

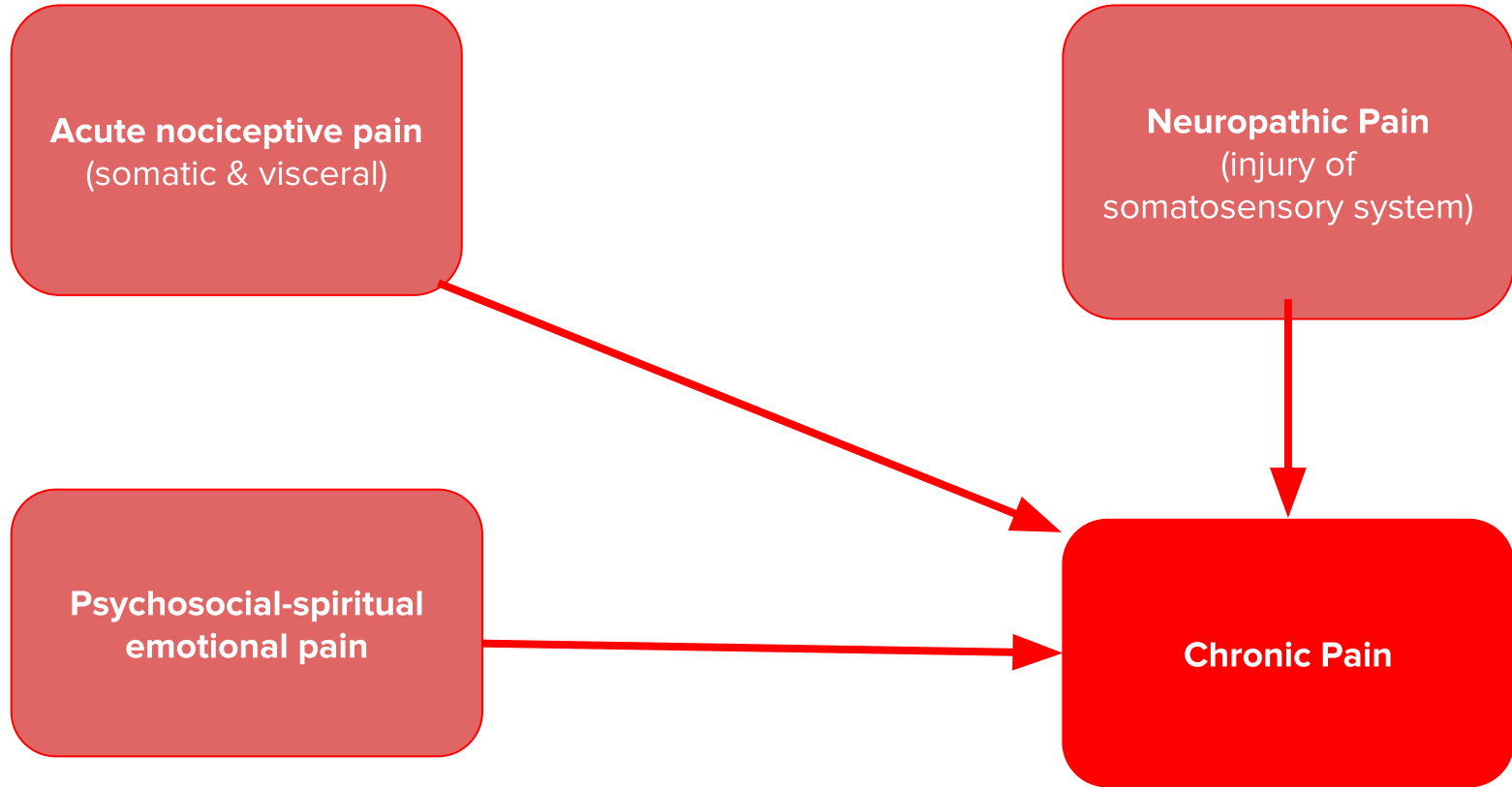
A Bayesian Model for Pediatric Chronic Pain

M-MA Kolloquium, 16.01.2017

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Epidemiology Pediatric chronic pain

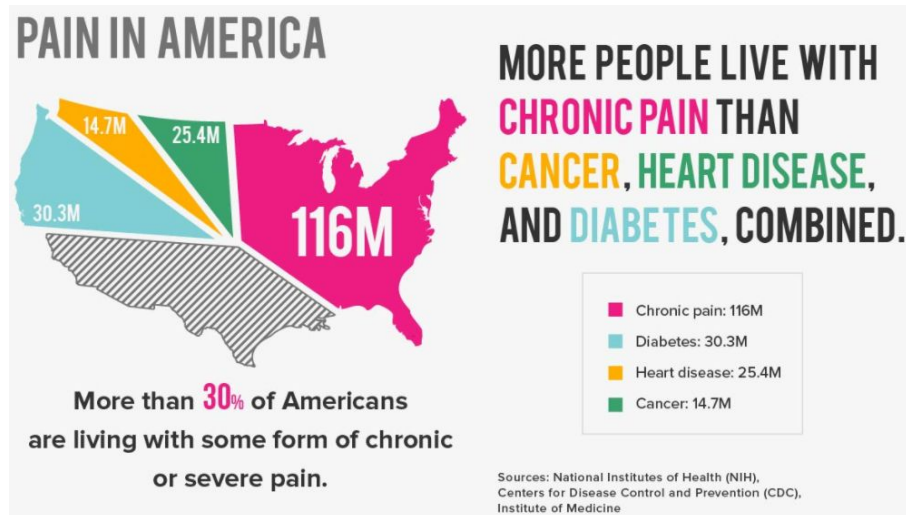
- Worldwide **3-5%** of children affected (*severely underdiagnosed*)
- 10% of hospitalized children show features of CP
- 3% disabled by pain, require **intensive treatment**
- **Time**-based definition: Pain that persists for **2** (Rome IV criteria) or **3** (ICD-10) months
- **Functional** definition:

“Pain that extends beyond the **expected period of healing**” and
“Hence lacks the **acute warning function** of physiological nociception. “

Turk & Okifuji; 2001

Economic impact Pediatric chronic pain

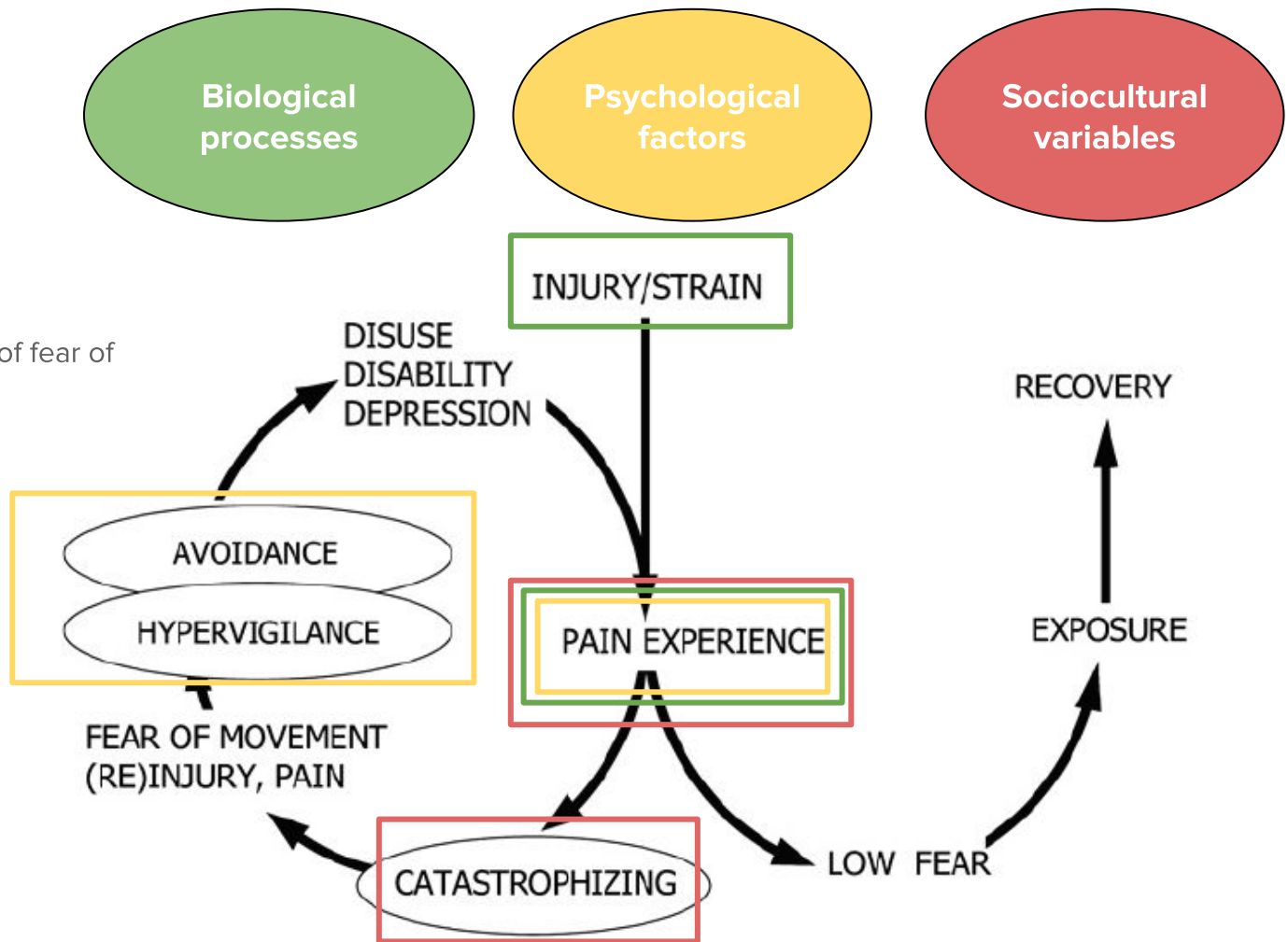
- **\$19.5 billion** per year Groenewald et al., 2014
 - Health services; social services; informal care; productivity loss of child and parent
- High risk of persistence into adulthood
 - About $\frac{1}{3}$, Walker et al., 2010
- \$600 billion costs annually for adults with chronic pain



Etiology

Vlaeyen, 2000

Cognitive behavioral model of fear of movement injury



Case example: Liz

Biological
processes

Psycho-
logical
factors

Socio-
cultural
variables

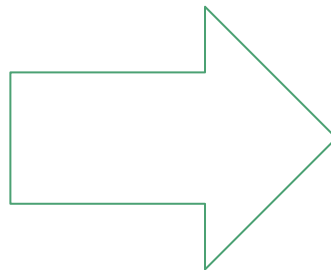


- Chronic abdominal pain for 5 years **after acute inflammation**
- Ever Since: **fear/ avoidance** of pain
- Terrible **fights** with single mother every morning before school
 - Missed substantial parts of grade 6-9
- **Socially isolated**; “outsider” among peer group
 - Aggressive behavior; narcissism
- **Helplessness**, frustration;
- **Pressure, tension**; productivity impaired (doctor visits; late for work)
- Decision to transfer Liz to private boarding school

Newer developments

**The role of expectations for
mental disorders**
(Hechler, Endres & Thorwart, 2016;
Rief et al., 2015)

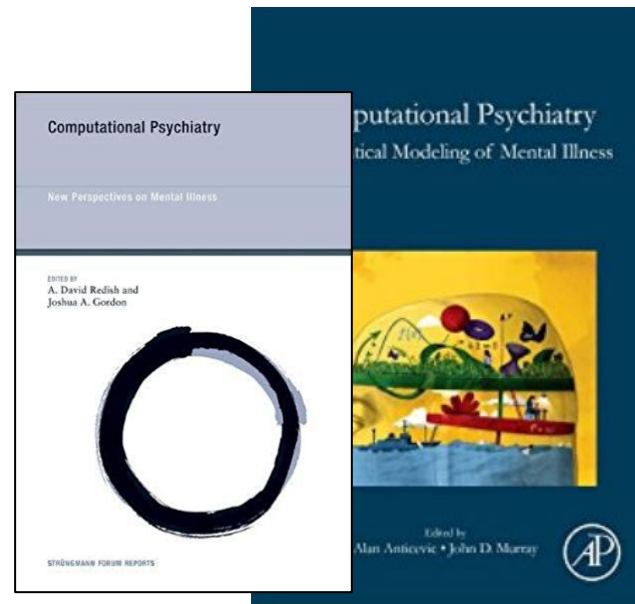
**computational
psychiatry**



**Interoceptive
predictive coding
theory of chronic pain**

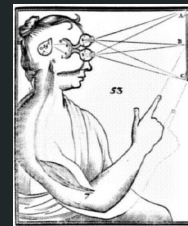
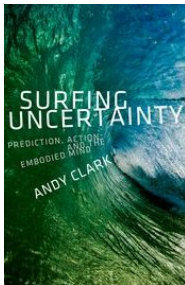
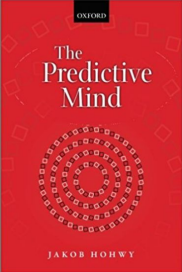
Computational psychiatry

- Diagnostic categories: **empirical basis** unclear
- Treatment selection: **“educated guessing”** (Huis, Maia & Frank, 2016)
- Connects neurosciences and psychiatry/ clinical psychology
- **Data driven approach**
 - Machine-learning methods on high-dimensional data
 - Improve disease classification
 - Predict treatment outcomes
 - Improve treatment selection
- **Theory driven approach**
 - Use models to represent underlying mechanisms
 - Rely on prior knowledge, explicit hypotheses



Expectations and predictions

- Discussed as **“core features of mental disorder”** Rief et al., 2015
 - Especially **persisting expectations**
 - No modification of expectation/ learning - despite **alternative evidence**
 - Maladaptive anticipatory responses
- Emergence of an **entire framework** focusing on the role of expectations/ predictions
- What is predictive coding?



Prediction Error framework

World represented in top-down predictions of sensory input

Brain is a prediction testing machine

Predictions query the world

→ **“Predictions + sensations influence perceptions”**

Goal: minimize prediction error

→ **Predictions determine sensations**

Ancient “representational” view

Senses form **representations** of world

Brain soaks everything up in a passive **bottom up** manner (S-R organ)

Only sensations produce perception

Top Down signals: only as feedback from the cognitive system on the signal

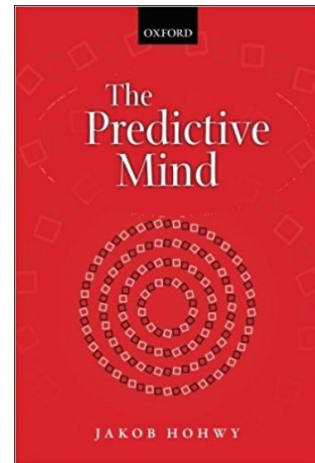
Predictive Coding...

Minimizing prediction error:

1. Change prior predictions
2. Move the body (active inference)
3. Sample sensory input differently

Both **action and perception** are **active** processes, serving to **minimize error**

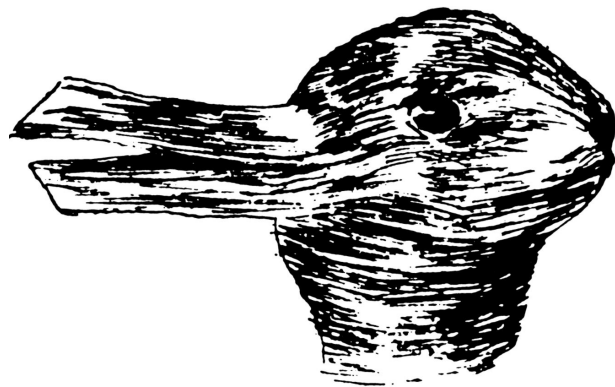
Associated: **Bayesian Brain** (eg Doya) and **Free energy** (Friston)



Hohwy, 2013

Predictive Coding...

... some examples you might already know



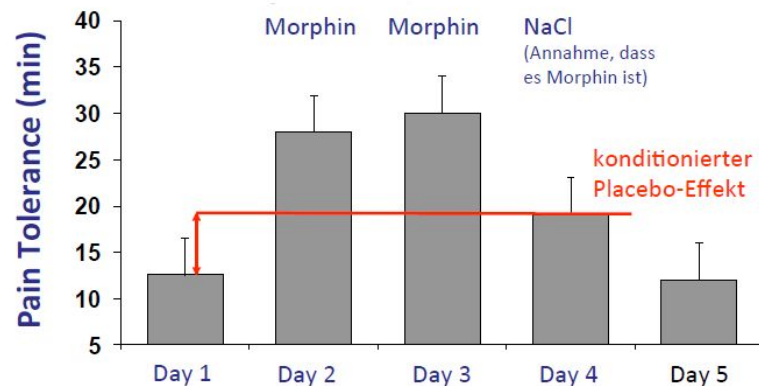
Interoceptive Predictive Coding

Seth, 2013; Seth & Friston, 2016; Barrett & Simmons, 2015

- So far: prediction drives perception of external world
- Interoceptive Predictive Coding:
 - Predictions (generated by models) also determine perception of interoceptive signals
- Interoceptive experiences are **limbic predictions** about the state of the body
 - [temperature; heart rate; glucose levels, inflammation; emotion; pain]
 - See EPIC model by Barrett & Simmons, 2015
- Visceromotor cortices generates **hormonal and immunological predictions**
 - Body deploys autonomic, **metabolic and immunological** resources
 - Responses underlie **allostatic** and **anticipatory** principles
- What about Pain?

Chronic Pain & predictive brains

- Buchel et al.: 2014
- Brain is not waiting passively for nociceptive stimuli - it is **active!**
 - Predicting pain based on prior experiences and expectations
- **Expectations influence pain perception**
- **Well-known example: “Placebo Analgesia”** (Beh. med. lecture - Amanzio & Benedetti, 1999)
 - Placebo hypogesias
 - Decreased sensation of pain!



Quick reminder: Bayes' theorem



Conditional Probability
Likelihood of **A**, given **B** is true

“Posterior probability”

Conditional Probability

Likelihood of **B**, given **A** is true

“Likelihood”

$$P(A|B) = \frac{P(B|A) P(A)}{P(B)}$$

Likelihood to observe **A**

Part of the ***“Prior”***

Likelihood to observe **B**

Evidence for B

Bayesian Pain

- To what probability do we perceive pain **given** we experienced a sensation? (Hechler, Endres & Thorwart, 2016)

$$P(A|B) = \frac{P(B|A) P(A)}{P(B)}$$

- Let **A** be the **PAIN**
- Let **B** be the **SENSATION...**



Bayesian Pain

Pain perception

The Probability of Perceiving Pain given we have experienced a sensation

Posterior

Active Inference and Learning

Represent beliefs about causal relationships between a sensation and pain

Likelihood

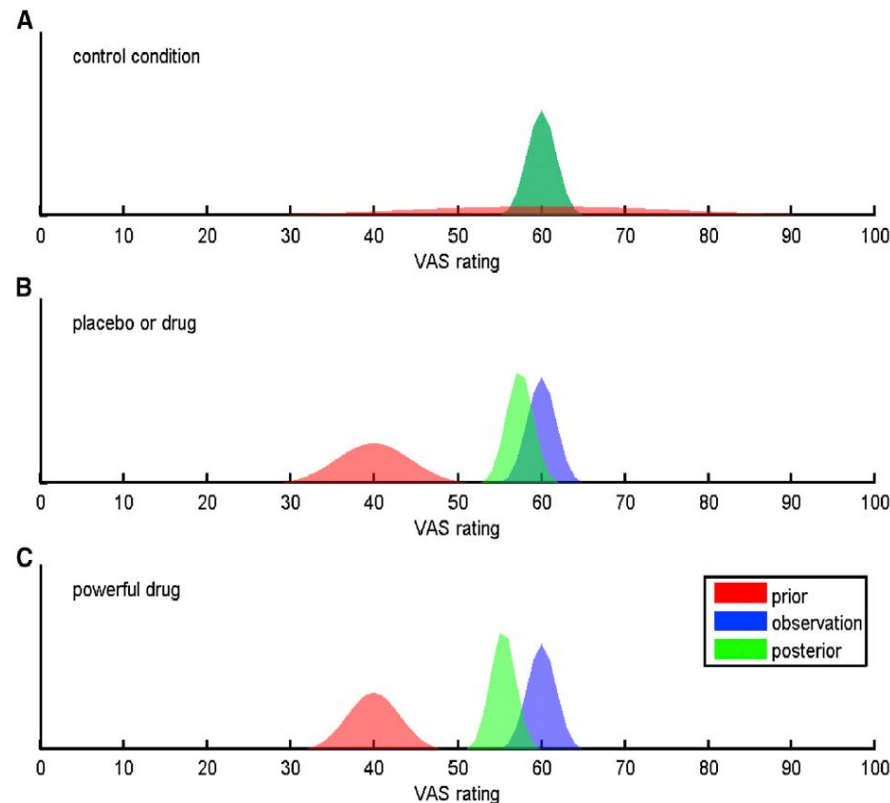
Prior probability of pain

$$p(\text{pain} \mid \text{sensation}) = \frac{p(\text{sensation} \mid \text{pain}) * p(\text{pain})}{p(\text{sensation})}$$

Probability of sensation

Bayesian Pain: Evidence

- Büchel et al., 2014 referring to Pollo et al, 2001
- Control Condition
 - Flat, uninformative prior
 - Perceived pain and sensual data: Match!
- B: Instruction: Either placebo or drug
 - Imprecise info → flat prior
 - Perceived pain smaller than sensual data
- C: Instruction: powerful analgesic drug
 - Narrow prior - precise information
 - Posterior distribution “moves” towards prior



What's underlying chronic pain?

- Heightened anticipation of pain (as a cause for random sensation) $p(pain)$
 - Dysfunctional longer term learning
- And active inference $p(sensation | pain)$

The diagram illustrates the Bayesian formula for pain perception. The formula is $p(pain | sensation) = \frac{p(sensation | pain) * p(pain)}{p(sensation)}$. Each term in the formula is linked by a red callout box:

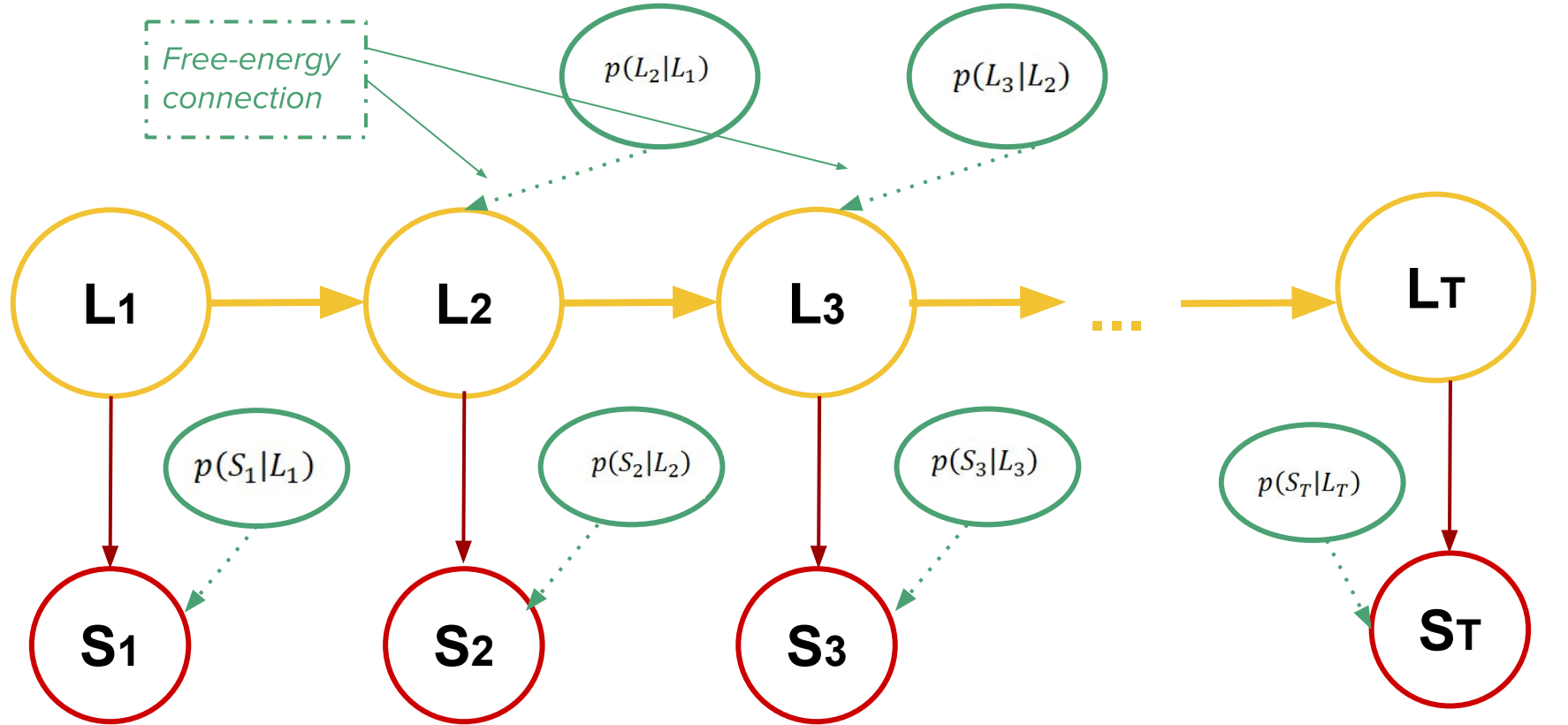
- Pain perception** points to $p(pain | sensation)$.
- Active Inference and Learning** points to $p(sensation | pain)$.
- Prior probability of pain** points to $p(pain)$.
- Prior probability of sensation** points to $p(sensation)$.

$$p(pain | sensation) = \frac{p(sensation | pain) * p(pain)}{p(sensation)}$$

Hierarchical Model



- What we want to model:
- **Expectations** as a **time series** of (conditional) **probabilities**
 - Representing **increasing anticipation** of pain
 - Learning processes (conditioning)
 - Active inference → actions generating pain (rubbing, muscle tension)
 - Attentional shifts
 - ... even when confronted with harmless sensations
- Example of abdominal pain
 - latent conditions {hunger; stomach rumbling; pain}
 - sensations {stomach pain; pressure, bloating; nociception}
- Hierarchical Markov Model



Dysfunctional learning over time (Result of prior)/ altered learning rate?

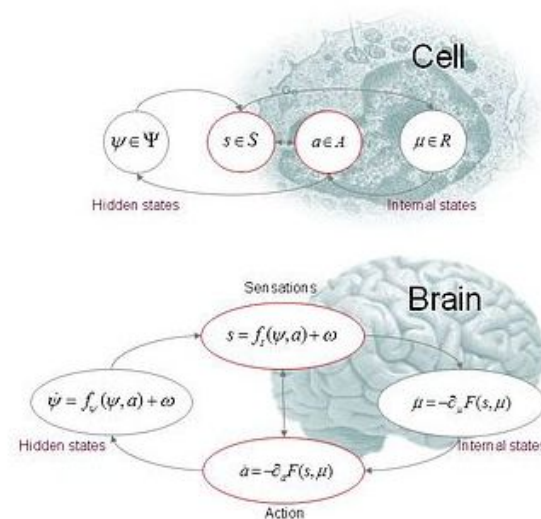
Likelihood model messed up?

Active inference: implicitly value pain state?

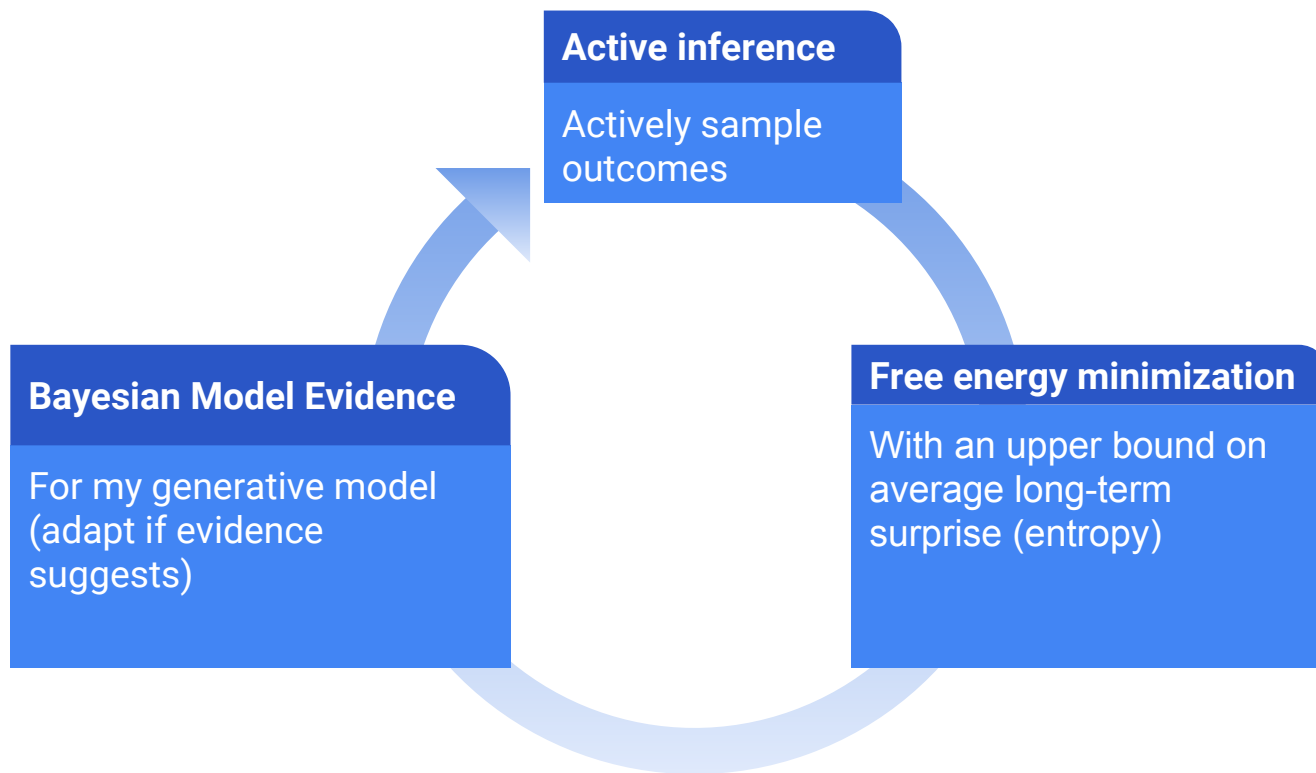
L = Latent conditions
S = sensations

What's the Free Energy Principle?

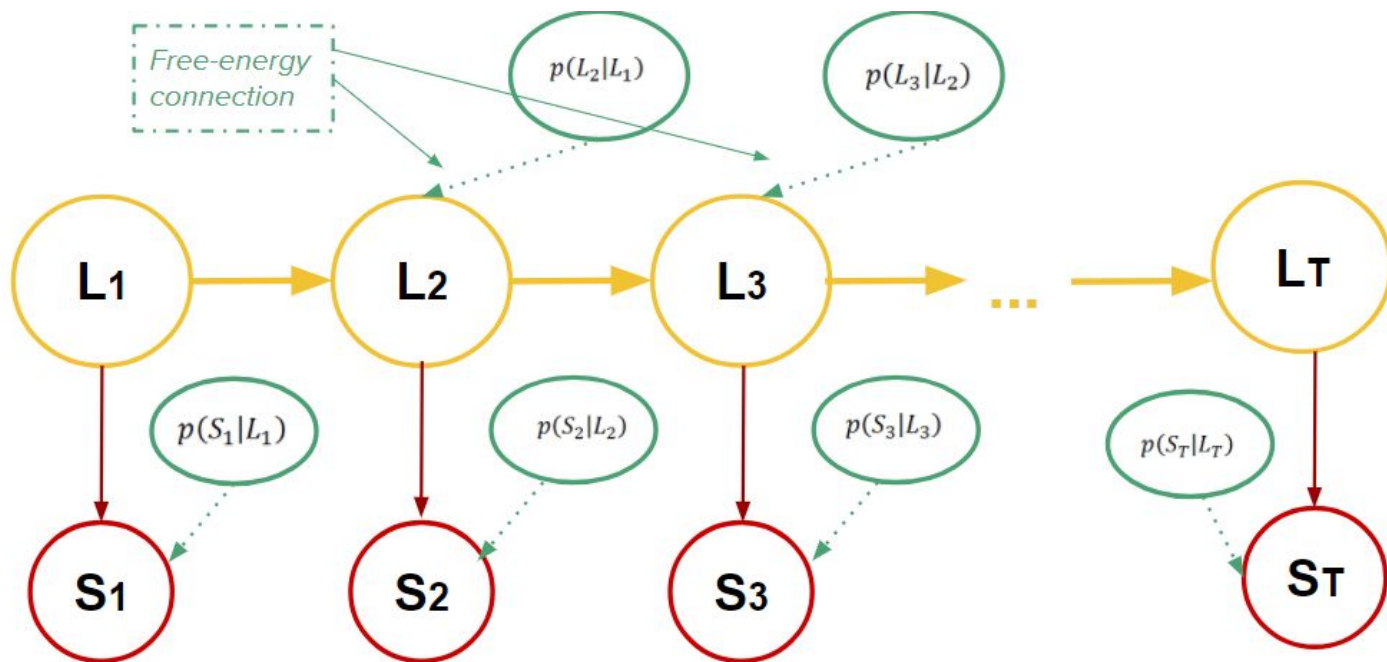
- Karl Friston University College London
- Concept from thermodynamics
- Related to Prediction Error Framework
- Biological systems maintain their order
 - by minimizing an **internal free-energy functional**
 - Related to idea of a “**Bayesian model evidence**”
 - Goal is to minimize **entropy** (or “surprise”)



What's the Free Energy Principle?



Message passing in Bayesian Networks

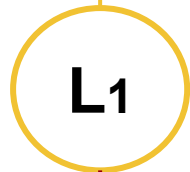


Message passing in Bayesian Networks

- **Sum product algorithm** for singly connected graphs
- Derive a factor graph from graphical model (*next slide*)
- In factors: collect all information from nodes, then send it to next node.
 - Sum over all variables...

L1 depends on this factor only.

$$P(L_1)$$



$$P(L_1|L_2)$$



L2 depends on this factor and the message it got from this one.

$$P(S_1|L_1)$$



S1 depends on this factor. All previous messages are marginalized here.

$$P(S_2|L_2)$$

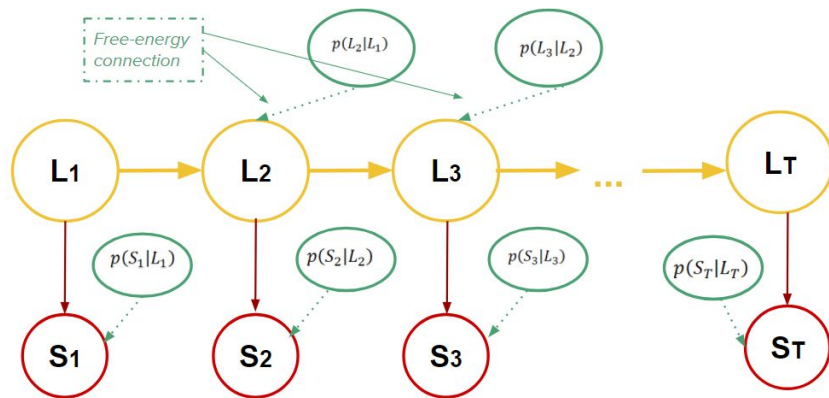


...

L = Latent conditions
S = sensations

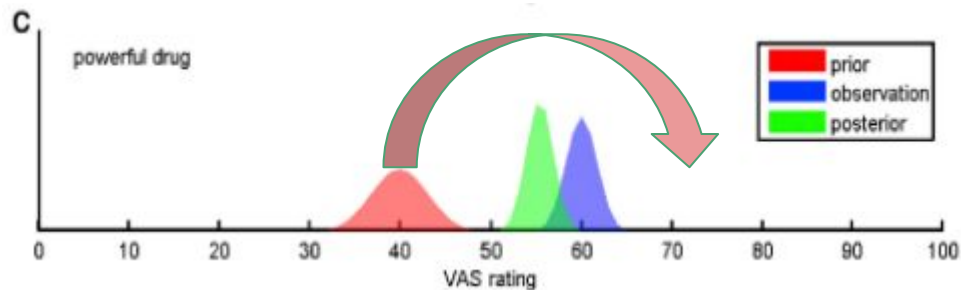
Summary: Preliminary graphical model

- Time series model
 - Increasing anticipation leads to pain perception on a theoretical level
- Conditional probabilities (hierarchy level) represent learning processes
- Message passing between nodes via Sum-Product algorithm
- Some free-energy learning



Modeling pediatric chronic pain data

- Collaboration with **Tanja Hechler**; Vestische Kinderklinik Datteln
- Questionnaire data on **pain predictions**
 - How likely do you think it is that sensation X caused by **pain**?
 - What causes sensation X? Name as many as possible.
- Maybe later: Experimental data on higher **pain prior** in children w CP



Outlook

- Next steps in my thesis project
 - Learn more about modeling, machine learning techniques & free energy learning
 - Learn more about computational psychiatry and PC framework
 - Get the modeling going somehow
- Best case:
 - Derive specific etiologic and therapeutic hypotheses
 - Identify mathematically informed therapy recommendations & simulate

Literature

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Thank you for your attention

Questions and comments?