
Assessment

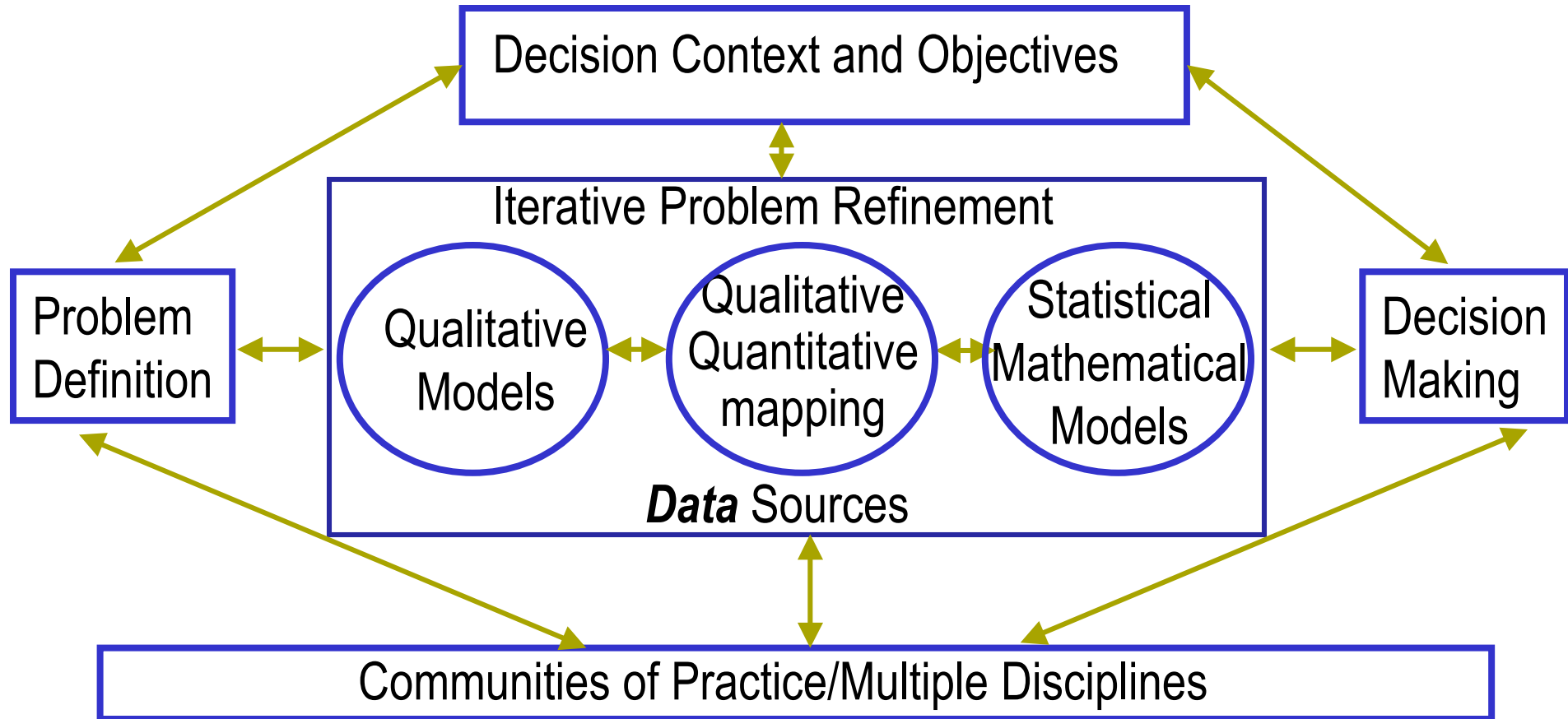
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Assessment Process

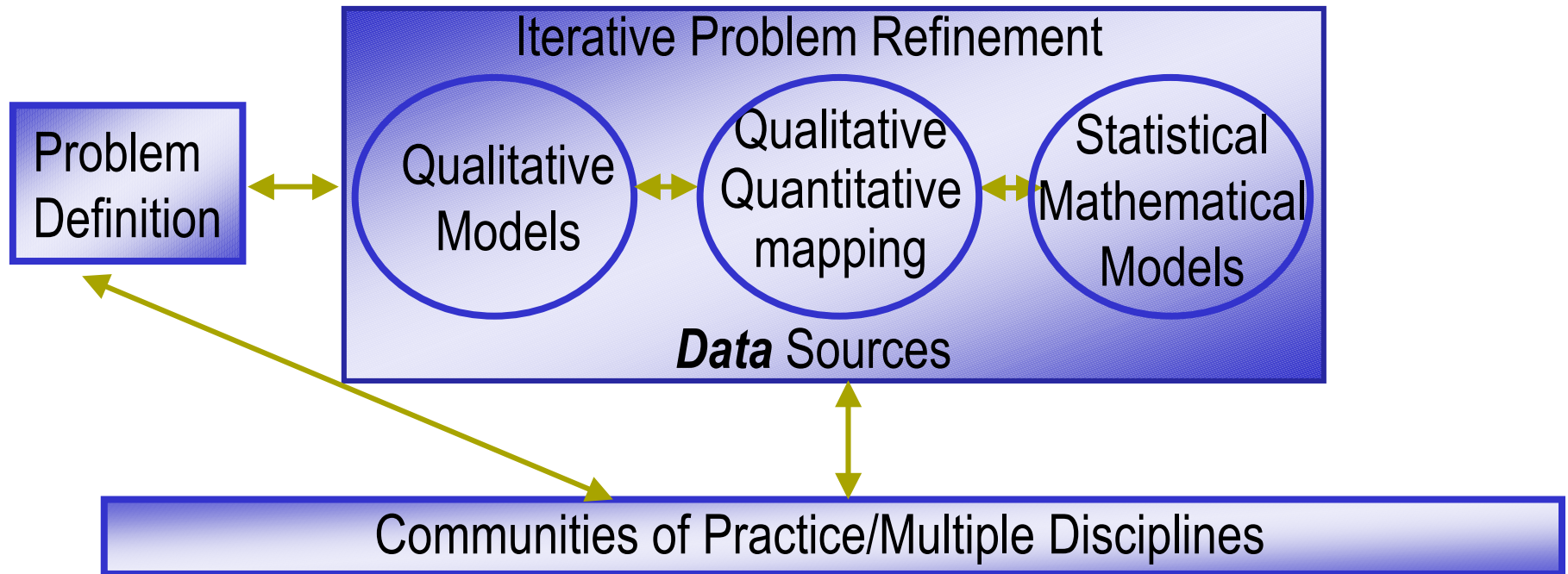
- Goal is to understand the complex system
- Run towards the goal by improving our knowledge about the system
 - Improve predictions of metrics (quantities of interest) about the system
 - Resolve the uncertainty in the predictions (e.g., reduce prediction error variance)
 - Improve the complex system representation and corresponding mathematical model(s)
 - Understand the modeling choices

Goal is too vague!

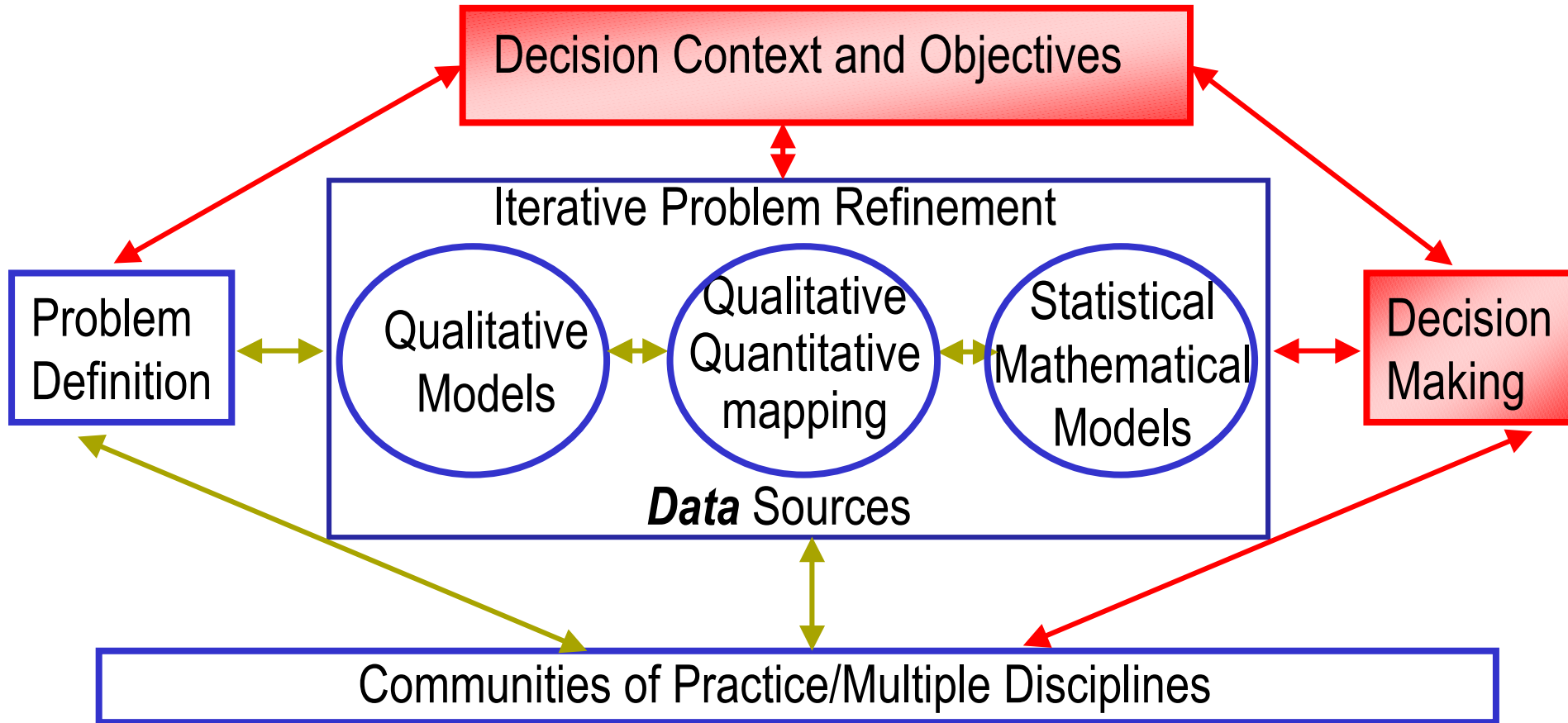
Complex Systems Analysis Process



Complex System Model!



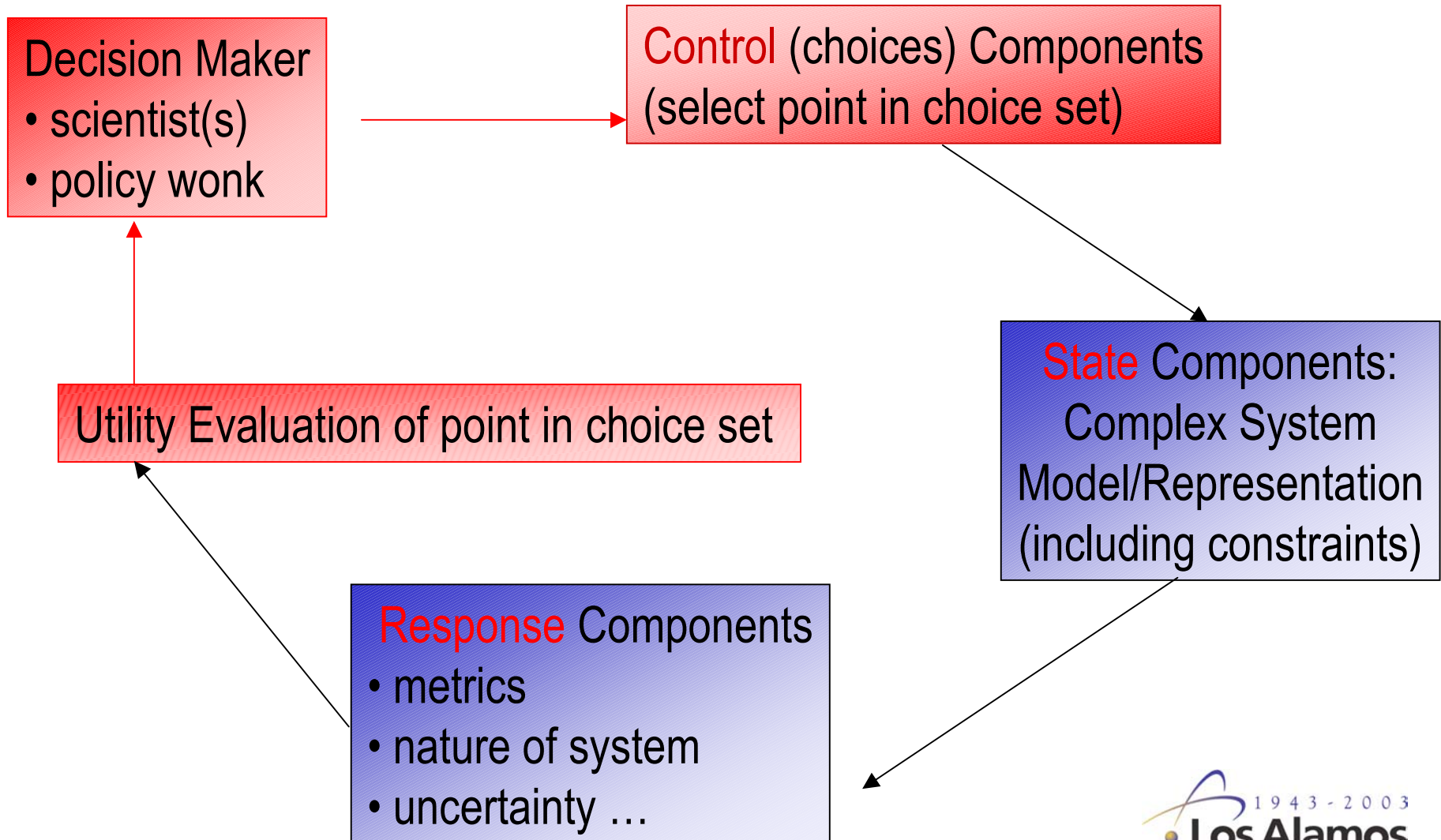
Decision Part of Process is Needed



General Decision Framework

- Decision making is really a problem of **resource allocation**
- All of the system variables, parameters, relationships, can be classified as either **State**, **Control**, or **Response** components
- **State** components (constraints and system itself) are the parts of the problem the decision maker does not control
 - budget allocation, system specifications, technology, potential and type of attack, size of release
- **Control** components (or choices) are the parts of the system the decision maker does control
 - time, materials, facilities, budget distribution, number of sensors, location of sensors
- **Response** components are the system attributes the decision maker is interested in
 - time to eradicate epidemic, reliability, performance, total cost

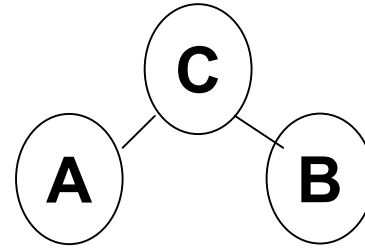
Decision Maker's View of Process



Simple Example

- Complex system is represented by simple linear regression model, $Y = \beta_0 + \beta_1 x + \varepsilon$
- No constraints
- Choices/states limited to values of x to observe the system, $y|x$
- Metrics/responses are the parameters estimates and their errors
- Goal is to reduce the estimation error for β_1 : $\text{var}(\hat{\beta}_1) = \frac{\sigma_\varepsilon^2}{n\sigma_x^2}$
- Solution is to select the most disperse values of x possible

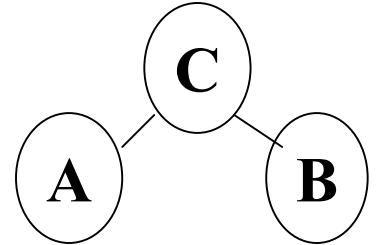
Simple Example



- System Model: $C=A+B$
- Cost constraints for “data” collection
- Choices need to be made on where/how to collect more “data”
- Goal is to reduce prediction error of response C
- Solution is to reduce prediction errors of A and B
- How does this tell me where to collect “data”?

Simple Example Continued

$$\begin{aligned} C &= \hat{C} + \varepsilon \\ &= \hat{A} + \varepsilon_A + \hat{B} + \varepsilon_B \end{aligned}$$



$$\begin{aligned} \text{Var}(C) &= \text{Var}(\hat{C}) + \text{Var}(\varepsilon) \\ &= \text{Var}(\hat{A}) + \text{Var}(\varepsilon_A) + \text{Var}(\hat{B}) + \text{Var}(\varepsilon_B) \end{aligned}$$

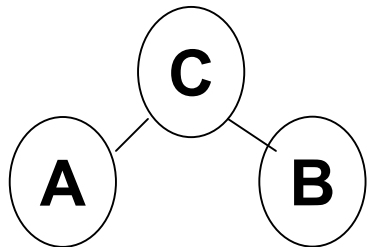
$$\text{Prediction Variance} = \text{Var}(\hat{C}) = \text{Var}(\hat{A}) + \text{Var}(\hat{B})$$

$$\text{Prediction Error Variance} = \text{Var}(\varepsilon) = \text{Var}(\varepsilon_A) + \text{Var}(\varepsilon_B)$$

$$\text{Want } \text{Var}(\hat{C}) \rightarrow \text{Var}(C) = \text{Var}(A) + \text{Var}(B)$$

$$\text{Therefore, want } \text{Var}(\varepsilon) = \text{Var}(\varepsilon_A) + \text{Var}(\varepsilon_B) \rightarrow 0$$

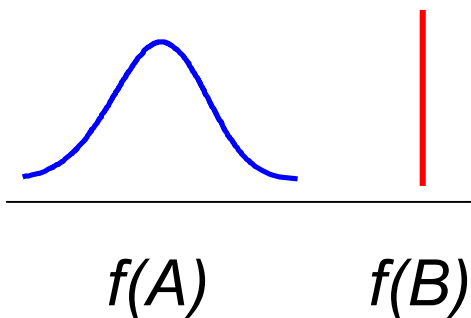
Simple Example Continued



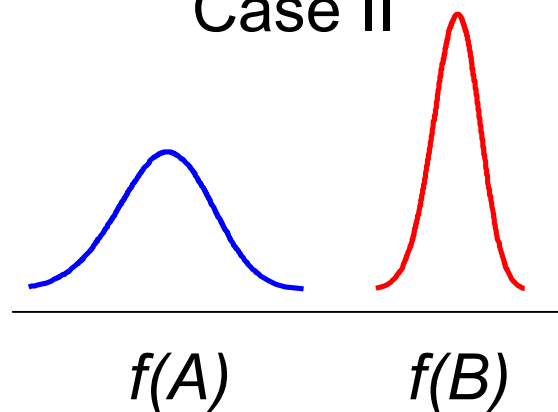
Want $Var(\hat{C}) \rightarrow Var(C) = Var(A) + Var(B)$

Therefore, want $Var(\varepsilon) = Var(\varepsilon_A) + Var(\varepsilon_B) \rightarrow 0$

Case I



Case II



SIMPLE EXAMPLE IS NOT SO SIMPLE!

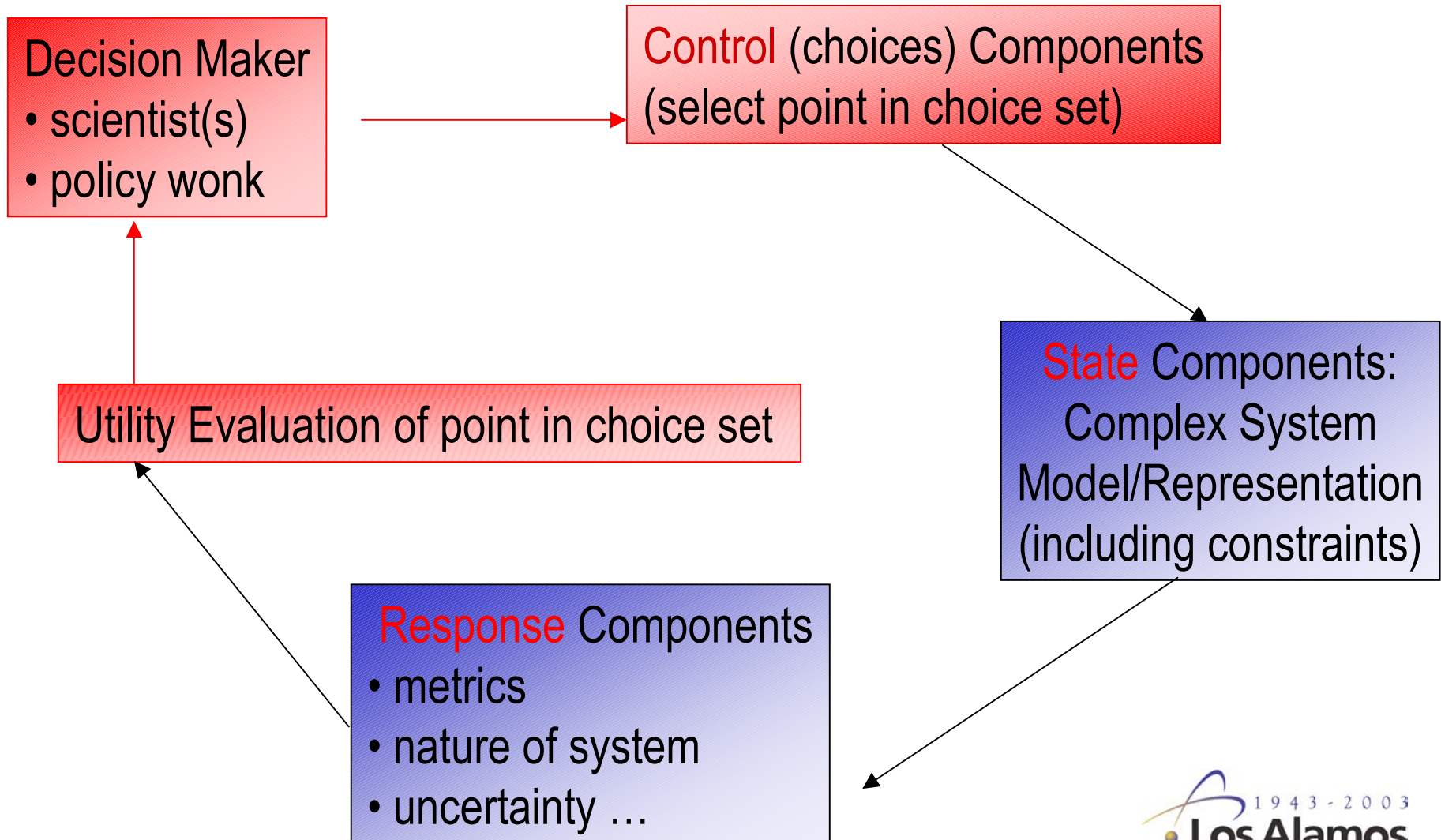
General Decision Framework

- With few controls and one or two response attributes, analyses that guide decision making can be straightforward – **maybe!**
- Decision making is typically not this simple:
 - multiple controls
 - multiple, conflicting responses
 - multiple time horizons
 - uncertainty
- Utility theory can provide a general framework

Optimal Decision Making

- Optimal decision making requires a single metric giving the relative worth to the decision maker of any set of responses
- This metric is given by the utility function
- Note that the response depends on the control and state components
- The optimal set of choices maximizes the decision maker's utility.
- Utility maximization requires a complete understanding of the entire complex system
- The utility maximization model is probably has the most empirical verification of any model in all of the social sciences - you do this every day.

Decision Maker's View of Process



The Nature Of The Solution: Tradeoffs

- The rate at which the decision maker is **willing** to exchange one response for another is given by the utility function
 - amount of vaccine for city A versus time to eradicate
 - Reliability versus performance
- The rate at which the decision maker **can** exchange one response for another is given by the system model
- The optimal solution is where the two exchange rates are equal
- With a complex problem, the optimal decision will depend upon a large number of specifications and assumptions.
- Decisions should be robust: small changes in model specifications should not produce major changes in decisions

Where do you start?

- Recognize the problem is hard, but not impossible
 - Great open, mathematically centric, research problems exist!!
- Statistical Experimental Design
 - Clear optimality criterion and theory
 - Useful to design sensitivity analyses
 - Useful in selection of new data collection scheme
- Hybrid Experimental Design
 - Extension of tradition design to information integration/data combination
- Foundations of Utility theory

Common Research Issues

- Uncertainty Quantification -- mathematics + philosophy
 - probabilistic
 - non-probabilistic
- Flexible representations
 - integration of “*models*”
 - analysis across multiple levels of granularity, space, and time
- Graphical model development
- Information integration
 - multiple and diverse information sources
 - updating: dynamic analysis for dynamic “*systems*”
- Knowledge
 - acquisition
 - representation
 - integration
 - quantification
- Multidisciplinary problem definition AND solution!