Cognitive Mapping

In the context of adoption of Risk Based Sampling

Neil McRoberts
Sara Garcia Figuera
nmcroberts@ucdavis.edu

University *of* California
Agriculture and Natural Resources

Topics for presentation

- Uncertainty and decision-making
  - Information & uncertainty
  - Modes of decision-making

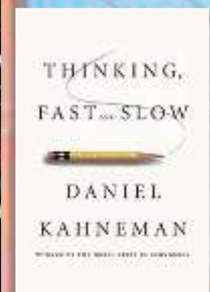
- Cognitive maps of complex problems
- Cognitive mapping of RBS adoption – audience participation exercise

Synthesizing a theory of slow adoption

Everett Rodgers

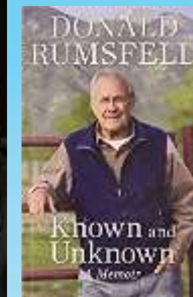
Perceived relative advantage
Compatibility/adaptability
Simplicity/ease of use
Opportunity to try
Observability of results

Daniel Kahneman



Problem framing/nudging
Prospect theory
Decisions:
Fast, easy but error-prone
OR
Slow, hard, but more accurate

Donald Rumsfeld



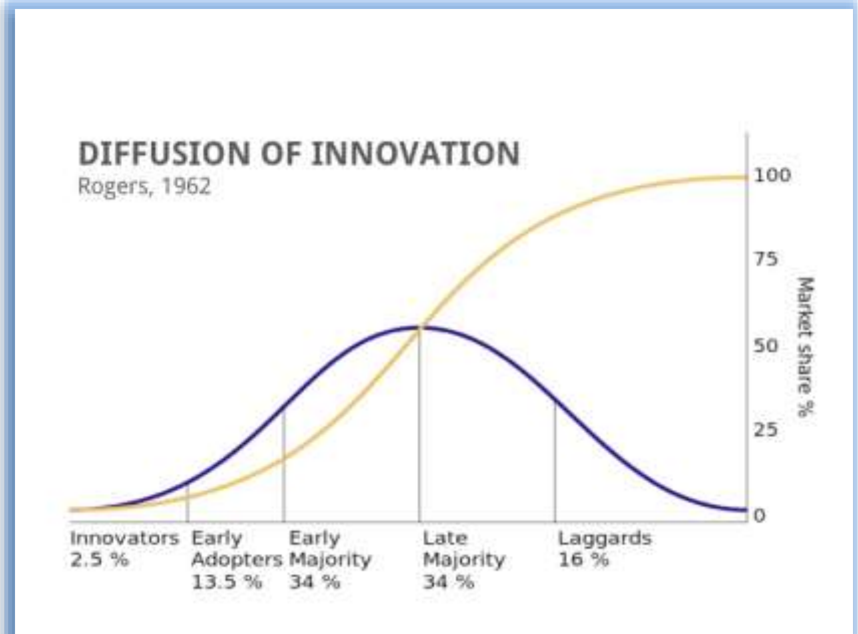
Typology of uncertainty/risks

Adoption of RBS as a classical innovation diffusion problem

1. Is RBS perceived as being, overall, advantageous?
2. Is the methodology being suggested compatible with their existing ways of working?
3. Is the methodology simple/easy to use?
4. Do inspectors have opportunity to see it in practice without having to use it?
5. Do inspectors have opportunity to try RBS in real situations, but with safety net of existing methodology in place?

How do these questions connect with Kahneman's work?

How does a synthesis of the two help us understand RBS adoption?



Kahneman: two systems for decision-making

System 1:
Fast
Low cognitive load
Uses heuristics,
Substitution of “similar” problems,
Bulk of decision-making
Easily tricked

System 2:
Slow
High cognitive load
Uses logic,
Evaluates evidence,
Prospect weights (utilities)
Less easily tricked

Reluctant acceptance of responsibility

Observable

Ease of use

Advantageous

Compatible

Trialable

Oversight

University of California
Agriculture and Natural Resources

The Rumsfeld (incomplete) typology of uncertainty

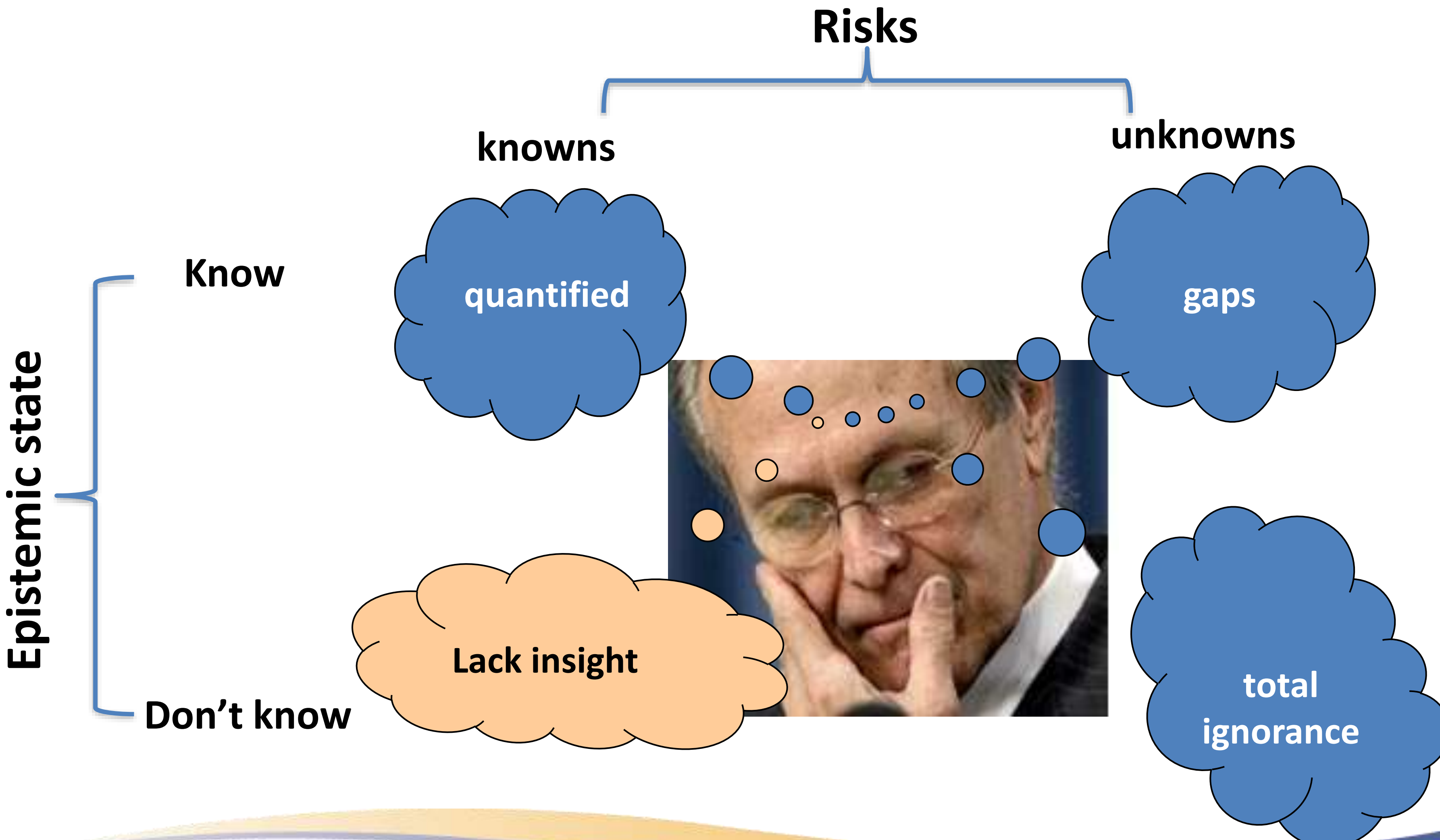
The Unknown
As we know,
There are *known knowns*.
There are things we know we know.
We also know
There are *known unknowns*.
That is to say
We know there are some things
We do not know.
But there are also *unknown unknowns*,
The ones we don't know
We don't know.

—Feb. 12, 2002, Department of Defense news briefing

http://www.slate.com/id/2081042/

For completeness there should also be *unknown knowns*

DR's typology of threats (risks)



Rumsfeld "space": a conceptual tool for understanding resistance to change

QBE Lab

You're here. You know what you know. System 1 is in charge. Decisions are easy but susceptible to error. Your organization wants you to move somewhere else in Rumsfeld space

KK

System 2 needs to take over while you learn things you know you don't know - for example, how to implement RBS

KU

System 2 needs to take over while your re-evaluate what you already know and gain new insights.

UK

System 2 needs to take over while you use meta-rules for dealing with complete uncertainty. You avoid coming here if at all possible.

UU

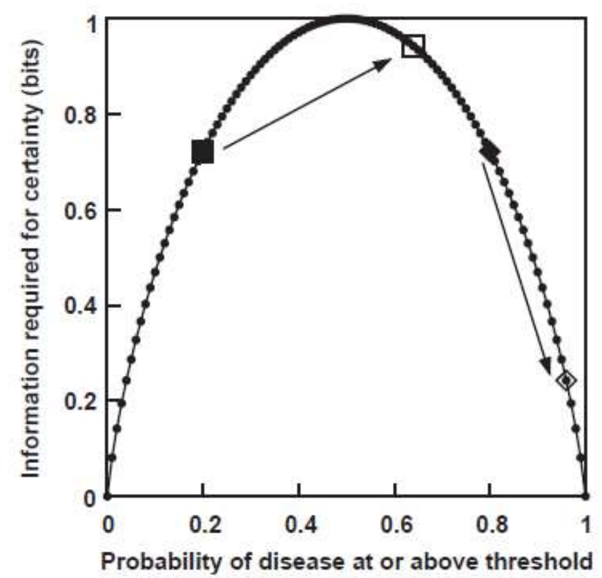


Fig. 5. The relationship between Shannon's information measure, *I*, and the probability of an event with two possible outcomes. Points are marked showing the information required by two farmers to decide whether disease is at or above or below a pre-specified threshold prior to (solid symbols) and after (open symbols) using a risk algorithm discussed by Yuen and Hughes (2002). The squares represent a farmer with a low prior probability of disease, the diamonds represent a farmer with a high prior probability of disease.

Constraints on adding complexity to decision processes (information theoretic interpretation)

QBE Lab

Relative Entropy measures distance of model from data
Estimated by (among others) Akiaike Information Criterion (AIC)

Distance from truth(Model) = S.S.(Model) + $2k\sigma^2_{err}$ +C

k is number of adjustable parameters
σ^2_{err} is the error variance
C is a constant (drops out in relative comparisons)

OR

Accuracy(Model) = (1/N)×(log(L)-*k*)

k as above
Log(L) log likelihood of model. N = number of data points

MDL ≅
min[*L*(*D*|*M*) + COMP(*M*)]

Minimum Description Length principle:
For any problem, choose the model that minimizes the combined length of the best description of the available data, given the model, plus shortest description of the model itself: min(accuracy + complexity)

Can use AIC (or MDL) to estimate required performance of new, more complex model over simpler, but poorer, existing one

QBE Lab

Accuracy(Model) = (1/N)×(log(*L*)-*k*)

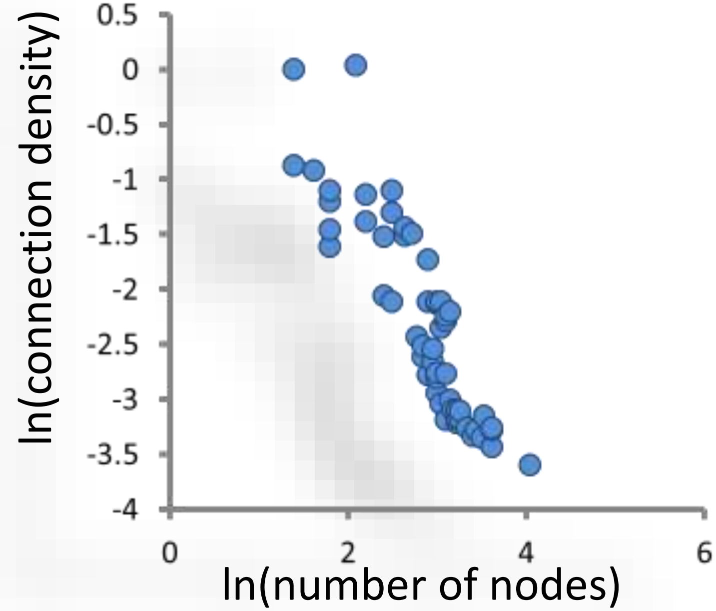
Suppose we fix Accuracy(Model)
Drop 1/N which is constant

$$\log(L_2)-(k+n) = \log(L_1)-k$$

$$L_2 = e^n \times L_1$$

Take home: If you add *n* new parameters to the user's decision model you should aim for e^n higher *L* to compensate the increase in complexity

Human cognitive maps show decline in complexity with size



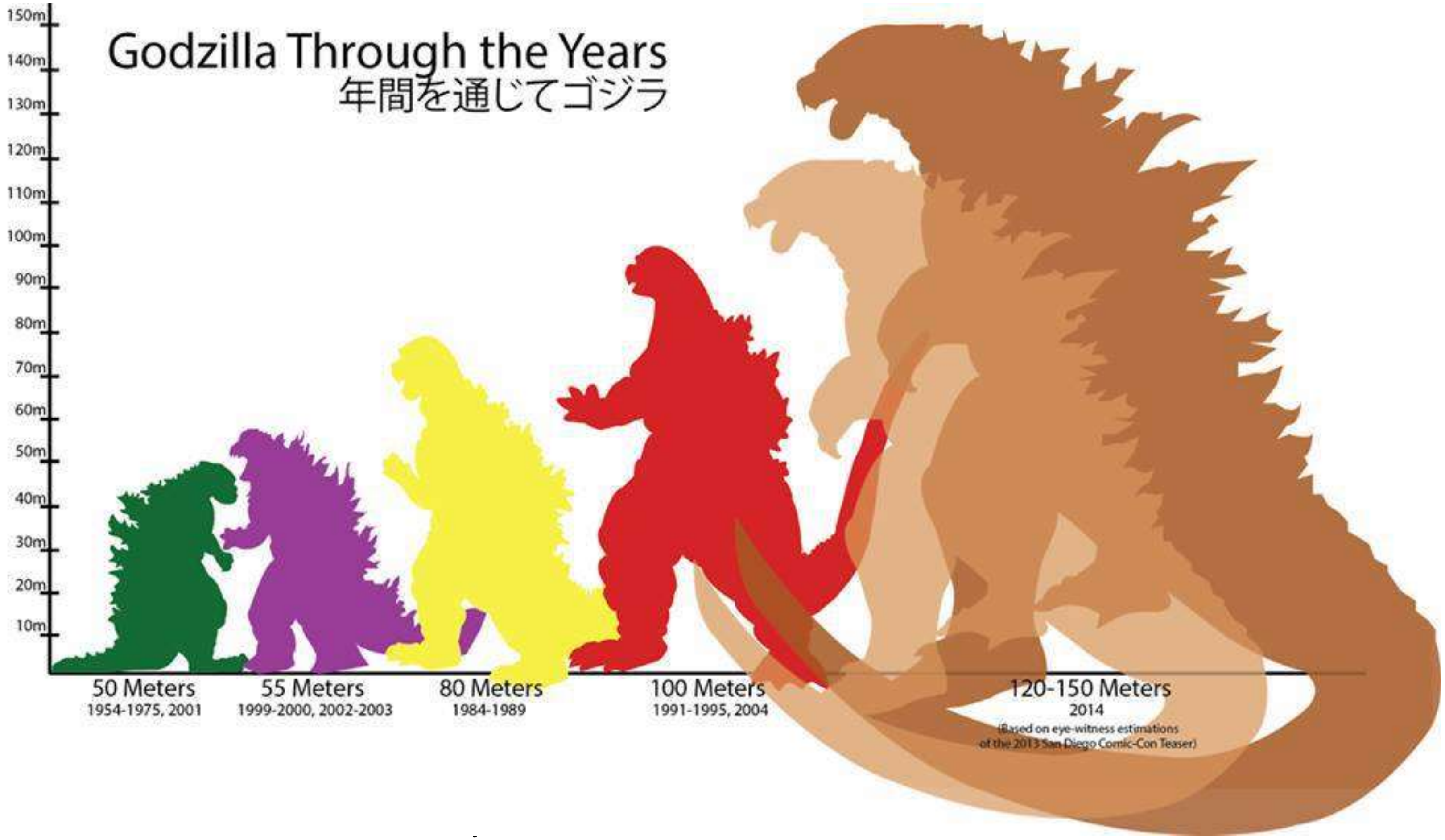
Modernity and the risk society

- **Current theoretical background developed by Anthony Giddens (LSE) and Ulrich Beck (Munich/LSE):**
  - **Function of modernity: greatest risks now come from actions of society not the external world**

- **Sociology-speak: Risk perception has both contextual and individualistic components, or;**
- **Science-speak: Risk perception is a P×E interaction**

- **An historical emphasis on typologies (i.e. risk-behaviour phenotypes).**
  - **Rodger's work on diffusion of innovations**
  - **David Pannell (WA) perspectives from Ag. Econ.**
  - **Edinburgh farmer scales Ian Deary, Joyce Willock (+others)**
  - **Much work on consumers**

The dimensions of risk



h

University *of* California
Agriculture and Natural Resources

Summary

- People like to use low-cognitive-cost but possibly error-prone (System 1) decision models
- Once something is learned it becomes System 1-like (e.g. driving a car)
- System 2 acts as overseer but System 2 “likes” to leave problem solving to system 1 and only steps in to solve problems when risk is high or outcomes are important.
- The choice between cheap/fast/possibly inaccurate and slow/complicated/more accurate is universal to signal detection systems in nature and human efforts in model selection/fitting.
- Learning a new method (such as RBS) involves experiencing increased uncertainty, which most people try to avoid
- Perceptions of risk are partly a social construct – response to risk is not a completely individual activity

Can use AIC (or MDL) to estimate required performance of new, more complex model over simpler, but poorer, existing one

QBE Lab

Accuracy(Model) = (1/N)×(log(L)-k)

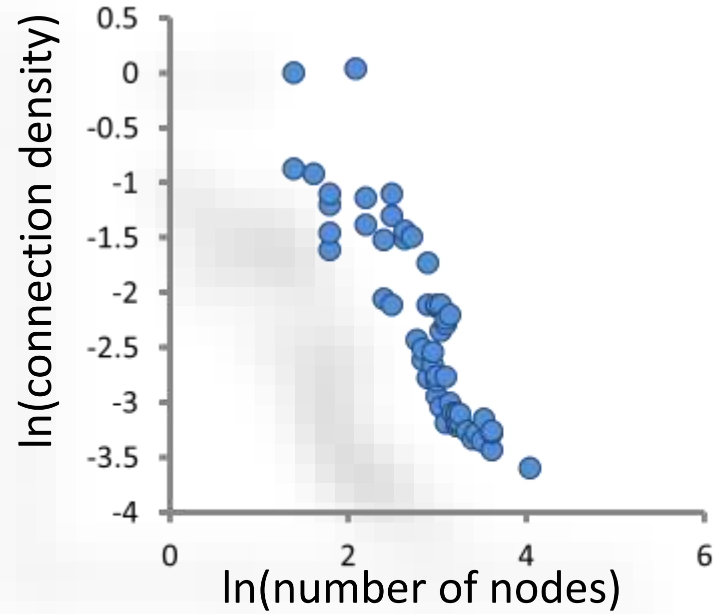
Suppose we fix Accuracy(Model)
Drop 1/N which is constant

$$\log(L_2)-(k+n) = \log(L_1)-k$$

$$L_2 = e^n \times L_1$$

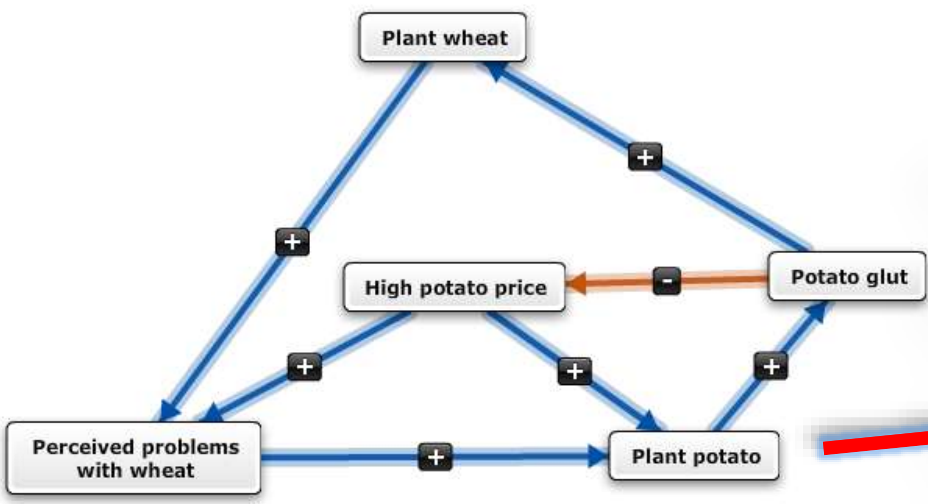
Take home: If you add n new parameters to the user's decision model you should aim for e^n higher L to compensate the increase in complexity

Human cognitive maps show decline in complexity with size

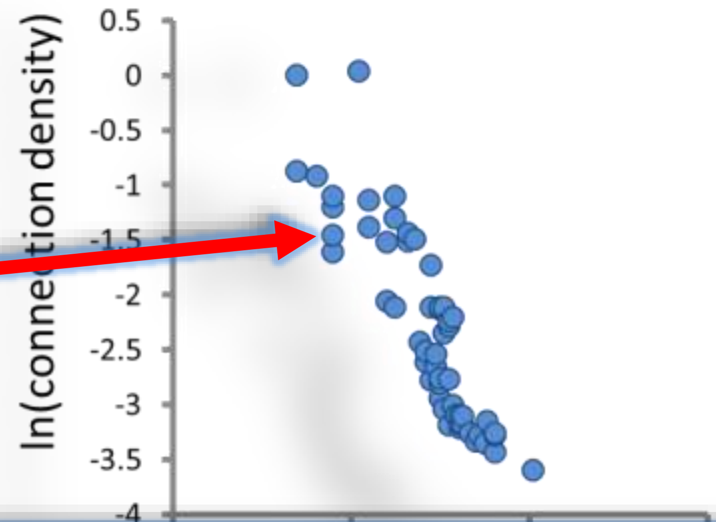


University of California
Agriculture and Natural Resources

Cognitive maps in Mental Modeler



Human cognitive maps show decline in complexity with size



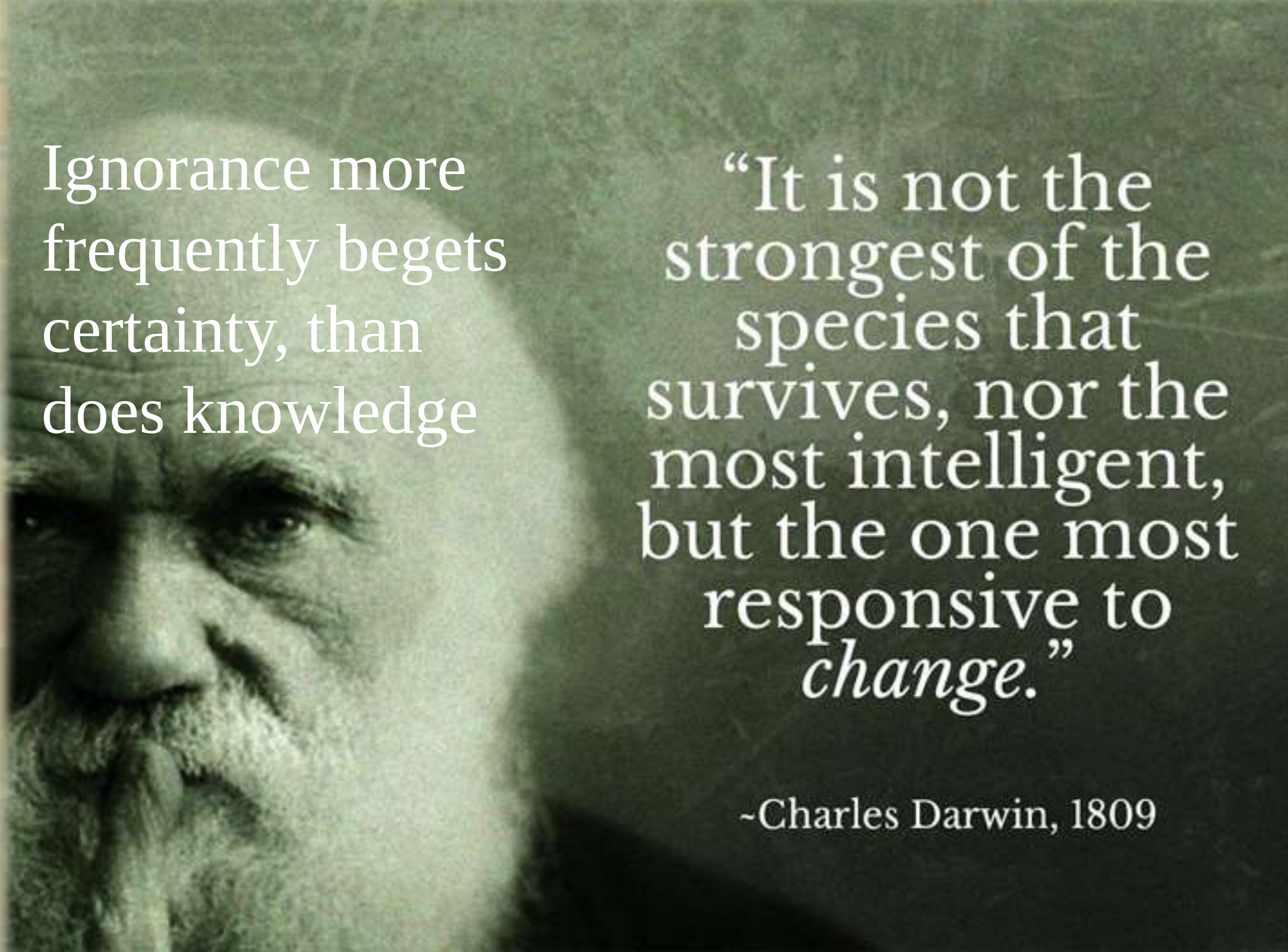
Plant potato	0	1	1	0	-1	-1	0	1	1	0	-1	-1	0	1	1	0	-1	-1	0	1
Perceived problems with wheat	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Potato glut	0	0	1	1	0	-1	-1	0	1	1	0	-1	-1	0	1	1	0	-1	-1	0
High potato price	1	0	0	-1	-1	0	1	1	0	-1	-1	0	1	1	0	-1	-1	0	1	1
Plant wheat	0	0	0	1	1	0	-1	-1	0	1	1	0	-1	-1	0	1	1	0	-1	-1

Audience participation time:

Build a cognitive model of drivers and constraints on adoption of RBS

(Switch to browser to run interactive model building)

Ignorance more frequently begets certainty, than does knowledge



Thank you

University *of* California
Agriculture and Natural Resources