On the development, connections, and opportunities of incorporating RFT within AI recommender systems.

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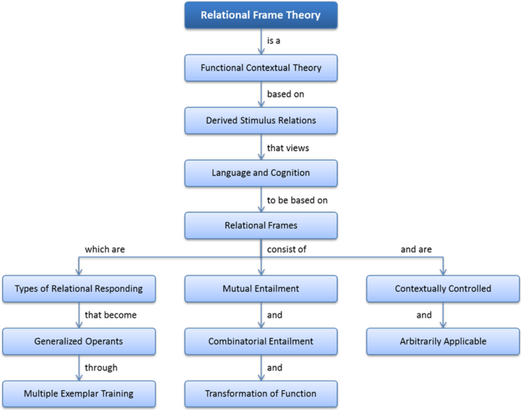
Introduction

- Relational Frame Theory
- AI as a data source form Recommender Systems
- Classic and Context-aware Recommender Systems
- Cold-start problems
- Linking concepts from psychology to AI & Recommender Systems.

Relational Frame Theory



: Taken from: https://foxylearning.com/tutorials/rft/3/4422-1008

Relational Frame Theory

- Mutual Entailment

$$C_{rel}\{A\ r_x\ B|||B\ r_y\ A\}$$

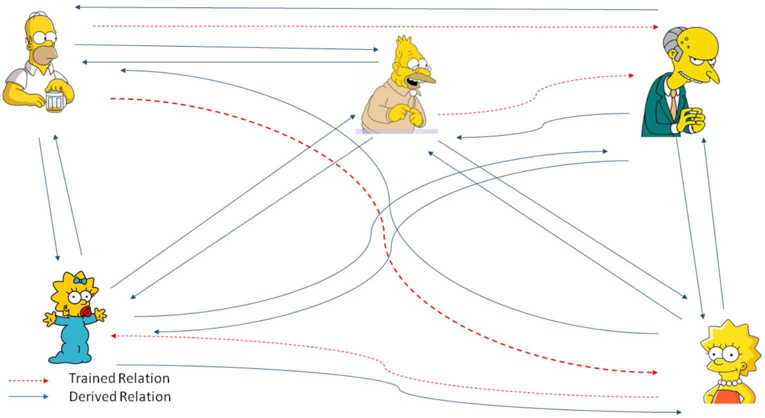
- Combinatorial Entailment

$$C_{rel}\{A\ r_x\ B \text{ and } B\ r_y\ C|||A\ r_p\ C \text{ and } C\ r_q\ A\}$$

- Transformation of Function

$$C_{func}[C_{rel}A\ r_x\ B \text{ and } B\ r_y\ C\{Af_1|||Bf_2 r_p \text{ and } Cf_3 r_q\}]$$

Derived Relations



: The Simpsons: Trained and Derived Relations

Derived Relations

For $n \geq 2$, $n \in \mathbb{Z}$, trained relations we get n^2 derived relations.

$$X_1 \xrightarrow{\text{Trained}} X_2 \quad \xrightarrow{\text{Trained}} X_3 \ldots \xrightarrow{\text{Trained}} X_n \xrightarrow{\text{Trained}} X_{n+1}$$

So we have:

$$2(n)+2(n-1)+2(n-2)+\ldots+2(n-(n-2))+2(n-(n-1))-(n) =$$

$$2\underbrace{(n+n+\ldots+n)}_{n\text{ times}}-2(1+2+\ldots+(n-1))-n =$$

$$2n^2 - 2\sum_{i=1}^{n-1} i - n =$$

$$2n^2 - 2(\frac{(n-1)(n)}{2}) - n =$$

$$2n^2 - (n^2 - n) - n =$$

$$2n^2 - n^2 + n - n =$$

$$n^2$$

Artificial Intelligence

- "artificial intelligence is the science of making machines do things that would require intelligence if done by man". Marvin Minskey (1961)
- We can think of AI as the knowledge basis that underlies a RS
  - Social Knowledge Source
  - Personal Knowledge Source
  - Context Knowledge Source

Recommender Systems

- "More Formally, the recommendation problem can formulated as follows: Let C be the set of all users and let S be the set of all possible items that can be recommended. Let u be a utility function that measures the usefulness of item s to user c, that is, $u : C \times S \rightarrow R$,where R is a totally ordered set. Then, for each user $c \in C$, we want to choose such item $s' \in S$ that maximizes the users utility. More formally:

$$\forall c \in C, \quad s'_c = \arg\max_{s \in S} u(c, s)."$$

(Adomavicius 2005)

Types of Recommender Systems

- Context-based
    - Recommends items that are similar to those preferred by the user in the past.
- Collaborative
    - Recommends items that people with similar preferences have liked in the past.
- Hybrid
    - A combination of context-based and collaborative approaches.

Context-Aware Recommender Systems

- Taking context into account.
  - What is context?
  - How does context affect our decision-making processes?
- This approach normally includes an additional parameter(s) to classic RSs.
- Elicitation.
  - Explicit elicitation.
  - Implicit elicitation.

Cold-Start Problem

- Two types of cold-start problems:
  - New-user cold-start where there is no data available for a new user.
  - New-item cold-start problem where there is no rating information for a new item.

Linking RFT to Recommender Systems

There is already a number of researchers that try to incorporate concepts from psychology into recommender systems and machine learning.

- Social Choice Theory (Li & Tang, 2016).
- AI teaching AI (Ammar *et al.* 2014).

Challenges of incorporating derived relations

- How can we incorporate the derived relations when the strength of the relation is not clear?
- There may be very little data available, sometimes no data at all.
- How can we elicit information about context?
- Computational time is very important.

- My question:
  How would a mathematical model of uncertainty, ignorance or vagueness help and be incorporated here?