Decision making under uncertainty

Including the issues of public perception and engagement

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Almost all important problems...

...involve considerable uncertainty.

At a personal level:
- Where to go to college
- Who to marry
- When and whether to have kids

In a company or other organization:
- Who to hire
- What products to develop

In a nation:
- How best to structure taxes
- How best to deal with social services & health care
- When to go to war
- When to sue for peace
The fact that there is uncertainty...

...should not by itself be grounds for inaction. Indeed, the consequences of doing nothing often carry comparable or larger uncertainty.

There is a large literature on analytical strategies for framing and making decisions in the face of uncertainty.
The resulting methods are now termed Decision Analysis

\[ \text{Max}\left[ \int p(x|c) \, U(x) \, dx \right] \]
There is also a large literature... based on empirical studies, that describes how people make decisions in the face of uncertainty.

Journal of Experimental Psychology: Human Learning and Memory

Judged Frequency of Lethal Events
Sarah Lichtenstein, Paul Slovic, Baruch Fishchoff, Richard Slovic, Richard L. Keen, Robert W. Bolger, and Thomas R. Nisbett, A Branch of Psychology

In this paper, we explore the role that, in general, is given in numerical form, for example, the future value of a particular event or of a student's grade point average. In making predictions and judgments about the likelihood of future events, people do not appear to follow the calculus of chance or the statistical theory of prediction. Instead, they rely on a limited number of heuristics which sometimes yield reasonable judgments and sometimes lead to severe and systematic errors (Kahneman & Tversky, 1972; Tversky & Kahneman, 1972, 1973). The present paper is concerned with the role of one of these heuristics—representativeness—in intuitive judgments.

Given specific evidence (e.g., a personal sketch), the issues under consideration (e.g., occupations or levels of achievement) can be ordered by the degree to which they are representative of that evidence. The thesis of this paper is that people predict by representatives, that is, select or order outcomes by the similarity to a prototype, or by the likelihood of a particular event or of a student's grade point average. In making predictions and judgments about the likelihood of future events, people do not appear to follow the calculus of chance or the statistical theory of prediction. Instead, they rely on a limited number of heuristics which sometimes yield reasonable judgments and sometimes lead to severe and systematic errors (Kahneman & Tversky, 1972; Tversky & Kahneman, 1972, 1973). The present paper is concerned with the role of one of these heuristics—representativeness—in intuitive judgments.

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Examples of cognitive heuristics

**Availability:** probability judgment is driven by ease with which people can think of previous occurrences of the event or can imagine such occurrences.

**Anchoring and adjustment:** probability judgment is frequently driven by the starting point which becomes an "anchor."

from Lichtenstein et al., 1978.
Finally there is a literature...

...on how to incorporate many of these ideas into policy analysis. For example:

In 10 to 15 minutes…

…there is no way to do justice to any of these literatures, or to the many other topics to which they are linked.

I will touch briefly on four topics:

1. The use of formal quantitative expert elicitation.

2. Limitations in the use of scenarios and integrated assessment models that focus on optimizing.


While the issues involved are all general, I will draw my examples from the domains of energy and climate change.
Why be quantitative?

Some ask:

Why be quantitative about uncertainty?

Aren’t words such as “likely” and “unlikely” perfectly adequate?

The problem is that such words can mean very different things in different circumstances and different things to different people in the same circumstance.
Words are not enough
An example from the EPA-SAB

The minimum probability associated with the word "likely" spanned four orders of magnitude.

The maximum probability associated with the word "not likely" spanned more than five orders of magnitude.

There was an overlap of the probability associated with the word "likely" and that associated with the word "unlikely"!

Without some quantification, qualitative descriptions of uncertainty convey little, if any, useful information.

The climate assessment community is gradually learning this lesson.

Steve Schneider and Richard Moss worked hard to promote a better treatment of uncertainty by the IPCC.

At my insistence, the first U.S. National Assessment Synthesis Team gave quantitative definitions to five probability words:

Many other communities have not yet got the message...
If I have good data...

...in the form of many observations of a random process, then I can construct a probability distribution that describes that process. For example, suppose I have the 145 years of rainfall data for San Diego, and I am prepared to assume that over that period San Diego's climate has been "stationary" (that is the basic underlying processes that create the year-to-year variability have not changed)...

Then if I want…

…a PDF for future San Diego annual rainfall, the simplest approach would be to construct a histogram from the data, as illustrated to the right.

If I want to make a prediction for some *specific* future year, I might go on to look for time patterns in the data. Even better, I might try to relate those time patterns to known slow patterns of variation in the regional climate, and modify my PDF accordingly.
In that way…

…I could construct a PDF and CDF for future San Diego rainfall that would look roughly like this.

However, suppose that what I really care about is the probability that very large rainfall events will occur.

Since there have only been two years in the past 145 years when rainfall has been above 60 cm/yr, I'll need to augment my data with some model, physical theory and expert judgment.
Expert elicitation takes time and care

Eliciting probabilistic judgments from experts requires careful preparation and execution.

Developing and testing an appropriate interview protocol typically takes several months. Each interview is likely to require several hours.

When addressing complex, scientifically subtle questions of the sorts involved with most problems in climate change, there are no satisfactory short cuts. Attempts to simplify and speed up the process almost always lead to shoddy results.

While I don’t have time to elaborate, there is compelling evidence that most of us are systematically overconfident...
Over Confidence

Percentage of estimates in which the true value lay outside of the respondent’s assessed 98% confidence interval.

Equilibrium change in global average temperature

200 years after a 2xCO₂ change

A similar study 15 years later…

…considered three scenarios of future forcing:

Summary of PDFs in $\Delta T$

- 2050
- 2200 Low
- 2200 High
- 2200 Medium
Climate sensitivity

Probability allocated to values above 4.5° C
Probability of a basic state change
Total aerosol forcing (at the top of the atmosphere)

Comparison with IPCC 4th assessment consensus results

IPCC reports area available at www.IPCC.ch
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Scenarios are widely used

For example, the last IPCC assessment made use of the very detailed SRES scenarios in making its projections.

While in principle there are ways to create scenarios that span ranges across the space of plausible futures, this is very rarely done.

Folks who construct scenarios often argue that they should not be viewed as “predictions” but rather as a strategy to help people think about how things might unfold in the future.

But, there is a problem with this argument…

SRES is at: www.ipcc.ch/ipccreports/sres/emission/index.php?idp=0
The more detail...

...that gets added to the “story line” of a scenario, the harder people find it to remember that there are typically many other ways that one could reach the same outcome, as well as many other possible outcomes that could result - this because of the heuristic of “availability.”

For additional elaboration of this and related arguments, and some suggestions for how to improve on past practice, see:

My colleagues and I…

…have been strong proponents for the use of integrated assessment, for example using these methods to explore the issue of acid rain (Rubin et al.). We thought that similar methods could be useful for addressing climate change.

Keeping Climate Research Relevant

The federal government must avoid repeating the mistakes it made in studying acid rain.


With NSF support we built CAM
To run the model:
1 - Double click on INPUTS to set up the scenario inputs;
2 - Double click on STRUCTURE to set up the model;
3 - Double click on OUTPUTS and evaluate the indicators.

ICAM
Integrated Climate Assessment Model

A very large hierarchically organized stochastic simulation model built in Analytica®.

See for example:

and
ICAM is focused on…

…doing a good job of dealing with uncertainty.

It treats all important coefficients as full probability distributions and produces results that are PDFs.

It contains switches that allow the user to use a variety of different functional forms.

We found that:

• One could get a large variety of answers depending on how you structured the model.

• In light of this, we concluded that global IA models that do optimization, using just one assumed structure, make absolutely no sense.
Accordingly…

…while others continue to build new IA models for the climate problem, or elaborate old ones, we have stopped doing global-scale IA for climate.

We are now focusing our attention on decisions that may actually contribute to reducing the adverse impacts of climate change, and on decision makers whose choices may actually do that. That is why our latest NSF center is the center for

**Climate and Energy Decision Making**

At its root, the climate problem is the problem of de-carbonizing the energy system.

Details at http://cedm.epp.cmu.edu
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Mental models methods

One problem with just asking people what they think about a topic like climate change, or “sustainability” is that you have to put information into your questions...and pretty soon you can’t tell if what people are saying is what they thought before you asked the question, or their inference based on the information in your question.

This multi-step process begins with a simple open-ended interview question.
Example of opening response in interview

**Interviewer**: "I'd like you to tell me all about the issue of climate change."

**Subject**: "Climate change. Do you mean global warming?"

**Interviewer**: "Climate change."

**Subject**: "OK. Let's see. What do I know. The earth is getting warmer because there are holes in the atmosphere and this is global warming and the greenhouse effect. Um... I really don't know very much about it, but it does seem to be true. The temperatures do seem to be kind of warm in the winters. They do seem to be warmer than in the past.. and.. hmm.. That's all I know about global warming."
Another example...

**Interviewer:** "Tell me all about the issue of climate change."

**Subject:** "Climate change? Like, what about it? Like, as far as the ozone layer and ice caps melting, water level raising, rainforest going down, oxygen going down because of that? All of that kind of stuff?"

**Interviewer:** "Anything else?"

**Subject:** "Well, erosion all over the place. Um, topsoils going down into everywhere. Fertilizer poisoning. "Interviewer: "Anything else that comes to mind related to climate change? Subject: "Climate change. Winter's ain't like they used to be. Nothing's as severe. Not as much snow. Nothing like that."
Another example...

**Interviewer:** "Tell me all about the issue of climate change."

**Subject:** "I'm pretty interested in it... The ice caps are melting -- the hole in the ozone layer. They think pollution from cars and aerosol cans are the cause of all that. I think the space shuttle might have something to do with it too, because they always send that up through the earth, to get out in outer space. So I think that would have something to do with it, too."

The identification of new concepts typically reaches an asymptote after 15-20 interviews.
The results... can then be used to develop a closed-form survey to get statistical power with large N.

In 1992, a mental-models-based survey in Pittsburgh, Pennsylvania, revealed that educated laypeople often conflated global climate change and stratospheric ozone depletion, and appeared relatively unaware of the role of anthropogenic carbon dioxide emissions in global warming. This study compares those survey results with 2009 data from a sample of similarly well-educated laypeople responding to the same survey instrument. Not surprisingly, following a decade of explosive attention to climate change in politics and in the mainstream media, survey respondents in 2009 showed higher awareness and comprehension of some climate change causes. Most notably, unlike those in 1992, 2009 respondents rarely mentioned ozone depletion as a cause of global warming. They were also far more likely to correctly volunteer energy use as a major cause of climate change; many in 2009 also cited natural processes and historical climatic cycles as key causes. When asked how to address the problem of climate change, while respondents in 1992 were unable to differentiate between general “good environmental practices” and actions specific to addressing climate change, respondents in 2009 have begun to appreciate the differences. Despite this, many individuals in 2009 still had incorrect beliefs about climate change, and still did not appear to fully appreciate key facts such as that global warming is primarily due to increased concentrations of carbon dioxide in the atmosphere, and the single most important source of this carbon dioxide is the combustion of fossil fuels.

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There has been…

…lots of work on strategies to support stakeholder involvement. Ortwin Renn is developing web-based guidance for IRGC.

My colleagues and I have developed a variety of strategies to support lay groups to make informed decisions about topics such as risk ranking, transmission line siting, and the development of portfolios of low carbon electricity generation technologies.

Example materials…

…from the work of Lauren Fleishman et al.

First study used paper materials:

Later studies have involved a computer tool:

Worked with experts at CMU and EPRI to review and refine the material.

The tool is available at: http://cedm.epp.cmu.edu/tool-public-lowcarbon.php
Acknowledgments

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