



Scientific foundations of the DeFuse project – demining by fusion of techniques



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Scientific objectives

- Obtain **general scientific knowledge** about the advantages of deploying a combined approach
- Eliminate confounding factors through **careful experimental design** and specific scientific hypotheses
- Test the general **scientific hypothesis is that there is little dependence** between missed detections in successive runs of the same or different methods
- To accept the hypothesis under **varying detection/clearance** probability levels
- To lay the foundation for new practices for mine action, but it is not within scope of the pilot project



Are today's methods not good enough?

- some operators believe that we already have sufficient clearance efficiency
- no single method achieve more than 90% efficiency
- clearance efficiency is **perceived** to be higher since many mine suspected areas actually have very few mines or a very uneven mine density
- today's post clearance control requires an unrealistically high number of sample to get statistically reliable results



Are combined methods not already the common practice?

- today's combined schemes are ad hoc practices with limited scientific support and qualification
- we believe that the full advantage of combined methods and procedures has not yet been exploited



Does the project require a lot of new R&D?

- no detection system R&D is required
- start from today's best practice and increase knowledge about the optimal use of the existing "toolbox"



Is it realistic to design optimal strategies under highly variable operational conditions?

- it is already very hard to adapt existing methods to work with constantly high and proven efficiency under variable operational conditions
- proposed combined framework sets lower demand on clearance efficiency of the individual method and hence less sensitivity to environmental changes
- the uncertainty about clearance efficiency will be much less important when combining methods
- overall system will have an improved robustness to changing operational conditions



Outline

- DeFuse objectives
- **Statistical modeling**
- The design and evaluation of mine equipment
- Improving performance by statistical learning and information fusion



Scientific approach

Scientists are born sceptical: they don't believe facts unless they see them often enough

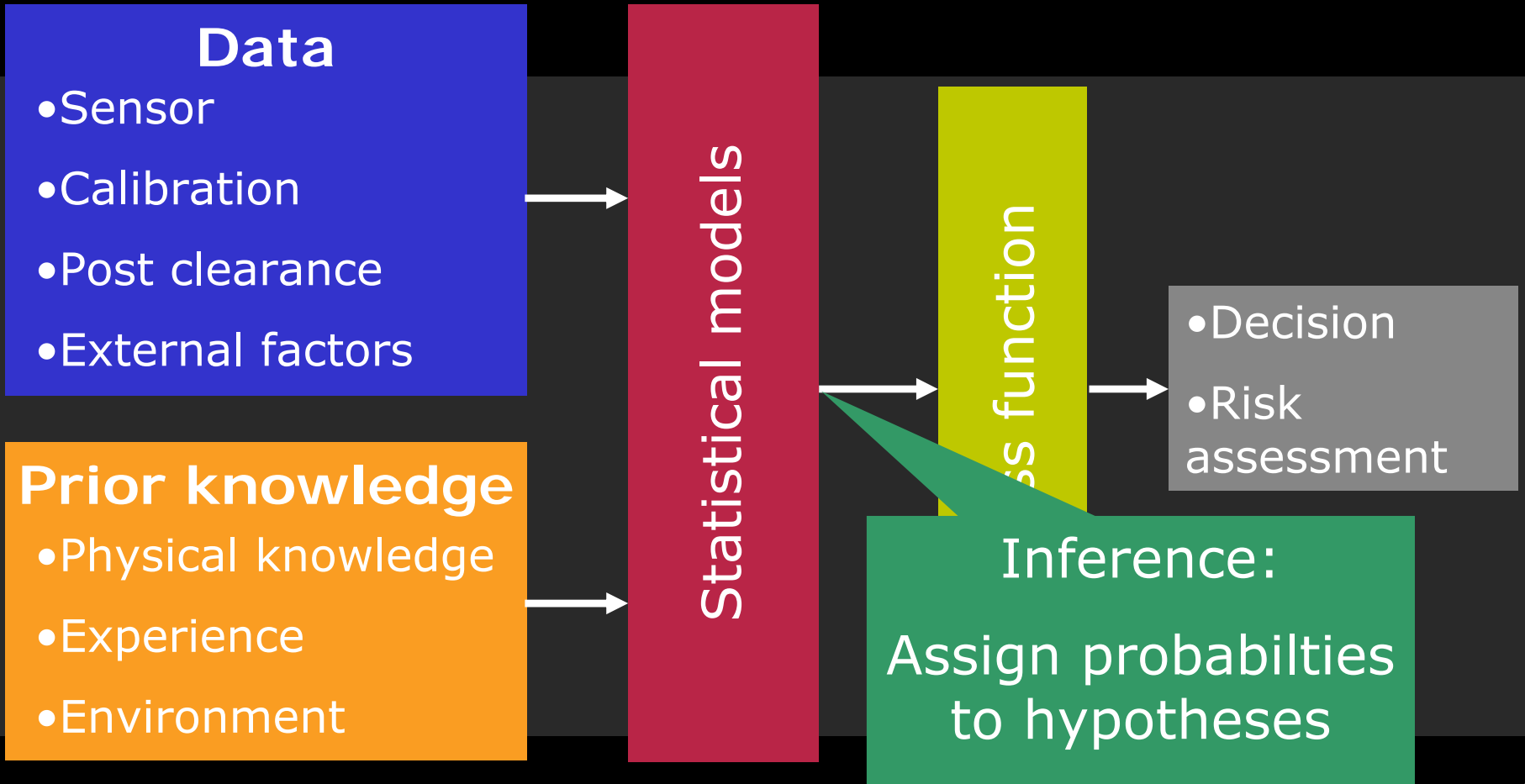


Why do we need statistical models?

- Mine action is influenced by many uncertain factors – statistical modeling is the **principled framework** to handle uncertainty
- The use of statistical modeling enables **consistent and robust** decisions with associated risk estimates from acquired empirical data and prior knowledge
- Pitfalls and misuse of statistical methods sometimes wrongly leads to the conclusion that they are of little practical use



The elements of statistical decision theory





What are the requirements for mine action risk

- Tolerable risk for individuals comparable to other natural risks

- **Goal**

- 99.6% is not an unrealistic requirement

- • But... today's methods achieve at most 90% and are hard to evaluate!!!

commercial etc.)

GICHD and FFI are currently working on such methods [Håvard Bach, Ove Dullum NDRF SC2006]

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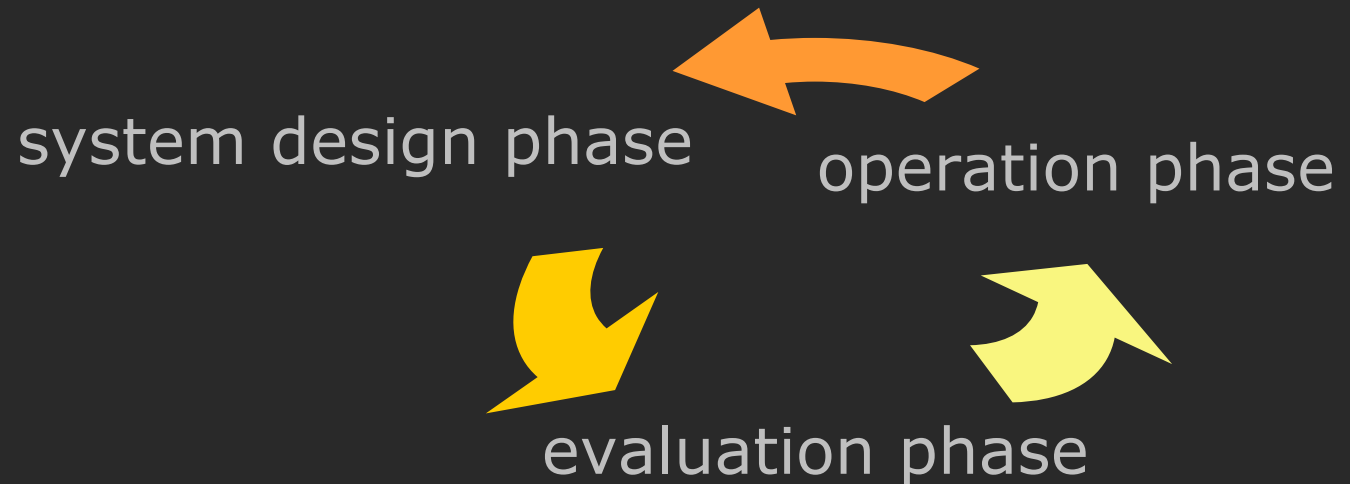
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Evaluation and testing

- How do we assess the performance/detection probability?
- What is the confidence?





Detecting a mine – flipping a coin

$$\textit{Frequency} = \frac{\text{no of heads}}{\text{no of tosses}}$$

probability = frequency when infinitely many tosses



99,6% detection probability

$$\textit{Frequency} = \frac{9960}{10000} = 99,6\%$$

One more or less detection changes
the frequency a lot!



Inferring the detection probability

- N independent mine areas for evaluation
- y detections observed
- true detection probability θ

$$P(y | \theta) \sim \text{Binom}(\theta | N) = \binom{N}{y} \theta^y \theta^{N-y}$$



Incorporating prior knowledge via Bayes formula

$$P(\theta | y) = \frac{p(\theta)}{P(y)}$$

The diagram illustrates the Bayes formula with a large orange arrow pointing from the prior $p(\theta)$ to the posterior $P(\theta | y)$. The word "prior" is written inside the arrow.



Prior probability of θ

- No prior
- Non-informative prior

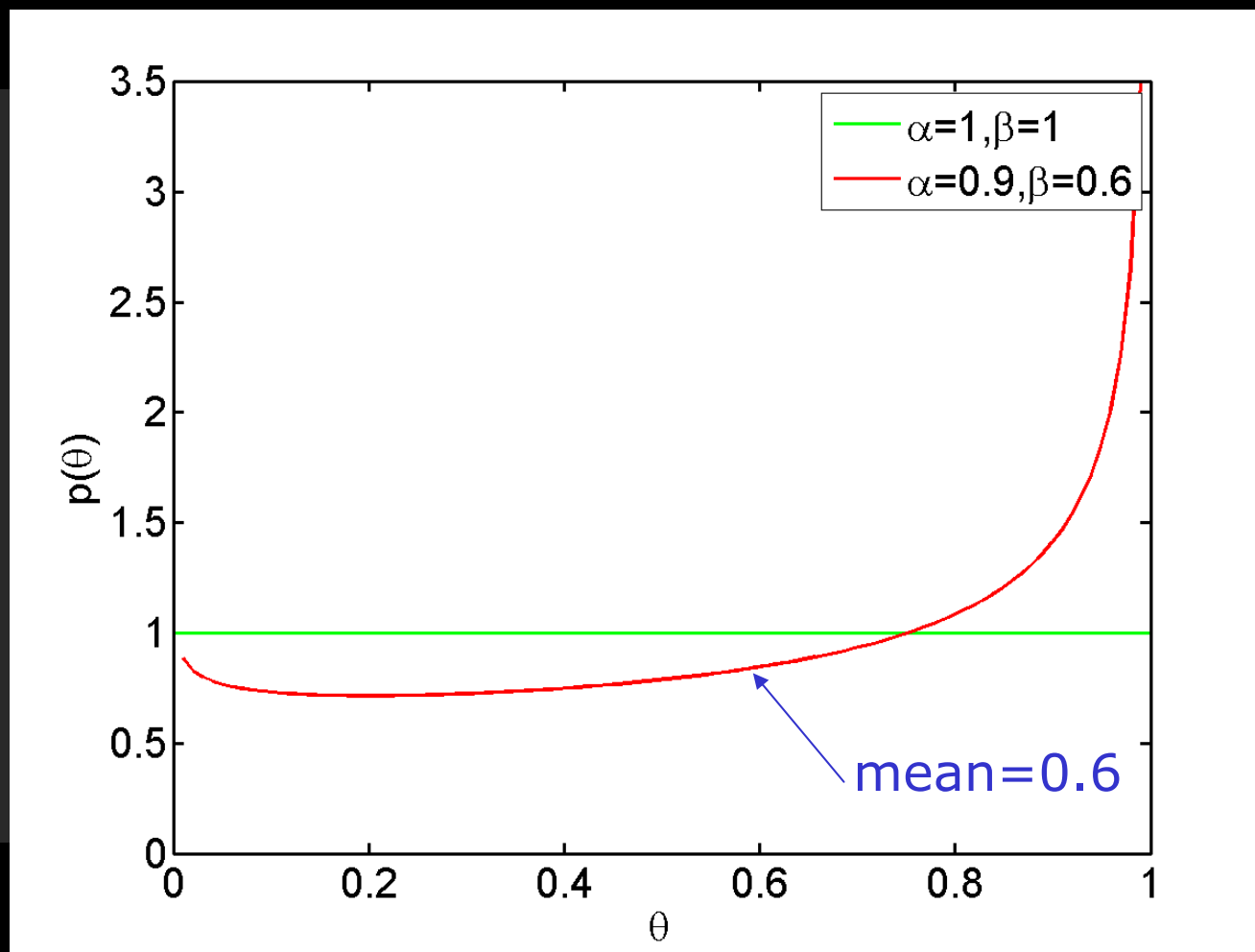
$$p(\theta) = \text{Uniform}(\theta \mid 0, 1)$$

- Informative prior

$$p(\theta) = \text{Beta}(\theta \mid \alpha, \beta)$$



Prior distribution





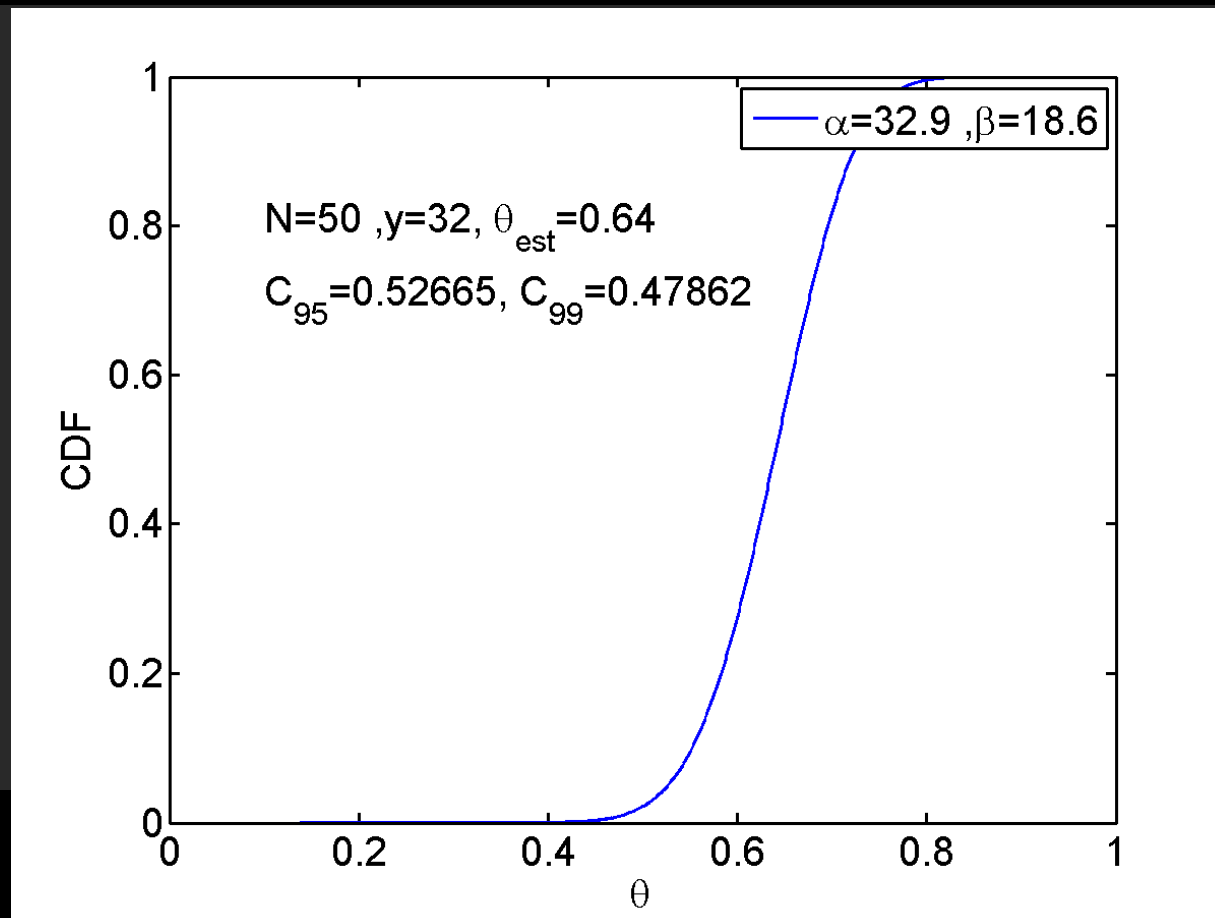
Posterior probability is also Beta

$$P(\theta | y) = \text{Beta}(\theta | y + \alpha, \beta + n - y) \sim \theta^{y+\alpha} \theta^{n-y+\beta}$$



HPD credible sets – the Bayesian confidence interval

interval $C_{1-\varepsilon} = \{\theta: P(\theta | y) \geq k(\varepsilon)\}, P(C | y) > 1 - \varepsilon$





The required number of samples N

- We need to be confident about the estimated detection probability

$$\text{Prob}(\theta > 99.6\%) = C_{1-\epsilon}$$

	$C_{95\%}$	$C_{99\%}$
$\theta_{est} = 99.7\%$	9303	18994
$\theta_{est} = 99.8\%$	2285	3995

	$C_{95\%}$	$C_{99\%}$
$\theta_{est} = 99.7\%$	8317	18301
$\theta_{est} = 99.8\%$	2147	3493

Uniform prior

Informative prior

$$\alpha=0.9, \beta=0.6$$



The required number of samples N

- We need to be confident about the estimated detection probability

$$\text{Prob}(\theta > 70\%) = C_{1-\varepsilon}$$

	$C_{95\%}$	$C_{99\%}$
$\theta_{est} = 85\%$	13	39
$\theta_{est} = 80\%$	44	99

	$C_{95\%}$	$C_{99\%}$
$\theta_{est} = 85\%$	12	33
$\theta_{est} = 80\%$	39	89

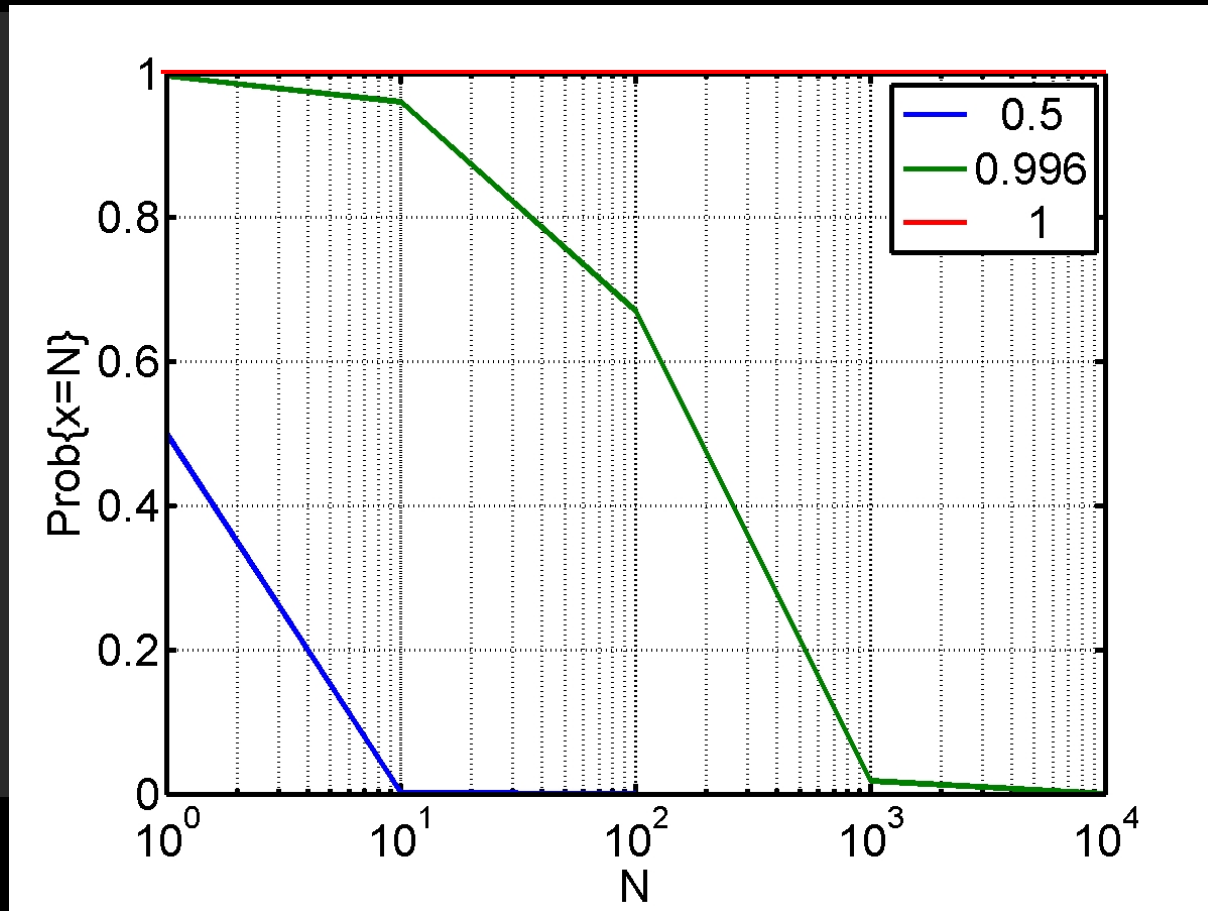
Uniform prior

Informative prior

$$\alpha=0.9, \beta=0.6$$



Probability of seeing a sequence of only true detections





Credible sets when detecting 100%

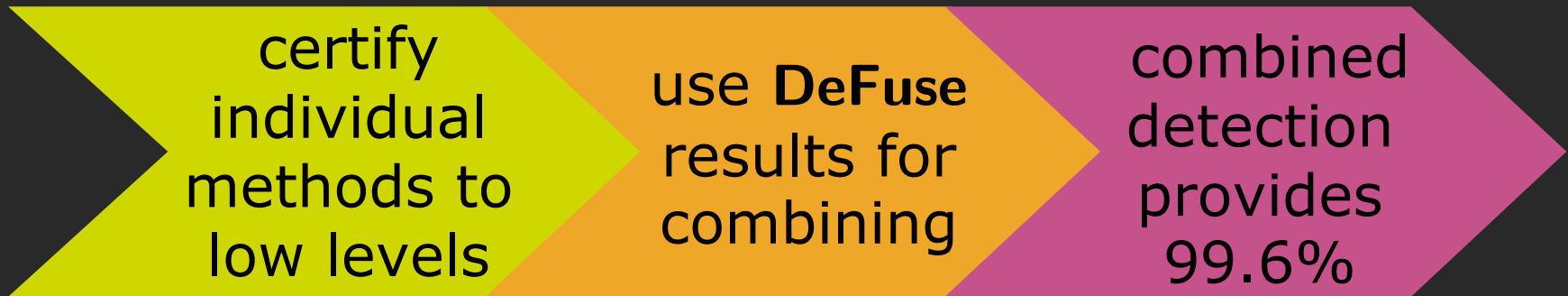
Minimum number of samples N

	Prob($\theta > 80\%$)	Prob($\theta > 99.6\%$)	Prob($\theta > 99.9\%$)
$C_{95\%}$	13	747	2994
$C_{99\%}$	20	1148	4602



Consequences

- It is unrealistic to check 99.6% detection rate is post clearance tests
- It is realistic to certify individual method to e.g. 70% detection rate





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Confusion matrix captures inherent trade-off

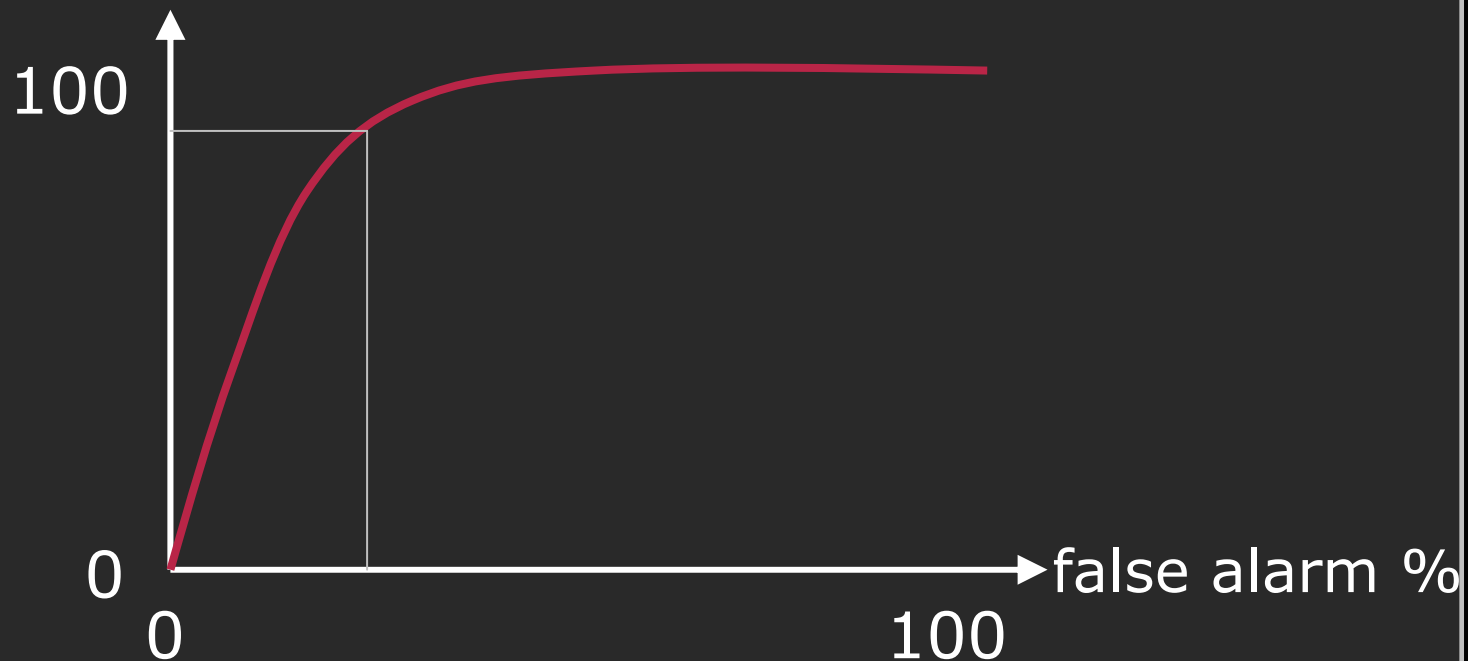
		True	
		yes	no
Estimated	yes	a	b
	no	c	d

- Detection probability (sensitivity):
 $a/(a+c)$
- False alarm:
 $b/(a+b)$



Receiver operations curve (ROC)

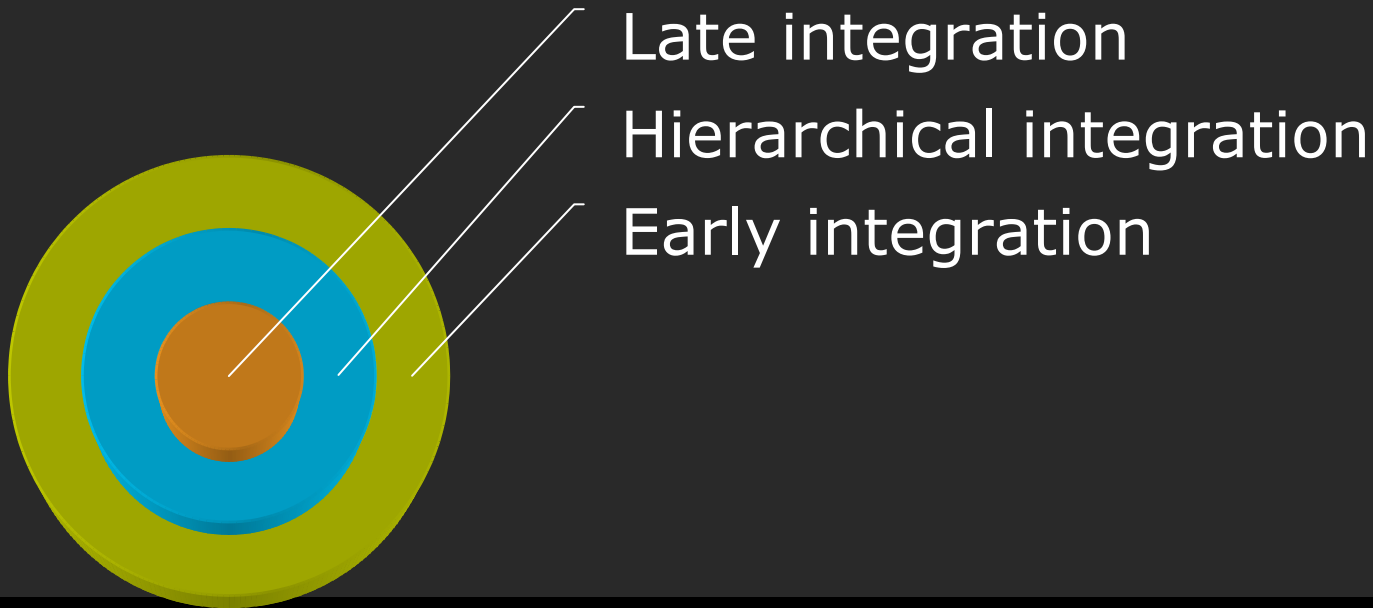
detection probability %





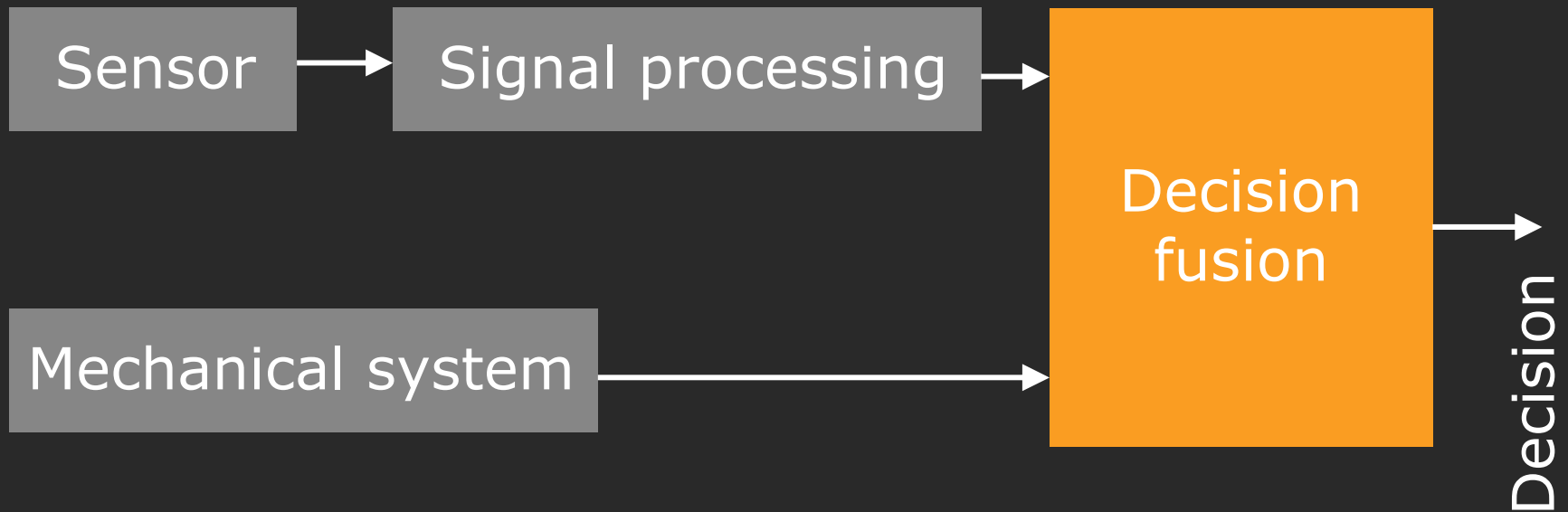
Improving performance by fusion of methods

- Methods (sensors, mechanical etc.) supplement each other by exploiting different aspect of physical environment





Late integration by decision fusion





Pros and cons

- ☺ Combination leads to a possible exponential increase in detection performance
- ☺ Combination leads to better robustness against changes in environmental conditions
- ☹ Combination leads to a possible linear increase in false alarm rate



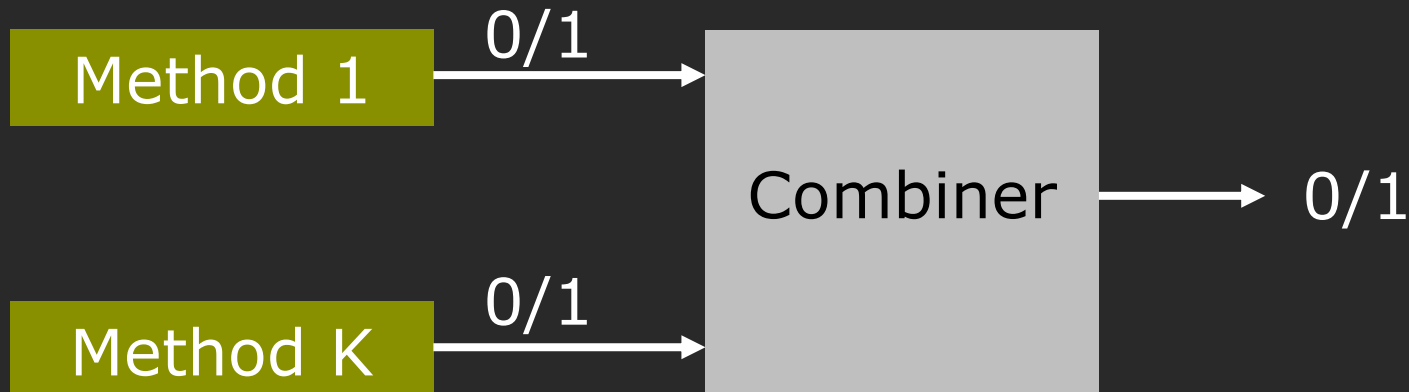
Dependencies between methods

Contingency tables

		Method j	
		yes	no
Method i	yes	c11	c10
	no	c01	c00



Optimal combination



Optimal combiner depends on contingency tables



Optimal combiner

Method		Combiner						
1	2	1	2	3	4	5	6	7
0	0	0	0	0	0	0	0	0
0	1	0	0	0	1	0	1	1
1	0	0	1	1	0	0	1	1
1	1	1	0	1	0	1	0	1

OR rule is optimal for independent methods

$2^{2^{K-1}} - 1$ possible combiners



OR rule is optimal for independent methods

Method 1: 1 0 0 1 0 0 1 0

Method 2: 0 1 0 0 1 0 0 1

Combined: 1 1 0 1 1 0 1 1

Independence to be confirmed by Fisher's test

$$\begin{aligned}
 P_d(OR) &= P(\hat{y}_1 \vee \hat{y}_2 = 1) \\
 &= 1 - P(\hat{y}_1 = 0 \wedge \hat{y}_2 = 0) \\
 &= 1 - P(\hat{y}_1 = 0 \mid y = 1) \cdot P(\hat{y}_2 = 0 \mid y = 1) \\
 &= 1 - (1 - P_{d1}) \cdot (1 - P_{d2})
 \end{aligned}$$



False alarm follows a similar rule

$$\begin{aligned} P_{fa}(OR) &= \\ P(\hat{y}_1 \vee \hat{y}_2 = 1 \mid y = 0) &= \\ = 1 - P(\hat{y}_1 = 0 \wedge \hat{y}_2 = 0 \mid y = 0) &= \\ = 1 - P(\hat{y}_1 = 0 \mid y = 0) \cdot P(\hat{y}_2 = 0 \mid y = 0) &= \\ = 1 - (1 - P_{fa1}) \cdot (1 - P_{fa2}) & \end{aligned}$$



Example

$$p_{d1} = 0.8, p_{fa1} = 0.1 \quad p_{d2} = 0.7, p_{fa2} = 0.1$$

$$p_d = 1 - (1 - 0.8) \cdot (1 - 0.7) = 0.94$$

$$p_{fa} = 1 - (1 - 0.1) \cdot (1 - 0.1) = 0.19$$

Exponential increase in detection rate
Linear increase in false alarm rate

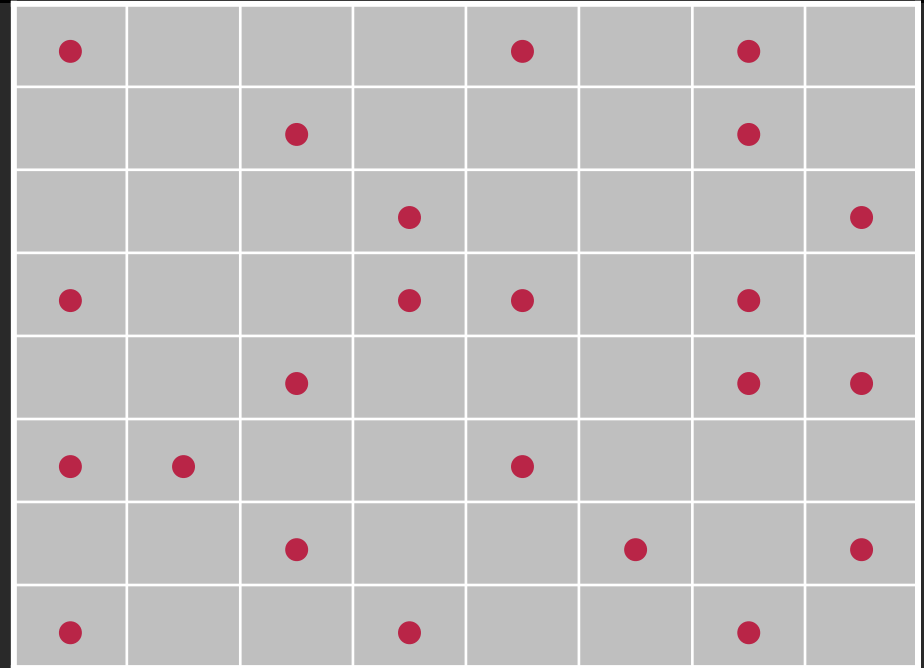
Joint discussions with: Bjarne Haugstad



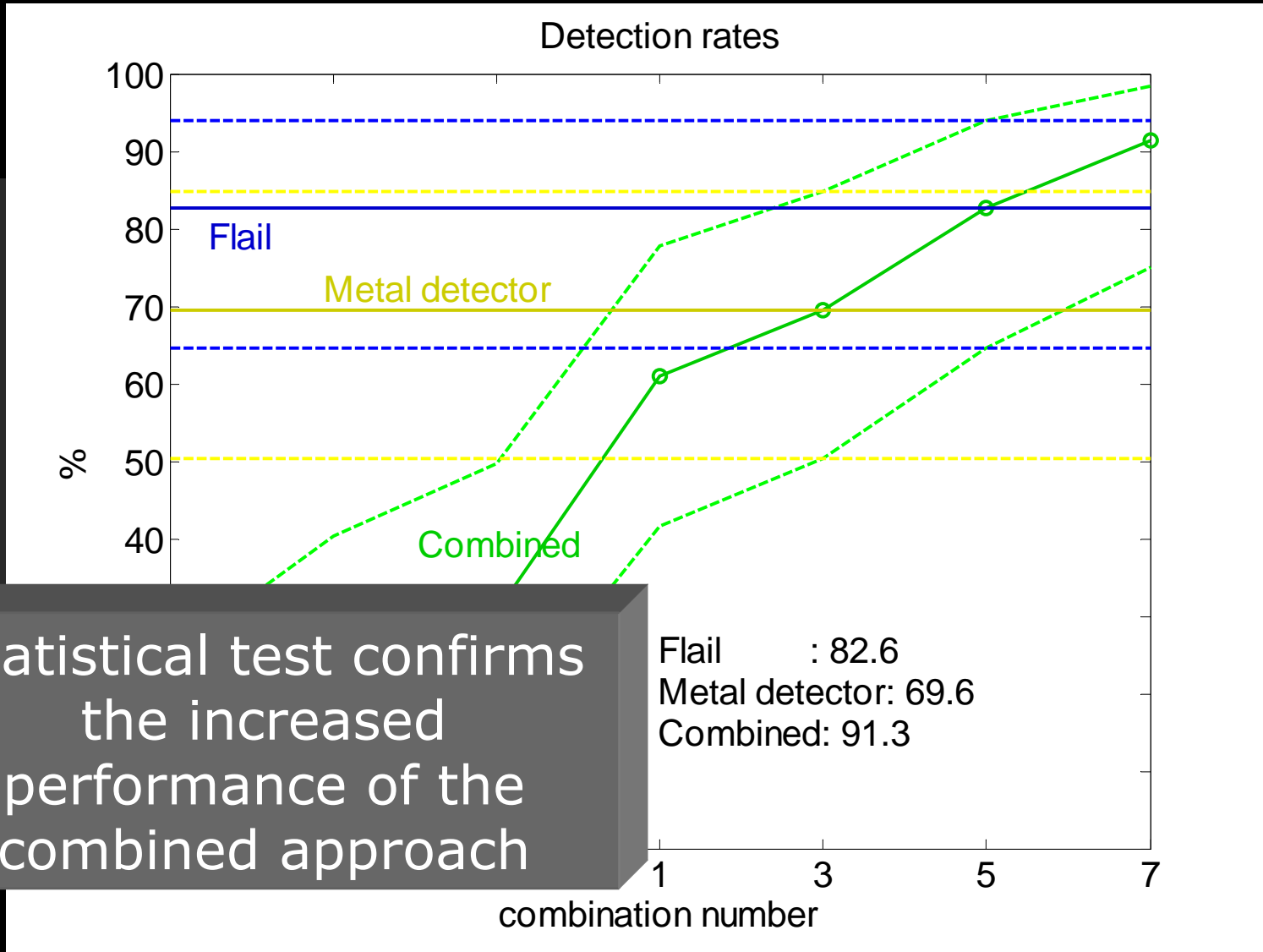
Artificial example

- $N=23$ mines
- Method 1: $P(\text{detection})=0.8$, $P(\text{false alarm})=0.1$
- Method 2: $P(\text{detection})=0.7$, $P(\text{false alarm})=0.1$
- Resolution: 100m

		True	
		yes	no
Estimated	yes	19	5
	no	4	36

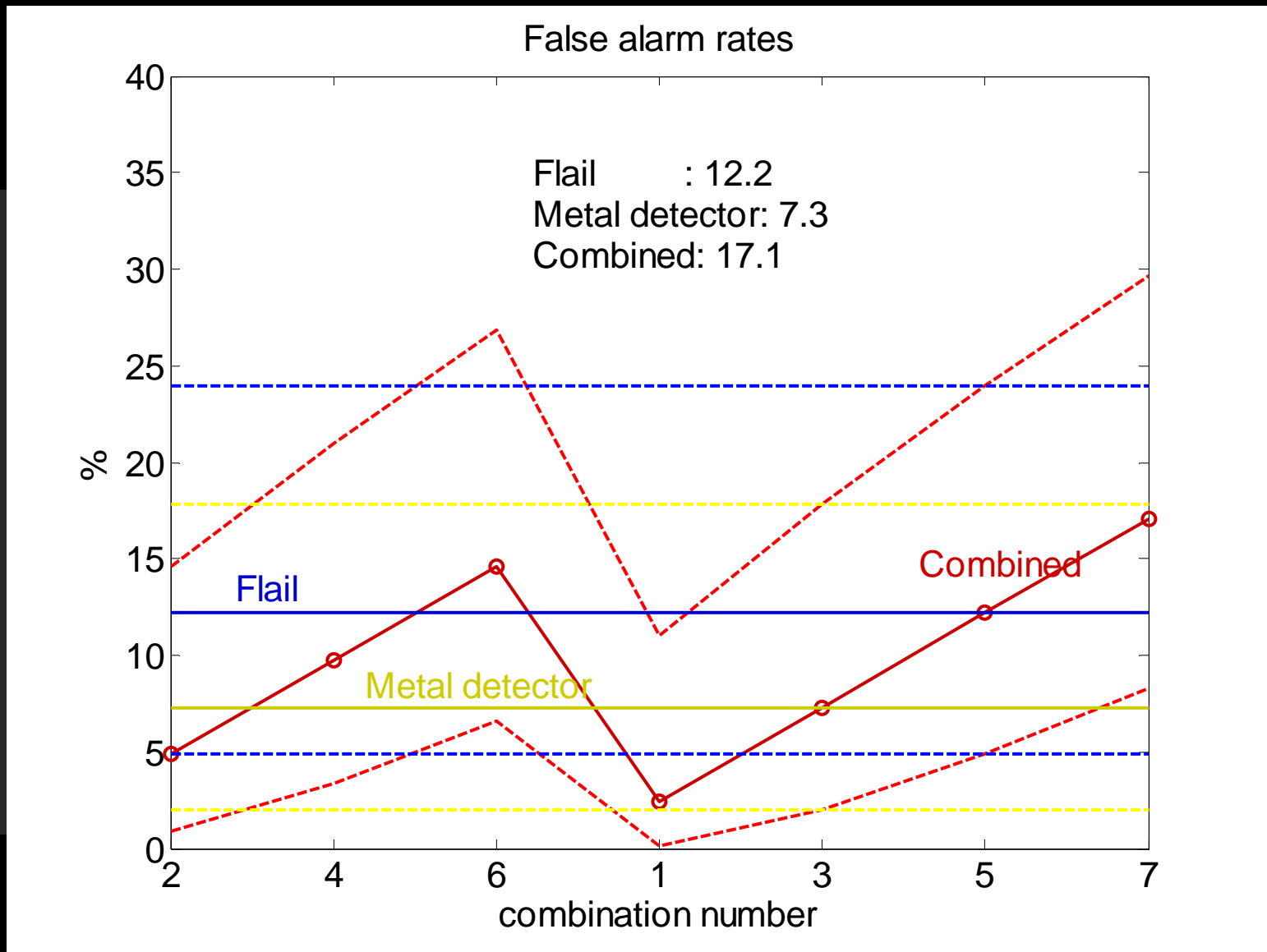


Confusion table for method 1



Statistical test confirms the increased performance of the combined approach

Flail : 82.6
 Metal detector: 69.6
 Combined: 91.3





Conclusions

- Statistical decision theory and modeling is essential for optimal use of prior information and empirical evidence
- It is very hard to assess the necessary high performance which is required to have a tolerable risk of casualty
- Combination of methods is a promising avenue to overcome current problems

