CSCE 581: Introduction to Trusted AI

Lectures 13 and 14: (Supervised) ML – Trust Mitigation

PROF. BIPLAV SRIVASTAVA, AI INSTITUTE

25TH AND 27TH FEB, 2025

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

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Organization of Lectures 13, 14

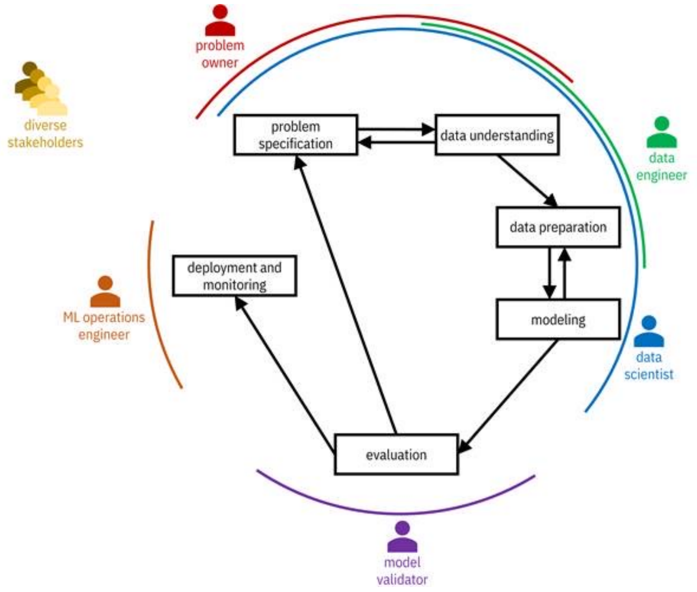
- Introduction Section
  - Recap from Week 6 (Lectures 11 and 12)
  - Announcements and News
- Main Section
  - L13: Mitigation - Explanation Methods
  - L14: Mitigation – Trust Certification / Rating
- Concluding Section
  - About next week – Lectures 15, 16
  - Ask me anything

Introduction Section

Recap from Week 6 (Lectures 11, 12)

- We looked at
  - Fairness methods
  - Overview of major mitigation techniques – explanation and rating

Recap: ML Pipelines



Highly Simplified View

Image Credit: Trustworthy Machine Learning, Kush Varshney

AI News

- Blog on Crawl-Walk-Run, as applied to an AI project
  - https://www.linkedin.com/pulse/crawl-walk-run-approach-ai-based-real-world-problem-biplav-srivastava-pxsre/

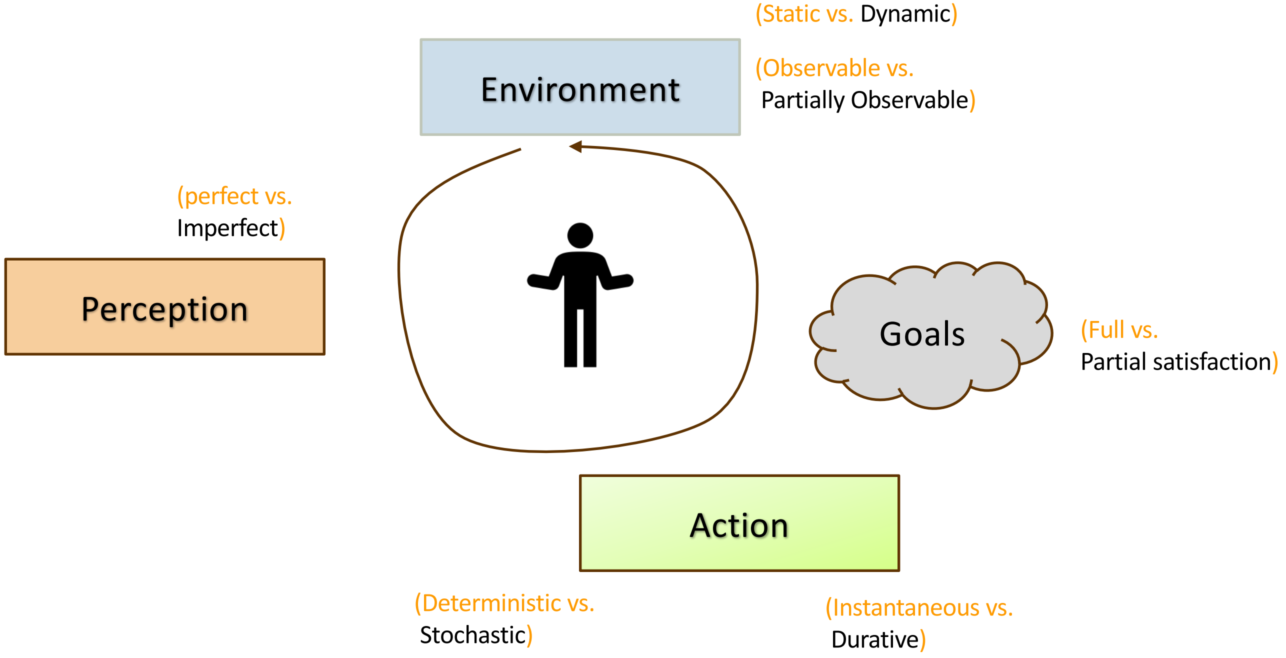
Announcement: Change to
Student Assessment

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



(Static vs. Dynamic)

Environment

(Observable vs. Partially Observable)

(perfect vs. Imperfect)

Perception

Goals

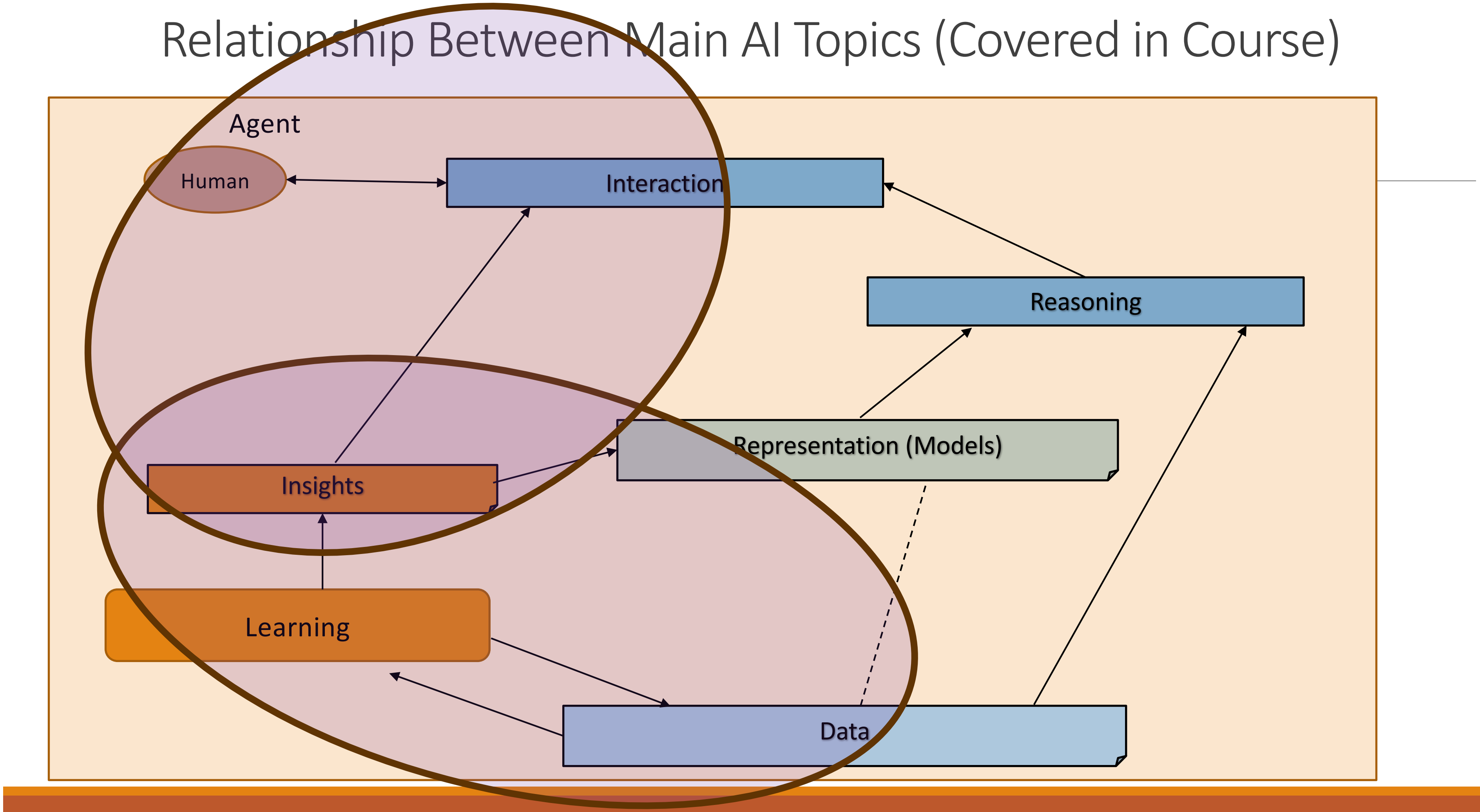
(Full vs. Partial satisfaction)

Action

(Deterministic vs. Stochastic)

(Instantaneous vs. Durative)

Relationship Between Main AI Topics (Covered in Course)



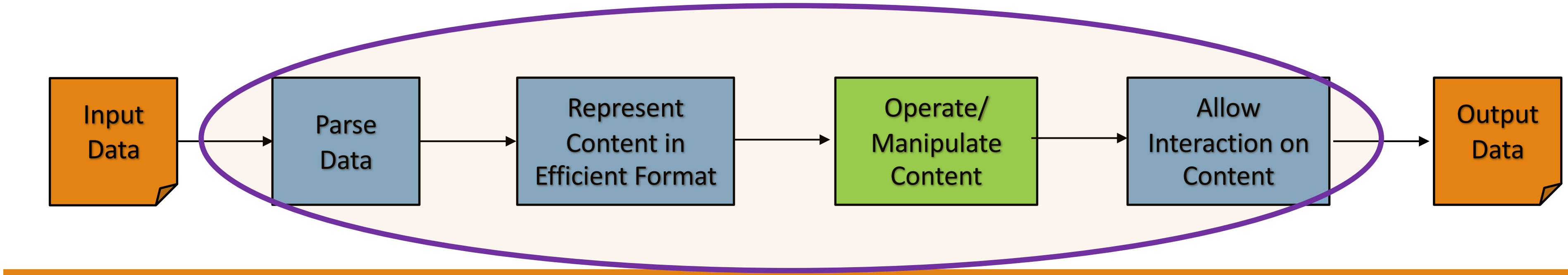
High Level Semester Plan (Adapted, Approximate)

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 Segment


Input Data
Parse Data
Represent Content in Efficient Format
Operate/ Manipulate Content
Allow Interaction on Content
Output Data

ML Pipelines and Trust-Based Intervention Considerations

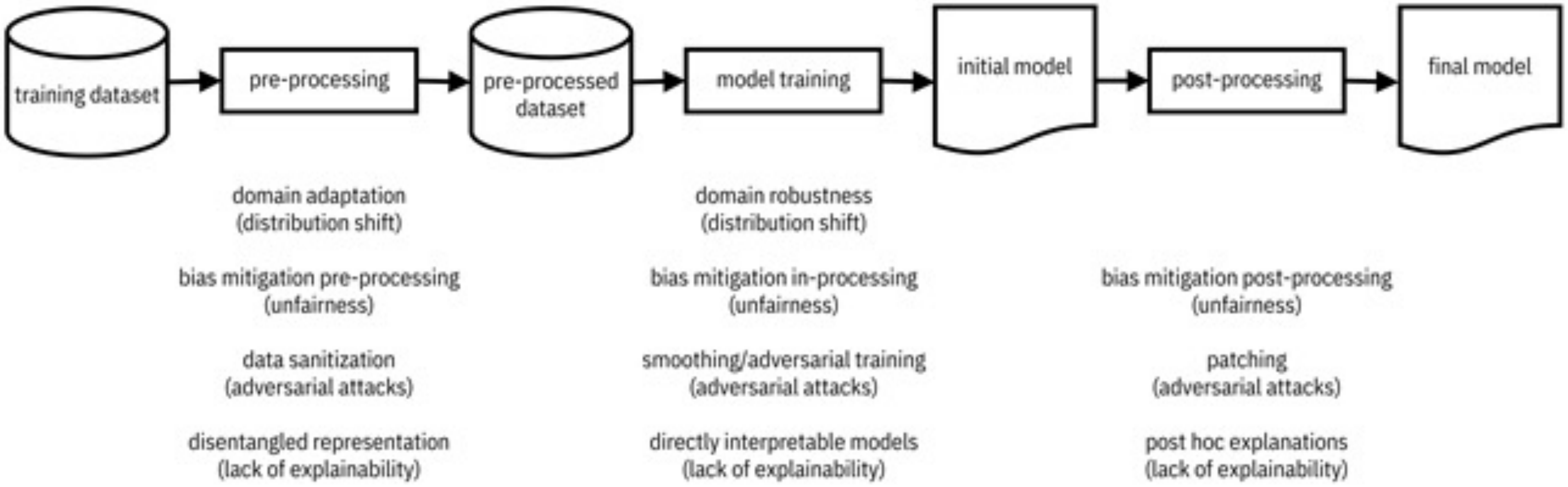

training dataset
pre-processing
pre-processed dataset
model training
initial model
post-processing
final model
domain adaptation (distribution shift)
bias mitigation pre-processing (unfairness)
data sanitization (adversarial attacks)
disentangled representation (lack of explainability)
domain robustness (distribution shift)
bias mitigation in-processing (unfairness)
smoothing/adversarial training (adversarial attacks)
directly interpretable models (lack of explainability)
bias mitigation post-processing (unfairness)
patching (adversarial attacks)
post hoc explanations (lack of explainability)

Image Credit: Trustworthy Machine Learning, Kush Varshney

Generating Explanations

Trust Issues – Mitigate via Explanations

- Explain behavior
  - Remove undesirable behavior ?
    - Explain that too?

Trust Dimensions
Competent
Reliable
Upholds human values
Allows human interaction

What is the Purpose of Explanations

Purposes for explanations in **psychology**

- To **predict similar events** in the future: *slippery roads can cause a fall*. Use information later.

  Explanations: correlational (similar or contrastive)

- For **diagnosis**: *why a system failed and then repair a part to bring it back to its normal function*

  Explanations: causal (states or state-action; past)

- To **affix blame**: *for a crime*

  Explanations: causal (state-actor; past)

- To justify or **rationalize an action**: *sweet to an enemy because of the strategic value of being nice on that occasion*

  Explanations: causal (state-action; past or future)

- In the service of **aesthetic** pleasure

Source: Keil F. C. (2006). Explanation and understanding. *Annual review of psychology*, *57*, 227–254.
https://doi.org/10.1146/annurev.psych.57.102904.190100
https://pubmed.ncbi.nlm.nih.gov/16318595/

Instructor (Biplav) comments

In AI, Stakeholders for Explanations

- Executives
  - Executives want to use explainability as a market differentiator. Do we need explanations?

Explanations: to predict, rationalize an action

- ML engineers
  - Developers want to improve models. How to improve model’s performance?
  - They want to debug their models. How to diagnose a problem?

Explanations: for diagnosis, to predict, rationalize an action, affix a blame

- End-users
  - End-users want to reap benefits. They want to understand business decisions emanating from usage of AI
    - Why was my loan denied?
    - Why a particular treatment was recommended or de-prioritized ?

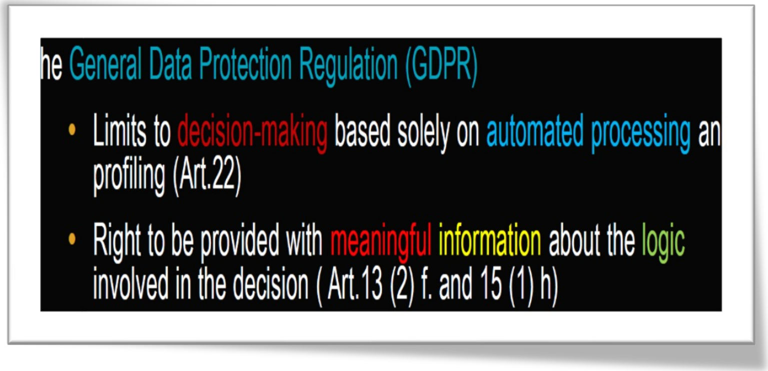
Explanations: rationalize an action, affix a blame

- Regulators
  - Based on existing laws, the AI (including the developer of AI) is evaluated to ensure that it does not discriminate towards the end users That is, based in application domain,
    - Patient does not get discriminated [Health]
    - The loan applicant is treated equally [Finance]
    - The job seeker …, the housing loan …, …

Explanations: to predict, affix a blame

Source: Explainable Machine Learning in Deployment, FAT* 2020, https://arxiv.org/pdf/1909.06342.pdf; Video: https://www.youtube.com/watch?v=Hofl4uwxtPA

AI Explainability from Legal Requirements

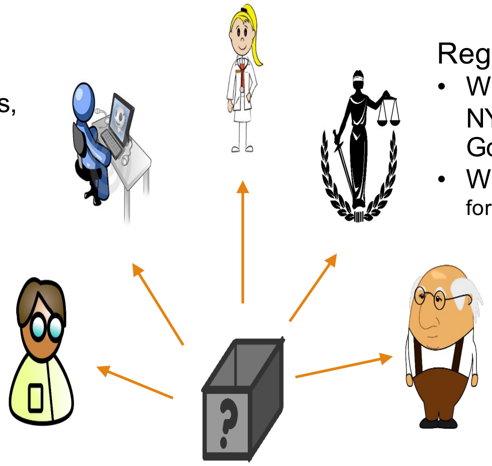


he General Data Protection Regulation (GDPR)

- Limits to decision-making based solely on automated processing an profiling (Art.22)
- Right to be provided with meaningful information about the logic involved in the decision (Art.13 (2) f. and 15 (1) h)

Explanations: rationalize an action

Meaningful explanations depend on the consumer



End Users
- Who: Physicians, judges, loan officers, teacher evaluators
- Why: trust/confidence, insights(

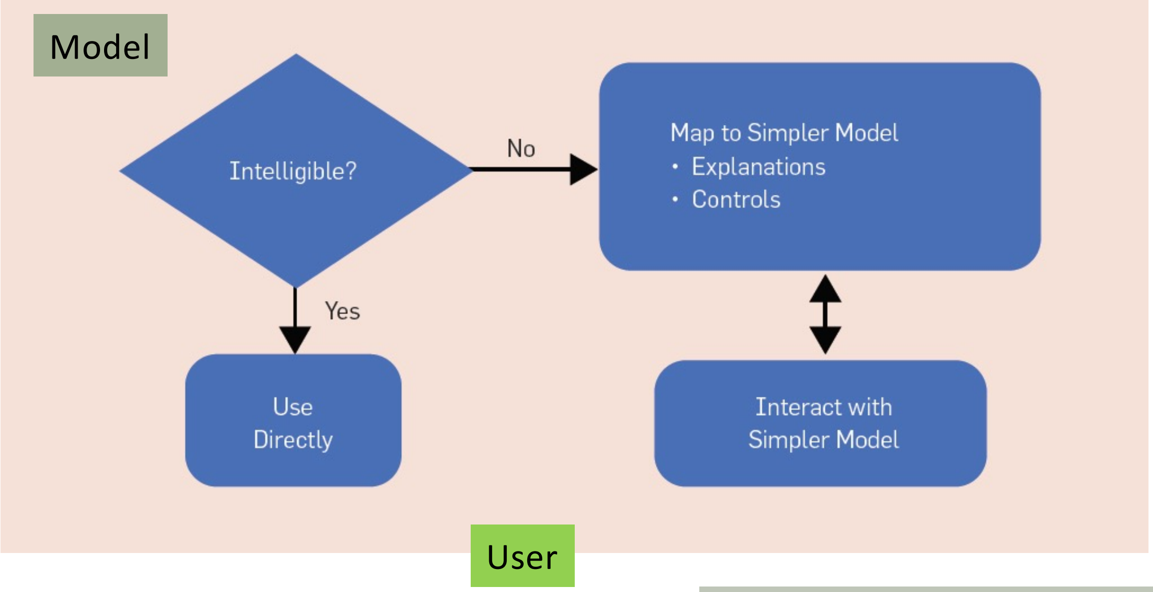
AI System builders, stakeholders
- Who: data scientists, developers, prod mgrs
- Why: ensure/improve performance

Regulatory Bodies
- Who: EU (GDPR), NYC Council, US Gov't, etc
- Why: ensure fairness for constituents

Affected Users
- Who: Patients, accused, loan applicants, teachers
- Why: understanding of factors

Must match the complexity capability of the consumer
Must match the domain knowledge of the consumer

Setting and Terminology: Intelligible Models and Explanations



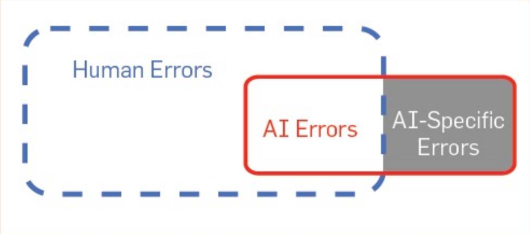
- Transparency: providing stakeholders with relevant information about how a model works
- Explainability: Providing insights into model's behavior for specific datapoints

Sources:

1. The Challenge of Crafting Intelligible Intelligence, Daniel S. Weld, Gagan Bansal, Communications of the ACM, June 2019, Vol. 62 No. 6, Pages 70-79, 10.1145/3282486
2. Explainable Machine Learning in Deployment, FAT* 2020.

Need for Intelligibility

The red shape denotes the AI's mistakes; its smaller size indicates a net reduction in the number of errors. The gray region denotes AI-specific mistakes a human would never make. Despite reducing the total number of errors, a deployed model may create new areas of liability (gray), necessitating explanations.



- **AI may have the wrong objective:** is AI right for the right reasons?
- **AI may be using inadequate features:** understand modeling issues
- **Distributional drift:** detect when and why models are failing to generalize
- **Facilitating user control:** guiding what preferences to learn
- **User acceptance:** especially for costly actions
- **Improving human insight:** improve algorithm design
- **Legal imperatives**

Source: The Challenge of Crafting Intelligible Intelligence, Daniel S. Weld, Gagan Bansal, Communications of the ACM, June 2019, Vol. 62 No. 6, Pages 70-79, 10.1145/3282486

Types of Explanation Generation Methods

- **Feature-based**: from the features of the data, which feature(s) were most important for given decision output
  - Example: For a loan, is it income or the person's age ?
- **Sample-based**: from data in training, which data points were important for given test point; helps understand sampling and its representation in wider population
  - Example: For a loan, what instances similar to the loan application would have gotten the loan ?
- **Counter-factual**: what-ifs – what do you change about the input to change the decision output
  - Example: For a loan, does getting an additional borrower insurance increase chance of getting the loan?
- Natural language

Source: Explainable Machine Learning in Deployment, FAT* 2020

References for AI Explainability

Papers

- The Challenge of Crafting Intelligible Intelligence, Daniel S. Weld, Gagan Bansal, Communications of the ACM, June 2019, Vol. 62 No. 6, Pages 70-79, 10.1145/3282486
- "Why Should I Trust You?" Explaining the Predictions of Any Classifier, Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin, in ACM's Conference on Knowledge Discovery and Data Mining, KDD2016; https://homes.cs.washington.edu/~marcotcr/blog/lime/, https://www.oreilly.com/content/introduction-to-local-interpretable-model-agnostic-explanations-lime/
- Explainable Machine Learning in Deployment, FAT* 2020, https://arxiv.org/pdf/1909.06342.pdf; Video: https://www.youtube.com/watch?v=Hofl4uwxtPA

Tutorial: XAI tutorial at AAAI 2020, https://xaitutorial2020.github.io/

Tool: AIX 360

Tool: https://aix360.mybluemix.net/

Video: https://www.youtube.com/watch?v=Yn4yduyoQh4

Paper: https://arxiv.org/abs/1909.03012

LIME – Local Interpretable Model-Agnostic Explanations

Paper: “Why Should I Trust You?” Explaining the Predictions of Any Classifier, Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin, ACM’s Conference on Knowledge Discovery and Data Mining, KDD2016

Blogs:

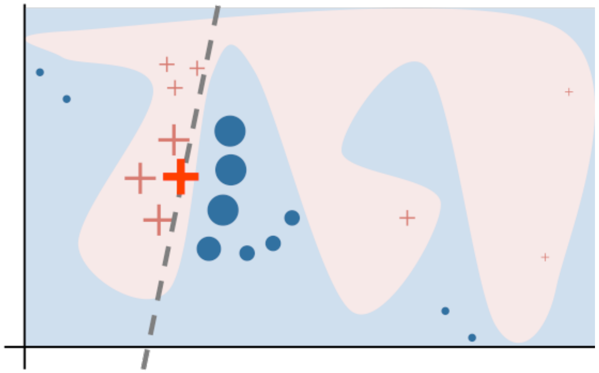
- https://homes.cs.washington.edu/~marcotcr/blog/lime/
- https://www.oreilly.com/content/introduction-to-local-interpretable-model-agnostic-explanations-lime/

Code: https://github.com/marcotcr/lime

Figures credit: Marco Tulio Ribeiro

LIME Key Idea

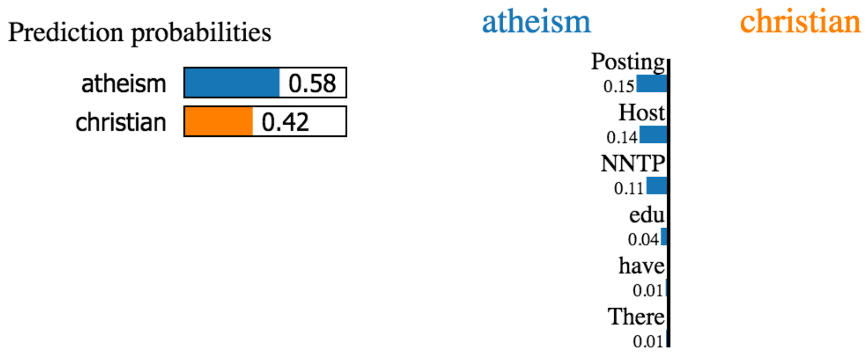
- Generate a local, linear explanation for any model
- How
  - Perturb near the neighborhood of a point of interest, X (**Local**)
  - Fit a linear function to the model’s output (**Linear**)
  - Interpret coefficients of the linear function (**Explain**)
  - **Visualize**
- Applicability
  - Any classification model!

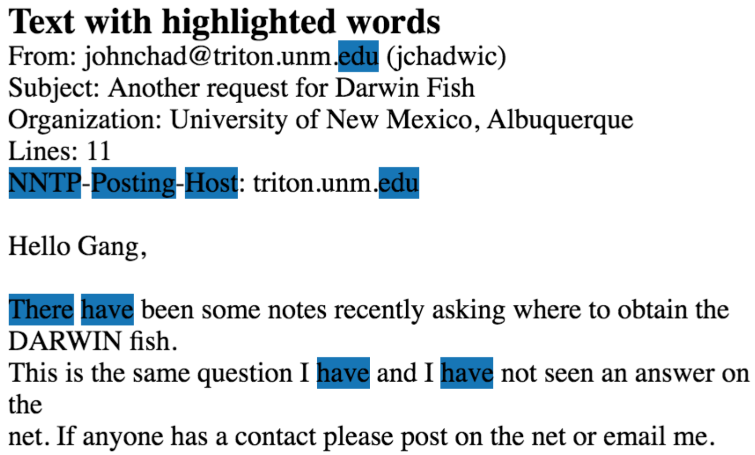


LIME on Text

Question: Why is a classifier with >90% accuracy predicting based on ?

Task: classifying religious inclination from email text





Text with highlighted words

From: johnchad@triton.unm.edu (jchadwic)
Subject: Another request for Darwin Fish
Organization: University of New Mexico, Albuquerque
Lines: 11
NNTP-Posting-Host: triton.unm.edu

Hello Gang,

There have been some notes recently asking where to obtain the DARWIN fish.
This is the same question I have and I have not seen an answer on the
net. If anyone has a contact please post on the net or email me.

"If we remove the words **Host** and **NNTP** from the document, we expect the classifier to predict **atheism** with probability 0.58 - 0.14 - 0.11 = 0.31"

Source: https://github.com/marcotcr/lime

Code Examples for Tabular Data

- LIME
  - Iris dataset and supervised classifiers – random forest and logistic regression, tabular data: https://github.com/biplav-s/course-tai/blob/main/sample-code/l9-explanations/LIME%20explanations%20on%20tabular%20data.ipynb

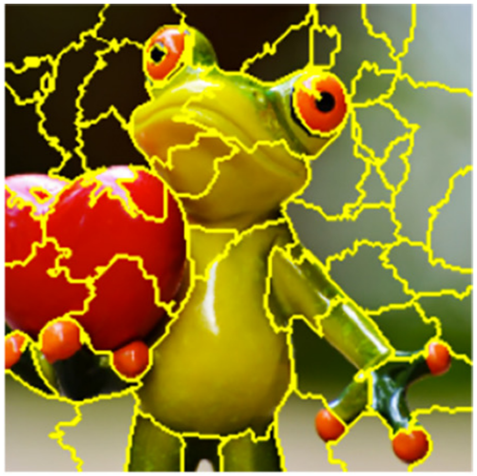
- Many other examples
  - https://github.com/biplav-s/course-d2d-ai/tree/main/sample-code/l12-explanability-autoai

LIME on Image

Question: Why is this a frog?

Divide image into interpretable components - contiguous superpixels

Original Image

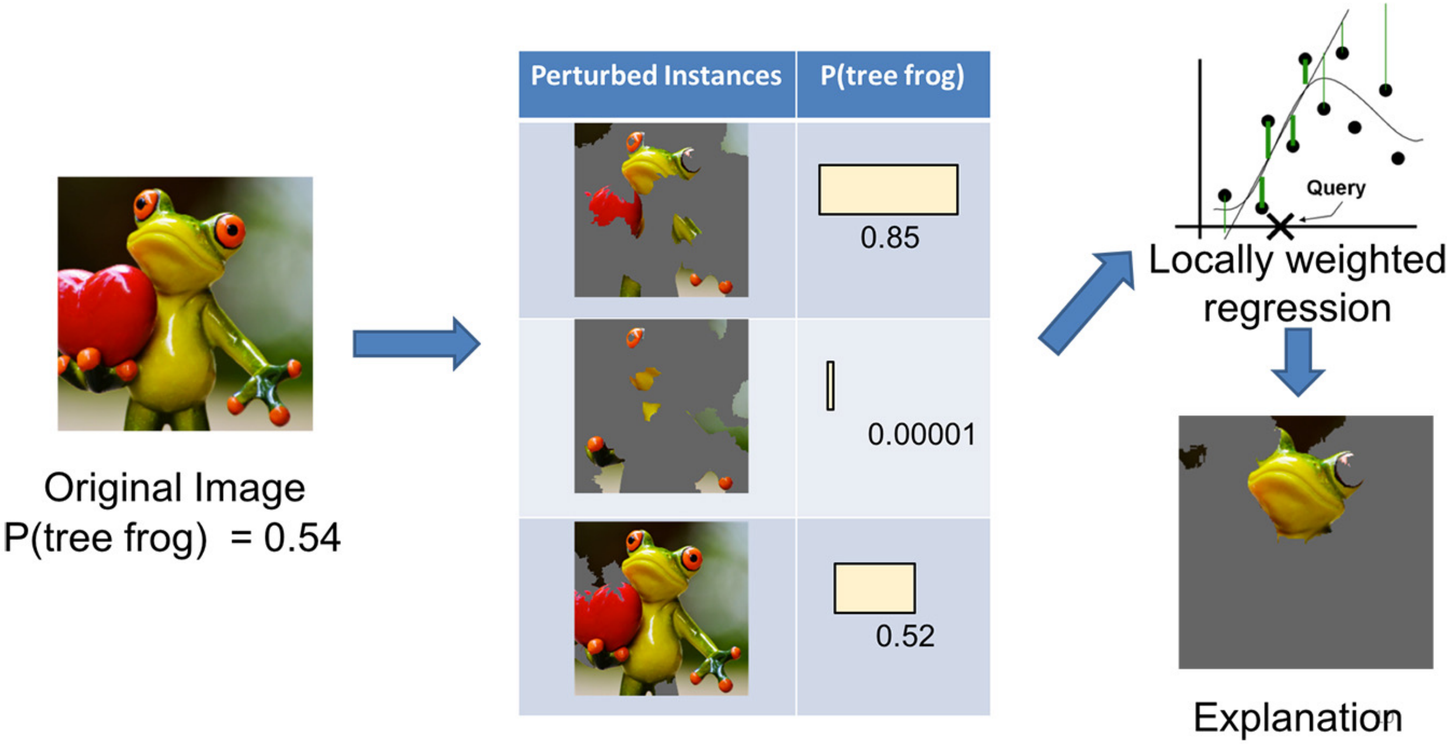


Interpretable Components

Source: https://www.oreilly.com/content/introduction-to-local-interpretable-model-agnostic-explanations-lime/

LIME

1. Generate a data set of perturbed instances by turning some of the interpretable components “off” (gray).
2. For each perturbed instance, calculate probability that a tree frog is in the image according to the model.
3. Learn a simple (linear) model on this data set, which is locally weighted
4. Output regions with highest positive weights as an explanation, graying out everything else.



Original Image

P(tree frog) = 0.54

Perturbed Instances	P(tree frog)
	0.85
	0.00001
	0.52

Locally weighted regression

Explanation

Source: https://www.oreilly.com/content/introduction-to-local-interpretable-model-agnostic-explanations-lime/

Explanation and Practical Implications

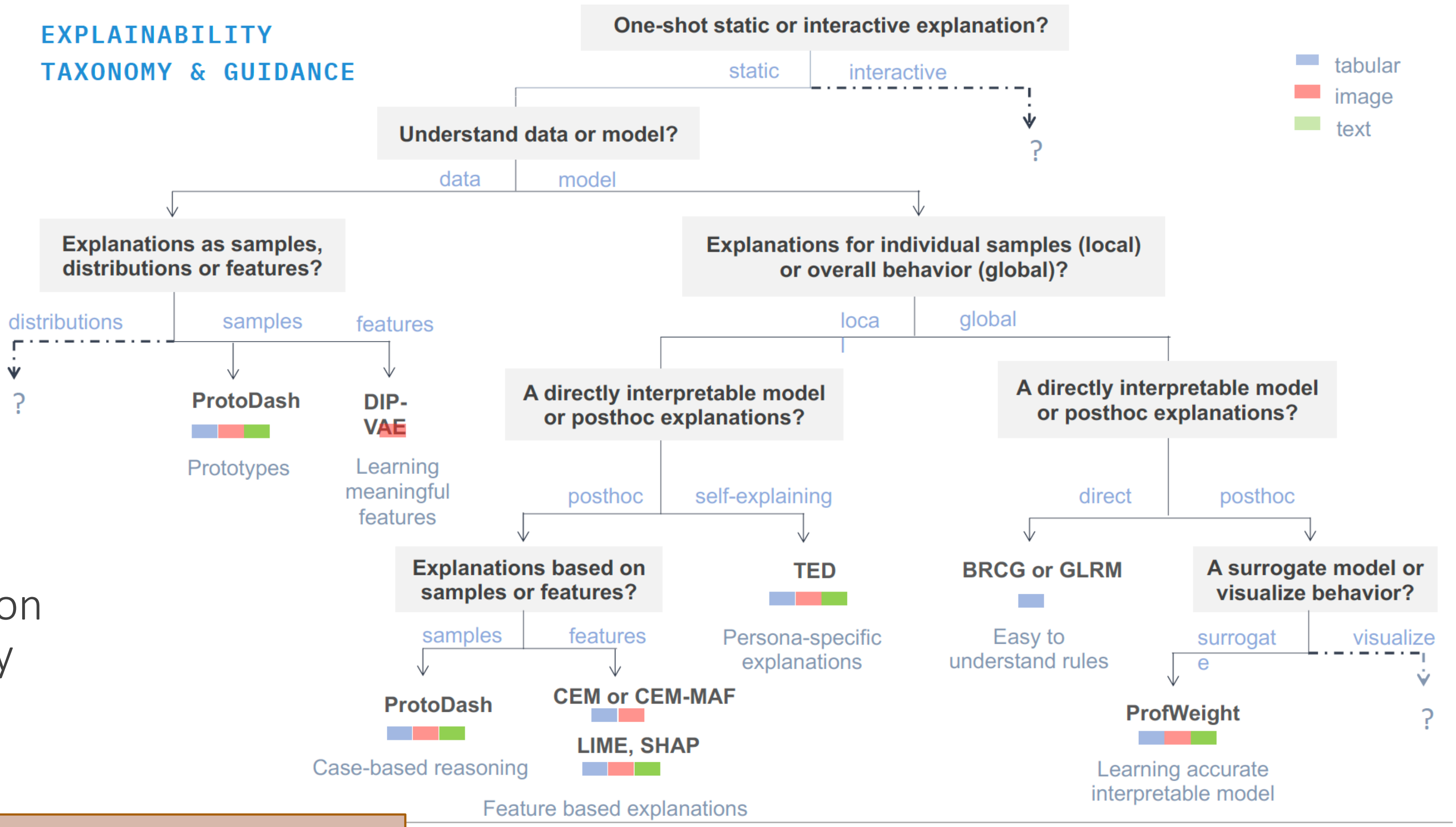
- Context
  - Problem: detect common cardiovascular conditions
  - Data: ECG data
  - Explanation: LIME
- References
  - Blog: https://www.ucsf.edu/news/2021/08/421301/ai-algorithm-matches-cardiologists-expertise-while-explaining-its-decisions
  - Paper: https://jamanetwork.com/journals/jamacardiology/article-abstract/2782549

InterpretML

- **Details**: https://github.com/interpretml/interpret?tab=readme-ov-file#citations
  - Whitebox (Glassbox) models: change learning code to introduce explainability support
  - Blackbox models: don’t change learning code

Interpretability Technique	**Type**
Explainable Boosting	**glassbox model**
APLR	glassbox model
Decision Tree	glassbox model
Decision Rule List	glassbox model
Linear/Logistic Regression	glassbox model
SHAP Kernel Explainer	blackbox explainer
LIME	**blackbox explainer**
Morris Sensitivity Analysis	blackbox explainer
Partial Dependence	blackbox explainer

Explanation Taxonomy



EXPLAINABILITY TAXONOMY & GUIDANCE

🟦 tabular
🟥 image
🟩 text

One-shot static or interactive explanation?

static

interactive

?

Understand data or model?

data

model

Explanations as samples, distributions or features?

distributions

samples

features

?

ProtoDash 🟦🟥🟩

Prototypes

DIP-VAE 🟥

Learning meaningful features

Explanations for individual samples (local) or overall behavior (global)?

loca

l

global

A directly interpretable model or posthoc explanations?

posthoc

self-explaining

Explanations based on samples or features?

samples

features

ProtoDash 🟦🟥🟩

Case-based reasoning

CEM or CEM-MAF 🟦🟥

LIME, SHAP 🟦🟥🟩

Feature based explanations

TED 🟦🟥🟩

Persona-specific explanations

A directly interpretable model or posthoc explanations?

direct

posthoc

BRCG or GLRM 🟦

Easy to understand rules

A surrogate model or visualize behavior?

surrogat
e

visualize

ProfWeight 🟦🟥🟩

Learning accurate interpretable model

?

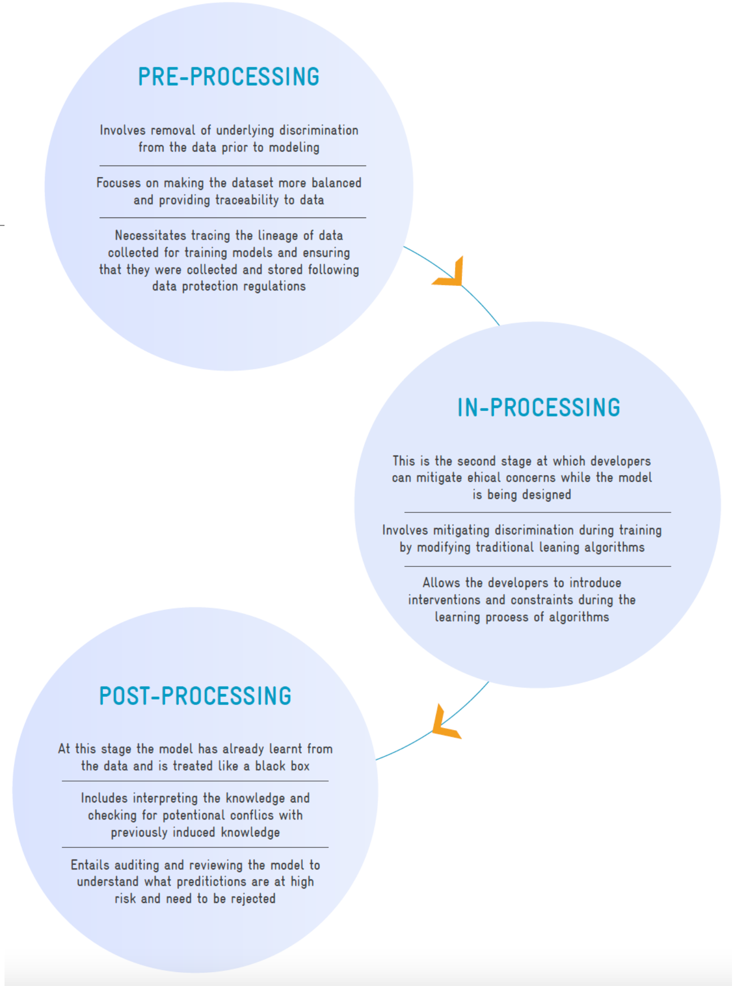
Figure Credit: Diptikalyan Saha and Vijay Arya, Oct 2021

Many Explanation Methods

- Review paper on many methods and data types (image, text, audio, and sensory domains):
  - **How Can I Explain This to You? An Empirical Study of Deep Neural Network Explanation Methods,** *Jeya Vikranth Jeyakumar, Joseph Noor, Yu-Hsi Cheng, Luis Garcia, Mani Srivastava,* Advances in Neural Information Processing Systems 33 (NeurIPS 2020), https://proceedings.neurips.cc/paper/2020/hash/2c29d89cc56cdb191c60db2f0bae796b-Abstract.html

Handbook on Data Protection and Privacy for Developers of Artificial Intelligence

- Details: https://www.dsci.in/content/privacy-handbook-for-ai-developers
  - PDF in Blackboard
  - Created for developers with focus on practical considerations
  - Inputs from people from a broad set of background



PRE-PROCESSING

Involves removal of underlying discrimination from the data prior to modeling

Focuses on making the dataset more balanced and providing traceability to data

Necessitates tracing the lineage of data collected for training models and ensuring that they were collected and stored following data protection regulations

IN-PROCESSING

This is the second stage at which developers can mitigate ehical concerns while the model is being designed

Involves mitigating discrimination during training by modifying traditional leaning algorithms

Allows the developers to introduce interventions and constraints during the learning process of algorithms

POST-PROCESSING

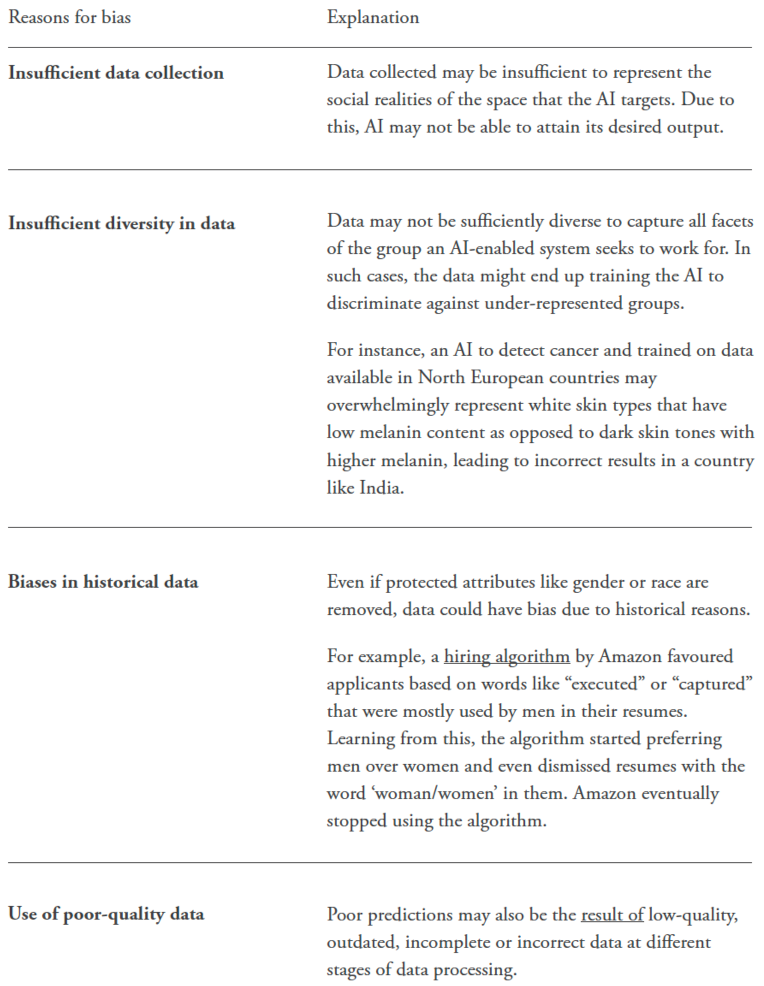
At this stage the model has already learnt from the data and is treated like a black box

Includes interpreting the knowledge and checking for potentional conflics with previously induced knowledge

Entails auditing and reviewing the model to understand what preditictions are at high risk and need to be rejected

Source: Handbook on Data Protection and Privacy for Developers of Artificial Intelligence, 2021

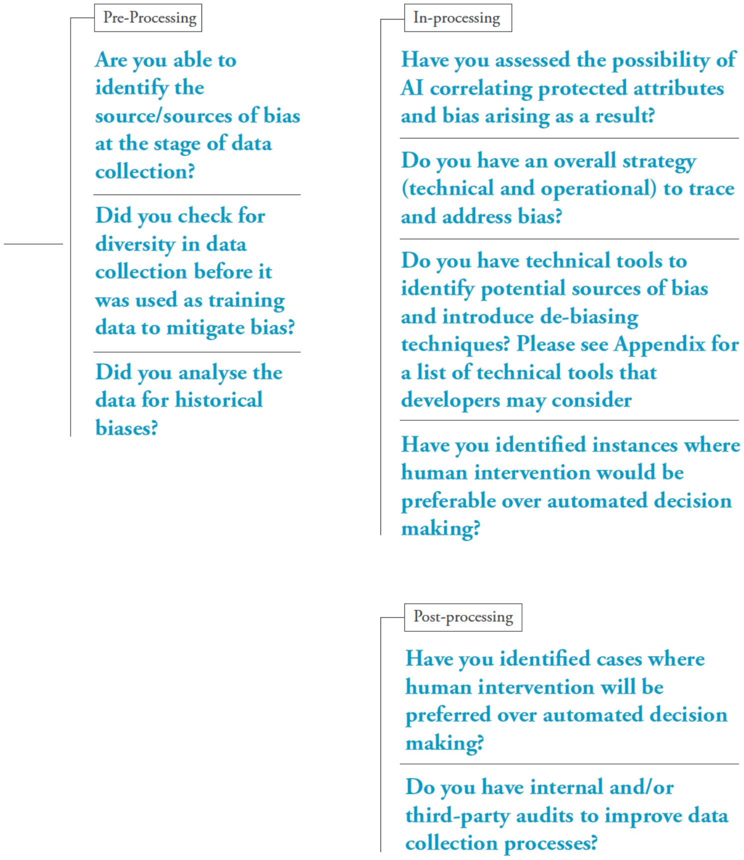
(Data-based) Reasons for Bias



Reasons for bias	Explanation
Insufficient data collection	Data collected may be insufficient to represent the social realities of the space that the AI targets. Due to this, AI may not be able to attain its desired output.
Insufficient diversity in data	Data may not be sufficiently diverse to capture all facets of the group an AI-enabled system seeks to work for. In such cases, the data might end up training the AI to discriminate against under-represented groups. For instance, an AI to detect cancer and trained on data available in North European countries may overwhelmingly represent white skin types that have low melanin content as opposed to dark skin tones with higher melanin, leading to incorrect results in a country like India.
Biases in historical data	Even if protected attributes like gender or race are removed, data could have bias due to historical reasons. For example, a hiring algorithm by Amazon favoured applicants based on words like "executed" or "captured" that were mostly used by men in their resumes. Learning from this, the algorithm started preferring men over women and even dismissed resumes with the word 'woman/women' in them. Amazon eventually stopped using the algorithm.
Use of poor-quality data	Poor predictions may also be the result of low-quality, outdated, incomplete or incorrect data at different stages of data processing.

Source: Handbook on Data Protection and Privacy for Developers of Artificial Intelligence, 2021

Developer Checklist



Pre-Processing

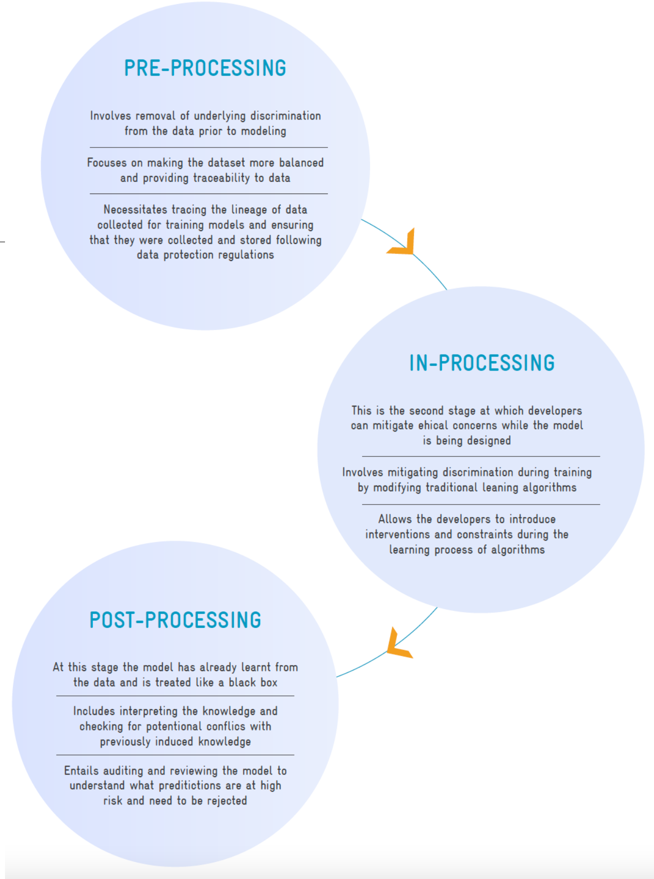
- Are you able to identify the source/sources of bias at the stage of data collection?
- Did you check for diversity in data collection before it was used as training data to mitigate bias?
- Did you analyse the data for historical biases?

In-processing

- Have you assessed the possibility of AI correlating protected attributes and bias arising as a result?
- Do you have an overall strategy (technical and operational) to trace and address bias?
- Do you have technical tools to identify potential sources of bias and introduce de-biasing techniques? Please see Appendix for a list of technical tools that developers may consider
- Have you identified instances where human intervention would be preferable over automated decision making?

Post-processing

- Have you identified cases where human intervention will be preferred over automated decision making?
- Do you have internal and/or third-party audits to improve data collection processes?



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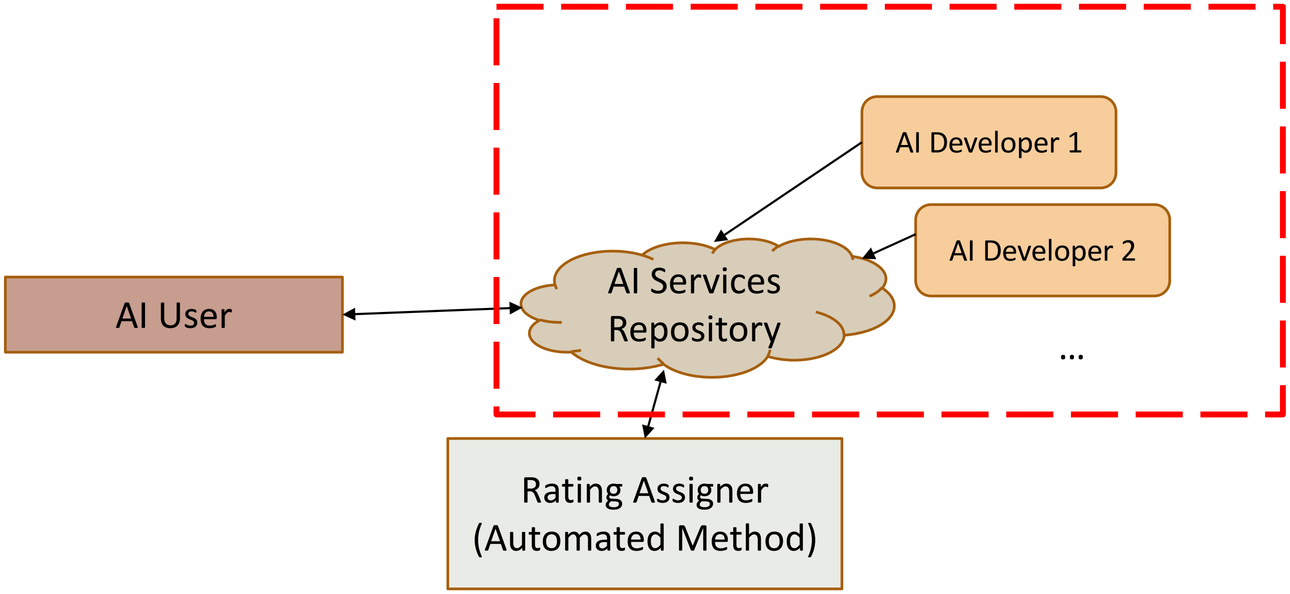
Generating Ratings / Certificates for AI's Assessed Behavior

Idea: Develop Automated Methods to Rate AI Systems That Can be Used for Communicating Trust in Black Box Setting



Trust Issues – Mitigate via Ratings

- Communicate behavior via certificates / ratings (increase transparency)
  - But, let humans make decisions

Trust Dimensions
Competent
Reliable
Upholds human values
Allows human interaction

Transparency Through Documentation of Rating

Documentation about

- Outcome (e.g., Nutrition label, Electronic DataSheet, Factsheet)
- Process (e.g., SEI Capability Maturity Model, ISO 9001)

Documentation by

- Producer (e.g., Nutrition label)
- Consumer (e.g., Yelp rating)
- Independent 3rd Party (e.g., JD Powers, NHTSA car crash)

Reference: AboutML Project at PAI - https://www.partnershiponai.org/about-ml-get-involved/#read

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

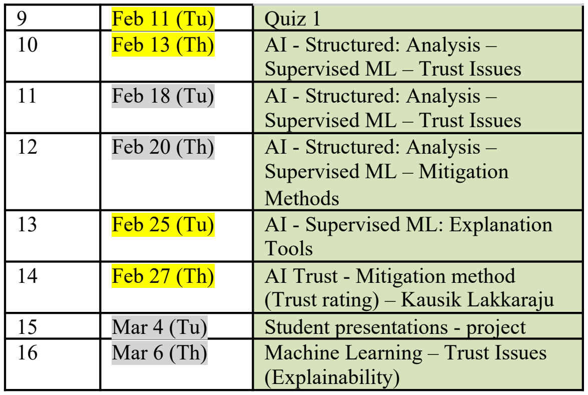
Week 7 (L13 and 14): Concluding Comments

- We looked at
  - Explanation methods
  - Generating trust certificates/ ratings

About Next Week – Lectures 15, 16

Lectures 15, 16:

- Student Projects - ”Walk” stage presentations
- ML/ Classification: Trust Mitigation – Explanation methods



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
13	Feb 25 (Tu)	AI - Supervised ML: Explanation Tools
14	Feb 27 (Th)	AI Trust - Mitigation method (Trust rating) – Kausik Lakkaraju
15	Mar 4 (Tu)	Student presentations - project
16	Mar 6 (Th)	Machine Learning – Trust Issues (Explainability)