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MEDICOVER

1st European Congress of Laboratory Medicine Medical Biopathology

Laboratory Medicine at the Clinical Interface ©

26-29 March 2025
Athens Conservatoire Greece

BIOPATHOLOGY
1st ELMed CONGRESS
26-29 MARCH 2025
ATHENS / GREECE

Under the Auspices of

MEDICOVER

When and how will AI be implemented in laboratory services?

Medicover Diagnostics

Dr. med. Jakob Adler

IHP Berlin, Germany

IMD Berlin, Germany

27.03.2025

CARING FOR YOUR HEALTH IS ALL WE DO

A short introduction of myself

IHP Berlin
Therapeutic Drug Monitoring

IMD Berlin
Clinical chemistry
Data Science

DGKL: Young Laboratory
Working Group
Digital Competence

IFCC Working Group
Digital Competence

Task Force Young Scientists
Corresponding member

Laboratory Physician, specialization: clinical chemistry, endocrinology, reference intervals, data science

Our question has three dimensions

1 What do we understand by AI?

2 When will AI be implemented?

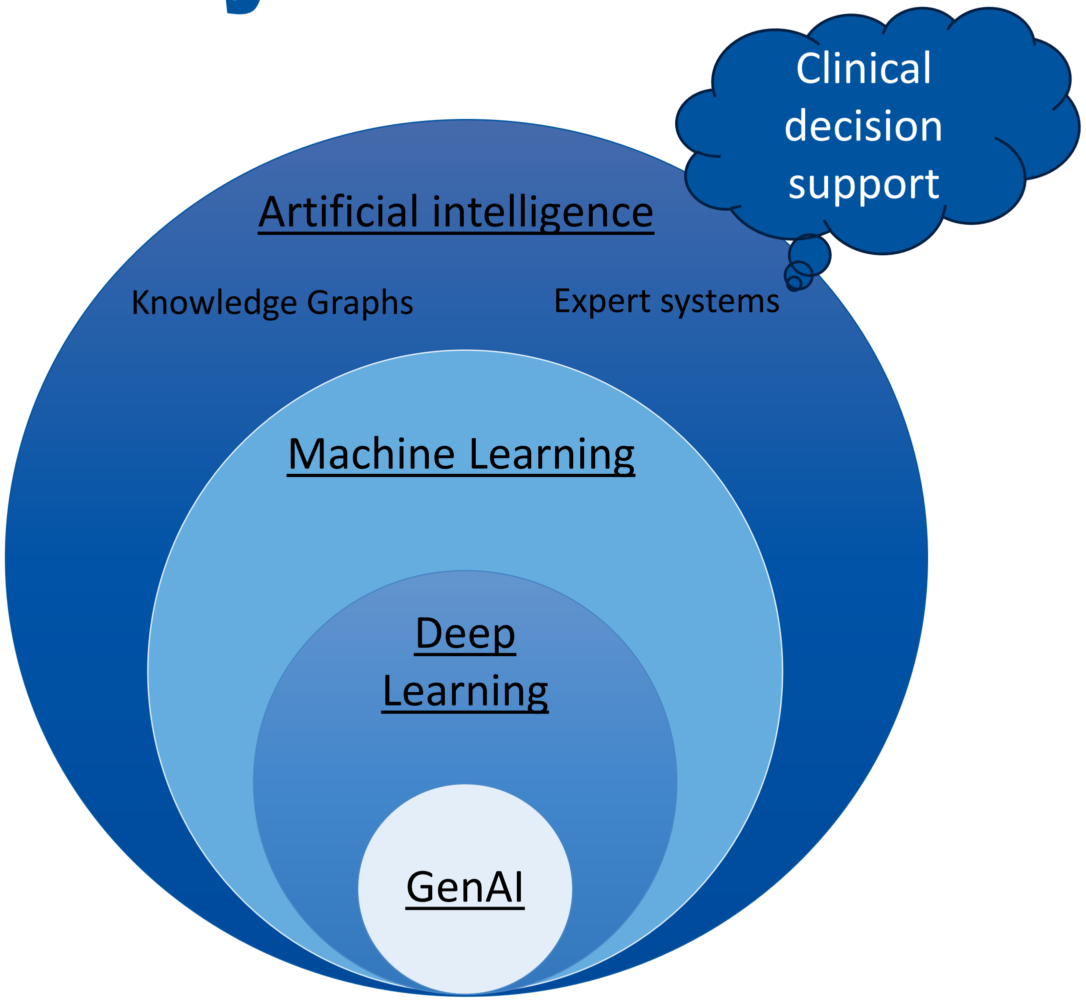
3 How can AI be implemented?

What do we understand by AI?

AI is defined very heterogeneously

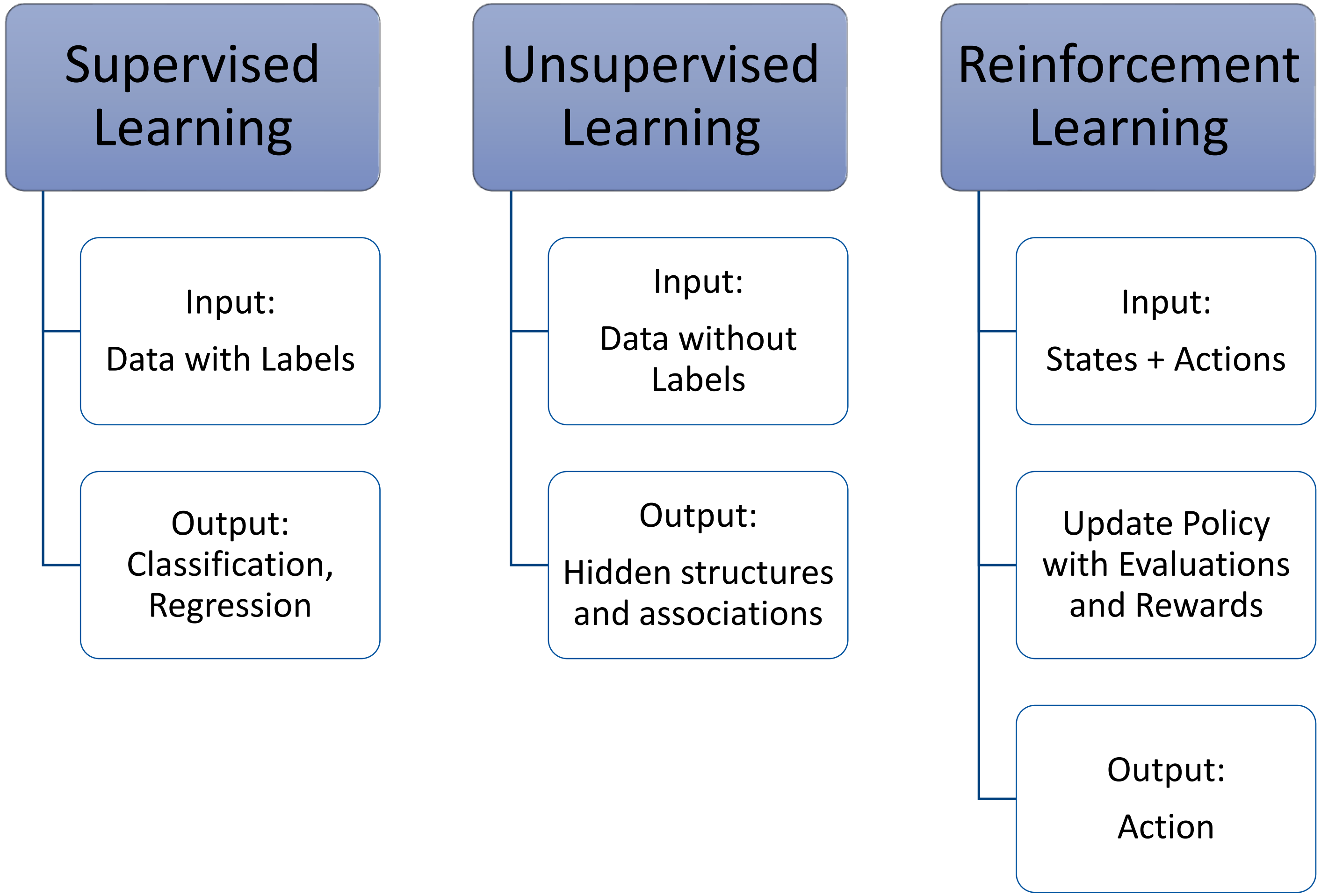
- Definition by EU AI Act:

- "a **machine-based system** that is designed to **operate with varying degrees of autonomy** and that **can be adaptive** once operational and **that derives outputs** such as predictions, content, recommendations or decisions that can affect physical or virtual environments **from inputs** received for explicit or implicit goals."

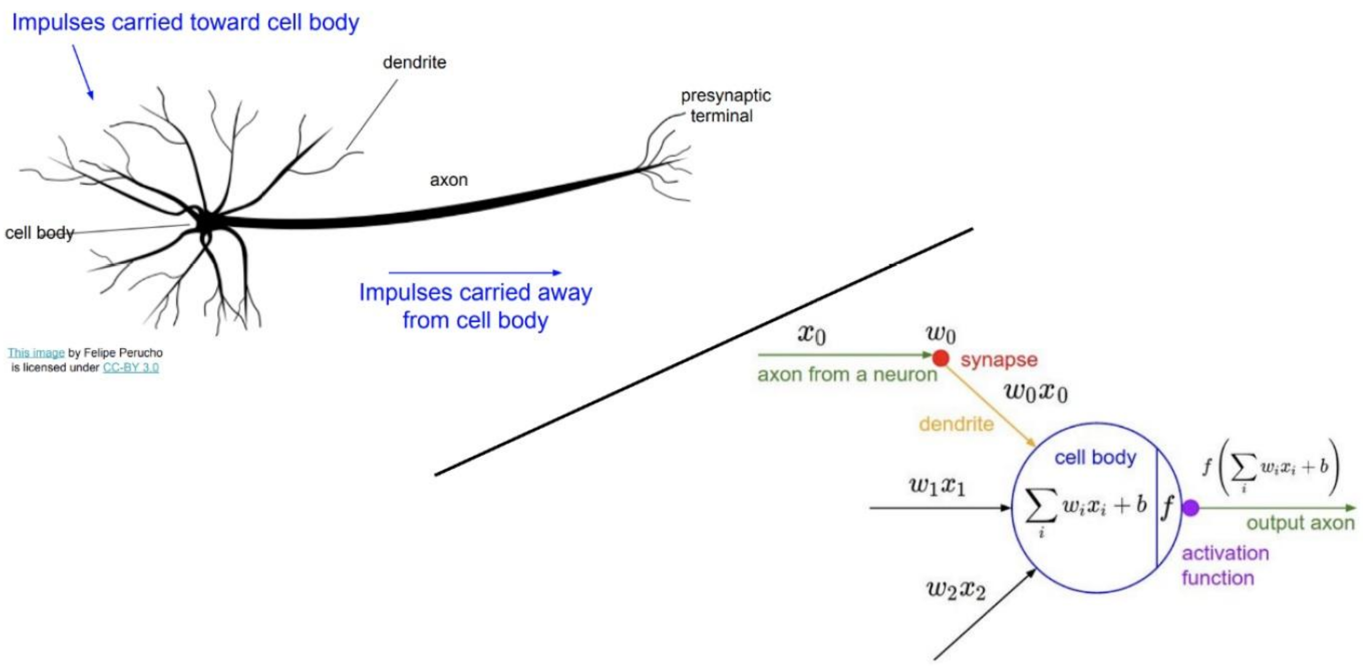


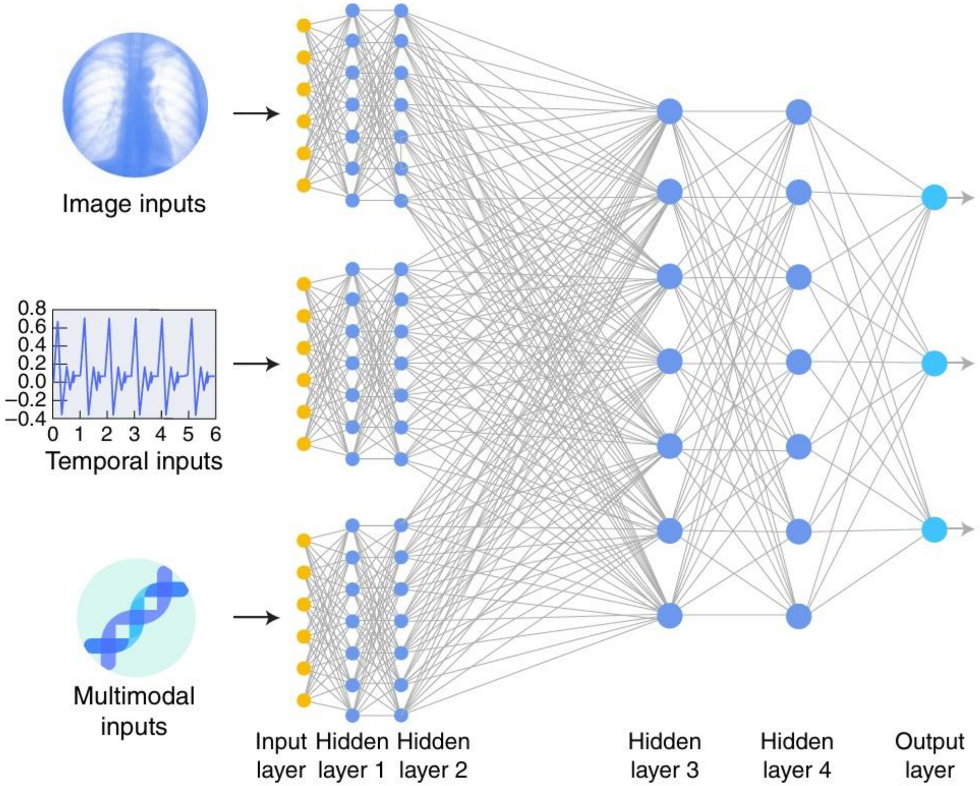
Machine Learning – many different algorithms

- Supervised Learning
  - Classification
  - Regression
- Unsupervised Learning
  - Dimensional reduction
  - Clustering
  - Association rule mining
- Reinforcement Learning



Deep Learning – Neural Networks

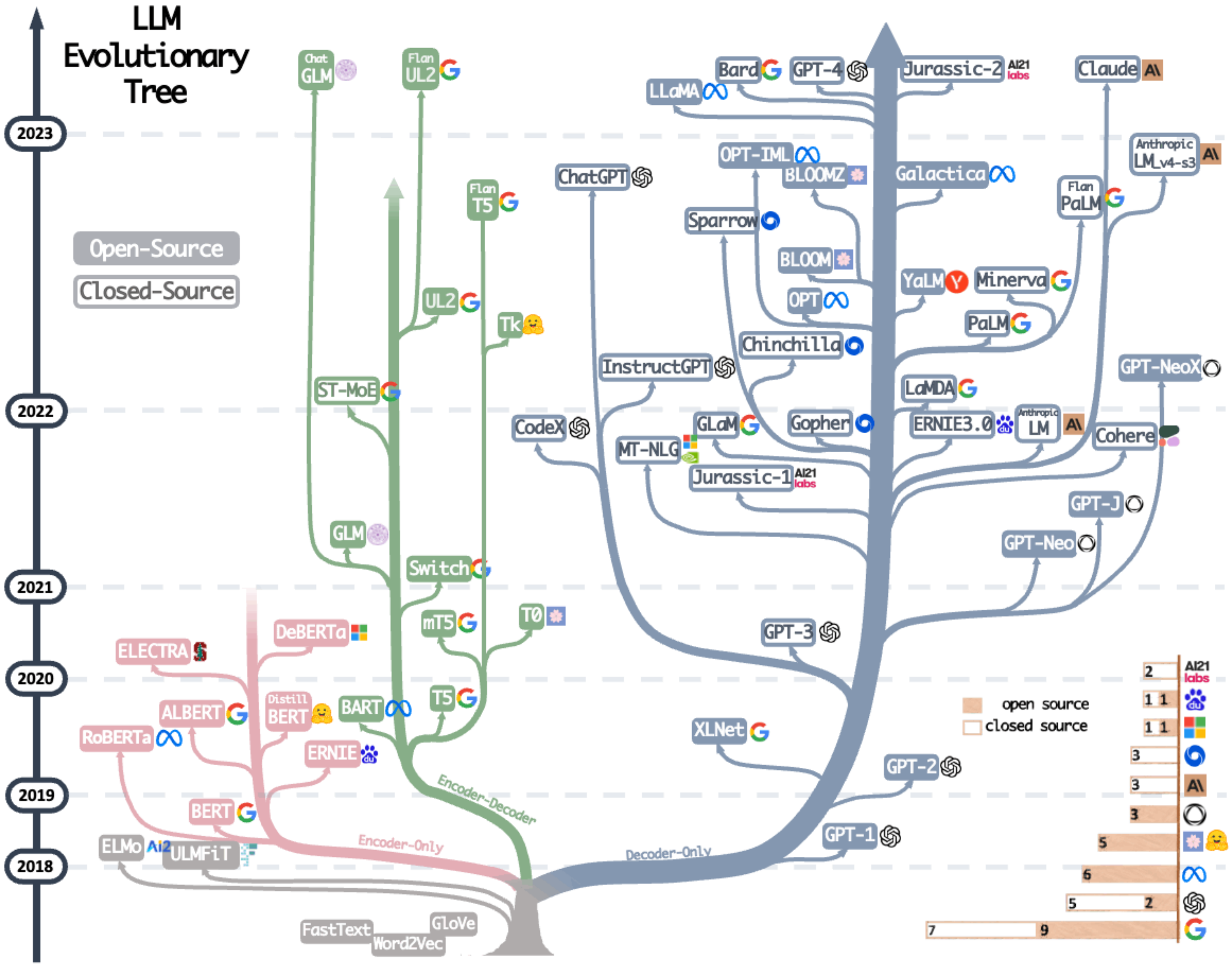




Reference: cs231n_2017_lecture4.pdf (stanford.edu)

Esteva A. et al., A guide to deep learning in healthcare, Nature Medicine 2019; 25: 24-29

Generative AI



Yang et al., Harnessing the Power of LLMs in practice: A Survey on ChatGPT and Beyond, arXiv, 2023, 2304.13712

When will AI be implemented?

In some areas AI is already here!

- AI-based automated cell sorting in differential blood count
- AI-based image recognition in ANA imaging
- AI-based prediction of blood glucose changes
- **880 FDA-approved AI-Tools**

Original Article
Diagnostic Hematology

Ann Lab Med 2021;41:44-50
https://doi.org/10.3343/alm.2021.41.1.44
ISSN 2234-3806 eISSN 2234-3814

ANNALS OF LABORATORY MEDICINE

Evaluation of the CellaVision Advanced RBC Application for Detecting Red Blood Cell Morphological Abnormalities

Seong Jun Park, M.D.*, Jung Yoon, M.D., Ph.D.*, Jung Ah Kwon, M.D., Ph.D., and Soo-Young Yoon, M.D., Ph.D.
Department of Laboratory Medicine, Korea University Guro Hospital, Seoul, Korea

Fields of application of AI

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Diagnostics and research	Processes in the laboratory
Use of AI for diagnostics/generation of knowledge	Use of AI to optimize processes in the laboratory
Use of algorithms to generate hypotheses, automated suggestions for finding texts, linking of previously separate spheres of knowledge, ...	AI-supported order entry, optimized request verification, intelligent sample routing, AI-supported QM (delta checks, autovalidation, etc.), billing management, customer service, generation of findings, information material, ...

Diagnostics

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Clinical Chemistry 66:9
1210–1218 (2020)
Pediatric Clinical Chemistry

A Machine Learning Approach for the Automated Interpretation of Plasma Amino Acid Profiles

Edmund H. Wilkes,[a] Erin Emmett,[b] Luisa Beltran,[b] Gary M. Woodward,[c] and Rachel S. Carling[b,d*]

npj | Digital Medicine
www.nature.com/npjdigitalmed
REVIEW ARTICLE OPEN
Check for updates

A systematic review of the applications of artificial intelligence and machine learning in autoimmune diseases

I. S. Stafford[1,2], M. Kellermann[1], E. Mossotto[1,2], R. M. Beattie[3], B. D. MacArthur[2] and S. Ennis[1]✉

DE GRUYTER
J Lab Med 2022; 46(5): 331–336

Christian Thiemann, Britta Klitzke, Philipp Martinetz, Philipp Grüning, Thomas Käster, Erhardt Barth, Jan Kramer and Thomas Martinetz*

Automated assessment of immunofixations with deep neural networks

Clin Chem Lab Med 2022; 60(12): 1984–1992
DE GRUYTER

Rui Zhou, Yu-fang Liang, Hua-Li Cheng, Wei Wang, Da-wei Huang, Zhe Wang, Xiang Feng, Ze-wen Han, Biao Song, Andrea Padoan, Mario Plebani* and Qing-tao Wang*

A highly accurate delta check method using deep learning for detection of sample mix-up in the clinical laboratory

Clinical Chemistry 67:10
1406–1414 (2021)
Automation and Analytical Techniques

Achieving Expert-Level Interpretation of Serum Protein Electrophoresis through Deep Learning Driven by Human Reasoning

Floris Chabrun,[a,b,*,†] Xavier Dieu,[a,b,†] Marc Ferre,[b] Olivier Gaillard,[c] Anthony Mery,[a] Juan Manuel Chao de la Barca,[a,b] Audrey Taisne,[a] Geoffrey Urbanski,[b,d] Pascal Reynier,[a,b,†] and Delphine Mirebeau-Prunier[a,b,†]

Diagnostics

DE GRUYTER
J Lab Med 2024; aop

Inga Trulson*, Stefan Holdenrieder and Georg Hoffmann

Using machine learning techniques for exploration and classification of laboratory data

DE GRUYTER
J Lab Med 2024; 48(5): 223–237

Sandra Klawitter, Johannes Böhm, Alexander Tolios and Julian E. Gebauer*

Automated sex and age partitioning for the estimation of reference intervals using a regression tree model

DE GRUYTER
J Lab Med 2024; 48(5): 215–222

Amani Al-Mekhlafi, Sandra Klawitter and Frank Klawonn*

Standardization with zlog values improves exploratory data analysis and machine learning for laboratory data

Diagnostics – generating new knowledge

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SCIENCE TRANSLATIONAL MEDICINE | RESEARCH ARTICLE

MULTIPLE SCLEROSIS

Multiple sclerosis endophenotypes identified by high-dimensional blood signatures are associated with distinct disease trajectories

Catharina C. Gross[1]*†, Andreas Schulte-Mecklenbeck[1]†, Olga V. Steinberg[1]†, Timo Wirth[1]†, Sarah Lauks[1]†, Stefan Bittner[2], Patrick Schindler[3,4,5], Sergio E. Baranzini[6], Sergiu Groppa[2], Judith Bellmann-Strobl[3,4], Nora Bünger[1], Claudia Chien[3,7,8], Eva Dawin[1], Maria Eveslage[9], Vinzenz Fleischer[2], Gabriel Gonzalez-Escamilla[2], Barbara Gisevius[10], Jürgen Haas[11], Martin Kerschensteiner[12,13], Lucienne Kirstein[1], Catharina Korsukewitz[1], Lisa Lohmann[1], Jan D. Lünemann[1], Felix Luessi[2], Gerd Meyer zu Hörste[1], Jeremias Motte[10], Tobias Ruck[1,14], Klemens Ruprecht[5], Nicholas Schwab[1], Falk Steffen[2], Sven G. Meuth[1,14], Friedemann Paul[3,4,5], Brigitte Wildemann[11], Tania Kümpfel[12], Ralf Gold[10], Tim Hahn[15], Frauke Zipp[2], Luisa Klotz[1]*‡, Heinz Wiendl[1]*‡, German Competence Network Multiple Sclerosis (KKNMS)§

nature medicine

Article

https://doi.org/10.1038/s41591-022-02116-3

Data-driven identification of post-acute SARS-CoV-2 infection subphenotypes

Received: 8 June 2022

Accepted: 2 November 2022

Published online: 1 December 2022

Check for updates

Hao Zhang[1], Chengxi Zang[1], Zhenxing Xu[1], Yongkang Zhang[1], Jie Xu[2], Jiang Bian[2], Dmitry Morozyuk[1], Dhruv Khullar[1], Yiye Zhang[1], Anna S. Nordvig[3], Edward J. Schenck[4], Elizabeth A. Shenkman[2], Russell L. Rothman[5], Jason P. Block[6], Kristin Lyman[7], Mark G. Weiner[1], Thomas W. Carton[7], Fei Wang[1] & Rainu Kaushal[1]

diagnostics

MDPI

Article

Machine Learning in Antibody Diagnostics for Inflammatory Bowel Disease Subtype Classification

Christiane Sokollik[1,†], Aurélie Pahud de Mortanges[2,†], Alexander B. Leichtle[3,4], Pascal Juillerat[5,6] and Michael P. Horn[3,*] on behalf of the Swiss IBD Cohort Study Group

Choose your fighter!

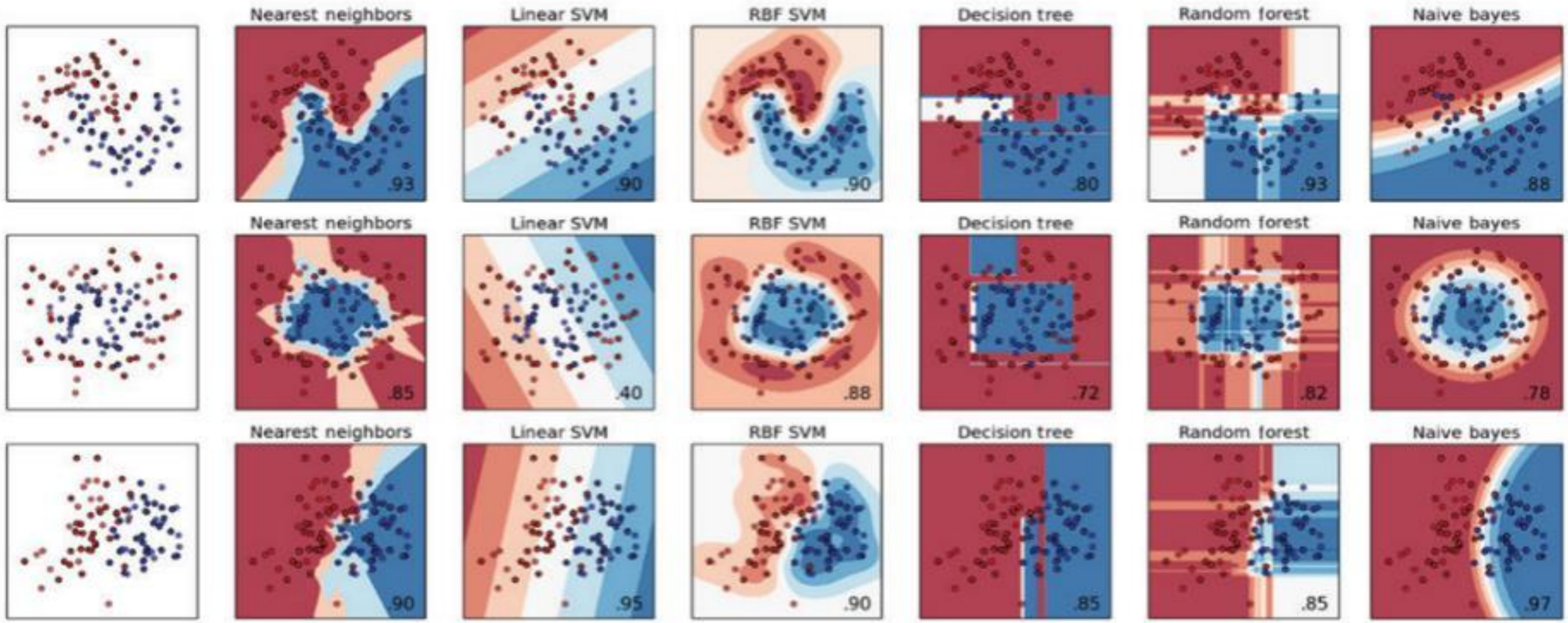


Figure 3: Visual comparison of the decision boundaries of several common ML classifiers in three data sets.
The plots show the training data as points in darker shaded colors and the testing data as lighter shaded colors. Classification accuracy of the test set is given in the bottom right corner. Adapted from an image by scikit-learn.org © 2010–2016, scikit-learn developers (BSD License).

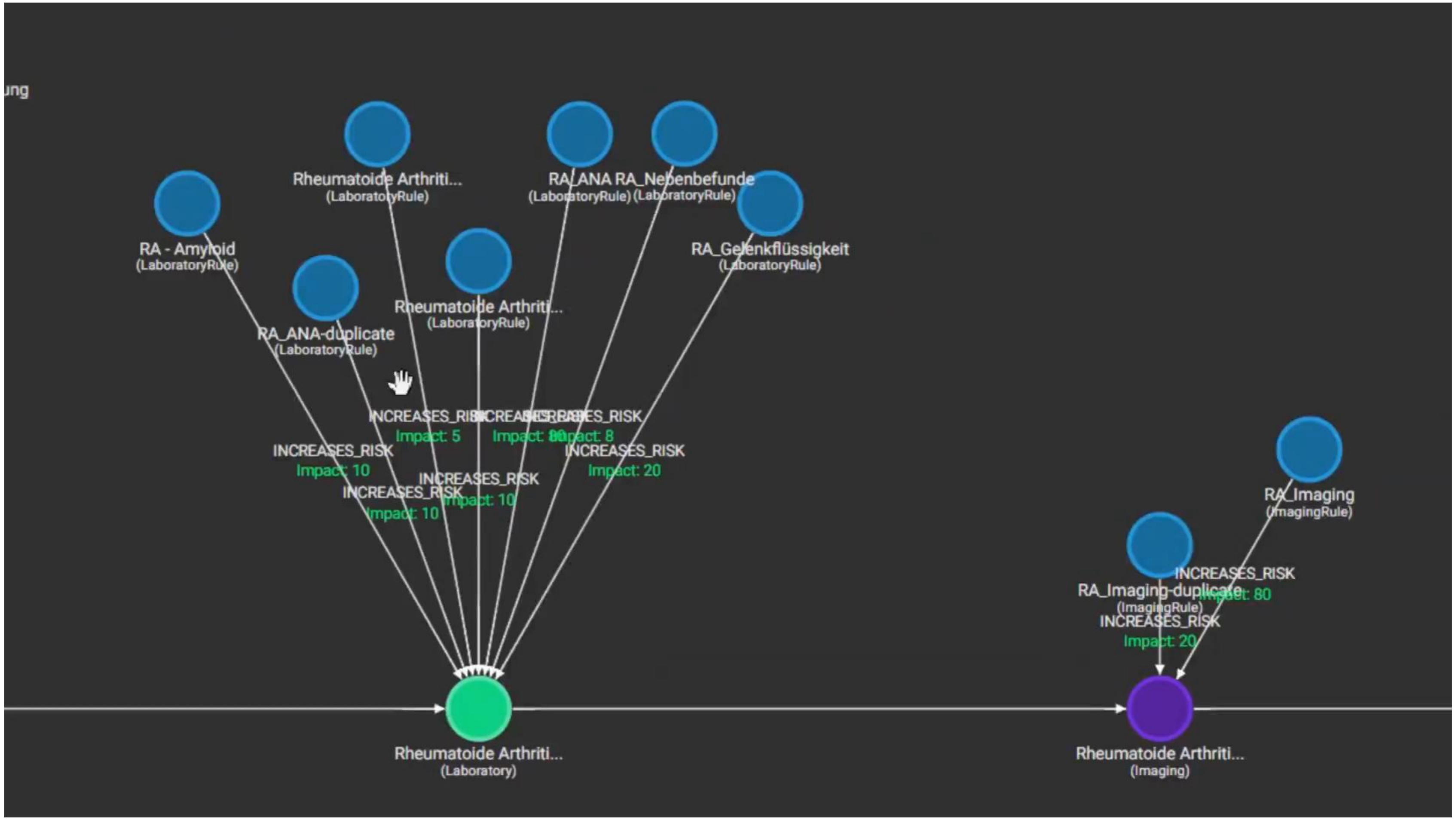
Cabitza/Banfi: Machine learning in laboratory medicine: waiting for the flood?, Clin Chem Lab Med 2018;56(4): 516 - 524

Processes - OE

DE GRUYTER J Lab Med 2023; 47(4): 171–179

Fabian Berns*, Niclas Heilig, Florian Stumpe and Jan Kirchhoff

Medical operational AI: artificial intelligence in routine medical operations



Literature research

- Many tools available:
  - Storm, Co-Storm
  - Gemini Deep research
  - Perplexity
  - Elicit
  - Research Rabbit
  - Consensus
  - …

arXiv > cs > arXiv:2402.14207

Computer Science > Computation and Language

[Submitted on 22 Feb 2024 (v1), last revised 8 Apr 2024 (this version, v2)]

Assisting in Writing Wikipedia-like Articles From Scratch with Large Language Models

Yijia Shao, Yucheng Jiang, Theodore A. Kanell, Peter Xu, Omar Khattab, Monica S. Lam

ResearchRabbit

Consensus

Find the best science, faster.

Data analytics and image creation

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AI data analysis (e.g. julius.ai)

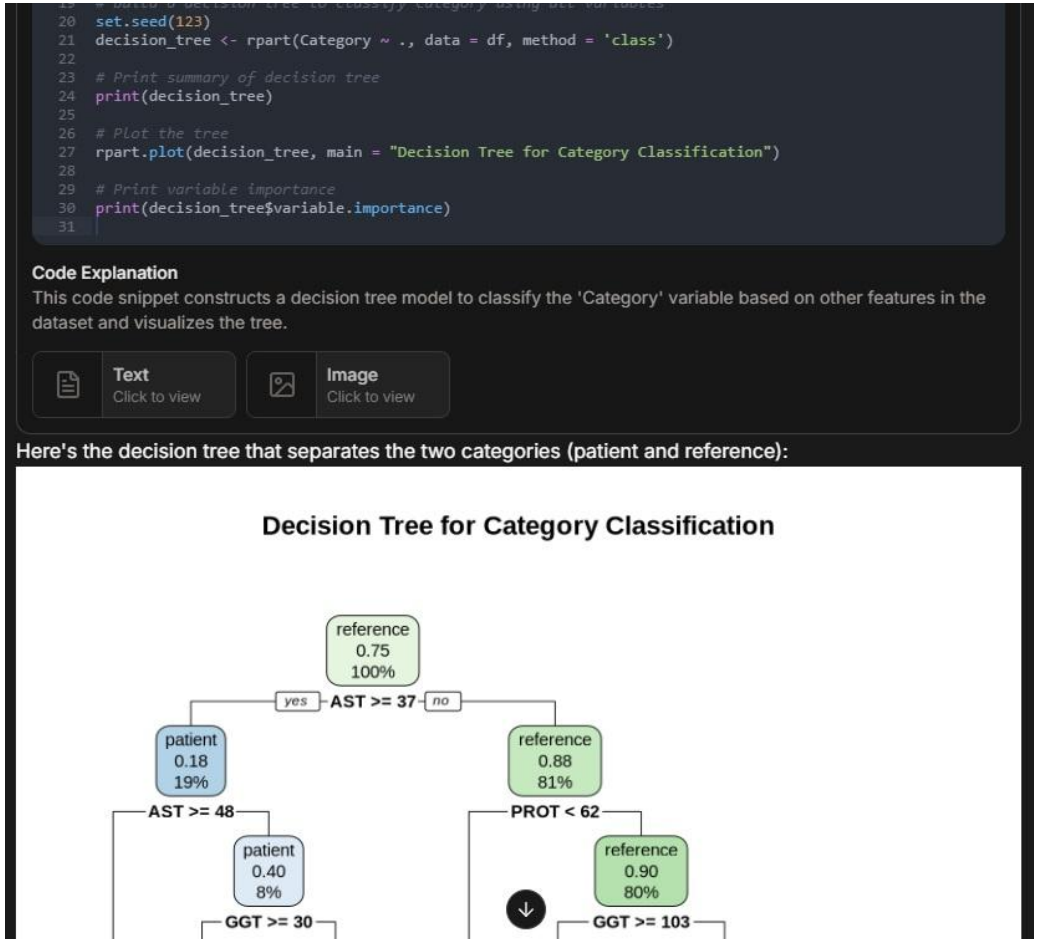
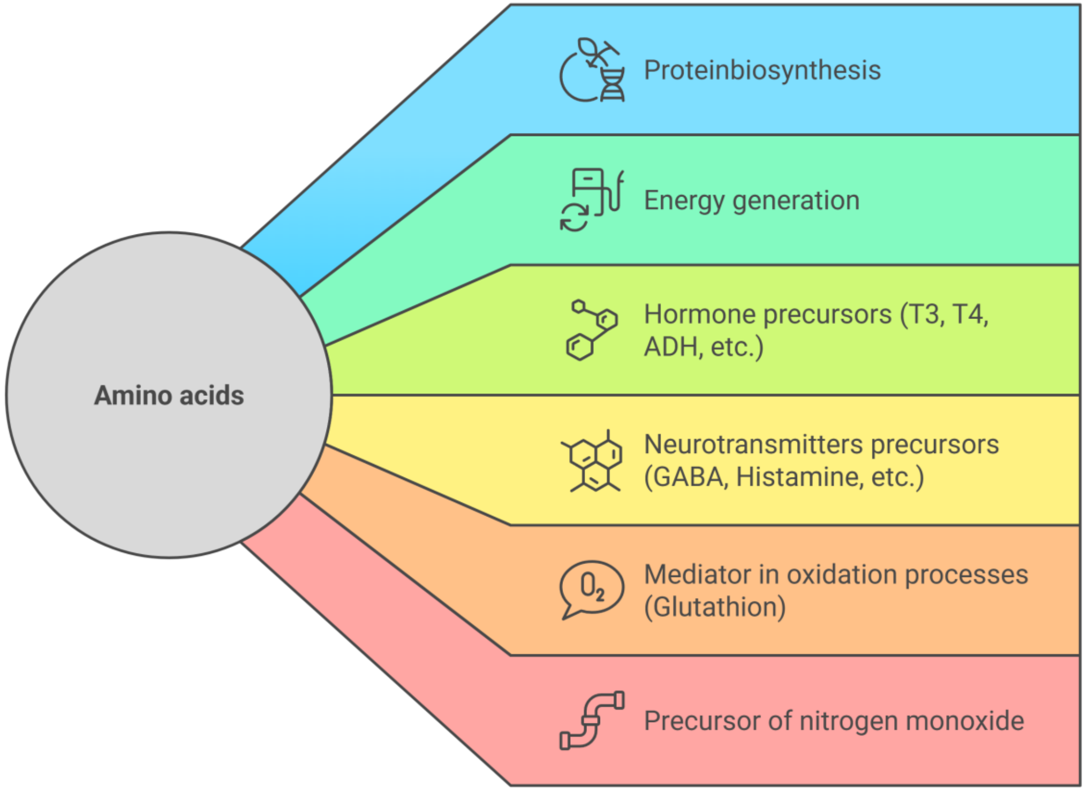


Image generation (e.g. napkin.ai)



Agentic AI – using AI agents

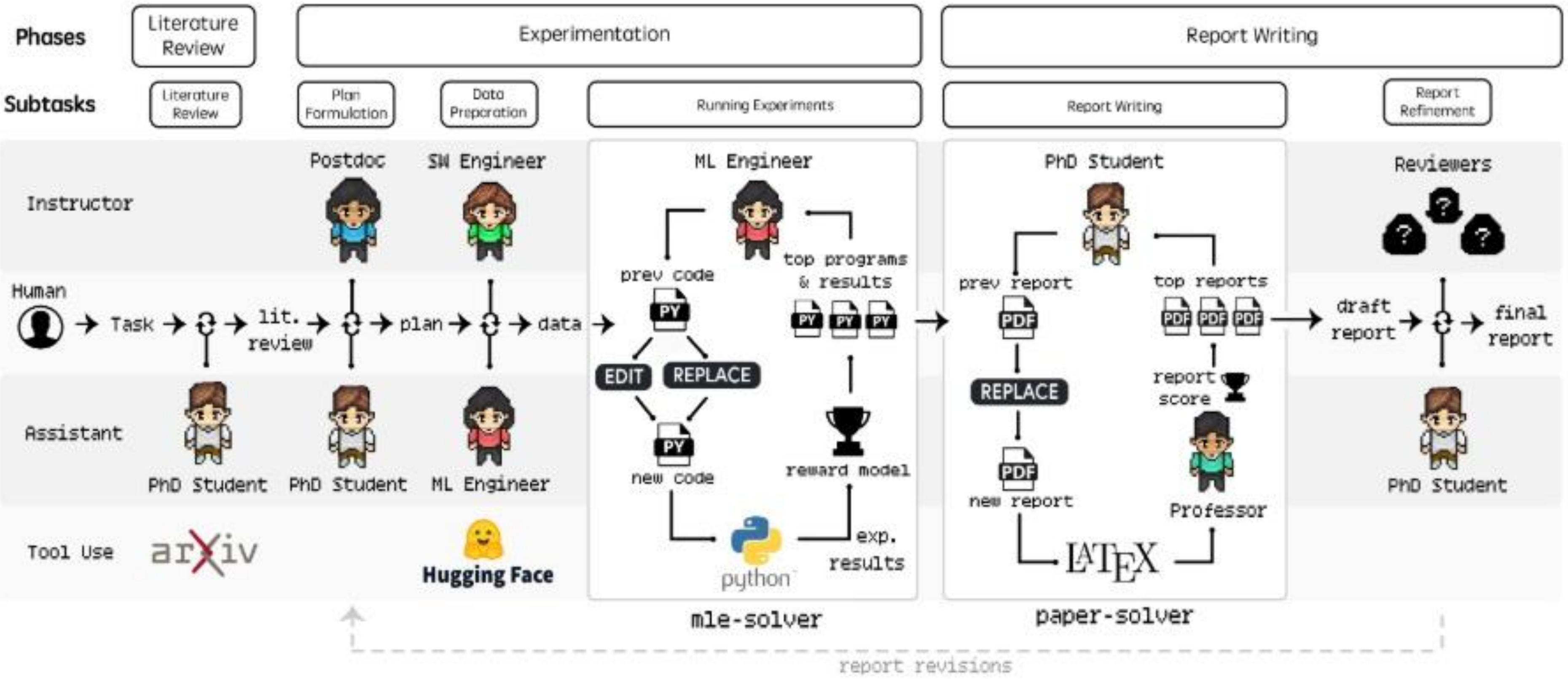
arXiv > cs > arXiv:2501.04227

Computer Science > Human-Computer Interaction

[Submitted on 8 Jan 2025]

Agent Laboratory: Using LLM Agents as Research Assistants

Samuel Schmidgall, Yusheng Su, Ze Wang, Ximeng Sun, Jialian Wu, Xiaodong Yu, Jiang Liu, Zicheng Liu, Emad Barsoum



How can AI be implemented?

FAIR Data Principles – High-quality data as the basis

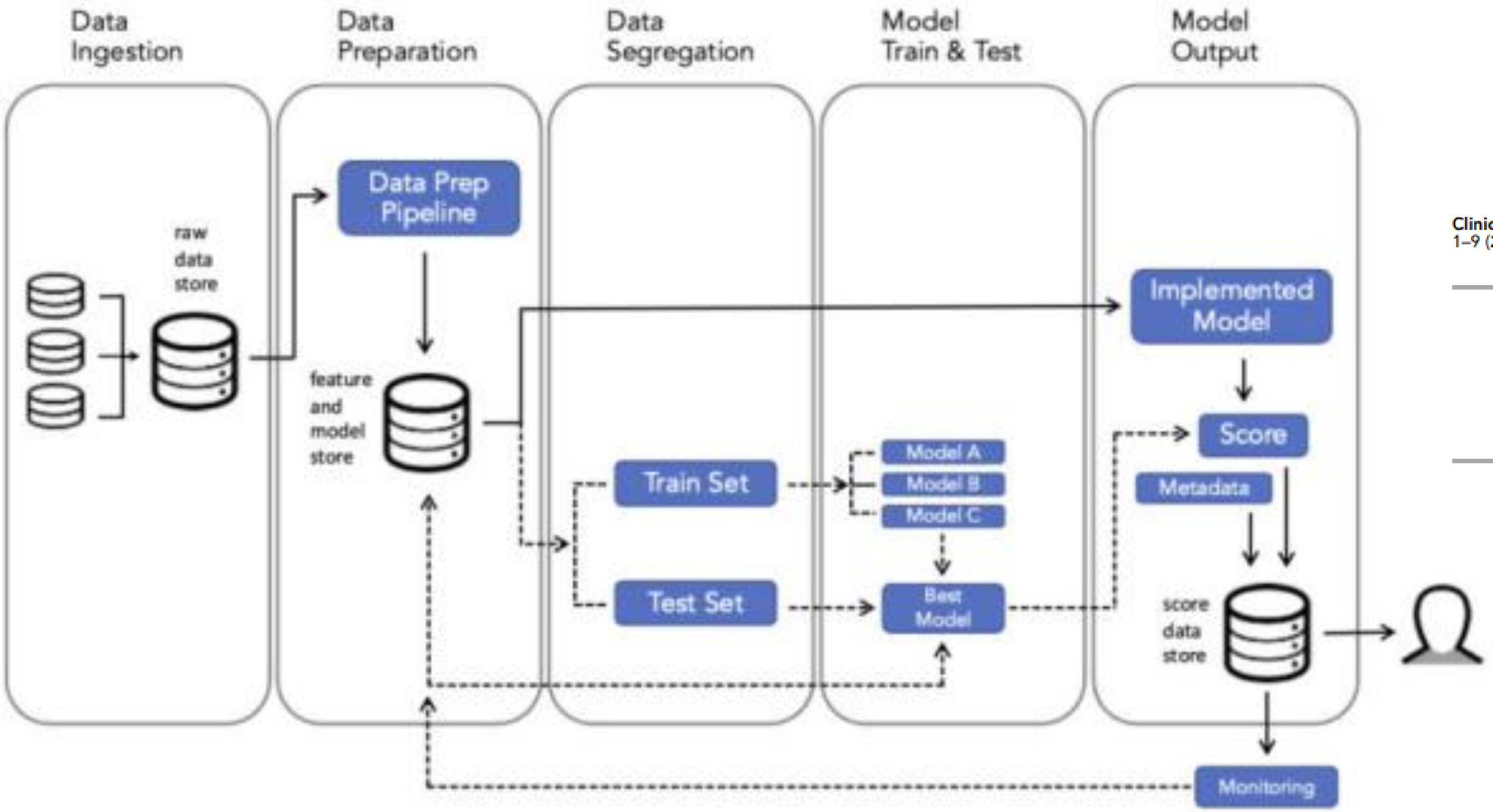
- Findable
- Accessible
- Interoperable
- Reusable

Requirements	Implementation
Findability	- Assign PIDs meaningfully. • Each PID should uniquely identify a single patient, which needs to be consistent between branch laboratories with parallel systems. • Develop solutions for unknown emergency patients, which allow correct assignment of test results when personal data is identified later on. • Develop solutions for analyses conducted for research purposes. Avoid cumulative PIDs. - Record actual sampling time instead of planned sampling time. - Connect all analytical devices to the lab IT system to avoid manual entries. - Connect the lab IT system to the hospital's central IT system to enable searches by clinicians and researchers.
Accessibility	- Protect lab data adequately with: • secure data storage solutions. • careful data governance. - Design ETL processes efficiently. - Consider the general consent status of patients and allow access to data accordingly. - Employ modern technical solutions such as multiparty computing and homomorphic encryption for merging data from different sites.
Interoperability	- Code analyses in a standardized manner, e.g., with LOINC codes. - Additionally, code the device manufacturer and kit version in a standardized way. - Code newly developed analyses in a homogenous way, even if no standardized codes are available yet. - Enable consolidation of data from different labs.
Reusability	- Provide detailed metadata to maximize reproducibility, including: • LOINC codes. • batch numbers. • quality management data. • SPREC codes.
+	- Offer your laboratory medicine expertise to clinicians and researchers, as no one knows the intricacies of your laboratory data better than you.

Abbreviations: ETL: extract—transform—load; lab: laboratory; LOINC: Logical Observation Identifiers Names and Code; PID: patient identifier; SPREC: Standard Preanalytical Code. + signifies the additional human resource (laboratory expertise).

Blatter et al., Big Data in Laboratory Medicine - FAIR Quality for AI?, Diagnostics 2022; 12: 1923

How to build a Machine Learning model



Clinical Chemistry 00:0
1–9 (2023)

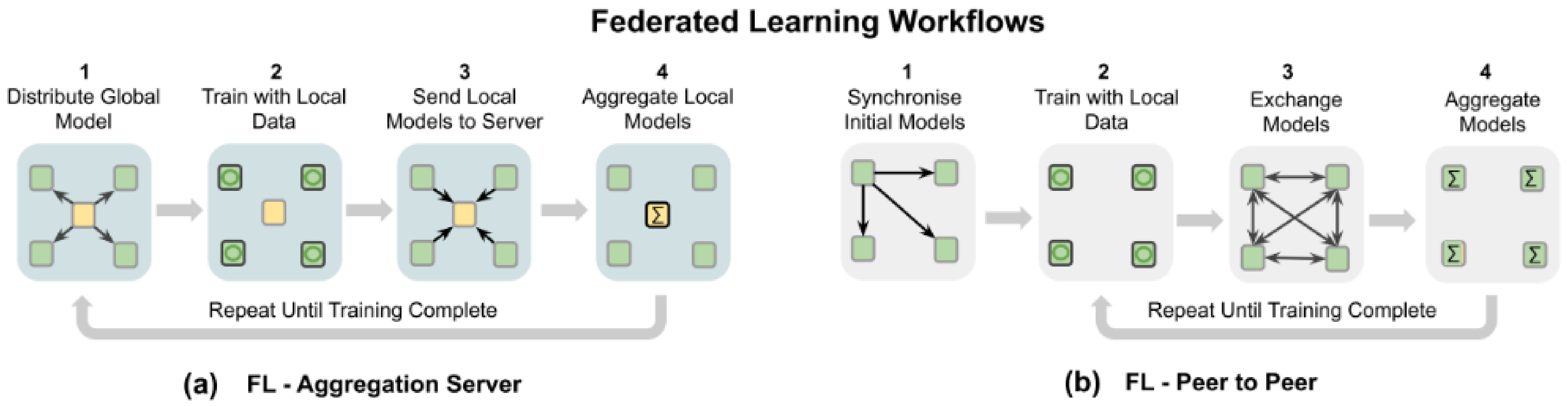
Special Report

Machine Learning in Laboratory Medicine: Recommendations of the IFCC Working Group

Stephen R. Master,[a,b,*] Tony C. Badrick,[c] Andreas Bietenbeck,[d] and Shannon Haymond[e,f,*]

Haymong/McCudden, Rise of the Machines: Artificial Intelligence and the Clinical Laboratory, J Appl Lab Med 2021; 6(6): 1640-1654

Federated Learning – keep your data

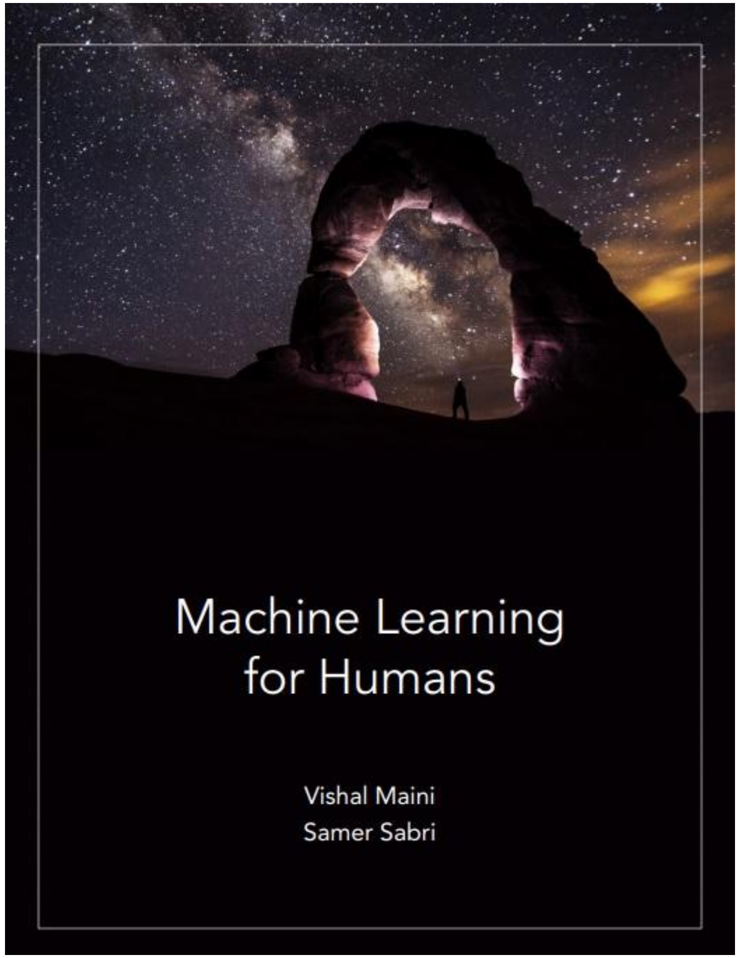


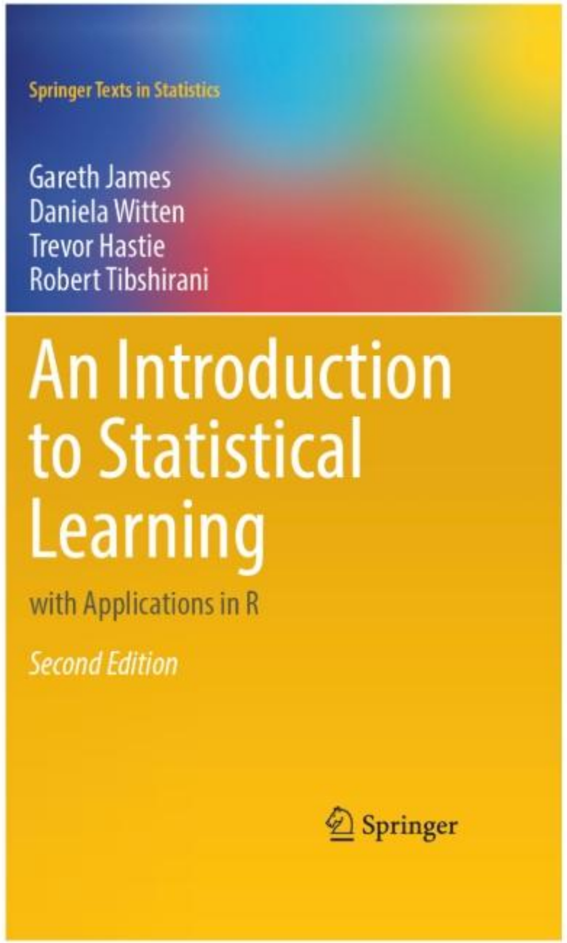
Rieke et al., The future of digital health with federated learning, npj Digital Medicine 2020; 3: 119

Questions to ask yourself

- Which AI use case do I want to implement? Is there an IVDR certified product?
- Which database do I need? Which kind of data preparation?
- What type of algorithm do I want to use and how will I validate the model?
- Have I followed all the recommendations? Could it be an LDT (IVDR)? How do I train my employees (EU AI Act)?
- How would I like to deploy my model? Cloud? On premise?

Recommendations





ISOBM Congress 2025 Germany

- Workshop: AI-Based Tools for Literature Research and Data Analysis

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Thank you!




CARING
FOR YOUR HEALTH
IS ALL WE DO

Reinforcement Learning - Sepsis

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RESEARCH ARTICLE

Superhuman performance on sepsis MIMIC-III data by distributional reinforcement learning

Markus Böck[1☯], Julien Malle[1☯], Daniel Pasterk[1☯]*, Hrvoje Kukina[1], Ramin Hasani[2], Clemens Heitzinger[1,3]

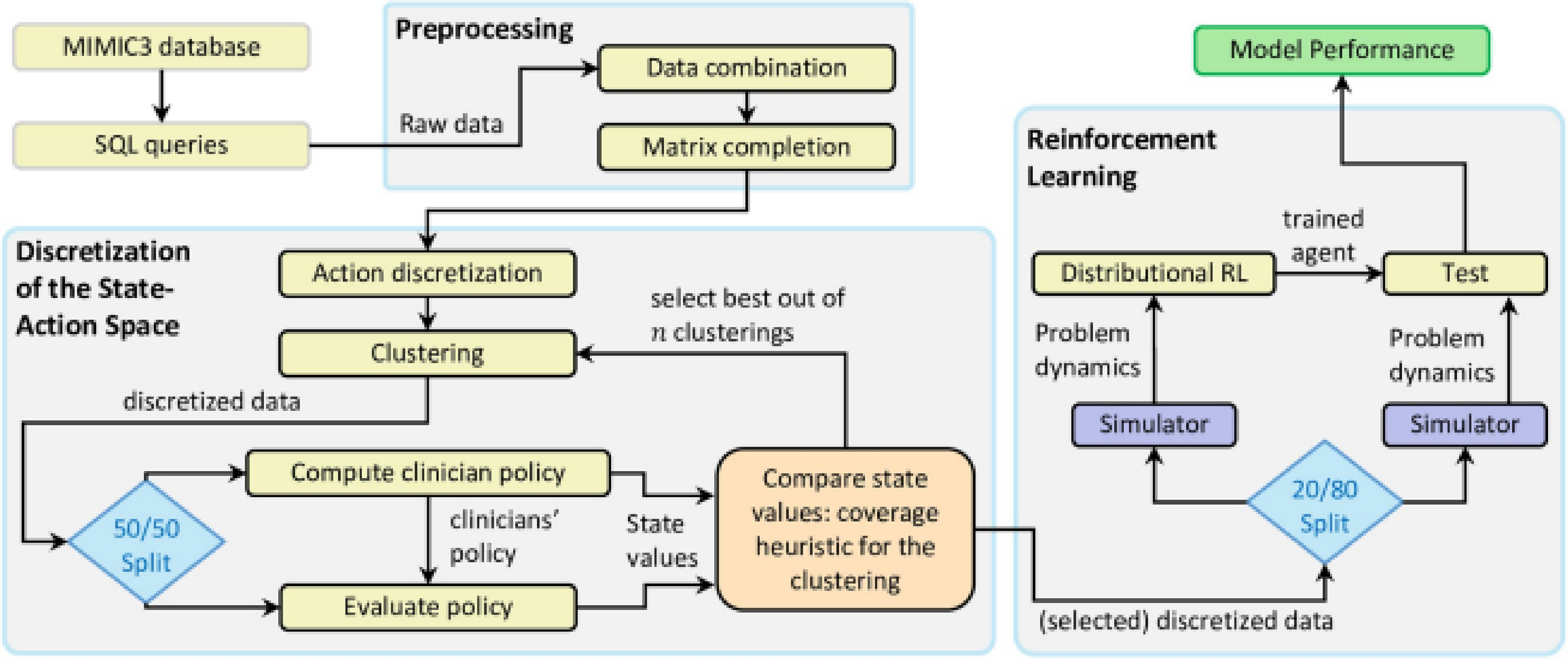

Fig 1. Overall data flow. The data flow including the three main challenges: preprocessing, state-action space representation, and reinforcement learning.

https://doi.org/10.1371/journal.pone.0275358.g001

Implementation

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Clinical Chemistry 69:7
690–698 (2023)

Special Report

Machine Learning in Laboratory Medicine: Recommendations of the IFCC Working Group

Stephen R. Master,[a,b,*] Tony C. Badrick,[c] Andreas Bietenbeck,[d] and Shannon Haymond[e,f,*]

Clinical Chemistry 70:11
1334–1343 (2024)

Mini-Review

Validating, Implementing, and Monitoring Machine Learning Solutions in the Clinical Laboratory Safely and Effectively

Nicholas C. Spies,[a,*] Christopher W. Farnsworth,[b] Sarah Wheeler,[c] and Christopher R. McCudden[d]

JOURNAL OF MEDICAL INTERNET RESEARCH Luo et al

Original Paper

Guidelines for Developing and Reporting Machine Learning Predictive Models in Biomedical Research: A Multidisciplinary View

Wei Luo[1*], PhD; Dinh Phung[2*], PhD; Truyen Tran[2*], PhD; Sunil Gupta[2*], PhD; Santu Rana[2*], PhD; Chandan Karmakar[2*], PhD; Alistair Shilton[2*], PhD; John Yearwood[2*], PhD; Nevenka Dimitrova[3*], PhD; Tu Bao Ho[4*], PhD; Svetha Venkatesh[2*], PhD; Michael Berk[2*], PhD, FRACP