AI-in-the-loop for healthcare

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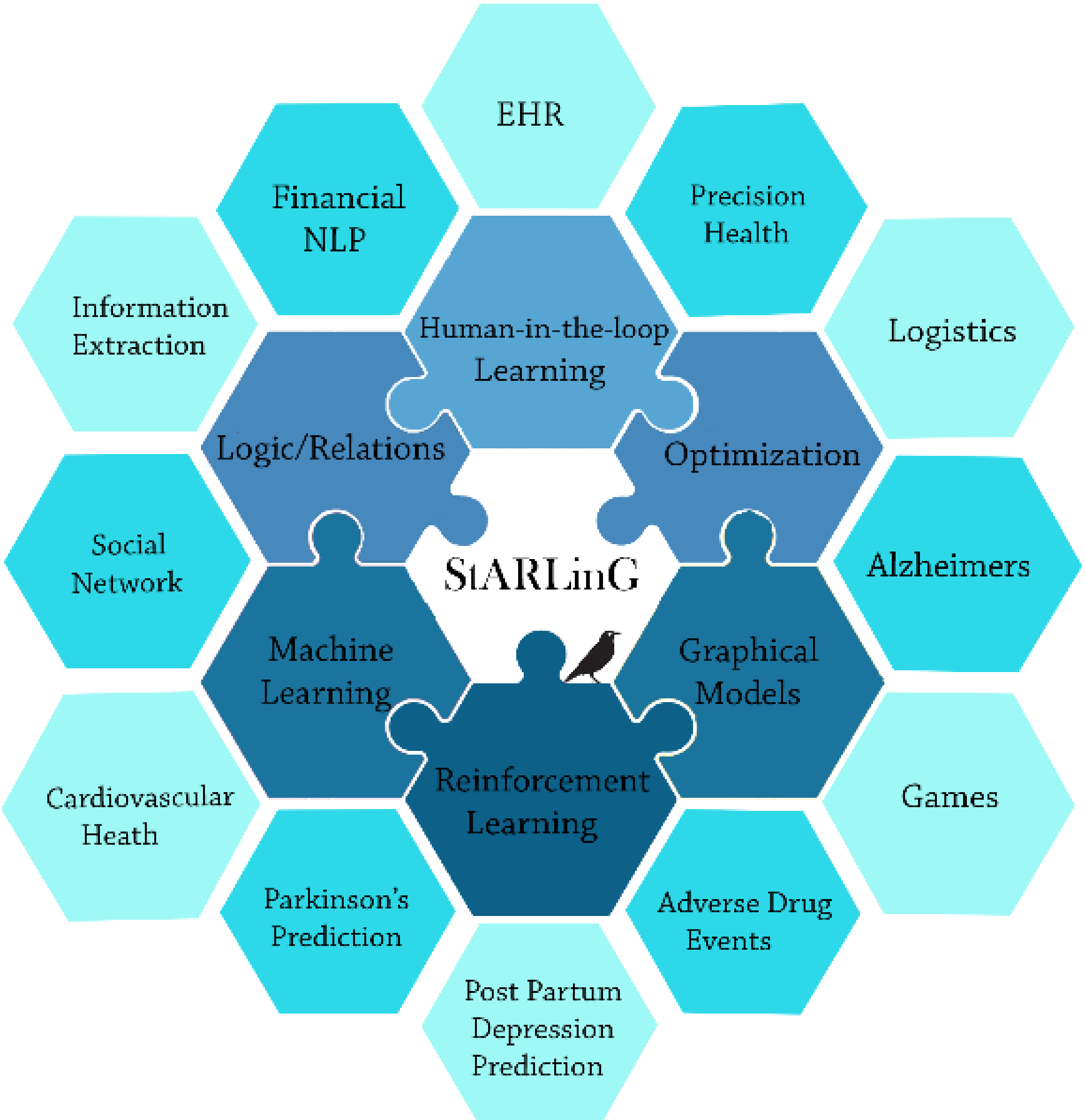
Who we are!

Current Students (PhD)
Siwen Yan, Athresh Karanam, Saurabh Mathur, Dr. Michael Skinner, Nikilesh Prabhakar, Ranveer Singh, Sahil Sidheekh, Pranuti Tenali

Alumni (PhD)
Harsha Kokel, Navdeep Kaur, Nandini Ramanan, Srijita Das, Devendra Singh Dhami, Mayukh Das, Phillip Odom , Shuo Yang, Tushar Khot, Yuqiao Chen, Brian Ricks

Key Collaborators
Kristian Kersting, Vibhav Gogate, Rishabh Iyer, Jude Shavlik, Gautam Kunapuli, David Page, Dan Roth, Jana Doppa, Ron Parr, Balaraman Ravindran, Prasad Tadepalli, Predrag Radivojac, David Poole, Kay Connelly, Clinical collaborators ….

Funding agencies
DARPA (Minerva, CwC, DEFT & Machine Reading), NSF (EAGER & SCH), AFRL, ARO (SIG, YIP, STIR), AFOSR (SBIR), NIH (R01), Indiana (Precision Medicine), XEROX PARC, Amazon, Intel, TURVO and Verisk Inc.



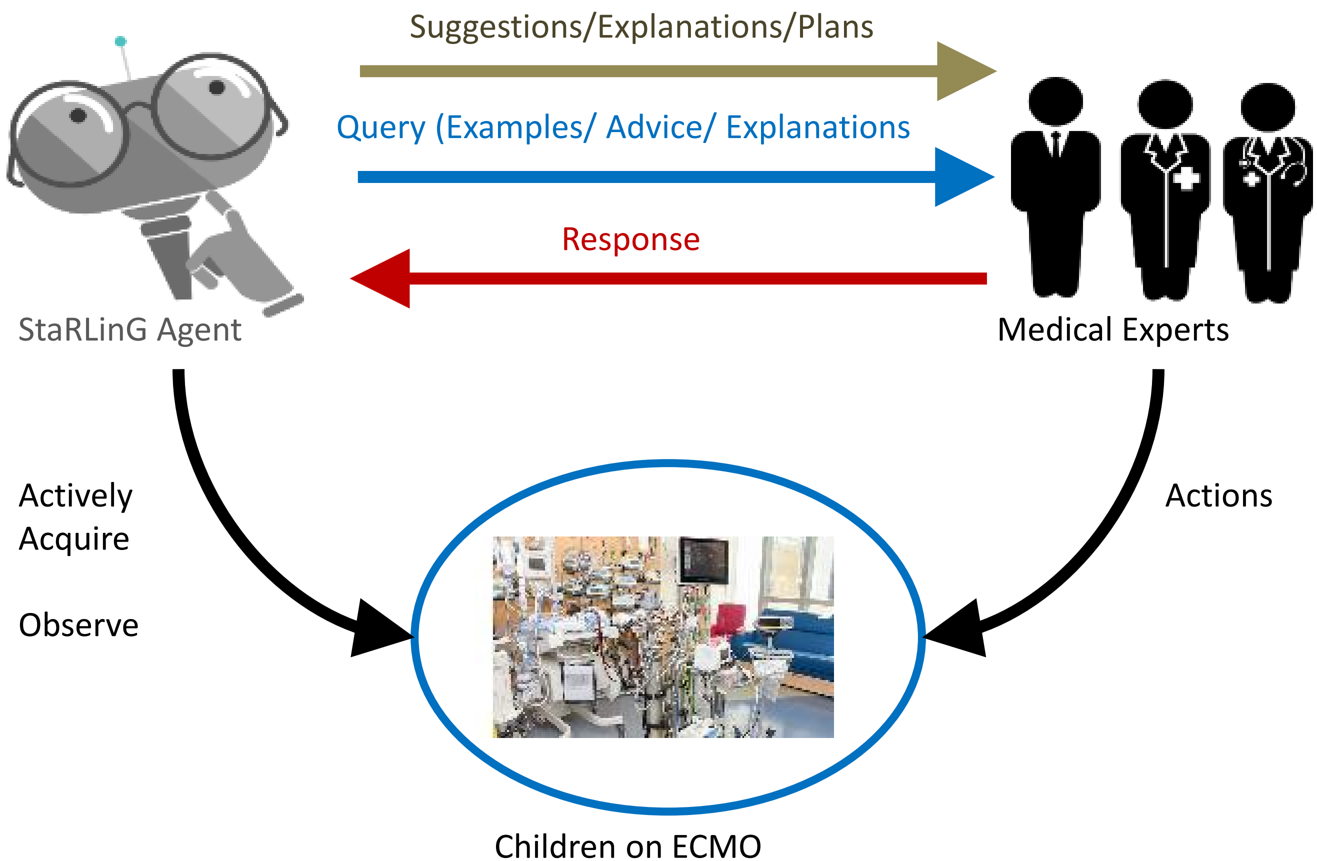
EHR
Financial NLP
Precision Health
Information Extraction
Human-in-the-loop Learning
Logistics
Logic/Relations
Optimization
Social Network
StARLinG
Alzheimers
Machine Learning
Graphical Models
Cardiovascular Heath
Reinforcement Learning
Games
Parkinson's Prediction
Adverse Drug Events
Post Partum Depression Prediction

What we do!

Human Allied AI

Can we build AI systems that can seamlessly interact with, learn from, collaborate with and potentially teach the human expert?

Human Allied AI? Or AI-in-the-loop?



Fern et al. IJCAI 07; Natarajan et al. ILP08, ILP09; Natarajan et al. KAIS 11; Fern et al. JAIR 14; Kunapuli et al. ICDM 13; Odom et al. AAAI 15, AAMAS 16, ECML 16, ILP 16, AIME 15; Yang et al. ICDM 14, ECML 13; Macleod et al. CHASE 16; Natarajan et al. IJCAI 18; Das et al. AAAI 19, HMCL WS 17, AAMAS 18; KBS 18, MLJ (Under Review); Ramanan et al. BIBM 17, KR 18; Dhami et al. AIME 17, Smart Health 18, AI for Good 19; Kaur et al. ILP 17,19, IJAR 20; Hayes et al. KCAP 17; Kokel AAAI 20;

Problem 1: Cardiovascular health

CARDIA EXAM COMPONENTS—ALL YEARS

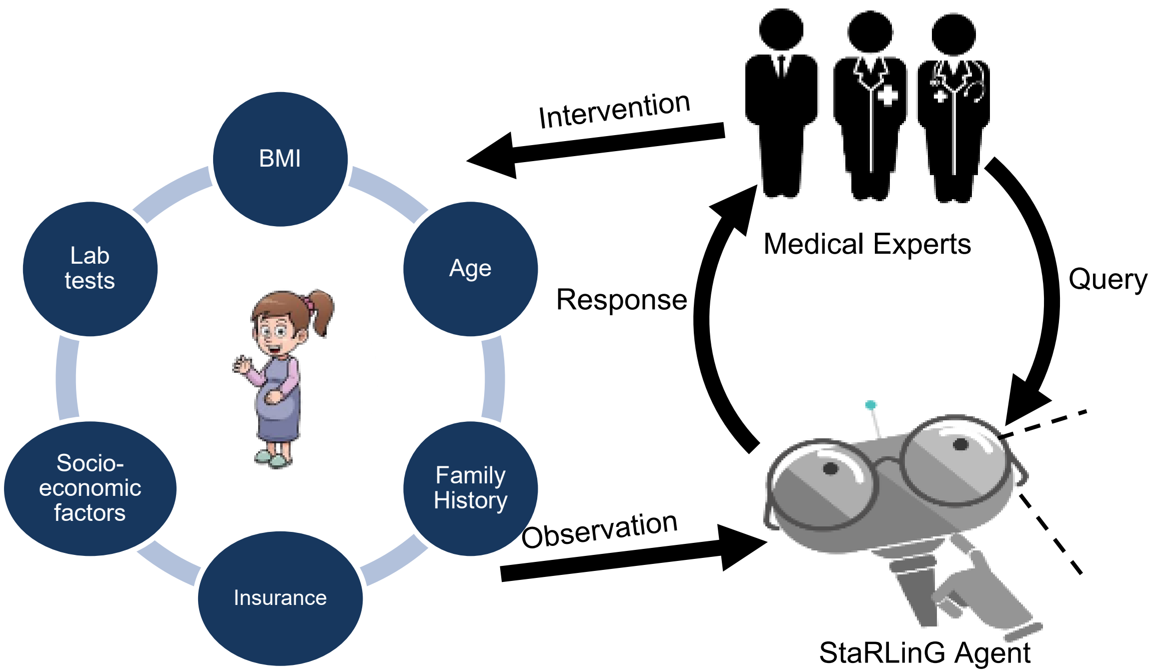
Schedule of components in the core study, substudies, and ancillary studies by CARDIA exam

	Year/Exam[1]							
	1985	1987	1990	1992	1995	2000	2005	2010
	0	2	5	7	10	15	20	25
CORE STUDY								
BLOOD PRESSURE								
Resting	X	X	X	X	X	X	X	X
Standing	-	X	-	-	-	-	-	-
Reactivity	-	X	-	-	-	-	-	-
CHEMISTRIES								
Genetic								
DNA Storage	-	-	X	-	X	X	X	X
Stored Cells for Cell Immortalization	-	-	-	-	-	X	-	-
Plasma								
Lipids	X	X	X	X	X	X	X	X
Lipoproteins	X	X	X	X	X	X	X	-
Apoproteins	X	X	-	-	-	-	-	-
CBC	X	-	-	-	-	-	-	-
Lp(a)	-	-	X	-	-	-	-	-
Fibrinogen	-	-	X	-	-	-	X	-
ApoE Phenotype	-	-	-	X	-	-	-	-
Stored Plasma	-	X	X	X	X	X	X	X
C-Reactive Protein	-	-	-	X	-	X	X	X
Interleukin-6	-	-	-	-	-	-	X	-
Serum								
Cotinine	X	-	-	-		-	-	-
SMAC 12	X	-	-	-	-	-	-	-
Fasting Insulin	X	-	-	X	X	X	X	X
Fasting Glucose	X	-	-	X	X	X	X	X
Oral Glucose Tolerance Test	-	-	-	-	X	-	X	X
Stored Serum	X	X	X	X	X	X	X	X
GGT	X	-	-	-	X	-	-	-
Serum Creatinine	X	-	-	-	X	X	X	X
Uric Acid	X	-	-	-	X	X	-	-
Urine								
Urinary Creatinine	-	-	-	-	X	X	X	X
Albuminuria	-	-	-	-	X	X	X	X
ANTHROPOMETRY								
Height	X	X	X	X	X	X	X	X
Weight	X	X	X	X	X	X	X	X
Skinfolds	X	X	X	X	X	-	-	-
Chest Circumference	-	X	X	-	-	-	-	-
Waist Circumference	X	X	X	X	X	X	X	X
Hip Circumference	X	X	X	X	X	-	-	X
Thigh Circumference	-	-	-	X	-	-	-	-
Elbow Breadth	X	X	-	-	-	-	-	-
Shoulder Breadth	-	X	-	-	-	-	-	-
Sitting Height	-	X	-	-	-	-	-	-
Toenails	-	X	-	-	-	-	-	-
Eye Color	-	-	X	-	-	-	-	-
Skin Reflectance	-	-	-	X	-	-	-	-
MEDICAL HISTORY								
Medical History	X	X	X	X	X	X	X	X
Illicit Drug Use	X	X	X	X	X	X	X	X
Death Certificate	-	X	X	X	X	X	X	X
Mortal Events	-	-	-	X	X	X	X	X
Safety Questionnaire	-	X	-	-	-	-	-	-
Interim Hospitalization	-	X	X	X	X	X	X	X
Chest Pain/Palpitations	-	-	X	-	X	-	-	-
History of Lung Problems	X	X	-	-	X	X	X	-
Oral Contraceptive History	-	-	-	-	X	-	-	-
Women's Reproductive Health	-	-	-	-	-	X	X	X
Sleep Habits	-	-	-	-	-	X	X	-
Tobacco	X	X	X	X	X	X	X	X
Alcohol	X	X	X	X	X	X	X	X
Weight History	X	X	-	-	-	-	-	X
Sociodemographics	X	X	X	X	X	X	X	X
FAMILY HISTORY QUESTIONNAIRE								
Family History	X	-	X	-	X	-	-	X
PHYSICAL ACTIVITY/FITNESS								
7-Day Physical Activity	X	-	-	-	-	-	-	-
Physical Activity Questionnaire	X	X	X	X	X	X	X	X
Graded Exercise Test	X	-	-	X	-	-	-	-
Baecke Questionnaire	-	-	X	-	X	-	-	-
Household Chores	-	-	-	X	X	-	-	-
Sedentary Behavior Questionnaire	-	-	-	-	-	-	-	X

[1] year of study indicates when original data collection occurred; assay or coding may occur later

Different data sets – CARDIA, Jackson heart study, Registry data from multiple hospitals

Problem 2 – Modeling Adverse Pregnancy Outcomes



Problem 3: EHRs

Journal of *Clinical Medicine* MDPI

Article

Predicting Cardiac Arrest in Children with Heart Disease: A Novel Machine Learning Algorithm

Priscilla Yu [1,*], Michael Skinner [2,3], Ivie Esangbedo [4], Javier J. Lasa [1,5], Xilong Li [6], Sriraam Natarajan [2] and Lakshmi Raman [1]

Machine Learning for Personalized Medicine: Predicting Primary Myocardial Infarction from Electronic Health Records

Jeremy C. Weiss, Sriraam Natarajan, Peggy L. Peissig, Catherine A. McCarty, David Page

An Anytime Querying Algorithm for Predicting Cardiac Arrest in Children: Work-in-Progress

Michael A. Skinner[1,2](✉), Priscilla Yu[2], Lakshmi Raman[2], and Sriraam Natarajan[1]

[1] University of Texas at Dallas, Dallas, TX 75080, USA
[2] University of Texas Southwestern Medical Center, Dallas, TX 75390, USA
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Modeling Heart Procedures from EHRs: An Application of Exponential Families

Shuo Yang*, Fabian Hadiji†, Kristian Kersting‡, Shaun Grannis§ and Sriraam Natarajan¶
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Identifying Adverse Drug Events by Relational Learning

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CRACS-INESC TEC and FCUP

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Wake Forest University

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University of Wisconsin–Madison

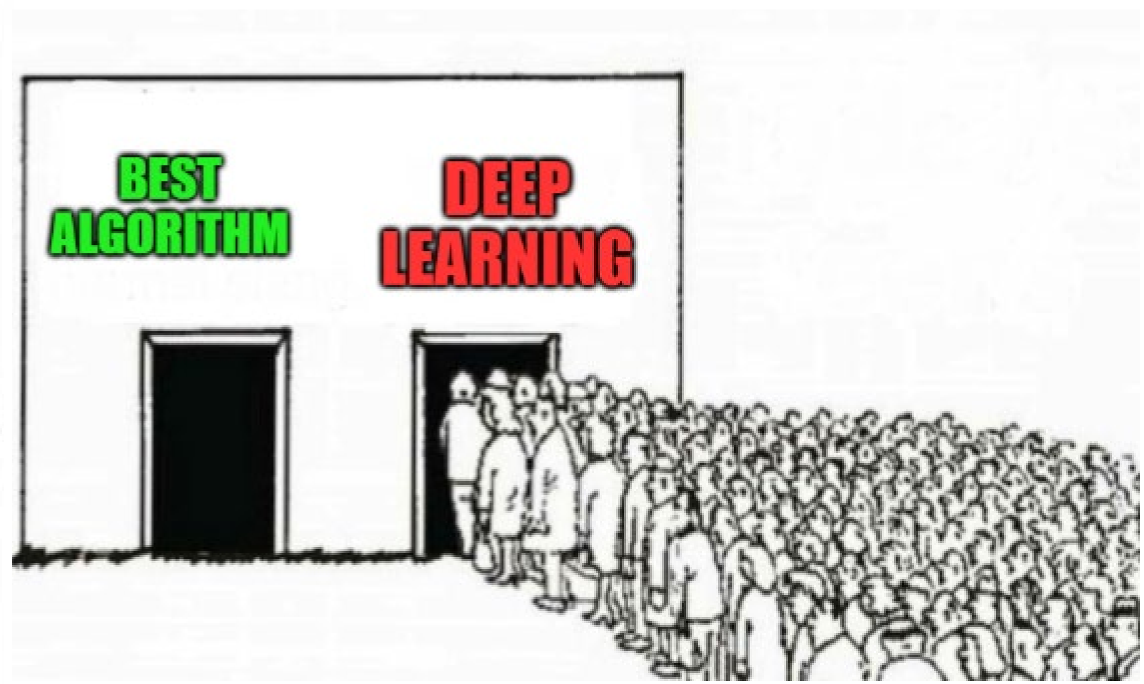
Peggy Peissig
Marshfield Clinic Research Foundation

Michael Caldwell
Marshfield Clinic

Challenges to HAAI

- Different **types and formats** of data
- Different **scales** of data
- Different **frequencies** of data streams
- **Noise** in measurements/sensors/data
- **Changes** in acquired knowledge
- **Uncertain side-effects** of actions
- **Partial observability** of the world
- **Long-term effects** of decision-making

Biggest challenge!



(Our) 3 Steps to HAAI

Learn “only” from data
Effective
Efficient
Generalizable
Personalized
Explainable
…
Ignores human knowledge

Allow “**richer**” human inputs

More than a “**mere labeler**”

Take advice and guidance

Allows for robust learning

Close the “**loop**”

Knows what it knows

Asks what it does **not** know

Student-teacher interaction

Teach the human!

Personal first foray – Adverse Drug Events
Cox-2 Timeline

Dec. 1998-May 1999,
Celebrex, Vioxx approved

2001,
Cox-2 sales top
$6 billion/year in US

2002,
Beginning of
APPROVe Study

Sept 2004,
Vioxx voluntarily
pulled from market

Dec. 2004,
FDA issues warning

April 2005,
FDA removes
Bextra from market

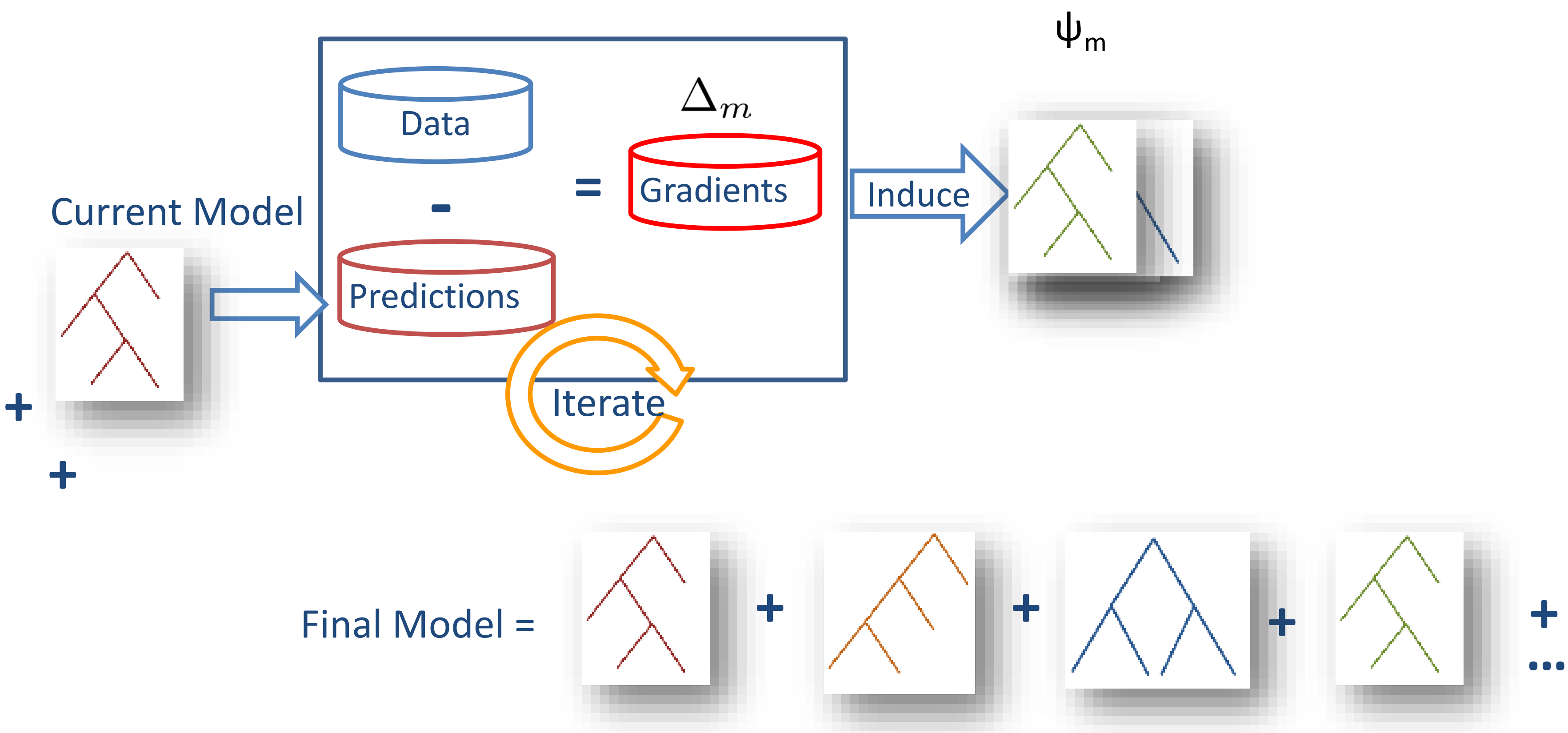
Rules for Cox2ib(A) :-	Pos	Neg	p-value
diagnoses(A,790.29, Abnormal_Glucose_Test, Other_Abn_Glucose).	333	137	6.80E-20
diagnoses(A,V54.89, Other_Orthopedic _Aftercare).	403	189	8.59E-19
diagnoses(A,V58.76, Aftcare_ Foll_ Surg _Of_Genitourinary Sys).	287	129	6.58E-15
diagnoses(A,V06.1, Diphtheria-Tetanus-Pertussis,Comb(Dtp)(Dtap)).	211	82	2.88E-14
diagnoses(A,959.19, Other Injury Of Other Sites Of Trunk).	212	89	9.86E-13
diagnoses(A,959.11, Other Injury Of Chest Wall).	195	81	5.17E-12
diagnoses(A,V58.75, Aftcar Foll Surg Of Teeth, Oral Cav, Dig Sys).	236	115	9.88E-11
diagnoses(A,V58.72, Aftercare Following Surgery Nervous Syst, Nec).	222	106	1.40E-10
diagnoses(A,410, Myocardial Infarction).	**212**	**100**	**2.13E-10**
diagnoses(A,790.21, Impaired Fasting Glucose).	182	80	2.62E-10

Outline

- Cardiovascular health
- Adverse Pregnancy Outcomes
- Learning from EHRs

Functional Gradient Boosting

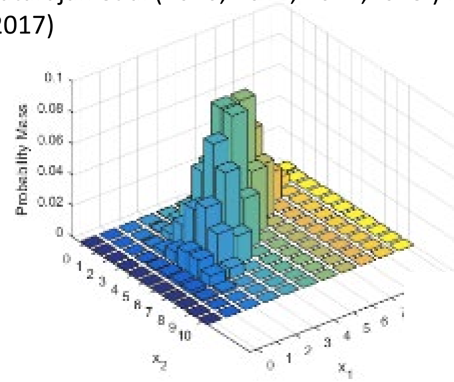
Learn multiple weak models rather than a single complex model



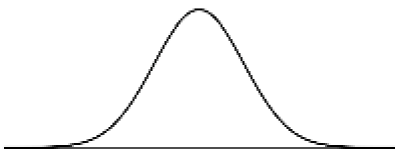
Friedman et al 2001, Dietterich et al. 2004, Natarajan et al. MLJ 2012

What can be learned?

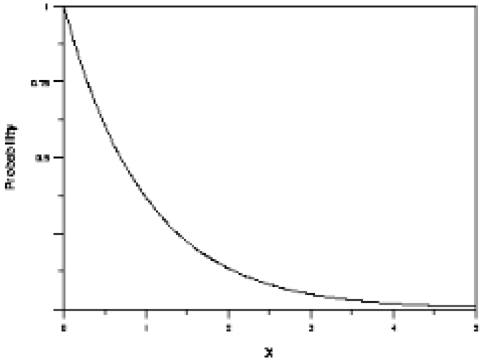
Natarajan et al (2010, 2011, 2012,2013) Khot et al (2011, 2013), Yang et al (2016), Hadiji et al (2015), Yang et al (2017)



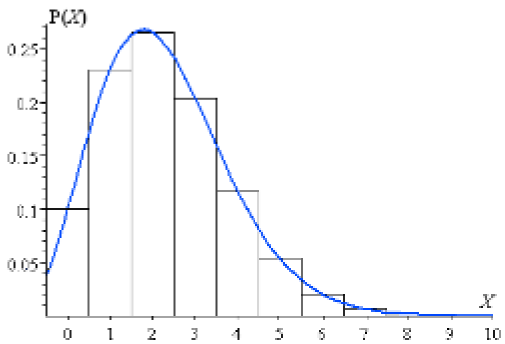
Multinomial



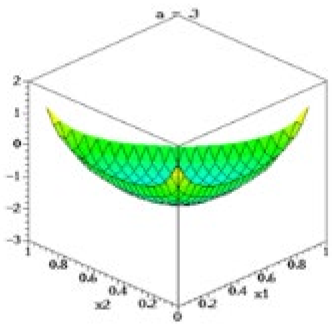
Gaussian



Exponential



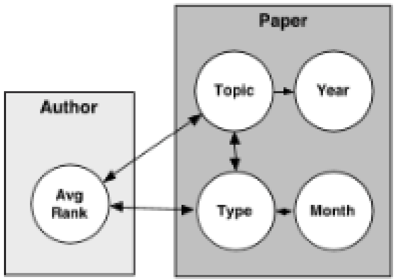
Poisson



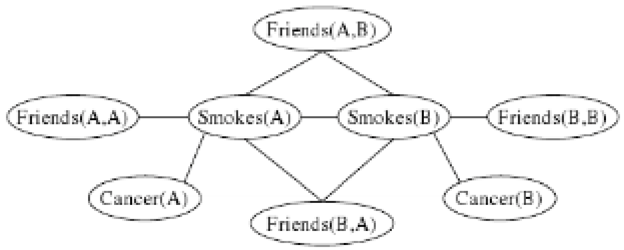
Dirichlet

Learning multiple models

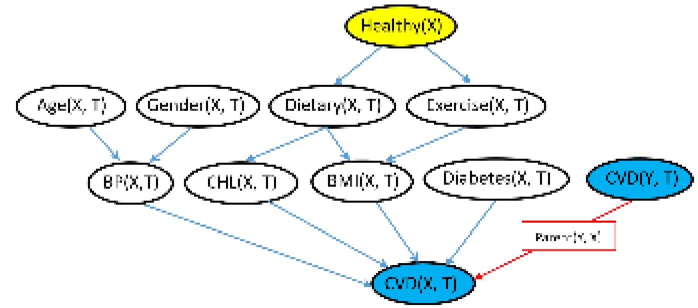
Natarajan et al (2010, 2011, 2012,2013) Khot et al (2011, 2013), Yang et al (2016), Ramanan et al 2018, 2020, Kaur et al. 2018,2020, Dhami et al, 2021, Das et al 2018



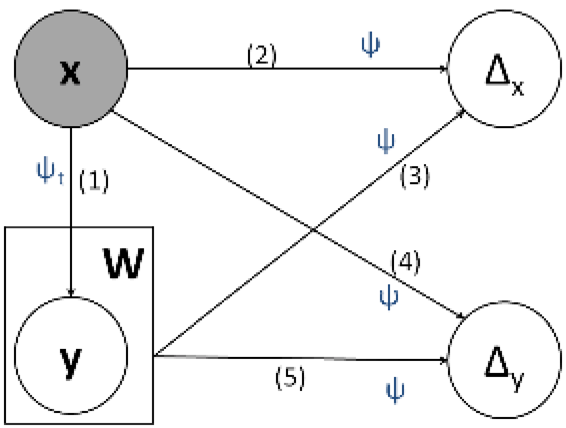
Relational Dependency network

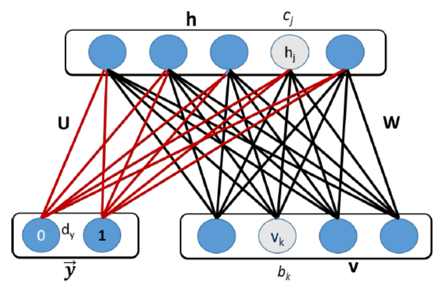


Markov Logic network
Relational Logistic Regression



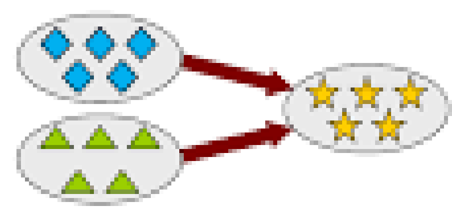
Relational CTBN





Relational RBM

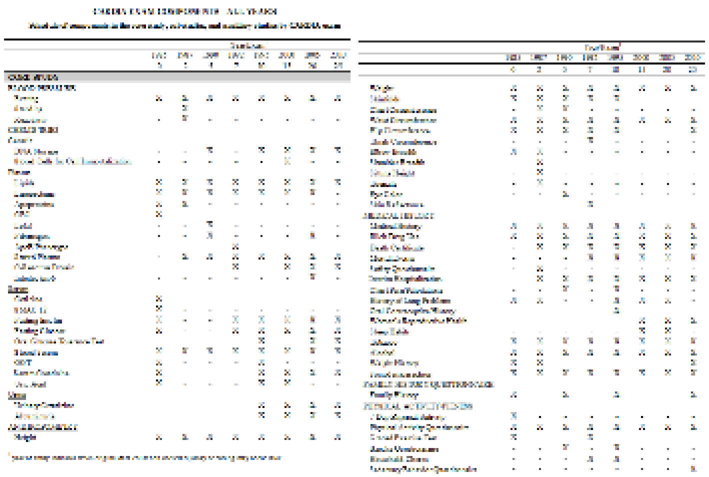
Imitation
Learning/Relational Policies



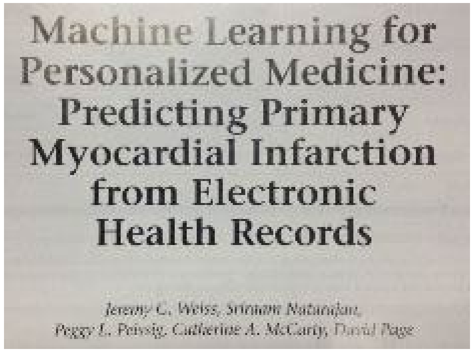
Transfer
Learning

Learning with Hidden data

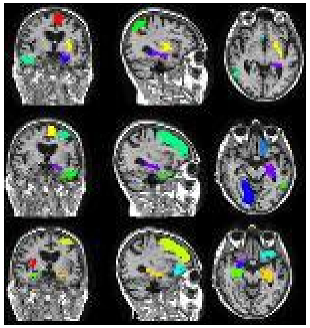
Several **Real** Applications



Cardiovascular study

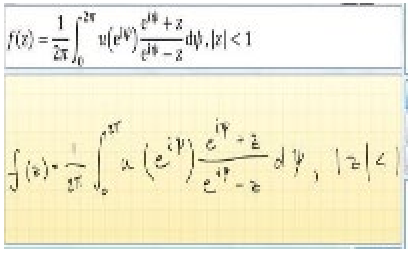


EHR



Alzheimer's

RTS Games



Handwriting Recognition

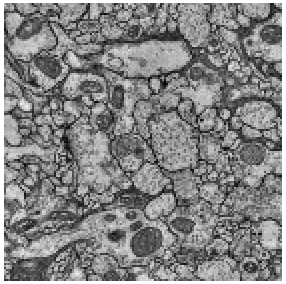
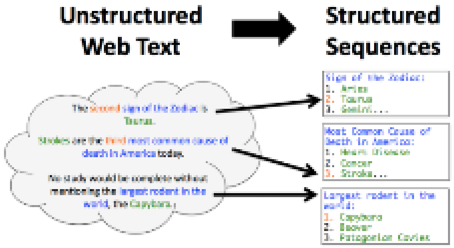
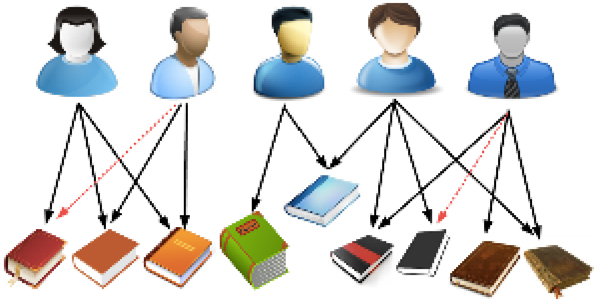


Image Segmentation/ Classification



Information Extraction



Recommendation System

Weiss et al. (2012,2013). Natarajan et al. (2013,2012, 2014, 2015), Shivram et al. (2014), Picado et al. (2014) Soni et al. (2016), Viswanathan et al. (2016), Odom et al. (2014,2015a, 2015b), Yang et al. (KBS 2017)

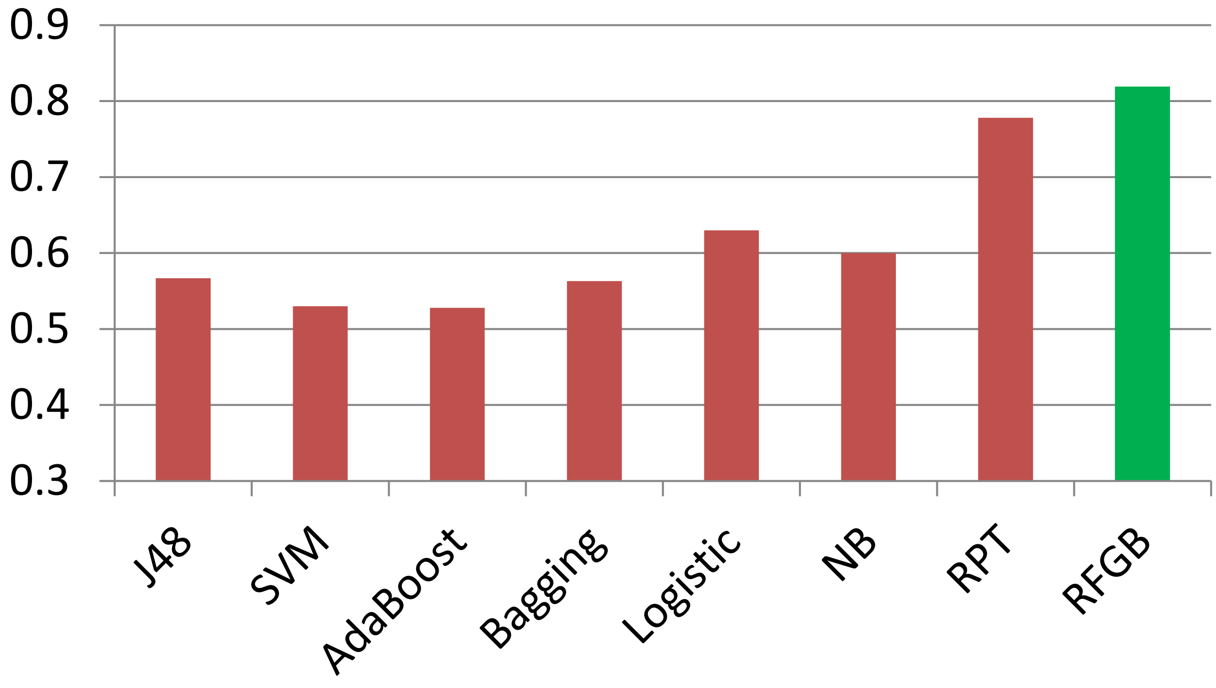
Atherosclerosis is the cause of the majority of Acute Myocardial Infarctions (heart attacks)

Plaque in the left Coronary artery

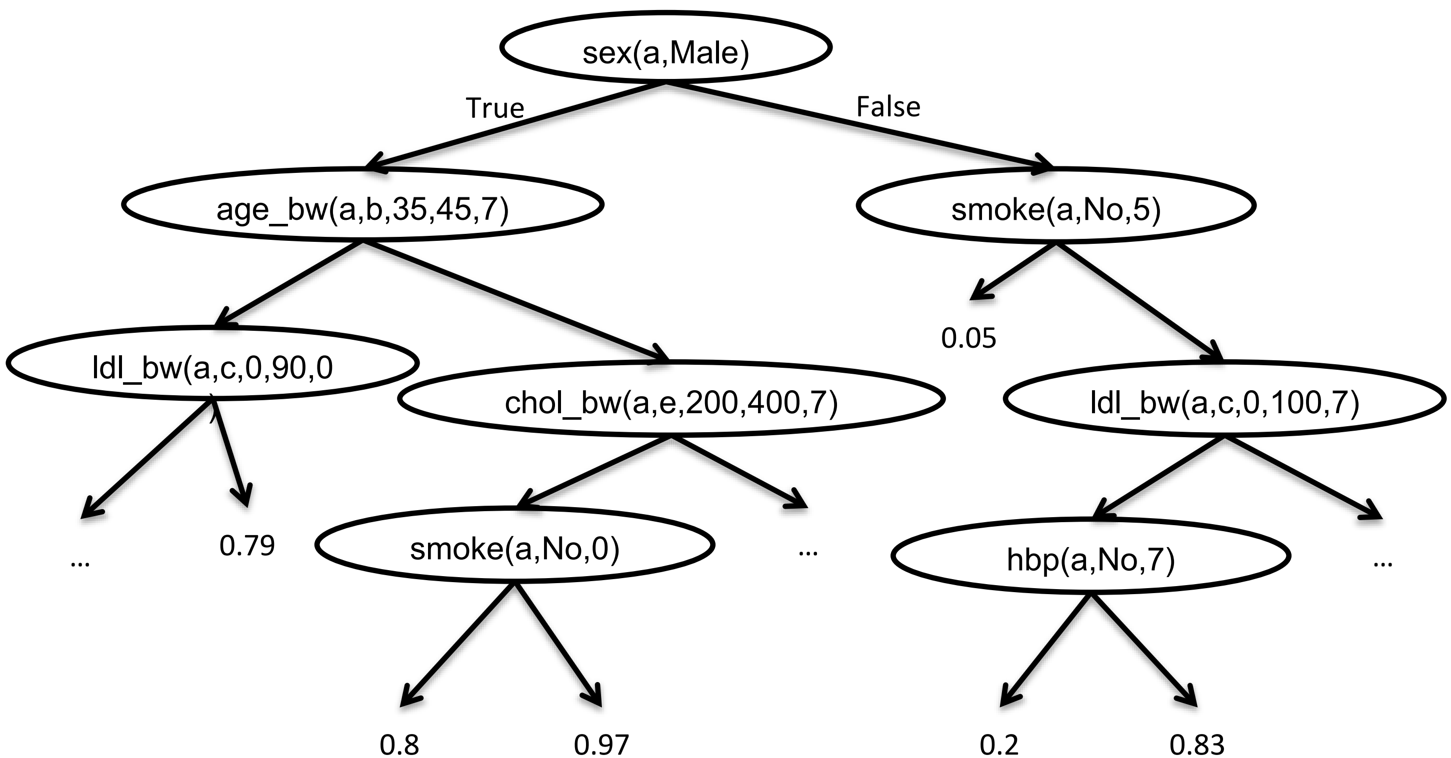
Circulation; 92(8), 2157-62, 1995

JACC; 43, 842-7, 2004

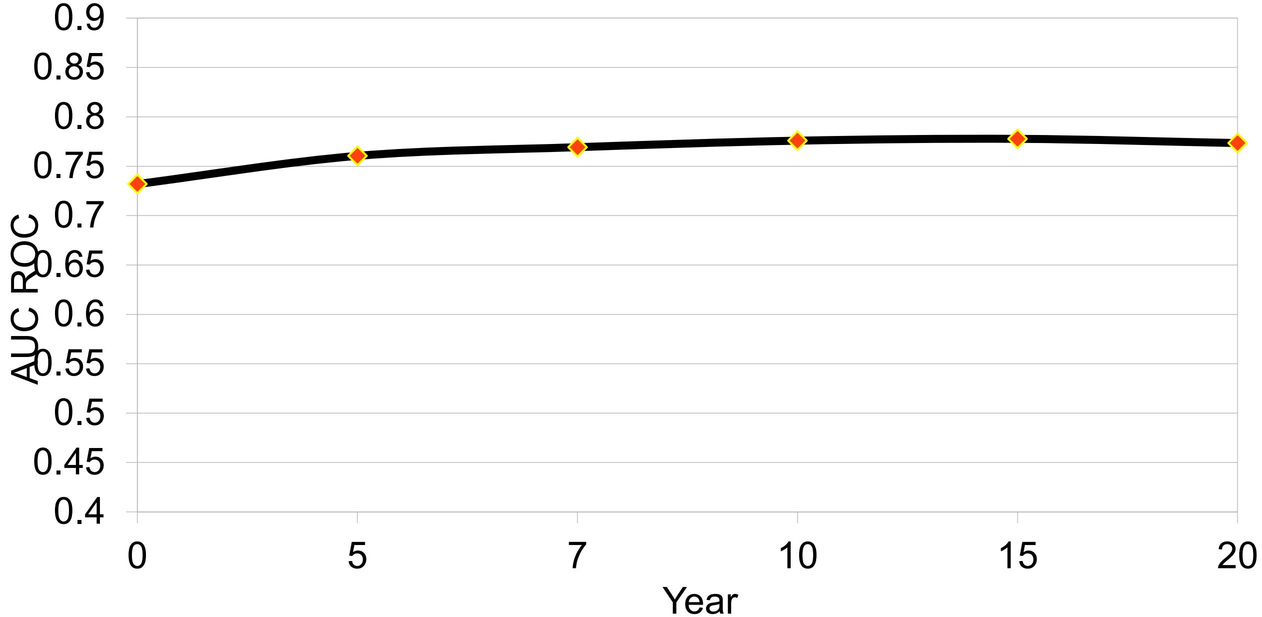
Results – AUC-ROC



Sample Learned Tree

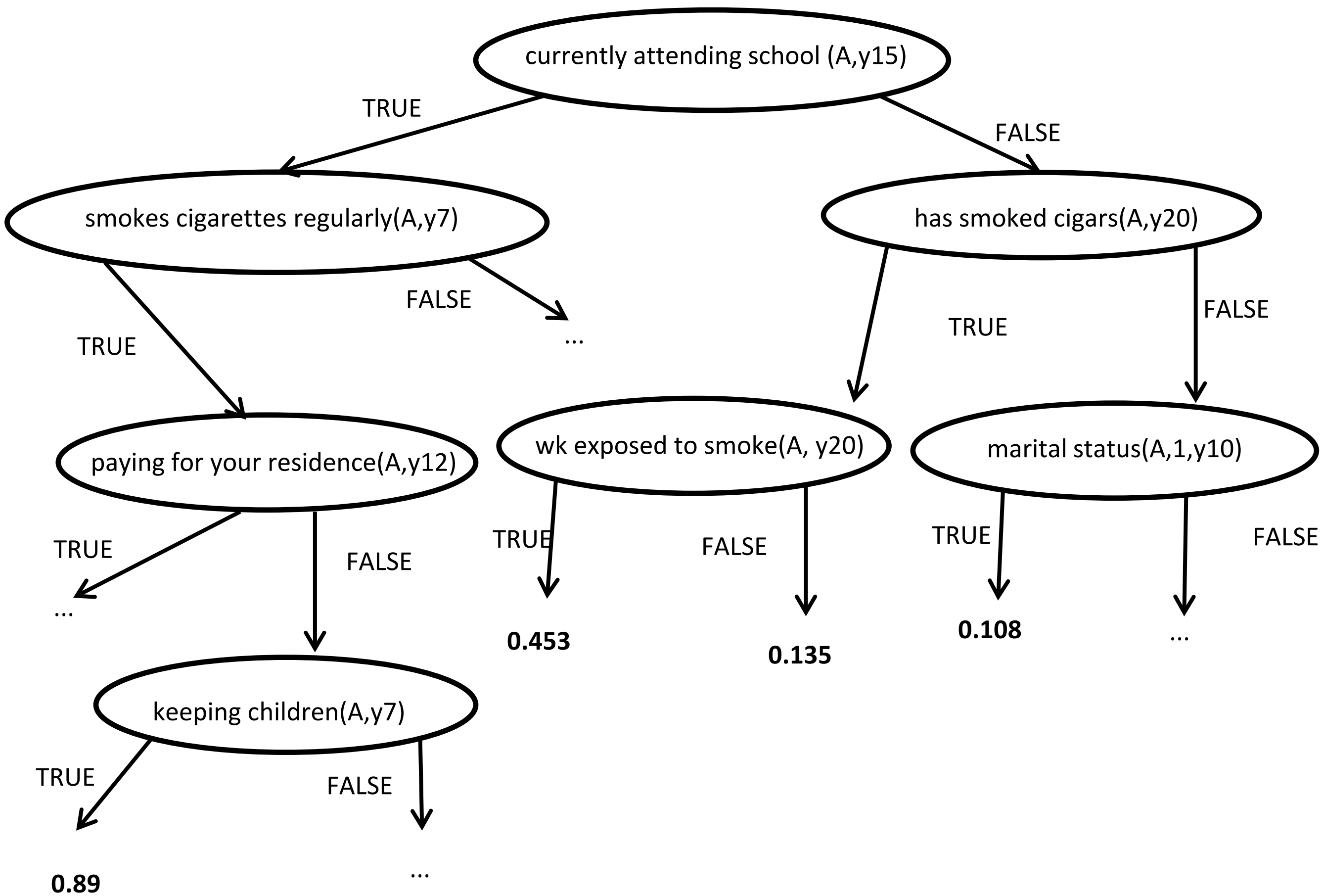


Year wise Growth of the Trees

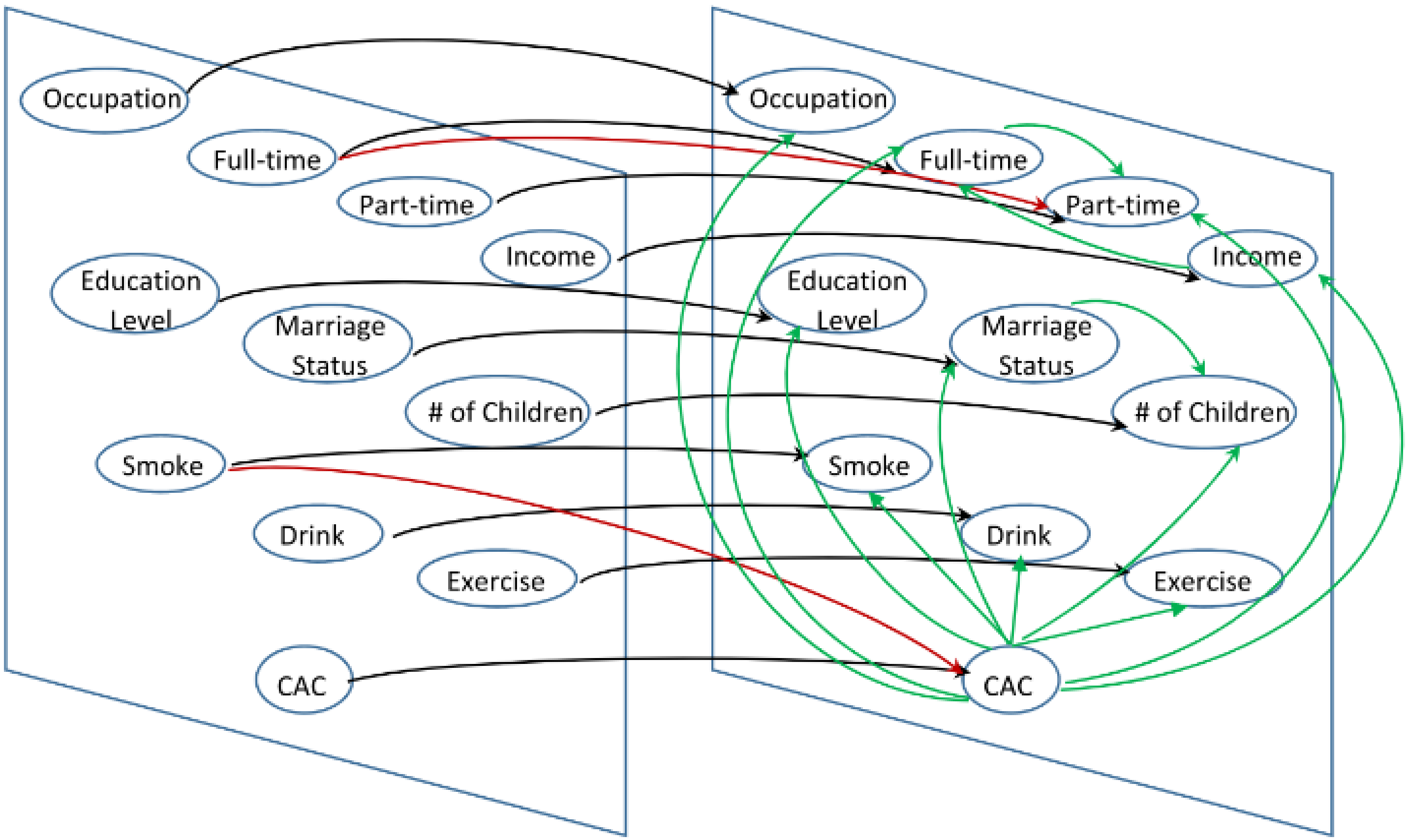


Beyond year 7 there is no improvement in the predictive performance

Learning From Only Socioeconomic Data



Temporal Model – Socioeconomic Data



Yang et al 2015

Physical Training Monitoring

- Goal: Predict and track a set of exercises
- Accelerometer data from 9 subjects
- Exercises consists of different types of walks (10 meter, 2 meter walks), different tugging exercises based (TUG 1, TUG 2, TUG 3) and sit to stand exercises (5STS, 5STS practice)

Results

- Two approaches
  - Edge impulse – online ML platform
  - Bi-LSTM with dropout
- Superior performance with Bi-LSTM

Task	Train Accuracy	Test Accuracy
Physical Training Classification	92.57	82.67

```
print(classification_report(y_test,predicted_test,target_names=le.classes_))

                 precision    recall  f1-score   support

  10 meter walk       0.91      0.93      0.92       491
 2 minutes walk       0.89      0.87      0.88       146
           5STS       0.80      0.82      0.81       165
  5STS Practice       0.81      0.76      0.79        29
          Other       0.95      1.00      0.97        39
          TUG 1       0.72      0.62      0.67       136
          TUG 2       0.62      0.72      0.67       127
          TUG 3       0.72      0.62      0.67       148

       accuracy                           0.82      1281
      macro avg       0.80      0.79      0.80      1281
   weighted avg       0.82      0.82      0.82      1281
```

Try it yourself

- https://starling.utdallas.edu/software/boostsrl/

Tutorial

- https://starling.utdallas.edu/software/boostsrl/wiki/

As with the standard gradient-boosting approach, our approach turns the model-learning problem to learning a sequence of regression models. The key difference to the standard approaches is that we learn relational regression models (i.e. regression models that operate on relational data). We assume the data to be in predicate-logic format and the output are essentially first-order regression trees where the inner nodes contain conjunctions of logical predicates.

Latest Release	License	Wiki
tag v1.0.0	license GPL-3.0	Documentation

Getting Started

Prerequisites:

- Java (tested with *openjdk 1.8.0_144*)

Installation:

- Download stable jar file.
- Download stable source with git.
  `git clone -b master https://github.com/boost-starai/BoostSRL.git`
- Nightly builds with git.
  `git clone -b development https://github.com/boost-starai/BoostSRL.git`

Basic Usage

```
[hayesall@hawk Datasets]$ ls -R Cora/
Cora/:
cora_bk.txt  test  train

Cora/test:
test_bk.txt  test_facts.txt  test_neg.txt  test_pos.txt

Cora/train:
train_bk.txt  train_facts.txt  train_neg.txt  train_pos.txt
[hayesall@hawk Datasets]$
```

BoostSRL assumes that data are contained in files with data structured in predicate-logic format.

Positive Examples:

```
father(harrypotter,jamespotter).
father(ginnyweasley,arthurweasley).
father(ronweasley,arthurweasley).
...
```

Negative Examples:

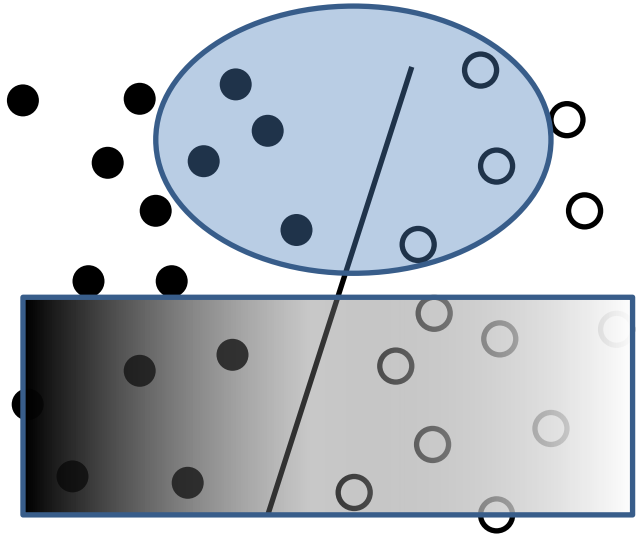
Outline

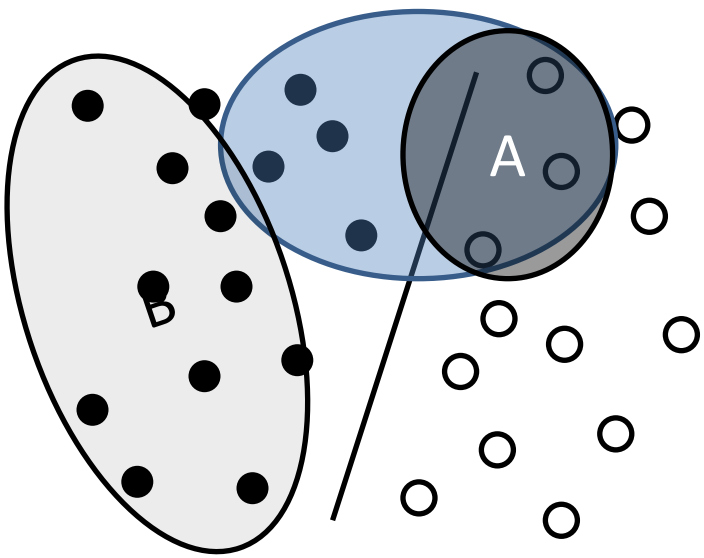
- Cardiovascular health
- Adverse Pregnancy Outcomes
- Learning from EHRs

Can we do more than learn just from data?

Monotonicity

As feature x ↑,
P(positive) ↑



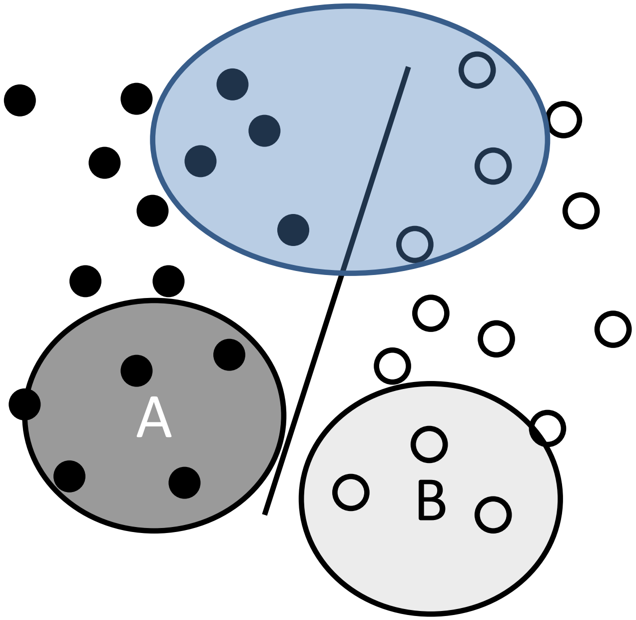


Precision/Recall Tradeoff

Fung et al. 2002, Towell & Shavlik 1994, Kunapuli et al. 2013; Yang et al. ECML ‘13, Yang et al. ICDM ‘14

Types of Advice

Preference Knowledge



Powerful framework that can incorporate different kinds of advice

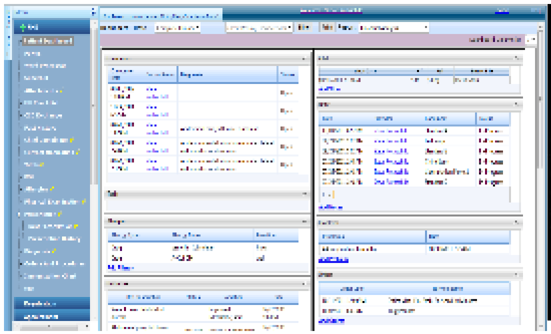
Odom et al. AAAI '15, Odom & Natarajan, Front. Robot. AI '18

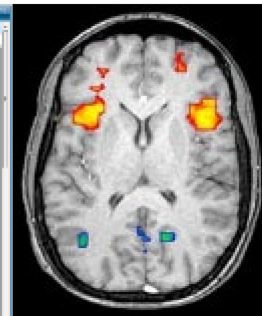
Types of Advice

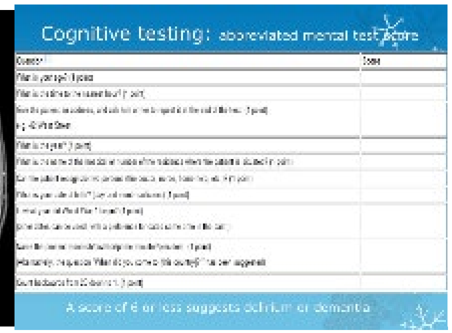
Privileged Information

Odom & Natarajan, Frontiers '18

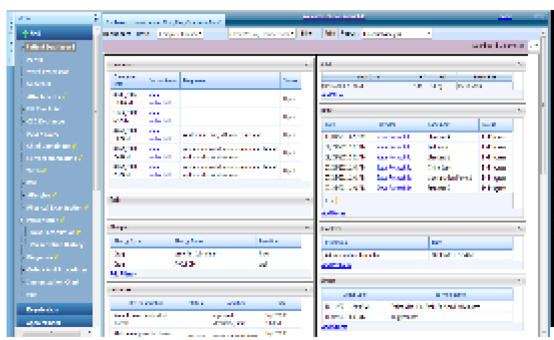
Training Phase

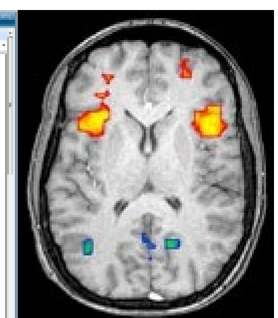






Deployment/
Test

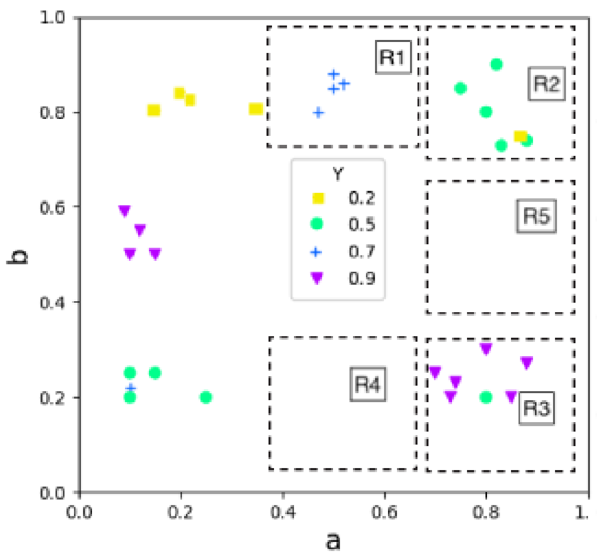




Pasunuri et al. BeyondLabeler '16, Odom & Natarajan '18

Boosting with Qualitative Constraints

Can we leverage qualitative domain knowledge when boosting – e.g., monotonic influence for regions where data is noisy[1]/absent[2]?



$$\boxed{a \underset{\prec}{\overset{Q+}{}} y}$$

[2]R5

[1]R1-R2

First unified gradient boosting with qualitative constraints for classification and regression

Easily extendable to relational domains.

E.g., Monotonicity constraint

$$\left.\mathbb{E}_{\psi}[\mathbf{n_L}] < \mathbb{E}_{\psi}[\mathbf{n_R}] + \varepsilon \right\} \zeta_{\mathbf{n}}$$

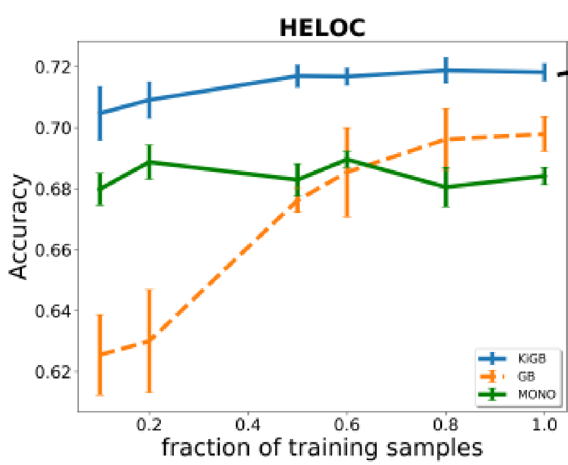
Kokel et al. AAAI 2020

Boosting with Qualitative Constraints

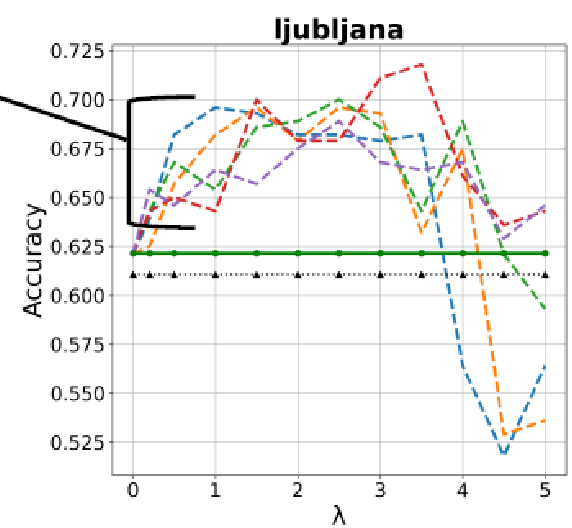
Objective

$$\underbrace{\underset{\psi_t}{\mathbf{argmin}} \sum_{i=1}^{N} \left(\tilde{y}_i - \psi_t(x_i)\right)^2}_{\textbf{loss function w.r.t data}} + \underbrace{\frac{\lambda}{2} \sum_{\mathbf{n} \in \mathcal{N}(\mathbf{x}_c)} \max\left(\zeta_{\mathbf{n}} \cdot |\zeta_{\mathbf{n}}|, 0\right)}_{\textbf{loss function w.r.t. advice}}$$

Results



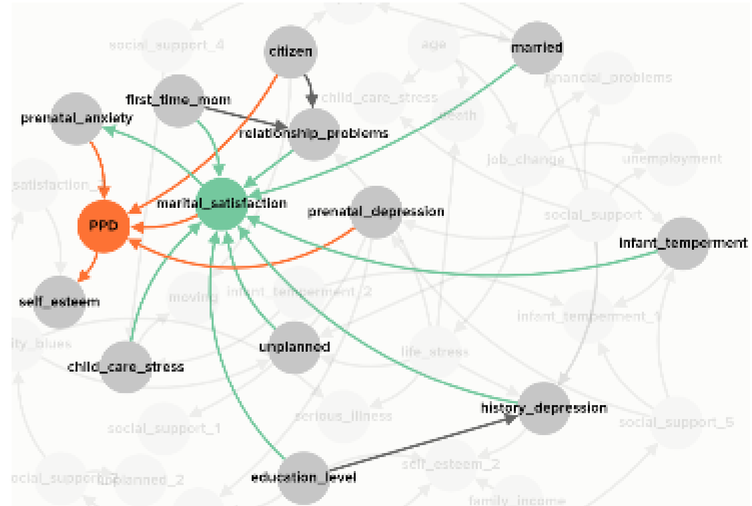
our method



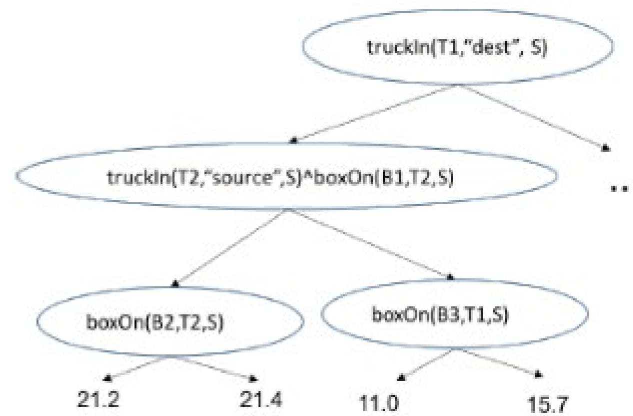
Kokel et al. AAAI 2020

Frameworks (considered) for Advice

- Probabilistic Graphical Models
  - Causal Models, Structure Learning
- Relational Probabilistic Models
  - Boosting, Lifted Inference
- Approximate counting
  - Faster inference



- Reinforcement Learning
  - RL, Relational RL
- Inverse Reinforcement Learning
  - KBIRL, Relational IRL
- Imitation Learning
- Probabilistic Planning
  - Preference Elicitation, Hierarchical Task Decomposition



The nuMoM2b study

- 10,038 **nulliparous** women from 8 centers around the US
- 4% of the women had **Gestational diabetes**
- Risk factors include
  - Age,
  - Race,
  - Body Mass Index,
  - Polycystic ovary syndrome,
  - Family History of diabetes,
  - Tobacco consumption,
  - Physical Activity (in METs) and,
  - Polygenic Risk Score

David M Haas, Corette B Parker, et al. "A description of the methods of the nulliparous pregnancy outcomes study: monitoring mothers-to-be (numom2b). American journal of obstetrics and gynecology, 2015.

Qualitative influences + Context-specific/conditional independencies

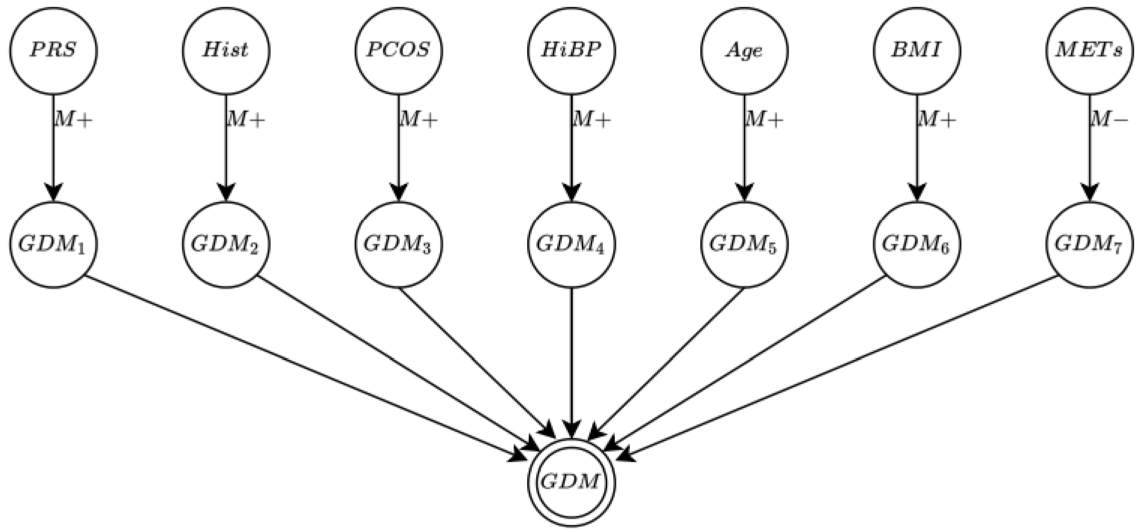


Fig. 5. Noisy-OR model used for the GDM dataset. Both QIs and causal independence knowledge are incorporated in this model. This representation shows that *PRS, Hist, PCOS, HiBP, Age and BMI* have a positive monotonic influence on GDM whereas *METs* have a negative monotonic influence. Additionally, all the risk factors are causally independent in this model.

Mathur et al. PSB 2023

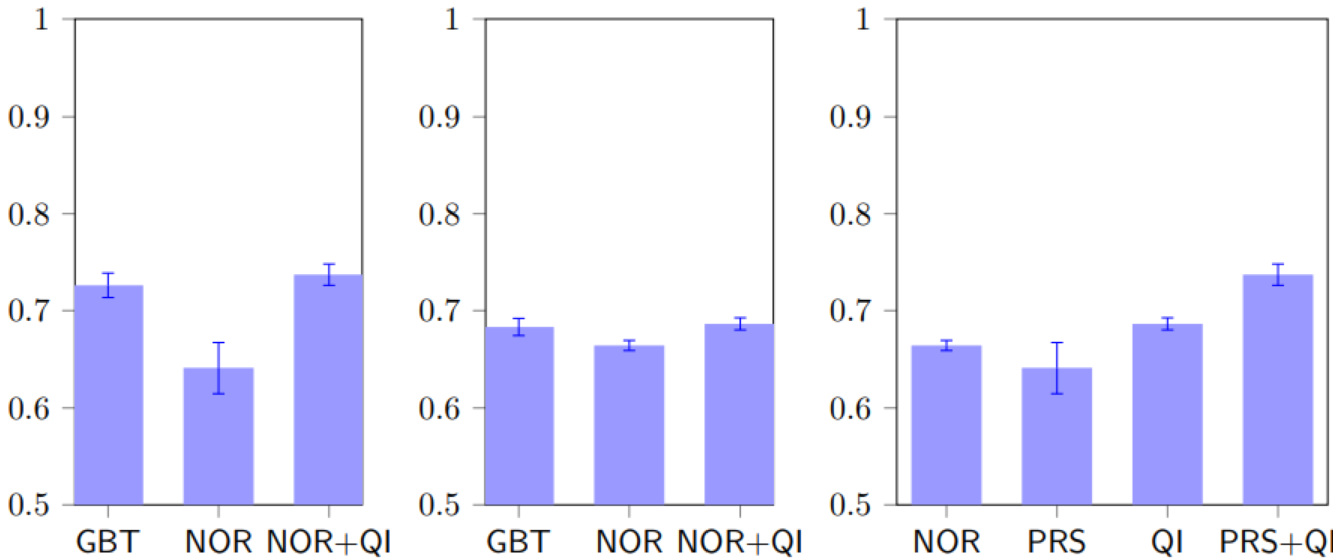
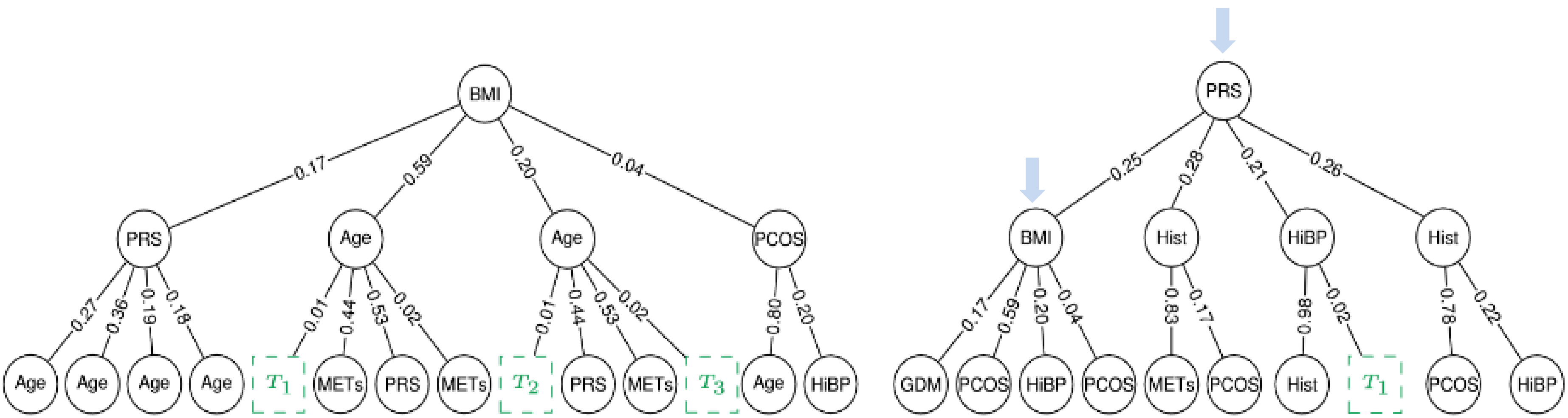


Fig. 6. The AUC-ROC scores for the Noisy OR model (NOR) as compared to the Gradient Boosted Trees model (GBT) with PRS (left) and without PRS (center). The AUC-ROC scores for the Noisy OR model (NOR) in the presence of PRS and Qualitative Influences (right). The bars show the mean score over 10 boostrap samples and the error bars show the standard deviation.

Knowledge-intensive learning is better!!!!

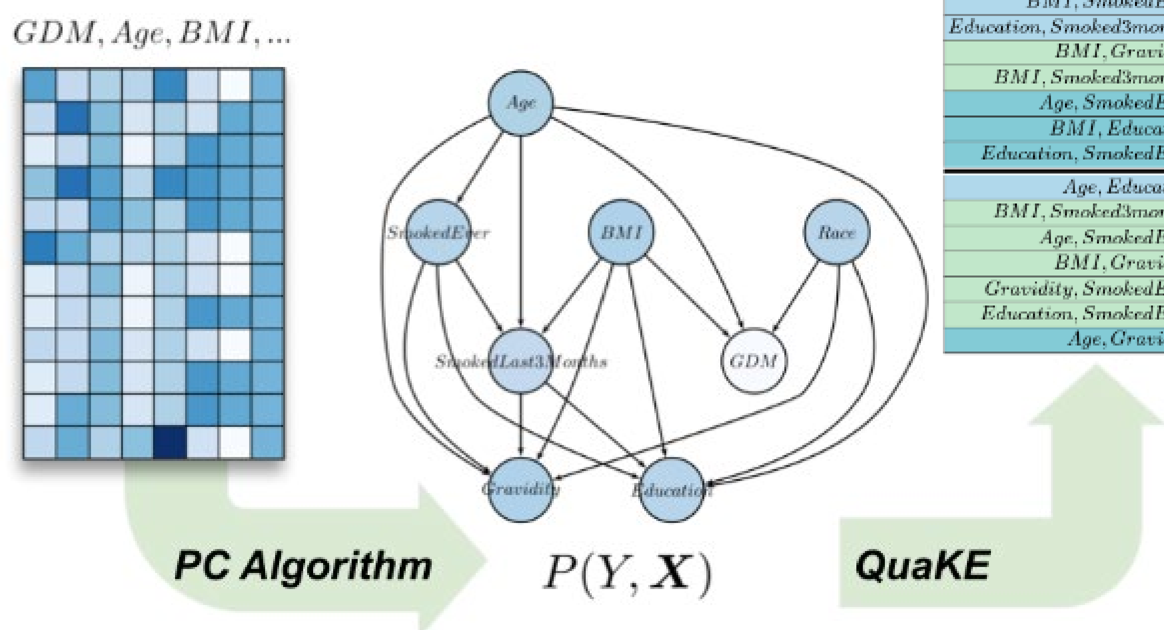
	Edge count		Parameter count		MSE on queries	
Data set	**LearnCNet**	**KICN**	**LearnCNet**	**KICN**	**LearnCNet**	**KICN**
ppd	**113.8**	114.1	205.7	**198.8**	0.2043	**0.1963**
adni	121.9	**57.8**	343.3	**246.4**	0.1825	**0.1636**
numom2b-a	179.4	**108.6**	422.2	**366.3**	0.0397	**0.0383**
numom2b-b	416.5	**220.9**	1,069.9	**905.7**	0.0515	**0.0445**

More concise and accurate models!



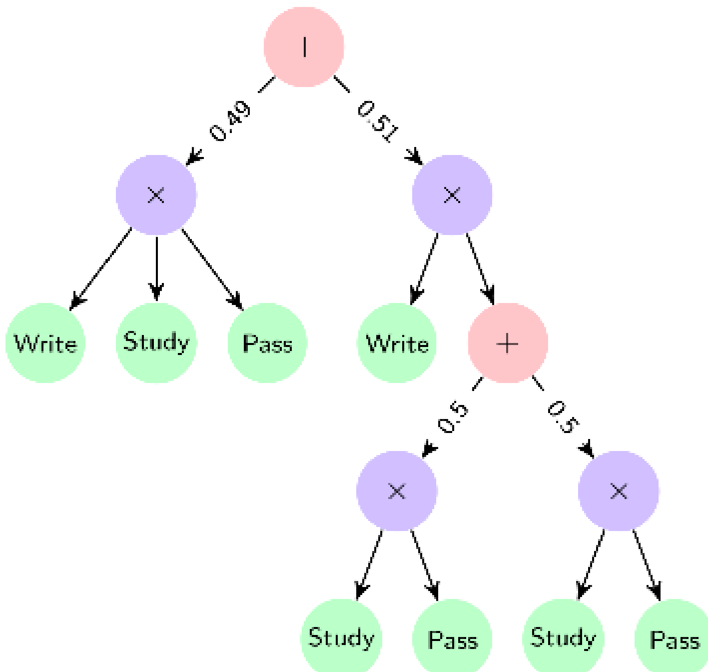
Reverse -- Can we learn these "advice"?

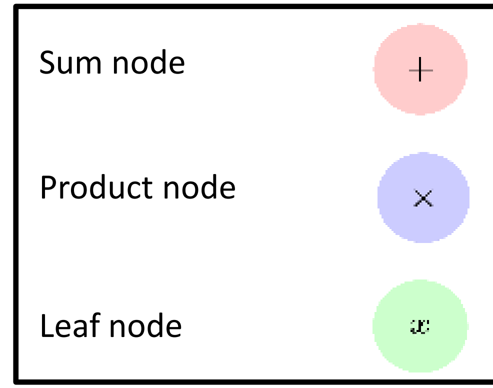
Rule	Prior Knowledge	QuaKE	Data Alone
$BMI \preceq^{M+} GDM$	✓	✓	✓
$Age \preceq^{M+} GDM$	✓	✓	✓
$Race \preceq^{M+} GDM$	✓	✓	✗
$Education \preceq^{M+} GDM$	✓	✓	✗
$Gravidity \preceq^{M+} GDM$	✓	✓	✗
$Smoked3months \preceq^{M+} GDM$	✓	✗	✗
$SmokedEver \preceq^{M+} GDM$	✓	✗	✗
$Age, BMI \preceq^{S+} GDM$	✓	✓	✓
$Age, Smoked3months \preceq^{S+} GDM$	✓	✓	✓
$BMI, SmokedEver \preceq^{S+} GDM$	✓	✓	✓
$Education, Smoked3months \preceq^{S+} GDM$	?	✓	✓
$BMI, Gravidity \preceq^{S+} GDM$	✓	✓	✗
$BMI, Smoked3months \preceq^{S+} GDM$	✓	✗	✓
$Age, SmokedEver \preceq^{S+} GDM$	✓	✗	✗
$BMI, Education \preceq^{S+} GDM$	✗	✓	✓
$Education, SmokedEver \preceq^{S+} GDM$	?	✗	✗
$Age, Education \preceq^{S-} GDM$	✓	✓	✓
$BMI, Smoked3months \preceq^{S-} GDM$	✗	✓	✗
$Age, SmokedEver \preceq^{S-} GDM$	✗	✗	✓
$BMI, Gravidity \preceq^{S-} GDM$	✗	✗	✓
$Gravidity, SmokedEver \preceq^{S-} GDM$	✗	✗	✓
$Education, SmokedEver \preceq^{S-} GDM$	?	✗	✓
$Age, Gravidity \preceq^{S-} GDM$	✓	✗	✗



Karanam et al., AIME 2021

Sum-product networks





Hoifun Poon and Pedro Domingos, "Sum-product networks: A new deep architecture", Proceedings of the Twenty-Seventh international conference on Uncertainty in artificial intelligence. 2011

Explaining an SPN in terms of its CSIs

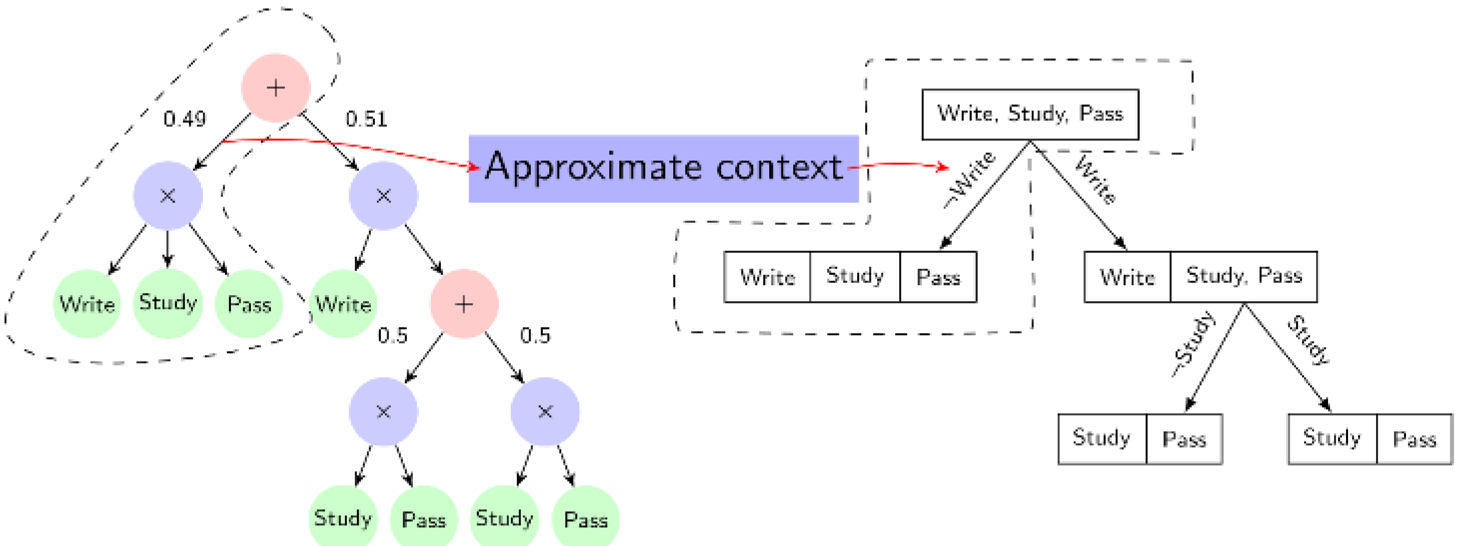
Given:

$\mathcal{M}$, a sum-product network that models P(GDM, **X**)

To Do:

Extract $\mathcal{T}$, a CSI-tree that explains $\mathcal{M}$

Explaining SPNs using CSI-trees



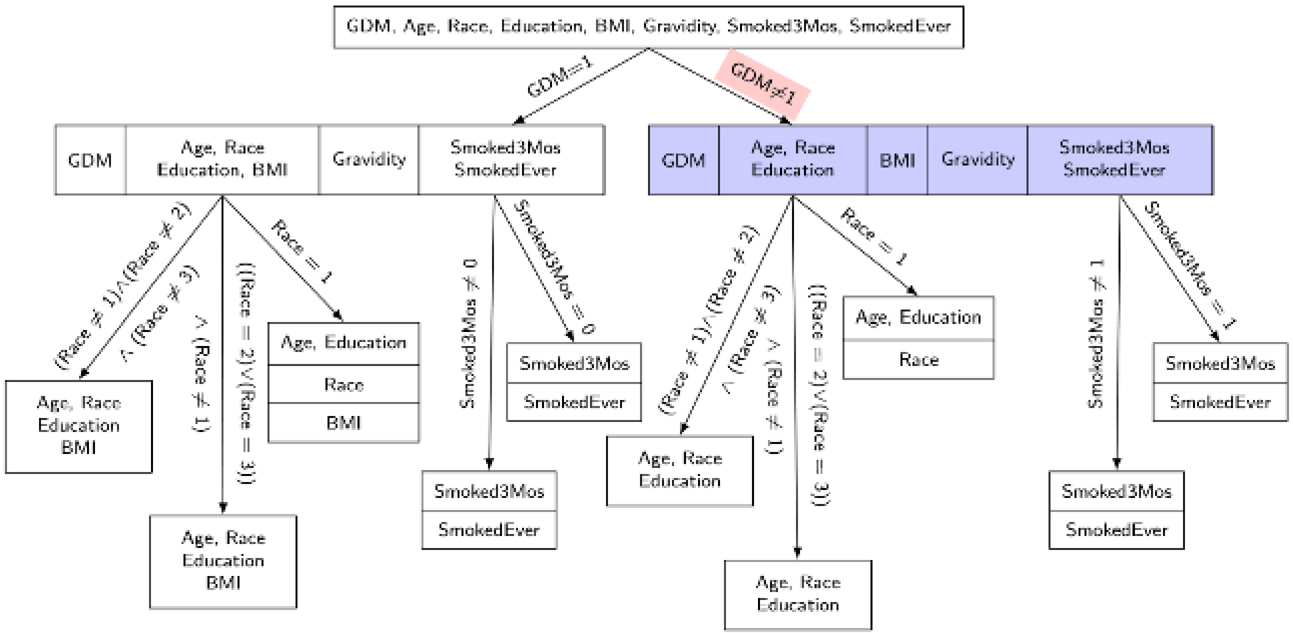
Karanam, Bhagirath Athresh, Saurabh Mathur, Predrag Radivojac, David M. Haas, Kristian Kersting, and Sriraam Natarajan. "Explaining Deep Tractable Probabilistic Models: The sum-product network case." PGM 2022.

$\mathcal{EXSPN}$ produces accurate and interpretable approximations

Table 1: Summary statistics for the CSI rules extracted from SPNs by $\mathcal{EXSPN}$ and the association rules by Apriori algorithm. NP - # Product Nodes, NR - # Rules, MA - Mean Antecedent length, MC - the Mean Consequent length, and CR - Compression Ratio.

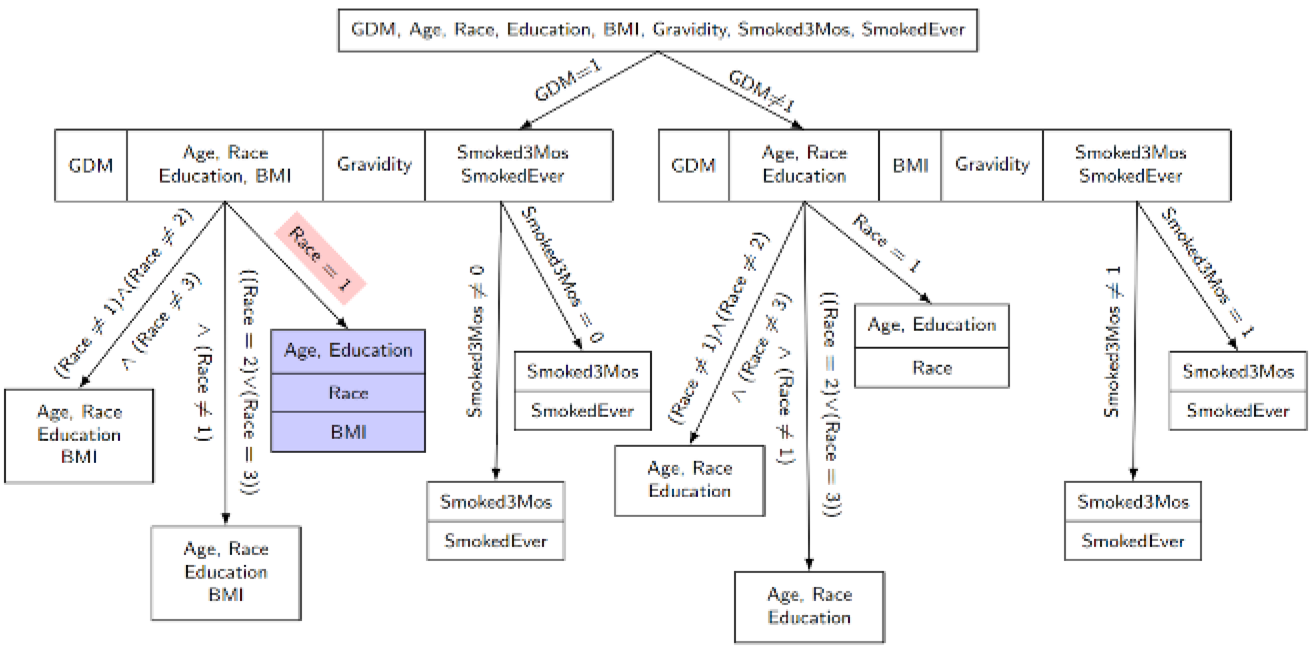
	SPN	All CSIs			Reduced CSIs				Association Rules		
Dataset	NP	NR	MA	MC	NR	MA	MC	CR	NR	MA	MC
Synthetic	7	7	2.29	2.57	**3**	1.33	2.67	2.33	12	1.25	1.25
Mushroom	39	39	5.90	8.54	**14**	4.79	7.93	2.79	10,704	2.87	2.43
Plants	342	342	9.60	9.61	**23**	6.22	7.09	14.87	1,043	1.72	1.40
NLTCS	74	74	9.84	3.32	**19**	6.32	4.05	3.89	165	1.96	1.28
MSNBC	8	**8**	4.12	5.75	**8**	4.12	5.75	1.00	16	2.38	1.00
Abalone	194	194	11.31	7.00	**4**	4.25	2.00	48.50	730	2.15	1.71
Adult	263	263	14.49	4.02	**19**	7.37	2.74	13.84	917	2.24	1.72
Wine	236	236	12.45	6.76	**5**	3.60	2.60	47.20	337	1.99	1.56
Car	18	18	5.22	2.50	**14**	5.21	2.64	1.29	19	1.58	1.00
Yeast	181	181	16.20	3.26	**10**	7.90	2.30	18.10	50	1.52	1.52
Earthquake	2	**2**	1.00	5.00	**2**	1.00	5.00	1.00	8	1.00	1.00
Cancer	2	**2**	1.00	5.00	**2**	1.00	5.00	1.00	18	1.79	1.05
Asia	10	10	3.70	3.50	**3**	2.67	4.00	3.34	456	2.20	1.84
nuMoM2b	104	104	10.60	2.33	**31**	6.55	2.19	3.35	21	1.29	1.14

BMI is independent of Age, Race, Education in the cohort without GDM



Allows for targeted interventions!

BMI is independent of Age, Education in the non-Hispanic, white cohort with GDM



Genetic and lifestyle risk factors for GDM

Polygenic Risk Score (PRS)

- Genetic predisposition to Type 2 diabetes
- Derived from the Diabetes Genetics Replication and Meta-analysis Consortium data
- Limited to subjects with European genetic ancestry

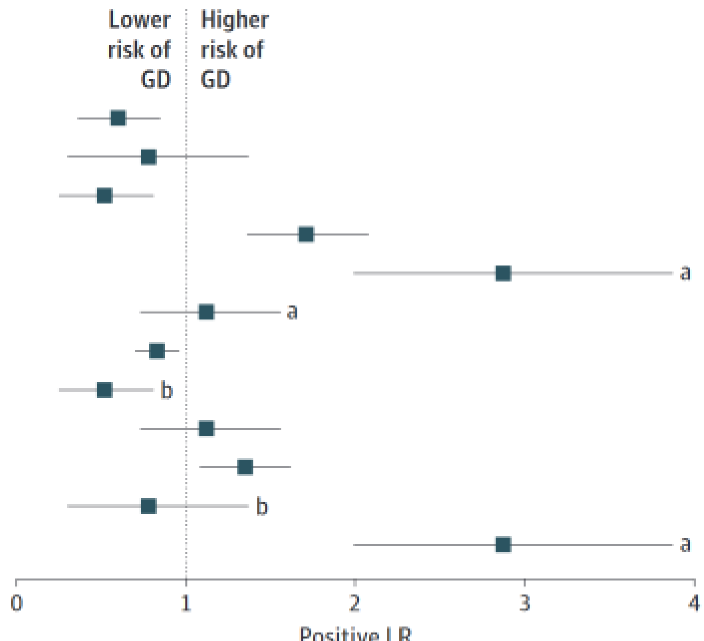
Exercise (METs)

- Measured in Metabolic equivalents of time (METs)
- Threshold of 450 from the Nurses' Health Study II

Pagel, Kymberleigh A., et al. "Association of Genetic Predisposition and Physical Activity With Risk of Gestational Diabetes in Nulliparous Women." JAMA network open (2022)

High-PRS & Low-METs synergistically influence risk of GDM

Context	Positive LR (95% CI)
PRS: bottom 25%	0.6 (0.4-0.9)
With METs <450	0.8 (0.3-1.4)
With METs ≥450	0.5 (0.3-0.8)
PRS: top 25%	1.7 (1.4-2.1)
With METs <450	2.9 (2.0-3.9)
With METs ≥450	1.1 (0.7-1.6)
METs ≥450	0.8 (0.7-1.0)
With PRS bottom 25%	0.5 (0.3-0.8)
With PRS top 25%	1.1 (0.7-1.6)
METs <450	1.3 (1.1-1.6)
With PRS bottom 25%	0.8 (0.3-1.4)
With PRS top 25%	2.9 (2.0-3.9)

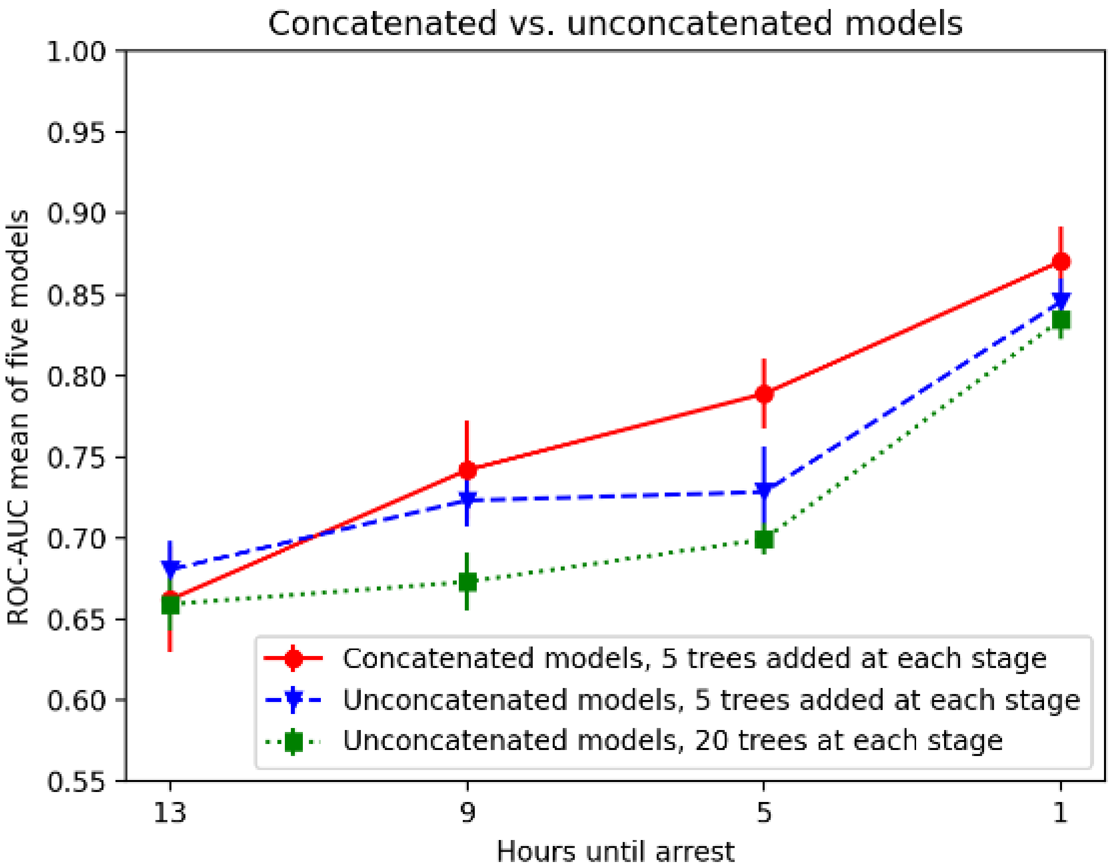


Pagel, Kymberleigh A., et al. "Association of Genetic Predisposition and Physical Activity With Risk of Gestational Diabetes in Nulliparous Women." JAMA network open (2022)

Outline

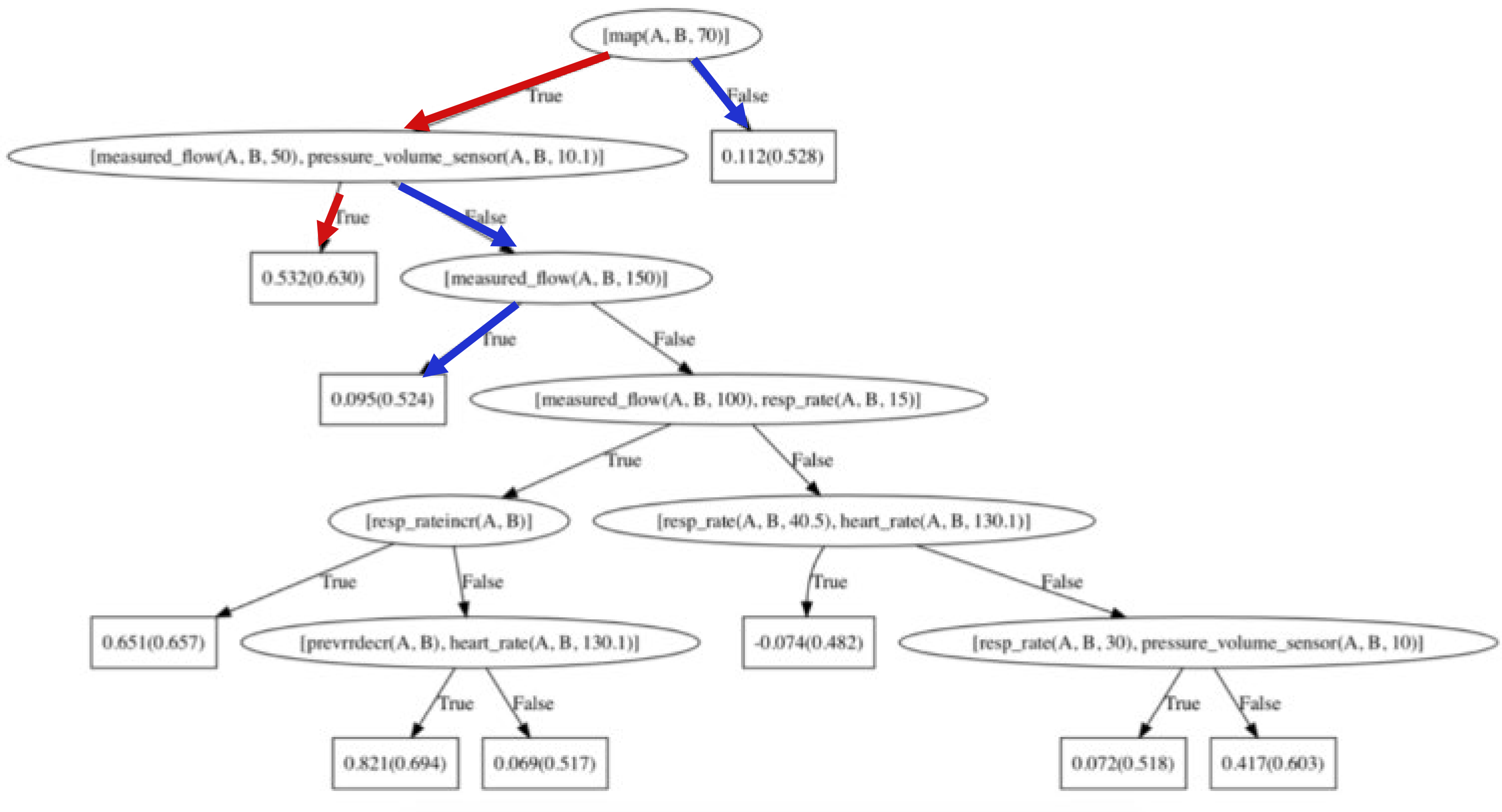
- Cardiovascular health
- Adverse Pregnancy Outcomes
- Learning from EHRs

Anytime prediction of (pediatric) cardiac arrest from EHR



Skinner et al. AIME 2022

Representative tree
Target: map_increase(A,B)



Michael A. Skinner, et al. AIME 2022

$$cond_i \Leftarrow finding_1 \wedge finding_2 \wedge ... \wedge finding_k$$

ECMO

Go to now 9/4/2019

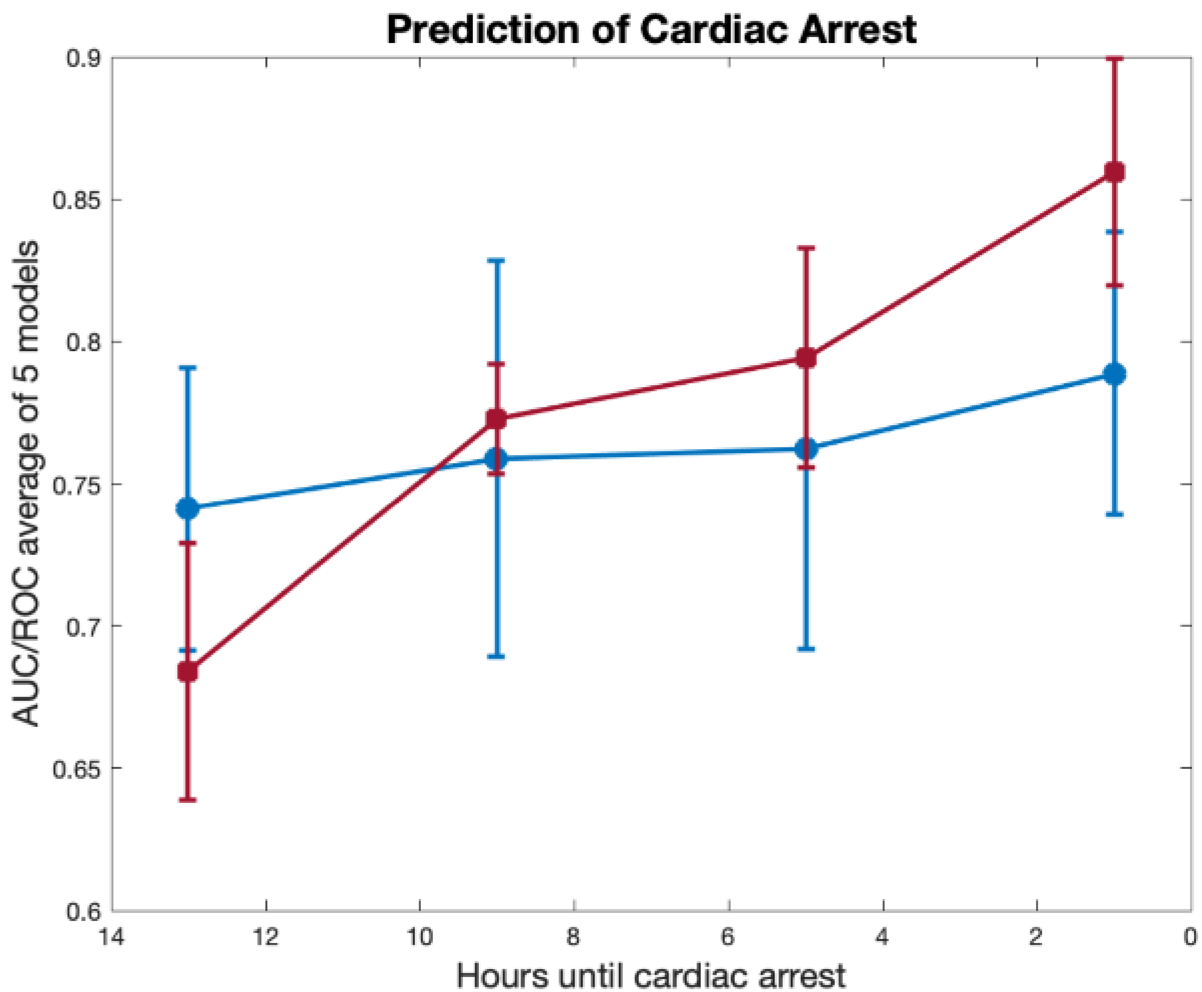
Wednesday 0400 - Wednesday 2259

1 hr 12 hr 24 hr | View All

C12	09/03 0700 - 09/04 0659			09/04 0700 - 09/05 0659																
1 hr:	04-05	05-06	06-07	07-08	08-09	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18	18-19	19-20	20-21	21-22	22-23	
O2																				
SvO2	75	69	71	75	74	67	68			65	73	74	79	81	77	78	77	83	79	SvO2
Sweep																				
Total Sweep	3.3	3.3	3.3	3.3	3.3	3.3	2.5			2.5	2.5	2.5	2.5	2.5	2.5	2+	2	1.5	1.5	Total Sweep
FiO2	0.21	0.21	0.21	0.21	0.21	0.21	0.21			0.21	0.3	0.3	0.3	0.25	0.25	0.21+	0.21	0.21	0.21	FiO2
O2 Flow	3.3	3.3	3.3	3.3	3.3	3.3	2.5			2.5	2.5	2.5	2.5	2.5	2.5	2+	2	1.5	1.5	O2 Flow
CO2 Flow	0	0	0	0	0	0	0			0	0	0	0	0	0	0+	0	0	0	CO2 Flow
Flows																				
Blood Flow (RPM)	2861	2860	2861	2860	2861	2861	2860			2790	2790	2790	2790	2790	2789	2790	2790	2791	2791	Blood Flow (RPM)
Blood Flow (mL/min)	4980	5038	5004	4900	4990	5070	5024			4995	4634	5088	4834	4755	4801	4731	4722	4620	4552	Blood Flow (mL/...
Blood Flow (mL/kg/min)	38.08	39.13	38.69	37.03	38.43	39.39	37.99			39.13	35.63	39.22	37.64	36.24	36.94	36.85	35.71	35.71	34.31	Blood Flow (mL/...
Measured Flow	4350	4470	4420	4230	4390	4500	4340			4470	4070	4480	4300	4140	4220	4210	4080	4080	3920	Measured Flow
ECMO Cardiac Index	1.78	1.83	1.81	1.73	1.8	1.84	1.78			1.83	1.67	1.84	1.76	1.7	1.73	1.73	1.67	1.67	1.61	ECMO Cardiac I...
Circuit Shunt	630	568	584	670	600	570	684			525	564	608	534	615	581	521	642	540	632	Circuit Shunt
Circuit Pressures																				
Pre-oxygenator	165	152	158	172	158	154	160			156	160	149	154	157	163	166	164	167	152	Pre-oxygenator
Post-oxygenator	138	123	134	145	137	130	135			128	138	122	127	136	140	141	139	143	133	Post-oxygenator
Gradient	27	29	24	27	21	24	25			28	22	27	27	21	23	25	25	24	19	Gradient
Volume Sensor	-49	-53	-50	-45	-49	-57	-5			-45	-42	-52	-52	-46	-45	-40	-39	-42	-38	Volume Sensor
Heparin																				
Heparin (unit/kg/hr)	12.59...	12.59...	12.59...	12.6 ...+	12.6 ...	12.59...	12.59...	12.59...	12.59...	12.59...	12 Un...+	12 Un...	14 Un...+	14 Un...	14 Un...	14 Un...	14 Un...	14 Un...	14 Un...	Heparin (unit/kg/...
Patient ACTs																				
ACT	160	160	155	160	166	160	160		143		138	143	155	149	155	155	155	160	160	ACT

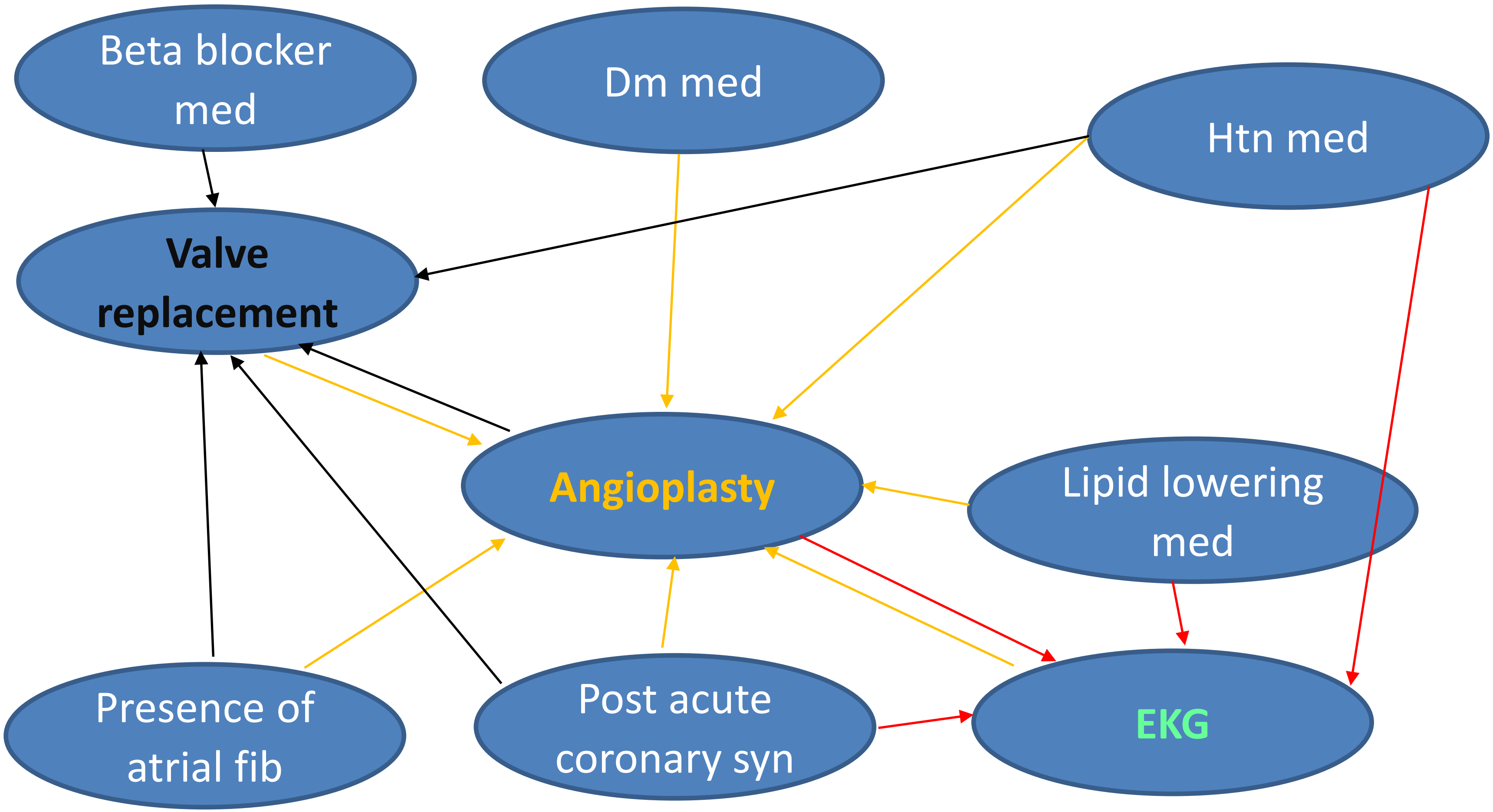
Rule No.	Weight	Logic rule
1	0.112	$\mathtt{mapincr}(\mathtt{A},\mathtt{B}) \Leftarrow \neg\mathtt{map}(\mathtt{A},\mathtt{B},60-70)$
2	0.532	$\mathtt{mapincr}(\mathtt{A},\mathtt{B}) \Leftarrow \mathtt{map}(\mathtt{A},\mathtt{B},60-70) \wedge \mathtt{measured\_flow}(\mathtt{A},\mathtt{B},20-50)\wedge$ $\mathtt{pressure\_volume\_sensor}(\mathtt{A},\mathtt{B},>10)$
3	0.095	$\mathtt{mapincr}(\mathtt{A},\mathtt{B}) \Leftarrow \mathtt{map}(\mathtt{A},\mathtt{B},60-70) \wedge \neg[\mathtt{measured\_flow}(\mathtt{A},\mathtt{B},20-50)\wedge$ $\mathtt{pressure\_volume\_sensor}(\mathtt{A},\mathtt{B},>10)] \wedge \mathtt{measured\_flow}(\mathtt{A},\mathtt{B},100-150)$
4	0.651	$\mathtt{mapincr}(\mathtt{A},\mathtt{B}) \Leftarrow \mathtt{map}(\mathtt{A},\mathtt{B},60-70) \wedge \neg[\mathtt{measured\_flow}(\mathtt{A},\mathtt{B},20-50)\wedge$ $\mathtt{pressure\_volume\_sensor}(\mathtt{A},\mathtt{B},>10)] \wedge \neg\mathtt{measured\_flow}(\mathtt{A},\mathtt{B},100-150)\wedge$ $\mathtt{measured\_flow}(\mathtt{A},\mathtt{B},50-100) \wedge \mathtt{resp\_rate}(\mathtt{A},\mathtt{B},\leq 15)\wedge$ $\mathtt{resp\_rateincr}(\mathtt{A},\mathtt{B})$
5	0.821	$\mathtt{mapincr}(\mathtt{A},\mathtt{B}) \Leftarrow \mathtt{map}(\mathtt{A},\mathtt{B},60-70) \wedge \neg[\mathtt{measured\_flow}(\mathtt{A},\mathtt{B},20-50)\wedge$ $\mathtt{pressure\_volume\_sensor}(\mathtt{A},\mathtt{B},>10)] \wedge \neg\mathtt{measured\_flow}(\mathtt{A},\mathtt{B},100-150)\wedge$ $\mathtt{measured\_flow}(\mathtt{A},\mathtt{B},50-100) \wedge \mathtt{resp\_rate}(\mathtt{A},\mathtt{B},\leq 15)\wedge$ $\neg\mathtt{resp\_rateincr}(\mathtt{A},\mathtt{B})\wedge\ \mathtt{heart\_rate}(\mathtt{A},\mathtt{B},>130)\wedge$ $[\exists \mathtt{C} \mid \mathtt{B}=\mathtt{C}+1 \wedge \mathtt{resp\_ratedecr}(\mathtt{A},\mathtt{C})]$
6	0.069	$\mathtt{mapincr}(\mathtt{A},\mathtt{B}) \Leftarrow \mathtt{map}(\mathtt{A},\mathtt{B},60-70) \wedge \neg[\mathtt{measured\_flow}(\mathtt{A},\mathtt{B},20-50)\wedge$ $\mathtt{pressure\_volume\_sensor}(\mathtt{A},\mathtt{B},>10)] \wedge \neg\mathtt{measured\_flow}(\mathtt{A},\mathtt{B},100-150)\wedge$ $\mathtt{measured\_flow}(\mathtt{A},\mathtt{B},50-100) \wedge \mathtt{resp\_rate}(\mathtt{A},\mathtt{B},\leq 15)\wedge$ $\neg\mathtt{resp\_rateincr}(\mathtt{A},\mathtt{B})\wedge\ \neg[\mathtt{heart\_rate}(\mathtt{A},\mathtt{B},>130)\wedge$ $[\exists \mathtt{C} \mid \mathtt{B}=\mathtt{C}+1 \wedge \mathtt{resp\_ratedecr}(\mathtt{A},\mathtt{C})]]$
7	-0.074	$\mathtt{mapincr}(\mathtt{A},\mathtt{B}) \Leftarrow \mathtt{map}(\mathtt{A},\mathtt{B},60-70) \wedge \neg[\mathtt{measured\_flow}(\mathtt{A},\mathtt{B},20-50)\wedge$ $\mathtt{pressure\_volume\_sensor}(\mathtt{A},\mathtt{B},>10)] \wedge \neg\mathtt{measured\_flow}(\mathtt{A},\mathtt{B},100-150)\wedge$ $\neg[\mathtt{measured\_flow}(\mathtt{A},\mathtt{B},50-100) \wedge \mathtt{resp\_rate}(\mathtt{A},\mathtt{B},\leq 15)]\wedge$ $\mathtt{resp\_rate}(\mathtt{A},\mathtt{B},>40)\wedge\ \mathtt{heart\_rate}(\mathtt{A},\mathtt{B},>130)$
8	0.072	$\mathtt{mapincr}(\mathtt{A},\mathtt{B}) \Leftarrow \mathtt{map}(\mathtt{A},\mathtt{B},60-70) \wedge \neg[\mathtt{measured\_flow}(\mathtt{A},\mathtt{B},20-50)\wedge$ $\mathtt{pressure\_volume\_sensor}(\mathtt{A},\mathtt{B},>10)] \wedge \neg\mathtt{measured\_flow}(\mathtt{A},\mathtt{B},100-150)\wedge$ $\neg[\mathtt{measured\_flow}(\mathtt{A},\mathtt{B},50-100) \wedge \mathtt{resp\_rate}(\mathtt{A},\mathtt{B},\leq 15)]\wedge$ $\neg[\mathtt{resp\_rate}(\mathtt{A},\mathtt{B},>40)\wedge\ \mathtt{heart\_rate}(\mathtt{A},\mathtt{B},>130)]\wedge$ $\mathtt{resp\_rate}(\mathtt{A},\mathtt{B},20-30)\wedge\ \mathtt{pressure\_volume\_sensor}(\mathtt{A},\mathtt{B},0-10)$
9	0.417	$\mathtt{mapincr}(\mathtt{A},\mathtt{B}) \Leftarrow \mathtt{map}(\mathtt{A},\mathtt{B},60-70) \wedge \neg[\mathtt{measured\_flow}(\mathtt{A},\mathtt{B},20-50)\wedge$ $\mathtt{pressure\_volume\_sensor}(\mathtt{A},\mathtt{B},>10)] \wedge \neg\mathtt{measured\_flow}(\mathtt{A},\mathtt{B},100-150)\wedge$ $\neg[\mathtt{measured\_flow}(\mathtt{A},\mathtt{B},50-100) \wedge \mathtt{resp\_rate}(\mathtt{A},\mathtt{B},\leq 15)]\wedge$ $\neg[\mathtt{resp\_rate}(\mathtt{A},\mathtt{B},>40)\wedge\ \mathtt{heart\_rate}(\mathtt{A},\mathtt{B},>130)]\wedge$ $\neg[\mathtt{resp\_rate}(\mathtt{A},\mathtt{B},20-30)\wedge\ \mathtt{pressure\_volume\_sensor}(\mathtt{A},\mathtt{B},0-10)]$

Anytime prediction of pediatric cardiac arrest from EHR



Wu et al Journal of clinical medicine 2023

Learning of cardiovascular procedures from EHR



Yang et al. 2017

Discriminative Learning

	Angioplasty				
	Random Forest	Logistic Regression	IPBoost	DNBoost	$\mathbf{DB^2N}$
AUC PR	0.824	0.751	0.868	0.905	0.887
Precision	0.815	0.690	0.840	0.898	**0.951**
Recall	0.798	0.663	0.766	0.805	**0.909**
F3	0.800	0.666	0.773	0.813	**0.913**
F5	0.799	0.664	0.769	0.808	**0.911**

	EKG				
	Random Forest	Logistic Regression	IPBoost	DNBoost	$\mathbf{DB^2N}$
AUC PR	0.833	0.847	0.861	0.916	**0.919**
Precision	0.783	0.7	0.791	0.857	**0.952**
Recall	0.756	0.76	0.750	0.833	**1**
F3	0.759	0.754	0.754	0.836	**0.995**
F5	0.757	0.758	0.751	0.834	**0.998**

	Valve Replacement				
	Random Forest	Logistic Regression	IPBoost	DNBoost	$\mathbf{DB^2N}$
AUC PR	0.748	0.718	0.82	0.866	**0.870**
Precision	0.816	0.684	0.750	0.835	**0.952**
Recall	0.824	0.709	0.773	0.86	0.767
F3	0.823	0.706	0.771	0.857	0.782
F5	0.824	0.708	0.772	0.859	0.772

Ramanan et al. 2017, 2020

Conclusions

- No ring to rule them all
  - Careful selection of algorithms are important
  - It is ok if the model is not deep
    - As long as the reasoning is not shallow ☺
- Human is an ally in learning and AI system needs to efficiently use human knowledge and input
- When designing human allied systems, communication is crucial
  - Effective communication ➔ Efficient learning

Next Steps

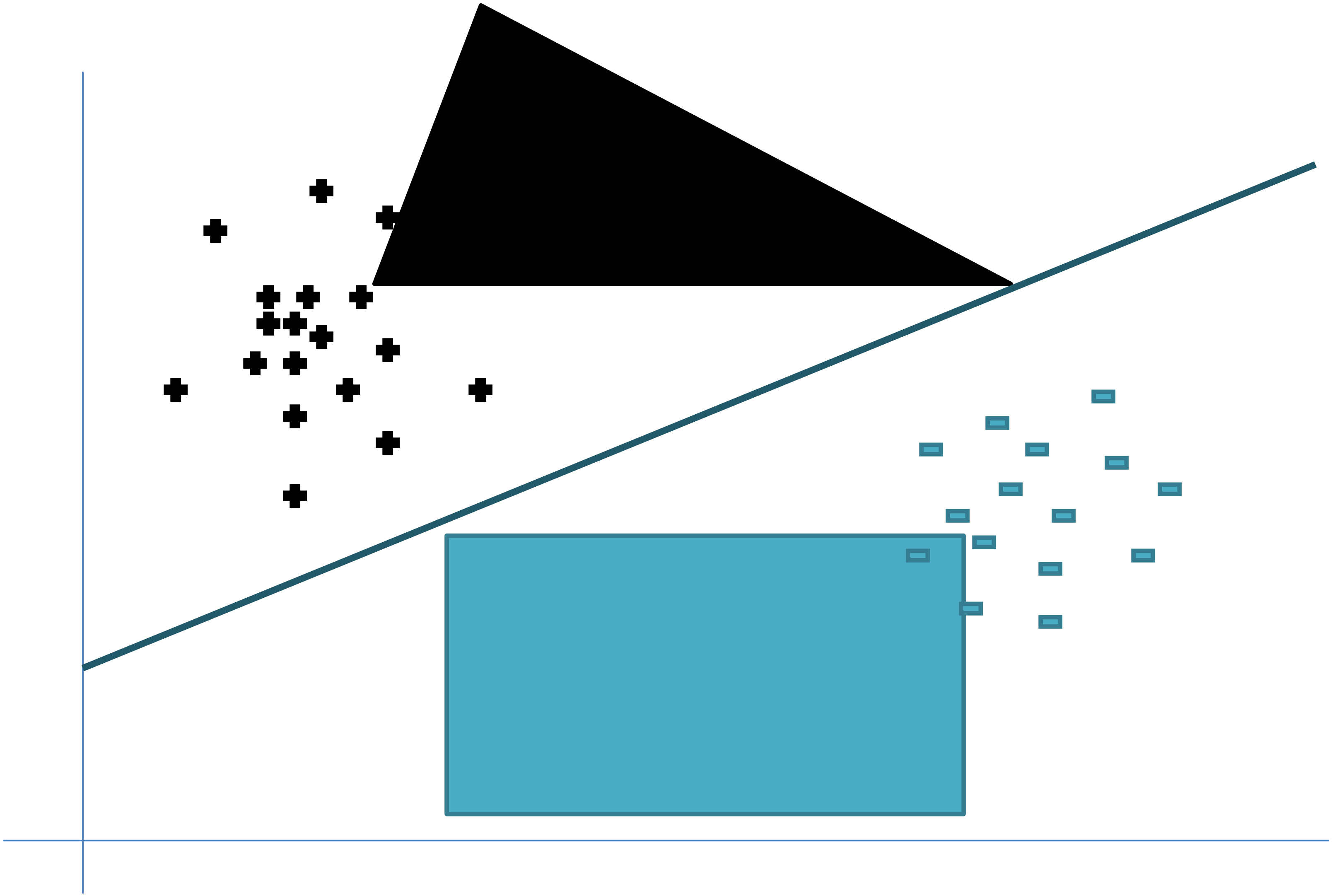
- Deployment: medicine, social science, traffic, journalism, … and the Data Science Genome: Machines read and understand data science publications and help the user with their problem at hand
- Learning from multiple experts
- Adapt to include safety/ethical constraints
- Learning from multiple modalities of communication
- Teach the human….

Ask your questions

@Sriraam_UTD

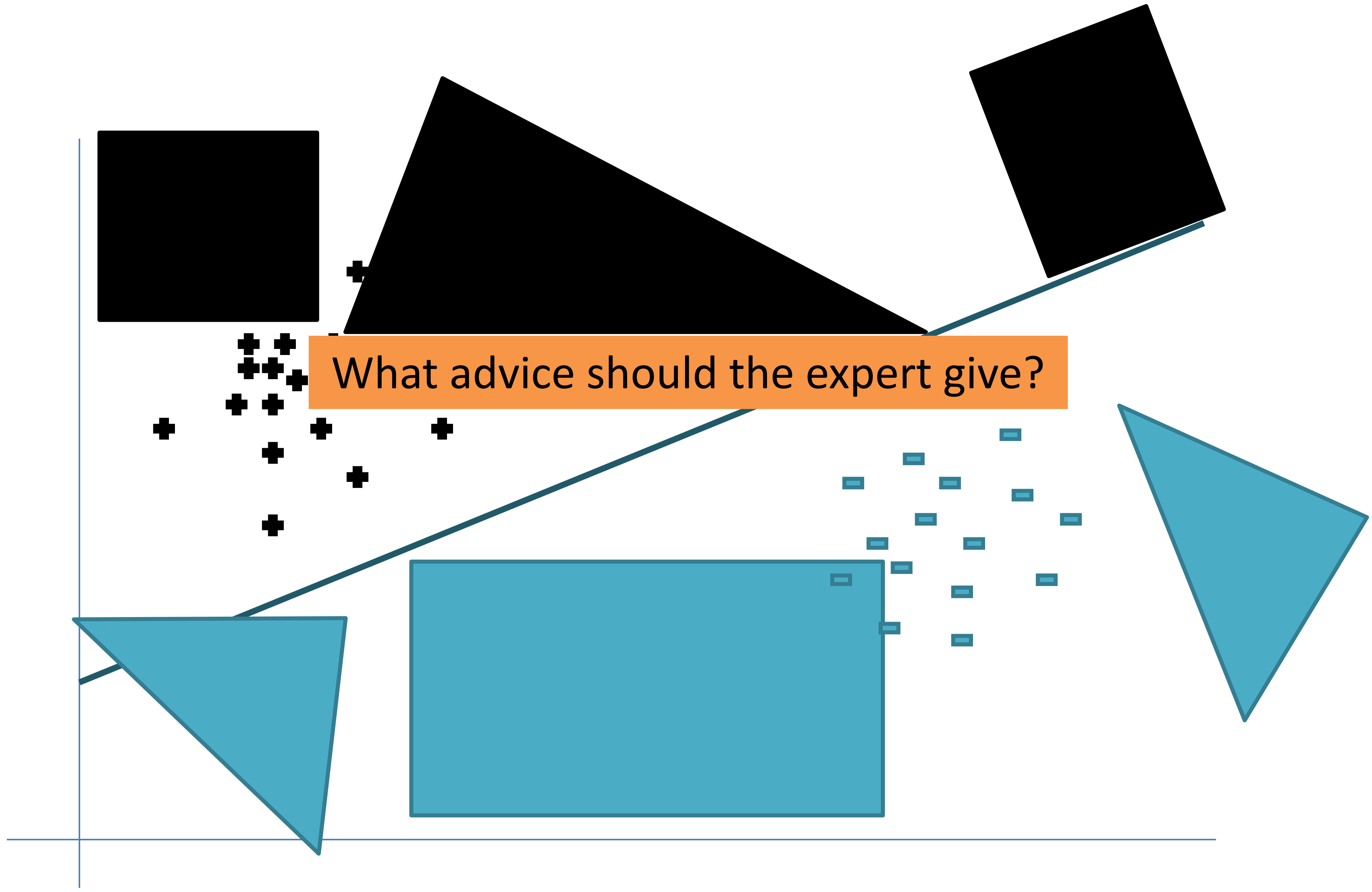
Thanks!

Knowledge-Based Learning

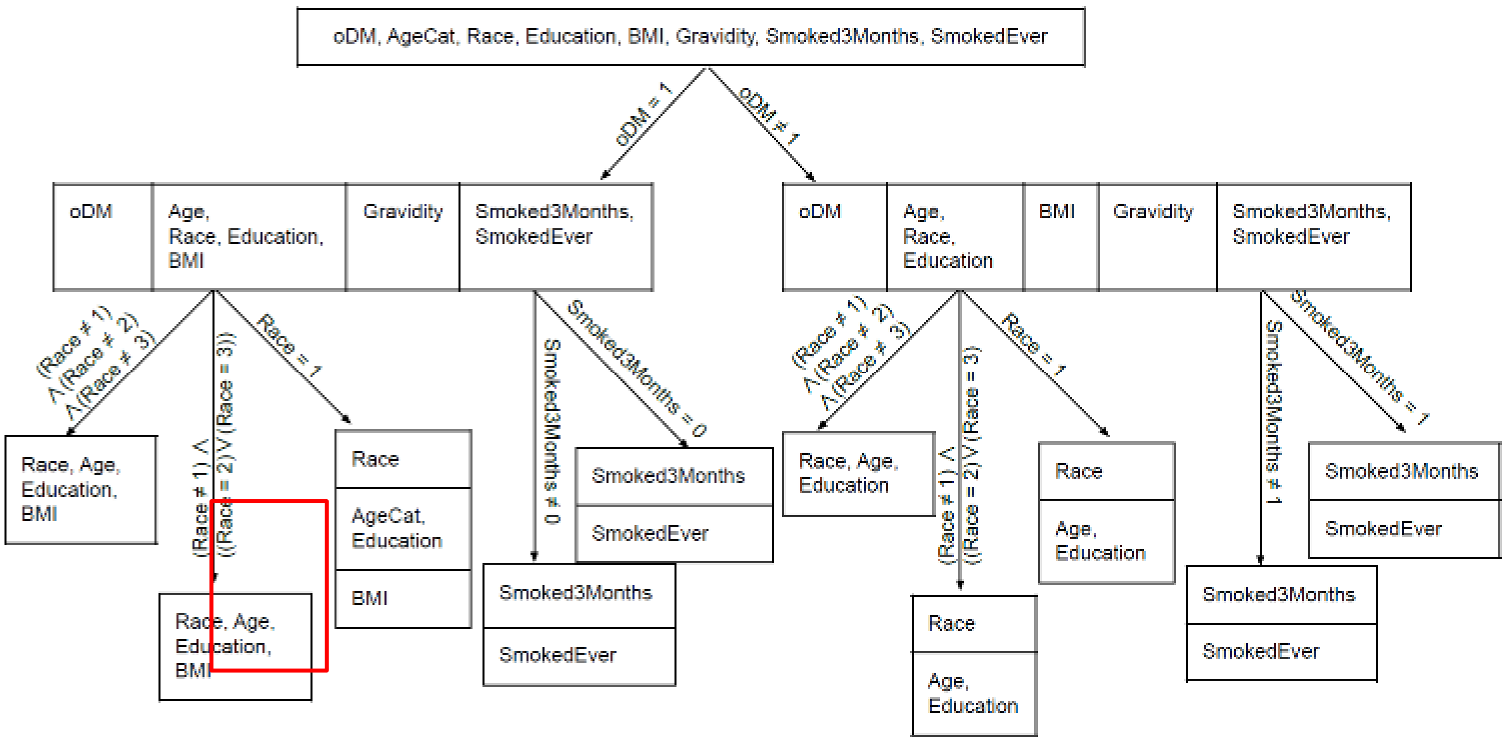


Fung et al. 2002

Knowledge-Based Learning



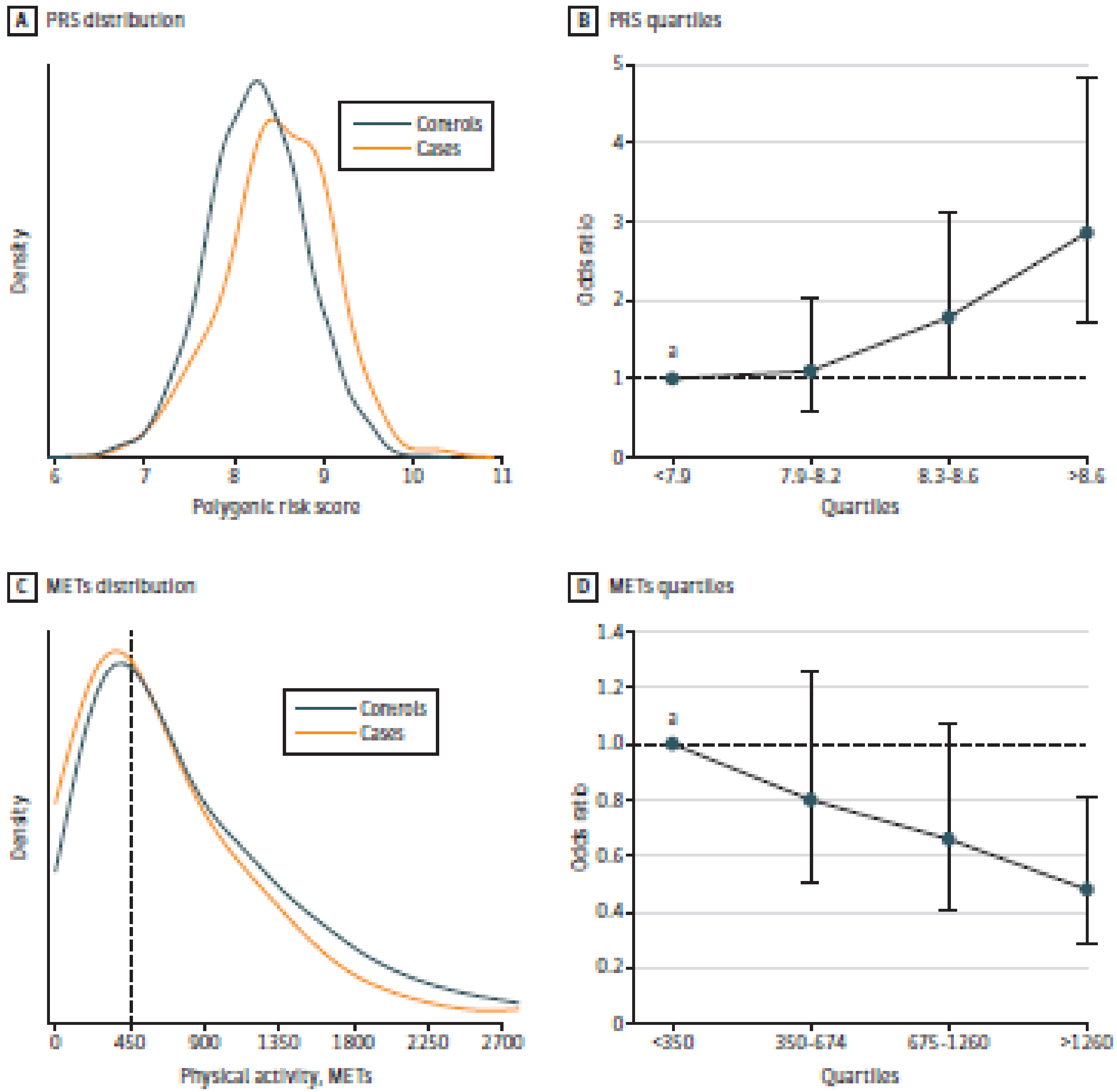
Example -- Explain the models



"BMI is independent of Age and Education in the non – hispanic white cohort with GDM"

Karanam et al, PGM 2022

Effect of polygenic risk scores and exercise in GDM



Pagel et al.,
JAMA Network Open
2022