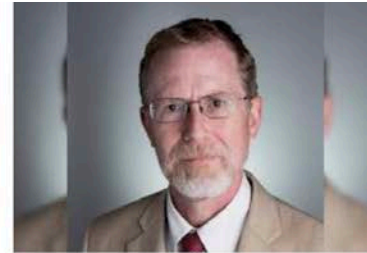
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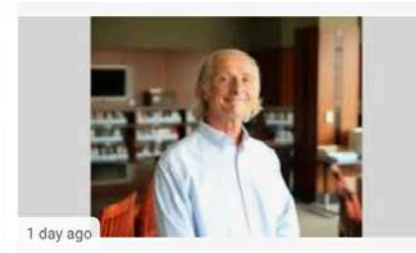
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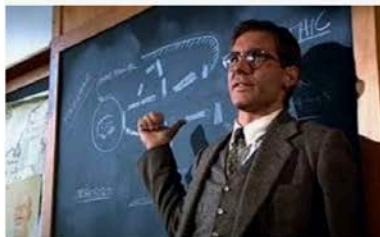
Should I Turn Down a Tenure-Track ...
chronicle.com



IU professor tweets article about ...
idsnews.com



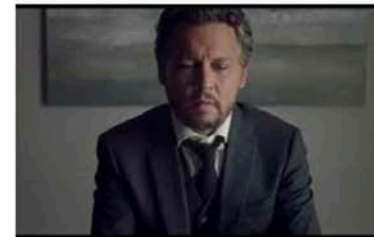
professor apologizes for saying N-word ...
nbcnews.com



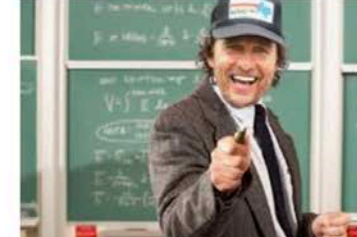
Professors You'll Get In College ...
bustle.com



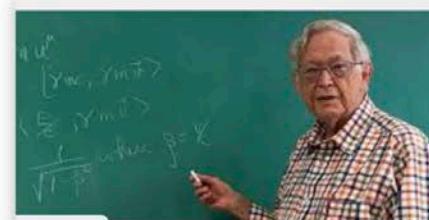
Interview with Professor Miller ...
buffalo.edu



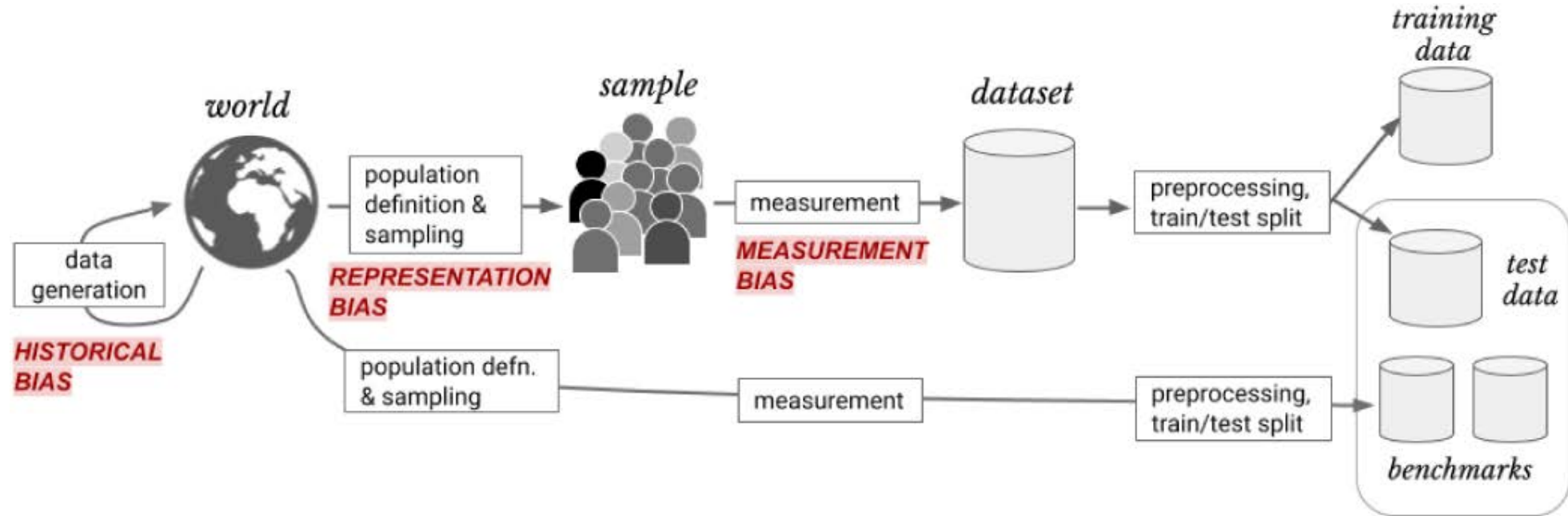
The Professor (2018) - IMDb
imdb.com



Official Course Syllabus
gen.medium.com



Bias in ML pipeline - 2021



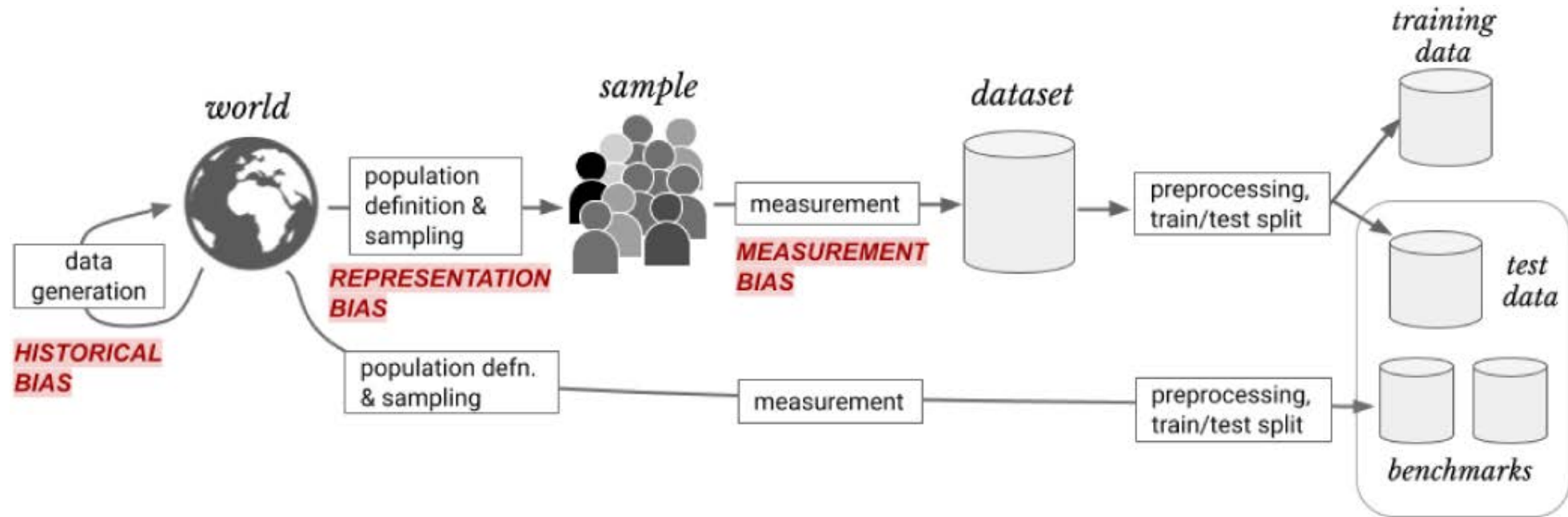
(a) Data Generation



Representation bias

- Representation bias occurs when the development **sample under-represents some part of the population**, and subsequently **fails to generalize well** for a subset of the use population.
Representation bias can arise in several ways:
 - *When defining the target population, if it does not reflect the use population.*
 - *When defining the target population, if contains under-represented groups.*
 - *When sampling from the target population, if the sampling method is limited or uneven.*
- *Examples:*
 - Where a corpus of images originates -> ImageNet: 45% from United States
 - What about changing populations? -> Measure today, model tomorrow?

Bias in ML pipeline - 2021

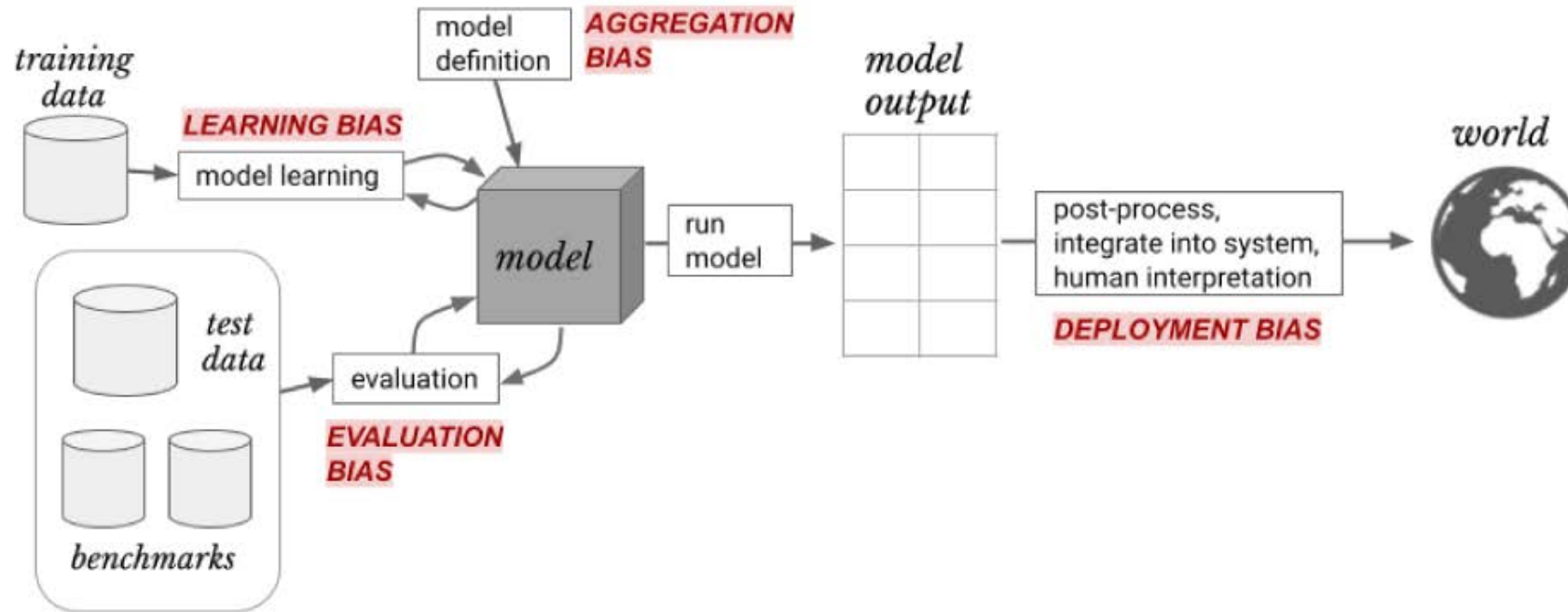


(a) Data Generation

Measurement bias

- Measurement bias occurs when choosing, collecting, or computing features and labels to use in a prediction problem. Typically, a feature or label is a proxy (a concrete measurement) chosen to approximate some construct (an idea or concept) that is not directly encoded or observable. Proxies become problematic when they are poor reflections or the target construct and/or are generated differently across groups, which can when:
 - *The proxy is an oversimplification of a more complex construct.*
 - *The method of measurement varies across groups.*
 - *The accuracy of measurement varies across groups.*
- *Examples:*
 - Proxy labels: arrest used for crime -> What populations are arrested more? Is this useful for predictive policing in terms of crime? Re-arrest as proxy for recidivism in sentencing and parole automation
 - How do US measure "successful student" -> GPA?

Bias in ML pipeline - 2021

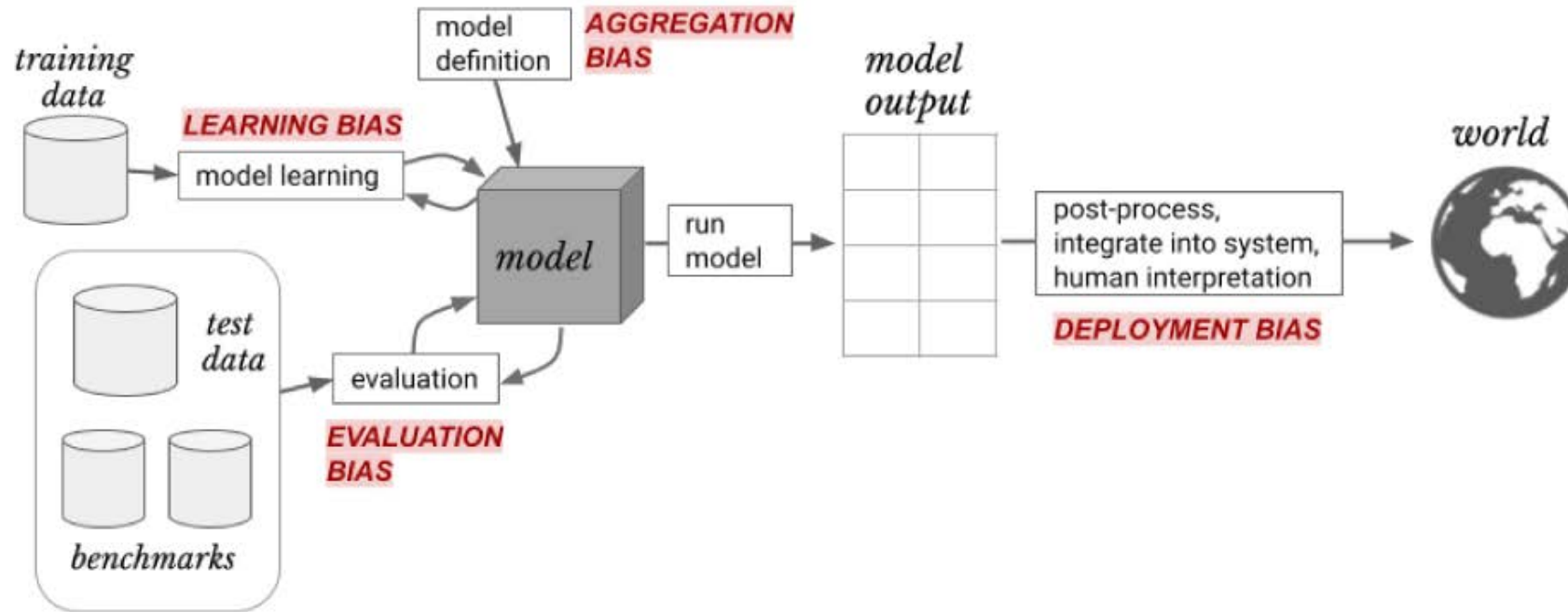


(b) Model Building and Implementation

Evaluation Bias

- **Evaluation bias occurs when the benchmark data used for a particular task does not represent the use population.**
- Evaluation bias ultimately arises because of a desire to quantitatively compare models against each other on a set of external datasets, but is often extended to make general statements about how good a model is.
- Such generalizations are often not statistically valid, and can lead to overfitting to a particular benchmark (and so the model is invalid on the other external datasets).
- **Evaluation bias can also be exacerbated by the choice of metrics that are used to report performance.** For example, aggregate measures can hide subgroup underperformance, but these singular measures are often used because they make it more straightforward to compare models and make a judgment about which one is “better.” Just looking at one type of metric (e.g., accuracy) can also hide disparities in other types of errors (e.g., false negative rate).
- Examples:
 - Benchmark data doesn't represent population -> Algorithm optimized on training data, then benchmarked on a different population

Bias in ML pipeline - 2021

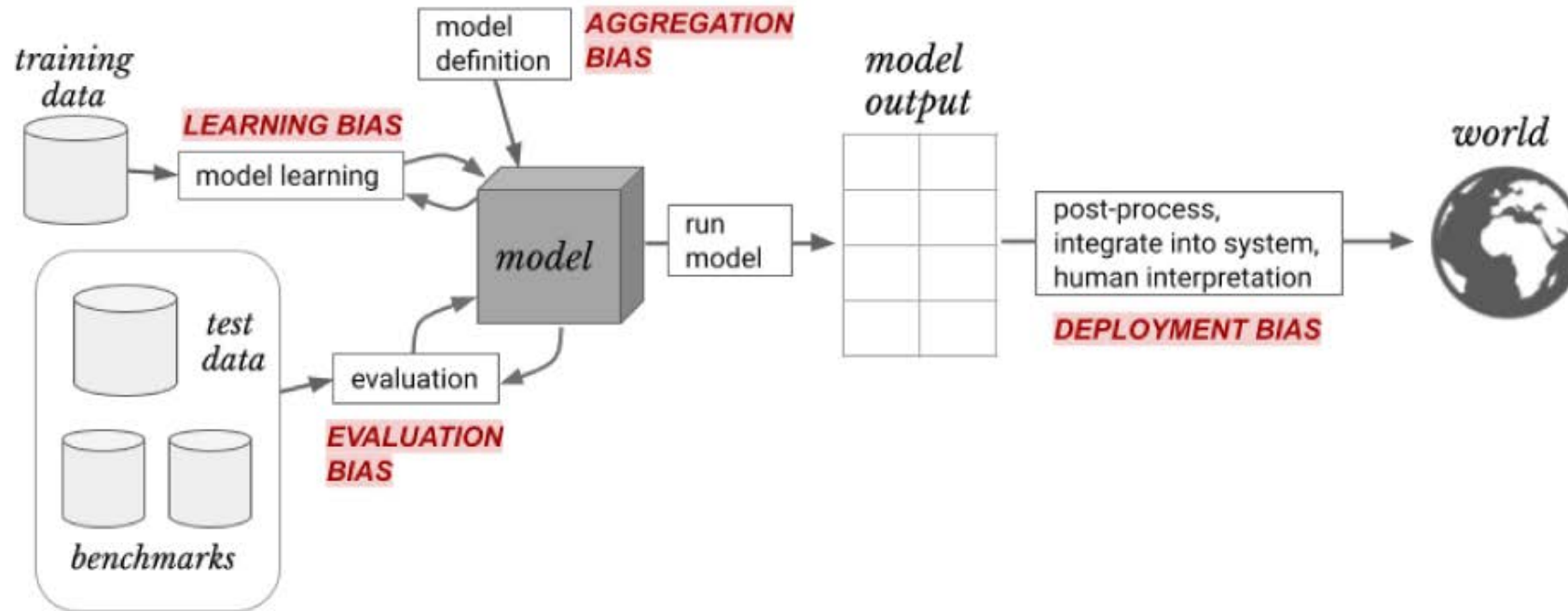


(b) Model Building and Implementation

Aggregation bias

- Aggregation bias arises when a one-size-fits-all model is used for data in which there are underlying groups or types of examples that should be considered differently. Underlying aggregation bias is an assumption that the mapping from inputs to labels is consistent across subsets of the data. In reality, this is often not the case. A particular dataset might represent people or groups with different backgrounds, cultures or norms, and a given variable can mean something quite different across them. Aggregation bias can lead to a model that is not optimal for any group, or a model that is fit to the dominant population (e.g., if there is also representation bias).
- *Examples:*
 - Don't use a single model across multiple groups
 - Diabetes across ethnicities and gender
 - Must factor different subgroups into account when aggregating data/modeling

Bias in ML pipeline - 2021

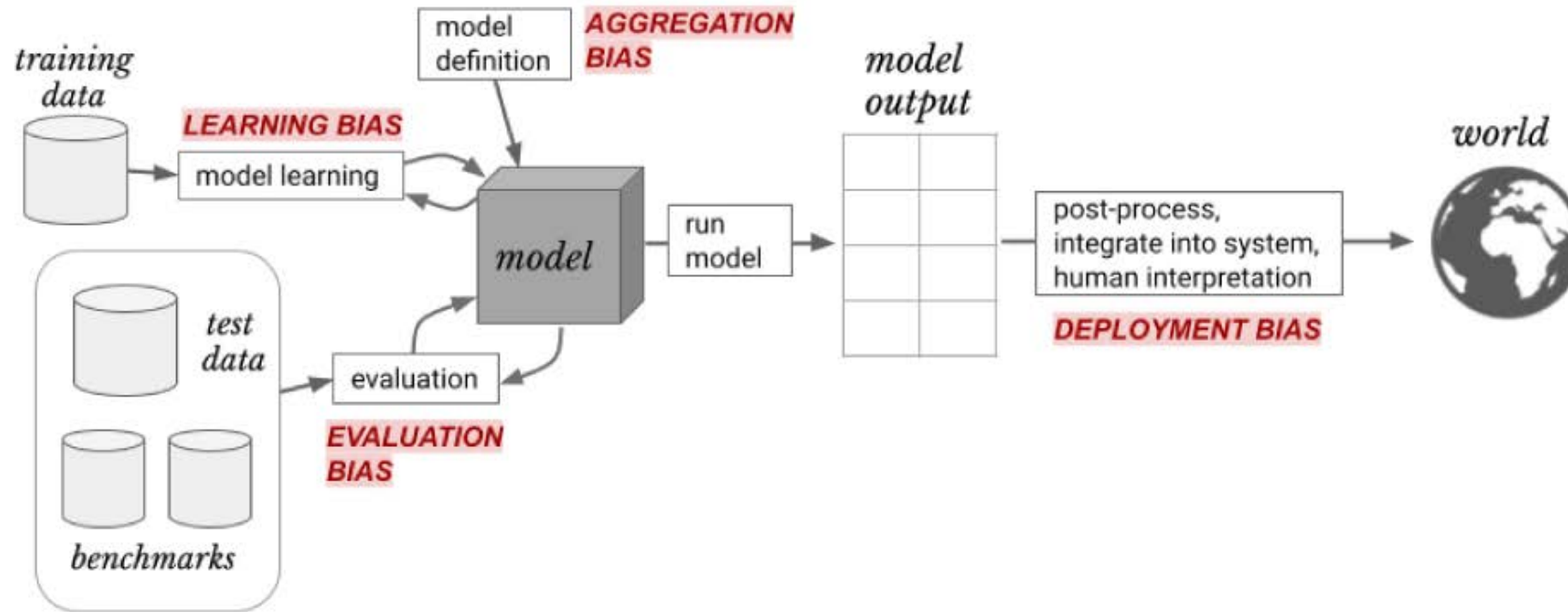


(b) Model Building and Implementation

Learning bias

- Learning bias arises when modeling choices amplify performance disparities across different examples in the data. For example, an important modeling choice is the objective function that an ML algorithm learns to optimize during training. Typically, these functions encode some measure of accuracy on the task (e.g., cross-entropy loss for classification problems or mean squared error for regression problems). However, issues can arise when prioritizing one objective (e.g., overall accuracy) damages another (e.g., disparate impact). For example, minimizing cross-entropy loss when building a classifier might inadvertently lead to a model with more false positives than might be desirable in many contexts.
- *Examples:*
 - Don't use a single model across multiple groups
 - Diabetes across ethnicities and gender
 - Must factor different subgroups into account when aggregating data/modeling

Bias in ML pipeline - 2021



(b) Model Building and Implementation

Deployment bias

- Deployment bias arises when there is a mismatch between the problem a model is intended to solve and the way in which it is actually used. This often occurs when a system is built and evaluated as if it were fully autonomous, while in reality, it operates in a complicated sociotechnical system moderated by institutional structures and human decision-makers.
In some cases, for example, systems produce results that must first be interpreted by human decision-makers. Despite good performance in isolation, they may end up causing harmful consequences because of phenomena such as automation or confirmation bias.
- *Examples:*
 - Algorithmic risk assessment tools in the criminal justice context are models intended to predict a person's likelihood of committing a future crime.

Bias Metrics

Basic fairness metric terminology

- **Sensitive attribute: a.k.a. A “Protected field” is an attribute that may need to comply with a particular fairness metric.**

It's important to note that not all attributes are sensitive by definition.

For example, US federal law protects individuals from discrimination or harassment based on the following nine protected classes: sex (including sexual orientation and gender identity), race, age, disability, color, creed, national origin, religion, or genetic information (added in 2008).

- **Proxy attribute: This means attributes that correlate to a sensitive attribute.**

For example, let's assume that for a specific use case, race and ethnicity are sensitive attributes. The dataset may also contain highly correlated fields for these two. For example, an individual's postal code might be highly correlated with them, making it a proxy attribute to the sensitive attribute value.

Basic fairness metric terminology

- **Parity: A parity measure is a simple observational criterion that requires the evaluation metrics to be independent of the salient group A .**
Such measures are static and don't take changing populations into account. If a parity criterion is satisfied, it does not mean that the algorithm is fair. These criteria are reasonable for surfacing potential inequities and are particularly useful in monitoring live decision-making systems.
- **Confusion matrix: Fairness metrics are most commonly applied to classification use cases.**
One should be familiar with the basics of a confusion matrix to understand the basic mathematics behind the most common fairness metrics. In a binary classification case, we will refer to one of the predicted classes as “Positive” while the other will be “Negative.” Given this configuration, common performance metrics can be derived. To generalize for a multiclass classification use case, we refer to the sensitive class (meaning a specific value out of the possible classification classes) as positive, while all others are negative.



Confusion matrix and metrics

		True condition			
		Total population	Condition positive	Condition negative	
Predicted condition	Predicted condition positive	True positive	False positive Type I error	$\text{Prevalence} = \frac{\sum \text{Condition positive}}{\sum \text{Total population}}$	$\text{Accuracy (ACC)} = \frac{\sum \text{True positive} + \sum \text{True negative}}{\sum \text{Total population}}$
	Predicted condition negative	False negative Type II error	True negative	$\text{Positive predictive value (PPV), precision} = \frac{\sum \text{True positive}}{\sum \text{Predicted condition positive}}$	$\text{False discovery rate (FDR)} = \frac{\sum \text{False positive}}{\sum \text{Predicted condition positive}}$
		$\text{True positive rate (TPR), Recall, Sensitivity, probability of detection, Power} = \frac{\sum \text{True positive}}{\sum \text{Condition positive}}$	$\text{False positive rate (FPR), Fall-out, probability of false alarm} = \frac{\sum \text{True negative}}{\sum \text{Condition negative}}$	$\text{False omission rate (FOR)} = \frac{\sum \text{False negative}}{\sum \text{Predicted condition negative}}$	$\text{Negative predictive value (NPV)} = \frac{\sum \text{True negative}}{\sum \text{Predicted condition negative}}$
		$\text{False negative rate (FNR), Miss rate} = \frac{\sum \text{False negative}}{\sum \text{Condition positive}}$	$\text{Specificity (SPC), Selectivity, True negative rate (TNR)} = \frac{\sum \text{True negative}}{\sum \text{Condition negative}}$	$\text{Positive likelihood ratio (LR+)} = \frac{\text{TPR}}{\text{FPR}}$	$\text{Diagnostic odds ratio (DOR)} = \frac{\text{LR+}}{\text{LR-}}$
				$\text{Negative likelihood ratio (LR-)} = \frac{\text{FNR}}{\text{TNR}}$	$\text{F}_1 \text{ score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$

To view the complete list of possible metrics, see https://en.wikipedia.org/wiki/Confusion_matrix.



Fairness Metrics

Setup & notation

- To illustrate fairness metrics in practice, we will use two real-life use cases of a loan approval process and an additional use case where the model attempts to predict the likelihood of an individual being convicted of criminal activity and sent to jail. **A binary classification** model predicts if we should give **a positive answer, i.e., loan approval/going to jail**, and, for our examples, **the protected attribute will be gender**.
- Given this setup, we will use the following notation:
 - A = possible values of the sensitive attributes (e.g., gender)
 - R = the output/prediction of the algorithm (e.g., positive $R=1$)
 - Y = the ground truth

The graph illustrations of each example show the threshold of positive model outputs for each group, where every output above the threshold will indicate a positive outcome.

Metric I: Group unawareness

- Group unawareness means that we don't want the gender of a person to impact in any way our decision to approve or reject a loan. In simple, intuitive words, we don't want the model to "use" gender as an attribute.
- Group unawareness is a straightforward and intuitive way to define fairness. An ML equivalent term to such a condition could be feature attribution.
- When we refer to unawareness, we are technically referring to the fact that we want 0 attribution for gender attributes.
- This can easily be measured using interpretation tools like *Lime*, *SHAP*, etc.

Metric I: Group unawareness

- There may be a “proxy sensitive attribute” in the data, which means attributes that correlate to a sensitive attribute. For example, an individual’s postal code may be a proxy for income, race, or ethnicity. So even if we willfully ignore the direct sensitive group, we may still have hidden awareness.
- The training data may contain historical biases. For example, women’s work histories are more likely to have gaps. Which may lower their loan requests’ probability of being approved.

Metric 2a: Demographic parity

A = possible values of the sensitive attributes (e.g., gender)
R = the output/prediction of the algorithm (e.g., positive R=1)
Y = the ground truth

- If we want to ensure the same approval rate for male and female applicants, we can use demographic parity. Demographic parity states that the proportion of each segment of a protected class (e.g., gender) should receive a positive outcome at equal rates.
- Let's say A is a protected class (in our case, sex):

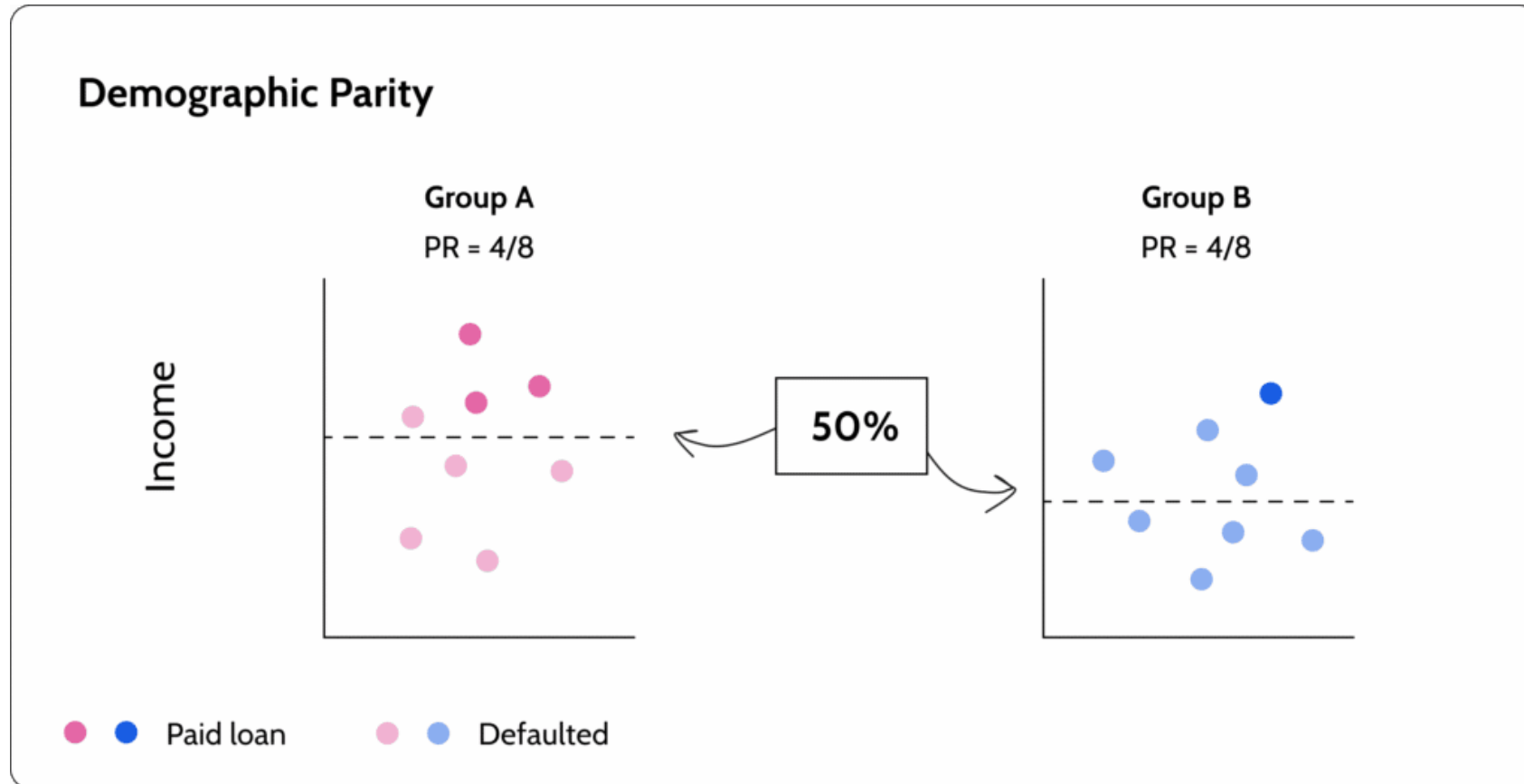
$$\forall w, m \in A \quad P(R = 1 | A = w) = P(R = 1 | A = m)$$

- Another way to look at it is to require that the prediction be statistically independent of the protected attribute.

$$\forall a \in A \quad P(R = 1 | A = a) = P(R = 1), \forall a \in A$$

or
$$P(R = 0 | A = a) = P(R = 0), \forall a \in A$$

Metric 2a: Demographic parity



In this illustration, we can see that half of each group is approved.



Metric 2b: Disparate impact

A = possible values of the sensitive attributes (e.g., gender)
R = the output/prediction of the algorithm (e.g., positive R=1)
Y = the ground truth

- **Disparate impact is a variation of demographic parity.** The calculation is the same as demographic parity, but instead of aiming for an equal approval rate, it aims to achieve a higher-than-specified ratio. It is commonly used when some privileged group is in play (a group that has a higher probability of getting a positive answer when there is no fairness problem).

For example, let's say that people with high incomes have a higher likelihood of returning the loan. On the face of things, it's OK for this group to have a higher approval rate than people with low income.

$$\left| \frac{P(R=1|A=unprivileged)}{P(R=1|A=privileged)} \right| \geq 1 - \epsilon, \epsilon \in [0, 1)$$

Metric 2b: Disparate impact

- On the flip side, we want to ensure that the approval ratio between these groups does not become too high. The [industry standard](#) here is a 4/5 rule. If the unprivileged group receives a positive outcome of less than 80% of the proportion of the privileged group, this is a disparate impact.
- Enforcing a specific ratio between groups may result in very qualified applicants not being approved or applicants with a low probability of returning the loan to be approved in the name of maintaining the ratio.

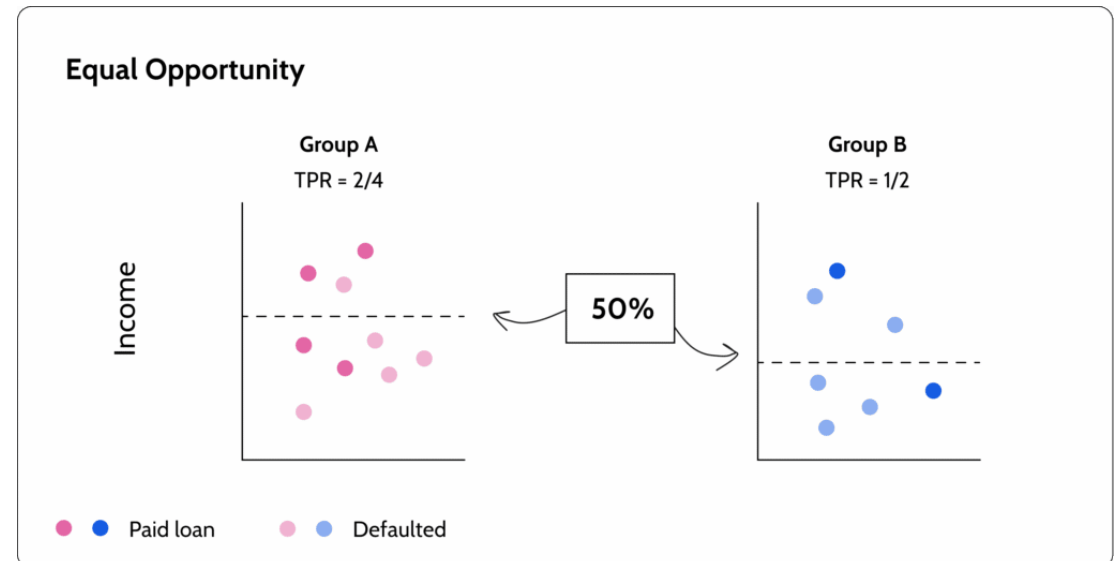
Metric 3: Equal opportunity

A = possible values of the sensitive attributes (e.g., gender)
R = the output/prediction of the algorithm (e.g., positive R=1)
Y = the ground truth

- Equal opportunity examines the true positive rate (TPR). Meaning it looks at the number of people that returned the loan to see the ratio of them that the model approved.

$$P(R = + | Y = +, A = a) = P(R = + | Y = +, A = b), \forall a, b \in A$$

In the illustration, we can see that both groups have the same TPR.
Meaning that we are basing our fairness calculation on the actual, not the prediction output.
This helps us mitigate some of the overbalancing risks inherent to demographic parity.



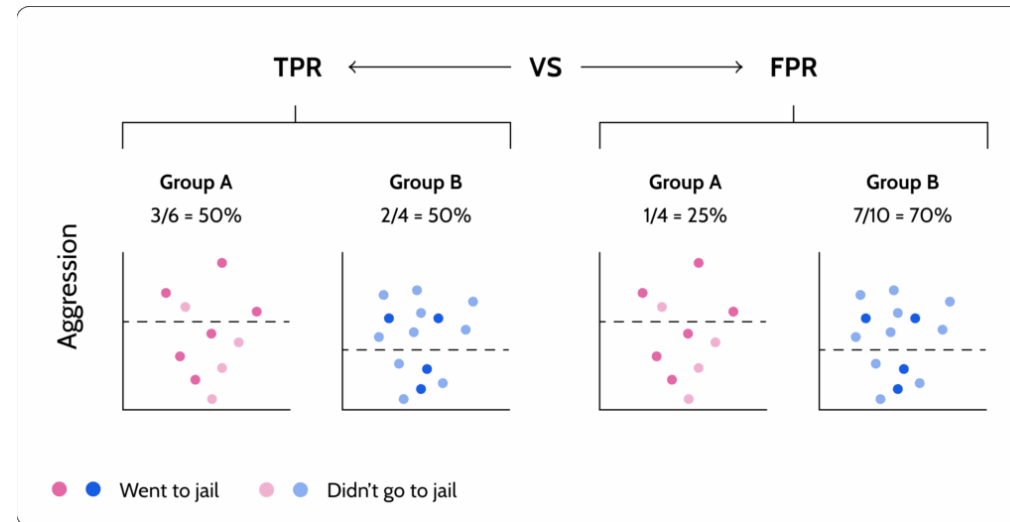
Metric 3: Equal opportunity

- It may not help close an existing gap between two groups:

Let's look at a model that predicts applicants who qualify for a job. Let's say Group A has 100 applicants, and 58 are qualified. Group B also has 100 applicants, but only 2 are qualified. If the company decides it needs 30 applicants, the model will offer 29 applicants from Group A, and only 1 from Group B as the TPR for both groups is $\frac{1}{2}$.

Metric 4: Equal odds

- To understand why equal opportunity is not good enough in some cases, let's look at a use case where we have a model that predicts if someone is a criminal **where the protected attribute is ethnicity**.
- Based on equal opportunity, the ratio of criminals that go to jail is equal between two ethnicities (see image).

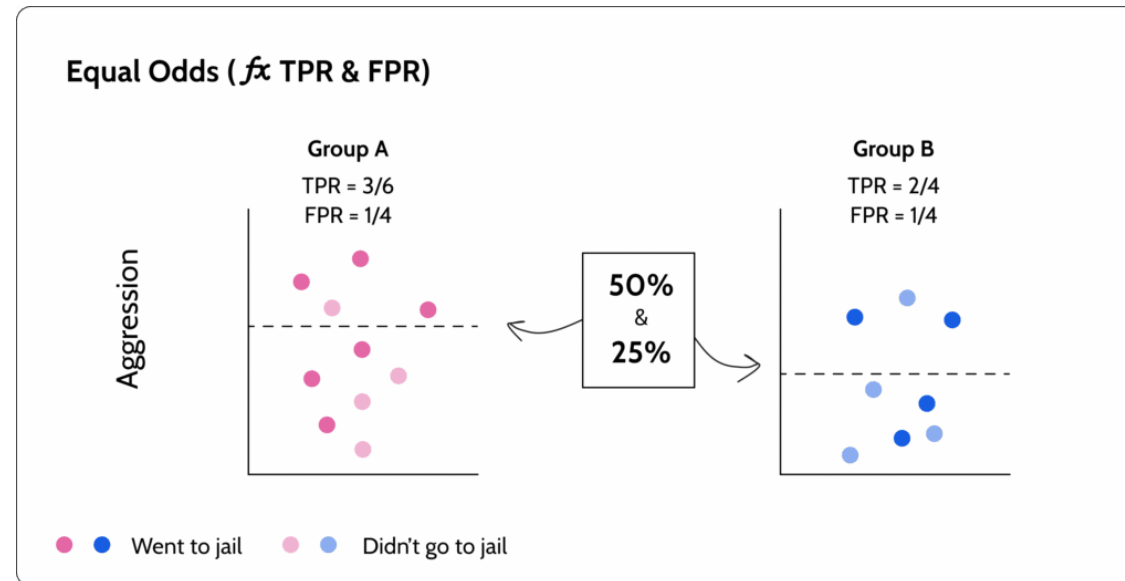


- However, we see that the FPR between the groups is different. The implication is that more innocent people from a specific sensitive group are sent to jail. In cases where we want to enforce equal TPR and FPR, we will use equal odds.
- Equal odds is a more restrictive version of equal opportunity.** In addition to looking at the TPR, it also looks at the FPR to find an equilibrium between them.

Metric 4: Equal odds

A = possible values of the sensitive attributes (e.g., ethnicity)
R = the output/prediction of the algorithm (e.g., positive R=1)
Y = the ground truth

$$P(R = + | Y = y, A = a) = P(R = + | Y = y, A = b), y \in \{+, -\}, \forall a, b \in A$$



- Equal odds is a very restrictive metric because it tries to achieve equal TPR and FPR for each group. Therefore, it may cause the model to have poor performance.

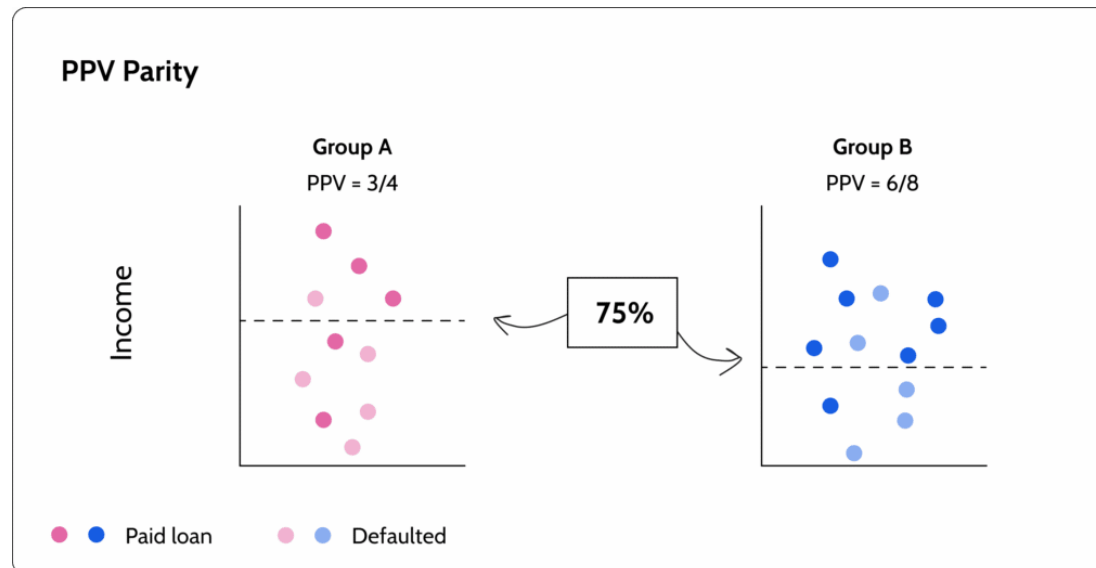


Metric 5: PPV-parity

A = possible values of the sensitive attributes (e.g., ethnicity)
R = the output/prediction of the algorithm (e.g., positive R=1)
Y = the ground truth

- **PPV-parity (positive predicted value) equalizes the chance of success, given a positive prediction.** In our example, we ensure that the ratio of people that actually return the loan out of all the people the model approved is the same in both groups. Meaning we want to see that the two groups have the same positive predicted value (PPV).

$$P(Y = + | R = +, A = a) = P(Y = + | R = +, A = b) \forall a, b \in A$$

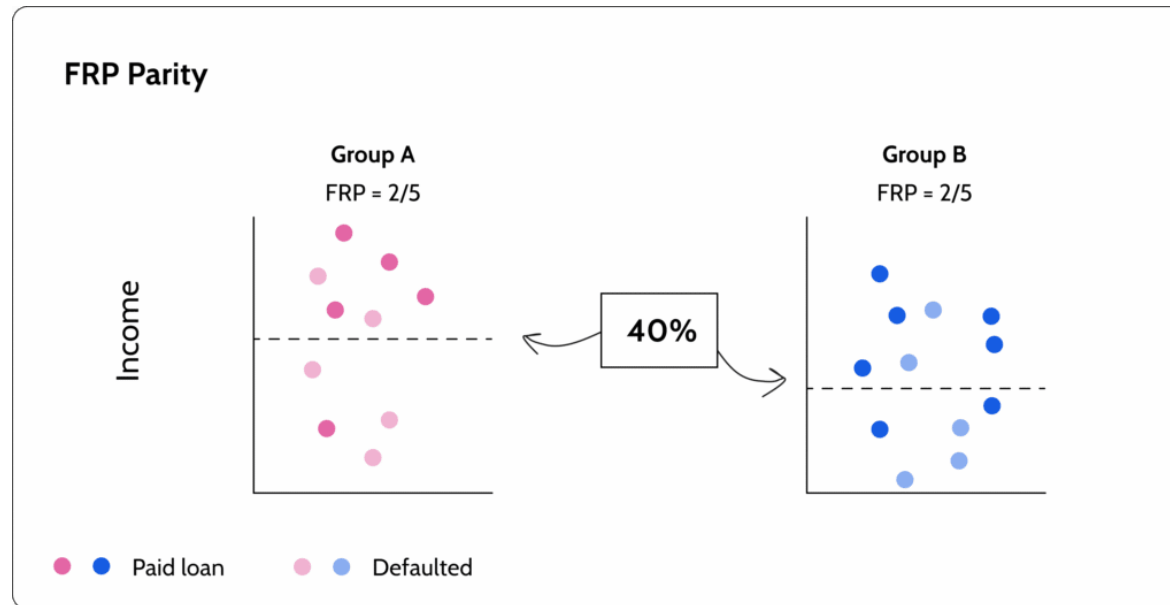


Metric 6: FPR-parity

A = possible values of the sensitive attributes (e.g., ethnicity)
R = the output/prediction of the algorithm (e.g., positive R=1)
Y = the ground truth

- **FPR-parity (false positive rate) is the exact opposite, it wants to ensure that the two groups have the same false positive rate (FPR).** In our example, we ensure that the ratio of people that the model approved but defaulted on their loan out of all the people that defaulted on their loan is the same in both groups.

$$P(R = + | Y = -, A = a) = P(R = + | Y = -, A = b) \quad \forall a, b \in A$$

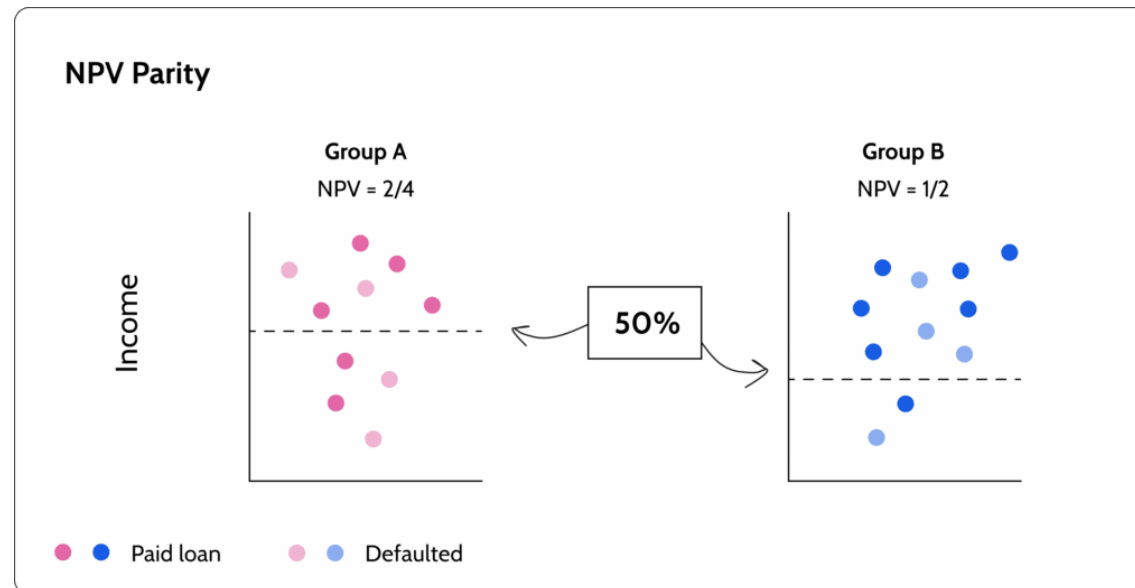


Metric 7: NPV-parity

A = possible values of the sensitive attributes (e.g., ethnicity)
R = the output/prediction of the algorithm (e.g., positive R=1)
Y = the ground truth

- NPV-parity (negative predicted value) says that we should ensure that the ratio of correctly rejecting people out of all the people the model has rejected is the same for each group.** We want the two groups to have the same negative predicted value (NPV).

$$P(R = - | Y = -, A = a) = P(R = - | Y = -, A = b) \forall a, b \in A$$





Open-source fairness metrics libraries

Open source library	Notes
AIF360	Provides a comprehensive set of metrics for datasets and models to test for biases and algorithms to mitigate bias in datasets and models.
Fairness Measures	Provides several fairness metrics, including difference of means, disparate impact, and odds ratio. It also provides datasets, but some are not in the public domain and require explicit permission from the owners to access or use the data.
FairML	Provides an auditing tool for predictive models by quantifying the relative effects of various inputs on a model's predictions, which can be used to assess the model's fairness.
FairTest	Checks for associations between predicted labels and protected attributes. The methodology also provides a way to identify regions of the input space where an algorithm might incur unusually high errors. This toolkit also includes a rich catalog of datasets
Aequitas	This is an auditing toolkit for data scientists as well as policymakers; it has a Python library and website where data can be uploaded for bias analysis. It offers several fairness metrics, including demographic, statistical parity, and disparate impact, along with a "fairness tree" to help users identify the correct metric to use for their particular situation. Aequitas's license does not allow commercial use.
Themis	An open-source bias toolbox that automatically generates test suites to measure discrimination in decisions made by a predictive system.
Themis-ML	Provides fairness metrics, such as mean difference, some bias mitigation algorithms, additive counterfactually fair estimator, and reject option classification.
Fairness Comparison	Includes several bias detection metrics as well as bias mitigation methods, including disparate impact remover, prejudice remover, and two-Naive Bayes. Written primarily as a test bed to allow different bias metrics and algorithms to be compared in a consistent way, it also allows additional algorithms and datasets.

And many others: Fairlens,...

Mitigation

Mitigation techniques

Pre-processing

Agnostic to
ML approach

In-processing

Modification of the algorithm to
remove discrimination

Some promising techniques are
based on adversarial networks

Post-processing

Agnostic to
ML approach

Policies

Datasheets and data statements

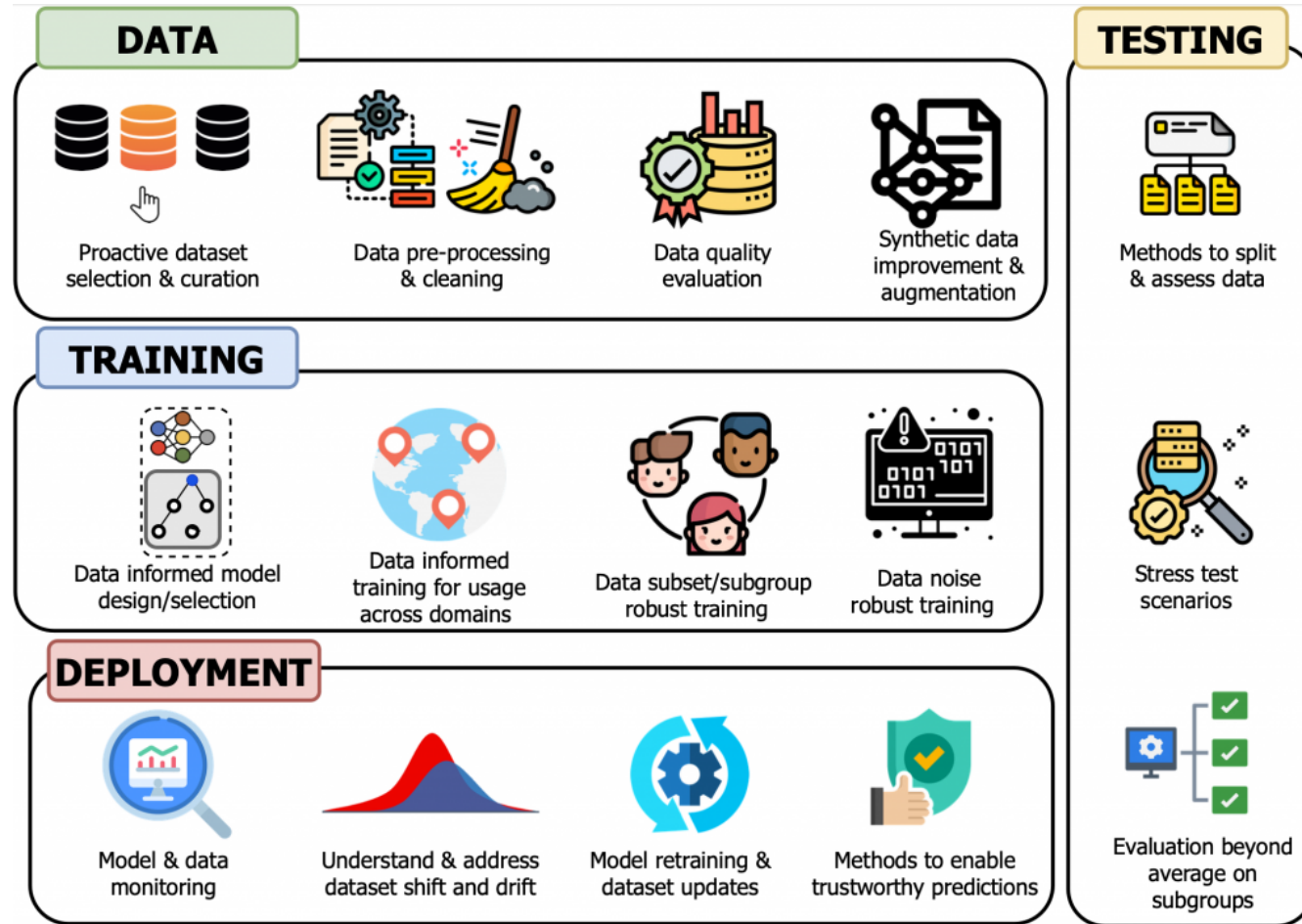
Impact assessments

Policies & Responsibility

- Amazon is responsible if its facial recognition system is not used according to guidelines
 - Guidelines given, who is responsible for ensuring the guidelines are followed?
- Because of abuse and false-positives, predictive policing and law-enforcement should be prohibited from using this software
 - Safety first



From Model-centric AI to Data-centric AI



From Prof. Michela Van Shaar website: <https://www.vanderschaar-lab.com/data-centric-ai/>

Overview

- Context
- Definition & Taxonomy
- Bias in ML
- **Ethics In AI is not only about fairness**

**ETHICS IN AI IS NOT ONLY ABOUT
FAIRNESS**

Beyond the question of fairness...



Timnit Gebru

<https://www.youtube.com/watch?v=T2oZvzgrill>

Beyond the question of fairness...



Lucile Sasstelli
Professor at University Cote d'Azur,
I3S CNRS Lab
Scientific Director of EFELIA
(French School of AI in Cote d'Azur)

Is data fixable? On the need of socially-informed practices in ML research and education (part 1)

Part 1: Deployment failures and approaches to data

Is data fixable? On the need of socially-informed practices in research and education (part 2)

Part 2: A more holistic perspective on data creation and expectations

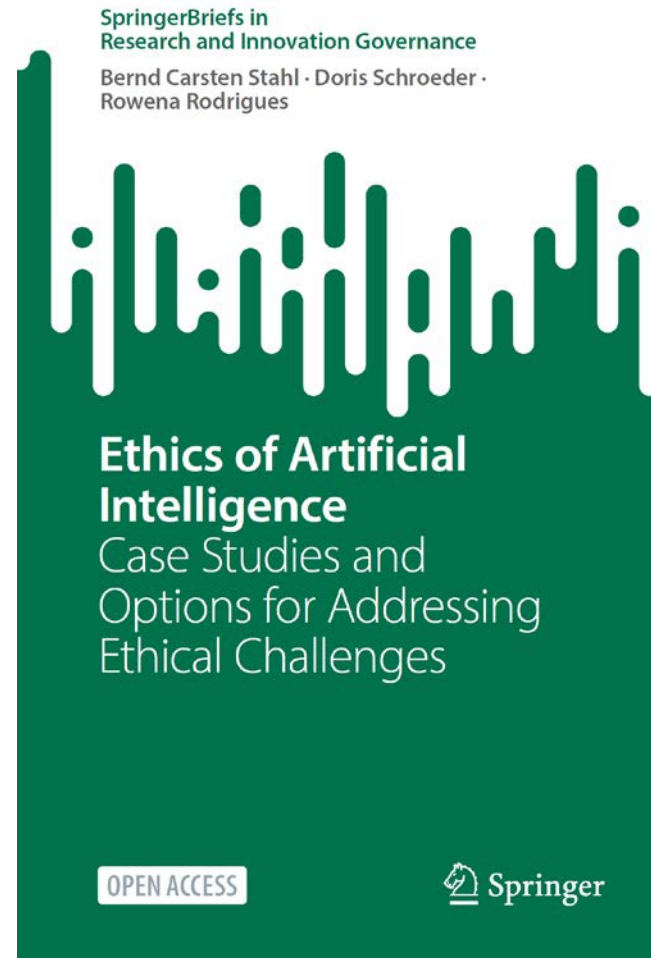
Is data fixable? On the need of socially-informed practices in ML research and education (part 3)

Part 3: AI ethics and our ML education practices

<https://webusers.i3s.unice.fr/~sassatelli/>



The Backbone of the module



<https://link.springer.com/book/10.1007/978-3-031-17040-9>

Table of contents

- **Unfair and Illegal Discrimination:** Cases of AI-Enabled Discrimination
- **Privacy:** Cases of Privacy Violations Through AI
- **Surveillance Capitalism:** Cases of AI-Enabled Surveillance Capitalism
- **Manipulation:** Cases of AI-Enabled Manipulation
- **Right to Life, Liberty and Security of Persons:** Cases of AI Adversely Affecting the Right to Life, Liberty and Security of Persons
- **Dignity:** Cases of AI in Potential Conflict with Human Dignity
- **AI for Good and the UN Sustainable Development Goals:** Cases of AI for Good or Not?

Any Question?