Project 2: Interpretable and Explainable Classification for Medical Data

Samuel Ruipérez-Campillo
PhD Candidate, MDS, IML, D-INFK
samuel.ruiperezcampillo@inf.ethz.ch

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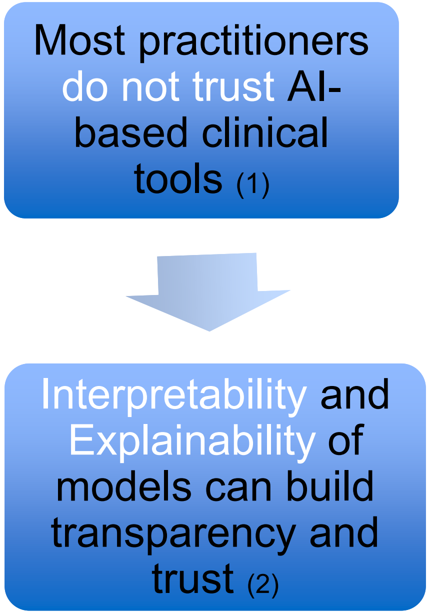
Big challenge to incorporate AI in clinical practice



Most practitioners do not trust AI-based clinical tools (1)

Interpretability and Explainability of models can build transparency and trust (2)

(1) https://www.fda.gov/media/143310/download

(2) He, J., Baxter, S.L., Xu, J. et al. The practical implementation of artificial intelligence technologies in medicine. Nat Med 25, 30–36 (2019)

Organisational

- Submit the report and code on Moodle until May 12th, 2025 (23:59)
- Report
  - **Must** be a PDF.
  - The report should be at most 4 pages (we encourage you to use the NeurIPS paper template)
  - The report should contain key figures.
  - ***You may include an 'Appendix' file of up to 5 pages for additional figures. It should contain only titles, figures, and figure captions—no extra text other than captions. Figures must be clear and legible when printed on A4, including readable axes, labels, etc. Figures with unreadable fonts will not be accepted.***
  - Should be self-contained, i.e. without references to code.
  - Code must be handed-in too and should follow the guidelines on the handout.
  - Underlined sections within questions specify how many points can be achieved by solving that specific subquestion.

Organisational

- You will also need to hand in your code (e.g. GitHub). Please include a requirements.txt or similar for your Python environment and a README.md explaining how to run your code.
- Do not train on the test sets and only provide results that are evaluated on the test set.
- Both datasets are publicly available on Kaggle. It is allowed to use publicly available code (apart from other groups' work) but make sure to properly reference external sources.
- For computation-heavy tasks, we have arranged access to the student cluster. The datasets can be accessed on /cluster/courses/ml4h/data_for_users/project2.
  Please refer to the introductory tutorial slides for more information about the student cluster.

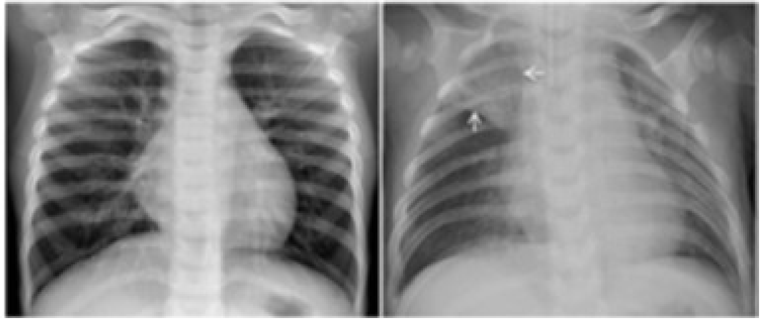
General Remarks

- As defined in the lecture, we will talk about ”Interpretability” in the context of intrinsically interpretable models, while we talk about “Explainability” in the context of a black-box model that requires an auxiliary method to explain its predictions.
- Interpretability and Explainability are not an exact science. There does not necessarily have to be a single correct answer.
- A partial goal of this project is that you use the materials available to you to teach yourself the methods that are being used.
- Using publicly available code is okay, but properly reference repositories when you use them. Of course, you are not allowed to use the code of other teams from the current and previous courses.
- Use the unique resources you are given.

Project 2: Interpretability and Explainability

Part 1: Tabular data for predicting coronary heart disease

Part 2: X-ray data for predicting pneumonia



Project 2: Interpretability and Explainability

Part 1: Tabular data for predicting coronary heart disease

Motivation for predicting heart disease

- Cardiovascular diseases (CVDs) are by far the number 1 cause of death globally. (1)
- CVD is an umbrella term for a number of heart-related conditions.
- Of those, coronary heart disease is the most common, being responsible for 16% of the world's total deaths. (2)
- In this project, you will train ML models for early detection of potential coronary heart diseases.
- With the help of interpretability and explainability, you will gain insights into which features are important indicators.
- These insights can be helpful for understanding the disease as well as build trust of doctors toward a (semi-)automated detection of heart diseases.

(1) IHME, Global Burden of Disease (2019)

(2) https://www.who.int/news-room/fact-sheets/detail/the-top-10-causes-of-death

Clinical Background (1,2,3)

- Coronary Heart Disease occurs when plaque builds up in the walls of the arteries.
- This narrows the arteries, leading to less oxygen-rich blood getting to your heart.
- Possible consequences:
  - Chest pain (=angina)
  - Heart failure
  - Blood clots that block blood flow
    - Heart muscles supplied by that artery begin to die
    - Heart attack

(1) https://www.nhlbi.nih.gov/sites/default/files/media/docs/Fact_Sheet_Know_Diff_Design.508_pdf.pdf

(2) https://www.mayoclinic.org/diseases-conditions/heart-failure/symptoms-causes/syc-20373142

(3) https://www.heart.org/en/health-topics/consumer-healthcare/what-is-cardiovascular-disease

Coronary Heart Disease Prediction Dataset (1,2)

- Aggregated dataset from
  1. Hungarian Institute of Cardiology. Budapest: Andras Janosi, M.D.
  2. University Hospital, Zurich, Switzerland: William Steinbrunn, M.D.
  3. University Hospital, Basel, Switzerland: Matthias Pfisterer, M.D.
  4. V.A. Medical Center, Long Beach and Cleveland Clinic Foundation: Robert Detrano, M.D., Ph.D.
- 918 Observations, 11 Features, 1 Binary response: Blood vessel diameter narrowing < or > 50%.
- Train/val - test split provided on Moodle and student cluster. Please use this split for comparability and reproducibility.
- Overall goal: Develop an automated ML model for the early detection of coronary heart disease and leverage interpretability or explainability to rationalize its predictions.

(1) http://archive.ics.uci.edu/ml/datasets/Heart+Disease

(2) https://www.kaggle.com/datasets/fedesoriano/heart-failure-prediction

Tasks for Part 1 (detailed description of deliverables in handout)

- Task 1: Exploratory Data Analysis
  - Before training any classifier, analyse the dataset at hand in order to get an understanding of the data.
  - Based on this, preprocess the data as you see fit.

Tasks for Part 1 (detailed description of deliverables in handout)

- Task 1: Exploratory Data Analysis
- Task 2: Logistic Lasso Regression
  - Lasso combines the logistic regression with a shrinkage factor, which sets unimportant coefficients to 0.
  - This provides interpretability by differentiating between important and unimportant features.

$$\hat{\beta} = \arg\min_{\beta} \; n^{-1} \sum_{i=1}^{n} (Y_i - X_i^T \beta)^2 + \lambda \|\beta\|_1$$

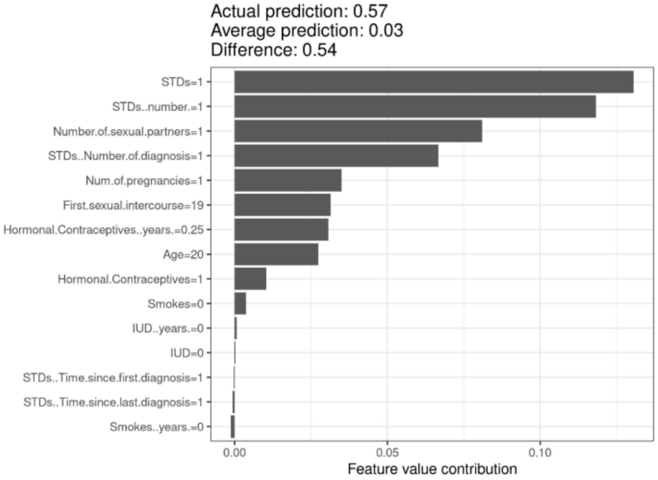
Tasks for Part 1 (detailed description of deliverables in handout)

- Task 1: Exploratory Data Analysis
- Task 2: Logistic Lasso Regression
- Task 3: Multi-layer Perceptrons + SHAP (1)
  - MLP's considered as black-boxes.
  - SHAP is a post-hoc explanation method that computes how much each feature contributes to the final prediction for any given ML model.

(1) https://papers.nips.cc/paper/2017/file/8a20a8621978632d76c43dfd28b67767-Paper.pdf

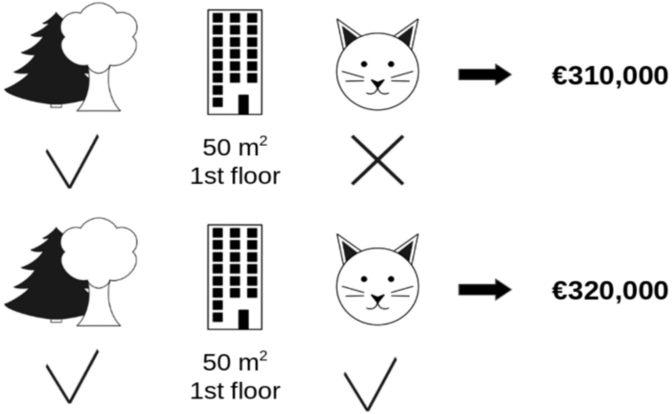
Shapley Values https://papers.nips.cc/paper/2017/file/8a20a8621978632d76c43dfd28b67767-Paper.pdf

- Feature contribution metric originating from **cooperative game theory.**
- Adapted and used for **post-hoc** ML explainability purposes.
- Shapley Values are the **average marginal contribution** of each feature to the difference between the given prediction and the average prediction.
- Average prediction is computed on a **reference group.**



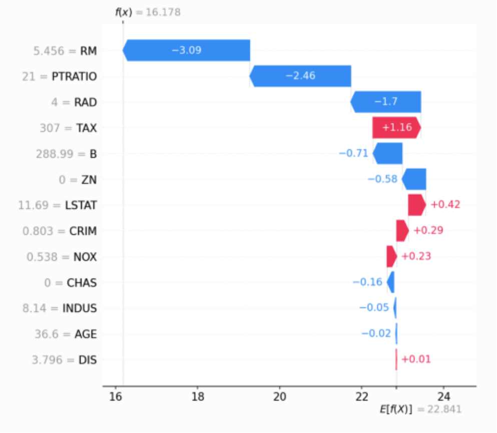
Shapley Values https://papers.nips.cc/paper/2017/file/8a20a8621978632d76c43dfd28b67767-Paper.pdf

- Intuition: It's inaccurate to define a feature's contribution to a prediction as the (marginal) effect of changing its value while keeping all other features fixed.
- This approach overlooks interactions between features.
- To account for these interactions, the marginal effect must be computed across all subsets of fixed feature values and then (weighted) averaged over these subsets.
- The Interpretable ML Book gives as good explanation on how to calculate the Shapley Values.



Shapley Values https://papers.nips.cc/paper/2017/file/8a20a8621978632d76c43dfd28b67767-Paper.pdf

- Axiomatic metric:
  - Think of each feature as a player in a team game trying to achieve a goal — in our case, a model prediction.
  - *Efficiency* means the total contribution of all features adds up exactly to the difference between the actual prediction and the average prediction. This ensures every feature gets credit fairly, and nothing is lost or added.
- Global feature importance
  - If we want to know which features matter most across the whole dataset, we average the absolute Shapley values for each feature.
  - This gives us a sense of which features consistently influence the predictions.

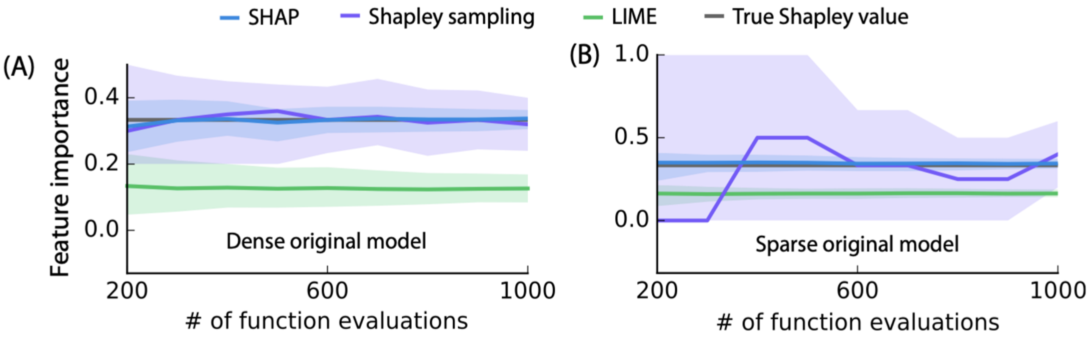


Shapley Values https://papers.nips.cc/paper/2017/file/8a20a8621978632d76c43dfd28b67767-Paper.pdf

- **Pros:**
  - Model-agnostic: Works with any model — you just need inputs and outputs.
  - Gives insight into both individual predictions (local) and overall trends (global).
- **Cons:**
  - Very slow if you have many features — the time to compute Shapley values grows exponentially.
  - In real-world datasets, we often need approximations to make it practical.
  - Not easy to understand at first — the game-theoretic background can be tricky.

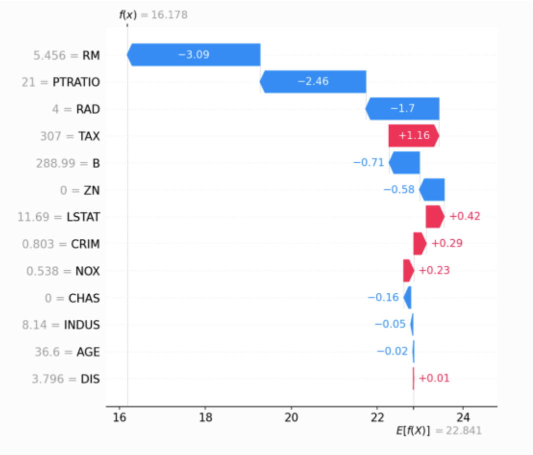
SHapley Additive exPlanations (SHAP)

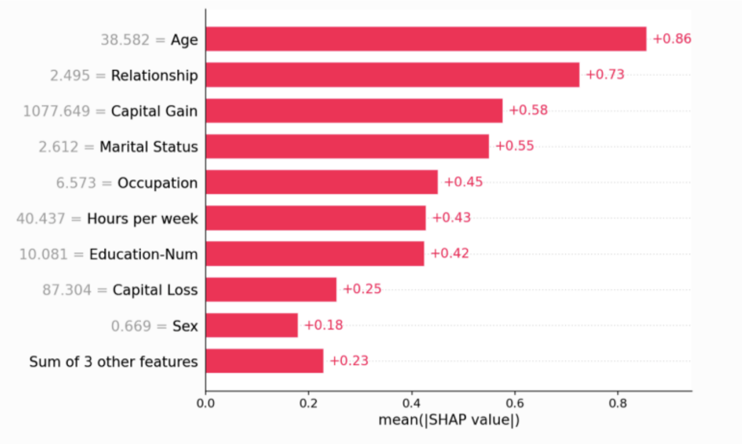
- **SHapley Additive exPlanations** (SHAP) combines sampling with other explainable approaches (i.e. Local Surrogate Models - LIME, DeepLift):
  - Increased **computational efficiency.**
  - **Improved approximation** of true Shapley Values.
- Various approximation methods :
  - Kernel SHAP: model-agnostic
  - Linear SHAP: independence assumption
  - Deep SHAP: deep networks

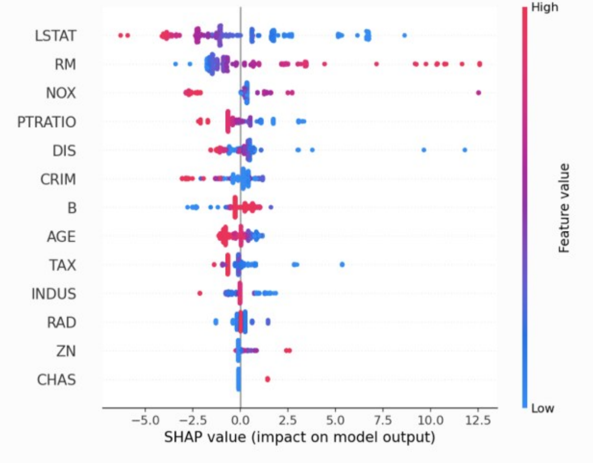


SHAP Python library https://shap.readthedocs.io/en/

- Provides automatic estimates of Shapley values for wide range of ML/DL models types. (1)
- Provides visualisations of Shapley values for explainability purposes. (2)







(1) https://shap.readthedocs.io/en/latest/api.html#explainers

(2) https://shap.readthedocs.io/en/latest/api.html#plots

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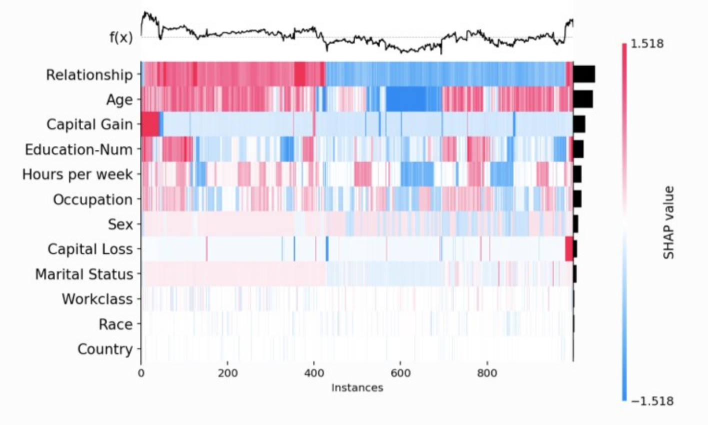
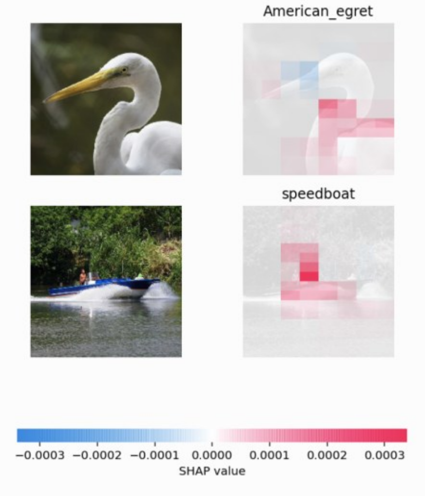
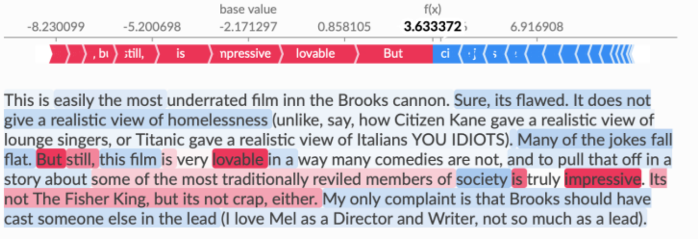






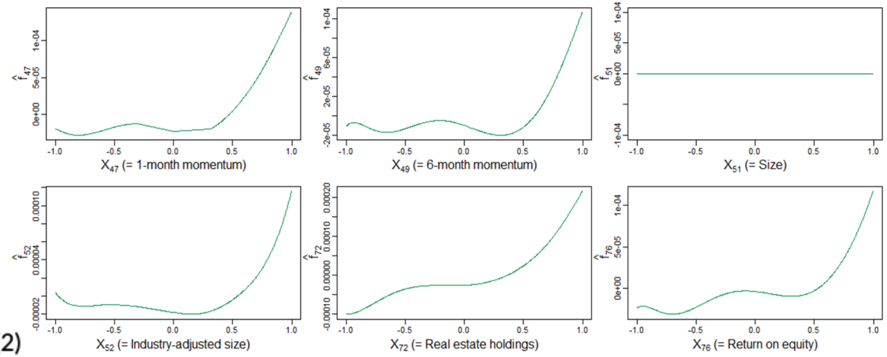
This is easily the most underrated film inn the Brooks cannon. Sure, its flawed. It does not give a realistic view of homelessness (unlike, say, how Citizen Kane gave a realistic view of lounge singers, or Titanic gave a realistic view of Italians YOU IDIOTS). Many of the jokes fall flat. But still, this film is very lovable in a way many comedies are not, and to pull that off in a story about some of the most traditionally reviled members of society is truly impressive. Its not The Fisher King, but its not crap, either. My only complaint is that Brooks should have cast someone else in the lead (I love Mel as a Director and Writer, not so much as a lead).

(1) https://shap.readthedocs.io/en/latest/api.html#explainers

(2) https://shap.readthedocs.io/en/latest/api.html#plots

Tasks for Part 1 (detailed description of deliverables in handout)

- Task 1: Exploratory Data Analysis
- Task 2: Logistic Lasso Regression
- Task 3: Multi-layer Perceptrons + SHAP
- Task 4: Neural Additive Models (1)
  - Instance of Generalized Additive Models (2)



$$g(\mathrm{E}(Y)) = \beta_0 + f_1(x_1) + f_2(x_2) + \cdots + f_m(x_m)$$

  - Where we choose $f_j = NN_j$
  - Interpretable

GAMs model the **expected value** of the output as a **sum of functions** applied to each feature:

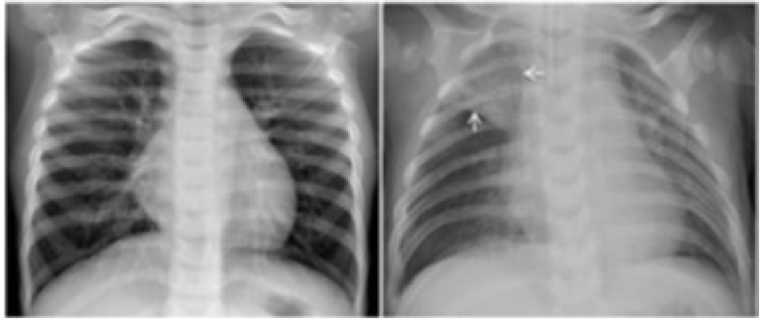
This means the prediction depends on *each input feature individually*, not their combinations — making the model **interpretable**.

(1) https://arxiv.org/pdf/2004.13912.pdf

(2) Hastie, T. J.; Tibshirani, R. J. (1990). Generalized Additive Models. Chapman & Hall/CRC

Project 2: Interpretability and Explainability

Part 2: X-ray data for predicting pneumonia



Motivation for predicting pneumonia

- For US adults, pneumonia is the most common cause of hospital admissions other than women giving birth (in 2011). (1)
- Pneumonia is the worldwide leading cause of death for children under 5 (in 2017). (2)
- Number of radiologists is growing slower than number of images they need to analyse. (3)
- In this project, you will train ML models to detect pneumonia from X-rays.
- With the help of interpretability and explainability, you will gain insights in whether your model uses the medically relevant parts of the image for its prediction or if it uses some biases / shortcuts.
- These insights builds trust in radiologists towards a (semi-)automated detection of pneumonia.

(1) https://academic.oup.com/ehjopen/article/1/1/oeab001/6294753

(2) https://ourworldindata.org/pneumonia

(3) https://www.diagnosticimaging.com/view/are-we-prepared-for-a-looming-radiologist-shortage-

Medical Imaging Techniques

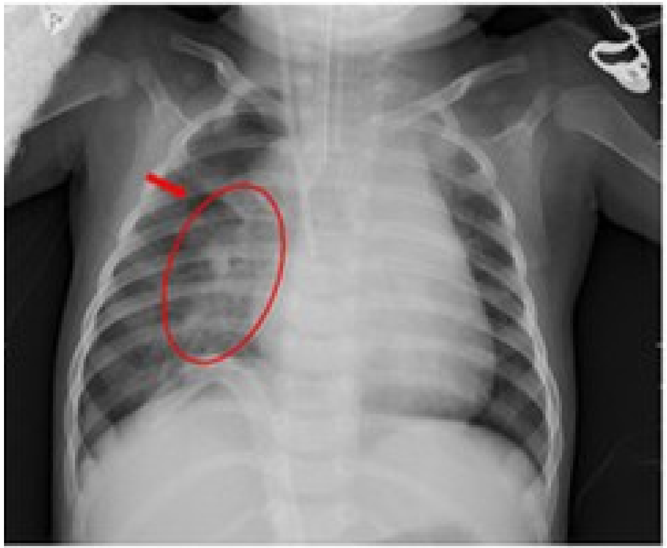
Medical Imaging Techniques are at the heart of our medical systems:

- Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Echographies , X-rays, …
- 1.18M CT exams & 1.06M MRI exams per year in Switzerland in 2019(1)
- Prevalence is increasing in Switzerland (+25% of scanners in CH over the past 5 years)(1)
- … increased workload for practitioners
- Interest from investment funds into Medical Imaging AI Companies (estimated 600M$ in 2020)(2)

(1) https://www.bfs.admin.ch/bfs/en/home/statistics/catalogues-databases/press-releases.assetdetail.16584130.html
(2) https://www.signifyresearch.net/medical-imaging/vc-funding-for-medical-imaging-ai-companies-tops-2-6-billion

Clinical Background

- Pneumonia is an infection that inflames the air sacs (alveoli) in one or both lungs.
- Typical symptoms: Chest pain when breathing, cough, fever, shortness of breath.
- To diagnose pneumonia, the infected tissue will show denser areas and therefore appear as white spots in the darker background of the lungs.



(1) https://healthmatch.io/pneumonia/pneumonia-chest-xray

(2) https://www.lung.org/lung-health-diseases/lung-disease-lookup/pneumonia/symptoms-and-diagnosis

(3) https://www.mdpi.com/2227-7390/8/9/1423

Chest X-Ray Dataset (1,2)

- Dataset of 1-5 year old children from Guangzhou Women and Children's Medical Center.
- 5,863 X-ray images (JPEG) annotated with pneumonia/no pneumonia.
- Train - val - test split provided directly on kaggle or student cluster. Feel free to rearrange train/val but please keep the testset as-is for comparability and reproducibility.
- Overall goal: Develop an automated ML model for the detection of pneumonia and leverage interpretability or explainability to investigate whether it uses the medically relevant features for its prediction.

(1) Kermany, Daniel S., et al. "Identifying medical diagnoses and treatable diseases by image-based deep learning." cell 172.5 (2018): 1122-1131.

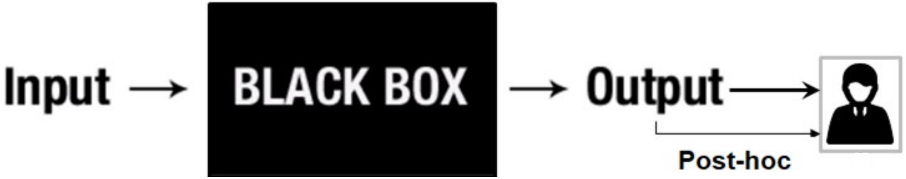
(2) https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia

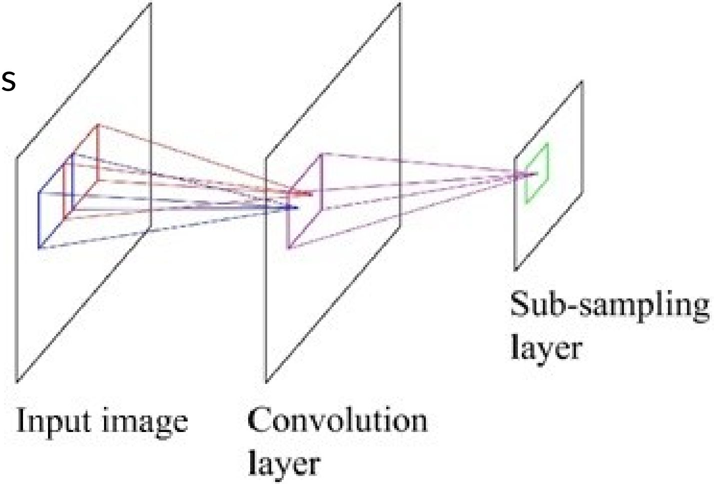
Tasks for Part 2 (detailed description of deliverables in handout)

- Task 1: Exploratory Data Analysis
  - Before training any classifier, analyze the dataset at hand in order to get an understanding of the data.
  - Do you see visual differences between healthy and disease patients?
  - Based on your findings, preprocess the data as you see fit.

Tasks for Part 2 (detailed description of deliverables in handout)

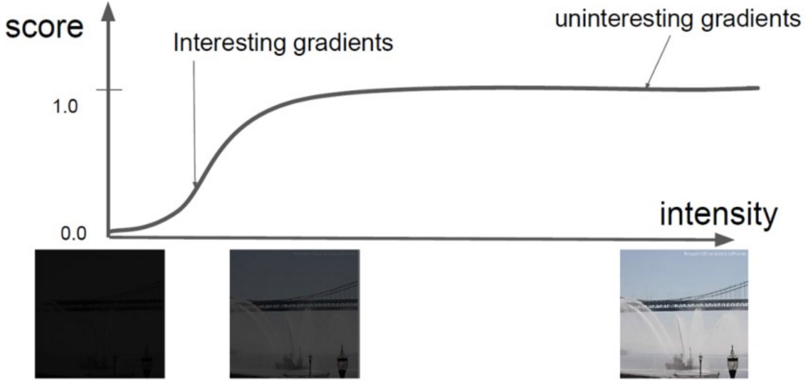
- Task 1: Exploratory Data Analysis
- Task 2: CNN Classifier
  - For Task 3 & 4, we want to use post-hoc explainability methods, which visualize the parts of the image a classifier utilizes for its predictions.
  - Thus, first design a small CNN classifier on which we can later on apply these methods.





Tasks for Part 2 (detailed description of deliverables in handout)

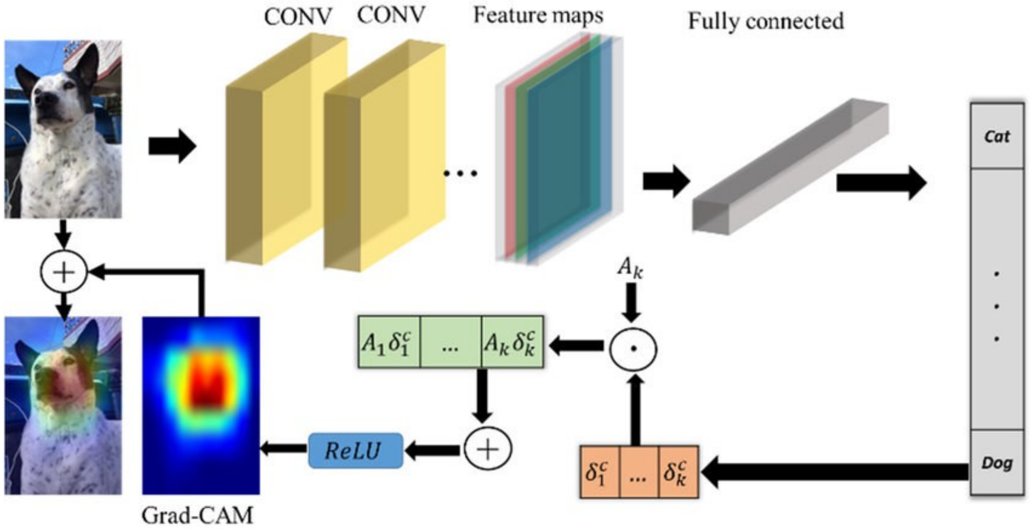
- Task 1: Exploratory Data Analysis
- Task 2: CNN Classifier
- Task 3: Integrated Gradients (1)
  - Gradient-based post-hoc methods take inspiration from the idea that the gradient of the prediction loss with respect to the input pixels indicates how important they are.
  - Gradients at image might not accurately describe importance of pixels for prediction.
  - Integrated Gradients sums up gradients over the path from a baseline (usually black image) to the image.



[1] Sundararajan, Taly, and Yan, “Axiomatic Attribution for Deep Networks.”

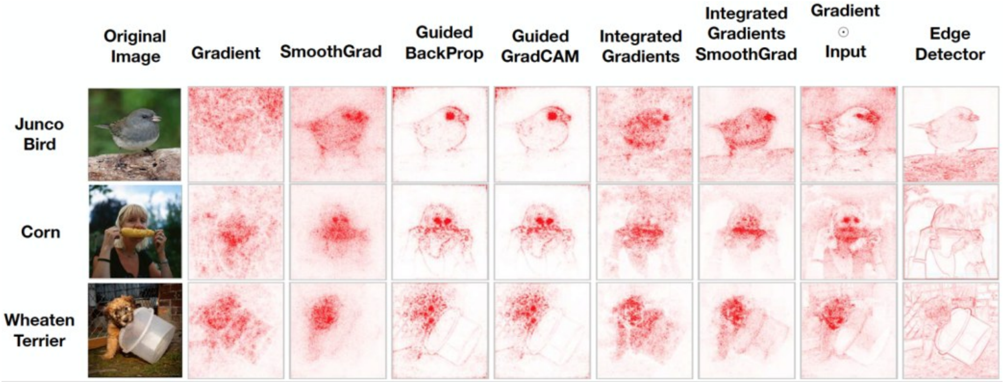
Tasks for Part 2 (detailed description of deliverables in handout)

- Task 1: Exploratory Data Analysis
- Task 2: CNN Classifier
- Task 3: Integrated Gradients
- Task 4: Grad-CAM (1)
  - Grad-CAM uses activation maps of last convolutional layer from forward pass, weighs them by gradients and upsamples them to input image.


CONV
CONV
Feature maps
Fully connected
Cat
Dog
A_k
$A_1\delta_1^c$ ... $A_k\delta_k^c$
δ_1^c ... δ_k^c
ReLU
Grad-CAM

(1) Selvaraju et al., "Grad-cam: Visual explanations from deep networks via gradient-based localization"

Tasks for Part 2 (detailed description of deliverables in handout)



- Task 1: Exploratory Data Analysis
- Task 2: CNN Classifier
- Task 3: Integrated Gradients
- Task 4: Grad-CAM
- Task 5: Data Randomization Test (1)
  - Show that many gradient-based post-hoc explainability methods work as edge detectors.
  - When randomly permuting labels of images, the resulting “important pixels” for classification should be random and non-sensical.
  - Instead, many methods still visualize similar important pixels as before randomization.
  - Effectively showing that methods are independent of model and classification task at hand and, thus, a bad explainer of the model.
  - A premise of interpretable models is that this would not happen for them

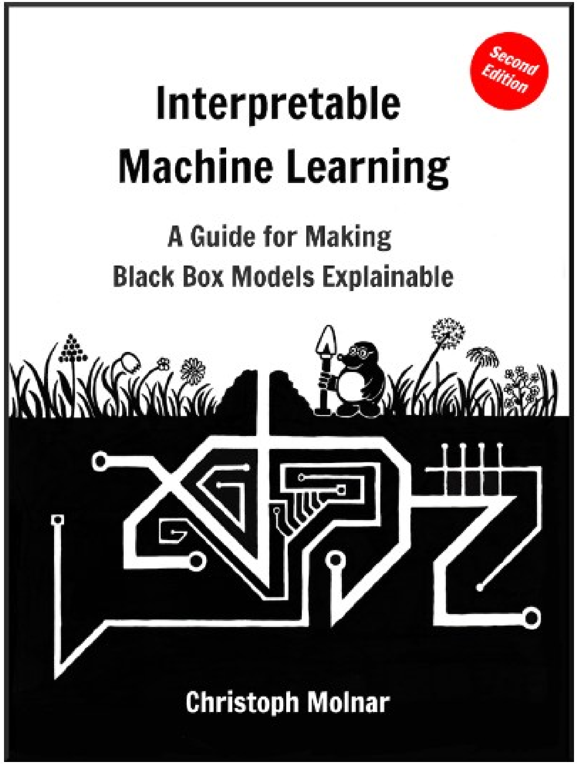
(1) Adebayo et al., “Sanity Checks for Saliency Maps.”

Part 3

- General questions allowing you to reflect on your learnings during the project

Supplementary Material

https://christophm.github.io/interpretable-ml-book/


Second Edition
Interpretable Machine Learning
A Guide for Making Black Box Models Explainable
Christoph Molnar