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Social Networks through the Prism of Cognition

A paper by Radoslaw Michalski, Boleslaw Szymanski, Przemyslew Kazienko, Christian Lebiere, Omar Lizardo, and Marcin Kulisiewicz

Opening

- Memories can be interpreted as a type of network, where one event can lead tie in with another.
  - Preparing for a party
  - Exchanges of dialogue
  - Social media posts

  What other kinds of memories can be interpreted as a network?

Event Perception

- Two Main Questions:
    - How do humans perceive social events?
    - How do networks try to replicated it?
- Social networks have events be distinct, and tie weights to them based on relevance.
    - Updated once every relevant event.
- Humans also vary the initial relevance of an event, and their perception of events change continuously.
    - Decisions on relevance are done through criteria they perceive to be relevant.

A Flawed Network

- There have been no models that have this dynamic style of retaining events.
- Cognition-Driven Social Network (CogSNet) model created to capture this.
    - Also includes other dynamics such as the gradual decay of memories.
- CogSNet model can, with suitable data, include individual sensitivity, emotional responses, or distractions during these events.

Creation of the Model

- Should be able to compute relevancy of social interaction
- While complex, memory has been simulated in previous models
  - ACT-R model replicates well-established primacy and recency effects for list memory.
- Limited Memory Capacity and Decay
  - Most events not stored in long-term memory due to space
  - As time passes, event details become harder to remember, getting forgotten
  - Actually similar to social media networks
    - Inspiration can be taken from

CogSNet model

- Graph $G = (V, E)$
- $V = \{v_1, \ldots, v_n\}$: n nodes
- $E = \{e_1, \ldots, e_m\}$: m edges
- $w_{ij}(t) = (v_i, v_j, w_{ij}(t))$: weight between 2 nodes
- t_{ij} = time preceding event
- Reinforcement Peak $0 < \mu \leq 1$
  - Impact of relevant event on weight, constant
- $f(t)$: forgetting function
  - $f(0) = 1$, nonincreasing
  - Forgetting intensity λ
  - Forgetting threshold $0 < \theta < \mu$

$$w_{ij}(t) = \begin{cases} \mu_{ijc_{ij}+1}, & \text{if } w_{ij}(t_{ij}) f(t - t_{ij}) < \theta, \\ \mu_{ijc_{ij}+1} + w_{ij}(t_{ij}) f(t - t_{ij}) \left(1 - \mu_{ijc_{ij}+1}\right), & \text{otherwise,} \end{cases}$$

Testing the Model

- Phone Call and Text Data
- Self-reports collected from human participants

- Interaction sequences implementation
  - Each event is time stamped
  - Weights are added to edges connecting nodes involved in the event.
  - Edge is active only at a given time t.

- Compared with a static binary network
  - All edges are time-independent
  - Makes all edges permanently active, which ignores time effects
  - Dynamic processes cannot be studied

Further Testing

- Incremental network solution
  - Accumulates events only up to the current time *t* of analysis
  - Used in early research papers
  - Dynamic network is a set amount of static time series graphs
  - Does not preserve interactions between graphs

- Baseline Models
  - Basic frequency-based reinforcement
  - Limit to only a set amount of the most recent events

- Forgetting Function
  - Can be any type,
  - But here, is just exponential and power

$$f^{\exp}(\Delta t) = e^{-\lambda \Delta t},$$

$$f^{\mathrm{pow}}(\Delta t) = \max(1, \Delta t)^{-\lambda},$$

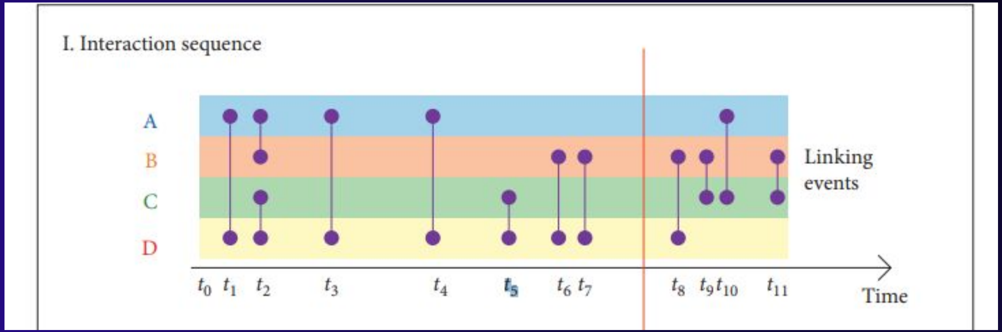
- Trace Lifetime
  - Time it takes for a memory to be forgotten

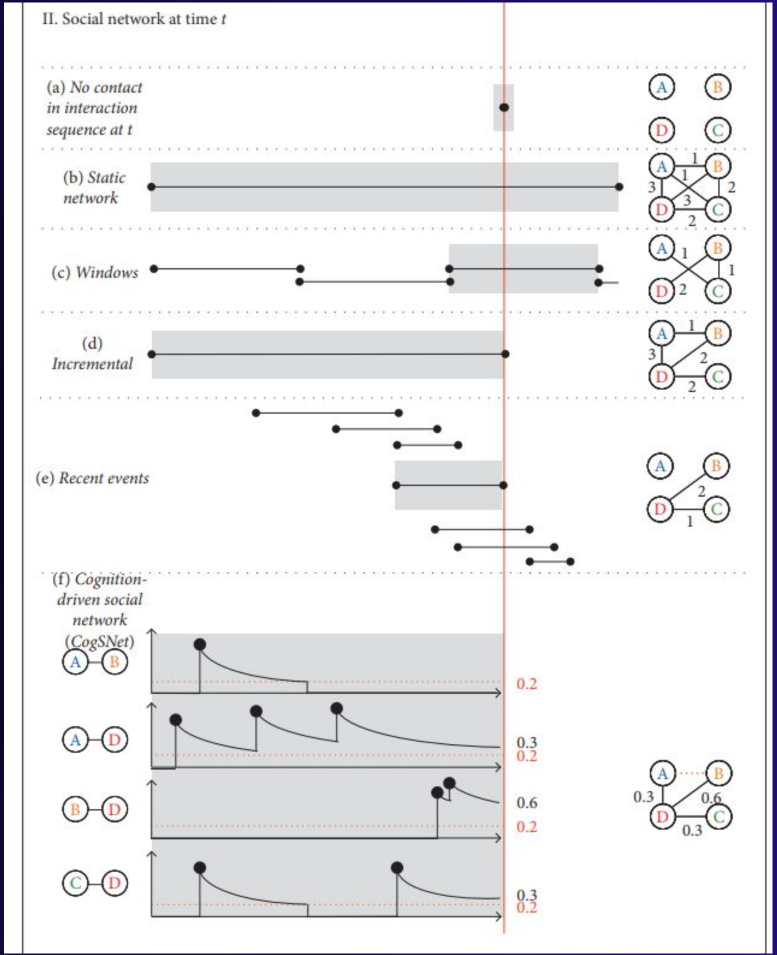
$$L^{\exp} = \frac{1}{\lambda}\ln\left(\frac{\mu}{\theta}\right),$$

$$L^{\mathrm{pow}} = \left(\frac{\mu}{\theta}\right)^{1/\lambda}.$$

Results

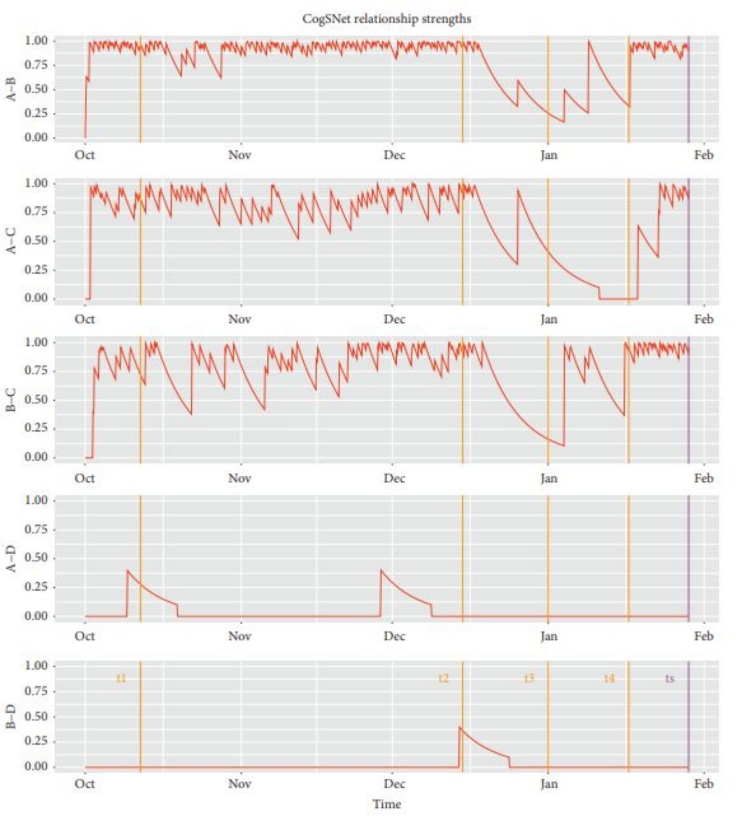
I: Sequence of interactions between 4 variables A, B, C, D
II: How different networks receive it

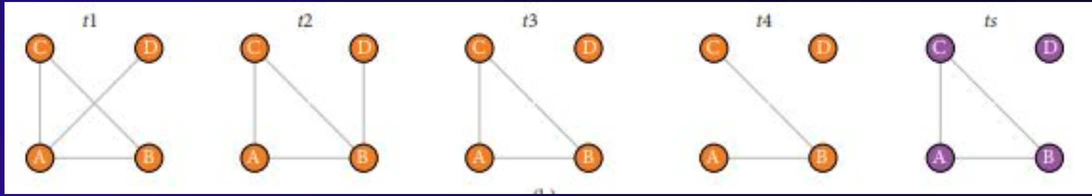




CogSNet Dynamic Social Network

Example of CogSNet network being generated from a subset of NetSense data.





Comparison

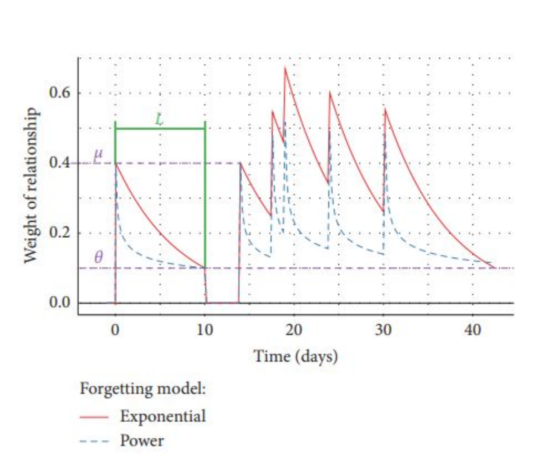
- Frequency-Based Model (FQ)
  - Ranked by most interactions
- Recency-Based Model (RD)
  - Ranked by most common interactions in a set recent interactions
- Random Sampling (RND)
  - Chooses a node, then randomly selects some of it’s interactions

- Jaccard Metric
  - Compares interactions produced by the model that are also in the survey
  - Divides it by the amount of unique models in both sets

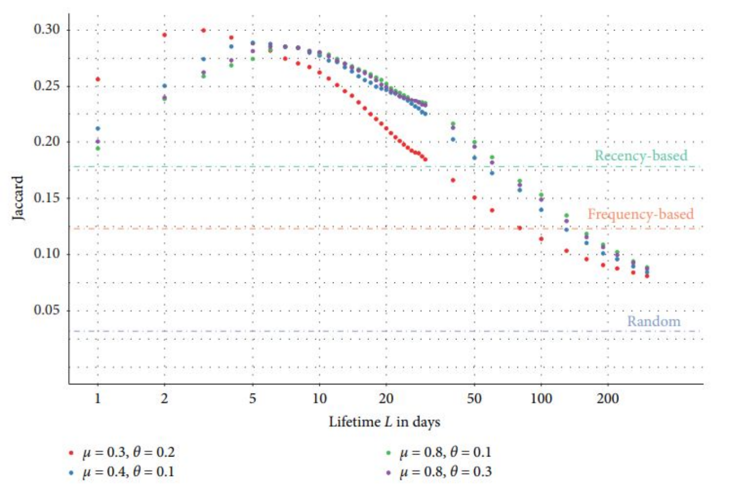
$$\text{Jaccard}(v_i) = \frac{\left|V_i^{\text{CogSNet}} \cap V_i^{\text{survey}}\right|}{\left|V_i^{\text{CogSNet}} \cup V_i^{\text{survey}}\right|},$$

Comparisons Exponential

CogSNet



Comparison



Expected Results: 1 week decline, 2 weeks forget

Exponent Jaccard

- CogSNet finishing earlier than the rest of the models results in it being the most significant

- RC Model is a distant second

Table 3: Setting of parameters for exponential forgetting function in computational experiments.

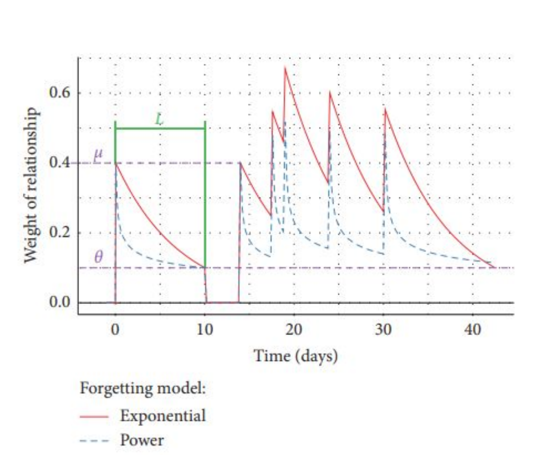
λ dependence on μ, θ, and L for exponential forgetting			
Lifetime L (days)	$\mu = 0.4$, $\theta = 0.1$	$\mu = 0.8$, $\theta = 0.3$	$\mu = 0.8$, $\theta = 0.1$
1	0.05776	0.04087	0.08664
2	0.02888	0.02043	0.04332
3	0.01925	0.01362	0.02888
4	0.01444	0.01022	0.02166
5	0.01155	0.00817	0.01733
6	0.00963	0.00681	0.01444
7	0.00825	0.00584	0.01238
8	0.00722	0.00511	0.01083
9	0.00642	0.00454	0.00963
10	0.00578	0.00409	0.00866
11	0.00525	0.00372	0.00788
12	0.00481	0.00341	0.00722
13	0.00444	0.00314	0.00666
14	0.00413	0.00292	0.00619
15	0.00385	0.00272	0.00578
16	0.00361	0.00255	0.00542
17	0.0034	0.0024	0.0051
18	0.00321	0.00227	0.00481
19	0.00304	0.00215	0.00456
20	0.00289	0.00204	0.00433
21	0.00275	0.00195	0.00413
22	0.00263	0.00186	0.00394
23	0.00251	0.00178	0.00377
24	0.00241	0.0017	0.00361
25	0.00231	0.00163	0.00347
26	0.00222	0.00157	0.00333
27	0.00214	0.00151	0.00321
28	0.00206	0.00146	0.00309
29	0.00199	0.00141	0.00299
30	0.00193	0.00136	0.00289
40	0.00144	0.00102	0.00217
50	0.00116	0.00082	0.00173
60	0.00096	0.00068	0.00144
80	0.00072	0.00051	0.00108
100	0.00058	0.00041	0.00087

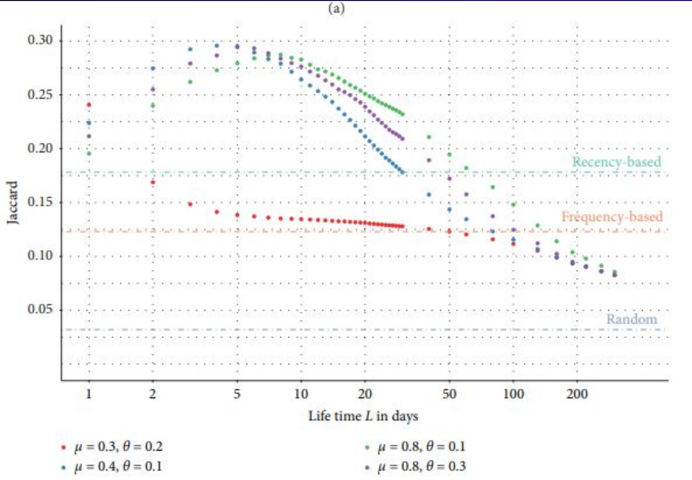
Comparisons Power

CogSNet

Comparison

Expected Results: 1 week decline, 2 weeks forget





Power Jaccard

- Performs significantly better than exponential.

- Standings between CogSNet and RC remain the same
  - RC's miniature success could be attributed to it's somewhat dynamic nature

Table 2: Setting of parameters for power forgetting function in computational experiments.

λ dependence on μ, θ, and L for power forgetting			
Lifetime L days	$\mu = 0.4,\ \theta = 0.1$	$\mu = 0.8,\ \theta = 0.3$	$\mu = 0.8,\ \theta = 0.1$
1	0.43621	0.30863	0.65431
2	0.3581	0.25337	0.53716
3	0.32415	0.22934	0.48623
4	0.30372	0.21489	0.45558
5	0.28957	0.20487	0.43435
6	0.27894	0.19736	0.41841
7	0.27055	0.19142	0.40583
8	0.26368	0.18656	0.39552
9	0.2579	0.18247	0.38685
10	0.25294	0.17896	0.37942
11	0.24862	0.1759	0.37293
12	0.2448	0.1732	0.3672
13	0.24139	0.17079	0.36208
14	0.23831	0.16861	0.35747
15	0.23552	0.16663	0.35328
16	0.23297	0.16483	0.34945
17	0.23062	0.16317	0.34592
18	0.22844	0.16163	0.34267
19	0.22643	0.1602	0.33964
20	0.22455	0.15887	0.33682
21	0.22278	0.15762	0.33418
22	0.22113	0.15645	0.3317
23	0.21957	0.15535	0.32936
24	0.2181	0.15431	0.32716
25	0.21671	0.15333	0.32507
26	0.21539	0.15239	0.32309
27	0.21414	0.15151	0.3212
28	0.21294	0.15066	0.31941
29	0.2118	0.14985	0.3177
30	0.21071	0.14908	0.31606
40	0.20188	0.14283	0.30282
50	0.19553	0.13834	0.29329
60	0.19062	0.13487	0.28594
80	0.18337	0.12974	0.27506
100	0.17811	0.12602	0.26717

Conclusion

- The CogSNet model performed significantly better than all other models.
  - However, due to the data being a relatively small amount of people interacting, some omitted variables could be involved.
  - This could be resolved by changing the parameters to a more individual basis
- Some interpretations on memory
  - Relationships
  - Alterations could be used for diseases