antropocaos

Argonautas del Caos

Cultural evolution and social learning

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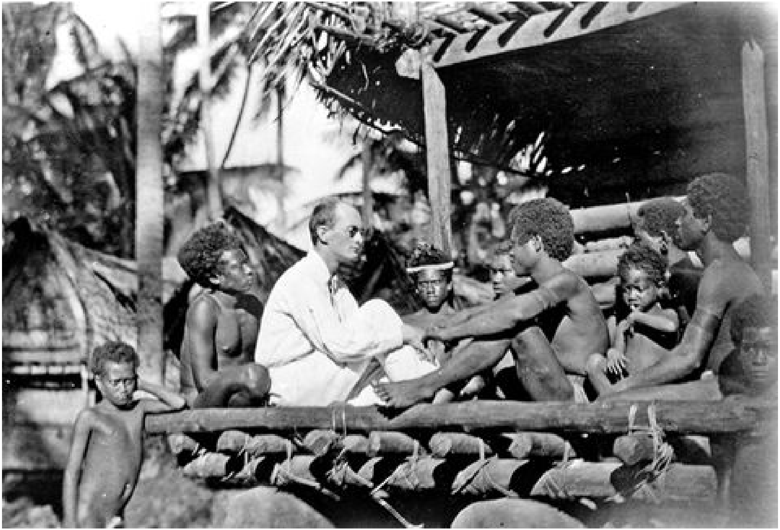
Anthropology



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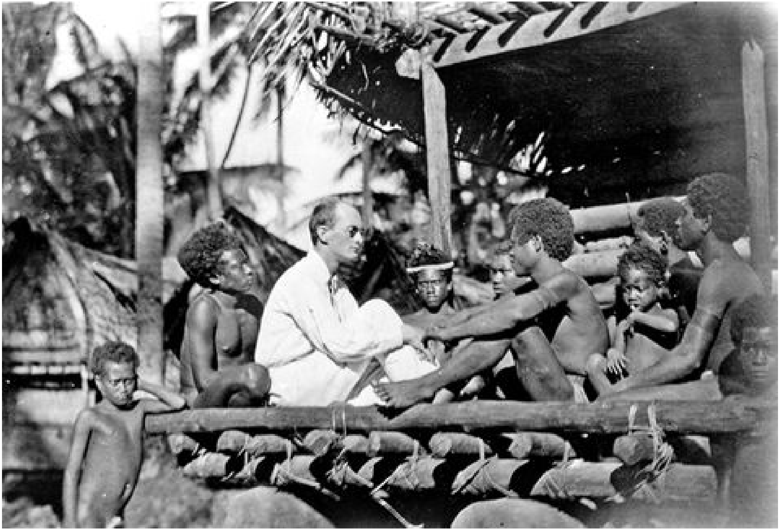
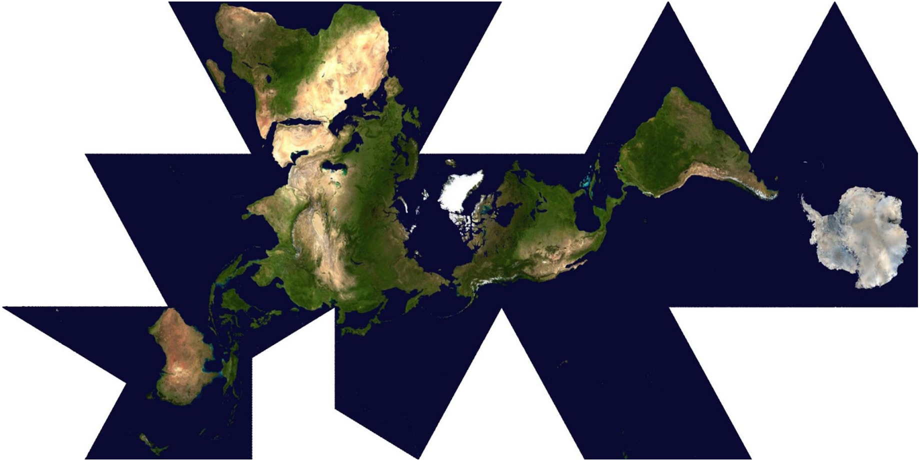
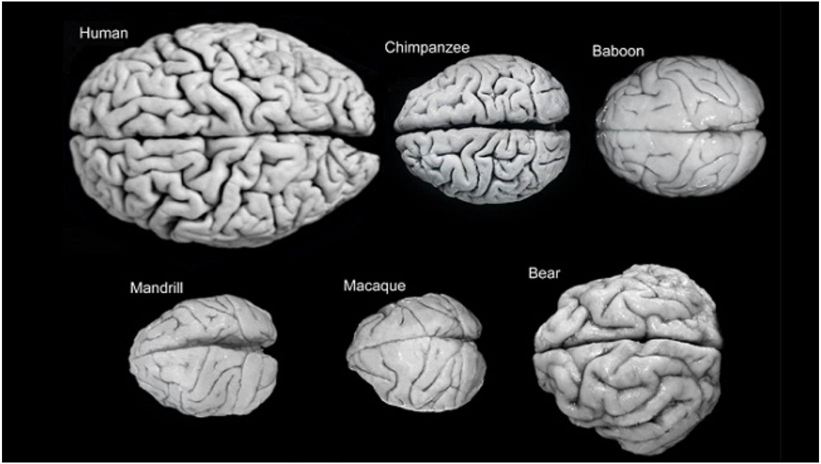


For a comprehensive, non-eurocentric, history of society see Enrique Dussel (Ecuador,Chile)
About Chinese science before opium wars see Needham Research Institute

Homo sapiens success



Cognitive niche hypothesis



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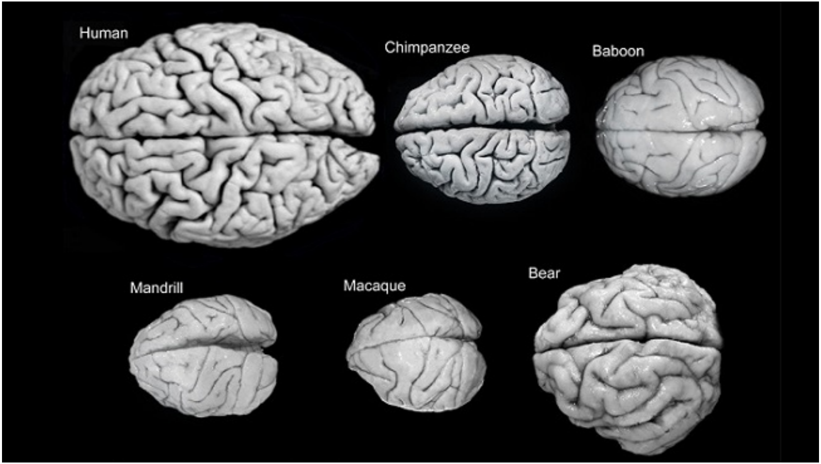

Our success is often explained in terms of our cognitive ability

Too complex to be alone

Well-adapted tools, beliefs, and practices are too complex for any single individual to invent during their lifetime even in hunter-gatherer societies

Cultural niche hypothesis

Humans accumulate, process and transmit knowledge across generations, leading to a cultural evolution process in which tools, beliefs, and practices arise as emergent properties of the social system.

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See Boyd, Richerson, Henrich The cultural niche: Why social learning is essential for human adaptation

Cultural evolution

We owe our success to our ability to learn from others (social learning)

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Books: Culture and the Evolutionary Process – Origine and Evolution of Cultures – Mathematical Models of Social Evolution.

Social learning

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- How social learning factors alter learning expected by the individual experience?

To answer them, we need a methodology to measure skill over time

Why Bayesian inference?

Allows us to optimally update a priori beliefs given a model and data.

Books: Bayesian data analysis – Bayesian Cognitive Modeling: A Practical Course

Where comes from?

	Not infected	Infected	
Not vaccinated	4	2	6
Vaccinated	76	18	94
	80	20	100

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Bayes theorem:

$$P(A_1|B_1) = \frac{P(B_1 \cap A_1)}{P(B_1)} = \frac{P(B_1|A_1)P(A_1)}{P(B_1)} \quad (1)$$

Scientific test example

There is a test that correctly detects zombies 95% of the time.

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Someone receive a positive test:
She has **only 8.7% chance** to actually be a zombie!?

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In this example all frequencies were observables

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Bayesian inference is about hidden variables
About our **belief distributions** of those hidden variables!

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A model is always there!

$$\underbrace{P(\text{Belief}|\text{Data},\text{Model})}_{\text{Posterior}} = \frac{\overbrace{P(\text{Data}|\text{Belief},\text{Model})}^{\text{Likelihood}}\,\overbrace{P(\text{Belief}|\text{Model})}^{\text{Prior}}}{\underbrace{P(\text{Data}|\text{Model})}_{\substack{\text{Evidence or}\\ \text{Average likelihood}}}}$$

- **Prior** belief (distribution):

$$P(B|M) = \frac{1}{\#\text{Beliefs}} \qquad \forall B \in \text{Beliefs}$$

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- **Posterior** belief (distribution):

$$P(B|D,M) = \frac{P(D|B,M)P(B|M)}{P(D|M)} \qquad \forall B \in \text{Beliefs}$$

The garden of forking paths

To update our beliefs (posterior), we need to consider every possible path in the model that could have lead us to the observed data (likelihood).

The garden of forking paths

Data (D): ● ○ ● Beliefs (B): ○○○○, ●○○○, ●●○○, ●●●○, ●●●●

Model (M): Data $\sim$ Binomial(n, p)

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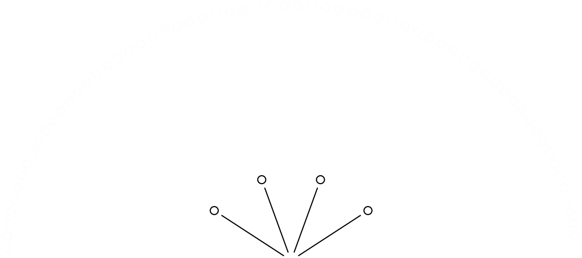

Ways given M and $B = \circ\circ\circ\circ$ (First marbel)

The garden of forking paths

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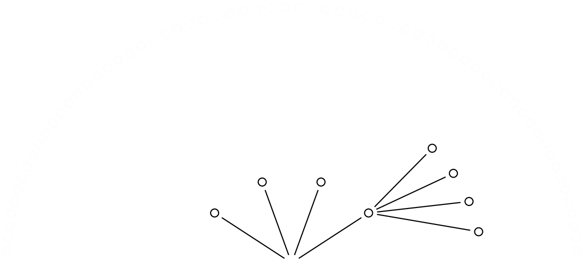

Ways given M and $B = \circ\circ\circ\circ$ (Second marbel)

The garden of forking paths

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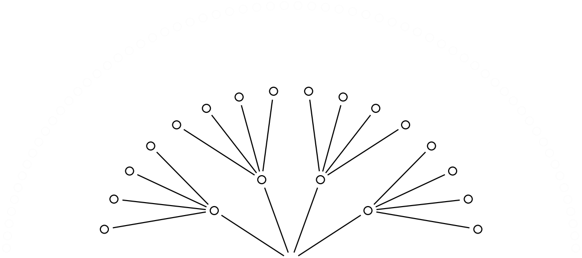

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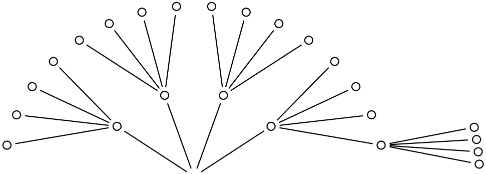

Ways given M and $B = ○○○○$ (Third marbel)

The garden of forking paths

Data (D): ● ○ ● Beliefs (B): ○○○○, ●○○○, ●●○○, ●●●○, ●●●●

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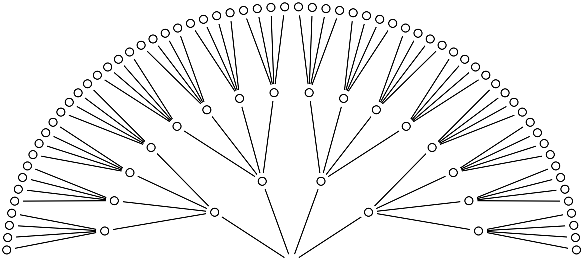

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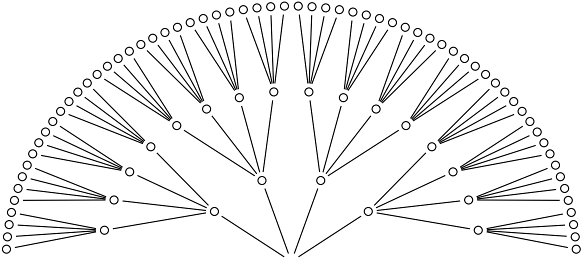

Ways given M and $B =$ ○○○○

Belief	Ways to produce ● ○ ●
○○○○	

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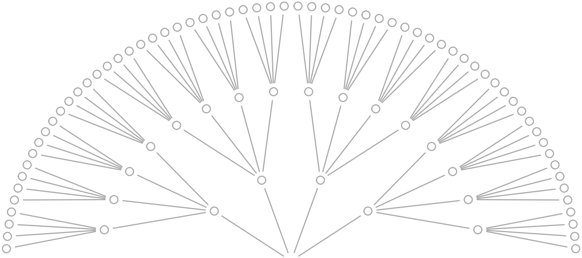

Ways given M and $B =$ ○○○○

Belief	Ways to produce ● ○ ●
○○○○	$0 \times 4 \times 0 = 0$

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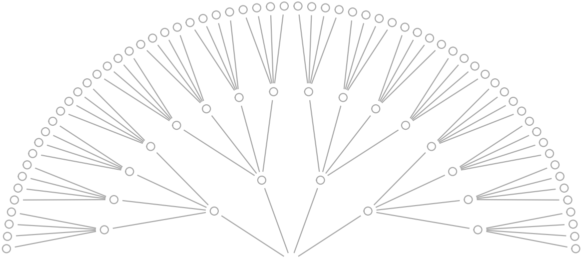

Ways given M and $B =$ ○○○○

Belief	Ways to produce ● ○ ●	Likelihood	Prior	Posterior $\propto$
○○○○	$0 \times 4 \times 0 = 0$	$\frac{0\times4\times0}{4\times4\times4} = \frac{0}{64}$	$1/5$	$\frac{0}{64}\,\frac{1}{5}$

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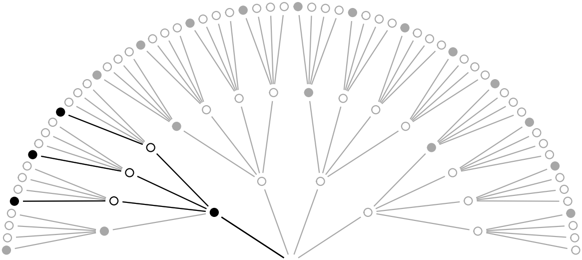

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●○○○	$1 \times 3 \times 1 = 3$	$3/64$	$1/5$	$\frac{3}{64}\,\frac{1}{5}$

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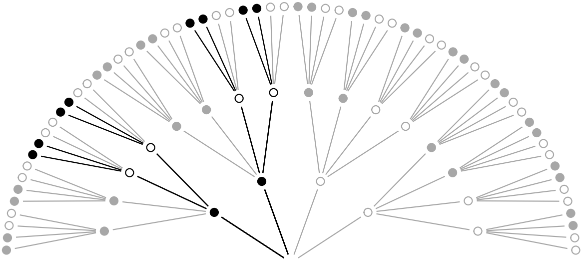

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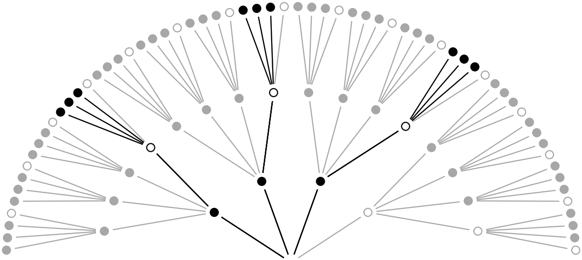

Ways given M and $B =$ ●●●○

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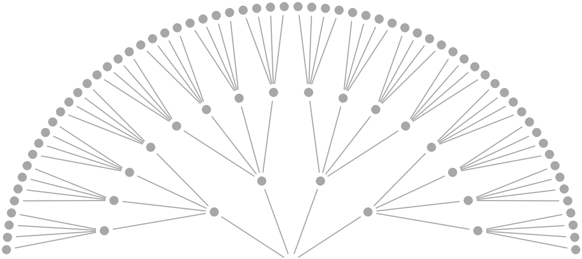

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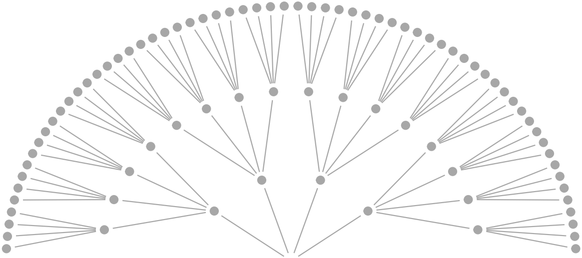

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				$P(D\|M)$

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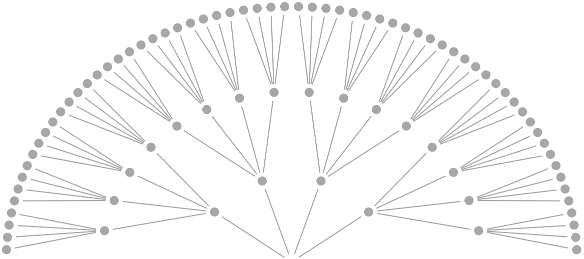

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				$\frac{3+8+9}{64\cdot5}$

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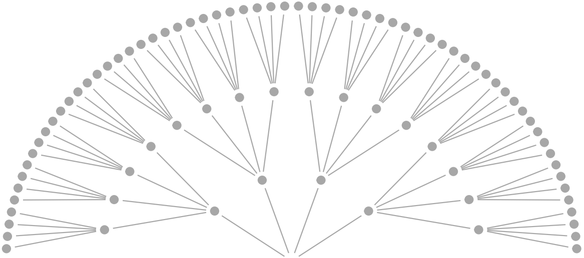


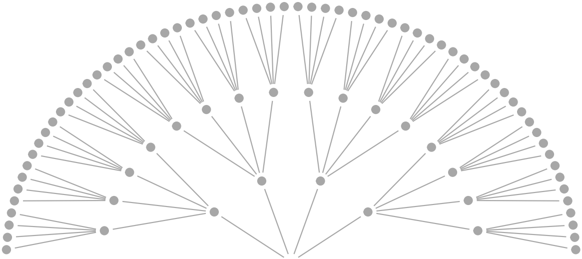
Ways given M and $B =$ ●●●●

Belief	Ways to produce ● ○ ●	Likelihood	Prior	Posterior $\propto$	Posterior
○○○○	$0 \times 4 \times 0 = 0$	$\frac{0 \times 4 \times 0}{4 \times 4 \times 4} = \frac{0}{64}$	$1/5$	$\frac{0}{64}\,\frac{1}{5}$	$\frac{0}{64}\,\frac{1}{5}\,\frac{64 \cdot 5}{3+8+9}$
●○○○	$1 \times 3 \times 1 = 3$	$3/64$	$1/5$	$\frac{3}{64}\,\frac{1}{5}$	
●●○○	$2 \times 2 \times 2 = 8$	$8/64$	$1/5$	$\frac{8}{64}\,\frac{1}{5}$	
●●●○	$3 \times 1 \times 3 = 9$	$9/64$	$1/5$	$\frac{9}{64}\,\frac{1}{5}$	
●●●●	$4 \times 0 \times 4 = 0$	$0/64$	$1/5$	$\frac{0}{64}\,\frac{1}{5}$	
				$\frac{3+8+9}{64 \cdot 5}$	

The garden of forking paths

Data (D): ● ○ ● Beliefs (B): ○○○○, ●○○○, ●●○○, ●●●○, ●●●●

Model (M): Data $\sim$ Binomial(n, p)



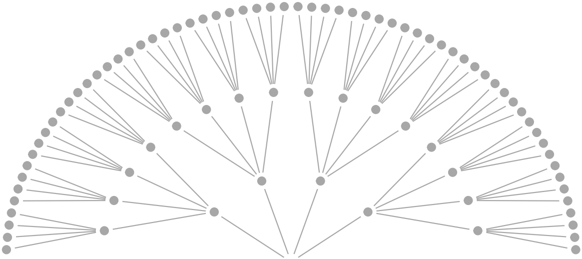
Ways given M and $B =$ ●●●●

Belief	Ways to produce ● ○ ●	Likelihood	Prior	Posterior $\propto$	Posterior
○○○○	$0 \times 4 \times 0 = 0$	$\frac{0\times4\times0}{4\times4\times4} = \frac{0}{64}$	$1/5$	$\frac{0}{64}\,\frac{1}{5}$	$\frac{0}{3+8+9} = 0.00$
●○○○	$1 \times 3 \times 1 = 3$	$3/64$	$1/5$	$\frac{3}{64}\,\frac{1}{5}$	
●●○○	$2 \times 2 \times 2 = 8$	$8/64$	$1/5$	$\frac{8}{64}\,\frac{1}{5}$	
●●●○	$3 \times 1 \times 3 = 9$	$9/64$	$1/5$	$\frac{9}{64}\,\frac{1}{5}$	
●●●●	$4 \times 0 \times 4 = 0$	$0/64$	$1/5$	$\frac{0}{64}\,\frac{1}{5}$	
				$\frac{3+8+9}{64\cdot5}$	

The garden of forking paths

Data (D): ● ○ ●   Beliefs (B): ○○○○, ●○○○, ●●○○, ●●●○, ●●●●

Model (M): Data $\sim$ Binomial(n, p)



Ways given M and $B =$ ●●●●

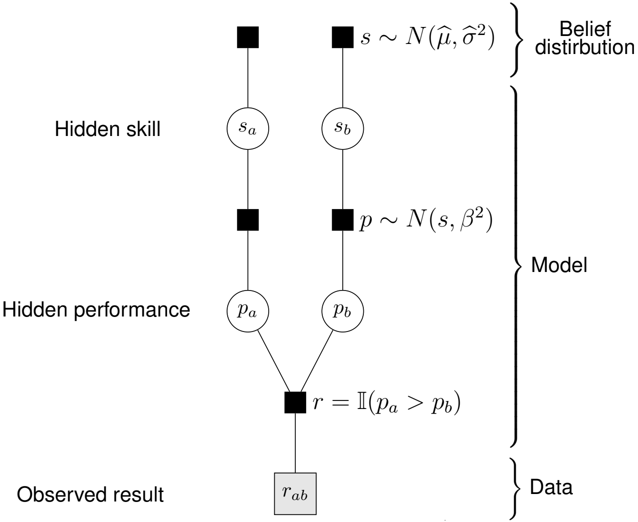
Belief	Ways to produce ● ○ ●	Likelihood	Prior	Posterior $\propto$	Posterior
○○○○	$0 \times 4 \times 0 = 0$	$\frac{0\times4\times0}{4\times4\times4} = \frac{0}{64}$	$1/5$	$\frac{0}{64}\,\frac{1}{5}$	$\frac{0}{3+8+9} = 0.00$
●○○○	$1 \times 3 \times 1 = 3$	$3/64$	$1/5$	$\frac{3}{64}\,\frac{1}{5}$	$\frac{3}{3+8+9} = 0.15$
●●○○	$2 \times 2 \times 2 = 8$	$8/64$	$1/5$	$\frac{8}{64}\,\frac{1}{5}$	$\frac{8}{3+8+9} = 0.40$
●●●○	$3 \times 1 \times 3 = 9$	$9/64$	$1/5$	$\frac{9}{64}\,\frac{1}{5}$	$\frac{9}{3+8+9} = 0.45$
●●●●	$4 \times 0 \times 4 = 0$	$0/64$	$1/5$	$\frac{0}{64}\,\frac{1}{5}$	$\frac{0}{3+8+9} = 0.00$
				$\frac{3+8+9}{64\cdot5}$	

Bayesian skill estimator

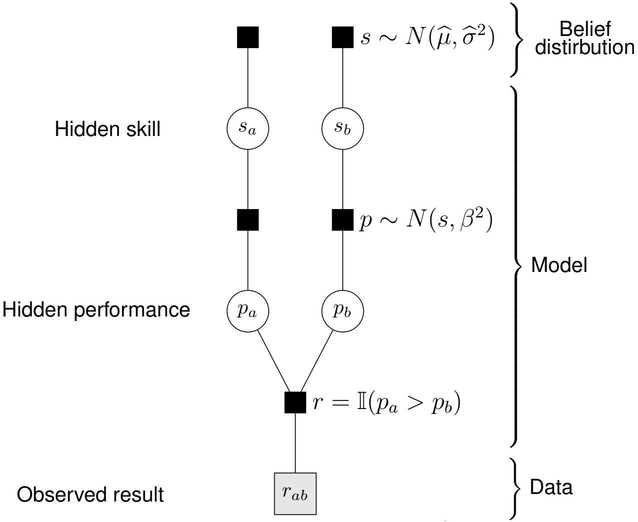
How to estimate skill of players?

Arpad Elo

Bayesian Elo factor graph



Bayesian Elo factor graph

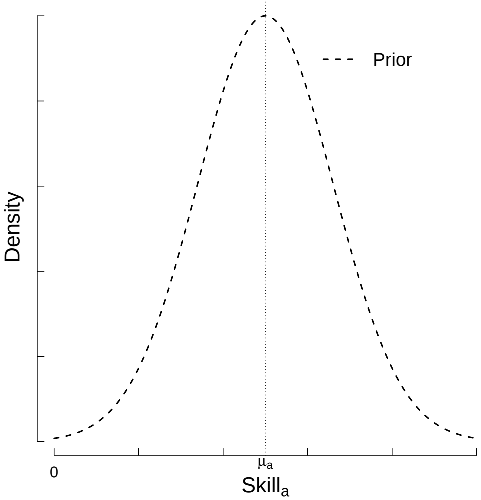


The factor graphs specifies the way to compute the posterior, likelihood, and evidence.

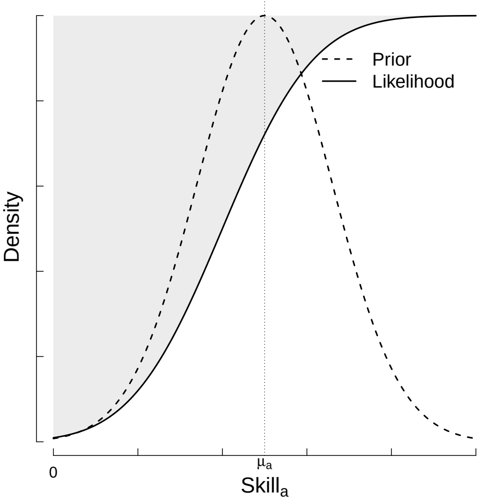
Kschischang FR, Frey BJ, Loeliger HA. Factor graphs and the sum-product algorithm. 2001

$$\overbrace{P(s_a \mid r_{ab}, \text{Elo model})}^{\text{Posterior}} \propto \overbrace{N(s_a \,|\, \widehat{\mu}_a, \widehat{\sigma}_a^2)}^{\text{Prior}} \; \overbrace{1 - \Phi(s_a \,| \widehat{\mu}_b, 2\beta^2 + \widehat{\sigma}_b^2)}^{\text{Likelihood}} \qquad \text{Win case}$$

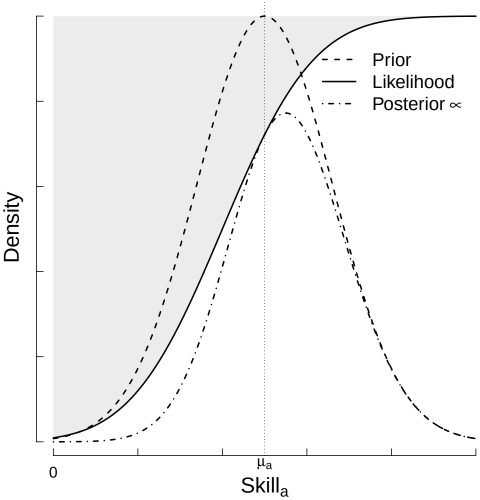
$$\overbrace{P(s_a \mid r_{ab}, \text{Elo model})}^{\text{Posterior}} \propto \overbrace{N(s_a \mid \widehat{\mu}_a, \widehat{\sigma}_a^2)}^{\text{Prior}} \; \overbrace{1 - \Phi(s_a \mid \widehat{\mu}_b, 2\beta^2 + \widehat{\sigma}_b^2)}^{\text{Likelihood}} \qquad \text{Win case}$$



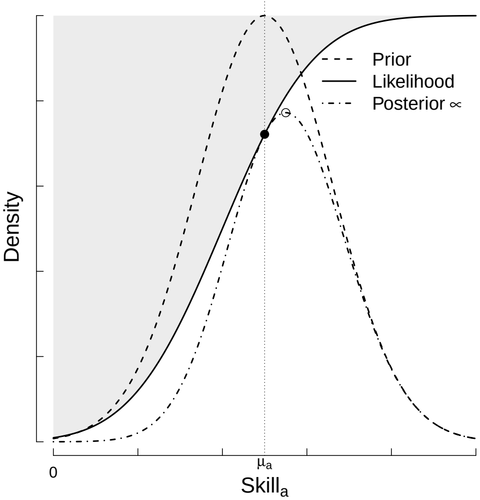
$$\overbrace{P(s_a \mid r_{ab}, \text{Elo model})}^{\text{Posterior}} \propto \overbrace{N(s_a \mid \widehat{\mu}_a, \widehat{\sigma}_a^2)}^{\text{Prior}} \; \overbrace{1 - \Phi(s_a \,|\widehat{\mu}_b, 2\beta^2 + \widehat{\sigma}_b^2)}^{\text{Likelihood}} \qquad \text{Win case}$$



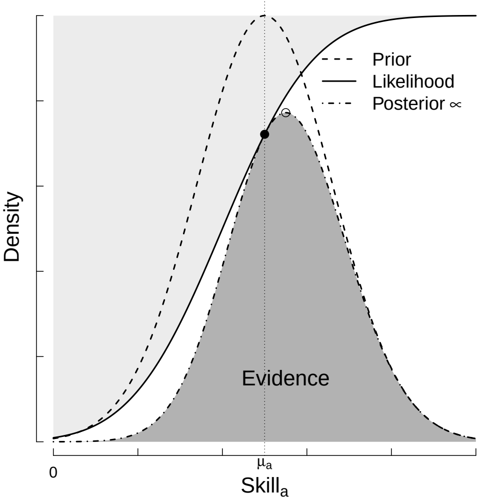
$$\overbrace{P(s_a \mid r_{ab}, \text{Elo model})}^{\text{Posterior}} \propto \overbrace{N(s_a \,|\, \widehat{\mu}_a, \widehat{\sigma}_a^2)}^{\text{Prior}} \; \overbrace{1 - \Phi(s_a \,|\widehat{\mu}_b, 2\beta^2 + \widehat{\sigma}_b^2)}^{\text{Likelihood}} \qquad \text{Win case}$$



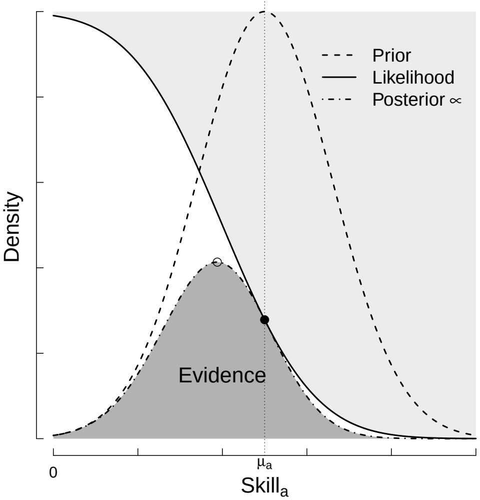
$$\overbrace{P(s_a \mid r_{ab}, \text{Elo model})}^{\text{Posterior}} \propto \overbrace{N(s_a \mid \widehat{\mu}_a, \widehat{\sigma}_a^2)}^{\text{Prior}} \; \overbrace{1 - \Phi(s_a \mid \widehat{\mu}_b, 2\beta^2 + \widehat{\sigma}_b^2)}^{\text{Likelihood}} \qquad \text{Win case}$$



$$\overbrace{P(s_a \mid r_{ab}, \text{Elo model})}^{\text{Posterior}} \propto \overbrace{N(s_a \mid \widehat{\mu}_a, \widehat{\sigma}_a^2)}^{\text{Prior}} \overbrace{1 - \Phi(s_a \mid \widehat{\mu}_b, 2\beta^2 + \widehat{\sigma}_b^2)}^{\text{Likelihood}} \qquad \text{Win case}$$

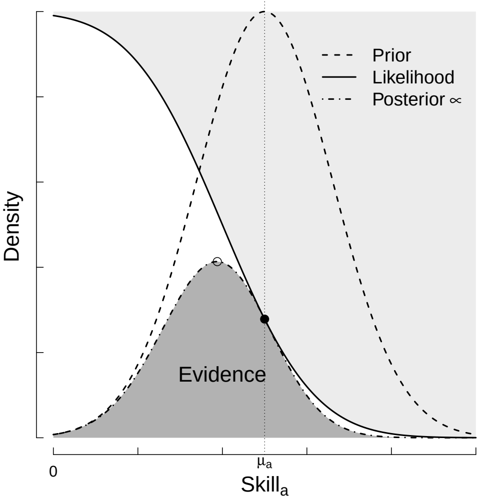


$$\overbrace{P(s_a \mid r_{ab}, \text{Elo model})}^{\text{Posterior}} \propto \overbrace{N(s_a \,|\, \widehat{\mu}_a, \widehat{\sigma}_a^2)}^{\text{Prior}} \; \overbrace{\Phi(s_a \,|\widehat{\mu}_b, 2\beta^2 + \widehat{\sigma}_b^2)}^{\text{Likelihood}} \qquad \text{Loose case}$$



$$\overbrace{P(s_a \mid r_{ab}, \text{Elo model})}^{\text{Posterior}} \propto \overbrace{N(s_a \mid \widehat{\mu}_a, \widehat{\sigma}_a^2)}^{\text{Prior}} \; \overbrace{\Phi(s_a \mid \widehat{\mu}_b, 2\beta^2 + \widehat{\sigma}_b^2)}^{\text{Likelihood}}$$

Loose case

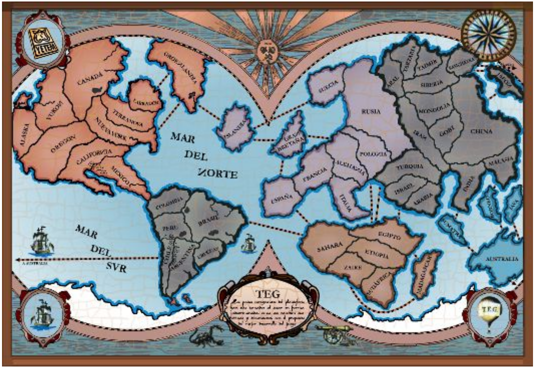


For a detailed demostration, see Landfried. TrueSkill: Technical Report. 2019

Could we detect social learning factors?

We have a lot of information available on the internet

Database



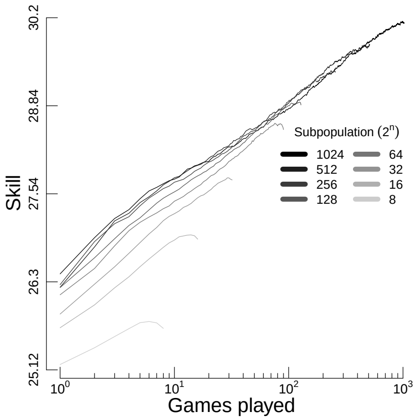
We set to investigate the impact of team play strategies on skill acquisition in Conquer Club

Law of practice

$$\text{Skill} = \text{Skill}_0 \, \text{Experience}^{\alpha}$$

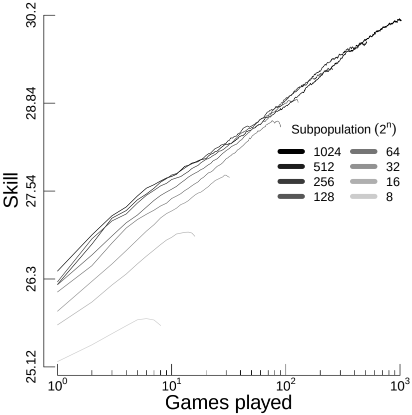
Law of practice

$$\text{Skill} = \text{Skill}_0 \ \text{Experience}^{\alpha}$$



Law of practice

$$\text{Skill} = \text{Skill}_0 \, \text{Experience}^{\alpha}$$

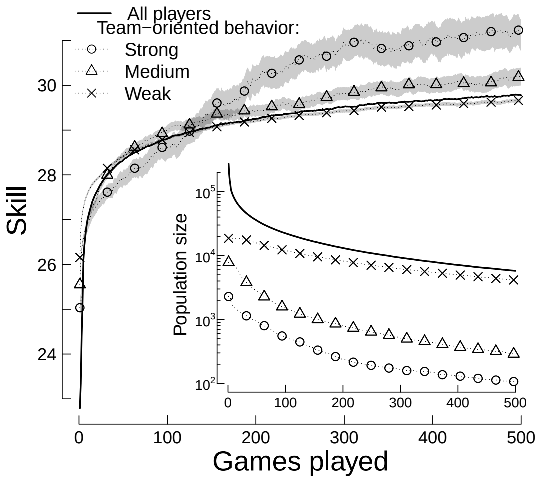


Learning by individual experience is always linear in log-log scale

Team oriented behavior

What is a better strategy?
Play in teams or individually?

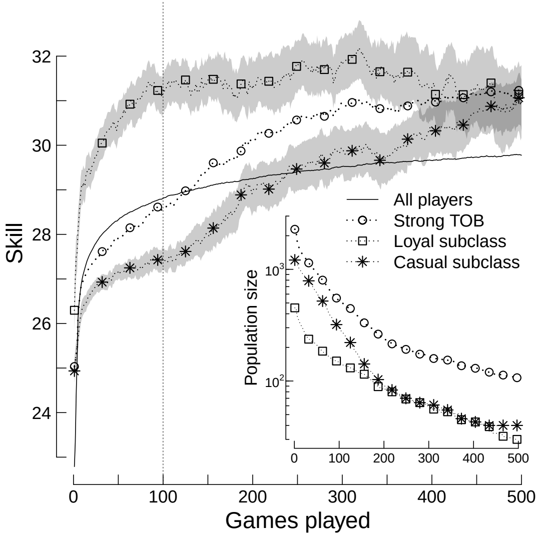
Team oriented behavior



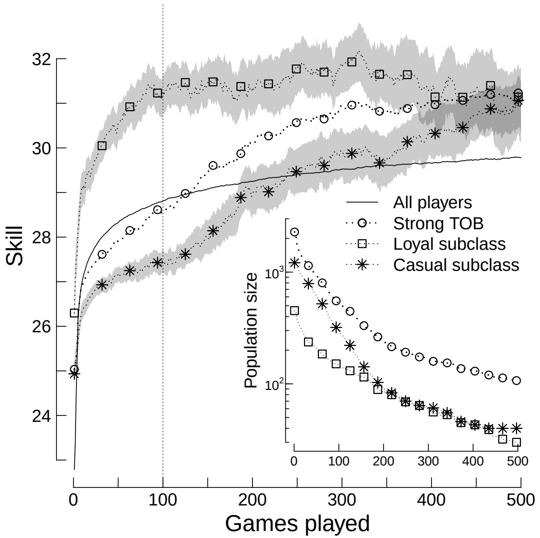
Loyal and causal teammates

What is a better strategy?
Repeat or vary teammates?

Loyal and causal teammates



Loyal and causal teammates



See paper: Landfried Faithfulness-boost effect: Loyal teammate selection correlates with skill acquisition improvement in online games. 2019.