Models of Perceptual Decision Making

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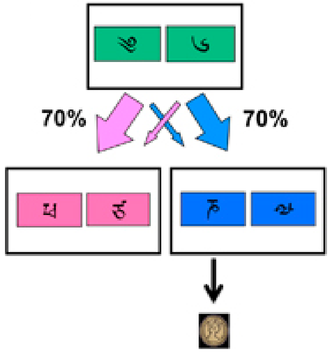
What are perceptual decisions?

In perceptual decision making, the subject's task is to resolve uncertainty about the nature of the stimulus.

Value-based decisions

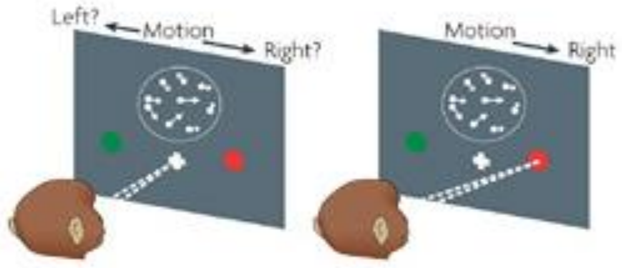
Glimcher, Daw, Niv, Gershman, Dayan, etc…



I know what's out there, but **I don't know what I should do** to achieve my goals

(focus has been on learning about value from past experience, exploration/exploitation, model making, etc)

Perceptual decisions



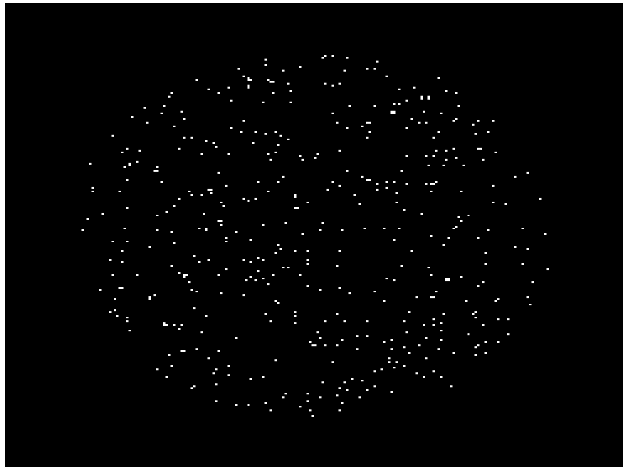
I'm not sure what's out there, but if I knew, I'd know what to do to achieve my goals

(focus has been on statistical inference, how beliefs are shaped and updated by evidence, etc)

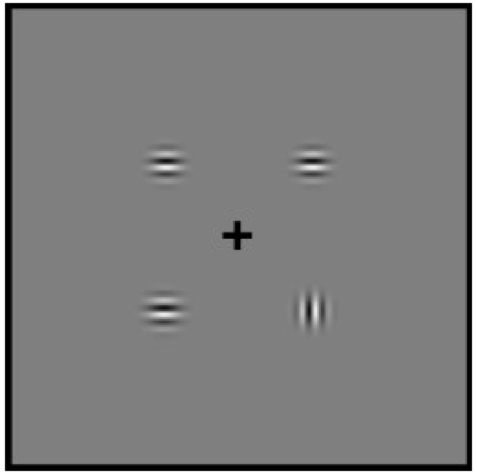
Newsome, Movshon, Shadlen, Romo, Mainen, Brody, Zador, etc….

What are perceptual decisions?

Are the dots moving left or right?



Does the display contain a target (vertical Gabor)?



Tasks used in Perceptual DM

Detection

Relevant question: Is something out there? Did something change?

Discrimination

Relevant question: That thing out there, which of several known categories does it belong to?

Estimation

Relevant question: Can you produce a reliable, analog, one-to-one map between your motor system and a (continuous) sensory stimulus?

Overview

Static model:

Signal Detection Theory (briefly)

Dynamic modelling:

Sequential Sampling Models

Diffusion decision model (DDM) and its ingredients

DDM Variants and Extensions

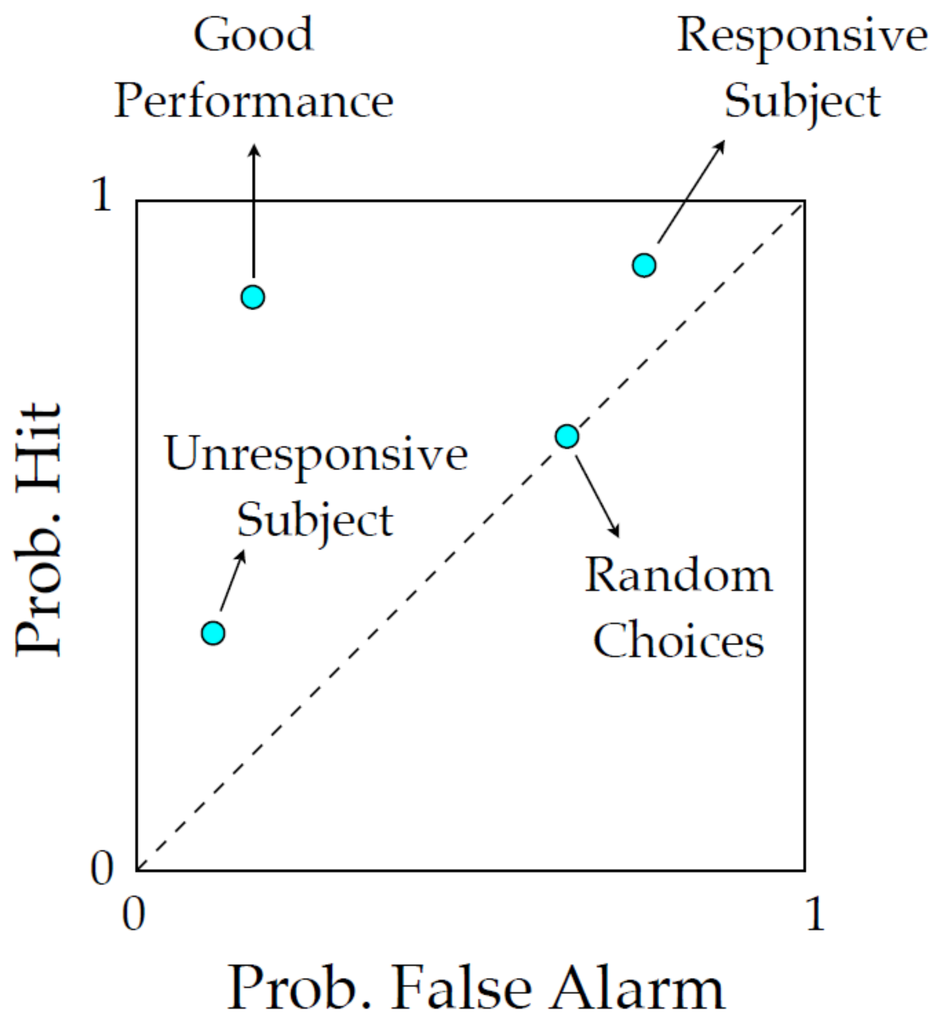
Sensory Detection

Consider an experiment in which every trial can be
no stimulus (noise) or stimulus, and subjects need to detect

Response	Signal	Noise
"Yes"	Hit	False alarm
"No"	Miss	Correct rejection
Total	*100%*	*100%*

Because columns sum to 100%, only 2 independent numbers
The convention is to use hits (H) and false alarms (FA)

Behaviour in H/FA Plane



Signal Detection Theory (SDT)

Gauss’ (1809) theory:a measurement based on an aggregation of elements, each independently subject to error, will be normally distributed.

Fechner (1860) found found there was trial-to-trial variability in whether pairs of similar stimuli were judged to be the same or different and attributed this to aggregated measurement errors of this kind.

Psychological Review
Vol 61, No 6, 1954

A DECISION–MAKING THEORY OF VISUAL DETECTION [1]

WILSON P. TANNER, JR. AND JOHN A. SWETS
University of Michigan

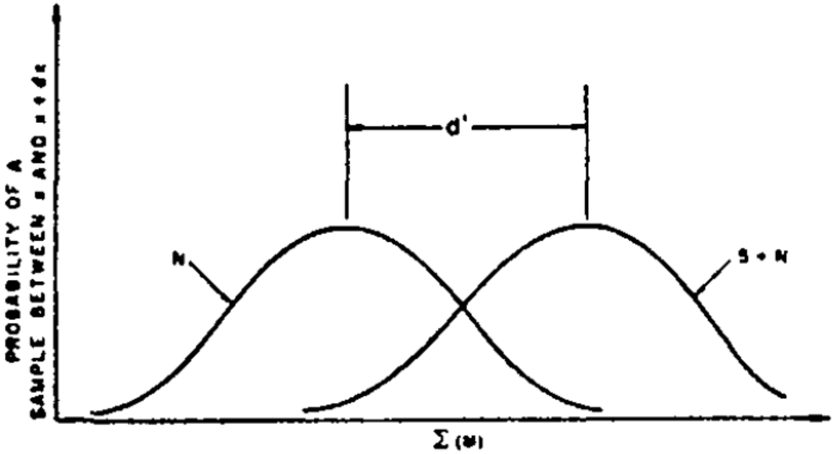
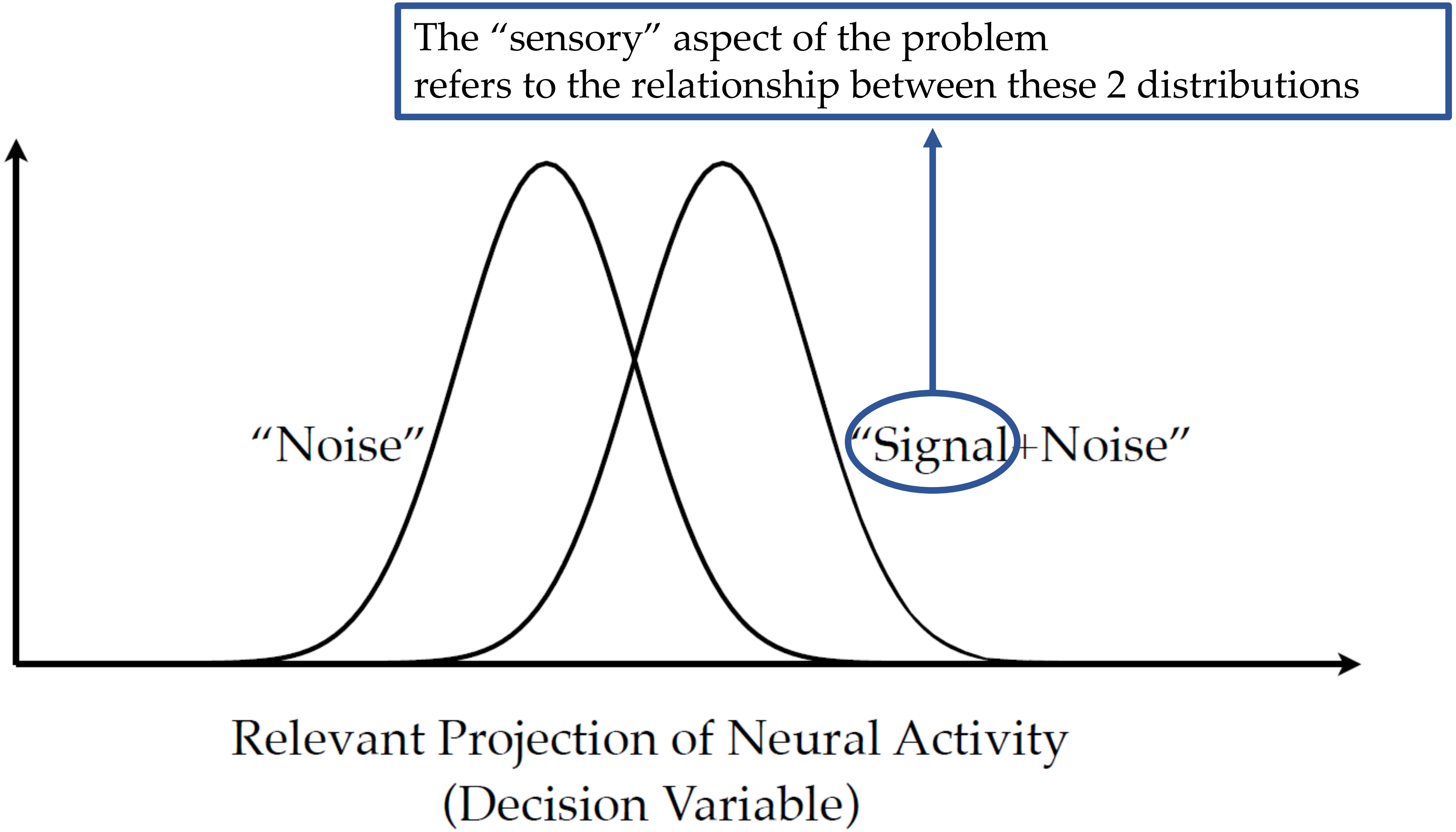


FIG. 3. Hypothetical distributions of noise and signal plus noise

Perceptual decision processes depend on extracting information from noisy sensory signals in the brain; therefore they are stochastic: The idea that cognitive representations are normally distributed then carried over to Signal Detection Theory.

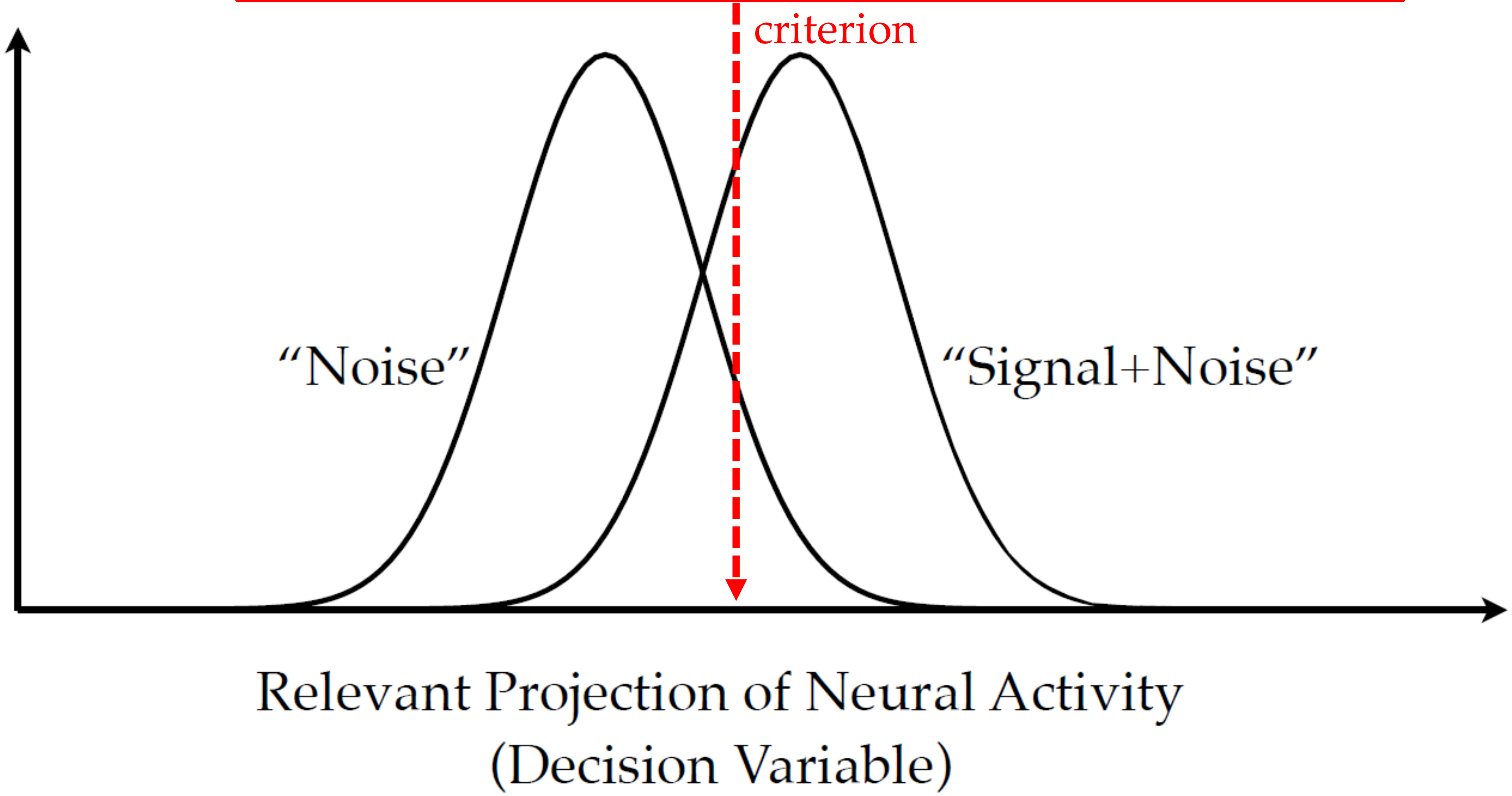
Signal Detection Theory (SDT)



Signal Detection Theory (SDT)

Standard assumption in SDT (in practice):
Gaussian noise with same variance for N and S+N

The “decision” aspect of the problem has to do with the mapping between the ‘decision variable’ and actions



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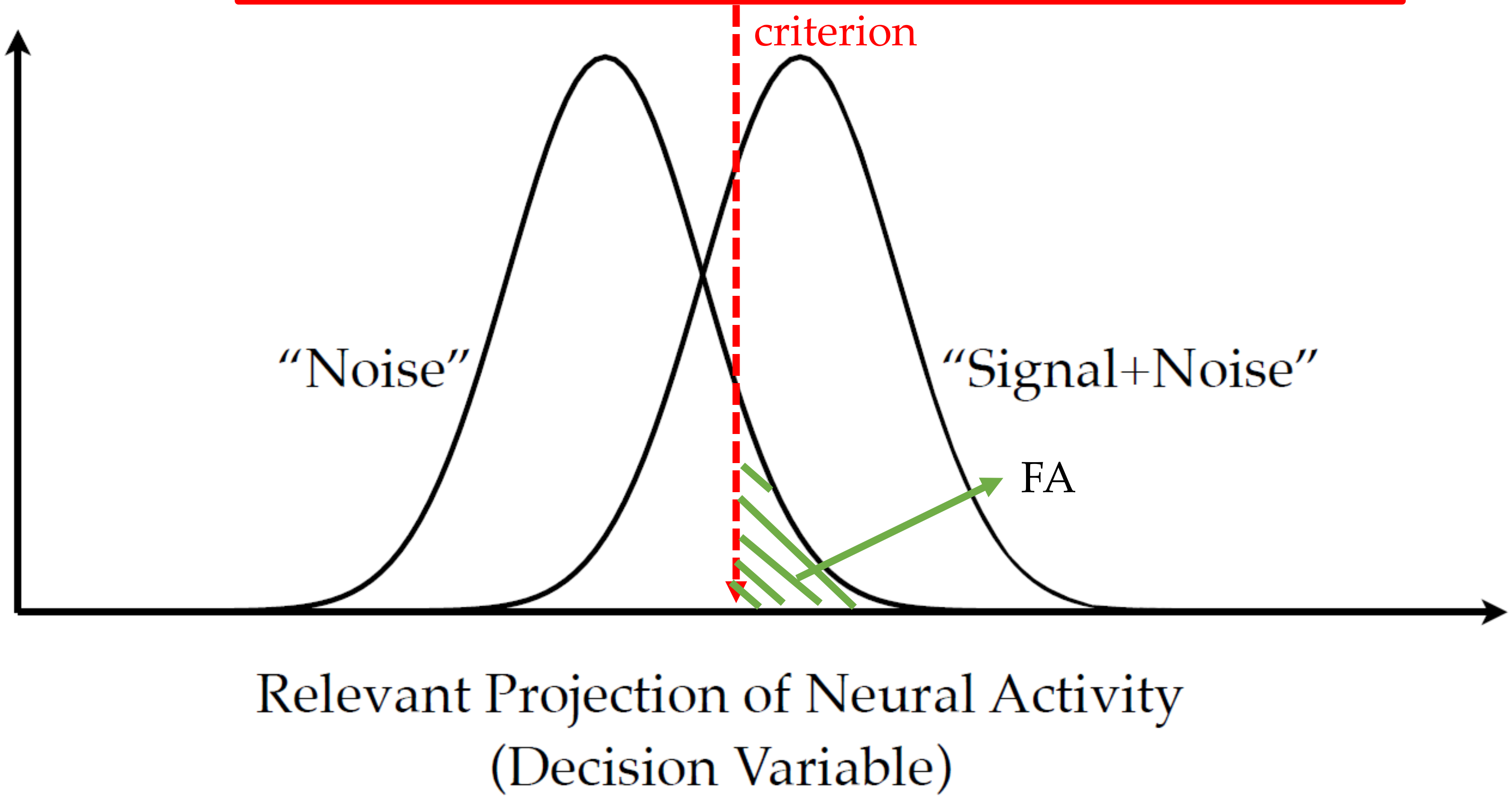

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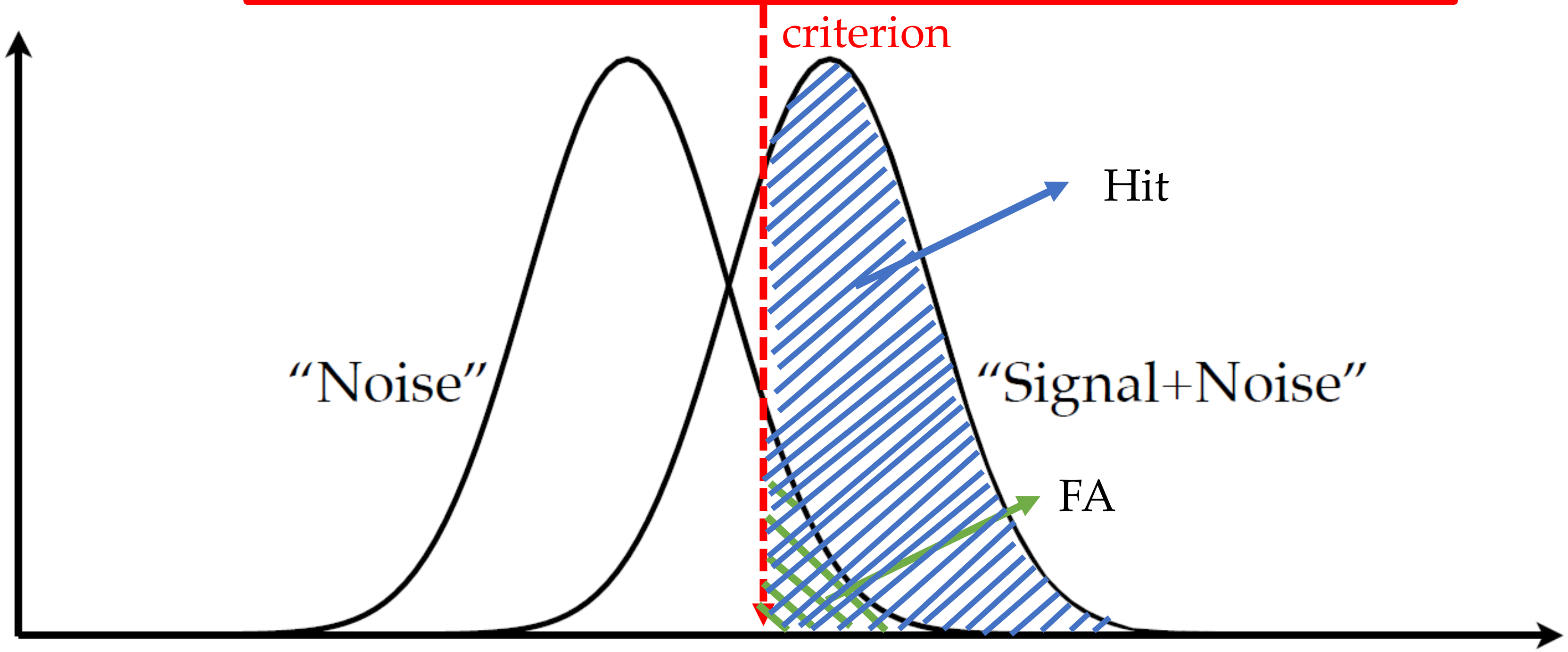
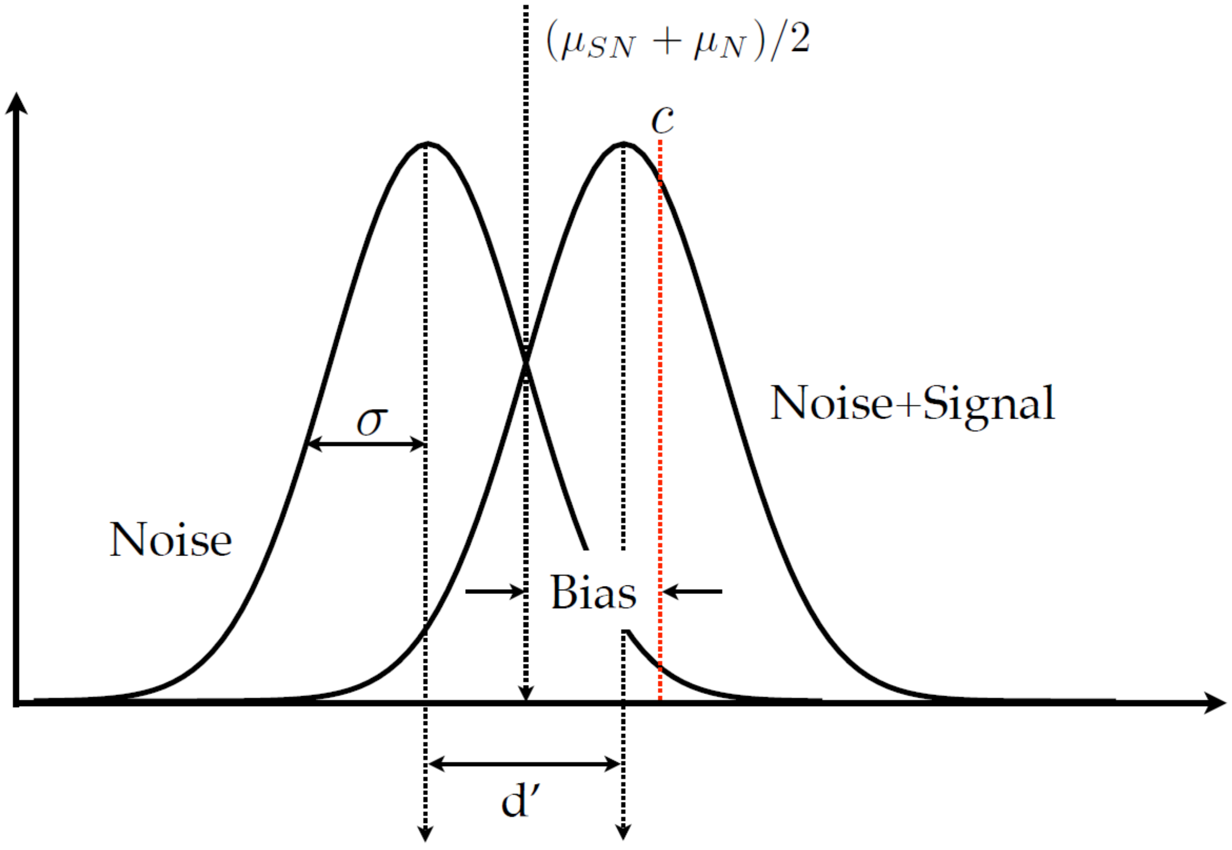


Relevant Projection of Neural Activity
(Decision Variable)

Parameters in SDT: d′ and Bias



$d' = \frac{\mu_{SN} - \mu_N}{\sigma}$ is supposed to represent the true measure of discriminability for a given stimulus strength. It is independent of the subject's strategies

The criterion *c* (bias) sets the response tendencies of the subject and can vary depending on various factors such as prior probability of stimulus occurrence, pay-offs, etc…

Discrimination tasks can be represented in the exact same way (differential task-relevant axis)

Signal Detection Theory: ROC curve

Prior manipulation

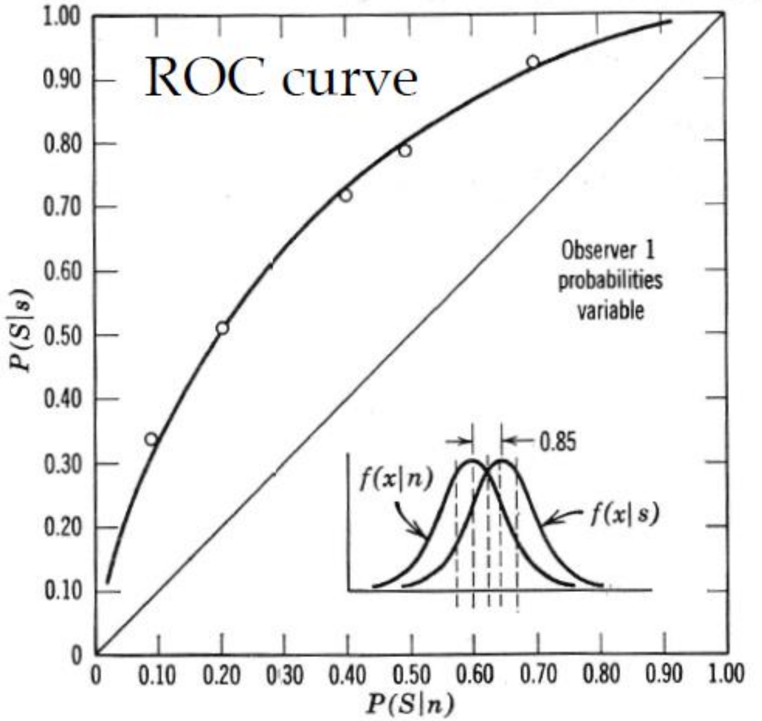
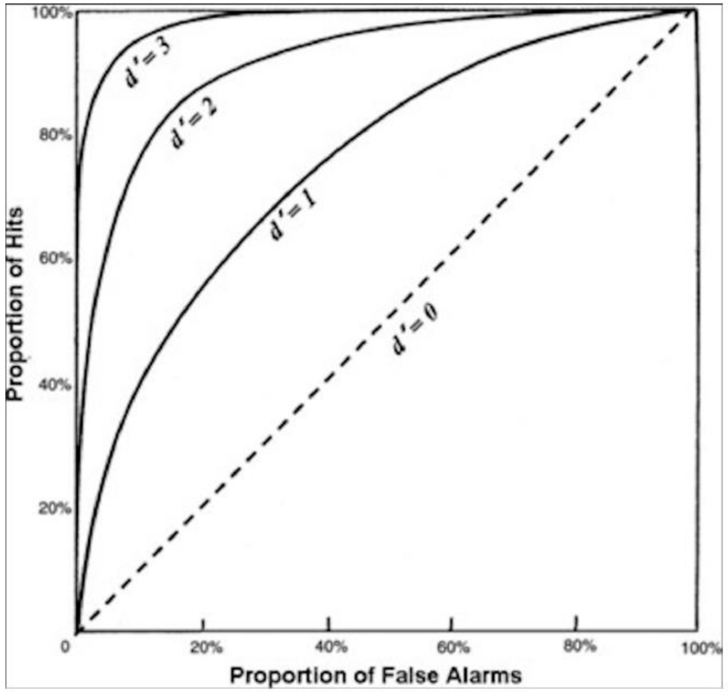


FIG. 4-1 An empirical ROC graph and a theoretical curve based on normal distributions of equal variance. The data points were obtained by varying the a priori probability of signal occurrence. Each point is based on 600 trials. The vertical dashed lines in the insert at lower right represent the decision criteria corresponding to the data points. The data were obtained in an auditory experiment. (Data from Tanner, Swets, and Green, 1956.)



The area under the ROC curve (AUC) provides a normalized (criterion independent) measure of sensitivity

Signal Detection Theory (SDT)

Signal Detection Theory represents a coherent description of the separation between ‘sensory-related’ and ‘response-related’ aspects of the task.

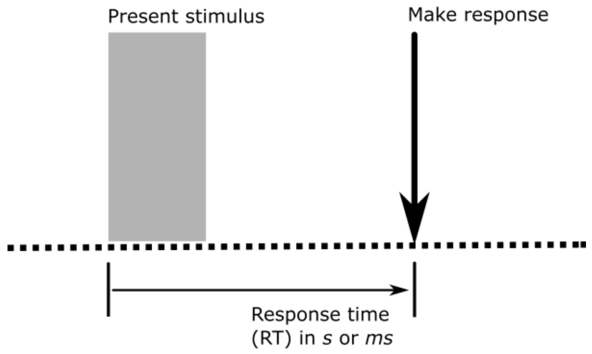
But what about the time taken to make a decision?

Swets et al, (1959) found that in an auditory detection task, d’ increased in proportion to the square root of the number of stimulus observation intervals…. Exactly as predicted by elementary sampling theory if the decision is based on independent noisy representations of the stimulus

This indicates efficient perceptual integration over time. However, SDT has no mechanism to describe the time taken to make a decision

Sequential Sampling Analysis

Decisions, like everything else, unfold with particular time courses



- The timing of decisions is a very valuable 'diagnostic' observable. We can learn about *how* decisions are made by caring about when they are made.

- Some RT tasks designed to be error free (e.g. <5%); In others RT and accuracy covary, need a model of the process that can produce both RT and accuracy

Sequential sampling theories describe situations where stimuli arrive 'in time' (i.e., sensory streams), and where agents decide both When and What to respond.

Response Times

• First studies of response times in the mid 1800s (Donders, Wundt, Helmholtz)

• Much slower than we would expect based on sensorimotor transmission delays in the brain and to transmit nervous impulse to muscle

• Probabilistic: Repeated presentation of the same stimulus leads to different RTs from one trial to the next

‘no matter how careful the observers they could differ in reporting a given event by up to half a second’ (Robinson, 2001)

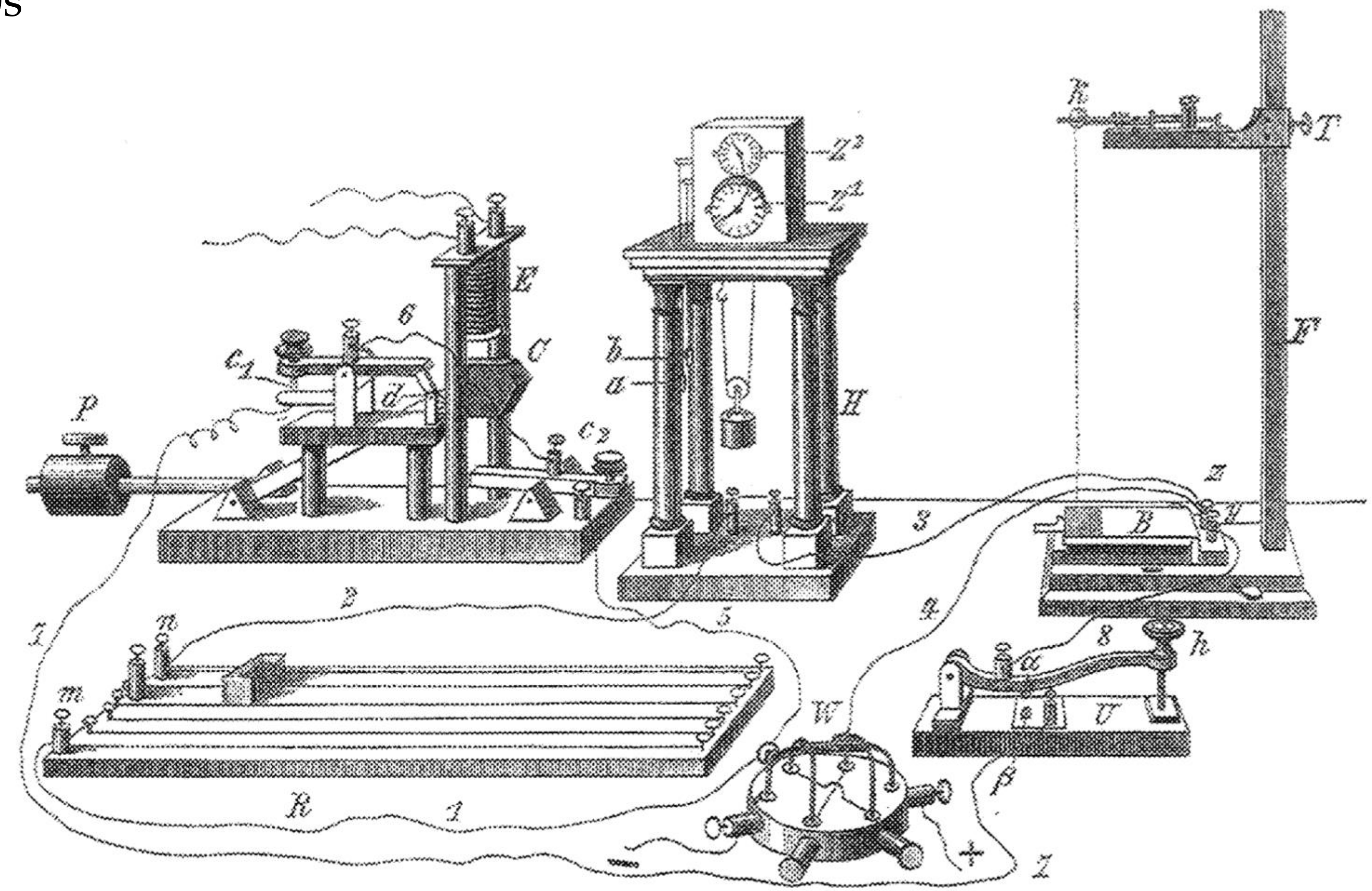
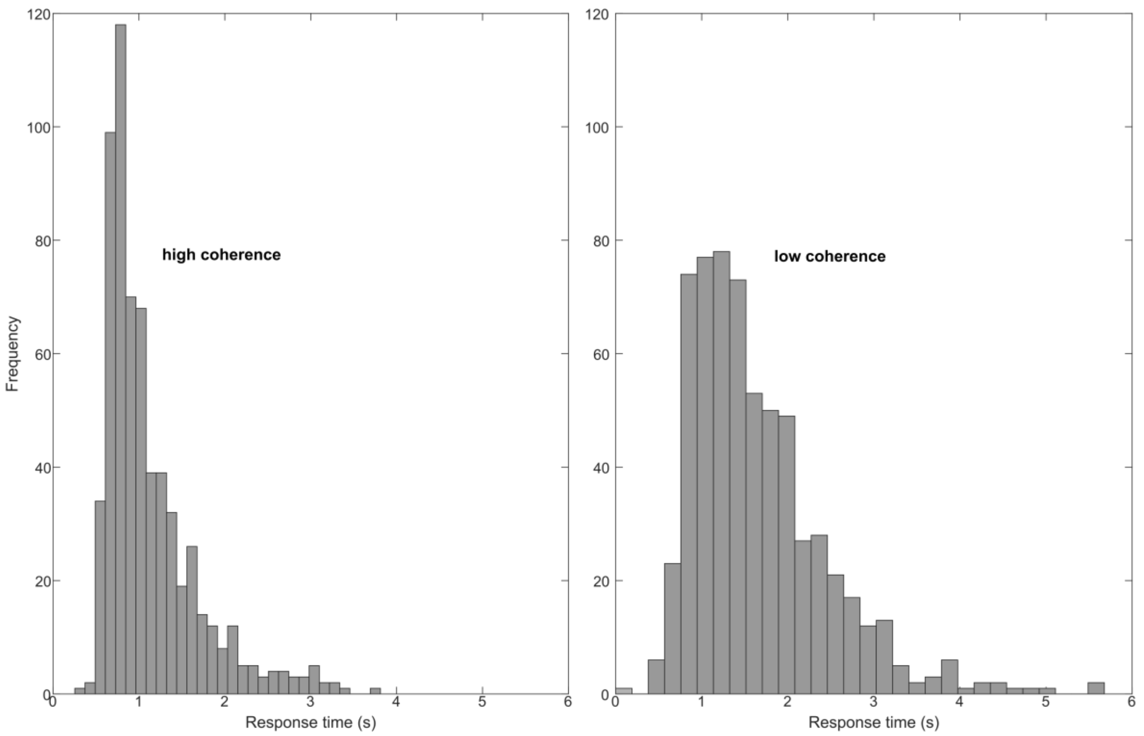


Figure 2. A typical reaction-time set-up in the Leipzing Institute, with auditory stimulus *F*, Pohl’s see-saw switch (*Wippe*) *W*, *Kontrollhammer C*, Hipp chronoscope *H*, rheostat *R*, and response key *U*. (Wundt, 1902–1903, Vol. 3, p. 388)

Response Times

- RT distributions unimodal, positively skewed
- Vary with task difficulty, instructions, context
- Rich history in experimental psychology of using the timing of action to infer the computations and mechanistic basis of certain cognitive processes



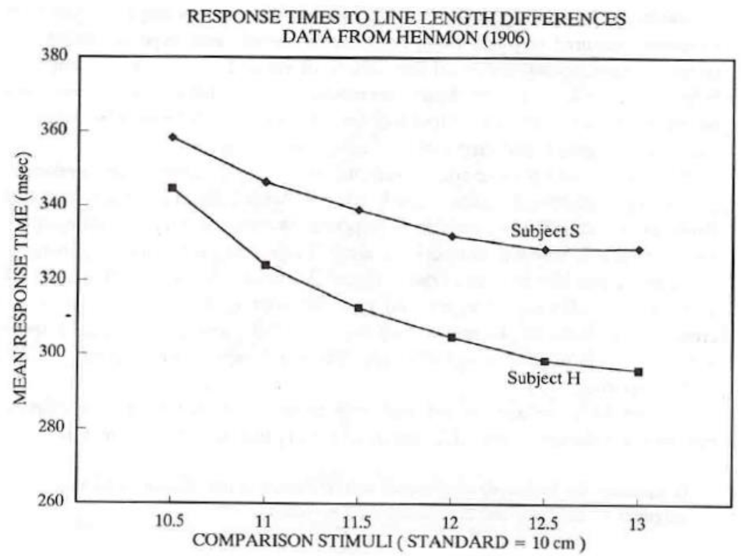
Encode Sensory Information → **Stimulus Identification (decision process)** → **Plan & Execute Action**

Stage Models of Response Time (Donders 1869, Sternberg 1969)

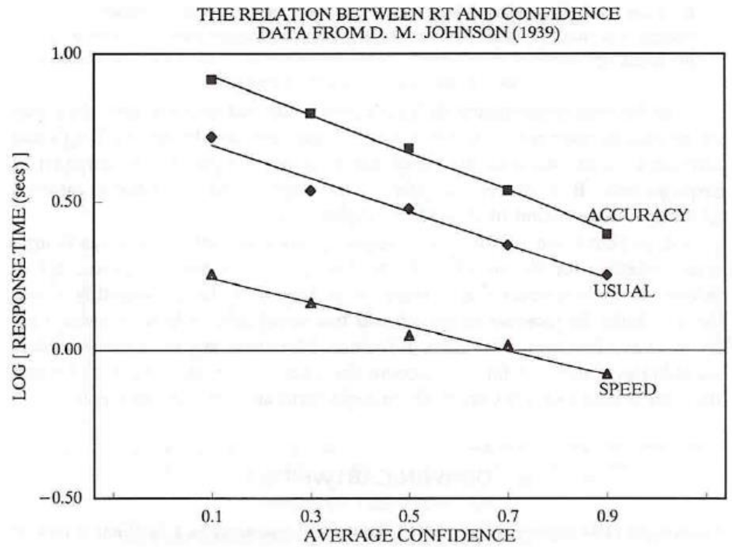
Speed Accuracy Trade-off

1) RT covaries with Accuracy as difficulty is changed, and RT keeps changing when accuracy has saturated.

2) When either RT or Accuracy are **strategically emphasized**, their average across conditions negatively covaries



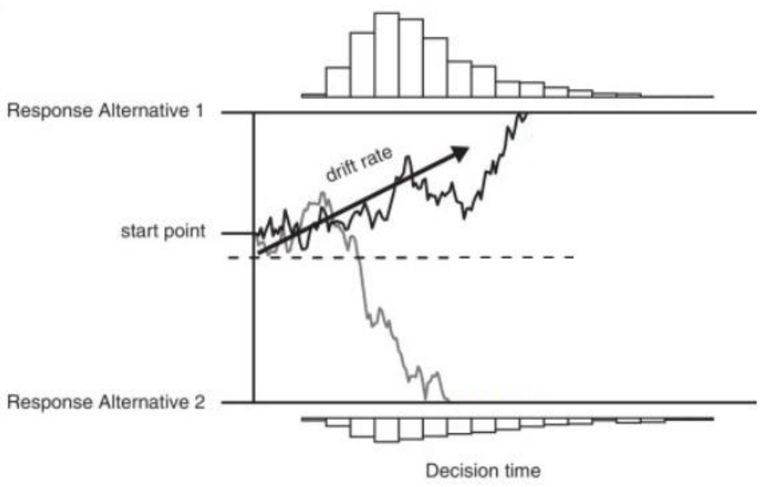
Henmon, 1911

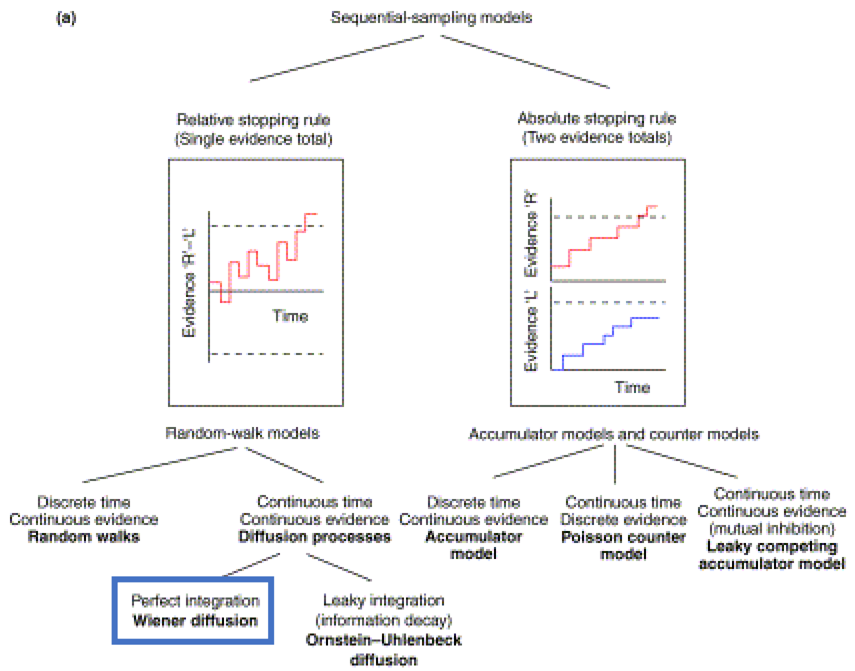


Johnson, 1939

The trade-off between speed and accuracy is the fundamental lawful relationship in sequential sampling. **How does it come about?**

Sequential sampling models for two-choice decisions





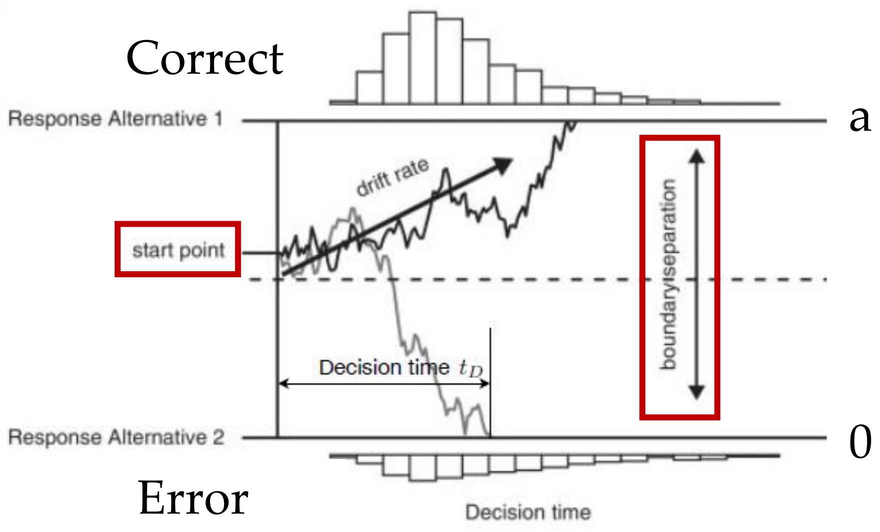
Smith & Ratcliff, 2004

- SSMs posit that the brain makes decisions by sampling noisy evidence over time, up to a threshold.

- Multiple model variants, e.g. relative vs absolute evidence accumulation

- Diffusion decision model (DDM) is the most popular, introduced by Roger Ratcliff (1978)

Diffusion decision model (DDM)



Accumulation of stochastic, temporally uncorrelated sensory evidence:

$$dX_t = \mu dt + \sigma dW_t$$

'decision variable'

Evidence accumulation

Zero-mean Gaussian noise with variance $\sigma^2 dt$ (diffusion)

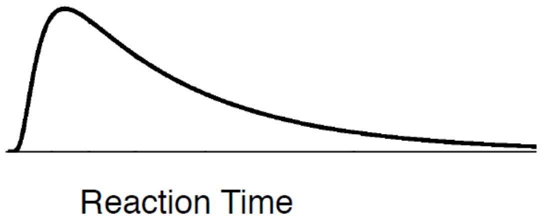
Simple Diffusion Model Parameters

- μ: Drift rate (strength of evidence)
- σ : Noise infinitesimal standard deviation (square root of diffusion coefficient). Often set to 1 or 0.1 by convention (scaling parameter).
- a : boundary separation
- z : start point (= a/2 for an unbiased decision)
- T_{er} : non-decision time

$$RT = t_D + t_{ND}$$

'non-decision time' sensory encoding and motor delays

DDM Predictions



For each set of parameters (i.e. for each experimental condition), we obtain a choice probability P(Correct) and two predicted RT distributions: correct and error responses. Standard diffusion model has an analytic solution

These can be then compared to the observed experimental data, with the goal of finding the best parameter set to explain the data (Model fitting).

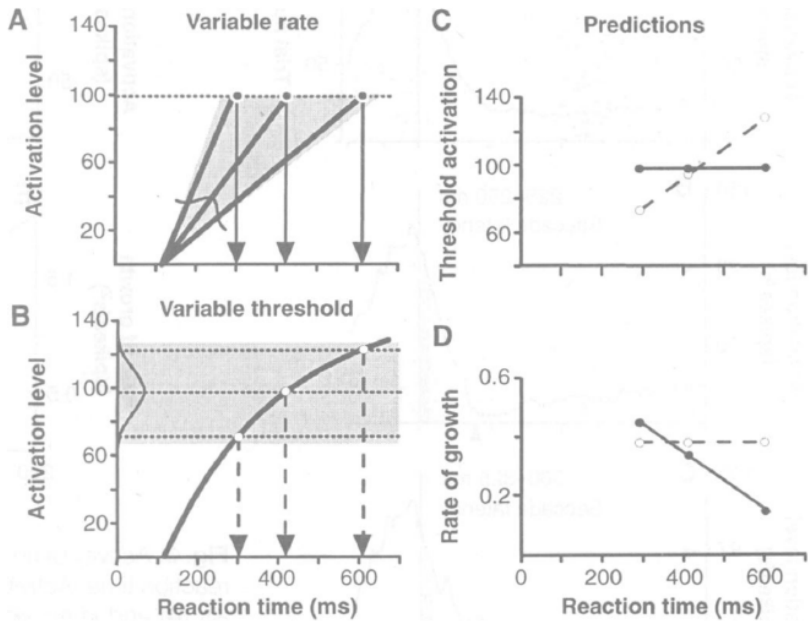
For reliable parameter estimation, we need to have multiple experimental conditions (e.g. discriminability levels), and a sufficient number of trials to capture the RT distribution shape.

Often, it is the goal of an experimenter to design manipulations that only change a single parameter--- ‘selective influence’, then all other parameters can be held constant across conditions. In practice, this isn't always realistic

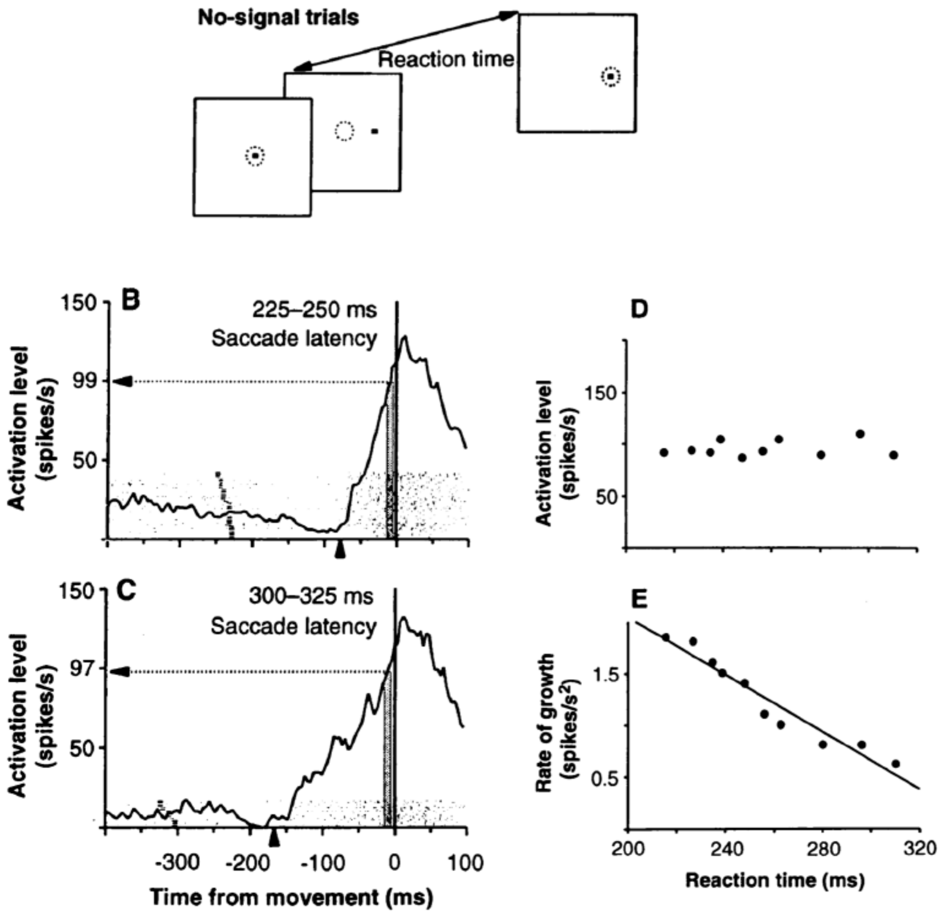
Empirical Basis of main tenets of DDM?

Single trial RT : Evidence for Decision Bound?

Hanes & Schall, 1996

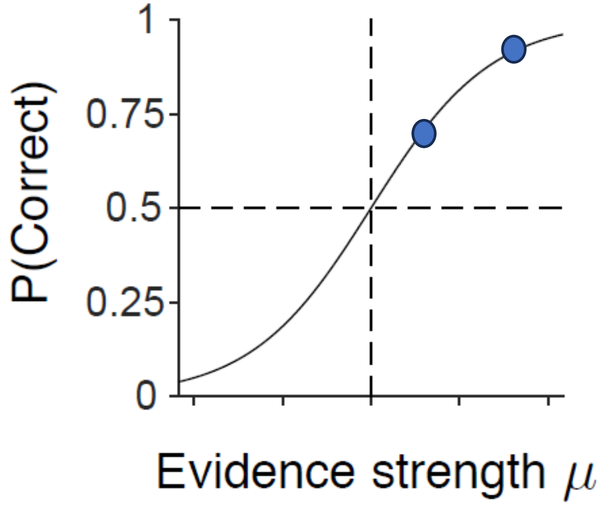


Primate; FEF (also, SC)



DDM Ingredients: Changing the strength of evidence

$$P(correct) = \frac{1}{1+exp(-2a\mu/\sigma^2)}$$



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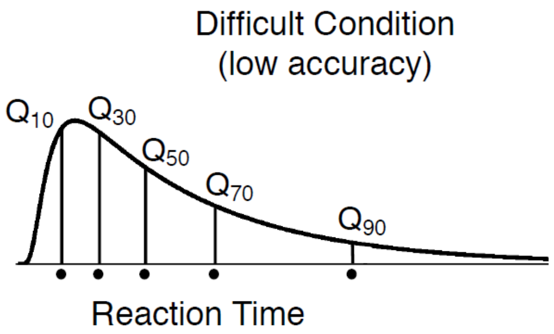

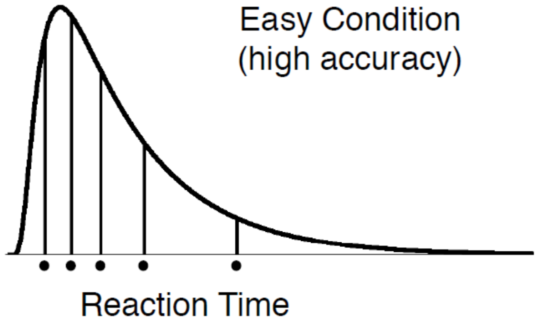

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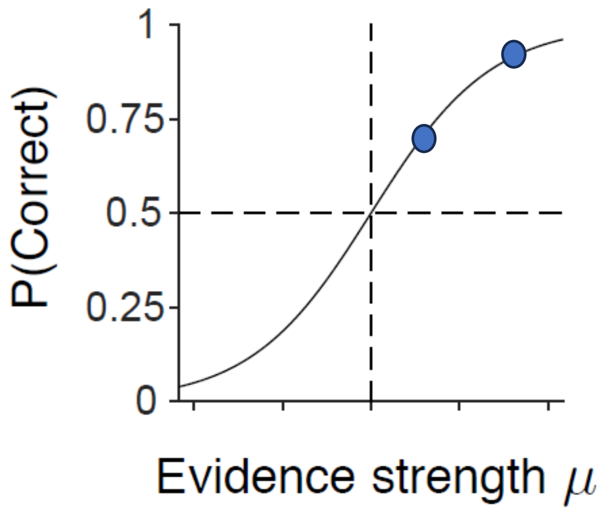

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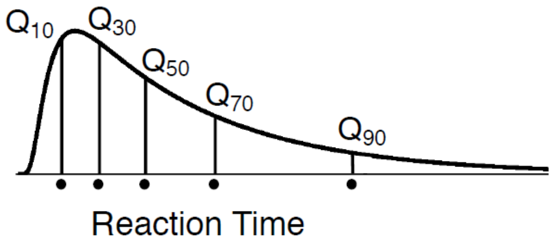

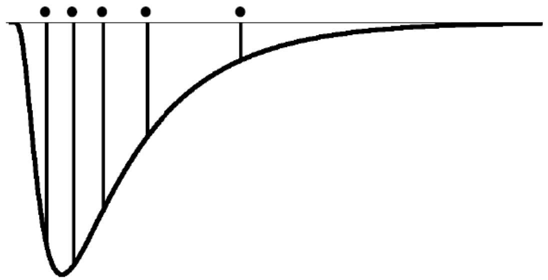

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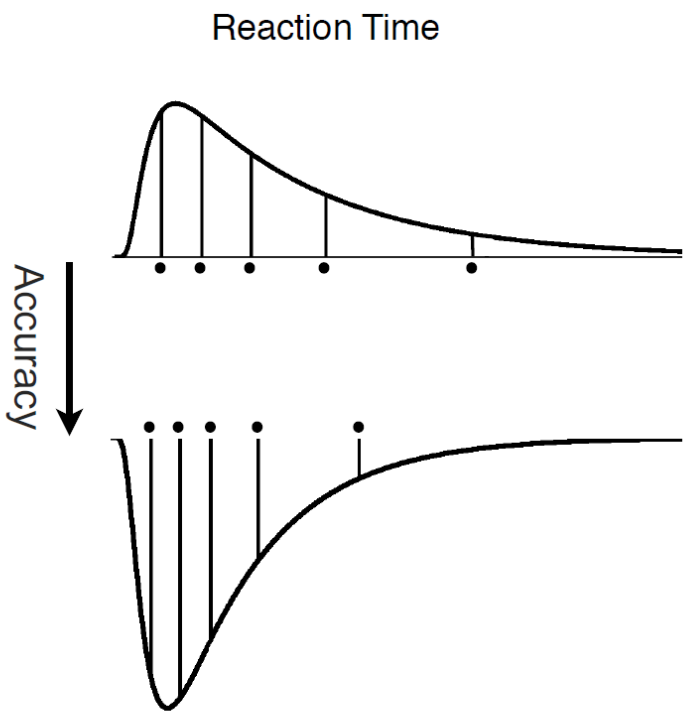

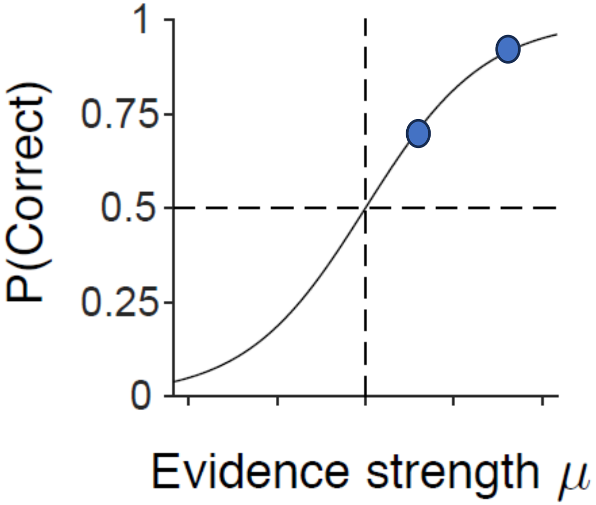

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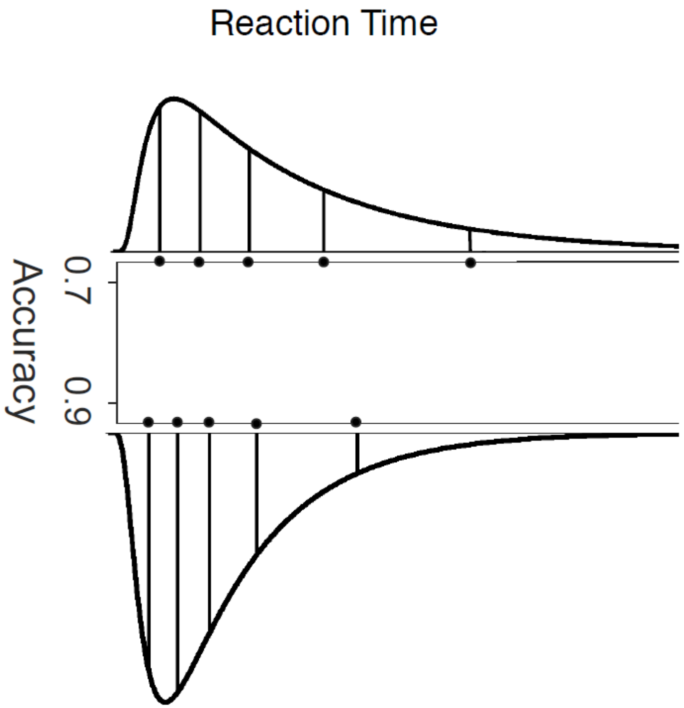

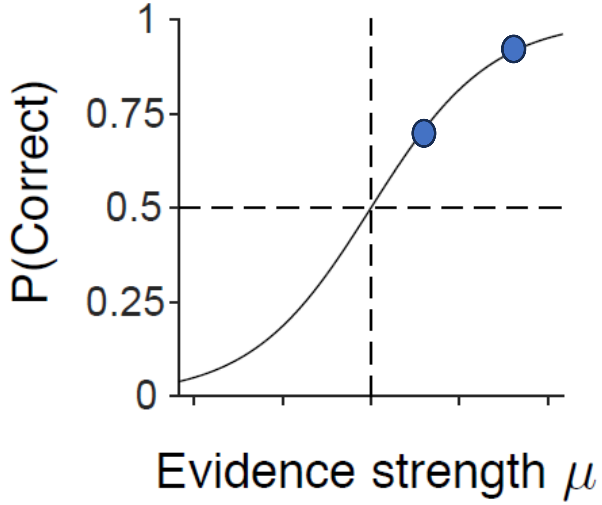

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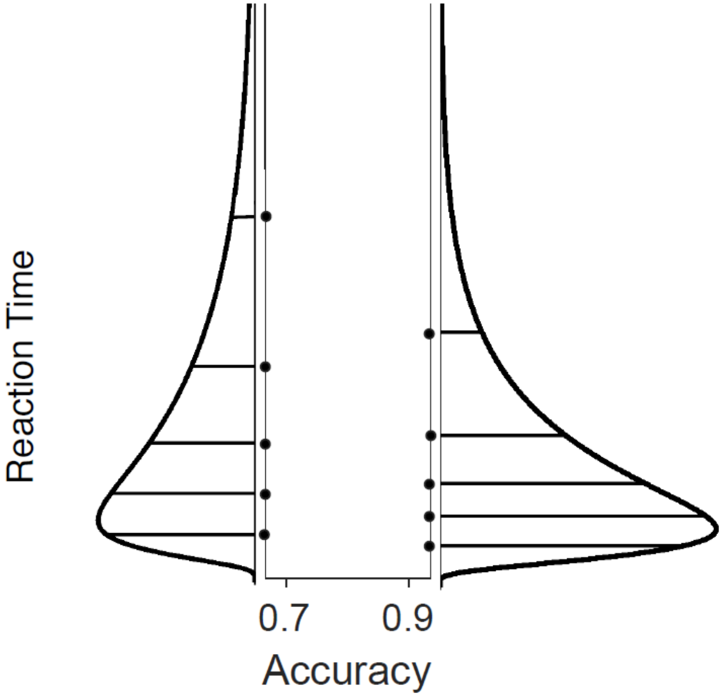

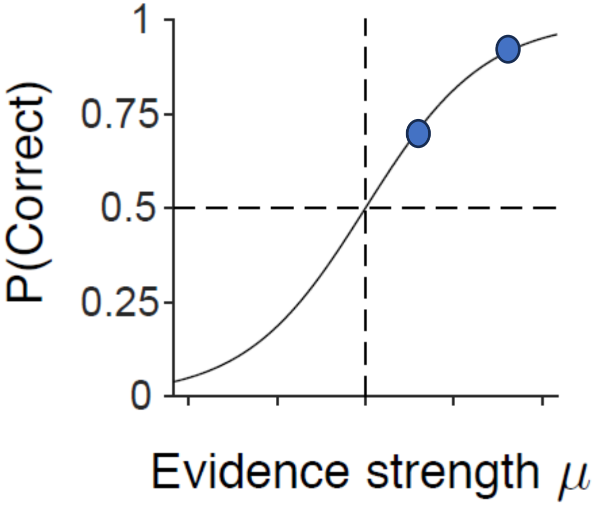

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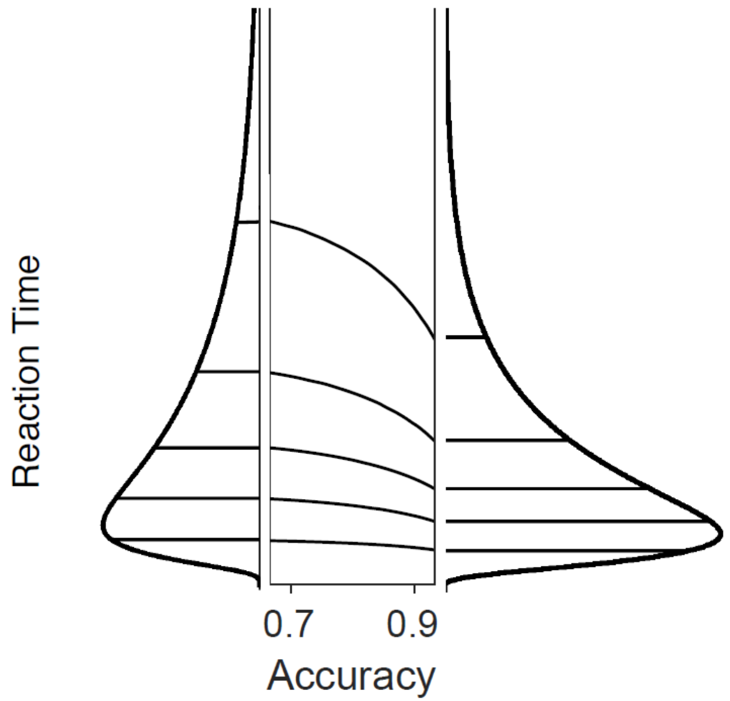

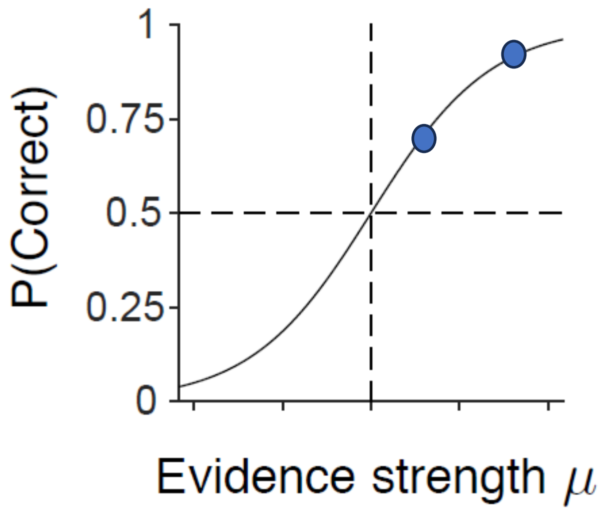

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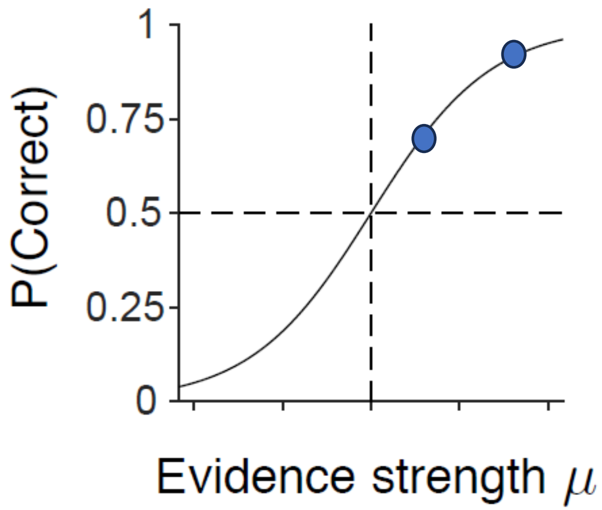

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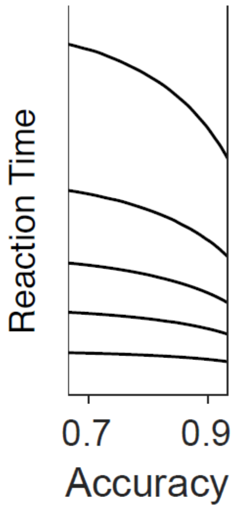

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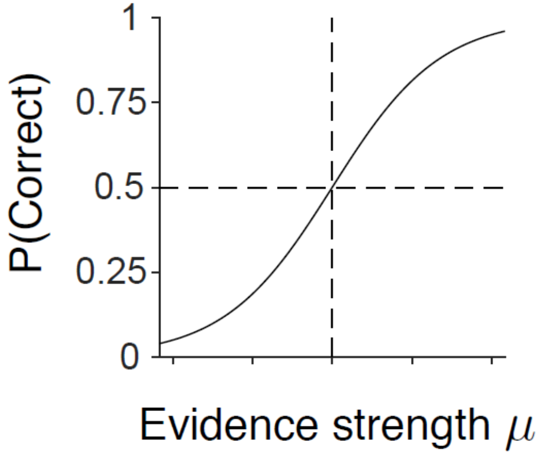
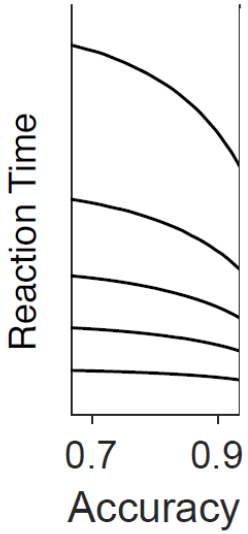
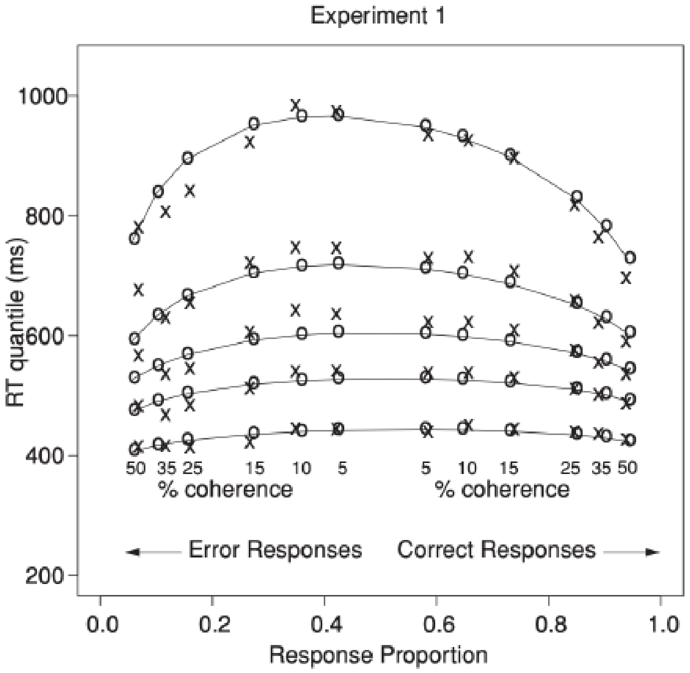




Increasing the drift rate makes decisions *faster,* more *accurate* and more *consistent*

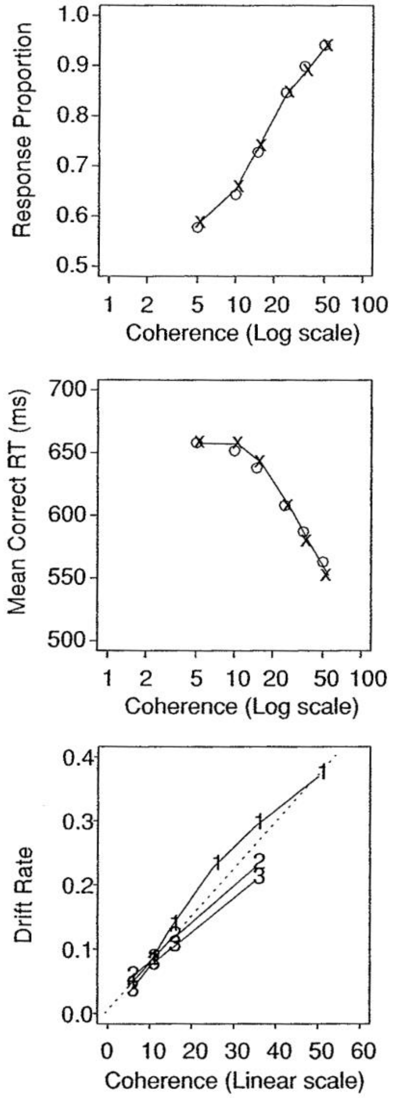
DDM Ingredients: Strength of evidence



- In experimental psychology, tendency to fit the drift rate separately for each condition, but it's helpful to use a model to interpret the strength of evidence

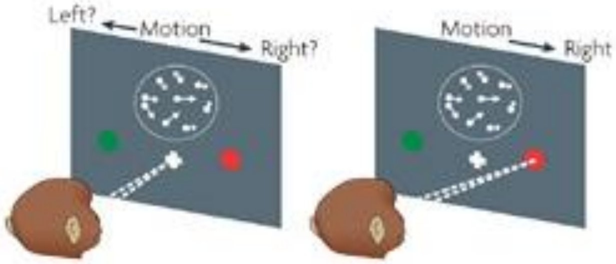
- In the random dot task, "evidence" is difficult to quantify ("motion energy")

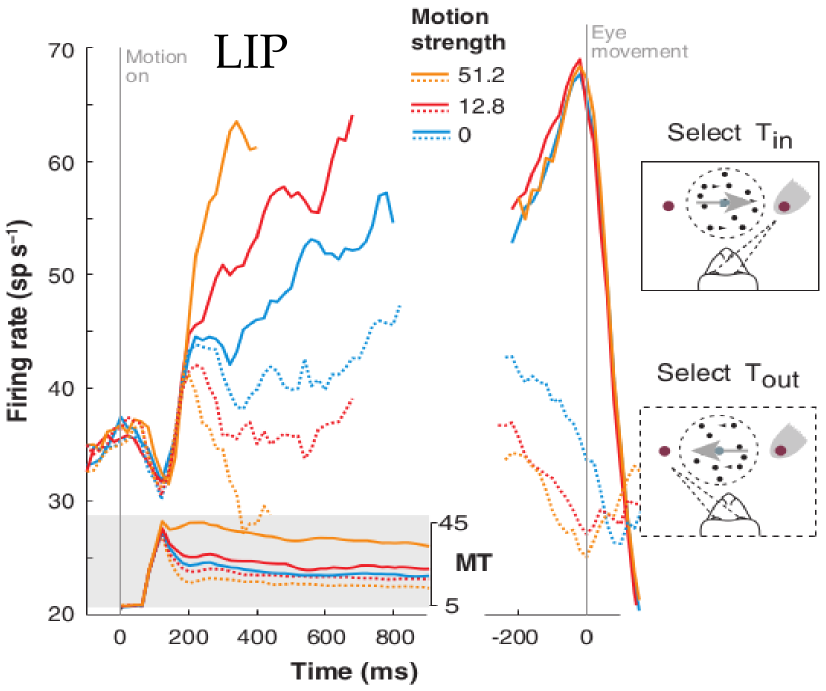
Strength of evidence ~ linear with coherence.



Ratcliff & McKoon, 2008

Neural correlates of the decision process



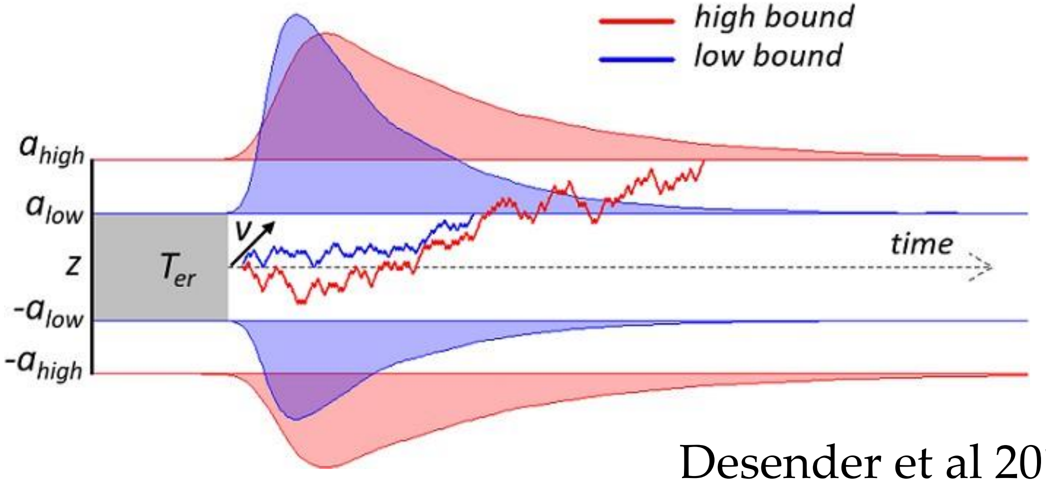


•Sensory neurons (MT) increase and stabilize in proportion to motion strength

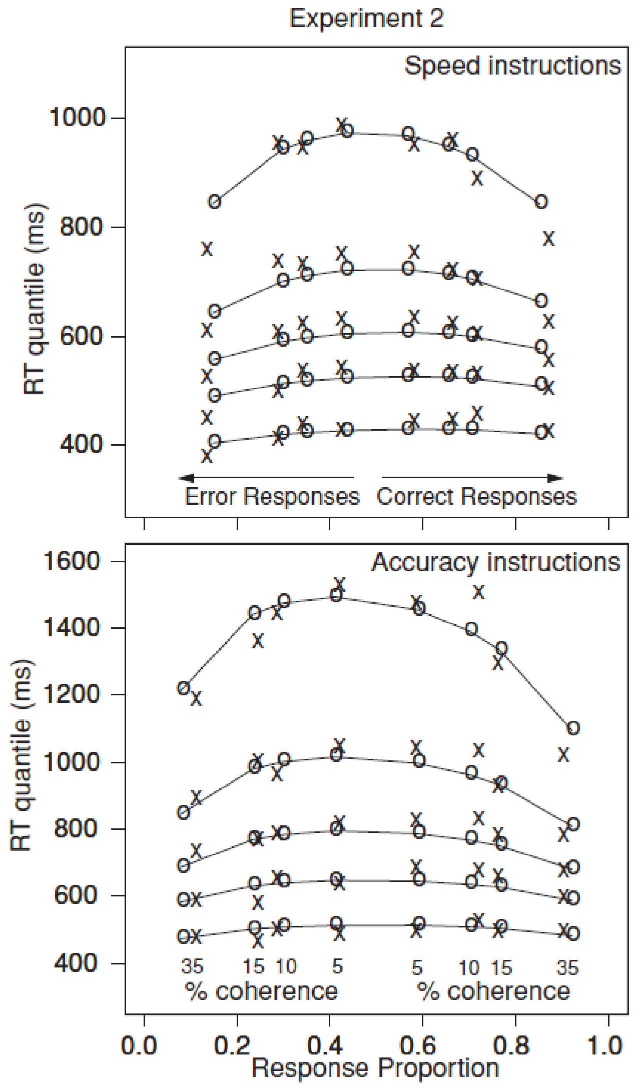
• Neurons associated with preparing a saccade (LIP) build at a rate proportional to motion strength at stimulus onset, up to a threshold level of activity at response

(Gold & Shadlen, 2007)

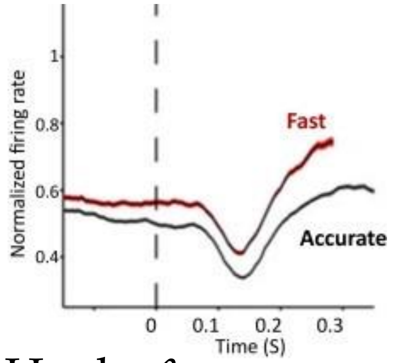
DDM Ingredients: Changing bound (speed accuracy trade off)



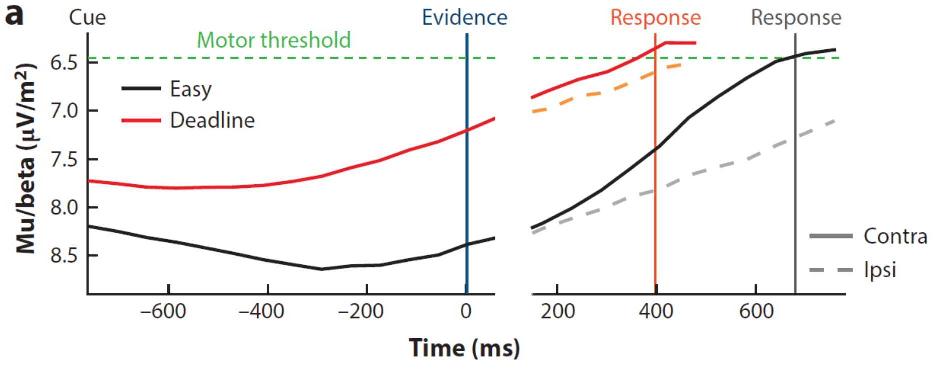
Desender et al 2019



The reduced bound is reflected in an increased starting level of build-to-threshold neural signals



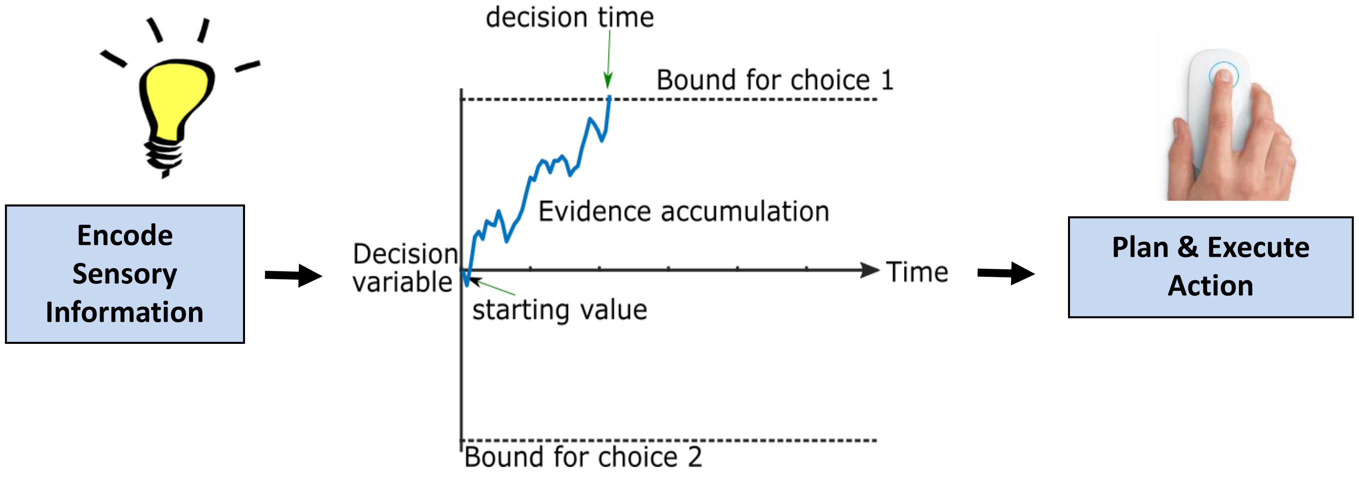
Hanks & Summerfield 2017



O'Connell & Kelly 2021

Ratcliff & McKoon, 2008

DDM Ingredients: non-decision time (T_{er})



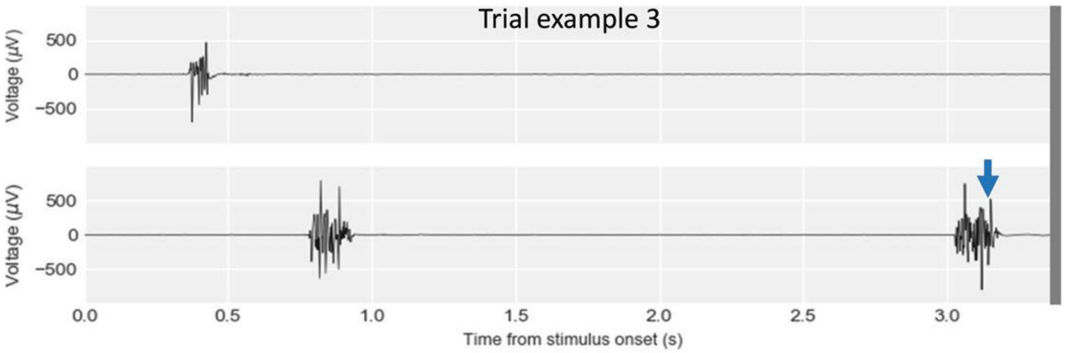
$$RT = t_D + t_{ND}$$

In the simple diffusion model, non-decision time is determined by a single parameter: $t_{ND} = T_{er}$ (time for encoding and response).

Usually assumed to be constant across stimulus discriminability levels, speed-accuracy instructions (but not always! See e.g. Dutilh et al., 2019)

Having a *high discriminability condition* can be important for accurate estimation

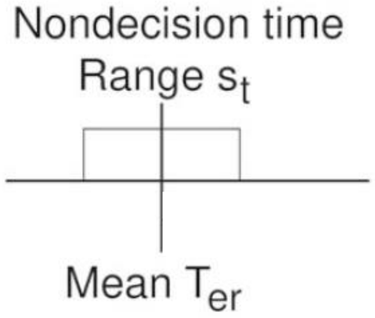
Caution: decision processes can continue past the point of movement initiation, suggesting there is continuous flow to the motor system

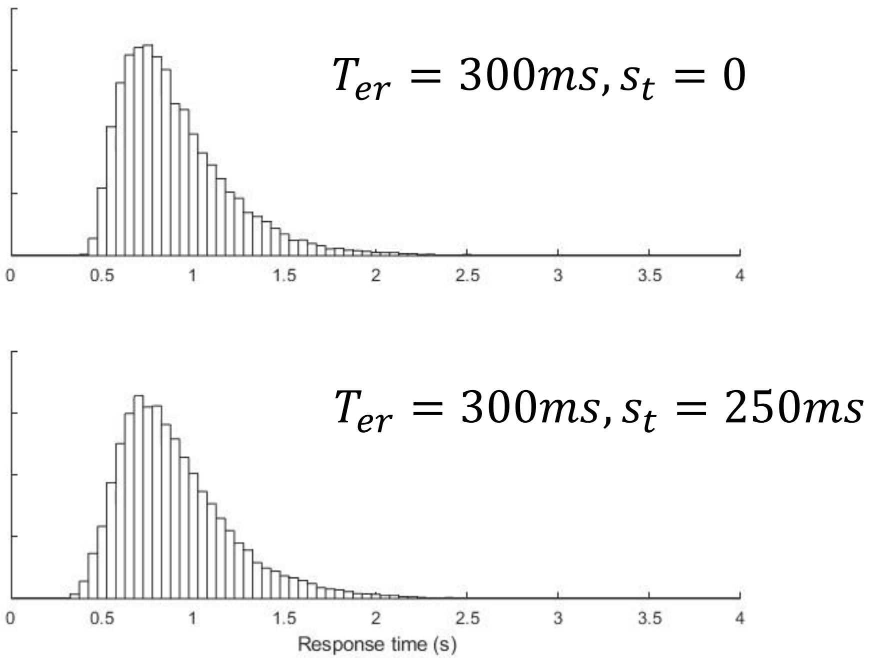


Servant et al. (2021)

DDM Ingredients: non-decision time variability (s_t)

$RT = t_D + t_{ND}$





In the full diffusion model, t_{ND} is a random variable, uniformly distributed with mean T_{er} and range s_t.

t_{ND} and t_D are assumed to vary *independently*

DDM Ingredients: variability in drift rate (η)

The simplest version of the diffusion model (assuming an unbiased starting point) produces RT distributions for errors and correct responses that are identical in shape, only scaled by the response probability.

But in real behavioural data, particularly in tasks with low discriminability where accuracy is stressed, errors will often be slower than correct responses.

The full diffusion model can generate *slow errors* through trial-to-trial variability in drift rate (e.g. due to attentional fluctuations):

$$\mu \sim N(\nu, \eta)$$

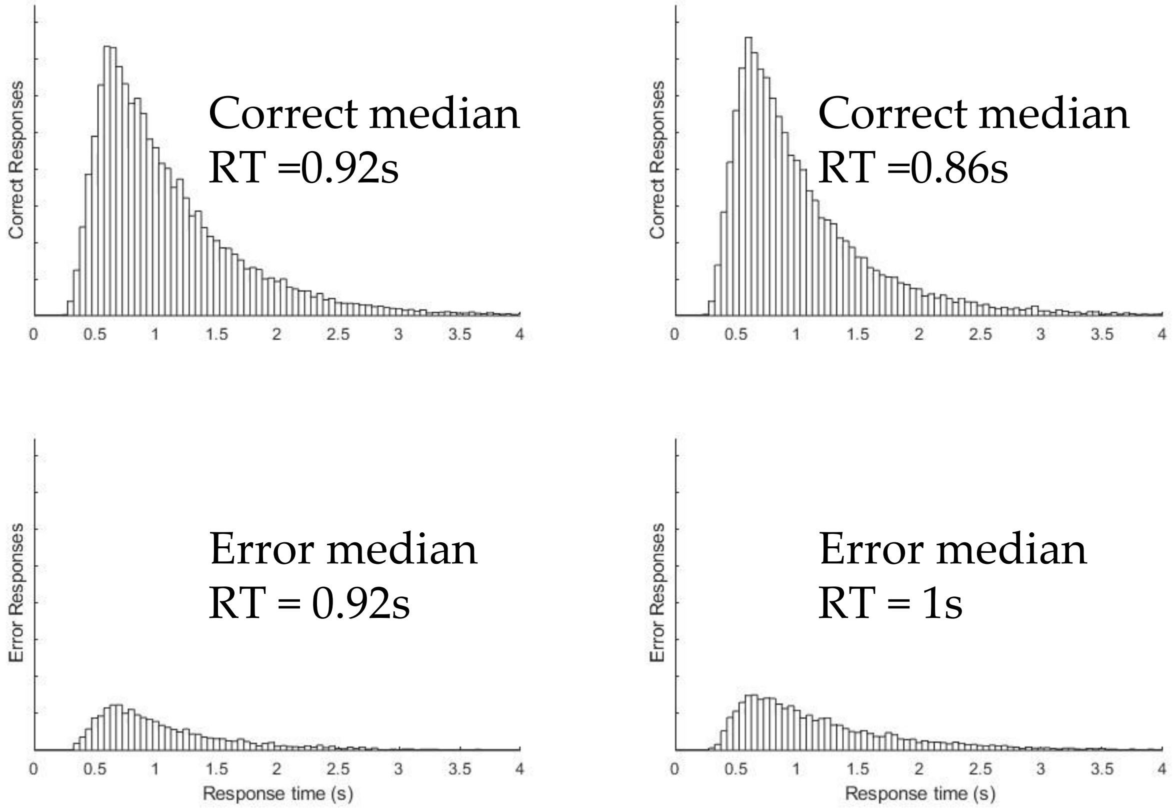
mean drift rate

drift rate variability

Intuitively, say $\mu_1 > \mu_2$, with P(Correct) = 0.9, 0.7 respectively

Mixture of distributions: the resulting correct RT distribution will have a higher proportion of trials with μ_1, while the error RT distribution will have a relatively higher number of (slower) trials with μ_2.

η=0 η >0



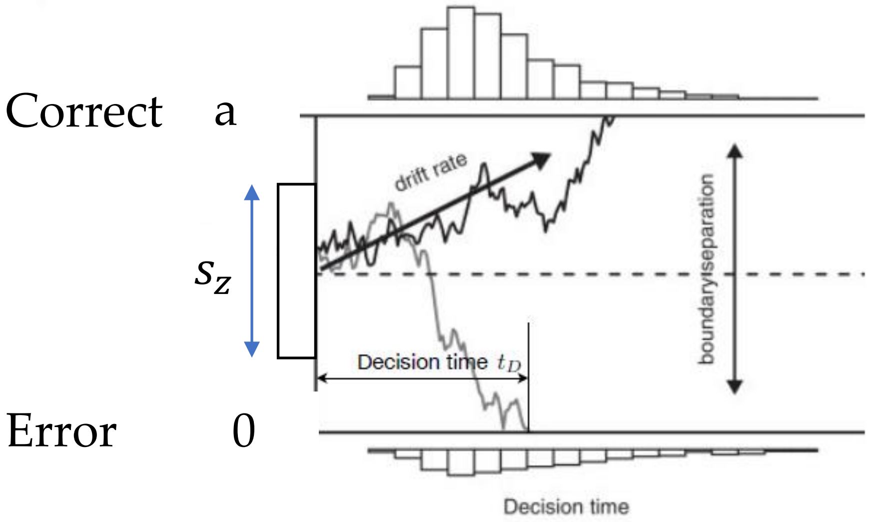
DDM Ingredients: variability in starting point (s_z)

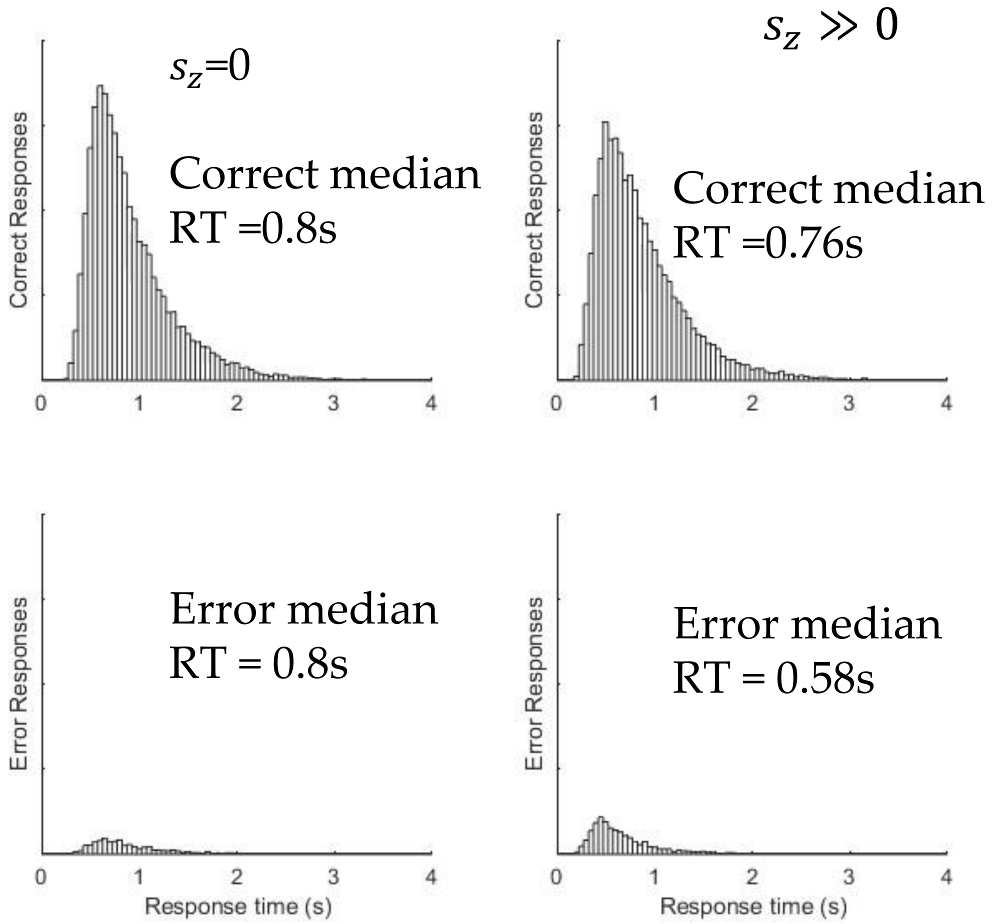
Sometimes, particularly in tasks with high discriminability where speed is stressed, errors will often be faster than correct responses.

The full diffusion model can generate *fast errors* through trial-to-trial variability in starting point.

Starting point can vary randomly due to the history of preceding stimuli or choices, or unexplained transient biases

For an (on average) unbiased decision, $z \sim U(a/2, s_z)$





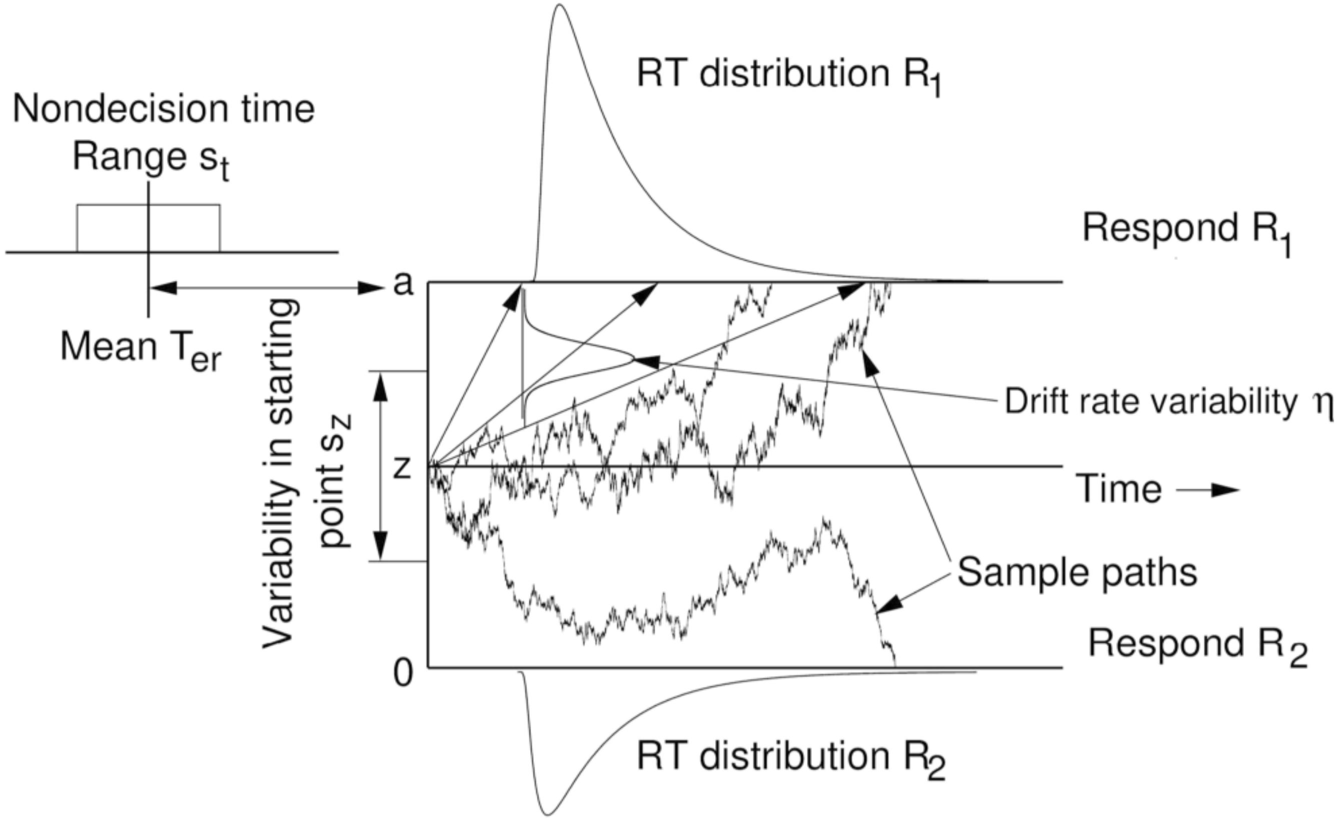
Parameters of 'Full' DDM

Simple Diffusion Model Parameters

- μ: Drift rate (strength of evidence)
- σ : Noise infinitesimal standard deviation
- a : boundary separation
- z : start point (= a/2 for an unbiased decision)
- T_{er} : non-decision time

Variability Parameters (include when needed)

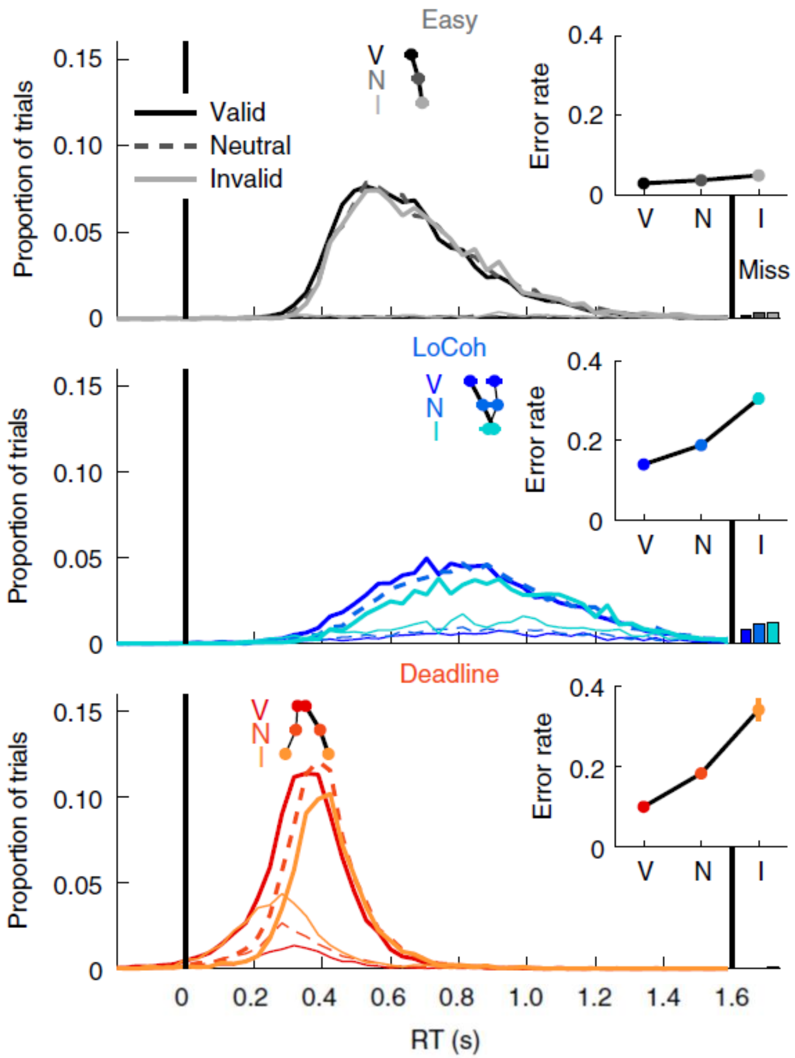
- η : Drift rate variability
- s_z : starting point variability
- s_t : non-decision time variability



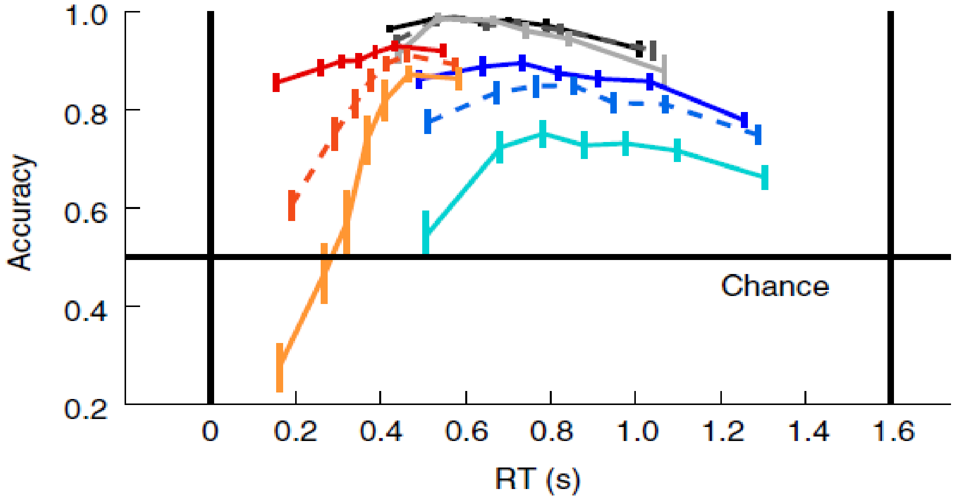
Smith (2023)

DDM Ingredients: Biases

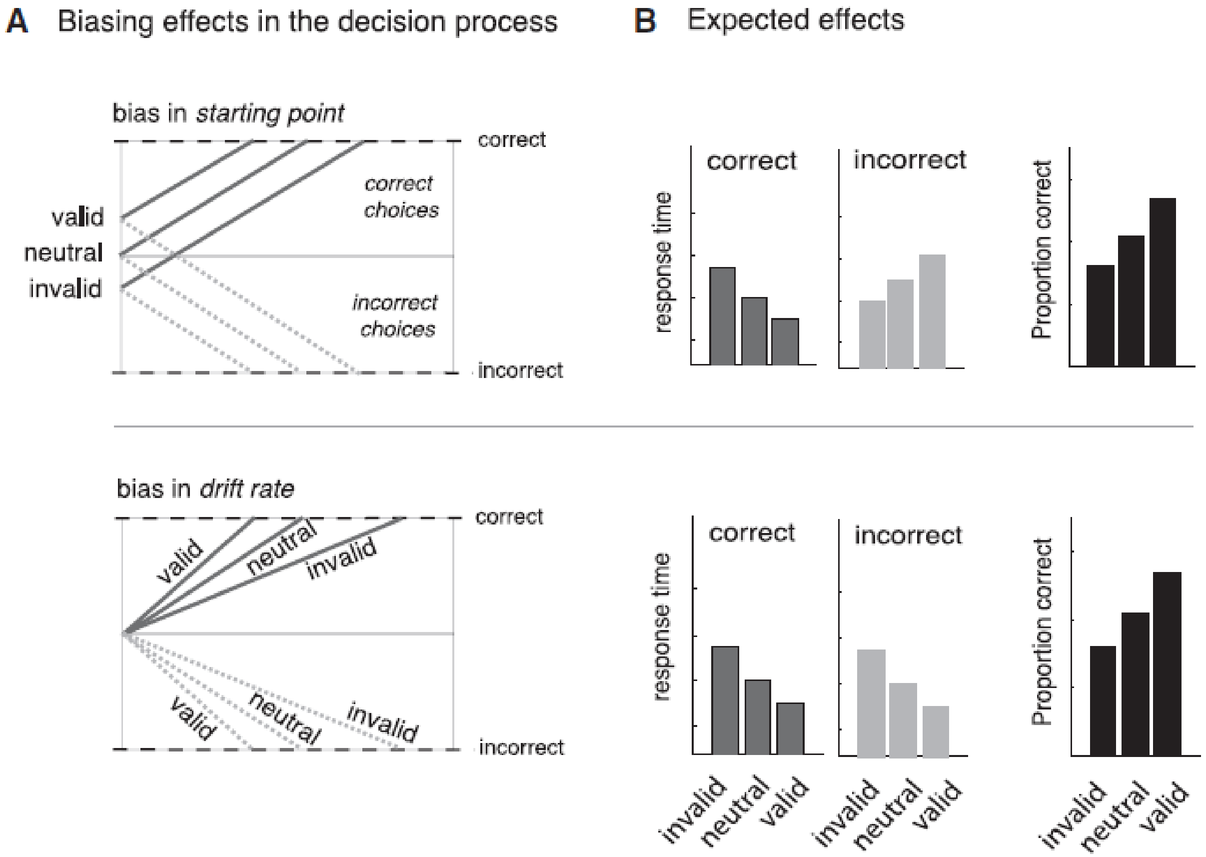
Decision process can be biased due to e.g. prior expectations or differing payoffs for the two alternatives.



Behavioural data from a prior-informed RDK task, with valid (80%), invalid (20%) and neutral-cued trials. (Kelly et al, 2021)

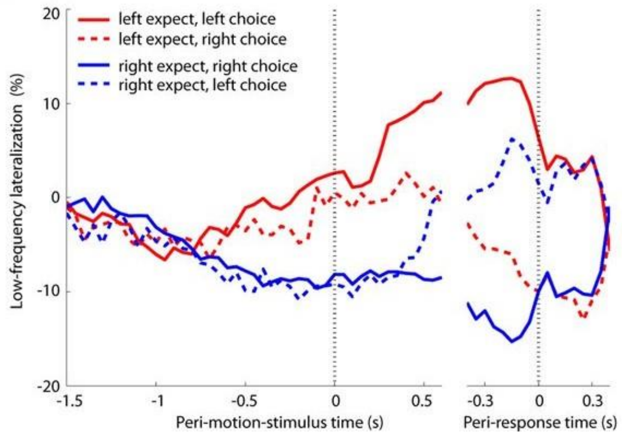


DDM Ingredients: Biases



Most studies have found that **starting point biases** largely explain prior and payoff biases in perceptual decision making.

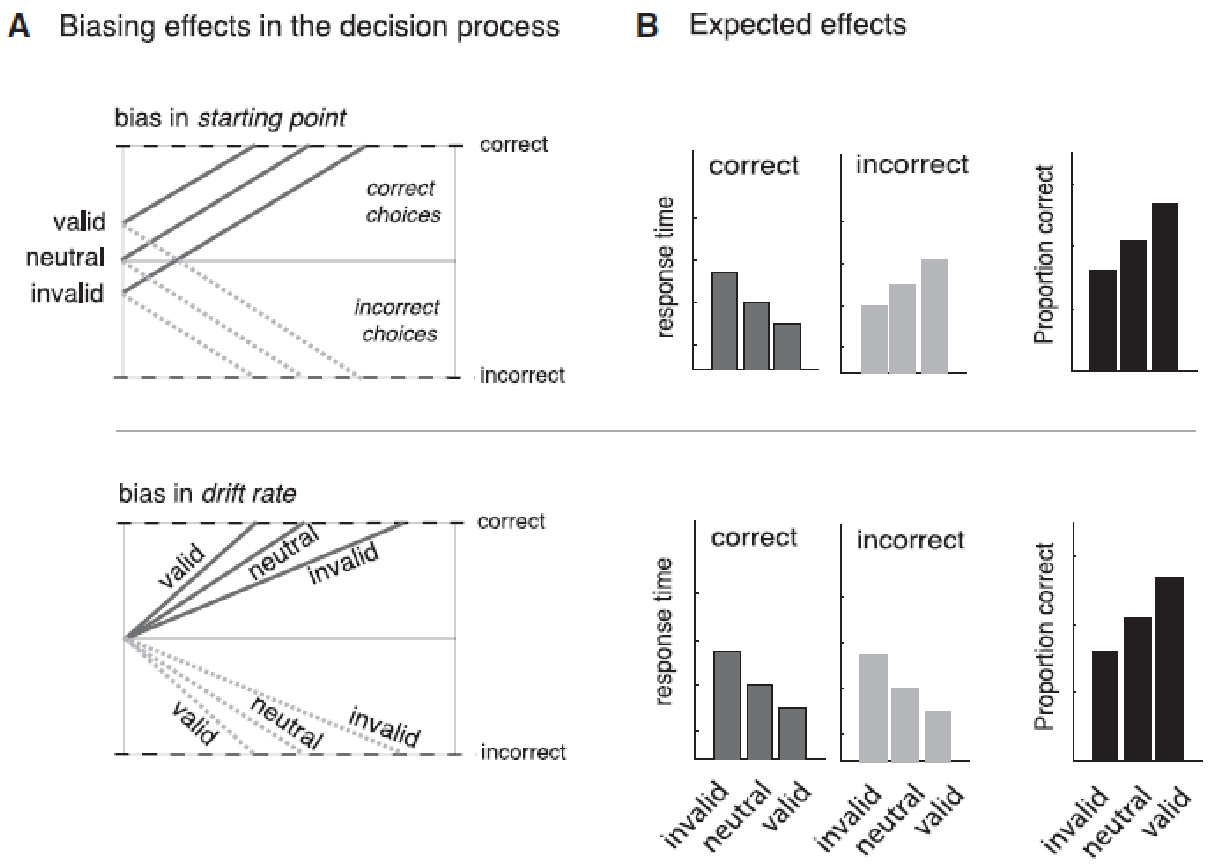
Starting point biases are reflected in neural signatures of motor preparation from human MEG/EEG (de Lange et al, 2013; Kelly et al., 2021)



Mulder et al., 2012 J. Neurosci

de Lange et al, 2013.

DDM Ingredients: Biases



Mulder et al., 2012 J. Neurosci

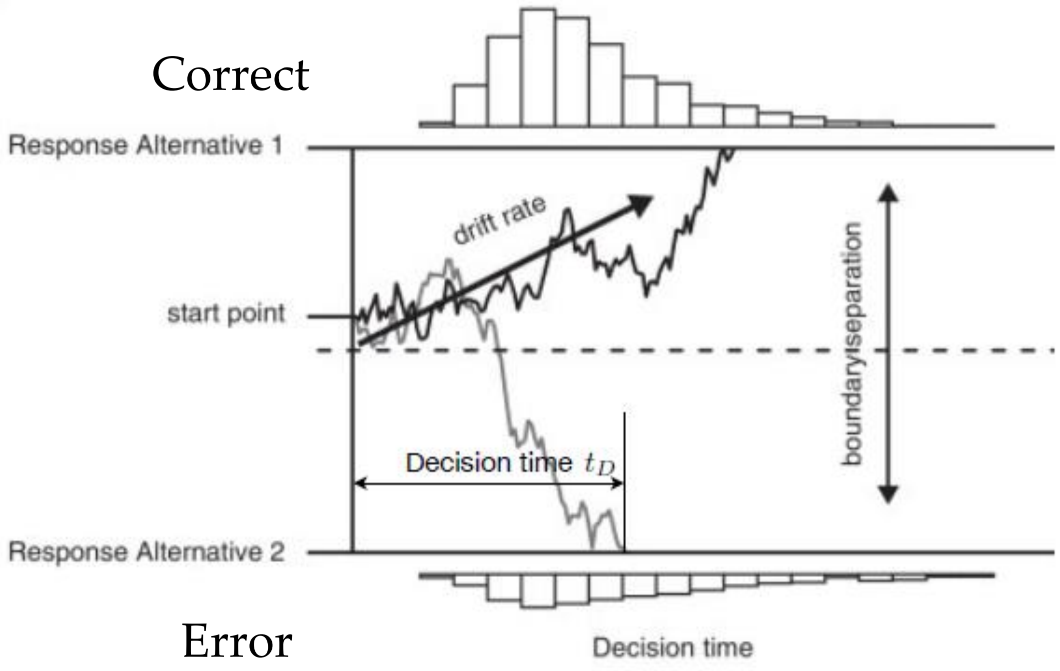
Drift rate biases are usually found **in addition to** starting point biases and are often found in asymmetrical tasks such as present/absent decisions (de Gee et al, 2017; Corbett & Smith, 2020).

They have also been found due to

- Payoff biases (Afacan-Seref et al, 2018, Leite & Ratcliff, 2011)

- Choice history (Urai et al, 2019)

Diffusion decision model (DDM)

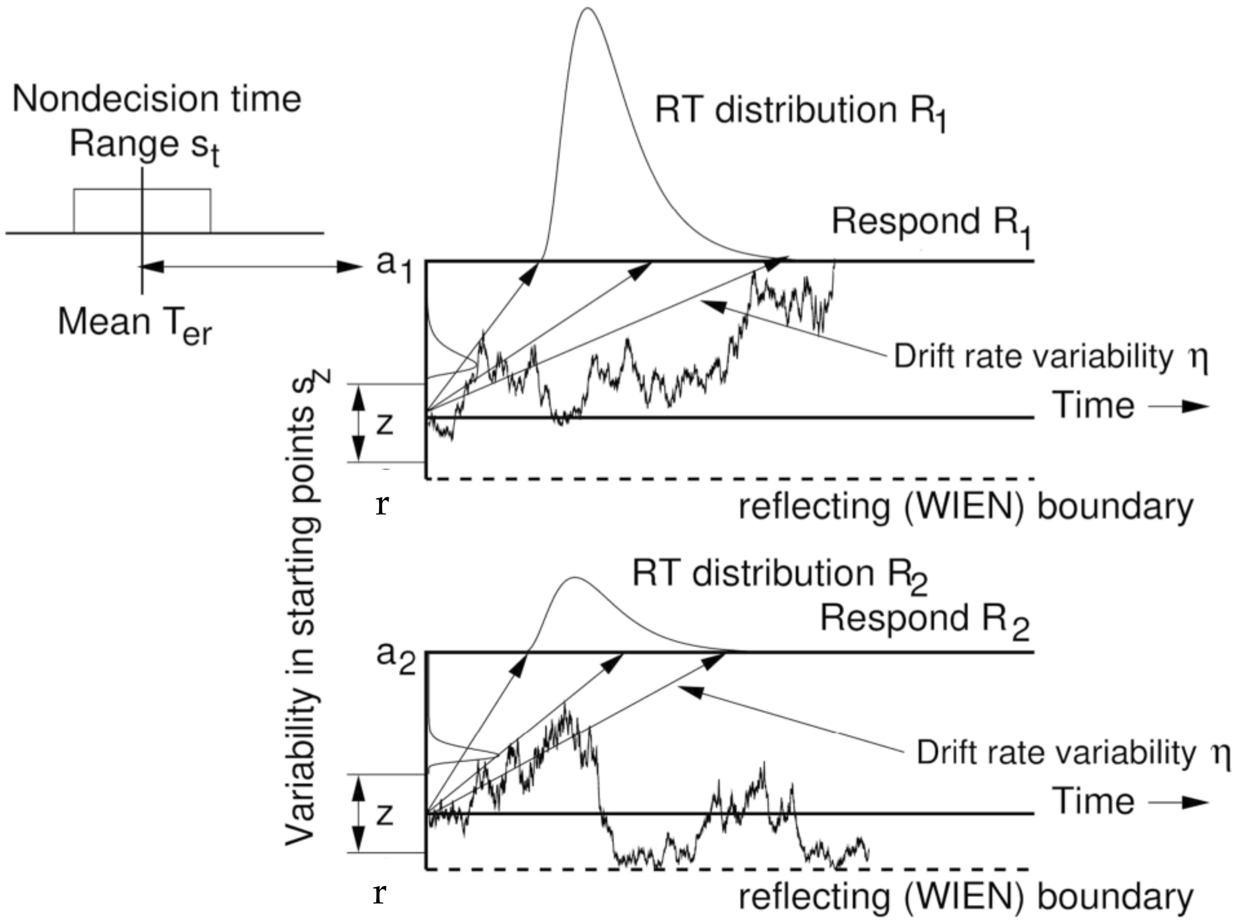


Rather than simply describing the properties of RT distributions mathematically, the DDM is a process model of decision making.

The model provides a (high-level) mechanistic description of how the brain deals with moment-to-moment variation in noisy sensory representations.

In doing so, it translates RT and accuracy into meaningful cognitive constructs (e.g. response caution; how biases affect decision formation) which can then be compared across interesting task conditions or individuals.

DDM Variants: Racing accumulators (dual diffusion model)



Smith 2023

Additional Parameters
- Two drift rates
- Two drift rate variability parameters (lognormal distributions)
- Two bounds a1, a2 (if not symmetric decision)
- Reflecting bound r

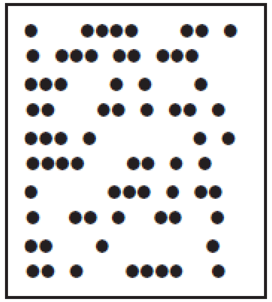
- As neural firing rates typically increase in cells responding to both selected and unselected alternatives, separate accumulation processes may be more neurally plausible

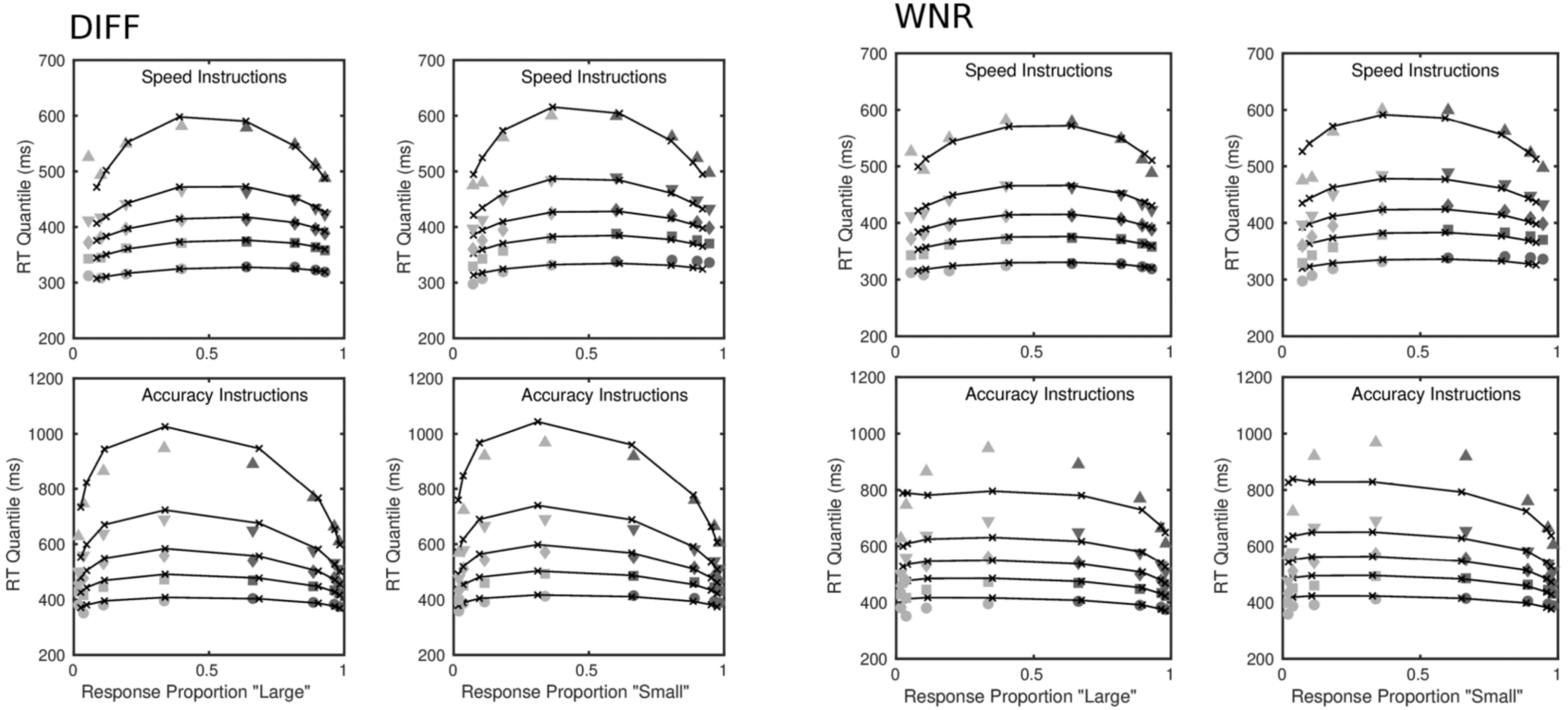
See also: Logan et al., 2014, Ratcliff & Smith, 2004; Ratcliff et al., 2007, Tillmanet al, 2020

DDM Variants: Racing accumulators

• Smith (2023) compared the fit of the standard (full) diffusion model (DIFF) vs dual racing Wiener processes (WNR) in 2 tasks.

• Here is the fit to data from a Ratliff (2008) numerosity task with an SAT manipulation: were there more or less than 50 dots?





• Dual diffusion model fails to capture the long tails of RT distributions in the accuracy condition: when there are two racing processes the probability that neither has terminated is lower

• Highlights why you need to fit the full RT distribution!!

• Allowed nondecision time and bounds, to vary with SAT

• WNR Dual diffusion drift rates were constrained to have the sum of the drift rates in the two accumulators to be equal across discriminability conditions

Smith 2023

Generalized Diffusion process & leakage

General equation for a diffusion process: $dX_t = A(X_t, t)\, dt + \sqrt{B(X_t, t)}\, dW_t$

- In the standard diffusion decision model, the drift (A) and diffusion (B) are constant over time within a single decision.

- Rather than assuming perfect integration, some models instead assume that evidence is "leaked" from the decision variable (Usher & McClelland, 2001).

In an Ornstein-Uhlenbeck process: $\mathrm{A}(X_t, t) = pX_t + q$

- When p is negative it represents leakage of the decision variable, pulling the accumulated evidence back to zero. The more evidence that has accumulated, the bigger an effect the leakage parameter will have.

- Leak has been in particular found to be helpful in accounting for behaviour in tasks in which the sensory evidence can change within a trial (e.g. Tsetsos et al., 2012; Trueblood et al, 2021)

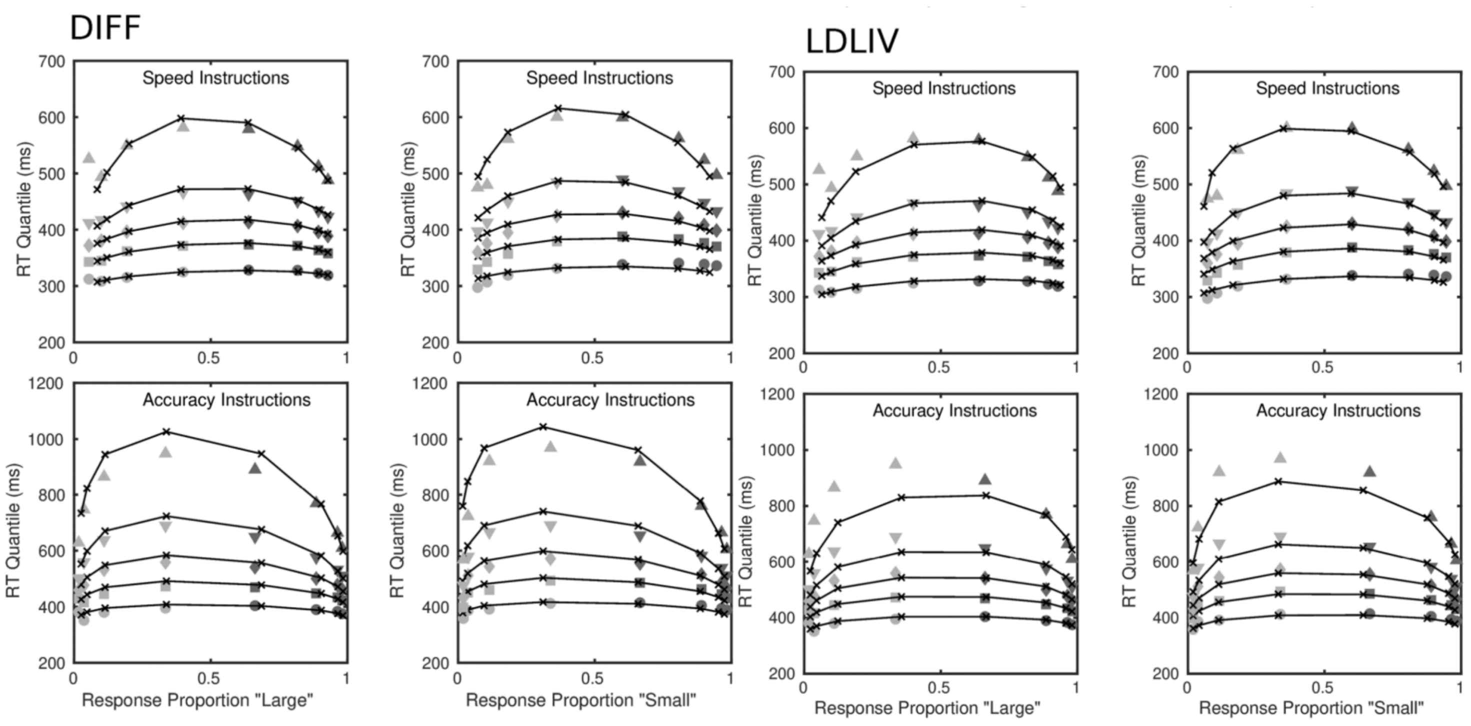
Racing accumulators with leakage

- Smith (2023) tested a new dual diffusion model– the Linear Drift, Linear Infinitessimal Variance model (LDLIV) that incorporated leaky accumulation.

$$dX_t = (pX_t + q)\,dt + \sqrt{2\sigma X_t}\,dW_t$$

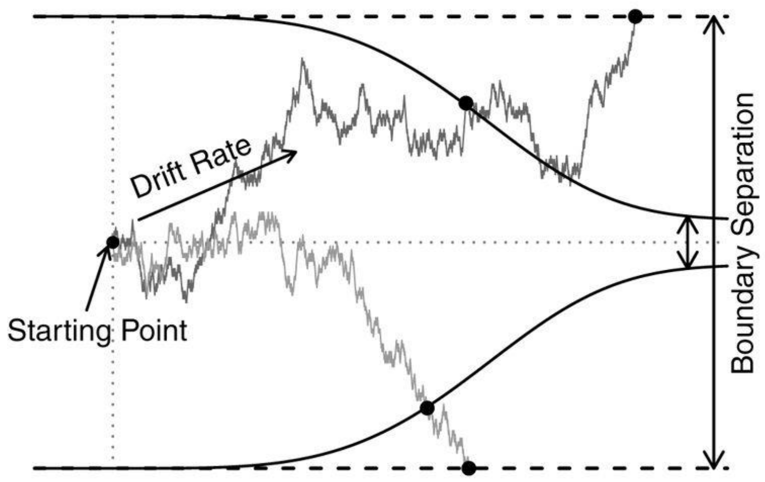
- The LDLIV model also has a diffusion coefficient that is scaled by the state of the decision variable, giving it a natural reflecting boundary at zero.

- This new model fit Ratcliff's (2008) data about as well as the standard diffusion model, with the under-estimate of the long tails greatly reduced as a result of the leakage.



Smith 2023

DDM Extensions: Collapsing bounds



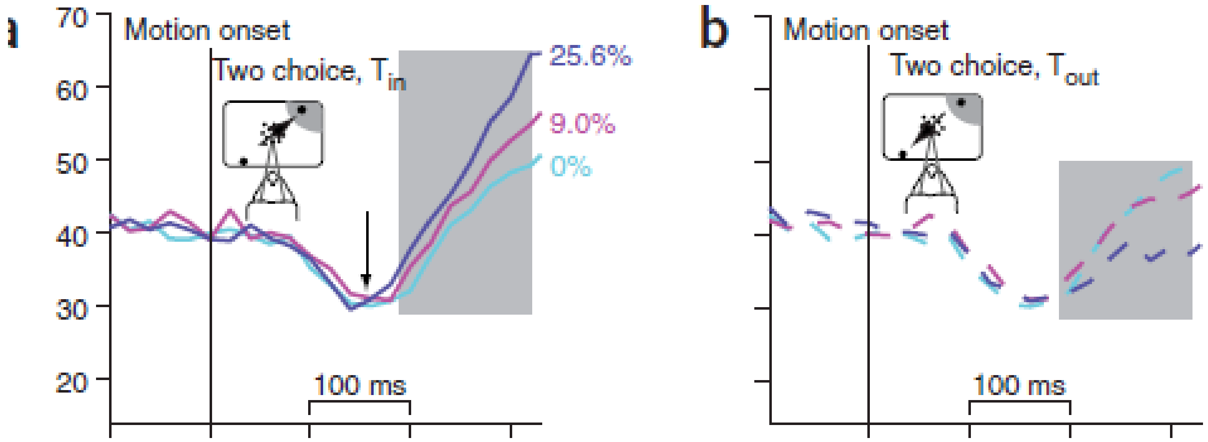
Hawkins et al., 2015

- Another mechanism to produce slow errors
- More symmetrical RT distributions
- Controversial in the literature.. (model mimicry)
- Evidence for collapsing bounds more often found with highly trained participants (NHPs) or deadlines
- Speed accuracy manipulations are sensitive to the specific instructions (!)
- But, collapsing bounds are inconsistent with the neuroscience (build to threshold signals)

DDM Extensions: Urgency

Several studies have found neurophysiological evidence for urgency—evidence independent components of the decision process that drive the neural decisions signals to their threshold

(Churchland et al, 2008, Thura & Cisek 2014, Heitz & Schall 2012, Hanks et al, 2015, Corbett et al, 2023)



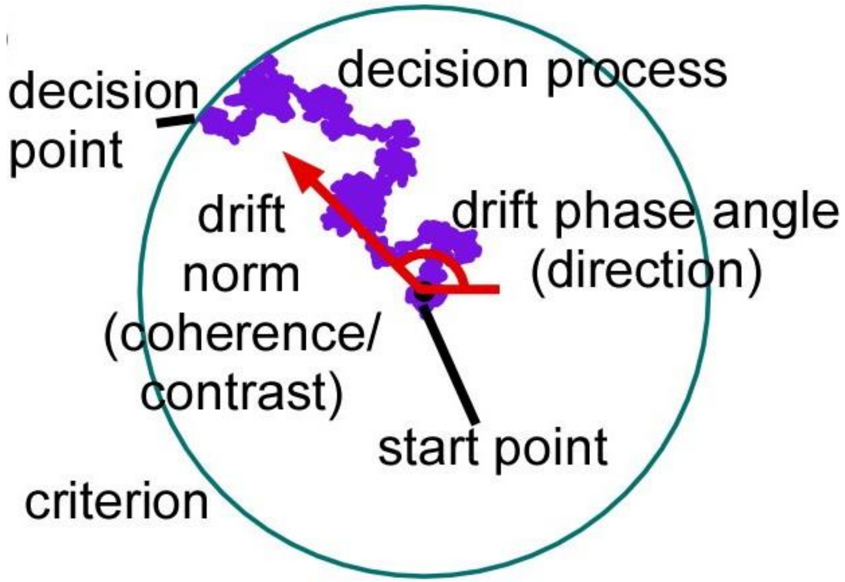
Churchland et al., 2008

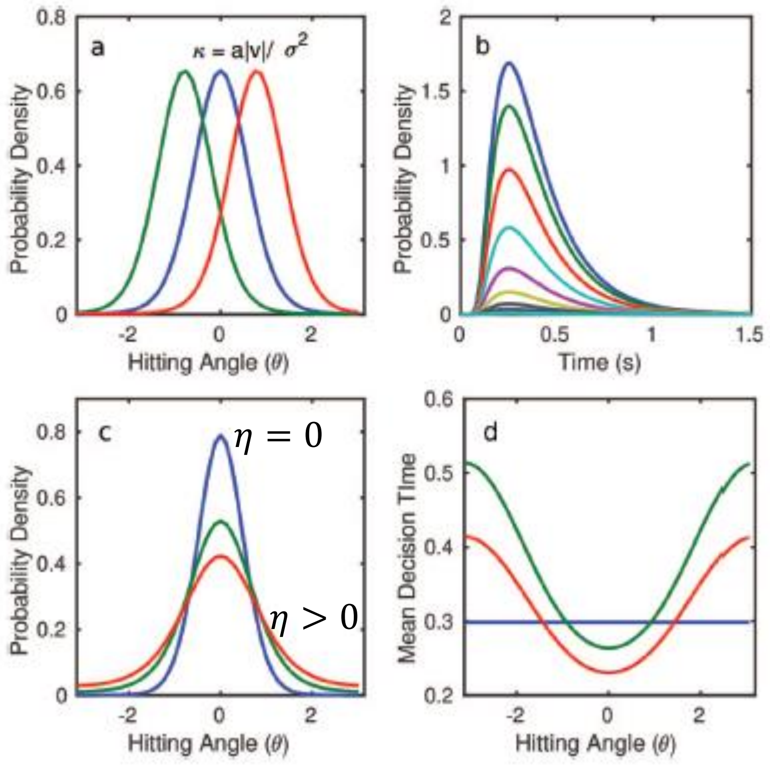
• In the context of racing accumulators, additive evidence independent urgency signals that increase with time can drive the decision variable to the bound (Ditterich 2006) ---mathematically equivalent to a collapsing bound.

•Urgency Gating Model (Cisek et al., 2009) instead magnifies the (leaky) one-dimensional accumulated evidence multiplicatively with a growing urgency signal.

• See Smith & Ratcliff, 2021, Trueblood et al 2021 for more discussion

DDM Extensions: Continuous Report





(Smith 2016).

- For decisions with outcomes on a continuum, the diffusion model has been extended to two-dimensional diffusion on a circle—the circular diffusion model (CDM, Smith 2016).

- Produces a Von Mises distribution of outcomes, and, similar to the 1D DDM, right-skewed RT distributions with the same (scaled) shape regardless of the location of the outcome.

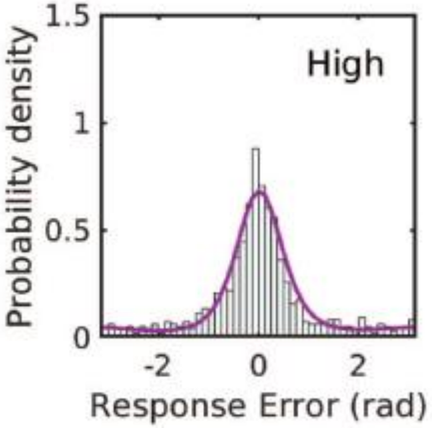
- Slow and fast errors can be generated with drift rate and criterion variability.

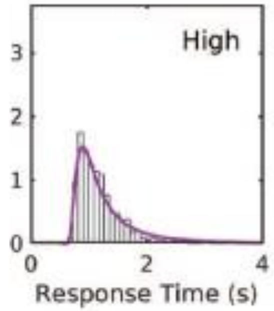
DDM Extensions: circular diffusion model (CDM)

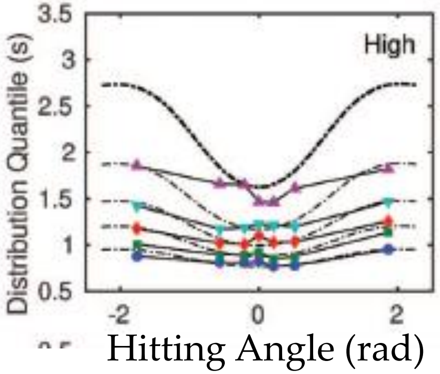
Outcome distributions aligned to the correct response (0 deg)

Marginal RT distribution

Joint distributions of accuracy and RT

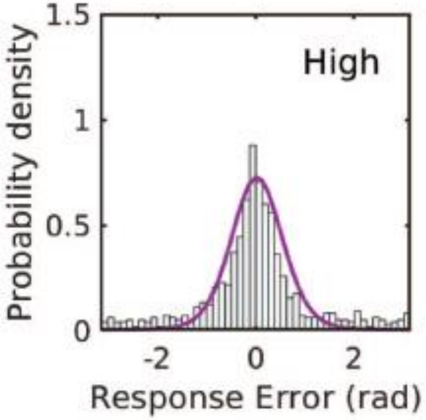


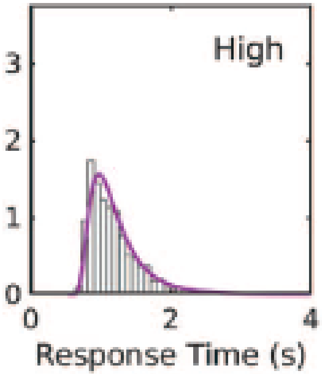


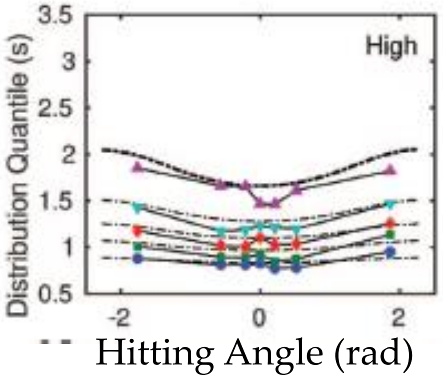


large η
can capture the heavy tails but predicts RTs for errors that are WAY slower than correct responses.

- Heavy tails are a common feature of difficult continuous report tasks. But the errors are *not* dramatically slower than correct responses







small η
Misses the heavy tails in the accuracy distribution

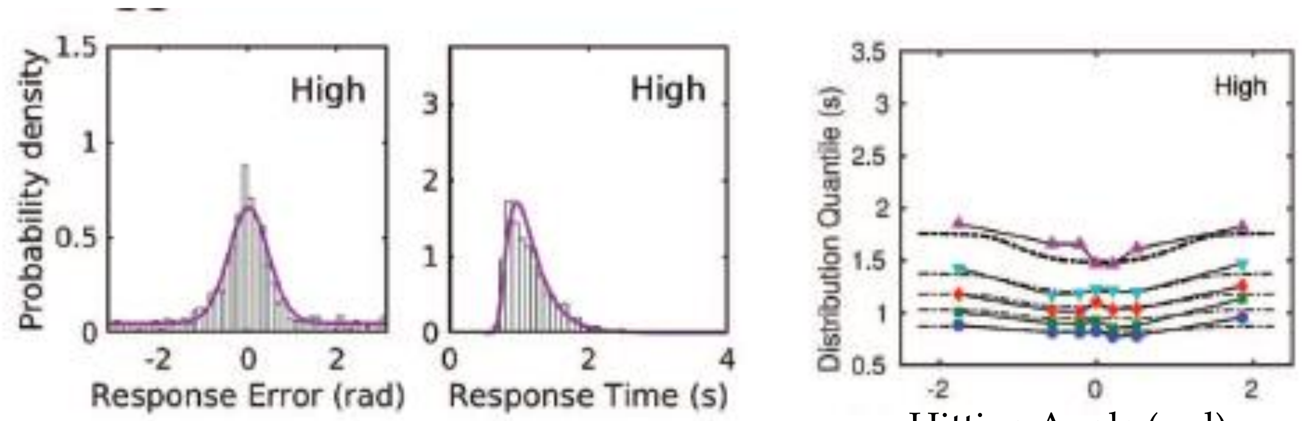
(Smith et al., 2020)

Mixture model: CDM with encoding failures

• How can we jointly capture the response time and accuracy distributions?

• Solution: on a proportion of trials, π, the drift phase angle will be drawn randomly (uniformly distributed around the circle). The drift *magnitude* stays the same, allowing the RTs to remain relatively consistent.

• Behaviour on these trials is attributed to encoding failures



Hitting Angle (rad)

DDM Extensions: Confidence

People can reliably form confidence judgements about the probability that their choices were correct, providing another valuable source of information about how decisions are formed and monitored.

Empirical observations about confidence

•Confidence reliably increases with stimulus discriminability

•Confidence increases with choice accuracy, even when the discriminability of the stimulus is controlled for: *Resolution of Confidence*

•People are more confident in faster decisions…
…unless they are faster because they were made under speed pressure

•When under speed pressure for the initial decision, the resolution of confidence increases

Table 1
Eight Empirical Hurdles a Model of Cognitive Performance Must Explain

Hurdle	Description	References
1. Speed–accuracy trade-off	Decision time and error rate are negatively related such that the judge can trade accuracy for speed.	Garrett (1922); D. M. Johnson (1939); Pachella (1974); Schouten & Bekker (1967); Wickelgren (1977)
2. Positive relationship between confidence and stimulus discriminability	Confidence increases monotonically as stimulus discriminability increases.	Ascher (1974); Baranski & Petrusic (1998); Festinger (1943); Garrett (1922); D. M. Johnson (1939); Pierce & Jastrow (1884); Pierrel & Murray (1963); Vickers (1979)
3. Resolution of confidence	Choice accuracy and confidence are positively related even after controlling for the difficulty of the stimuli.	Ariely et al. (2000); Baranski & Petrusic (1998); Dougherty (2001); Garrett (1922); D. M. Johnson (1939); Nelson & Narens (1990); Vickers (1979)
4. Negative relationship between confidence and decision time	During optional stopping tasks there is a monotonically decreasing relationship between the decision time and confidence where judges are more confident in fast decisions.	Baranski & Petrusic (1998); Festinger (1943); D. M. Johnson (1939); Vickers & Packer (1982)
5. Positive relationship between confidence and decision time	There is a monotonically increasing relationship between confidence and decision time where participants are on average more confident in conditions when they take more time to make a choice. This relationship is seen when comparing confidence across different conditions manipulating decision time (e.g., different stopping points in an interrogation paradigm or between speed and accuracy conditions in optional stopping tasks).	Irwin et al. (1956); Vickers & Packer (1982); Vickers, Smith, et al. (1985)
6. Slow errors	For difficult conditions, particularly when accuracy is emphasized, mean decision times for incorrect choices are slower than mean decision times for correct choices.	Luce (1986); Ratcliff & Rouder (1998); Swensson (1972); Townsend & Ashby (1983); Vickers (1979)
7. Fast errors	For easy conditions, particularly when speed is emphasized, mean decision times for incorrect choices are faster than mean decision times for correct choices.	Ratcliff & Rouder (1998); Swensson & Edwards (1971); Townsend & Ashby (1983)
8. Increased resolution in confidence with time pressure	When under time pressure at choice, there is an increase in the resolution of confidence judgments.	Current article; Baranski & Petrusic (1994)

Pleskac & Busemeyer, 2010

Confidence: single vs dual stage models

- Confidence usually probed after the initial choice is made

- *Single stage models* posit that confidence is based on the same information that produced the initial decision

- *Dual stage models* posit that evidence accumulation continues post response to inform the confidence judgement. If the evidence has been extinguished, accumulation can continue from *memory*, or from the *sensorimotor pipeline* (Resulaj et al., 2009)

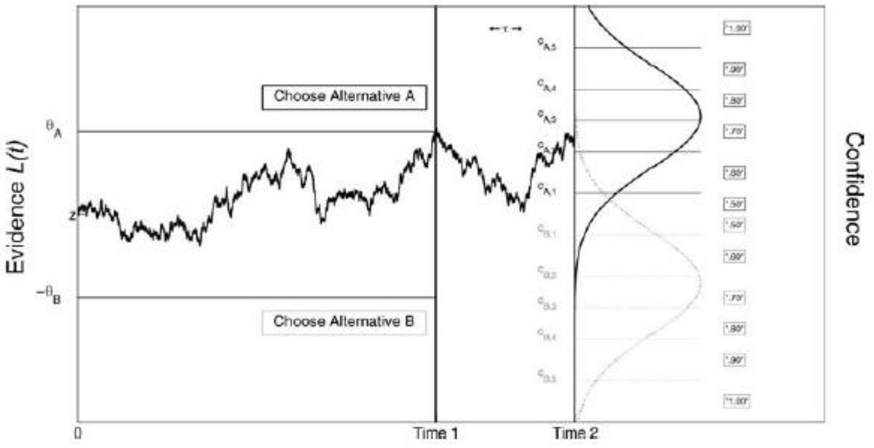
- In the standard DDM, the level of evidence at response is always the same and so obviously not representative of choice confidence. Trial RT is related to the probability of a decision being correct, but is not sufficient to explain many of the empirical findings.

- Accumulator models can compare the balance of evidence in the 2 accumulators (Vickers 1979), but predict that confidence resolution should be lower under speed pressure.

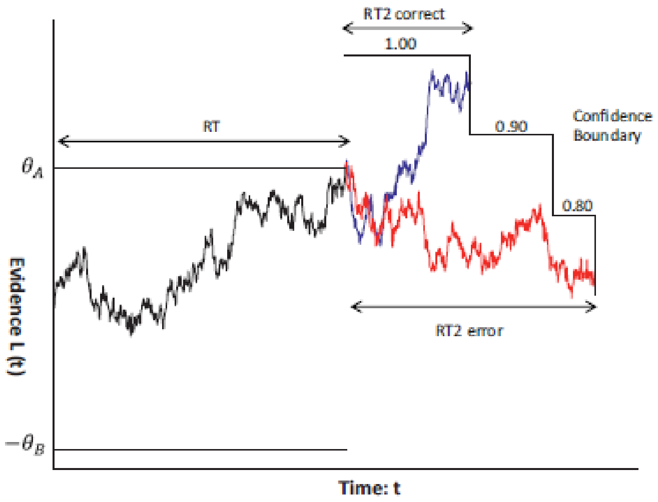
DDM Extensions: post-choice accumulation

With post-decision evidence accumulation, confidence resolution will naturally occur as new evidence is more likely to be consistent with correct choices and inconsistent with errors. When the initial decision is made under speed pressure, allowing the post-decision accumulation to continue for longer will lead to increased confidence resolution.

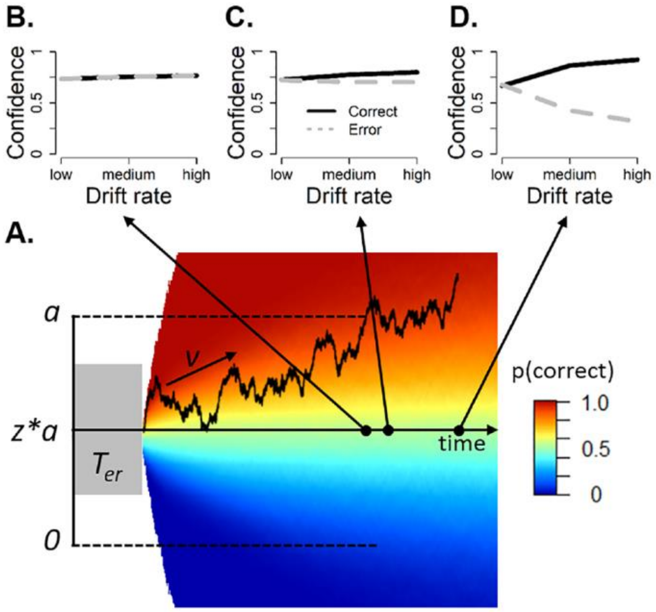
2 stage dynamic signal detection Pleskac & Busemeyer, 2010



Collapsing confidence bound: Moran et al., 2015



Signatures of confidence depend on post-decision processing time: Desender et al, 2021



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