Data Fusion & Resource Management (DF&RM) Dual Node Network (DNN) Association Hypothesis Evaluation

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Data Fusion & Neural Networks (DF&NN)

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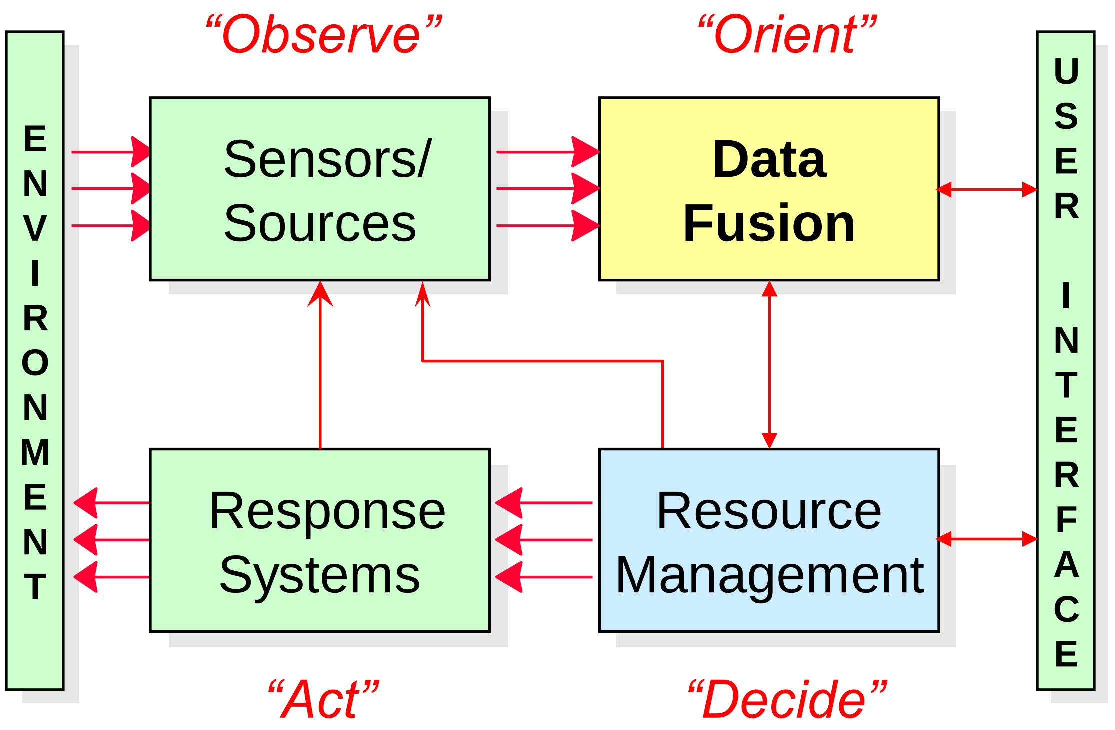
Briefing Objectives

- Provide an understanding of the roles for Data Fusion & Resource Management (DF&RM)
- Describe how the Data Fusion heritage can be used to “jump-start” dual Resource Management solutions
- Describe DF&RM Dual Node Network (DNN) Technical Architecture
- Provide Problem-to-Solution Mappings for Data Association
- Provide Baseline Max A Posteriori (MAP) Data Association Hypothesis Evaluation Equations

AGENDA

- ❖DF&RM Dual Node Network (DNN) Technical Architecture
- ➢Distributed Data Fusion Node Networks
- ➢Data Association Hypothesis Evaluation Alternatives

Fusion & Management Lie in the Gap Between "Observe" and "Act"



- ***Data Fusion*** is the process of combining data/information to estimate or predict the state of some aspect of the world.
- ***Resource Management*** is the process of planning/ controlling response capabilities to meet mission objectives

Sensor Fusion Exploits Sensor Commonalities and Differences

TARGET OR ENTITY OF INTEREST

	DETECTION		KINEMATICS		CLASSIFICATION	
	CONFIDENCE	**COVERT COVERAGE**	**RANGE**	**ANGLE**	**CLASS**	**TYPE**
RADAR	FAIR	POOR	GOOD	FAIR	FAIR	POOR
EO/IR	FAIR	FAIR	POOR	GOOD	FAIR	FAIR
SIGINT	FAIR	FAIR	FAIR	FAIR	GOOD	GOOD

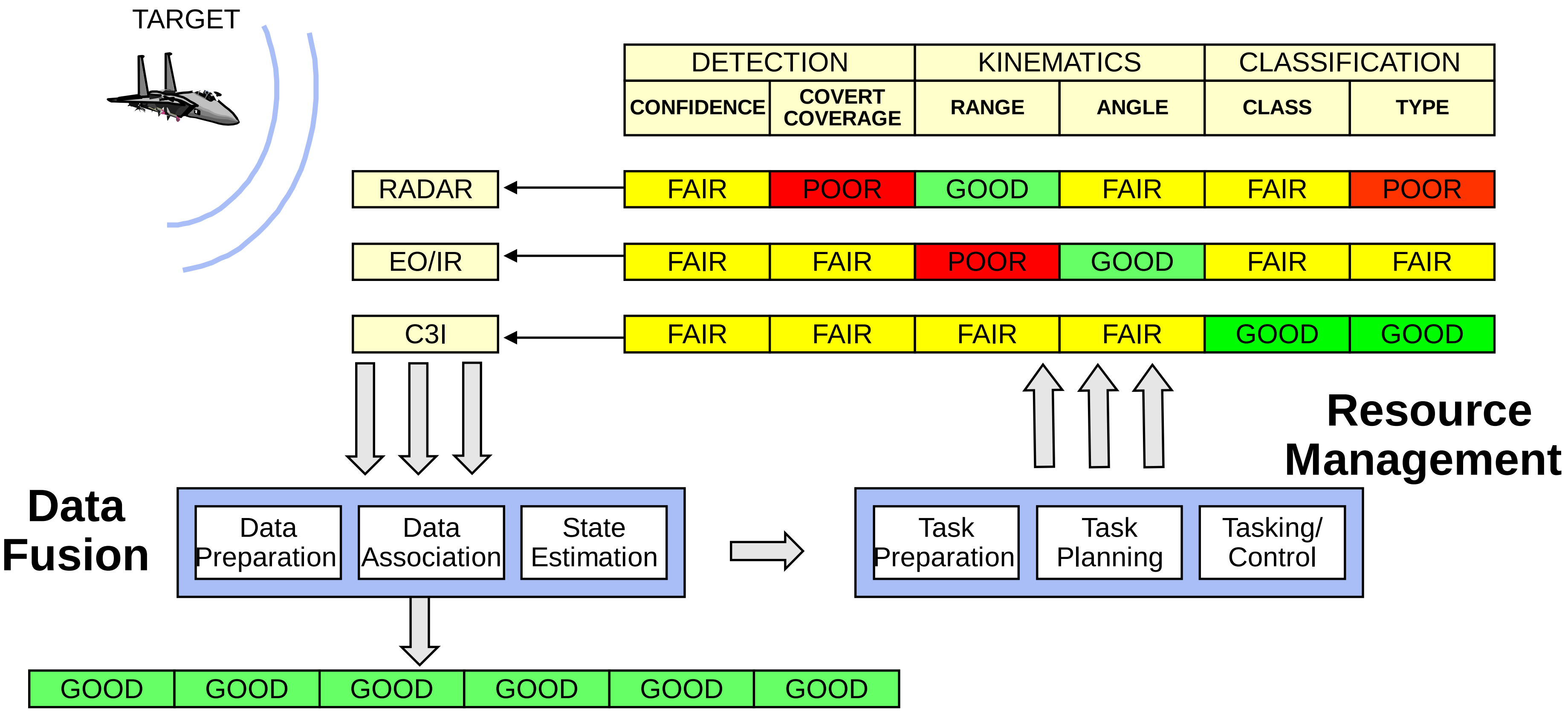
Data Fusion

Data Preparation | Data Association | State Estimation

GOOD	GOOD	GOOD	GOOD	GOOD	GOOD

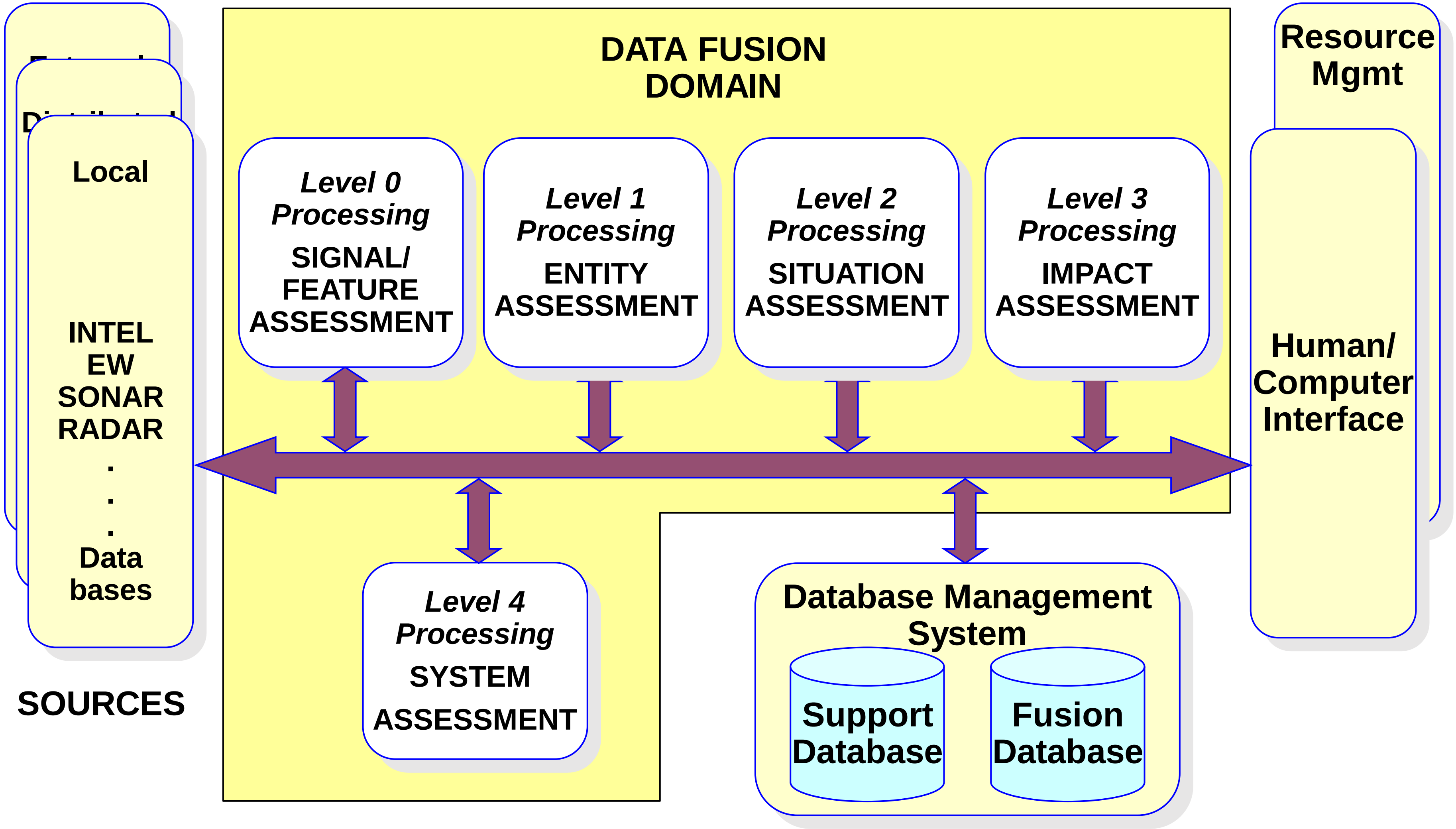
Data Association Uses Overlapping Sensor Capabilities so that State Estimation Can Exploit their Synergies

Resource Management Exploits Sensor Commonalities & Differences
(Sensor Management Example)



Sensor Task Planning Uses Overlapping Sensor Capabilities so that Control Can Exploit their Synergies

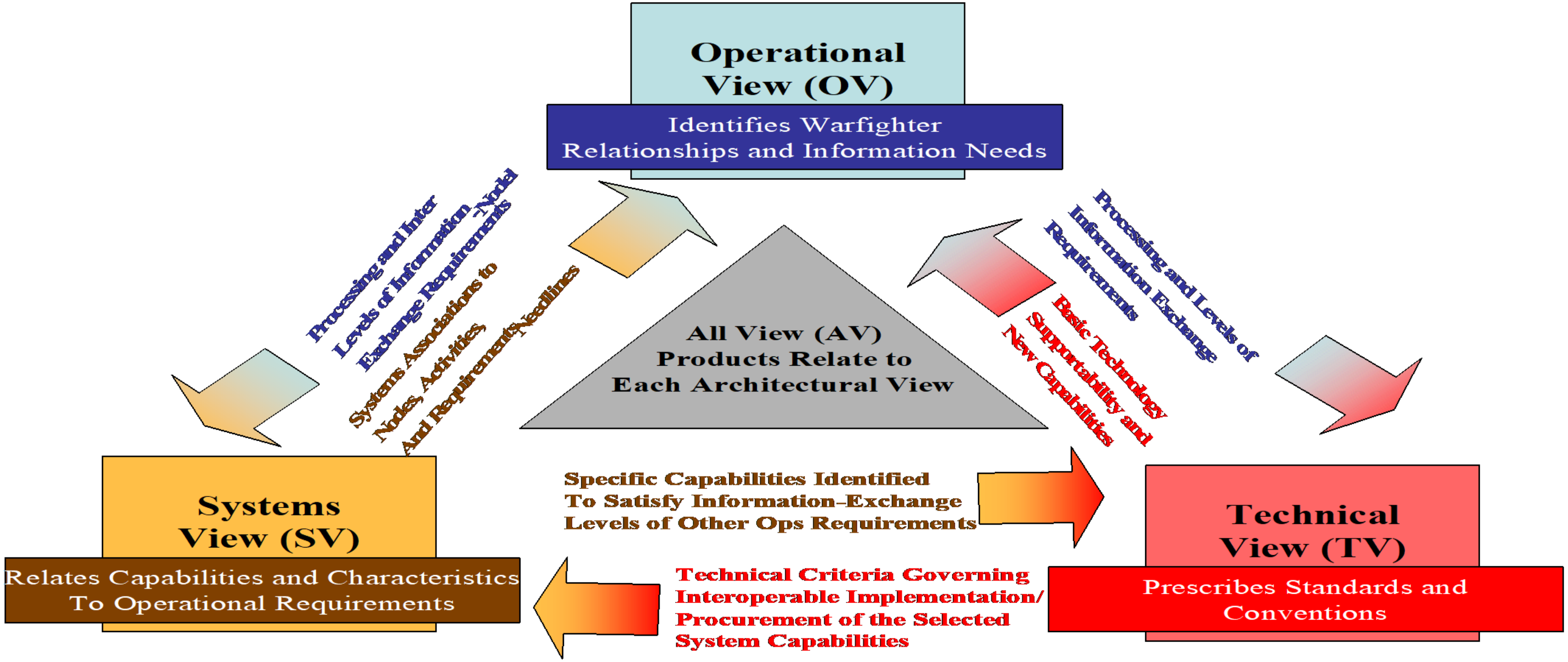
2004 Revision of the Joint Director’s Lab Data Fusion Model



Using a Fusion & Management Architecture Will Stop One-of-a-Kind Software Developments

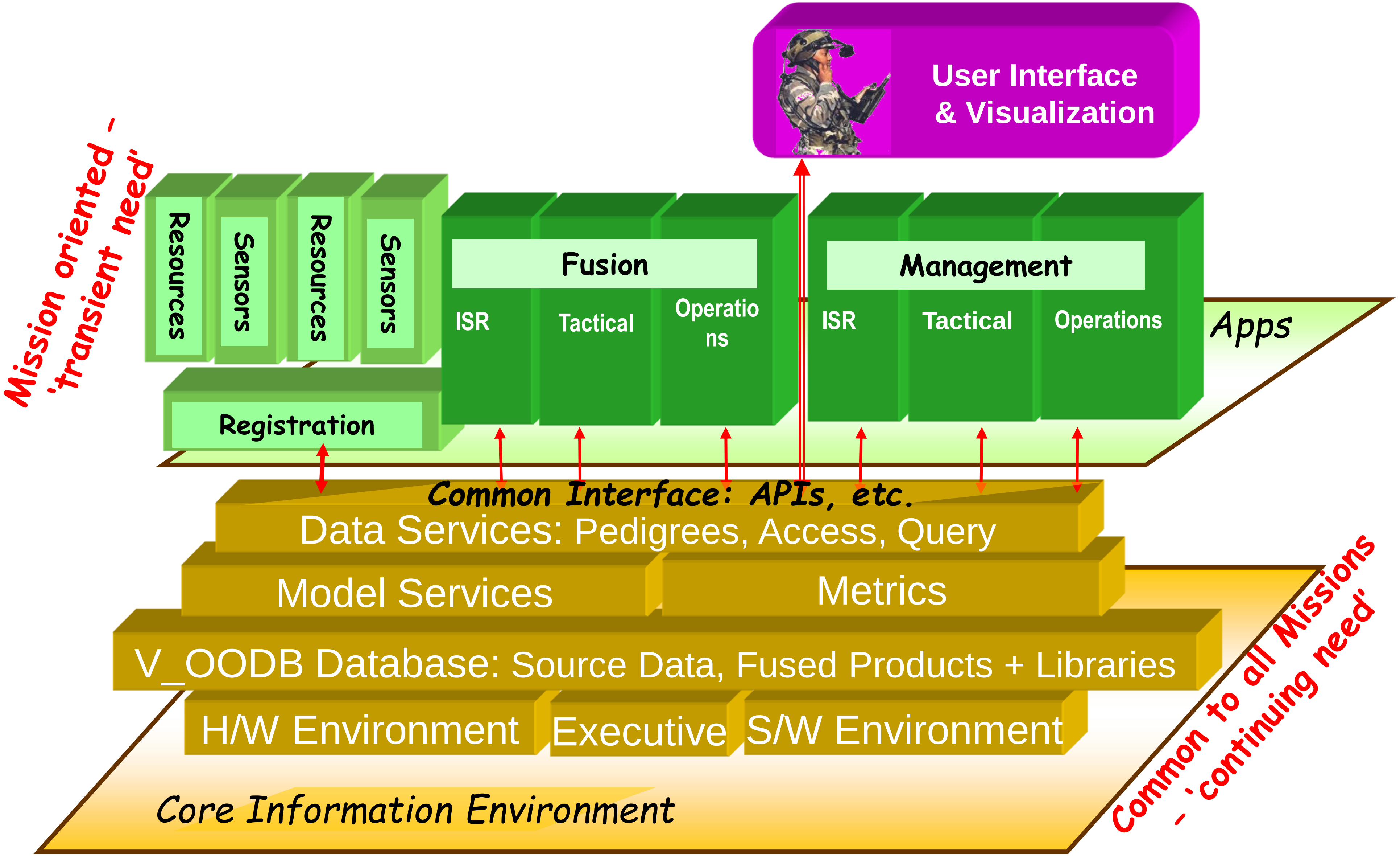
- **Architectures are frequently used mechanisms to address a broad range of common requirements to achieve <u>interoperability and affordability</u> objectives**
- **An architecture (IEEE definition) is a structure of <u>components</u>, their <u>relationships</u>, and the principles and <u>guidelines</u> governing their design and evolution over time**
- **An architecture should:**
  - Identify a focused purpose with sufficient breadth to achieve affordability objectives
  - Facilitate user understanding/communication
  - Permit comparison, integration, and interoperability
  - Promote expandability, modularity, and reusability
  - Achieve most useful results with least cost of development

Role for DF&RM DNN Technical Architecture Within the "DoD Architecture Framework"

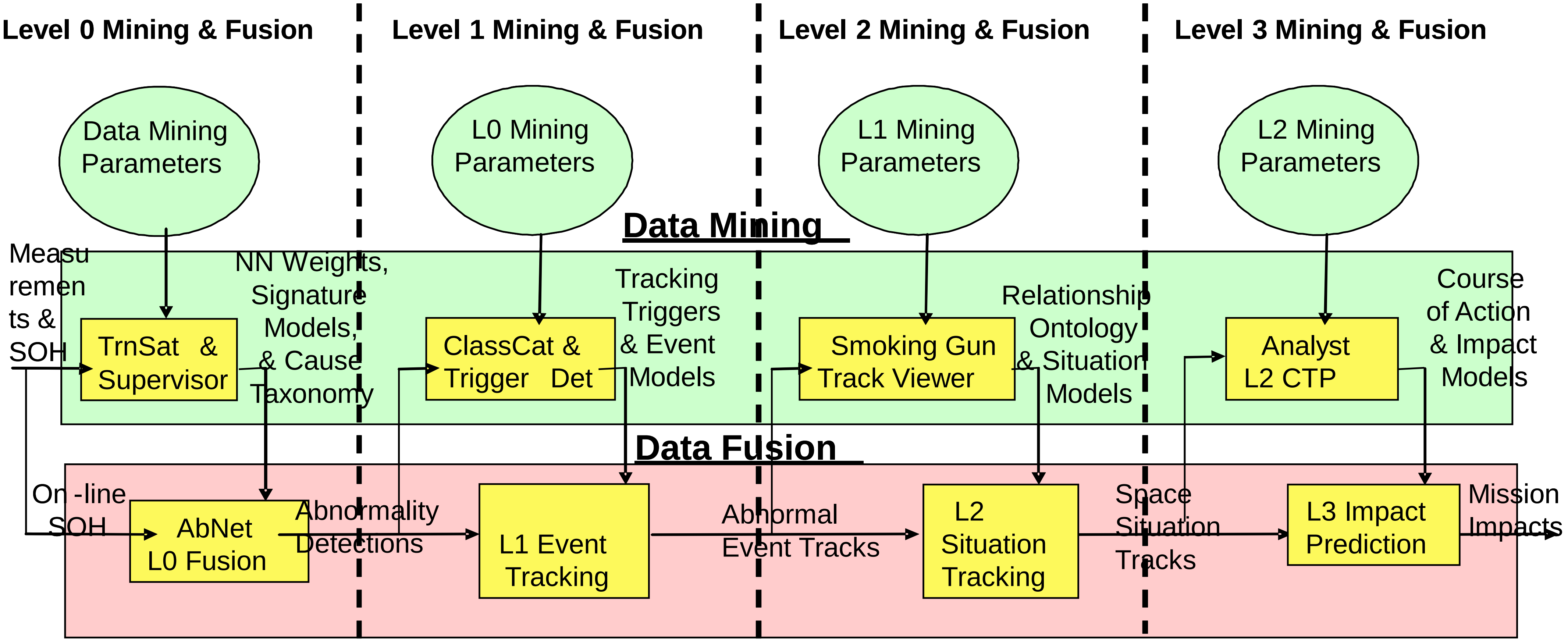


- The operational architecture provides the "what and who" operational needs
- The technical architecture provides "problem-to-solution space" guidance
- The systems architecture defines the "how" to build the operational system

DF&RM DNN Technical Architecture Applies at Application Layer

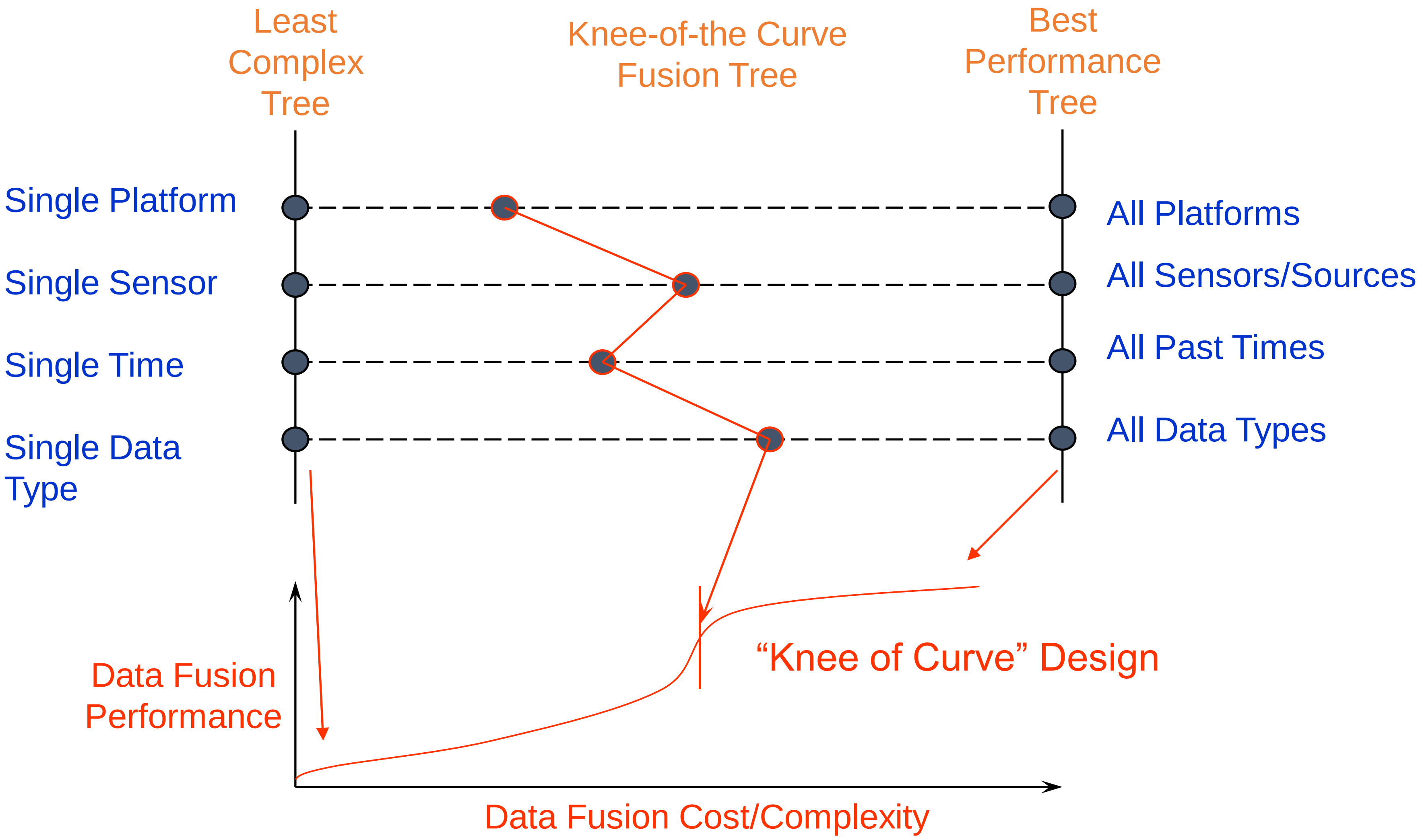


Data Mining Provides DF&RM Models

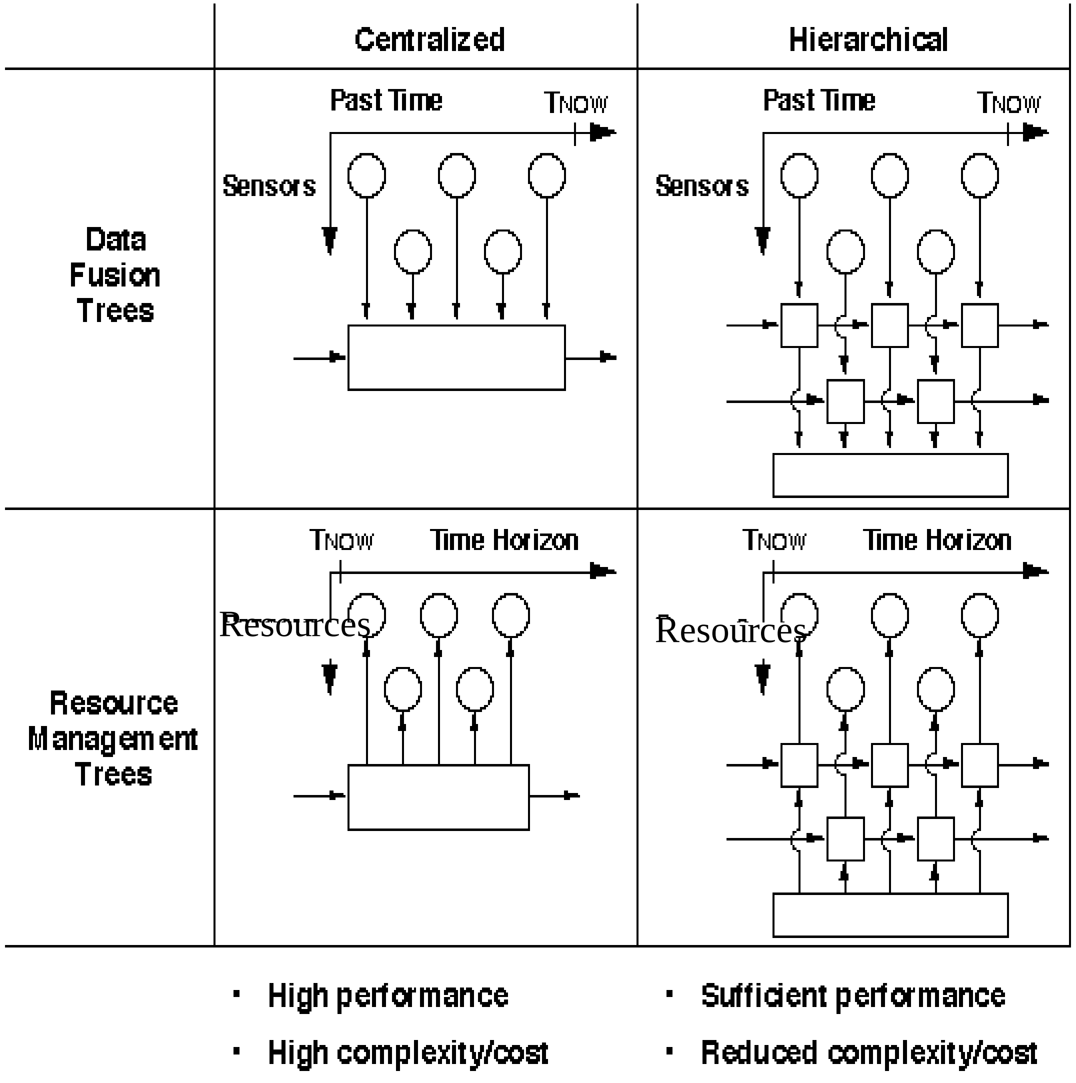


- Data Mining discovers and models some as aspect of data input to each fusion level
- Data Fusion combines data to estimate/predict the desired state at each fusion level

Fusion Network Selected to Balance Performance & Complexity



DF&RM Trees Divide & Conquer the Problem



- Fusion tree defines batching of data by
  - Sensor/source
  - Past time
  - Data type
- Management tree defines batching of commands by
  - Resource (sensor or response)
  - Time horizon
  - Command type

Each node in each tree generates, evaluates, and selects solutions for knee-of-the-curve performance vs. cost

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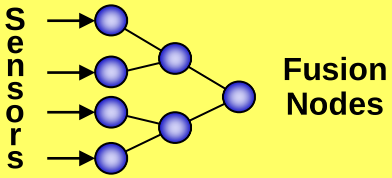
DF/RM Duality Allows Similar Approaches & Consistent Operation

DATA FUSION

Fusion Architecture

- "Fan-in" Tree



- Data batching by source, past time or data type

Association

- Exploit overlapping measurement observables
- Generate, evaluate & select association hypotheses

Estimation

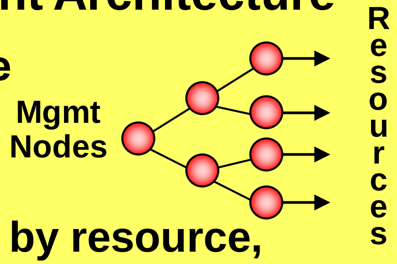
- Exploit independent measurement observables
- Use associations w/ *a priori* parameters to compute estimates

DUALITY

RESOURCE MGMT

Management Architecture

- "Fan-out" Tree



- Task batching by resource, time horizon or command type

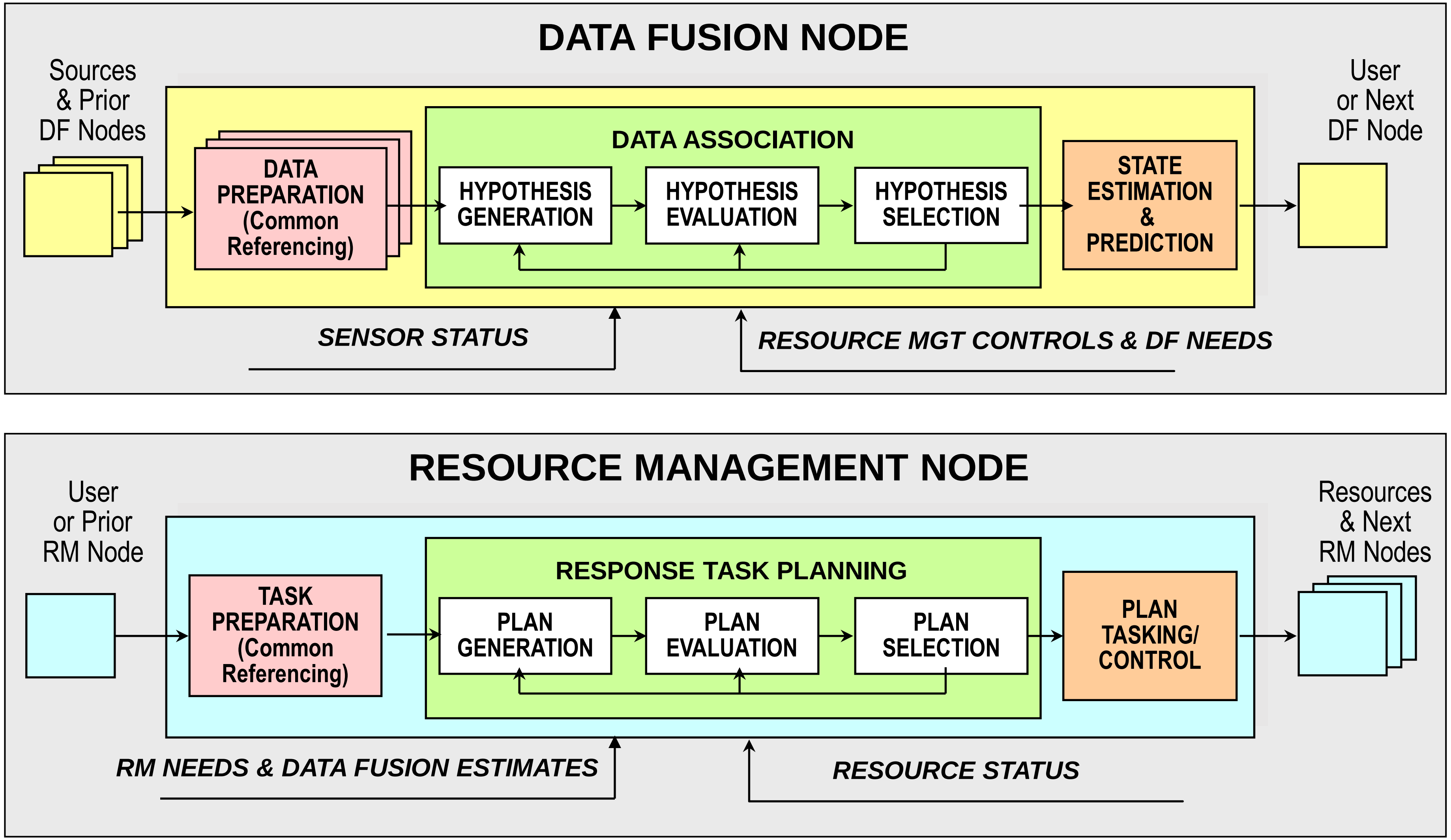
Response Planning

- Exploit overlapping resource capabilities
- Generate, evaluate & select response plans

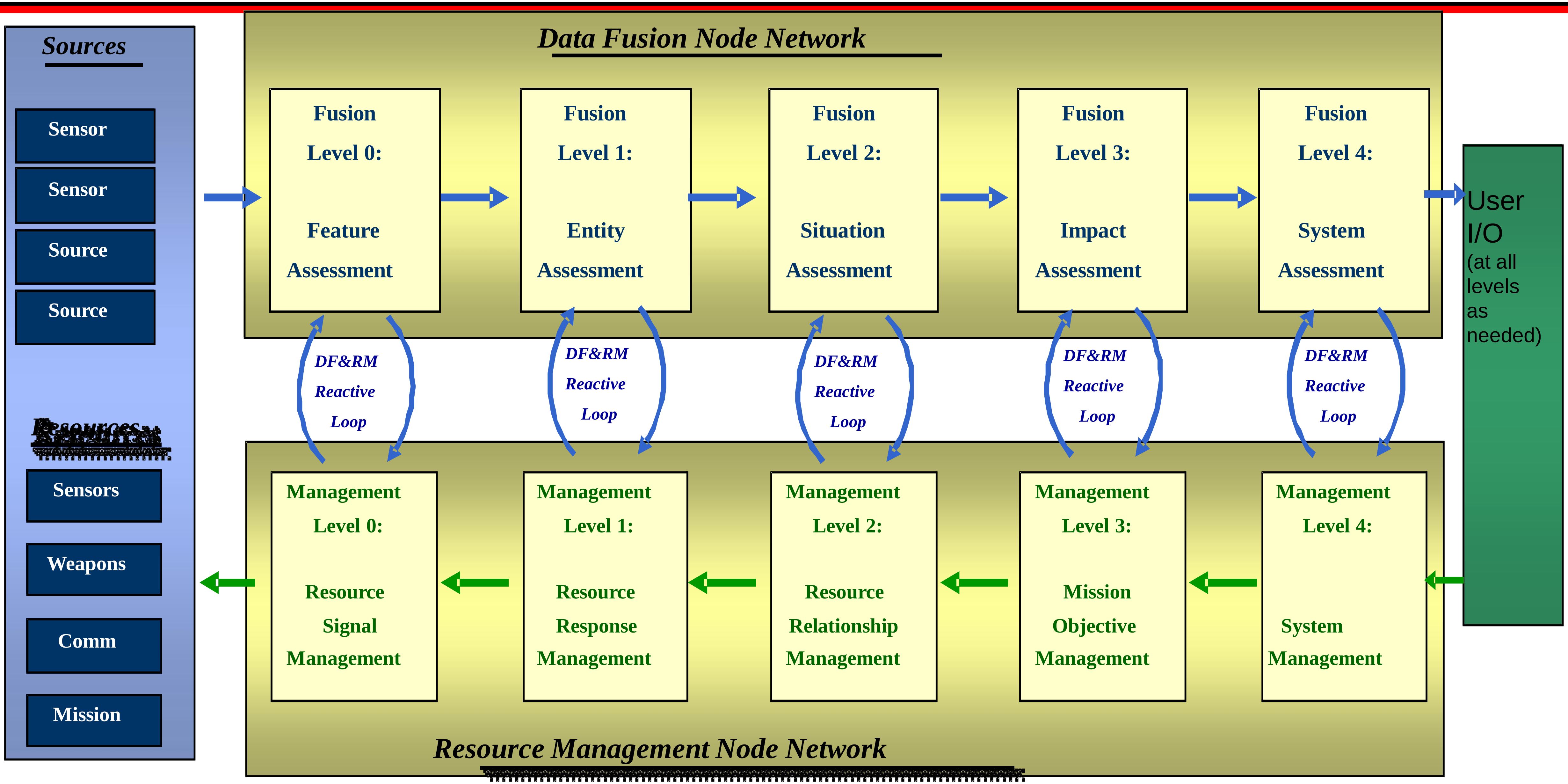
Control

- Exploit independent resource capabilities
- Use assignments w/ performance parameters to compute control

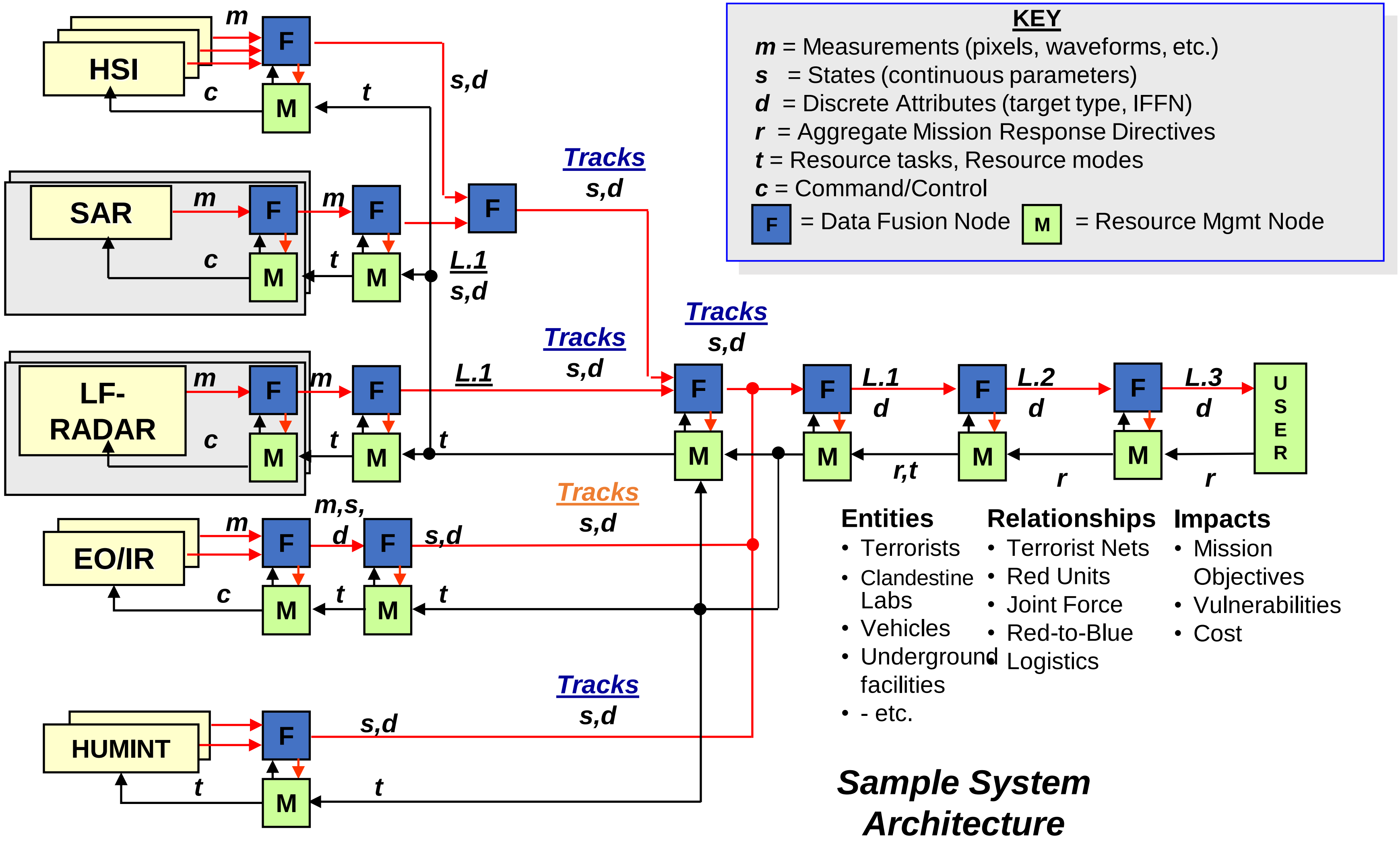
DF & RM Node Duality Facilitates Understanding of Alternatives & Reuse



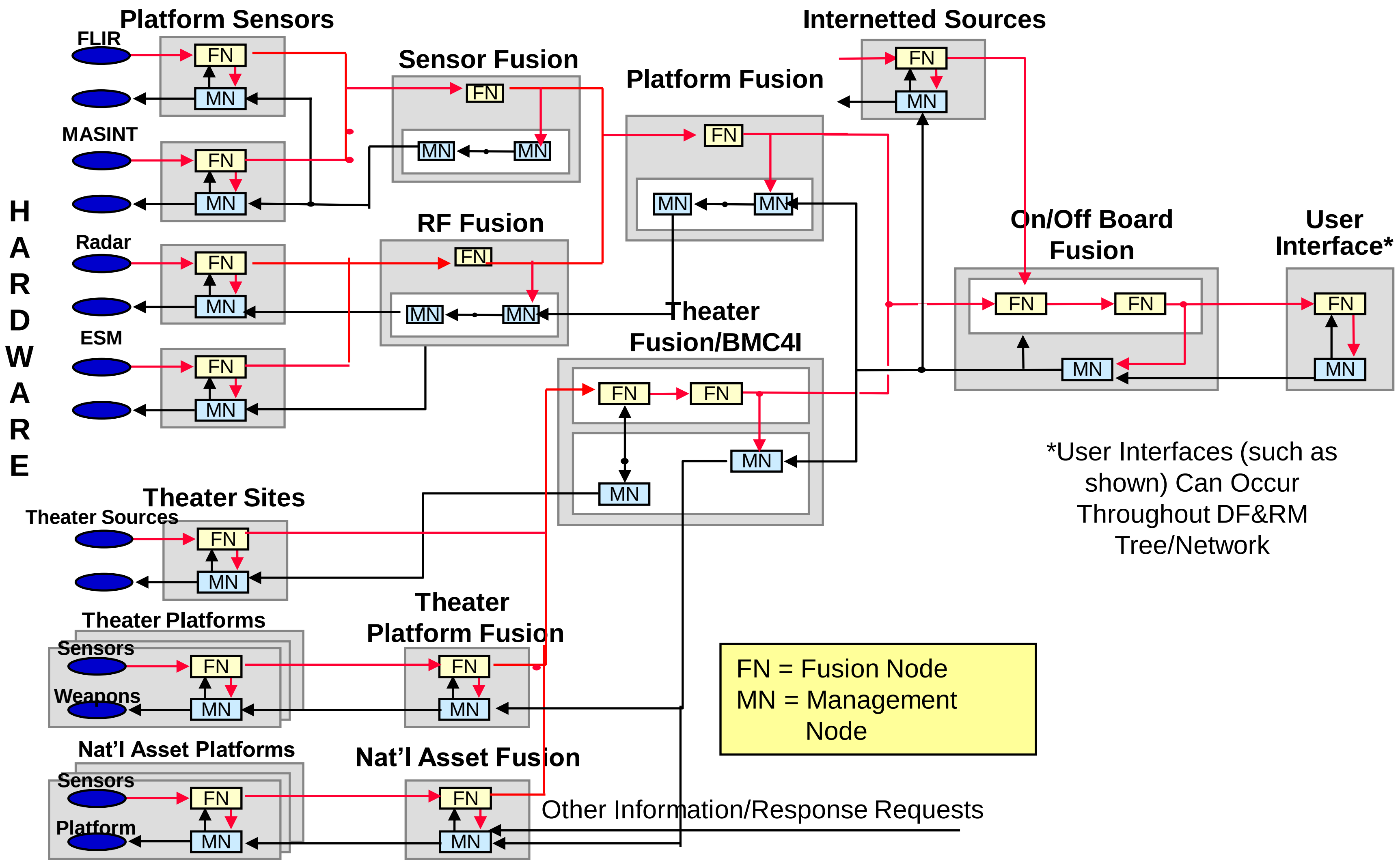
Sample Interlaced Network of DF&RM Dual Level Interactions



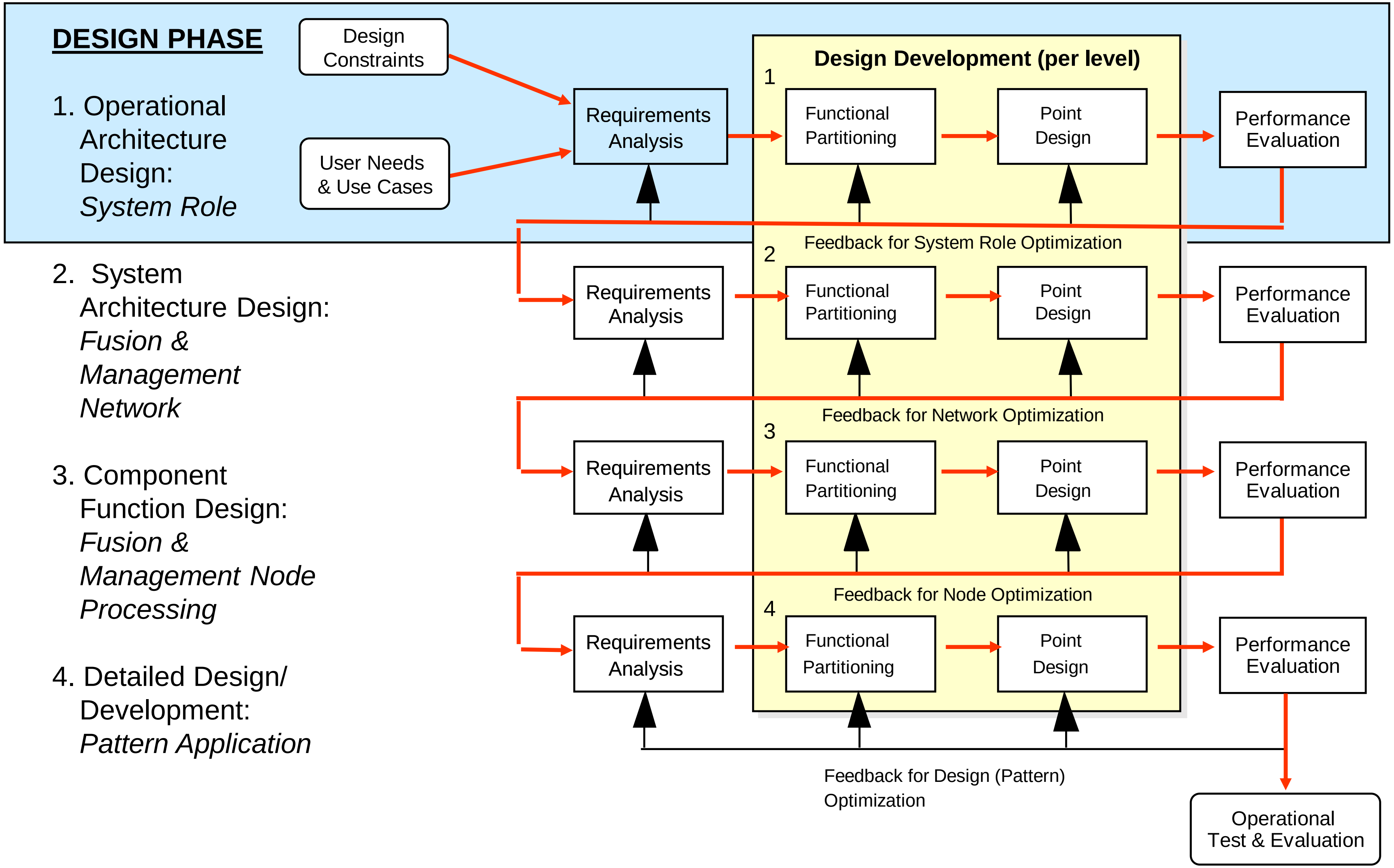
Sample DF&RM Node Network for Battlefield Awareness



Sample Interlaced Tree of DF&RM Nodes



The DNN Architecture DF&RM System Engineering Process Includes Rapid Prototyping



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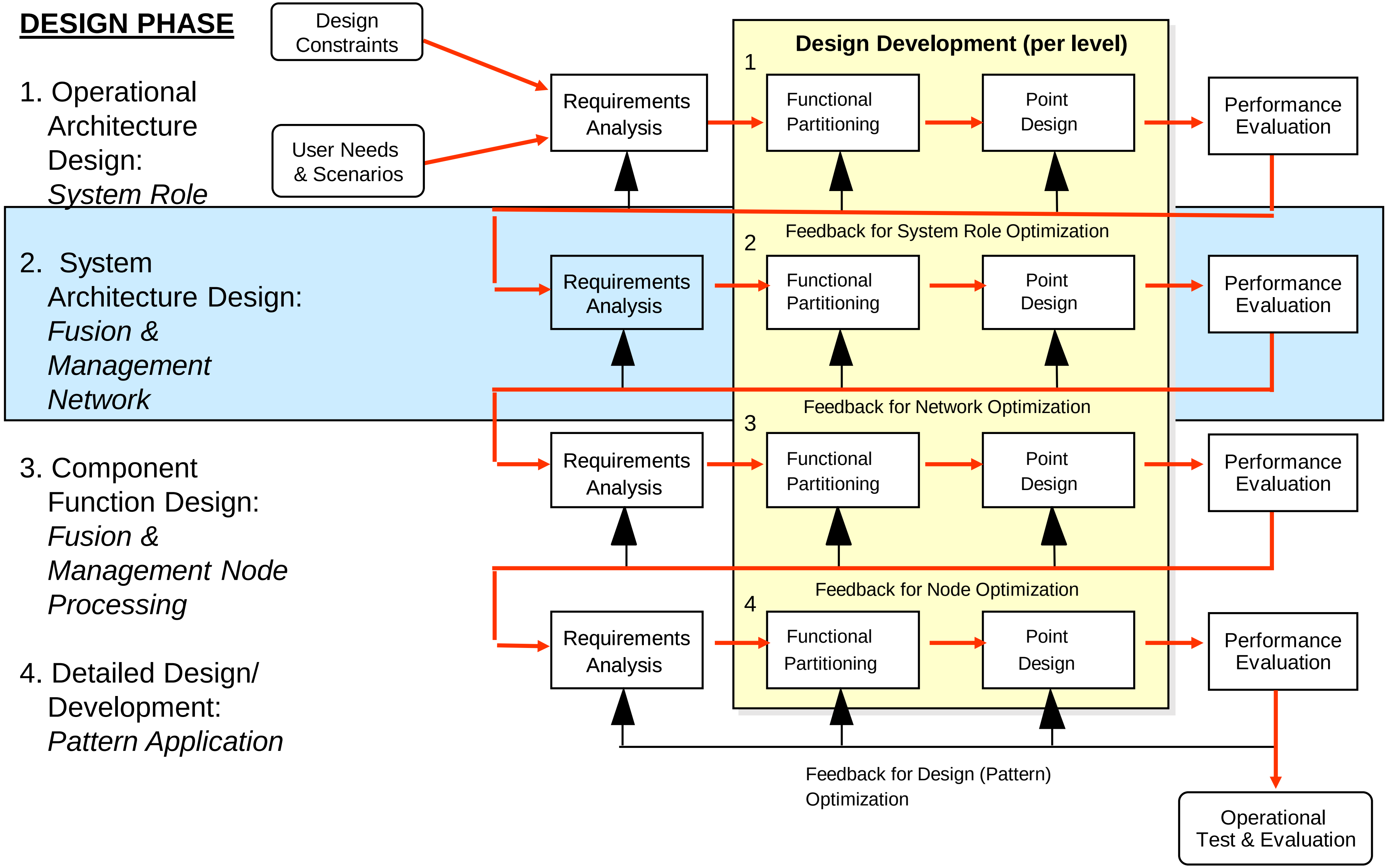
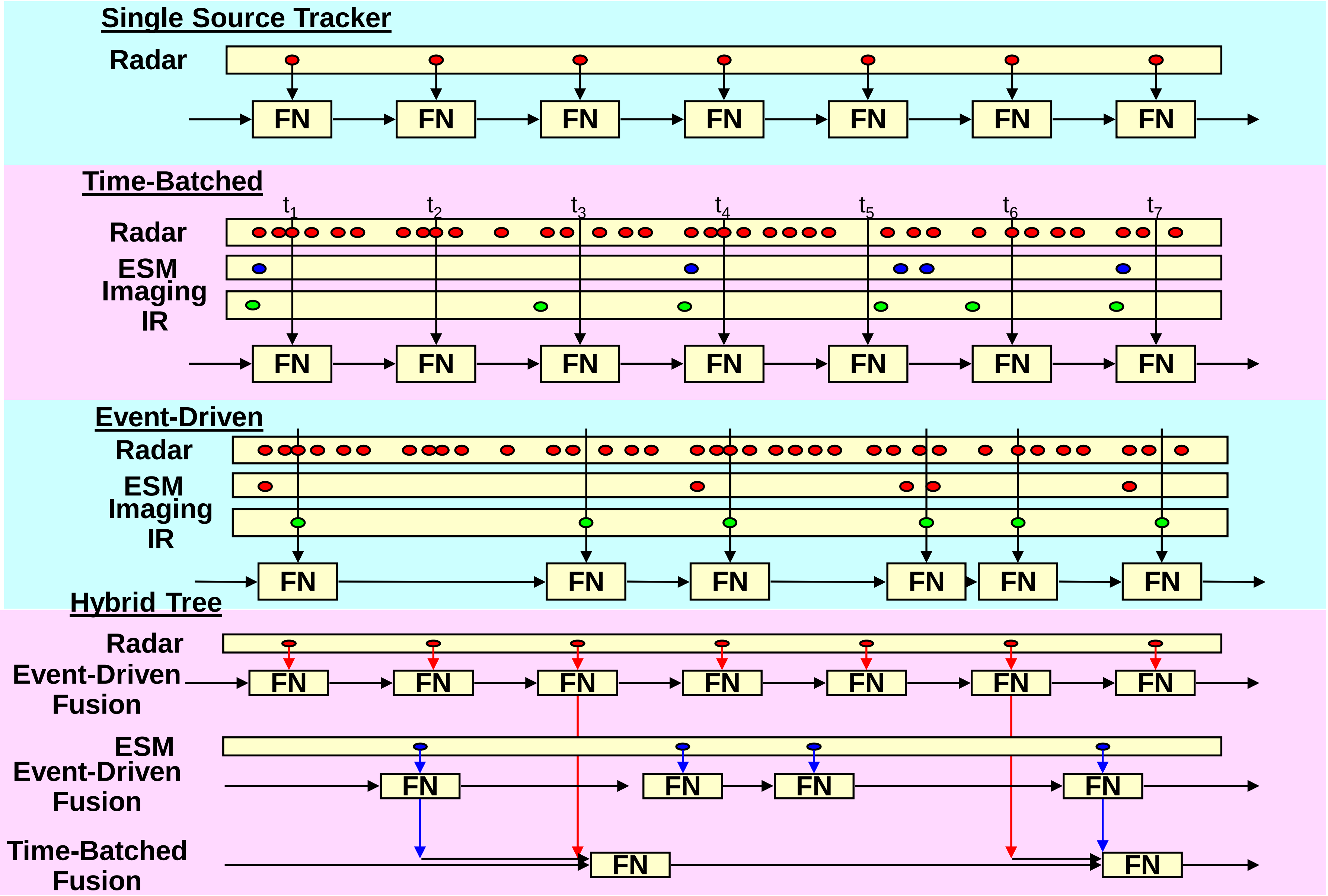
- Distributed Data Fusion Node Networks

- Data Association Hypothesis Evaluation Alternatives

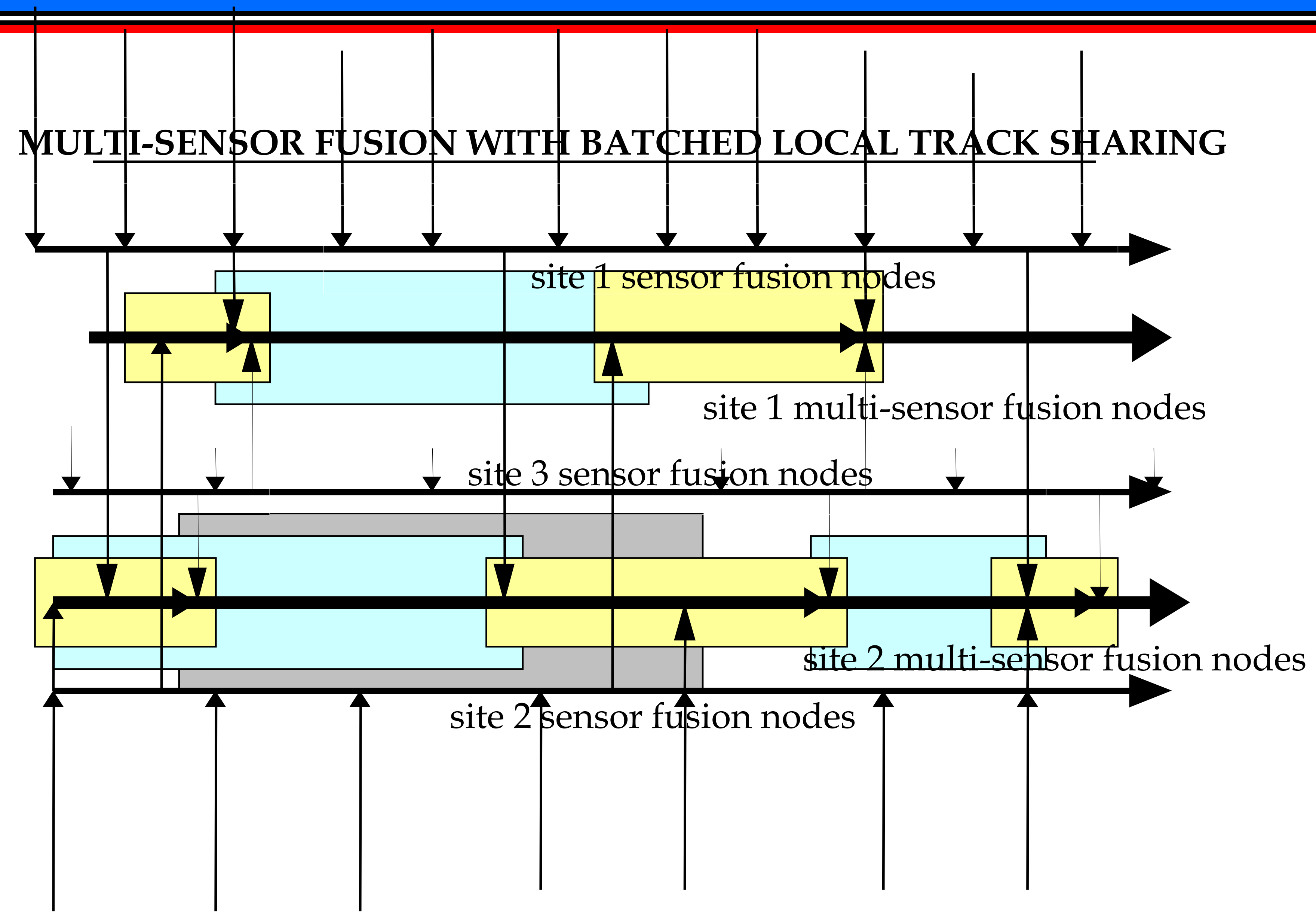
The DNN Architecture DF&RM System Engineering Process



Fusion Node Network Examples



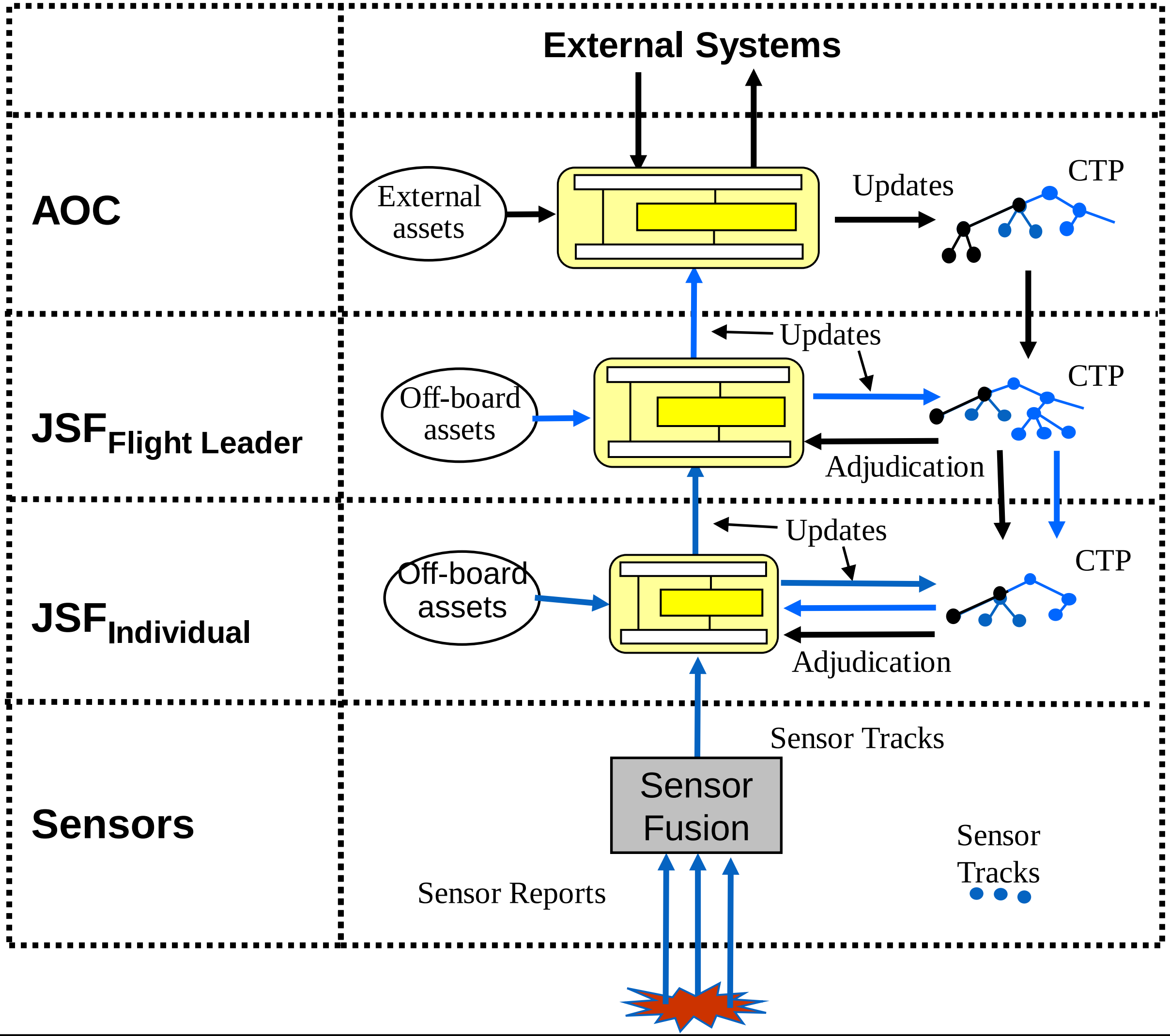
Global Track Reinitialization with Local Track Sharing



Complementarity of Five Distributed Tracking Fusion Networks

FUSION TREES		PERFORMANCE	DESCRIPTORS		
Multi-Sensor Fusion with	**Data Communicated**	**Track Reinitialization**	**Sensor Tracker Impacts**	**Track Error Correlations**	**Flexibility Issues**
Measurement Sharing	sensor measurements	no reinitialization	sensor track tailoring at global sites	none	highest bandwidth comm
Sensor Node Track Reinitialization	local track state	sensor filter reinitialization after send	sensor filter modifications needed	sensor filter process noise correlations	simultaneous comm output
Tracklets From Tracks	local track state	no reinitialization	only standard KF updates	inverse KF to remove correlations	For non-maneuvering entities
Local Track Sharing	local track state (plus reports)	global track reinitialization	use tailored sensor trackers as is	process noise & misalignments correlate	Sending reports Increases BW
Globlal Track Sharing	global track state	no global filter	use tailored sensor trackers as is	correlations reduce accuracy	ID with pedigree fused

Fusion Updates CTP with New Data; Adjudication Maintains Consistency



high-latency information path

intermediate-latency information path

low-latency information path

Note: Alerts of sufficient confidence and priority propagate immediately to all affected nodes at all levels

Advisements Sent up and Directives Sent Down Echelons Insure Consistency of the Operational Picture.

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The DNN Architecture DF&RM System Engineering Process

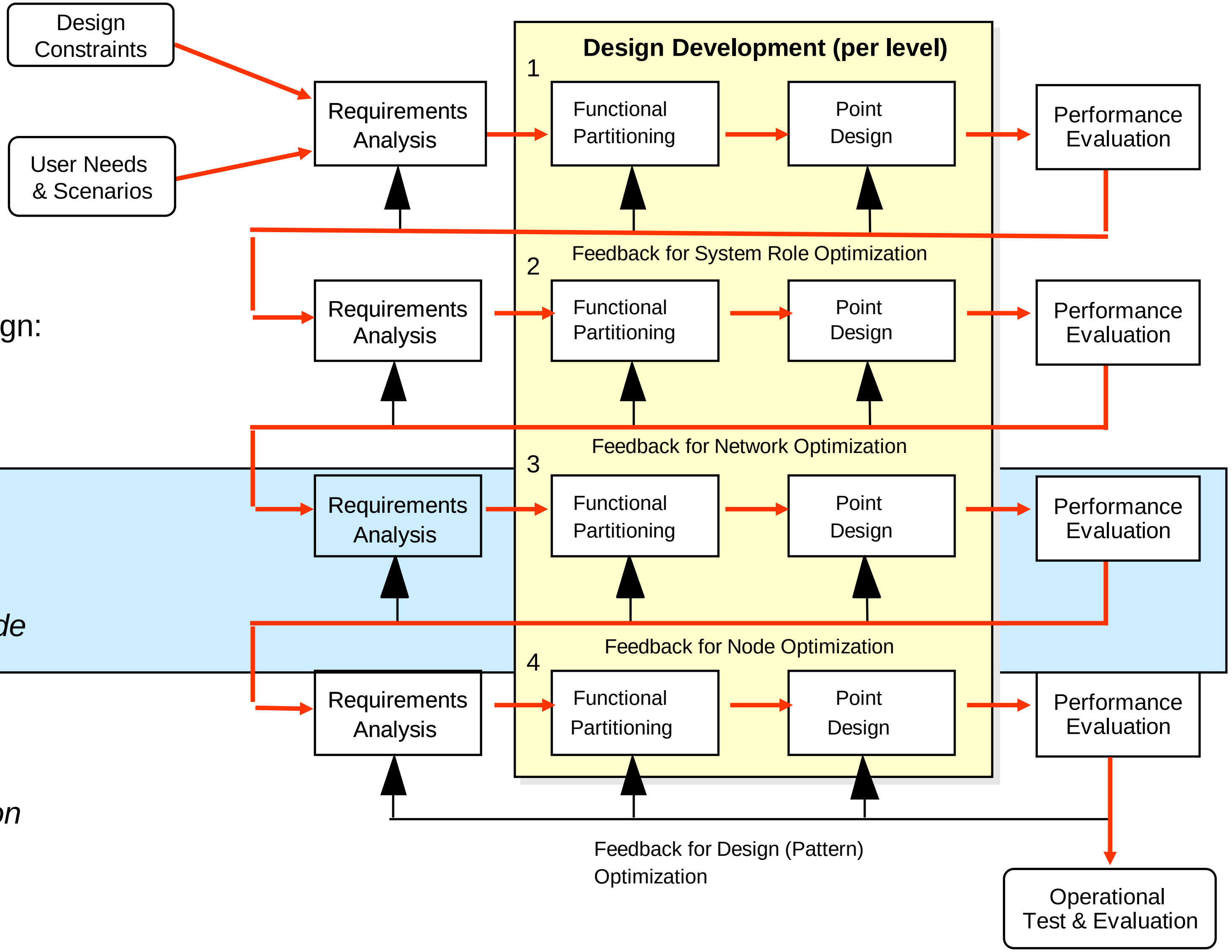
DESIGN PHASE

1. Operational Architecture Design: *System Role*

2. System Architecture Design: *Fusion & Management Network*

3. Component Function Design: *Fusion & Management Node Processing*

4. Detailed Design/ Development: *Pattern Application*



Data Association Problems Occur at All Fusion Levels

(2-D Assignment Matrix Examples)

Level 0 Feature/Signal Assessment

Rows: Features Measurements/ — Columns: Entity Features/Signals

0.20	0.01	0.44	0.30	0.02	0.20
0.02	0.16	0.11	0.01	0.56	0.15
0.03	0.02	***Scores***		0.01	0.01
0.07	0.19	0.03	0.17	0.31	0.23
0.11	0.01	0.46	0.12	0.15	0.16
0.67	0.02	0.01	0.20	0.09	0.01

Level 1 Entity Assessment

Rows: Entity Reports/Tracks — Columns: Entity Tracks

0.20	0.01	0.44	0.30	0.02	0.20
0.02	0.16	0.11	0.01	0.56	0.15
0.03	0.02	***Scores***		0.01	0.01
0.07	0.19	0.03	0.17	0.31	0.23
0.11	0.01	0.46	0.12	0.15	0.16
0.67	0.02	0.01	0.20	0.09	0.01

Level 2 Situation Assessment

Rows: Entities/ Relationships — Columns: Entity Aggregations/Relationships

0.20	0.01	0.44	0.30	0.02	0.20
0.02	0.16	0.11	0.01	0.56	0.15
0.03	0.02	***Scores***		0.01	0.01
0.07	0.19	0.03	0.17	0.31	0.23
0.11	0.01	0.46	0.12	0.15	0.16
0.67	0.02	0.01	0.20	0.09	0.01

Level 3 Impact Assessment

Rows: Entities/ Relationships — Columns: Plans/COAs

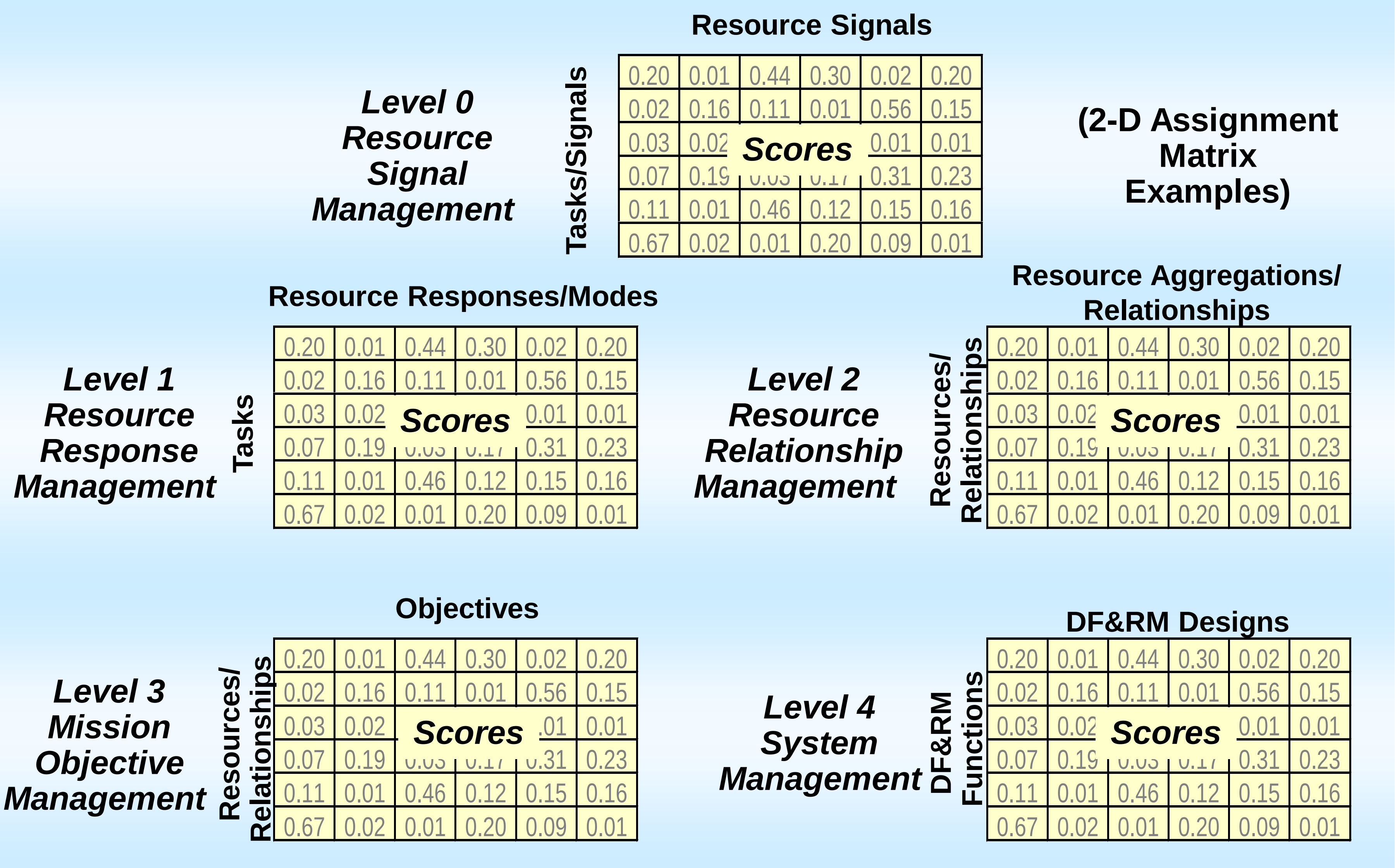
0.20	0.01	0.44	0.30	0.02	0.20
0.02	0.16	0.11	0.01	0.56	0.15
0.03	0.02	***Scores***		.01	0.01
0.07	0.19	0.03	0.17	0.31	0.23
0.11	0.01	0.46	0.12	0.15	0.16
0.67	0.02	0.01	0.20	0.09	0.01

Level 4 System Assessment

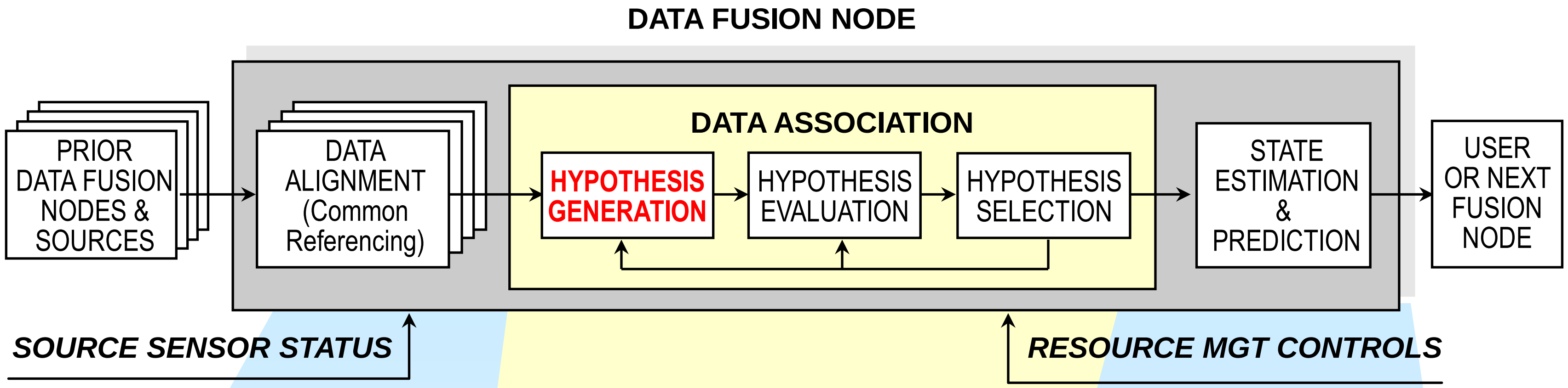
Rows: DF&RM Outputs — Columns: Truth/Desired

0.20	0.01	0.44	0.30	0.02	0.20
0.02	0.16	0.11	0.01	0.56	0.15
0.03	0.02	***Scores***		0.01	0.01
0.07	0.19	0.03	0.17	0.31	0.23
0.11	0.01	0.46	0.12	0.15	0.16
0.67	0.02	0.01	0.20	0.09	0.01

Resource Management Has Dual Response Planning Problems at All Levels



Data Association Is the Core of Data Fusion



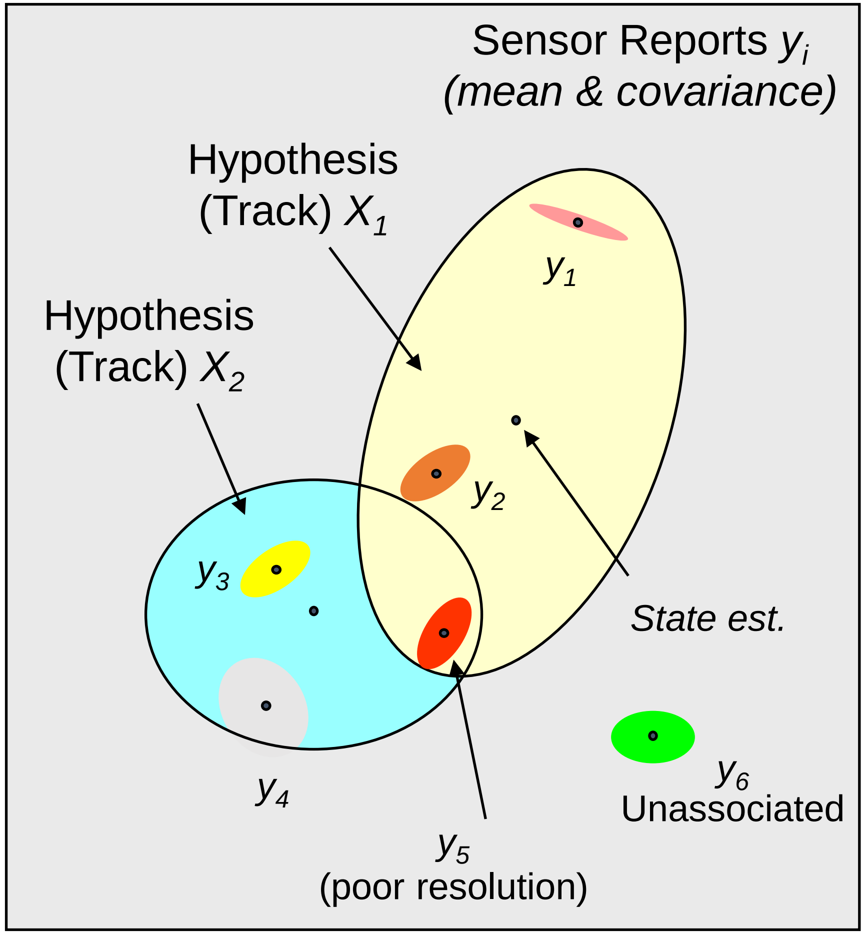
- **DETECT AND RESOLVE DATA CONFLICTS**
- **CONVERT DATA TO COMMON TIME AND COORDINATE FRAME**
- **COMPENSATE FOR SOURCE MISALIGNMENT**
- **NORMALIZE CONFIDENCE**

- **GENERATE FEASIBLE & CONFIRMED ASSOCIATION HYPOTHESES**
- **SCORE HYPOTHESIZED DATA ASSOCIATIONS**
- **SELECT, DELETE, OR FEEDBACK DATA ASSOCIATIONS**

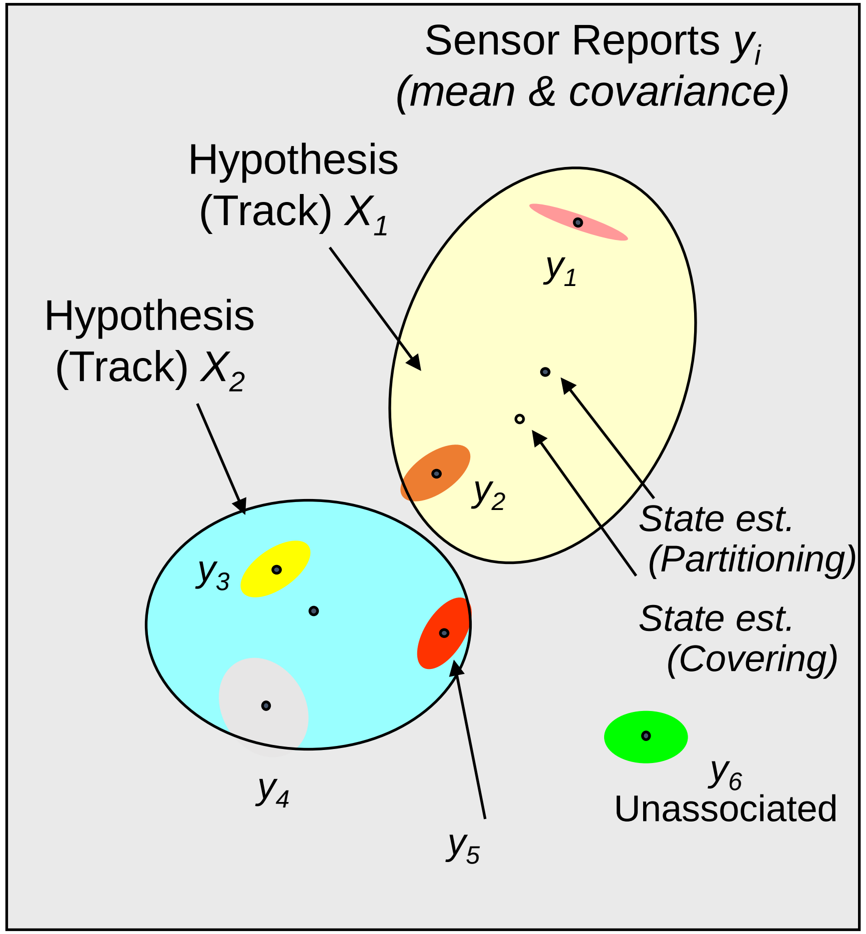
- **ESTIMATE/PREDICT ENTITY STATES**
  - KINEMATICS, ATTRIBUTES, ID, RELATIONAL STATES
- **ESTIMATE SENSOR/SOURCE MISALIGNMENTS**
- **FEED FORWARD SOURCE/ SENSOR STATUS**

Level 1 Entity Data Association Is a Labeled Set Covering Problem

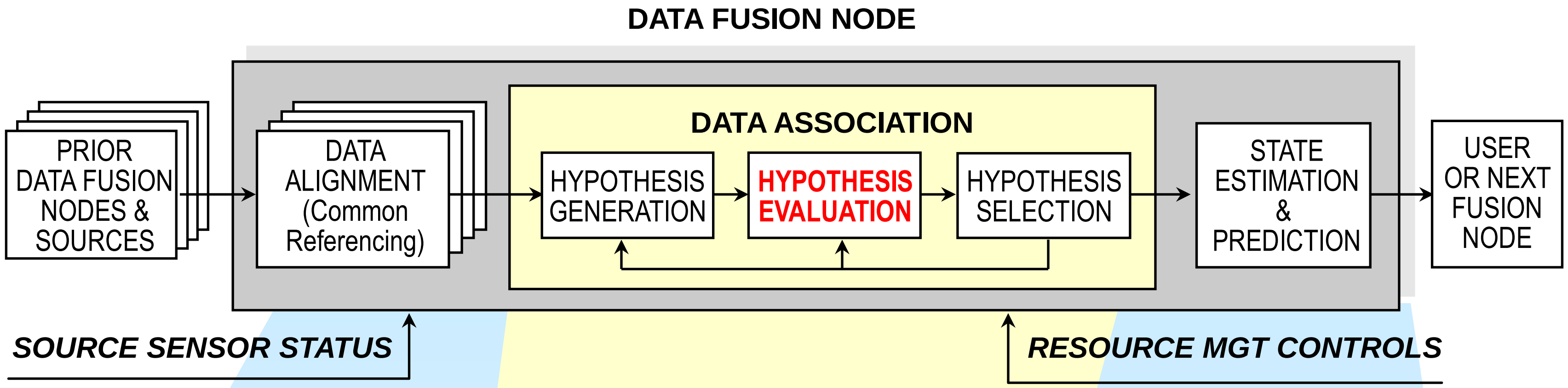
Set Covering



Set Partitioning



Hypothesis Evaluation Is the Core of Data Association



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- **SCORE HYPOTHESIZED DATA ASSOCIATIONS**
  - KINEMATICS, ATTRIBUTES, ID, RELATIONAL STATES TRACK CONFIDENCES
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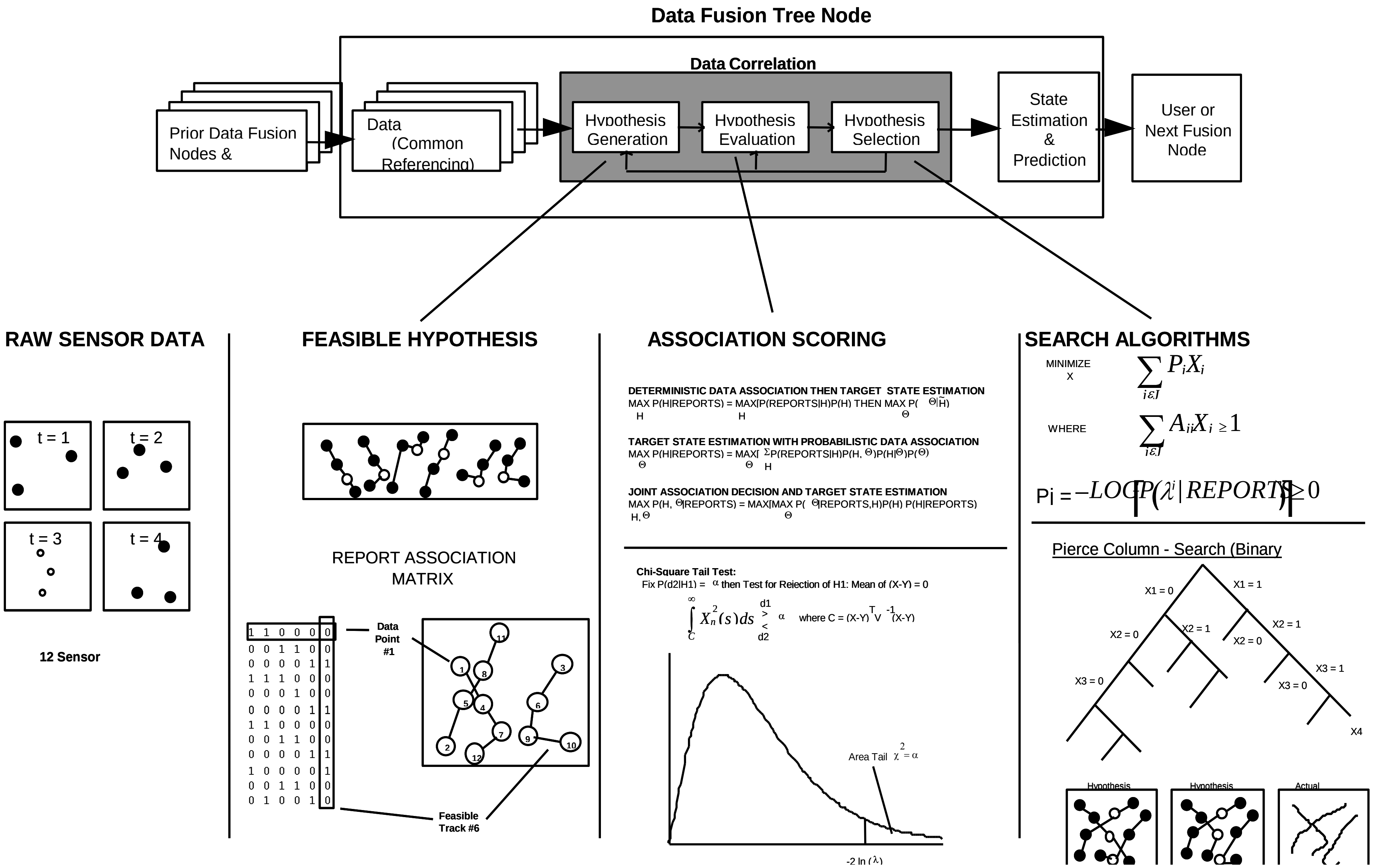
Processing Load Is Balanced Within Each Fusion Node Component



Applicability of Alternative Scoring Schemes (1 of 2)

- Probabilistic: Preferred if statistics known
  - > Chi-Square Distance
    - Doesn't require prior densities
    - Useful for comparing multi-dimensional Gaussian data
    - However, no natural way to incorporate attribute and *a priori* data
  - > Max Likelihood
    - Doesn't require unconditional prior densities, $p(x)$
    - Does require conditional priors, $p(Z|x)$
  - > Bayesian Maximum a Posteriori (MAP)
    - Naturally combines kinematics, attribute, and a priori data
    - Provides natural track association confidence measure
    - However, requires prior probability (e.g. kinematics and class) densities; difficult to specify

Applicability of Alternative Scoring Schemes (2 of 2)

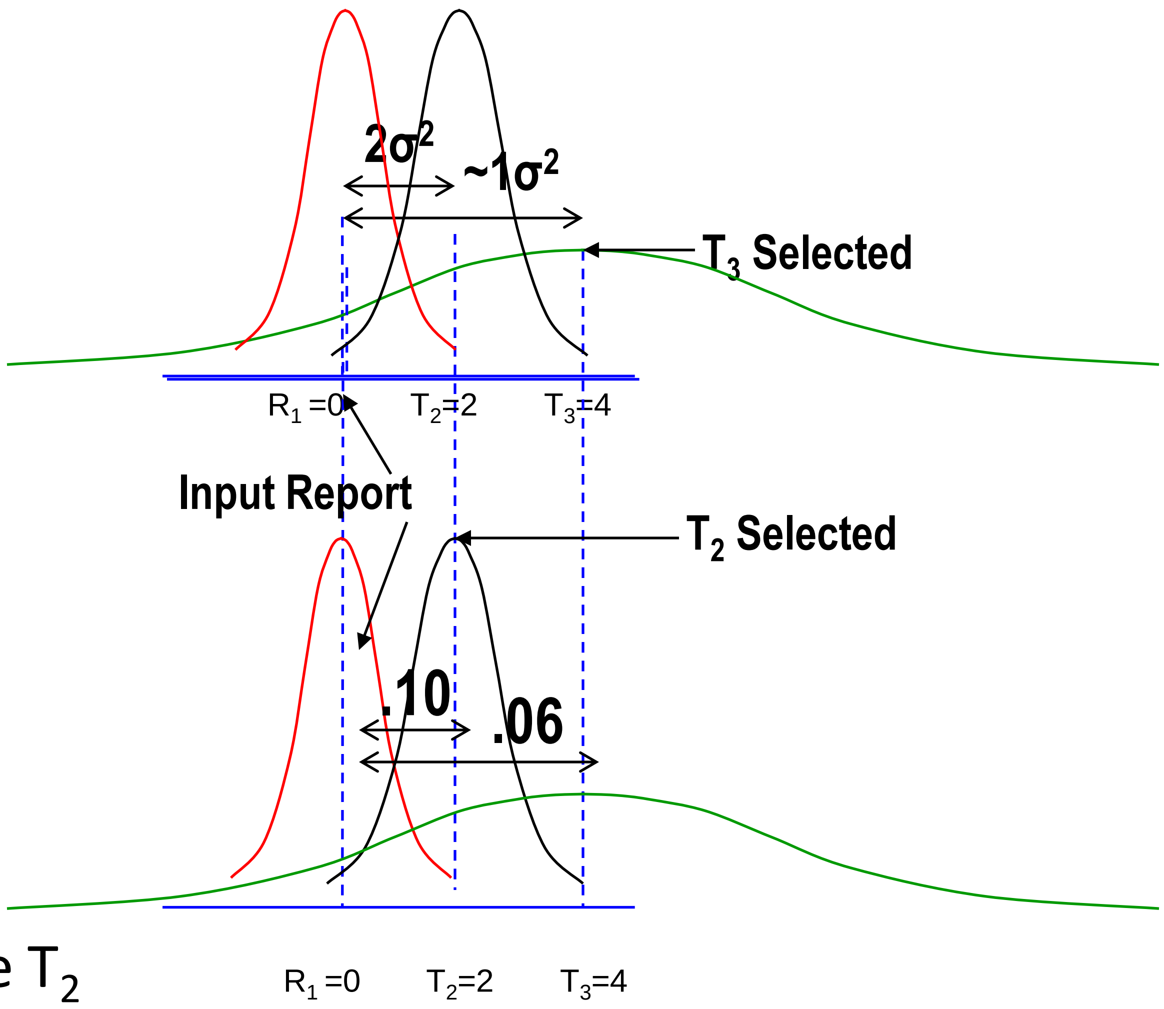
- Non-Probabilistic: Useful if high uncertainty in the uncertainty
  - > Evidential (Dempster-Shafer)
    - – Non-statistical: User specifies evidence “mass” values (support and plausibility numbers)
    - – Essentially 2-point calculus (uniform uncertainty-in-the-uncertainty with simple knowledge combination rules)
  - > Fuzzy Sets
    - – User specifies membership functions to represent the uncertainty-in-the-uncertainty
    - – User specifies fuzzy knowledge combination rules (e.g., sum, prod, max/min) which are much easier compute than second-order Bayesian
    - – More complex to develop, maintain, and extend
  - > Confidence Factors and Other *ad hoc* Methods
    - – Explicit derivation of logical relationships
    - – Generally *ad hoc* weightings to relate significance of factors
    - – Can include information theoretic and utility weightings

MAP Scoring Correctly Balances Less Accurate Further Away Tracks

- <u>Chi-square (Mahalanobis) Scoring</u>:
  - $I^tV^{-1}I=[R_1-T_2]^2/[\sigma_R{}^2+\sigma_{T2}{}^2] = 2^2/[1+1]=2$
  - $I^tV^{-1}I=[R_1-T_3]^2/[\sigma_R{}^2+\sigma_{T3}{}^2]=4^2/[1+16]=16/17$
  - R associated to 1 sigma away but further distance away less accurate T_3

- <u>Max. *a Posteriori* (Bayesian)</u>:
  - $[2\pi V]^{-.5}\, e(-.5I^tV^{-1}I) =[6.28*2]^{-.5}$

  $e(-.5[R_1-T_2]^2/[\sigma_R{}^2+\sigma_{T2}{}^2]) \sim .28\, e^{-1} \sim .10$
  - $[2\pi V]^{-.5}\, e(-.5I^tV^{-1}I) =[6.28*17]^{-.5}\, e(-.5[R_1-T_3]^2/[\sigma_R{}^2+\sigma_{T3}{}^2]) \sim .097\, e^{-.47} \sim .060$
  - R is associated to the closer more accurate T_2



Alternative MAP Association Scoring

- **Deterministic Data Association then target estimation**

$$\max_{H} P(H|REPORTS) = \max_{H}[P(REPORTS|H)P(H)\ THEN\ \max_{\theta} P(\theta|\hat{H})$$

- **Target state estimation with probabilistic data association**

$$\max_{\theta} P(\theta|REPORTS) = \max_{\theta}[\sum_{H} P(REPORTS|H,\theta)P(H|\theta)]P(\theta)$$

- **Joint association decision and target state estimation**

$$\max_{H,\theta} P(H,\theta|REPORTS) = \max_{H}[\max_{\theta} P(\theta|REPORTS,H)]P(H|REPORTS)$$

H is the association hypothesis and Theta is the track state.

Max A Posteriori (MAP) Hypothesis Scoring

- The total scene hypothesis score is the product of the individual hypothesis scores for the 5 possible hypothesis types:
  - association hypotheses
  - pop-up (i.e., track initiation) hypotheses
  - input false alarm (FA) hypotheses
  - track propagation (missed coverage) hypotheses
  - drop track (false track) hypotheses
- Pd and Pfa use track association confidences and incorporate the entity birth and death statistics
- Track confidence estimates are needed to differentiate the 5 hypotheses types
- When the class tree uncertainty-in-the-uncertainty is high it is not used in scoring

Source Noncommensurate Attributes Scored Using Entity Class Tree

- Sources 1 & 2 have noncommensurate attributes if for an exhaustive set of disjoint of entity classes, K,

$$P(Z(S_1) \mid Z(S_2), \text{Class } K, Y(S_i), H) = P(Z(S_1) \mid \text{Class } K, Y(S_1), H)$$

where,

  - $Z(S_i)$ is the set of measured attributes (i.e., all non kinematics measurements) from each source i,
  - H is the association hypothesis between sources S_1 & S_2,
  - $Y(S_i)$ are the measured kinematics from the two sources
  - All source attributes not conditionally independent are treated as separately commensurate parameters

- For commensurate sources, feature differences are scored

Sample Hierarchical Disjoint Entity Class Taxonomy

Entity Type Declarations (Statistics per Truth Type)

- **Helicopter (M)**
  - Manually classified: 1.0
- **Tracked Vehicle (A)**
  - **T72 (A,M)**
    - T72: 36
    - M60: 1.6
    - M1: 1.6
    - BMP: 20
    - FV432: 10.4
    - Spartan: 10.4
    - HMMWV: 0
    - Unknown: 20
  - **M60 (A,M)**
    - M60: 53.6
    - T72: 0
    - M1: 5.6
    - BMP: 0
    - FV432: 10.4
    - Spartan: 10.4
    - HMMWV: 0
    - Unknown:20
  - **M1A2 (A,M)**
    - M1: 53.6
    - T72: 1.6
    - M60: 2.4
    - BMP: 0
    - FV432: 11.2
    - Spartan: 11.2
    - HMMWV: 0
    - Unknown: 20
  - **Challenger (M)**
  - **Warrior (M)**
  - **BMP (A,M)**
    - BMP: 50.4
    - T72: 5.6
    - M60: 1.6
    - M1: 0
    - FV432: 10.4
    - Spartan: 10.4
    - HMMWV: 1.6
    - Unknown: 20
  - **FV432 (A,M)**
    - FV432: 41.6
    - T72: 6.4
    - M60: 6.4
    - M1: 6.4
    - BMP: 6.4
    - Spartan: 6.4
    - HMMWV: 6.4
    - Unknown: 20
  - **Spartan (A,M)**
    - Spartan: 41.6
    - T72: 6.4
    - M60: 6.4
    - M1: 6.4
    - BMP: 6.4
    - FV432: 6.4
    - HMMWV: 6.4
    - Unknown: 20
- **Unknown (A,M)**
  - includes personnel
  - includes helicopters if automatically detected
- **Wheeled Vehicle (A)**
  - **HMMWV (A,M)**
    - HMMWV:40
    - T72: 1.6
    - M60: 4.8
    - M1: 0
    - BMP: 16
    - FV432: 8.8
    - Spartan: 8.8
    - Unknown: 20
  - **Range Rover (M)**
- **Unclassified (A)**
  - No ATR

<u>Note:</u> Values based on simulation test results except for FV432, Spartan, and Unknown which were added in based on engineering judgment.

A: automated
M: manual

Max a Posteriori Association Hypothesis Scoring

The total scene hypothesis score is the product of scores for 5 types of S to T association hypotheses of kinematics, Y, attributes, Z, and entity class confidences, K:

1. **Association Hypotheses**

   $P(Y(S) | Y(T),H)\ P(Z(S), Z(T) | Y(S), Y(T), H)\ P(H) = \{ |V|^{-1/2} \} \exp[-1/2\{I^T V^{-1} I\}] \bullet \{\Sigma_K[P(K | Z(T),Y(T), H)\ P(K | Z(S),Y(S), H)/P(K | Y(T),Y(S), H)]\} \bullet [1-P_{FA}(S)]\ [1- P_{FA}(T)]\ P_D(S)\ P_D(T)$

2. **Pop-up (i.e., Track Initiation) Hypotheses**

   $P(Y(S) | Y(T),H)\ P(Z(S), Z(T) | Y(S), Y(T), H)\ P(H) = \{E(|V|^{-1/2})\} \exp[-1/2\{\mu\}] \bullet [1-P_{FA}(S)]\ [1- P_D(T)]\ P_D(S)$

3. **False Alarm (FA) Hypotheses**

   $P(Y(S) | Y(T),H)\ P(Z(S), Z(T) | Y(S), Y(T), H)\ P(H) = \{ E(|V|^{-1/2})\} \exp[-1/2\{\mu\}] \bullet P_{FA}(S)\ P_D(S)$

4. **Propagation Hypotheses**

   $P(Y(S) | Y(T),H)\ P(Z(S), Z(T) | Y(S), Y(T), H)\ P(H) = [1-P_{FA}(T)]\ [1- P_D(S)]\ P_D(T)$

5. **Track Drop Hypotheses**

   $P(Y(S) | Y(T),H)\ P(Z(S), Z(T) | Y(S), Y(T), H)\ P(H) = P_{FA}(T)\ P_D(T)$

Scoring Nomenclature

- $Y(S)$ are the sensor report Gaussian kinematics with covariance R
- $Y(T)$ are the track Gaussian kinematics with covariance P^{+}_{k},
- H is one of 5 association hypothesis types, E is expectation fcn
- $|V|$ is determinant of innovations covariance, $V = H\,[P^{+}_{k}]\,H^{T} + R$,
- μ is the mean of the chi-square statistic (i.e., $\{I^{T} V^{-1} I\}$)
- I is the innovations vector, $I = Y(S) - H\,Y(T)$,
- $P(K)$ are the confidences of the disjoint entity class tree,
- $Z(T)$ [$Z(S)$] are the parameters/attributes from the track [report],
- $P_D(S)$ [$P_D(T)$] is the sensor [track file] probability of detection
- $P_{FA}(S)$ [$P_{FA}(T)$] is the sensor [track file] probability of false alarm,

Approximate Class Confidence Generation from Declarations

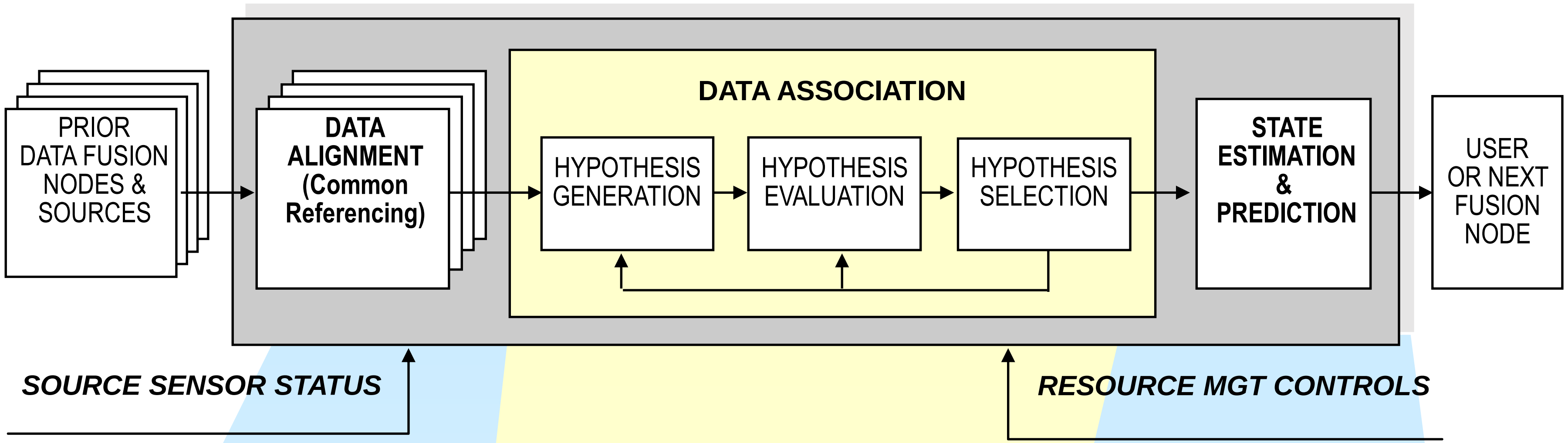
- $P(K|D) = P(D|K)\,P(K) / \Sigma_T(P(\text{Truth } T)\,P(D\ |\text{Truth } T)$ where
- P(K|D) is the probability of the entity being of class K <u>given the specified sensor declaration D</u> that is computed for all the possible disjoint classes. These terms are inserted for the n P(K|Z(S),Y(S), H) sensor report disjoint classification type confidences.
- P(K) is the a priori probability of the entity being of class K
- P(D|K) is the probability that the declaration D is made given the entity is of class K from the declaration confusion matrix
- P(D |Truth T) is the probability of the specified declaration D given the entity is of truth type T from the declaration confusion matrix where T varies over the possible scenario truths
- P(Truth T) is the a priori probability of the truth in the scenario being of type T where T varies over the possible scenario truths

MAP Scoring Uses Kinematics, ID, Track Confidence & Pedigree Information

- Uses the separation point on the PDF as the kinematics score, so high uncertainty tracks do not overly attract reports as w/chi-square scoring
- Bayesian scoring and update of the classification uncertainties with pedigree of noncommensurates used for class error correlation compensation or separate noncommensurate class vectors
- Track confidence estimation provides rigorous basis for the scoring of the four non-association hypotheses
- Misalignment bias states & uncertainties added for scoring and to remove relative misalignments

Track Confidence Is Updated Using Source Parameters & Association Results

DATA FUSION NODE



- **DETECT AND RESOLVE DATA CONFLICTS**
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- **ESTIMATE/PREDICT ENTITY STATES**
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Track Confidences Needed for MAP: Bayesian Equations for COP Track Confidence Have Been Derived

- Propagation of Probability for Entity Track in Consistent Operational Picture (COP) & False Track
- Track Confidence Contribution to Association Hypothesis Scoring
- Update of Probability of Entity Track in COP and False Track Confidences With Track Propagations and Pop Ups
- Update of COP Probability of False Track for Associated Tracks, Propagated Tracks, & Pop Ups

Hyp Eval Problem to Solution Space Mapping

SOLUTION SPACE		Probabilistic						Possibi-listic		Logic/Symbolic				Neural			Unified
PROBLEM SPACE	AdH	Lkl	Bay	NP	Chi	CEA	Inf	DS	Fuz	S/F	SD	ES	C-B	US	FF	Rec	RS
INPUT DATA																	
• Identity/attributes		Y	Y		N												Y
• Kinematics		Y	Y		Y												Y
• Parameter attributes			Y	Y	Y												Y
• A priori sensor data		N	Y		N												Y
• Linguistic data	Y					Y		Y	Y		Y						Y
• Spatio-temporal										Y							Y
• High uncertainty								Y	Y								Y
• Unknown structure														Y	Y	Y	
• Non-parametric data	Y			Y			Y		Y								
• Partial data											Y						
• Differing dimensions					Y												
• Differing conditionals						Y											
• Error PDF known		N	Y	Y	N		N	N	N	N	N	N	N	N	N	N	N
SCORE OUTPUT																	
• Yes/no, pass-through	Y																
• Discrete score bins	Y									Y	Y	Y	Y	Y	Y	Y	
• Numerical scores		Y	Y	Y	Y	Y	Y										Y
• Multi scores per								Y									Y
• Confidence function									Y								Y
PERFORM MEAS																	
• Low cost/complexity	Y	Y	Y	Y	Y	N	N	N	N	N	N	N	Y	Y	Y	Y	N
• Compute efficiency										N		N	Y	Y	Y	Y	
• Score accuracy	N	Y	Y	N	Y	Y		Y	Y	N	N	N	N	N	N	N	Y
• User adaptability										Y		Y	Y	Y	Y	Y	
• Training set required													N	N	Y	Y	
• Self-coded/trained		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	
• Robustness to error													Y	Y	Y	Y	
• Result explanation	N									Y	Y	Y	Y	Y	Y	Y	
• High processing Avail	N		N	N		y	Y		N	Y		Y	Y	Y	Y	Y	

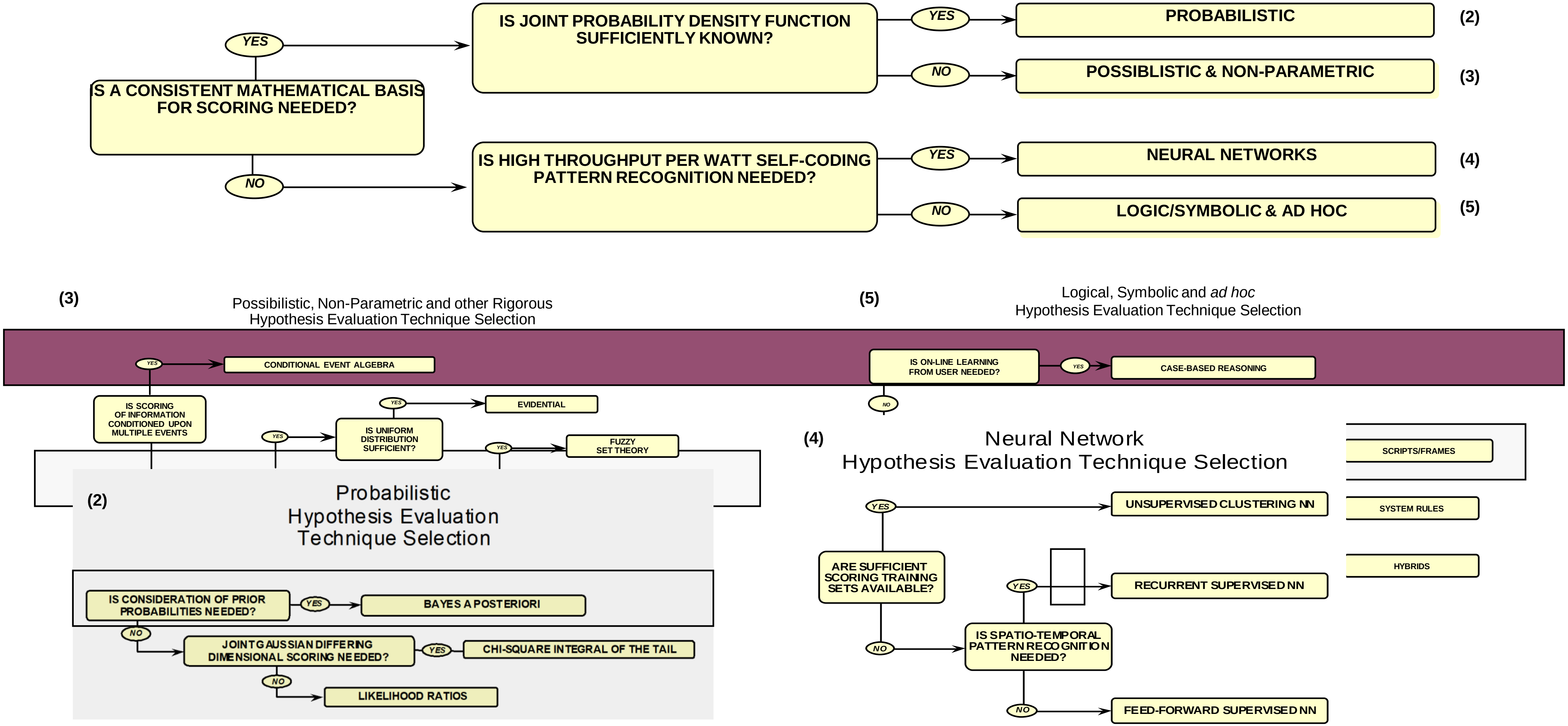
KEY

AdH Ad Hoc
Lkl Likelihood
Bay Bayesian
NP Non-parametric
Chi Chi-Squared
CEA Conditioned Event Algebra
Inf Information Theoretic
DS Dempster-Shafer
Fuz Fuzzy Logic
S/F Scripts/ Frames
SD Semantic Distance
ES Expert Systems
C-B Case-Based Reasoning
US Unsupervised Learning
FF Feed-Forward
Rec Recurrent Supervised Learning
RS Random Set

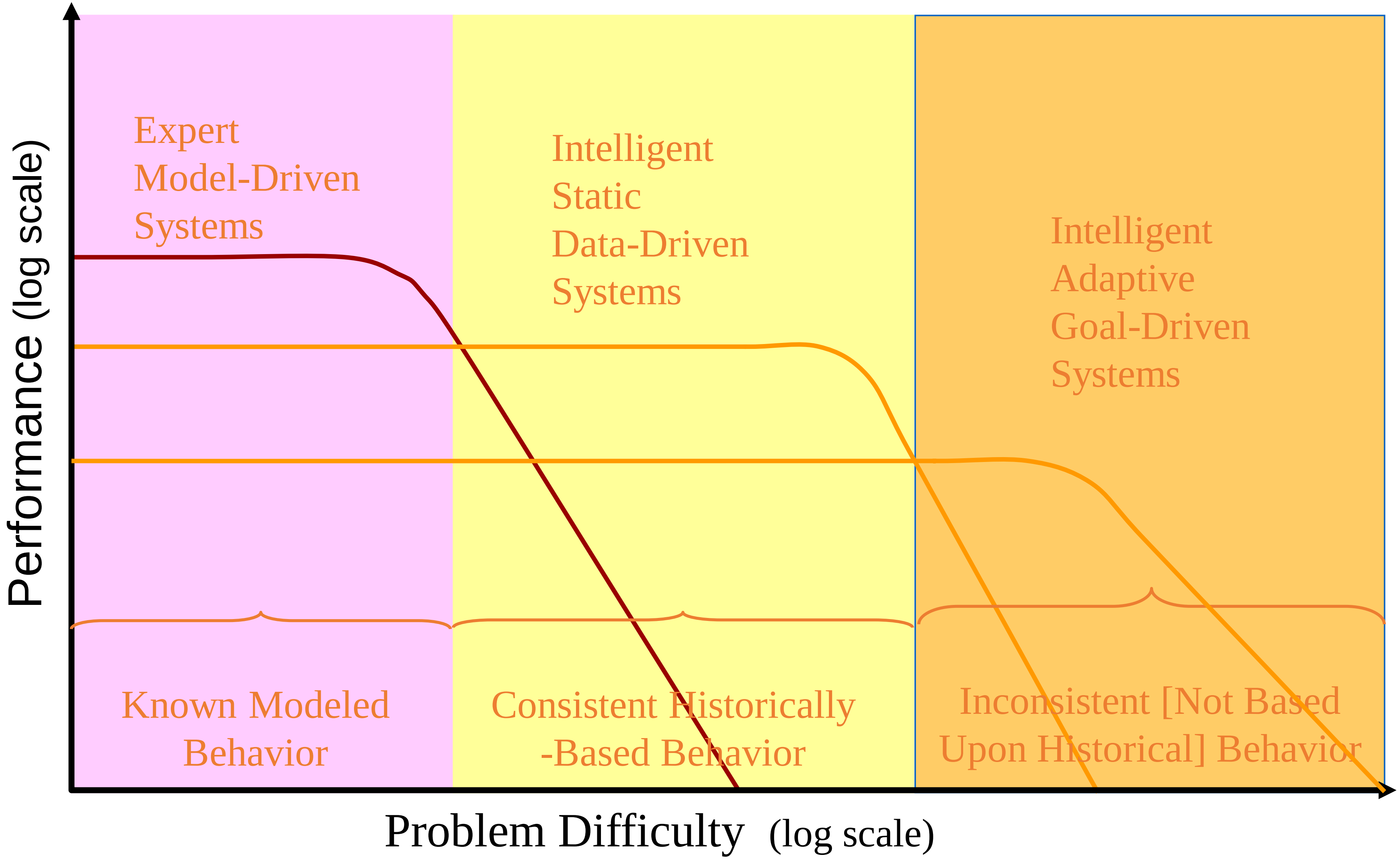
Alternative DF&RM Techniques Are Synergistic

Methods	Approach	Event Representation	Problem Domain	Solution Development	Costs/Risks	Performance	Verification	Speed
Ad Hoc	analyst driven	table look-up	predefined fixed features	rule-of-thumb	simple not upgradable	approximate; brittle	all cases tested	fast table look-up
Probabilistic	algorithm driven	pointwise probability	rigorously defined features	analyst solves rigorously	upgradable SW	precise; extendable	alternative path tests	via path parallelization
Possibilistic	algorithm driven	uncertainty-in-the-uncertainty	feature uncertainties known	analyst solves approximation	upgradable; more complex	Broader app's; extendable	alternative path tests	via path parallelization
Logic/ Symbolic	rule driven	setwise degree of membership	expert described features	expert defines rules	rule compatibility/ scalability	gets close; user adaptable	rules explanation	via rule parallelization
Neural Networks	self-organized	firing level patterns	unknown feature relationships	data driven; user objectives	training breadth; HW scalability	approximate; non-linear interpolation	numerous training cases	massively parallel chips
Unified	algorithm & rule driven	normalized representation	combinations of the above	analyst solves hybrid	most complex	most breadth	alternative path tests	via approximation

Decision Flow for Technique Selection
(Hypothesis Evaluation Example)

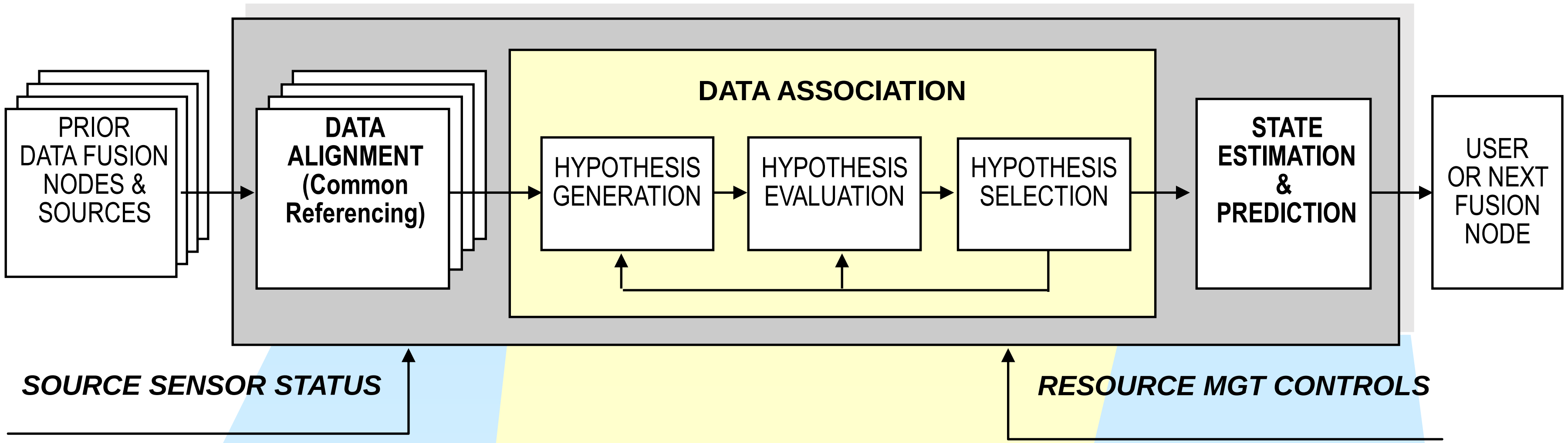


Solution Selection Depends upon Problem Difficulty



Hypothesis Selection Determines How Alternative Association World Views to Be Maintained

DATA FUSION NODE



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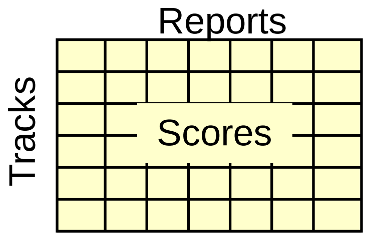
Hypothesis Selection Problem

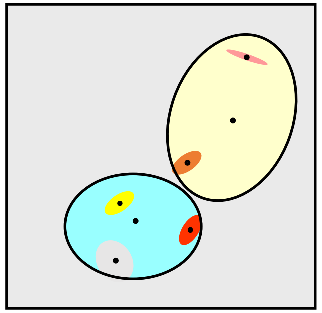
- Need to Search through Association Matrix to find best Global Hypothesis



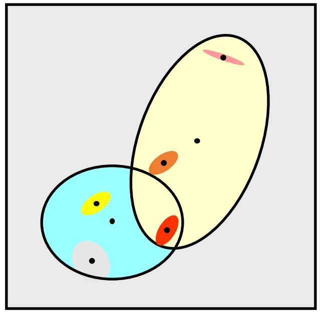
  - Association Matrix:
  - Types of Global Hypotheses
    - Set Partitioning: no two tracks (local hypotheses) share a report
    - Set Covering: There may be shared reports
- N-D Approaches: Search All Scans by All Sources
  - Globally Optimal Solution
  - Computationally Demanding (NP-Hard: $\leq$ Exponential Run-Time)
- 2-D Approaches: Search only Current Scan
  - Locally Optimal Solution
  - Polynomial Run-Time

TYPES OF GLOBAL HYPOTHESIS

Set Partitioning



Set Covering



Conversion of Association Matrix for 2-D Assignment Problem

	Current Reports			No Observation	
Current Tracks	$-\ln[P(R_1,T_1 \mid H)P(H)]$	$-\ln[P(R_2,T_1 \mid H)P(H)]$	$-\ln[P(R_3,T_1 \mid H)P(H)]$	$-\ln P(H_2)$	inf
	$-\ln[P(R_1,T_2 \mid H)P(H)]$	$-\ln[P(R_2,T_2 \mid H)P(H)]$	$-\ln[P(R_3,T_2 \mid H)P(H)]$	inf	$-\ln P(H_2)$
Track Initiation or FA	$-\ln P(H_1)$	inf	inf	0	0
	inf	$-\ln P(H_1)$	inf	0	0
	inf	inf	$-\ln P(H_1)$	0	0

- "No Observation" columns added to denote the better hypothesis, H_2, of false or propagated tracks for unassociated tracks
- "No Association" rows added to denote the better hypothesis, H_1, of false alarm or initiated tracks for unassociated reports
- Zero's in lower right box discourage selection of non-association hypotheses

Entity Class Tree Confidence Update With Noncommensurate Sources

$$P(\text{class } C \mid \text{all } S_i, H) = \{\Pi_i \; [\{P(C|S_i,H)/P(C|Y(S_i \text{ all } i), H)\} \, P(C| \; Y(S_i \text{ for all } i), H)] \;\} \, / \, \Sigma_K \{\Pi_i \; [\{P(K|S_i,H)/P(K| \; Y(S_i \text{ all } i), H)\} \, P(K| \; Y(S_i \text{ for all } i), H)]\}$$

$$\text{if } P(C|H) \neq 0 \qquad [= 0 \;\; \text{if } P(C|H)=0]$$

- C is the element of the fused entity class tree being updated,
- S_i for each source i is its measured data [both kinematic and attribute]
- $P(C|Y(S_i), H)$ is the probability of an entity of type C given only kinematics data from source i & H, the association hypothesis,
- K is the index of type disjoint tree classes [summed over for normalization],
- $P(C|S_i,H)$ are the entity class tree confidences based upon all measurements from each source i

Sample Interlaced Network of DF&RM Dual Level Interactions