Towards models of collective memory

R. Ramanujam

The Institute of Mathematical Sciences
Chennai - 600 113
email: jam@imsc.res.in

Logic and Cognition, ICLA, March 2, 2019

First words . . .

- Thanks to Sujata and Torben for this opportunity and to IIT,D for the wonderful atmosphere.
- Please feel free to interrupt any time to comment or question.
- `Statutory Warning`: The talk presents some ideas, and few results.

Summary

Collective memory is a notion of interest in social algorithms.

- Social algorithms have an underlying logical structure.
  - They operate on a common ground, which requires social memory.
  - Question: How do such social memories form ?
  - We suggest: by repeated reinforcement, and rich rules for interaction in neighbourhoods.
- Our analysis:
  - A model inspired by large games and population protocols.
  - Logicisation seems to offer new challenges.

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- Consider a social algorithm such as elections. What is the memory relevant here ?
- What kind of collective historical reasoning underlies social identity ?

Memory is not a notebook

I saw this man years ago: now I have seen him again, I recognize him, I remember his name. And why does there have to be a cause of this remembering in my nervous system? Why must something or other, whatever it may be, be stored up there in any form? Why must a trace have been left behind? Why should there not be a psychological regularity to which no physiological regularity corresponds? If this upsets our concept of causality then it is high time it was upset.

Ludwig Wittgenstein

Can memory be collective ?

Strictly speaking, there is no such thing as collective memory – part of the same family of spurious notions as collective guilt. But there is collective instruction . . . All memory is individual, unreproducible; it dies with each person. What is called collective memory is not a remembering but a stipulating*: that this is important, and this is the story about how it happened, with the pictures that lock the story in our minds.*

Susan Sontag
Regarding the pain of others

Automata theory and memory

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- Memory is constituted by states of being of the automaton.
- Observations cause intentional memory updates.
- Logicians are used to equating automata and logics.
- Thus interdependence between momeory and reasoning is familiar territory.

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- Interacting agents rely on memory external to them.
- Rich and flexible models available in distributed computing.
- The cloud as globally accessible private memory.

Social theory

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- What are the logical properties of collective remembering ?
- What is the rationale followed by a group in ascribing / stipulating collective importance to events and their remembering ?
- Why is a particular idealisation chosen ?

A simple model inspired by large games and population protocols.

Signal distributions

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- Let $I \in \mathcal{C}$ and $|I| = k$. A **distribution** over I is an m tuple of integers $\mathbf{y} = (y_1, \ldots, y_m)$ such that $y_j \geq 0$ and $\Sigma_{j=1}^{m} y_j = k, \quad 1 \leq j \leq m$.

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- The jth component of $\mathbf{y}$ gives the number of agents in the neighbourhood I who give signal γ_j.
- $\mathbf{Y}[I]$ is the set of all signal distributions of a neighbourhood I.

An example

Two signals $\{g, b\}$, standing for "good" and "bad".

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- If they are exactly even, they continue evenly matched.
- After repeated interactions over many neighbourhoods, it is reasonable to expect that one of the two perceptions becomes stable over the entire population of agents. This is what we consider the ”collective memory”.

Details

For $I \in \mathcal{C}$, Γ^I denotes a vector of signals, one for each of the agents in I. Every such vector induces a distribution over Γ in $\mathbf{Y}[I]$.

- A group automaton over $\mathcal{C}$ is a pair $M = (\delta, \iota)$, where $\iota : \Sigma \to \Gamma$, and δ is a finite family of transition relations $\delta_I \subseteq (\mathbf{Y}[I] \times \Gamma^I)$, where $I \in \mathcal{C}$.

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- Interactions occur in neighbourhoods nondeterministically.
- Each interaction induces a state transition that is determined only by the distribution of signals: it does not depend on who is signalling what, but how many are producing each signal.
- Such interactions keep occurring repeatedly until a stable configuration is reached.

Configuration graph

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- Vertices are configurations and edges are labelled by neighbourhoods:.
- $\chi' = \chi \oplus \Gamma^I$ (with some abuse of notation).
- ι induces an initial configuration χ_0.
- A history ρ is any finite or infinite path in G_M starting from χ_0.

Fairness

It is essential that a history allows for signalling to spread across neighbourhoods.

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- Spanning histories (infinite): every infinitely often enabled interaction (by the transition rule) takes place infinitely often.
- Different condition: the union of neighbourhoods in a history span all of N.
- Reaching stable configurations requires some such assumptions.

Algorithmic question

Is a stable configuration reachable ?

- Theorem: Given a system M, whether a stable configuration is reachable is decidable.

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- Theorem: Given a system M, whether a stable configuration is reachable is decidable.
- Unfortunately, the size of the configuration graph can be very large (though finite) as also the description of δ, so decidability amounts to very little.

Discussion

How do systems of signalling in neighbourhoods embody reasoning about collective memory ?

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How do systems of signalling in neighbourhoods embody reasoning about collective memory ?

- History model allows us to define epistemic temporal logics can be defined, so we can employ to discuss dynamics.
- The model holds considerable promise.
- Reinforcement of memory that comes through repeated interactions.
- Complex social rules that determine influence in signalling.

Closing remarks

- Social algorithms involve not only rule following, but also neighbourhood (or interaction) structures, motivation and enforcement, and large scale dynamics can be important.

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- Social algorithms involve not only rule following, but also neighbourhood (or interaction) structures, motivation and enforcement, and large scale dynamics can be important.
- The notion of collective memory seems an essential component of social algorithms.
- We have the beginnings of a model, but much more exploration is needed before definitive reasoning can be made.
- A central question: what is the logical status of memory ? (Is remembrance a modality ?) We see it as infrastructure for reasoning.

Discussion time

Thank you.

Questions, comments, suggestions welcome; also, please write to jam@imsc.res.in.