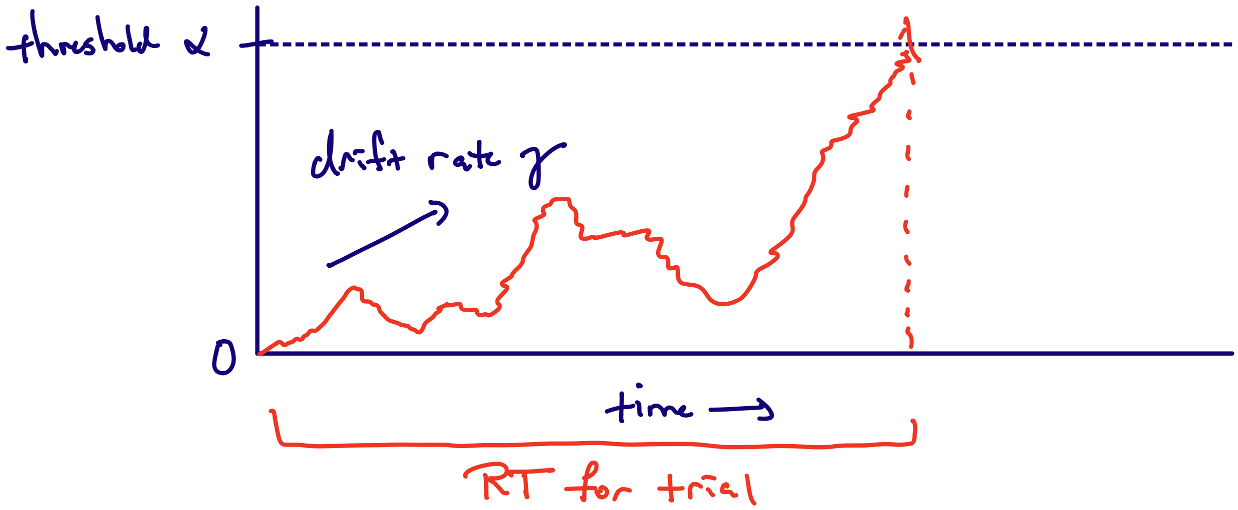
Lecture 9 - the EZ diffusion model

Wald model: sequential sampling model w/ one boundary



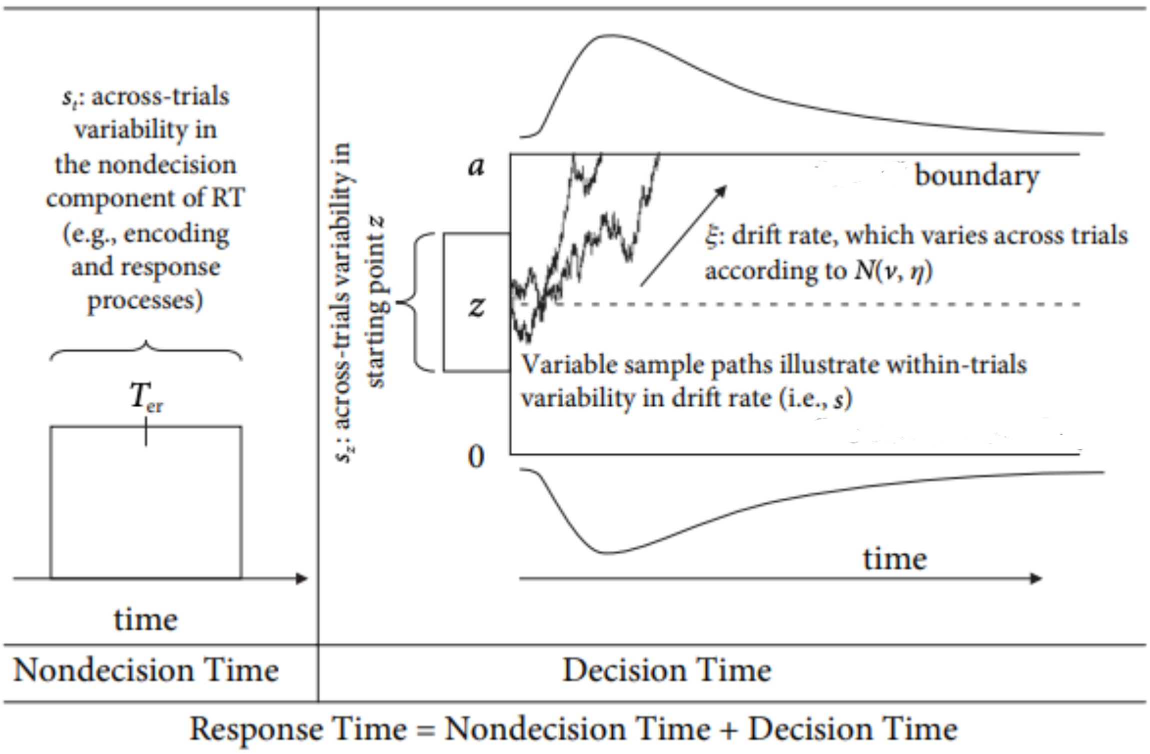
Disadvantages:

1. only one boundary – doesn't account for errors
2. accumulator starts at 0 – doesn't account for nondecision processes (i.e., perception & motor initiation)

↳ better approach? –

Diffusion model (R. Ratcliff)

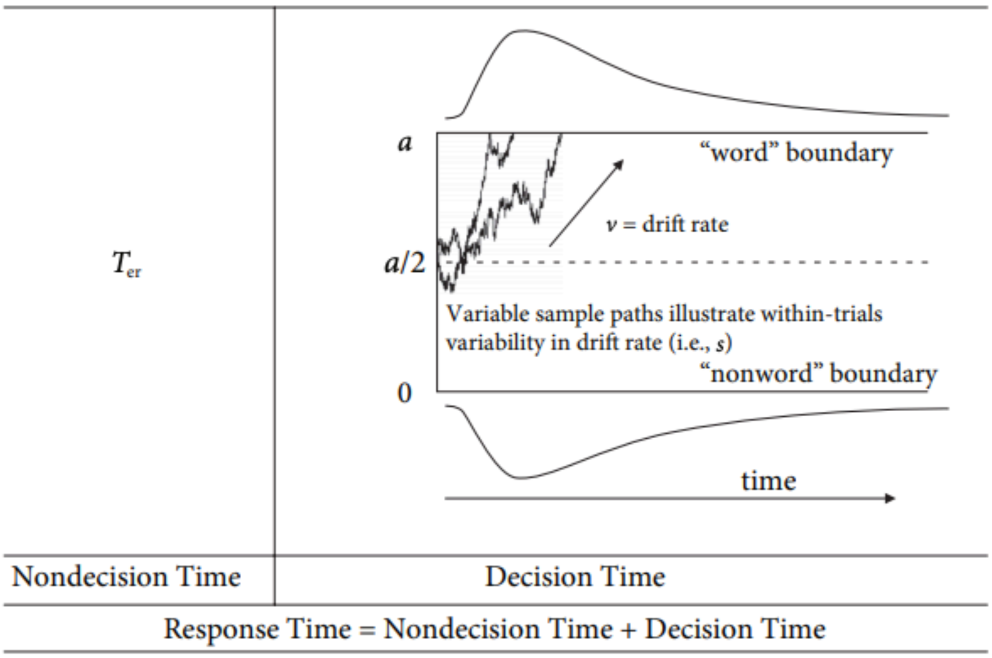
Diffusion model:



Seven parameters!

1. mean drift rate (ν)
2. across-trial variability in drift rate (η)
3. Boundary separation (a)
4. Mean starting point (z)
5. Across-trial range in starting point (s_z)
6. mean of nondecision component (T_{er})
7. across-trial range in nondecision time (s_t)

In 2007, Wagenmakers, van der Mas, & Grasman proposed some simplifying assumptions:



Three ~~Seven~~ parameters!

1. mean drift rate (v)
2. ~~across-trial variability in drift rate (η)~~
3. Boundary separation (a)
4. ~~Mean starting point (z)~~
5. ~~Across-trial range in starting point (s_z)~~
6. mean of nondecision component (T_{er})
7. ~~across-trial range in nondecision time (s_t)~~

As a result, this "EZ"-diffusion model can be estimated from only three pieces of information:

1. mean of RTs
2. variance of RTs
3. proportion of correct trials.

Analytic steps:

1. calculate drift rate

$$v = \mathrm{sign}\left(P_c - \frac{1}{2}\right) \cdot s \cdot \left[\frac{\mathrm{logit}(P_c)\left[P_c^2\, \mathrm{logit}(P_c) - P_c\, \mathrm{logit}(P_c) + P_c - \frac{1}{2}\right]}{\mathrm{Var}(RT)}\right]^{\frac{1}{4}}$$

↳ where $s = 0.1$

and $\mathrm{logit}(P_c) = \log\left(\frac{P_c}{1 - P_c}\right)$

"log odds"

2. then, calculate boundary separation

$$a = \frac{s^2 \operatorname{logit}(P_c)}{v}$$

↳ convert to "threshold" by taking

$$\text{threshold} = \frac{a}{2}$$

3. calculate nondecision time as

$$T_{er} = \text{mean}(RT) - \text{mean}(DT)$$

where

$$\text{mean}(DT) = \left(\frac{a}{2v}\right) \frac{1 - \exp\left(-\frac{va}{s^2}\right)}{1 + \exp\left(-\frac{va}{s^2}\right)}$$

Implementation in R:

```r
# load data from Faulkenberry, Bowman, and Vick (2018)
# experiment on size congruity effect
X = read.csv("https://raw.githubusercontent.com/tomfaulkenberry/physNumComparisonTask/master/results/data/subject_104.csv")

# break into congruity conditions
X_congruent = subset(X, congruity=="congruent")
X_incongruent = subset(X, congruity=="incongruent")
```

Note: size congruity effect = which number is physically larger?

Congruent trials:

2 8

Incongruent trials

2 8

slower!

```r
# extract summary statistics for each condition
mRT_congruent = mean(X_congruent$response_time)
mRT_incongruent = mean(X_incongruent$response_time)

varRT_congruent = var(X_congruent$response_time)
varRT_incongruent = var(X_incongruent$response_time)

Pc_congruent = mean(X_congruent$correct)
Pc_incongruent = mean(X_incongruent$correct)
```

Get mean, variance, & % correct for each condition

```
# fit EZ-diffusion model

# first, fit congruent trials
mRT = mRT_congruent
varRT = varRT_congruent
Pc = Pc_congruent

# Step 1 - calculate drift rate
L = log(Pc/(1-Pc)) # logit function
x = L*(Pc^2*L - Pc*L + Pc - .5)/varRT
driftRate1 = 0.1*sign(Pc-0.5)*x^(1/4)

# calculate threshold
a = 0.01*log(Pc/(1-Pc))/driftRate
threshold1 = a/2

# calculate nondecision time
y = -100*driftRate*a
MDT = a/(2*driftRate) * (1-exp(y))/(1+exp(y))
nondecisionTime1 = mRT - MDT
```

Once the drift rate, threshold, & NDT are computed, repeat for incongruent trials. and then compare.