Signal detection theory as bridge for Bayesian statistics and modelling

Bayes@Lund, 2019-05-07

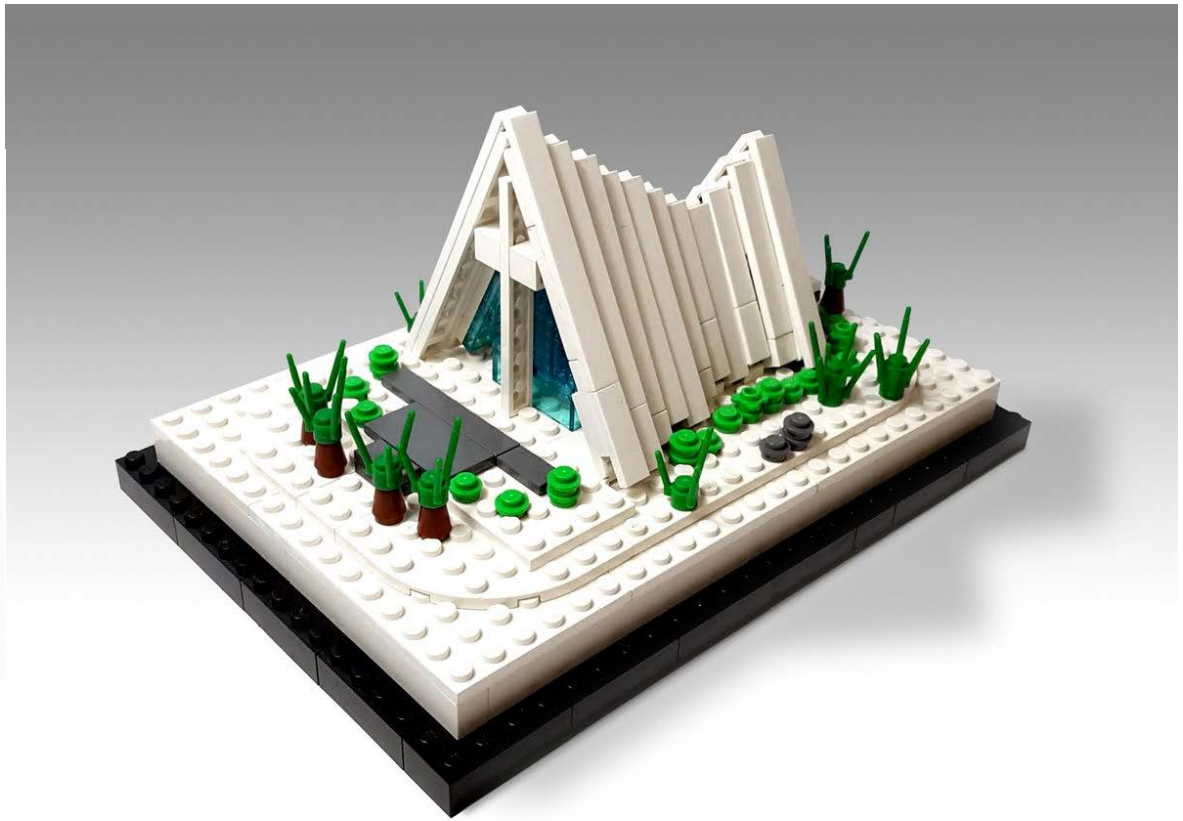
Presenter: Gerit Pfuhl

UiT The Arctic University of Norway

In cooperation with Robert Biegler, NTNU

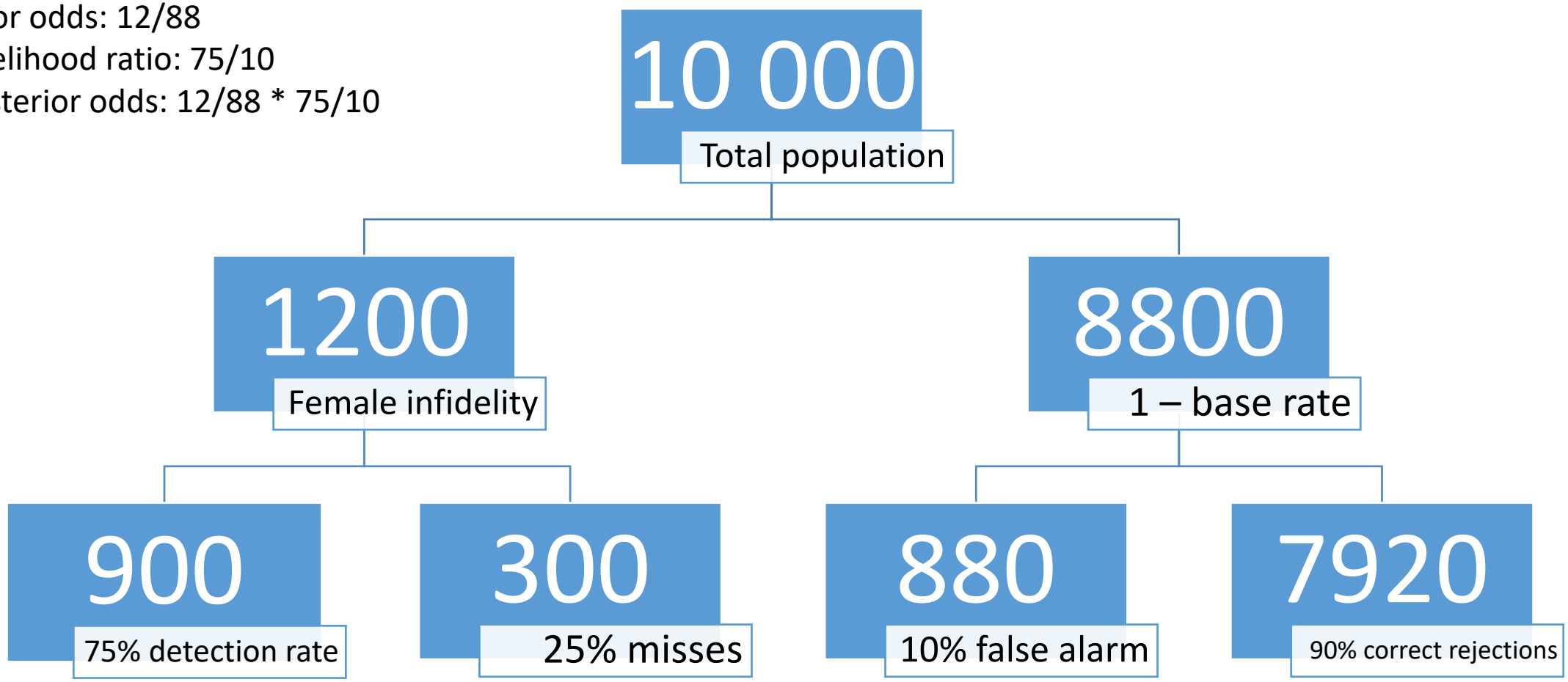
Background: assume no prior knowledge

ILLUSTRATION BY STEPH BRAVO

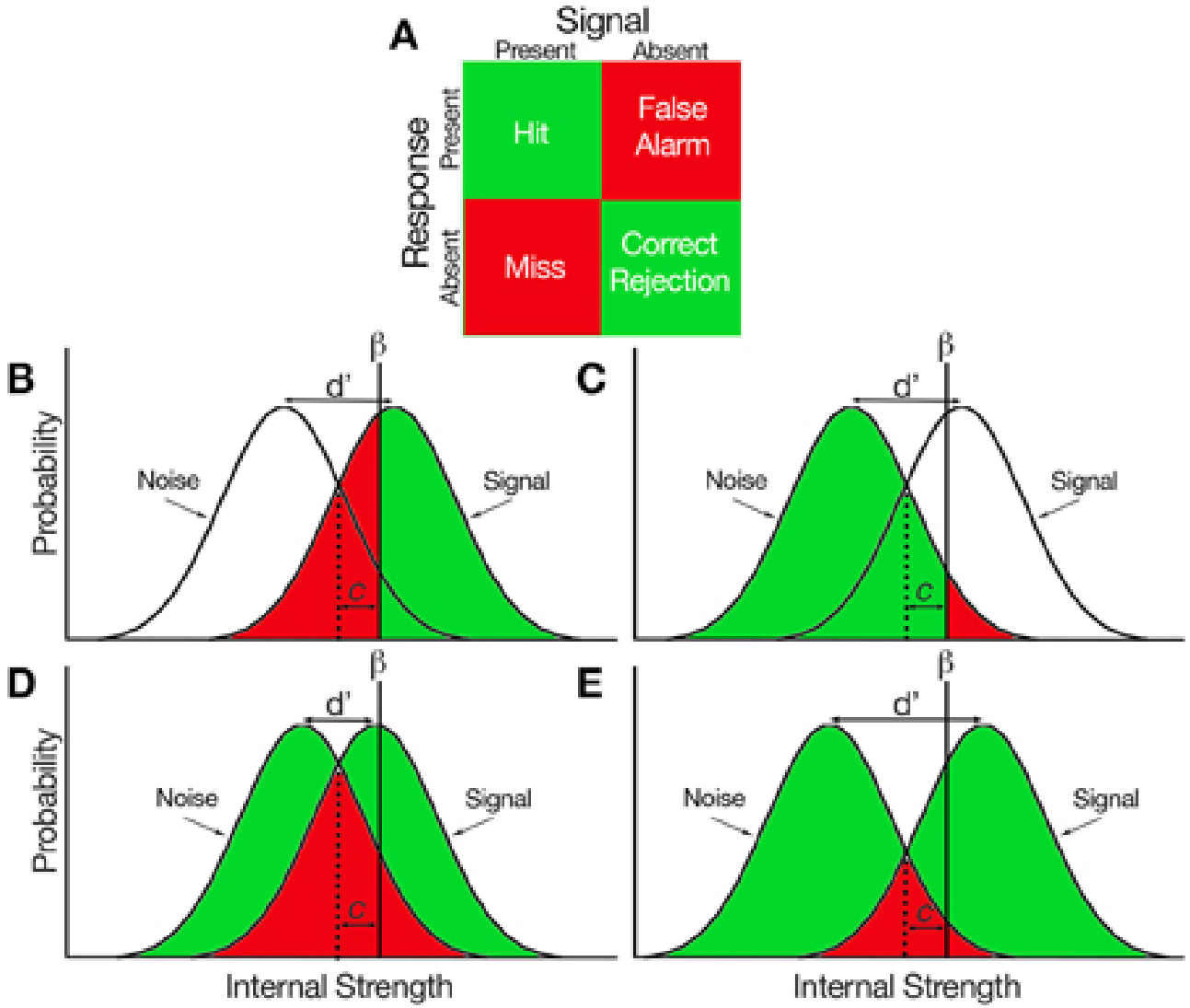


How sure are you that your partner is cheating?

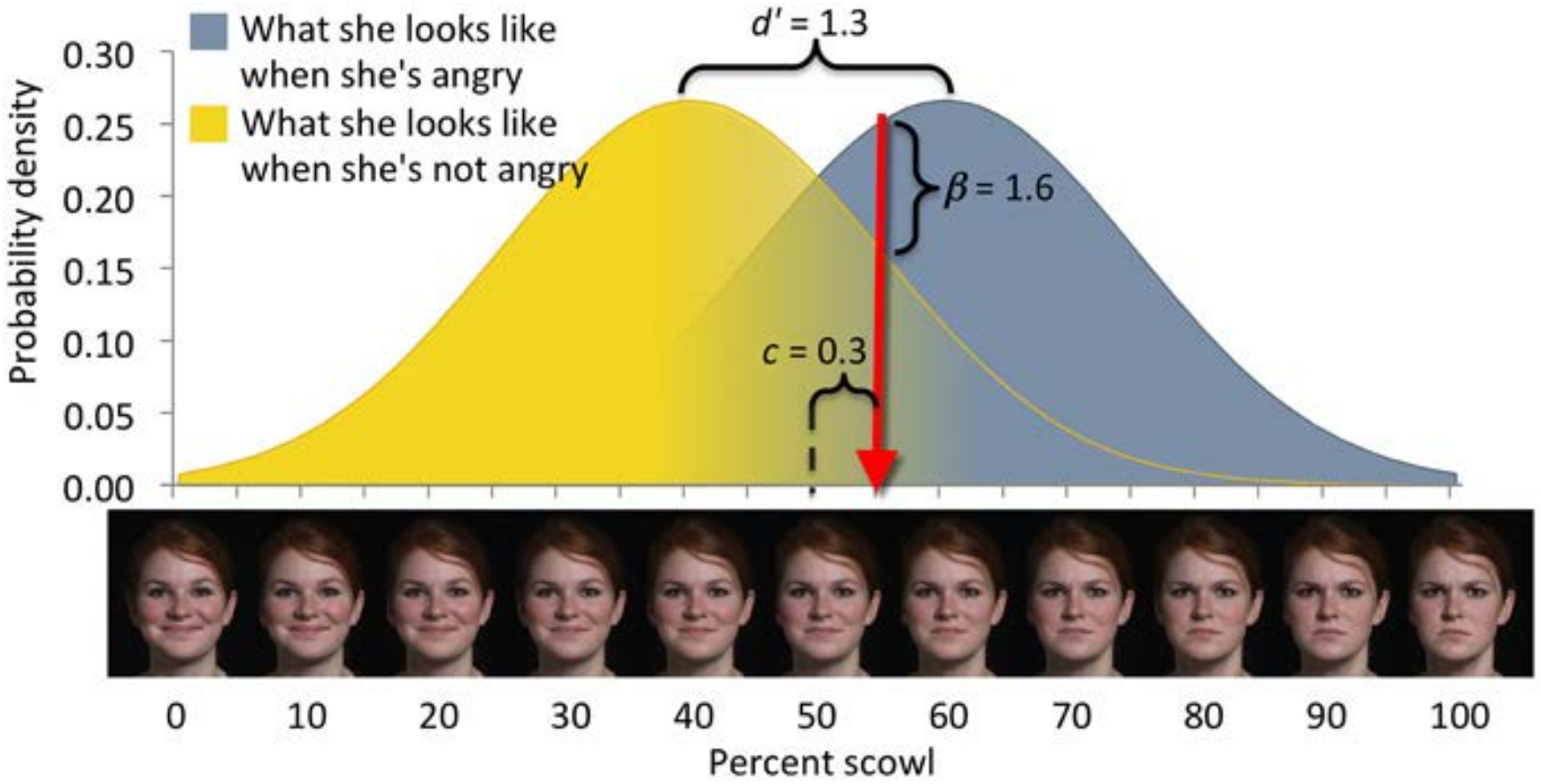
Prior odds: 12/88
Likelihood ratio: 75/10
Posterior odds: 12/88 * 75/10



Where do the numbers come from?

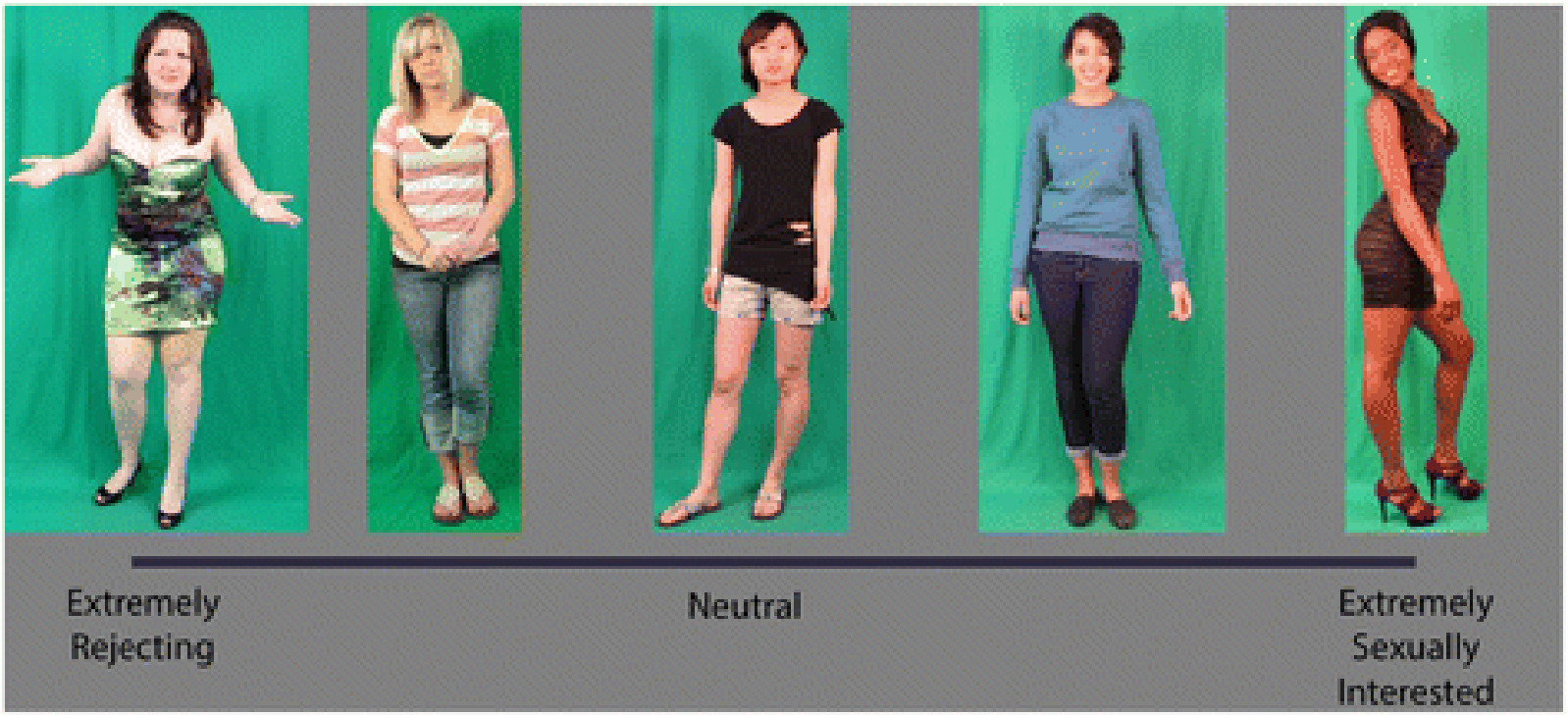


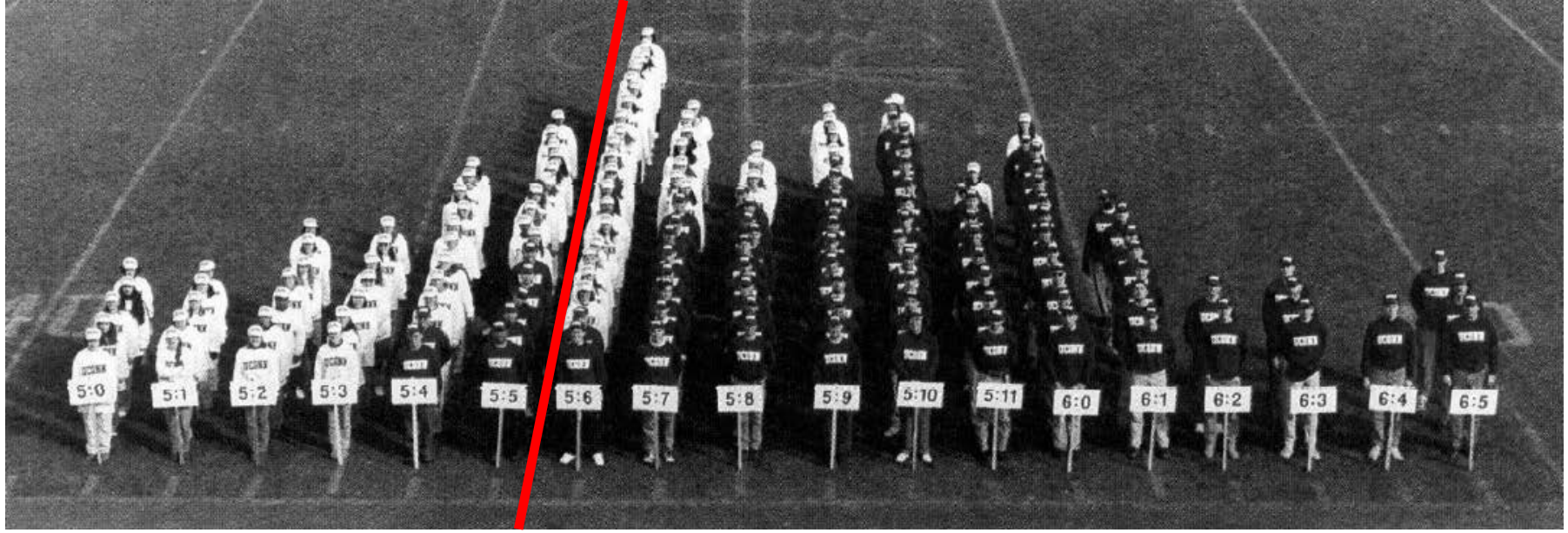
Introduce probabilities as uncertainties



From Lynn et al. 2015

A real world example: male perception – intuitive understanding of uncertainty (noise)

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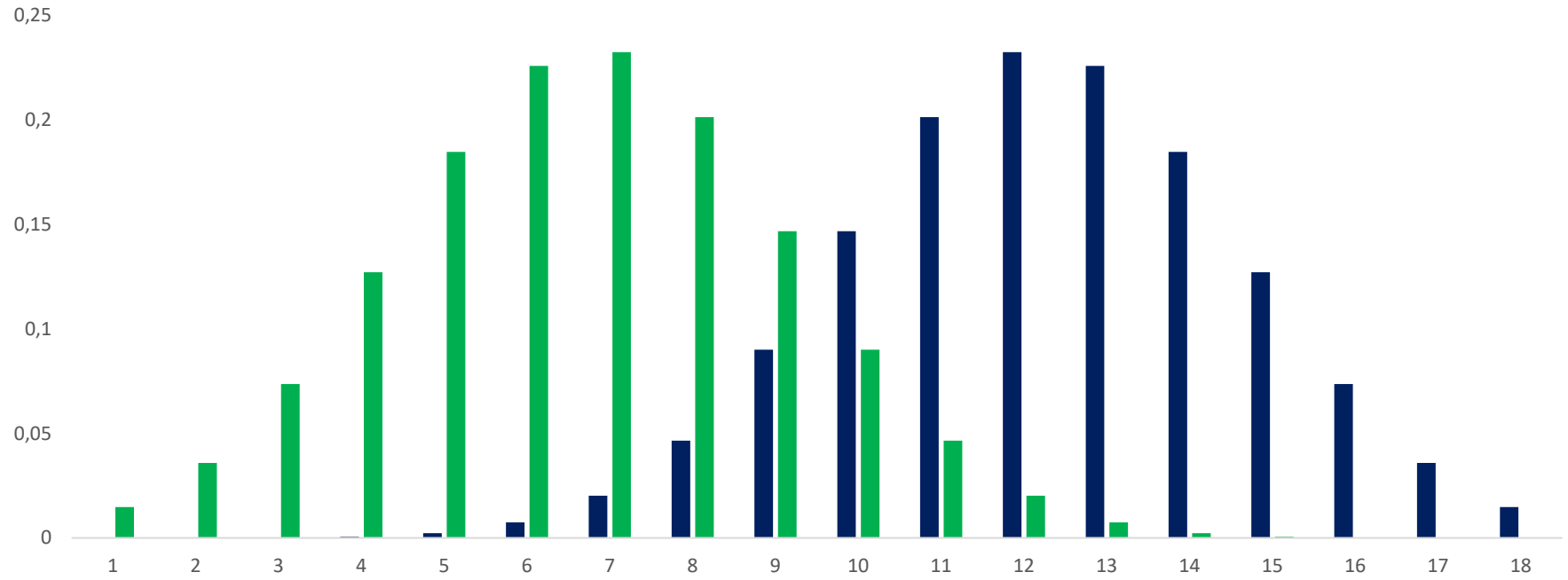
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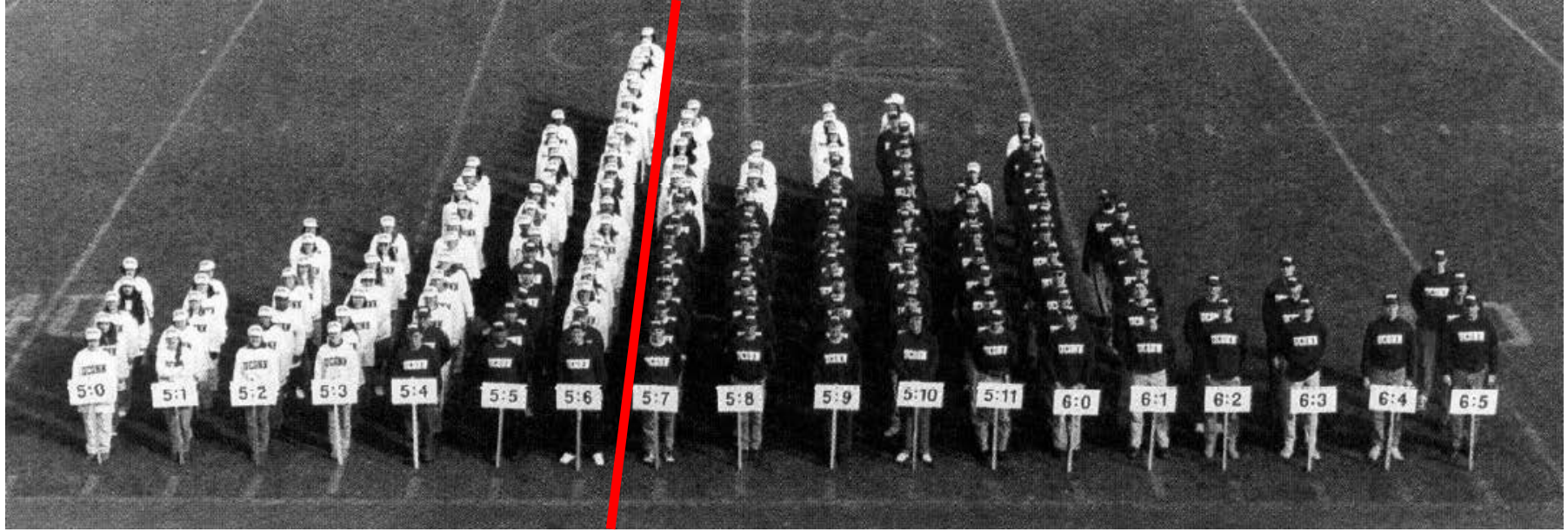
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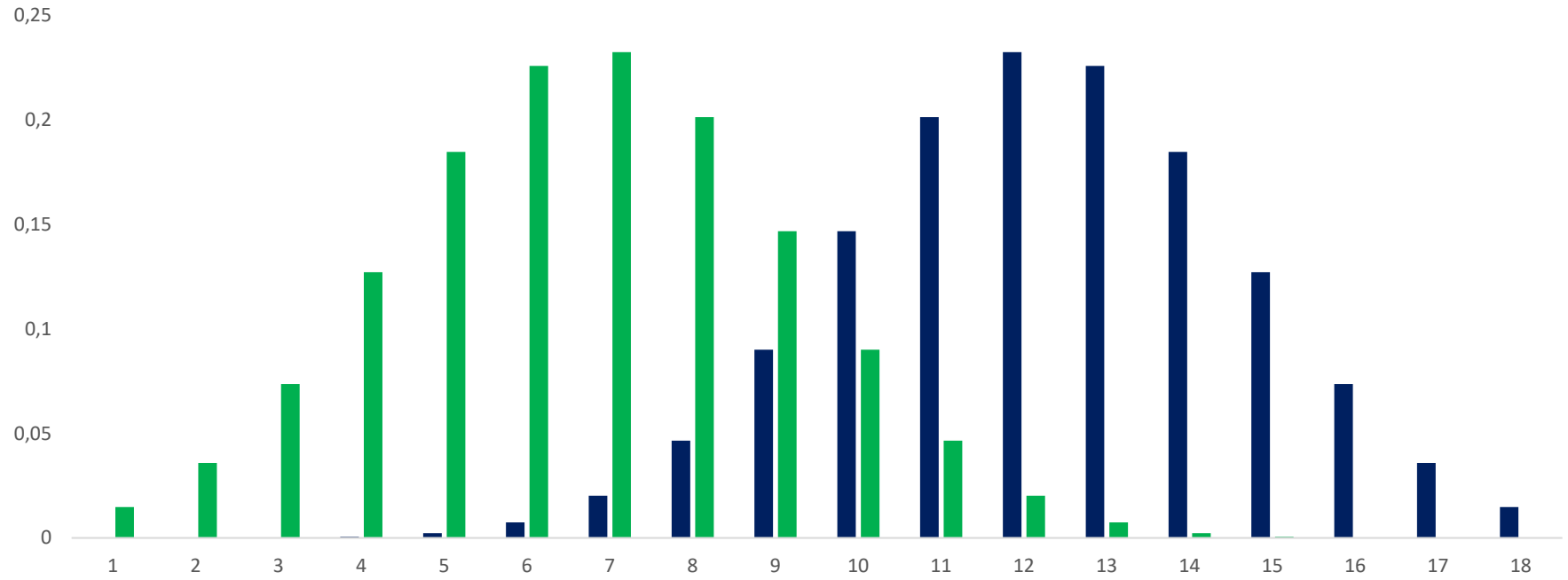
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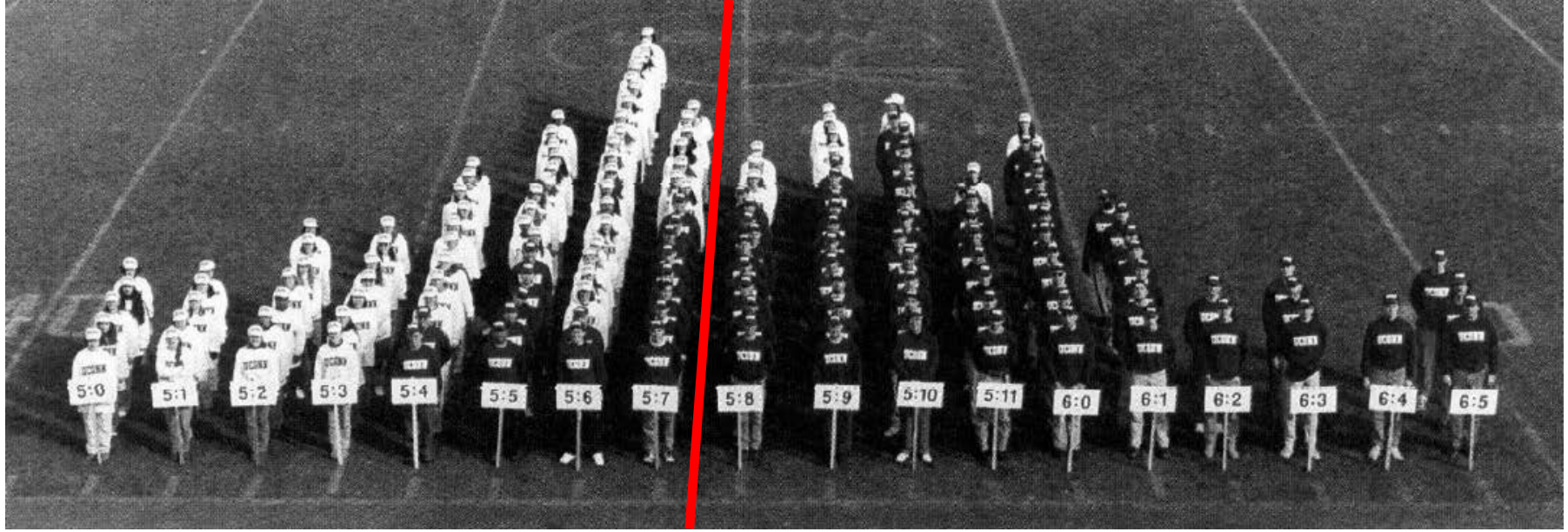
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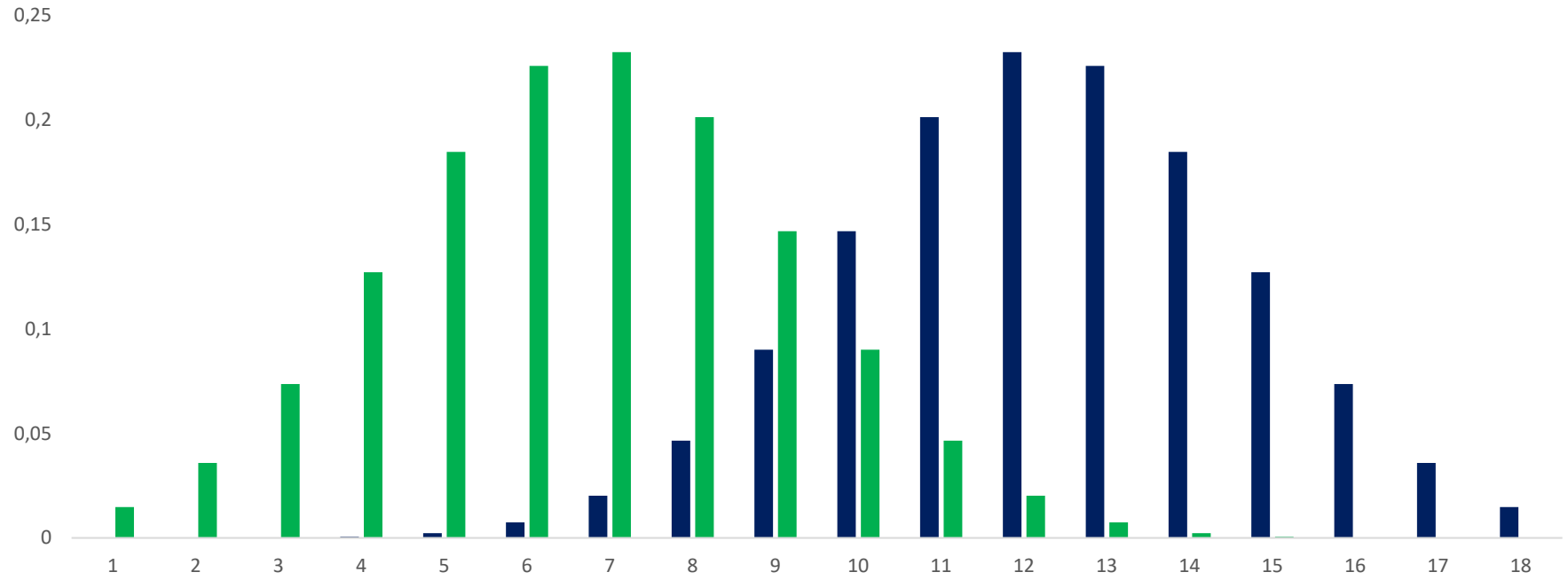
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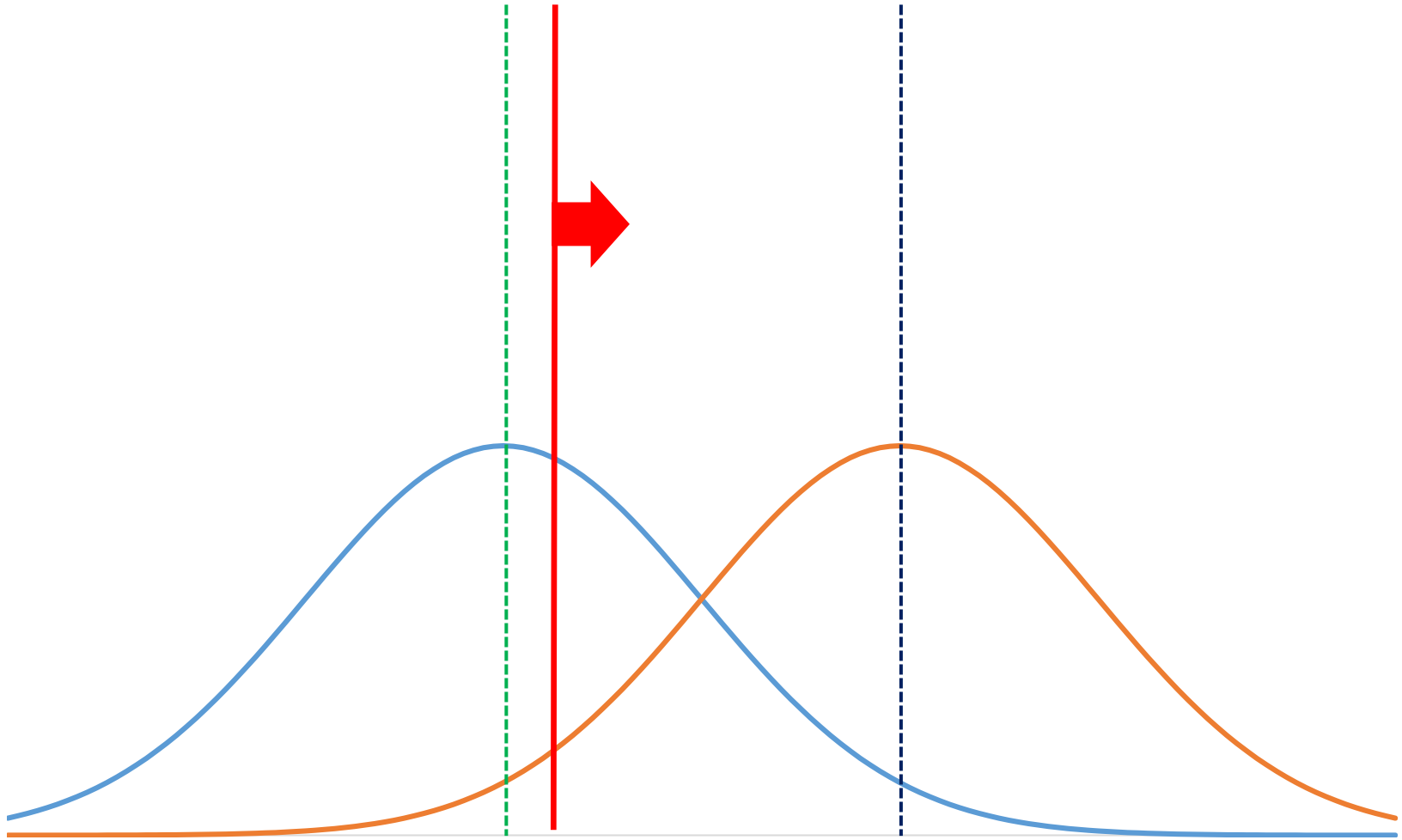
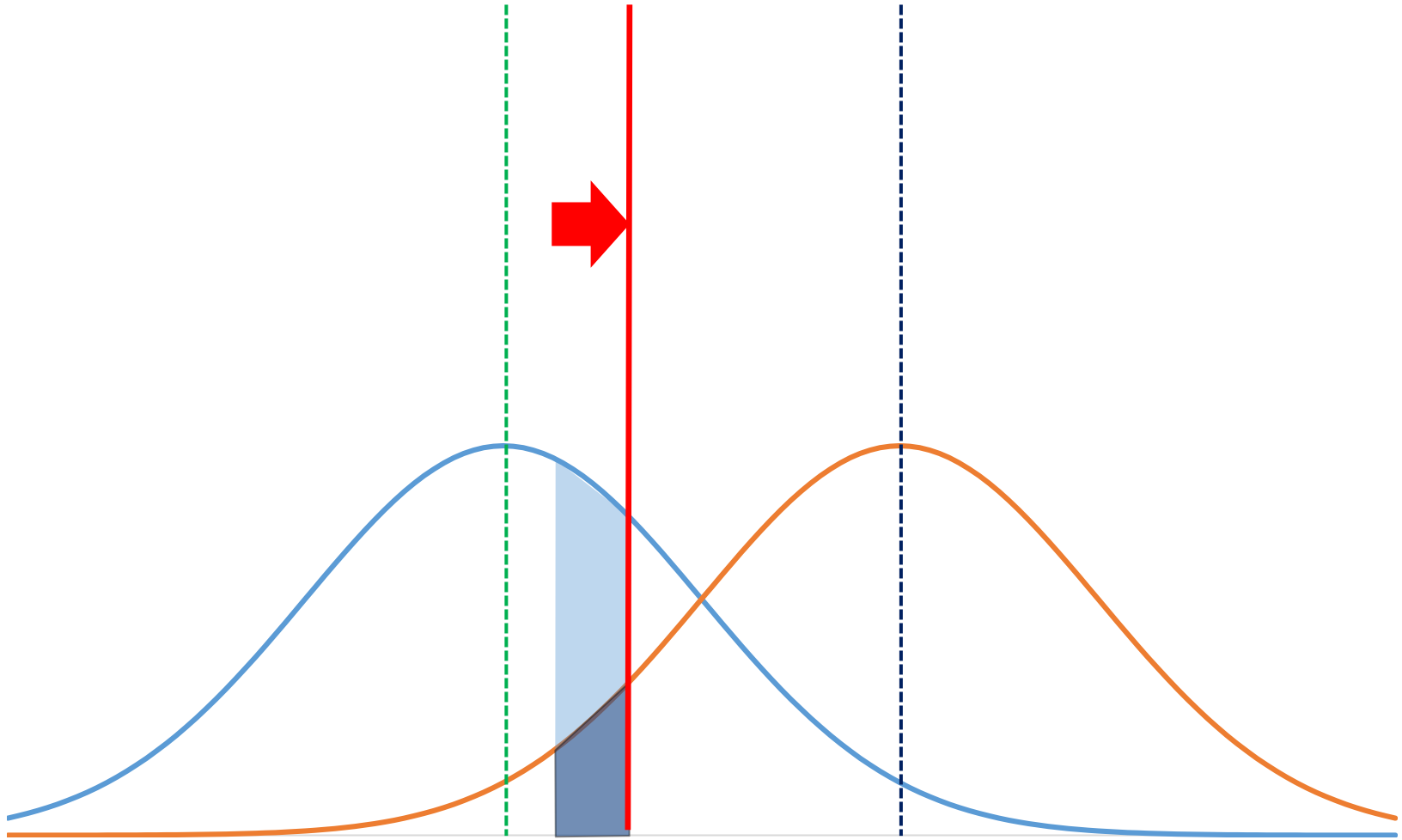
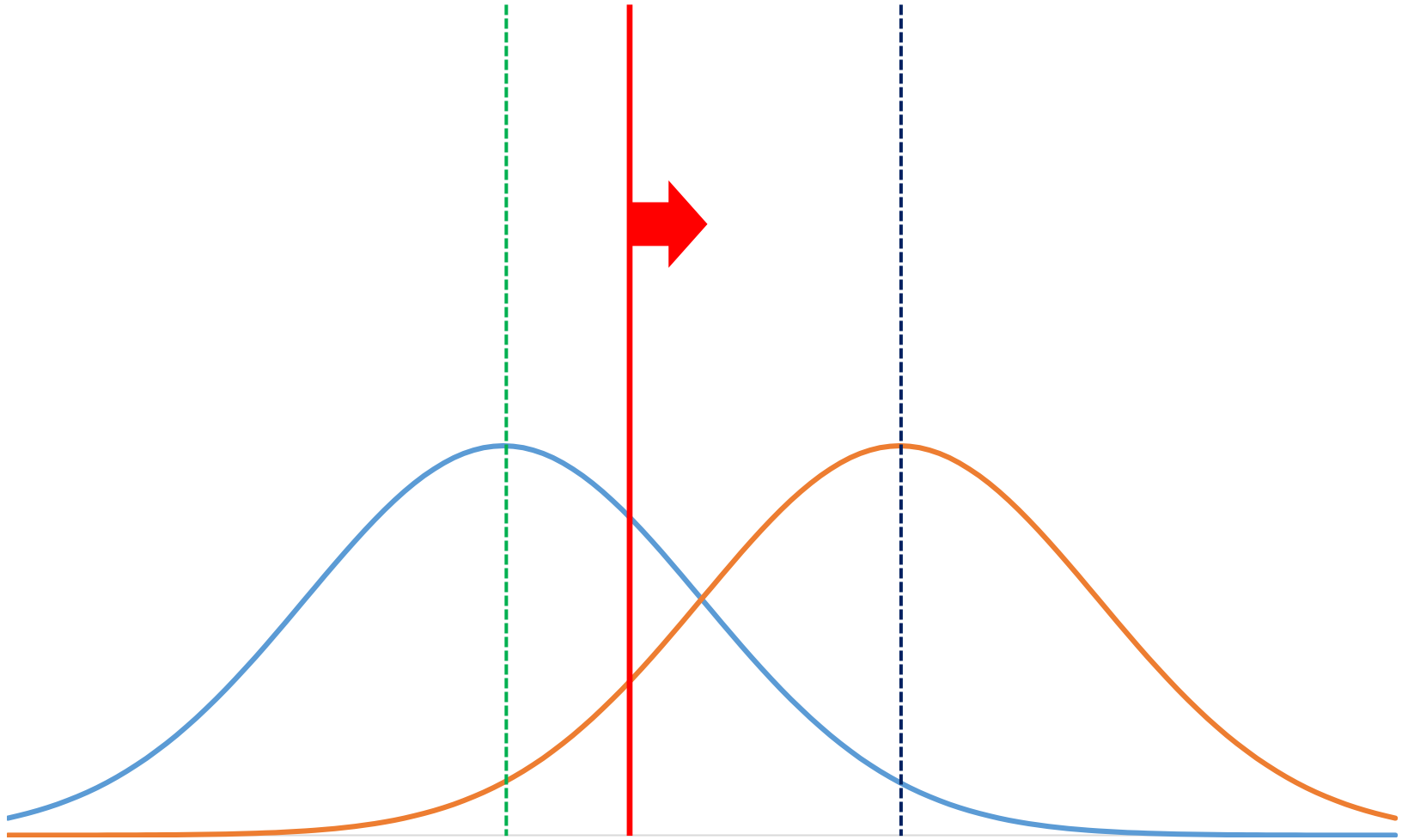
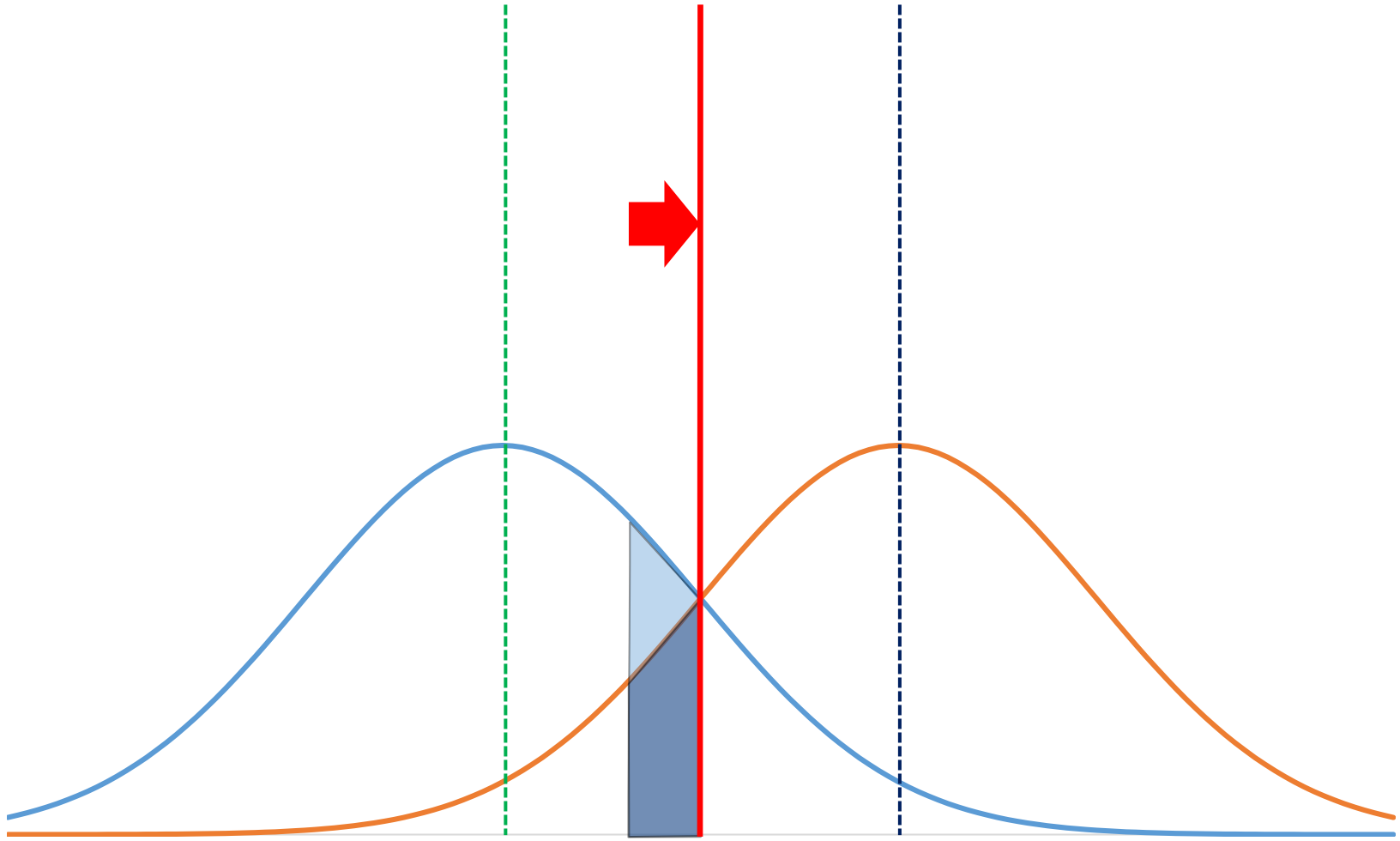
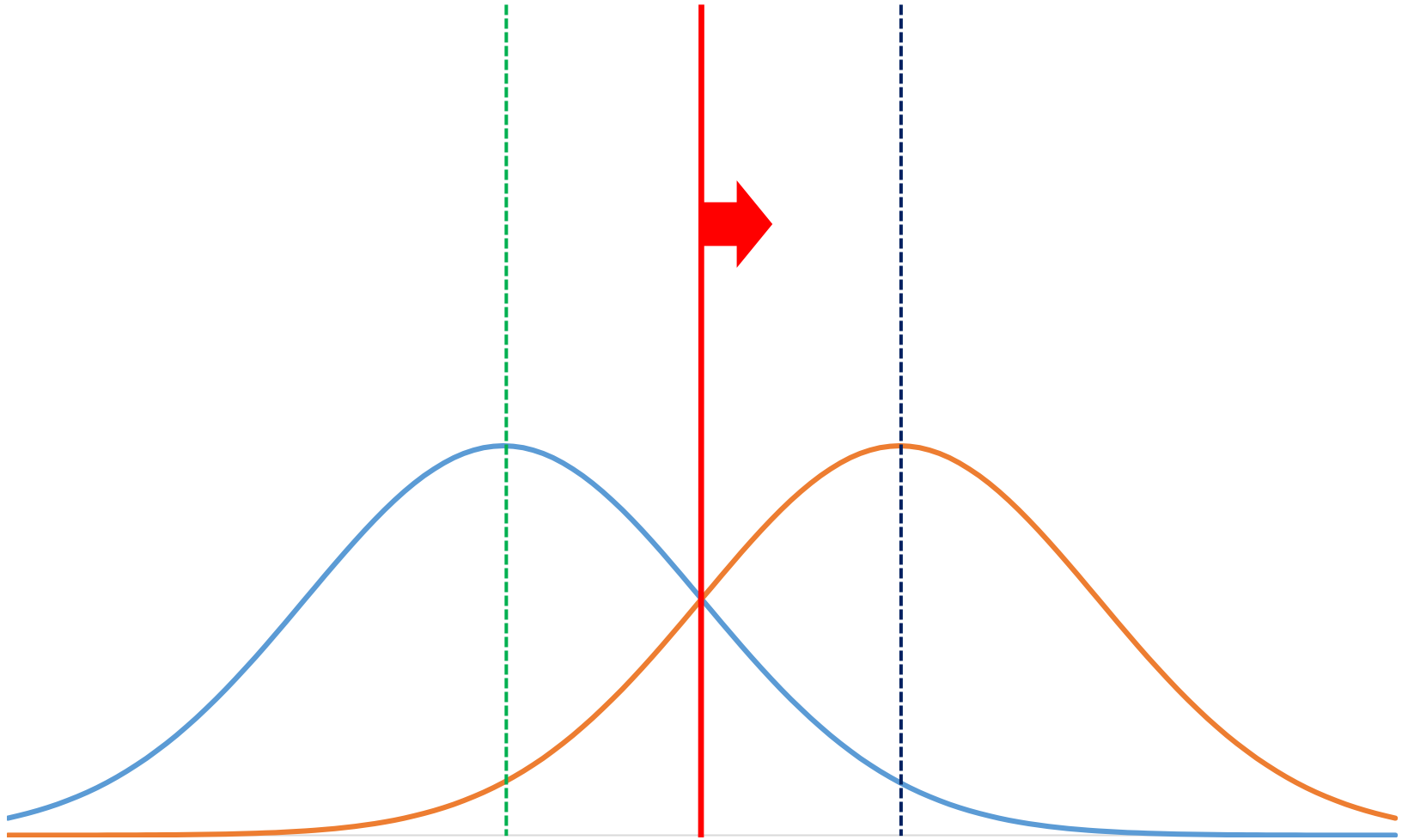
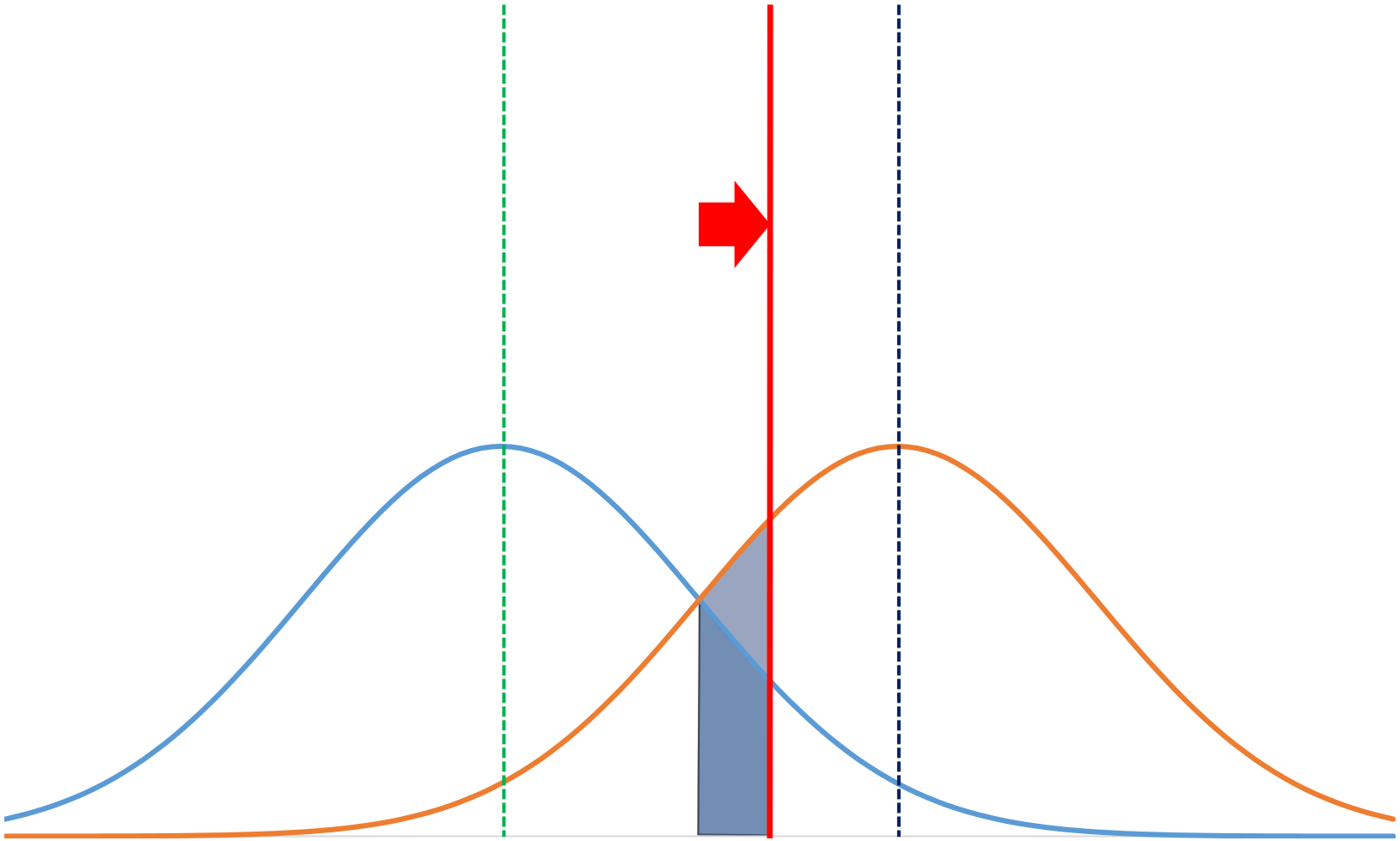


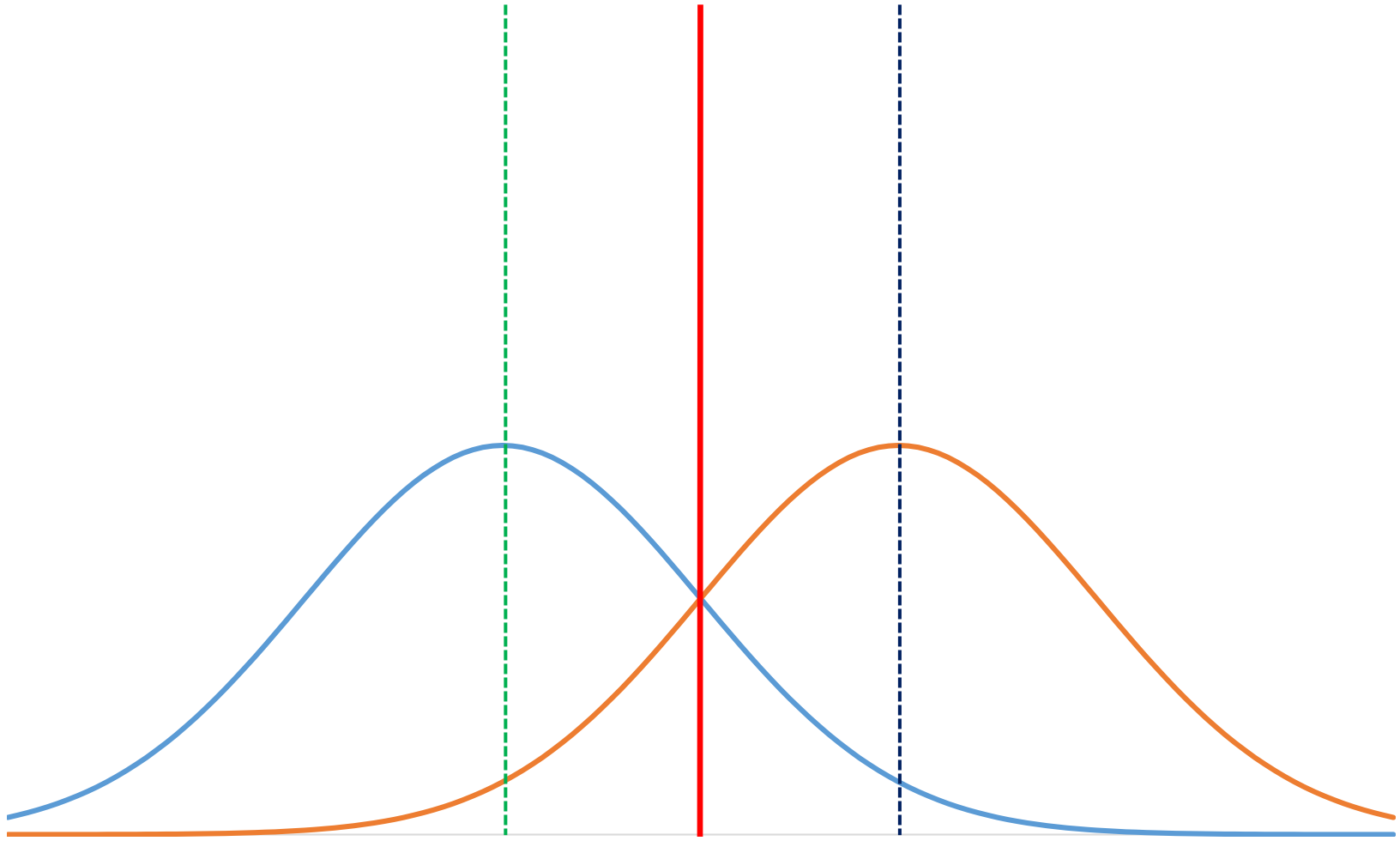


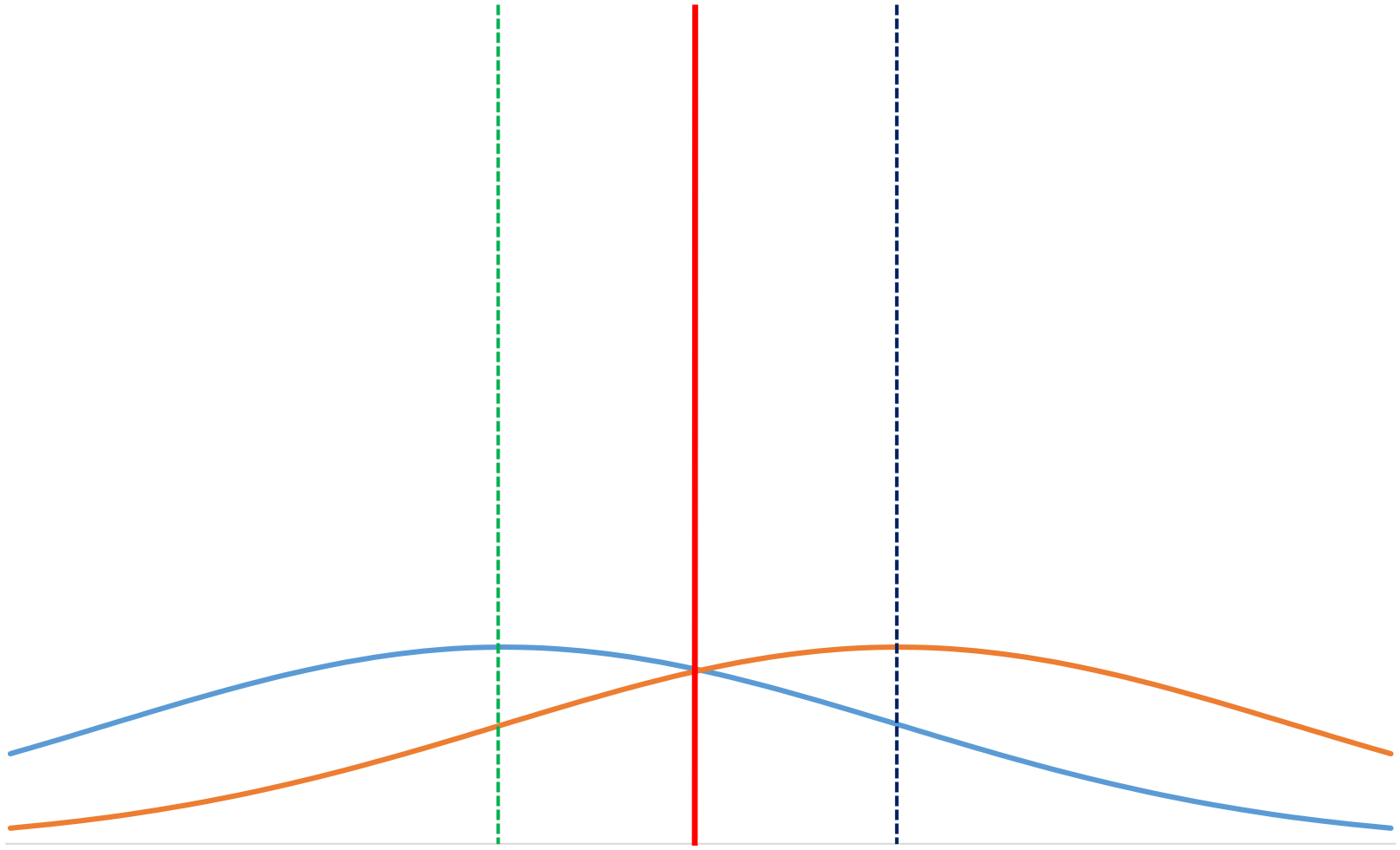


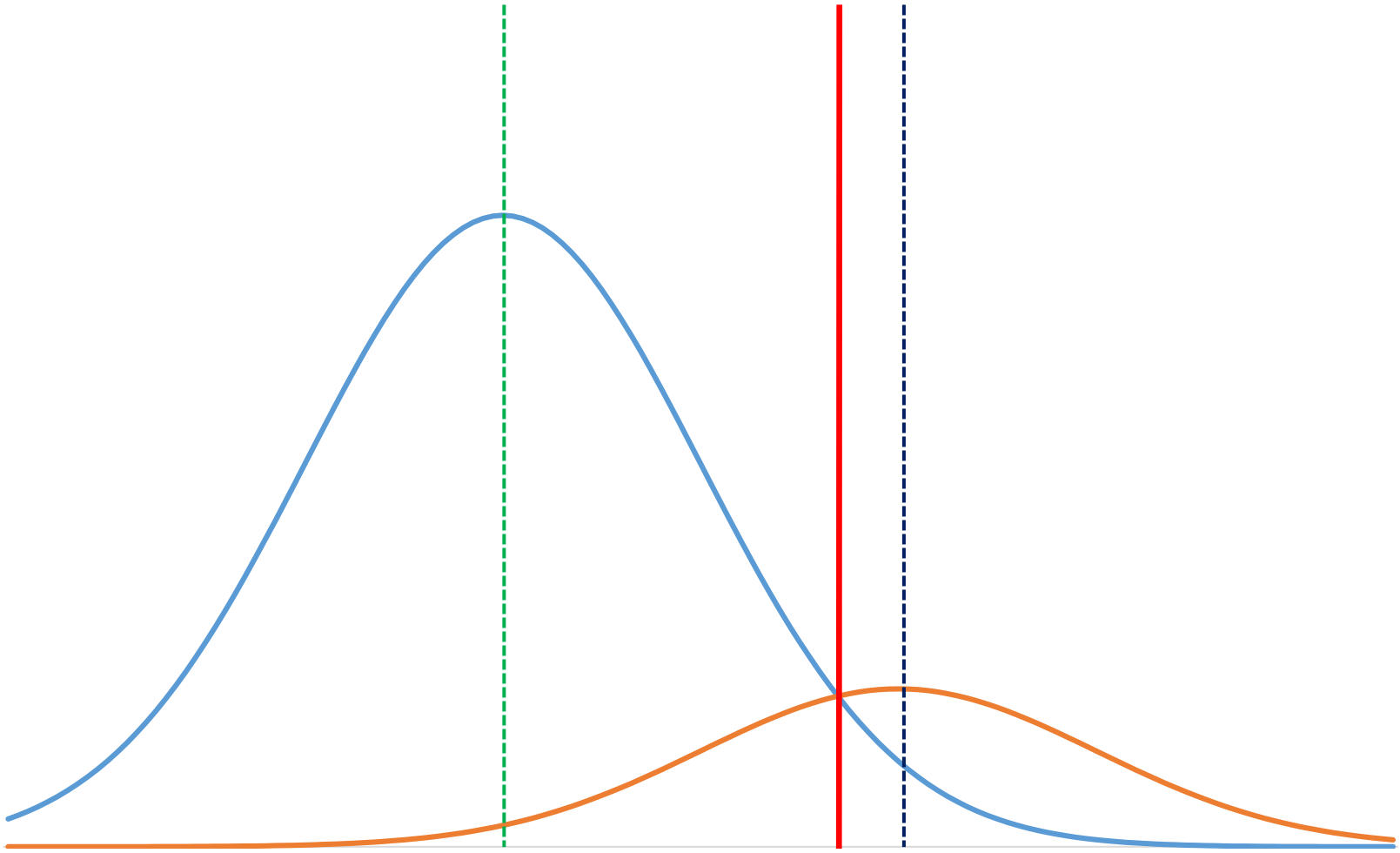


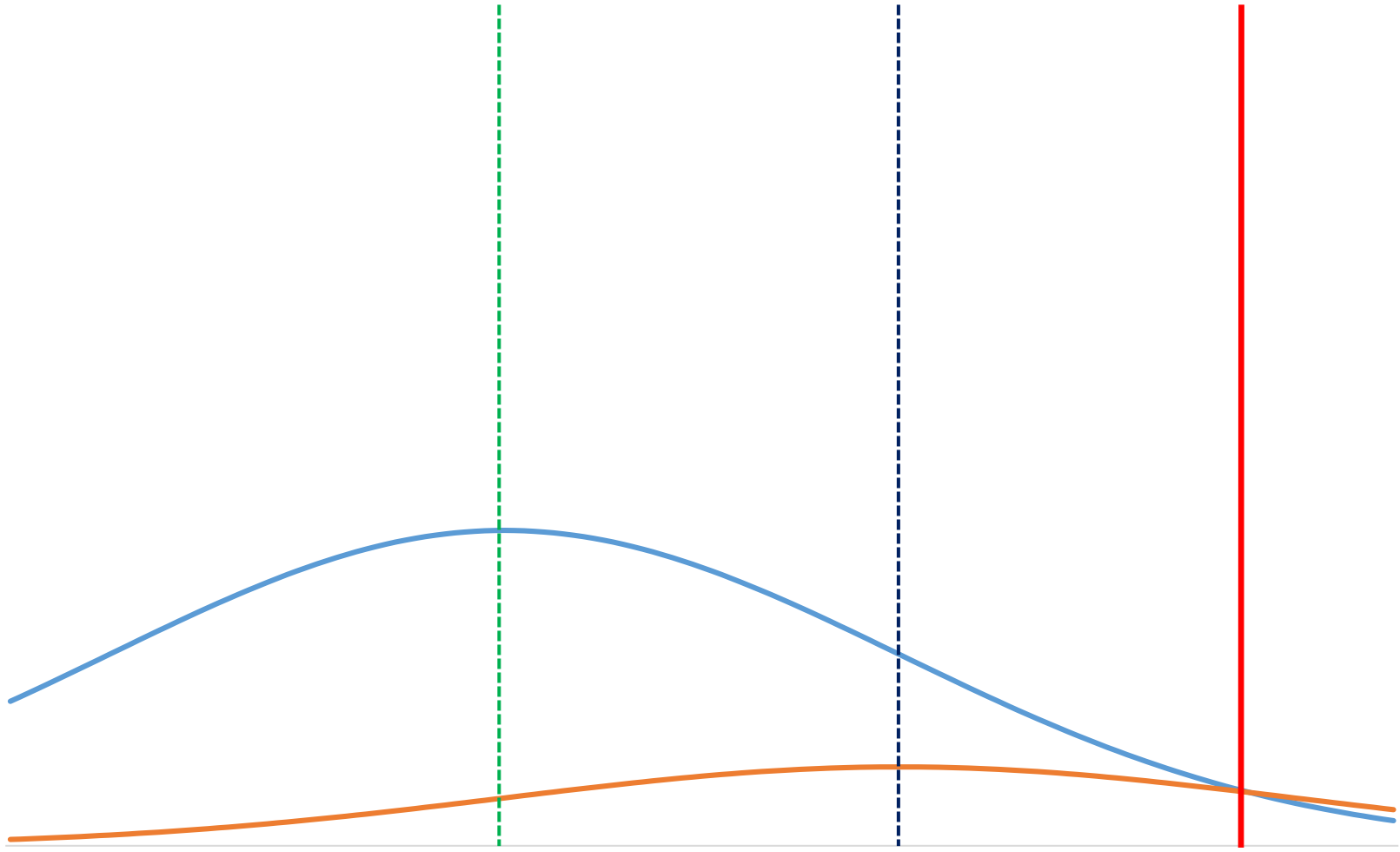




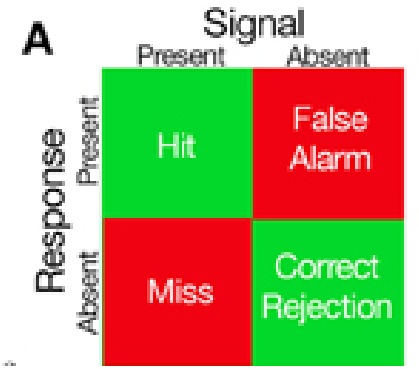








Bayes theorem and p-value fallacies



two types of errors in hypothesis testing

Test result	If H0 is true	If H0 is false
If H0 is rejected	α	1 - β (power)
If H0 is not rejected	1 - α	β

Prior odds = if you have two hypotheses you know nothing about: 1/1
Likelihood ratio often 80/5 = 16/1
Posterior odds = 1/1 * 16/1

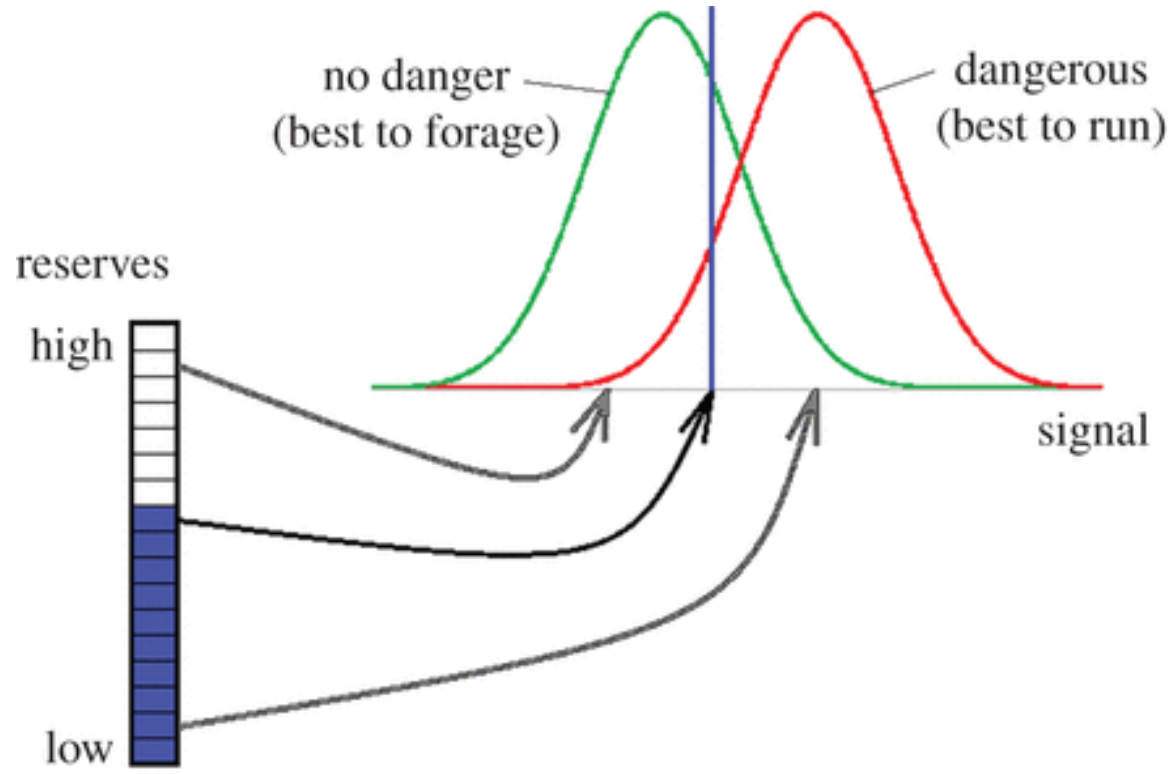
from Bayes theorem to Bayesian decision theory

students see that updating old information with new information is what they do (but not always, links to cognitive biases)

Relationship frequentist to Bayesian stats

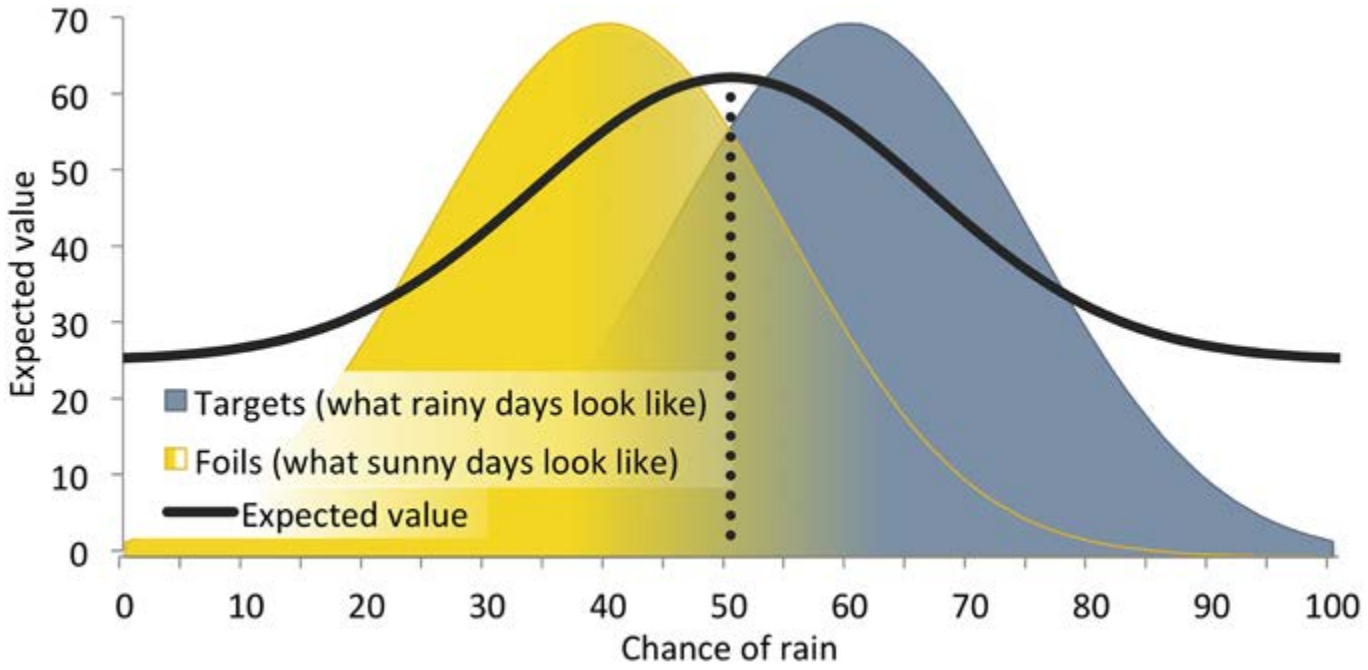
But doubt that anything is useful still, as real world seems to be full of biases

Introduce risk in Signal detection theory



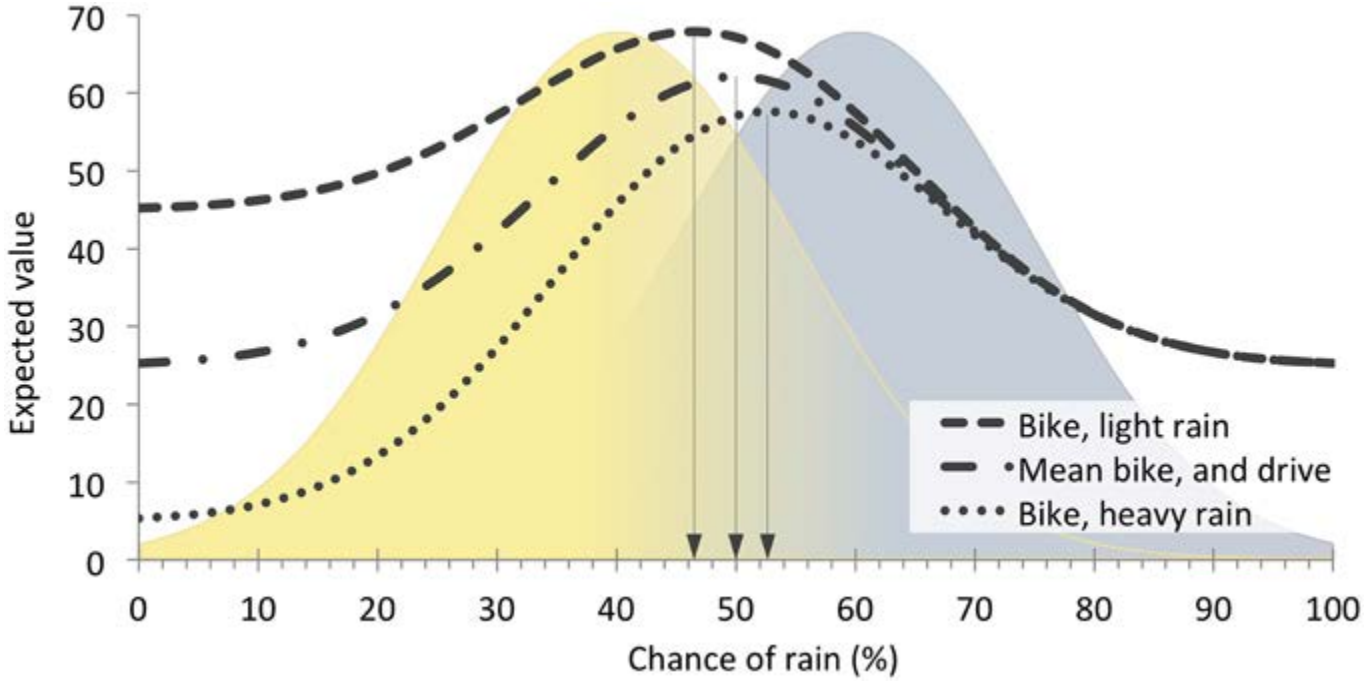
Predation risk or starvation risk changes the decision criterion

Unbiased decision criterion = symmetrical EV



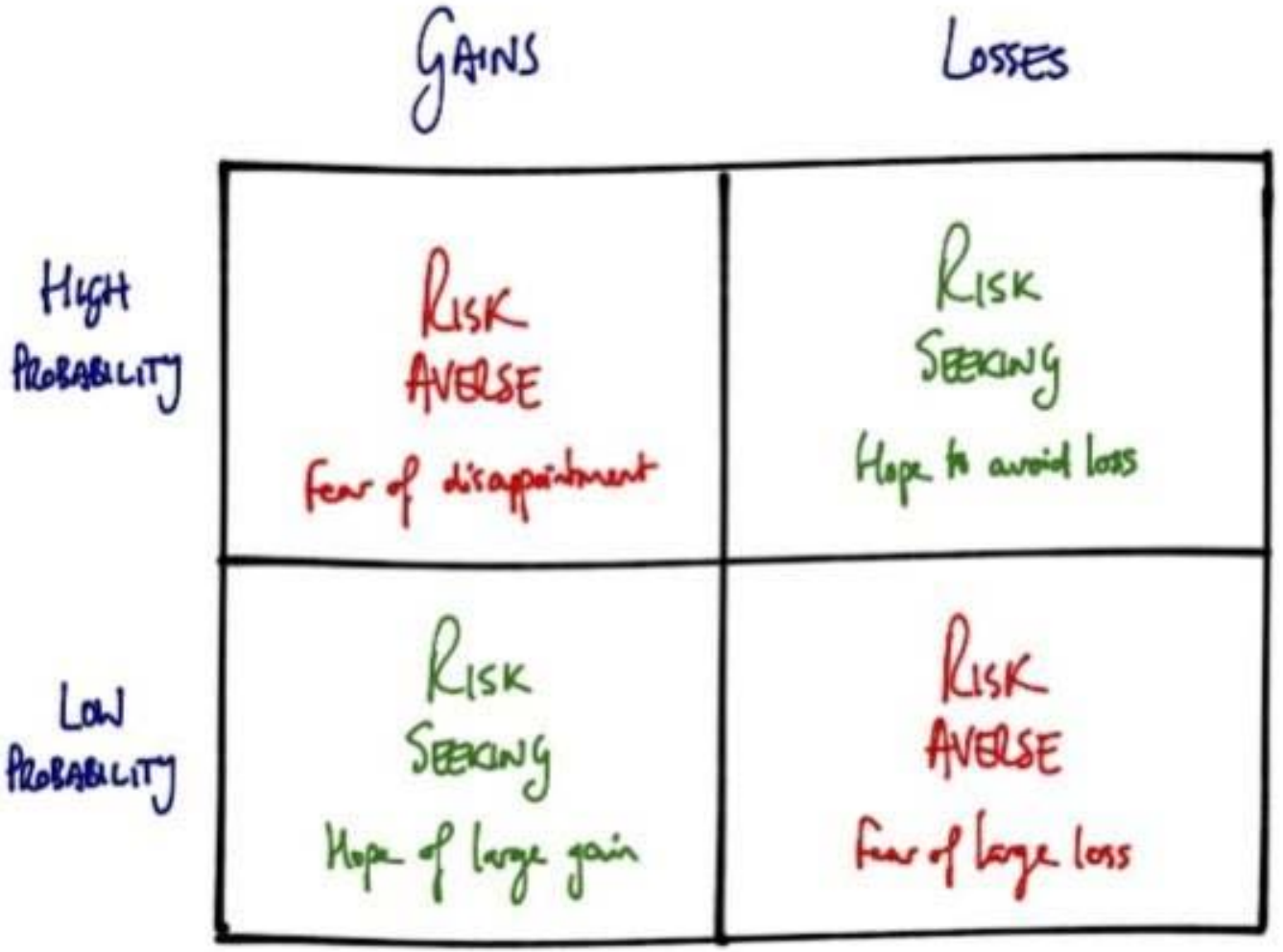
From Lynn et al. 2015

Biased decision criterion from asymmetrical EV



From Lynn et al. 2015

Men are risk seeking in the mating game



Expected utility in male perception – outcome variability

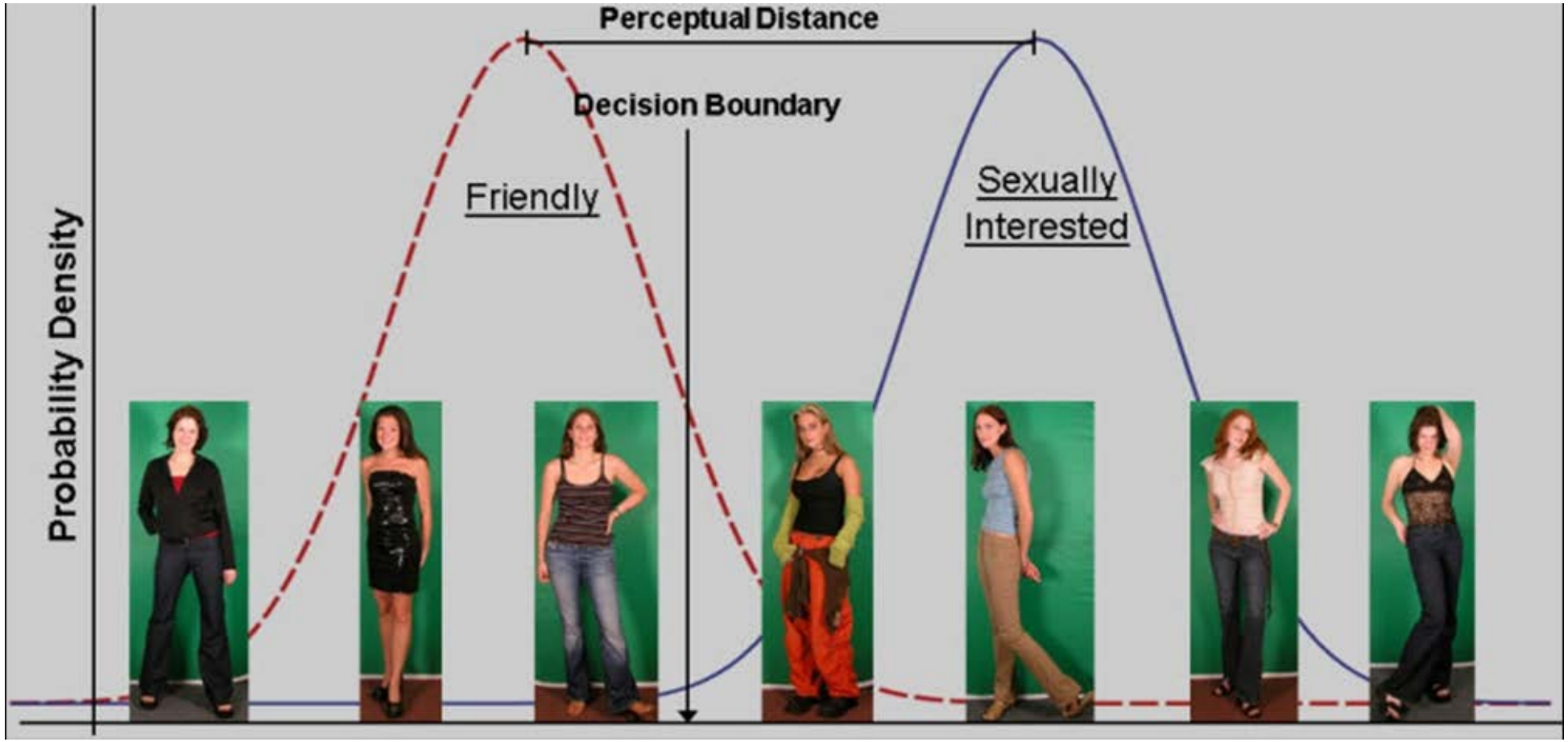
x_i …all possible results => mating/offspring or no mating/ no offspring
p_i… probability of the results: 1:100
v … value function, means relative value in the decision-maker's mind
π … probability weighting function

$V = \pi(.01) * v(\text{offspring}) + \pi(.99) * v(\text{no offspring})$

We know: $\pi(.01) > .01$ due to overweighting of small probabilities

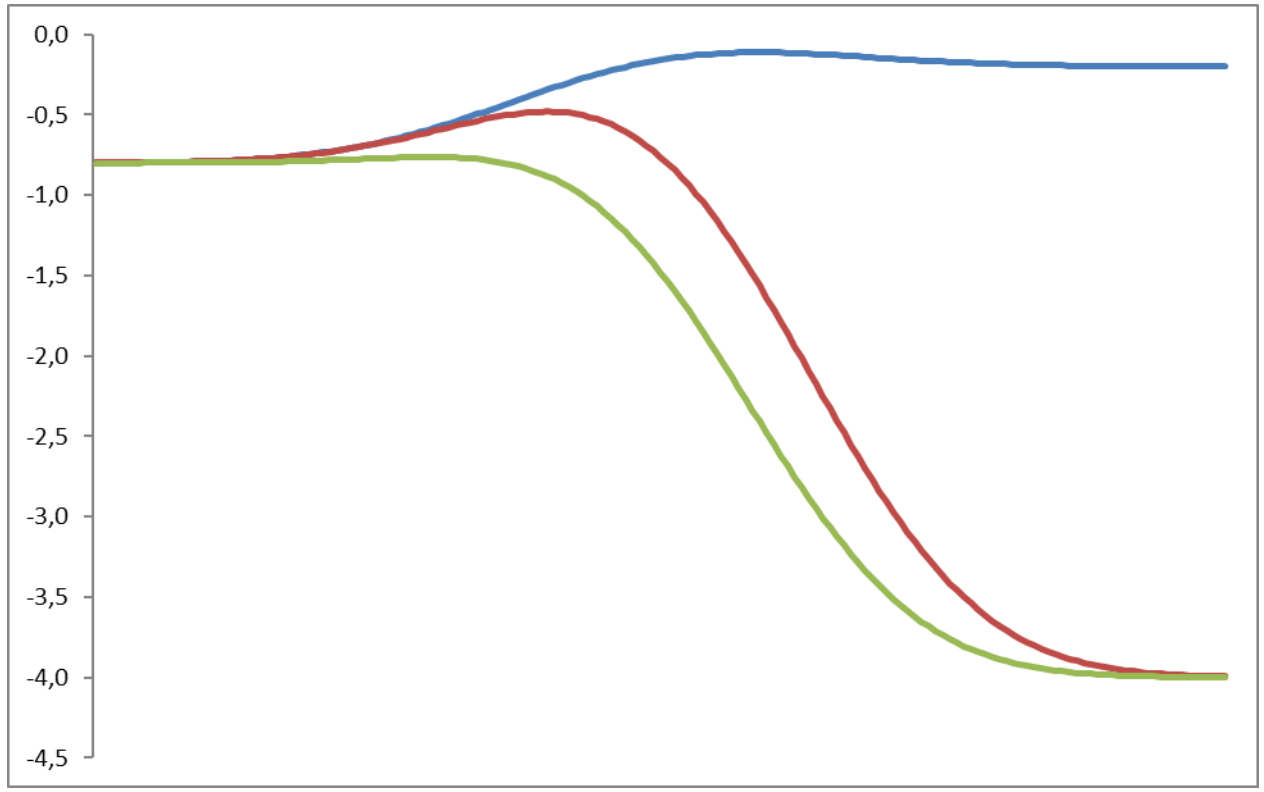
We know: loss is aversive, gain is attractive

Decision criterion in male perception

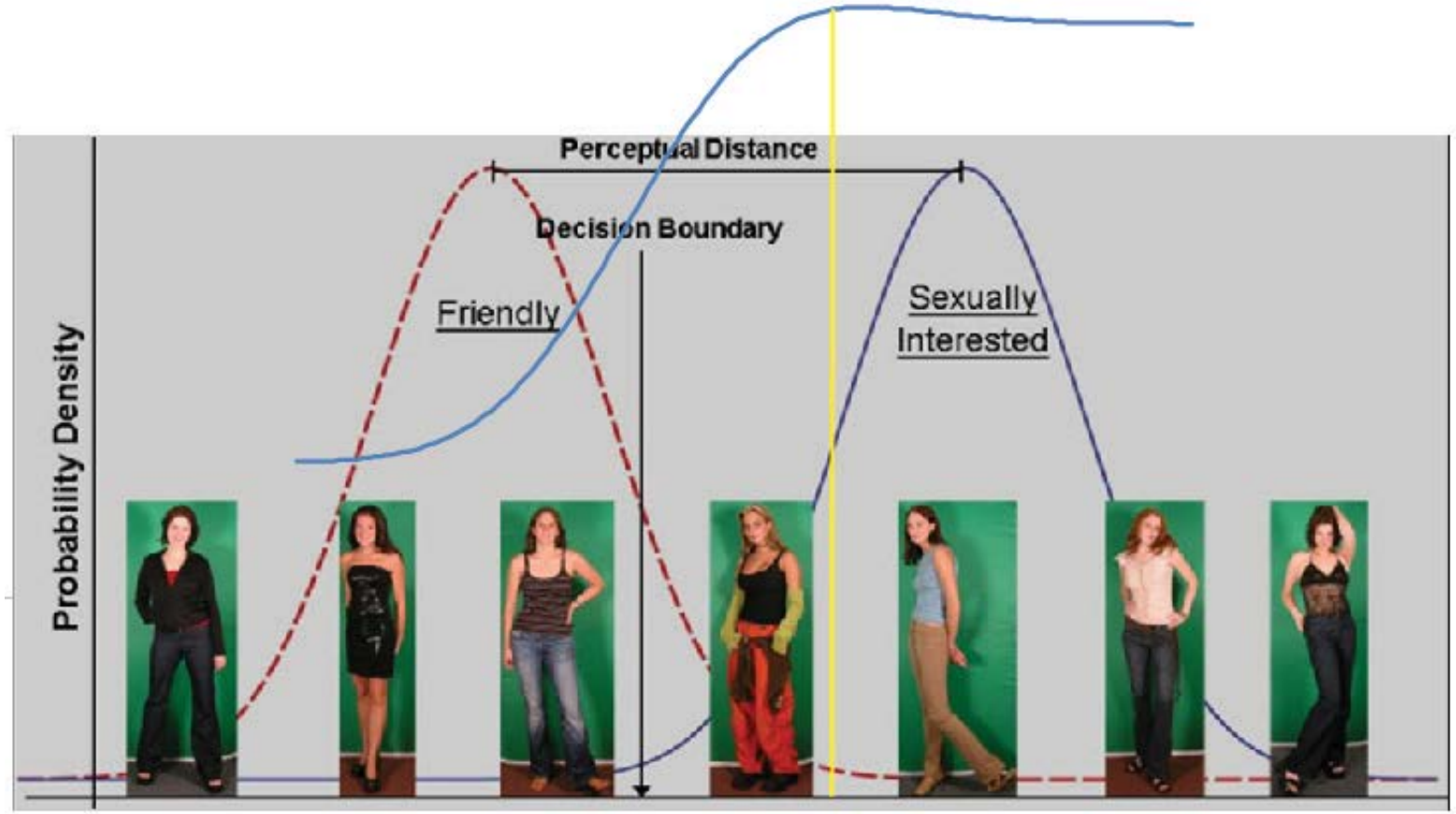


#metoo or bachelor risk changes the decision criterion

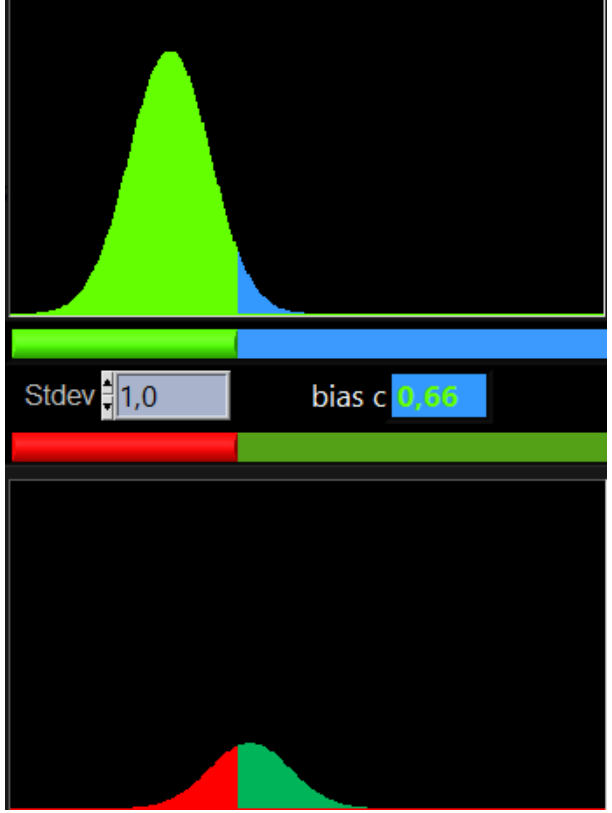
Combining perceptual and economic uncertainty – integrated framework

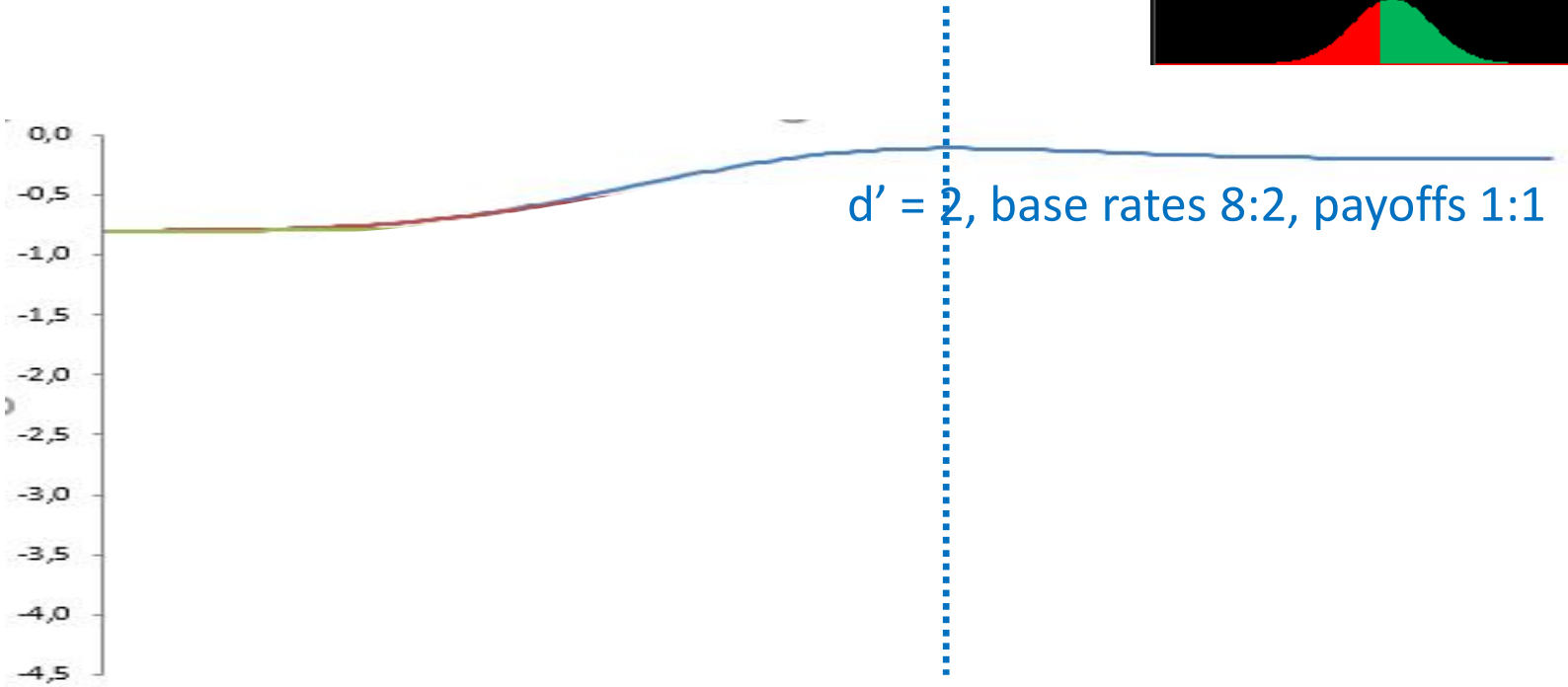


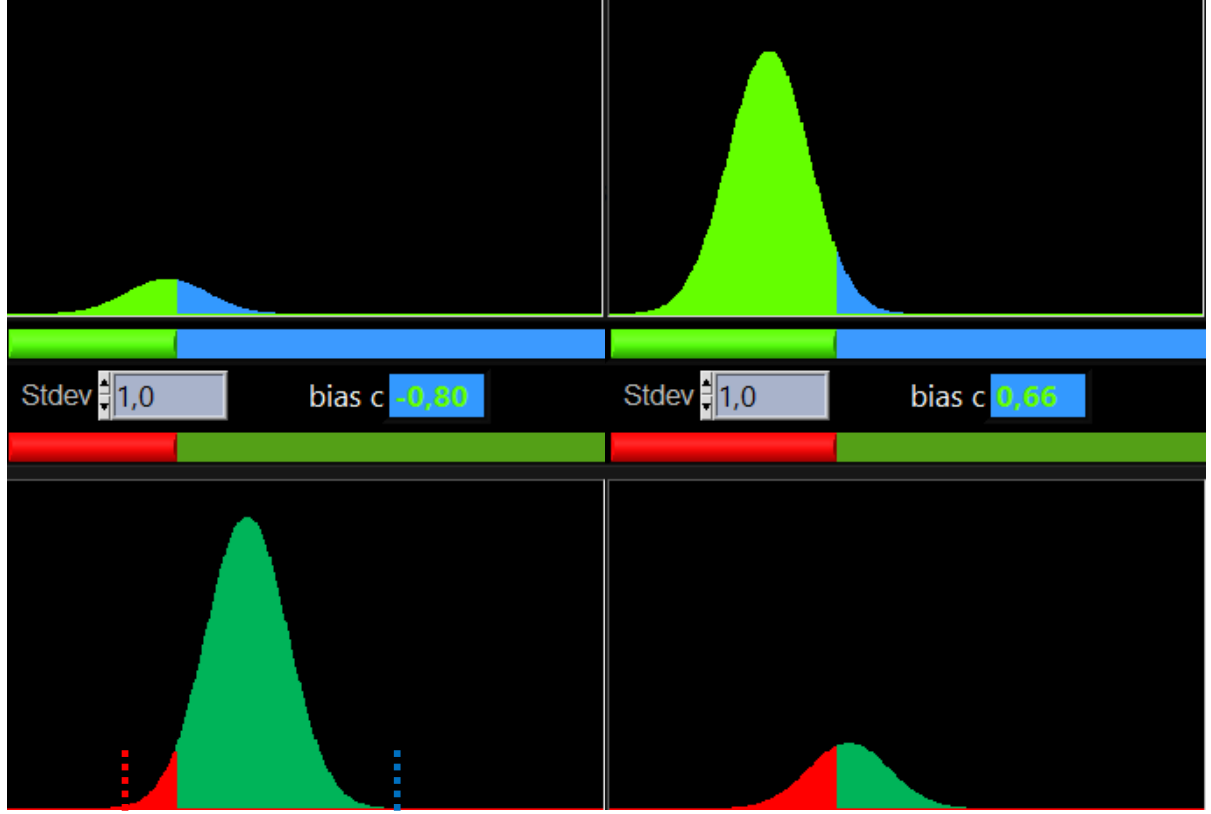
Male perception according to Error management theory



Hands-on exercises with labview program - Expected utility in SDT



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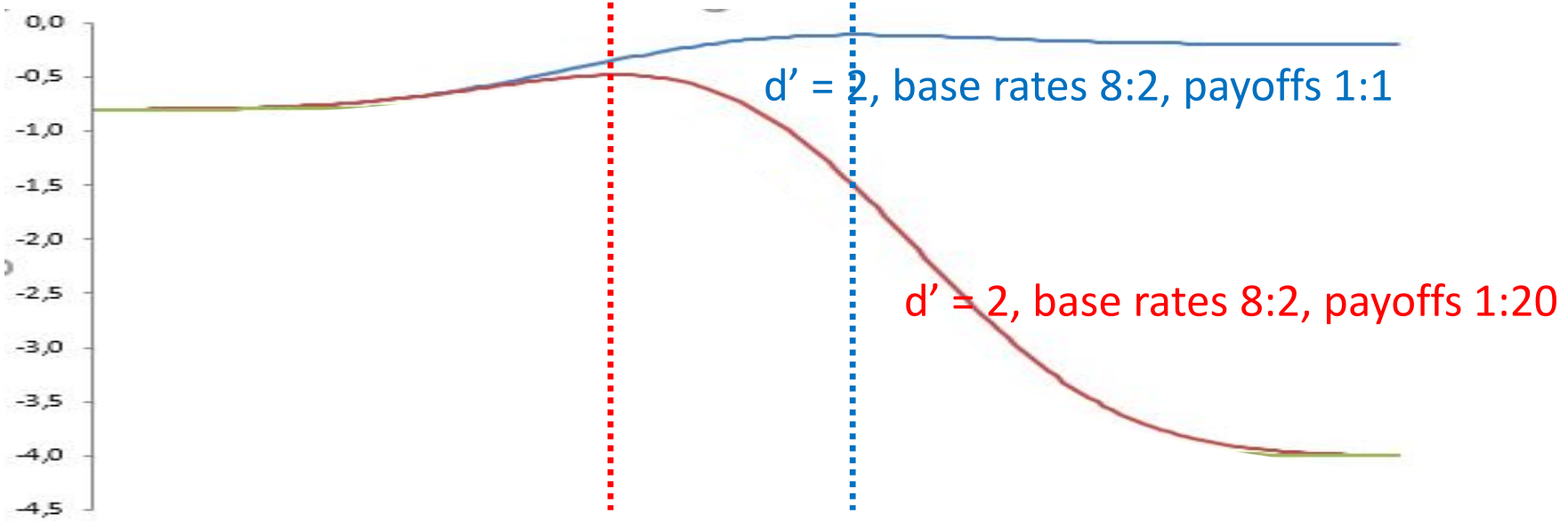
bias c -0,80
Stdev 1,0
bias c 0,66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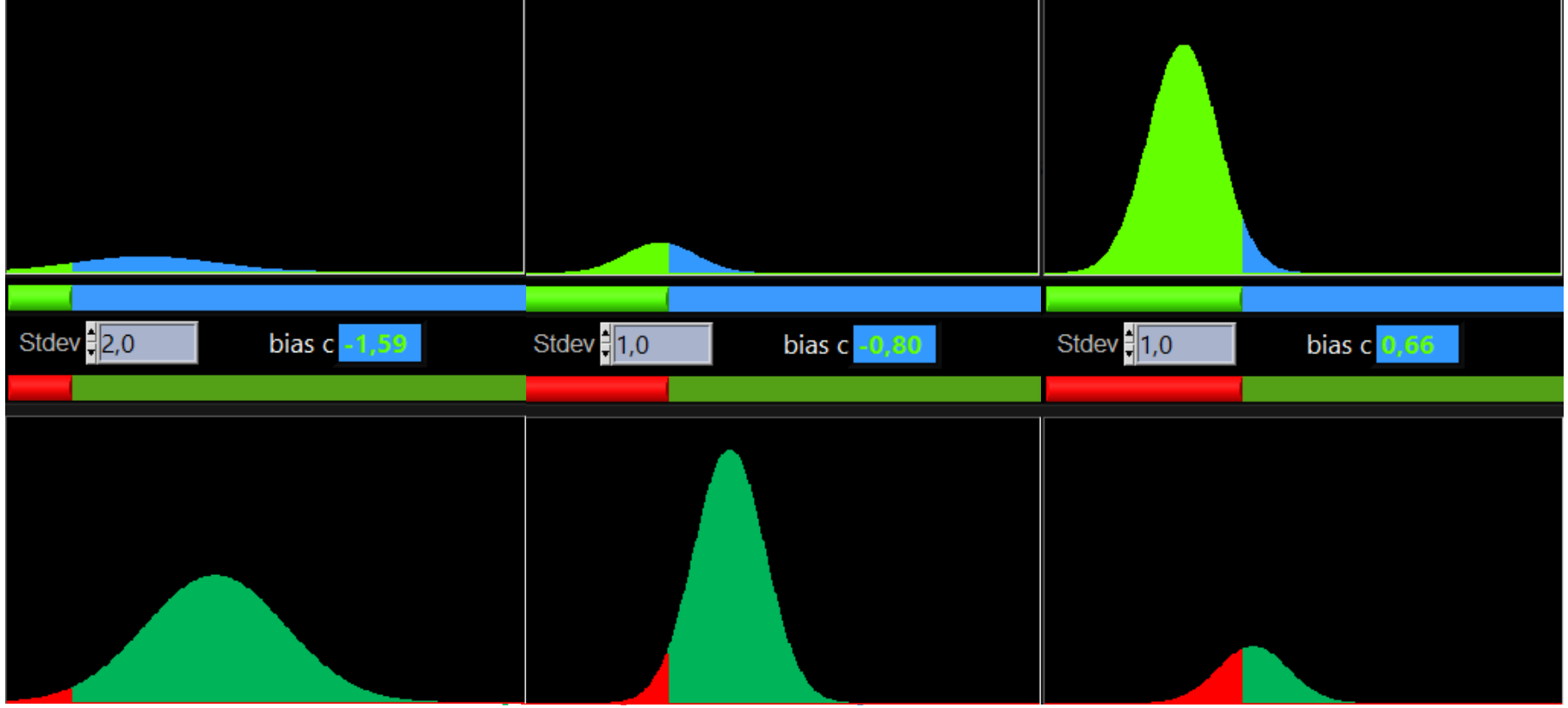
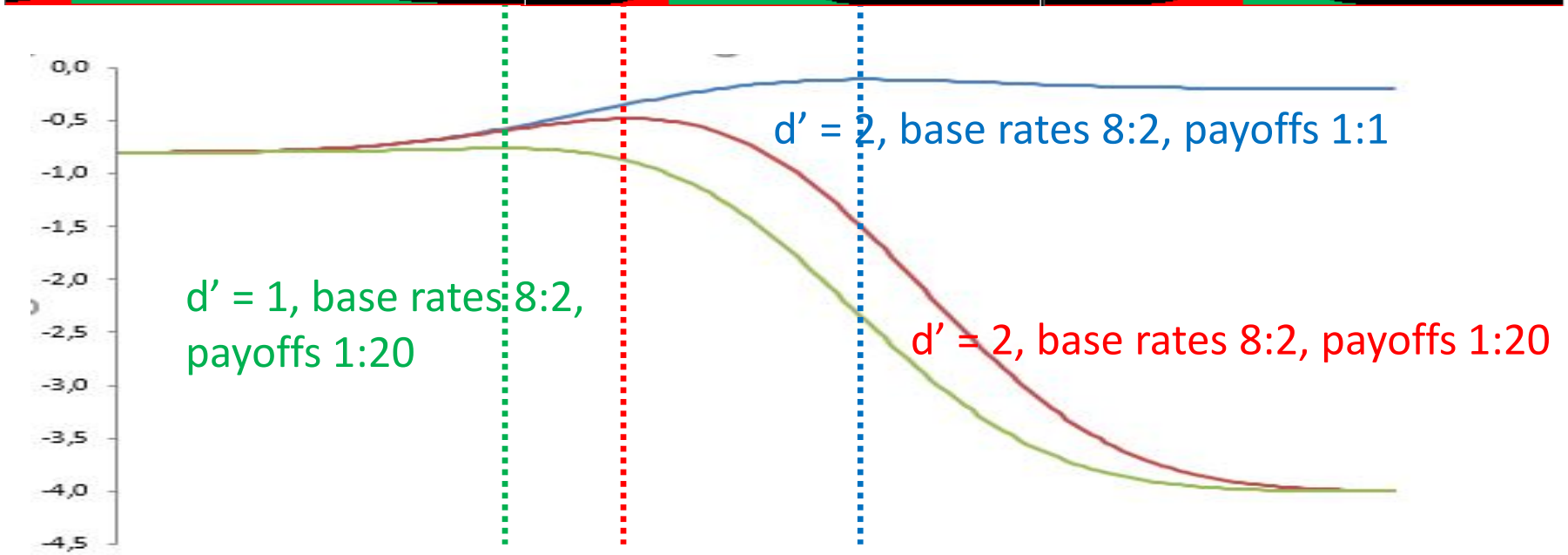
d’ = 2, base rates 8:2, payoffs 1:1
d’ = 2, base rates 8:2, payoffs 1:20


Stdev 2,0
bias c -1,59
Stdev 1,0
bias c -0,80
Stdev 1,0
bias c 0,66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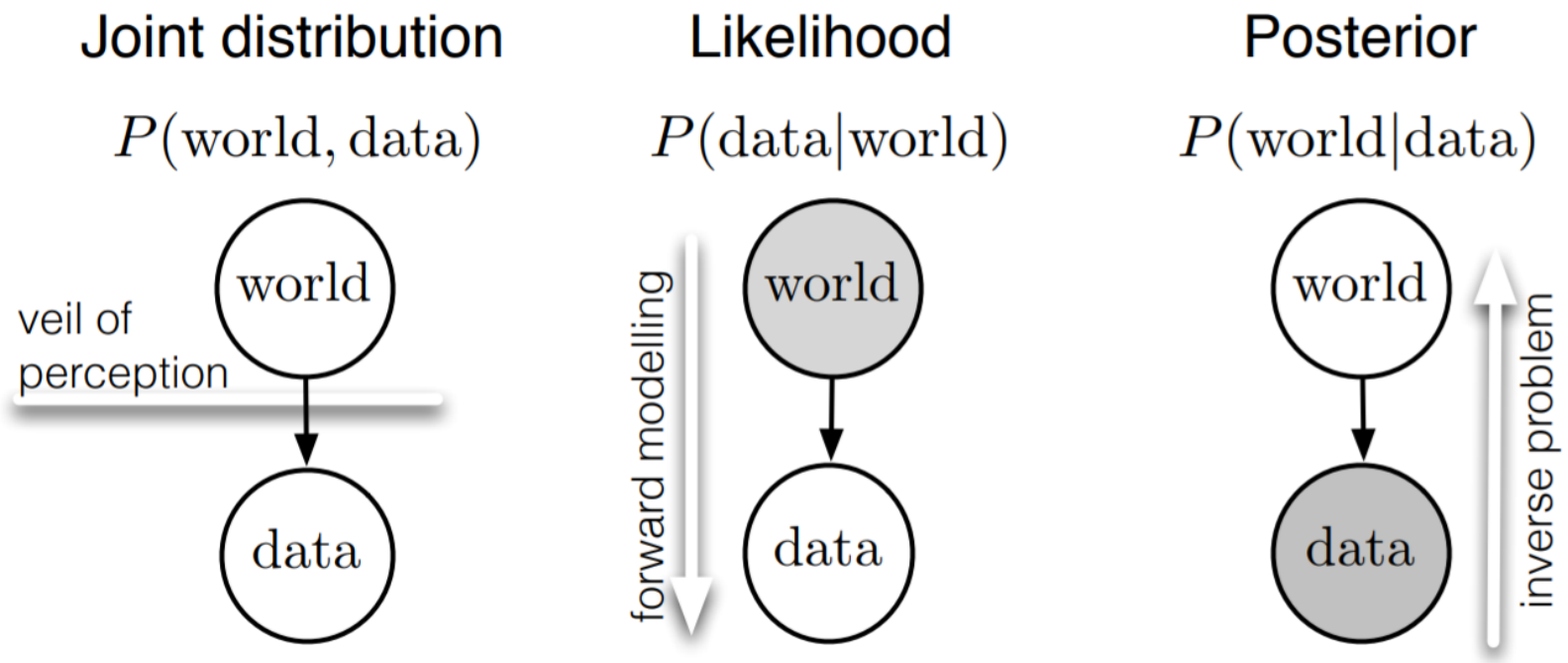
d' = 2, base rates 8:2, payoffs 1:1
d' = 1, base rates 8:2, payoffs 1:20
d' = 2, base rates 8:2, payoffs 1:20

Be experimenter vs be the participant



From Vincent 2015


Thanks for listening, Happy to take your questions