ADSA14: Development and Deployment of Fusible Technologies at the Checkpoint

What can happen when subsystems are fused?

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Summary

What area is being addressed?

Trace detection

What is the problem?

Detector fusion as an approach towards improved performance

How is it being solved?

Through careful consideration of detector performance and utilization of all available information regarding the detection task.

Why does it matter?

Fused systems present an important avenue for improving detection capability, but does not guarantee improvement in and of itself.

Summary

Detection = Data + Decision Rule

The ability of the data acquired to support the decision problem associated with target detection provides an upper limit on the quality of the detection.

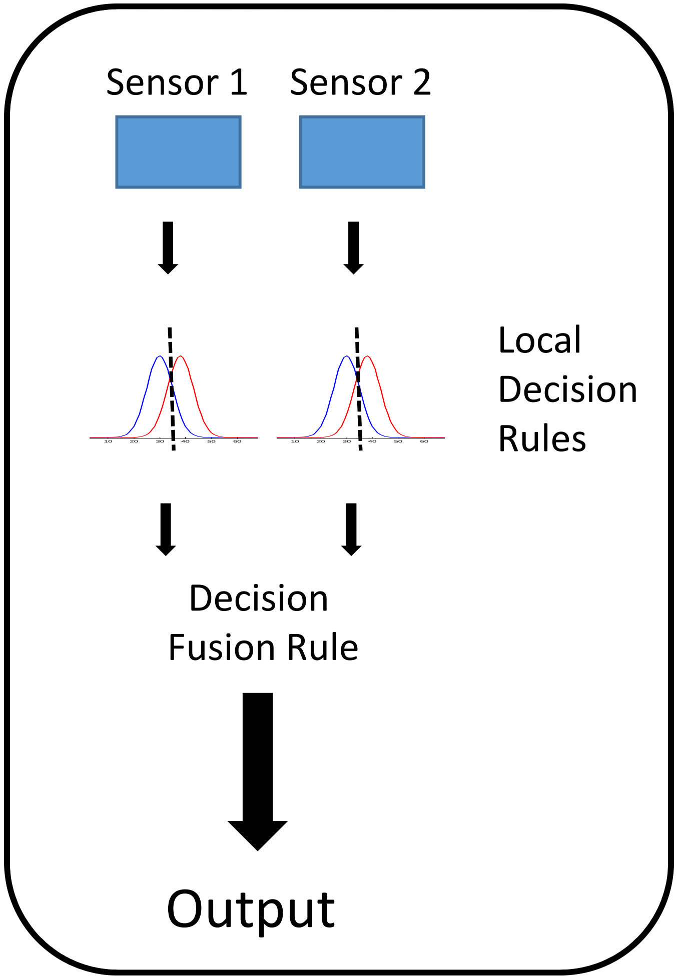
Fusion of multiple data sources can improve detection quality if it provides a marginal increase in the support for the decision problem underlying the detection.

Reliably taking advantage of fusion requires an understanding of the underlying decision problem and the manner in which measured data relates to this problem.

There is more potential in fusing systems with more access “under the hood” (i.e. black boxes with limited output present fewer options and reduced certainty for predictable improvement)

A Scenario…

Suppose you have two detection systems for a given target compound, C.



Sensor 1

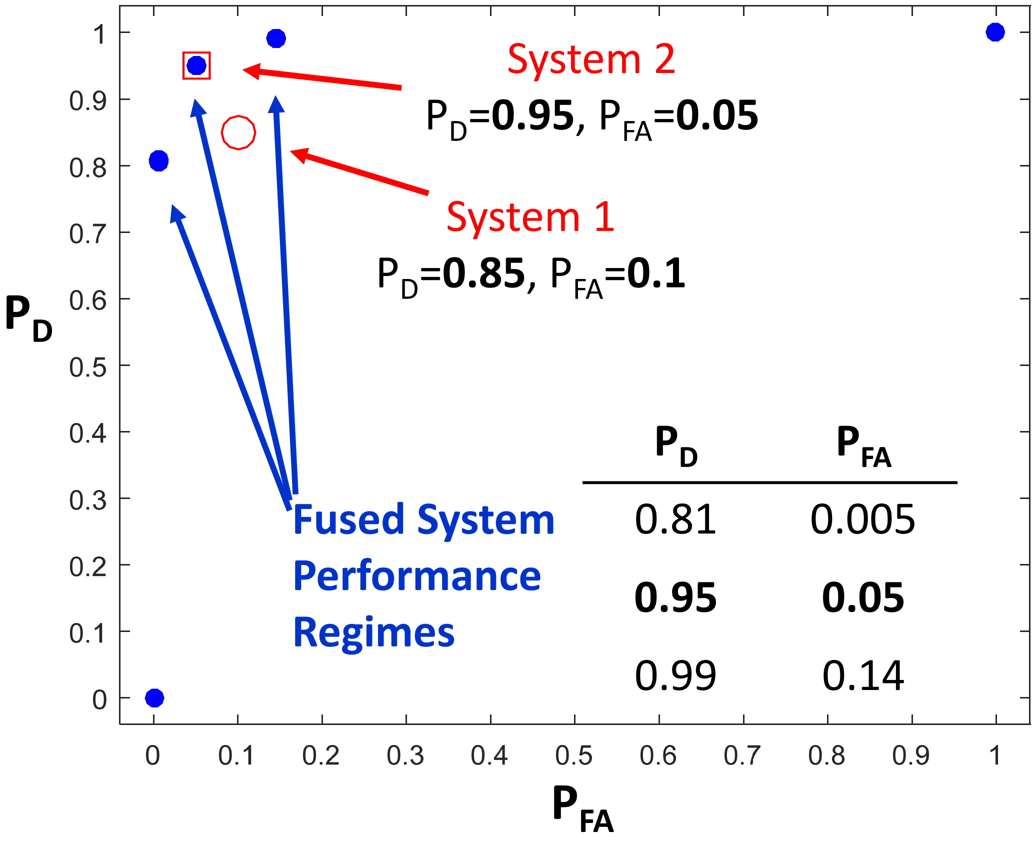
Sensor 2

Local Decision Rules

Decision Fusion Rule

Output

Fused System Performance Regimes (blue dots)



System 2

P_D=**0.95**, P_{FA}=**0.05**

System 1

P_D=**0.85**, P_{FA}=**0.1**

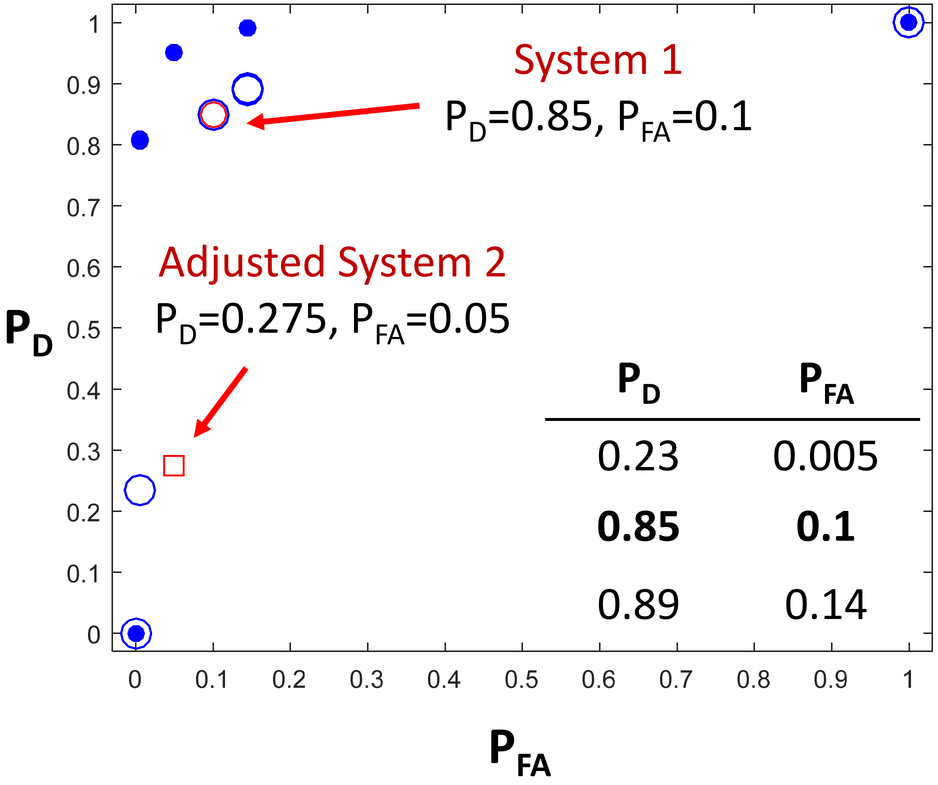
Fused System Performance Regimes

P_D	P_{FA}
0.81	0.005
0.95	**0.05**
0.99	0.14

Suppose now that system one alarms for any one of four equally likely target compounds, {A, B, C, D}

System two will alarm for {A, B, C, D} at a correspondingly reduced P_D related to the relative frequency of each target.

Fused System Performance Using Adjusted Sensor 2 P_D



System 1

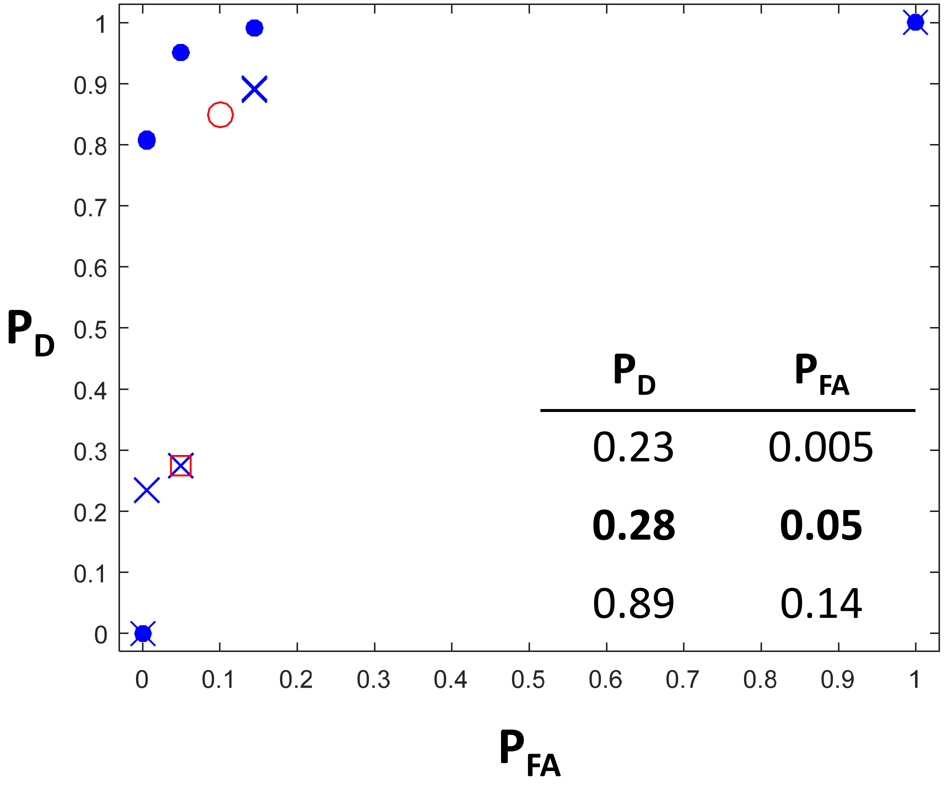
P_D=0.85, P_{FA}=0.1

Adjusted System 2

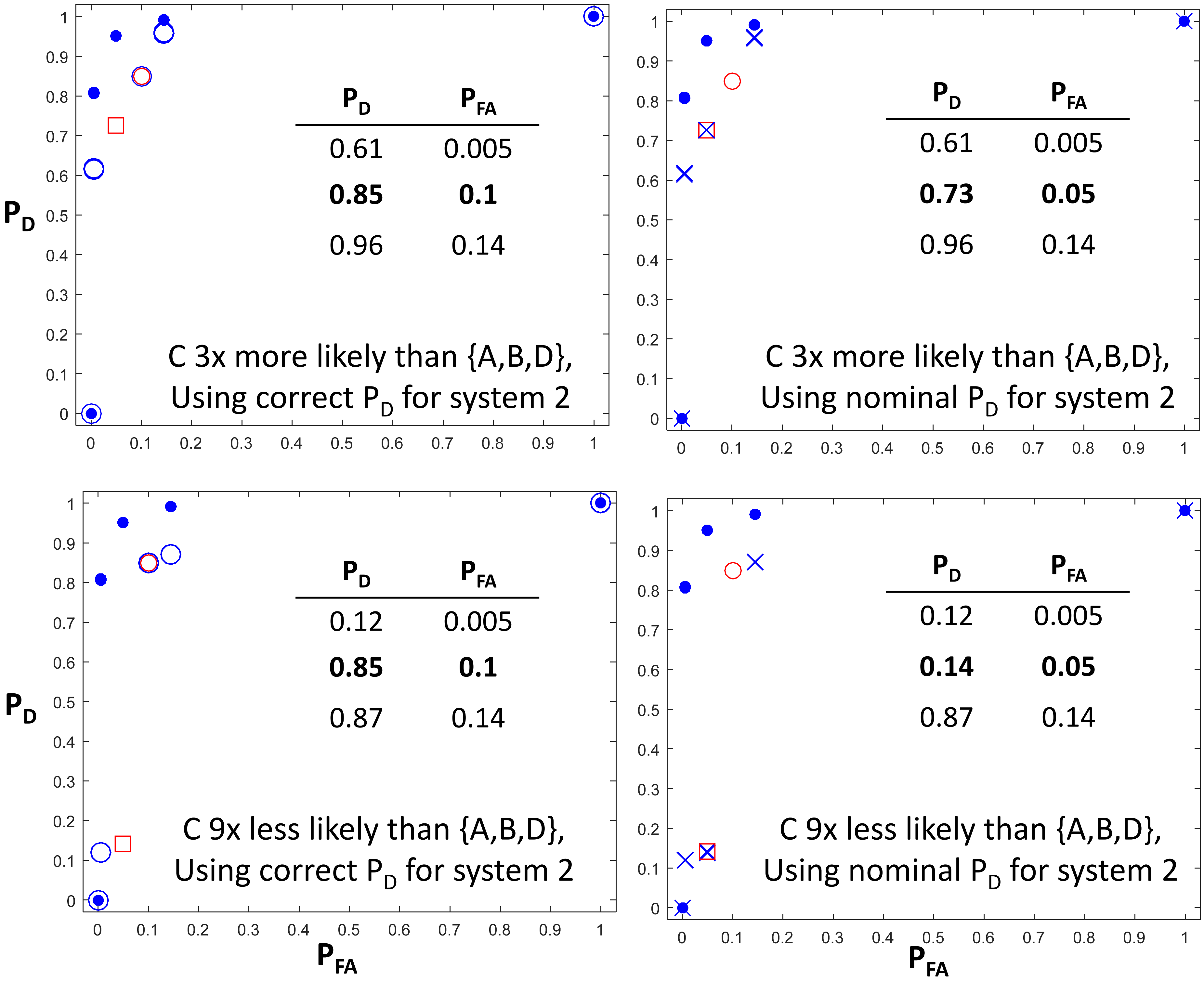
P_D=0.275, P_{FA}=0.05

P_D	P_{FA}
0.23	0.005
0.85	**0.1**
0.89	0.14

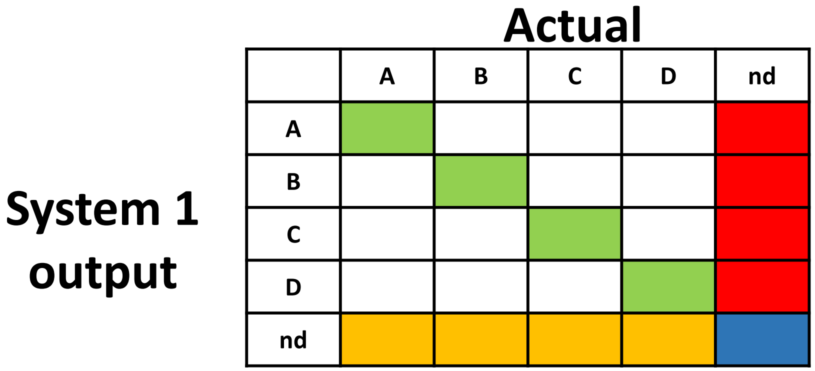
Fused System Performance Using Nominal Sensor 2 P_D



P_D	P_{FA}
0.23	0.005
0.28	**0.05**
0.89	0.14


P_D
P_FA
P_D P_FA
0.61 0.005
0.85 **0.1**
0.96 0.14
C 3x more likely than {A,B,D},
Using correct P_D for system 2
P_D P_FA
0.61 0.005
0.73 **0.05**
0.96 0.14
C 3x more likely than {A,B,D},
Using nominal P_D for system 2
P_D P_FA
0.12 0.005
0.85 **0.1**
0.87 0.14
C 9x less likely than {A,B,D},
Using correct P_D for system 2
P_D P_FA
0.12 0.005
0.14 **0.05**
0.87 0.14
C 9x less likely than {A,B,D},
Using nominal P_D for system 2
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

Suppose now that system one identifies which of the four target compounds, {A, B, C, D} it has detected.



Actual

System 1 output

	A	B	C	D	nd
A	🟩				🟥
B		🟩			🟥
C			🟩		🟥
D				🟩	🟥
nd	🟨	🟨	🟨	🟨	🟦

Detections
False Alarms
Missed Detections
Correct Negatives

System two can be used to augment system one to improve detection of target C.

Detects C Poorly

$P_{D,A} = P_{D,B} = P_{D,D} = \mathbf{0.95}$
$P_{D,C} = \mathbf{0.55}, P_{FA} = \mathbf{0.1}$

$P_{D,C} = \mathbf{0.95}, P_{FA,C} = \mathbf{0.05}$

P_D	P_{FA}
0.74	0.076
0.95	**0.13**
0.96	0.15

System 1

Fuse with System 2

Overall Fused System Performance Regimes for {A,B,C,D}

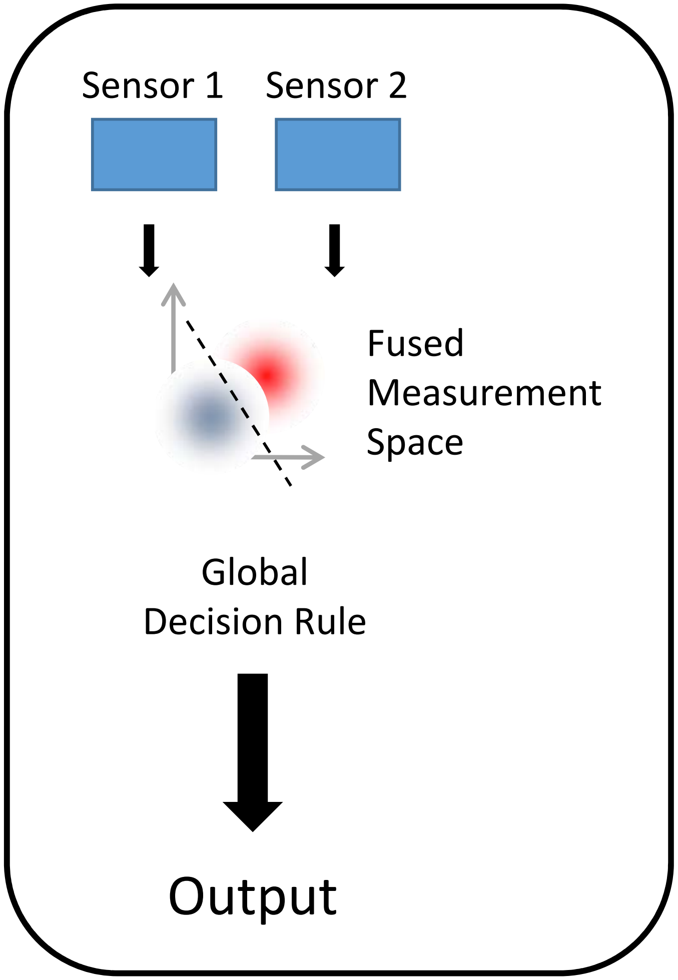
Detects C Well

$P_{D,A} = P_{D,B} = P_{D,D} = \mathbf{0.82}$
$P_{D,C} = \mathbf{0.95}, P_{FA} = \mathbf{0.1}$

$P_{D,C} = \mathbf{0.95}, P_{FA,C} = \mathbf{0.05}$

P_D	P_{FA}
0.84	0.088
0.85	**0.10**
0.86	0.15

Beyond decision fusion...



Sensor 1

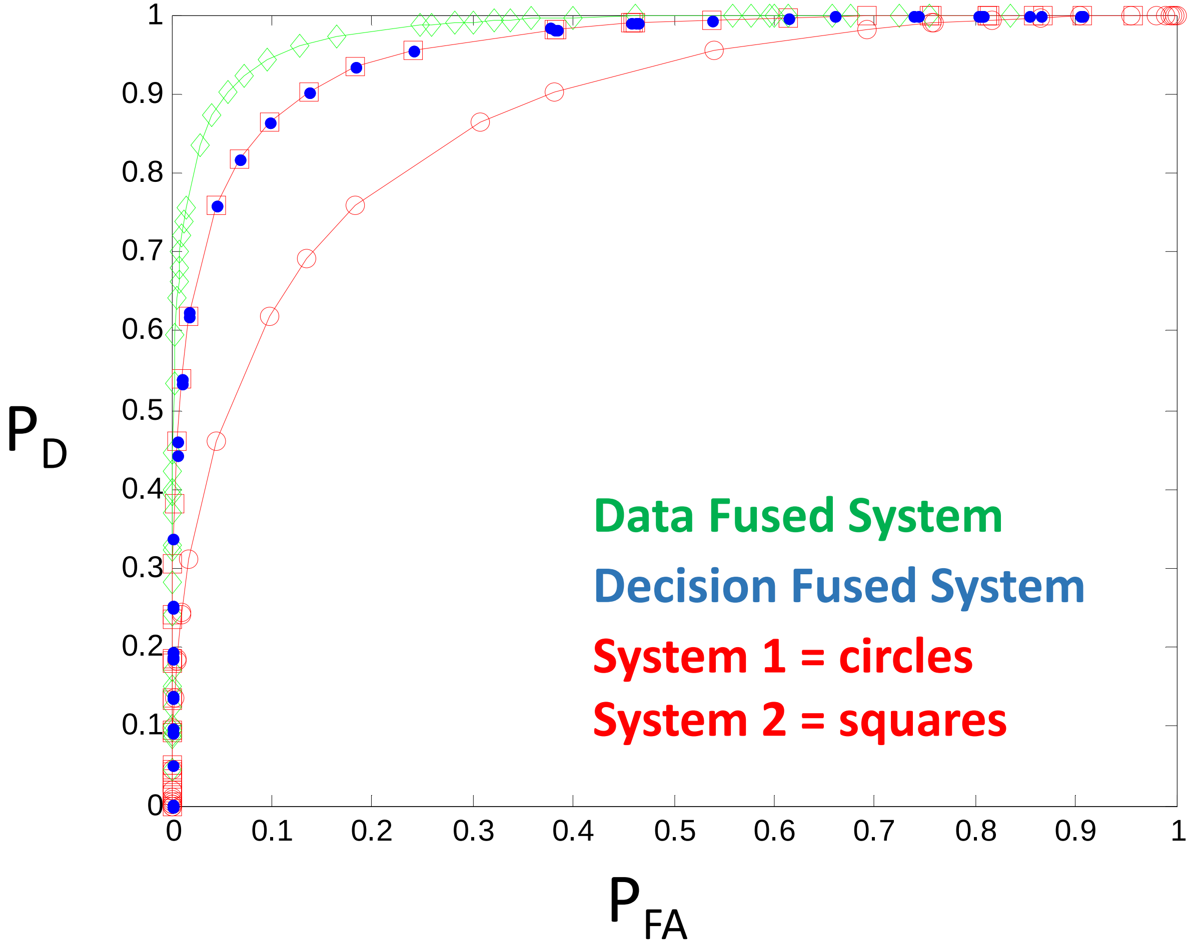
Sensor 2

Fused Measurement Space

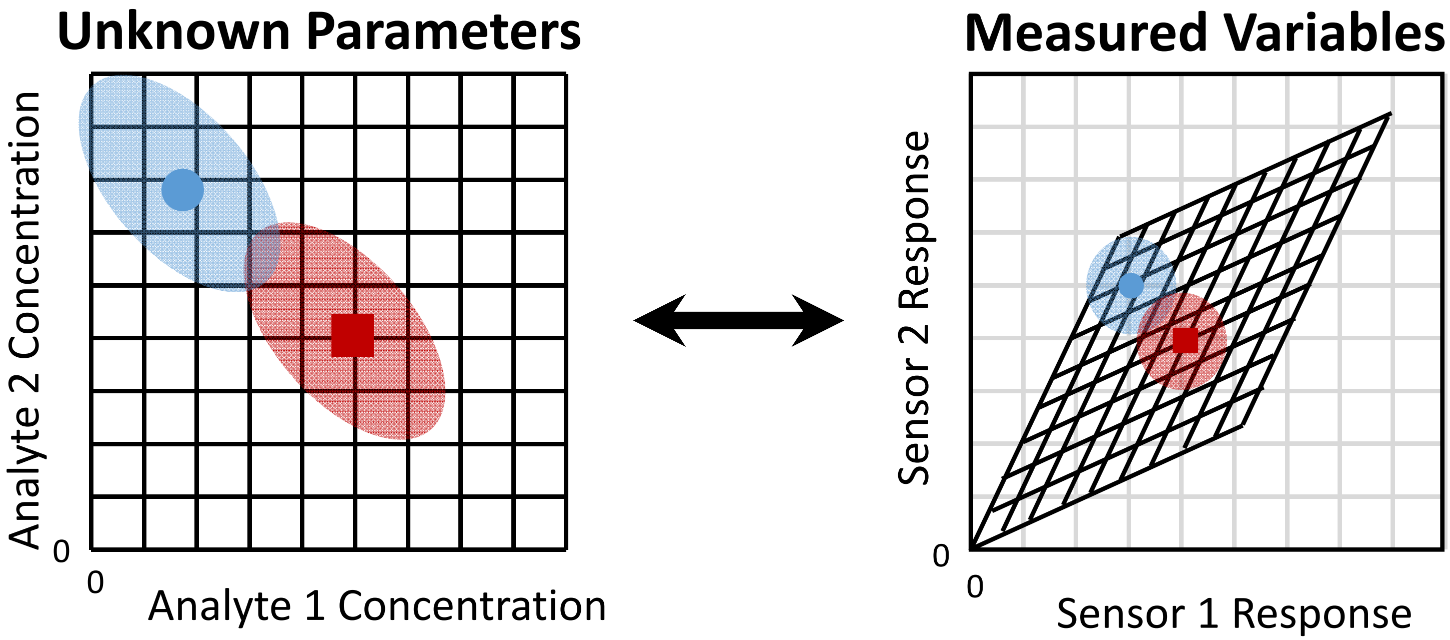
Global Decision Rule

Output

ROC curves for simulated decision and data-fused sensor systems comprised of two subsystems



An information-theoretic view of system fusion



The Fisher information matrix (FIM) describes the information that a set of measured variables, **x** carries about a set of unknown parameters, ***θ***, of a distribution that models **x**.

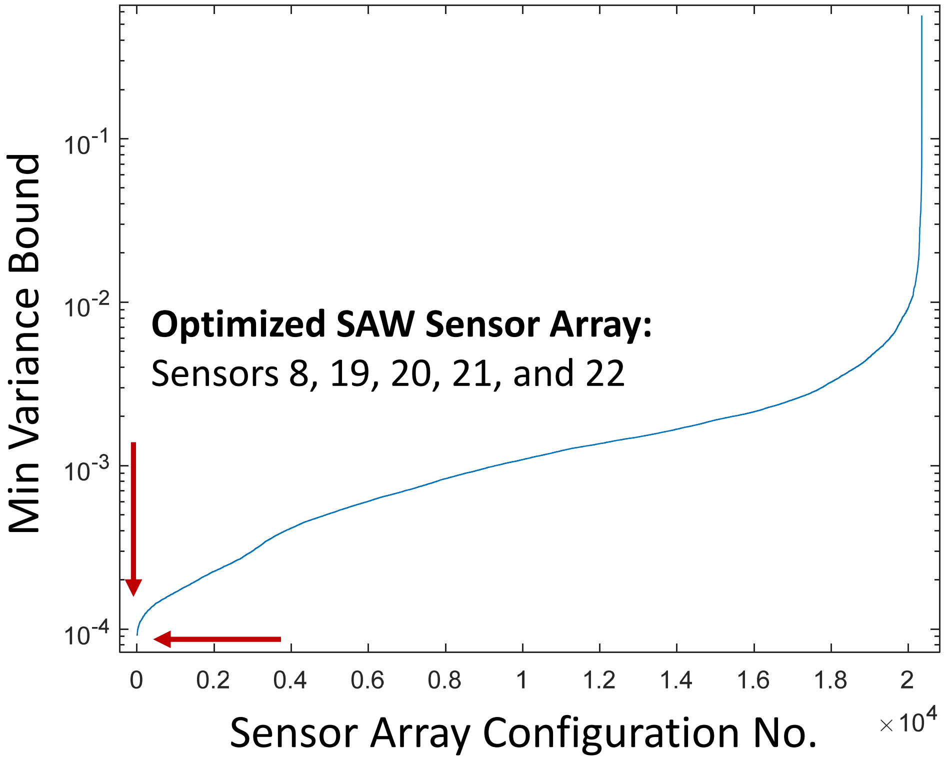
$$J_{ij}(\theta)=\int d\mathrm{x}\, p(\mathrm{x}|\theta)\left(\frac{\partial}{\partial\theta_i}\ln p(\mathrm{x}|\theta)\right)\left(\frac{\partial}{\partial\theta_j}\ln p(\mathrm{x}|\theta)\right)$$

The FIM provides a lower bound for the variance of any estimator predicting ***θ*** from **x,** via the Cramér-Rao bound.

$$\Sigma\geq J^{-1}(\theta), \quad \det\Sigma\geq\det J^{-1}(\theta)$$

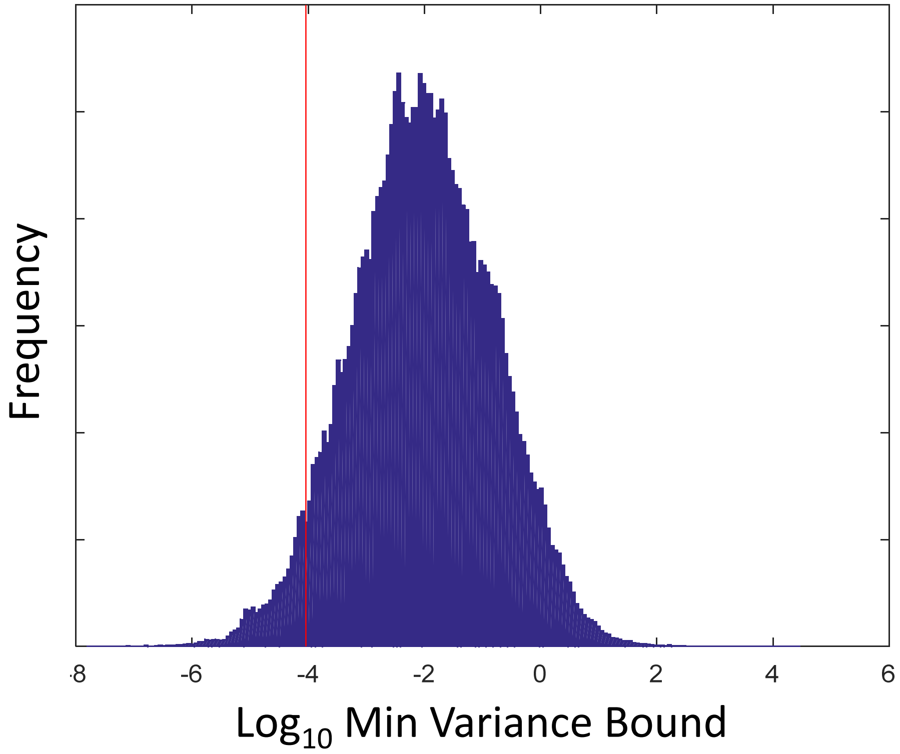
Optimizing Sensor Array Design

The minimum variance bound derived from the Fisher information can be thought of as a measure of the analytical limitation of a sensor array



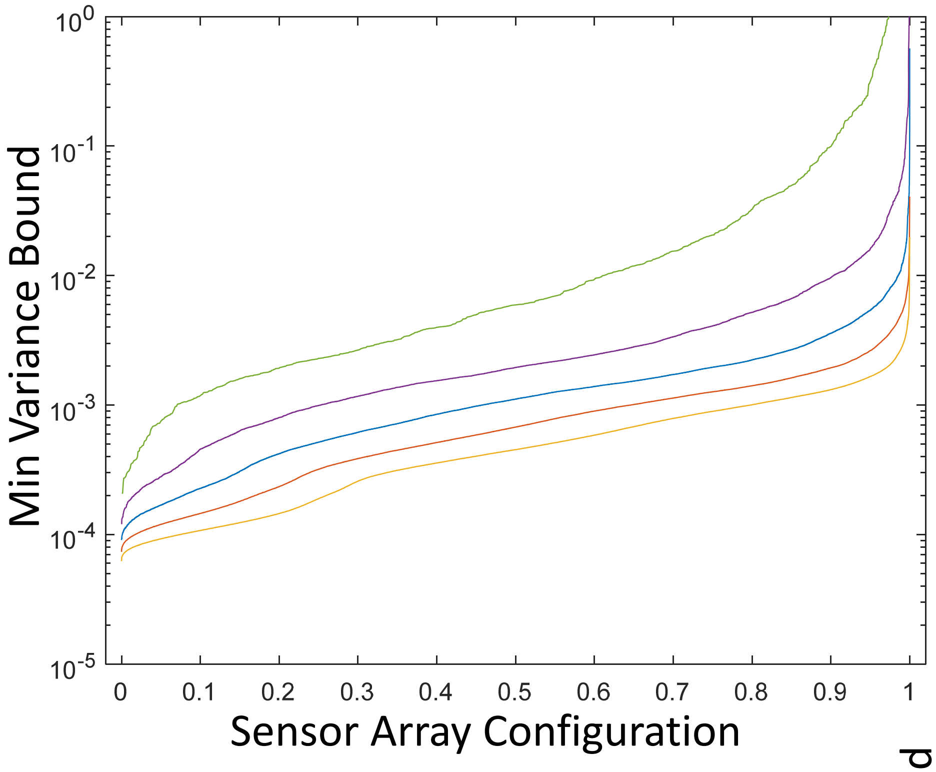
Optimized SAW Sensor Array:
Sensors 8, 19, 20, 21, and 22

Example: an optimal SAW sensor array configuration is determined for a specific set of three target analytes: 4-bromophenol, ethylphenylether, and phenyl acetate



However, this optimization results in a **greater variance bound** for **95%** of the other ternary mixtures.

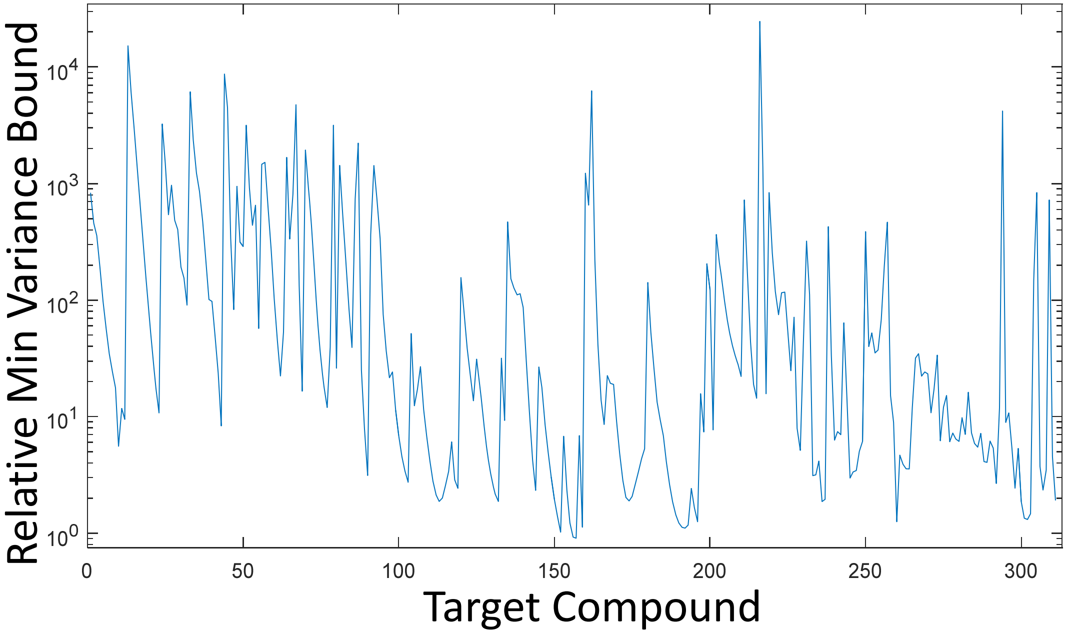
Quantifying Marginal Gain/Loss in Performance



Optimizations for 3, 4, 5, 6 and 7-sensor arrays show the marginal decline in variance bound as more sensors are used.

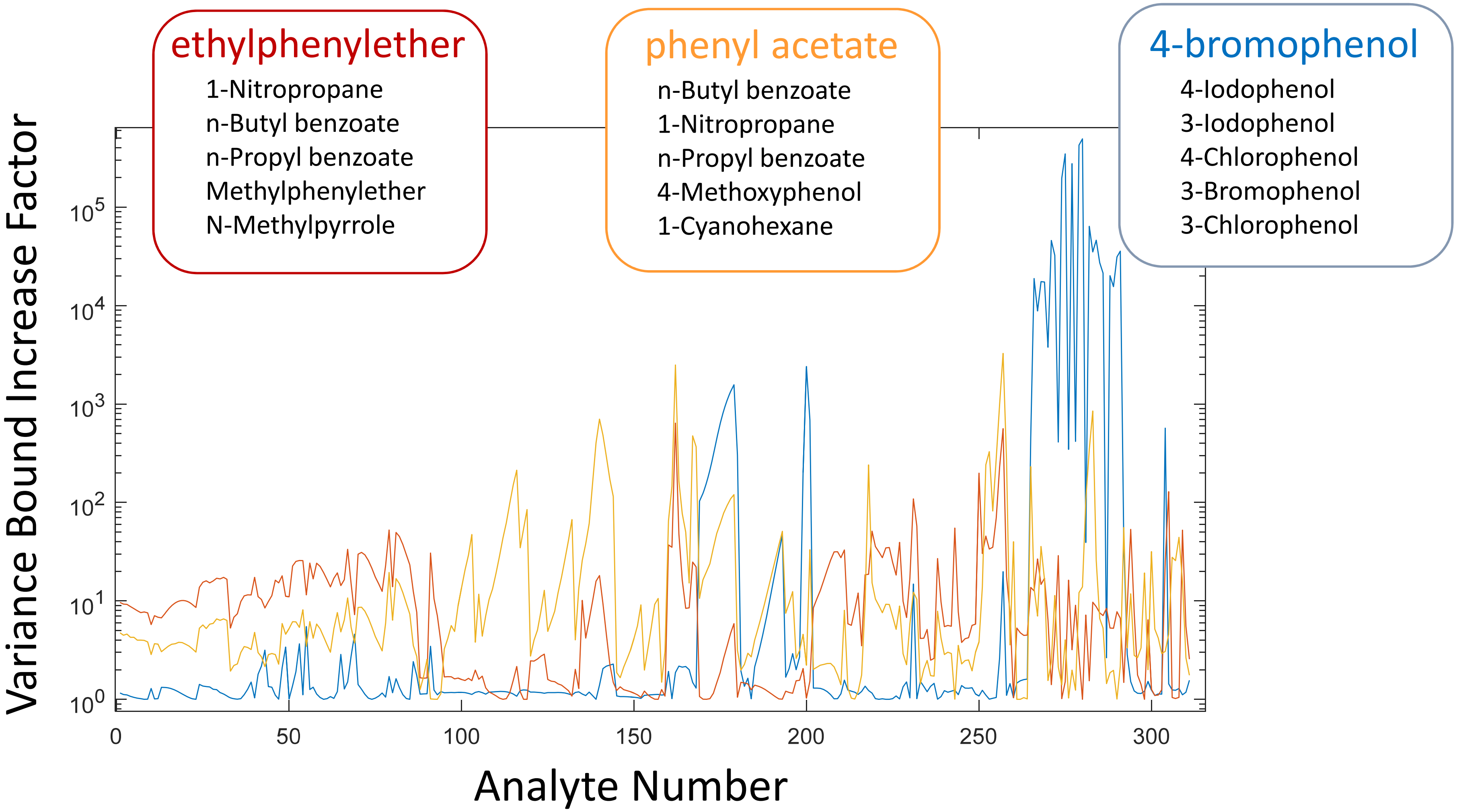
The optimal 7 sensor array exhibits a minimum variance bound 30% that of the optimal 3-sensor array.

The marginal increase in minimum variance bound associated with adding analysis of an additional target from the library to the previously optimized five sensor array.



Identifying Target-Specific Interferents

Analyte-specific variance bounds can be extracted to investigate potential interference problems with other compounds.



ethylphenylether

- 1-Nitropropane
- n-Butyl benzoate
- n-Propyl benzoate
- Methylphenylether
- N-Methylpyrrole

phenyl acetate

- n-Butyl benzoate
- 1-Nitropropane
- n-Propyl benzoate
- 4-Methoxyphenol
- 1-Cyanohexane

4-bromophenol

- 4-Iodophenol
- 3-Iodophenol
- 4-Chlorophenol
- 3-Bromophenol
- 3-Chlorophenol