Psychophysical Aspects of Choice Behavior

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Why Should Economists Study the Brain?

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- Standard approach in economics: seek to explain observed choices as those preferred by the decisionmaker, from among the choices available on the given occasion

    - neglected issue: ways in which the subjective representation of the decision situation, upon which the decision must be based, may differ from objective characteristics

      — even "behavioral economists" often seek to explain anomalous behavior in terms of non-standard preferences over actual outcomes

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  — but measurement of neural activity can help to discipline theory development

Example 1: Stochastic Choice

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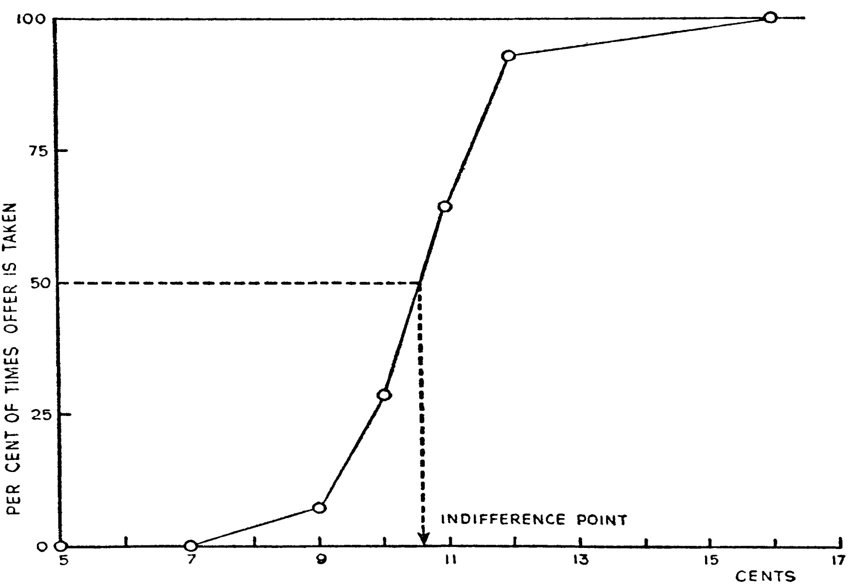
- Yet experiments show that subjects' choices between particular options involve a random element: same subject need not choose the same way, if same options are repeated (sometimes only minutes later)

  — but probability of choice often varies systematically with characteristics

Mosteller and Nogee (1951)



Explaining Stochastic Choice

- Stochasticity of choice between goods often explained by postulating randomness of preferences (e.g., McFadden, 1974)

  — but less plausible as an explanation of random choice between lotteries

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- Alternative possibility: randomness of subjective representation on the basis of which judgment of value is made

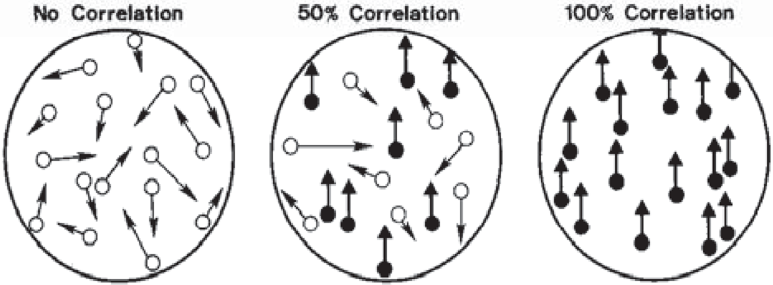
- In fact, such randomness of responses is a common feature of perceptual judgments

Stochasticity of Perceptual Judgments

- Long experimental literature in psychophysics shows that discrimination between stimuli is both imprecise and probabilistic:
  - probability of correct discrimination of relative brightness, direction of motion, etc., increasing function of objective difference

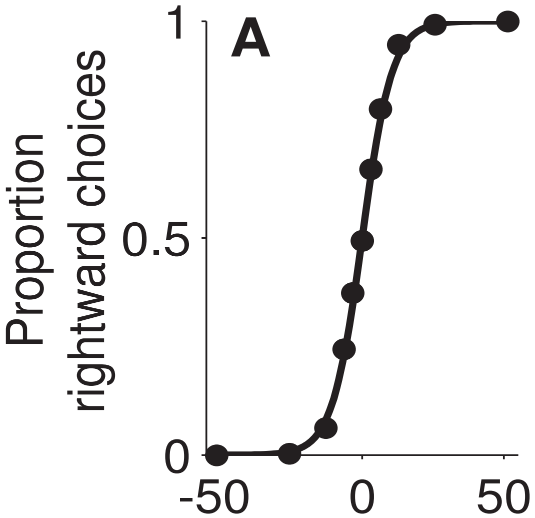
    ("psychometric function")

Motion Discrimination: Moving-Dot Stimuli



Different possible degrees of "motion strength."

Motion Discrimination: Shadlen *et al.* (2007)

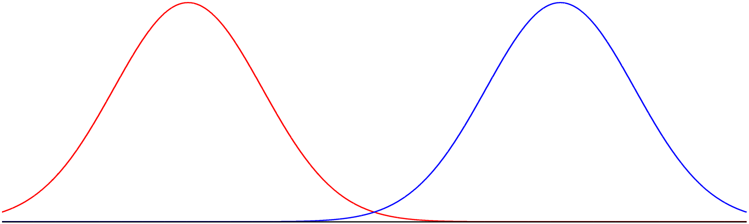


horizontal axis: "motion strength" to the right, moving-dot stimulus

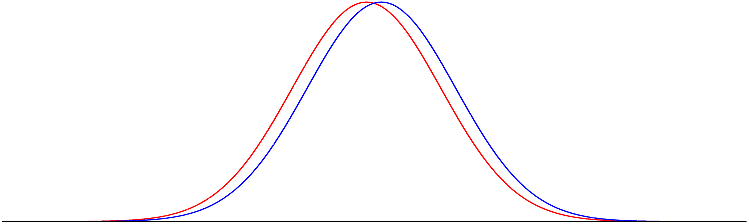
Stochasticity of Perceptual Judgments

- Conventional interpretation: each (objective) stimulus is associated with a probability distribution of possible subjective representations ("percepts")
  - stochastic errors in classification attributed to overlap of these distributions
  - "signal detection theory" (e.g., Green and Swets, 1966) seeks to infer the distributions of subjective representations needed to account for behavioral data

Signal Detection Theory



low overlap ⇒ probability of error near zero



high overlap ⇒ probability of error near 50%

Stochasticity of Perceptual Judgments

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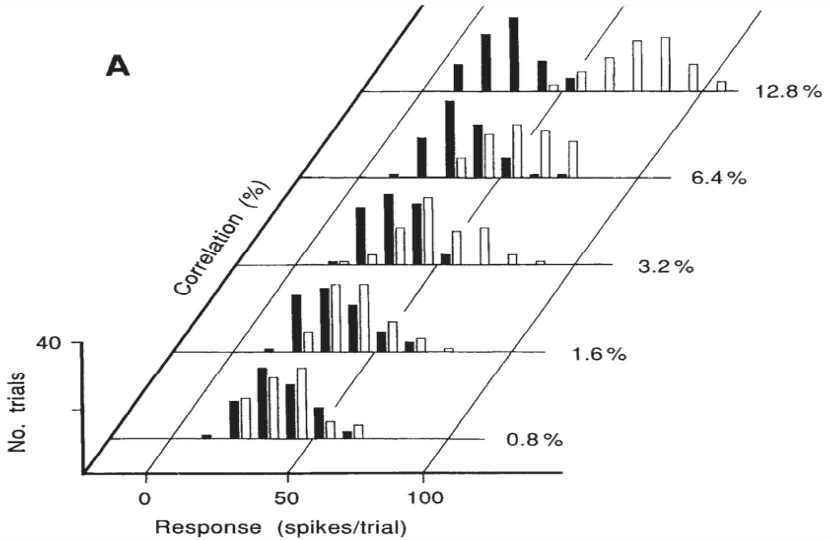
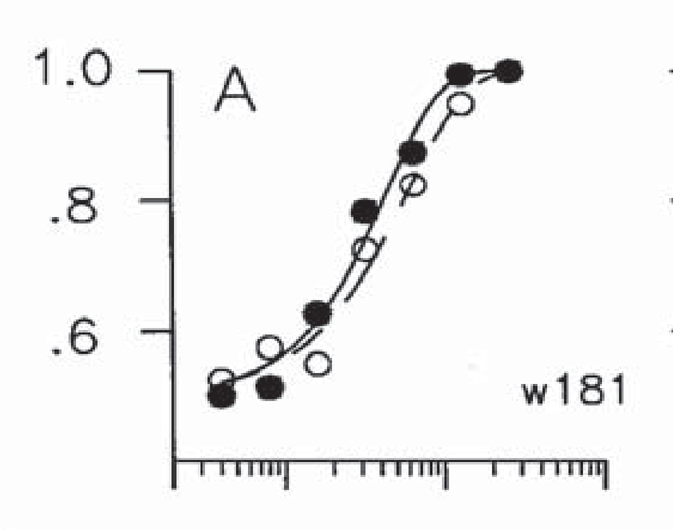
  - stochastic errors in classification attributed to overlap of these distributions
  - "signal detection theory" (e.g., Green and Swets, 1966) seeks to infer the distributions of subjective representations needed to account for behavioral data
- Originally purely an "as-if" hypothesis; but now confirmed by neural measurements

Neurons in Area MT: Britten *et al.* (1992)



Histograms of number of spikes in MT neuron.

Neurons in Area MT: Britten *et al.* (1992)



“Neurometric” and “psychometric” curves compared.

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   — e.g., should expect speed-accuracy trade-off as in perceptual classification tasks

   - in fact, using decision time data to infer degree of intensity of preference between different options, in addition to data on choices themselves, can increase accuracy with which choices between new pairs of options are predicted: Clithero and Rangel (2013), Krajbich, Oud and Fehr (2014)

Explaining Stochastic Choice

2. allows a choice-based evaluation of welfare (policies evaluated from standpoint of personal objectives that are inferred from people's choices) without simply identifying whatever is chosen on any occasion with what people most want

   — becomes a reasonable goal of policy to reduce mistakes (or costliness of mistakes)

Example 2: "Tunnel Vision"

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- Analogous to familiar perceptual phenomena: deterioration of performance on perceptual tasks due to inattention;

  — "inattentional blindness" (Simons and Chabris, 1999), "attentional capture" (Yantis, 1993)

Example 3: Choice-Set Size Effects

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- Example: "choice overload"

    - Iyengar and Lepper (2000): 30 percent of customers buy when offered 6 types of jam; — only 3 percent buy, when offered 24 types

    - Iyengar *et al.* (2004): larger number of options reduces fraction who participate in 401(k) plan

Choice-Set Size Effects

- Effect of additional options easier to understand if one supposes that representation of options is inaccurate, and becomes more so when larger number must be represented

- Again, similar phenomena familiar from sensory domains: increased inaccuracy due to division of attention (Shaw, 1984)

Limits on the Capacity to Discriminate

- Both of these types of phenomena suggest: a theory of choice needs to take into account the existence of a finite capacity to discriminate between different situations

  — such that the need to simultaneously represent multiple aspects of a situation reduces the accuracy with which some (or all) of them can be represented

- Studying the nature of resource constraints in perceptual domains may be valuable in suggesting how best to formulate such a constraint

Limits on the Capacity to Discriminate (1)

- How to quantify such limits?

- A simple approach often used by decision theorists in economics: assume a finite bound on the number of different states that can be distinguished (e.g., Gul, Pesendorfer and Strzalecki, 2013)

  — subjective representation is a (coarser or finer) partition of the possible states of the world

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- The problem of choosing such a partition optimally (if actions must be chosen based on the coarse representation of the state) is just the problem of optimal quantization in coding theory

  — the problem of how such classifications can be learned is a standard ("unsupervised learning") problem in machine learning

Bound # of Distinct Representations?

- Not a formalization consistent with psychophysical evidence: stimuli are not assigned deterministically to non-overlapping categories (with however a limit on the number of categories)

  — instead, categorizations are probabilistic, in the case of sufficiently similar stimuli

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  — instead, categorizations are probabilistic, in the case of sufficiently similar stimuli

- One observes a bound on the number of distinct stimuli that can be distinguished with perfect accuracy

  — yet if one increases the number of stimuli that must be distinguished, the result is not that the same small number of categorizations continue to be used (though with multiple stimuli given a single name), but rather that classifications become increasingly random

"Absolute Judgment" Experiments

- Pollack (1952): subjects are asked to classify auditory tones of different frequencies, according to their place in a sequence of n possible tones

  — baseline case: tones equally spaced in log frequency (over range 100 cps – 8000 cps)

  — tones presented in random order; correct classification indicated after each response

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- Finding: subjects can classify with virtually perfect accuracy (with sufficient training) as long as $n = 2, 3$, or 4;

  — but responses become stochastic if $n = 5$, and progressively less predictable as n increases (up to 14)

"Absolute Judgment" Experiments

- Quantifying randomness of responses:
  - if ex ante probability of stimulus s is π_s, and conditional probability of response r when stimulus s is presented is p_{sr}, then mutual information between S and R is

$$I = \sum_{sr} \pi_s p_{sr} \log \frac{p_{sr}}{p_r}$$

where $p_r \equiv \sum_s \pi_s p_{sr}$ is unconditional probability of response r

"Absolute Judgment" Experiments

- I measures how informative the response R is about the true stimulus S:
  - note that $0 \leq I \leq \log n$

    — lower bound $I = 0$ if R is independent of S (so totally uninformative);

    — upper bound $I = \log n$ if $r = s$ with certainty (maximally informative);
  - and introducing additional randomness into either the value of s entered as input, or the report that is given of the output r, necessarily reduces I

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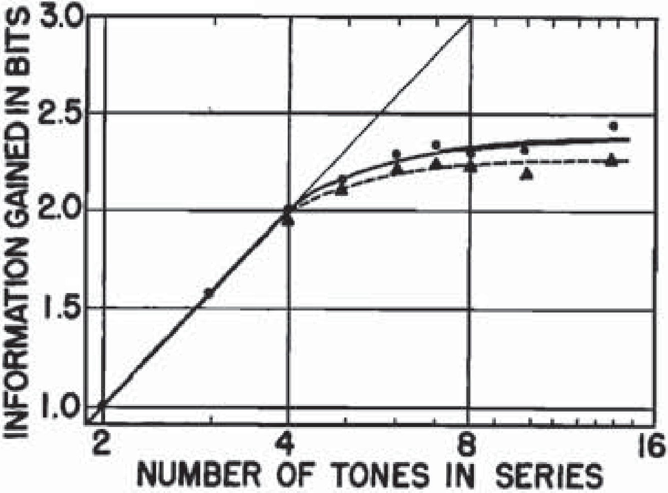
- Pollack finds that $I \approx \log n$ for $n \leq 4$, but remains nearly the same for all $n \geq 6$

Absolute Judgments of Frequency: Pollack (1952)



solid curve: averaging I for indiv. subjects; dashed curve: pooling

"Absolute Judgment" Experiments

- Similar results obtained for other stimulus attributes: loudness of tones, length of lines, areas of geometric figures, brightness of lights, intensity of electric current, etc.:
  - I does not increase with further increases in n, beyond a (low) upper bound
  - upper bound on I around 2-2.5 binary digits per stimulus presentation
- Literature reviewed in Miller (1956), Laming (2011)

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  - upper bound on I around 2-2.5 binary digits per stimulus presentation
- Literature reviewed in Miller (1956), Laming (2011)
- Suggests an alternative way of quantifying limit on capacity to make fine distinctions: upper bound on mutual information between true choice situation (attributes of available choices) and subjective representation of this situation

Limits on the Capacity to Discriminate (2)

- Sims (2003, 2011) theory of "rational inattention": DM has that partial information about the decision situation that is most valuable (allows the highest average payoff to be obtained), given the decision situation, subject to an upper bound on mutual information between the true state of the world and subjective representation

Limits on the Capacity to Discriminate (2)

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  - Sims often writes as if he has in mind a conscious decision to direct limited attentional resources in one direction rather than another, given an understanding of the available tradeoffs with regard to accuracy of one's choices

    — but one may equally well view the allocation of attention as reflecting an unconscious mechanism, that is simply efficient in an environment with certain statistical regularities, as a result of a process of adaptation

Rational Inattention

- Theory has been applied to:
  - modeling delays in the adjustment of firms' prices, payrolls, etc., to changing market conditions
  - delays in adjustment of households' spending to changes in income
  - differential speeds of adjustment to economic news of different types
  - explaining the finite elasticity of response of a supplier's sales to a price change, even when essentially identical goods are also available from other sellers
  - explaining co-movement of different asset prices

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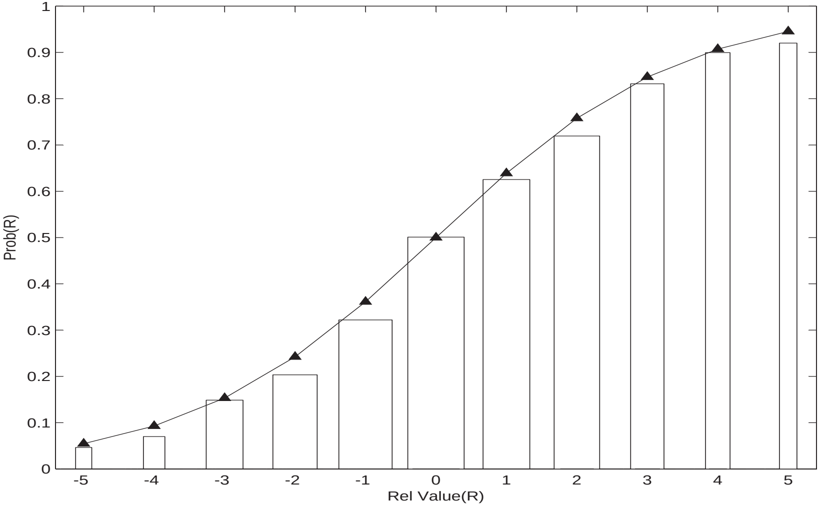
  - in fact, in binary-choice setting, predicts that "psychometric function" should be a logistic function of the value difference between the two options, as often found in experimental data (Woodford, 2008; Cheremukhin *et al.*, 2011; Matejka and McKay, 2013)

    — without needing to postulate special distribution function for utility variations, or exogenously specified errors

Choice Data of Krajbich *et al.* (2010)



fit of RI model with one free parameter

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  - form of restriction that is cognitively realistic, though not part of Sims theory in pure form

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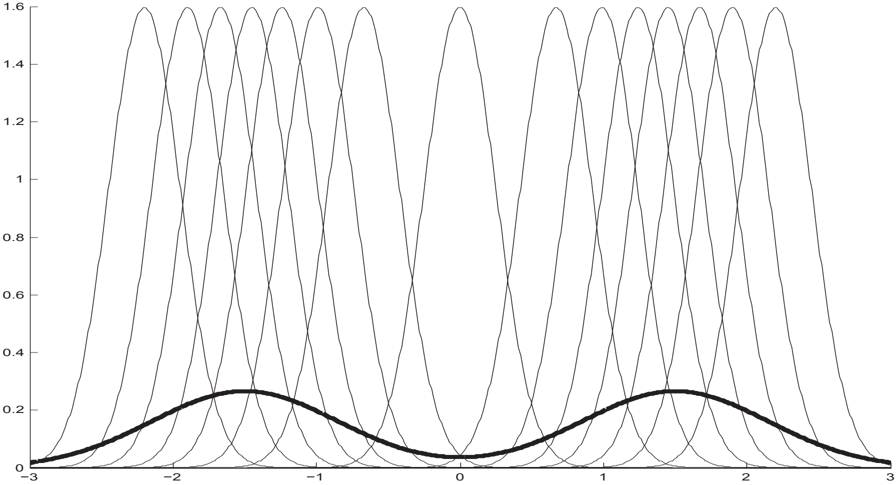
   - making additional distinctions only increases I in proportion to the frequency with which the distinctions **matter**

     — so trivial cost of making fine discriminations among very-low-probability states

Bound on Mutual Information?

2. In the case of a continuously-distributed true state, and task of minimum-MSE estimation of the state (or equivalent task), RI implies should have equal uncertainty about the state, whether a high-probability or low-probability state has occurred (Woodford, 2014)

Posterior Uncertainty With Rational Inattention



thick curve: prior; thin curves: posteriors

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- Instead, regions of cortex associated with sensory processing allocate more resources to discrimination among more frequently occurring stimuli, allowing finer discriminations in that case

Example: Discrimination of Orientation

- Well-established that humans (and animals) can make sharper discriminations between differing orientations that are near-vertical or near-horizontal, than between oblique orientations (“oblique effect”: Appelle, 1972)

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- Animal neurophysiology studies (e.g., of macaque V1) show this explained by allocation of greater processing resources to the former types of discriminations:

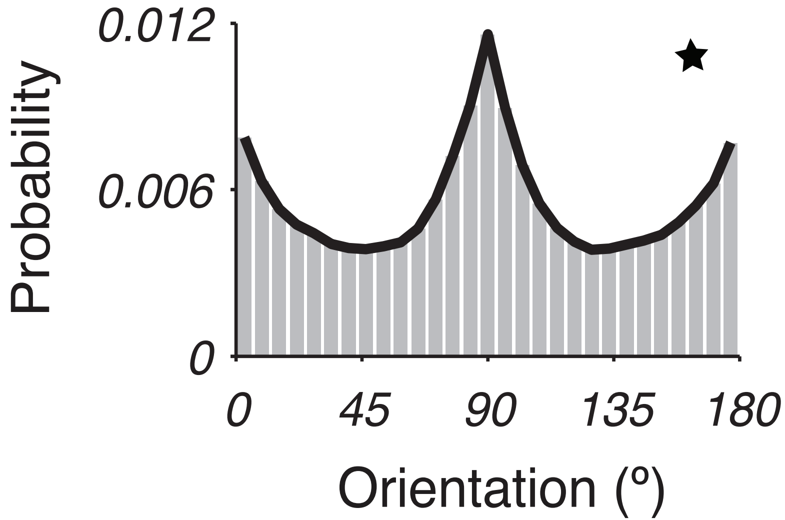
  - larger number of neurons with "preferred orientation" near vertical or horizontal than near oblique angles
  - narrower "tuning curves" for neurons with preferred orientations near vertical or horizontal

(Mansfield, 1974; Li *et al.*, 2003; Wang *et al.*, 2003)

Example: Discrimination of Orientation

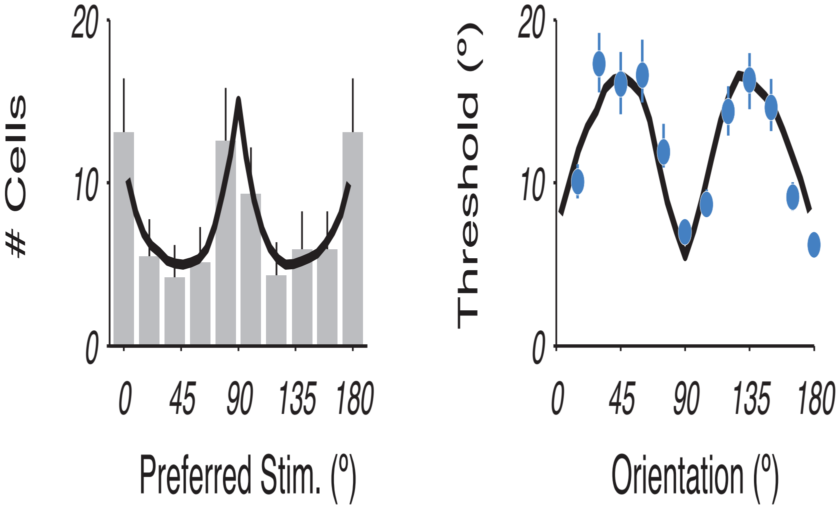
- This can be viewed as efficient given the fact that in both natural and man-made environments, horizontally and vertically oriented edges occur more frequently than oblique orientations (Ganguli, 2012)

Orientation Discrimination (Ganguli, 2012)



Frequency distribution of edges in scenes

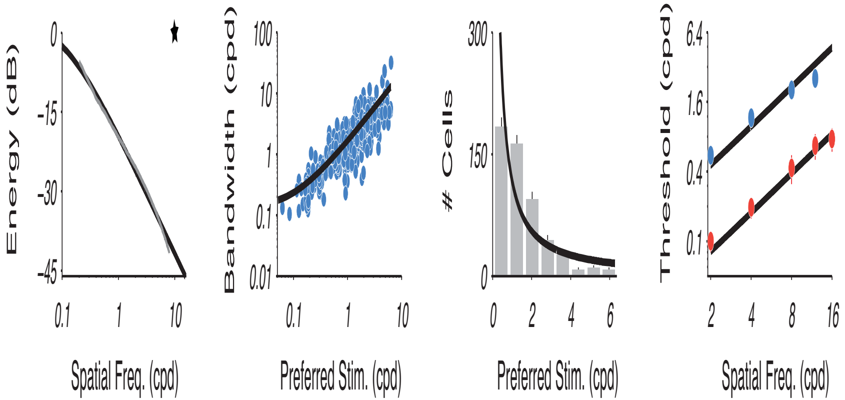
Orientation Discrimination (Ganguli, 2012)



Environmental frequency determines cell density,

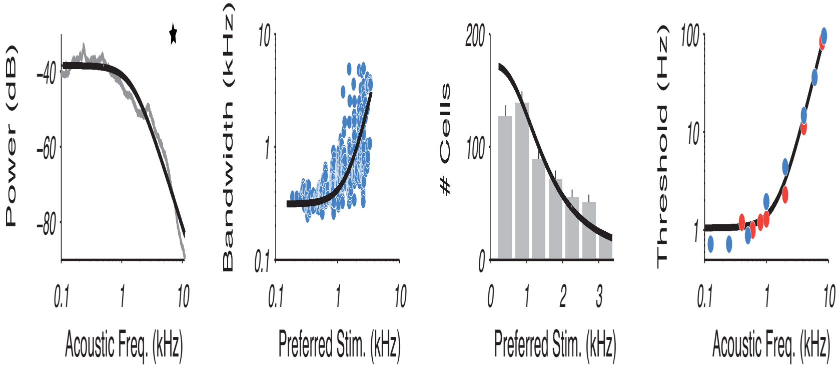
discrimination thresholds

Discriminating Spatial Frequency (Ganguli, 2012)



Environmental frequency determines tuning curve widths, cell density, discrimination thresholds

Discriminating Acoustic Frequency (Ganguli, 2012)



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Bound on Mutual Information?

- General pattern: more precise discriminations made over parts of the range of stimuli with greater probability density

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- Explanation seems to be: finer discriminations require more neurons devoted to that kind of processing (allowing narrower tuning curves and/or more averaging of the noise in individual neuron's response)

  — which has a biological cost independently of how often given stimuli will be encountered

Bound on Mutual Information?

3. If only cost of additional observations depends on the mutual info between observation and the true state (including past history of signals as part of that "state," as Sims does), then additional repetitions of same observation (independent repetitions of same "experiment") become progressively less costly, because less new information

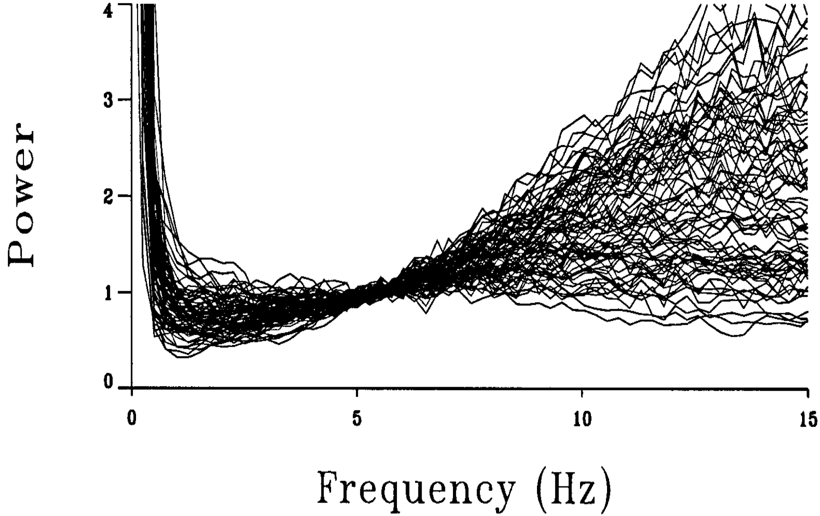
   $\Rightarrow$ redundancy of additional observations not a reason not to collect them; only count against limit on processing capacity to the extent that they do provide new information

Bound on Mutual Information?

- But neural coding often seems to be organized to minimize redundancy (Barlow, 1961, 1989; Atick, 1992)

  - principle used to explain structure of visual receptive fields in the retina, LGN, and primary visual cortex
  - also used to explain temporal processing in cat LGN cells (Dan, Atick and Reid, 1996)

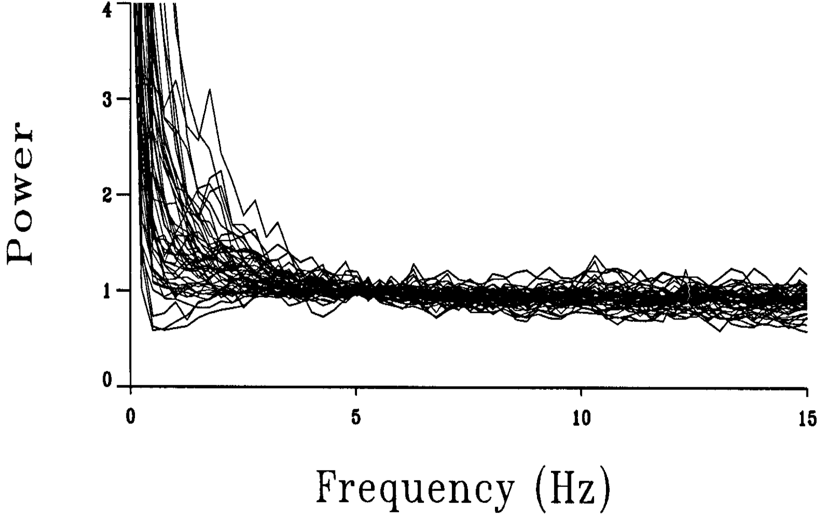
Temporal Processing in Cat LGN (Dan *et al.*)



Power spectrum of spike trains from 51 cells

Input: white noise

Temporal Processing in Cat LGN (Dan *et al.* 1996)



Power spectrum of spike trains from 51 cells

Input: *Casablanca*

Limits on the Capacity to Discriminate (3)

- In each case, the problem with the mutual information bound is its assumption that the capacity to make discriminations that are not frequently used should not be costly

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- Alternative proposal (Woodford, 2012): an upper bound on the quantity

$$C(p) \equiv \max_{\pi} I(\pi, p)$$

where p denotes the family of conditional probabilities $p(r|x)$ for each possible external state x, and $I(\pi, p)$ is the mutual information between X and R when external states occur with ex ante probabilities π

Bound on Required Channel Capacity

$$C(p) \equiv \max_{\pi} I(\pi, p)$$

- A criterion that depends only on the conditional probabilities p, not the frequency with which different states are encountered

  — bound is on the capacity to transmit information, whether it is effectively utilized in a given environment or not

  — Shannon's definition of "channel capacity"

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  — Shannon's definition of "channel capacity"

- In the case of a deterministic classification, $C = \log n$

  — depends only on the number of categories, regardless of how frequently used

Bound on Required Channel Capacity

- Can be thought of as measure of "effective number of categories" that can be distinguished

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  - finite bound on C consistent with data of Pollack *et al.:* $C \approx I$ in absolute judgment experiments, as long as uniform distribution is close to being the info-maximizing π

  - but bound on C **wouldn't** allow arbitrary number of precise categories simply because environmental frequencies are non-uniform

An Efficient Coding Hypothesis

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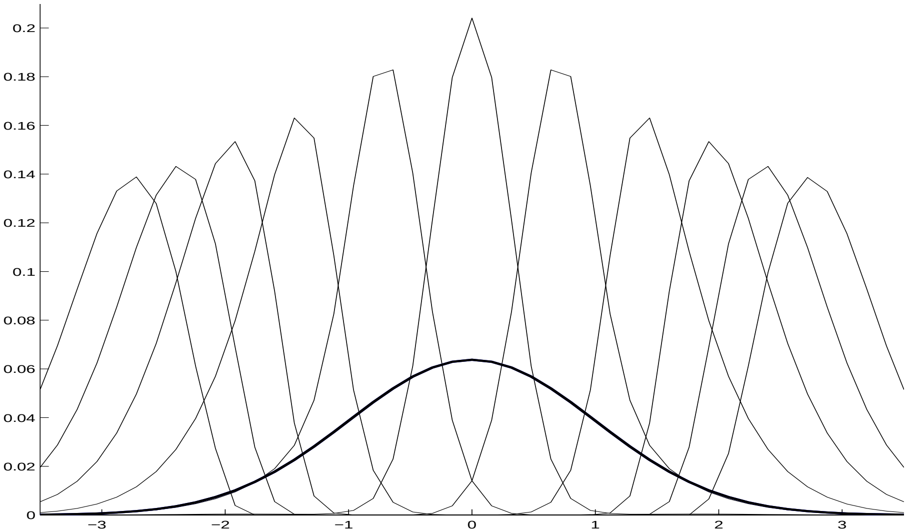
  — explanation for "focusing illusions," "tunnel vision," etc.

- But also implies, in case of a single continuously-distributed attribute, that representation should be less precise in case of states with smaller ex ante probability

Posterior Uncertainty With Efficient Coding



thick curve: prior; thin curves: posteriors

Efficient Coding and Biased Valuations

- This non-uniform allocation of capacity to discriminate over the range of variation in a single attribute can lead to biases in choice

  — even supposing that the information contained in the subjective representation of the choice situation is used optimally

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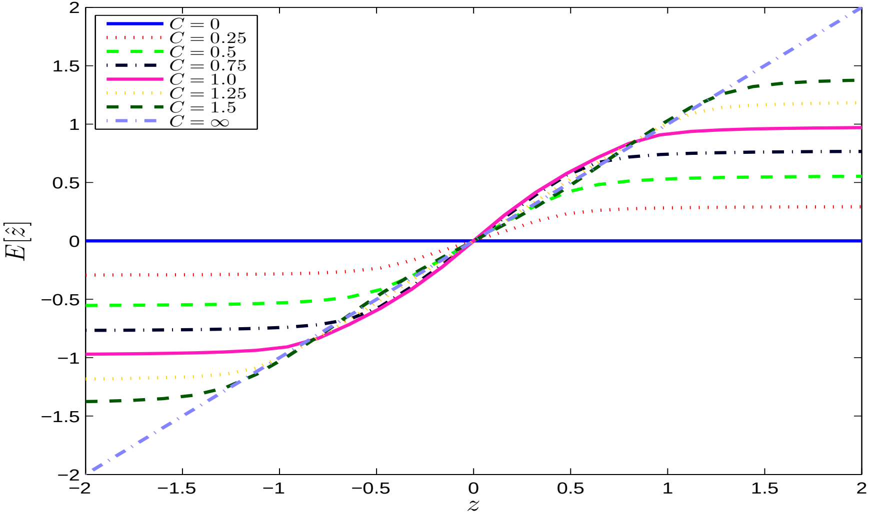
  - example: Gaussian prior for a real variable x, goal is minimization of MSE of estimate of x
  - for given bound on C, the efficient coding is independent of prior mean and variance:

    — coding a function of **normalized** state $z \equiv (x - \mu)/\sigma$, minimum-MSE estimate of z also independent of μ and σ

Mean Estimated Value vs. True Value

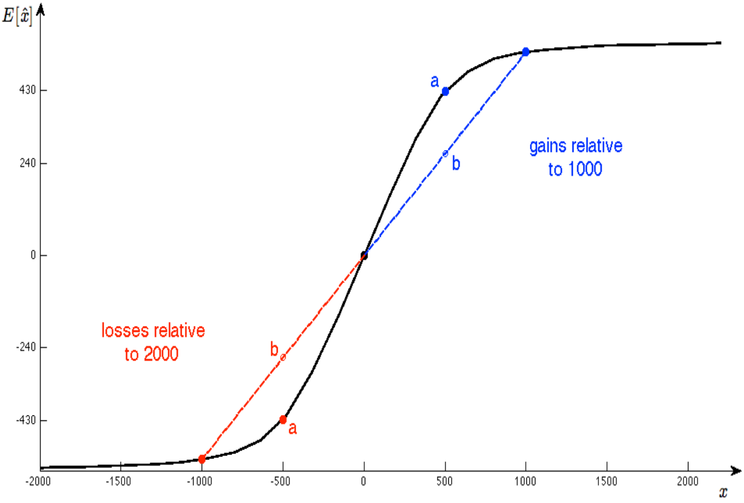


case of Gaussian distribution of true values

Efficient Coding and Biased Valuations

- This "S-shaped" relationship provides a possible explanation for the form of the "value function" postulated by prospect theory (Kahneman and Tversky, 1979)
    - can simultaneously explain risk-averse choices in the domain of gains, and risk-seeking choices in the domain of losses

Mean Subjective Valuations of Lotteries



certain gain preferred on average, but risky losses preferred as well

Efficient Coding and Biased Valuations

- Viewing the phenomenon as resulting from finite-precision coding, rather than an arbitrary fact about how different things are valued, not only provides a functional explanation, but also implies that it should be present to a greater or lesser extent depending on degree of scarcity of processing capacity

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- DeMartino *et al.* (2006): significant correlation between decreased asymmetry between gain and loss domains and higher activity in rOFC and vmPFC

    - growing body of fMRI evidence suggests that subjective values of options are represented in vmPFC (e.g., Bartra, McGuire and Kable, 2013; Rangel and Clithero, 2014; Platt and Plassmann, 2014)

Efficient Coding and Biased Valuations

- Porcelli and Delgado (2009): acute stress results in increased asymmetry between gain and loss domains
    - AlAbsi *et al.* (2002) find stronger cortisol reaction to stress associated with improved performance on sensory perception task, but reduced ability to do mental arithmetic; suggest stress reaction reduces **capacity allocated to working memory**

Efficient Coding and Biased Valuations

- These studies interpret their results in terms of a "dual systems" view
  - OMPFC involved in allowing "rational" processes to override "emotional" reactions
  - stress results in activation of "automatic" process rather than more deliberate, rational one

Efficient Coding and Biased Valuations

- These studies interpret their results in terms of a "dual systems" view
  - OMPFC involved in allowing "rational" processes to override "emotional" reactions
  - stress results in activation of "automatic" process rather than more deliberate, rational one
- But one might instead suppose that a single process is always used, simply with more or less precise coding, depending on available processing capacity

Conclusions

- There are advantages to thinking of many choice phenomena as resulting from decisions based on imprecise subjective coding of features of the choice situation

- It may be possible to understand the form of such representations using similar principles to those that explain aspects of perceptual coding in sensory domains

  — in particular, efficient allocation of scarce perceptual capacity

Conclusions

- There are advantages to thinking of many choice phenomena as resulting from decisions based on imprecise subjective coding of features of the choice situation

- It may be possible to understand the form of such representations using similar principles to those that explain aspects of perceptual coding in sensory domains

  — in particular, efficient allocation of scarce perceptual capacity

- This is one of the more obvious areas in which findings from neuroscience can guide theory development in economics

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