



# Selecting variables from sensor data using principal components and partial least squares



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Session 25: Precision livestock farming for animal health and welfare  
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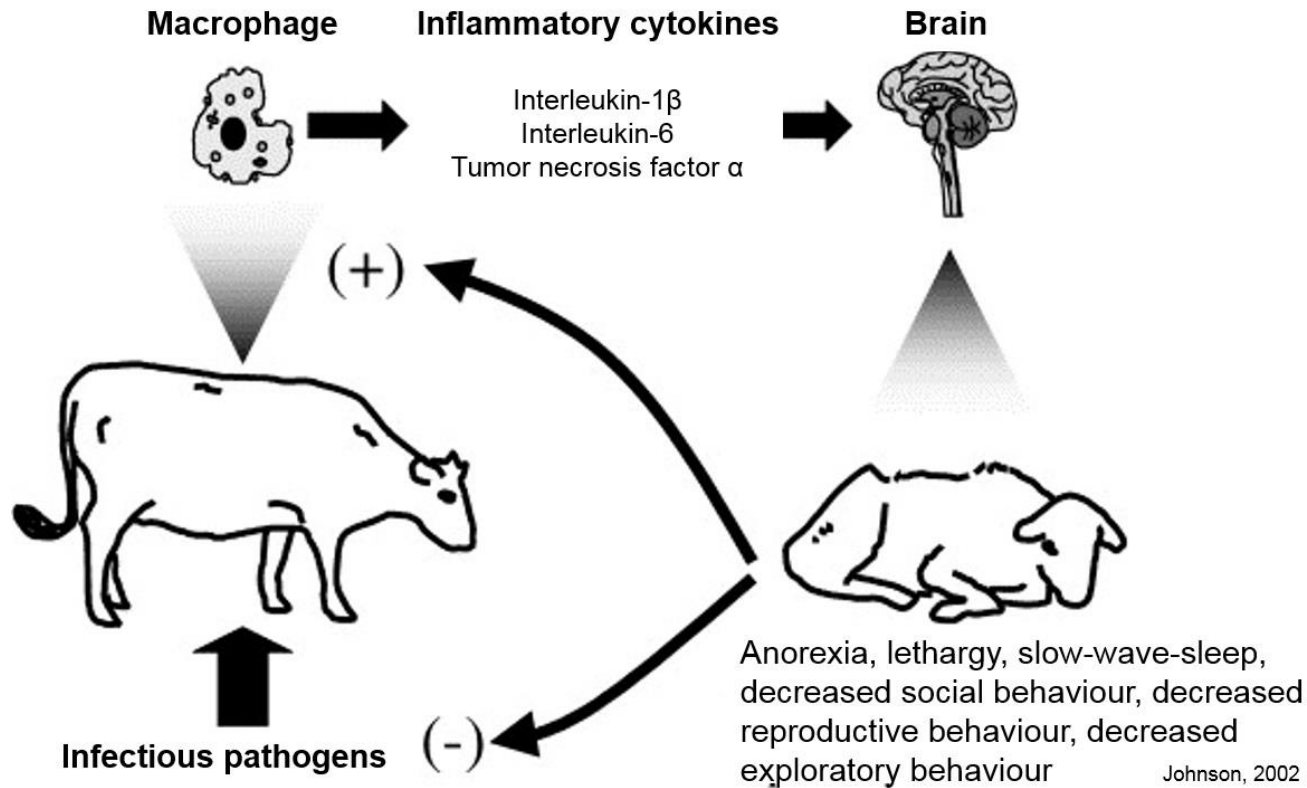
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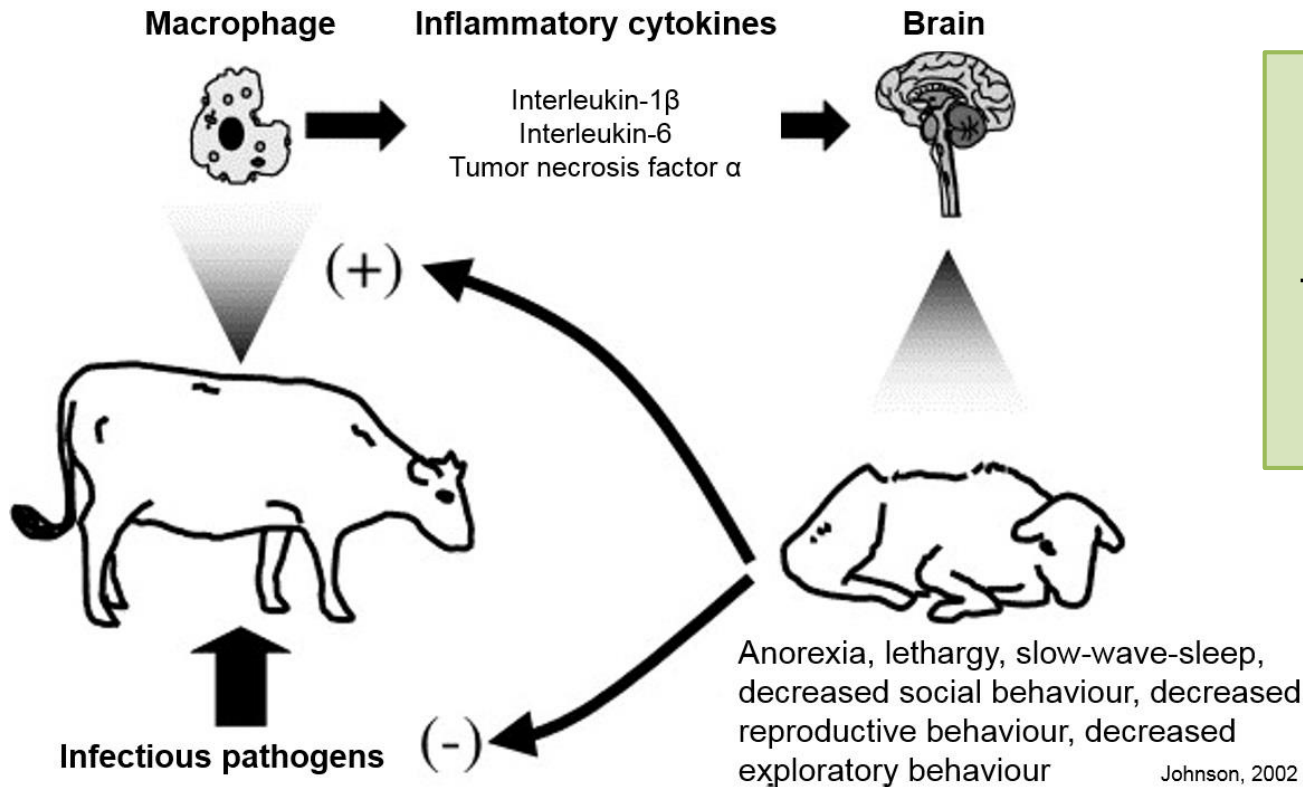


# Sickness behaviour





# Sickness behaviour



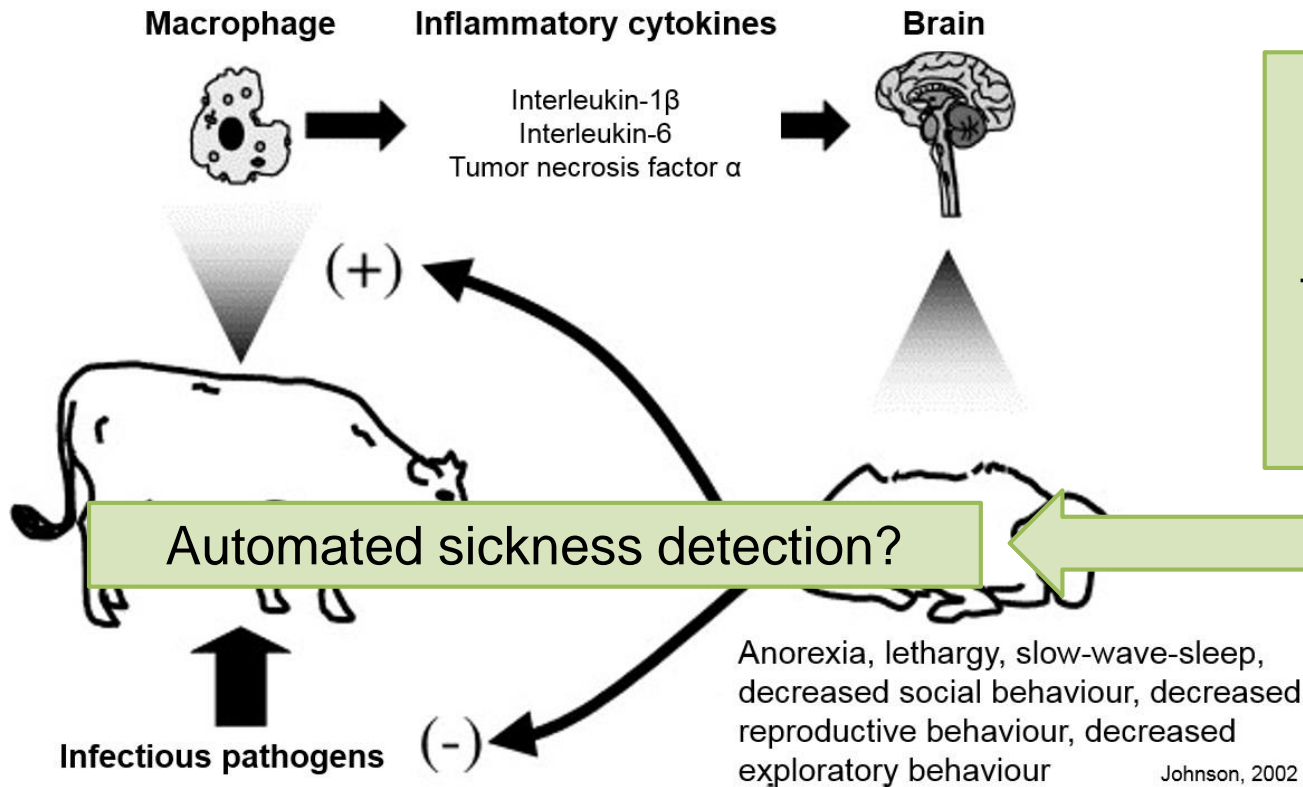
Resting, activity and feeding behaviour changes proceed in the same direction for the most common production diseases



Extent of changes is individual



# Sickness behaviour



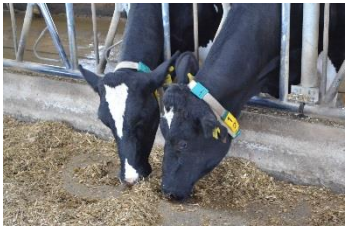
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Extent of changes is individual



# Automated sickness detection?

## Data collection

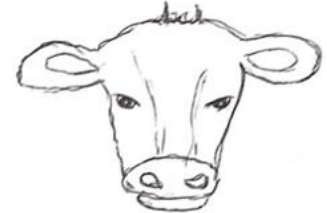


## Computation/Analysis



## Decision

Healthy



Sick





# Aim of the study

## Data collection

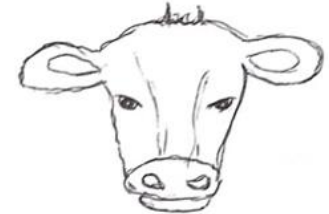


## Computation/Analysis



## Decision

Healthy



**Selecting variables from sensor data by using principal component analysis and partial least squares model to identify sick dairy cows using multivariate CUSUM charts**



# Data

## Raw data

480 milking cows

Diagnoses (veterinarian, claw trimmer)

→ Mastitis, claw issues/lameness, metabolic disorders

## Selection criteria

>50 days with observations (9/2018 to 4/2019)

No missing values (except for days of disease)

## Final data set

298 cows with 44,852 observation days

$n_{\text{healthy}} = 154$

$n_{\text{sick}} = 144$





# Sensor information



Neck sensor



Leg sensor



Milking parlour





# Sensor information



Neck sensor



Neck activity, feeding,  
rumination, inactivity  
→ 4 variables



Leg sensor



Milking parlour



Milkyield, milk flow,  
conductivity  
→ total, quarterwise  
→ 15 variables



# Sensor information



Neck sensor



Leg sensor

Leg activity, walking,  
lying, standing,  
lying → standing,  
→ 5 variables

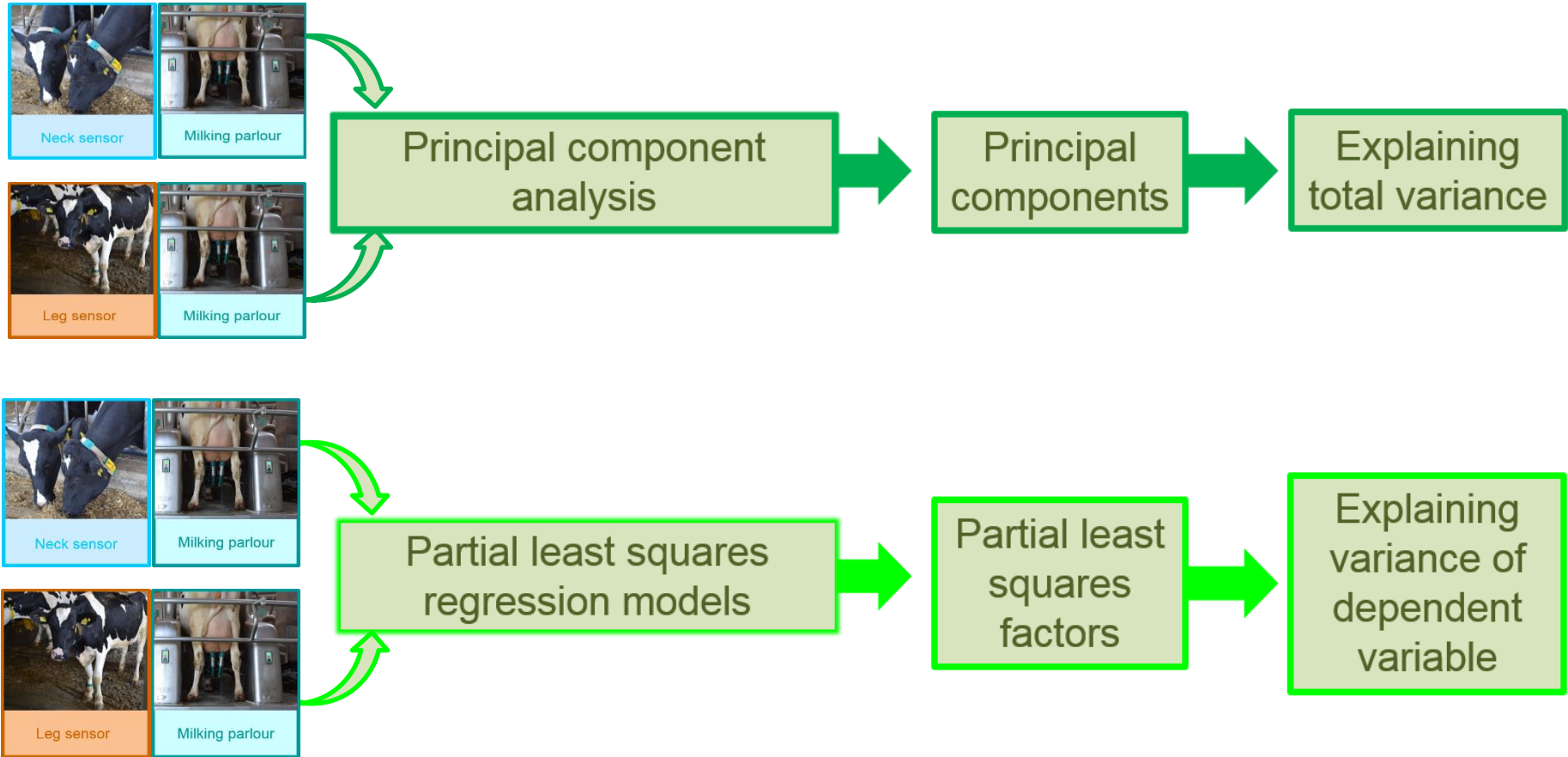


Milking parlour

Milkyield, milk flow,  
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→ 15 variables

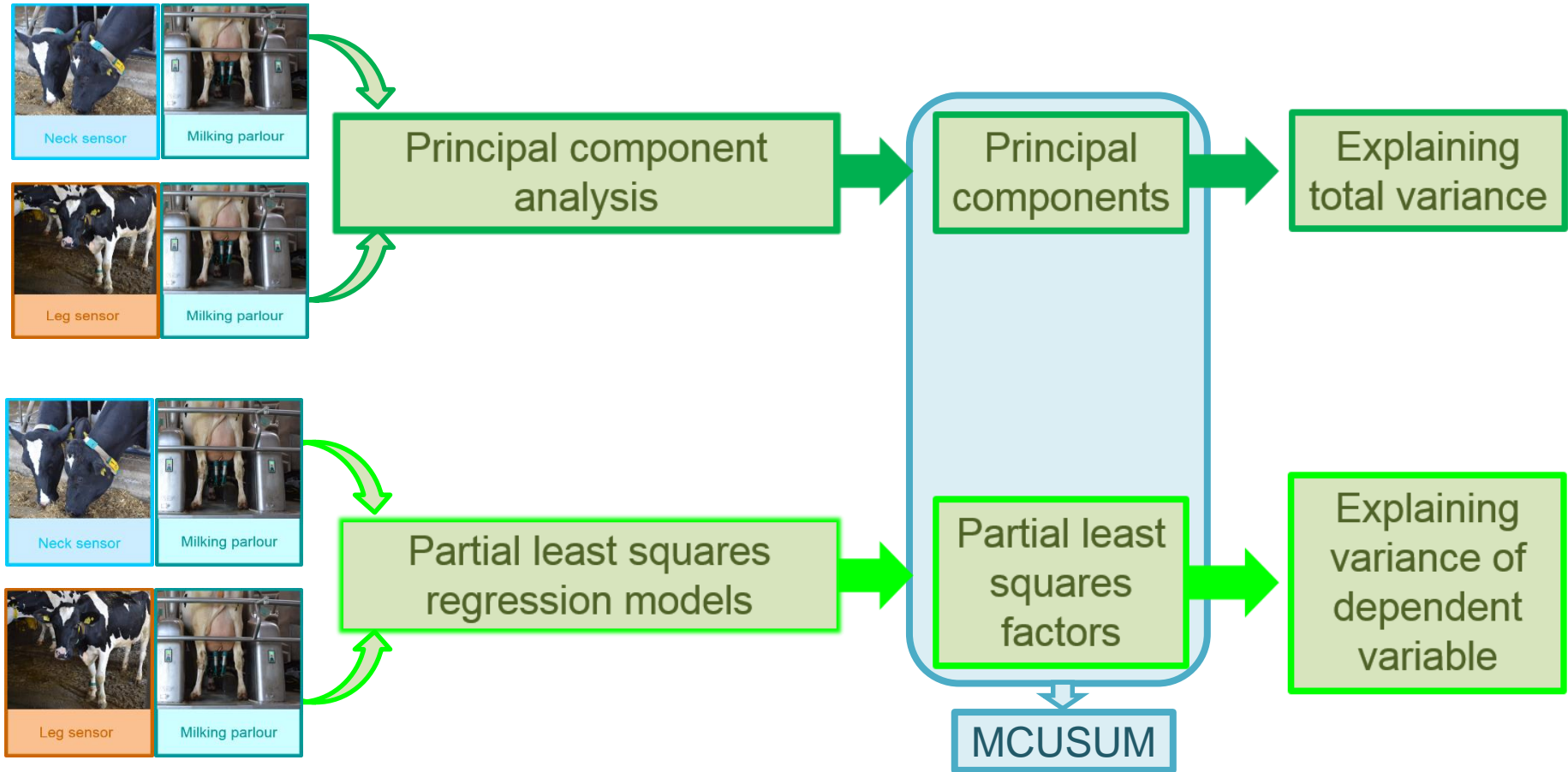


# Method





# Method





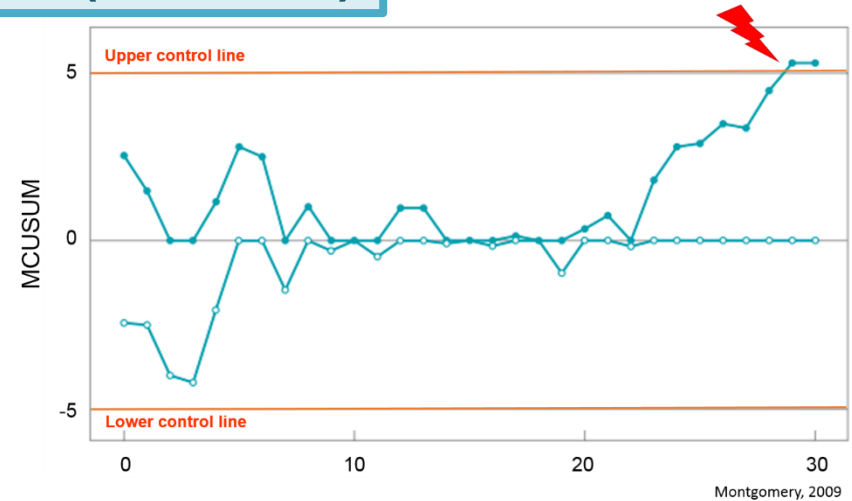
# Method

## Multivariate cumulative sum control chart (MCUSUM)

Calculated according to Miekley et al. 2013

Individual level

Threshold values tested: 1 to 15







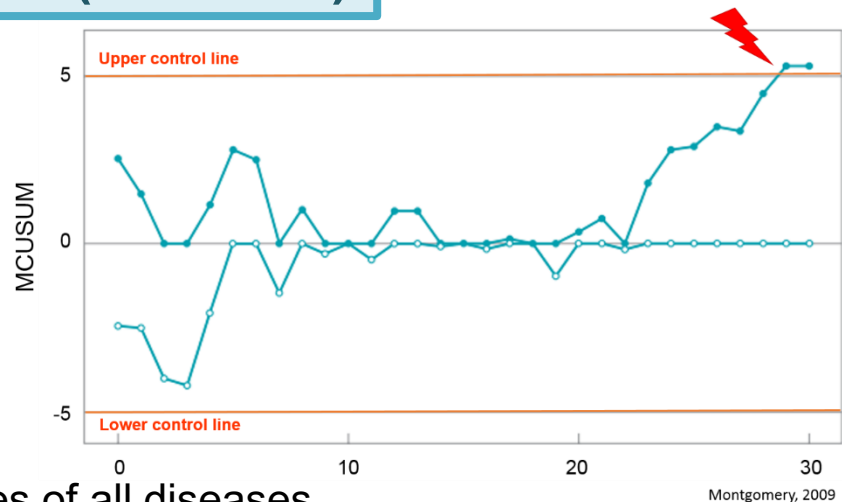
# Method

## Multivariate cumulative sum control chart (MCUSUM)

Calculated according to Miekley et al. 2013

Individual level

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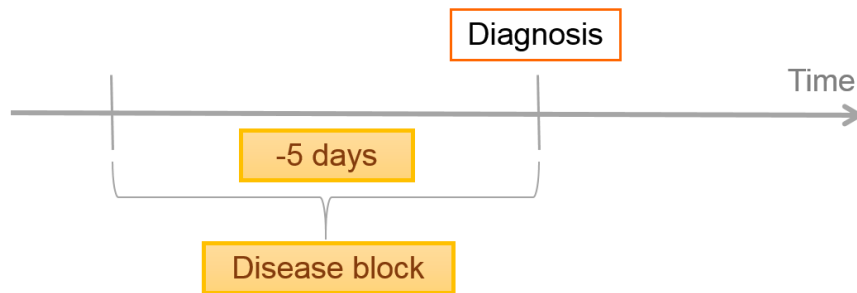


## Quality of classification

Sensitivity, specificity, false-positive-rate (FPR)

Block sensitivity

→ Percentage of correctly detected diseases of all diseases





# Variable selection



Neck sensor

Milking parlour

## Principal component analysis

5 principal components

72% of total variance explained

PC	Cumulative explained total variance (%)
1	29.7
2	45.3
3	60.6
4	67.2
5	72.3

Variables selected

Milkyield, conductivity,  
feeding, rumination

## Partial least squares

3 PLS-factors

2% of healthstatus' variance explained

PLS-factor	Cumulative explained variance (%)
1	1.2
2	1.9
3	2.0

Variables selected

Conductivity, feeding, rumination



# Variable selection



## Principal component analysis

5 principal components

74% of total variance explained

PC	Cumulative explained total variance (%)
1	28.2
2	43.5
3	58.5
4	68.3
5	74.1

Variables selected

Milkyield, conductivity, leg activity, walking, lying

## Partial least squares

4 PLS-factors

1.5% of healthstatus' variance explained

PLS-factor	Cumulative explained variance (%)
1	0.9
2	1.3
3	1.4
4	1.5

Variables selected

Milk flow, conductivity, standing

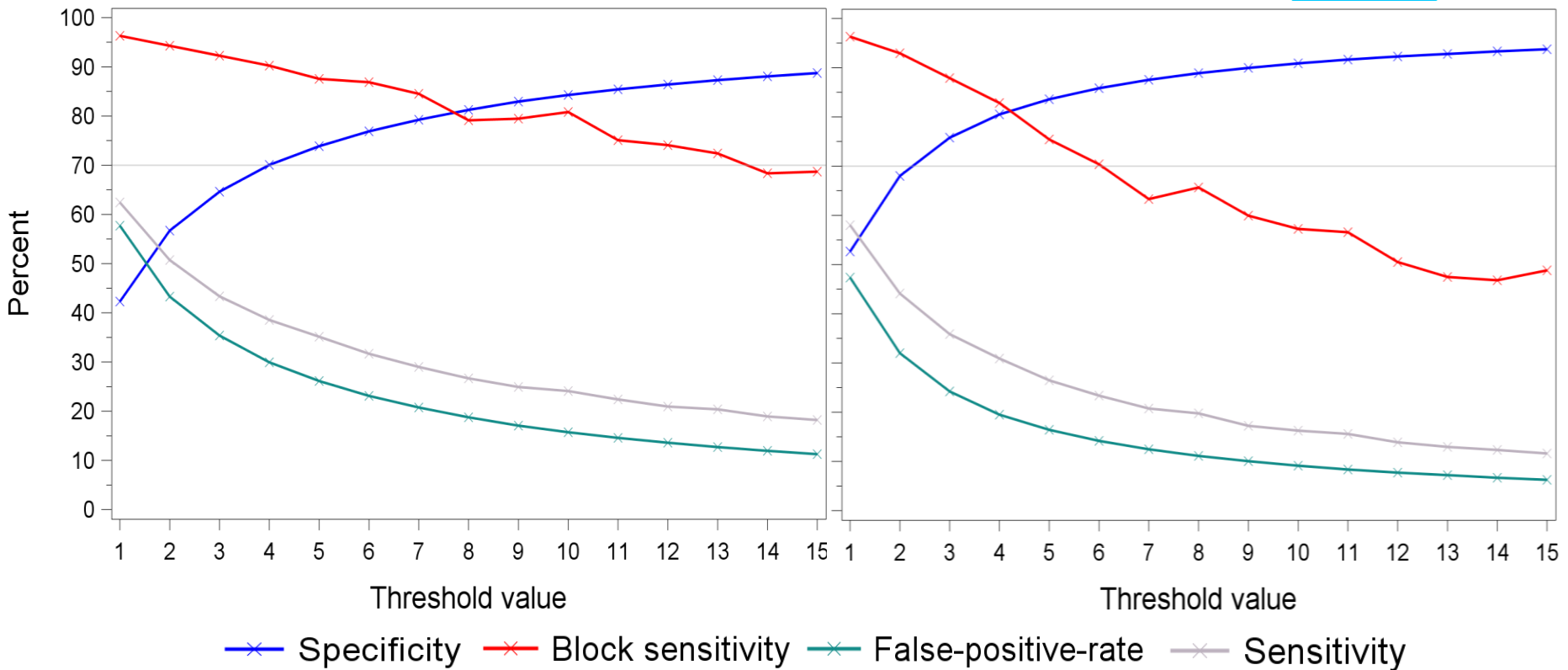


# Classification parameters



## Principal components

## PLS-factors



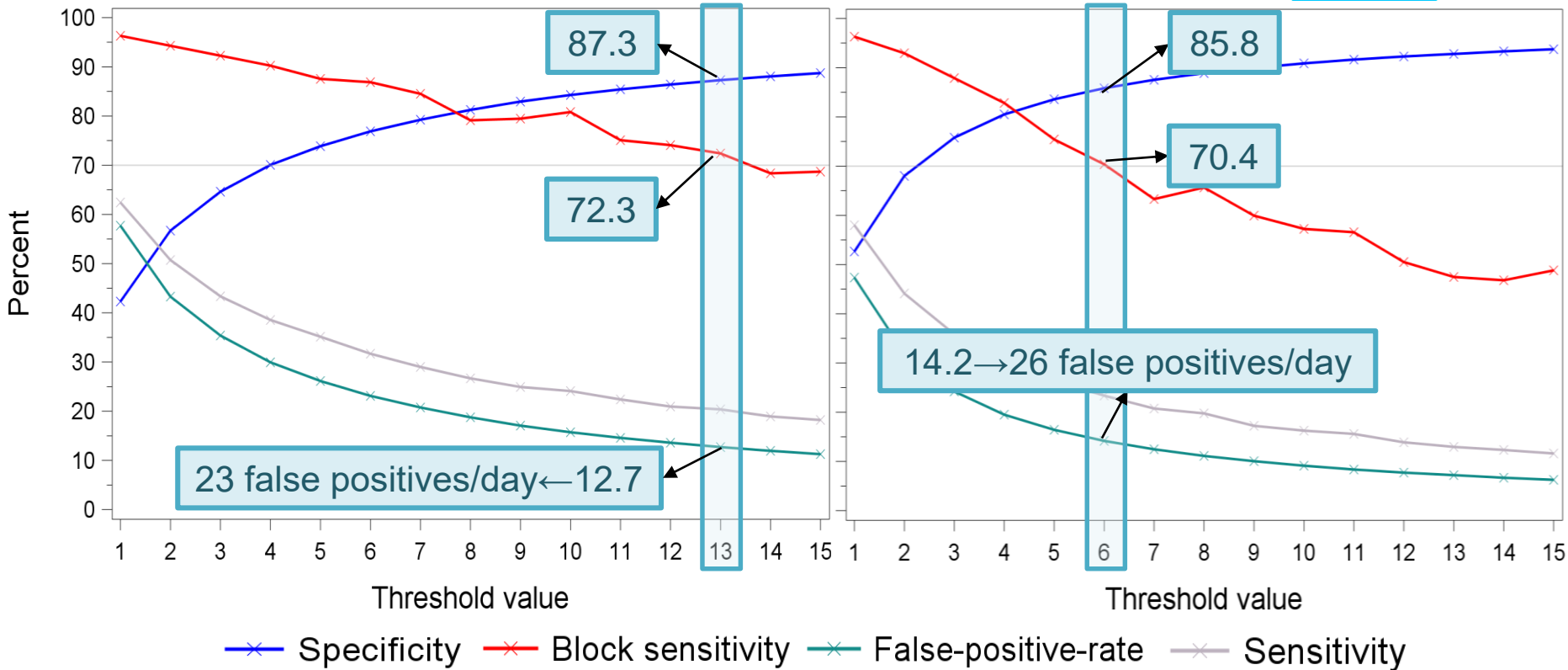


# Classification parameters



## Principal components

## PLS-factors



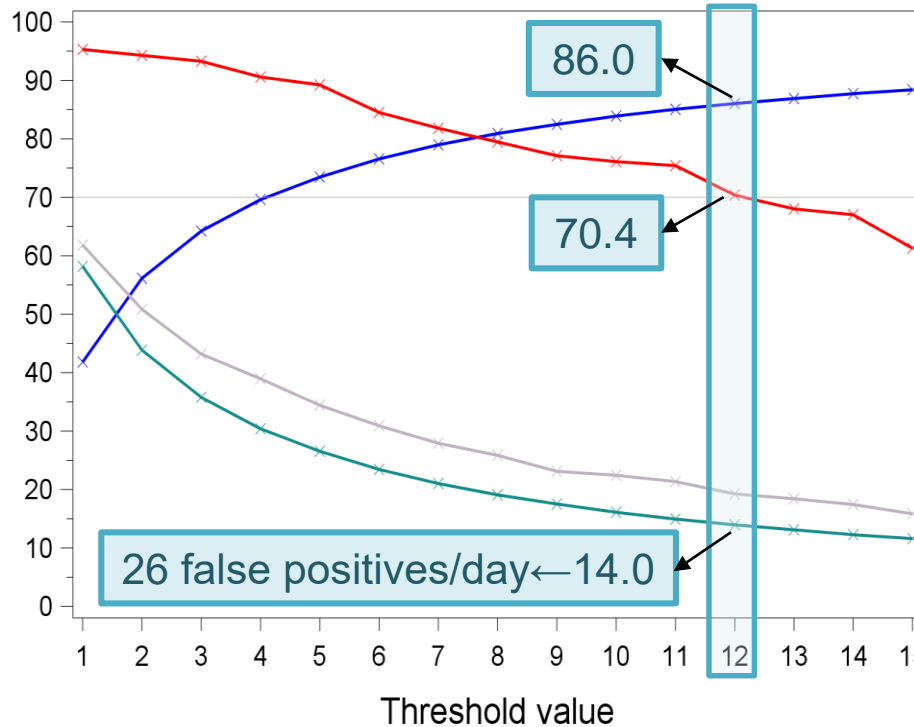




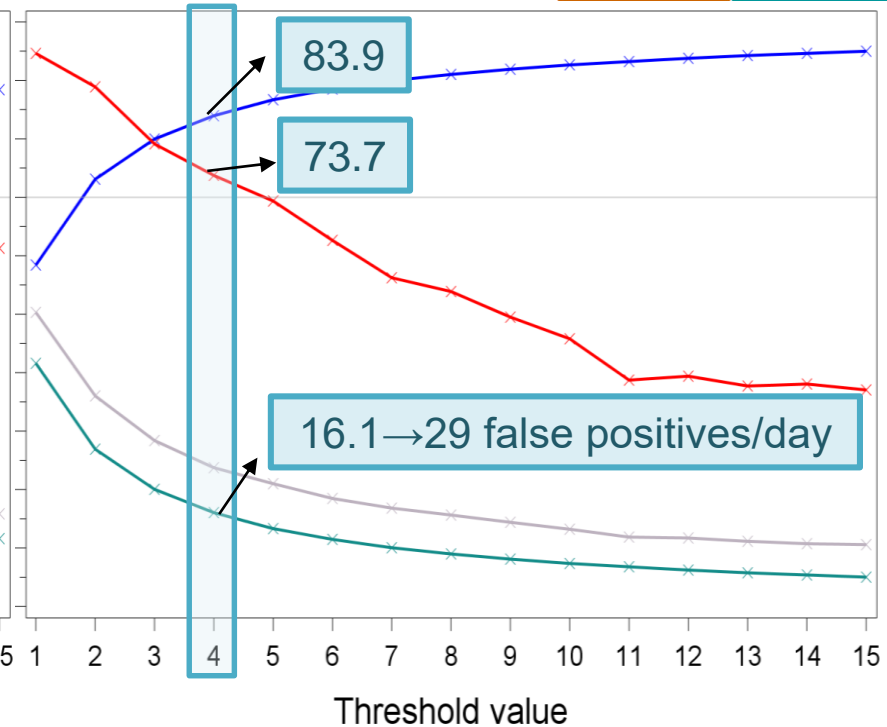
# Classification parameters



## Principal components



## PLS-factors

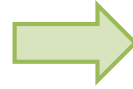


—×— Specificity —×— Block sensitivity —×— False-positive-rate —×— Sensitivity



# Discussion

**Variable selection successful**



Sickness behaviour

Behavioural variables stress principal components and PLS-factors

→ Both attached sensors



# Discussion

**Variable selection successful**



Sickness behaviour

Behavioural variables stress principal components and PLS-factors

→ Both attached sensors

**MCUSUM**

**- Potential for sickness detection at individual level**

**Acceptable qualities of classification**

Comparable to other studies (Miekley et al. 2013, Kramer et al. 2009)

Implementation of this algorithm

Practical conditions

→ Average daily herd size 185 animals

→ 24 to 44 false positive alarms a day

Workload ↑



# Conclusion

**Principal components** and **PLS-factors** → **MCUSUM charts**

Acceptable sickness detection

**Sensor type has only a slight effect**

Impact of behavioural information > milk parameters

**Implementation of algorithm**

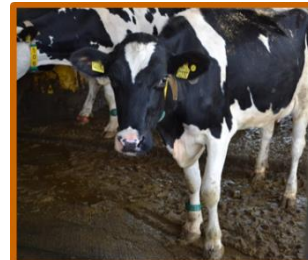
False-positive-Rates need still improvement

Aimed at  $\leq 10\%$

Feasibility  $\uparrow$



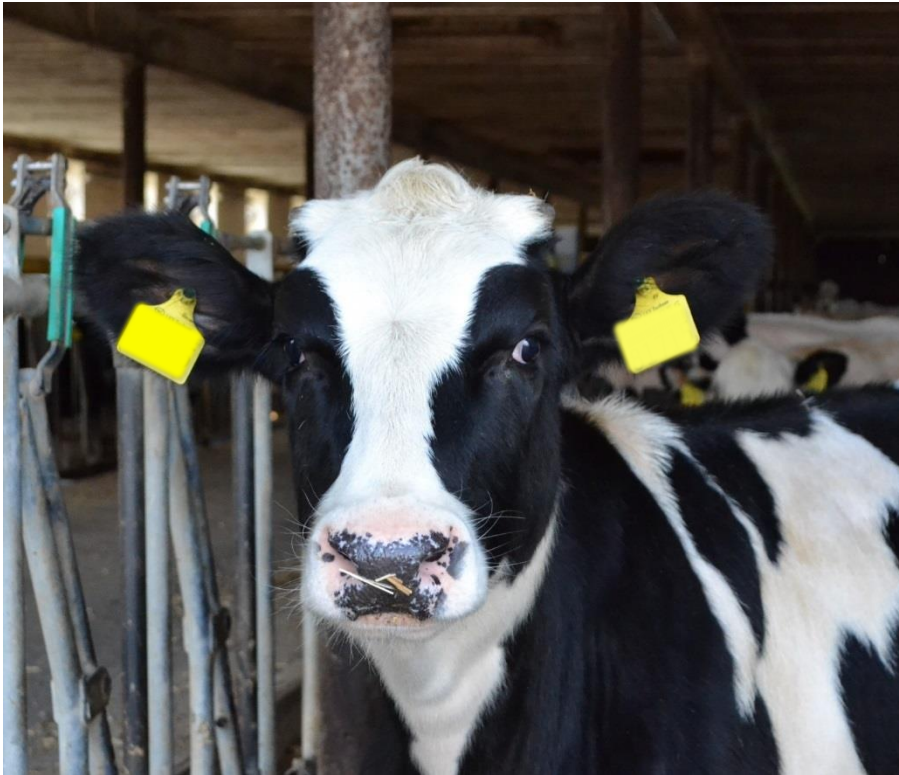
Neck sensor



Leg sensor



# Thank you for your attention



With support from



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of Food  
and Agriculture

**ptble**

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für Landwirtschaft und Ernährung

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German Bundestag



H. WILHELM SCHAUMANN STIFTUNG