



Quantum-like model of uncertainty for dynamic decision making

Aleksej Gaj, Miroslav Kárný

gajaleks@fjfi.cvut.cz

FNSPE, CTU

Department of Adaptive Systems Institute of Information Theory and Automation

In previous episodes:

• 2022

• 2023

About use of Everett's interpretation of quantum mechanics in decision making ver. 0.1 Aleksej Gaj gajaleks@fifi.cvut.cz FNSPE, CTU Supervisor: Ing. Miroslav Kárný, DrSc.

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Conclusions

Quantum FPD

- is a new approach with DM inspired by physical formalism
- provides better modelling and reasoning at micro and macro level
- considers human-like judgement (e.g. zooming) and cognition
- opens a way for general human Al
- may bring interesting mathematics to those who are interested in

Thank you for your attention!

Does quantum version of DM make sense? Aleksej Gaj gajaleks@fjfi.cvut.cz FNSPE, CTU Supervisor: Ing. Miroslav Kárný, DrSc.

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A. Gai | SPMS 202

Intermediate conclusions

- Current status: Learning... learning... learning
- Partially got inspired by Everett's theory and FPD
- Aim: to get promising theoretical approach that could provide mathematical reasons why qDM describes human behaviour
- The most expected answer: "Is gDM indeed needed?"
- being formalized and prepared for review by experts in QM



• SPMS 2024?

Thank you for your attention!

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Motivation

Discrepancy: traditional theories vs observed human judgements:

- Judgements are based on *indefinite states* (aka superposition of all definite states).
- Judgements interfere and introduce uncertainty => order effect.
- Judgements do not obey Boolean logic => classic probability theory is not enough
- Humans' "*irrationality*", i.e. deviation from rational decision making
- Human's sensitivity to a decision-making *context*
- Paradoxes (Ellsberg, Allais) connected with *uncertainty and risk*

Closed decision loop



• Agent:

- *influences/learns* the environment behavior
- influences/improves own knowledge about the environment (model, loss function, ...)
- **Examples:** control; automation; reinforcement learning; prediction; filtering.
- Applications: autonomous cars; IoT; (smart) robotics; forecasting; Deep Learning; non-invasive examinations (e.g. medical one); language and image processing, etc.

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Main idea

To analyse general formulation of decision making (DM) problem

Key aspects of the proposed solution:

- DM problem is formalised via behaviours ordered by a loss function.
- Uncertainty is independent on decision strategy (no hidden feedback).
- Use SVD of matrix of losses
 - \Rightarrow atomic events are vectors; random events form subspaces of a Hilbert space.
- Schrödinger equation describes time evolution of uncertainty
 - ⇒ need of non-Kolmogorov's probability



Notions:

- behaviour b = (g, a, k)
- g ignorance (uncertainty is a *part* of g)
- k knowledge (e.g. data up to time t at which a is chosen)
- $r: \mathbf{k} \rightarrow \mathbf{a} \text{decision rule}$
- $S = (r_1, r_2, ...) \text{strategy} = a \text{ sequence of decision rules}$

Main steps

- ∃ order of behaviours ≤_b that
 - is complete
 - preserves transitivity
- \exists loss function $z : \mathbf{b} \mapsto \mathbf{R}$ that ranks order $\leq_{\mathbf{b}}$ and
 - is isotone with $\leq_{\mathbf{b}}$
 - preserves equivalence on b
- *S* and *U* are pointers to strategy/uncertainty, resp.
- $S, U \rightarrow \mathbf{b}$ and existence of $z \Rightarrow \exists$ matrix of losses $\mathbb{L}_{S,U}$, with \mathbf{S}, \mathbf{U} countable
- Apply SVD to split \mathbb{L} into U dependent and S dependent parts

$$\mathbf{L} = \underbrace{\mathbb{V} \cdot \mathbb{D}}_{\mathbb{S}} \cdot \mathbb{U}^* = \mathbb{S} \cdot \mathbb{U}^* = \mathbb{S} \cdot \underbrace{\mathbb{P} \cdot \mathbb{P}^*}_{=\mathbb{I}} \cdot \mathbb{U}^*$$

Quantification of order on a set of strategies

- Define a set of functions $\Lambda \coloneqq \{l_S \colon U \to \mathbb{R} \mid \exists S \in S \colon l_S(U) = \mathbb{L}_{S,U}\}$.
- Functional $\Upsilon(l_S) = \sum_j \mathcal{K}(l_S(U_j), U_j) p(U_j)$ quantifies order of strategies ($\mathcal{K}(\cdot)$ is increasing): $S_1 \leq_S S_2 \iff l_{S_1} \leq_A l_{S_2} \iff \Upsilon(l_{S_1}) \leq \Upsilon(l_{S_2}),$
- Model uncertainty by atomic random events U_i and consider them as elements in a \mathcal{H} space.
- For each U_j , define a unique unit vector $|\eta_j\rangle$ in \mathcal{H} , dim $(\mathcal{H}) = card(\mathbf{U})$.
- Using Gleason theorem, a measure on \mathcal{H} can be written as $\mu(\eta_j) = \langle \eta_j | \hat{T}_{\mu} | \eta_j \rangle$ with non-negative kernel $\hat{T}_{\mu} = \text{diag}(p(U_1), p(U_2), ...), \text{ tr}(\hat{T}_{\mu}) = 1.$
- The functional in quantum probability reads: $\Upsilon(l_S) = \sum_j \mathcal{K}(l_S(U_j), U_j) \mu(\eta_j)$ and optimal strategy is

 $S^{opt} = \arg\min_{S \in \mathbf{S}} \Upsilon(l_S).$

In one-shot (static) case: the solution coincides with classical Kolmogorov's theory. 10

Dynamic case: two time-scales formalism

 $strategy \ \mathbf{S} = \{S_1, S_2\}$ uncertainty $\mathbf{U} = \{U_1, U_2, \dots, \}$

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Dynamic case

 $(S_2, U_1)
ightarrow b_{2,1}$ _____ $(S_2, U_2)
ightarrow b_{2,2}$ _____ $(S_2,U_3)
ightarrow b_{2,3}$ ____ $(S_2, U_\infty)
ightarrow b_{2,\infty}$ _____ t_{k+1} Distinguish: discrete times (actions applied) and continuous time when uncertainty evolves

• At $\tau \in (t_k, t_{k+1})$, U changes and we express this by introducing matrix $\mathbb{M}_{t_k, \tau}$ that

 $\mathbb{U}_{t_k+\tau} = \mathbb{M}_{t_k,\tau} \cdot \mathbb{U}_{t_k}$ (as \mathbb{U}_{t_k} and $\mathbb{U}_{t_k+\tau}$ are unitary, $\mathbb{M}_{t_k,\tau}$ is unitary too)

• By introducing $\mathbb{M}_{t_k,\tau} = exp(i\tau \mathbb{H}_t)$, \mathbb{H}_t - positive semidefinite matrix

 $\mathbb{U}_{t_k+\tau} = exp(i\tau\mathbb{H}_t) \cdot \mathbb{U}_{t_k}$ - looks similar to ansatz

• By deriving $\frac{\partial}{\partial \tau}$ we got the Schrödinger's equation

$$\frac{\partial}{\partial \tau} \mathbb{U}_{t_k + \tau} = i \mathbb{H}_t \cdot \mathbb{U}_{t_k + \tau} \tag{*}$$

with \mathbb{H}_{t} interpreted as energy.

Random events are subspaces of \mathcal{H} and (*) transforms uncertainty ($\mathbb{M}_{t,\tau}$ rotates vector $|\eta_{i,t}\rangle$ in \mathcal{H}):

$$\mu(\eta_{j,t+\tau}) = \langle \eta_{j,t} | \underset{\text{A. Gaj | SPMS 2024}}{\mathbb{M}_{t,\tau}} \mathbb{T}_{\mu,t} \mathbb{M}_{t,\tau} | \eta_{j,t} \rangle.$$

Summary

$$\mathbb{L} = \begin{pmatrix} \mathbb{L}_{1,1} & \mathbb{L}_{1,2} & \dots & \mathbb{L}_{1,\infty} \\ \mathbb{L}_{2,1} & \mathbb{L}_{2,2} & \dots & \mathbb{L}_{2,\infty} \end{pmatrix}$$

Aim: to show *uncertainty dynamics* in DM

Used: general formulation of DM problem and realistic assumptions

Findings:

- Explanation why quantum modelling is inevitable
- Dynamic case: Schrödinger eqn describes time evolution of uncertainty => quantum modelling
- *Static case:* the solution coincide with classical DM theory

Possible future work:

- Solve partially observable Markov decision process in quantum setting
- Compare the with DM based on Open Quantum System approach
- More deep analysis of interrelations with physics (e.g. commutativity aspects, etc.)

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Q & A

Operators H_t used in the exponential representation of the unitary operators: it seems that one should proceed under condition of their commutativity? i.e., that $[H_t, H_s] \equiv H_t H_s - H_s H_t = 0$.

- Time-evolution of uncertainty is "valid" within one decision epoch. At the end the agent takes a new action and changes the situation.
- Generally, commutativity of Hamiltonians from two different decision epochs, say (t_k, t_{k+1}) and (t_{k+1}, t_{k+2}) might have some meaning.
- A detailed analysis whether (and under what conditions) the commutativity matters is to be studied in future.

Q & A

Your basic equation is the Schrödinger equation (3.31). In the finite dimensional case its solution would generally fluctuate forever. Is it not an obstacle for getting a decision in finite time?

• No, its not. Equation (3.31) models evolution of uncertainties between decision epochs $t_1, \ldots, t_k, t_{k+1}, \ldots$ (chosen by the agent) in which it selects the actions. Thus, whenever the solution (3.31) be, the agent selects a new action irrespectively.