A Quantum Walk Model For Emotion Transmission In Serial Reproduction Of Narratives

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Abstract

A quantum walk model is developed for emotion transmission in serial reproduction of narratives. The readers' emotions are represented by density operators, and the influences of the narratives on the readers' emotions are modeled by applying the controlled unitary operators to the density operators. The performance of the quantum model is evaluated on a large corpus of narratives, compared to that of the Bayesian Markov chain model. The quantum model not only outperforms the Bayesian model for all five emotion transmissions presented in the corpus but can also account for order effects in serial reproductions. These results suggest a promising first step towards extending quantum-like models to explain group-level cognition.

Keywords: computational modeling; serial reproduction; quantum cognition; emotion transmission;

Introduction

Numerous empirical findings in cognitive psychology have exhibited anomalies concerning the classical benchmark defined by Kolmogorovian probability axioms and the rules of Boolean logic, triggering a whole new scope of research: the development of models for decision-making based on the quantum formulation of probability theory (Busemeyer & Bruza, 2012; Haven, Khrennikov, & Khrennikov, 2013; Khrennikov, Basieva, Dzhafarov, & Busemeyer, 2014; Pothos & Busemeyer, 2013, 2022). Although these quantum models provide deep insights into the cognitive anomalies, their scopes are typically confined to the individual level. The next stage of this line of research is to extend quantum models of cognition to the group level. This is very important in understanding anomalies at the group level and how information processing could affect information propagation in social networks and group decision making.

Serial reproduction is an experimental scheme where participants are asked to reproduce a stimulus (e.g. narratives, images), and the reproduced stimulus will then be reproduced by the next participant in a chain. Serial reproduction is chosen as the starting point of developing quantum models in group-level for two reasons: (1) Serial reproduction is an information path of a social network; (2) Large amount of research works, both experimental (Lyons & Kashima, 2003; Lee, Gelfand, & Kashima, 2014; Breithaupt, Li, Liddell, Schille-Hudson, & Whaley, 2018) and theoretical (Xu & Griffiths, 2010; Hemmer & Steyvers, 2009; Meylan, Nair, & Griffiths, 2021), have been done.

In the remainder of this paper, we will first summarize the Bayesian Markov chain model (Xu & Griffiths, 2010), and present our new quantum model for serial reproduction. We will then compare the performance of the quantum model with the Bayesian model in explaining emotion transmission in a large corpus of serial reproduction of narratives. We finally discuss how the quantum model can account for potential order effects in serial reproduction.

Bayesian model for serial reproduction

According to Xu & Griffiths (2010), the outcome of serial reproduction is a sequence of memory reconstructions by the participants in a chain. At step $n+1$, the model assumes that the participant A_{n+1}'s previous experience establishes a prior of the true state of the world μ, with $\mu \sim N(\mu_0, \sigma_0^2)$, and that the noisy observation x_n has a Gaussian distribution with μ as its center, $x_n|\mu \sim N(\mu, \sigma_x^2)$. The reconstructed true state given the noisy observation $\mu|x_n$ then follows the Gaussian distribution $N(\lambda x_n + (1-\lambda)\mu_0, \lambda\sigma_x^2)$, where $\lambda = 1/(1+\sigma_x^2/\sigma_0^2)$ (Gelman et al., 2013). Since the reproduced stimulus with attribute values x_{n+1} (e.g. length of a fish in a drawing) only depends on the previous x_n, the process is a Markov chain with transition probability

$$p(x_{n+1}|x_n) = \int p(x_{n+1}|\mu)p(\mu|x_n)d\mu, \tag{1}$$

where $x_{n+1}|\mu \sim N(\mu, \sigma_x^2)$. Using the above results, serial reproduction for stimuli with one-dimensional attribute can be seen as a first-order autoregressive process, denoted as AR(1):

$$x_{n+1} = (1-\lambda)\mu_0 + \lambda x_n + \varepsilon_{n+1} \tag{2}$$

where $\varepsilon_{n+1} \sim N(0, \sigma_x^2 + \sigma_n^2)$ with $\sigma_n^2 = \lambda\sigma_x^2$.

Quantum model for serial reproduction

The quantum walk model for serial reproduction is illustrated in Figure 1. The model is developed from a more general quantum walk model for idea propagation in social network (Zhang & Busemeyer, 2021).

The opinion of the nth participant A_n conveyed in the stimulus they generate, denoted as S_n, is modeled by a quantum state $|\psi_n\rangle$ with density operator $\rho_{A_n} = |\psi_n\rangle|\psi_n\rangle^\dagger$, where $\dagger$ denotes the Hermitian conjugation. The initial opinion state of participant A_{n+1} is modeled by a quantum state $|X_{n+1}\rangle$

with density operator $X_{A_{n+1}} = |X_{n+1}\rangle|X_{n+1}\rangle^\dagger$. For binary attributes, $|\psi_n\rangle$ and $|X_{n+1}\rangle$ are two-dimensional states with norm 1 (with respect to the L^2 norm), and thus can be written as a linear combination of two orthonormal basis choice states $|0\rangle$ and $|1\rangle$, where $|0\rangle$ represents answering "Yes" for the attribute with probability 1, and $|1\rangle$ represents answering "No" with probability 1. The above construction could also work for one-dimensional attributes measured by ratings (Ashtiani & Azgomi, 2015; Martínez-Martínez & Sánchez-Burillo, 2016), where $|0\rangle$ now represents the maximum of the rating scale, and $|1\rangle$ represents the minimum. The ratings are then encoded by a linear mapping from the probabilities of $|0\rangle$ and $|1\rangle$. For example, on a rating scale with range [0,5], the state $\frac{1}{\sqrt{2}}|0\rangle + \frac{1}{\sqrt{2}}|1\rangle$ corresponds to a rating of 2.5.

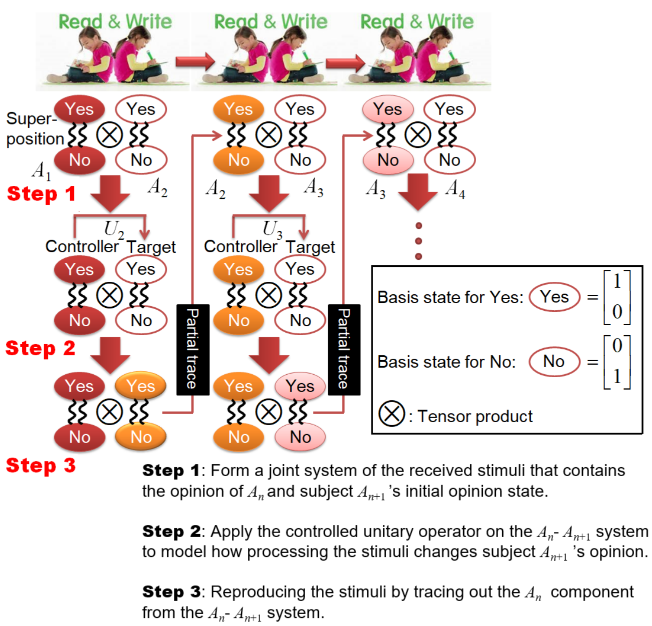

Figure 1: Quantum model for serial reproduction. The opinion state in this example is modeled by a two-dimensional vector containing the probability amplitudes of answering "Yes" or "No" for some attributes of the stimulus. The influence of the opinion of participant A_{n+1} by the opinion of A_n expressed in the stimulus S_n is modeled by applying a controlled unitary operator U_{n+1} on the A_n-A_{n+1} joint system, where the A_n part of the joint system represents the controller state, and the A_{n+1} part represents the target state. The opinion state expressed in the reproduced stimulus S_{n+1} is obtained by taking partial trace to trace out the A_n component from the joint system, after A_{n+1} has processed S_n. The reproduced stimulus S_{n+1} will then be received and reproduced by the next participant in the chain.

In step 1, we form a joint system of the opinion of participant A_n conveyed in stimulus S_n, and the initial opinion of A_{n+1} who receives S_n. The joint system is modeled using a tensor product:

$$\rho_{n,n+1} = \rho_{A_n} \otimes X_{A_{n+1}}. \quad (3)$$

In step 2, we model how, after processing stimulus S_n, the opinion of participant A_{n+1} is influenced by A_n's. For one-dimensional attributes, we first define the following controlled unitary operator:

$$U_{n+1} = M_0 \otimes R(b_{0,n+1}\theta_{0,n}) + M_1 \otimes R(b_{1,n+1}\theta_{1,n}) \quad (4)$$

In Equation 4, $R(\phi)$ is the two-dimensional rotation operator that models how processing stimulus S_n changes the opinion of A_{n+1}. The rotation angle ϕ for A_{n+1} is determined by the product of the content power of S_n regarding choice represented by choice state $|i\rangle$, denoted as $\theta_{i,n}$, and the reading bias of A_{n+1} regarding choice represented by $|i\rangle$, denoted as $b_{i,n+1}$. M_0 and M_1 are projections onto the choice states $|0\rangle$ and $|1\rangle$ correspondingly. The controlled unitary operator is then applied to the joint system operator $\rho_{n,n+1}$:

$$\rho_{n+1} = U_{n+1} \cdot \rho_{n,n+1} \cdot U_{n+1}^\dagger, \quad (5)$$

where ρ_{n+1} represents the joint system of A_n's opinion conveyed in stimulus S_n and A_{n+1}'s opinion after A_{n+1} has processed S_n. When applying the controlled unitary operator, the ρ_{A_n} part of the joint system density operator $\rho_{n,n+1}$ acts as the controller state, and the $X_{A_{n+1}}$ part acts as the target state (see Equation 3). The controller state is not altered by applying U_{n+1}, and it controls how the target state $X_{A_{n+1}}$ is changed by U_{n+1}. We adopt the control unitary operator, because the opinion of participant A_n in stimulus S_n can control how A_{n+1}'s initial opinion, encoded in $X_{A_{n+1}}$, is changed after A_{n+1} has processed S_n , but the opinion in S_n is not altered by A_{n+1} processing S_n.

Finally, in step 3, we model how, after processing S_n, participant A_{n+1} reproduces stimulus S_{n+1} that conveys their opinion. To do so, we take the partial trace of ρ_{n+1} to trace out the components involving the opinion of A_n:

$$\rho_{A_{n+1}} = Tr_{A_n}(\rho_{n+1}). \quad (6)$$

The reproduced stimulus S_{n+1} with state $\rho_{A_{n+1}}$ will then be reproduced by A_{n+2} and so on.

In short, there are two theoretical advantages of the quantum walk model over the Bayesian model for serial reproduction. First, the quantum walk model can predict nonlinear relations between x_n and x_{n+1}, which are the measured values of attributes for S_n and S_{n+1} correspondingly. This non-linearity arises naturally from quantum probability theory. Second, the quantum walk model can be easily generalized into a model that explains order effects in serial reproductions. We will discuss these advantages in more detail later.

Emotion transmission in narratives

Emotion plays a central role in serial reproduction of narratives (Nabi & Green, 2015; Bilandzic, Kinnebrock, & Klingler, 2020; Breithaupt, Li, & Kruschke, 2022). Emotion transmission refers to how the intensity of emotions conveyed in narratives develops during serial reproductions. Previous research (Thompson & Griffiths, 2021; Stubbersfield,

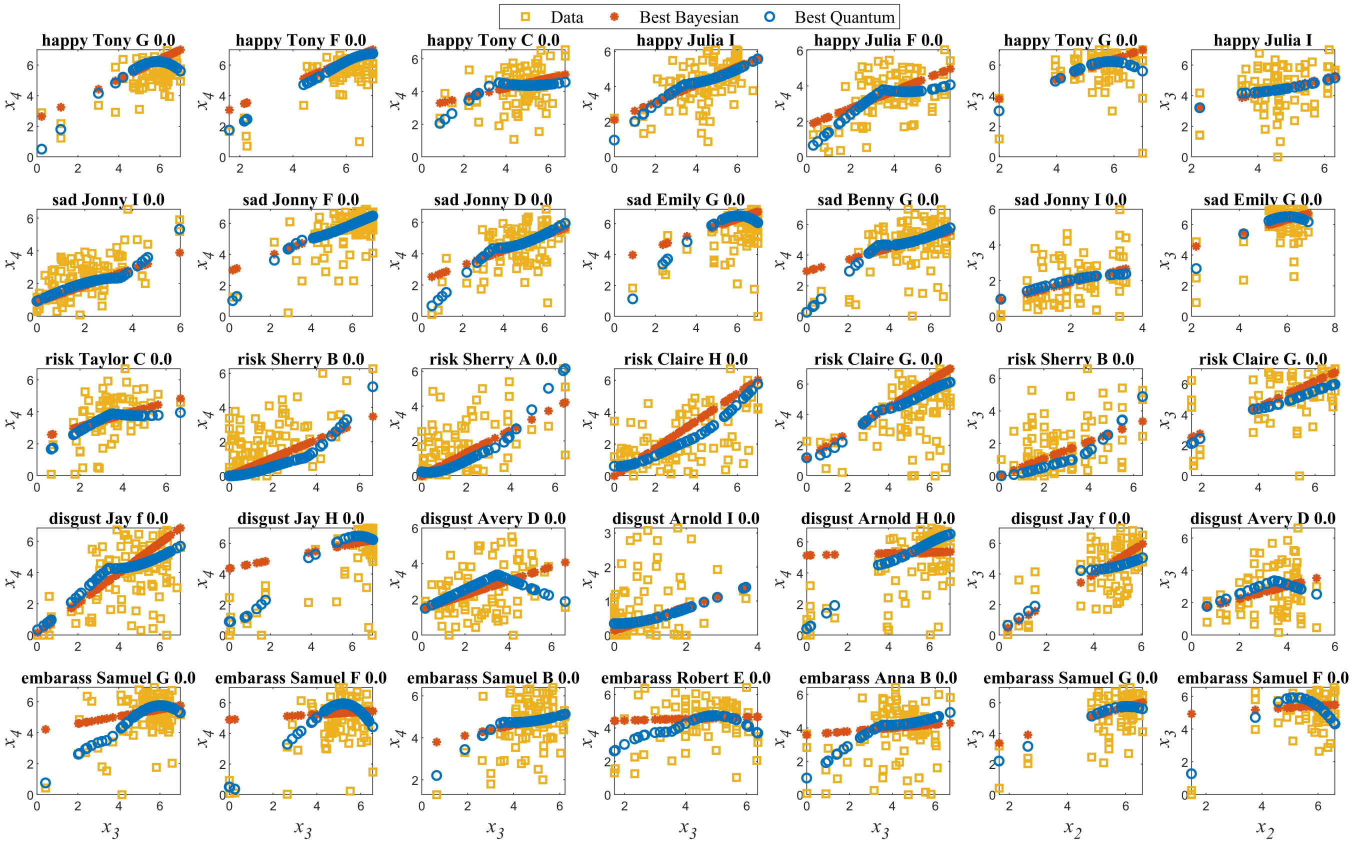

Figure 2: The scatter plots of models' predictions and the data. For all sequences whose heads are the selected original narratives displayed in the titles, the ratings x_{n+1} from the data, the predicted rating of $\hat{x}_{n+1}$ given data x_n by the best version of the Bayesian model (in terms of lowest mean BIC for the emotion), and that by the best version of the quantum model, are all plotted against x_n from the data. The predictions are computed as the means of the best-fitted normal distributions for the sequences before the distributions are truncated to [0,7]. The first five columns show x_4 vs x_3, while the last two show x_3 vs x_2, and each row corresponds to one emotion. As observed above, the quantum model can sometimes produce nonlinear predictions of x_{n+1} as a function of data x_n, while the Bayesian autoregressive model only generates linear predictions. This non-linearity of the quantum model arises from computing quantum probabilities from the complex-valued probability amplitudes.

Tehrani, & Flynn, 2015; Breithaupt et al., 2022) found that different emotions can transmit very differently and that the transmission, as a function of the steps of the serial reproduction process, is systematic. We consider emotion transmission as the starting point to examine our quantum model for serial reproduction because (1) emotion transmission is important and systematic in narratives; (2) the intensity of emotions is often measured by a one-dimensional rating variable; (3) a recent study (Breithaupt et al., 2022) develops a large corpus (`https://osf.io/tpw5e/`) about emotion transmission (19,086 retellings; 12,840 participants). The specific dataset examined in this work is a subset of the data in Breithaupt et al., (2022). In this dataset, there are 96 original narratives, denoted as S_1, and a total number of 8243 sequences developed from these original narratives (different original narratives might be the heads of a different number of sequences). In each sequence, there are three retellings besides the original narrative, denoted as S_2, S_3, and S_4, and the retelling S_n is generated by the participant who reads the previous retelling S_{n-1}. For each original narrative, the transmission of one of the five emotions: happiness, sadness, risk, disgust, or embarrassment, is examined. The intensity of emotions is measured using a rating scale from 0 to 7, with "7" meaning the emotion is strongly presented in the narrative and "0" meaning the emotion is not presented at all (a slider was used that recorded and displayed the ratings to one decimal). The ratings are performed by another group of participants who do not participate in the serial reproduction, and the final rating x_n for retelling S_n is computed as the mean of all ratings given to S_n. On average, each first retelling was rated by an average of 5.62 raters, each second retelling by 3.27 raters, and each third retelling by 4.52.

Bayesian model for emotion transmission

We develop four versions of Bayesian models: (1) [BS3][1] is the same as the model in Xu & Griffiths (2010), where a

[1]The texts in "[]" are the version names of the models. The reason for naming is explained in the caption of Figure 3.

uniform prior $\mu \sim N(\mu_0, \sigma_0)$ and a uniform observation noise σ_x^2 are assumed for each participant in the same sequence (for one-dimensional attributes, the model is the AR(1) process shown in Equation 2); (2) [BSA5] is the same as the first version except that we assume a changing observation noise for each participant; (3) [BSB5] is the same as the first version except that rather than a uniform prior, we assume that each participant uses either the reconstruction prior $\mu_1 \sim N(3.5-\phi, \sigma_0)$ with probability ω, or $\mu_2 \sim N(3.5+\alpha, \sigma_0)$ with probability $1-\omega$, where $\phi, \alpha \in [0, 3.5]$ and ω are free parameters; (4) [BSAB7] is the same as the third version except that we assume each participant has different observation noises. In practice, since participants are not trained on a specific prior before serial reproduction, the number of reconstruction priors of the participants for this between-participant serial reproduction task could potentially be more than two. However, the main focus of this work is to compare the quantum and the Bayesian models, and thus it is more important to ensure that the quantum model and the Bayesian model share the same assumptions as of the above versions.

Quantum model for emotion transmission

For emotion transmission, we adopt a special controlled unitary operator:

$$U_{n+1} = \begin{cases} M_0 \otimes R(\kappa_n P_{0,n} + \beta_n) + M_1 \otimes I_2 & P_{0,n} \geq 0.5 \\ M_0 \otimes I_2 + M_1 \otimes R(\kappa_n P_{0,n} + \beta_n) & P_{0,n} < 0.5 \end{cases} \quad (7)$$

where $P_{0,n} \in [0,1]$ is the $(1,1)$ entry of ρ_{A_n} that encodes the probability of the emotion being presented in narrative S_n, I_2 is the two-dimensional identity matrix, and κ_n and β_n are rotation parameters. The reason for adopting this special unitary is that the unitary operator U_n in Equation 4 is designed for narratives with contents of various attributes and readers with different biases to these attributes. When the narratives are of a single one-dimensional attribute, the bias parameter $b_{k,n}$ can be lumped into the content parameter $\theta_{k,n}$.

We develop four versions of quantum models corresponding to each version of the Bayesian model: (1) [Q4] is the four-parameter version of the quantum model which contains an initial opinion state $X = \cos\phi\,|0\rangle + \sin\phi\,|1\rangle$ with free parameter ϕ that is the same for each participant in the same sequence, a reconstruction noise σ_0 which is constant for each participant, and two rotation parameters β, κ where $\kappa_n = \kappa$ and $\beta_n = \beta$ for all n; (2) [QA6] is the same as the first version except that, rather than assuming a constant reconstruction noise, we set a separate σ_n for each participant A_n; (3) [QB6] is the same as the first version except that participants either use initial opinion state $X = \cos\phi\,|0\rangle + \sin\phi\,|1\rangle$ with probability ω, or use $Y = \cos\alpha\,|0\rangle + \sin\alpha\,|1\rangle$ with probability $1-\omega$, where ϕ, α and ω are free parameters, and $\cos^2\phi \leq \frac{1}{2}$ and $\cos^2\alpha \geq \frac{1}{2}$ ($\cos^2\alpha = \cos^2\phi = \frac{1}{2}$ corresponds to the rating 3.5); (4) [QAB8] is the same as the third version, except that we set a separate σ_n for each A_n. We assume that all of κ_n, β_n are the same to reduce the fitting complexity. Since the emotion ratings are in the scale [0,7], the predicted nth rating by the quantum model is given by

$$\hat{x}_n = 7 \times P_{0,n}. \quad (8)$$

Similarly, the initial state for the nth narrative S_n is set to be the two dimensional vector,

$$|\psi_n\rangle = \sqrt{x_n/7}\,|0\rangle + \sqrt{1-x_n/7}\,|1\rangle\,, \quad (9)$$

where x_n is the rating from the data. Finally, the predicted value $\hat{x}_n$ will be the mean of a normal distribution with standard deviation σ_n for computing the likelihood of data x_n given the model.

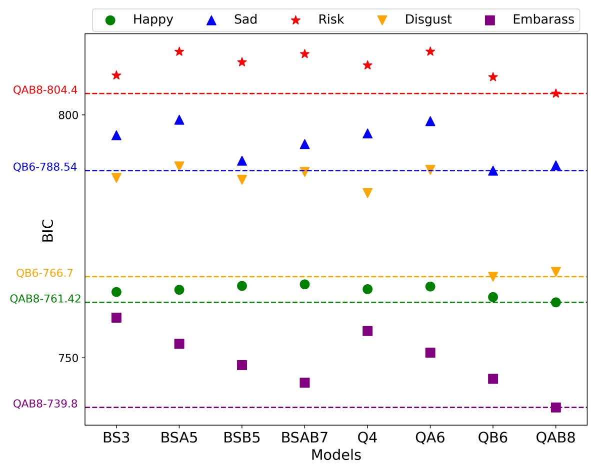

Figure 3: Mean BICs over all initial narratives, for each of the five emotions and each version of the models. The models' names are shown in the x axis, where "BS" stands for Bayesian, and "Q" stands for quantum, "A" stands for versions with a changing observation noise, and "B" stands for versions with two initial beliefs ("AB" means both are presented). The numbers at the end of the names show the number of parameters of the models. The dashed lines represent the lowest BIC scores for the emotion corresponding to the color of the line. The name of the model with the lowest BIC for each emotion and the lowest BIC are labeled in the y axis.

Fitting the models

We fit one set of parameters for all sequences of retellings with the same original narrative S_1. By this, we assume that the rating x_{n+1} of any sequence with the same previous narrative S_n follows the same probability distribution and that all sequences starting at the same S_1 transmit emotion in the same way. The models are compared using the Bayesian Information Criterion score (BIC). Since both models use Gaussian likelihood functions while the emotion ratings are in the range [0, 7], we truncate the Gaussian functions to [0, 7] when computing the BICs. The fitting is performed using the particle swarm algorithm in Matlab global optimization toolbox with a swarm size of 320 and a maximum iteration of 2000.

The fittings are performed 3 times to check for any convergence to a local minimum since multiple local minimums can exist for the quantum model.

Results and discussions

Figure 3 shows the results of the BIC fittings. Overall, we found that at least one version of the quantum model provides a better fit of the data compared to any version of the Bayesian model in terms of mean BIC scores over all initial narratives for each emotion.

One reason why the quantum model achieves a better performance is that it can predict a nonlinear relationship between the emotion rating x_n of the narrative S_n and rating x_{n+1} of S_{n+1}, while the AR(1) Bayesian model assumes a linear relationship between x_n and x_{n+1}. Figure 2 shows how this non-linearity might explain the data better. The nonlinearity here is a natural effect in any quantum probability model, as quantum probability models are based on complex-valued probability amplitudes, whose magnitude squares are the probabilities. In our model, probability amplitudes are converted into probabilities in Equation 5, where both the controlled unitary that encodes the transition probability amplitudes and its Hermitian conjugate are applied to the joint state. And because of this nonlinear conversion from probability amplitudes to probabilities, the model can produce nonlinear predictions even if the controlled unitary operator itself is a linear operator. Except for this part of the model, any other operations including tensor products, partial traces, and the mapping from quantum probabilities to ratings are linear.

Another potential reason could be that for data with a multi-modal distribution, the quantum model could be more sensitive to the multi-modality. As evident in the examples shown in Figure 4, the quantum model can detect some multi-modalities that the Bayesian model doesn't detect.

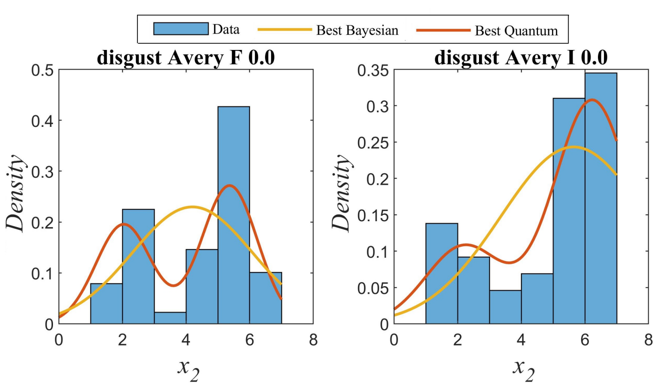

Figure 4: Example original narratives where the quantum model detects a multi-modal distribution and thus produces a better fit, while the Bayesian model does not. The distribution is over the rating x_2 of all sequences starting from these original narratives. The best-fitted quantum model, in terms of the lowest mean BIC, is of version "QB6", and the best-fitted Bayesian is of version "BSB5".

Order effects in serial reproduction

In the previous sections, we examine a simple case of serial reproduction: reading and rewriting a narrative where only a one-dimensional attribute (one type of emotion) of the narrative is measured. However, in practice, serial reproduction might also involve making judgments about the received stimulus before or after reproducing the stimulus, and measurement of multiple attributes of the received stimulus. For example, in Lee et al., (2014), participants are first asked to rate both the extent of guilt and the extent of favor of two conflicting parties (strangers and friends) about the received stimulus, and then to reproduce this stimulus. It is a well-known phenomenon (Hogarth & Einhorn, 1992; Krosnick & Alwin, 1987; White, Pothos, & Busemeyer, 2014) that when multiple judgments are made and multiple attributes are measured, the order of judgments and measurements could affect participants' judgments and opinions. In serial reproduction, since the reproduced stimulus is related to the opinions of the participants, changing the order of tasks and attributes could potentially change the reproduced stimulus. A very important feature of the quantum model is that it can be easily generalized into a model that captures these order effects, and we will briefly discuss examples of two types of order effects that the quantum model accounts for.

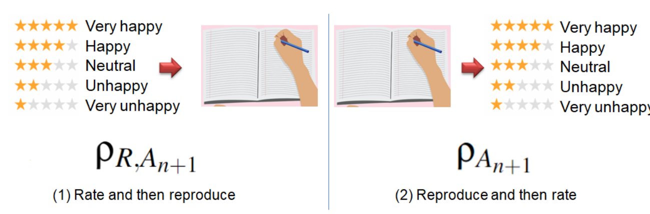

Figure 5: An illustration of the first type of order effect. Participants either first rate how strong an emotion conveyed in the received narrative is, and then reproduce the narrative, or rate after reproducing the narrative. The order effect in the reproduced narrative is a result of the state after processing the previous narrative $\rho_{A_{n+1}}$ collapsing into an eigenstate $\rho_{R,A_{n+1}}$ after rating the emotion.

The first type of order effect is produced by making a choice before/after reproducing a narrative. Consider asking the same participant to both rate how happy the received narrative is, and reproduce the narrative, as illustrated in Figure 5. To explain this order effect, we first need to extend the existing two-dimensional quantum model into a five-dimensional one. The same as in the two-dimensional case, after processing the narrative from A_n, participant A_{n+1} 's initial state $X_{A_{n+1}}$ is evolved into $\rho_{A_{n+1}}$ through Equation 5 and Equation 6, assuming an extended controlled unitary operator. If a rating of happiness R is made before the narrative reproduction, participant A_{n+1} 's opinion states will collapse into an eigenstate $\rho_{R,A_{n+1}}$ corresponding to the rating R. In this case, the reproduced narrative is modeled by the collapsed state $\rho_{R,A_{n+1}}$. On the other hand, if the ratings are made after reproducing the narrative, the reproduced narrative is modeled by the state $\rho_{A_{n+1}}$. An order effect is then predicted by the quantum model when $\rho_{R,A_{n+1}} \neq \rho_{A_{n+1}}$.

The second type of order effect is produced by a similar experimental paradigm as that of the first, except that instead of asking a single conceptual rating question either before or after writing, we ask two questions about two different attributes of the received narratives, one before and one after rewriting (see Figure 6). For example, let the two attributes be happy and disgusting contents of the received narratives. Measuring the happy content first would potentially guide the participant towards writing a happy story, and vice versa if we were to measure disgusting content first. The quantum model explains this order effect as follows. We first extend the model to five-dimensional, and obtain $\rho_{A_{n+1}}$ using the same stimuli processing procedure as in Equation 5 and Equation 6. Let $\rho_{R_h,A_{n+1}}$ and $\rho_{R_d,A_{n+1}}$ be the eigenstates $\rho_{A_{n+1}}$ will collapse into after rating happiness as R_h and rating disgust as R_d respectively. For rating happy content first, the reproduced narrative will have state $\rho_{R_h,A_{n+1}}$, and vice versa for rating disgusting content first. When $\rho_{R_h,n+1} \neq \rho_{R_d,n+1}$, the states of reproduced narratives for the two different orders will therefore be different. Conceptually, this means that the opinion of participant A_{n+1} changes differently when different content is measured first. As a result, the reproduced narratives for the two different orders might convey different intensities of happiness and disgust.

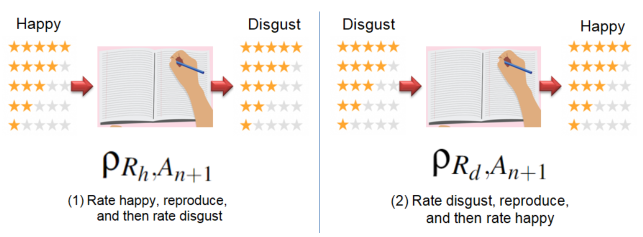

Figure 6: An illustration of the second type of order effect. Participants are asked to rate two attributes about the received narrative (e.g. happy and disgusting contents), and we manipulate the order of measuring these two attributes. The order effect in the reproduced narrative is modeled by different changes to the state of the reproduced narrative in the two different orders.

Conclusions

We develop a quantum walk model for serial reproduction. The quantum model was compared with a linear Bayesian model on a large dataset about emotion transmission in narratives. The quantum model not only produces a lower mean BIC than the Bayesian model for all five types of emotion transmissions examined but can also account for order effects in serial reproduction. Our results suggest that the quantum-like features of human cognition remain in human communication and affect the idea propagation in group-level cognition.

Future work will focus on different types of order effects in serial reproductions. We will compare the quantum walk model's performance with that of other existing models for order effects in group decision making. Besides, as mentioned, participants may have a wide range of initial beliefs about the strength of an emotion presented in their writings. Thus, a hierarchical model with a distribution of initial beliefs, either quantum or Bayesian, could be developed to better explain the data examined in this work.

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