

Pacific Northwest  
NATIONAL LABORATORY

Proudly Operated by **Battelle** Since 1965

# Integration of Experimental and Textual Data for Biosurveillance

BOBBIE-JO WEBB-ROBERTSON  
BJ@PNNL.GOV

August 28, 2012

Biosurveillance Conference, Washington, DC

# Motivation

**Investigators/analysts need “confidence” metrics to enable justified and rapid decision making.**

# Motivation

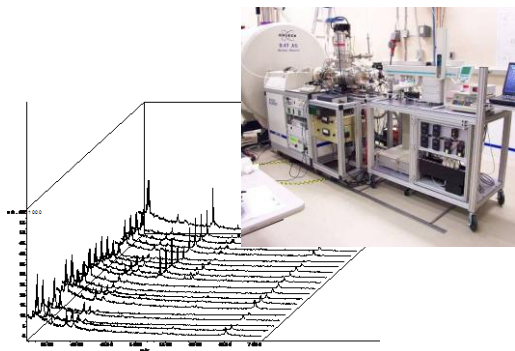
**Investigators/analysts need “confidence” metrics to enable justified and rapid decision making.**

## **Sample**



# Motivation

Investigators/analysts need “confidence” metrics to enable justified and rapid decision making.



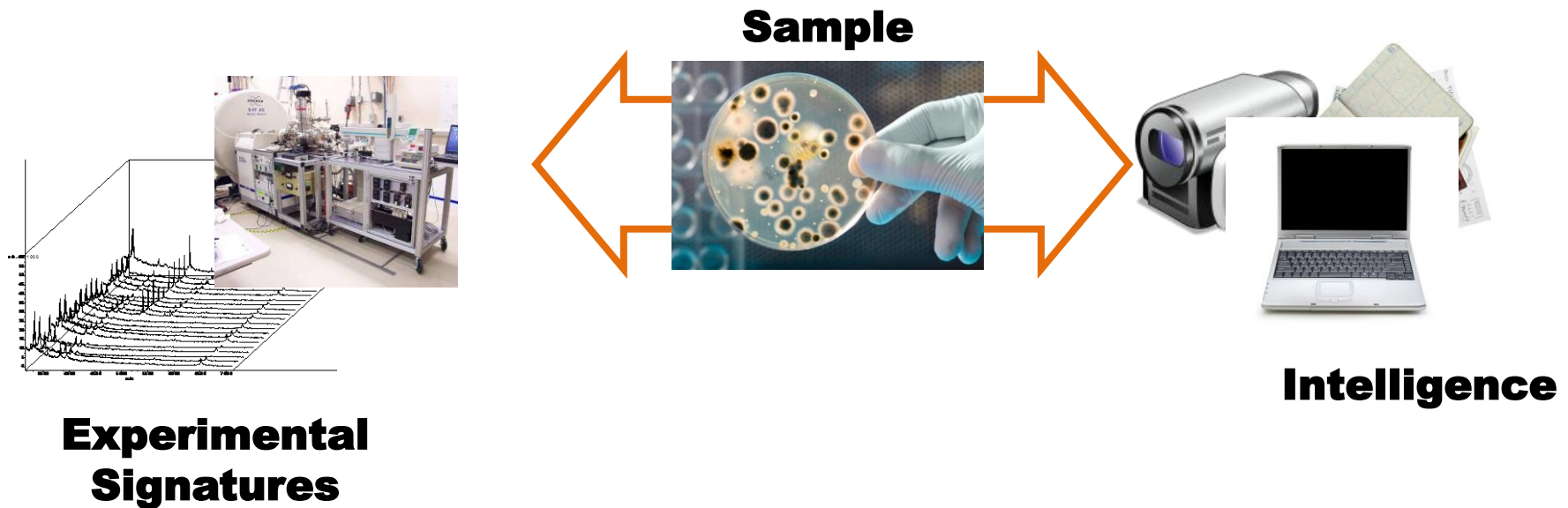
**Experimental  
Signatures**

**Sample**



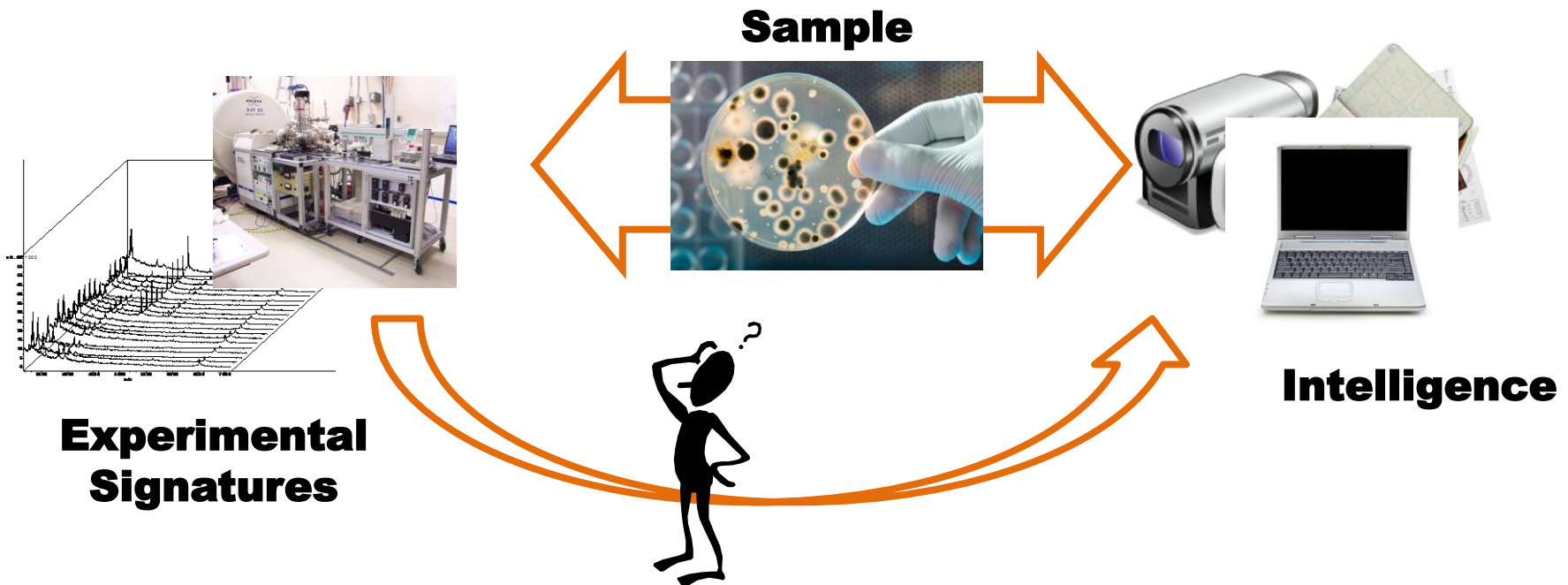
# Motivation

Investigators/analysts need “confidence” metrics to enable justified and rapid decision making.



# Motivation

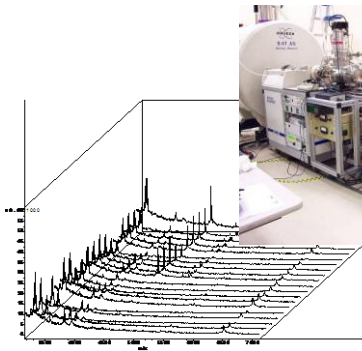
Investigators/analysts need “confidence” metrics to enable justified and rapid decision making.





# Motivation

Investigators/analysts need “confidence” metrics to enable justified and rapid decision making.



**Experiment  
Signatures**



**Intelligence**

# Integration Problem



Pacific Northwest  
NATIONAL LABORATORY

*Proudly Operated by Battelle Since 1965*

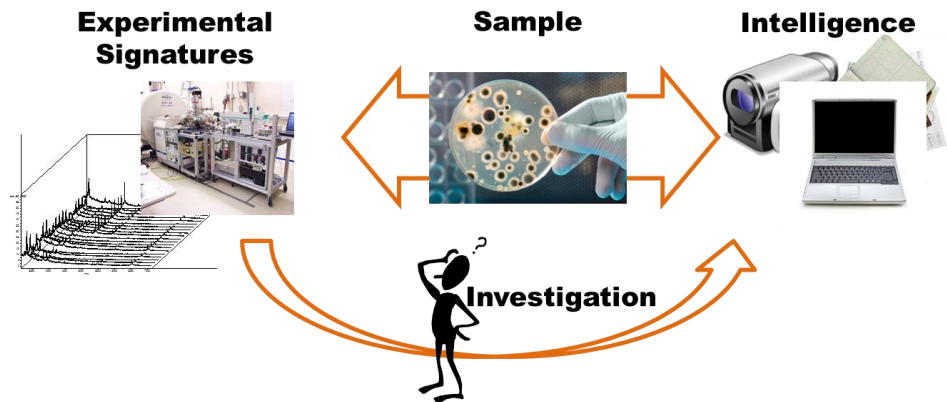
**How do we tie together the “experimental” and “intelligence” signatures to help the analyst/investigator?**



## How do we tie together the “experimental” and “intelligence” signatures to help the analyst/investigator?

### ► Challenge

- Research is compartmentalized into domains
- Statistical confidence metrics from multiple sources of evidence have not been well defined for bioforensics/  
bio-surveillance



# Approach – Bayesian networks

## **Bayesian Statistics Naturally fits forensic and surveillance type problems**

Outcome is conditionally related to the sources of evidence

# Approach – Bayesian networks

## Bayesian Statistics Naturally fits forensic and surveillance type problems

Outcome is conditionally related to the sources of evidence

### ► Bayes theorem


$$\begin{array}{ccc} \textit{Posterior} & \textit{Likelihood} & \textit{Prior} \\ \downarrow & \downarrow & \downarrow \\ P(O | E) = \frac{P(E | O)P(O)}{P(E)} \end{array}$$

## Bayesian Statistics Naturally fits forensic and surveillance type problems

Outcome is conditionally related to the sources of evidence

### ► Bayes theorem

*Posterior*      *Likelihood*      *Prior*


$$P(O | E) = \frac{P(E | O)P(O)}{P(E)}$$

Probability that a person  
become sick with the flu  
given (*O*) their age (*E*)


# Approach – Bayesian networks

## Bayesian Statistics Naturally fits forensic and surveillance type problems

Outcome is conditionally related to the sources of evidence

### ► Bayes theorem

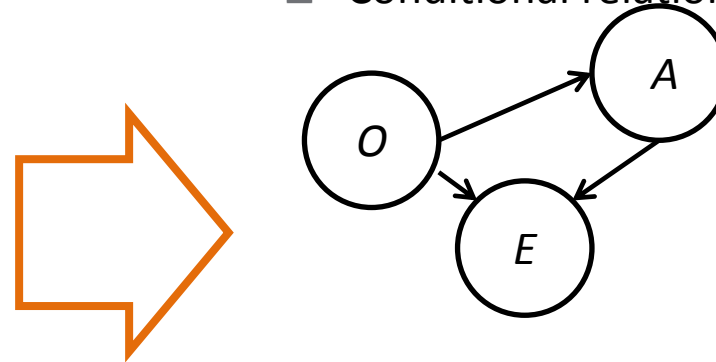
*Posterior*      *Likelihood*      *Prior*


$$P(O | E) = \frac{P(E | O)P(O)}{P(E)}$$

Probability that a person become sick with the flu given (*O*) their age (*E*)

### ► Bayes network

■ Conditional relationships



$$P(O | E, G) \propto P(E | G, O)P(G | O)P(O)$$

Probability that a person become sick with the flu given (*O*) their age (*E*) and gender (*G*)

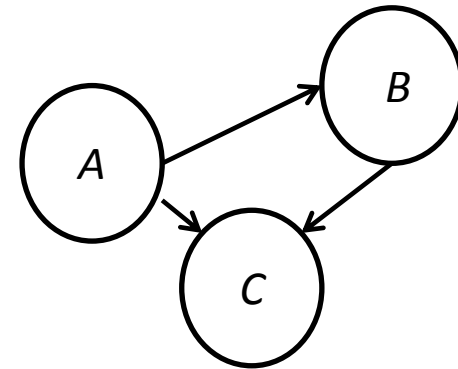
# Approach – Bayesian networks

## ▶ Allows

- Integration of heterogeneous data types
- Multiple complex relationships
- Incomplete information

## ▶ Yields

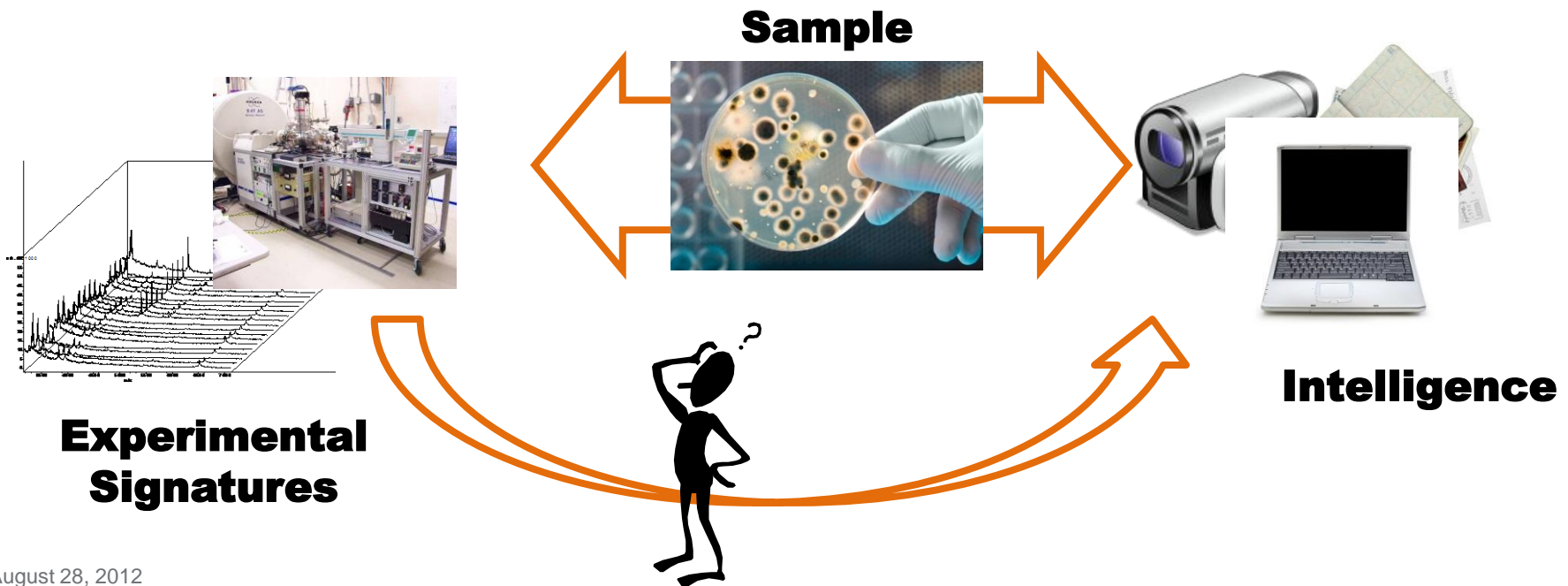
- Probabilistic measure of the outcome
- Probabilistic Interrogation of intermediate nodes



$$P(C | A, B)P(B | A)P(A)$$

# Microbial Forensics

Microorganism-based forensics do not offer investigators “confidence” metrics associated with the sample to gain insight into individuals or places with information pertinent to the investigation.

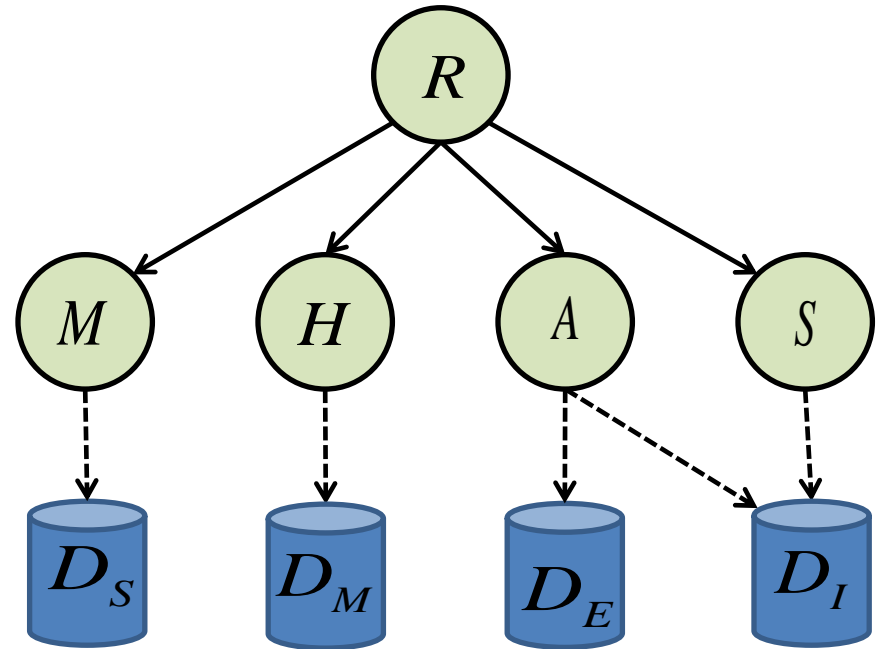






# Approach – Existing Experimentally deriving network (culture media recipe)

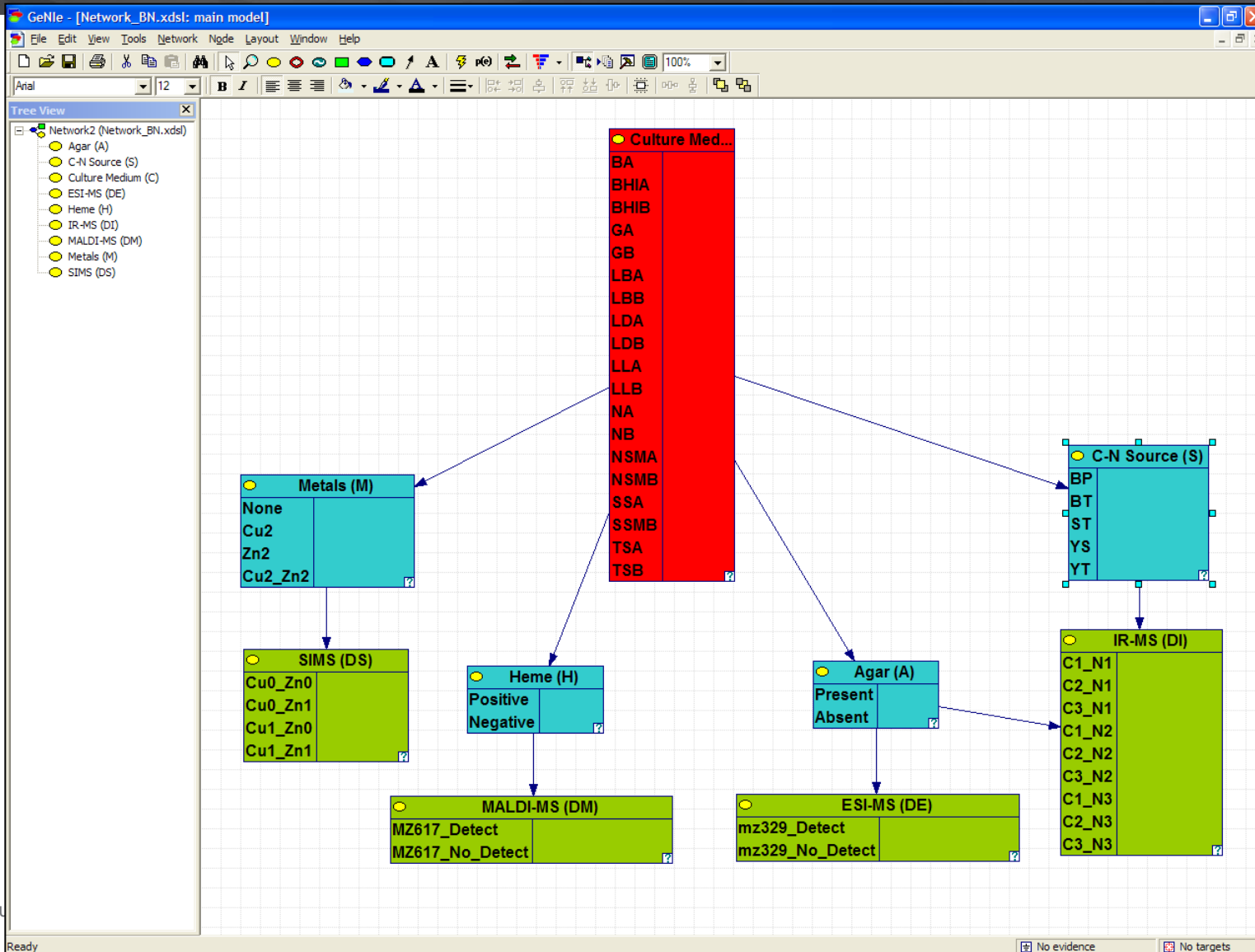
Prior work (Jarman et al., 2008) demonstrated that using disparate analytical measurements ( $D_S$ ,  $D_M$ ,  $D_E$ ,  $D_I$ ) of Bacillus spores could yield a predictive model of production environment ( $R$ )



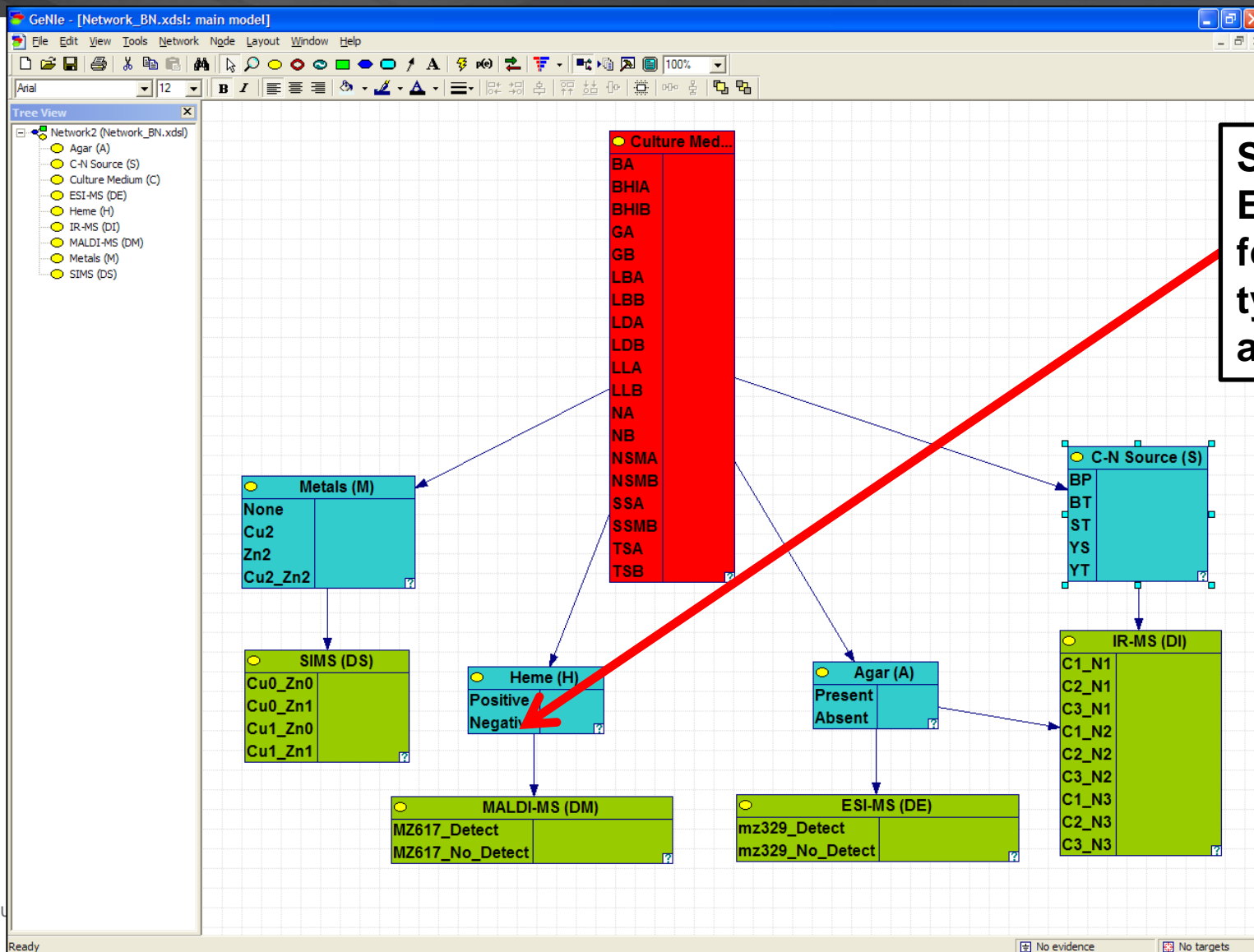
$$P(R | D_S, D_M, D_E, D_I)$$

**Computed using GeNIe tool for visualization**

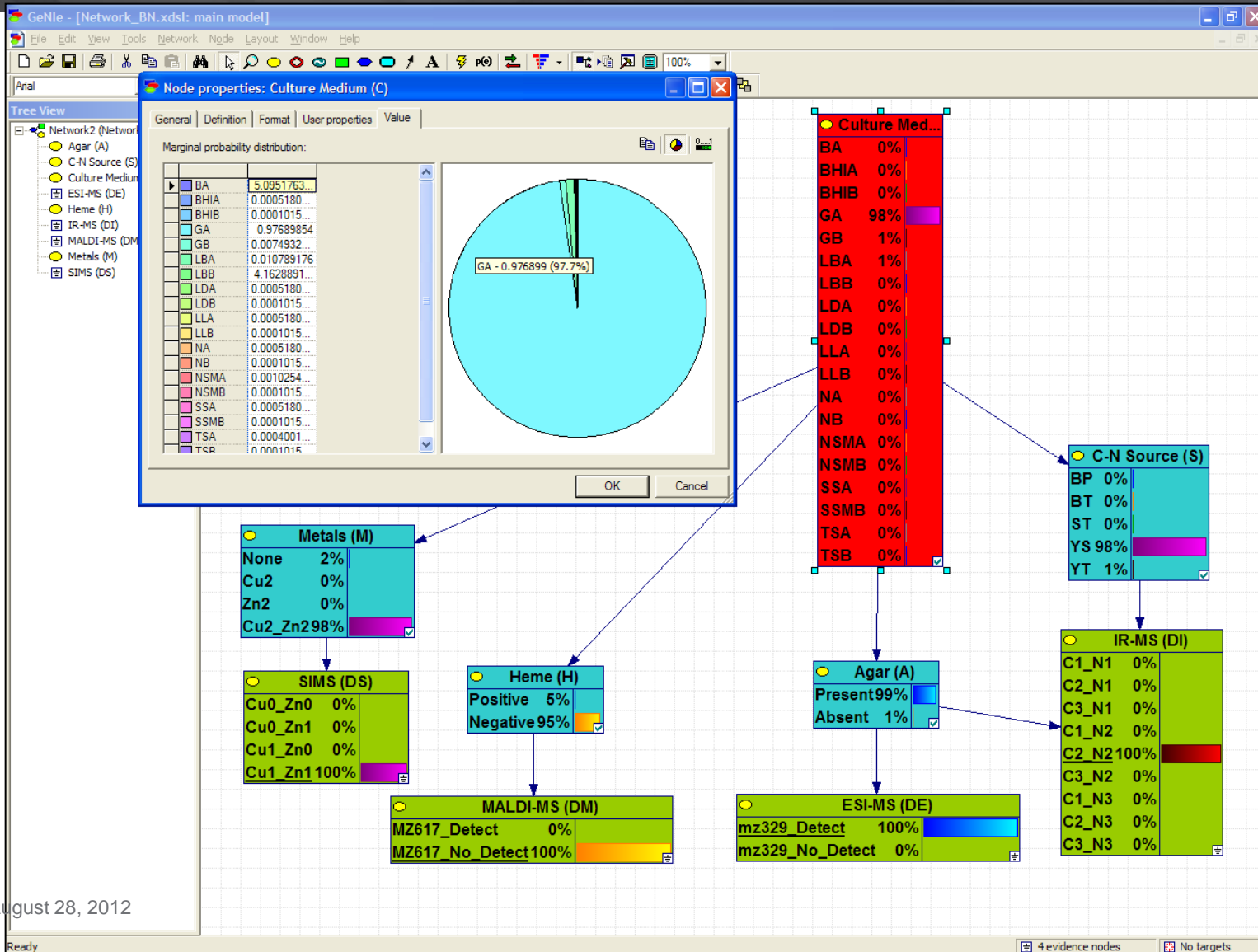
# Approach – Existing Experimentally deriving network (culture media recipe)



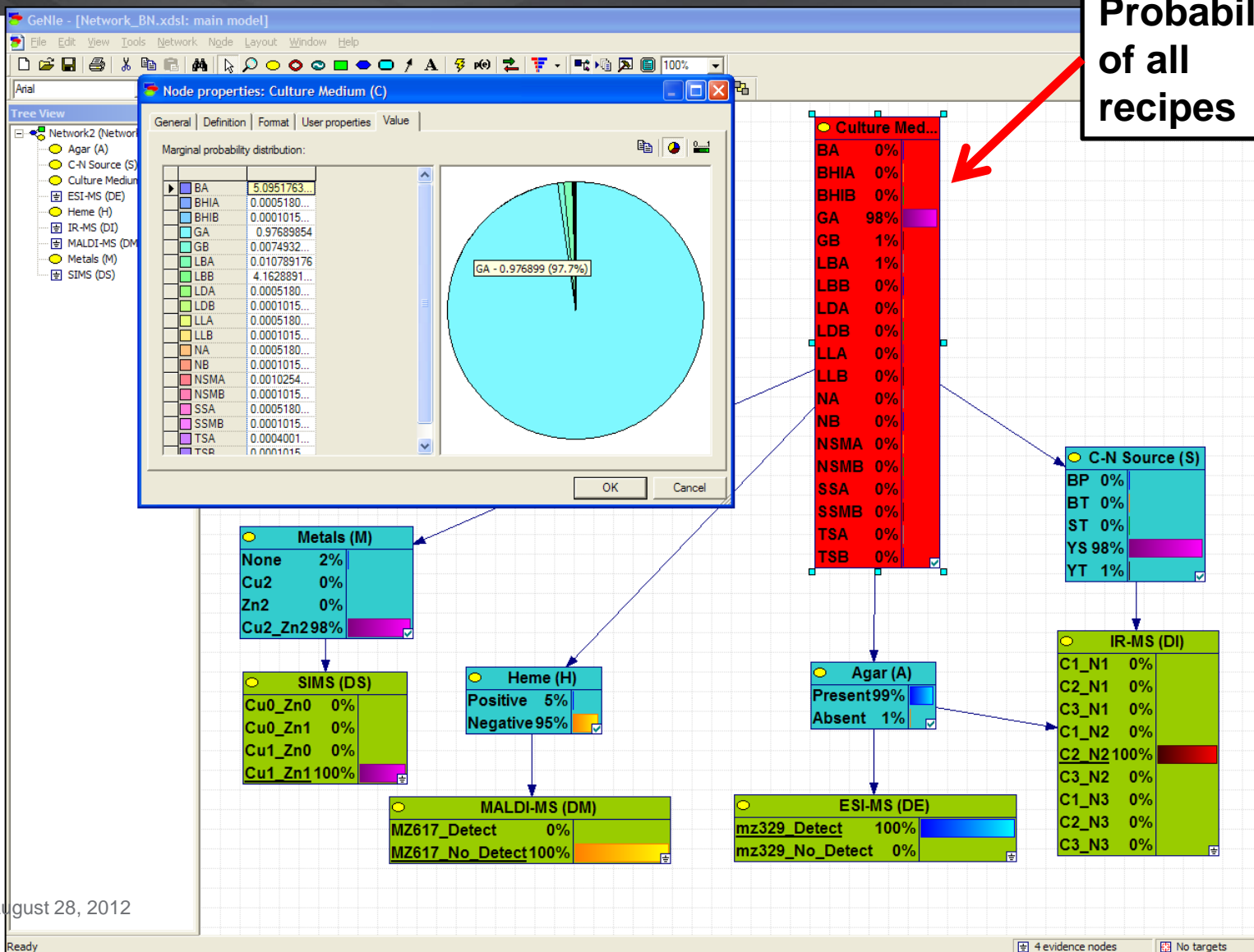
# Approach – Existing Experimentally deriving network (culture media recipe)



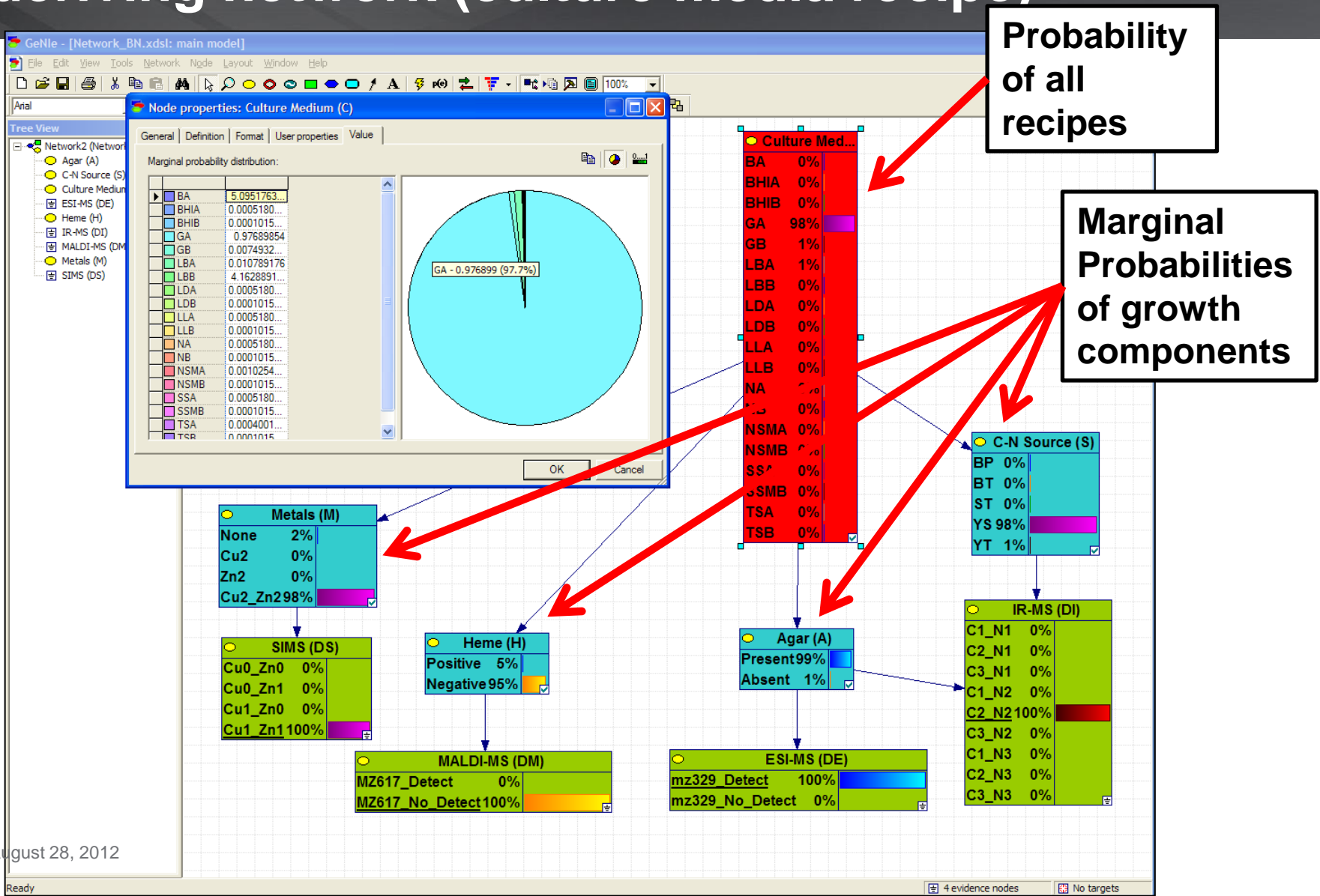
# Approach – Existing Experimentally deriving network (culture media recipe)



# Approach – Existing Experimentally deriving network (culture media recipe)



# Approach – Existing Experimentally deriving network (culture media recipe)

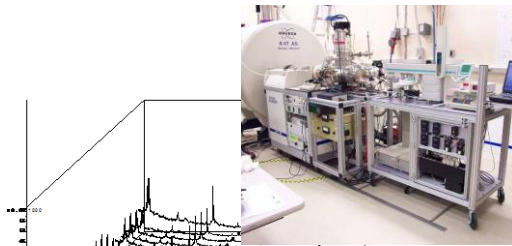




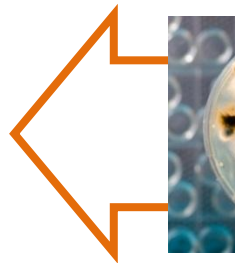


# Integration Problem – Building the Bayesian network

How can you identify institutions that have experience with the kind of culturing practice pointed to by the experimental evidence?



**Experimental Signatures**

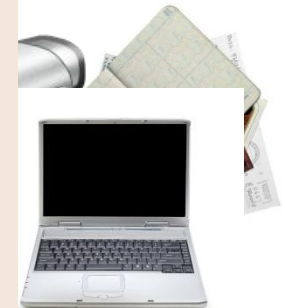


**RESULTS**

Ranked list of *candidate Institutions* where sample could have been grown

$P(\text{Institution}_k | \text{Experimental Data})$

1	23% @ Institution A
2	22% @ Institution B
3	15% @ Institution C
4	8% @ Institution D
5	...



**Intelligence**



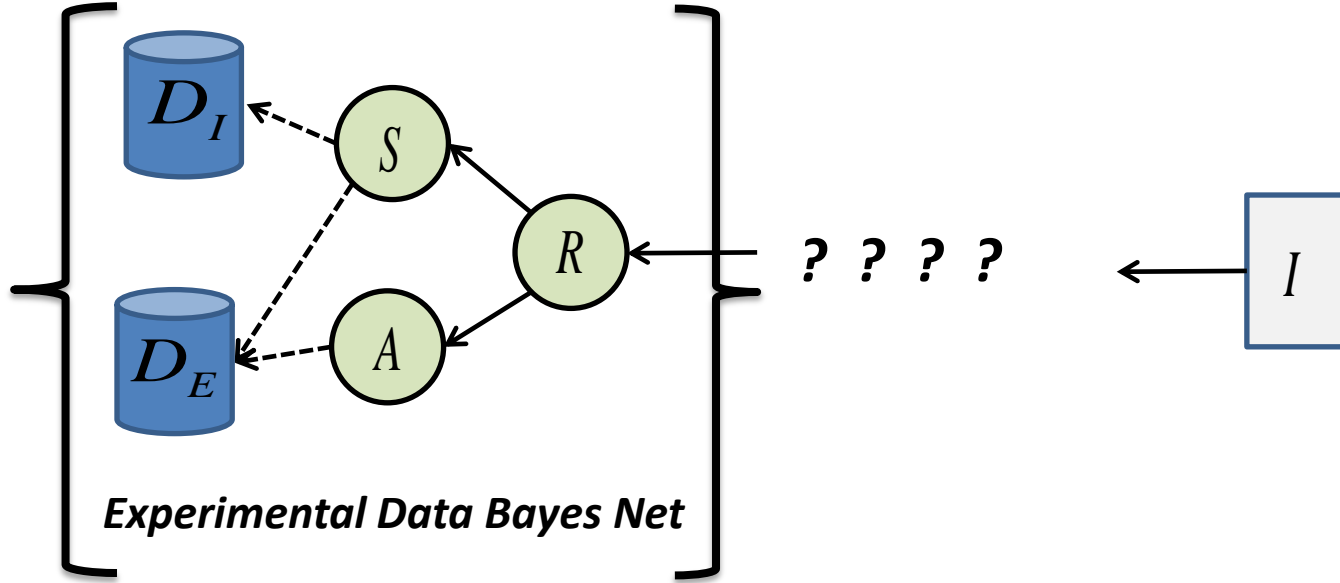




# Integration Problem – Building the Bayesian network

How can you identify institutions that have experience with the kind of culturing practice pointed to by the experimental evidence?

$$P(I_j | D_E, D_I)$$



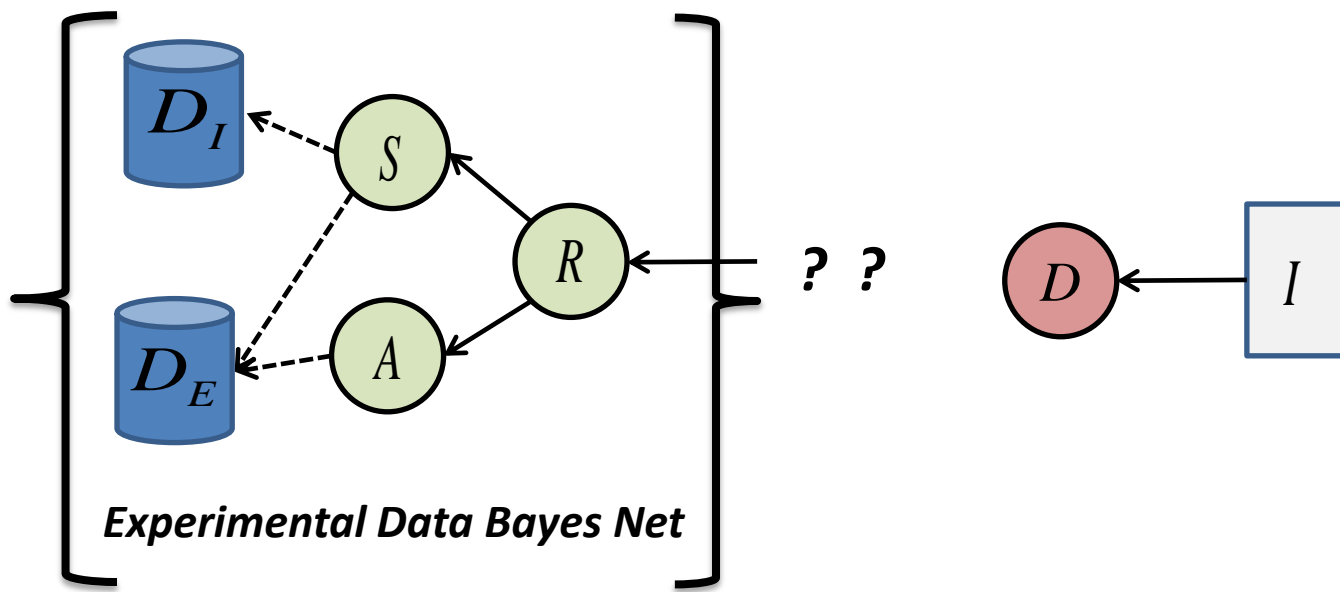
*Prediction of culturing recipe from institution is not feasible.*



# Integration Problem – Building the Bayesian network

How can you identify institutions that have experience with the kind of culturing practice pointed to by the experimental evidence?

$$P(I_j | D_E, D_I)$$



*Institutions tie to documents*

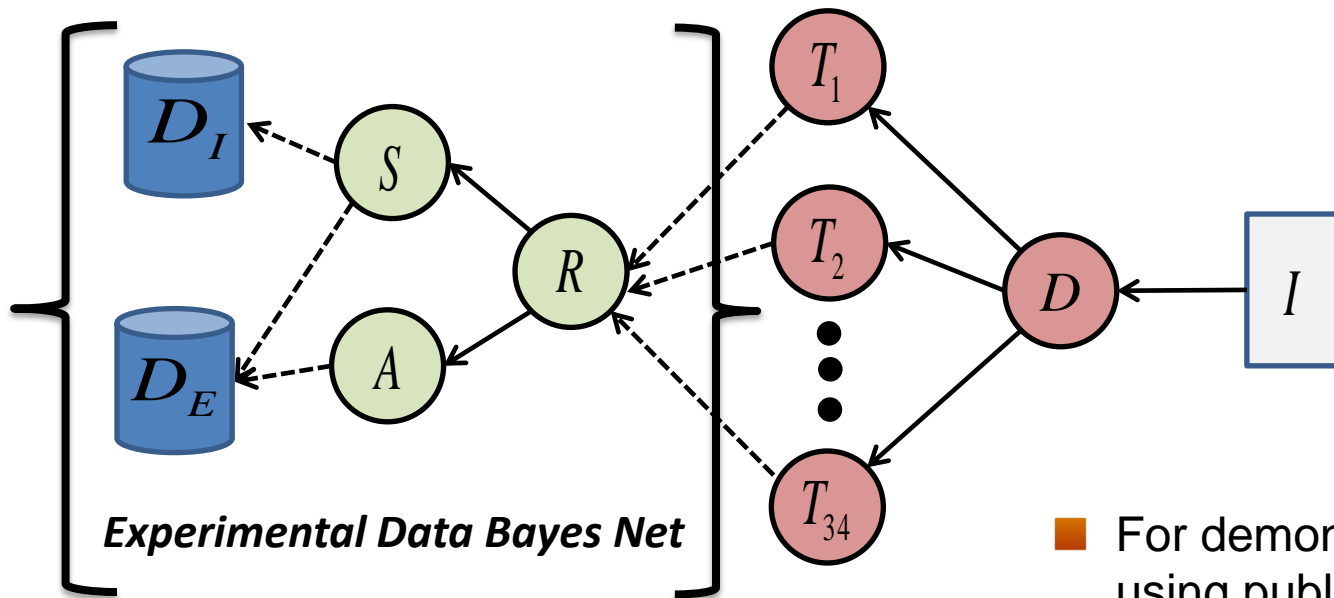
*Challenge to predict recipes directly from document*



# Integration Problem – Building the Bayesian network

How can you identify institutions that have experience with the kind of culturing practice pointed to by the experimental evidence?

$$P(I_j | D_E, D_I)$$



*Use  
automated  
text  
scanning  
(key words)*

- For demonstration we focus on using published journal articles in the public domain.



# Integration Problem – Building the Bayesian network

How can you identify institutions that have experience with the kind of culturing practice pointed to by the experimental evidence?

$$P(I_j | D_E, D_I)$$

Use automated



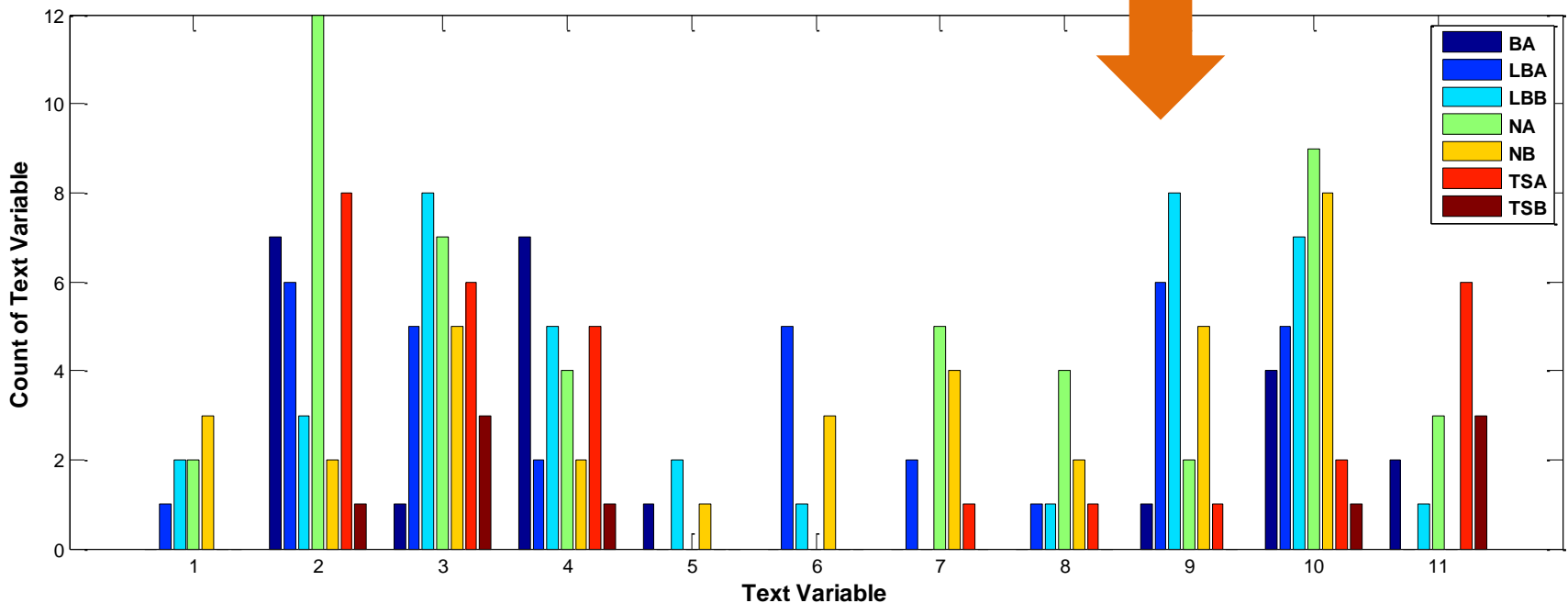
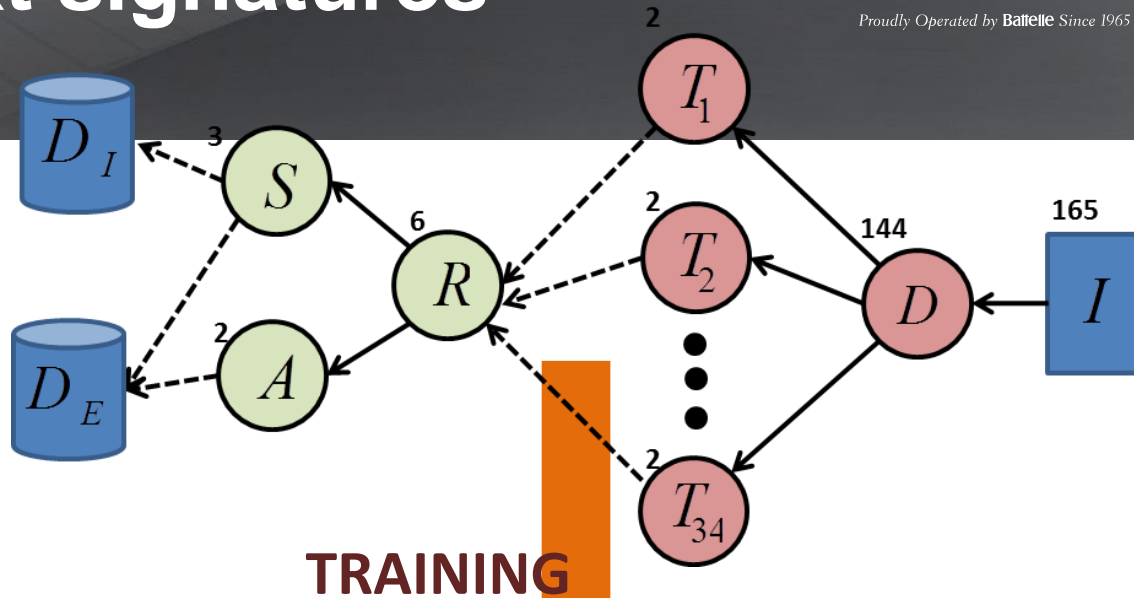
$$P(I_j | D_E, D_I) = \frac{\sum_D \sum_T \sum_R \sum_S \sum_A P(D_E | A) P(D_E, D_I | S) P(A | R) P(S | R) \prod_q [P(R | T^{(q)}) P(T^{(q)} | D)] P(D | I) P(I)}{\sum_I \sum_D \sum_T \sum_R \sum_S \sum_A P(D_E | A) P(D_E, D_I | S) P(A | R) P(S | R) \prod_q [P(R | T^{(q)}) P(T^{(q)} | D)] P(D | I) P(I)}$$



- For demonstration we focus on using published journal articles in the public domain.

# Open-source text signatures

Hand curated documents show a discriminatory pattern between culture medium recipes



## INFORMATION

- ▶ 144 total documents
  - 52 documents hand curated
  - 92 additional documents
- ▶ 165 institutions

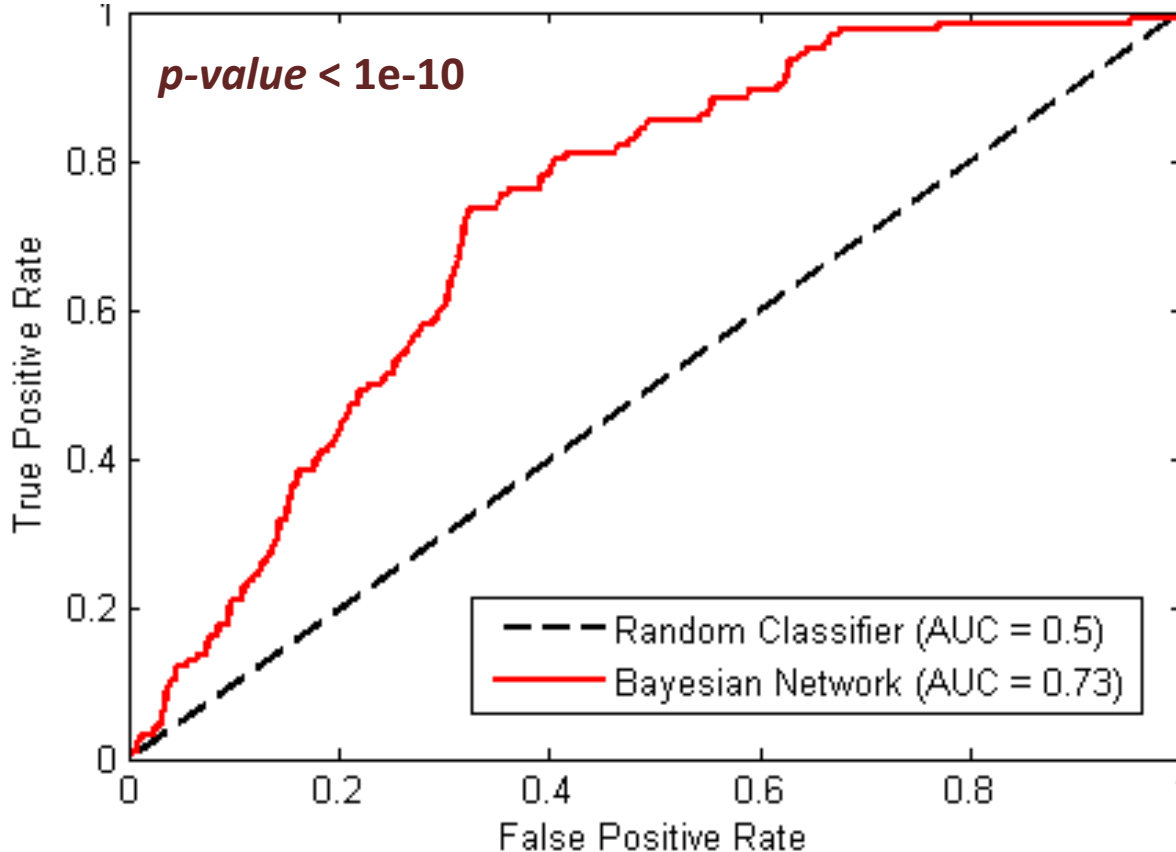
## EVALUATION

- ▶ Cross-validation (bootstrapping): 52 documents
- ▶ Area under Receiver Operating Characteristic curve (AUC)

***Random Classifier will given an AUC of 0.5***

***Perfect Classifier will give an AUC of 1.0***

# AUC Statistically Higher than Random



- Issues with Validation
  - Presumably many “false” are “true”
  - Limited to the culture medias of the hand curation

**Bayesian**

$0.71 \pm 0.17$

**Random**

$0.48 \pm 0.124$

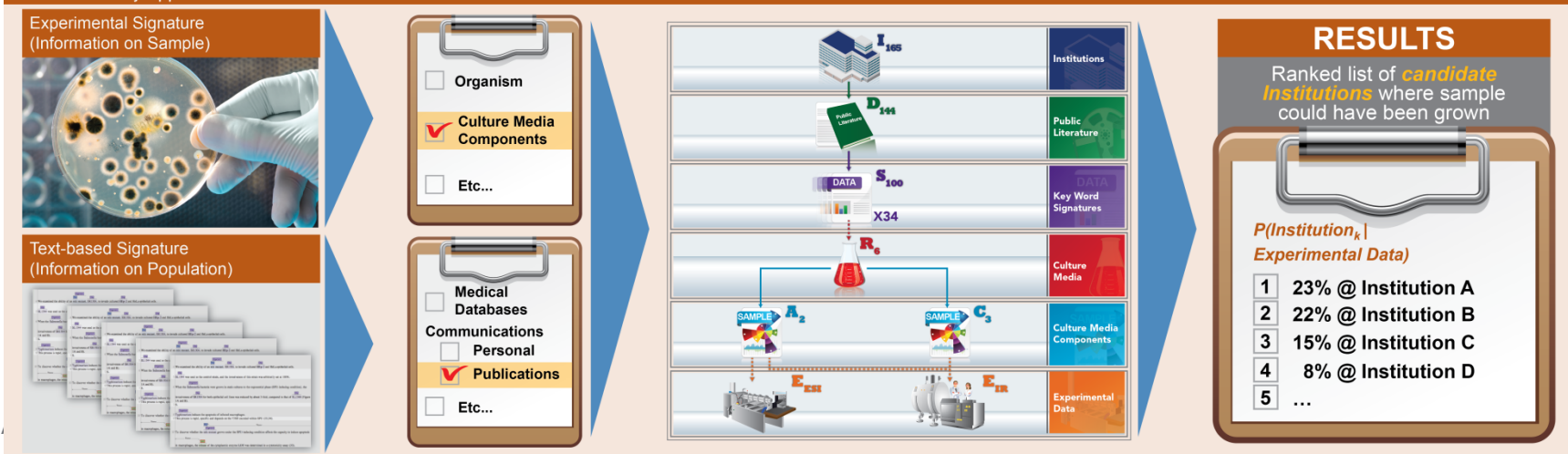




# Advantages of the Bayesian Network Approach

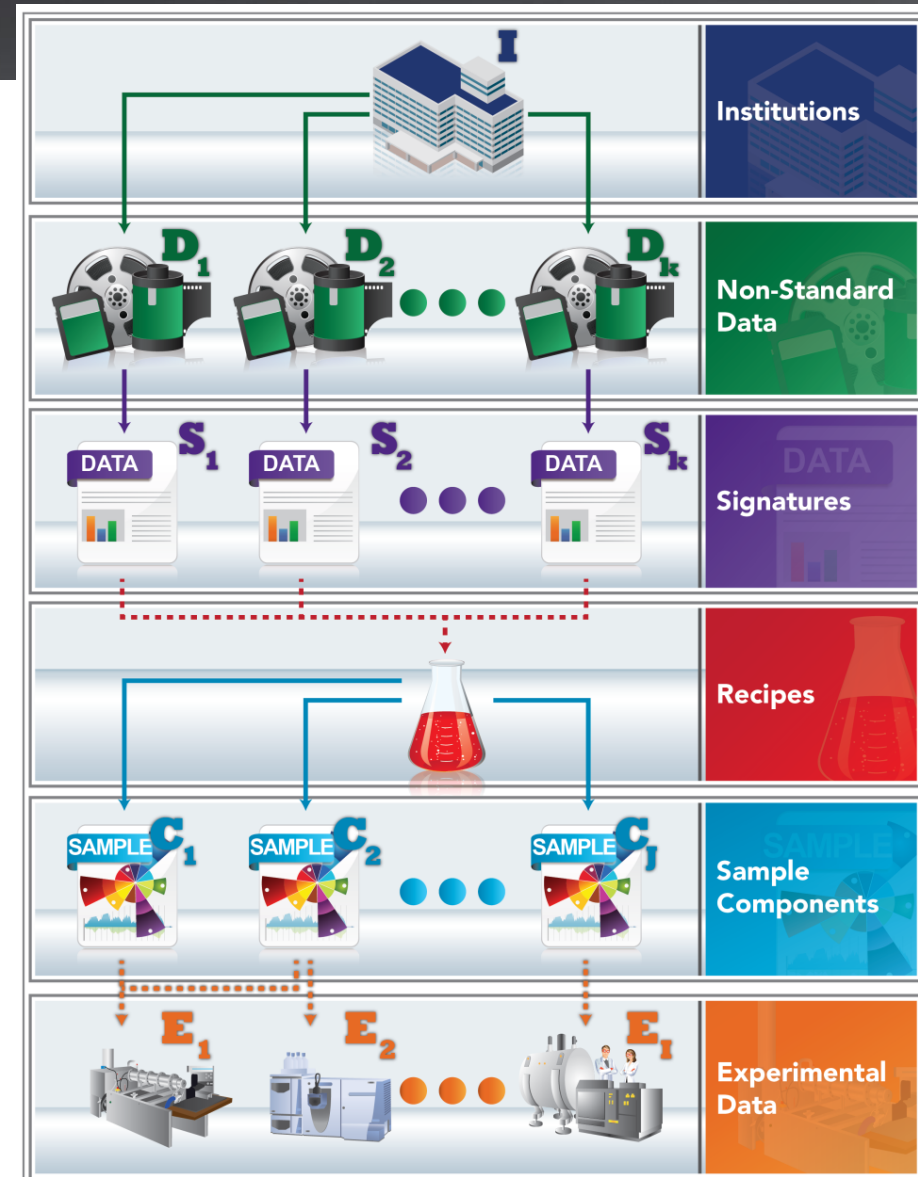
- ▶ More experimental and/or soft data streams can be added
- ▶ Modify the final probability (e.g., foreign vs. domestic, individual researchers)
- ▶ Automated approach, any number of documents (institutions, people) can be evaluated
- ▶ ***Yields a easy to interpret confidence metric***

FIGURE 1 - Basic analysis pipeline



# Looking Forward: Bioforensics and Biosurveillance

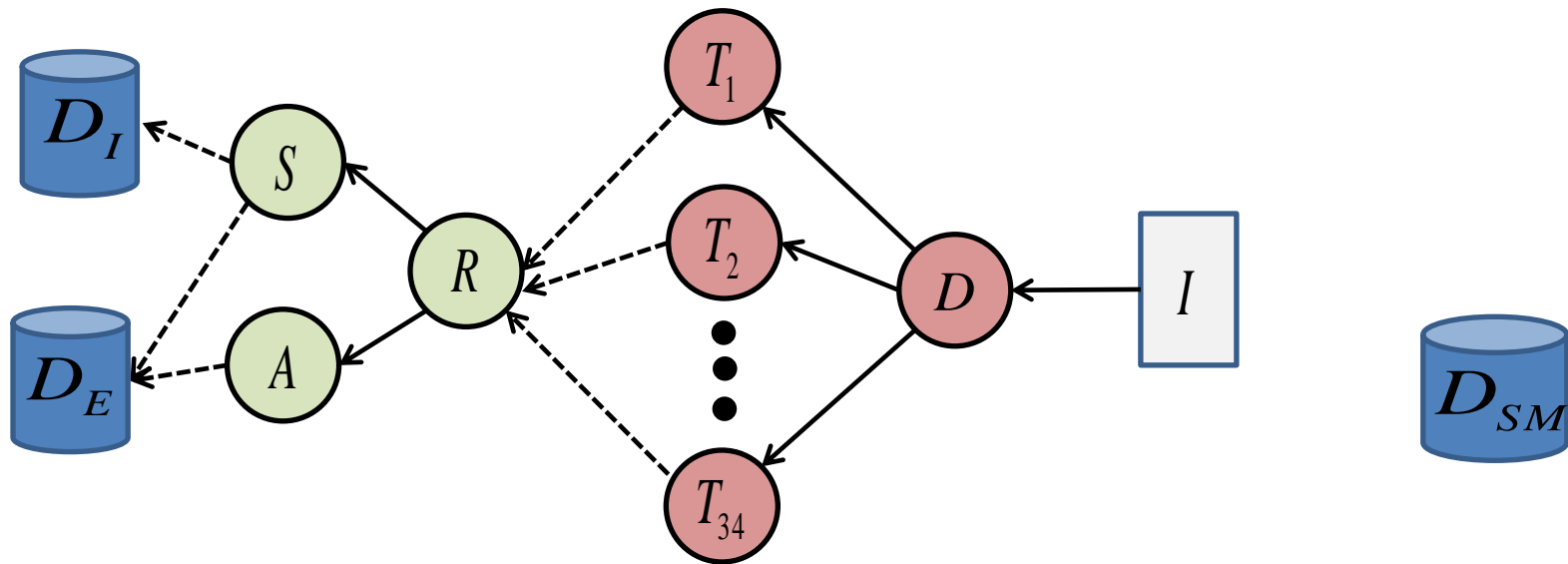
- ▶ Expand to include more “who” and “where”
  - Means more nodes, types of information (e.g., social media)
- ▶ Dynamic Bayesian networks
  - Evaluate a “threat” over time





# Adding non-traditional “soft” data to the existing network

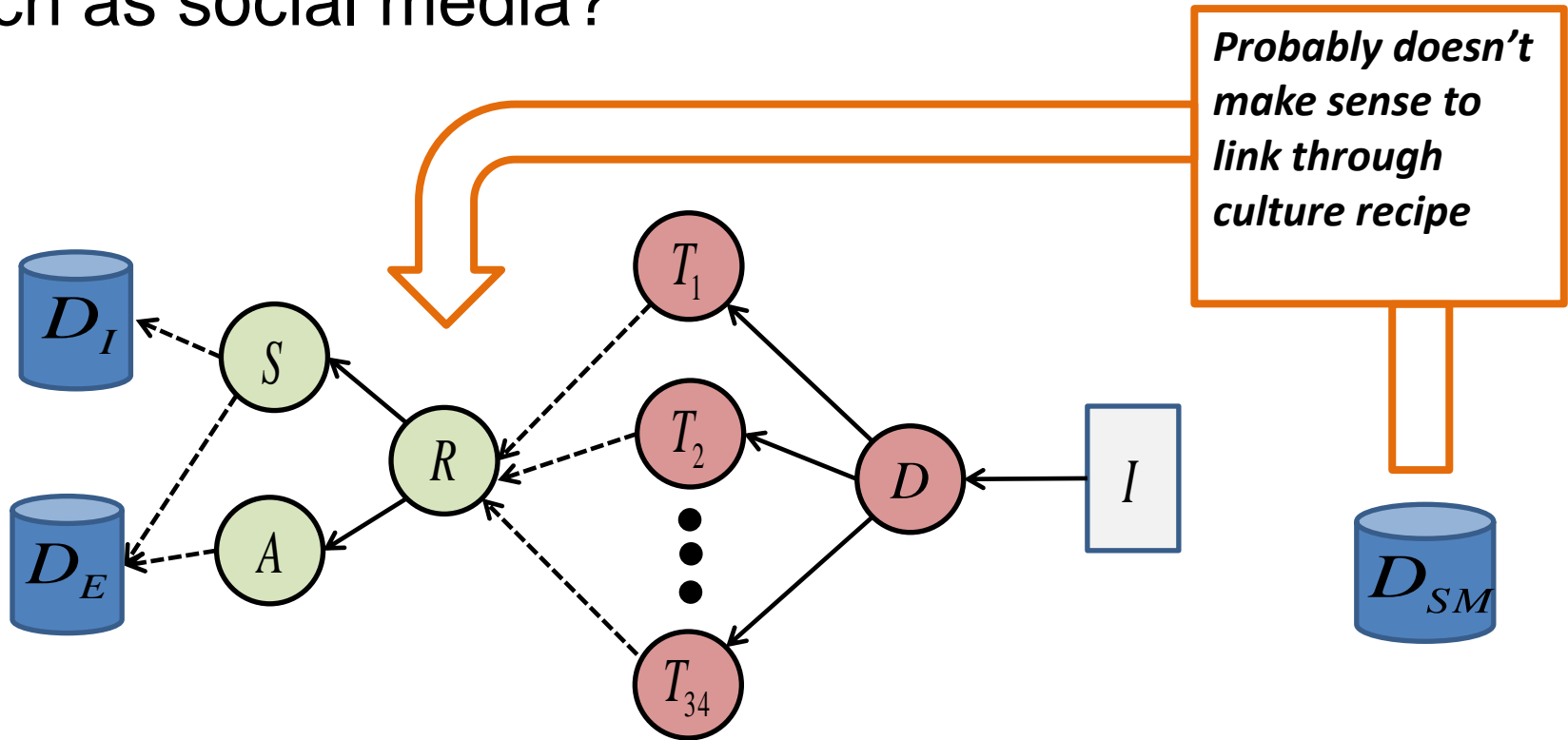
How can we link in some new source of soft data, such as social media?





# Adding non-traditional “soft” data to the existing network

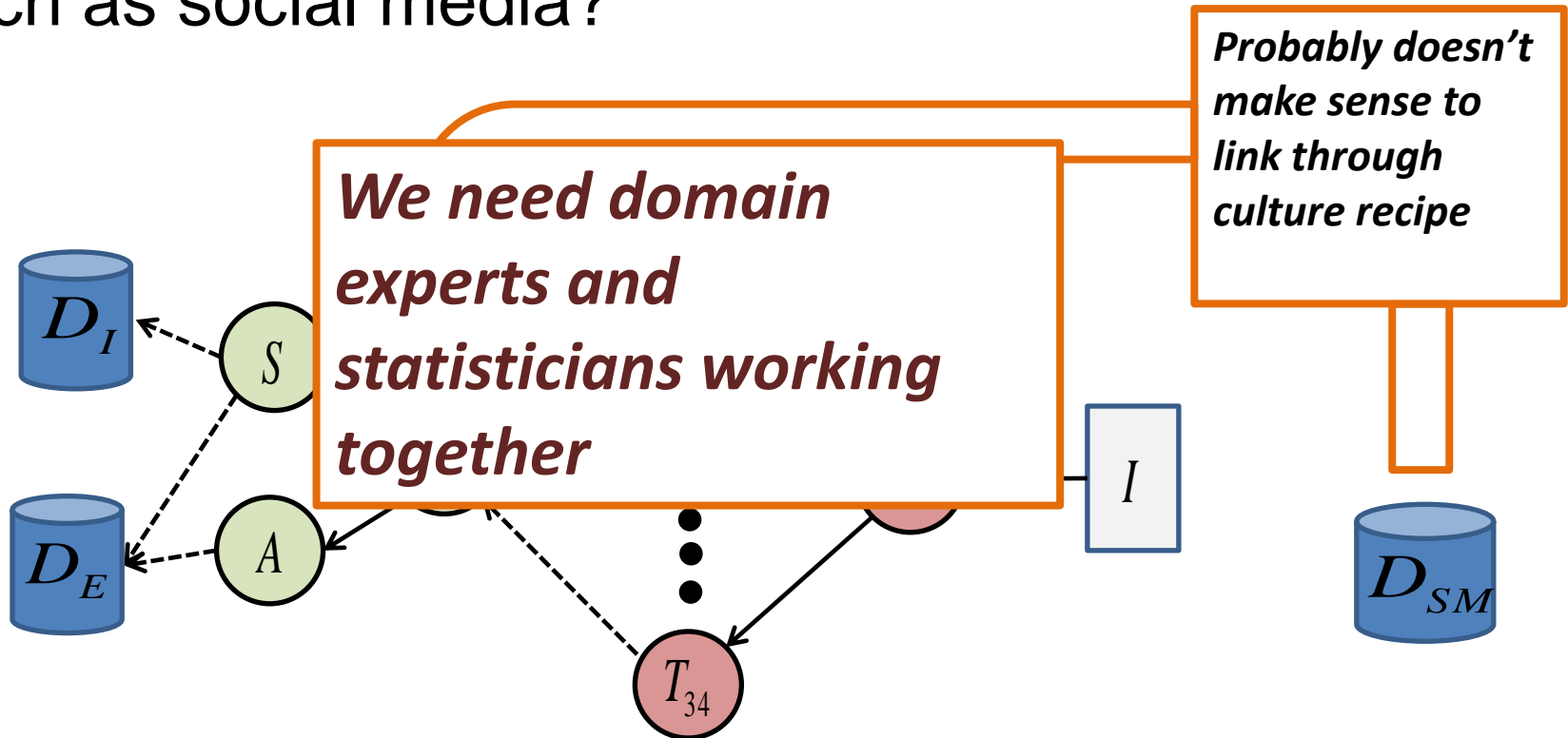
How can we link in some new source of soft data, such as social media?





# Adding non-traditional “soft” data to the existing network

How can we link in some new source of soft data, such as social media?

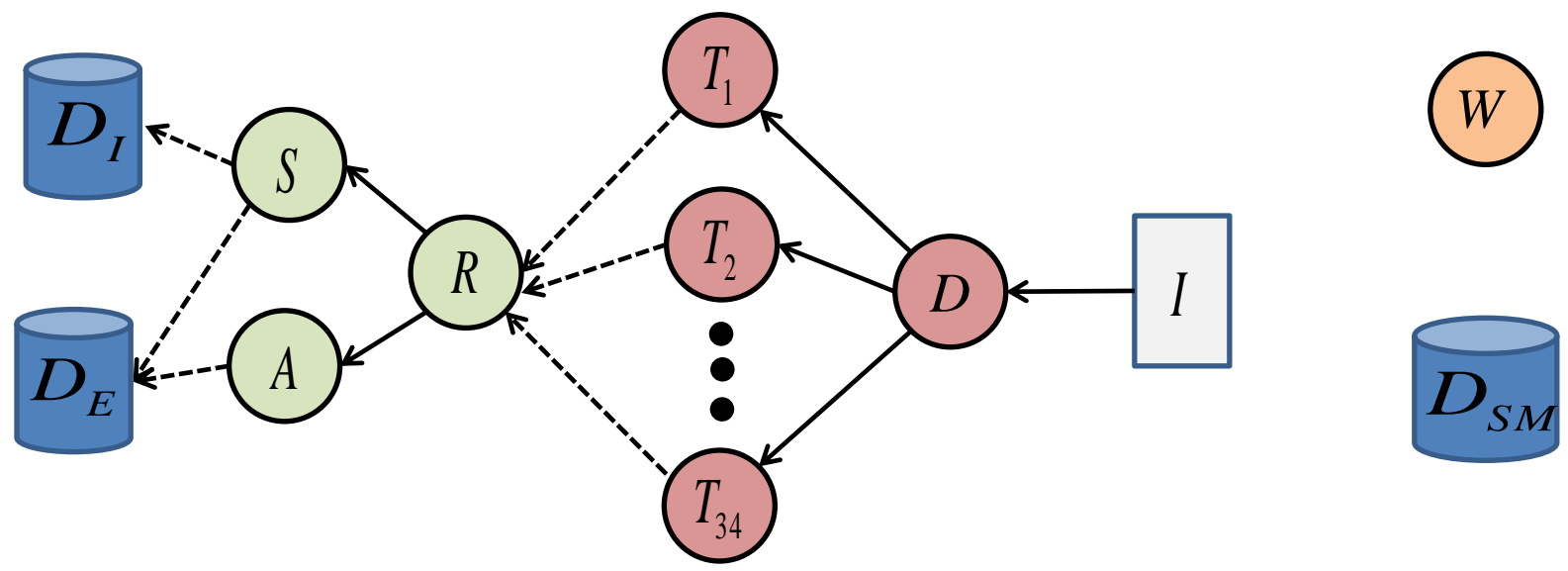




# Adding non-traditional “soft” data to the existing network

One approach would be to add a “warning” node

- ▶ Compute the probability that there is a threat ( $W$ ) given the “individual” and data source ( $D_{SM}$ )

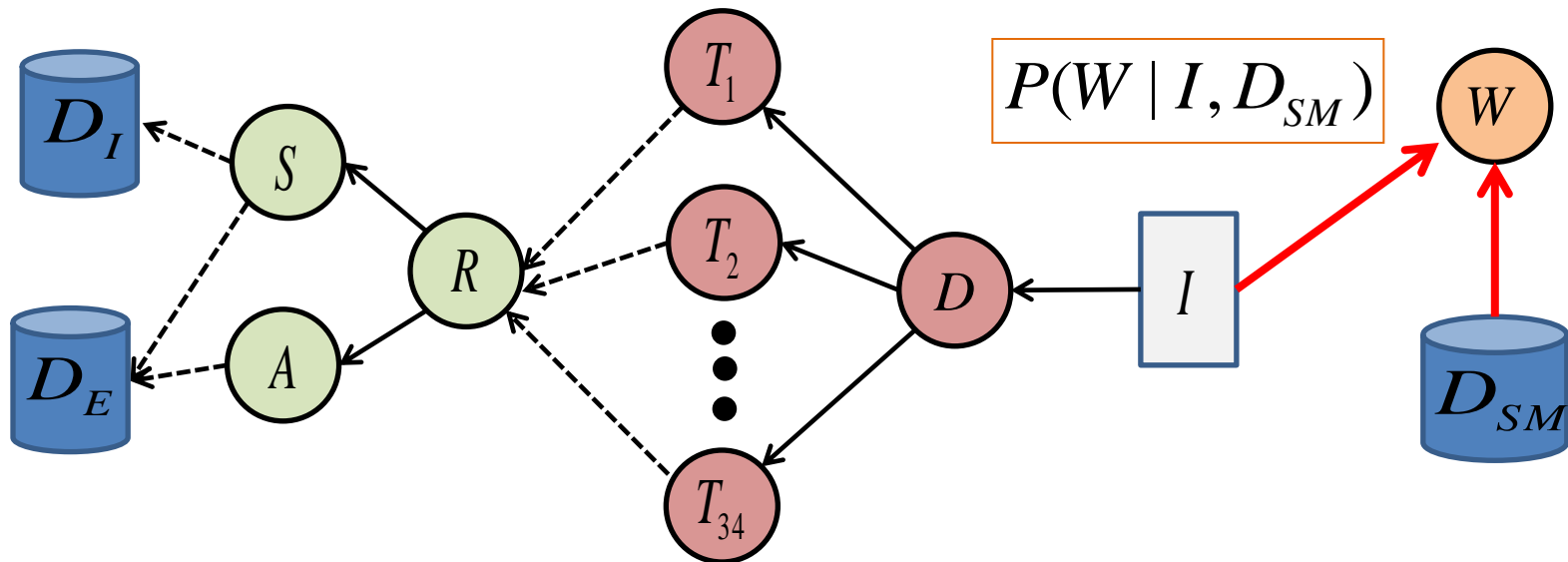




# Adding non-traditional “soft” data to the existing network

One approach would be to add a “warning” node

- ▶ Compute the probability that there is a threat ( $W$ ) given the “individual” and data source ( $D_{SM}$ )



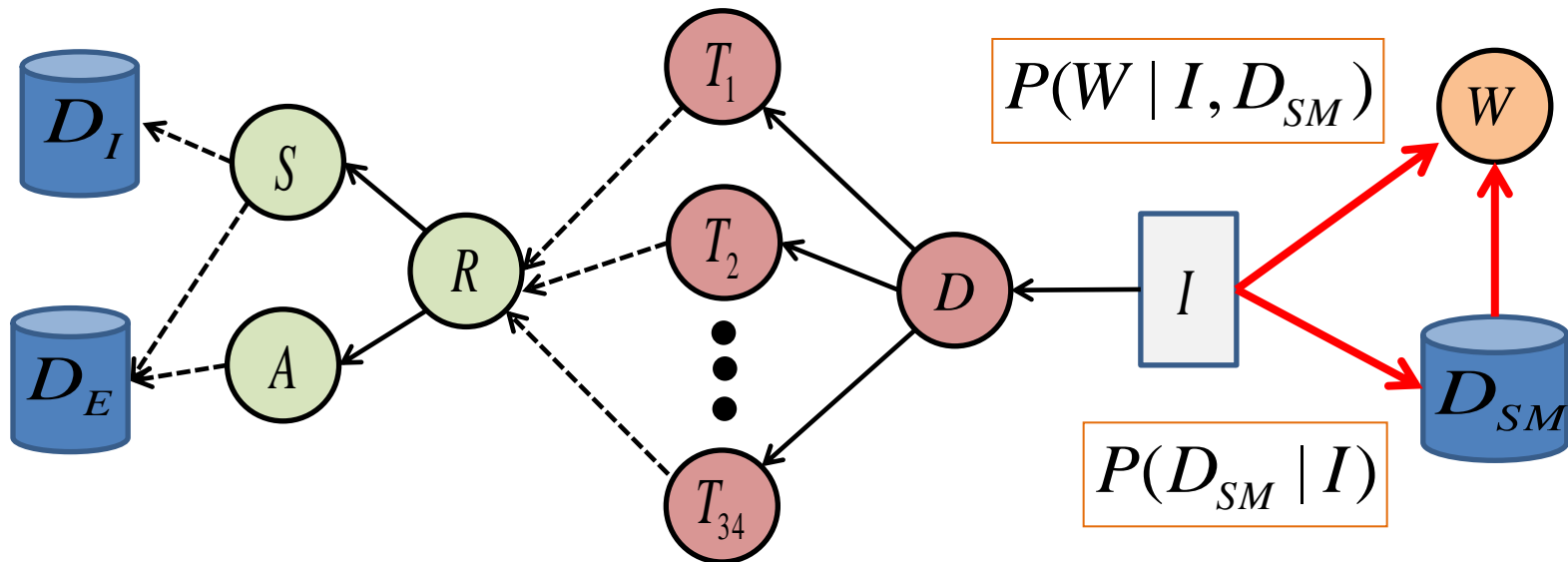




# Adding non-traditional “soft” data to the existing network

One approach would be to add a “warning” node

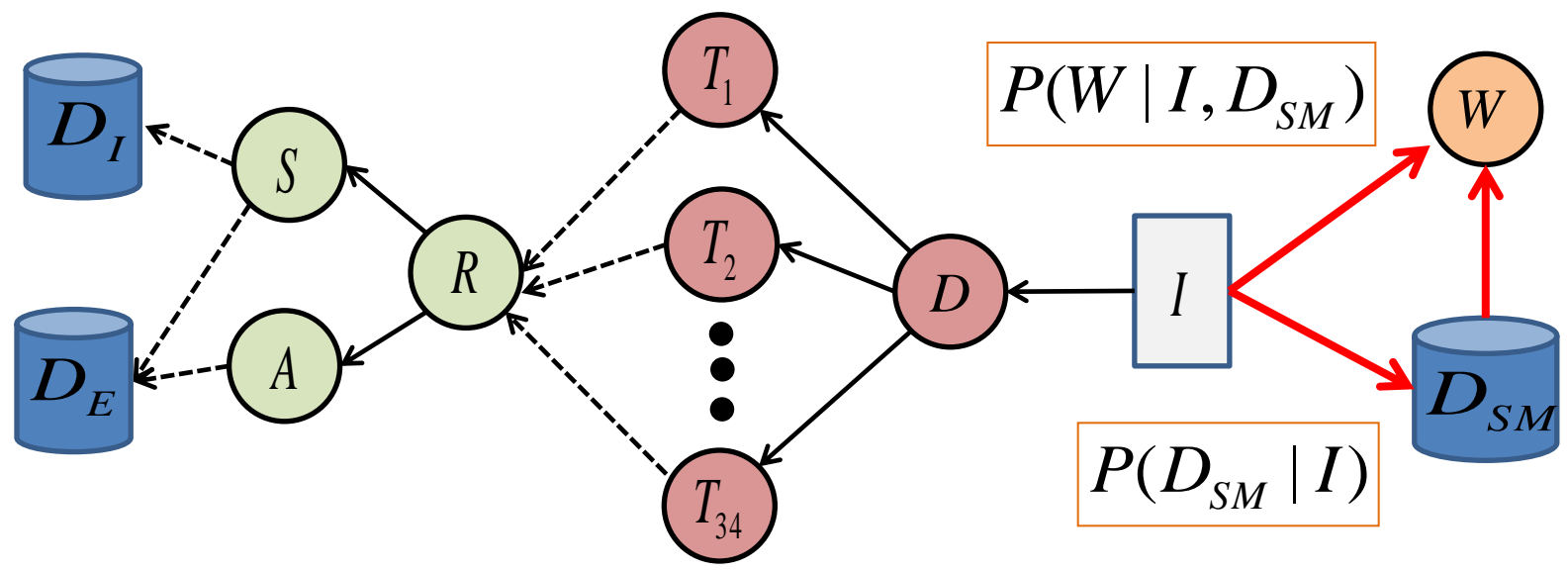
- ▶ Compute the probability that there is a threat ( $W$ ) given the “individual” and data source ( $D_{SM}$ )
- ▶ Link individuals/institutions to social media





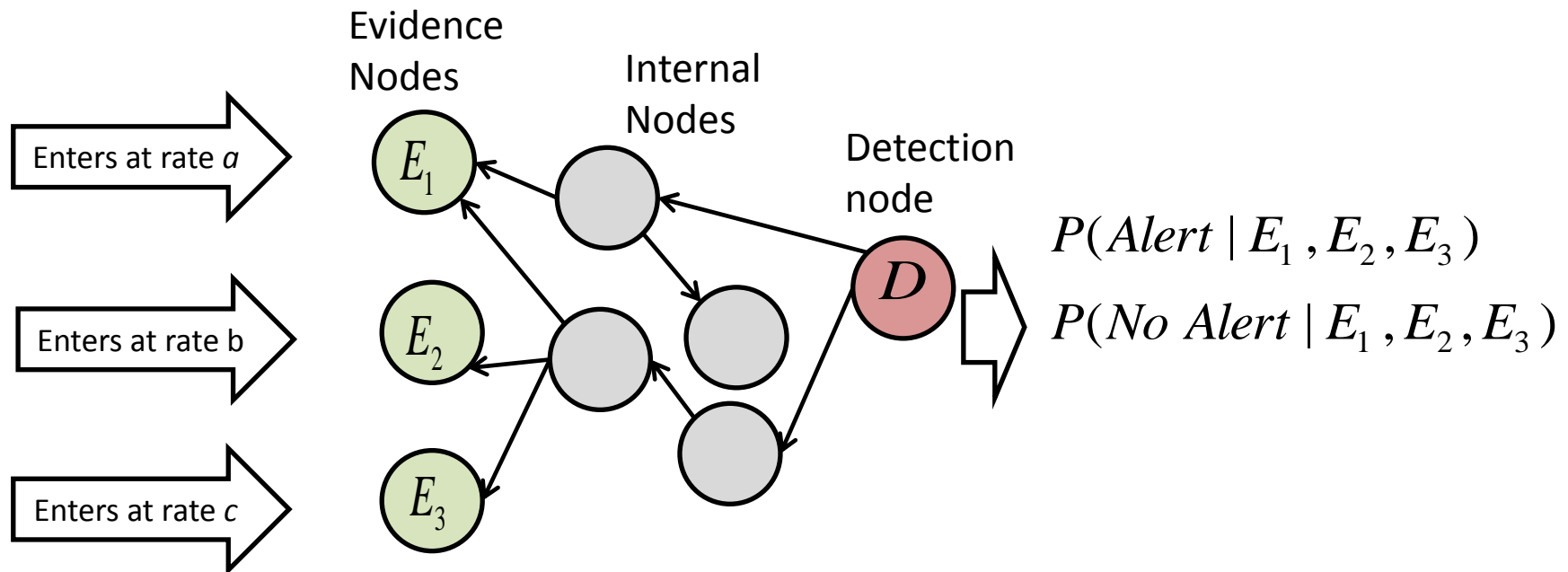
# Adding non-traditional “soft” data to the existing network

$$P(I_j | D_E, D_I, D_{SM}) = \frac{\sum_{I \dots W} \sum P(D_E, D_I | I) P(W | I, D_{SM}) P(D_{SM} | I) P(I)}{\sum_{I \dots W} \sum \sum P(D_E, D_I | I) P(W | I, D_{SM}) P(D_{SM} | I) P(I)}$$



# Adding a dynamic component

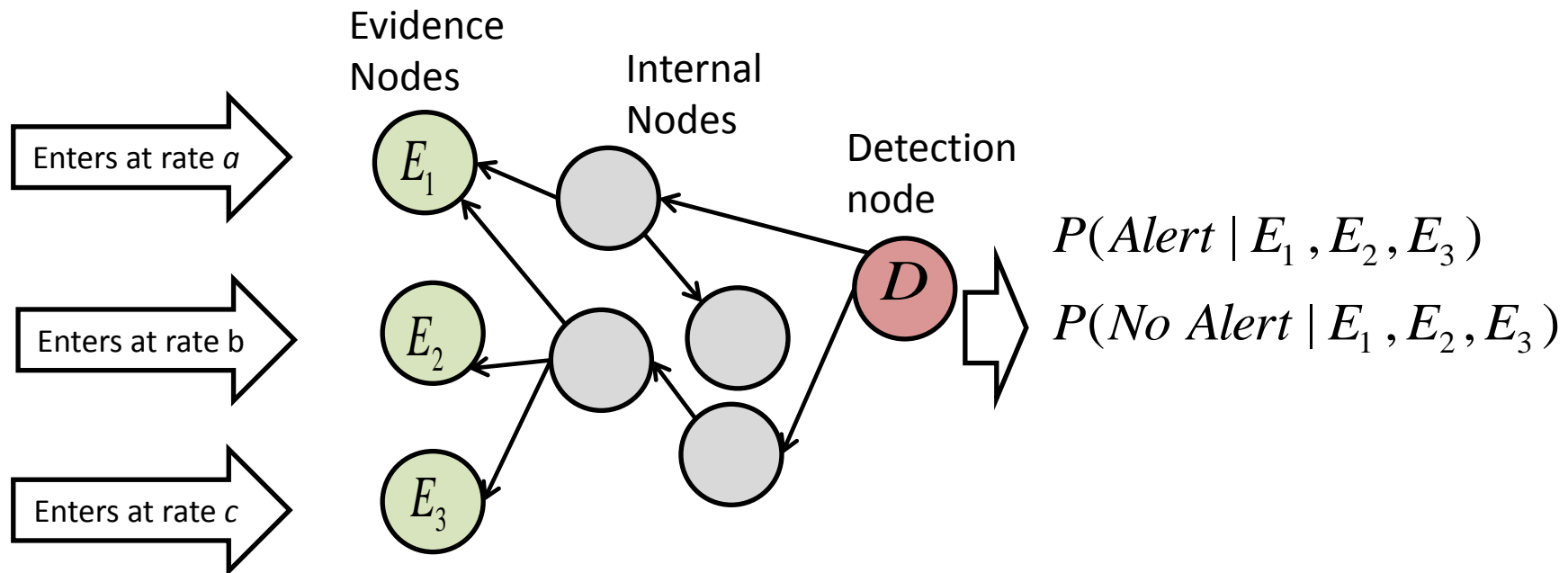
**Generally, integration of multiple 'orthogonal' streams of data improves predictive capability**



# Adding a dynamic component

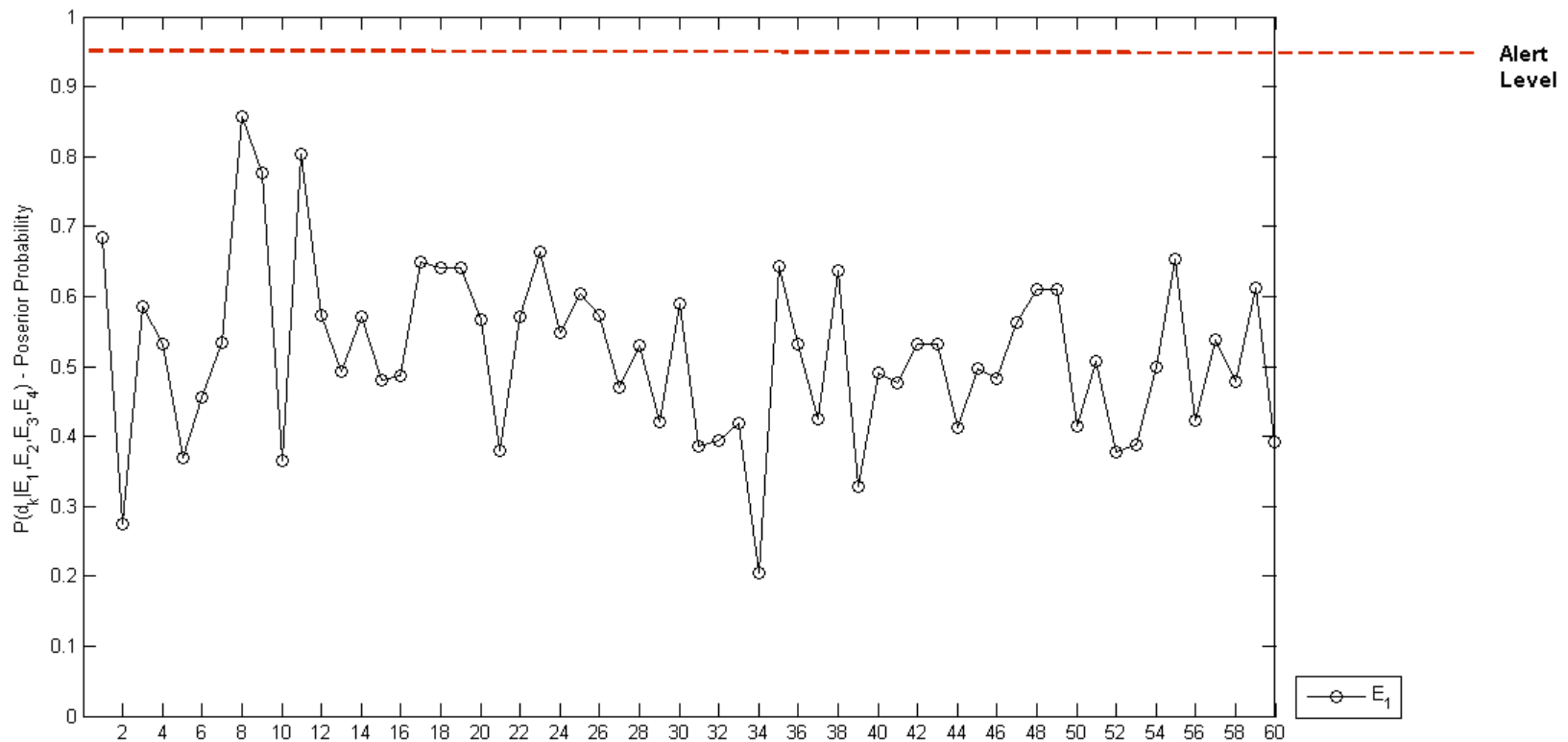
**Generally, integration of multiple ‘orthogonal’ streams of data improves predictive capability**

- ▶ Automated nature of the network allows continual update of the probability at rate of the fastest source of data.



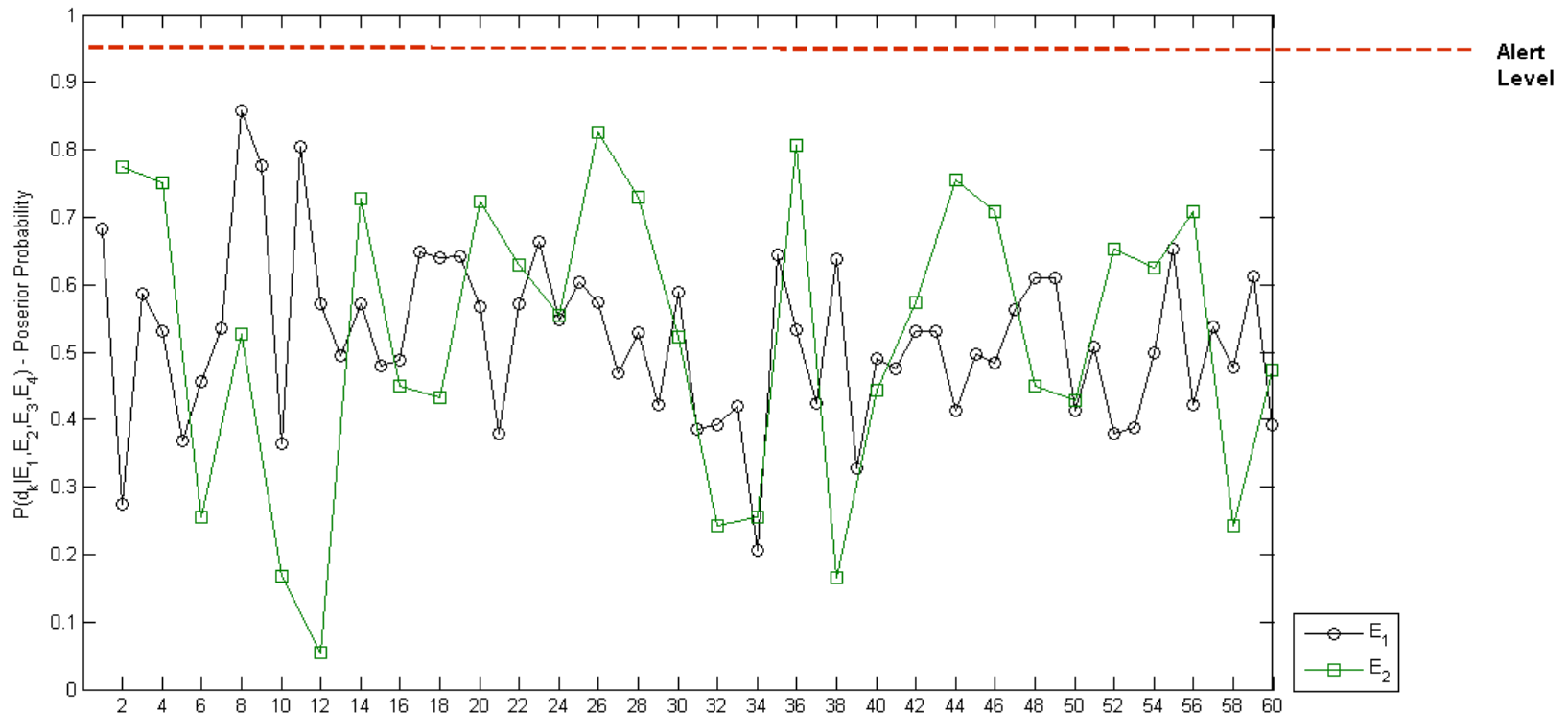
# Adding a dynamic component

Integration can identify an “alert” where individual data streams may not



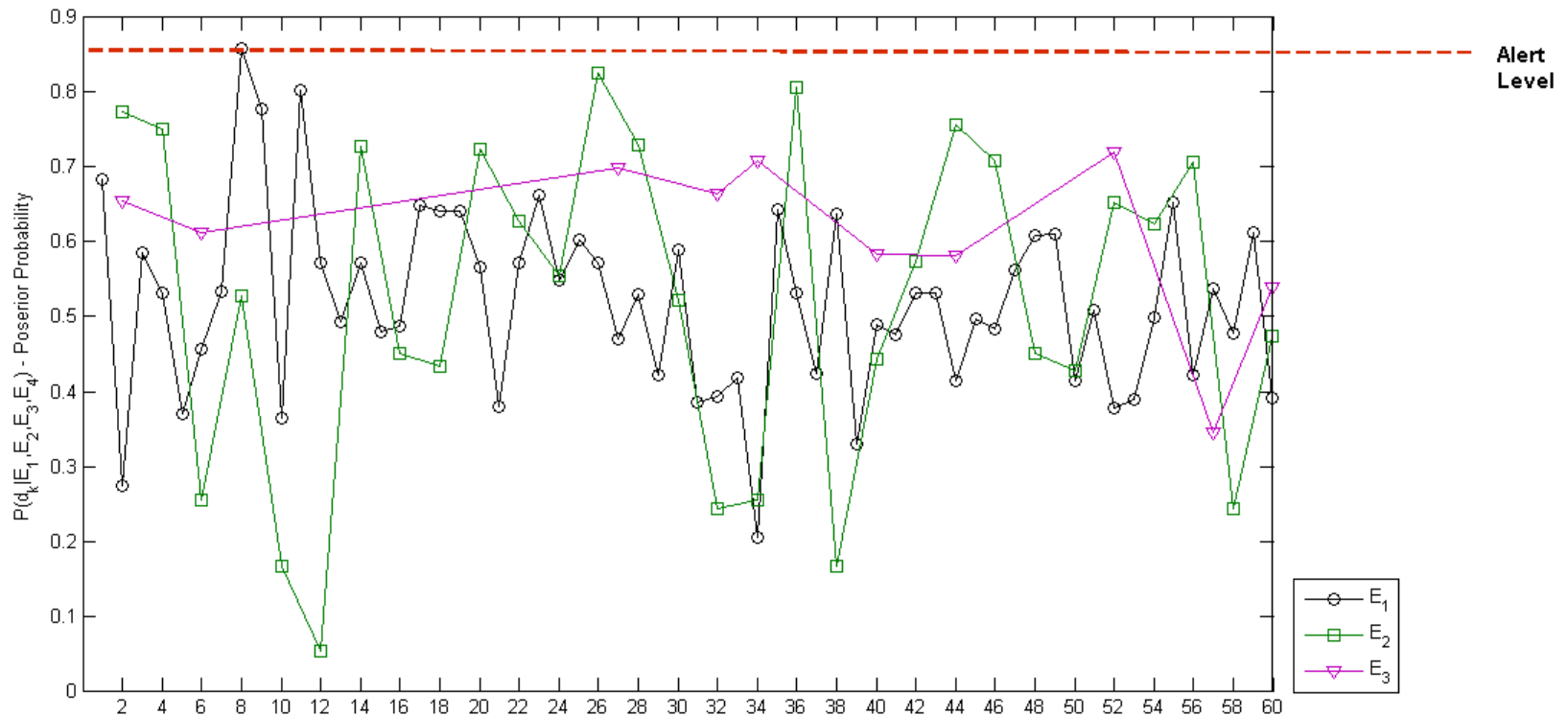
# Adding a dynamic component

Integration can identify an “alert” where individual data streams may not



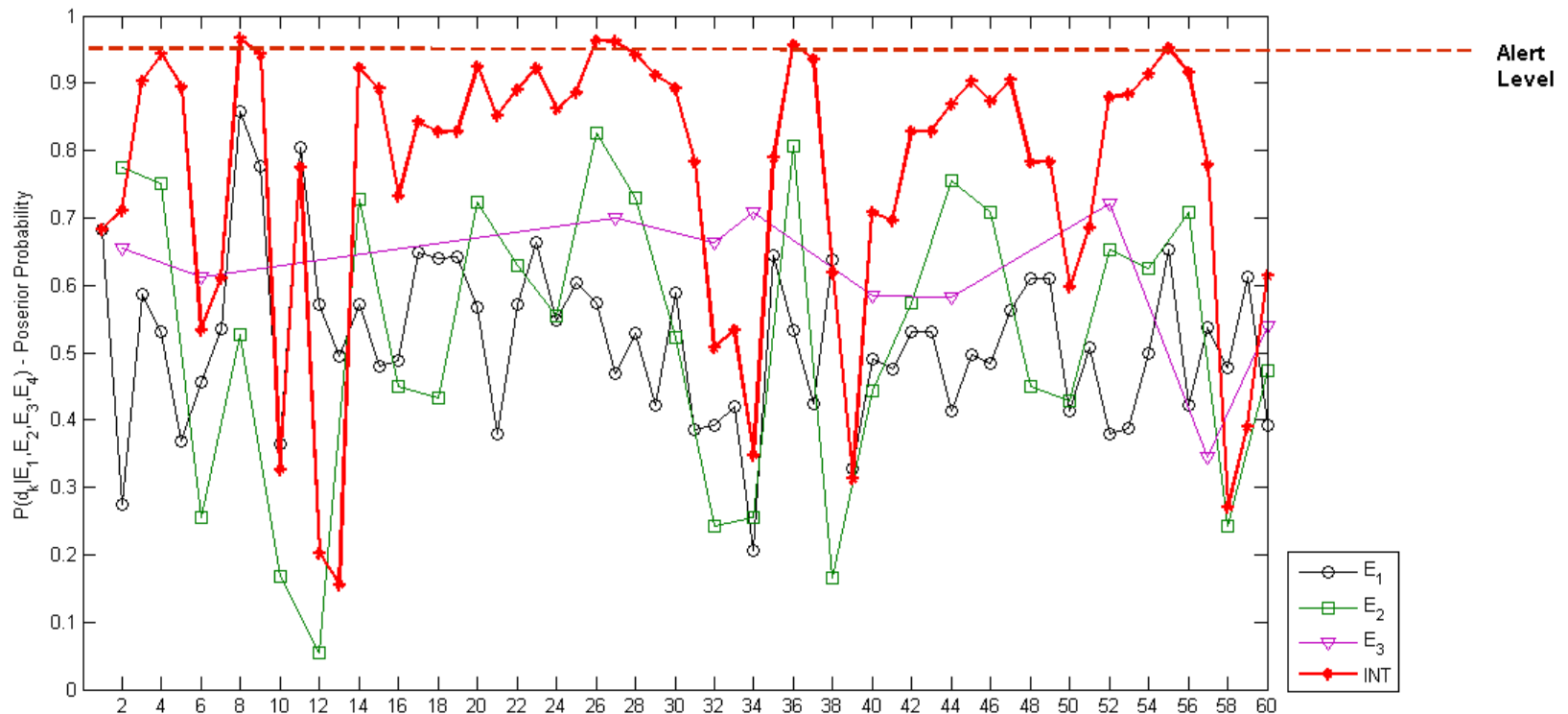
# Adding a dynamic component

Integration can identify an “alert” where individual data streams may not



# Adding a dynamic component

Integration can identify an “alert” where individual data streams may not





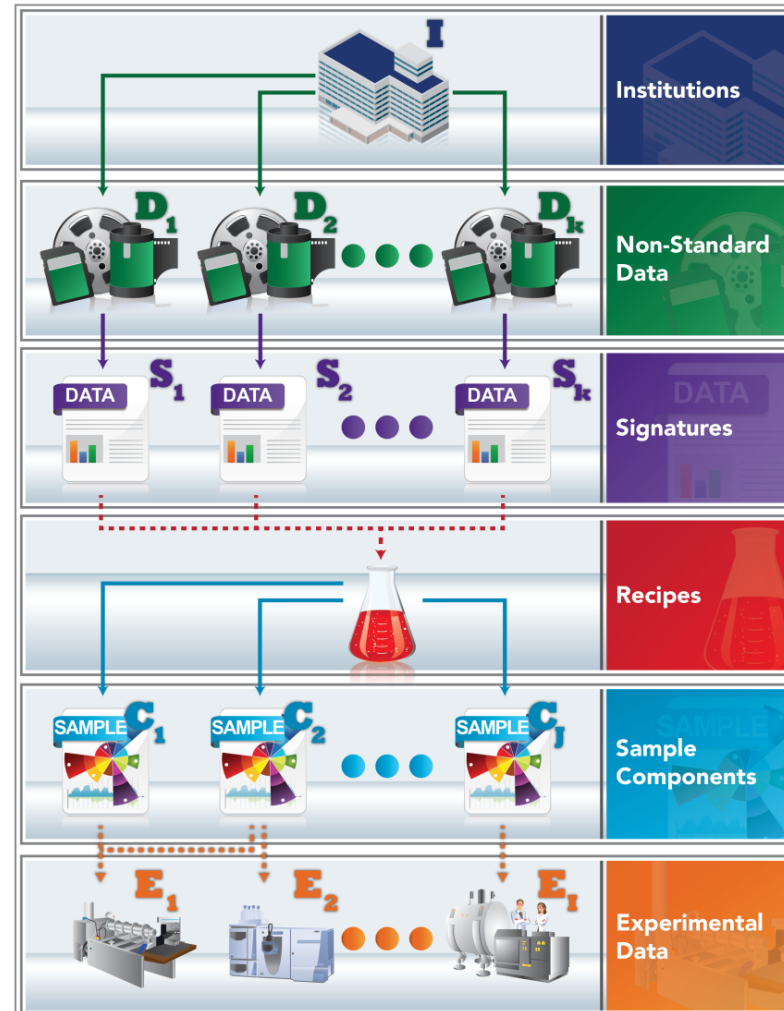
# Acknowledgments

## ▶ Funding

- Department of Homeland Security
- LDRD (Signature Discovery Initiative)

## ▶ Staff

- B Webb-Robertson (statistics)
- Courtney Corley (informatics/text analytics)
- Helen Kreuzer (bioforensics/experimentation)
- Lee Ann McCue (microbiology/Computational Biology)
- Karen Wahl (bioforensics/experimentation)



# Contact Information

**Bobbie-Jo Webb-Robertson**  
**Senior Research Scientist**  
**Computational Biology & Bioinformatics**  
**Pacific Northwest National Laboratory**

**902 Battelle Blvd / J4-33**

**Richland, WA 99352**

**Tel: (509) 375-2292**

**[bj@pnnl.gov](mailto:bj@pnnl.gov)**