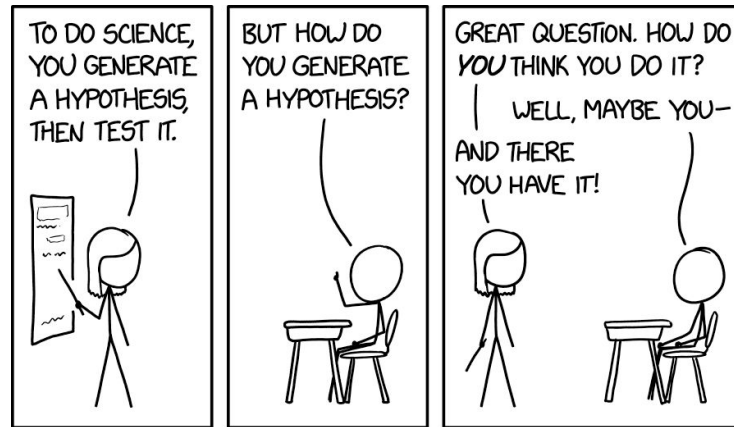


# What are hypotheses?



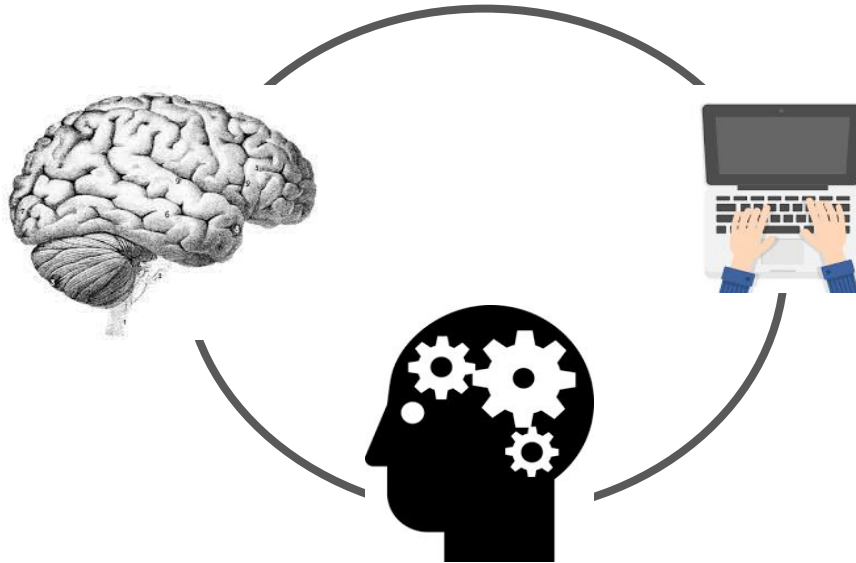
# Another quiz.

5m.

# Learning goals

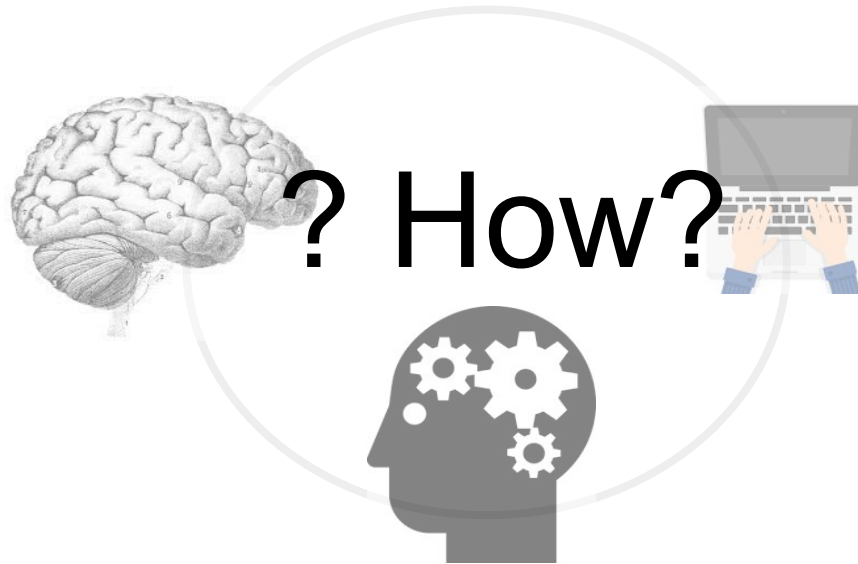
1. Situate hypothesis within the scientific method.
2. Learn about guidelines for hypothesis generation.
3. Refresh your understanding of hypothesis-testing.
4. Interpret evidence according to current scientific standards.

Cog. Neuro. unites the **brain**, **cognition**, and **behavior**



**Cognitive Neuroscience Research Methods**

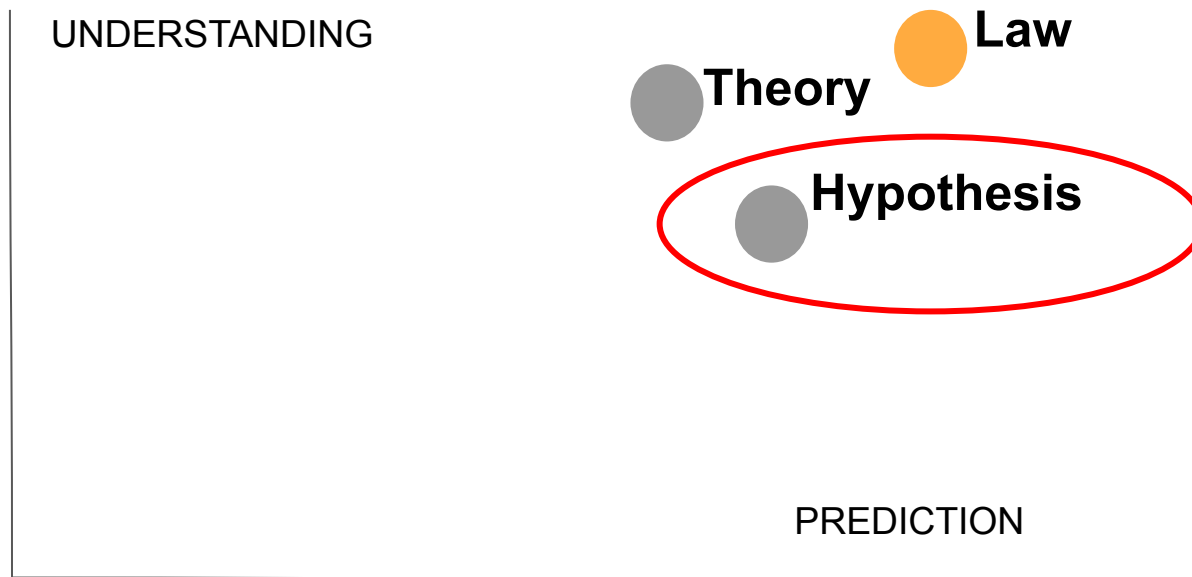
Cog. Neuro. unites the **brain**, **cognition**, and **behavior**



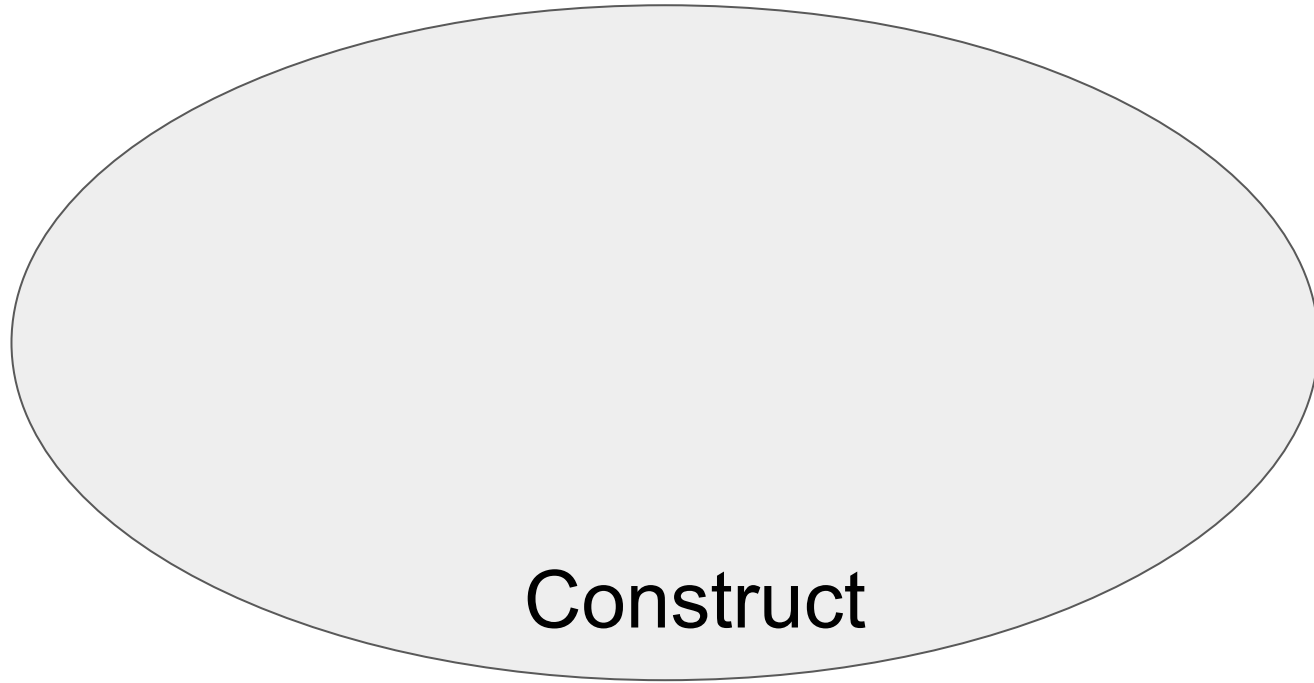
**Cognitive Neuroscience Research Methods**

A hypothesis is a prediction tested with experimentation.

# Complementary trade-offs

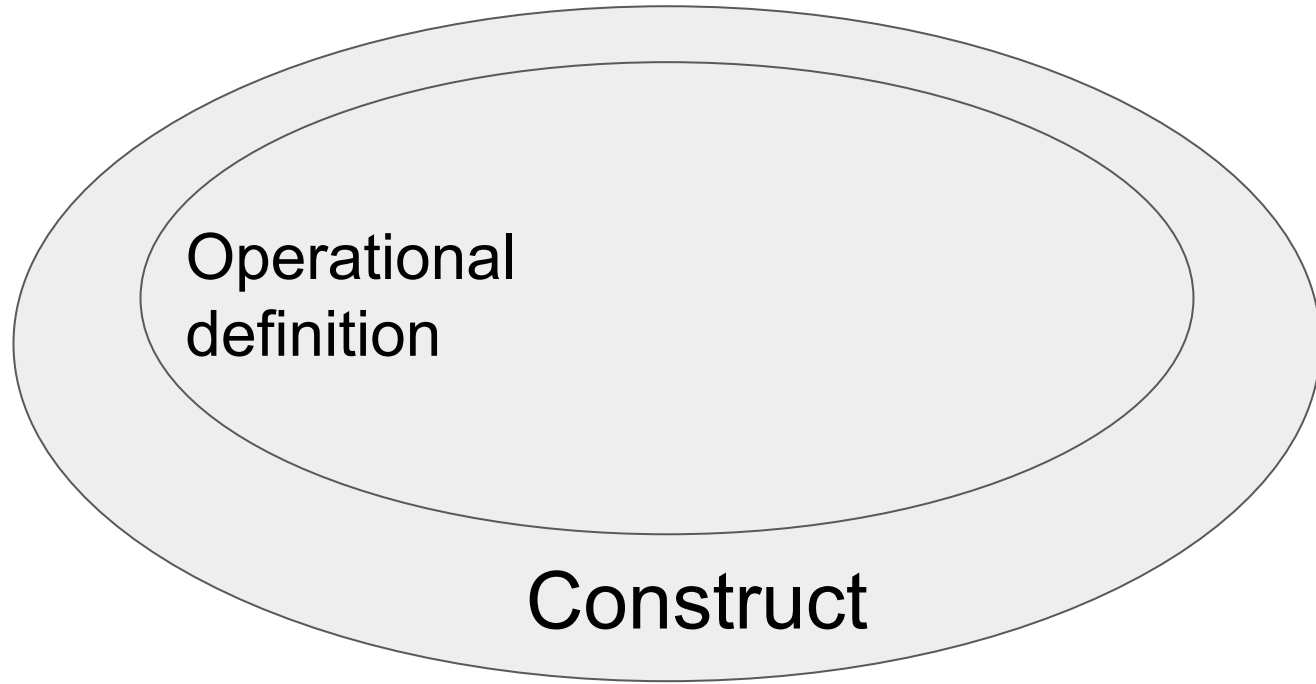


# Contextualizing hypotheses

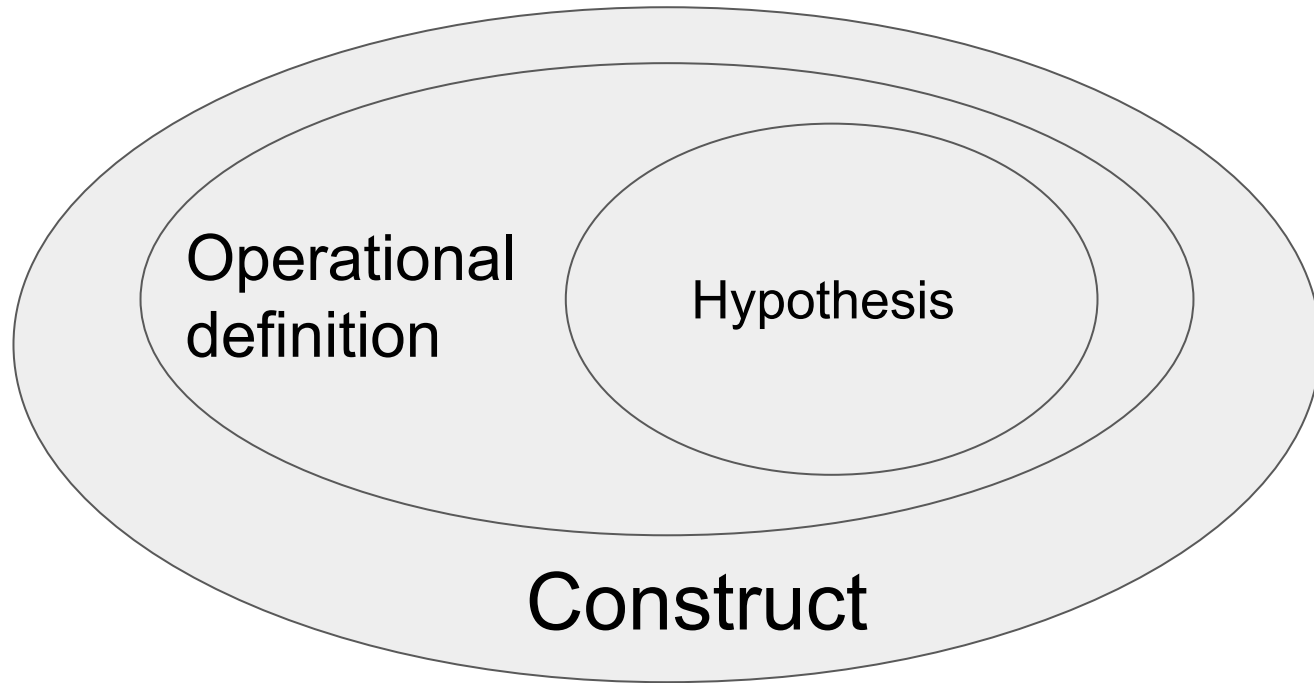




# Contextualizing hypotheses



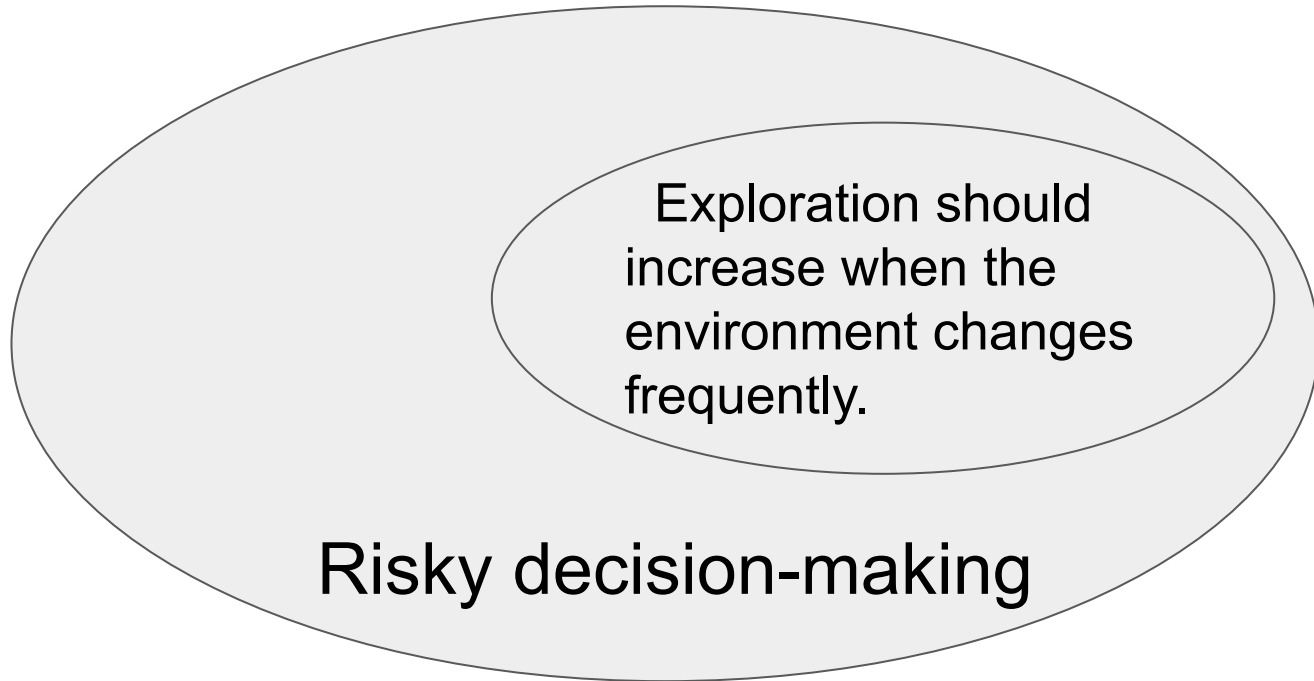
# Contextualizing hypotheses



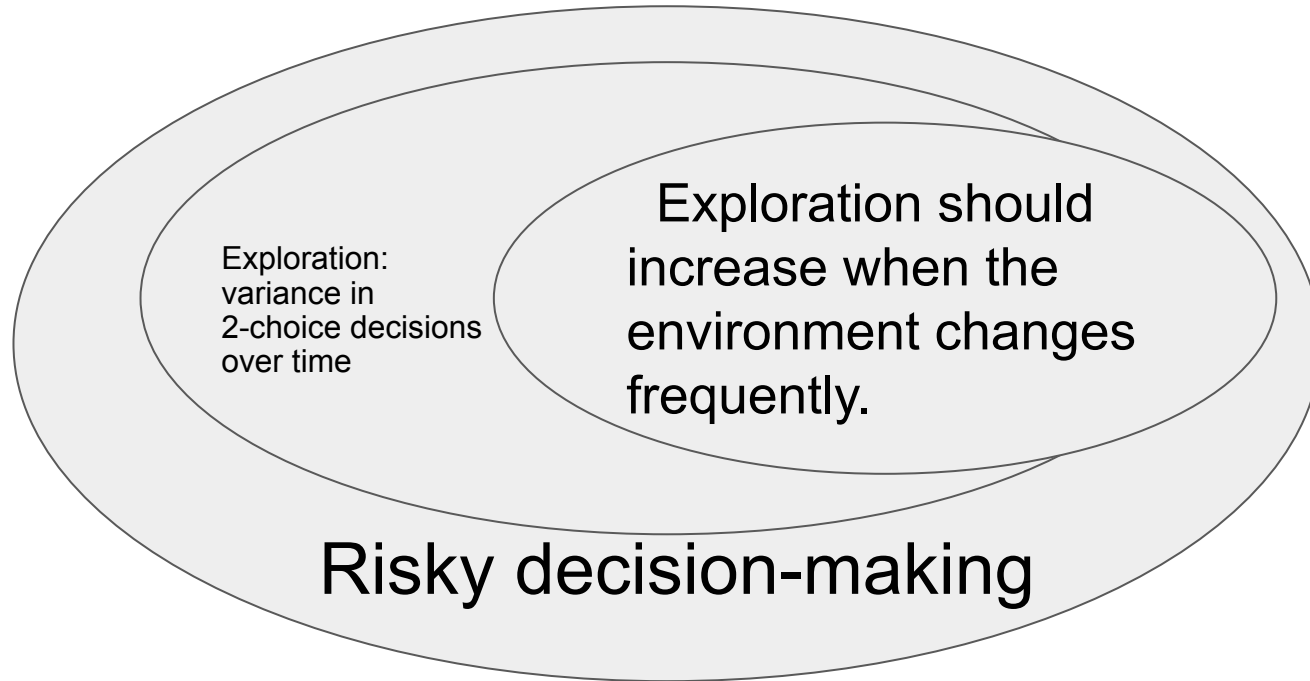
# Contextualizing hypotheses



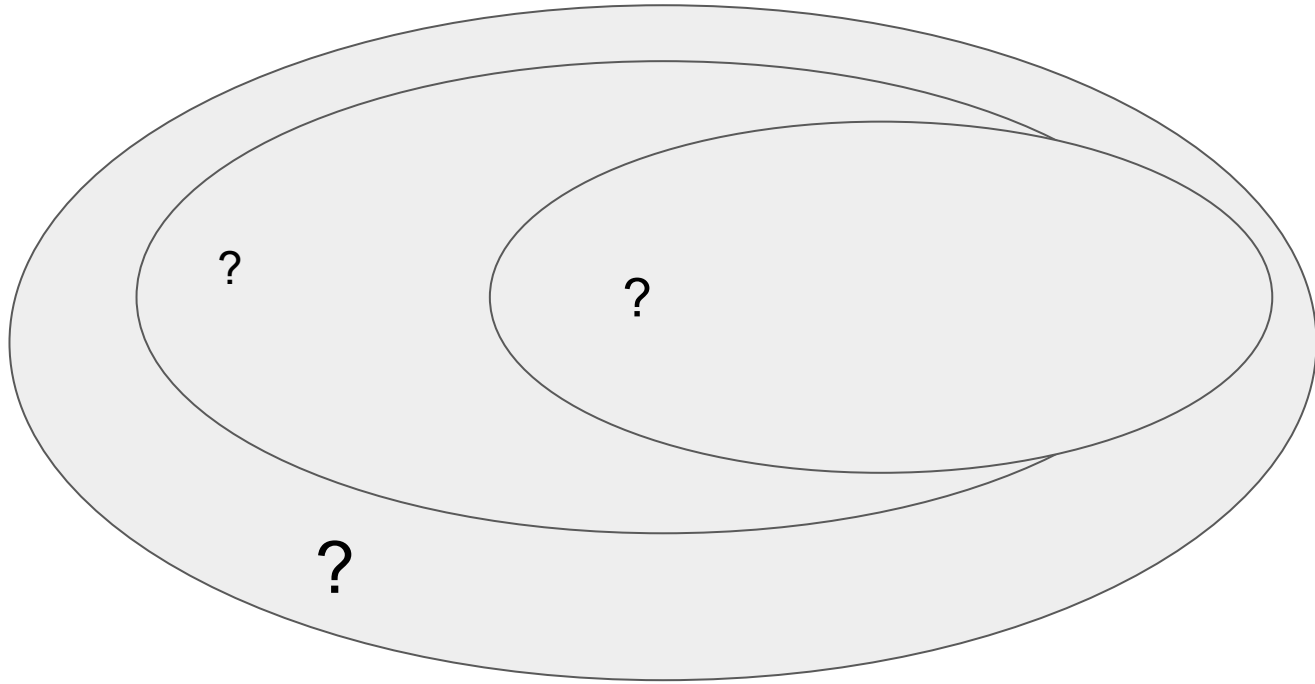
# Contextualizing hypotheses



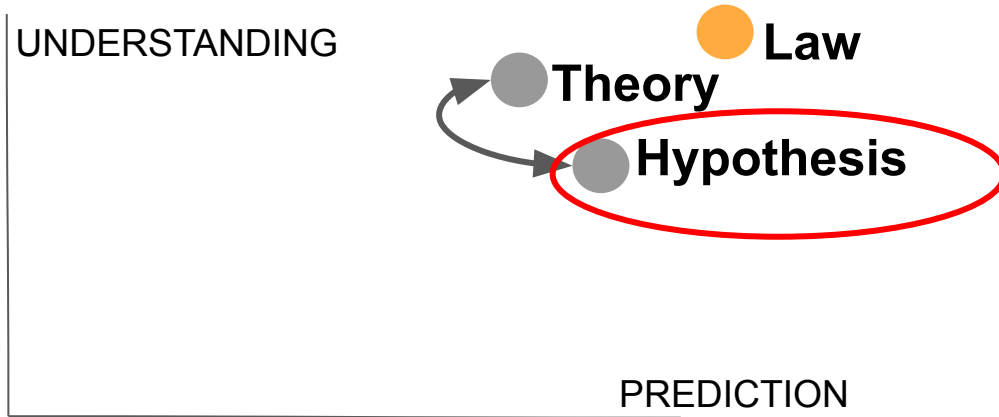
# Contextualizing hypotheses



# Contextualizing hypotheses



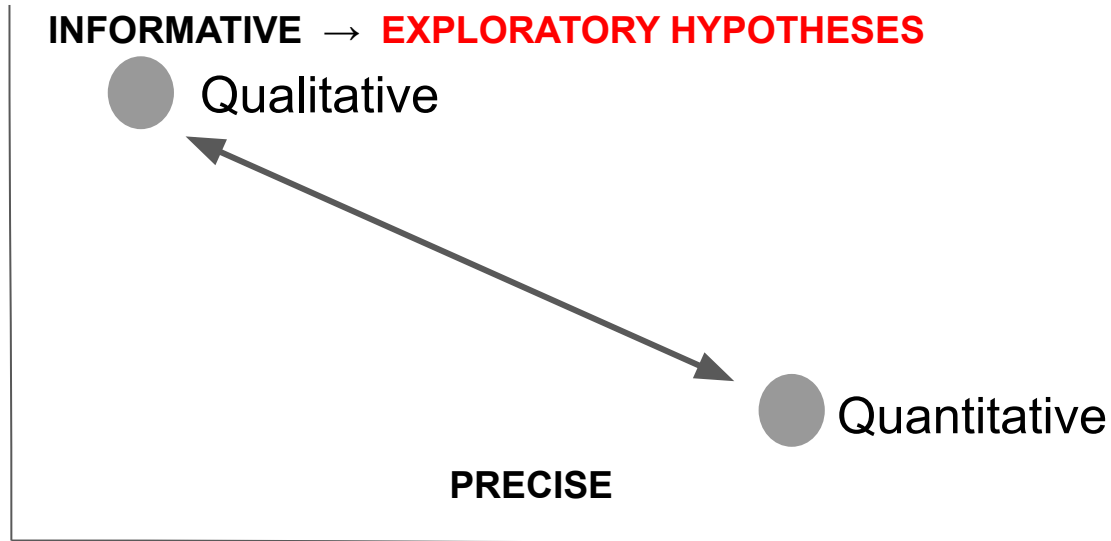
Hypotheses → Theory → Hypotheses...



**Theory emerges from repeated hypothesis evaluation.** It serves 2 functions:

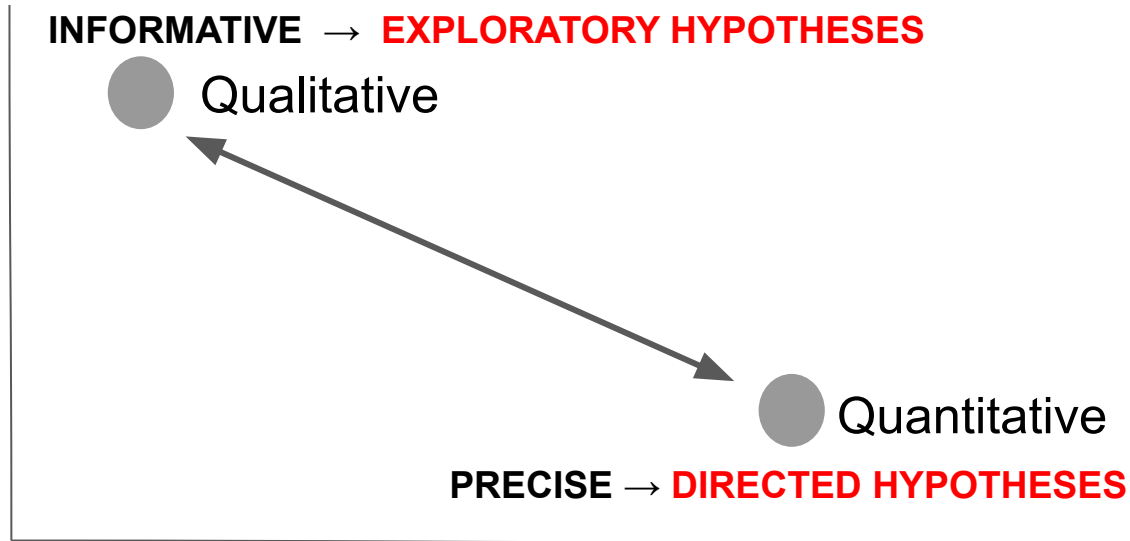
- Explains exp. observations in a systematic way
- Generates *new* knowledge by guiding new exp. hyp.

# How specific should our hypotheses be?

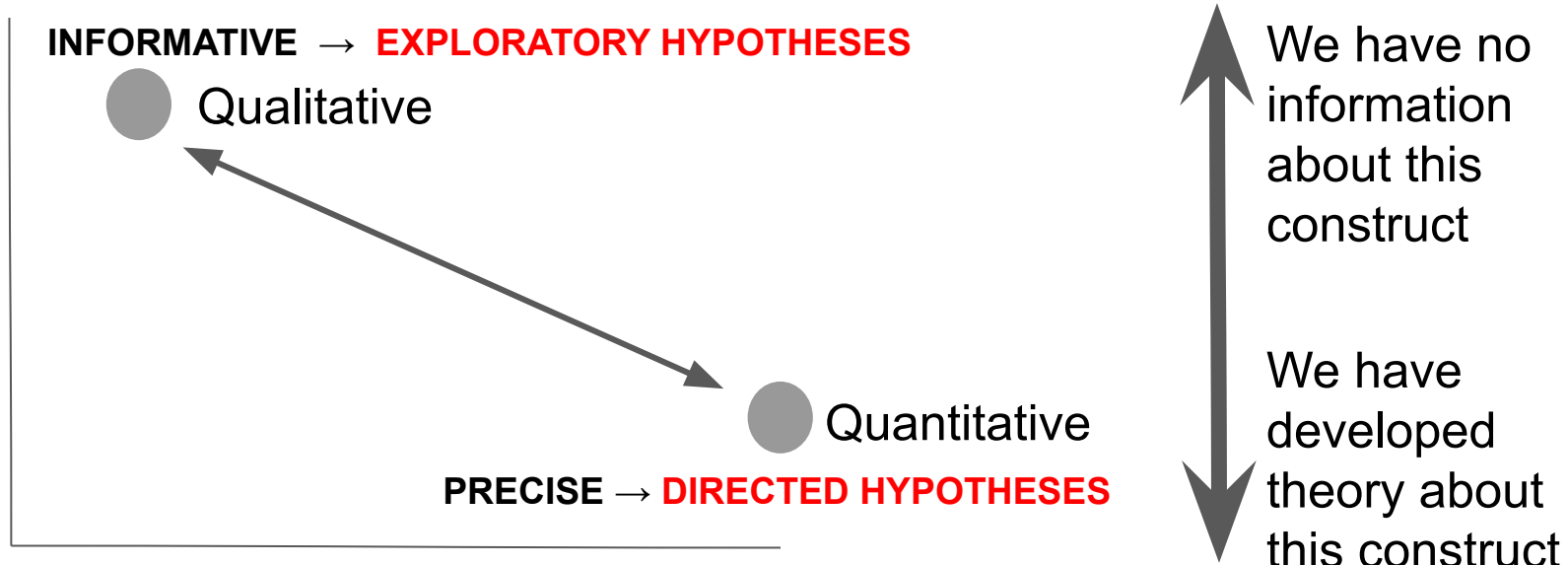




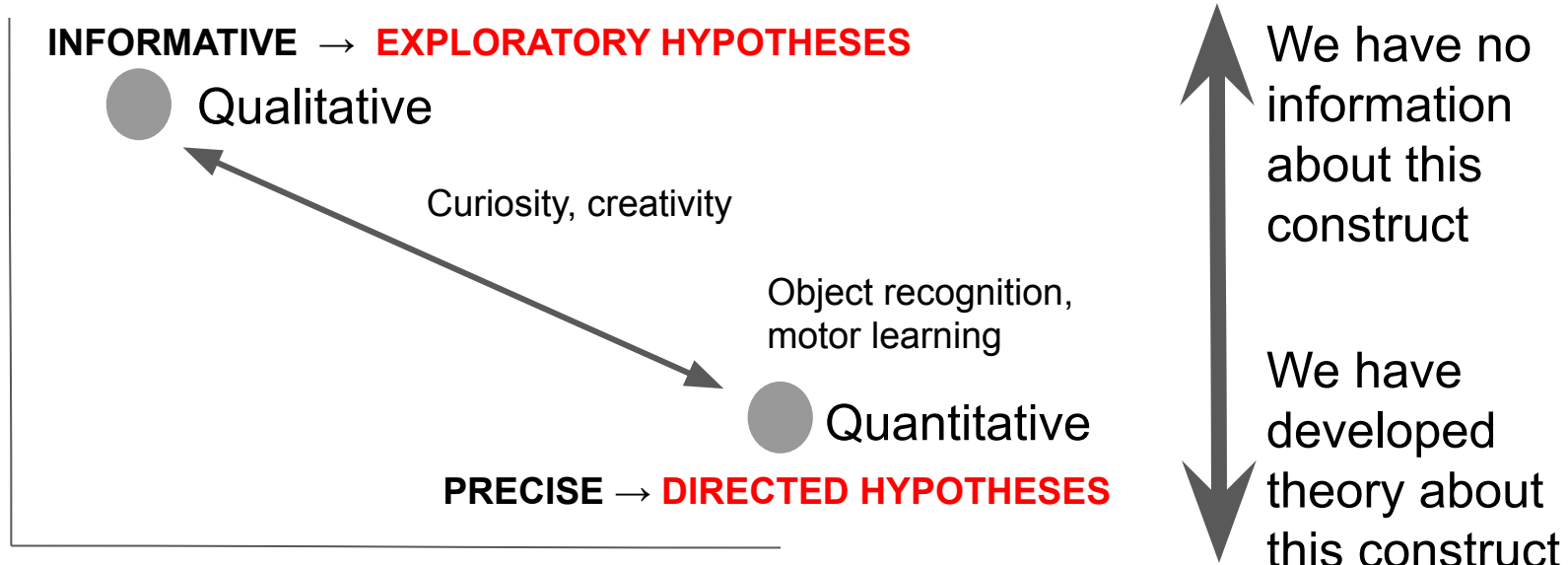
# How specific should our hypotheses be?



How specific should our hypotheses be? It depends.



How specific should our hypotheses be? It depends.



# Hypothesis generation

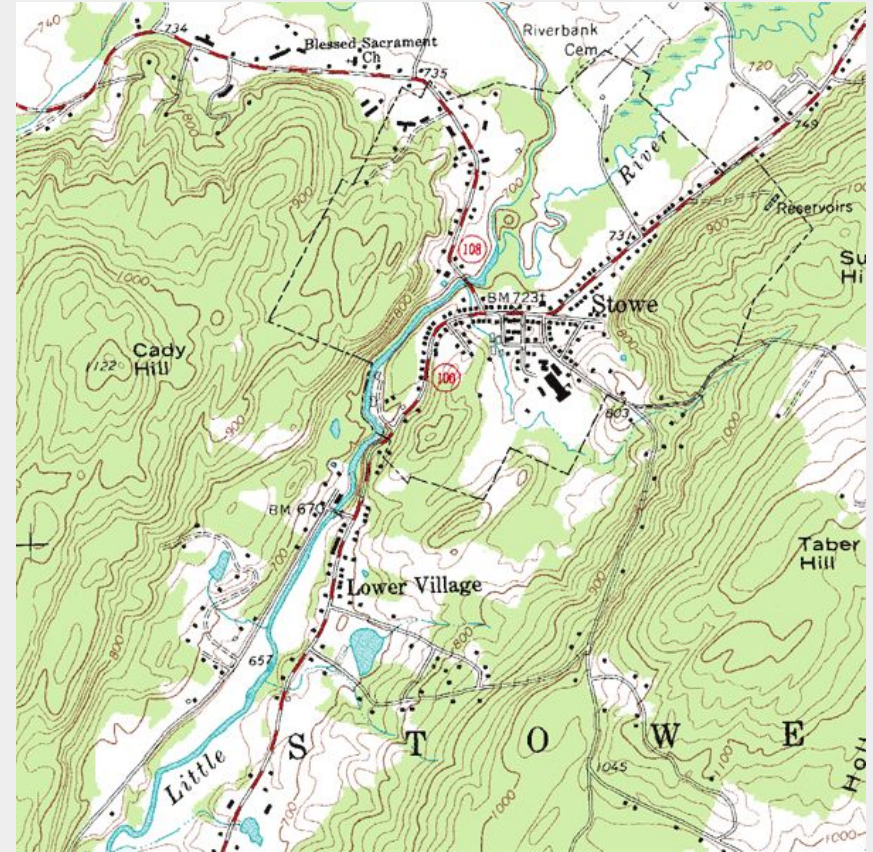
Let's pretend we're interested in decision-making.



<https://www.dreamstime.com/dog-choosing-food-jack-russell-terrier-looks-donut-apple-dog-choosing-food-jack-russell-terrier-looks-image212511914>

# Grasp what we know.

In order to build new things, understand old things. So read read read. We read about the learning processes that drive decision-making and think.



# Find the gap.

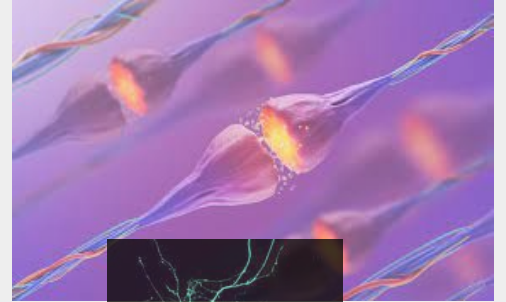
We find there's little work on how information seeking interacts with reinforcement-driven decisions.



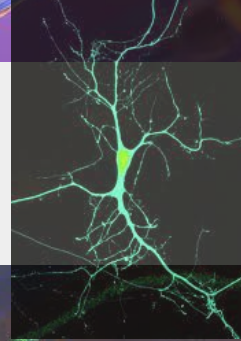
# Change the level of abstraction.

We find there's little work on the neural systems that guide decision-making at the molecular scale. There are clues in the mesoscale dynamics.

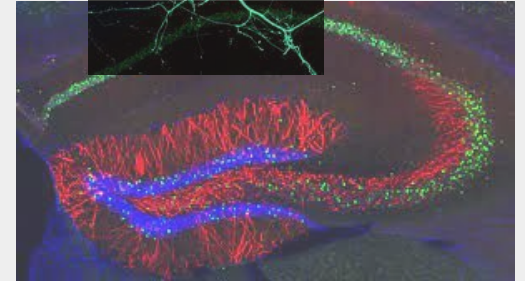
**Microscale:  
Molecular  
Neuro**



**Mesoscale:  
Cellular**



**Macroscale:  
Circuit-level /  
whole-brain  
dynamics**



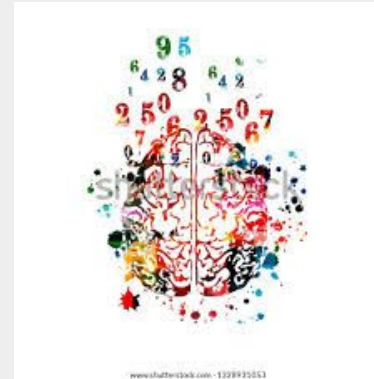


# Draw a connection between fields.

Giving machine learning algorithms “imagination” (AKA data augmentation) improves “decision-making” for increased prediction accuracy. There’s emerging work on imagination benefitting learning in humans, which is related to decision-making. Does a similar algorithm drive adaptive decision making in humans?



Machine-learning → neuro.



# Extend a finding.

Under what conditions does information-seeking drive decisions more than reinforcement does?

Qualify conditions under which a finding is true.

Conditional	$p \rightarrow q$
Converse	$q \rightarrow p$
Inverse	$\sim p \rightarrow \sim q$
Contrapositive	$\sim q \rightarrow \sim p$
Biconditional	<i>"p if and only if q"</i>

# Hypothesis testing

# Kinds of statistical testing

**Parametric:** Relies on hard assumptions (parameters) about the distribution of your data (often normality among others)

**Frequentist: relies on a binary decision rule about statistical significance, often with a threshold of  $p \leq .05$**

**Non-parametric:** Minimizes assumptions about your data; often computationally intensive

**Bayesian: quantifies the degree of belief in a hypothesis according to the strength of the evidence**

# Different approaches to statistical error

## Frequentist

- **Type 1:** rejecting the null hypothesis when it's actually true
- **Type 2:** failing to reject the null hypothesis when it's actually false
- **Confidence intervals** express estimation uncertainty

## Bayesian

- “**Minimum Bayes risk criterion**” quantifies estimation error (Bayesian answer to Type 1 / Type 2 error)
- “**Credible intervals**” express estimation uncertainty

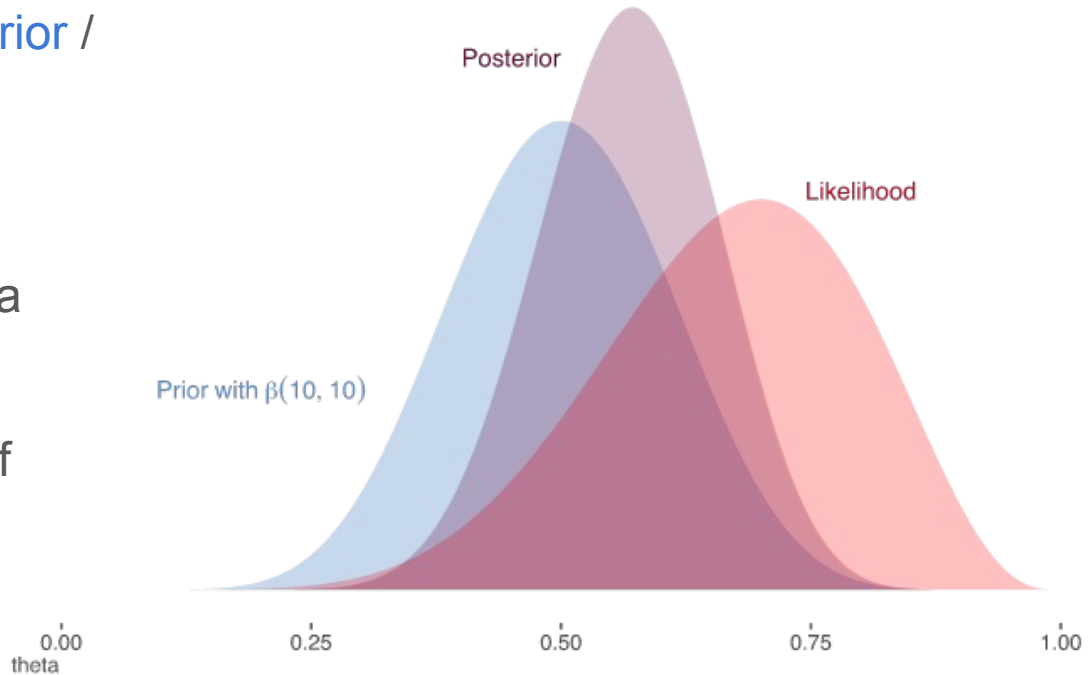
# Bayesian approach: shifting belief according to evidence

**Posterior** = **likelihood** \* (**prior** / evidence)

**Prior** = previous belief

**Likelihood** = likelihood of a hypothesis given the data

**Posterior** = updated belief



# Bayesian approach: shifting belief according to evidence

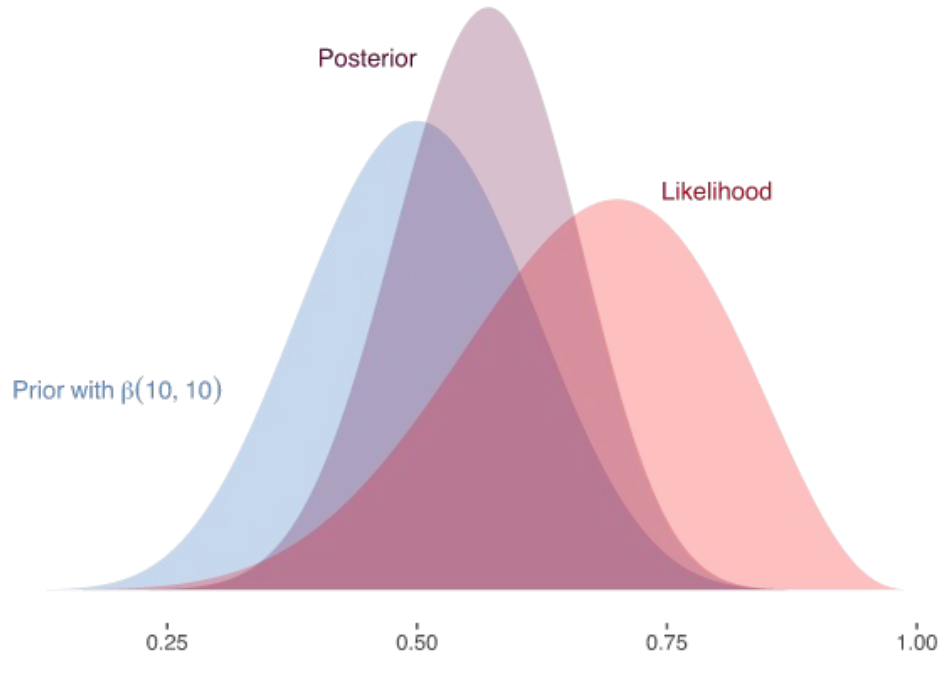
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**Posterior** = updated belief

**Strength of evidence** shifts the posterior distribution (distance between prior and likelihood)



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# Bayesian approach: shifting belief according to evidence

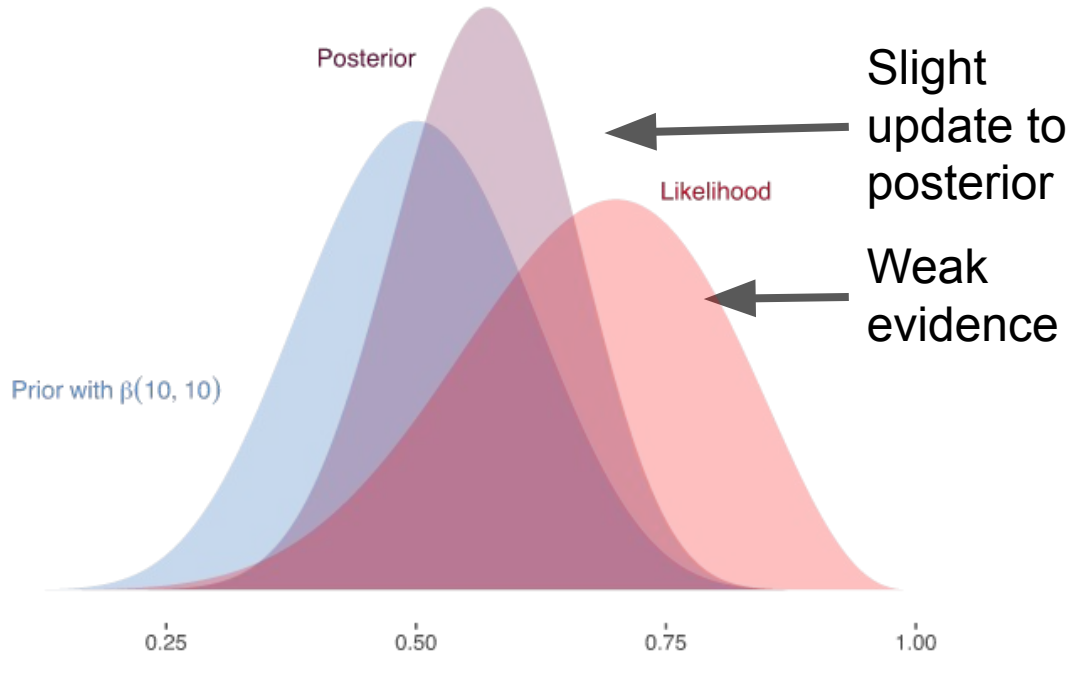
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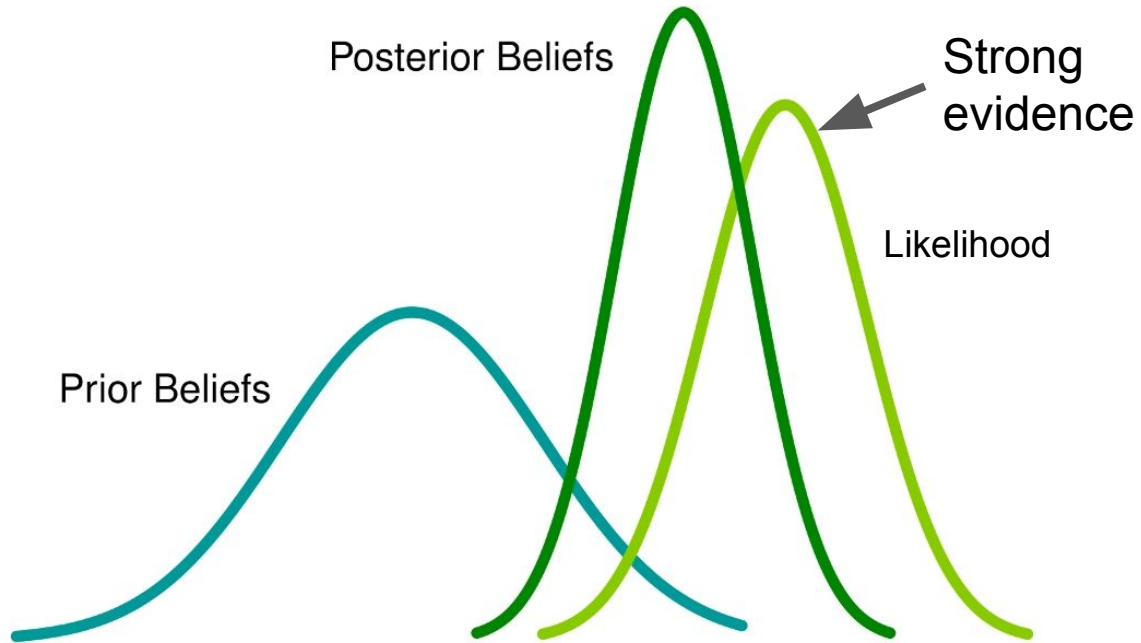
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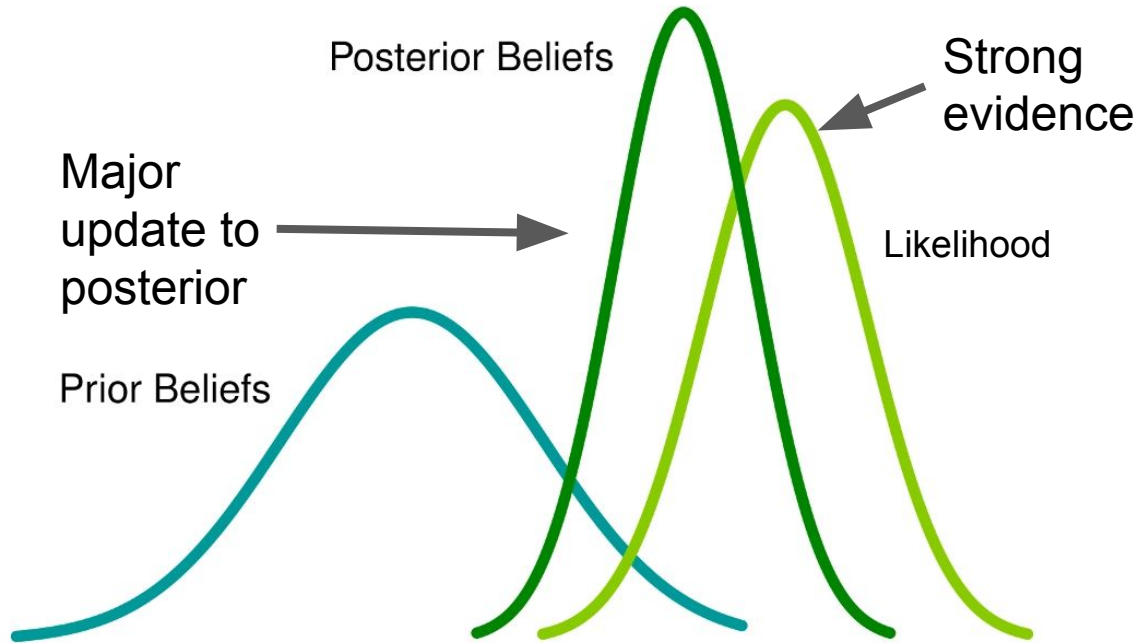
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# Frequentist approach: Rejecting or accepting a null

**Null Hypothesis (H<sub>0</sub>):** A hypothesis predicting a default state of the world

H<sub>0</sub>: *"There are no areas that preferentially respond to edges"*

Null Prediction (P<sub>0</sub>): *"All areas will respond equally as strong to images of faces as to images of objects"*

**Research Hypothesis (H<sub>r</sub>):** One of many hypotheses that describe a deviation from the null hypothesis

H<sub>r</sub>: *"There are specific brain regions that preferentially respond to edges."*

Research Prediction (P<sub>r</sub>): *"There are a specific set of areas that will respond more to images of edges than images of objects"*

# Interpreting evidence

A  $p$ -value in NHST is an existence claim.

**P-values alone do not tell you about the size of an effect, simply that it exists.**

The alpha level is often set to .05 → 5% chance that the null hypothesis would be true given the observed data

Null (nil) hypotheses in Null Hypothesis Statistical Testing (NHST) are often a comparison with 0.

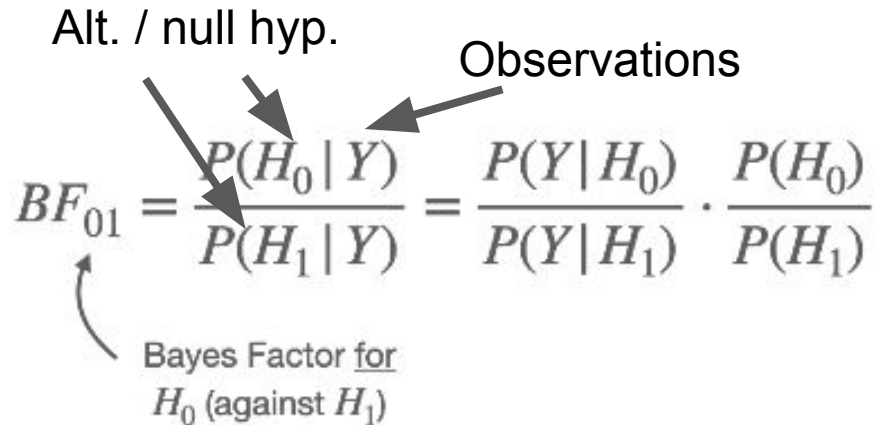
# A Bayes factor quantifies degree of evidence for hyp.

Bayes factors quantify the amount of evidence you have for your research hypothesis(es) relative to your alternative hypothesis(es) as a ratio.

Alt. / null hyp.      Observations

$$BF_{01} = \frac{P(H_0|Y)}{P(H_1|Y)} = \frac{P(Y|H_0) \cdot P(H_0)}{P(Y|H_1) \cdot P(H_1)}$$

Bayes Factor for  $H_0$  (against  $H_1$ )



- Determine the relative evidence for one hypothesis against the other.
- $BF_{ij}$  identifies whether the observed data are more likely to arise from hypothesis  $i$  ( $H_i$ ) than from hypothesis  $j$  ( $H_j$ ).

# A Bayes factor quantifies degree of evidence for hyp.

No equivalent of  $p < 0.05$  for BFs, so have to make inferential heuristics based on the strength of evidence.

$BF_{01}$	$P(H_0   Y)$	Evidence
<b>1-3</b>	0.50-0.75	weak
<b>3-20</b>	0.75-0.95	positive
<b>20-150</b>	0.95-0.99	strong
<b>&gt;150</b>	>0.99	very strong




A hypothesis is a prediction tested with experimentation.

# Fun for today




1. Develop a hypothesis.
2. Test it.
  - a. Describe construct
  - b. Describe operationalization
  - c. Design an experiment. Include specific IVs and DVs.
  - d. Describe the method, including data collection and the stat. tests you would use.
3. Imagine the results. Draw and interpret them.
4. Communicate the results in an abstract using the CCC rule and submit them.

# Next 3 classes = paper presentations

This is a graded discussion: 10 points possible due Feb 9 at 12:01am

 **7a. Linking papers (for people presenting on 2/9)** Jan 30 at 12:32pm  
K. Alexandria Bond

Describe the link between the two papers you've chosen to present (and cite them).

Search entries or author Unread    ✓ Subscribed

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