

Social Drift-Diffusion Model [1]

Information Cascades in Social Systems

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Intro

Social Situations and Information Cascades

- Online Environments - spread of news
- Pedestrians crossing a road
- Financial Markets
- Consumer Preferences
- Political Opinion Formation

A dynamic-theory of social decision making/ process-level account of the choices and response times (RTs) of individuals in dynamic social systems

DDM as a model for evidence accumulation process during decision making accounts for:

- speed-accuracy trade-off
- the construction of preferences
- the formation of confidence judgements
- the emergence of response bias
- the interplay between attention and evidence accumulation.

DDM assumes that in a 2AFC task, the subject is accumulating evidence for one or other of the alternatives at each time step (there is also an initial level of evidence), and integrating that evidence until a decision threshold is reached.

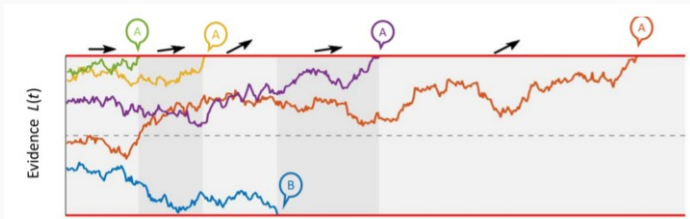


Figure 1: A generic example of DDM

The jaggedness arises because each sample of evidence is noisy (i.e., the stimuli itself and the cognitive and neural processes introduce variability into the evidence accumulation)

Social DDM

In the case of social DDM, the evidence comes from two sources: *personal information*, gathered from sampling the physical environment (e.g., for visual or auditory cues), and *social information*, gathered by observing the behaviour of others.

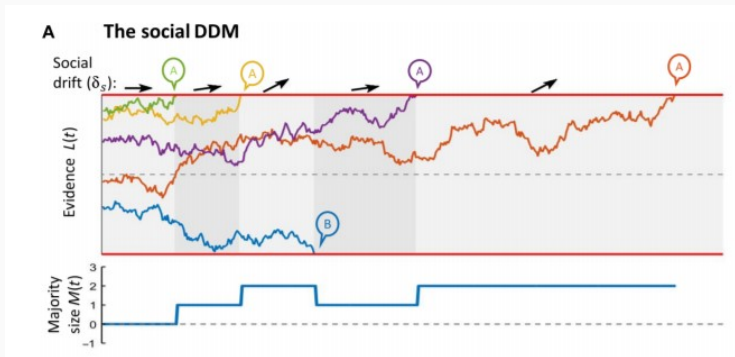


Figure 2: Drift rate shifting toward choice threshold favoured by the majority

The model for Cumulative Evidence at time point t

The model is given by

$$L(t + \Delta t) - L(t) = (\delta_p + \delta_s(t)) \Delta t + \epsilon \sqrt{\Delta t}$$

where δ_p is the personal information uptake rate, and

$$\delta_s(t) = sM(t)^q$$

$$M(t) = N_A(t) - N_B(t)$$

$$\epsilon \sim N(0, \sigma_{\text{noise}})$$

$$\beta = \frac{1}{1 + e^{-a(C-b)}}$$

$$L(0) = (2\beta - 1)\theta$$

Here δ_s is the social information uptake rate, $M(t)$ is what the majority is, ϵ is random noise, and β is the scaled initial bias, and C is the confidence in opinion. $s, q, \sigma_{\text{noise}}, a, b$ are adjustable parameters, We stop evolving when L hits $\pm\theta$, and that is when we consider the decision is made.

- s influences the strength of the social drift rate
- q shapes the power function
- a determines how sensitive the start point is to changes in confidence
- b captures other factors besides confidence in the personal decision that affect the start point

Empirical Study

Predator Detection task

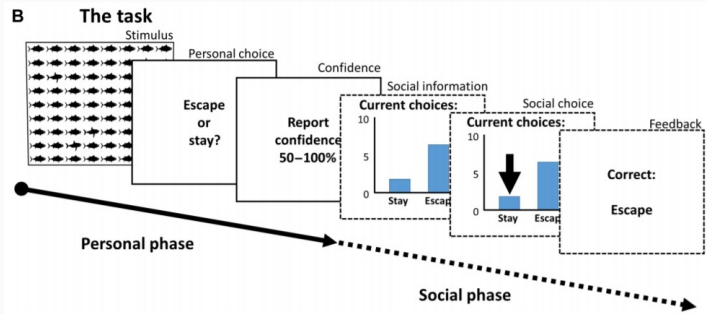


Figure 3: Stages of the predator detection task.

Group Size- small ($n=3$), medium ($n=7$ to 10), large ($n=15-17$)

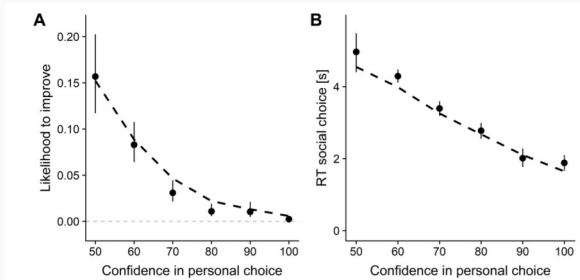
Stimulus- 2s, Escape - ≥ 5 sharks, Stay- ≤ 4

5s + 5s for Personal choice and Confidence Social Information

Phase- first updated after 3s and then iteratively every 2s for 20s

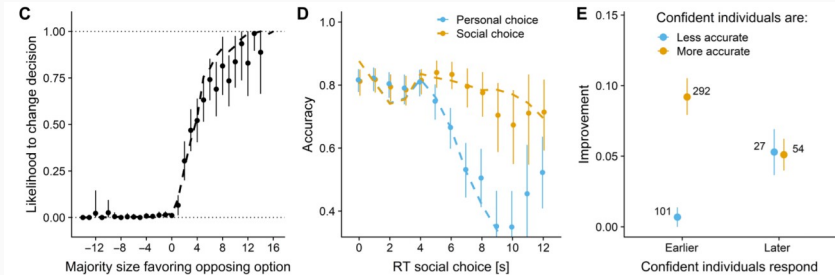
Results

Empirical Results



Participants reporting higher confidence in their personal choice (A) improved less and (B) responded earlier during the social choice

Empirical Results

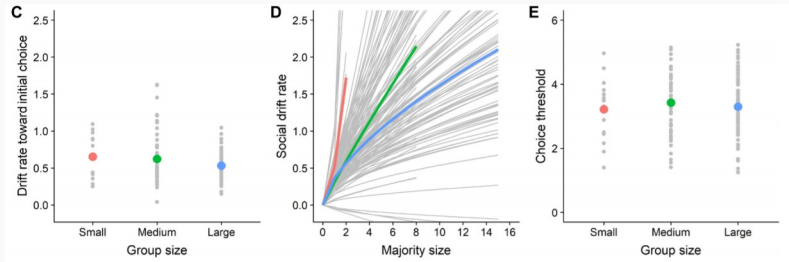


(C) The larger the majority favouring the opposing option, the more likely participants were to change their decision.

(D) The choices of participants who responded later in the social choice were less accurate in the personal choice but improved more in the social choice

(E) Participants improved most when more confident individuals were more accurate (i.e., positive confidence-accuracy correlation;) and responded earlier (i.e., negative accuracy-RT correlation)

Empirical Results



(C) Evidence tended to drift toward the choice threshold of the option chosen during the personal phase, independent of group size.

(D) The larger the majority favoring an option, the more strongly participants drifted toward the choice threshold favored by the majority. Participants in smaller groups had a stronger drift (convex shape) given the same majority size as compared to larger groups (concave shape).

(E) The choice threshold θ , reflecting a participant's willingness to wait for social information, did not differ between group sizes

Conclusions from Emperical data

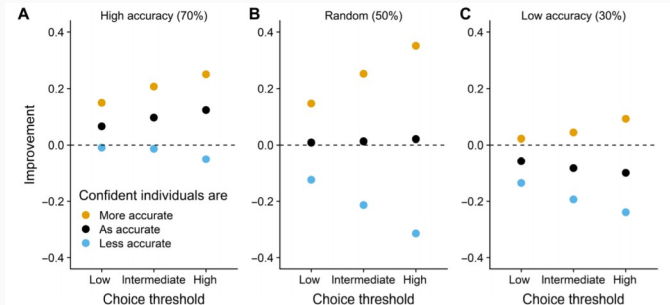
- Individuals base their start point on their personal choice and reported confidence;
- individuals drift toward the correct option, their initially chosen option, or neither of the two;
- individuals drift toward the option favoured by the majority.

Agent Based Modelling

The social DDM also allows to conduct agent-based simulations with processes closely resembling the participants' behavior. The following parameters were varied:

- confidence-accuracy relationship by assigning either higher, similar, or lower confidence to agents with a correct choice compared to agents with a wrong choice
- the agents' personal accuracy by assigning 30, 50, 70% correct personal choices to agents
- the willingness to wait for social information by assigning a low, intermediate, or high choice threshold

ABS of DDM



- Groups with a high average personal accuracy improved, unless confident agents were less accurate than under-confident ones
- Groups with a personal accuracy of 50, 30% only improved when confident agents were more accurate than under-confident ones
- a higher choice threshold strengthened the positive impact of confident individuals being more accurate as well as the negative impact of confident individuals being less accurate

Parameter Estimation

Discretisation

On discretising (L in steps of Δ and time in steps of h we obtain a probabilistic evolution (Markov process) given by, i.e,

$$L \in \{i\Delta \mid -k \leq i \leq k\}$$
$$p_{ij} = \begin{cases} \frac{1}{2\alpha} \left(1 \pm \frac{u}{\sigma^2} \sqrt{h}\right) & \text{if } j = i \pm 1 \\ 1 - \frac{1}{\alpha} & \text{if } j = i \\ 0 & \text{otherwise} \end{cases}$$

where $u = \delta_p + \delta_s$. Obviously since the decision is made when L hits $\pm\theta$, the states $-k, k$ are absorbing (once L is in this state, evolution stops).

We simulate the Markov chain by an MCMC (Markov chain Monte-Carlo) estimation.

Transition Probability matrix

$$P = \left[\begin{array}{c|c} P_I & 0 \\ \hline R & Q \end{array} \right] = \begin{array}{c} \begin{matrix} 1 & m \\ 1 & 0 \\ m & 1 \end{matrix} \\ \begin{matrix} 2 & 3 & \dots & m-2 & m-1 \\ p_{12} & 0 & & 0 & 0 \\ 0 & 0 & & 0 & 0 \\ 0 & 0 & & 0 & 0 \\ \vdots & \vdots & & \vdots & \vdots \\ m-3 & 0 & 0 & p_{m-3,m-2} & 0 \\ m-2 & 0 & 0 & p_{m-2,m-2} & p_{m-3,m-1} \\ m-1 & 0 & p_{m-1,m} & 0 & 0 \end{matrix} \end{array}$$

P_I matrix with the two absorbing states

R matrix containing the transition probabilities that eventually lead to the absorbing states in a single transition

Q is a matrix including the remaining transition probabilities



A. N. Tump, T. J. Pleskac, and R. H. J. M. Kurvers.

Wise or mad crowds? the cognitive mechanisms underlying information cascades.

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