AI INSTITUTE #AIISC
UNIVERSITY OF SOUTH CAROLINA

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CSCE 581: Introduction to Trusted AI

Lectures 9 and 10: Quiz 1, (Supervised) ML - Trust

PROF. BIPLAV SRIVASTAVA, AI INSTITUTE

11TH AND 13TH FEB, 2025

Carolinian Creed: "I will practice personal and academic integrity."

Credits: **Copyrights of all material reused acknowledged**

Organization of Lectures 9, 10

- Introduction Section
  - Recap from Week 4 (Lectures 7 and 8)
  - Announcements and News
- Main Section
  - L9: Quiz 1
  - L10: Trust issues in (Supervised) ML
- Concluding Section
  - About next week – Lectures 11, 12
  - Ask me anything

Introduction Section

Recap from Week 4 (Lectures 7, 8)

- We looked at
  - Supervised ML algorithms, ML tools
  - Deep-dive into German credit

- Project descriptions finalized

AI News

- DeepSeek R1 – a POV from our own analysis
  (https://drive.google.com/file/d/1gKKM0sEcp5u6pA05jETZSCQZNJSN7SJt/view?usp=sharing)

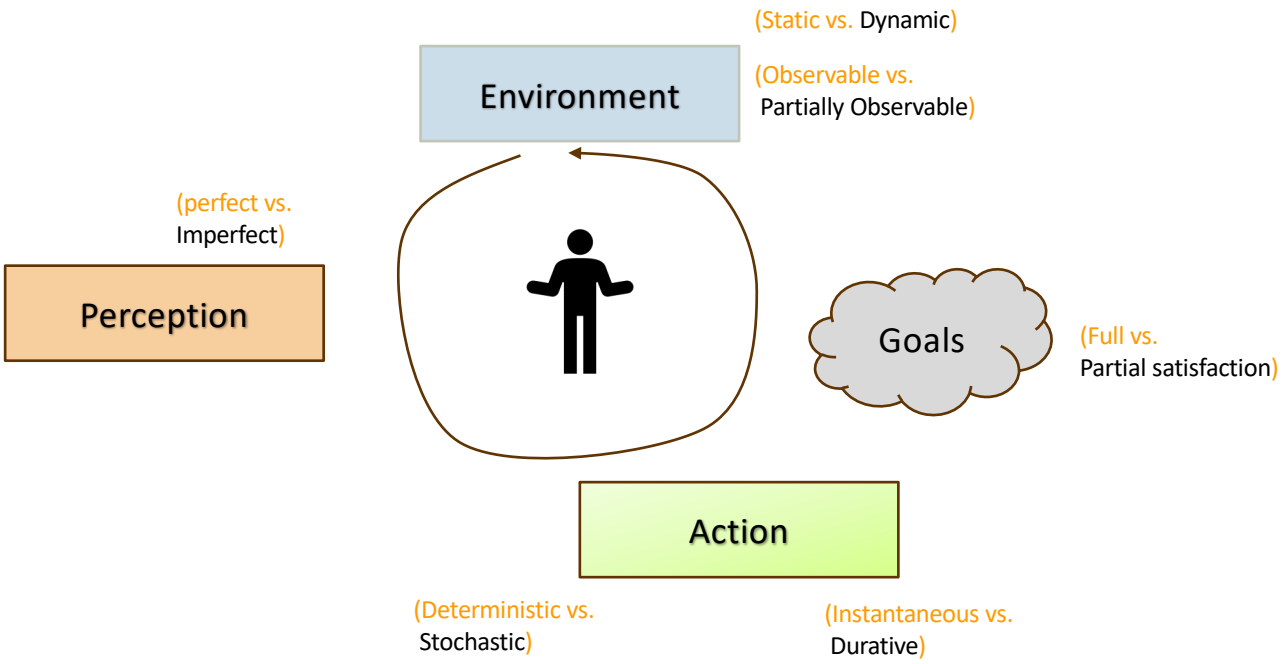
Announcement: Change to Student Assessment

A = [920-1000]
B+ = [870-919]
B = [820-869]
C+ = [770-819]
C = [720-769]
D+ = [670-719]
D = [600-669]
F = [0-599]

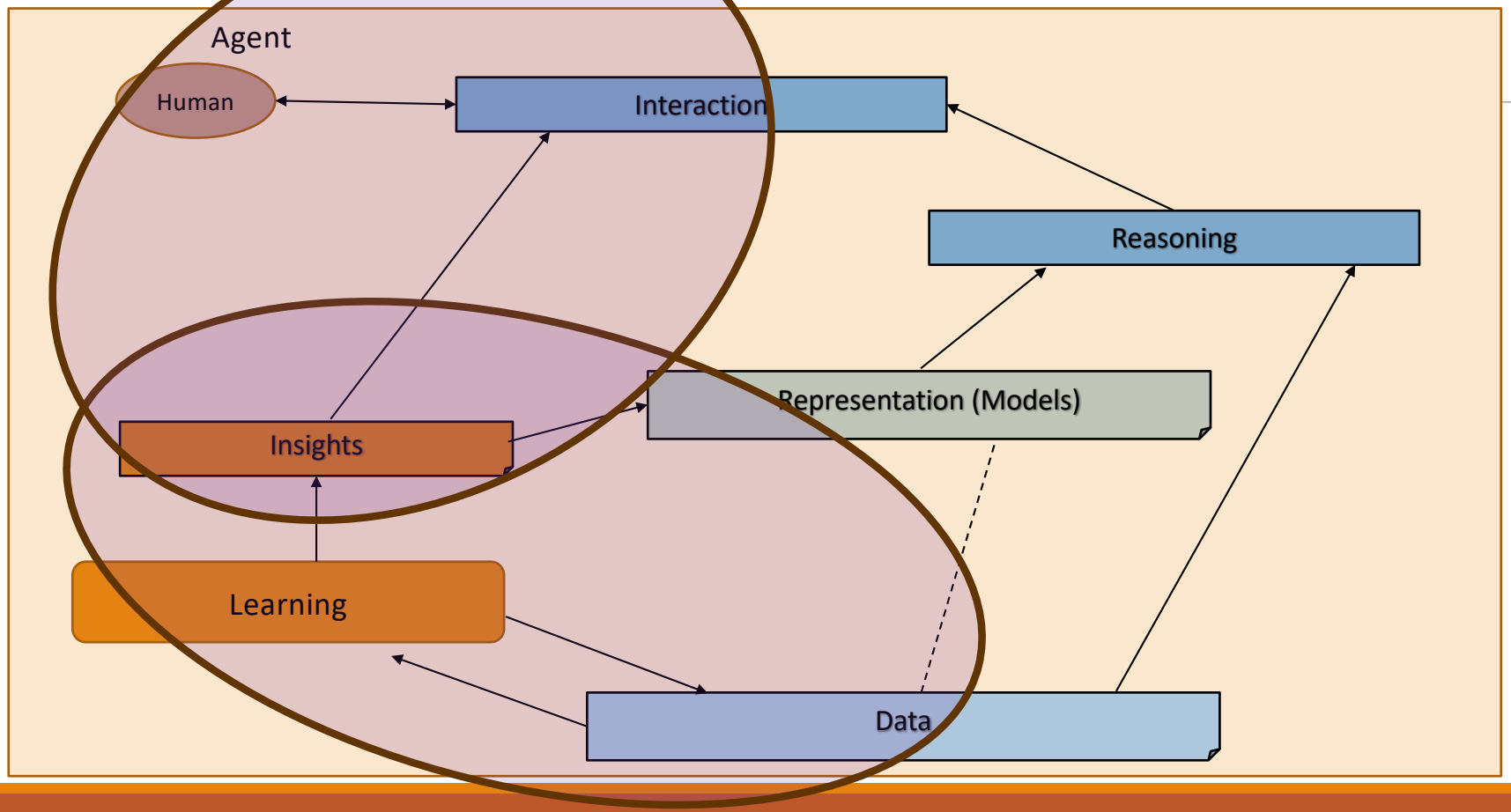
Tests	Undergrad	Grad
Course Project – report, in-class presentation	600	600
Quiz – 2 quizzes	200	200
Final Exam	200	100
Additional Final Exam – Paper summary, in-class presentation		100
Total	1000 points	1000 points

Change: 4 quizzes to 2; no best of 3

Intelligent Agent Model



Relationship Between Main AI Topics (Covered in Course)



High Level Semester Plan (Adapted, Approximate)

CSCE 581 –

- Week 1: Introduction
- Week 2: Background: AI - Common Methods
- Week 3: The Trust Problem
- Week 4: Machine Learning (Structured data) - Classification
- Week 5: Machine Learning (Structured data) - Classification – Trust Issues
- Week 6: Machine Learning (Structured data) – Classification – Mitigation Methods
- Week 7: Machine Learning (Structured data) – Classification – Explanation Methods
- Week 8: Machine Learning (Text data, **vision**) – Classification, **Large Language Models**
- Week 9: Machine Learning (Text data) - Classification – Trust Issues, LLMs
- Week 10: Machine Learning (Text data) – Classification – Mitigation Methods
- Week 11: Machine Learning (Text data) – Classification – Explanation Methods
- Week 12: Emerging Standards and Laws, **Real world applications**
- Week 13: Project presentations
- Week 14: Project presentations, Conclusion

AI/ ML topics and with a focus on fairness, explanation, Data privacy, reliability

Main Section

Lecture 7: Quiz 1

Recall Exercise: German Credit

Datasets

- UCI Dataset:
  - Weka: https://www.ics.uci.edu/~mlearn/MLRepository.html (e.g., download: https://prdownloads.sourceforge.net/weka/uci-20070111.tar.gz)
  - Check in UCI – variants:
  - https://archive.ics.uci.edu/dataset/573/south+german+credit+update

- Weka
  - Direct link: https://github.com/Waikato/weka-3.8/blob/master/wekadocs/data/credit-g.arff
  - As part of development packages
    - like DataHub, https://datahub.io/machine-learning/credit-g#python

German Credit Data

https://archive.ics.uci.edu/ml/datasets/Statlog+%28German+Credit+Data%29

- Dataset that classifies people's credit risk based on their individual attributes such as Age, Income, Gender, etc.
  - 1000 rows of data, each with 20 attributes to check bias against
- Each entry represents an individual who takes credit from a bank
- Each entry is classified as *Good* or *Bad* credit risk based on their profile

1. Credit amount (numerical);
2. Credit duration (numerical);
3. Credit purpose (categorical);
4. Status of existing checking account(categorical);
5. Status of savings accounts and bonds (categorical);
6. Number of existing credits (numerical);
7. Credit history(categorical);
8. Installment plans (categorical);
9. Installment rate(numerical);
10. Property (categorical);
11. Residence (categorical);
12. Period of present residency (numerical);
13. Telephone (binary);
14. Employment (categorical);
15. Employment length (categorical);
16. Personal status and gender (categorical); 1
17. Age (numerical);
18. Foreign worker (binary);
19. Dependents (numerical);
20. Other debtors (categorical);
21. Credit score (binary)

Example Instance:

A11 6 A34 A43 1169 A65 A75 4 A93 A101 4 A121 67 A143 A152 2 A173 1 A192 A201 1

Example record: Alice is requesting a loan amount of 1567 DM for a duration of 12 months for the purpose of purchasing a television, with a positive checking account balance that is smaller than 200 DM, having less than 100 DM in savings account, and having one existing credit at this bank. She duly paid existing credits at the bank till now and has no other installment plan. She possesses a car and owns a house, has been living at the present residence for one year and has a registered telephone. She is a skilled employee, working in the present employment for past four years. She is a 22-year-old married female and is a German citizen. She has one dependent and no guarantors. The recorded outcome for Alice (attribute #21) is a good credit score.

Dua, D. and Graff, C. (2019). UCI Machine Learning Repository [http://archive.ics.uci.edu/ml], Irvine, CA: University of California, School of Information and Computer Science

VERMA, S., AND RUBIN, J. 2018. FAIRNESS DEFINITIONS EXPLAINED. IN PROCEEDINGS OF THE INTERNATIONAL WORKSHOP ON SOFTWARE FAIRNESS, FAIRWARE '18, 1–7. NEW YORK, NY, USA: ASSOCIATION FOR COMPUTING MACHINERY, HTTPS://WWW.ECE.UBC.CA/~MJULIA/PUBLICATIONS/FAIRNESS_DEFINITIONS_EXPLAINED_2018.PDF

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  - 1000 rows of data, each with 20 attributes to check bias against
- Each entry represents an individual who takes credit from a bank
- Each entry is classified as *Good* or *Bad* credit risk based on their profile
  - It is **worse** to class a **customer as good when they are bad**, than it is to class a **customer as bad when they are good**.

1. Credit amount (numerical);
2. Credit duration (numerical);
3. Credit purpose (categorical);
4. Status of existing checking account(categorical);
5. Status of savings accounts and bonds (categorical);
6. Number of existing credits (numerical);
7. Credit history(categorical);
8. Installment plans (categorical);
9. Installment rate(numerical);
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17. Age (numerical);
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21. Credit score (binary)

Review detailed data exploration at:
https://www.kaggle.com/sanyalush/predicting-credit-risk

Example record: Alice is requesting a loan amount of 1567 DM for a duration of 12 months for the purpose of purchasing a television, with a positive checking account balance that is smaller than 200 DM, having less than 100 DM in savings account, and having one existing credit at this bank. She duly paid existing credits at the bank till now and has no other installment plan. She possesses a car and owns a house, has been living at the present residence for one year and has a registered telephone. She is a skilled employee, working in the present employment for past four years. She is a 22-year-old married female and is a German citizen. She has one dependent and no guarantors. The recorded outcome for Alice (attribute #21) is a good credit score.

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Trust Issues

Context: German Credit Data's Analysis

- Review detailed data exploration at:
https://www.kaggle.com/sanyalush/predicting-credit-risk

- Notice issues in lending ?
  - No single female
  - Discrimination by gender, age, … ?

Discussion on Reading Material - 1

"Biases in AI Systems", Ramya Srinivasan, Ajay Chander
Communications of the ACM, August 2021, Vol. 64 No. 8, Pages 44-49
10.1145/3464903

https://cacm.acm.org/magazines/2021/8/254310-biases-in-ai-systems/fulltext

Taxonomy of Biases

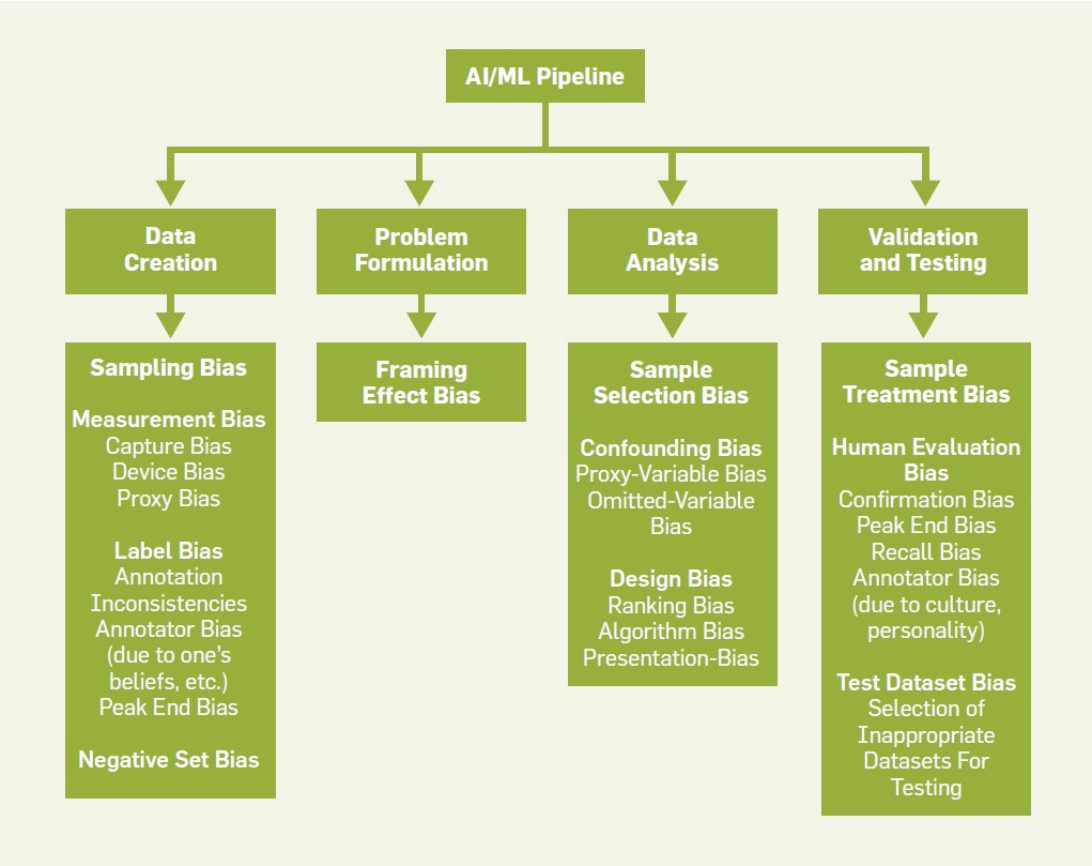
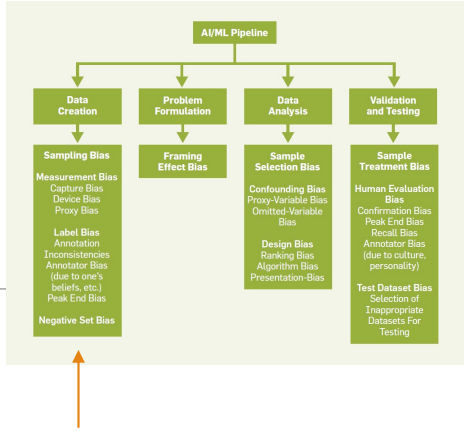


Figure courtesy: "Biases in AI Systems", Ramya Srinivasan, Ajay Chander, CACM 2021

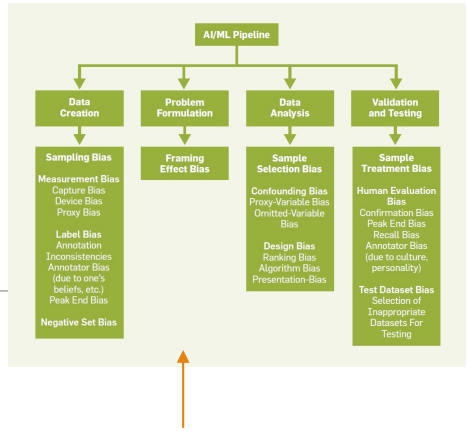
Data Creation Biases



- Sampling bias
  - Selecting specific types of instances more than others
  - Examples:
    - Twitter for finding traffic on a road (assumptions: one social media platform, driver v/s riders)
    - FaceTime for recording accidents (assumptions: a company product, having smart phone)
  - Measurement bias
    - Proxies uses instead of true values (arrests for crime, hospital visits for health)
  - Label bias
    - Inconsistent usage of terms, Subjectivity, peak effect – memory based bias from psychology
    - Serious bottleneck for supervised methods
  - Negative set bias
    - Not having enough data for negative classification

Figure courtesy: "Biases in AI Systems", Ramya Srinivasan, Ajay Chander, CACM 2021

Problem Formulation Bias

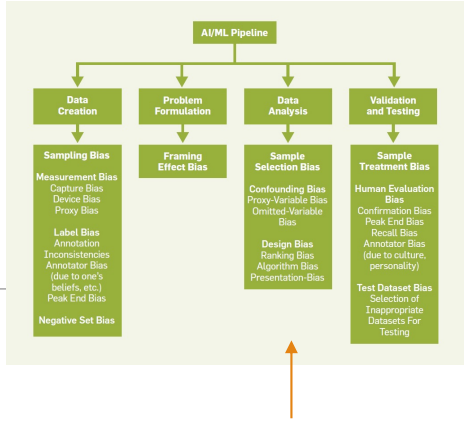


- "What cannot be measured cannot be controlled"

- Framing Effect Bias
  - Compas: predicting recidivism – criminals re-offending
    - Pro-republica claim: biased against black defendants as the group was associated with a higher false-positive rate (**equalized odds** and **equality of opportunity fairness** criteria)
      - **Equalized odds**: if protected and unprotected groups have equal true positive rate and false positive rate
    - Northpointe: scores satisfied fairness from the viewpoint of **predictive rate parity**
      - **Predictive rate parity**: precision, the number of the true positives divided by the total number of examples predicted positive within a group, same within groups

Figure courtesy: "Biases in AI Systems", Ramya Srinivasan, Ajay Chander, CACM 2021

Data Analysis Bias

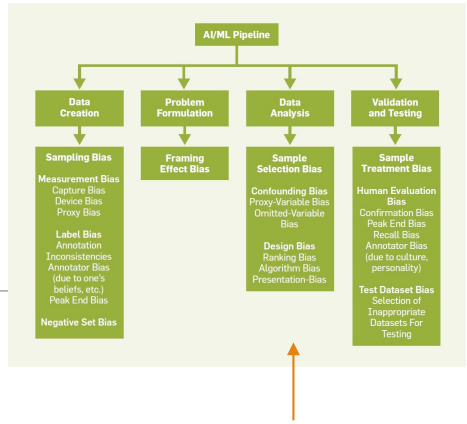


Due to algorithmic properties or computational limitations

- Sample Selection Bias
  - "selection of individuals, groups, or data for analysis in such a way that the samples are not representative of the population intended to be analyzed"
  - Example – *"In analyzing the effect of motherhood on wages, if the study is restricted to women who are already employed, then the measured effect will be biased as a result of conditioning on employed women"*
- Confounding Bias
  - Common causes that affect both inputs and outputs, but are not accounted for. Example – "*admissions to a graduate school are based on the person's previous grade point average. There might be other factors, however, such as ability to get coaching, which in turn may be dependent on sensitive attributes such as race; and these factors may determine the grade point average and admission rates*"
  - Proxy variables: there are proxies for protected variables being omitted; indirect bias
  - Omitted variables: model does not consider variables

Figure courtesy: "Biases in AI Systems", Ramya Srinivasan, Ajay Chander, CACM 2021

Data Analysis Bias



Due to algorithmic properties or computational limitations

- Design Bias
  - Ranking Bias: Which top results to be shown? What should be the cut-off?
- Presentation Bias: where and how the result is presented?

Figure courtesy: "Biases in AI Systems", Ramya Srinivasan, Ajay Chander, CACM 2021

Validation and Testing Bias

- Human Evaluation Bias
  - Human's biases: confirmation bias, peak end effect, and prior beliefs
- Test Dataset Bias
  - Faces issues similar to (training) dataset selection
  - Further, is it appropriate for application in hand and up-to-date over time?

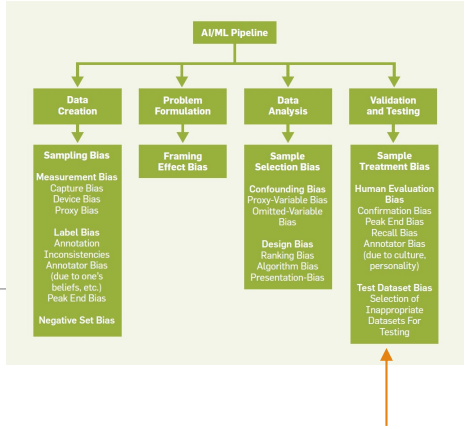


Figure courtesy: "Biases in AI Systems", Ramya Srinivasan, Ajay Chander, CACM 2021

Guidelines for Developers

- Draw a structural diagram illustrating various features of interest and their interdependencies
  - To avoid bias, all features that associated with the target feature of interest is important
- Understand which features of the data are sensitive based on the application
  - Understand the laws: protected by law
  - Best practices that are good to have
- Datasets used for analysis should be representative of the true population under consideration
- Standardize rules for annotating data
- Validate model with representative population, not a subset

Discussion on Reading Material - 2

"Data science and AI in the age of COVID-19 - Reflections on the response of the UK's data science and AI community to the COVID-19 pandemic", Alan Turing Institute, 2021

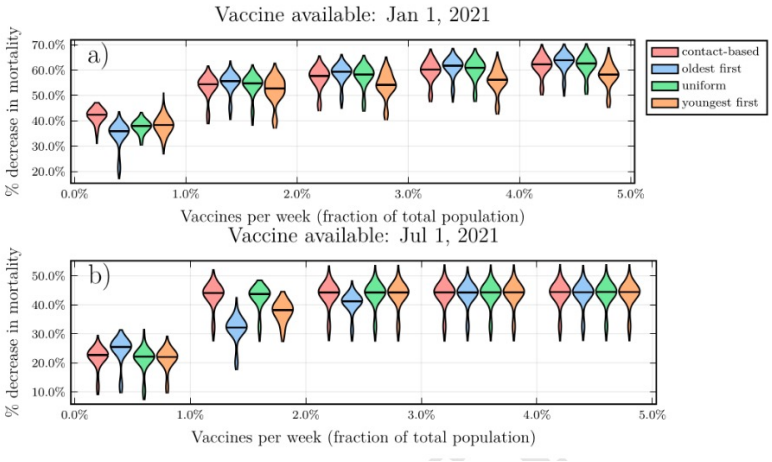
- Approach of report
  - A series of workshops in academic circles in Nov and Dec 2020
  - Discussions and findings distilled into the report

Example AI Usage: Distribution of Vaccines

- **Problem**: Limited supply, larger demand, many technologies, recipient hesitancy; How do distribute equitably, fairly and efficiently
- Possible (automated) solutions
  - Random: pick receiver based on random choice
    - **Benefit**: Easy to implement
    - **Problems**: Equitable but not fair, receiver may not be at risk or not want it, others wanting it may not get it
    - **Question**: assumes we can give vaccine quickly to the selected person
  - Prioritized random: make a prioritized list of groups, assign randomly in each group
    - **Benefit**: identifies affected groups
    - **Problems**: receiver may not want the vaccine
    - **Question**: who comes up with groups?, is it rewarding groups who have not been taking precautions ? Assumes we can give vaccine quickly to the selected person
  - ...
  - Benefit-cost: based on contribution to economy
    - **Benefit**: efficient

Impact of Decisions in Vaccine Distribution

- Article: 'The Pandemic Is a Prisoner's Dilemma Game'
- Prioritising COVID-19 vaccination in changing social and epidemiological landscapes, Sep 2020.
- Choices
  - impact of vaccinating 60+ year-olds first;
  - <20 year-olds first;
  - uniformly by age; and
  - a novel contact-based strategy
- Insights
  - Vaccination reduces median deaths by 32%-77% (22%-63%) for January (July) availability, depending on the scenario.
  - Vaccinating 60+ year-olds first prevents more deaths (up to 8% more) than transmission-interrupting strategies



Discussion on Reading Material

"Data science and AI in the age of COVID-19 - Reflections on the response of the UK's data science and AI community to the COVID-19 pandemic", Alan Turing Institute, 2021

- Findings
  1. Researchers responded to COVID need with enthusiasm leading to a large number of projects
     1. **Word-wide* (for context)**: protein to aid disease detection and treatment (**molecular scale**), the analysis of patient data like images and conditions to improve patient care (**clinical scale**) and analysis of cases and social media to predict disease severity, understand mis-information and communicate effectively (**societal scale**).
     2. **UK specific examples**: model disease spread, navigate lockdown
  2. Major hurdle was lack of "robust and timely data", especially access and standardization
     1. Develop protocols for collecting and managing protected data
     2. Develop protocols for generating anonymized and synthetic data

* Joseph Bullock, Alexandra Luccioni, Katherine Hoffmann Pham, Cynthia Sin Nga Lam, and Miguel Luengo-Oroz. Mapping the landscape of artificial intelligence applications against covid-19. In Journal of Artificial Intelligence Research 69, 807-845, 2020.

Discussion on Reading Material

"Data science and AI in the age of COVID-19 - Reflections on the response of the UK's data science and AI community to the COVID-19 pandemic", Alan Turing Institute, 2021

- Findings
  3. Concern over inequality and exclusion slowed progress. Inadequate representation and engagement from some groups
  4. Challenge in communicating research findings to policy makers and public. Specifically, timeliness, accuracy and clarity.
     - Communication among experts
     - Communication among researchers and policy makers
     - Communication among researchers and public

* Joseph Bullock, Alexandra Luccioni, Katherine Hoffmann Pham, Cynthia Sin Nga Lam, and Miguel Luengo-Oroz. Mapping the landscape of artificial intelligence applications against covid-19. In Journal of Artificial Intelligence Research 69, 807-845, 2020.

Project Discussion

Course Project

- **Framework**
  1. (Problem) Think of a problem whose solution may benefit people (e.g., health, water, air, traffic, safety)
  2. (User) Consider how the primary user (e.g., patient, traveler) may be solving the problem today
  3. (AI Method) Think of what the solution will do to help the primary user
     1. Solution => ML task (e.g. classification), recommendation, text summarization, …
     2. Use a foundation model (e.g., LLM-based) solution as the baseline
  4. (Data) Explore the data for a solution to work
  5. (Reliability: Testing) Think of the evaluation metric we should employ to establish that the solution will works? (e.g., 20% reduction in patient deaths)
  6. (Holding Human Values) Discuss if there are fairness/bias, privacy issues?
  7. (Human-AI) Finally, elaborate how you will explain the primary user that your solution is trustable to be used by them

Project Discussion: What to Focus on ?

- Problem: you should care about it
- Data: should be available
- Method: you need to be comfortable with it. Have at least two – one serves as baseline
- Trust issue
  - Due to Users
    - Diverse demographics
    - Diverse abilities
    - Multiple human languages
  - Or other impacts
- What one does to mitigate trust issue

Rubric for Evaluation of Course Project

Project

- Project plan along framework introduced (7 points)
- Challenging nature of project
- Actual achievement
- Report
- Sharing of code

Presentation

- Motivation
- Coverage of related work
- Results and significance
- Handling of questions

Project Discussion

1. Create a private Github repository called "CSCE581-Spring2025-<studentname>-Repo". Share with Instructor (biplav-s)
2. Create a folder called "Project". Inside, create a text file called "ProjectPlan.md" (or "ProjectPlan.txt") and have details by the next class (Jan 30, 2025)

1. Title:
2. Key idea: (2-3 lines)
3. Who will care when done:
4. Data need:
5. Methods:
6. Evaluation:
7. Users:
8. Trust issue:

Concluding Section

Week 4 (L7 and L8): Concluding Comments

- We looked at
  - Supervised ML algorithms, ML tools
  - Deep-dive into German credit

- Project descriptions finalized

About Next Week – Lectures 11, 12

Lectures 11, 12: Trust and Mitigation

- ML/ Classification: Trust Issues
- ML/ Classification: Mitigation

5	Jan 28 (Tu)	Common AI methods: ML Landscape
6	Jan 30 (Th)	AI - Structured: Analysis – Supervised ML
7	Feb 4 (Tu)	AI - Structured: Analysis – Supervised ML
8	Feb 6 (Th)	Project discussion (1)
9	Feb 11 (Tu)	Quiz 1
10	Feb 13 (Th)	AI - Structured: Analysis – Supervised ML – Trust Issues
11	Feb 18 (Tu)	AI - Structured: Analysis – Supervised ML – Trust Issues
12	Feb 20 (Th)	AI - Structured: Analysis – Supervised ML – Mitigation Methods