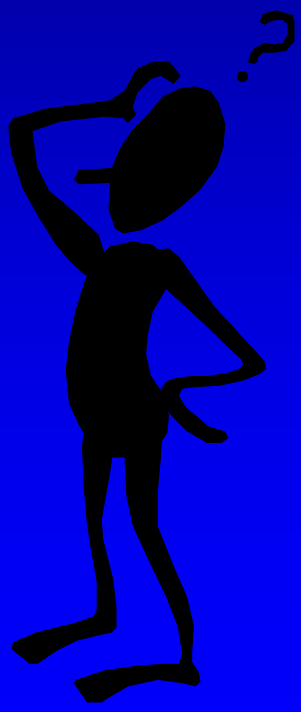
Visualizing Uncertainty



William B. Thompson

Sarah Creem-Regehr

Grace Hansen

Lace Padilla

Heidi Kramer

School of Computing

Department of Psychology

University of Utah

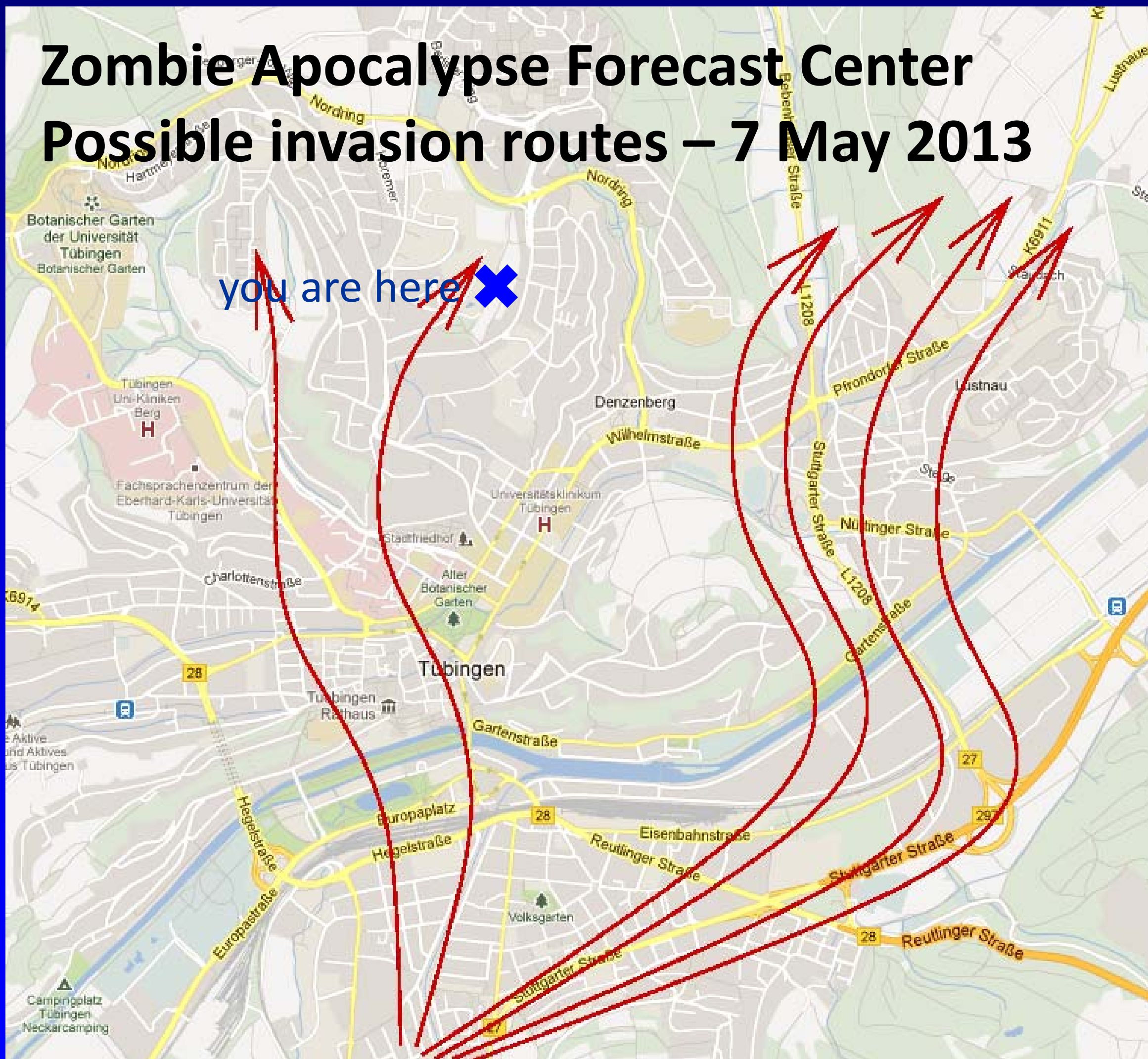
"Given the importance of the public understanding of health, economic, and environmental risk, it may appear remarkable that so little firm guidance can be given about how best to communicate uncertainty."

-- Spiegelhalter, Pearson, and Short, *Science*, 2011

Example:

- Evacuate?

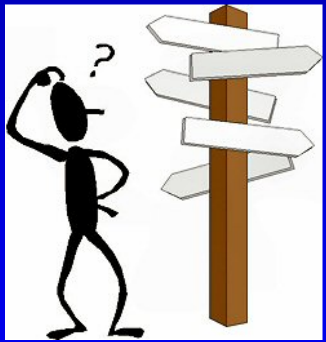
Example:



- Evacuate?
  - Decision is harder!
    - More information to process
    - Choices less clear

Visualizing output of computational models

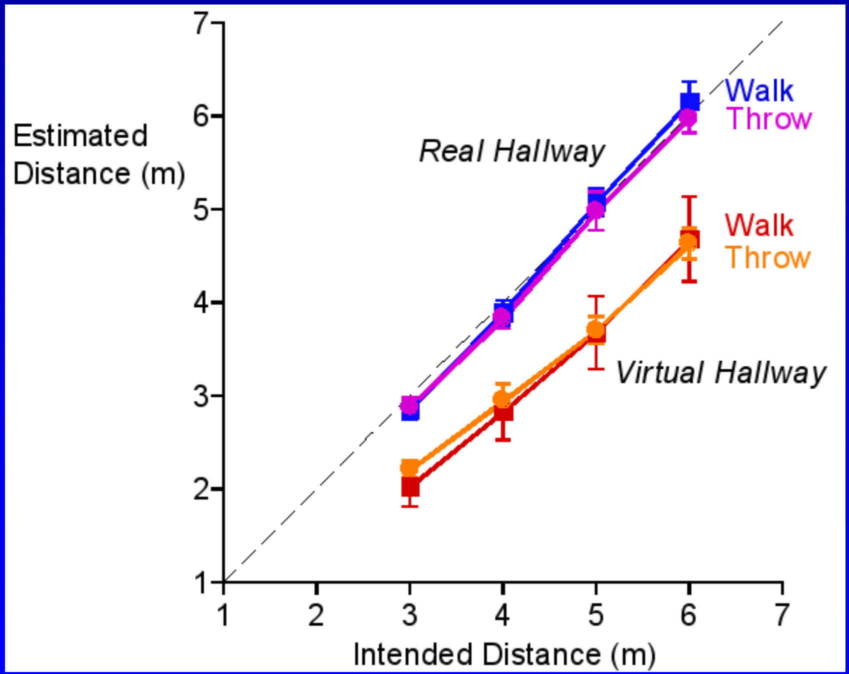
- Computational modeling used to support decisions in a wide range of applications
  - Engineering design, medicine, transportation, public safety, environmental policy, …
- Computational models inevitably have associated errors and uncertainties

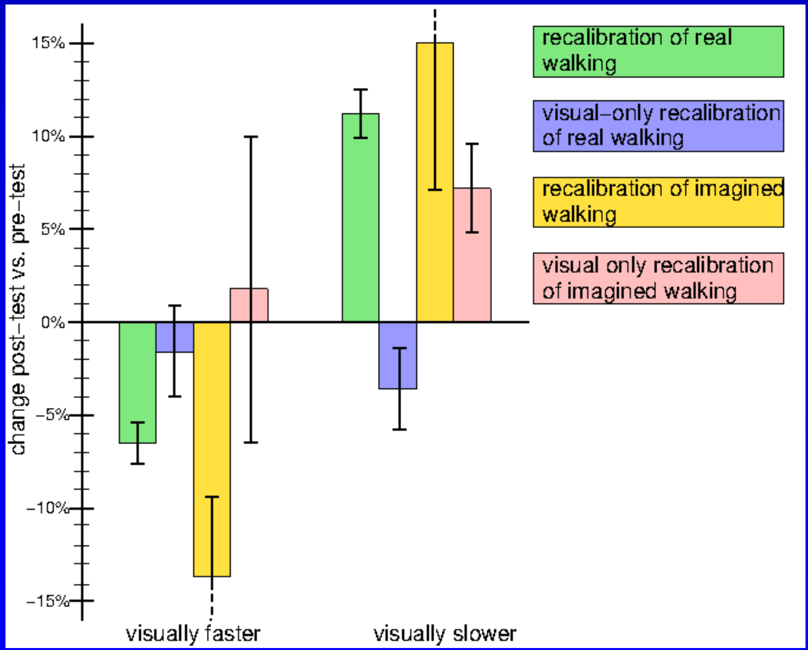


- Substantial progress has been made on *uncertainty quantification* of such models
- Much less progress has been made on *uncertainty communication* to decision makers

Uncertainty communication

- We have all had experience with uncertainty communication!

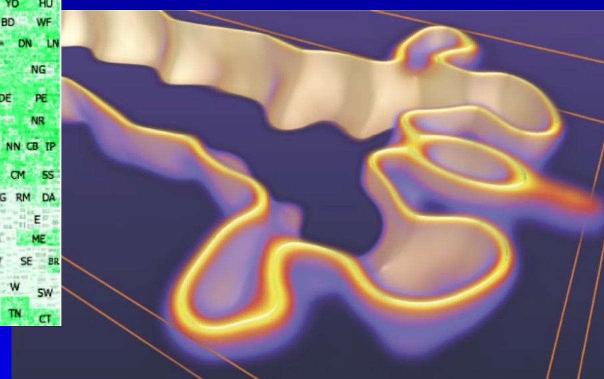




Uncertainty communication

- What about more complex data?

Slingsby, Dyles, & Wood, *IEEE-TVCG*, 2011



Pothkow & Hege, *IEEE-TVCG*, 2011

Sanyal et al., *IEEE-TVCG*, 2010

  – Can people effectively use such visualizations?
  – What is the measure of effectiveness?

Visual representations of uncertainty

- Two alternatives are common:
  - Using separate visual encodings for data and uncertainty of data
  - Direct encoding of variability of data

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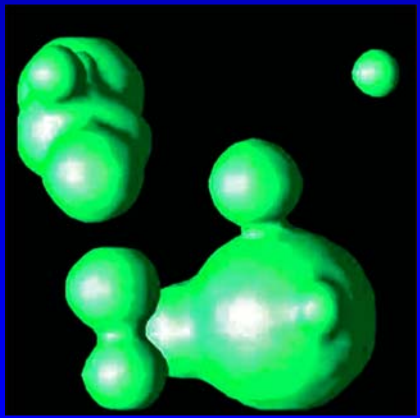
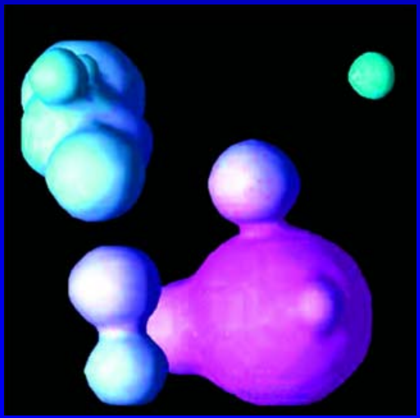
Uncertainty in surface geometry:

Grigorian & Rheingans, *IEEE-TVCG*, 2004



value only



value plus uncertainty

  - What is the meaning of the uncertainty "value"?

Visual representations of uncertainty

- Two alternatives are common:
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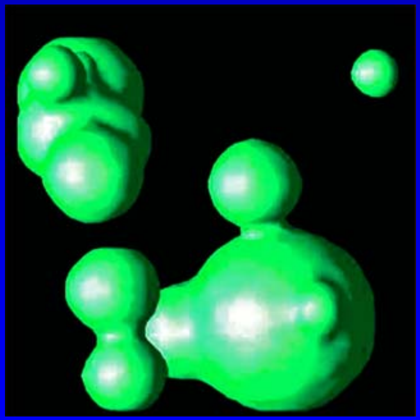
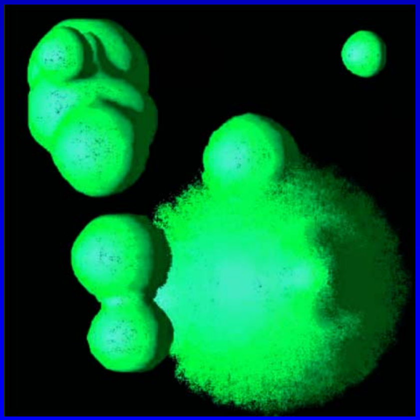
Uncertainty in surface geometry:

Grigorian & Rheingans, *IEEE-TVCG*, 2004



value only



value plus uncertainty

  - What is the impact on visual bandwidth?

Visual representations of uncertainty

- Two alternatives are common:
  - Using separate visual encodings for data and uncertainty of data
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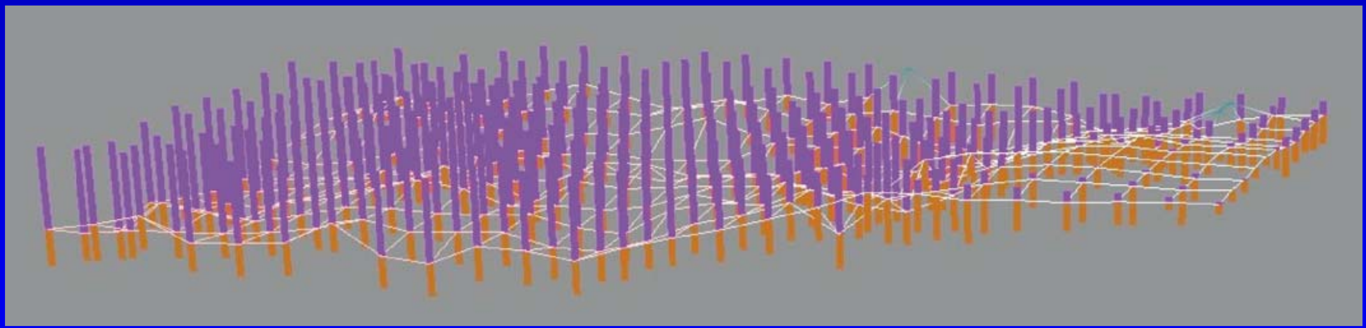
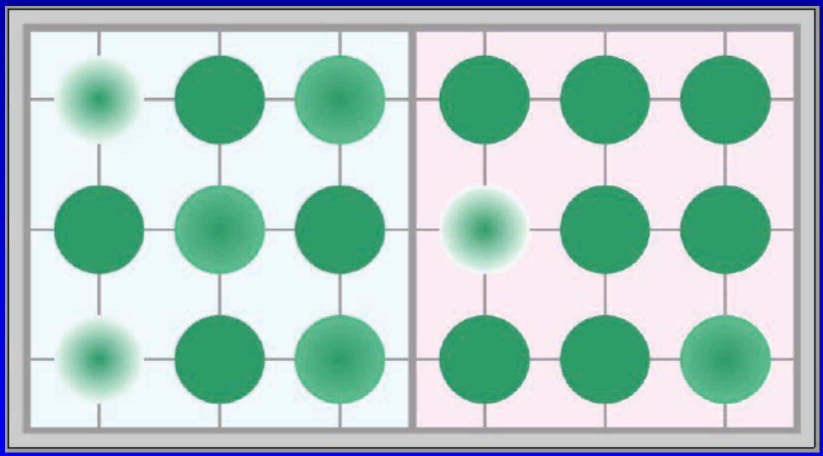


Cliburn et al., *Computers & Graphics*, 2002

  - What is the impact on visual bandwidth?

How do we know what works?

- Subjective reporting of uncertainty “value” is common



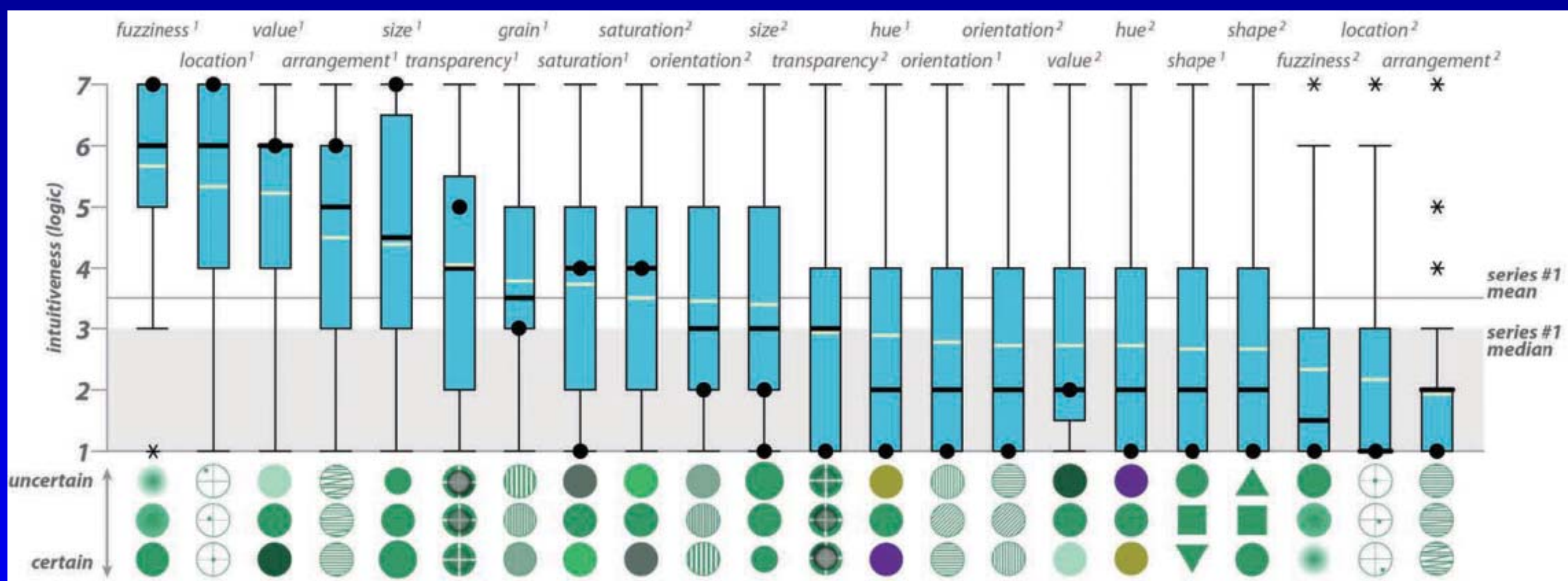
Click on the map region for which information is least certain overall

MacEachren et al., *IEEE-TVCG,* 2012

  - Question of interest: how well users can distinguish between two different visually represented values?
    - In many studies, uncertainty is the only attribute evaluated!

How do we know what works?

- Subjective reporting of uncertainty "value" is common



MacEachren et al., *IEEE-TVCG,* 2012

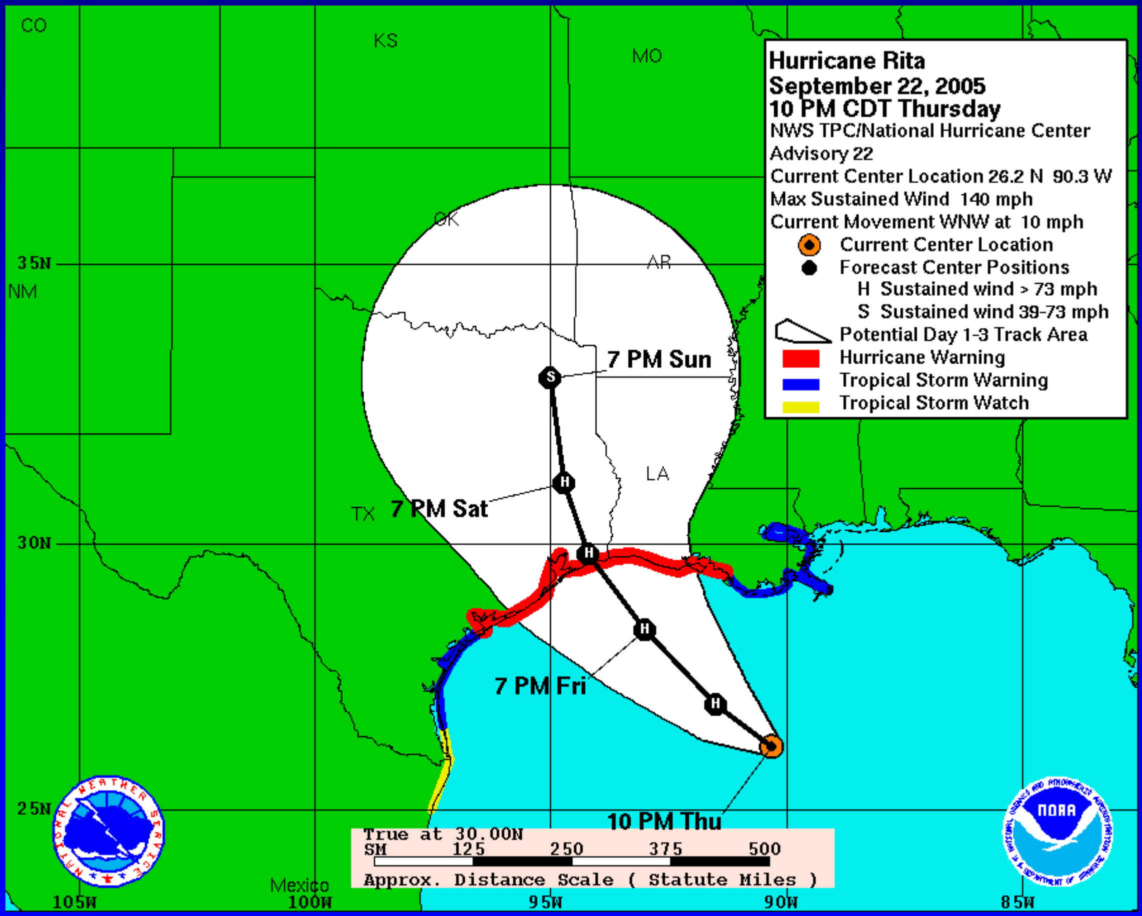
  - Question of interest: "intuitive" sense of uncertainty.
  - In many studies, uncertainty is the only attribute evaluated!

How do we know what works?

- Subjective reporting of uncertainty “value” is common
  - Problems:
    - *Uncertainty* rarely defined in a precise manner
    - *Performance-preference* dissociation
    - Comparisons of *visual channels* rarely well controlled
- What about task-based user studies?
  - Problems:
    - Difficult to do controlled studies
    - No direct way to associate visualization with cognition

How do we know what works?

- Reporting of probability rather than uncertainty



  - May not say much about *cognition* of uncertainty

How do we know what works?

- What to do???

How do we know what works?

[T]he design of effective visualizations is as much a challenge for cognitive science as for computer and information science, and ... these disciplines must collaborate closely on the development of new information technologies and visualization design.

Mary Hegarty
IEEE Vis 2010

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Computer Science
- Computational theoretical framework
- Testable theories
- Application problems

Perceptual Science
- Theoretical frameworks based on cognitive and neuroscience
- Testable theories
- Basic science problems

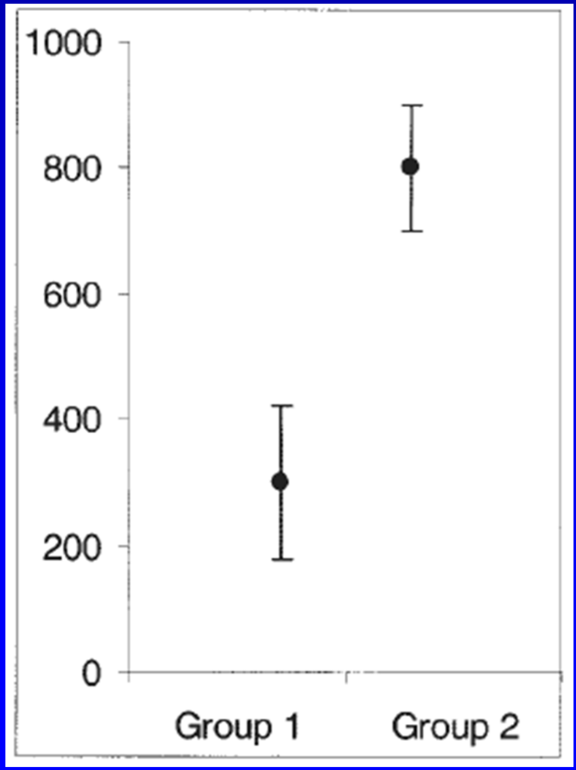
What we know about cognition of uncertainty

- Naïve users have difficulty using uncertain information and often resort to heuristics

Tversky & Kahneman, *Science*, 1974

- Uncertainty even misunderstood by scientists!

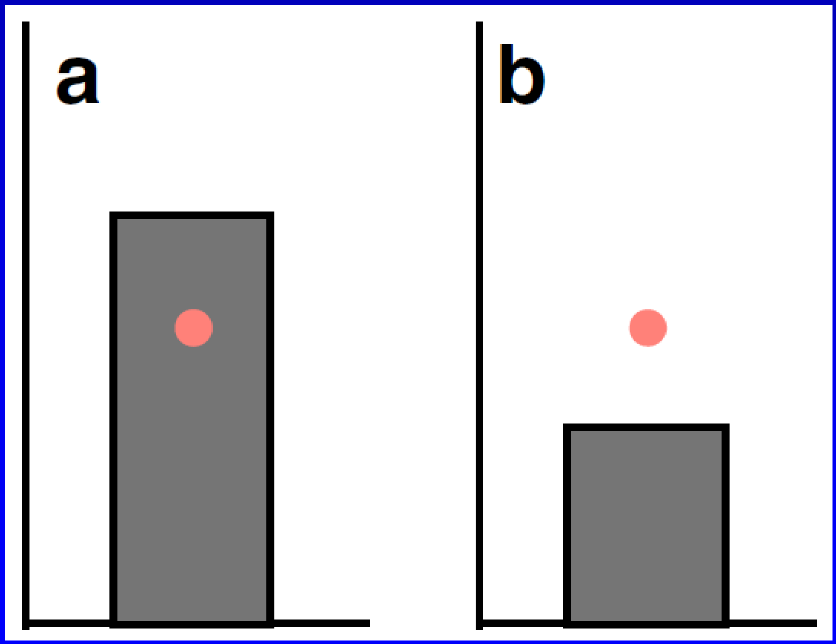
Belia et al., *Psych. Methods*, 2005



What we know about cognition of uncertainty

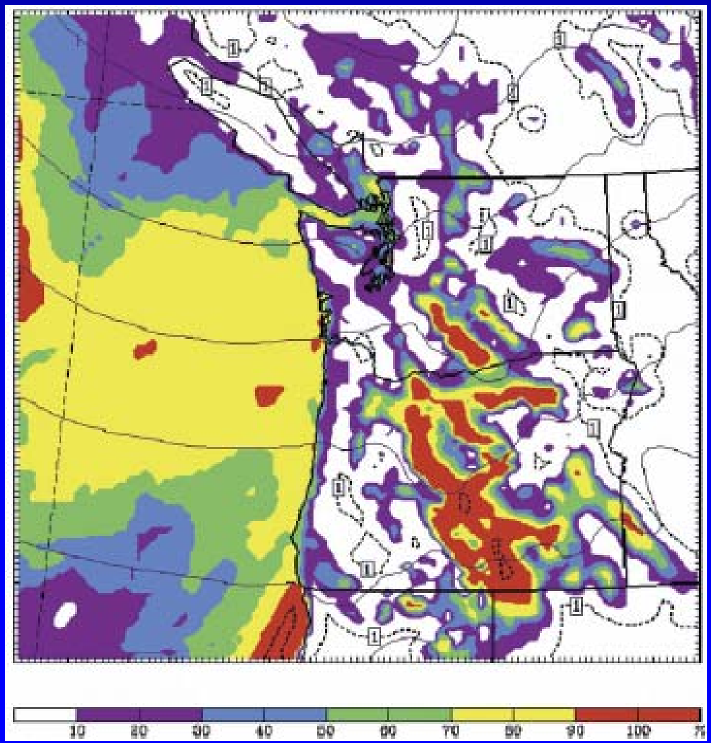
- Perceptual issues interact with cognition to cause additional difficulties

Newman & Scholl, *Psycho. Bull. Rev.*, 2012



What we know about cognition of uncertainty

- Sometimes information about uncertainty improves accuracy of decision making
  - At least for weather…

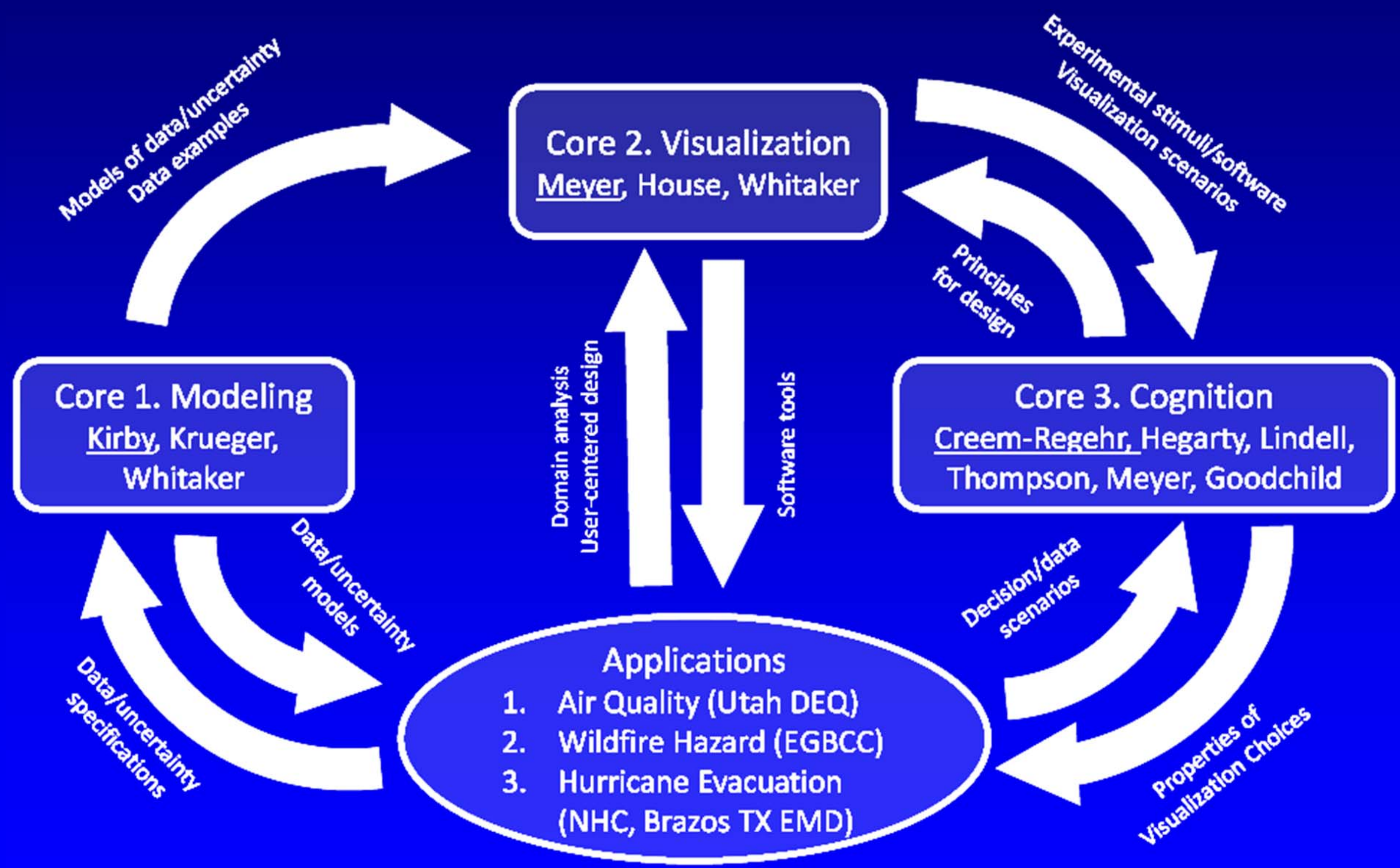


Joslyn et al., *Weather and Forecasting*, 2007
Joslyn & LeClerc, *JEP:Applied*, 2012

Our approach (the big picture)

- Modeling, Display, and Understanding Uncertainty in Simulations for Policy Decision Making
  - $3m, 4 year NSF-funded research effort
  - Four institutions
    - University of Utah (lead)
      - Ross Whitaker (PI), Sarah Creem-Regehr, Robert Kirby, Steven Krueger, Miriah Meyer, William Thompson
    - Clemson University
      - Donald House
    - University of California – Santa Barbara
      - Mary Hegarty, Michael Goodchild
    - Texas A&M
      - Michael Lindel, Carla Prater

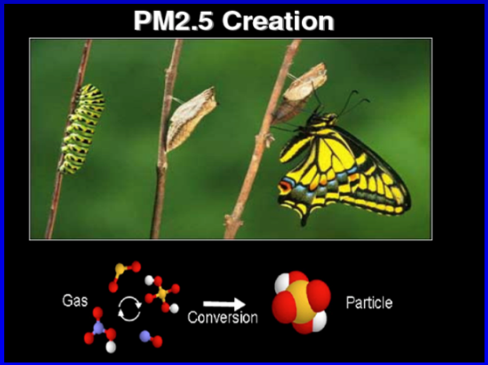
Our approach (the big picture)



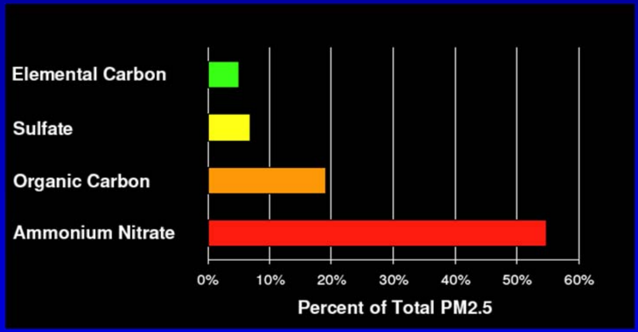
Application: Air Quality Management

- Goal: Model PM2.5 distribution in Utah, and understand the relationship between sources and levels

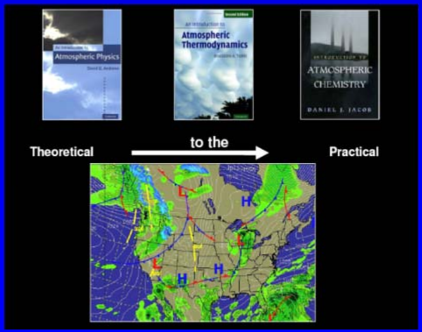
Observables



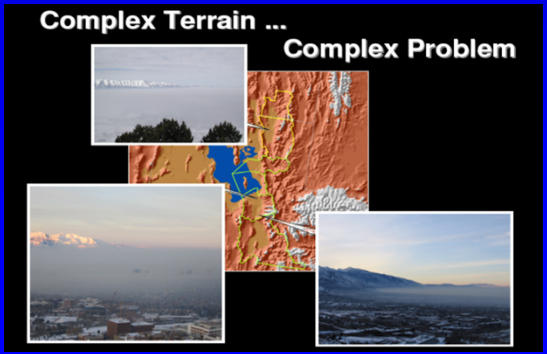
How it is created



What we breathe



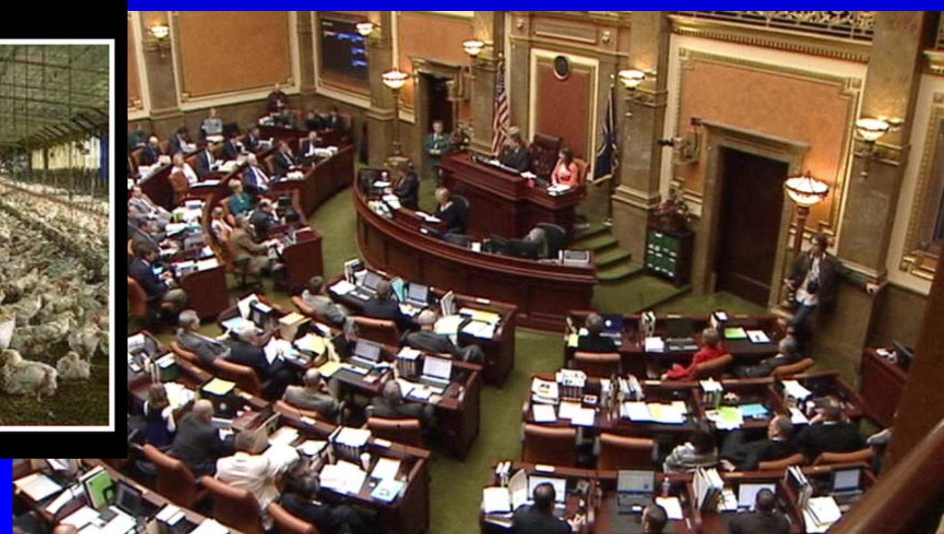
Models for its physics



Input and Boundary Complexities

Application: Air Quality Management

- Goal: Model PM2.5 Distribution in Utah, and understand the relationship between sources and levels



Application: Fire Risk Management

- Pre-position wildfire fighting resources

Prediction in June, 2012

Reality in July, 2012

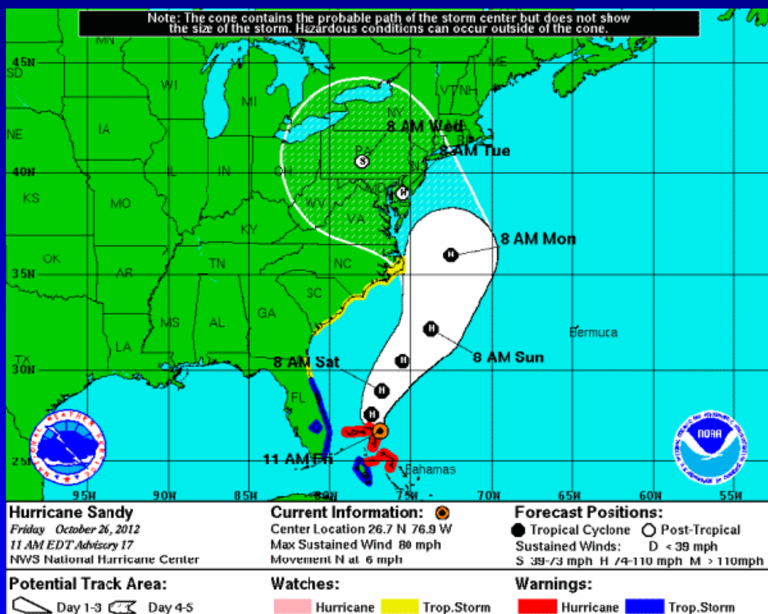
Application: Fire Risk Management

- Some of the sources of uncertainty:
  - Wind direction and speed
  - Precipitation
  - Relative humidity
  - Ruel types (trees and grass)
  - Random “unforeseen” events (e.g. lightening)

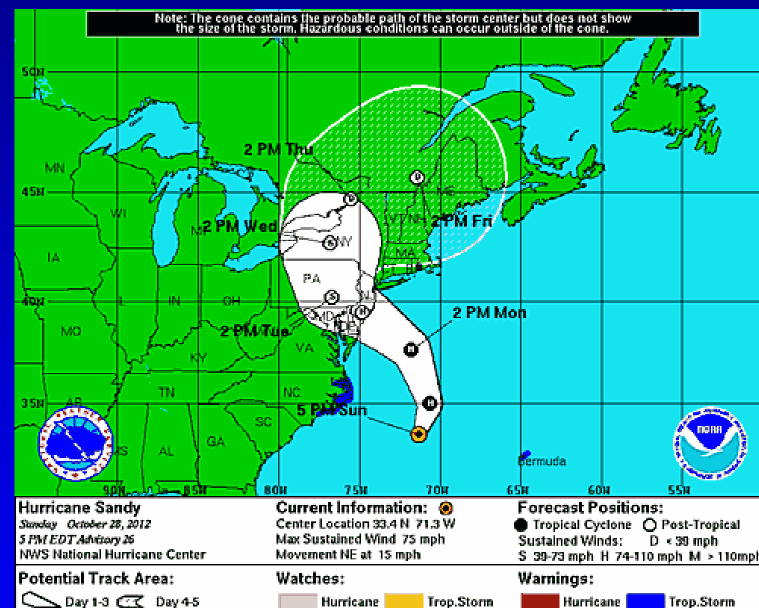
⋮

Application: Hurricane Evacuation Management

- Support for decisions about evacuation areas



Friday, October 26, 2012



Sunday, October 28, 2012

  - Center is forecast path
  - Width is 67% of five past years of forecasts

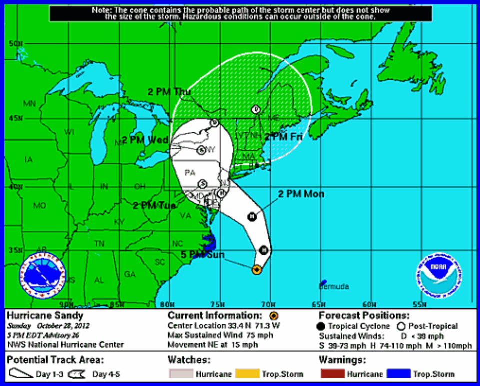
Application: Hurricane Evacuation Management

- Some of the sources of uncertainty:
  - Wind conditions (at different heights in the atmosphere)
  - Sea-surface water temperature
  - Different dynamics models (having different variants of humidity models, etc.)
  - Incorporation of historical track history

⋮

Our approach (cognition)

- Three phases:
  - Basic perceptual science concerning comprehension of visually presented uncertainty
  - Evaluations of the effect of context and instructions
  - Examination of uncertainty comprehension in domain-specific applications



The first step

- Adopt a Bayesian view of uncertainty quantification
  - Use probability distributions to model both random events and partial knowledge of the world.
- Base evaluation on performance in Bayesian inference tasks
  - Presumption is that such tasks require *cognition* of uncertainty, not just *perception* of amount of uncertainty.
- Start simple!

The first step

- Can people reason about visually presented uncertainty in a simple but non-trivial situation?
  - Limit to maximum likelihood Bayesian classification task
  - Limit to univariate normal distributions
    - Still allows tasks involving multiple instances of univariate distributions, indexed by some other variable
  - Limit to participants naïve to the mathematics of maximum likelihood Bayesian classification
    - Precludes solutions involving extraction of quantitative properties of distributions, followed by mathematical (non-visual) analysis of those values.

Maximum likelihood classification task

- Maximum likelihood (minimum error) classification:
  - Choose S_i such that $P(S_i|x) \geq P(S_j|x)$ for all j
    - $S_i,\ i = 1, \dots, N$, is a set of *class labels*
    - x is a set of features
- Bayes' law: $P(S_i|x) = \frac{P(x|S_i)P(S_i)}{P(x)}$
- Under a set of (very) restrictive assumptions, the maximum likelihood classifier becomes:
  - Choose S_i such that $P(x|S_i) \geq P(x|S_j)$ for all j

Scenario

Almost all current weather forecasts include a specific prediction for future high and low temperatures, even though the temperature may end up being different than predicted. The plots you will see in this experiment represent the outcomes of two new temperature forecasting systems for a specific date, along with the actual high temperature for that date. Both systems report forecast temperatures in a manner that indicates the amount of uncertainty in the predictions for the given day. Neither system is more accurate than the other on average over the course of the year. For each plot, you will be asked to indicate which of the two systems made the more accurate forecast, taking into account the information about the uncertainty of the forecast in your answer.

Scenario

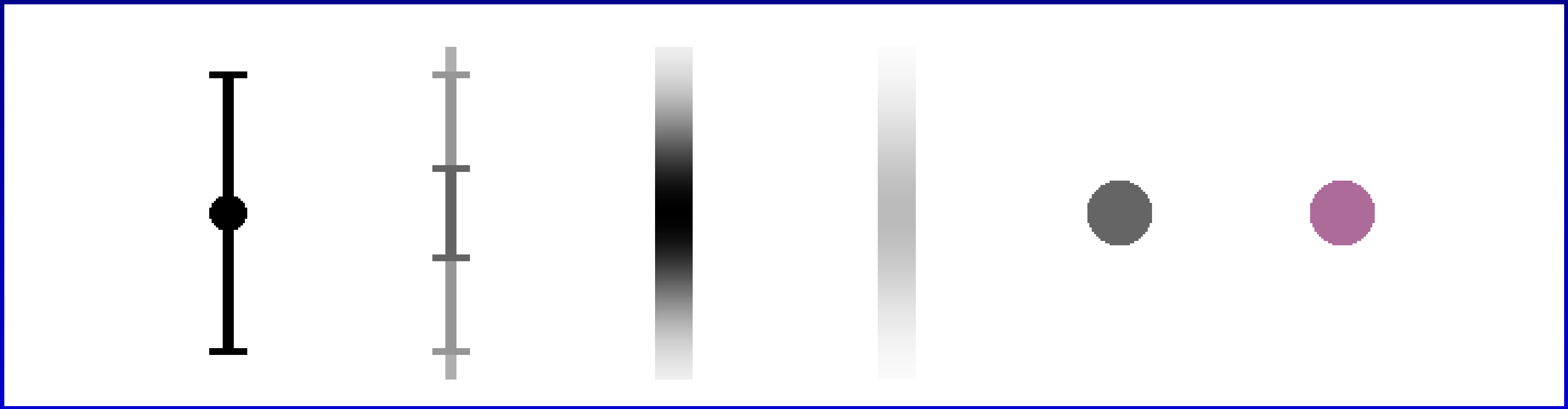
The output of each forecasting system will be indicated using this graph. The right portion shows how the temperature forecasts are represented. There are examples of the forecast graphic representing three different levels of uncertainty, paired with their associated probabilistic bell curves. The left portion of the screen shows the graph that you will be using to make your decision. The higher a graphic is on the graph, the higher the temperature forecast it represents. The cross in the middle represents the actual temperature for the forecasted day. Please compare the actual temperature with the temperature forecasts to decide which forecast was more accurate.”

Experimental framework

- Explore how choice of “best forecast” is affected by:
  - Nature of visual indication of forecast uncertainty
  - Relative uncertainty of the forecasts
    - As quantified using a normal distribution pdf

- Hypotheses:
  - Choice is affected by nature of visual indicator
  - Choice is affected by nature of relative uncertainties
  - Some/all visual indicators produce “better” choices than a nearest mean strategy
    - Better in Bayesian sense

Candidate visual encodings



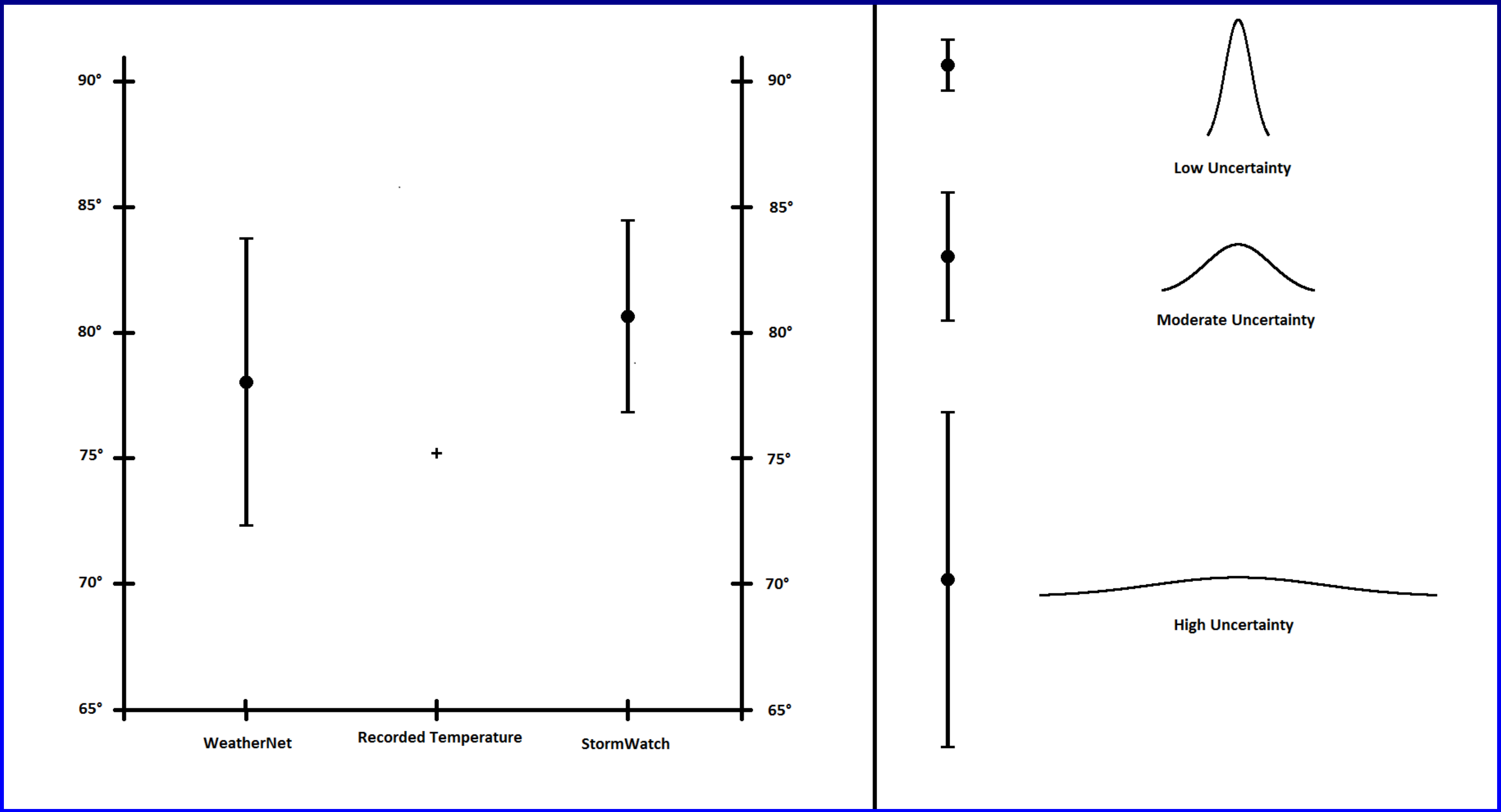
- Vertical position of glyph indicates mean value

Candidate visual encodings

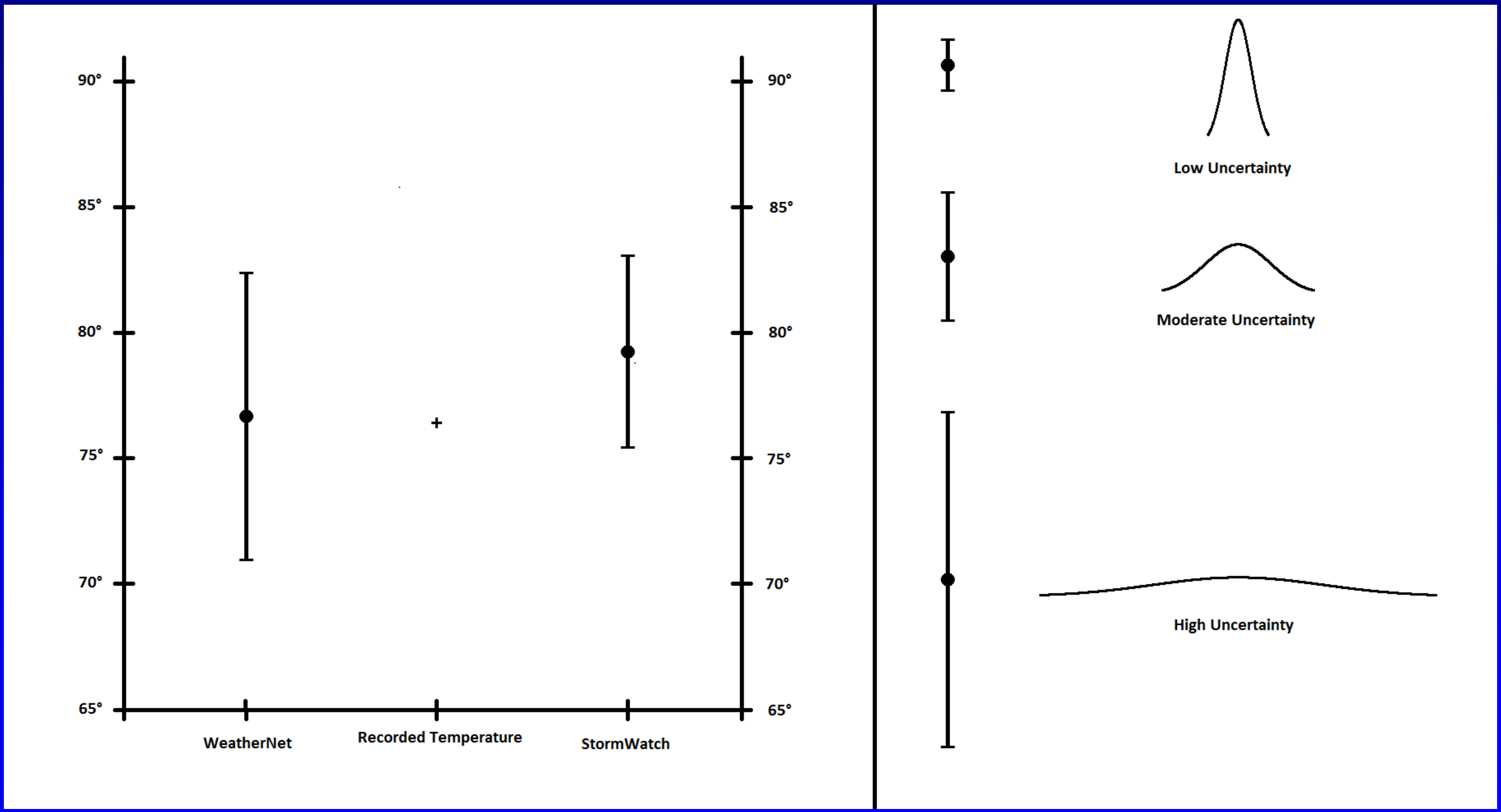
– First three directly encode distribution of possible temperature values

– Last two independently encode value and uncertainty of value

conf_95 trials



conf_95 trials



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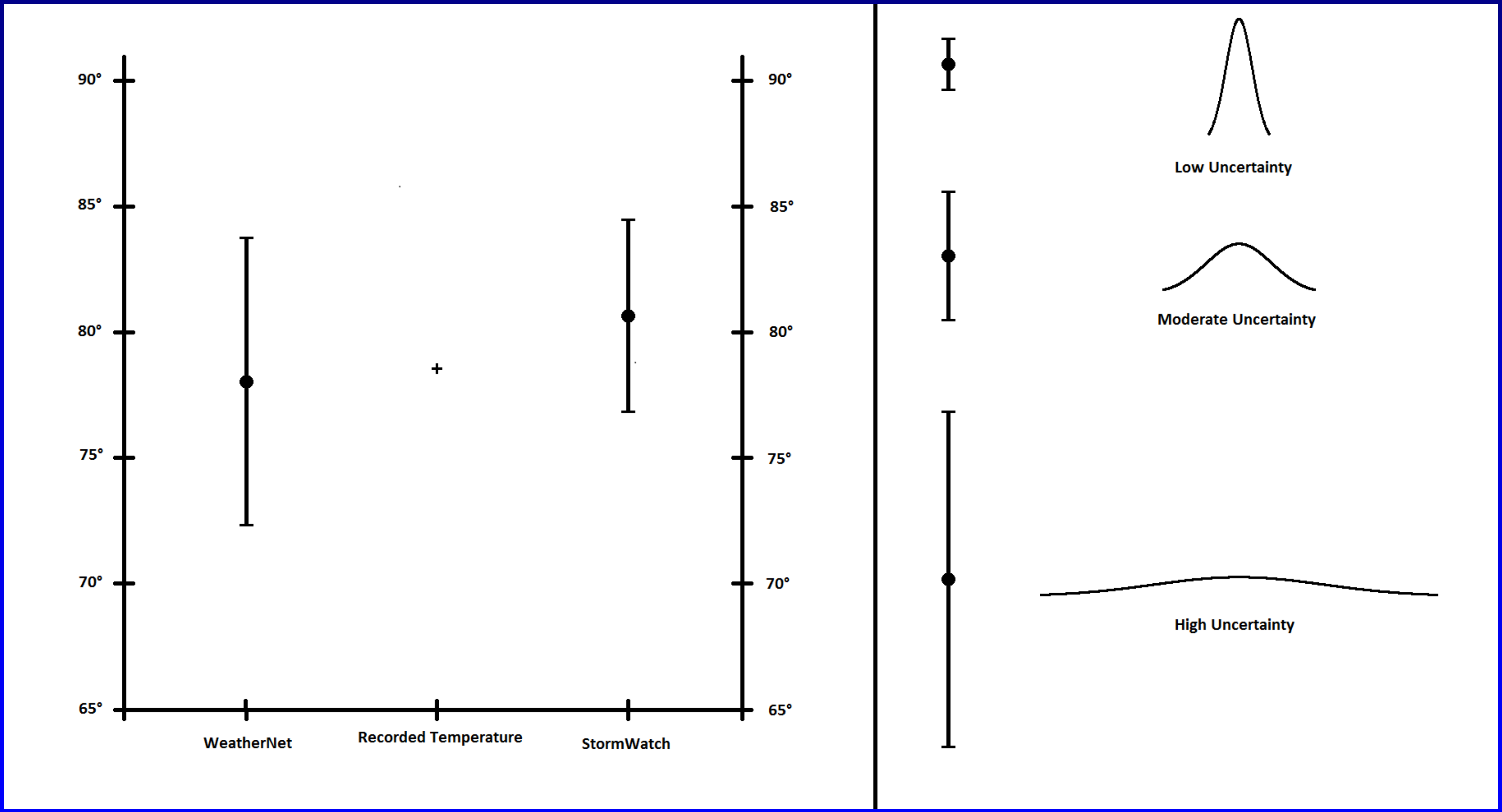

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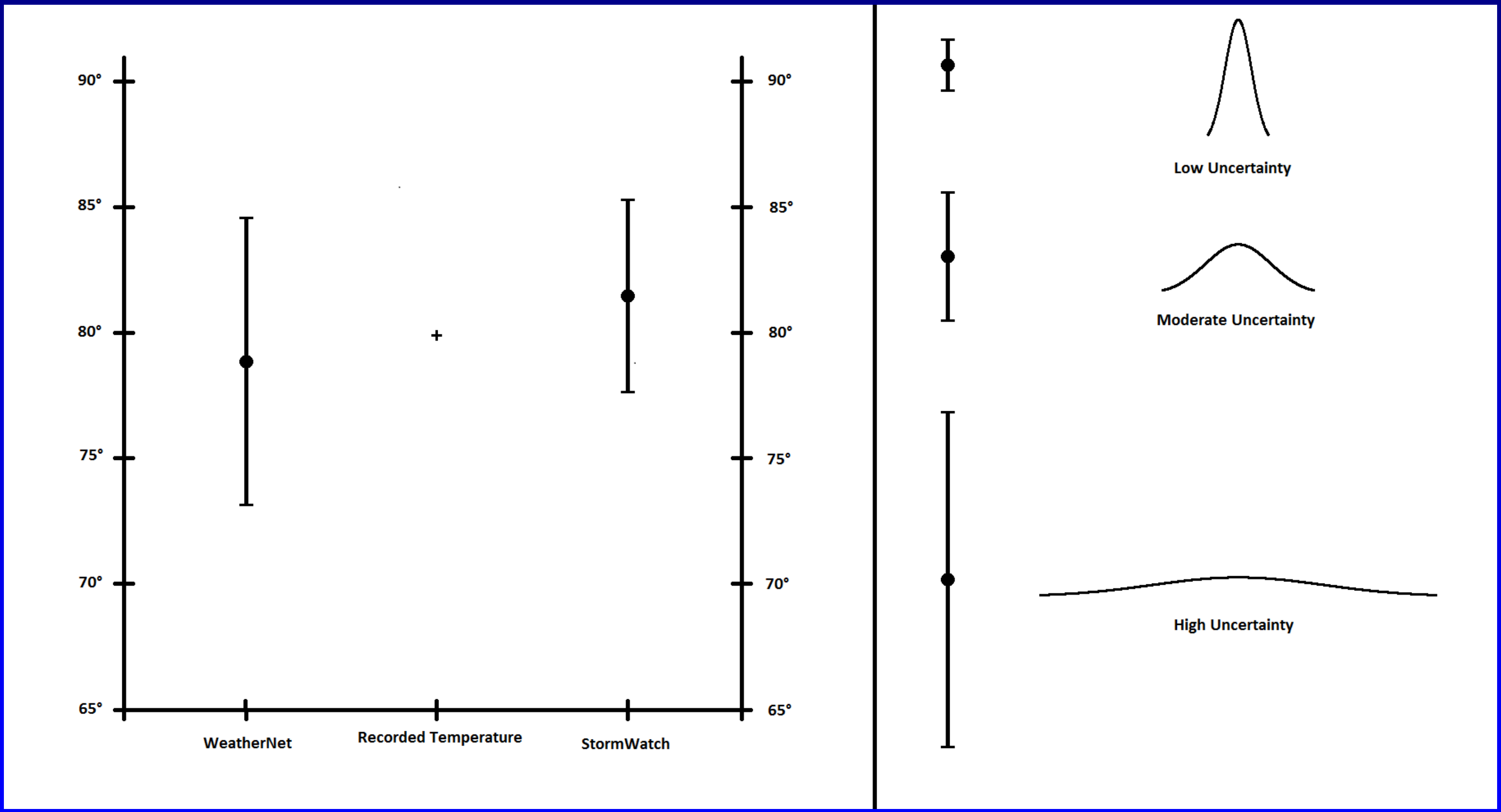

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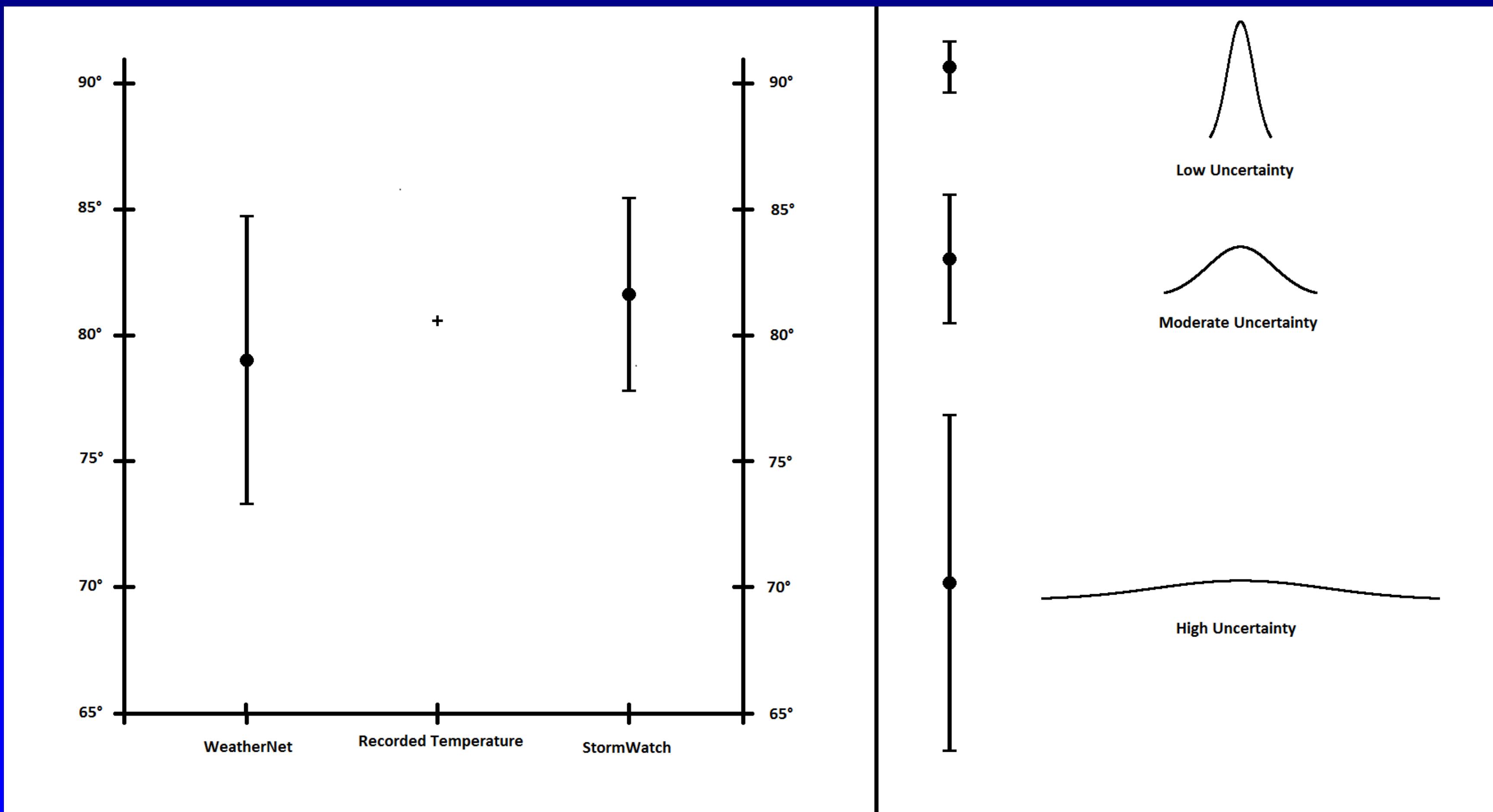

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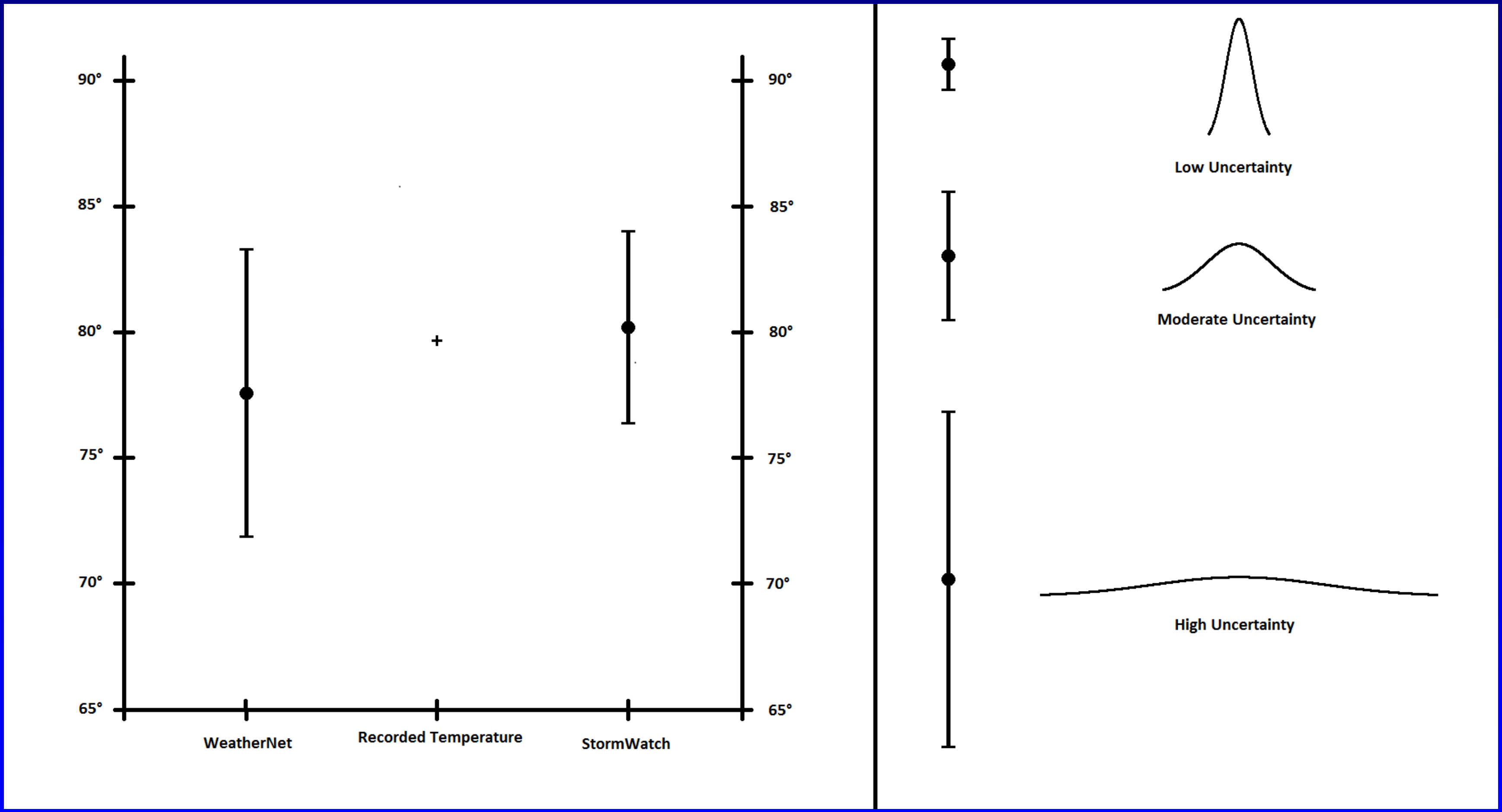

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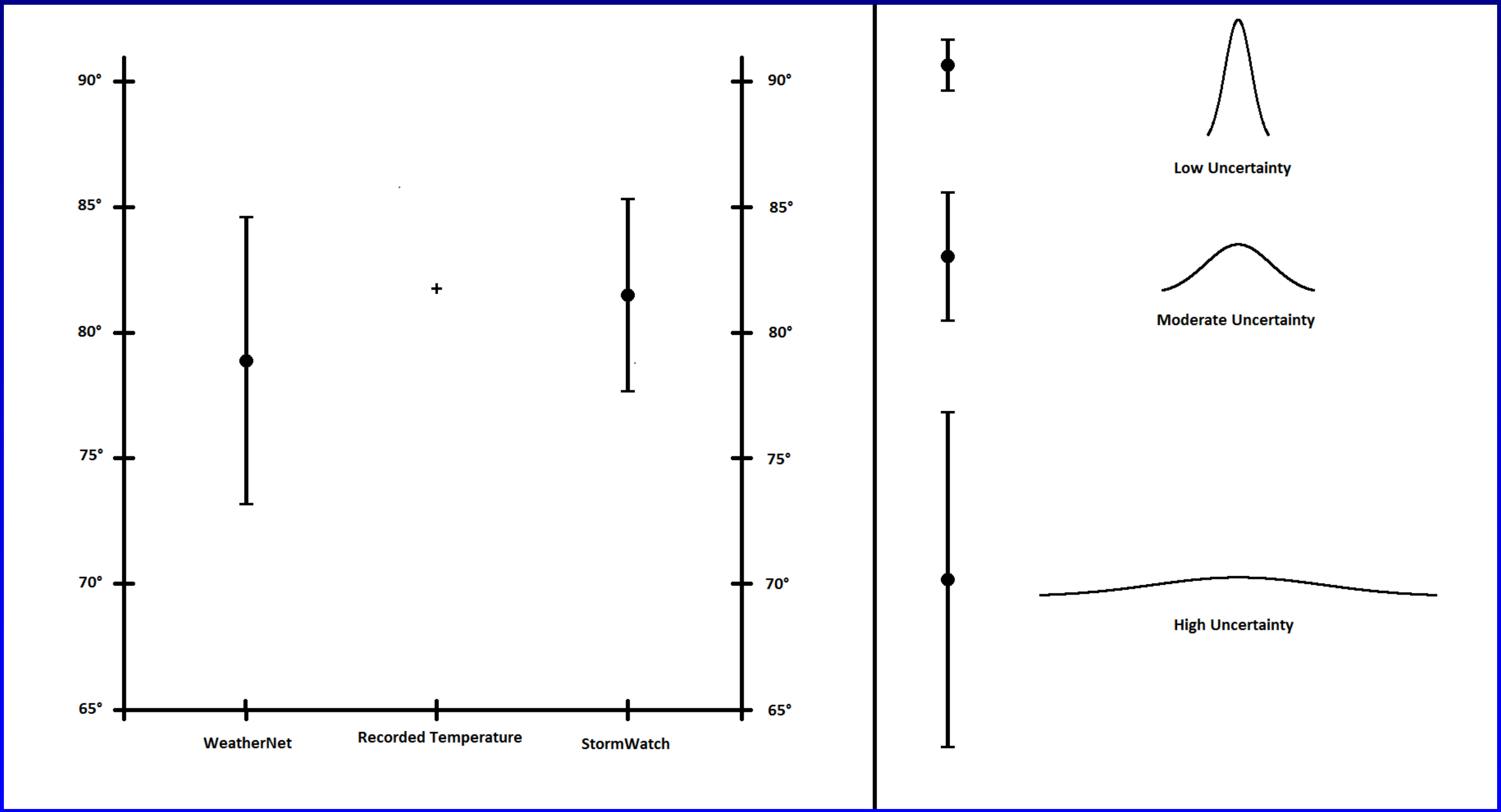

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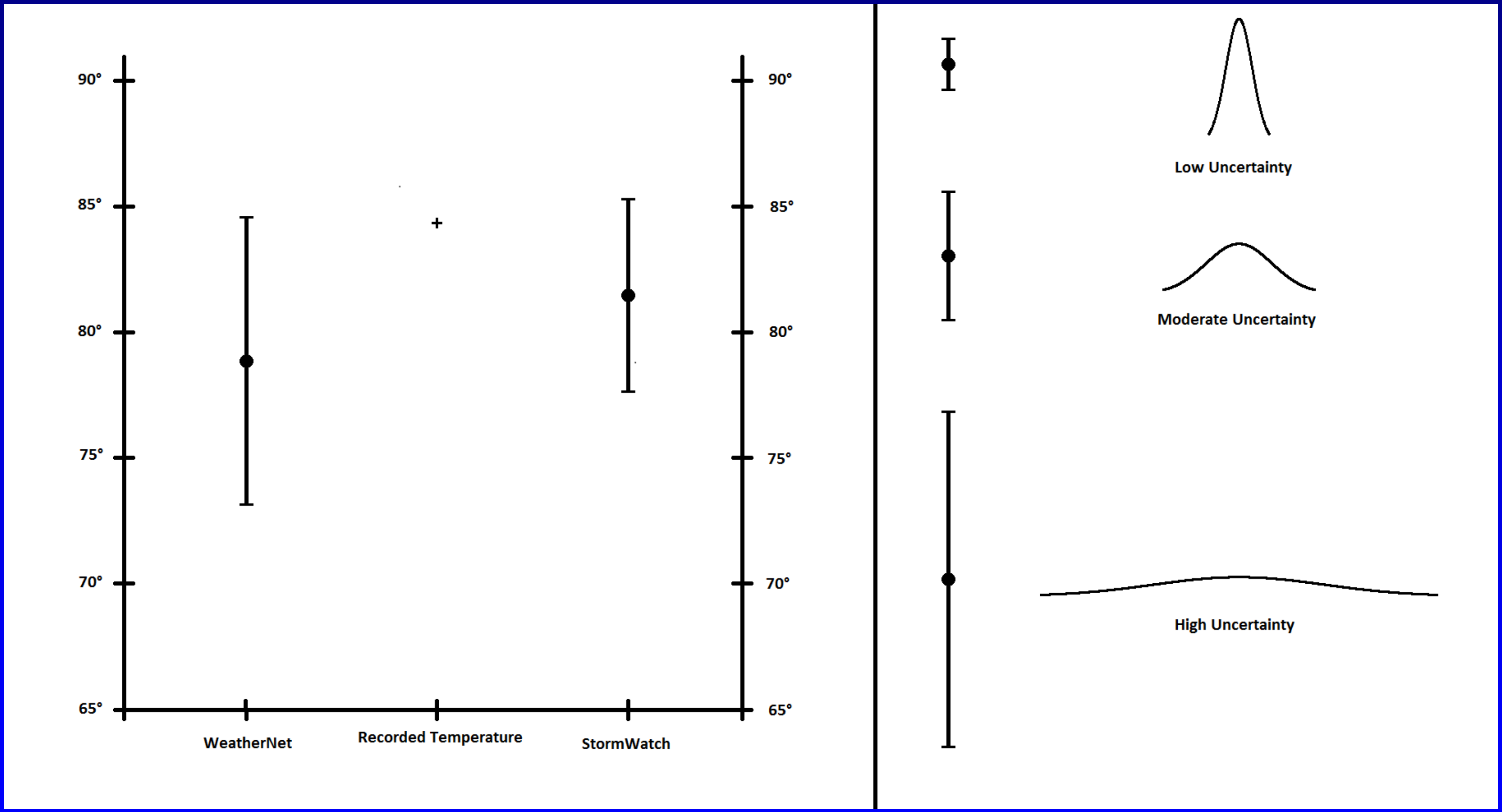
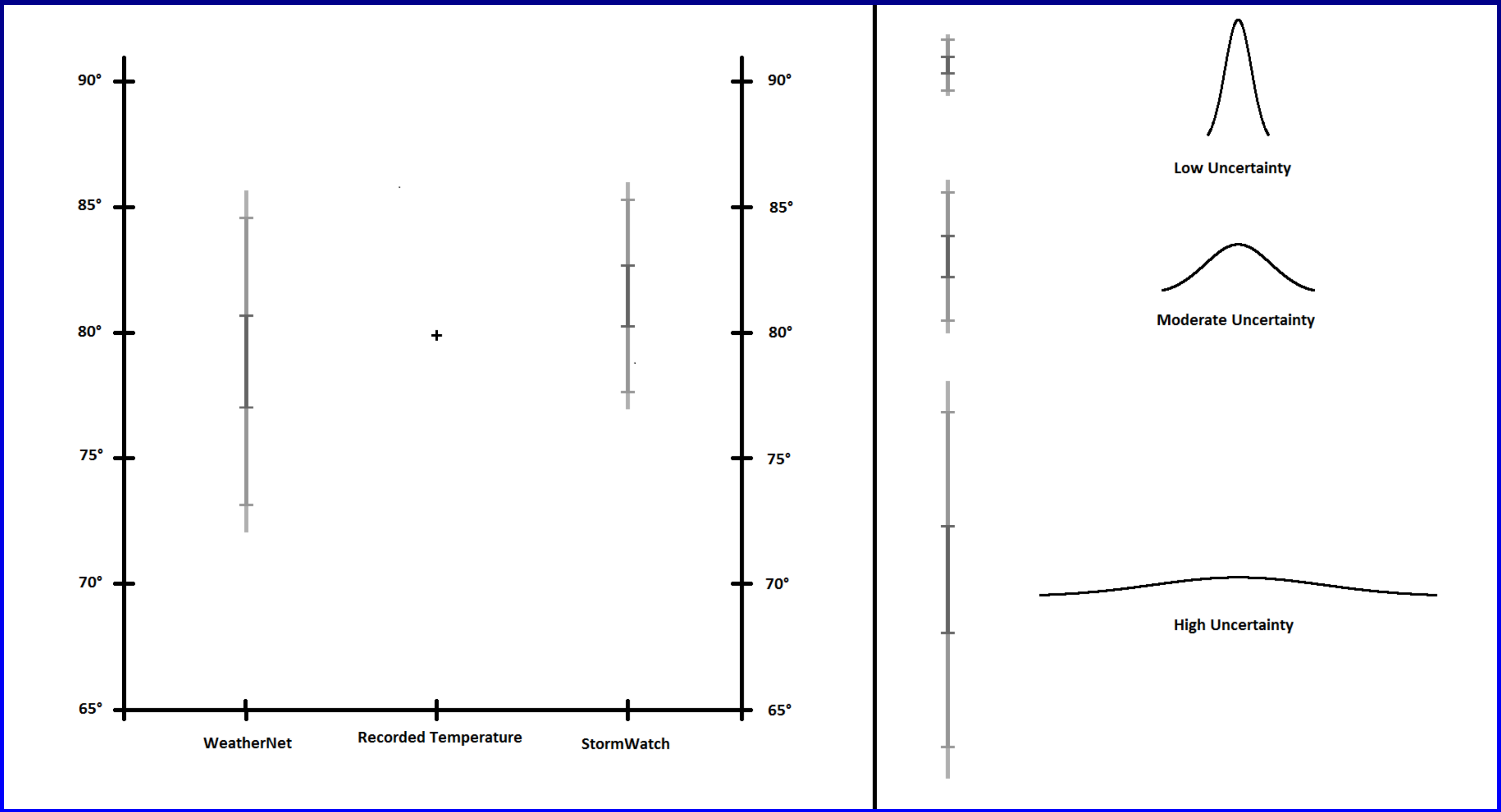
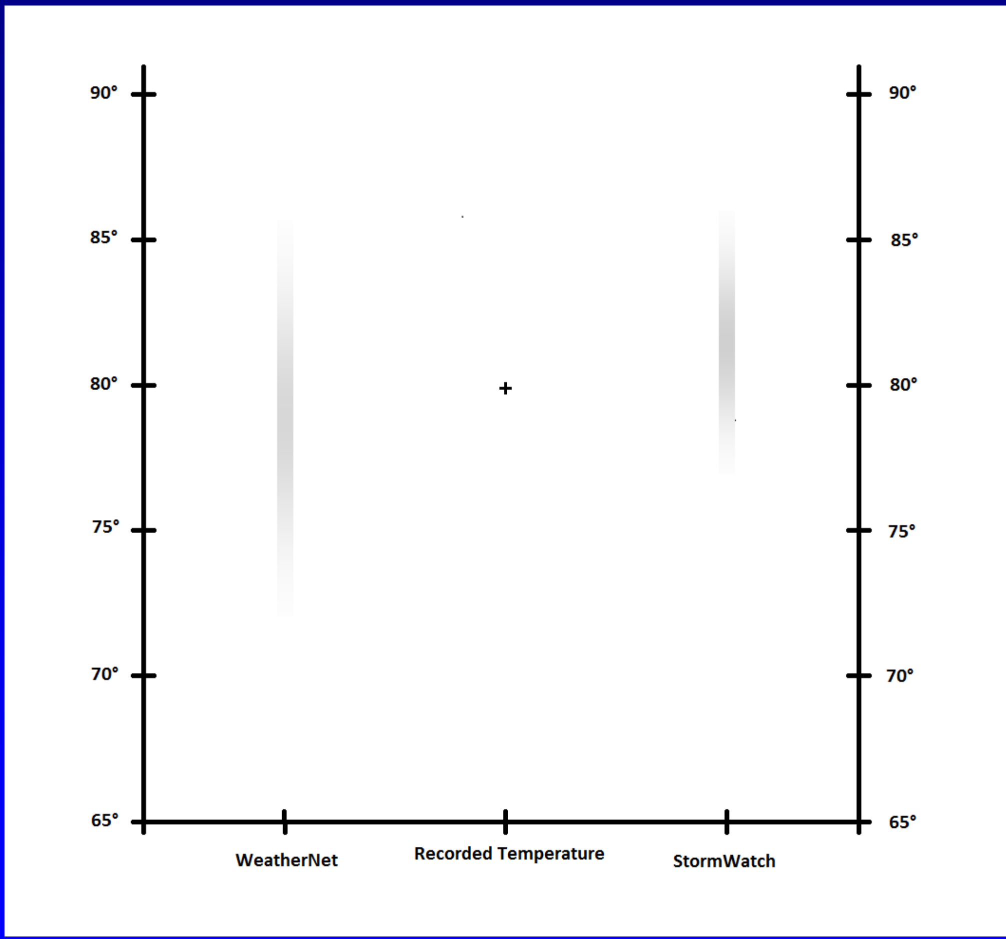
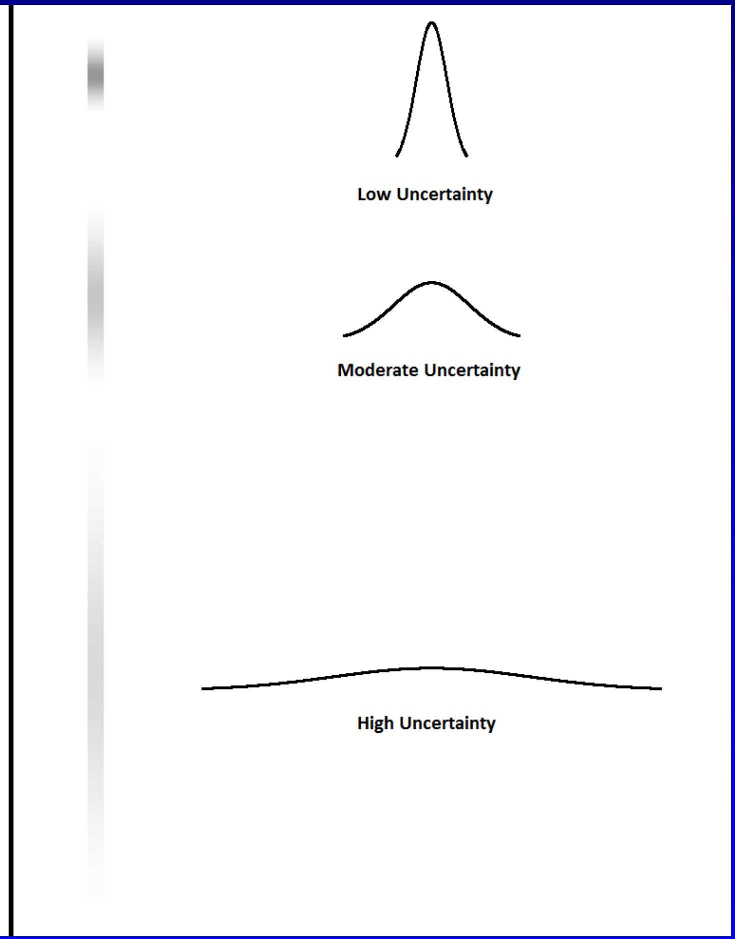


conf_47_95_98 trial

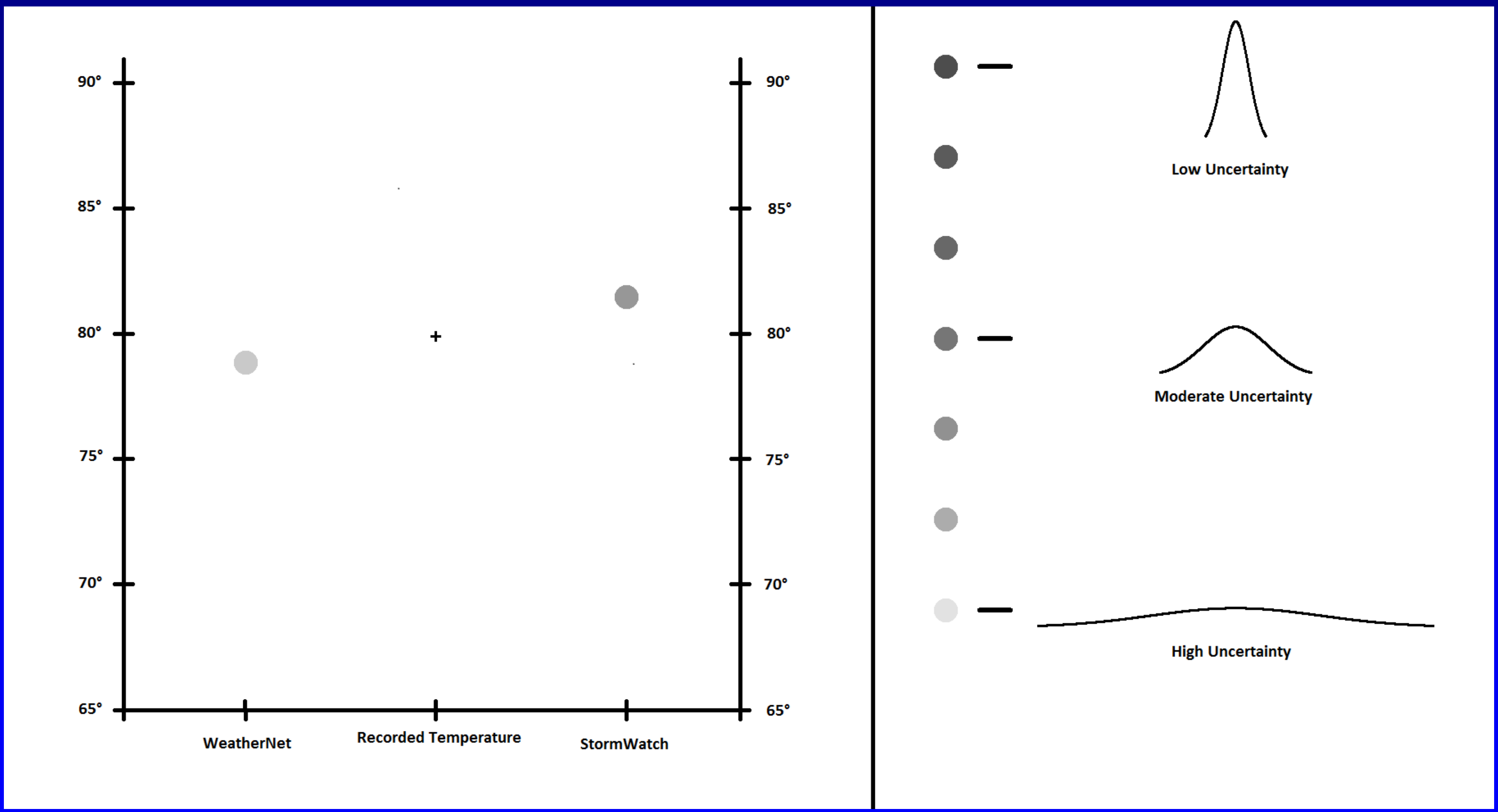


pdf_unorm trial



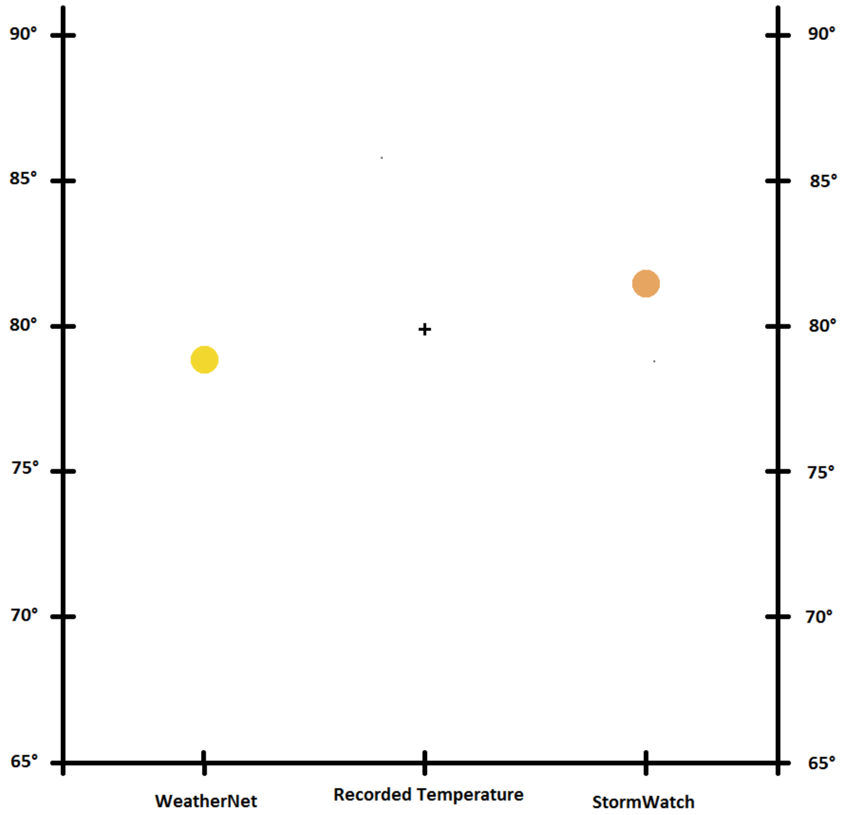


dot trial



90°
85°
80°
75°
70°
65°
WeatherNet
Recorded Temperature
StormWatch
Low Uncertainty
Moderate Uncertainty
High Uncertainty

cdot trial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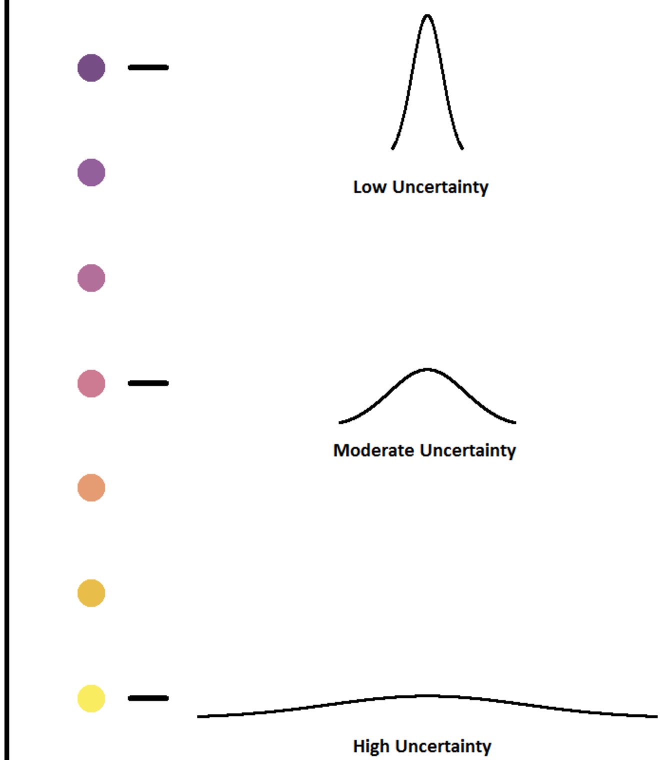
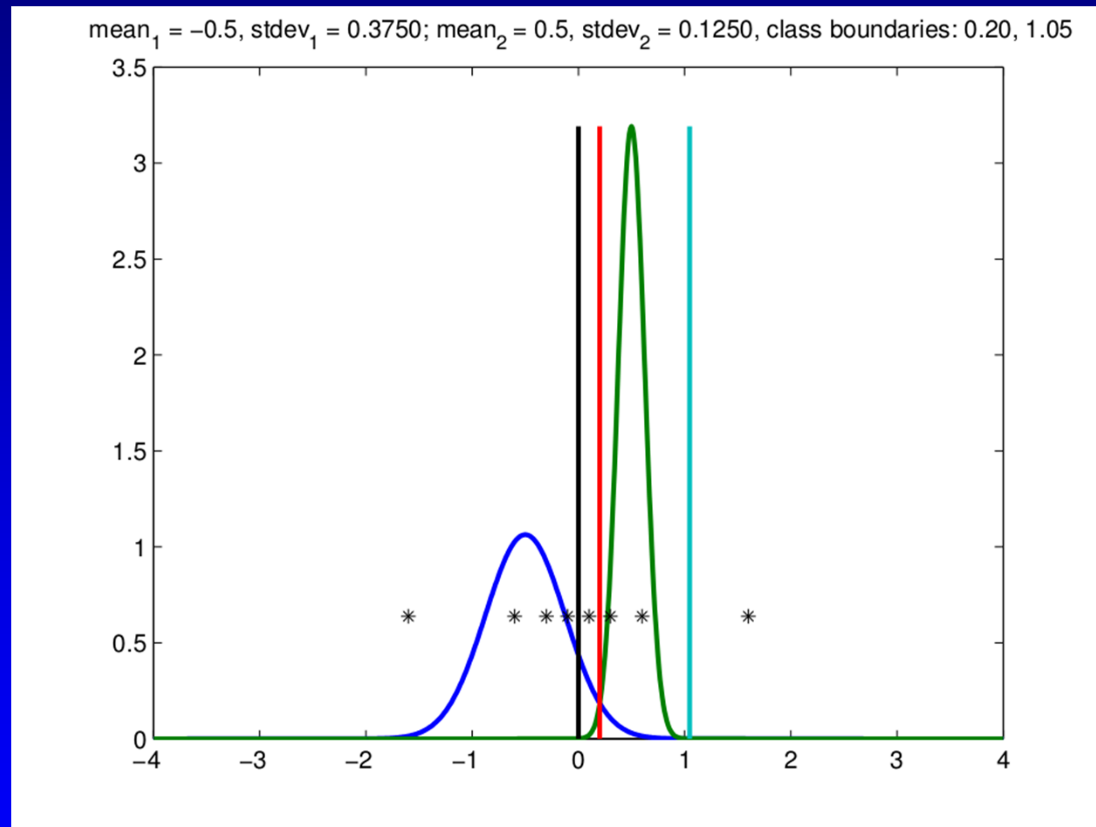

Low Uncertainty
Moderate Uncertainty
High Uncertainty

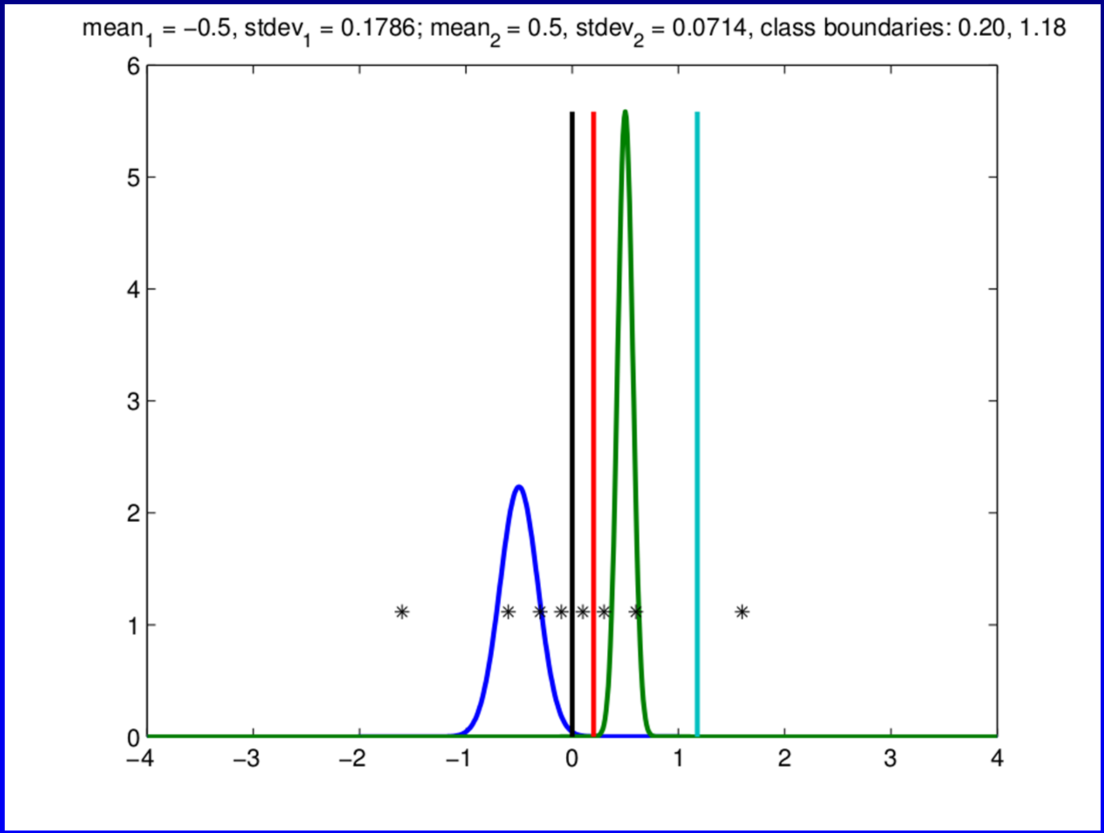
Candidate distributions

- Distribution set 1:
  - Small overlap of distributions
  - Decision boundary biased *towards* distribution with smaller σ
    - Smaller σ => "more certain"



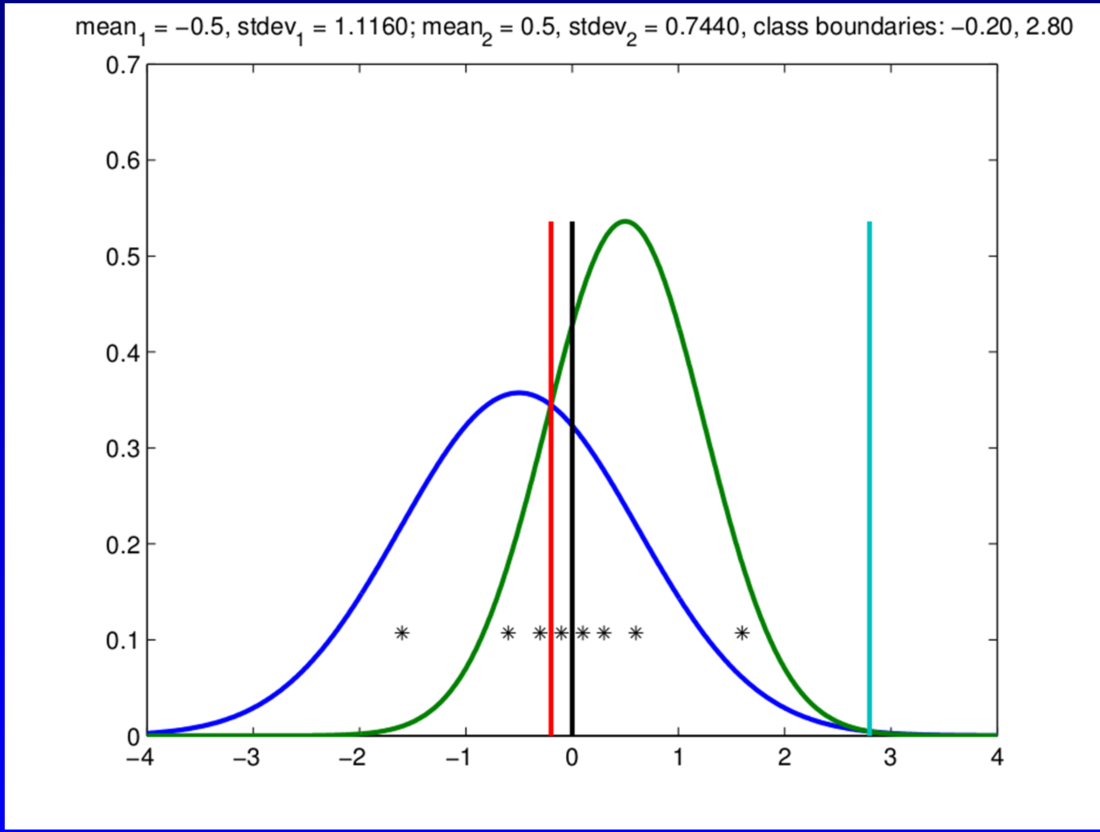
Candidate distributions

- Distribution set 2:
  - Small overlap of distributions
  - Decision boundary biased *towards* distribution with smaller σ
    - Smaller σ => “more certain”



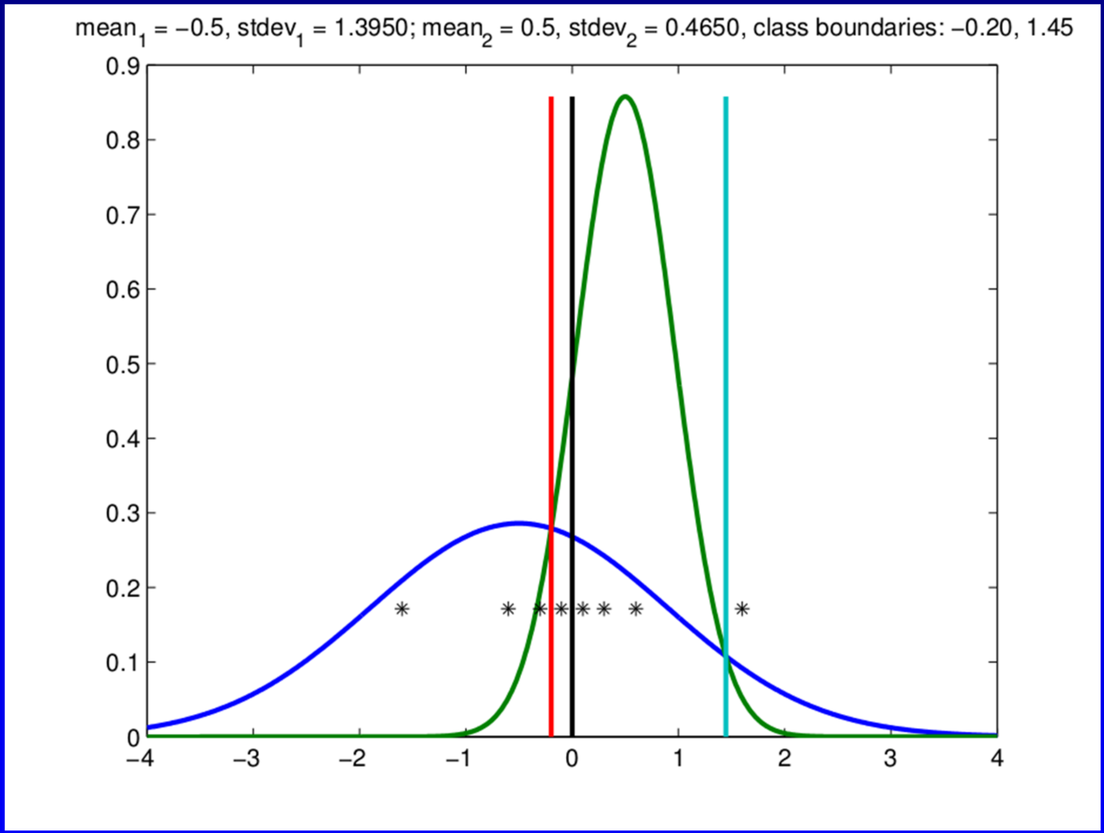
Candidate distributions

- Distribution set 3:
  - Large overlap of distributions
  - Decision boundary biased *away* from distribution with smaller σ
    - Smaller σ => "more certain"

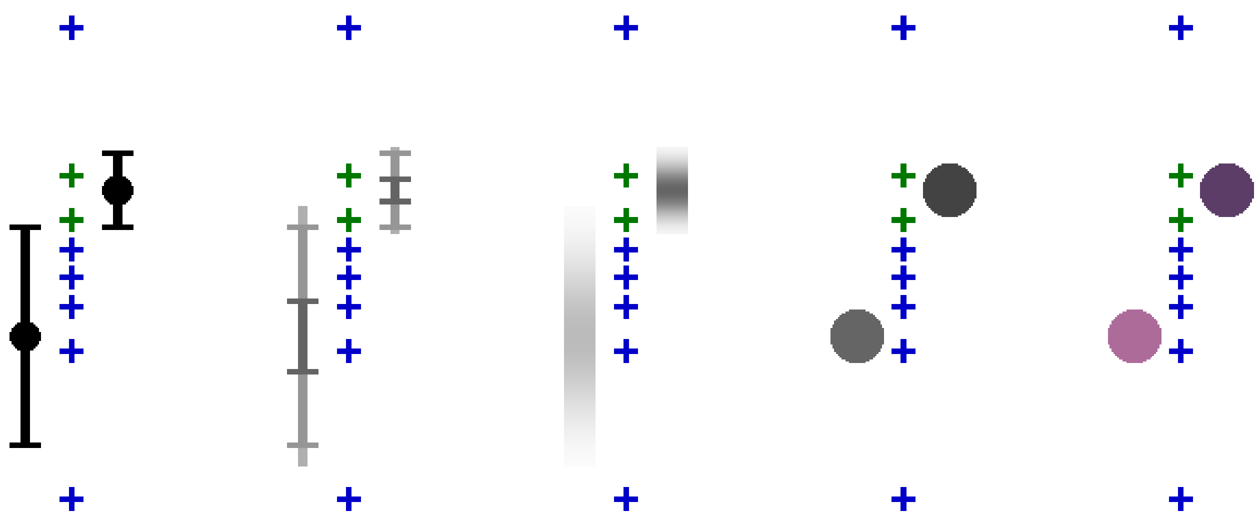


Candidate distributions

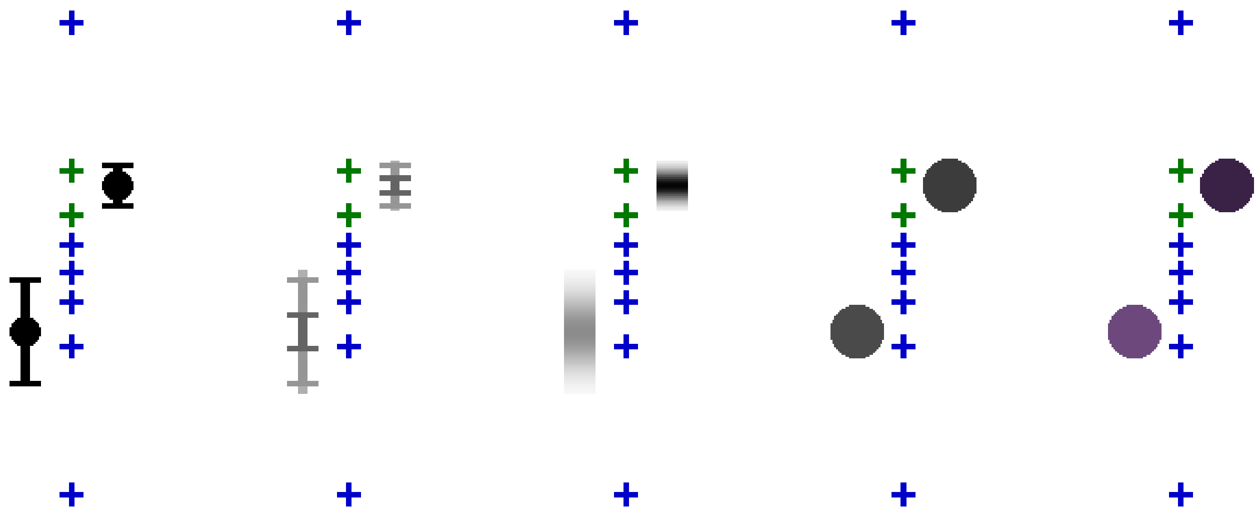
- Distribution set 4:
  - Large overlap of distributions
  - Decision boundary biased *away* from distribution with smaller σ
    - Smaller σ => "more certain"



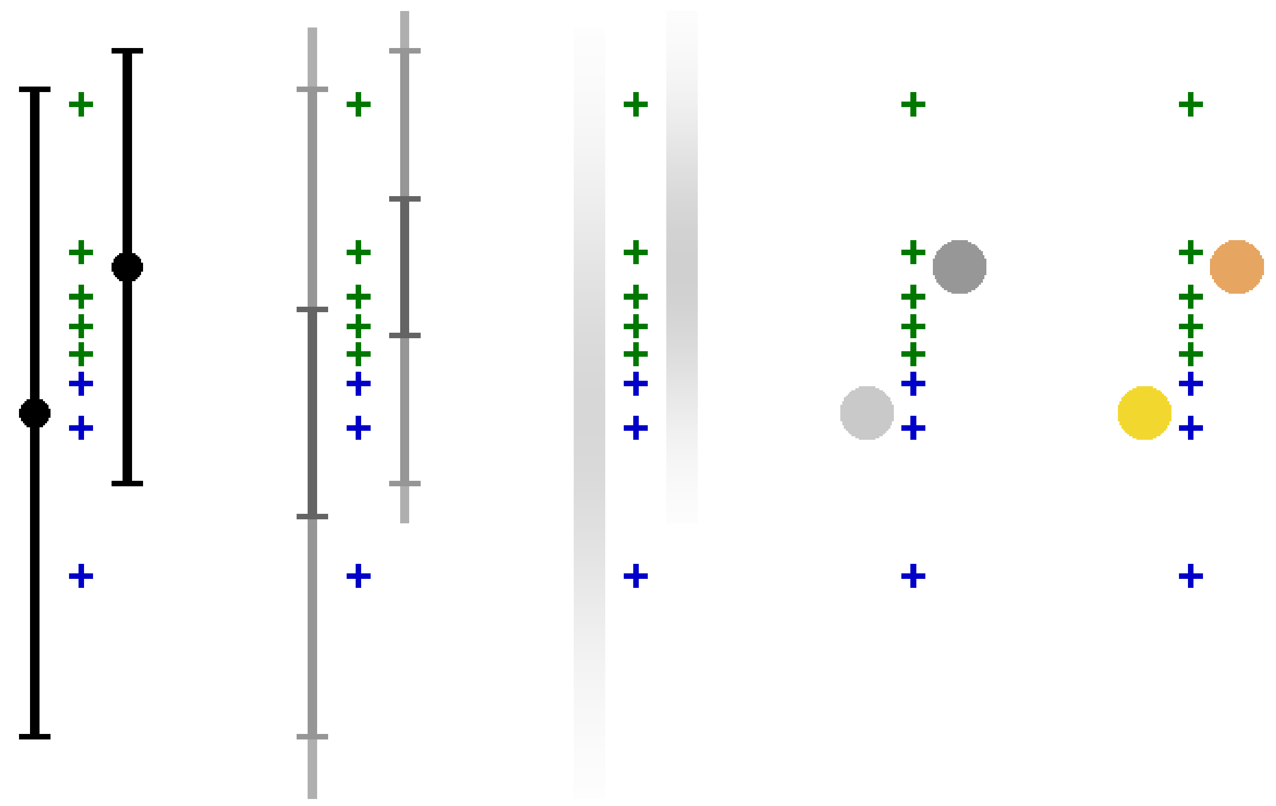
Distribution set 1



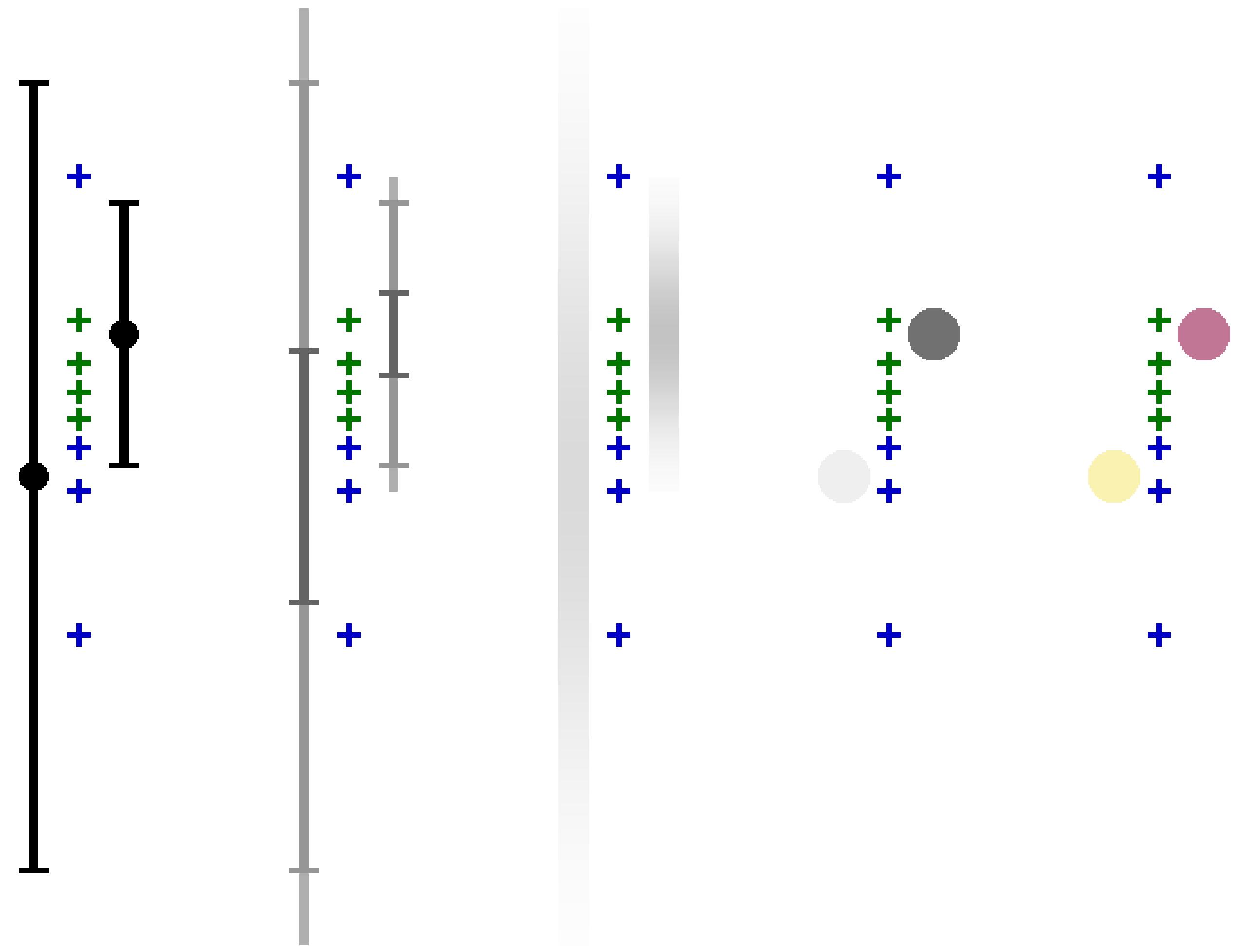
Distribution set 2



Distribution set 3

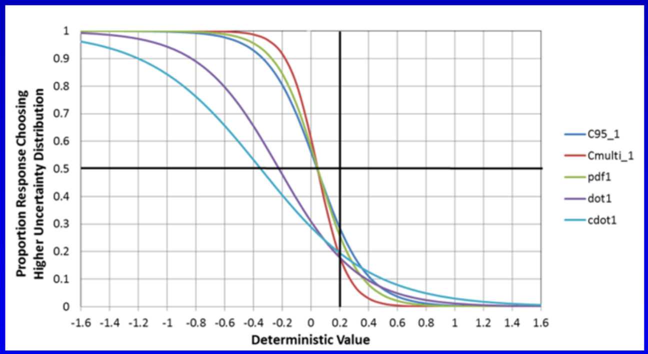


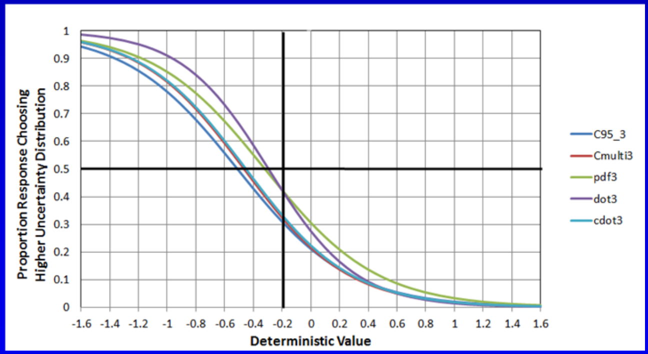
Distribution set 4

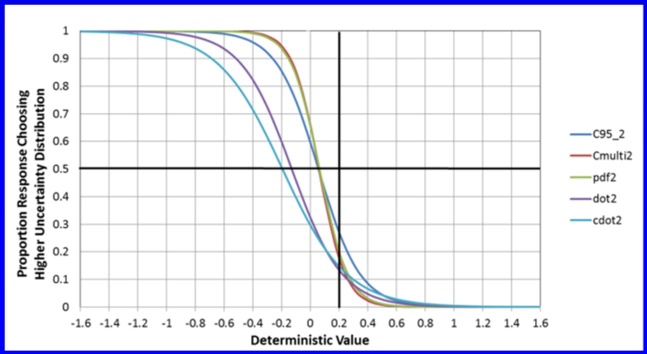


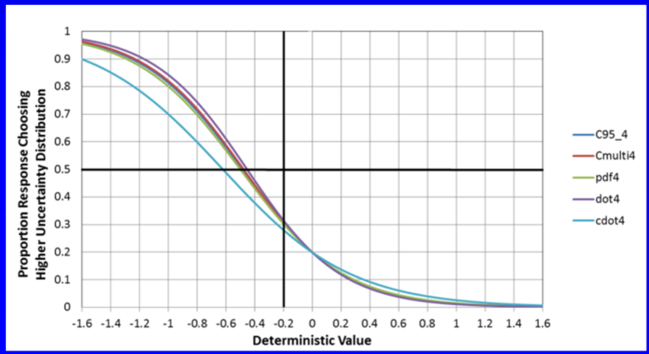
Preliminary results

- Bias in decisions indicated by a switch from favoring distribution with more uncertainty (left below) to distribution with less uncertainty (right below)
  - Plots from logistic regression:



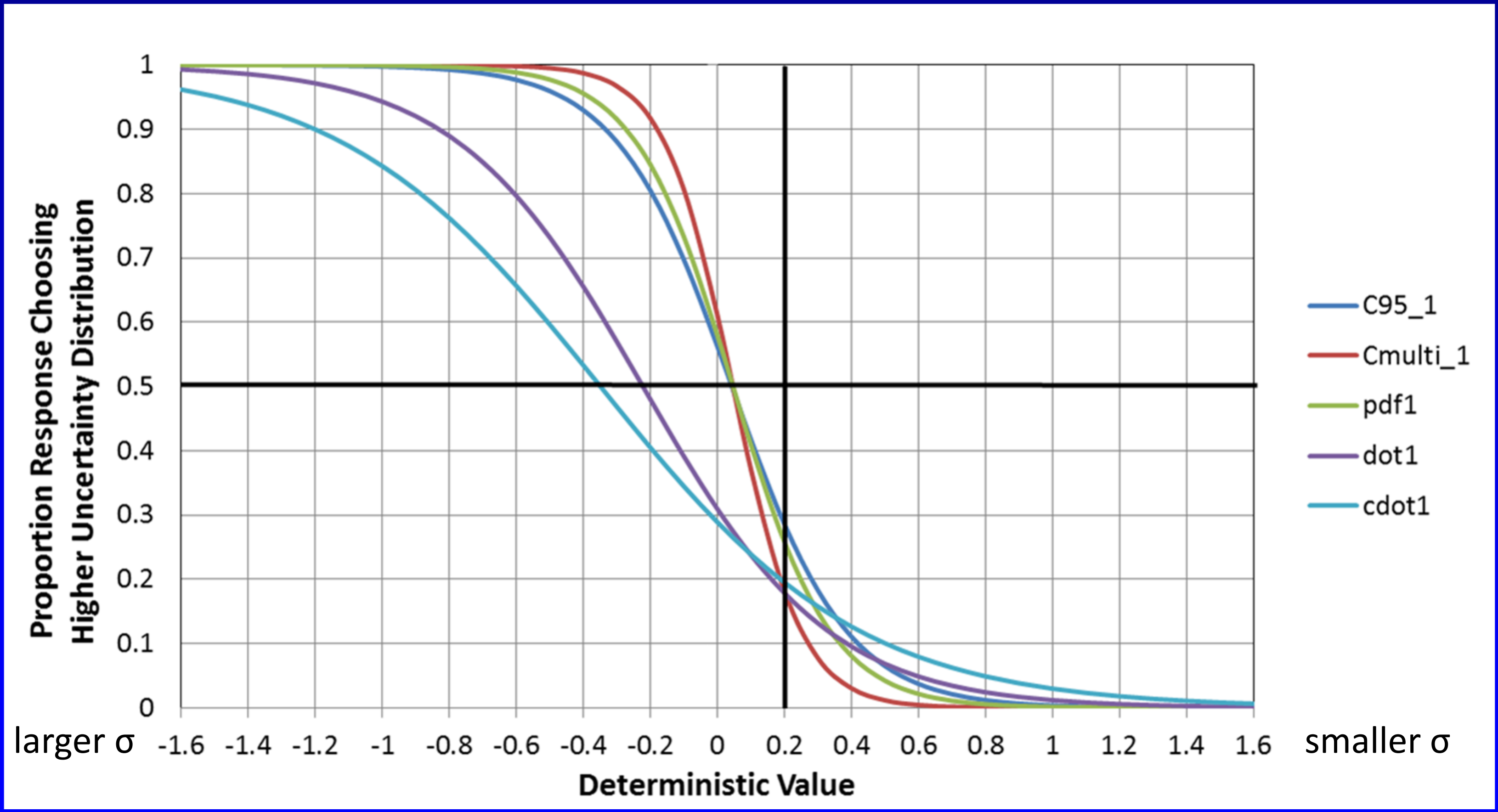






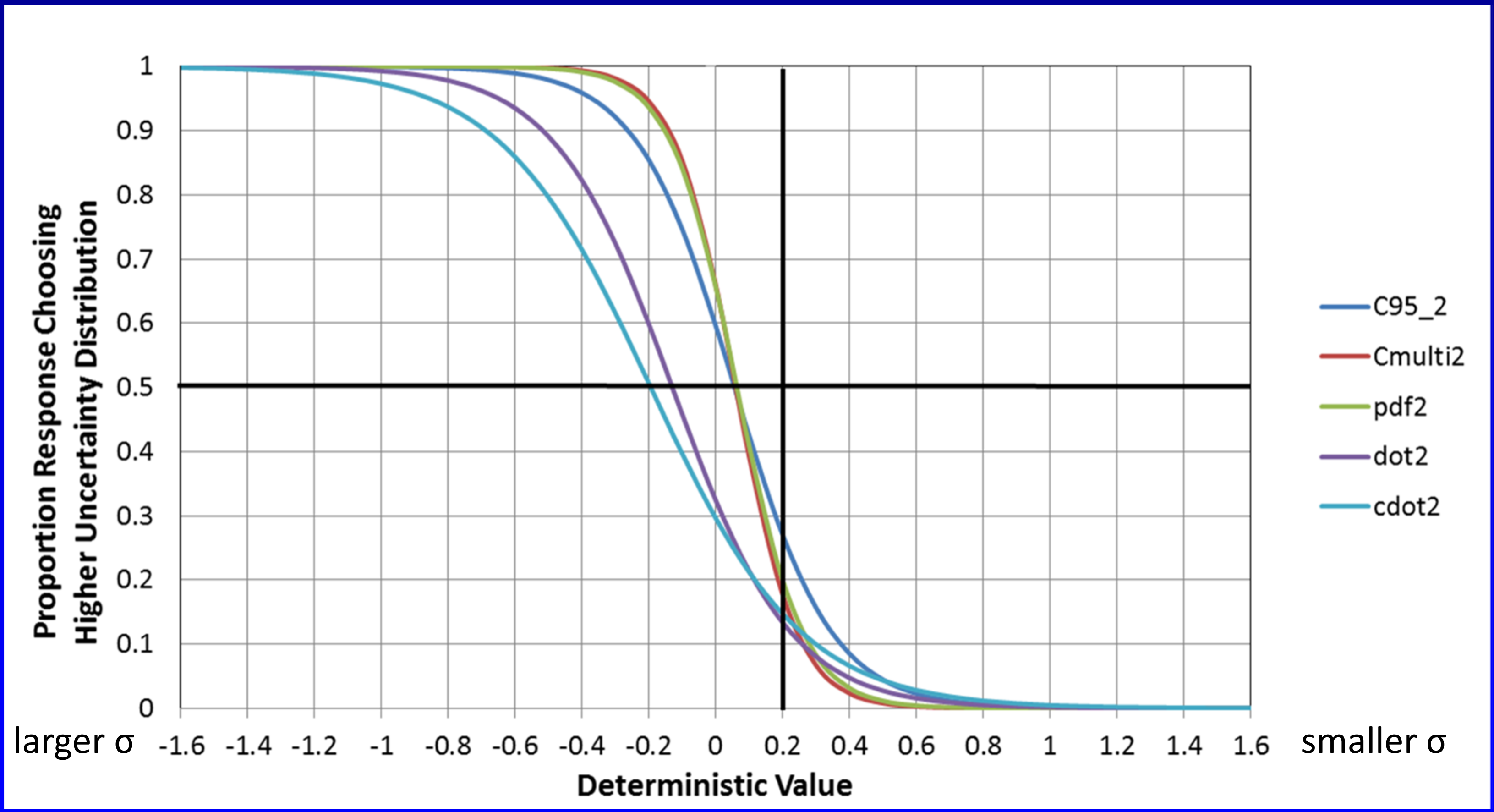
Preliminary results

- Distribution set 1 (small overlap of distributions)



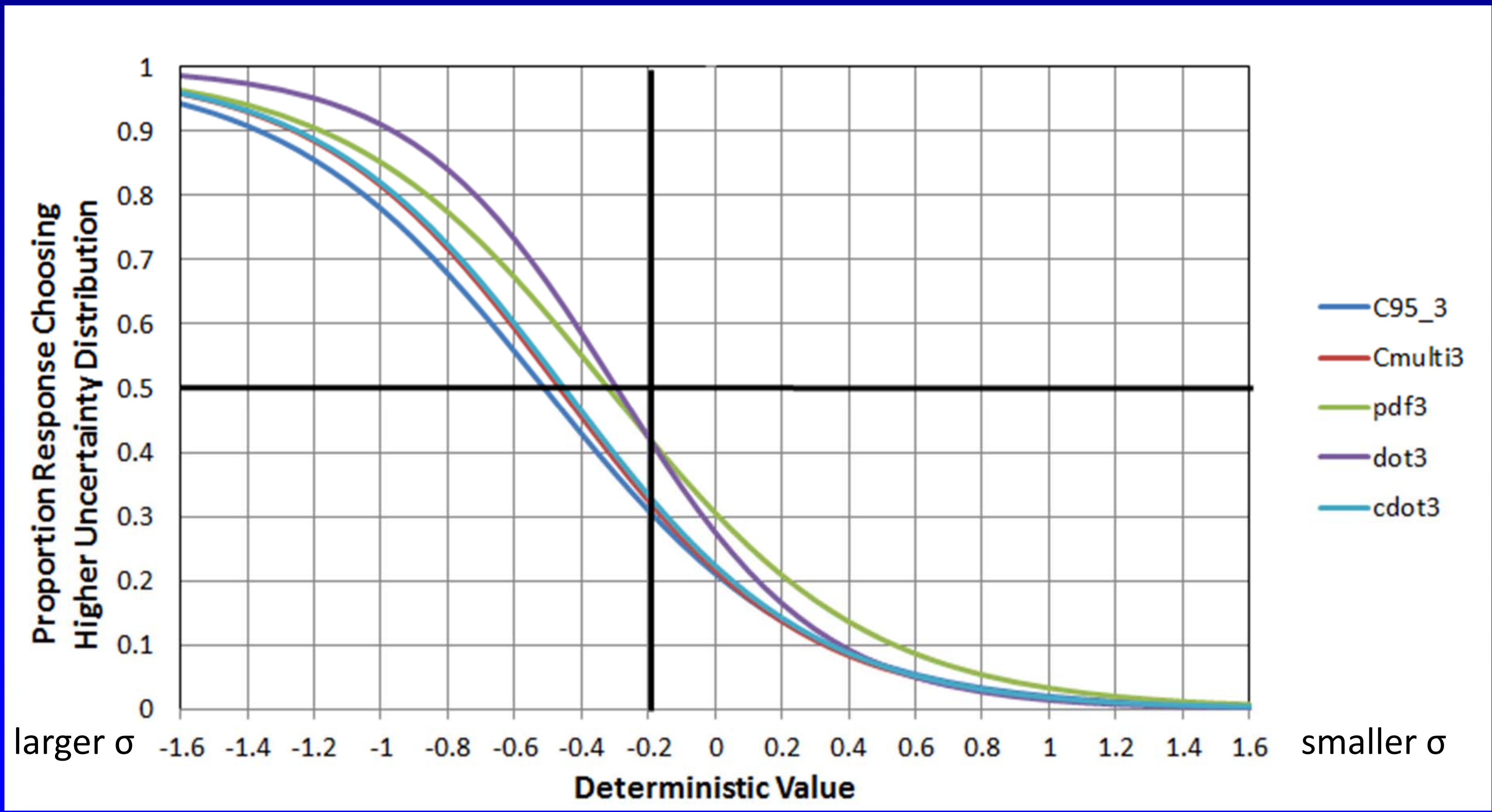
Preliminary results

- Distribution set 2 (small overlap of distributions)



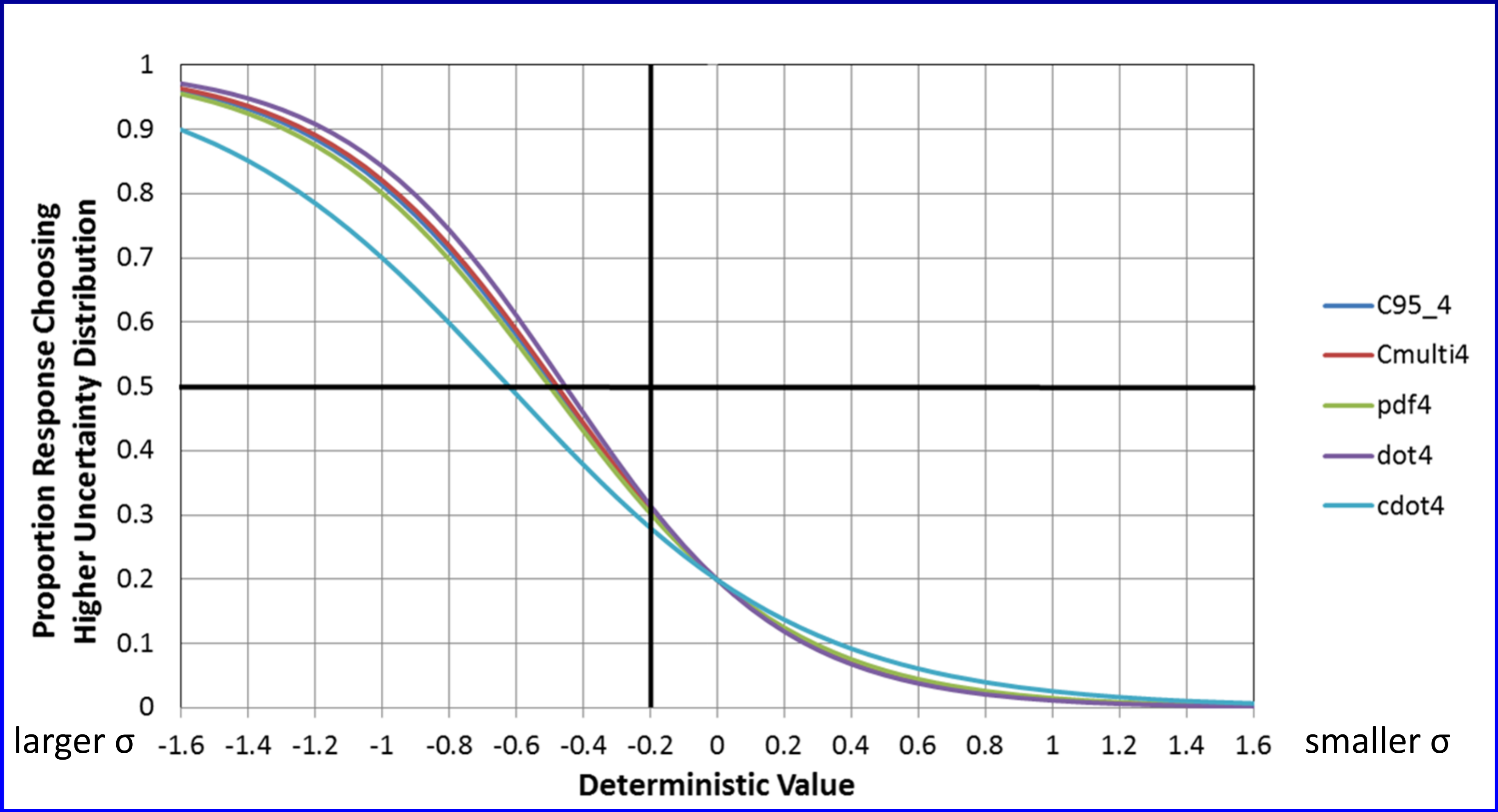
Preliminary results:

- Distribution set 3 (large overlap of distributions)



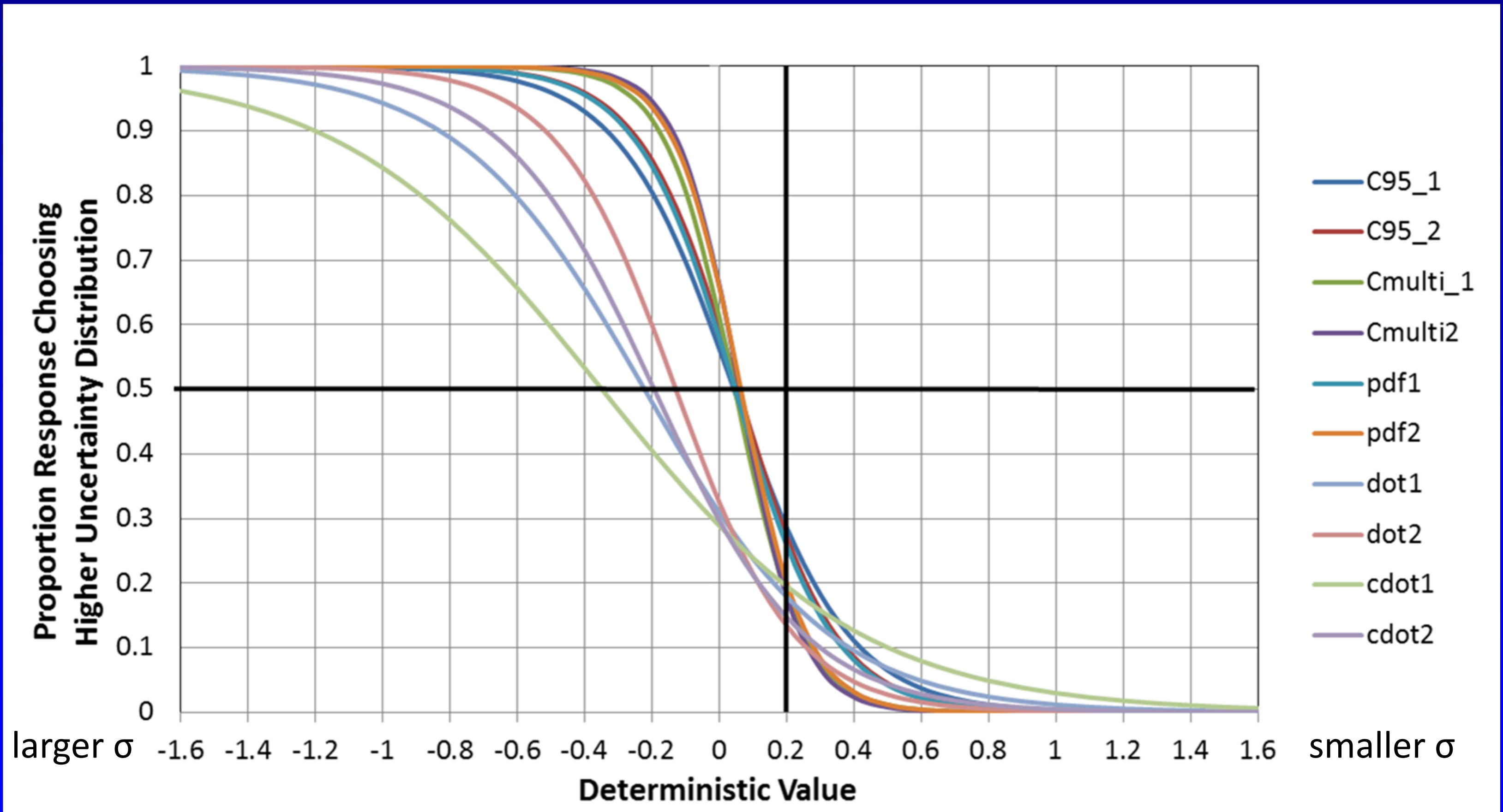
Preliminary results

- Distribution set 4 (large overlap of distributions)



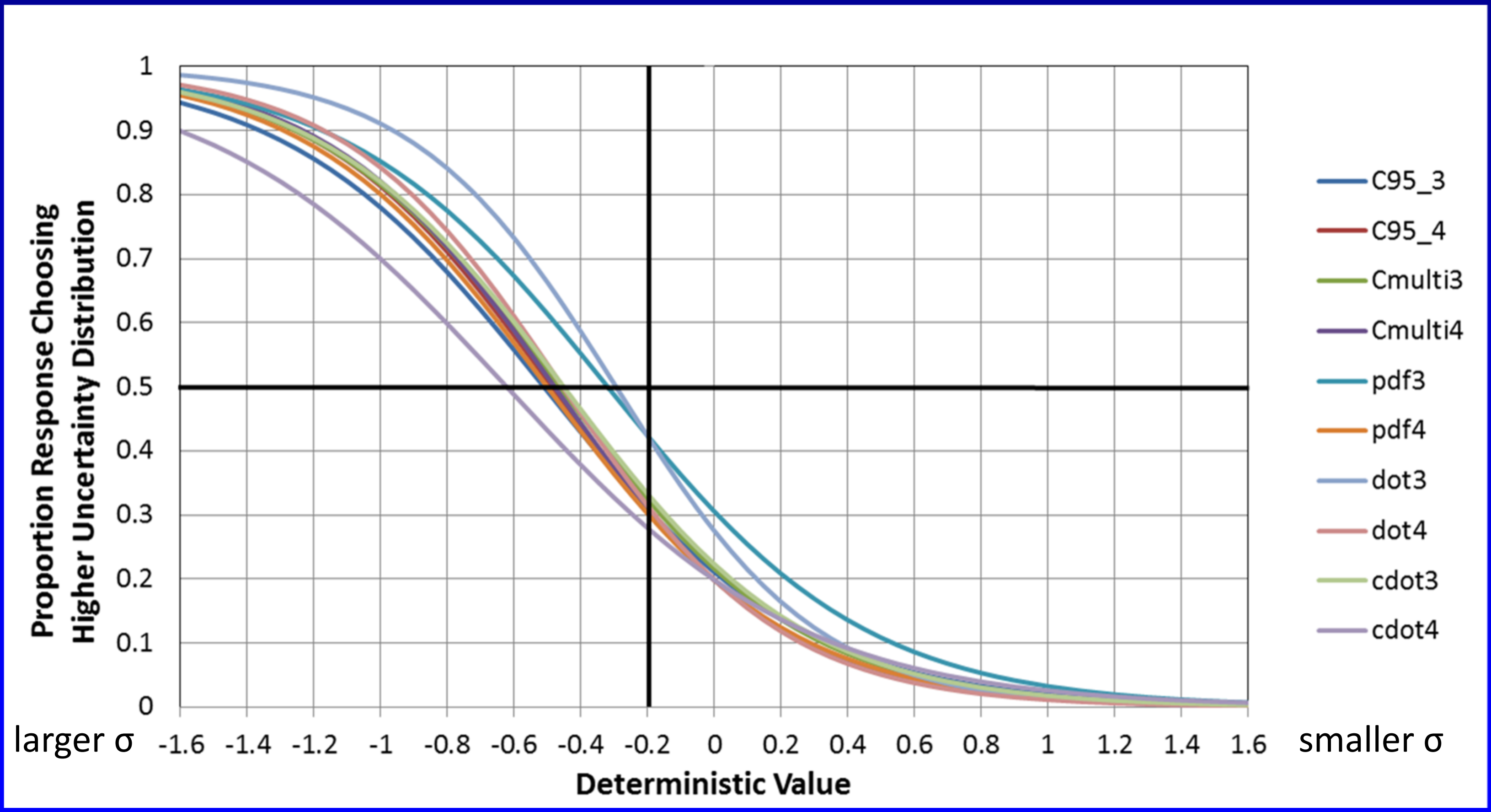
Preliminary results

- Distribution sets 1 and 2 (small overlap of distributions)



Preliminary results

- Distribution sets 3 and 4 (large overlap of distributions)



Preliminary results -- discussion

- Distribution sets 1 and 2 (small overlap of distributions)
  - Distribution-based glyphs show little or no uncertainty-based bias
  - Dot-based glyphs show a bias favoring more certain distribution
    - Dot-based glyphs opposite to optimal decision bias
- Distribution sets 3 and 4 (large overlap of distributions)
  - All glyphs show uncertainty-based bias favoring more certain distribution
    - Consistent with optimal decision bias

Moving forward

- Is support of Bayesian inference what matters?
  - We know that people have a hard time making unbiased decisions under uncertainty
  - We also know that computer are quite good at this

▶ Shouldn't a "good" visualization just provide the answer?

Moving forward

- When is visualizing uncertainty most important?
  - Analysis vs. exploration
  - Decision support vs. explanation
- Can visually presented uncertainty help structure a user's reasoning?
  - Compensate for bias
  - Draw attention to relevant information
  - Slow down inference process to allow for a more reasoned response
    - *System 2* processing

Moving forward

- Should we move beyond Bayesian representations of uncertainty?
  - They fit well with existing methods of uncertainty quantification
  - … but it may be that visualizing other types of uncertainty is key in policy decision making
    - Separately quantifying likelihood from evidence
- What about time?
  - Reasoning about temporal events
  - Reasoning process executing over time

Acknowledgements

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Modeling, Display, and Understanding Uncertainty in Simulations for Policy Decision Making

`http://www.sci.utah.edu/vis-uncertainty.html`

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