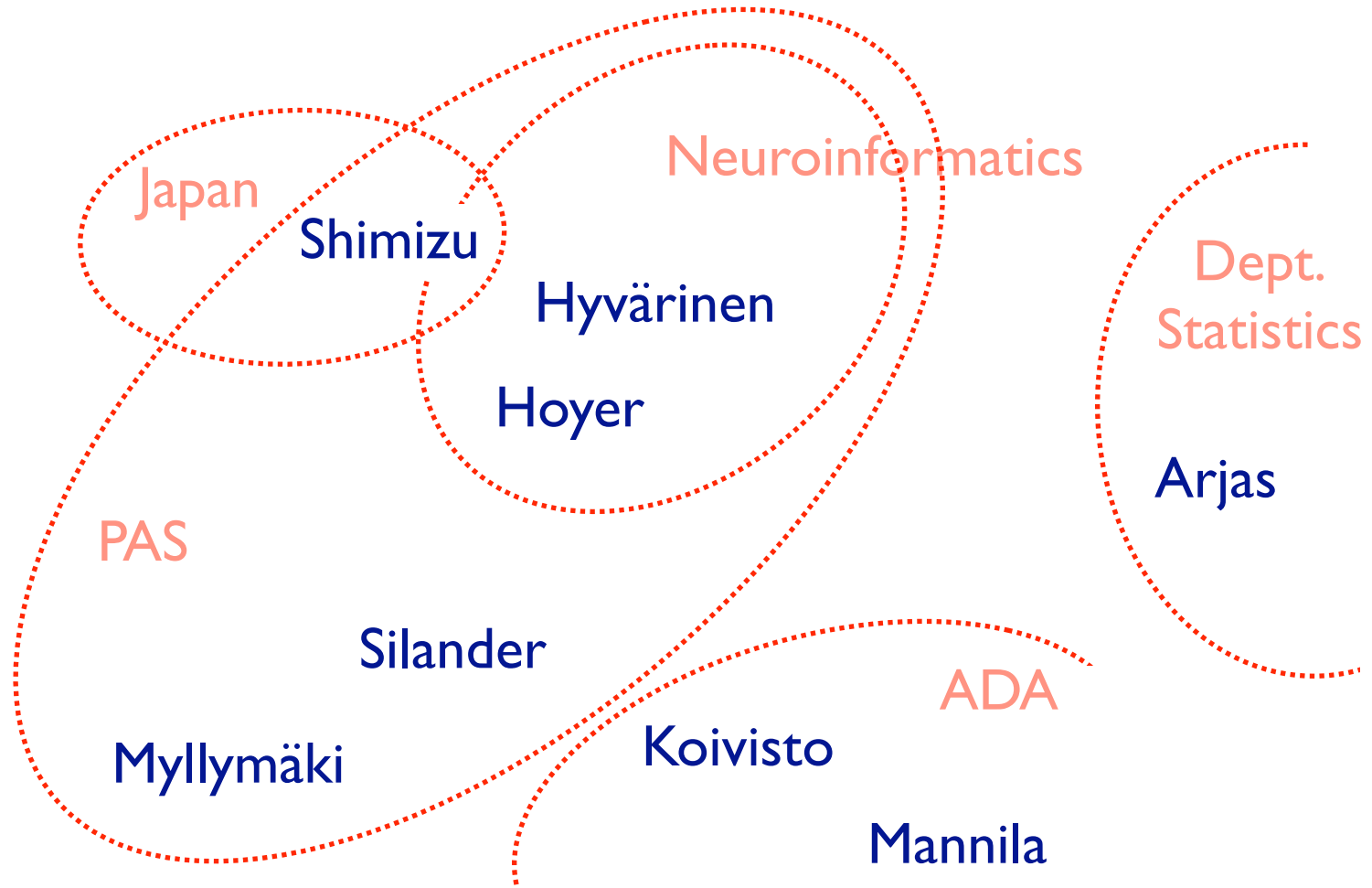
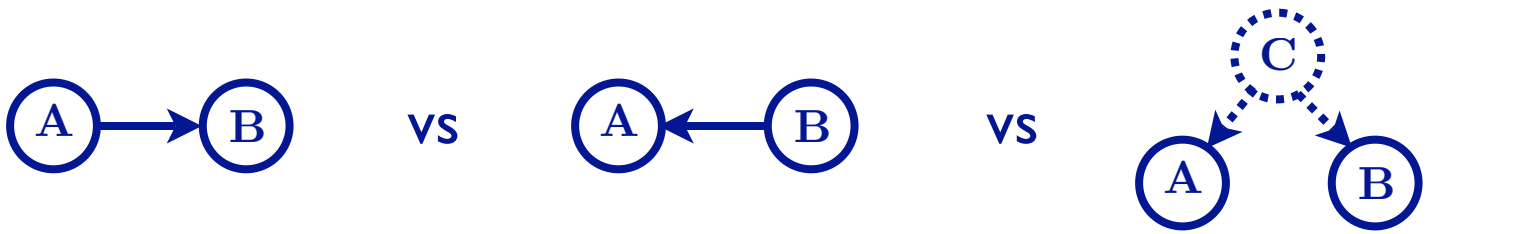
Causal inference @ HIIT



Patrik Hoyer / Neuroinformatics group / PAS / HIIT retreat / 10.5.2007

Causal inference?

- Learning network models (just like Bayesian networks) but attempting to distinguish between 'equivalent' networks...

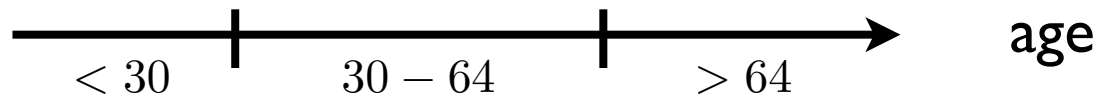


$P(A)\,P(B|A)$ $\quad$ $P(B)\,P(A|B)$ $\quad$ $\sum_C P(C)\,P(A|C)\,P(B|C)$

...to predict the consequences of actions!

Numerical variables!

- ordinal, ratio scale, or continuous variables, e.g.



- relationships between variables smooth

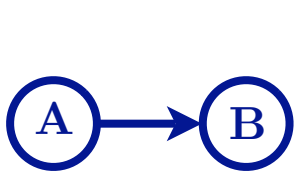
- classical methods assume categorical variables and arbitrary relationships:

  very general but also quite inefficient

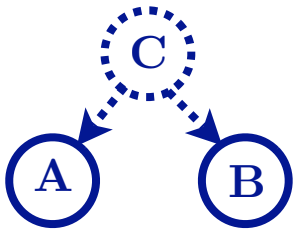
Linear models

(with S. Shimizu, A. Hyvärinen, Y. Kano, A. Kerminen & M. Palviainen)

- Continuous variables & linear relationships (arguably the 'smoothest' possible functions)
- Non-gaussianity allows us (using ICA) to identify the model where others have failed



vs



can distinguish these based on $P(A, B)$!

$$A := e_A$$
$$B := rA + e_B$$

$$C := e_C$$
$$A := r_1 C + e_A$$
$$B := r_2 C + e_B$$

Nonlinear models

(current work)

- Since causal interactions are identifiable for the linear non-gaussian model, it should be possible to do almost as well if the relationships are relatively smooth
- Interested in all kinds of numerical data, both discrete and continuous