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Zurich<sup>UZH</sup>**

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**JOINT WORK WITH PROF. DR. REINHARD FURRER**

**EBPI PHD RETREAT JANUARY 29 - JANUARY 30, 2018**

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# **ADVANCES IN ADDITIVE BAYESIAN NETWORK APPLIED TO OBSERVATIONAL SYSTEM EPIDEMIOLOGY DATASETS**

- ▶ *Classical aim in epidemiology is to investigate relationship between covariate and ONE outcome*
  - ▶ *Typically based on expert knowledge*
- 

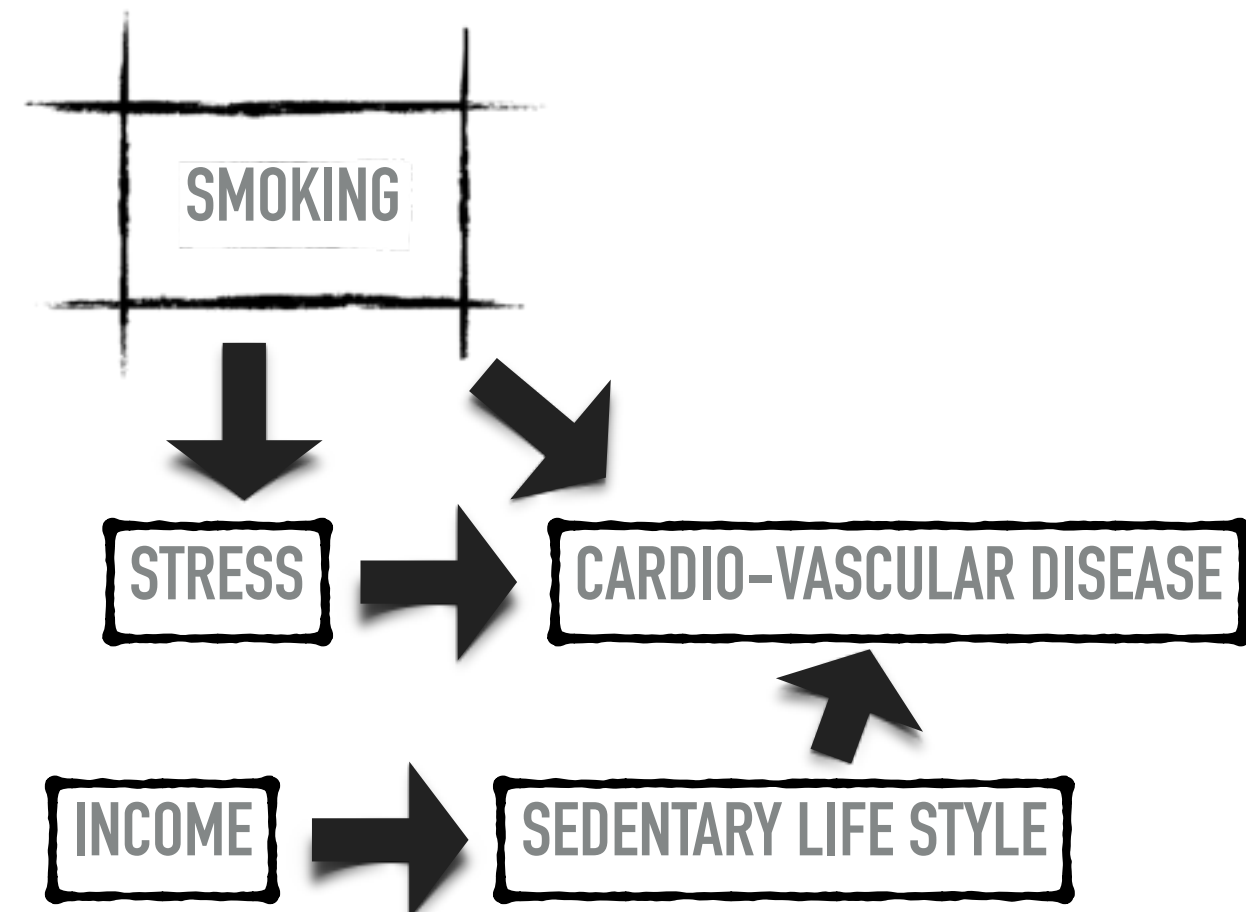
## **Issues:**

- ▶ Multi-collinearity
- ▶ Dependence
- ▶ Confounders
- ▶ **Multivariate** versus **Multivariables**

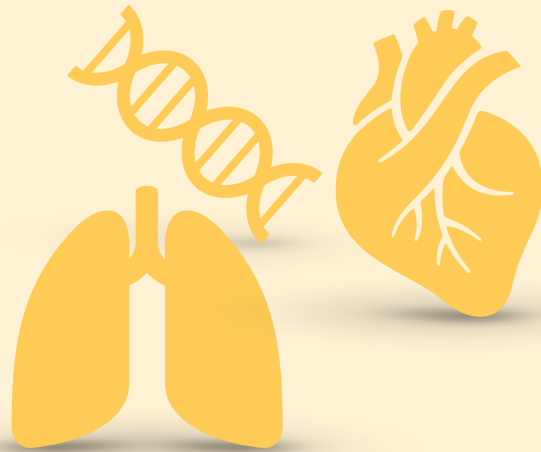
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  - ▶ *Typically based on expert knowledge*
- 

### Issues:

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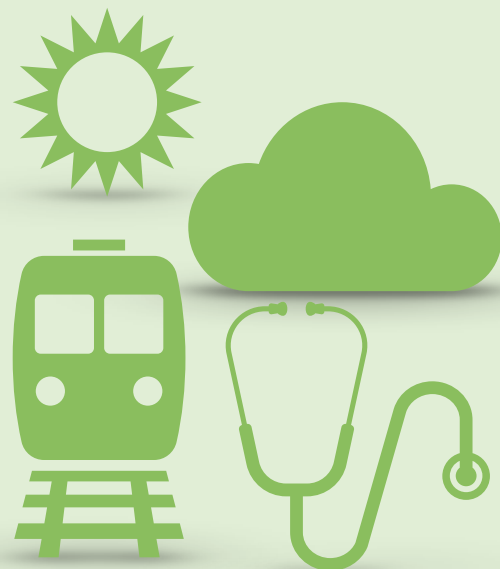
*Enderlein and al. (1996)*

**DISEASE LEVEL**

- ▶ Multiple outcomes/Scores
- ▶ Target variables for intervention
- ▶ Beginning of the coil of discovery

**POPULATION LEVEL**

- ▶ Demographic data
- ▶ Meta population information
- ▶ Cluster

**ENVIRONMENT LEVEL**

- ▶ External factors
- ▶ Ecology
- ▶ Living condition

**Example****▶ Metabolic syndrom**

- ▶ A clustering of 3/5 medical conditions

- ▶ Observational data

- ▶ Age, gender, ...

- ▶ Random effect

- ▶ Weather condition

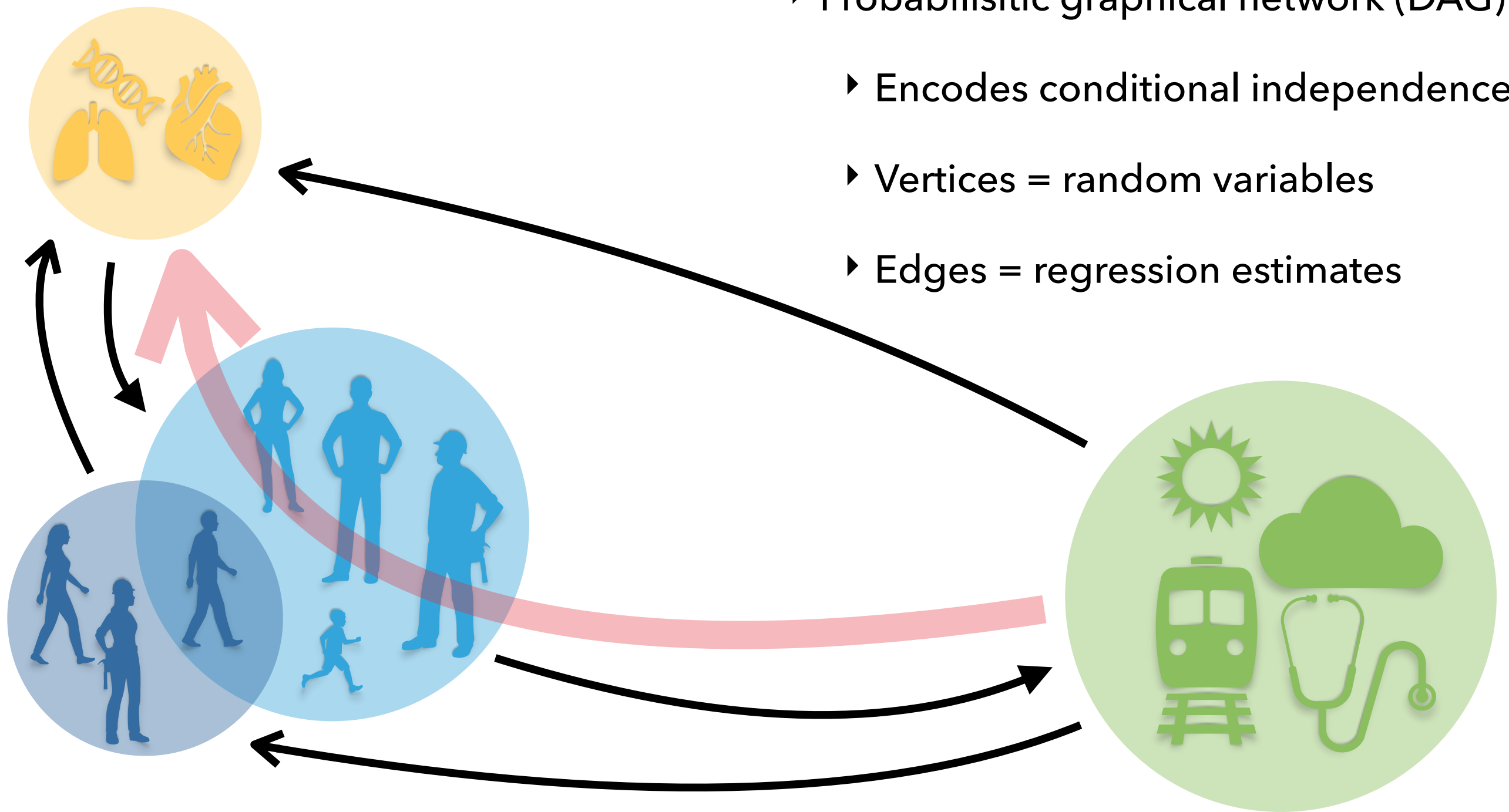
- ▶ Socio-economic condition

- ▶ Housing

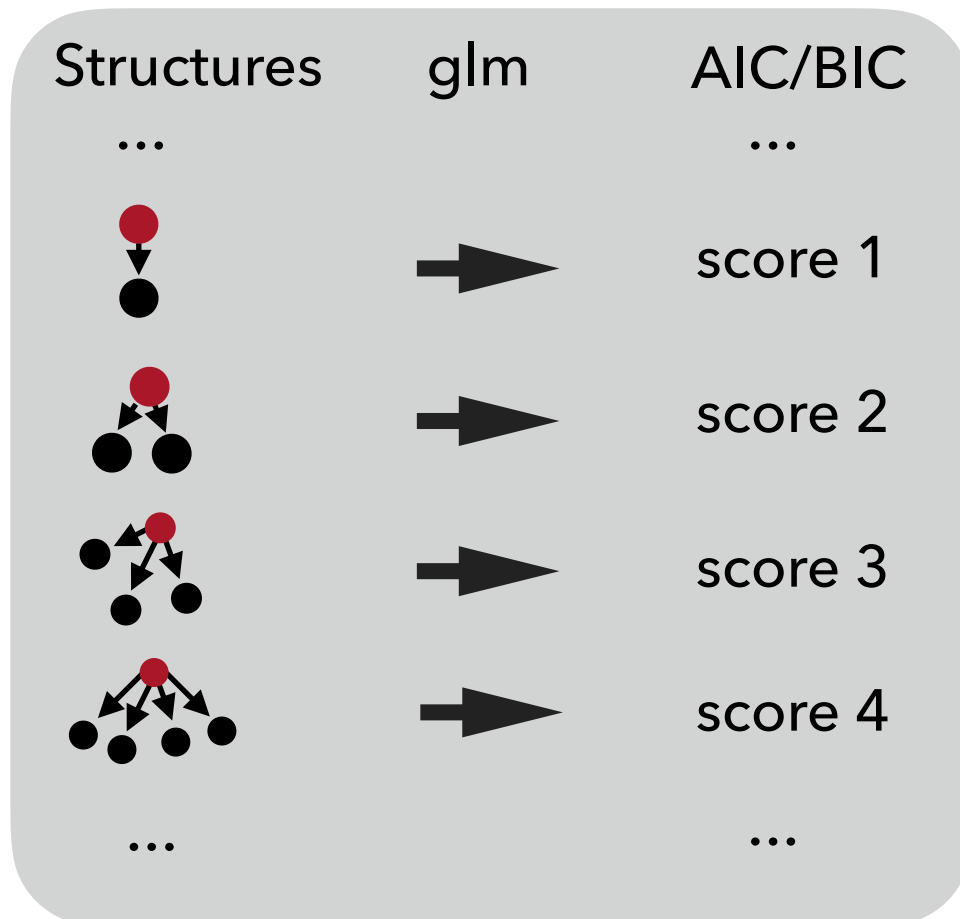
**Main purpose of ABN:** Sort out **directly** associated versus **indirectly** associated, as they are not primary target for intervention

## Bayesian Network

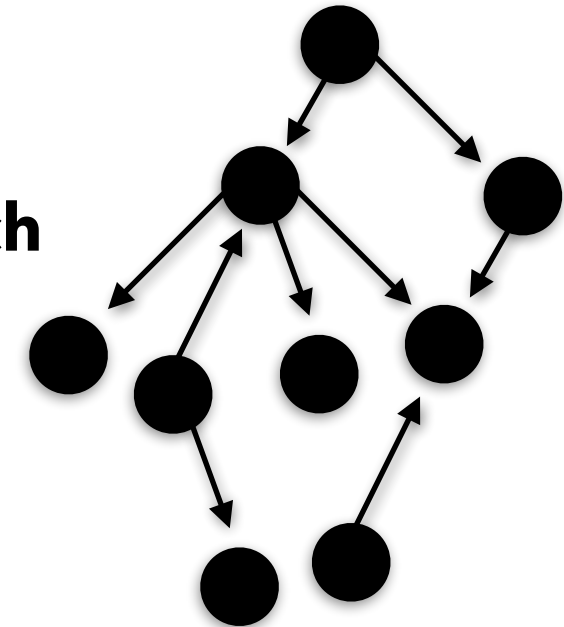
- Probabilistic graphical network (DAG)
  - Encodes conditional independence
  - Vertices = random variables
  - Edges = regression estimates



## Search and score algorithm

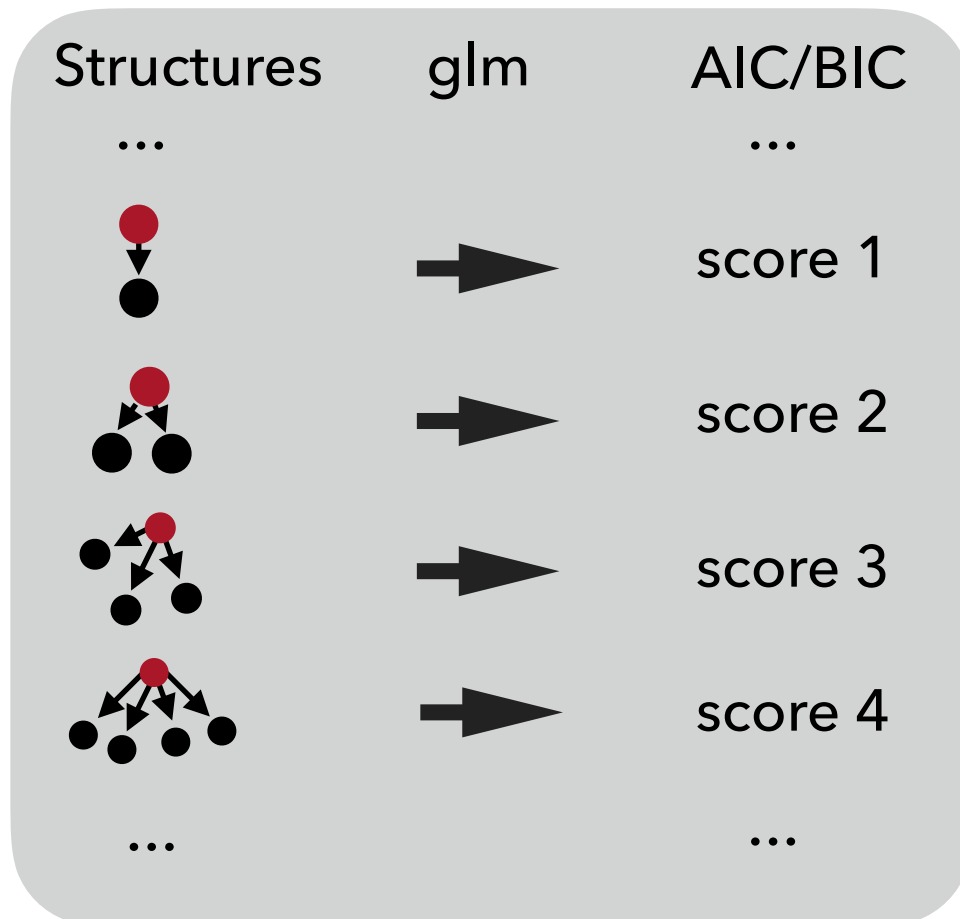


Exact or heuristic search

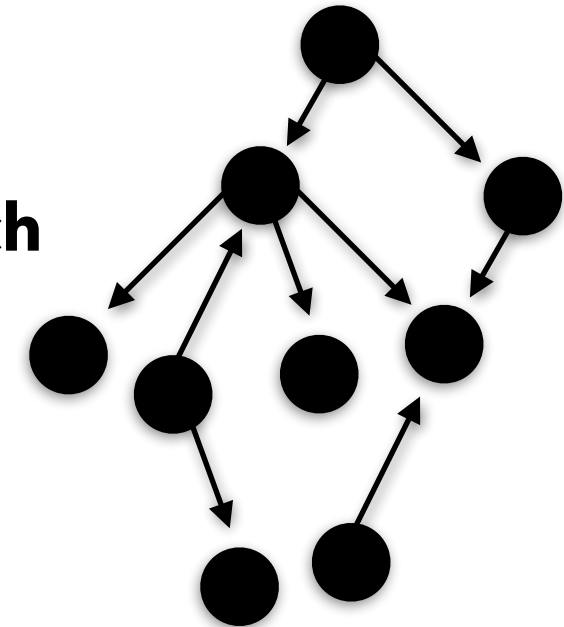


Bayesian network with  
highest posterior  
probability

## Search and score algorithm



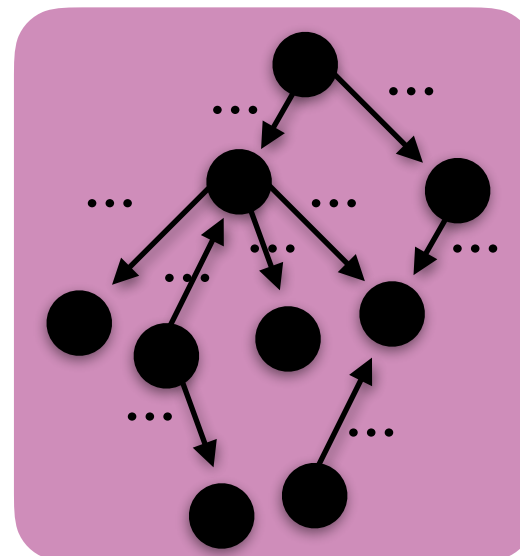
Exact or heuristic search



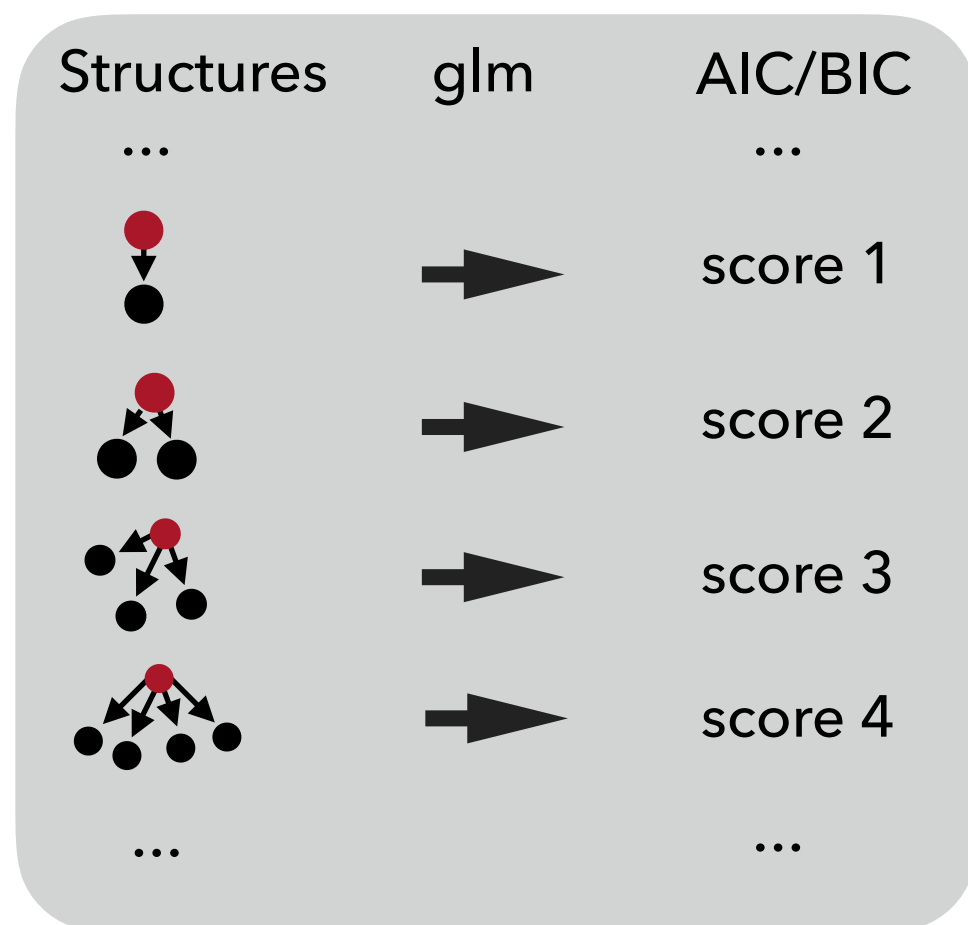
Bayesian network with  
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probability

## Parameter estimation

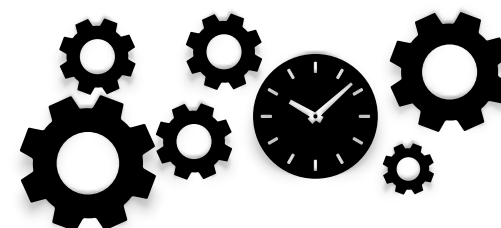
- ▶ compute marginal posterior density
- ▶ regression estimate



## Search and score algorithm

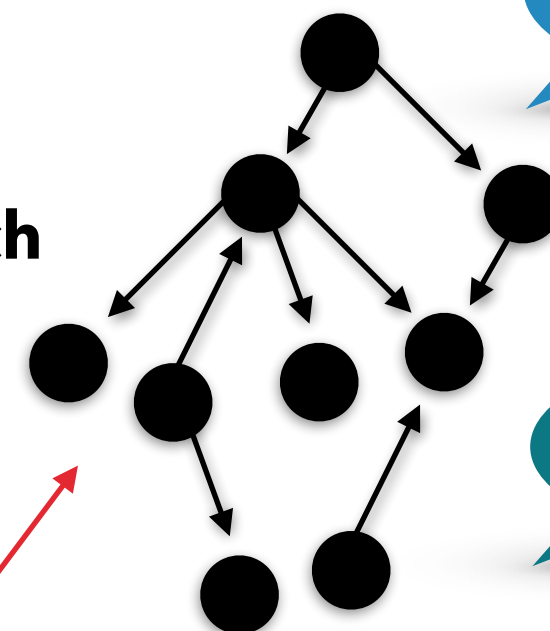


Exact or heuristic search



**Causality!**

*Ban/Retain  
structures*



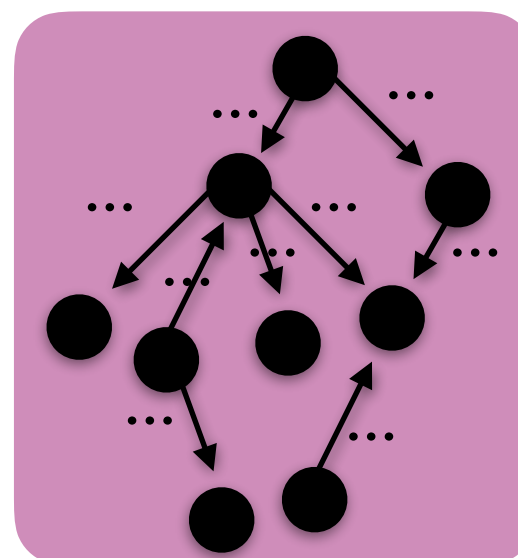
Adjustment

Random effect

Bayesian network with  
highest posterior  
probability

## Parameter estimation

- compute marginal posterior density
- regression estimate



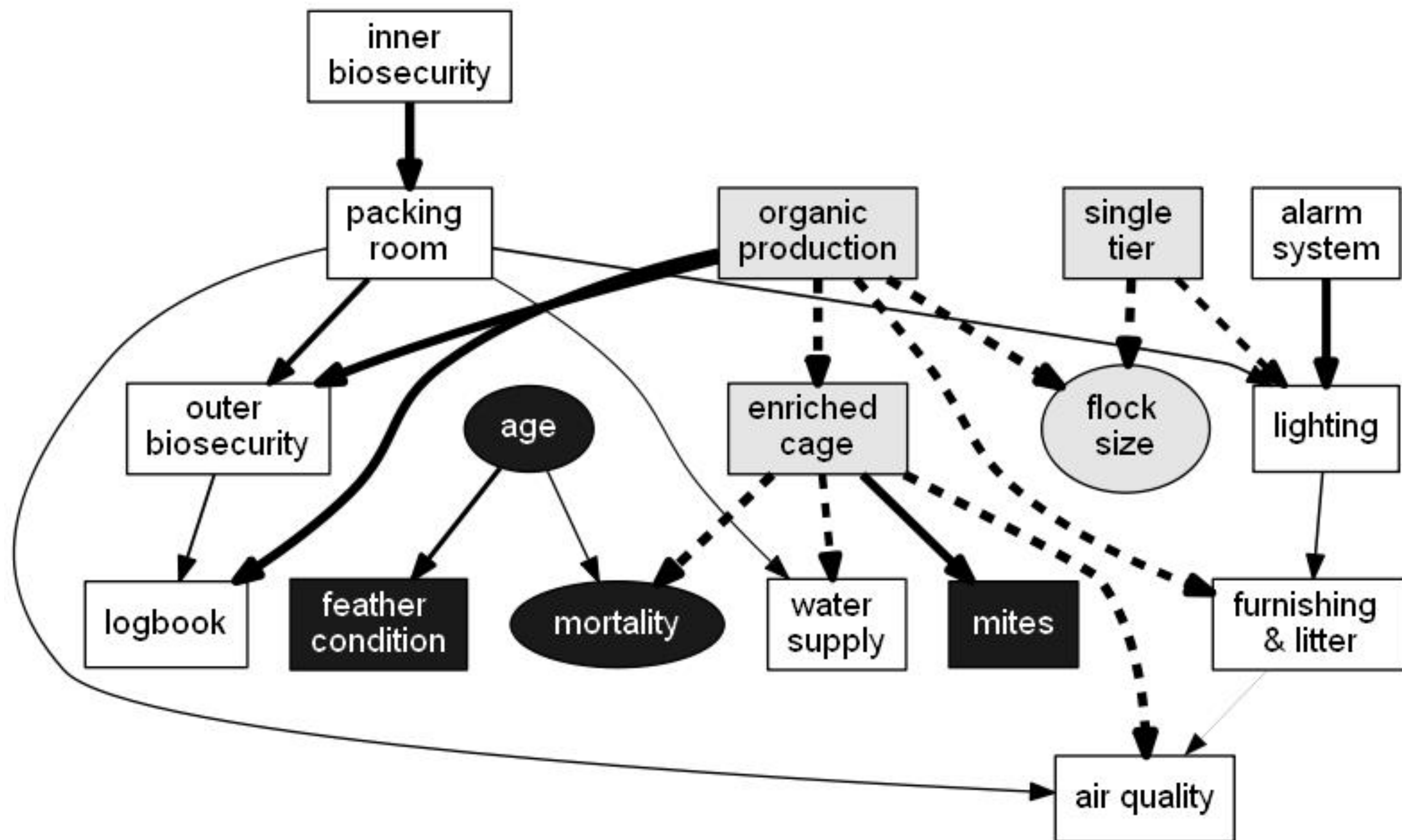
**Using R**

*buildscorecache()*

*mostprobable()*

*fitabn()*





*Arianna Comin et al (2017); Revealing the structure of the associations between housing system, facilities, management and welfare of commercial laying hens using Additive Bayesian networks*

- ▶ Simple output
- ▶ Arc coefficients: easy to interpret
- ▶ Statistical guarantees

### **Current implementation**

- ▶ Distributed as an R package (CRAN)
- ▶ Bayesian regression based on INLA (lm, logit and Poisson) with possibly **random effect**
- ▶ Most probable search (**exact search**) and Hill climber (heuristic approach)

### **(Very!) Near Future features**

- ▶ Arc strength based on Mutual Information
  - ▶ Significance not p-value based
- ▶ GLM implementation (data separation, multinomial variable, adjustment)
  - ▶ Multiple scores: AIC, BIC, MDL

- Search algorithm based on Mutual Information

Increasing order of complexity!

- Penalized by  $\chi^2$  (*de Campos et al, 2006*)

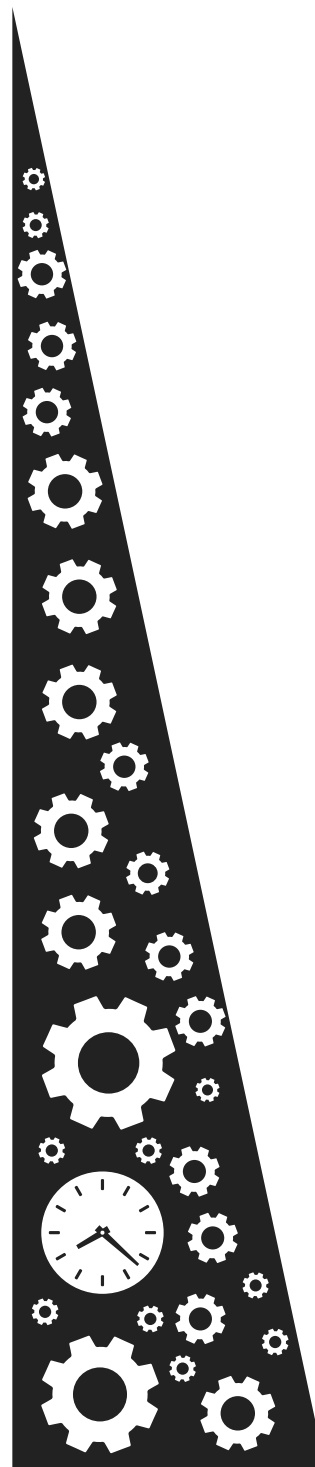
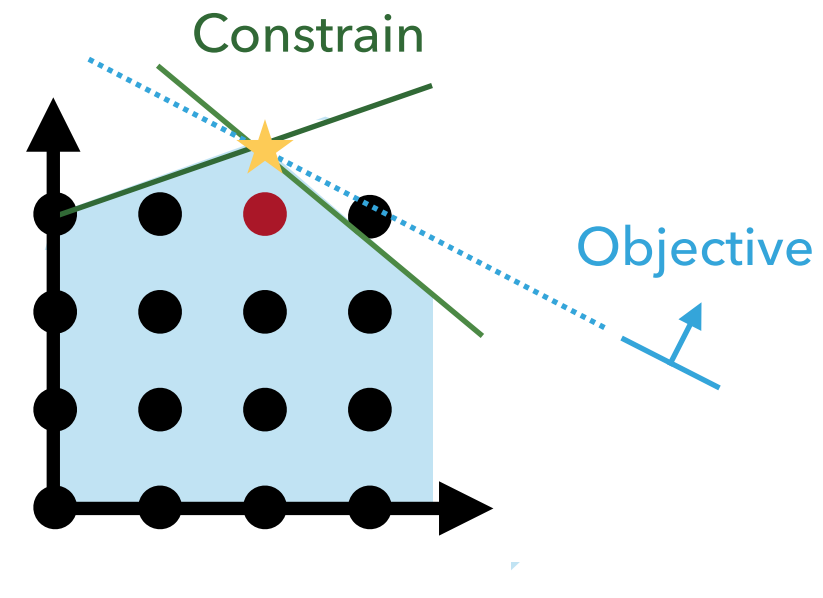
- Algorithmic search implementation

- Heuristic search/Hybrid search
  - Integer programming (*Cussens, 2012*)

- Bayesian regression work horse

- Stan implementation
  - Diaconis-Ylvisaker conjugate priors (*Pittavino et al, 2016*)

- **Causal belief:** Informative prior structure *versus* incomplete synthetic observations



# VARRANK

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## System epidemiology

- ▶ Typically the set of possible variables is formidable
  - ▶ The classical approach for variable selection is based on prior scientific knowledge (29%)<sup>1</sup>
  - ▶ Change of estimate (18%)<sup>1</sup>
  - ▶ Stepwise model selection (16%)<sup>1</sup>
- ▶ No prior model
- ▶ Not one outcome experiment

## varrank

## Variable ranking for better time allocation

- ▶ Variable ranking based on a set of variable of importance
- ▶ Model free. Based on information theory metrics
- ▶ Mixture of variables (continuous and discrete). Discretisation through rule/clustering
- ▶ Ranking of 100 variables with 100'000 observations in ~14 minutes! (forward greedy search)

<sup>1</sup> *Walter et al (2009)*

$f_i$  candidate feature to be ranked

**C** set of variables of importance

$$H(X) = \sum_{n=1}^N P(x_n) \log P(x_n)$$

**S** set of already selected variables

$$\text{MI}(X; Y) = \sum_{n=1}^N \sum_{m=1}^M P(x_n; y_m) \log \frac{P(x_n; y_m)}{P(x_n)P(y_m)}$$

$$\text{score}_i = \text{MI}(f_i; \mathbf{C}) - \beta \sum_{f_s \in \mathbf{S}} \alpha(f_i, f_s, \mathbf{C}) \text{MI}(f_i; f_s)$$

*Estévez and al. (2009)*

$$\beta = 1/|\mathbf{S}| \text{ and } \alpha(f_i, f_s, \mathbf{C}) = \frac{1}{\min(H(f_i), H(f_s))}$$

# VARRANK

## MAXIMUM RELEVANCE MINIMUM REDUNDANCY

$f_i$  candidate feature to be ranked

**C** set of variables of importance

**S** set of already selected variables

$$H(X) = \sum_{n=1}^N P(x_n) \log P(x_n)$$

Average amount  
of information of  
one RV

$$MI(X; Y) = \sum_{n=1}^N \sum_{m=1}^M P(x_n; y_m) \log \frac{P(x_n; y_m)}{P(x_n)P(y_m)}$$

Mutual dependence  
between two RV

### Greedy search

Forward - argmax

$$\text{score}_i = \underbrace{MI(f_i; \mathbf{C})}_{\text{Relevance}} - \beta \sum_{F_s \in \mathbf{S}} \underbrace{\alpha(f_i, f_s, \mathbf{C})}_{\text{Normalization}} \underbrace{MI(f_i; f_s)}_{\text{Redundancy}}$$

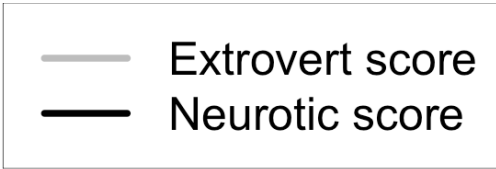
*Estévez and al. (2009)*

$$\beta = 1/|\mathbf{S}| \text{ and } \alpha(f_i, f_s, \mathbf{C}) = \frac{1}{\min(H(f_i), H(f_s))}$$

EPI: 3570 observations and 57 variables

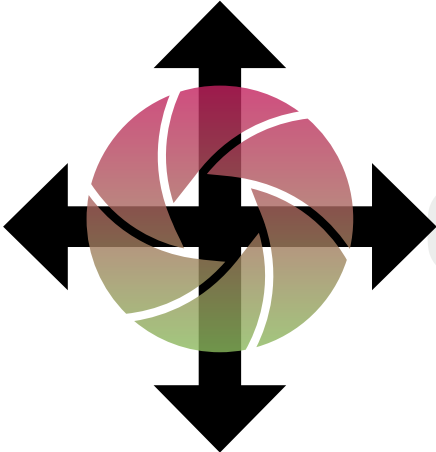
Structure of EPI:

✓ Lie scale (9 responses)



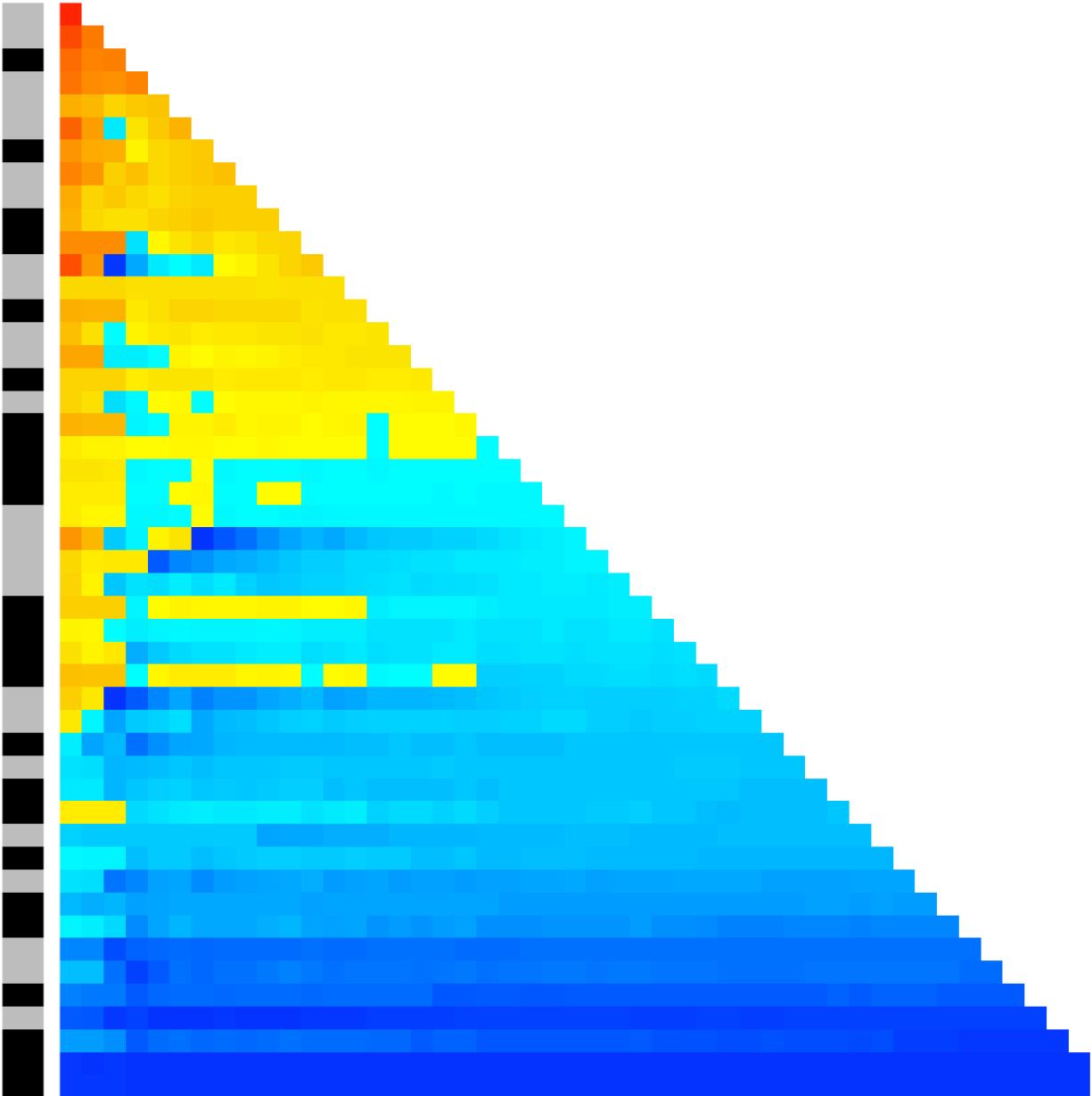
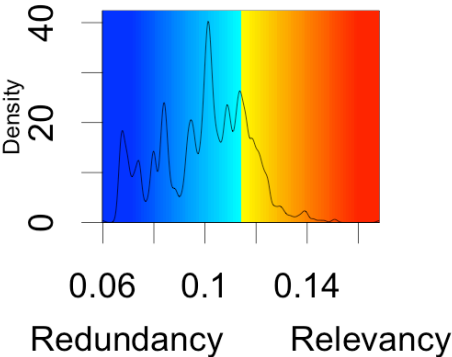
Extrovert score (24)

Neurotic score (24)

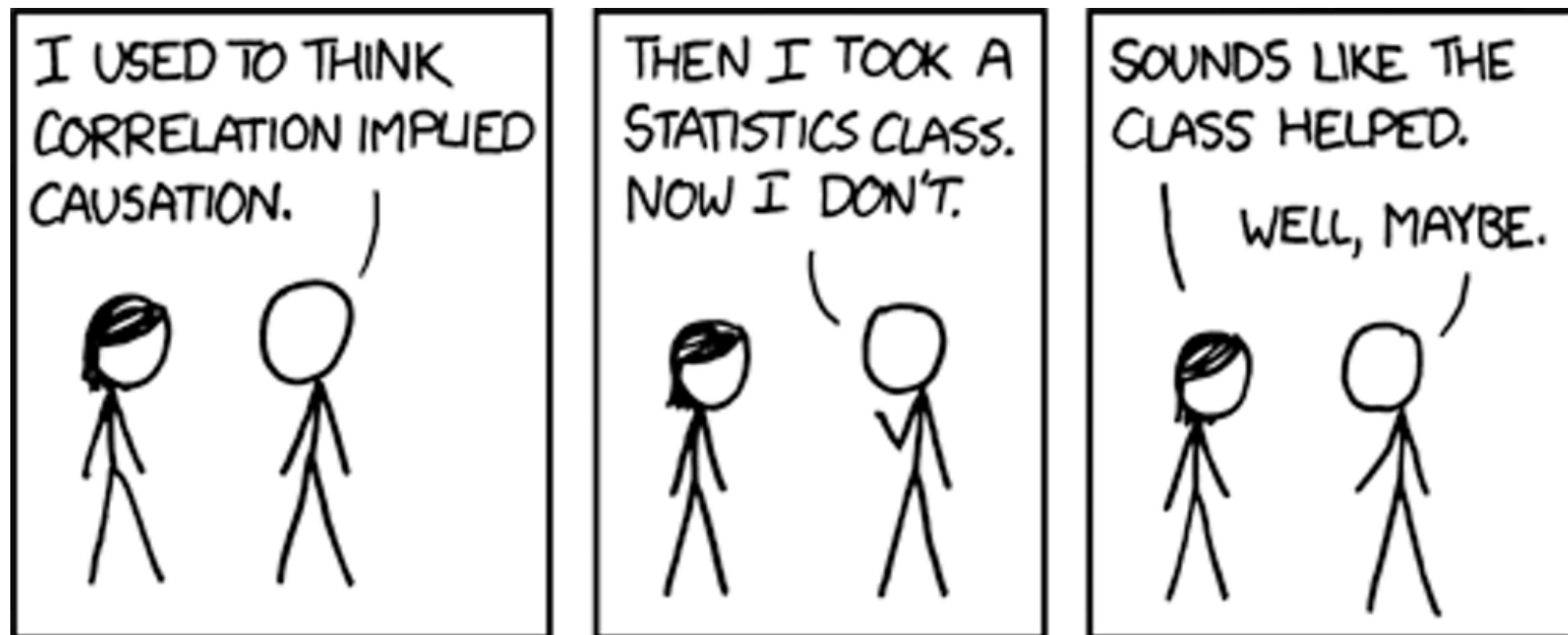


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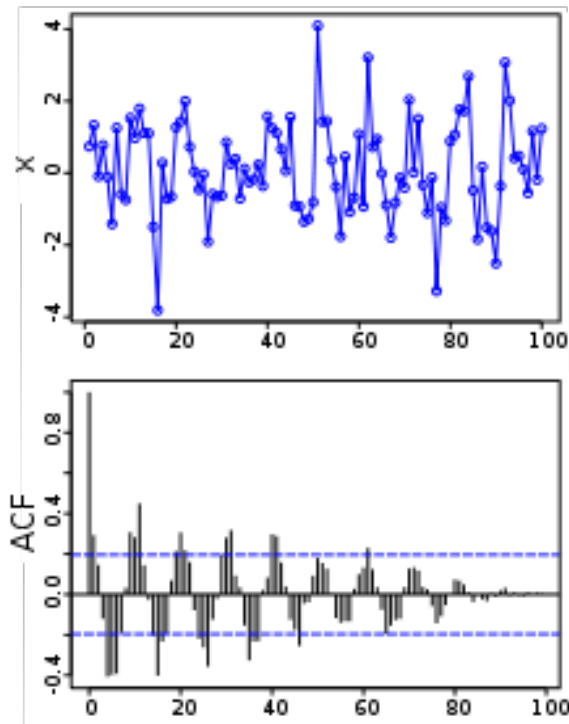
**Looking forward for your questions, inputs or remarks ...**





# Backup slides

# TSABN



## Time series regression

- ▶ OLS estimates
- ▶ Goodness of fit metrics

*Variance-Covariance*

$$\begin{pmatrix} \sigma_{y_1}^2 & \sigma_{y_1 y_2} & \cdots & \sigma_{y_1 y_n} \\ \sigma_{y_1 y_2} & \sigma_{y_2}^2 & \cdots & \sigma_{y_2 y_n} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{y_1 y_n} & \sigma_{y_2 y_n} & \cdots & \sigma_{y_n}^2 \end{pmatrix}$$

## tsabn as a time series extension of abn

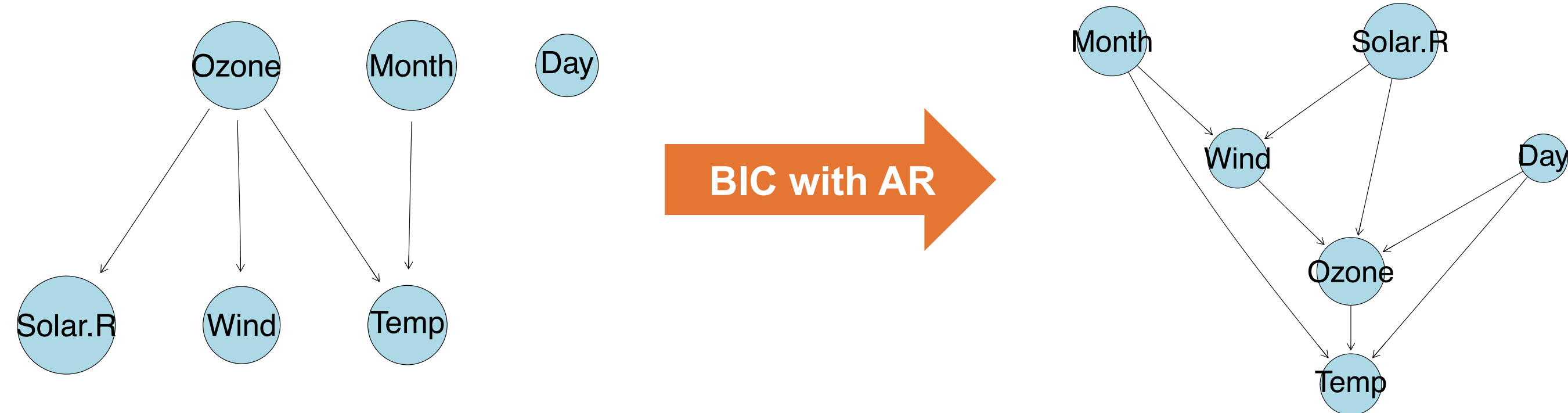
- ▶ Extending ABN to correlated errors
- ▶ Several implemented scores: AIC, BIC, MDL
- ▶ Errors Autocorrelation: ARMA procedure with Autoregressive modelling
  - ▶ Kalman filter

## Future work

- ▶ Implementation of Granger causality score for BN learning

Daily readings of the air quality values from May to September 1973

111 observations on 6 variables

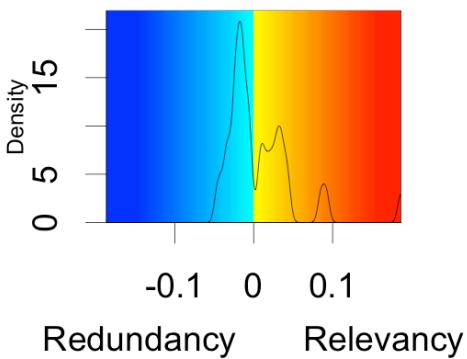


### Future work:

Hourly readings of the PM2.5 and 6 other chemical compounds data of US embassy in Beijing with meteorological data from Beijing Capital International Airport from 2013 to 2017

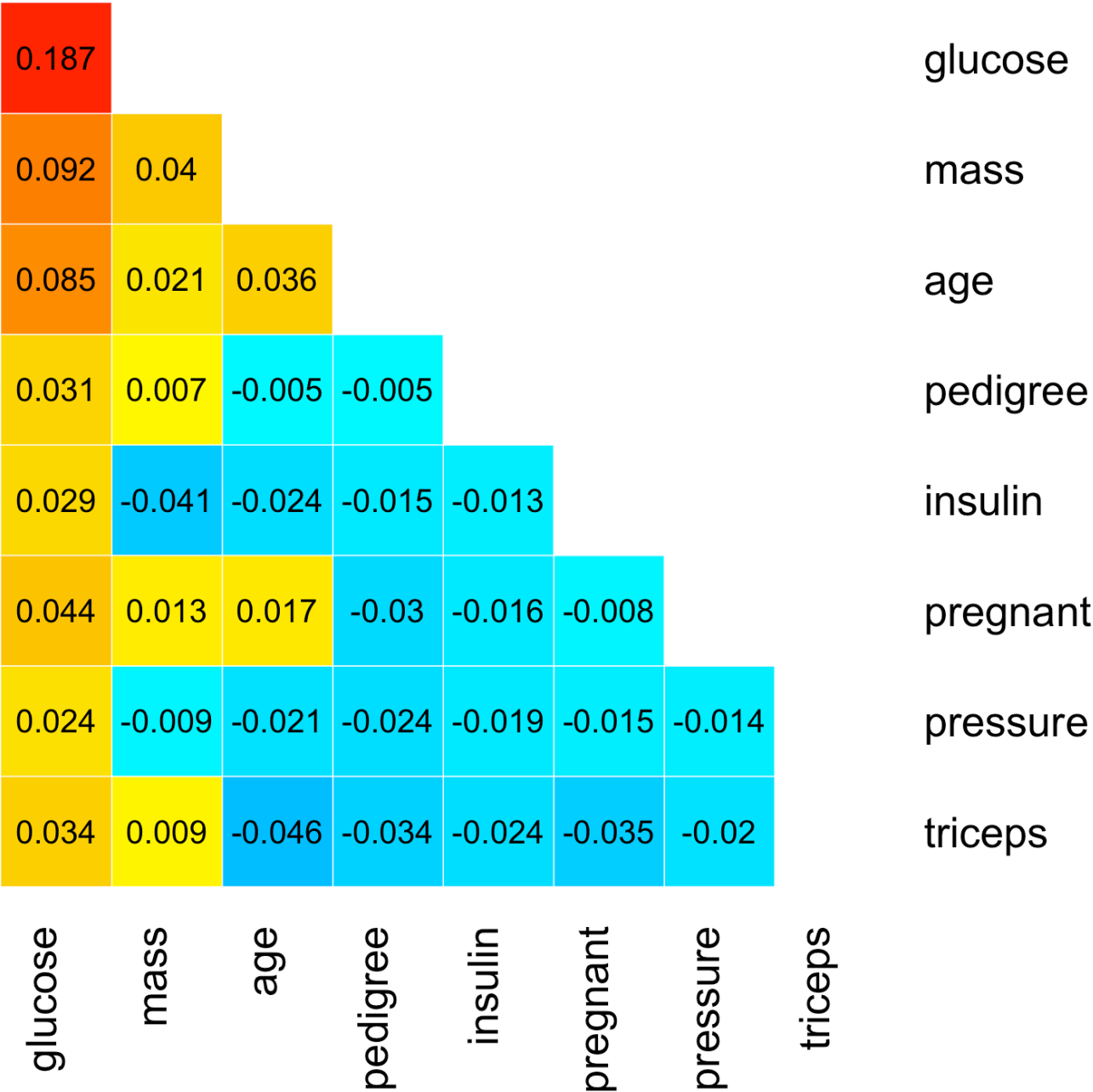
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DIABETE



Pima Indians Diabetes Database

768 observations on 9 variables





**That is all folks!**