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Module 3: Ethics in AI

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Why consider ethics?

- Ethical issues in AI systems can be particularly dangerous
  - Can have significant impacts on people’s lives
  - Difficult to detect
  - May not violate any laws

Module 3 Objectives:

At the conclusion of this module, you should be able to:

1) Explain the goals of Fair, Accountable and Transparent AI
2) Identify sources of bias in AI projects
3) Implement strategies to mitigate potential ethical risks

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Fair, Accountable & Transparent AI

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Ethical risks of AI

Allocative harm

- Opportunities or resources are withheld from certain people/groups
- Examples:
  - Automated resume review system selects primarily male candidates for interviews for a technical role
  - Men and women with identical backgrounds receive different credit limits in applying for a credit card

Solon Barocas, Kate Crawford, Aaron Shapiro, and Hanna Wallach. 2017. The problem with bias: from allocative to representational harms in machine learning. Special Interest Group for Computing, Information and Society (2017).

Ethical risks of AI

Representational harm

- Certain people/groups are stigmatized or stereotyped
- Examples:
  - Computer vision model which identifies all female doctors as nurses

Solon Barocas, Kate Crawford, Aaron Shapiro, and Hanna Wallach. 2017. The problem with bias: from allocative to representational harms in machine learning. Special Interest Group for Computing, Information and Society (2017).

Ethical AI

- Three criteria of ethical AI systems:
  - **Fair**
  - **Accountable**
  - **Transparent**

Fairness

- Roots in anti-discrimination laws
- No single universal definition of fairness

Individual fairness

People who are similar should receive similar outcomes

Group fairness

Different groups should experience similar levels of positive outcome or rates of errors

- Individual and group fairness can come into tension

Accountability

- Clear responsibility for outcomes
- Users have recourse if they identify issues
- Key considerations:
  1. **Who is responsible** for system performance?
  2. On **what set of values and laws** is the system based?
  3. **What recourse do users have** if the system is not behaving in accordance with values and laws?

Transparency

- Users have visibility into data usage and model functioning
- Methods of providing transparency:

Interpretable models

Feature importance

Simplified approximations

Counterfactual explanations

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Types & Sources of Bias

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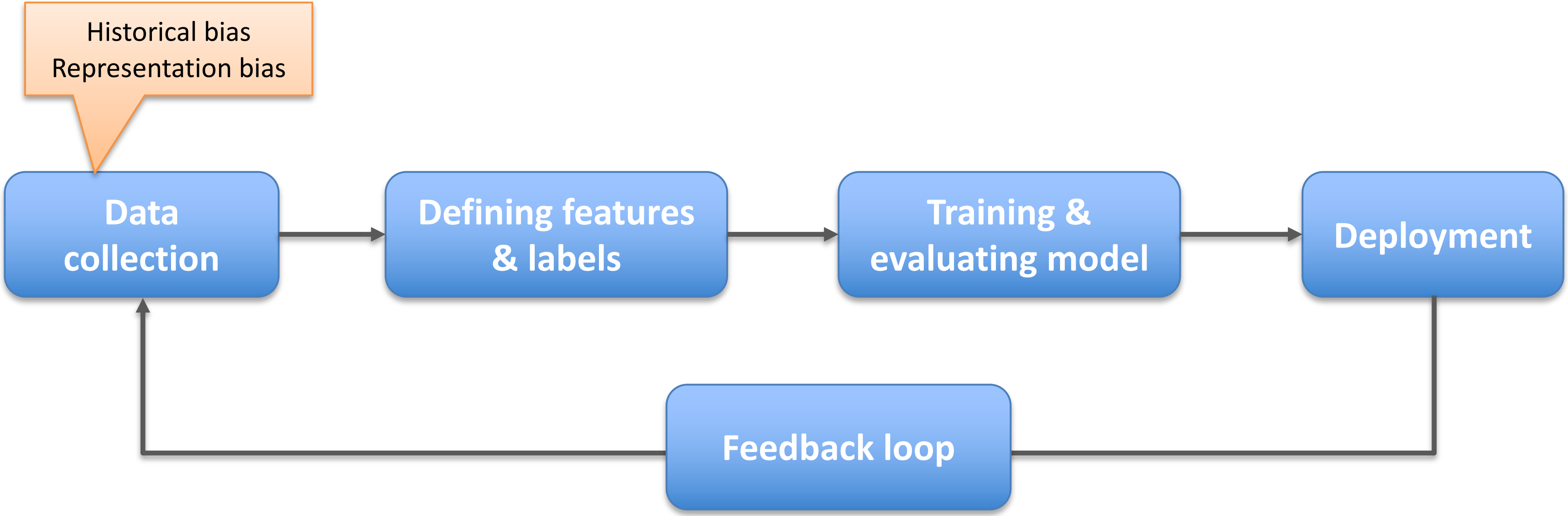
Algorithmic bias

- AI systems often considered to be neutral, but can have many biases
- Systemic errors that create unfair outcomes for individuals or groups
- Can enter into AI systems in many ways:
  - Pre-existing perceptions of system creators
  - Design of data collection or model
  - Unanticipated use of system

Sources of bias



Suresh, Harini, and John V. Guttag. "A Framework for Understanding Sources of Harm throughout the Machine Learning Life Cycle." arXiv preprint arXiv:1901.10002 (2019).

Historical bias

- Collected data reflect existing biases in the world around us at the time of data collection

Example

- Word embeddings trained on large-scale text associate occupational words such as “nurse” or “engineer” more strongly with women and men, respectively

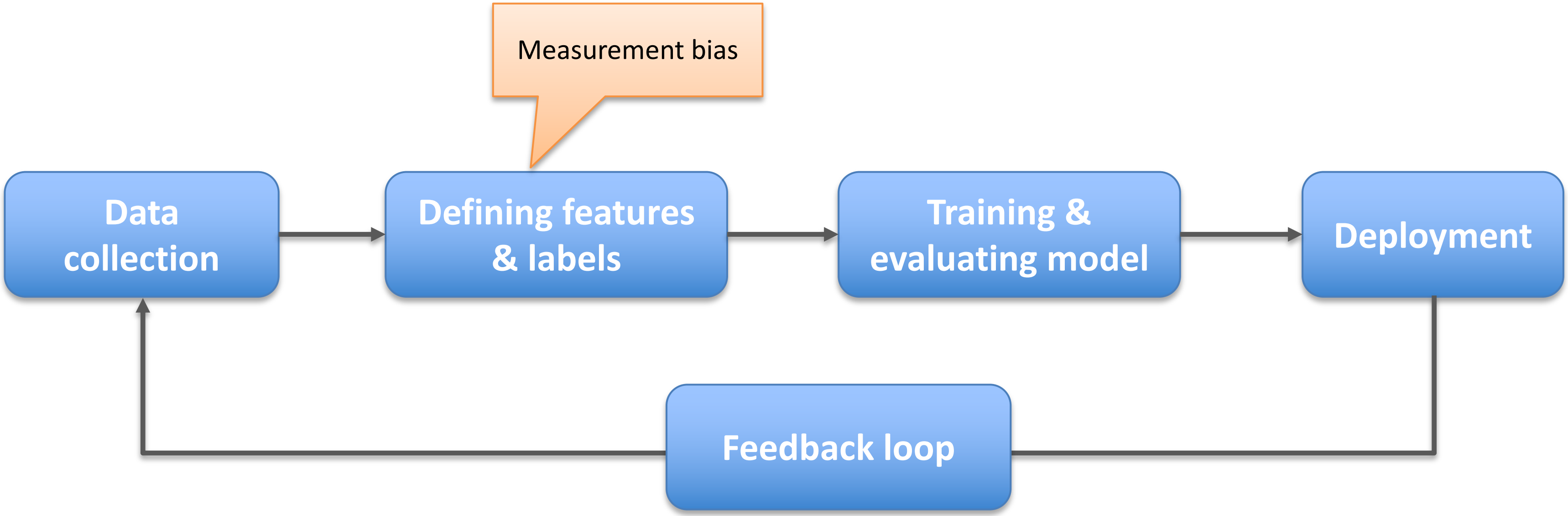
Representation bias

- Training dataset is not representative of the entire target population
  - Certain groups are naturally under-represented in the training data
  - Sampling method results in uneven data collected

Examples

- Certain medical dataset contains only a small % of pregnant women
- City of Boston’s pothole app flagged issues in younger, affluent neighborhoods

Sources of bias



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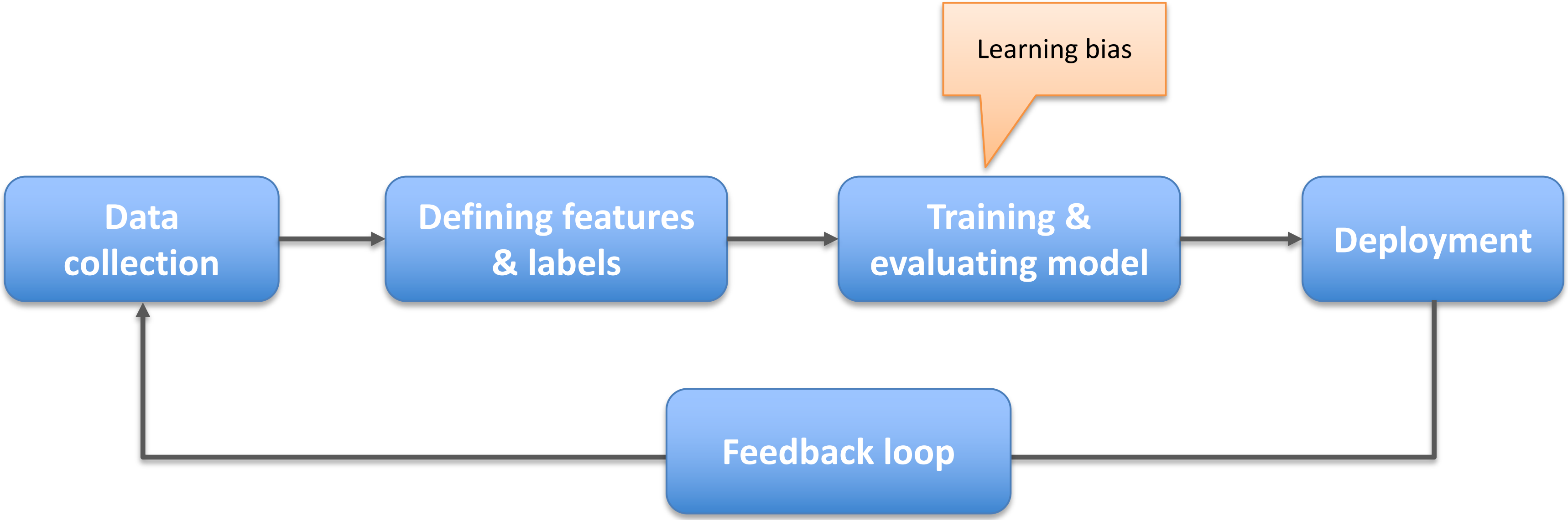
Measurement bias

- Features or labels chosen to represent some construct are poor reflections of it, or vary across groups
  - Proxy is an oversimplification
  - Method of measurement or accuracy varies across groups

Examples

- GPA as a proxy for student learning success
- Count of manufacturing anomalies across sites

Sources of bias



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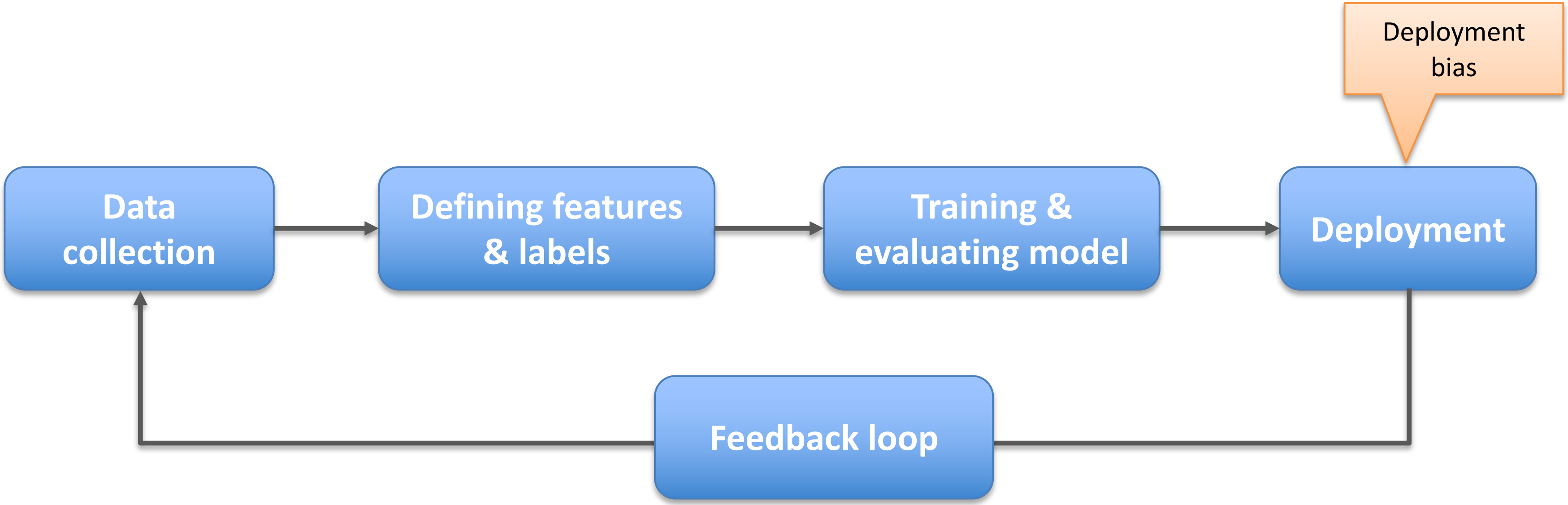
Learning bias

- Modeling choices amplify performance disparities across groups
- Cost function may optimize aggregate performance at the expense of consistency across groups (disparate impact)

Examples

- Use of demographic data to predict likelihood of criminals to re-offend
- Prioritizing smaller models at the expense of underrepresented attributes

Sources of bias



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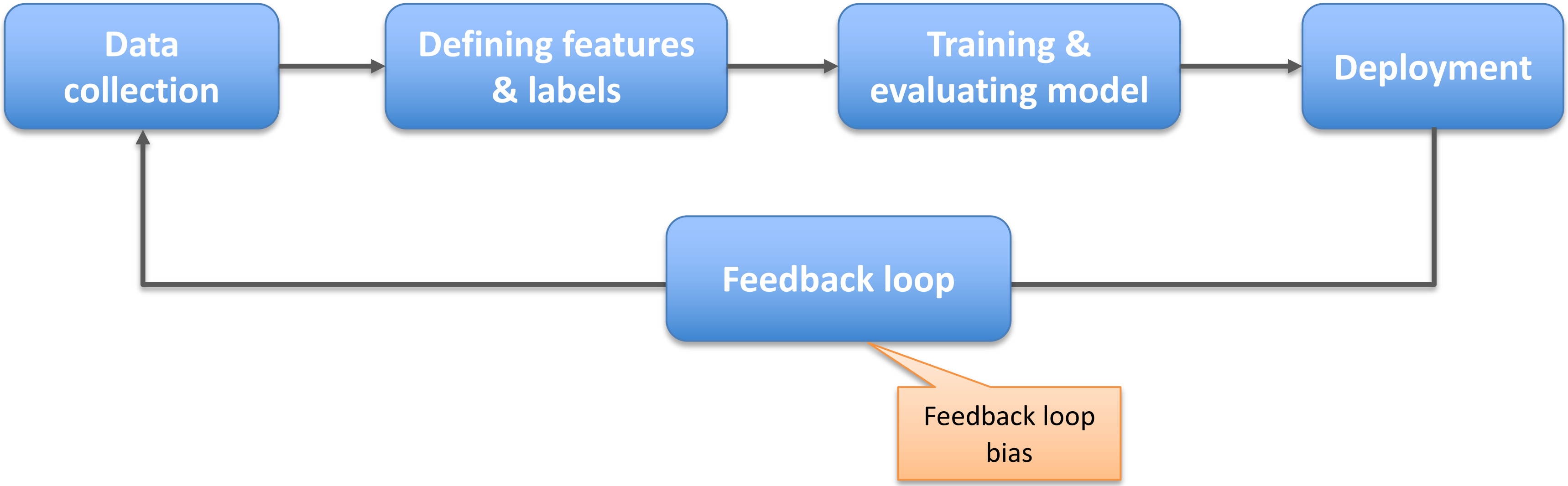
Deployment bias

- Mismatch between how a tool was intended to be used and how it is used in practice
- Occurs when system developers consider tool in isolation of usage environment

Example

- Automated teacher evaluation tool used to terminate low rated teachers

Sources of bias



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Feedback loop bias

- The design of a system incorporates a feedback loop which influences the training data and thus the model outputs

Example

- Product recommendation engine which bases ordering of items on number of positive reviews

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Mitigating Potential Ethical Risks

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Tools to Mitigate Ethical Risk

- Datasheets for datasets
- Ethical checklist
- Ethical pre-mortems

Datasheets for datasets

- Creation and selection of data is the most common source of bias
- There is currently no standardized process for documenting datasets in the ML community
- In most other industries, all inputs are accompanied by a standard datasheet describing composition and use

See Gebru, et al. Datasheets for Datasets. https://arxiv.org/pdf/1803.09010.pdf

Objectives of a dataset datasheet

- For **dataset creators**
  - Encourage best practices in collecting data
  - Foster reflection on risks and implications of use
- For **dataset consumers**
  - Provide transparency to support decisions on whether/how to use dataset
- For **users of models**
  - Contribute to explainability of model outputs

Ethical Checklist (1/2)

Project Selection & Scoping

- Is the problem we are solving a symptom of a bigger issue?
- Is AI the right tool for the job?

Building the Team

- Does the team include or consider individuals who will ultimately be affected by the tool?
- Does our team reflect diversity of opinions and backgrounds?

Data Collection

- Does collecting data impede on anyone's privacy?
- Have we collected appropriate user consents to use the data?
- Were the systems and processes used to collect the data biased against any groups?
- Have we studied and understood possible sources of bias in our data?

Based on Fritzler, Alan. "An Ethical Checklist for Data Science." https://www.dssgfellowship.org/2015/09/18/an-ethical-checklist-for-data-science/

Ethical Checklist (2/2)

Analysis / Modeling

- Has the team introduced bias in the variable selection or modeling?
- Should the team include features that could be discriminatory?
- Is the analysis sufficiently transparent?
- Have we tested for fairness with respect to different user groups?
- Have we tested for disparate error rates among different user groups?

Implementation

- Are the people using our models aware of its shortcomings?
- Do we have a mechanism for redress if people are harmed by the results?
- Have we listed how this technology can be attacked or abused?
- Do we test and monitor for model drift to ensure our software remains fair over time?

Based on Fritzler, Alan. “An Ethical Checklist for Data Science.” https://www.dssgfellowship.org/2015/09/18/an-ethical-checklist-for-data-science/

Ethical pre-mortems

- Involve diverse group of stakeholders
- Anticipate ethical issues occurring
- What might cause them?
- Why might they turn into major issues?
- How can we prevent them?

Detecting & Resolving Fairness Issues

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Defining fairness goals

Set specific goals for system to work fairly
across user groups:

1. **Define groups of significance**
   - Age? Race? Gender? Location? Etc.
   - Combinations?
2. **Determine what "fair" means**
   - Same error rates across groups?
   - Same level of positive outcome across groups?

Defining fairness goals

Example: automated loan approvals

- How should the groups be defined?
- How should we define fairness?
  - Give loans at same rate to different groups, even if they have different rates of historical payback?
  - Give loans proportional to each group's historical payback rate?

Fairness auditing

- Develop a fairness auditing plan
  - Training data collection
  - Test set formation
  - Test set performance
  - Production monitoring
- Fair AI tools simplify the process of evaluating fairness
- Requires access to demographic attributes of interest

Feedback Loops

- Risks may take time to materialize, and environmental factors change with time
- Feedback loop mechanisms
  - Invite user feedback
  - Triage systemic vs. individual issues
  - Regularly review identified ethical risks
- Accountability for executing feedback mechanisms and risk follow up

Resolving Fairness Issues

Three options for resolving fairness issues:

1. Change the data
2. Change the model
3. Change the system

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Wrap-up

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Wrap-Up

- Many possible sources of bias in building models
- Ethical risks in AI systems can have significant consequences
- Objective is Fair, Accountable and Transparent AI
- Anticipation of fairness issues is key to mitigation