

# CCN Lecture

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## Depression & Reinforcement Learning (cont.)

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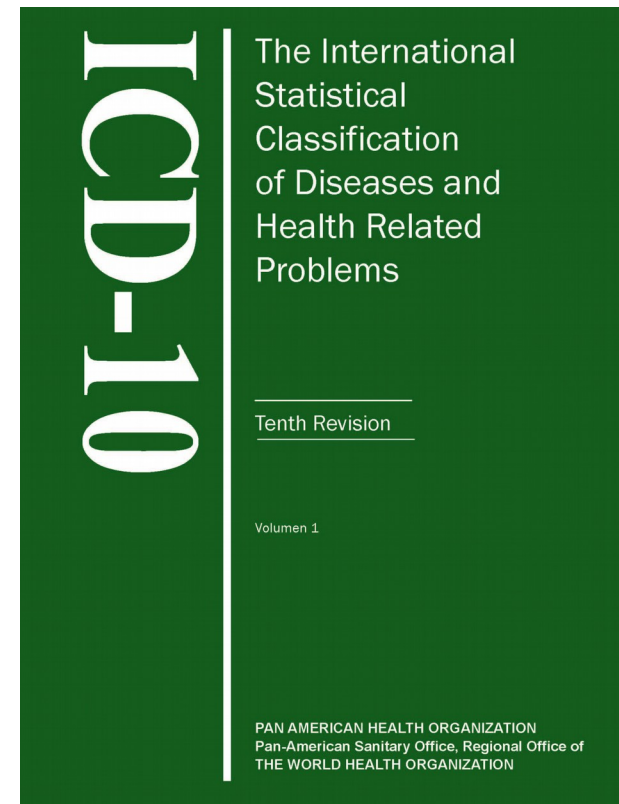
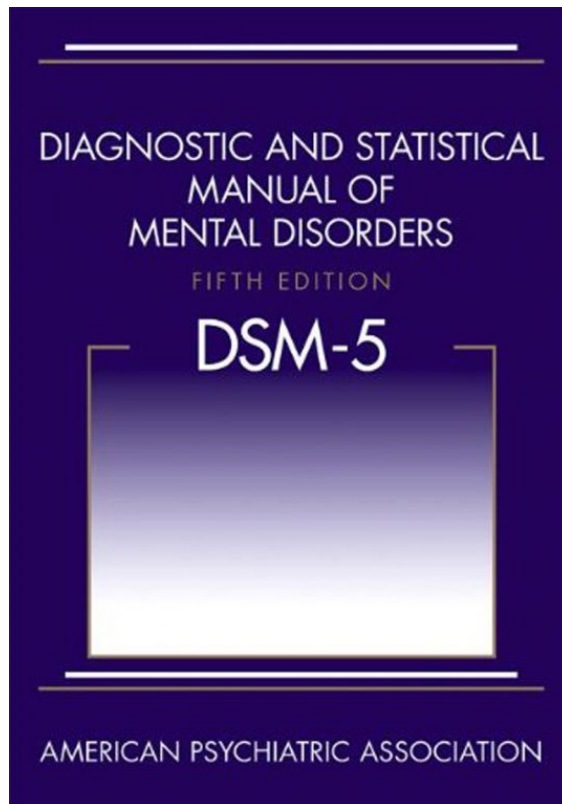
# Outline

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- Depression
- Reinforcement Learning (RL)
- RL Impairments in Depression
- → Modelling Theory

# Major Depressive Disorder (MDD)

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# Major Depressive Disorder (MDD)

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- Symptoms:
  - **Depressed mood**
  - **Anhedonia** (inability to experience pleasure)
  - Loss of energy, fatigue
  - Change in weight or appetite
  - Insomnia / Hypersomnia
  - Psychomotor agitation / retardation
  - Feelings of worthlessness or excessive or inappropriate guilt
  - Concentration difficulties
  - Suicidal thoughts / ideation

# Major Depressive Disorder (MDD)

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- Categorical view has little basis in biology?
  - Research moves towards dimensional view
- RDoC framework
  - Multiple levels of analysis
    - Neural circuitry, genes, behaviour
- Endophenotypes
  - Anhedonia
  - Neuroticism



# Treatment

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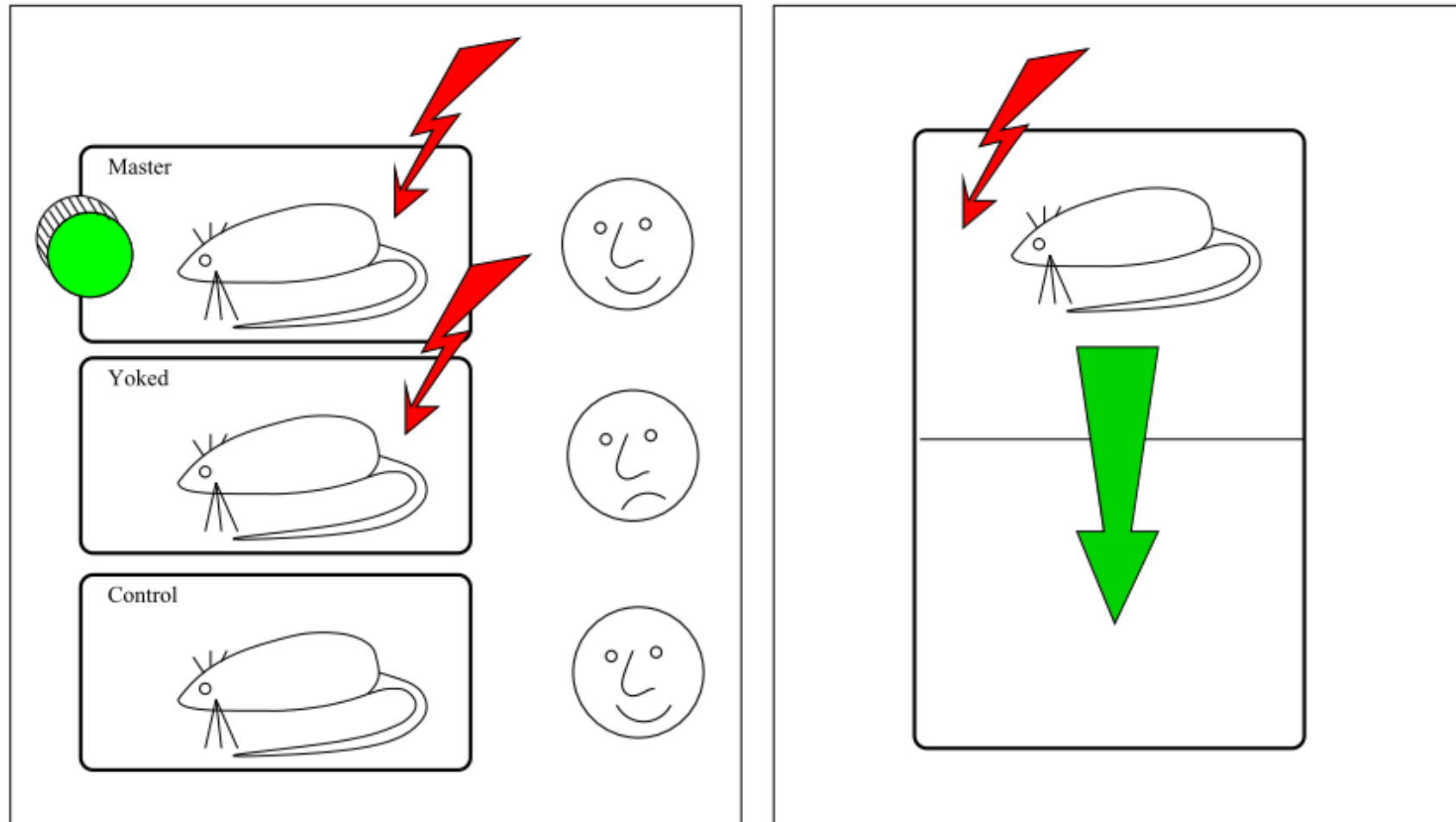
- Cognitive Behavioural Therapy (CBT)
- Antidepressant medication
  - Selective Serotonin Reuptake Inhibitors (SSRIs)
    - Primary first line treatment
  - Serotonin-Norepinephrine Reuptake Inhibitor (SNRIs)
  - Tricyclic Antidepressants (TCAs)
- Electroconvulsive therapy (ECT), Surgery
  - Very severe, treatment-resistant cases

# MDD Theories

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- **Cognitive Theory** (Beck, 2008)
  - Negative cognitive schemas (CBT targets those)
  - e.g. biased recalling of negative events
- **Learned Helplessness** (Seligman, 1972)
- **Stress** → deficits in reinforcement / reward processing (learning) → **anhedonia** (Pizzagalli, 2014)
  - 70-80% of Major Depressive Episodes preceded by major life event

# Learned Helplessness



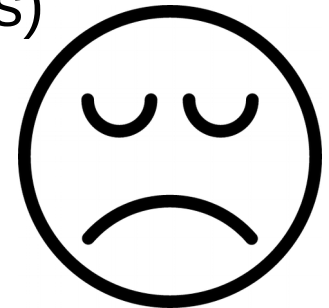
Huys et al., 2008; NIPS



# Impact

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- High (lifetime) prevalence (esp. in developed countries)
  - USA: 16.2% (Kessler et al., 2003)
  - UK / Europe: 7-10% (Ayuso-Mateos et al., 2001)
  - Depression rates are rising (e.g. Mojtabai et al., 2016)
- High economic impact (Europe: €92 billion in 2010) (Olesen et al., 2012)
- People are suffering
  - Risk factor for suicide (Olfson et al., 2017)
    - And suicide rates are increasing
  - Cognitive Impairments (e.g. Snyder, 2013)
    - Attention, concentration, executive functioning, working memory, ...
  - Impairments in Reinforcement Learning (Chen et al., 2015)



# RL Impairments in MDD

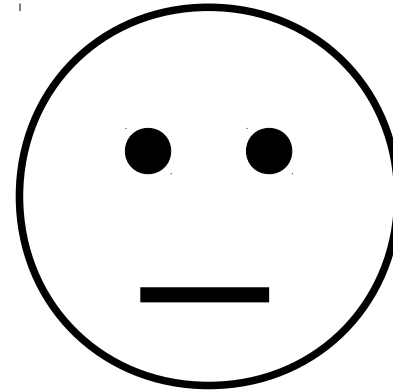
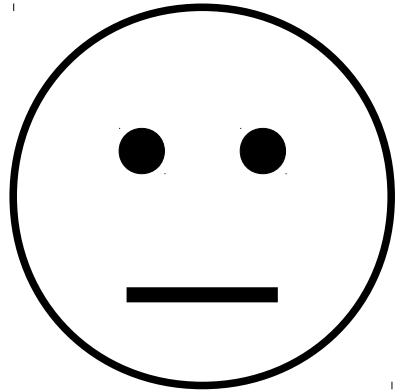
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- Signal Detection Task
- fMRI studies
- Computational Modelling
  
- Iowa Gambling Task (?)
- Reversal Learning (?)



# Signal Detection Task (e.g. Pizzagalli et al., 2005)

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- One stimulus rewarded more often
  - (healthy) participants become biased towards it

# Reinforcement Learning (RL)

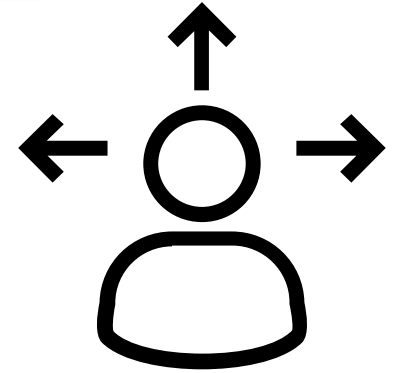
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- Update values

$$V(t + 1) = m \times V(t) + \varepsilon \times (\rho \times r(t) - V(t))$$

- Decide between two options

$$p(a | V, \theta) = \frac{1}{1 + \exp(-\beta \times (V_a - V_b))}$$



# MDD Modelling Studies (behavioural)

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- Chase et al., 2010
  - Lower learning rates
- Kunisato et al., 2012
  - Lower temperature parameter
- Huys et al., 2013
  - Lower reward sensitivity
- Beevers et al., 2013
  - Higher temperature parameter
- Dombrovski et al., 2010
  - Lower memory [in suicide attempters]



# Brain Activity

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- **Model-based fMRI** (e.g. Kumar et al., 2008; Gradin et al., 2011)
  - No real behavioural differences
  - Abnormal reward prediction errors
  - Abnormal expected reward values

# (Behavioural) Modelling

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- How do I actually “fit” a model to data?
  - Try to find “optimal” values for the parameters of the model that our data “most likely”  
(maximize the probability of observed choices)

# Maximize the Likelihood

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$$L = p(A | V, \theta) = \prod_{a \in A} p(a | V, \theta)$$

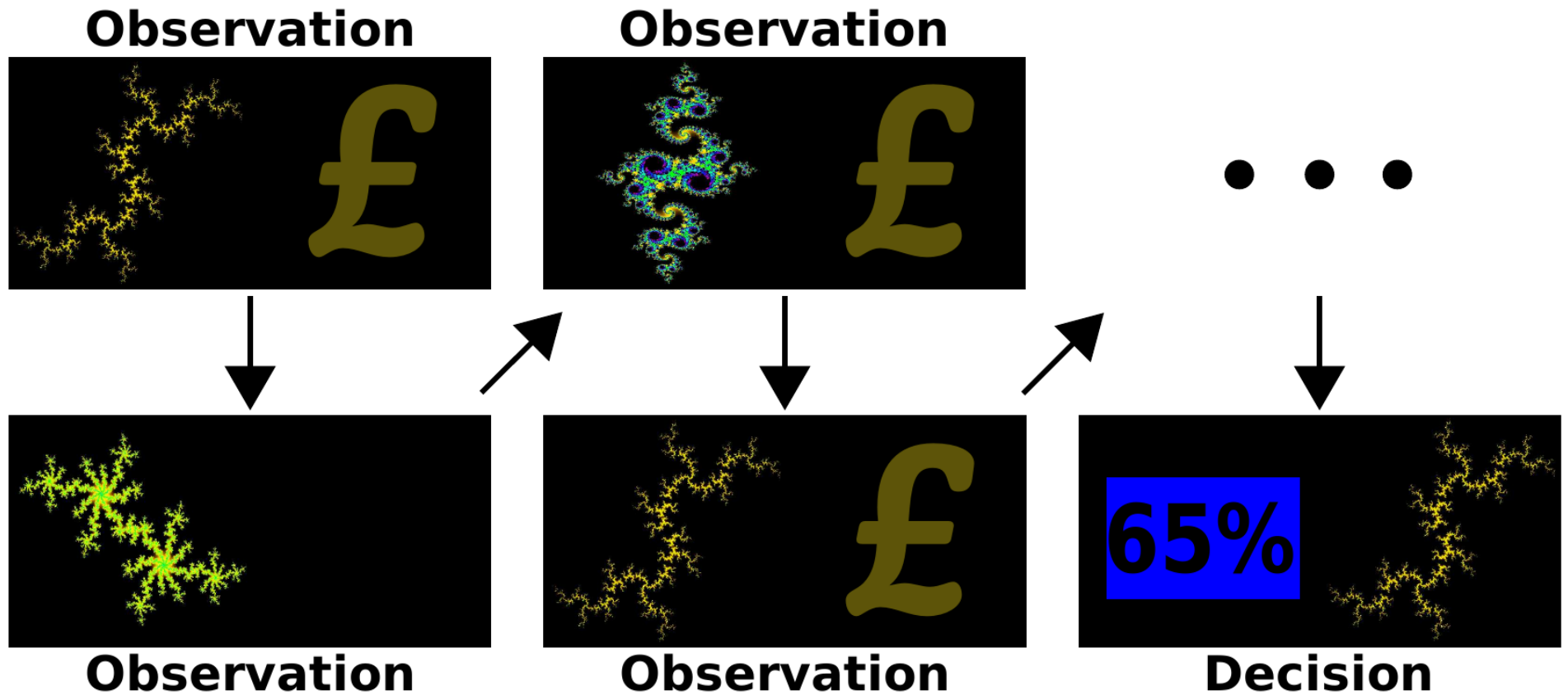
- Multiplying lots of small numbers is a bad idea... take the log instead!
- Instead of maximizing log likelihood  $\rightarrow$  we usually minimize negative log likelihood

$$NLL = - \sum_{a \in A} \log p(a | V, \theta)$$



# Example Experiment

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Stankevicius et al., 2014; Further work in progress

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# Our Model

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- Value Update

$$V_i^{t+1} = A \times V_i^t + r_i^t$$

- Decision

$$p(\text{choose fractal } i) = \frac{1}{1 + \exp(-\beta(f(V_i) - \phi_i))}$$

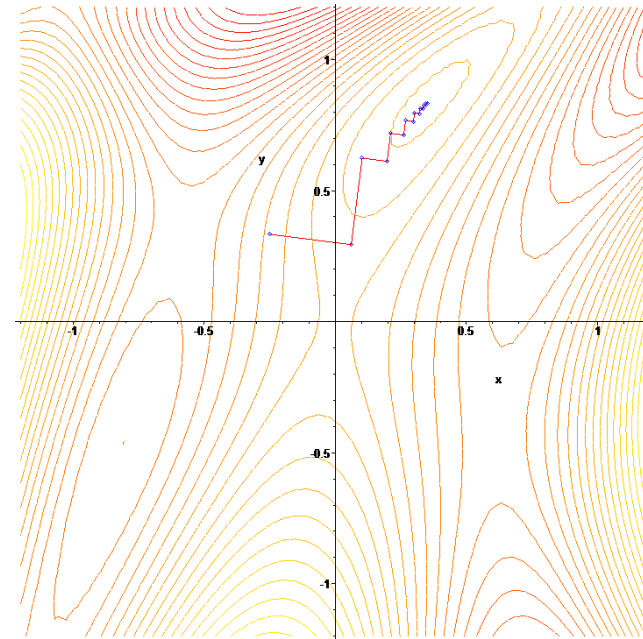
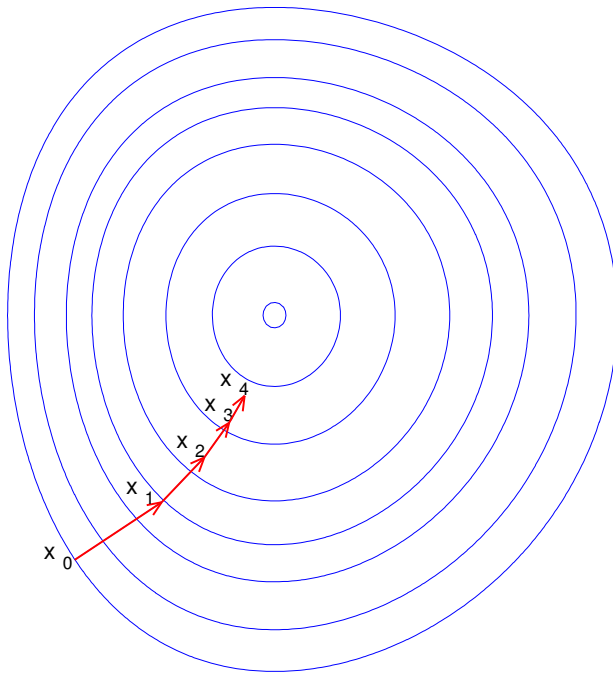
# NLL in MATLAB

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```
1 function nll = neg_log_likelihood(data, theta)
2     A = theta(1);
3     beta = theta(2);
4     X = data.decisions;
5     T = data.num_trials;
6     r = data.obs_rewards;
7     p = data.phis;
8     V = zeros(T, 1);
9     for i = 1:size(r, 2)
10         V = A*V + r(:, i);
11     end
12     probs = logsig(X .* beta .* (V/4 - p));
13     nll = -sum(log(probs));
14 end
```

# Estimate parameters

- Different options (e.g. gradient descent)
  - We will simply use one of the built-in functions



# Possible Issues

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- Lots of local minima
- Surface around minima is very flat
- Initialise with different starting points
  - Randomly
  - Grid

# fminunc

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```
1 f = @(x)(neg_log_likelihood(data, x));  
2 thetas = fminunc(f, [0;0]);
```

# How good is our estimation?

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- If we are making inferences based on specific parameter values (e.g. look at group differences), we better make sure that those estimates are reliable
- **Simulate data** from estimated parameters
  - Does generated data “look like” the original data? (similar summary statistics, evolution of values, ...?)
    - How much does the generated data vary?
  - Re-fit parameters to simulated data and compare parameters (e.g. look at the correlation: hopefully close to 1)
    - How much do the simulated parameters vary?

# How good is our estimation?

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- Look at the curvature (Hessian / 2<sup>nd</sup> order derivative) at the estimated point (Hessian returned by `fminunc`)
  - Take inverse to get covariance matrix



# Correlated Estimated Parameters

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- Might cause issues during inference
  - e.g. if two parameters are (highly) negatively correlated
    - We can arbitrarily change one of the parameters and then adjust the second parameter so as to keep the previous “maximum” likelihood (extreme example)
    - What does that mean if we are interested in the actual values of these parameters (e.g. for group comparisons)?

# Correlated Estimated Parameters

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- As long as the  $\text{abs}(\text{correlation}) < 1$  both parameters will explain “something”
  - Unclear what value between 0 and 1 would be “too high”; will depend on the problem; use simulations
- Parameters might actually be correlated
  - People who learn faster (higher learning rate) might be better at “remembering” what they learned (lower discounting)
- Make sure parameters are distinguishable in the mathematical formulation
  - c.f. reward sensitivity and inverse temperature

# Constraining Parameters

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- Often we know what range of values is sensible for specific parameters ( $0 < \text{learning rate} < 1$ )
  - Want to make sure estimated parameters lie within that range
  - E.g. force parameters to be positive by exponentiating them at the beginning of the likelihood function
    - Optimisation function (fminunc) can search whole space (-inf to +inf)

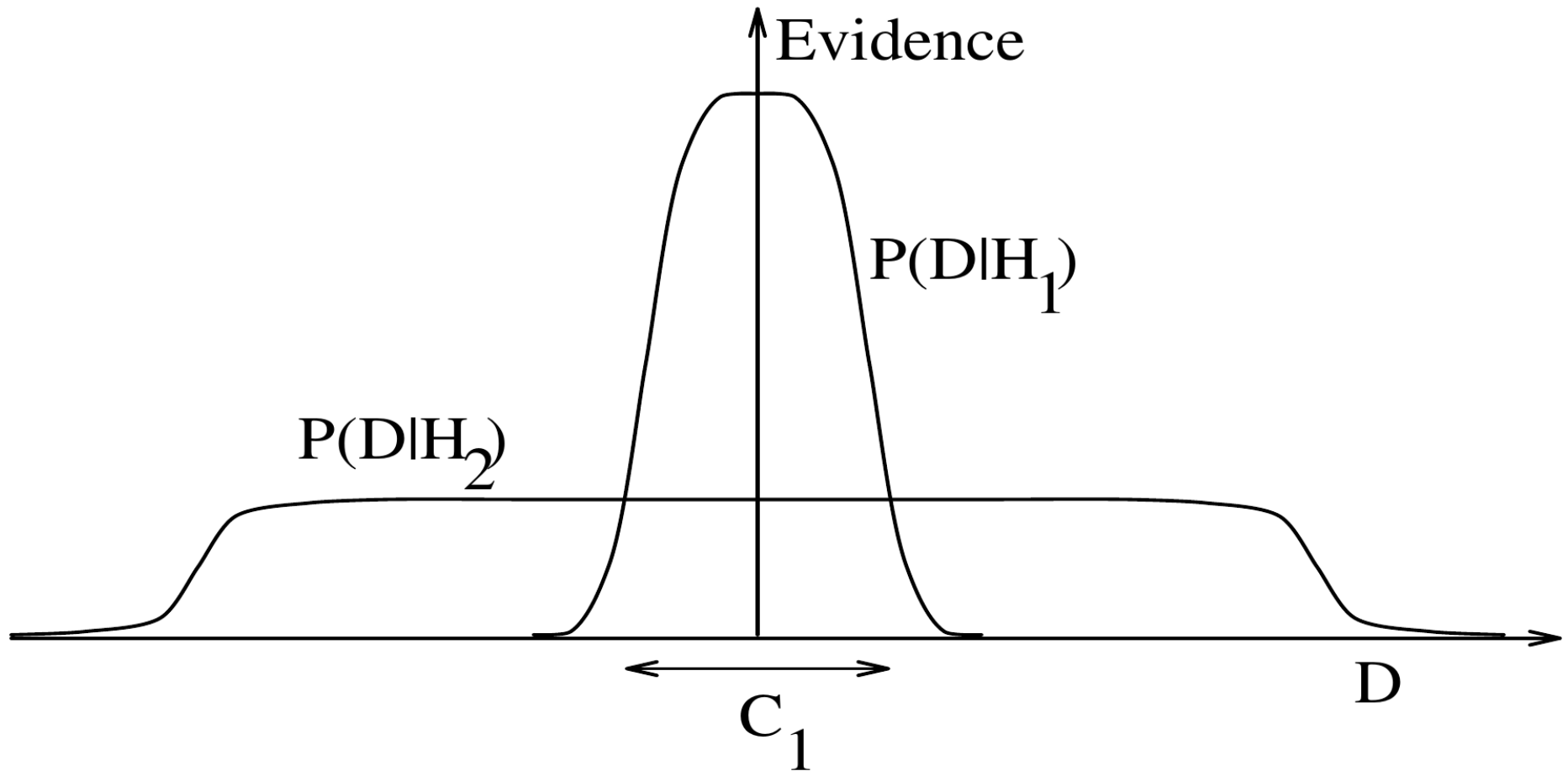
# Model Comparison

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- How do we choose a model (hypothesis)?
- We want a Trade-off
  - Which model fits our data best? (accuracy)
    - Likelihood
  - Which model is the simplest? (complexity)
    - Number of parameters
- Turn to Bayesian model comparison...

# Occam's razor

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MacKay, 2003

# Bayesian Model Comparison

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- ... or rather approximations

$$AIC = 2 \times NLL + 2 \times d$$

$$BIC = 2 \times NLL + d \times \log(n)$$

- Calculate for each model
- Choose model with **lowest** value (if difference > 10)
- Note that adding “redundant” parameters might affect the comparisons

# Model Recovery Simulations

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- **Do we have the data we need to answer the questions we are asking?**

- Confusion matrix

- For each model  $m$

- Generate data from  $m$
    - Fit all models to this data

- Does model comparison choose  $m$ ?
    - (repeat steps inside loop multiple times)

	H1	H2	H3
H1	20	0	0
H2	0	19	1
H3	0	1	19

# References

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# Images

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- [http://img.zanda.com/item/07091220000003/1024x768/Diagnostic\\_and\\_Statistical\\_Manual\\_of\\_Mental\\_Disorders.jpg](http://img.zanda.com/item/07091220000003/1024x768/Diagnostic_and_Statistical_Manual_of_Mental_Disorders.jpg)
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