# The ${ }^{S} \boldsymbol{t r}_{\mathrm{a}_{\mathrm{n}}} \mathrm{Ge}_{\mathrm{e}}$ World of 

## Human Decision Making

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## Israel Institute of Technology



[^0]The strange world of human decision makingfoibles02.tex
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## Part I

## Foibles

## § Main Source:

Plous, Scott, 1993,
The Psychology of Judgment and Decision Making, chapter 12.

1 Catch-All Underestimation Bias

## 【 Sources:

- Fischhoff, B., P. Slovic, and S. Lichtenstein. 1978. Fault trees: Sensitivity of estimated failure probabilities to problem representation. Journal of Experimental Psychology: Human Perception Performance, 4: 330344.
- Michael Smithson and Yakov Ben-Haim, Reasoned Decision Making Without Math? Adaptability and Robustness in Response to Surprise, Risk Analysis, to appear. Pre-print: http://info-gap.com/content.php?id=23


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- Combine events in 1 super-event: E1 E2 E3 Event


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- delayed by traffic,
- distracted at lunch,
- etc.

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- Folks usually give a lower number than the sum of numbers they would give to the probabilities of - being late to rise,
- delayed by traffic,
- distracted at lunch,
- etc.
- The super-event skips details; ignores unanticipated surprising events.


## I Managing the CAUB:

- Exploit foibles to manage a foible.

II Managing the CAUB:

- Exploit foibles to manage a foible.
- Include a "novel outcome" category when eliciting probabilities:

Detailed descriptions of unknowns will tend to increase the intuitive probability of surprise.

## 2 Compound Events

## § Simple and compound events:

- Simple event depends on 1 outcome. E.g. 1 -stage lottery.
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- Simple event depends on 1 outcome. E.g. 1 -stage lottery.
- Compound event depends on multiple outcomes. E.g.
2-stage lottery.


## $\S$ Conjunctive 2-stage lottery:

 must win in both stages.
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§ People tend to over estimate probability of conjunctive events.
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§ Example (conjunctive):

- System with 500 independent parts.
- Each part essential.
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§ Example (conjunctive):
- System with 500 independent parts.
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- Probability of success of each part is 0.99
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§ Example (conjunctive):
- System with 500 independent parts.
- Each part essential.
- Probability of success of each part is 0.99
- What is the probability of success?
- Folks surprised that prob of system success $<1 \%$.
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§ Example (conjunctive):
- System with 500 independent parts.
- Each part essential.
- Probability of success of each part is 0.99
- What is the probability of success?
- Folks surprised that prob of system success $<1 \%$.
§ People tend to under estimate probability of disjunctive events.

3 Confusion of the Inverse
§ Woman examined for breast cancer. - Lump detected in breast.

- Chance of malignancy: 1 in 100 .
§ Woman examined for breast cancer.
- Lump detected in breast.
- Chance of malignancy: 1 in 100.
- X-ray mammogram performed.

Correct classification:

- $80 \%$ of malignant tumors.
- $90 \%$ of benign tumors.
§ Woman examined for breast cancer.
- Lump detected in breast.
- Chance of malignancy: 1 in 100.
- X-ray mammogram performed.

Correct classification:

- $80 \%$ of malignant tumors.
- $90 \%$ of benign tumors.
- Mammogram result: positive.
§ Woman examined for breast cancer.
- Lump detected in breast.
- Chance of malignancy: 1 in 100.
- X-ray mammogram performed.

Correct classification:

- $80 \%$ of malignant tumors.
- $90 \%$ of benign tumors.
- Mammogram result: positive.
§ 95 out of 100 physicians said: $75 \%$ chance of cancer.
§ Woman examined for breast cancer.
- Lump detected in breast.
- Chance of malignancy: 1 in 100.
- X-ray mammogram performed.

Correct classification:

- $80 \%$ of malignant tumors.
- $90 \%$ of benign tumors.
- Mammogram result: positive.
§ 95 out of 100 physicians said: $75 \%$ chance of cancer.
§ Evidently, physicians assumed that chance of cancer given positive test equals chance of positive test given cancer.
§ What do you think???
§ Woman examined for breast cancer.
- Lump detected in breast.
- Chance of malignancy: 1 in 100.
- X-ray mammogram performed.

Correct classification:

- $80 \%$ of malignant tumors.
- $90 \%$ of benign tumors.
- Mammogram result: positive.
§ 95 out of 100 physicians said: $75 \%$ chance of cancer.
§ Evidently, physicians assumed that chance of cancer given positive test equals chance of positive test given cancer.
$\S$ This is the confusion of the inverse.


## § How would a statistician decide?

 Bayes' theorem.$$
\begin{equation*}
p(\mathbf{c a n} \mid \mathbf{p o s})=\frac{p(\mathbf{c a n}, \mathbf{p o s})}{p(\mathbf{p o s})} \tag{1}
\end{equation*}
$$

## § How would a statistician decide?

Bayes' theorem.

$$
\begin{align*}
p(\mathbf{c a n} \mid \text { pos }) & =\frac{p(\mathbf{c a n}, \mathbf{\text { pos }})}{p(\mathbf{p o s})}  \tag{4}\\
& =\frac{p(\mathbf{p o s} \mid \mathbf{c a n}) p(\mathbf{c a n})}{p(\text { pos }, \mathbf{c a n})+p(\text { pos }, \text { benign })} \tag{5}
\end{align*}
$$

$\S$ How would a statistician decide?
Bayes' theorem.

$$
\begin{align*}
& p(\mathbf{c a n} \mid \mathbf{p o s})=\frac{p(\mathbf{c a n}, \mathbf{p o s})}{p(\mathbf{p o s})}  \tag{7}\\
&=\frac{p(\mathbf{p o s} \mid \mathbf{c a n}) p(\mathbf{c a n})}{p(\mathbf{p o s}, \mathbf{c a n})+p(\text { pos }, \text { benign })}  \tag{8}\\
& p(\mathbf{p o s} \mid \mathbf{c a n}) p(\mathbf{c a n}) \\
& p(\operatorname{pos} \mid \mathbf{c a n}) p(\mathbf{c a n})+p(\mathbf{p o s} \mid \text { benign }) p(\mathbf{b e n i g n}) \tag{9}
\end{align*}
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& p(\mathbf{c a n} \mid \mathbf{p o s})=\frac{p(\mathbf{c a n}, \mathbf{p o s})}{p(\mathbf{p o s})}  \tag{10}\\
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& \frac{p(\mathbf{p o s} \mid \mathbf{c a n}) p(\mathbf{c a n})}{p(\text { pos } \mid \mathbf{c a n}) p(\mathbf{c a n})+p(\mathbf{p o s} \mid \text { benign }) p(\text { benign })} \\
&=\frac{(0.8)(0.01)}{(0.8)(0.01)+(0.1)(0.99)}  \tag{12}\\
&=0.075 \ll 0.75 \tag{13}
\end{align*}
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$\S 95$ out of 100 physicians were wrong.
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$\S 95$ out of 100 physicians were wrong.
$\S$ Why is error so common?
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Bayes' theorem.

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\begin{align*}
& p(\mathbf{c a n} \mid \mathbf{p o s})=\frac{p(\mathbf{c a n}, \mathbf{p o s})}{p(\mathbf{p o s})}  \tag{20}\\
&=\frac{p(\mathbf{p o s} \mid \mathbf{c a n}) p(\mathbf{c a n})}{p(\mathbf{p o s}, \mathbf{c a n})+p(\mathbf{p o s}, \text { benign })}  \tag{21}\\
& \frac{p(\mathbf{p o s} \mid \mathbf{c a n}) p(\mathbf{c a n})}{p(\text { pos } \mid \mathbf{c a n}) p(\mathbf{c a n})+p(\mathbf{p o s} \mid \text { benign }) p(\text { benign })}  \tag{22}\\
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$\S 95$ out of 100 physicians were wrong.
$\S$ Why is error so common?
§ How to decide, if those probabilities are unknown?

4 Optimism Bias: It'll Never Happen to Me

## § Optimism bias:

Positive outcomes
are viewed to be more likely than negative outcomes.


FIGURE 12.1
These are the stimuli used by David Rosenhan and Samuel Messick (1966) in their study of probability estimation.

Figure 1: From Plous, p. 135.

## § Experiment:

- 150 cards with either "smile" or "frown".
- Subjects must guess "smile" or "frown" before each draw.


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These are the stimuli used by David Rosenhan and Samuel Messick (1966) in their study of probability estimation.

Figure 2: From Plous, p. 135.

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- When $70 \%$ are "smile": $68.2 \%$ success.


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Figure 3: From Plous, p. 135.

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- Subjects must guess "smile" or "frown" before each draw.
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Figure 4: From Plous, p. 135.
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- 150 cards with either "smile" or "frown".
- Subjects must guess "smile" or "frown" before each draw.
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§ Frequency of "negative" outcomes underestimated.
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§ Optimism bias w/ other positive and negative events:
- Positive:

High salary, home ownership, etc.

- Negative: drinking problem, heart attack, etc.
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## § Questions:

- Does education alleviate optimism bias?
§ Frequency of "negative" outcomes underestimated.
§ Optimism bias w/ other positive and negative events:
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High salary, home ownership, etc.

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§ Questions:
- Does education alleviate optimism bias?
- Is the optimism bias healthy or harmful?
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- Positive:

High salary, home ownership, etc.

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§ Questions:
- Does education alleviate optimism bias?
- Is the optimism bias healthy or harmful?
- Is optimism bias a reaction to uncertainty or is it wishful thinking?


## 5 Conservatism

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People revise probability estimates, given new data, by smaller amount than needed.

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Answer: 0.5.
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- Pick 12 balls blindly from chosen urn.
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- Pick 12 balls blindly from chosen urn.
- Find: 8 red and 4 blue balls.
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- What is prob that urn 2 was chosen?
- Most people answer 0.7 to 0.8 .
- Bayesian posterior probability is 0.97 .
- Most people revise prior probability (0.5) less than justified.
§ From Plous, p.140:
"On June 3, 1980, officers at the U.S. Strategic Air Command (SAC) were routinely watching for signs of a Russian missile attack. The shift had thus far passed uneventfully, and there were no signs of what was about to happen.
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"Suddenly, a computer display warned that the Russians had just launched a sortie of land- and submarine-based nuclear missiles. In several minutes, the missiles would reach the United States.
"SAC responded immediately. Across the country, more than 100 nuclear-armed B-52 bombers were put on alert and prepared for take-off. Nuclear submarine commanders were also alerted, and missile officers in underground silos inserted their launch keys into position. The United States was ready for nuclear war.
"Then, just three minutes after the warning had first appeared, it became clear that the alert was a false alarm. American forces were quickly taken off alert, and a number of investigations were initiated. Following a second false alert several days later, the Defense Department located the source of error. As it turned out, a computer chip worth $\$ 0.46$ had malfunctioned. Instead of registering the number of incoming missiles as a string of zeros, the chip had intermittently inserted 2 s in the digital readout."
$\S$ That was a serious accident.
- Corrective measures taken.
- No harm done.
- How did people respond?
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§ Opponents of nuclear deterrence felt less safe. §
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§ How do you explain this diversity?
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§ Opponents of nuclear deterrence felt less safe.
$\S$ Supporters of nuclear deterrence felt more safe.
§ How do you explain this diversity?
§ Explanations:
- Re-inforcing prior opinions.
- Conservatism.
- Self interest.
- Lack of integrity.

7 Risk Compensation
§ Source: John Adams, 1995, Risk.
§ "The potential safety benefit of most improvements to roads and vehicles is, it seems, consumed as a performance benefit; as a result of safety improvements it is now possible to travel farther and faster for approximately the same risk of being killed." (Adams, p.144)

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- Better safety devices makes people more reckless.


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§ Example: Icy corner.
- Hi-speed camera detects tire quality.
- Higher speed observed with better tires.
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§ Why???
§ Risk compensation:
- Better safety devices makes people more reckless.
- People adjust behavior to keep danger constant.
§ Example: Icy corner.
- Hi-speed camera detects tire quality.
- Higher speed observed with better tires.
§ Why???
- People ignore uncertainty?
- People keep risk-level constant?
- People are foolish?

8 Optimizer's Curse

## § Sources:

- Smith, James E. and Robert L. Winkler, 2006, The optimizer's curse: Skepticism and postdecision surprise in decision analysis, Management Science, Vol. 52, No. 3, pp.311-322.
- Thaler, Richard H., 1992, The Winner's Curse: Paradoxes and Anomalies of Economic Life, Princeton University Press.
- Lecture notes:
$\backslash$ lectures $\backslash$ risk $\backslash$ lectures $\backslash$ optimizers-curse03.pdf
§ Choose from $N$ options:
- $v_{i}=$ Unknown true value of $i$ th option.
- $V_{i}=$ Known unbiased estimate of $v_{i}$.
§ Large value desired.
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§ Regret:
- Choose alternative $i$, expecting $V_{i}$.
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- Regret, or disappointment: $V_{i}-y_{i}$. Positive regret if $y_{i}<V_{i}$.
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Positive regret if $y_{i}<V_{i}$.
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- Regret, or disappointment: $V_{i}-y_{i}$.

Positive regret if $y_{i}<V_{i}$.
§ Outcome optimization: $i^{\star}=\arg \max _{i} V_{i}$
$\S$ Is this is a good strategy? What would you do?
$\S$ Expect positive regret from $V_{i^{\star}}: \mathrm{E}\left(V_{i^{\star}}-y_{i^{\star}}\right)>0$.
On average, outcome optimum:

- Is over-estimate. ○ Has positive regret.
$\S$ Simple example.
$\S$ The true values, $v_{i}$, all precisely equal zero. They are not random variables.


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$\S$ The estimates, $V_{i}$, are $\mathcal{N}(0,1)$, fig. 5, left.

Figure 1 The Distribution of the Maximum of Three Standard Normal Value Estimates


Figure 5: Smith and Winkler (2006), fig. 1.

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Figure 1 The Distribution of the Maximum of Three Standard Normal Value Estimates


Figure 6: Smith and Winkler (2006), fig. 1.
§ The mean of $V_{i^{\star}}$ is 0.85 , fig. 6 , right.
§

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Figure 7: Smith and Winkler (2006), fig. 1.
§ The mean of $V_{i^{\star}}$ is 0.85 , fig. 7 , right.
§ Thus the average regret, $\mathrm{E}\left(V_{i^{\star}}-0\right)$, is 0.85 .

## $\S$ Simple example.

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§ Is outcome optimization a good strategy?
$\S$ What do engineers mean by "optimal design"?

## Part II

## Uncertainty

$\S$ We have reviewed many
human foibles of decision making:

- Catch-All Underestimation Bias.
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§ Part of the problem is uncertainty:
Ignorance, surprise, change.
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§ Part of the problem is uncertainty:
Ignorance, surprise, change.
§ We now look at uncertainty.

9 Theories and the Real World

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§ Science will improve tomorrow.
Hence today we are ignorant.


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§ Science will improve tomorrow.
Hence today we are ignorant.
§ Is ignorance probabilistic?

10 Principle of Indifference

## § Question: Is ignorance probabilistic?

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- Elementary events, about which nothing is known, are assigned equal probabilities.
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§ Principle of indifference (Bayes, LaPlace, Jaynes, ... ):
- Elementary events, about which nothing is known, are assigned equal probabilities.
- Uniform distribution represents complete ignorance.
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§ Principle of indifference (Bayes, LaPlace, Jaynes, ...):
- Elementary events, about which nothing is known, are assigned equal probabilities.
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§ The info-gap contention:
The probabilistic domain of discourse does not encompass all epistemic uncertainty.
§ Question: Is ignorance probabilistic?
§ Principle of indifference (Bayes, LaPlace, Jaynes, ...):
- Elementary events, about which nothing is known, are assigned equal probabilities.
- Uniform distribution represents complete ignorance.
§ The info-gap contention:
The probabilistic domain of discourse does not encompass all epistemic uncertainty.
$\S$ We will consider common misuses of probability.
10.1 2-Envelope Riddle
$\S$ The riddle:
- You are presented with two envelopes.
- Each contains a positive sum of money.
- One contains twice the contents of the other.
- You choose an envelope, open it, and find $\$ 50$.
- Would you like to switch envelopes?
§ You reason as follows:
- Other envelope contains either $\$ 25$ or $\$ 100$.
- Principle of indifference:
- Assume equal probabilities.

The expected value upon switching is:
E.V. $=\frac{1}{2} \$ 25+\frac{1}{2} \$ 100=\$ 62.50$. $\$ 62.50>\$ 50$.

- Yes! Let's switch, you say.
§ The riddle, re-visited:
- You are presented with two envelopes.
- Each contains a positive sum of money.
- One contains twice the contents of the other.
- You choose an envelope, but do not open it.
- Would you like to switch envelopes?
§ You reason as follows:
- This envelope contains $\$ X>\$ 0$.
- Other envelope contains either $\$ 2 X$ or $\$ \frac{1}{2} X$.
- Principle of indifference:
- Assume equal probabilities.

The expected value upon switching is:
E.V. $=\frac{1}{2} \$ 2 X+\frac{1}{2} \$ \frac{1}{2} X=\$\left(1+\frac{1}{4}\right) X>X$.

- Yes! Let's switch, you say.
§ You reason as follows:
- This envelope contains $\$ X>\$ 0$.
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- Yes! Let's switch, you say.
§ You wanna switch again? And again? And again?
10.2 Keynes' Example
$\S \rho=$ specific gravity $\left[\mathrm{g} / \mathrm{cm}^{3}\right]$ is unknown:

$$
1 \leq \rho \leq 3
$$

§
$\S \rho=$ specific gravity $\left[\mathrm{g} / \mathrm{cm}^{3}\right]$ is unknown:

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§ Principle of indifference:
Uniform distribution in $[1,3]$, so:

$\S$ Uniform distribution in $[1,3]$, so:

$$
\operatorname{Prob}\left(\frac{3}{2} \leq \rho \leq 3\right)=\frac{3}{4}
$$


$\S \phi=$ specific volume $\left[\mathrm{cm}^{3} / \mathrm{g}\right]$ is unknown:

$$
\frac{1}{3} \leq \phi \leq 1
$$

§
$\S \phi=$ specific volume $\left[\mathrm{cm}^{3} / \mathrm{g}\right]$ is unknown:

$$
\frac{1}{3} \leq \phi \leq 1
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## § Principle of indifference:

Uniform distribution in $\left[\frac{1}{3}, 1\right]$, so:

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\operatorname{Prob}\left(\frac{1}{3} \leq \phi \leq \frac{2}{3}\right)=\frac{1}{2}
$$



## $\S$ These two events are identical:

$$
\underbrace{\left(\frac{1}{3} \leq \phi \leq \frac{2}{3}\right)}_{\text {Specific volume }} \equiv \underbrace{\left(\frac{3}{2} \leq \rho \leq 3\right)}_{\text {Specific gravity }}
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§ Hence their probabilities are equal:

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\underbrace{\operatorname{Prob}\left(\frac{1}{3} \leq \phi \leq \frac{2}{3}\right)}_{\text {Specific volume }}=\underbrace{\operatorname{Prob}\left(\frac{3}{2} \leq \rho \leq 3\right)}_{\text {Specific gravity }}
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$\S$ The Culprit: Principle of indifference.
$\S$ These two events are identical:

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$\S$ The Culprit: Principle of indifference.
§ Ignorance is not probabilistic. It's an info-gap.

11 Pascal's Wager
§ We now ask: Why is it difficult to make a binary decision under ignorance?
$\S$ We now ask: Why is it
difficult to make a binary decision under ignorance?
§ Examples of binary decisions:

- God, no God?
- Truth, no truth?
- Seeing is believing?
- This theory is true or false?


Figure 10: Blaise Pascal, 1623-1662.
The wager is described in Pensées as:
"'God is, or He is not.' Reason can decide nothing here. . . . Heads or tails will turn up. What will you wager? . . .
"If you gain, you gain all; if you lose, you lose nothing. Wager, then, without hesitation that He is. ... Since there is an equal risk of gain and of loss, ..."
$\sim \sim$ Pascal's Wager $\sim \sim$


Figure 11: Blaise Pascal, 1623-1662.
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§ When "reason can decide nothing":

- 1st paragraph: Is probability a good tool?
$\sim \sim$ Pascal's Wager $\sim \sim$


Figure 12: Blaise Pascal, 1623-1662.
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§ When "reason can decide nothing":

- 1st paragraph: Is probability a good tool?
- Do you have a better suggestion?

$$
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Figure 13: Blaise Pascal, 1623-1662.
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§ When "reason can decide nothing":

- 1st paragraph: Is probability a good tool?
- Do you have a better suggestion?
- 2nd paragraph:

Is reasoning from the consequences legitimate?

12 Lewis Carroll's Transcendental Probability

## Lewis Carroll's

$\sim \sim$ Transcendental Probability $\sim \sim$


Figure 14: Dodgson, 1832-1898.


Figure 15: Alice
"A bag contains 2 counters, as to which nothing is known except that each is either black or white. Ascertain their colours without taking them out of the bag."

## Lewis Carroll's

$\sim \sim$ Transcendental Probability $\sim \sim$


Figure 16: Dodgson, 1832-1898.


Figure 17: Alice
"A bag contains 2 counters, as to which nothing is known except that each is either black or white. Ascertain their colours without taking them out of the bag."

Answer: "One is black, and the other white."
§ Carroll assumed equal probabilities.
Was he justified?
§ Are such simple examples useful?

13 3-Door Problem (Monty Hall Problem)

## § Sources:

- Plous, chapter 12.
- Yakov Ben-Haim, 1996,

Robust Reliability in the
Mechanical Sciences, section 7.1.

## § Prize in 1 of 3 boxes: ? ? ?

## $\S$ Prize in 1 of 3 boxes: ? ? ?

$\S$ Choose a box:
C
?
?
§ Prize in 1 of 3 boxes: ? ? ?
§ Choose a box:
§ M.C. knows where the prize is.
§ M.C. opens an empty box:
§
$\S$ Prize in 1 of 3 boxes: ? ? ?
§ Choose a box:
§ M.C. knows where the prize is.
§ M.C. opens an empty box: C E T
§ Want to change your choice?

$$
C \Longrightarrow T
$$

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§ Is the situation binary indifference?
C T
$\S$ Prize in 1 of 3 boxes: ? ? ? ?
$\S$ Choose a box:
C ?
§ M.C. opens an empty box: $\mathbf{C} \quad \mathbf{T}$
§ Want to change your choice?

$$
C \Longrightarrow T
$$

§ Is the situation binary indifference?
C T
§ Is the change justified?
§
§ Prize in 1 of 3 boxes: ? ? ?
§ Choose a box:
C
?
?
§ M.C. knows where the prize is.
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§ Want to change your choice?

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§ Is the situation binary indifference?
C $\quad$ T
§ Is the change justified?
§ What have you assumed? Equal probabilities?
§
§ Prize in 1 of 3 boxes: ? ? ?
§ Choose a box:
C ?
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§ M.C. opens an empty box: C C T
§ Want to change your choice?

$$
C \Longrightarrow T
$$

§ Is the situation binary indifference?
C $\quad$ T
§ Is the change justified?
§ What have you assumed? Equal probabilities?
§ Would you reach the same decision for any probability distribution?

14 Principle of Indifference: Continuation
§ We now generalize our discussion.
14.1 Shackle-Popper Indeterminism

## § Intelligence:

What people know, influences how they behave.

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What people know, influences how they behave. § Discovery: What will be discovered tomorrow cannot be known today.

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What people know, influences how they behave.
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What will be discovered tomorrow cannot be known today.
§ Indeterminism:
Tomorrow's behavior cannot be modelled completely today.
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What people know, influences how they behave.
§ Discovery:
What will be discovered tomorrow cannot be known today.
§ Indeterminism:
Tomorrow's behavior cannot be modelled completely today.
§ Information-gaps, indeterminisms, sometimes cannot be modelled probabilistically.
§ Intelligence:
What people know, influences how they behave.
§ Discovery: What will be discovered tomorrow cannot be known today.
§ Indeterminism:
Tomorrow's behavior cannot be modelled completely today.
§ Information-gaps, indeterminisms, sometimes cannot be modelled probabilistically. § Ignorance is not probabilistic.

## $\S$ Two types of discoveries:

- Discover what does exist (recovery).
- America.
- HIV virus.
- House keys.
$\S$ Two types of discoveries:
- Discover what does exist (recovery).
- America. ○ HIV virus. ○ House keys.
- Discover what does not exist (invention).
- Mathematical theorem (Hardy disagreed).
- Idea of freedom.
- Beethoven's 5th symphony.
$\S$ Two types of discoveries:
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§ Two corresponding types of universe:
- Discover what does exist.

Closed universe. Creation ended.

- Planck before 1905.

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Open universe. Creation continues.

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§ Two corresponding types of universe:
- Discover what does exist.

Closed universe. Creation ended.

- Planck before 1905.
- Maimonides' argument for God: creation.
- Discover what does not exist.

Open universe. Creation continues.

- Planck after 1905, maybe.
- Einstein's argument for God, maybe:
"Subtle is the Lord, but malicious He is not."
14.2 Shackle-Popper and the Newtonian Paradigm


## § Shackle-Popper indeterminism:

- Discovery and intelligent knowledge-based behavior.


## § Shackle-Popper indeterminism:

- Discovery and intelligent knowledge-based behavior.
- Unavoidable uncertainty about the future.
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§ Newtonian paradigm:
- Stable, universal, discoverable laws of nature.
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§ Shackle-Popper indeterminism:
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§ Is there a conflict here?
§ Shackle-Popper indeterminism:
- Discovery and intelligent knowledge-based behavior.
- Unavoidable uncertainty about the future.
§ Newtonian paradigm:
- Stable, universal, discoverable laws of nature.
- Science underlies prediction and control.
§ Is there a conflict here?
$\S$ Yes.
- Shackle-Popper: Open universe.
- Newton: Closed universe.


## Early modern:



Figure 18: Newton, 1642-1727. Figure 19: Comte, 1798-1857.

## Late modern:



Figure 20: Shackle, 1903-1992. Figure 21: Popper, 1902-1994.
§ Newton, Comte, Positivism:

- Creation ended. Universe fixed.
- There are true (final) laws of nature.
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- Do you have expl of a theory that is essentially true?
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- Do you have expl of a theory that is essentially true?
- Examples:
- Aristotle's law of inertia.
- Galileo's law of inertia.
- Newton's laws of dynamics.
- Einstein's special relativity.

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- Theories (models) give insight.
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§ If not Newton, then what?
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- Are they good for anything?

And if so, why do buildings fall, markets crash . . .
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- Economics: Why the frequent surprises?


Figure 22: Henry Adams 1838-1918.
"Images are not arguments, but the mind craves them. [T]wenty images better than one, especially if contradictory; since the human mind has already learned to deal in contradictions."
§ Models, the more the merrier.


Figure 23: Henry Adams 1838-1918.
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§ Models, the more the merrier.
§ Is this a Newton-Comte or Shackle-Popper idea?

### 14.3 Intelligent Learning System: Example

## Inflation Prediction



Figure 24: US inflation vs. year, 1961-1965.


Figure 25: US inflation vs. year, 1961-1965.


Figure 26: US inflation vs. year, 1961-1966.

## § '61-'65: Linear?

## § '61-'66: Piece-wise linear? Quadratic?



Figure 27: US inflation vs. year, 1961-1965.


Figure 28: US inflation vs. year, 1961-1966.


Figure 29: US inflation
vs. year, 1961-1993.

## § '61-'65: Linear?

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§ '61-'93: A mess?


Figure 30: US inflation vs. year, 1961-1965.
§ US inflation '61-'65:

- Model '61-'65 for predicting '66.
- Use data and contextual insight:

Economy heating up. No data yet.


Figure 31: US inflation vs. year, 1961-1965, and least squares fit (solid) and other fit (dash).
§ Least squares and other fit: fig. 31.

## § Evaluate fit:

- Fidelity to history (-). - Fidelity to future (--).
- Which is "Newton-Comte" or "Shackle-Popper"?


Figure 32: US inflation vs. year, 1961-1965, and least squares fit (solid) and other fit (dash).


Figure 33: Robustness vs. critical root mean squared error for inflation 1961-1965 for least squares fit (solid) and other fit (dash).
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§ Robust of LS and other fit: fig. 33.
- Curve-crossing: preference reversal.
- Is this pragmatic or principled?
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$\S$ What is rationality?
- Is there only one rationality?
- Should all rational people always agree?


# Human decision making 

under uncertainty
is

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{ }^{\mathrm{S}} \boldsymbol{t}^{\mathrm{r}_{\mathrm{n}}} \mathrm{G}_{\mathrm{e}}
$$




[^0]:    $\backslash$ lectures $\backslash$ talks $\backslash$ lib $\backslash$ foibles02.tex © Yakov Ben-Haim 28.10.2015

