

# A Causal Perspective on Challenges for AI in Precision Medicine



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## TL;DR

- We provide a classification of tasks in precision medicine.
- Many of them require answering causal questions.
- Many popular AI methods are not designed to consider causality.
- We provide causal interpretation rules.

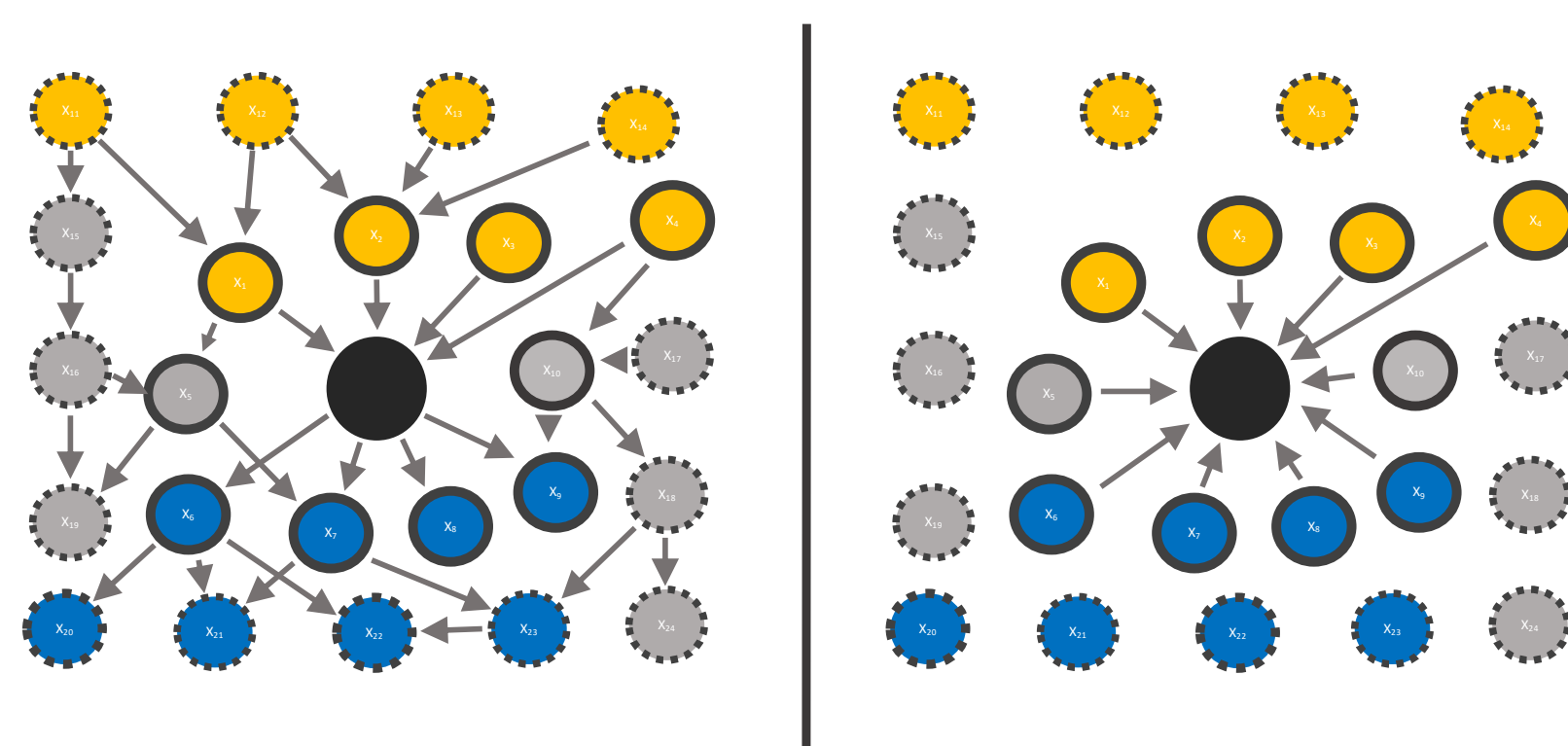
## Classification of Tasks

Non-Causal	Causal
- diagnosis	- risk factor identification
- genotyping/phenotyping	- treatment recommendation
- disease outbreak/progression prediction	- genotype to phenotype mapping
	- treatment development
	- treatment effect prediction
	- understanding of disease mechanism

## Prediction with AI

Supervised Machine Learning: Learn function  $\hat{f} : X \rightarrow Y$  such that empirical risk  $E[\mathcal{L}(\hat{f}(X), Y)]$  is minimal.

Minimal Bayes optimal set of features: Minimal set of features  $R$  such that all other variables  $X_i \in \Omega \setminus R$  become independent of  $Y$  ( $Y \perp X_i | R$ ). This so-called *Markov Blanket* may not only include variables that cause  $Y$ . A change of  $\hat{Y}$  (model) as a result of a change in  $X$  may therefore not correspond to a change in  $Y$  (real world).



**Left:** Underlying causal graph. **Right:** Dependencies as perceived by the AI model.

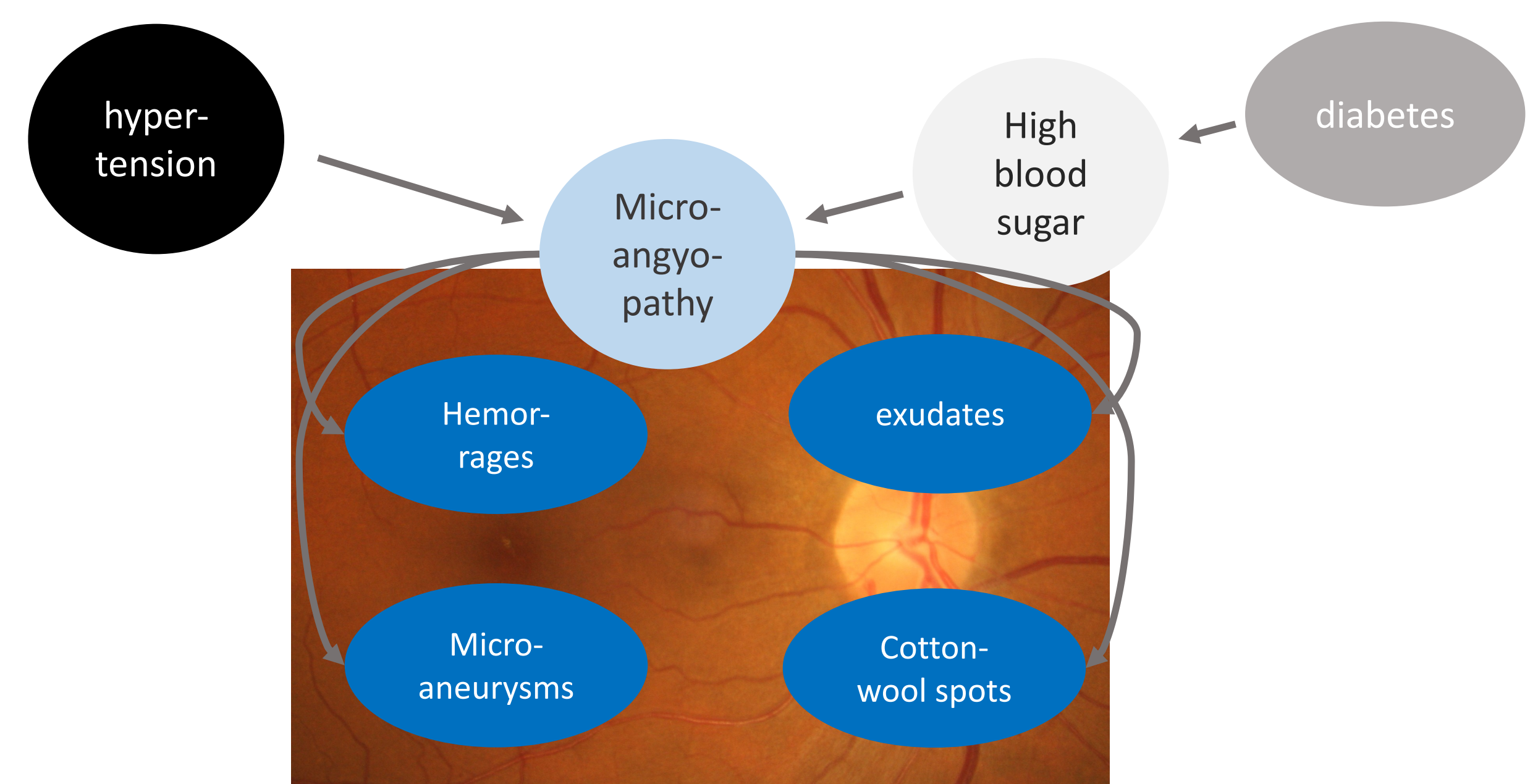
Given a target  $Y$  (black) not only causes (yellow), but also effects (blue) and context variables (grey) are in  $R$  (here thick black outline).

## Causal Interpretation Rules

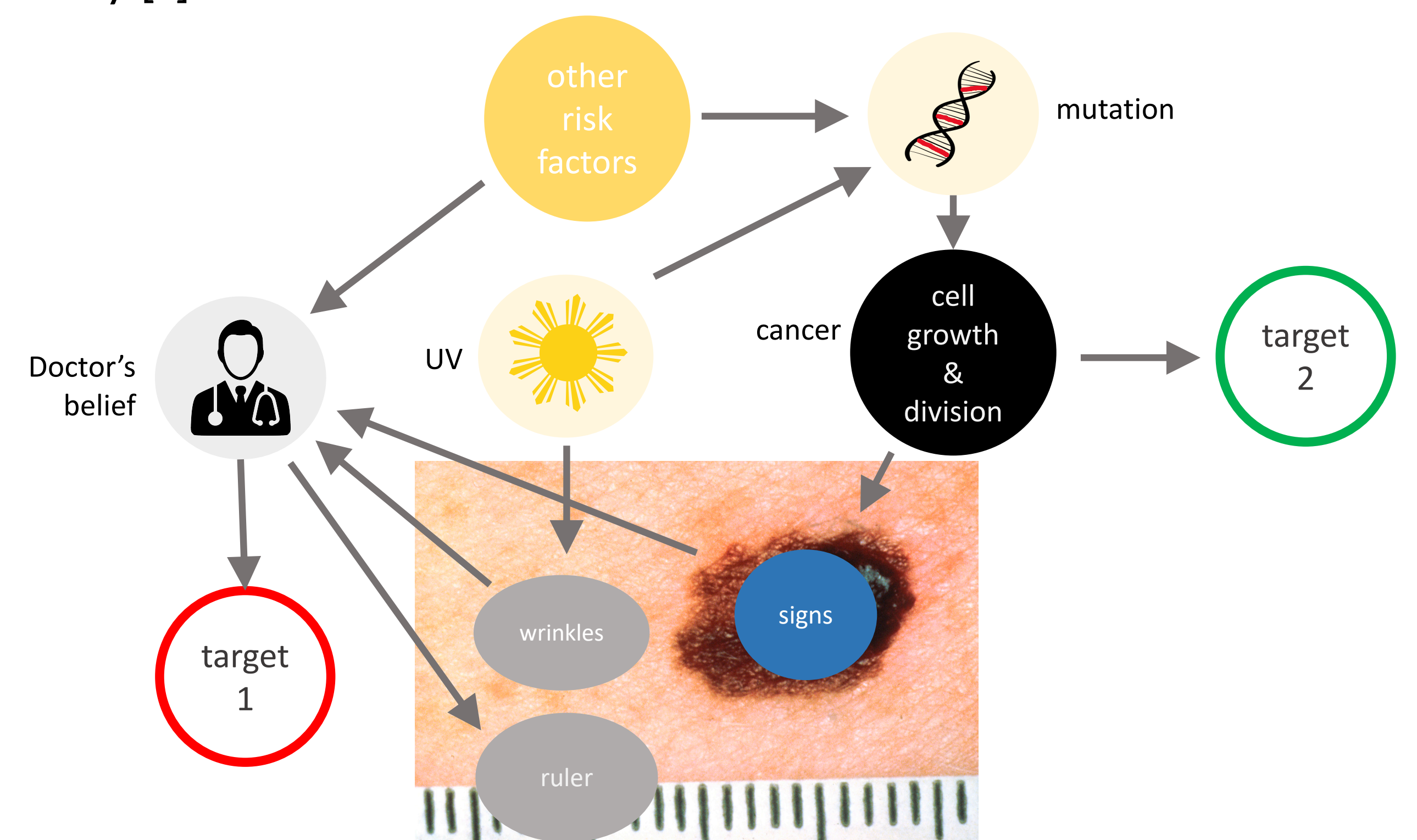
assumptions	types in R	types not in R
-	● ● ●	● ● ●
causal sufficiency (CS)	● ● ●	● ● ●
no ● observed	● ●	● ●
no ● observed	● ●	● ●
CS and no ● observed	● ●	● ●
CS and no ● observed	● ●	● ●
<b>Type Legend:</b>		
● causes =	● direct causes	and ● indirect causes
● effects =	● direct effects	and ● indirect effects
● no cause or effect =	● ( ● direct cause of ● )	and ● ( ● and not ● )

Based on [5]. *Causal sufficiency*: No variable that causes more than one observed variable is unobserved.

## Examples



**Collider/Differential diagnosis:** When assessing the presence of hypertensive retinopathy, knowledge about whether the patient has diabetes helps distinguish the condition from diabetic retinopathy. Inspired by [1].



**Hidden Confounding/Associated Signs:** UV radiation causes both the ageing of skin (wrinkles) and genetic mutation that leads to skin cancer. Wrinkles may therefore be included in a skin cancer diagnosis model.

**Target dependence:** A medical doctor may place a ruler in photographs of tumors to indicate their size. Depending on whether our label reflects the doctors belief (target 1) or the actual condition (target 2) a model may rely on the presence of a ruler for its diagnosis. Inspired by [2, 3]. Photograph taken from [4].

## References

- [1] Abramoff, M. D., Lavin, P. T., Birch, M., Shah, N., and Folk, J. C. Pivotal trial of an autonomous AI-based diagnostic system for detection of diabetic retinopathy in primary care offices. *npj Digital Medicine* 1, 1 (2018).
- [2] Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., and Thrun, S. Dermatologist-level classification of skin cancer with deep neural networks. *Nature* 542, 7639 (2017), 115–118.
- [3] Hilton, L. The Artificial Brain as Doctor. *Dermatology Times* (2018).
- [4] Unknown. Asymmetrical Melanoma. *NIH National Cancer Institute*.
- [5] Weichwald, S., Meyer, T., Özdenizci, O., Schölkopf, B., Ball, T., and Grosse-Wentrup, M. Causal interpretation rules for encoding and decoding models in neuroimaging. *NeuroImage* 110 (2015), 48–59.