The unpredictability of human opinion dynamics

Corentin Vande Kerckhove, Samuel Martin, Pascal Gend, Julien M. Hendrickx*

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Introduction

Many individual judgments are mediated by observing others' judgments. This is particularly noticeable in the online world. The availability of online data has lead to a recent surge in trying to understand how online social influence impacts human behaviour. Recent studies used online *in vitro* experiment to identify the micro-level mechanisms susceptible to explain the way social influence impacts human decision making (e.g., distance to the average opinion [2]). These recent online *in vitro* studies have lead to posit that the so-called linear consensus model may be appropriate to describe the way individuals revise their judgment. The prediction accuracy of a model is limited to the extend the judgment revision process is a deterministic process. However, there are empirical evidences [3] showing that the opinion individuals display is a sample of an internal probabilistic distribution. Following these results, the present article details a new experiment to estimate the unpredictability level of the judgment revision mechanism. Estimating the intrinsic unpredictability provides a limit beyond which no one can expect to improve the predictions.

Material

To quantify opinion dynamics subject to social influence, we carried out online experiments on a website that we built, which received participants from a crowdsourcing platform. Two types of experiments were designed. While in the uncontrolled experiment, only real participants took part in the study, in the control experiment, synthetic participants were also introduced to replicate similar experimental conditions.

Uncontrolled experiment

When a participant took part in an uncontrolled experiment, they joined a group of 6 participants and played 30 games of the same sort related to 30 distinct pictures. Two types of games were designed : the *gauging game*, in which the participants evaluated color proportions and the *counting game*, where the task required to guess the number of a certain item in the picture. A game consisted of 3 rounds with the same picture where participants provided their judgment independently in the first round and could update their estimate based on the past judgments of the others. The data regarding the uncontrolled experiment were collected during July, September and October 2014. Overall, 654 distinct participants from 70 distinct countries took part to the study.

*C.V. and S.M. contributed equally to this work. S. M. and P. G. are with Université de Lorraine, CRAN, UMR 7039 and CNRS, CRAN, UMR 7039, 2 Avenue de la Forêt de Haye, Vandœuvre-lès-Nancy, France. C. V. K. and J. M. H. are with Large graphs and networks group, Université Catholique de Louvain, Avenue Georges Lemaitre, 4 B-1348 Louvain-la-Neuve, Belgium. C. V. K. is a F.N.R.S./FRIA research fellow. Research partly supported by the Belgian Interuniversity Attraction Poles and by an Actions incitatives CRAN 2014. Contact : corentin.vandekerckhove@uclouvain.be.

Control experiment

What variation in the judgment revision process would occur if a participant were exposed twice to exactly the same game with identical sets of initial judgments? The control experiment served to measure this degree of unpredictability. To create replicated experimental conditions, the judgments of five out of the six participants were synthetically designed. Among the 30 games, 20 games had been designed to form 10 pairs of replicated games with an identical picture used in games of a pair. Since the initial judgment of the real participant could not be controlled, the 15 synthetic judgments in the second replicate had to be shifted in order to maintain constant the initial judgment distances in each replicate. The shift was computed in real time to match the variation of the real participant initial judgments between the two replicates. The same shift was applied to all rounds to keep the synthetic judgments consistent over rounds. This provided exactly the same set of initial judgments up to a constant shift in each pair of replicated games. The data regarding the control experiment were collected during May and June 2015. Overall, 207 distinct participants took part in the study.

Methods

Consensus model

In previous work [1], we showed how judgment revision can be modeled using a time-varying influenceability consensus model. In mathematical terms, $x_i(r)$ denotes the opinion of individual i at round r and its evolution is described as

$$x_i(r+1) \ = \ x_i(r) \ + \ \alpha_i(r) \cdot (\bar{x}(r) - x_i(r)) \tag{1}$$

where $r = 1, 2$ and where $\bar{x}(r)$ is the mean opinion of the group at round r. This model is based on the *influenceability* $\alpha_i(r)$ of participants, a factor representing to which extent a participant incorporates external judgments.

Unpredictability in judgment revision

When a participant takes part to a game, their actual second judgment depends on several factors and can always be described as

$$x_i(2) = f_i^1(x_i(1), x_{others}(1), picture) + \eta, \tag{2}$$

where $x_{others}(1)$ denotes the vector of initial judgments from the others, f_i^1 describes how a participant revises their judgment in average depending on their initial judgment and external factors. The term *picture* is the influence of the picture on the final judgment. The quantity η captures the intrinsic variation made by a participant when making their second round judgment despite being exposed to the same set of intitial judgments and identical picture. The standard deviation std(η) measures the intrinsic unpredictability of the judgment revision process. By definition of f_i^1, no other model can be more precise, but this function is unknown. To be able to derive a measure of unpredictability, we assume that the function f_i^1 splits into two components :

$$f_i^1(x_i(1), x_{others}(1), picture) = \lambda g_i^1(x_i(1), x_{others}(1)) + (1-\lambda) h_i^1(picture),$$

separating the dependency of the second round judgment on past judgments dependency regarding the picture. The parameter $\lambda \in [0, 1]$ is to be estimated. It is further assumed that if the initial judgments are shifted by a constant shift, the g_i^1 component in the second round judgment will on average be shifted in the same way. Under these assumptions, it can be shown that the intrinsic variation estimation can be empirically measured as

$$\mathrm{std}(\eta) = \sqrt{\mathrm{mean}\left(\frac{1}{2}(x_i'(2) - x_i(2) - \lambda(x_i'(1) - x_i(1)))^2\right)} \tag{3}$$

where the mean is taken over all repeated games and all participants and where the prime notation is taken for judgments from the second replicated game in the control experiment. The constant $\lambda \in [0, 1]$ is found by minimizing std(η) to be as conservative as possible. The measure of third round intrinsic unpredictability is similar to the second round and is ommited here.

Results

The intrinsic variation estimation (3) is used to validate the prediction efficiency of the consensus model. We expressed the predictive power of a model by a crossvalidation *root mean square error* (RMSE), as detailed in our previous paper [1]. Errors are computed for the consensus model and for a null model that assumes constant opinions. The difference between the two errors is assessed relatively to the unpredictability measure obtained from the control experiment, since no model can make better predictions than this threshold (Fig. 1). Taking the intrinsic unpredictable variation thresholds as a reference, the relative prediction *RMSE* is more than halved when using the consensus model (1) instead of the null model with constant opinions. In other words, more than two thirds of the prediction error made by the consensus model is due to the intrinsic unpredictability of the decision revision process.

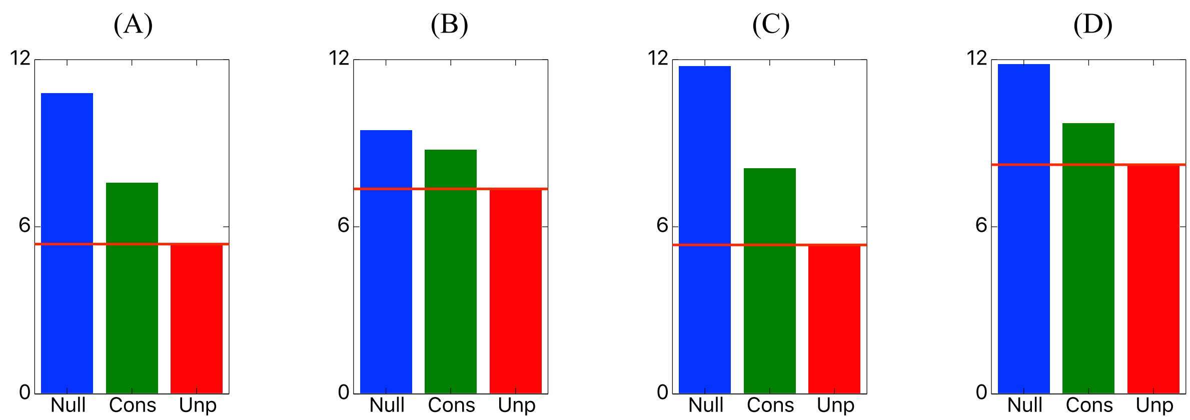

Figure 1: **Root mean square error**. (A), (B) : the second round judgments, (C), (D) : the third round judgments. (A), (C) *gauging game*, (B), (D) *counting game*. Null : null model of constant opinion. Cons : consensus model (1). Unp : intrinsic unpredictable variation.

References

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