

CSCE 590-1: Trusted AI

Lecture 9: AI: Supervised ML / Trust / Explanations

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16TH SEP, 2021

Carolinian Creed: “I will practice personal and academic integrity.”

Organization of Lecture 9

- Introduction Segment
 - Recap from Lecture 8
 - Project discussion
- Main Segment
 - Explanation
 - Explanation Method: LIME
 - Book: Handbook on Data Protection and Privacy for Developers of Artificial Intelligence
- Concluding Segment
 - About next lecture – Lecture 10
 - Ask me anything

Introductory Segment

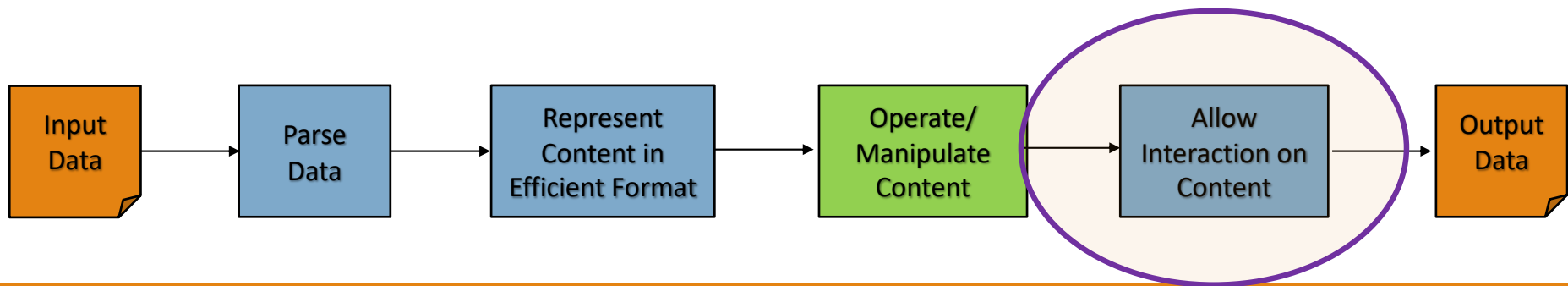
Recap of Lecture 8

- We looked at bias definitions
 - Five categories: C1: predicted outcome, C2: predicted and actual outcome, C3: predicted probabilities and actual outcome , C4: similarity based, C5: causal reasoning
 - Reviewed with respect to German-credit as example
- Metrics should not only be technically sound but practically useful
 - Did role-playing to discuss: for loans, loan applicant, banker and regulator roles
 - **We can consider for the class: coding language (Python, Java, ...) domain. Roles: Student, instructor, university ?**
- Most definitions are theoretical exercises while law catches up; little technical guidance to developers

Project Discussion – Review Projects

- Information to be shared by students
 - Go to Google sheet: <https://docs.google.com/spreadsheets/d/1VAX8ntb5zBQ-vOdsMHMhvEdwoaCZtuBaO4kJdkSA4eQ/edit?usp=sharing>
 - Create a Google drive called “CSCE 590-1 Trusted AI (<YourName>)” and share with instructor: firstname.lastname@gmail.com
 - Put shared url in Column E
 - Put project title in column G
 - Create a folder in shared directory call project. Under it, have a Google doc called “Project Description”. In it, have the following as bullets with associated details: **Problem, User, AI Method, Data, Reliability: Testing, Holding Human Values, Human-AI interaction.** See next slide for framework and guidance on what to put.
- Put Github location for your code in F
 - Create one repository
 - For each quiz, project, etc, create a sub-folder

Main Segment



Generating Explanations

What is the Purpose of Explanations

- Explanation and understanding
 - Frank C Keil, <https://pubmed.ncbi.nlm.nih.gov/16318595/>
- Purposes for explanations in **psychology**
 - To predict similar events in the future: *slippery roads can cause a fall*. Use information later.
 - For diagnosis: *why a system failed and then repair a part to bring it back to its normal function*
 - To affix blame: *for a crime*
 - To justify or rationalize an action: *sweet to an enemy because of the strategic value of being nice on that occasion*
 - In the service of aesthetic pleasure

In AI, Stakeholders for Explanations

- Executives
 - Explainability as a market differentiator. Do we need explanations?
- ML engineers
 - How to improve model's performance?
- End-users
 - Understand business decisions emanating from usage of AI
 - Why was my load denied?
 - Why a particular treatment was recommended or de-prioritized ?
- Regulators
 - Prove that you did not discriminate based on existing laws

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

Meaningful explanations depend on the consumer

the General Data Protection Regulation (GDPR)

- Limits to **decision-making** based solely on **automated processing** and 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)

AI System builders, stakeholders

- Who: data scientists, developers, prod mgrs
- Why: ensure/improve performance

End Users

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

Regulatory Bodies

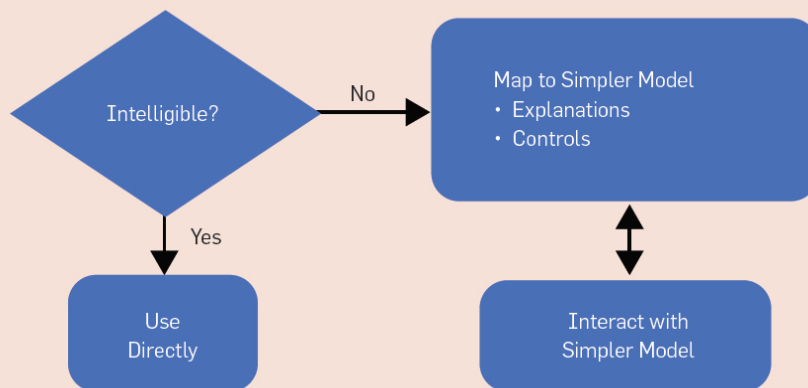
- Who: EU (GDPR), NYC Council, US Gov't, etc
- Why: ensure fairness for constituents

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



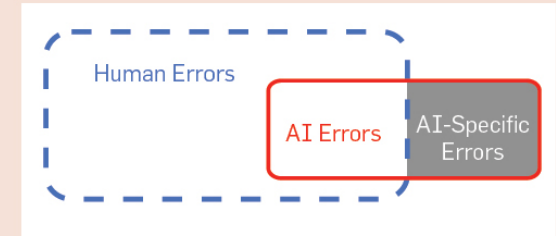
- Transparency: providing stakeholders with relevant information about how a model works
- Explainability: Providing insights into model's behavior for specific datapoints

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 Explanations

- **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

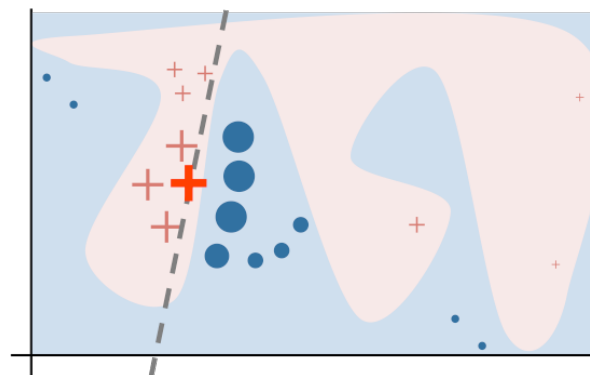
Blogs:

- <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>

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 ?

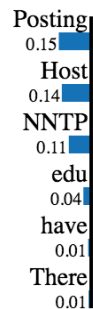
Task: classifying religious inclination from email text

Prediction probabilities



atheism

christian



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

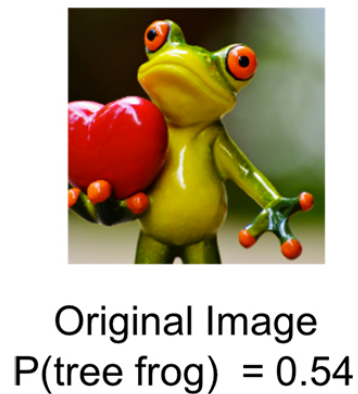



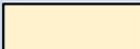

Interpretable
Components

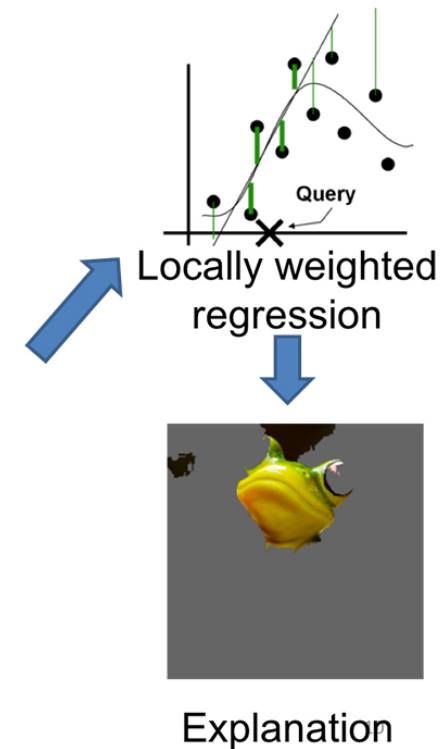
Source: <https://www.oreilly.com/content/introduction-to-local-interpretable-model-agnostic-explanations-lime/>

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.



Perturbed Instances	$P(\text{tree frog})$
	<div><div></div>0.85</div>
	<div><div></div>0.00001</div>
	<div><div></div>0.52</div>



Explanation and Practical Implications

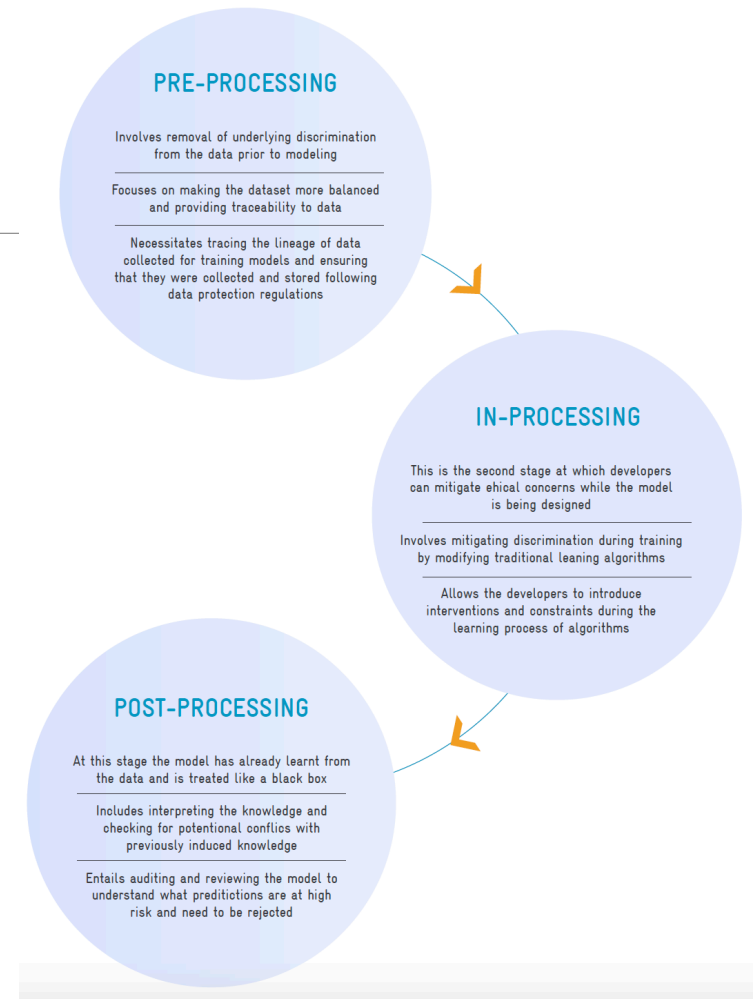
- Context
 - Problem: detect common cardiovascular conditions
 - Data: ECG data
 - Explanation: LIME
- References
 - Blog: <https://www.ucsf.edu/news/2021/08/421301/ai-algorithm-matches-cardiologists-expertise-while-explaining-its-decisions>
 - Paper: <https://jamanetwork.com/journals/jamacardiology/article-abstract/2782549>

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),
<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



(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	<p>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.</p> <p>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.</p>
Biases in historical data	<p>Even if protected attributes like gender or race are removed, data could have bias due to historical reasons.</p> <p>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.</p>
Use of poor-quality data	Poor predictions may also be the <u>result of</u> low-quality, outdated, incomplete or incorrect data at different stages of data processing.

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?

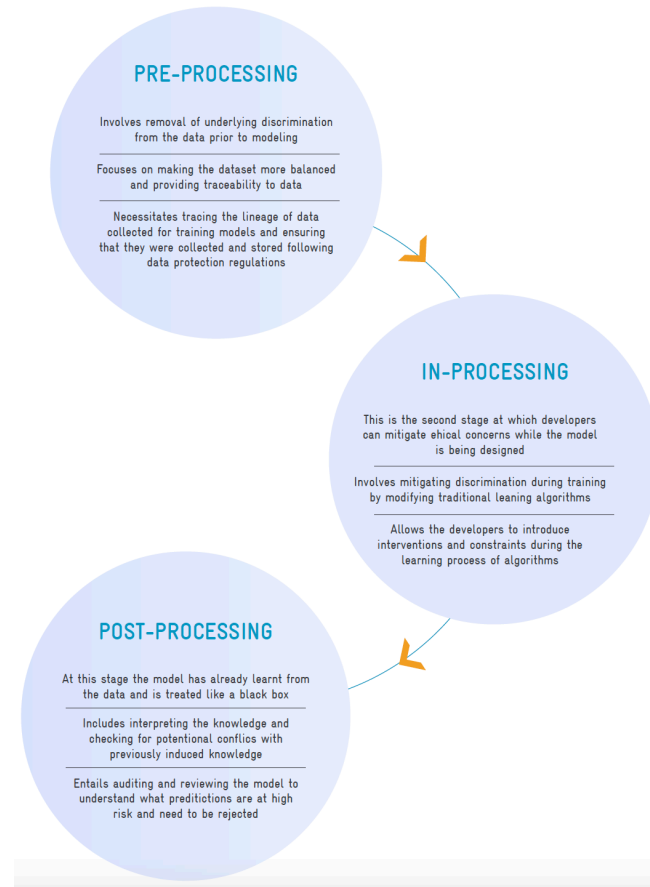
Do you have technical tools to identify potential sources of bias and introduce de-biasing techniques? Please see Appendix for a list of technical tools that developers may consider

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?



Developer Checklist

Concluding Segment

Lecture 9: Concluding Comments

- We looked at explanation
 - From psychology literature of its purpose
 - An automated method for AI models, LIME
 - Survey paper on explanation methods
- We reviewed guidance on model development
 - Book: Handbook on Data Protection and Privacy for Developers of Artificial Intelligence

About Next Lecture – Lecture 10

Lecture 10: Guest Speaker – Techniques from IBM

- Modified Logistics
 - Time: 10:00 – 11:15 am
 - Location: Seminar room, AI Institute – 5th floor at 1112 Greene St., Columbia; Science and Technology Building
 - Speaker to join over Blackboard
- Speaker: **Diptikalan Saha**, IBM Research
<https://researcher.watson.ibm.com/researcher/view.php?person=in-diptsaha>

Sep 21 (Tu)	Invited Guest – AI - Supervised ML: External Talk/ IBM's Approach
Sep 23 (Th)	Invited Guest – AI - Supervised ML: External Talk/ Working Session