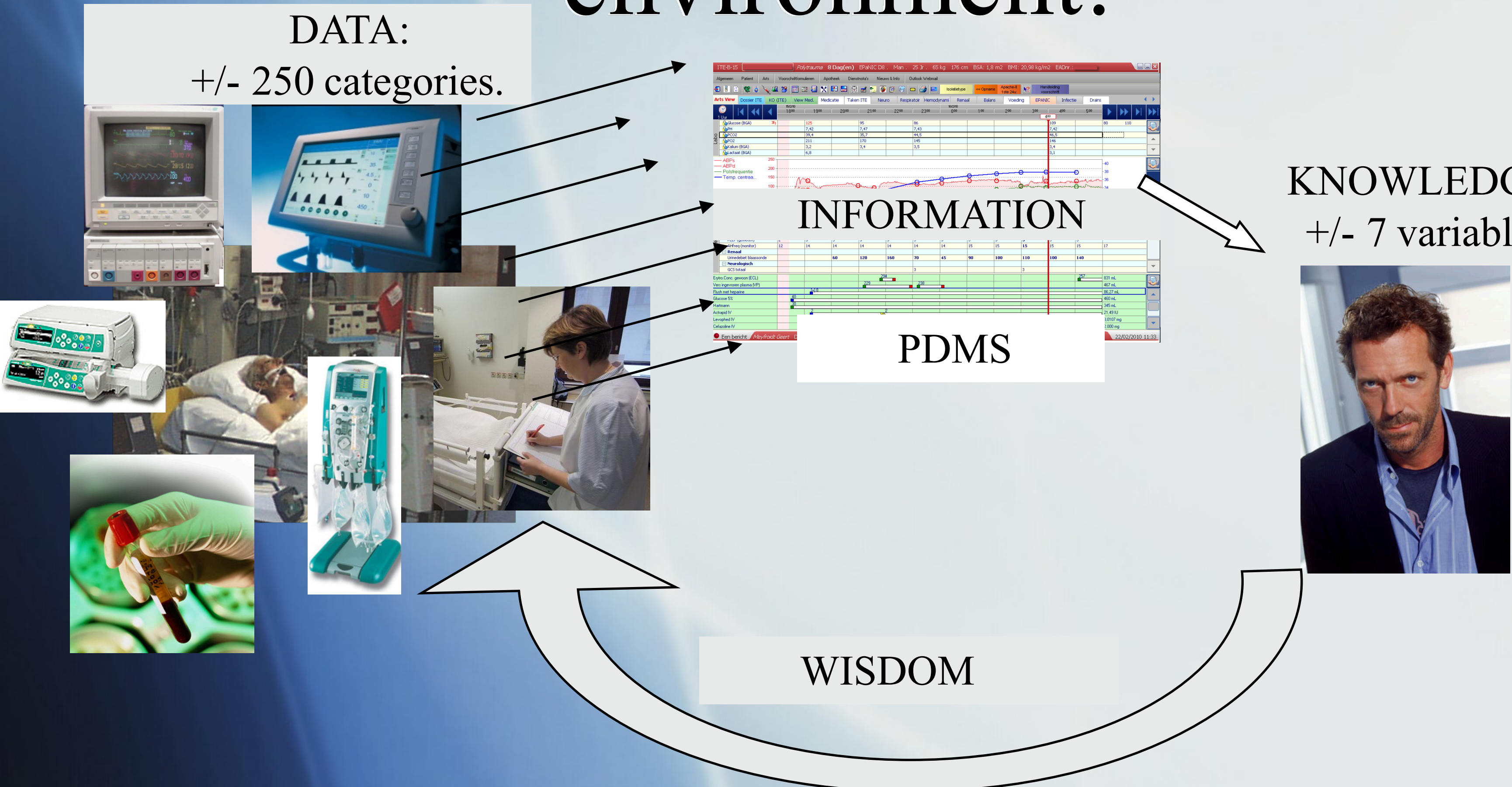
Computerized data management in the ICU.

PREDICTIVE MODELING, TIME SERIES ANALYSIS AND OPPORTUNITIES FOR SUPPORT OF CARE.

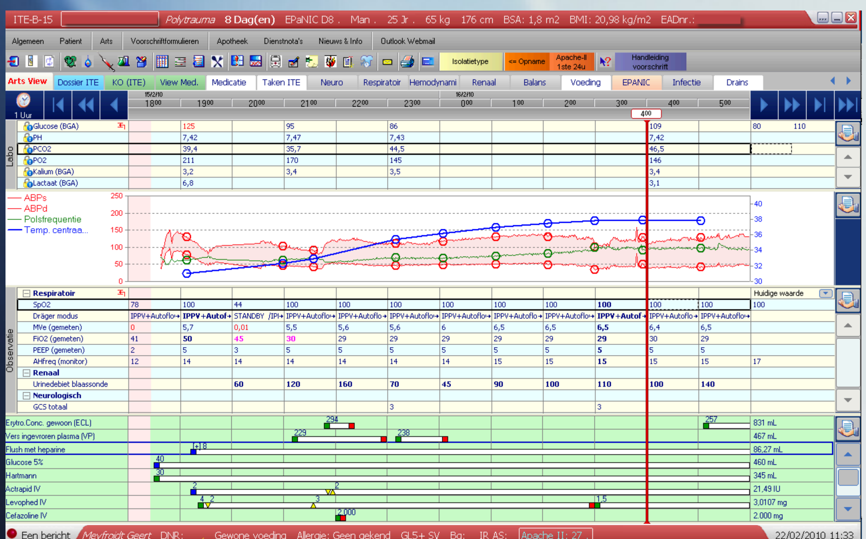
Geert Meyfroidt
SIZ award 2011

Intensive care unit: data rich environment!



Ackoff RL: From Data to Wisdom. J Appl Syst Analis, 1989
Miller G: The magical number seven plus or minus two. Psychol review, 1956

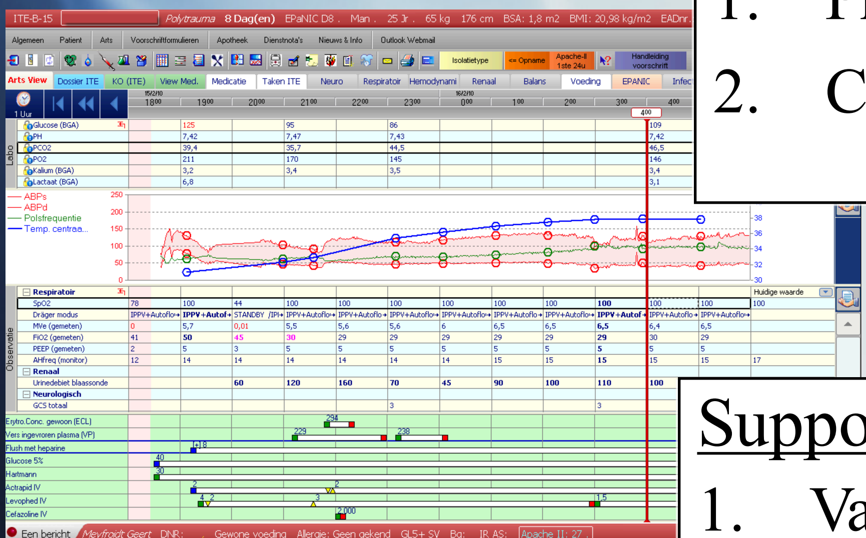
Patient data management system



- “Reporting”
  - Monitors
  - Lab
  - Devices (MV,RRT, …)
  - Observations
  - ….
- Prescription: CPOE
- Decision support

Van Bemmel JH, Musen MA, Handbook of Medical Informatics, 2002

Computerized data management



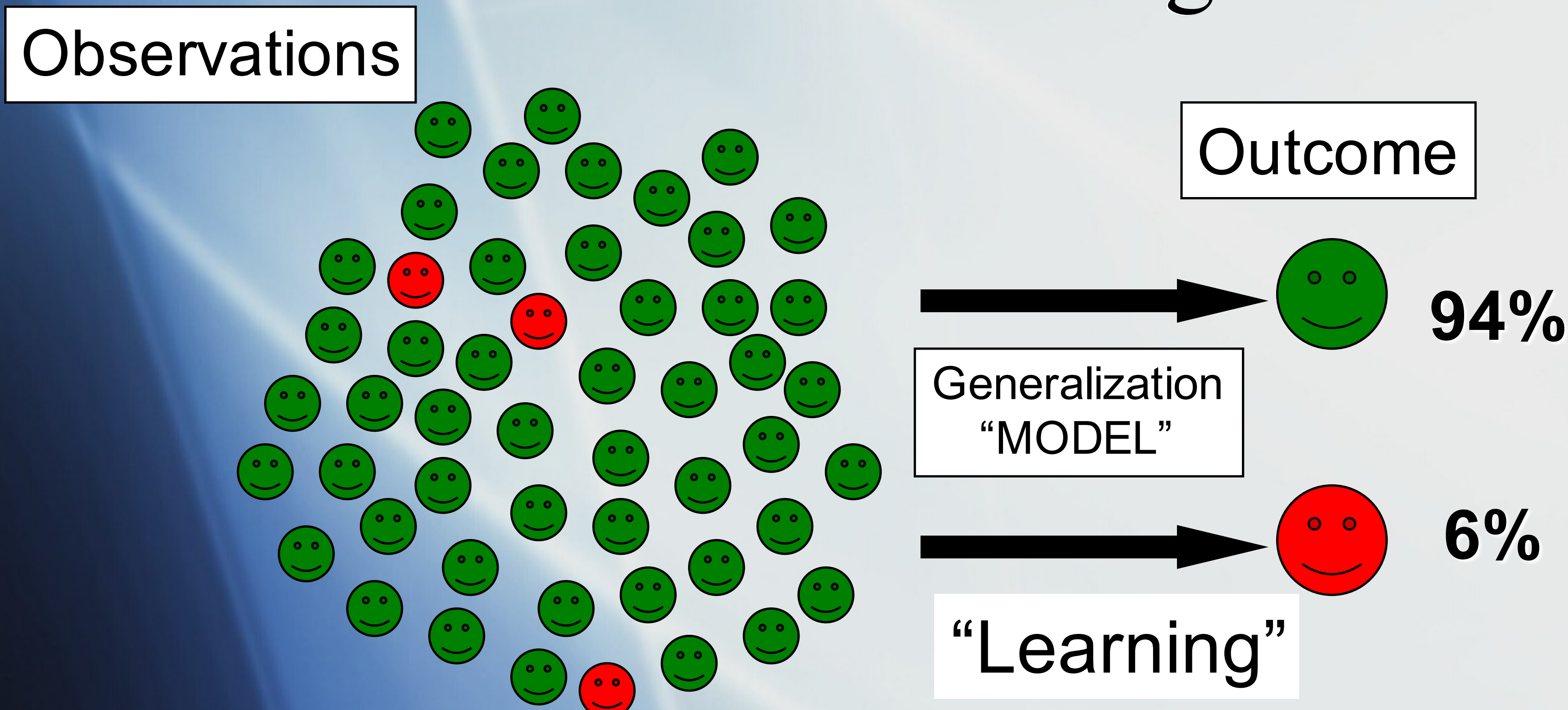
Predictive modeling

1. Proof of concept
2. Cardiac surgery: ICU discharge

Support of care

1. Variability and glycemic control
2. Impact of an alert on tight glycemic control

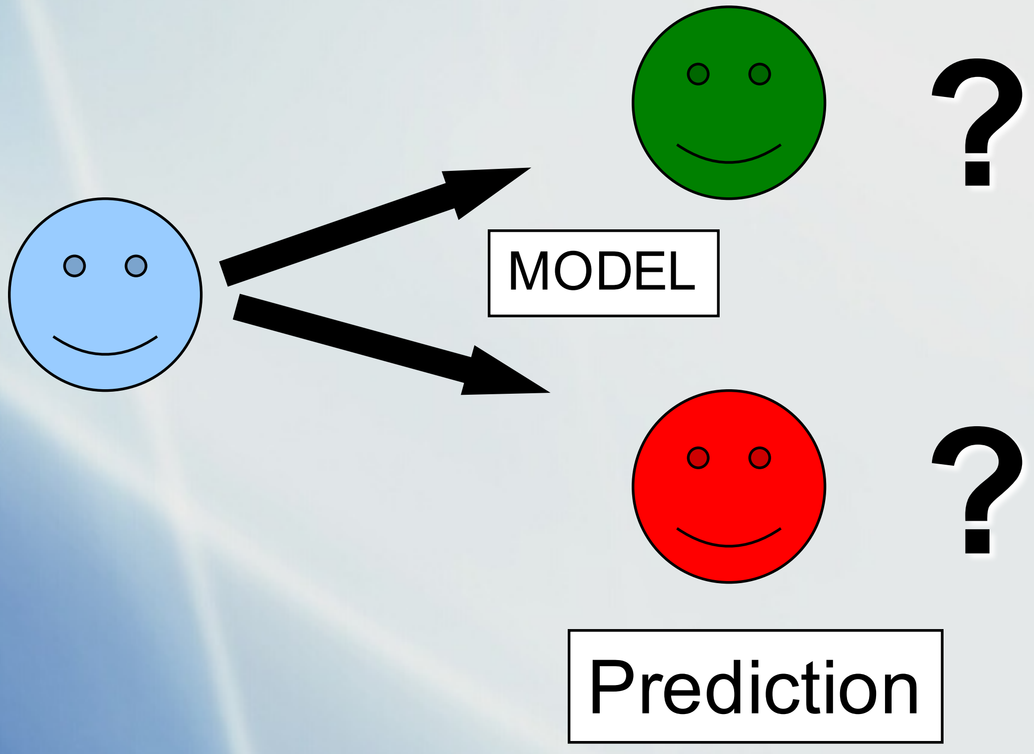
Predictive modeling



Admission: demographics, medical history, admission diagnosis, ...
Observations, lab, medication. ...
Devices: monitor, ventilator, renal replacement therapy, ...

PDMS

Predictive modeling



Data mining and machine learning

- Automatic learning
- Incorporation of background knowledge
- Examples
  - Weather forecasts
  - Fraudulent bank transactions
  - IBM Watson project
  - Genome studies
  - ...

Meyfroidt G et al: *Best Pract & Res Clin Anaesth 23 (2009) pp. 127-143*

Machine learning and ICU predictions: proof of concept

The New England Journal of Medicine

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INTENSIVE INSULIN THERAPY IN CRITICALLY ILL PATIENTS

Greet Van den Berghe, M.D., Ph.D., Pieter Wouters, M.Sc., Frank Weekers, M.D., Charles Verwaest, M.D., Frans Bruyninckx, M.D., Miet Schetz, M.D., Ph.D., Dirk Vlasselaers, M.D., Patrick Ferdinande, M.D., Ph.D., Peter Lauwers, M.D., and Roger Bouillon, M.D., Ph.D.

1548 patients

-Admission data

-“Once daily” data

Predictive tasks:

1. ICU mortality
2. ICU LOS > 3 days
3. Development of renal failure
4. Recovery from renal failure

Meyfroidt G et al: *Best Pract & Res Clin Anaesth 23 (2009) pp. 127-143*

Ramon J, Fierens D, Güiza F, Meyfroidt G, et al. *Adv Eng Inf (2007)21 (3) pp 243-256*

Machine learning and ICU predictions: proof of concept

aROC > 0.80

Apache II aROC = 0.75

Task	Day	DT	RF	NB	TAN
Mortality	admission	0.79	0.82	0.88	0.86
ICU LOS > 3 d	admission	0.75	0.79	0.83	0.83
Renal failure:development	n-2	0.82	0.86	0.86	0.88
	n-3	0.84	0.87	0.87	0.88
	n-4	0.83	0.88	0.87	0.87
Renal failure:recovery	n-1	0.82	0.87	0.80	0.85
	n-2	0.80	0.84	0.78	0.84
	n-3	0.80	0.85	0.80	0.87
	n-4	0.81	0.86	0.81	0.87

(10-fold cross validation)

Meyfroidt G et al: *Best Pract & Res Clin Anaesth 23 (2009) pp. 127-143*

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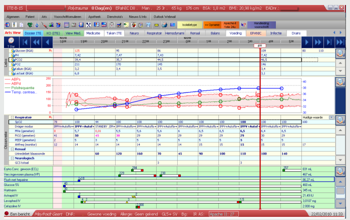
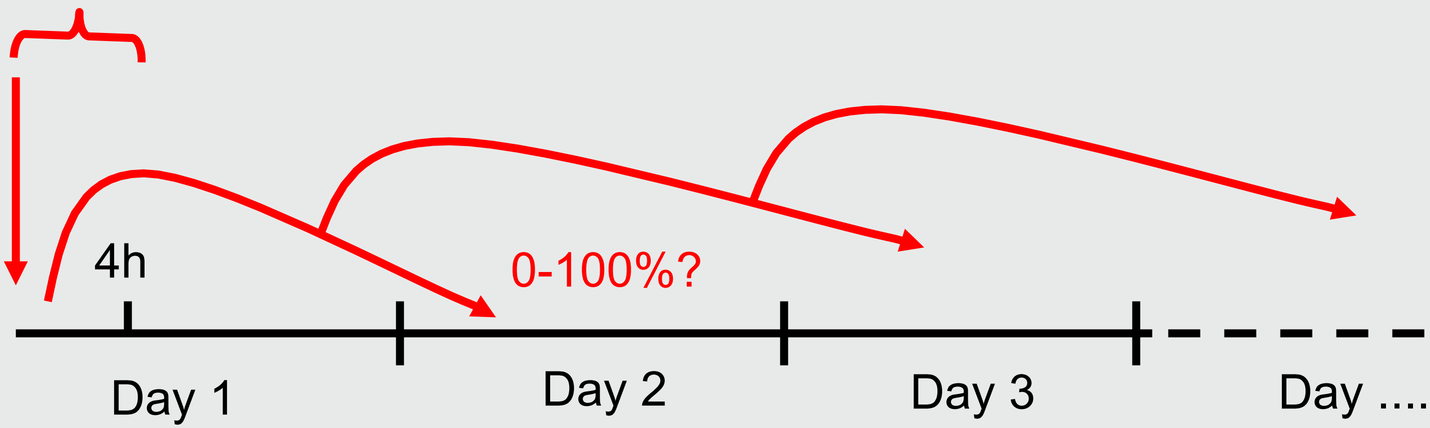
Predicting ICU length of stay after cardiac surgery



2. Prediction of the day of discharge



Predicting ICU length of stay after cardiac surgery

Probability of discharge on the day after surgery?

	aROC		Brier Score	
Gaussian Processes (n=499)	>0.75		<0.25	
EuroSCORE (n=499)	0.726	=	0.324	S
Nurse (6 u) (n=396)	0.695	S	0.245	S
Physician (6 u) (n=159)	0.758	=	0.216	S

BS= Mean $[p_n - o_n]^2$

Predicting ICU length of stay after cardiac surgery

Prediction of the day of discharge?

	LPF	LPF=0	RMSRE
Gaussian Processes (n=499)	0 (0 - 0.4)	40%	0.408
EuroSCORE (n=499)	-0.3 (-0.5 - 0) S	19% S	0.643
Nurse (6 u) (n=396)	0 (0 - 0.3) =	38% S	0.522
Physician (6 u) (n=159)	0.2 (0-0.4)	31%	0.612

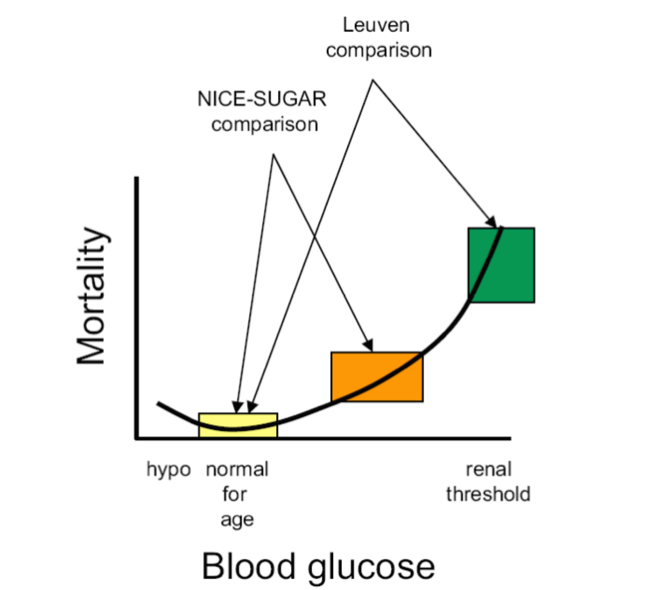
$$LPF = \frac{D_{actual} - D_{predicted}}{D_{actual}}$$

Predicting ICU length of stay after cardiac surgery: conclusion

- Computer predicts better than Euroscore, and more reliably than clinician
- Models are not universally applicable but can be ‘relearned’ in a different clinical context.

Tight glycemic control

Elevated blood sugar levels are associated with increased mortality



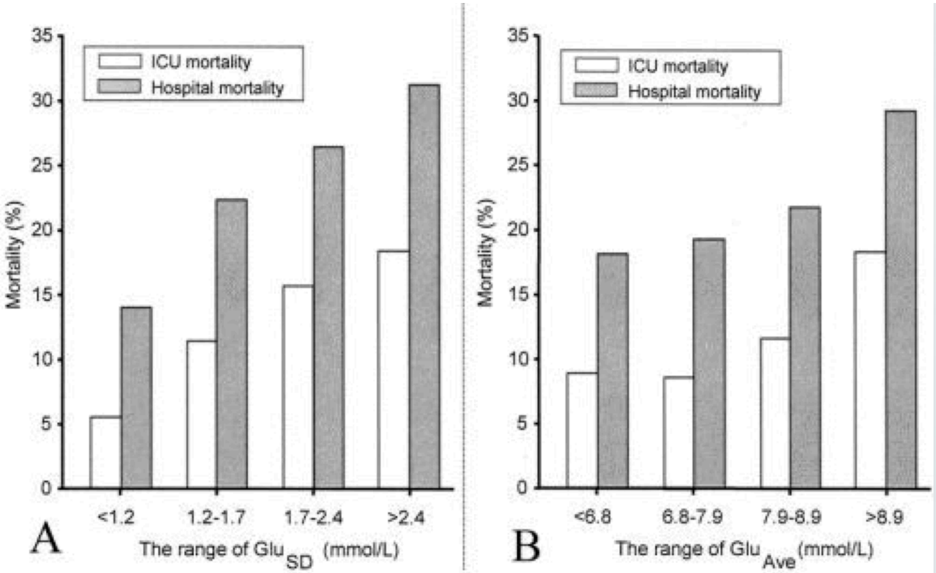
Van den Berghe et al. *J Clin Endocrinol Metab* .2009

Van den Berghe et al, NEJM 2001
Van den Berghe et al, NEJM 2006
Vlasselaers et al, Lancet 2009
NICE-SUGAR study, NEJM 2009

Normalization of glycemia with intensive insulin therapy reduces ICU mortality in certain clinical settings.

Tight glycemic control

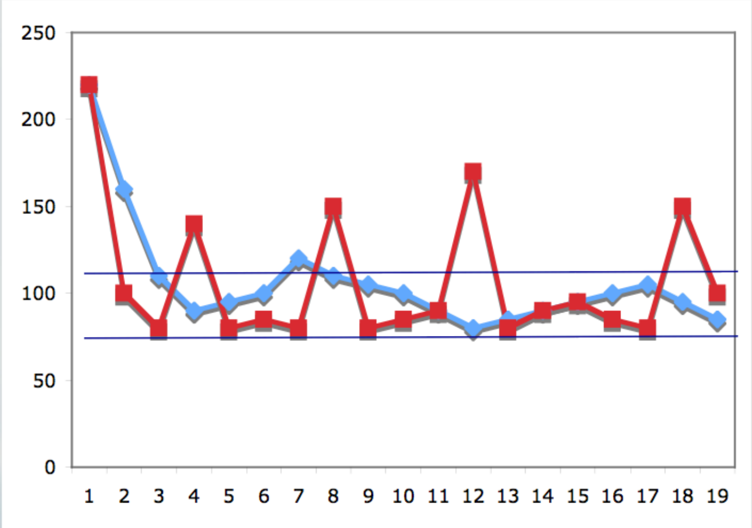
Increased blood glucose amplitude variability (BGAV) is associated with mortality



Egi et al, Anesthesiology 2006

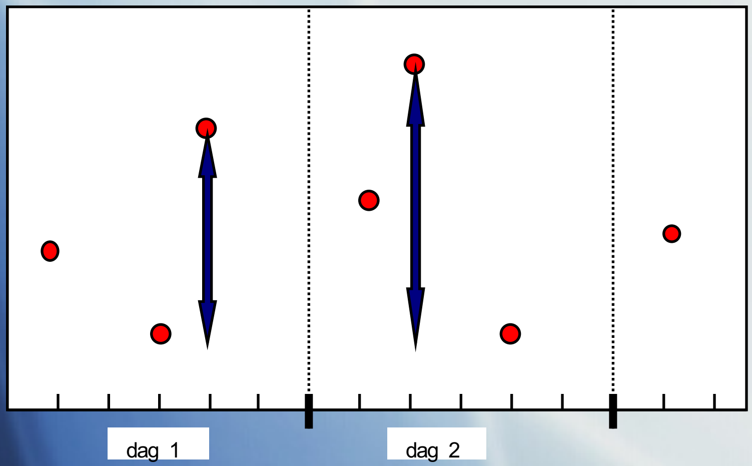
Egi et al, Anesthesiology 2006
Wintergerst et al, Pediatrics 2006
Krinsley et al, Crit Care Med 2008
Dosset et al, Am J Surg 2008
Ali et al, Crit Care Med 2008

Hyperglycemia-induced oxidative stress?



Mean blood glucose 107 mg/dl

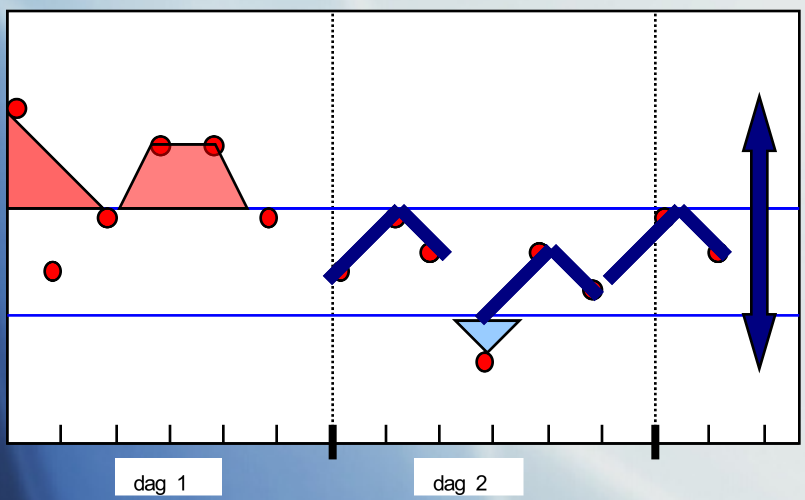
Tight glycemic control: level and/or variability?



MICU+SICU: n=2748
-level: -mean morning
-hypo
-BGAV: -mean daily Δ BG

Van den Berghe et al, NEJM 2001, 2006
Meyfroidt G et al. Crit Care Medicine 2010

Tight glycemic control: level and/or variability?



MICU: n=1200

-level:	-HGI
	-HoGI
-BGAV:	-SD BG
-pattern:	-ApEn

Van den Berghe et al, NEJM 2006
Meyfroidt G et al. Crit Care Medicine 2010

Tight glycemic control: level and/or variability?

	Conventioneel	Intensief	P-value	
Mean morning BG	151 (27)	104 (23)	<0.0001	SICU MICU
Hypoglycemie	2%	11%	<0.0001	
Mean daily Δ BG	59 (38-90)	72 (52-97)	<0.0001	
HGI	58 (36-74)	14 (9-22)	<0.0001	MICU
HoGI	0.09 (0.00-0.36)	0.90 (0.34-1,5)	<0.0001	
SD BG	38 (29-50)	36 (29-49)	0.161	
ApEn	1.7 (0.3)	1.6 (0.3)	0.126	

Multivariabele log. regressie

MORTALITEIT

Meyfroidt G et al. Crit Care Medicine 2010

Tight glycemic control: impact of a computer alert

- IIT in Leuven
  - By nurses
  - Paper guideline (intranet)
    - Incomplete
    - Partially procedural/declarative
    - Informal

'Intuitive decision making'
No strict 'if-then' protocol

Meyfroidt G et al, Intensive Care Medicine 2011

Tight glycemic control: impact of a computer alert

BG > 180 mg/dl
Patient can eat

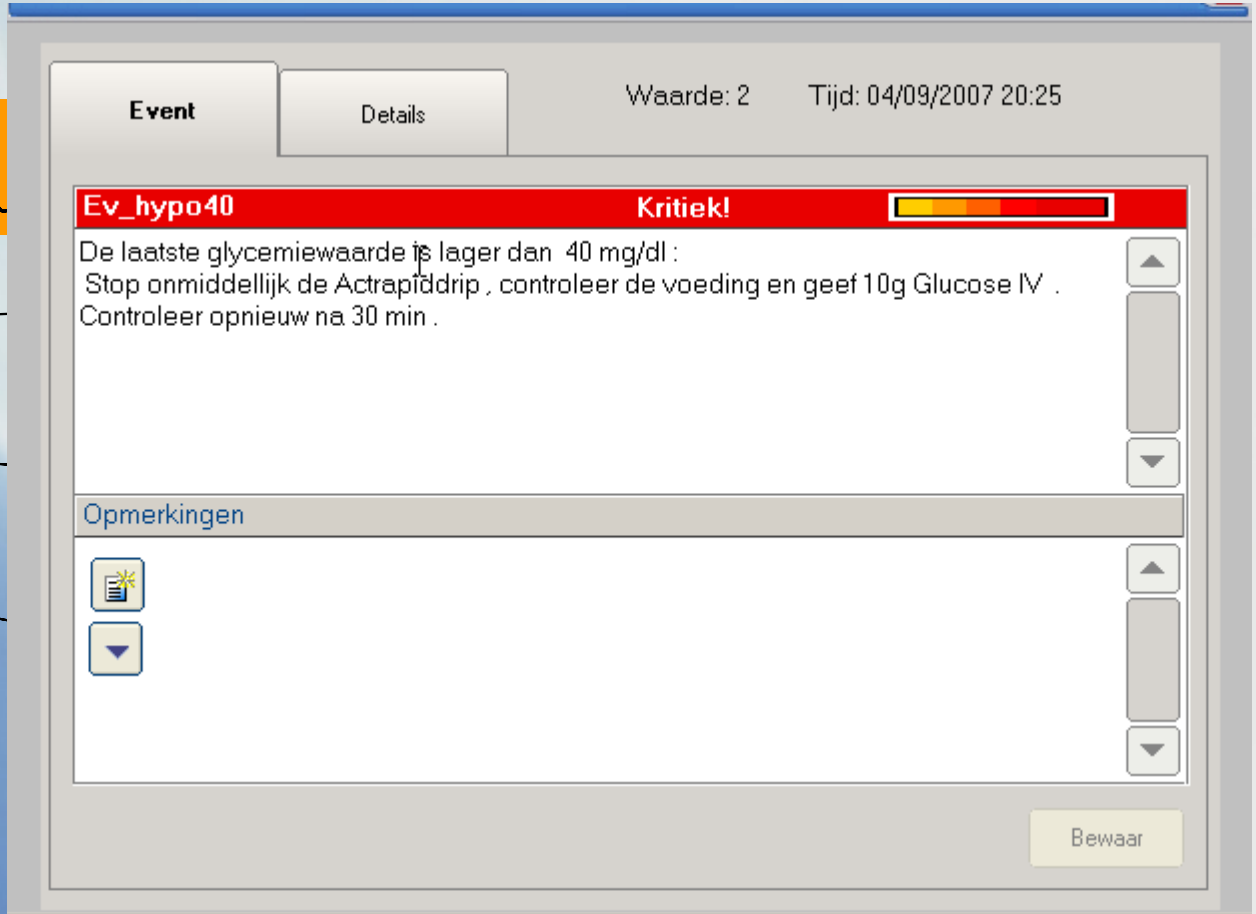
Adapt insulin. New
BG control in 1u

BG >110 mg/dl
IV- and/or enteral nu

BG 60-80 mg/dl

BG 40-60 mg/dl

BG < 40 mg/dl



Tight glycemic control: impact of a computer alert

	Pre-alert (729) 2/2007-7/2007	Alert (644) 8/2007-2/2008	P-value
Blood glucose level			
Mean BG	112	110	0.002
HGI	10	9	0.004
# BG values >110	33%	30%	0.008
# BG values < 80	6%	6%	0.845
# pat. with hypo < 40	6.5%	4%	0.043
BGAV			
SD BG	28	28	0.566
BG monitoring			
# measurements/pt/d	7.7	7.7	0.891

Meyfroidt G et al, Intensive Care Medicine 2011

Computerized data management in the ICU

Conclusions

Conclusions

- Advanced data analysis with automatically learning methods allows for the construction of customized clinically relevant predictive models.
- BGAV is an important feature that should be assessed when comparing blood glucose control strategies.
- Even a simple computer alert is able to have a significant impact on the quality of tight glycemic control.

Present and future research

- ICU capacity planner for cardiac surgery
- Early warning alert for elevated ICP events in brain injured patients
- Prediction of bad outcome after brain injury
- Early warning alert for AKI
- Prediction of pharmacokinetics
- Time series summary statistics: morphological clustering
- Text mining: clinical notes

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- SIZ