Sensory specific satiation: using Bayesian networks to combine data from related studies

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AGROTECHNOLOGY & FOOD SCIENCES GROUP
WAGENINGEN UR

Outline of the presentation

I. Bayesian networks vs. Bayesian statistics

II. Sensory specific satiation: two related studies

III. Bayesian networks to combine data

- Necessary requirement
- Inference - individual networks
- Inference - combined network

IV. Take-home messages

Bayesian networks software

HUGIN EXPERT

Bayesian networks vs. Bayesian statistics

Bayesian statistics

- a **philosophy** in statistics – *Bayesian vs. Frequentist*

e.g., ANOVA models with both 'approaches'

- assumptions: **prior distributions** of all parameters

- calculate **posterior distributions** of the parameters

Bayesian networks

- a modeling **technique** in machine learning

Bayesian network models vs. ANOVA models

- assumptions: **conditional independence** among variables

- relates to Bayes theorem when making **inference**

$$P(A|B) = \frac{P(B|A)\,P(A)}{P(B)}$$

Thomas Bayes

18th-century British mathematician

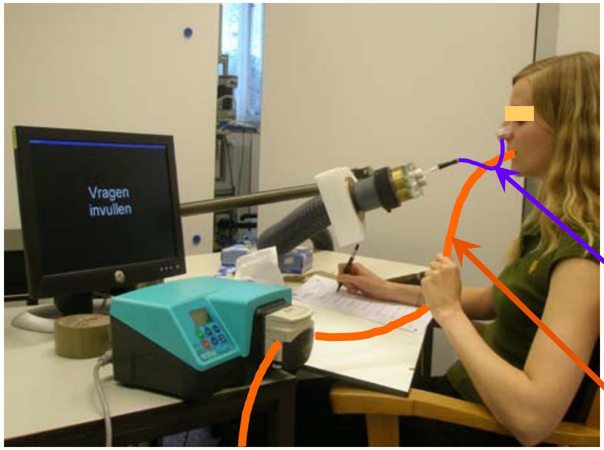
Sensory specific satiation:
two related studies (1)

Hypothesis: more flavor → lower intake

Aroma study

Taste study

normal consumption



2 tomato soups dif. in **salt concentration** (bottomless soup bowl)

4 tomato aroma release profiles via retronasal tube

same soup base pumped with constant rate

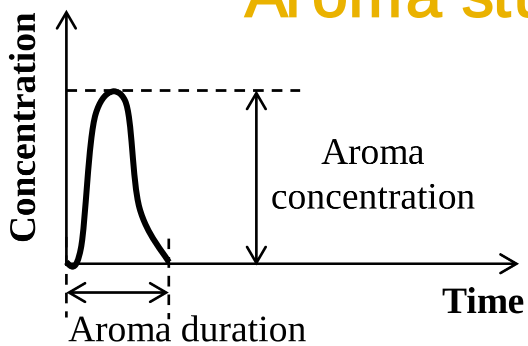
***adlib.* intake** = amount of soup eaten till pleasantly satiated

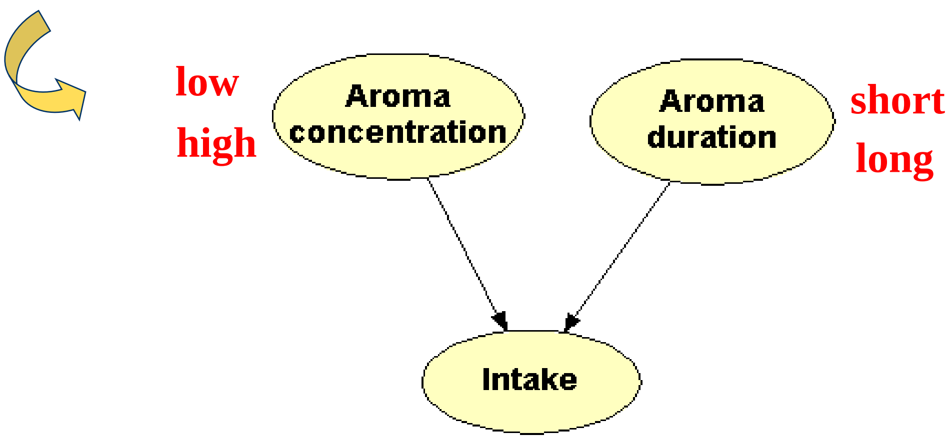
- # subjects = 38
- # test conditions = 4
- **# observations = 118** *(not all subjects finished 4 conditions)*

- # subjects = 48
- # test conditions = 2
- **# observations = 48 x 2 = 96**

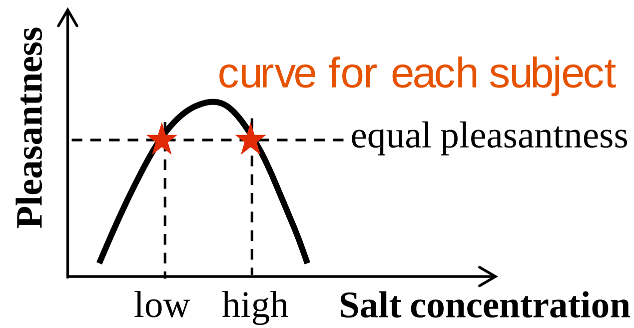
Sensory specific satiation:
two related studies (2)

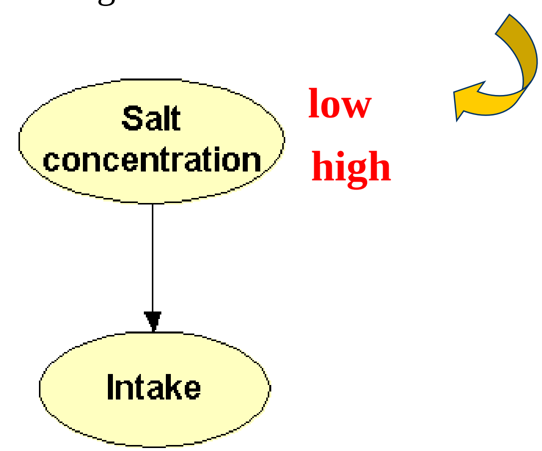
Aroma study





Taste study

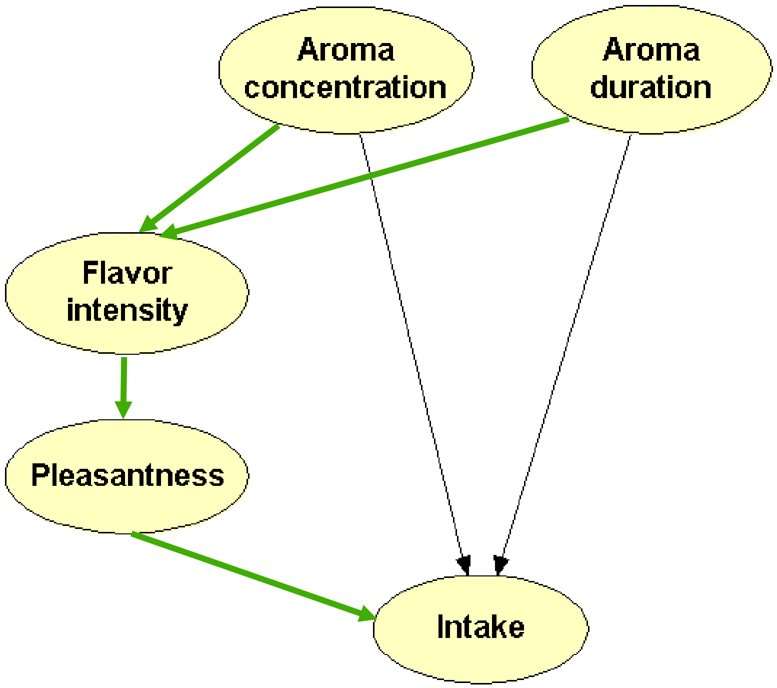




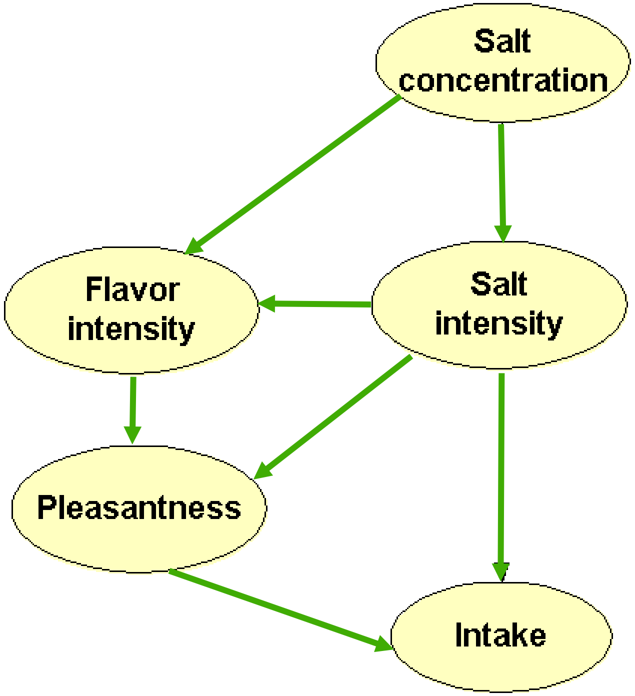
	compared to **normal consumption** of soups
low	1.5 times lower
high	7 times higher
short	equal (3 seconds)
long	longer (18 seconds)

Two related studies
building network structure (1)

Aroma study



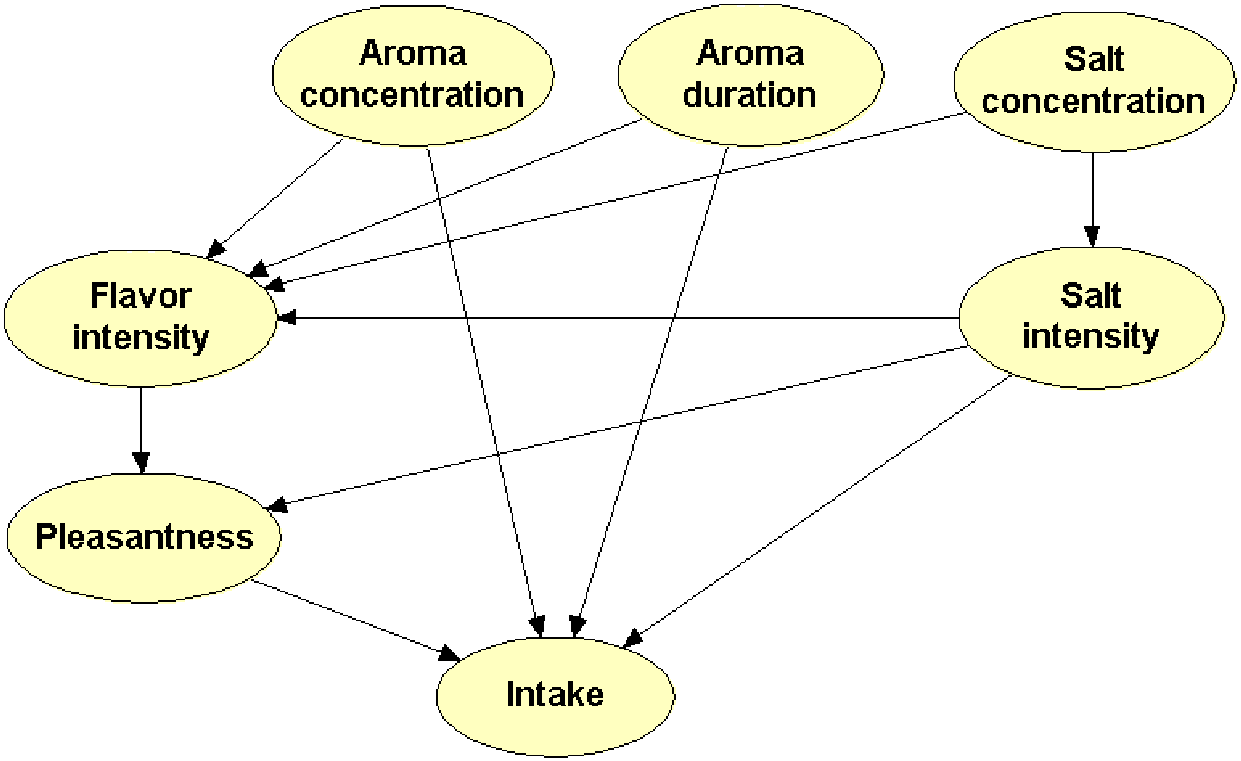
Taste study



- Include other available variables into each network
- Expert knowledge → define partly network structure

Two related studies
building network structure (2)

Combined network



- All relationships were defined by expert knowledge + hypothesis
- **Data** → BNs software can ‘learn’ **new relationships**

Bayesian network to combine data

Necessary requirement

Combined database

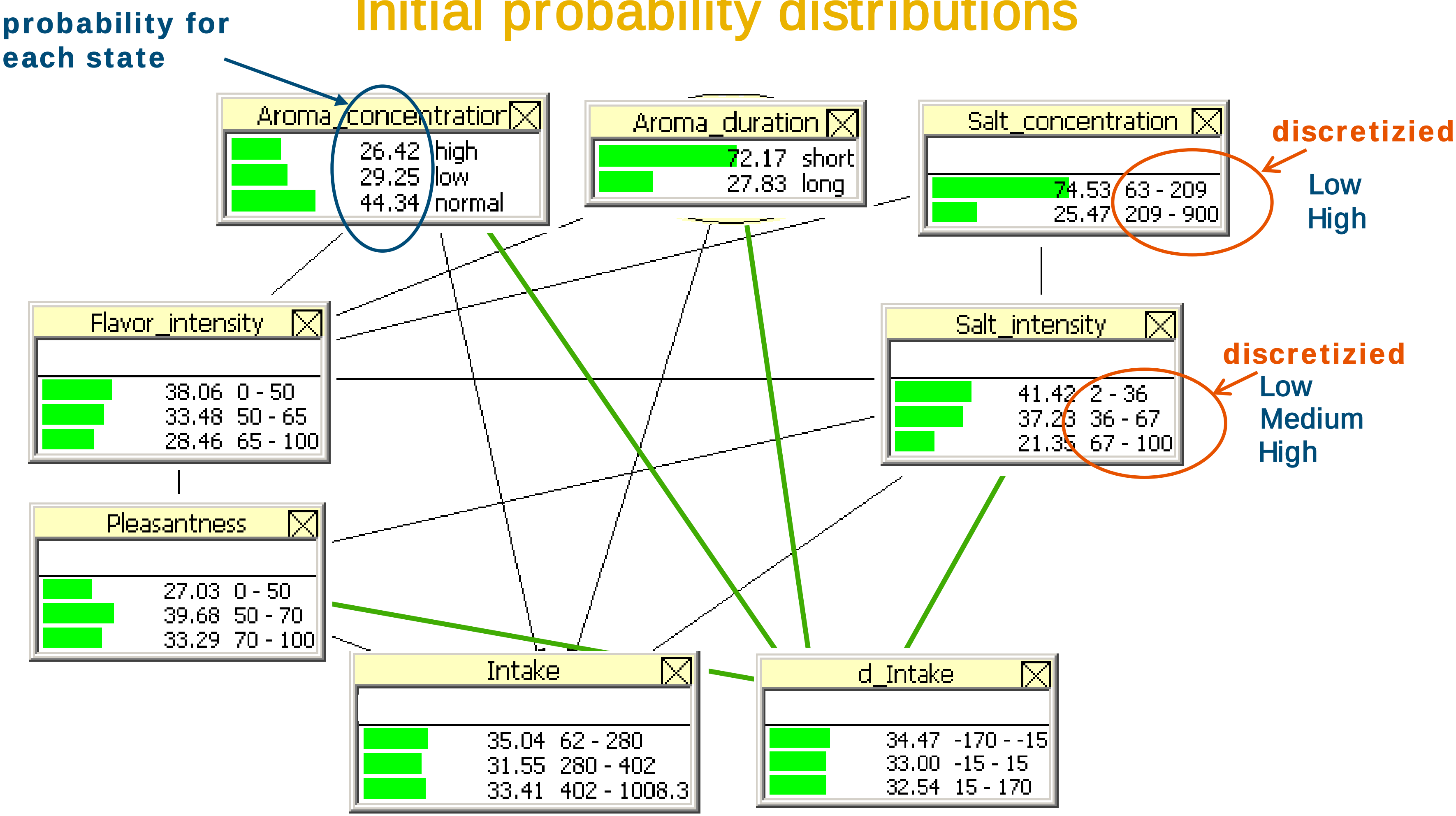
	Aroma concentration	Aroma duration	Salt concentration	Salt intensity	Flavor intensity	Pleasantness	Intake
Aroma study	low	short	calculated	MISSING			
Aroma study	low	long					
Aroma study	high	short					
Aroma study	high	long					
						available	
Taste study	**normal**	**short**	low				
Taste study	**normal**	**short**	high				

- **Design** of 'Aroma study' → define 'Aroma concentration' and 'Aroma duration' values for 'Taste study'
- **Extra experiment / leave 'MISSING'** → estimate 'Salt intensity' values for 'Aroma study'

Bayesian network to combine data

Inference

Initial probability distributions

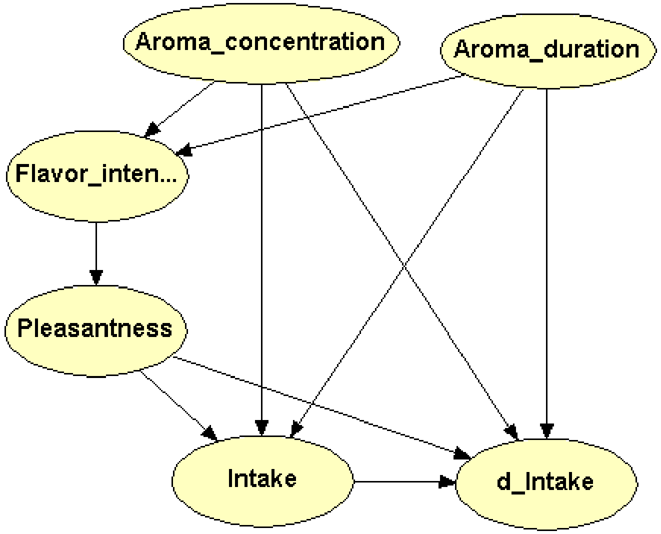


$\boxed{\text{d\_intake} = \text{intake} - \text{mean}_{\text{subject}}}$

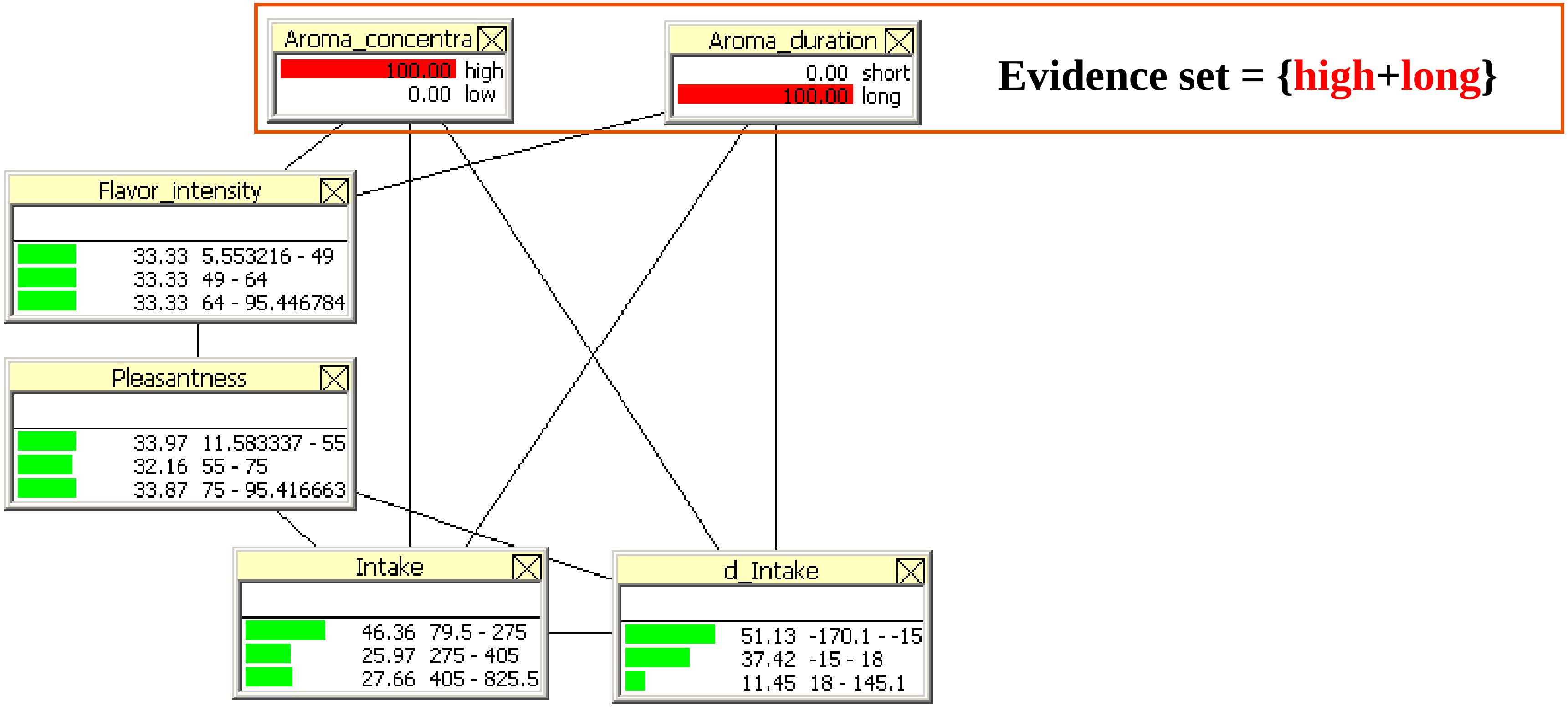
→ *capture within-subject variation*

Inference

Aroma network

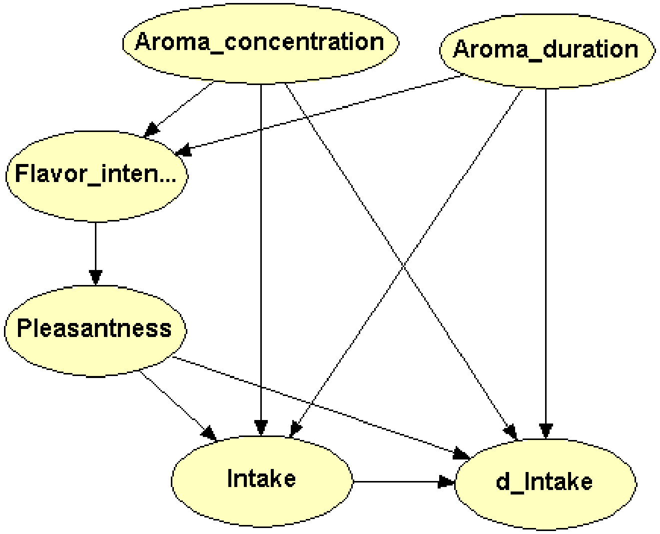


'Inference' = calculation of probabilities of interest given the model (Heckerman, 1995)

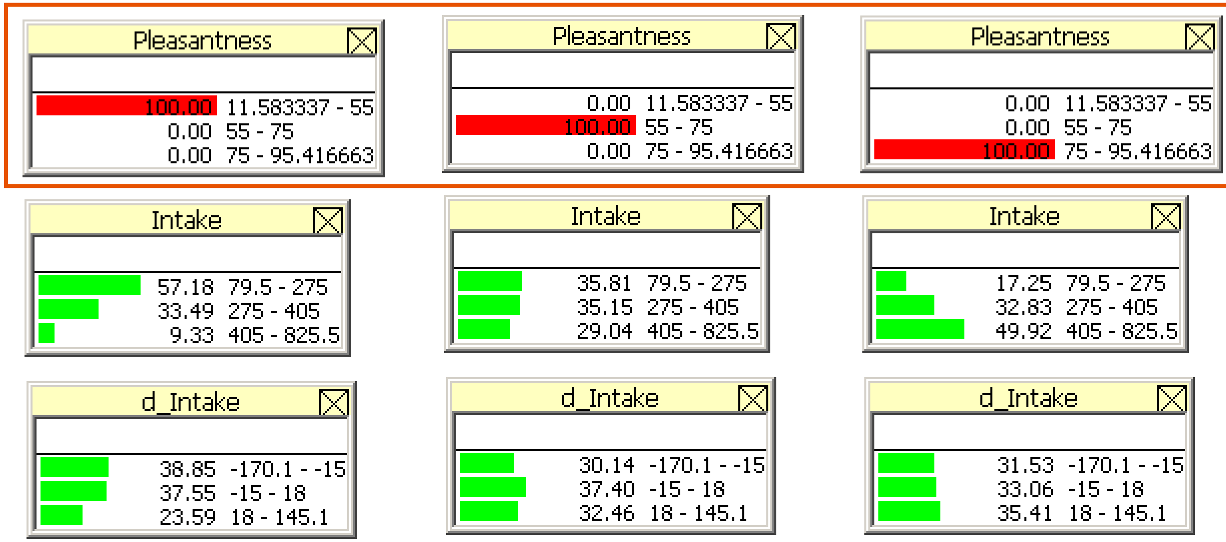


Inference

Aroma network



'Inference' → examine any relationships in the model network



'Pleasantness'

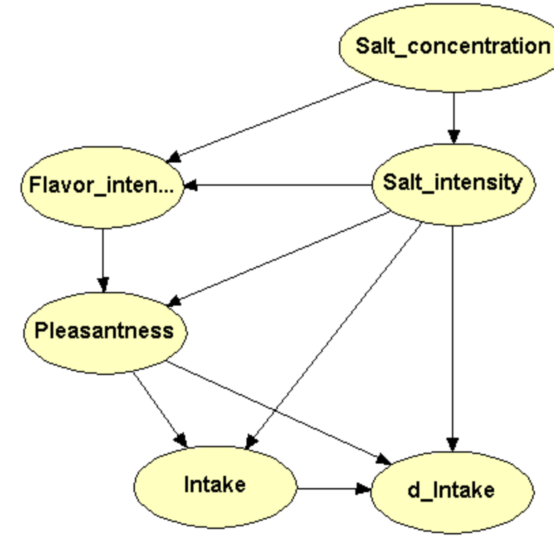
'Intake'

'd_Intake'

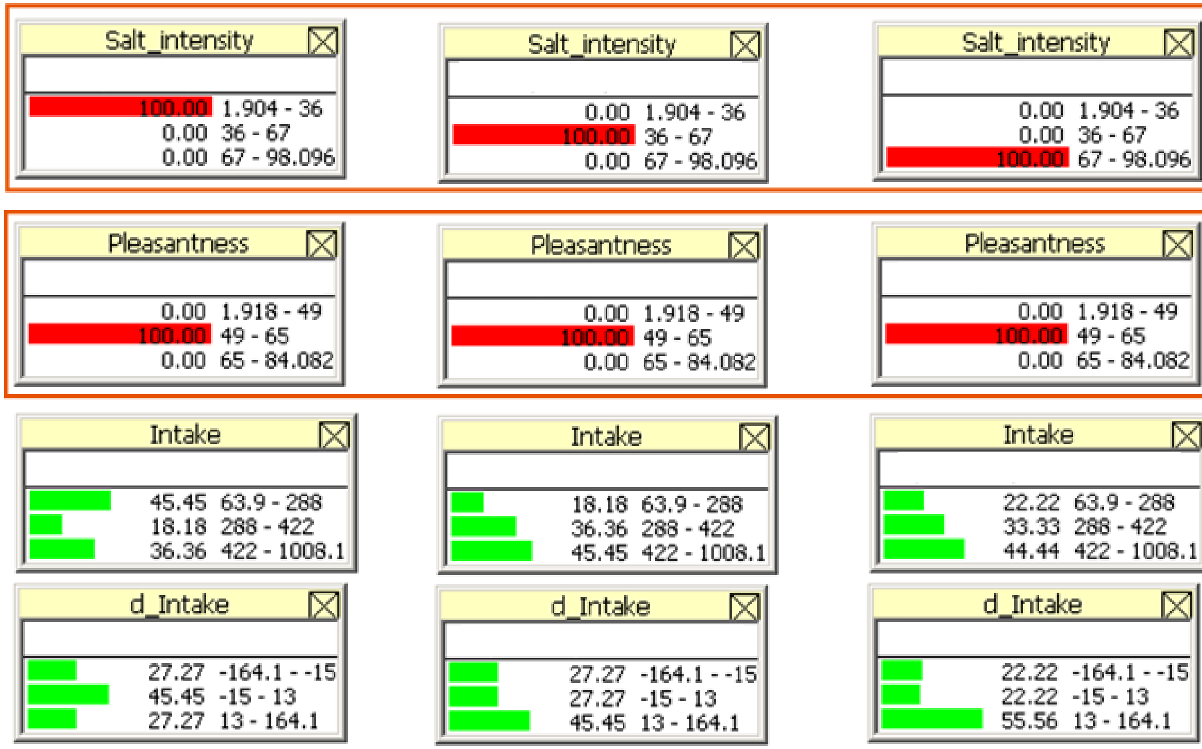
→ *'Pleasantness' influences the food intake over a population to a larger extent compared to its influence on the individual intake*

Inference

Taste network



'Inference' → examine any relationships when *fixing* the value of one variable



'Salt intensity' ↗

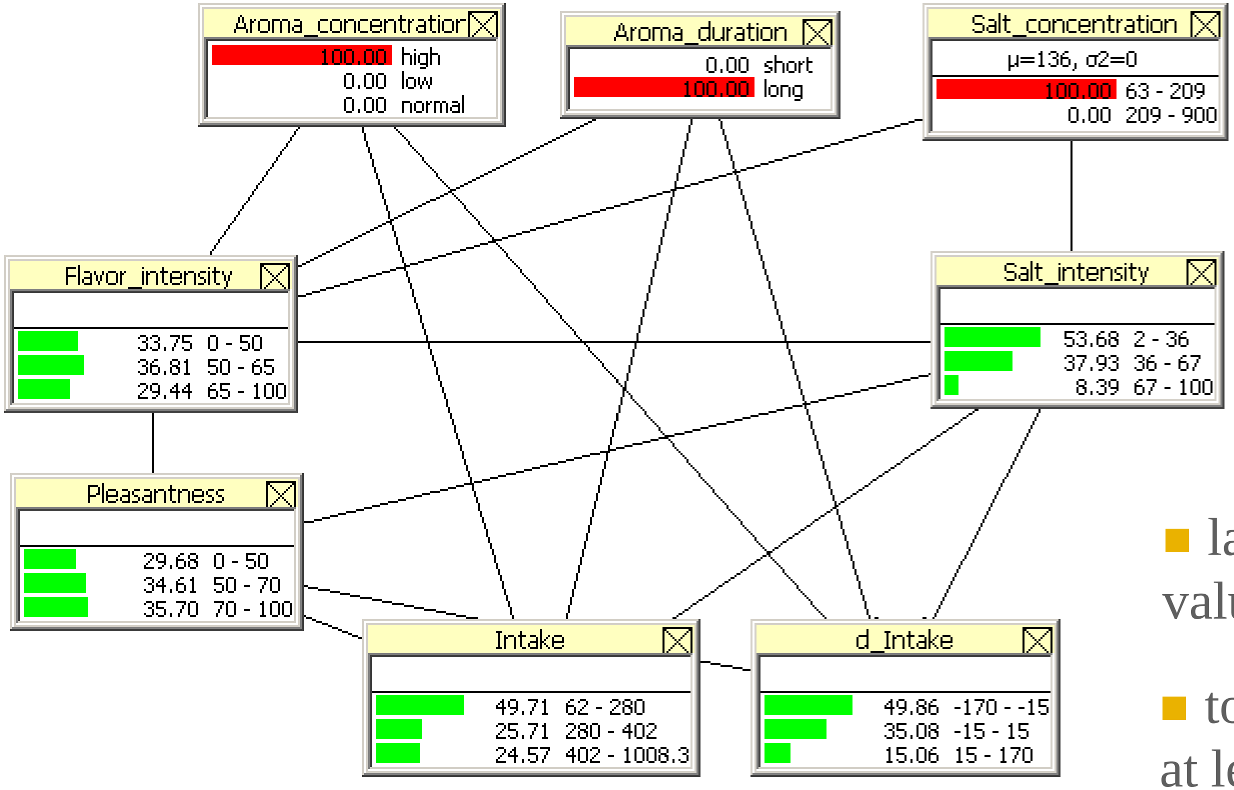
'Pleasantness' ~ **fixed** within [49, 65)

large increase *less change*

Inference

Combine network

‘Inference’ → predict the **interaction** between ‘Aroma aspects’ and ‘Salt concentration’



warnings

- large # ‘Salt intensity’ values MISSING
- total # observations ~ 200 vs. at least 800 needed [5 times # parameters of ‘Intake’]

Take-home messages

- **Recommendations for designing experiments**:

  Start with 'big network', define variables & their levels

  Conduct 'small studies', get information on variables of interest in one study from other studies

- **Bayesian networks give possibilities to**:
  - Incorporate expert knowledge
  - Combine data from related studies
  - Communicate complex problems

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