

CAT in the box:

A CausalAI – Tsetlin Machine Duo

Enabling explainable Stroke Diagnosis and Prevention



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Presenter

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Meet the team



Bio-optics and photonics

Post-docs

Microscopic Heat Engine Light-Sheet Microscopy

Happy place

Sci-Fi and Fantasy books



Our Mosaic:

PhD in computer science Al Engineers R&D project management



Our Projects



DAMIS



Advanced remote management system for operational efficiency in water distribution networks through intelligent systems





PREV-ICTS



Clinically supported stroke scenario recognition, visualization, inference and simulation platform



DETECT



Automated technical detection and labeling in industrial engine technical diagrams using computer vision



SMARTQAM



New advanced QA testing platform using autonomous AI and full coverage





RIVER EU



New AI for a more resilient and sustainable steel supply chain

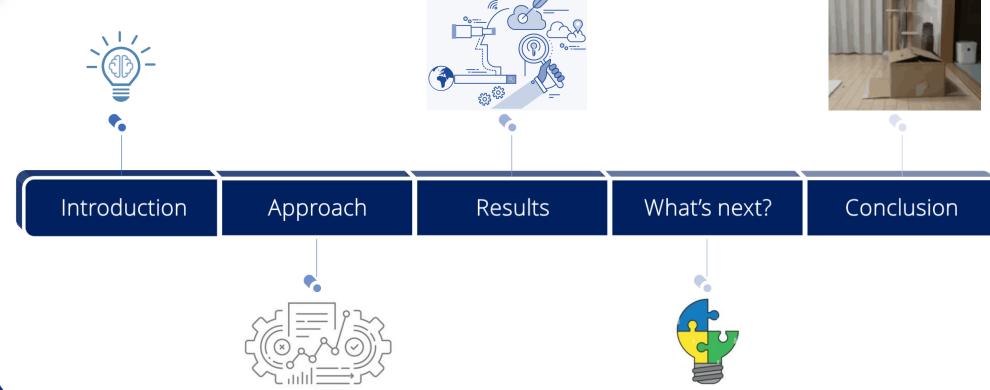




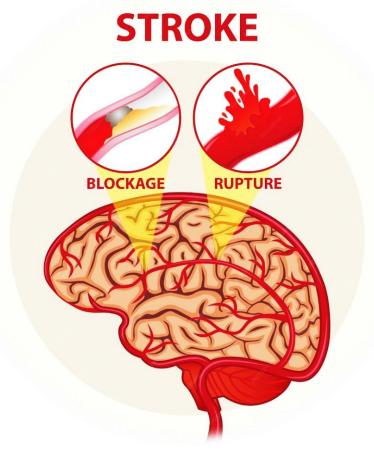




Outline



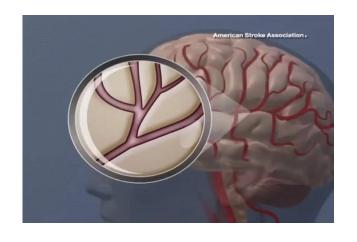
Alteration of blood supply to the brain



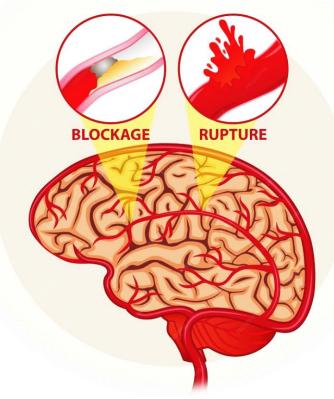


Alteration of blood supply to the brain

Ischemic ~87% of all strokes







Haemorrhagic ~10-15% of all strokes





As per World Stroke Organisation,

- ✓ 2nd leading cause of death
- √ \$890 billion annually
 - ✓ \$1 trillion by 2030





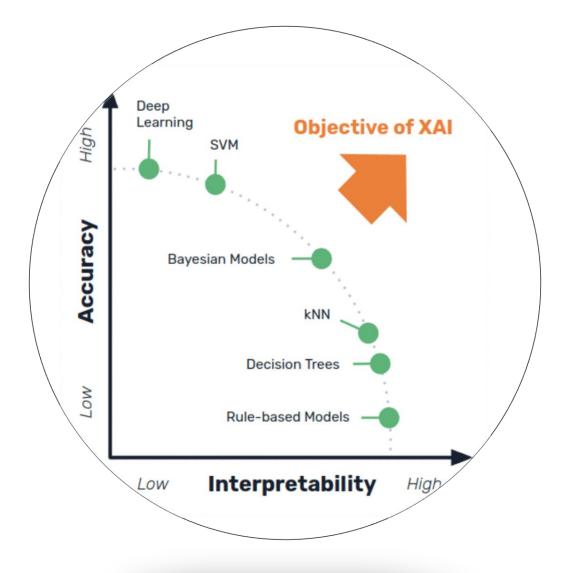
As per World Stroke Organisation, **12.2M** ✓ 2nd leading cause of death new strokes each year √ \$890 billion annually √ \$1 trillion by 2030 people are living with are linked to 10 the stroke modifiable Estimated aftermath risk factors 35% In Spain, increase in 10 years 143M people over age 25 will 1 in 5 have experience recurrent stroke in their lifetime stroke



Our goal is to understand,

1. What contributes to stroke possibility?

- 2. Can we derive prevention strategies?
 - Influence of specific biomarkers



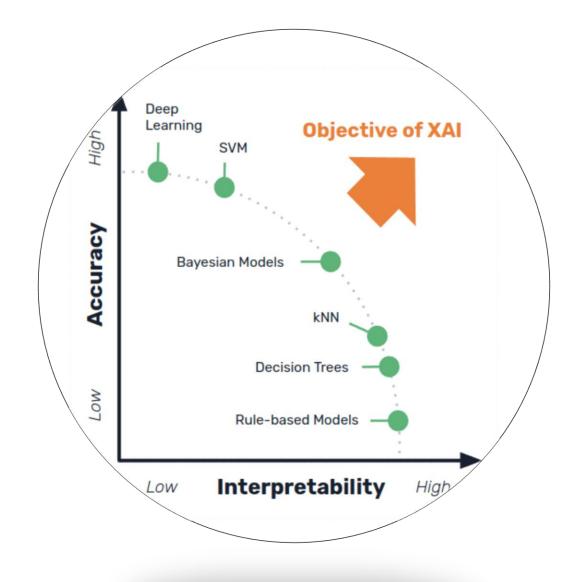


Approach

Our goal is to understand,

- 1. What contributes to stroke possibility?
 - Causal Al not just correlations!
- 2. Can we derive prevention strategies?
 - Influence of specific biomarkers
 - Rule based learning model Tsetlin Machine

If A and not B, then class X





The ladder of causation

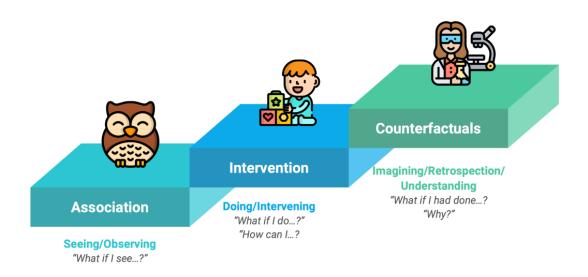


Image by Esra Simsek (based on Pearl's Ladder of Causation)



The ladder of causation

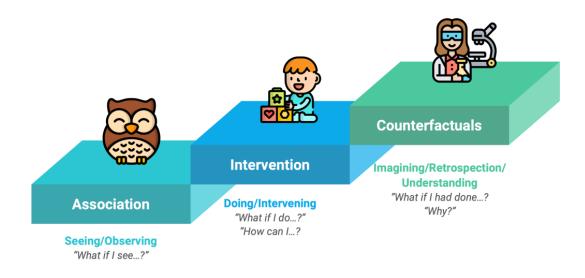


Image by Esra Simsek (based on Pearl's Ladder of Causation)

Tsetlin Machine

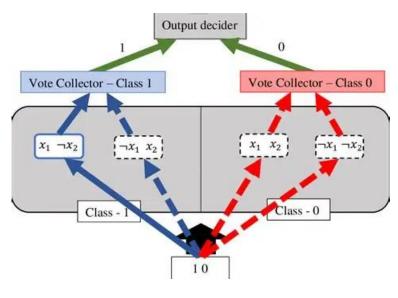
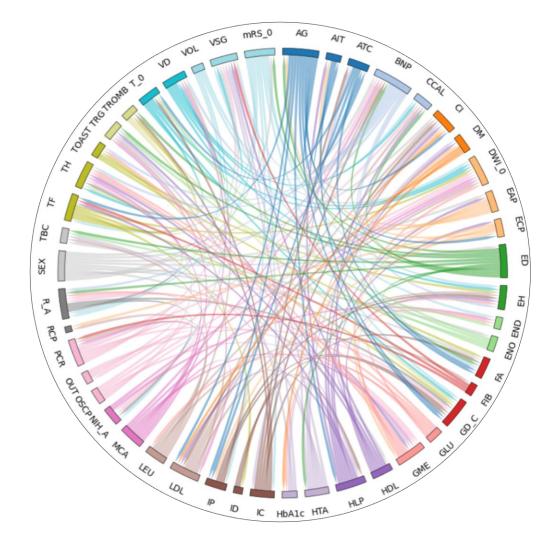


Image from 10.48550/arXiv.2005.05131 by Ole-Christoffer Granmo



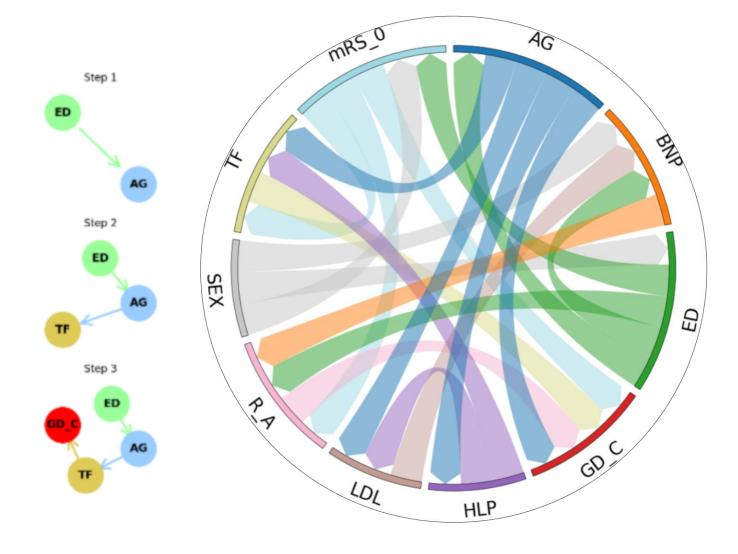
Causal discovery,

- 1. Shows effects of each feature on others
- 2. Directional identifying cause and effect
- 3. How to identify the most influential ones?





- Degree Centrality:
 Number of direct connections
 Higher value → broad influence
- Betweenness Centrality:
 A node's link to others
 Higher value → critical link
- 3. Compare with domain knowledge!

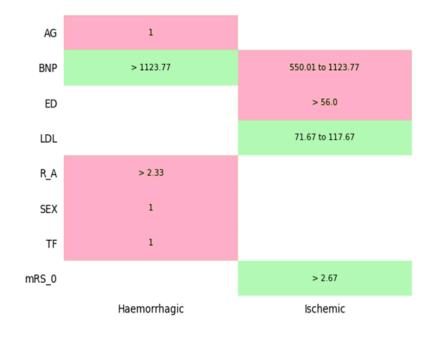




Results

Rules/clauses of Tsetlin Machine,

- 1. Binarization with bins for continuous variables
- 2. Voting weights for each generated clause
- 3. Helps identify,
 Most important features for a class
 Their value ranges





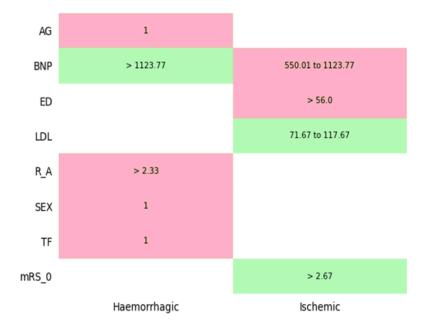
Results

Rules/clauses of Tsetlin Machine,

The clause for ischemic stroke would then be:

if mRS_0 > 2.67 and LDL between 71 – 117 mg/dL and Age NOT > 56 and BNP NOT between 550 – 1123 pg/mL then Ischemic.

Preliminary results* - subject to further investigation





Introduction Approach Results Results What's next?

- ✓ Remove bias in class distribution
- ✓ More robust model training
- ✓ More scenarios to run

More data



- ✓ Remove bias in class distribution
- ✓ More robust model training
- ✓ More scenarios to run

More data

Improve causal inference

- ✓ Check for 'hidden' confounders
- ✓ Advanced algorithms for causal discovery
- ✓ Ensure the direction of causality with domain knowledge

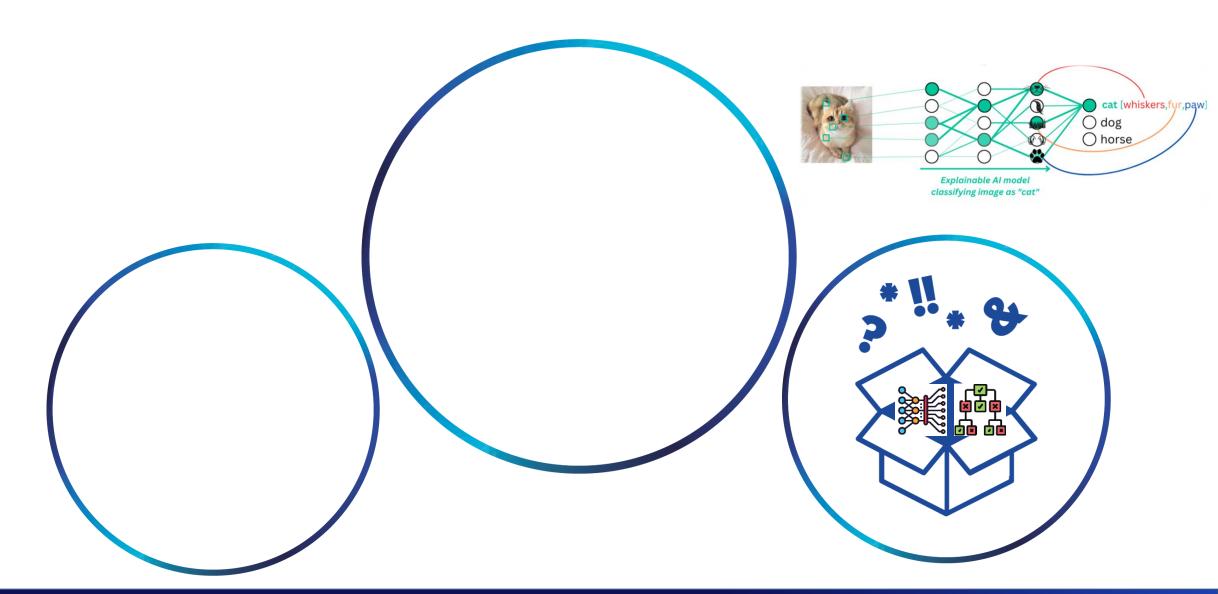


Introduction Approach What's next? Results Results ✓ Remove bias in class distribution ✓ More robust model training More data ✓ More scenarios to run ✓ Check for 'hidden' confounders Improve ✓ Advanced algorithms for causal discovery causal ✓ Ensure the direction of causality with inference domain knowledge ✓ Improve binarization with domain knowledge Fine tune

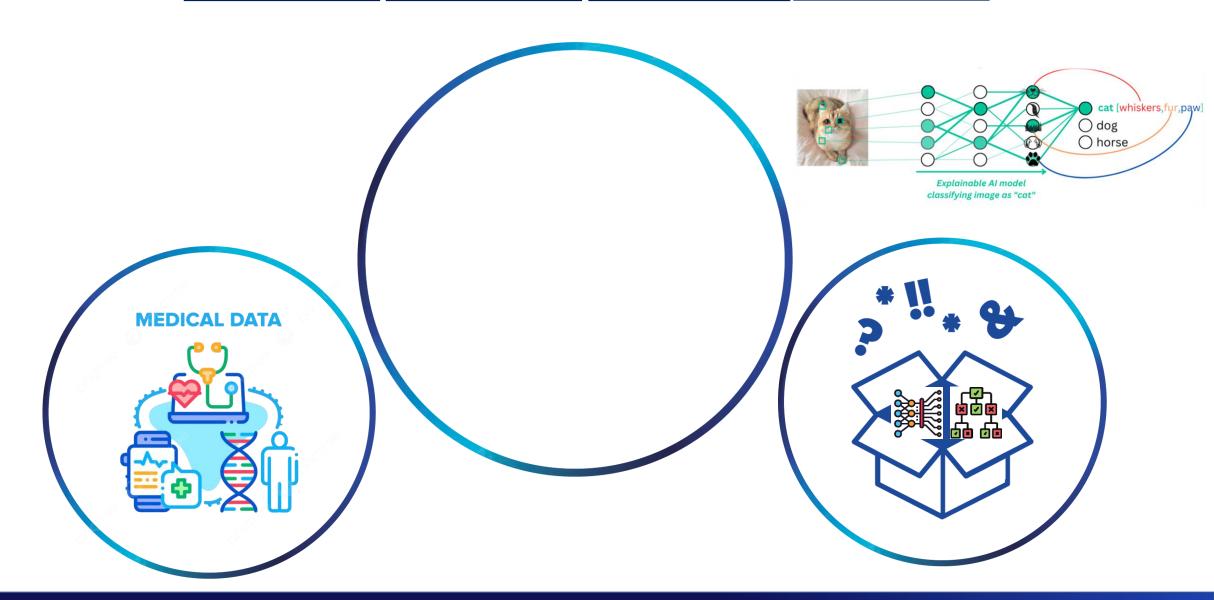
- ✓ Resampling of data
- ✓ Clause weight distribution

TM clauses





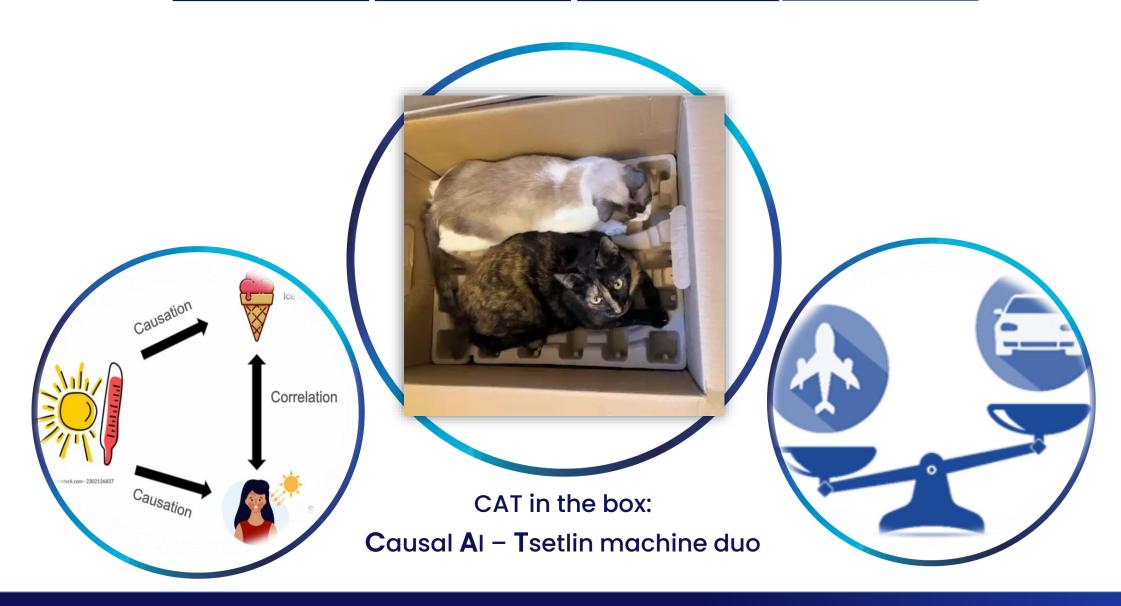
















Thank you!

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