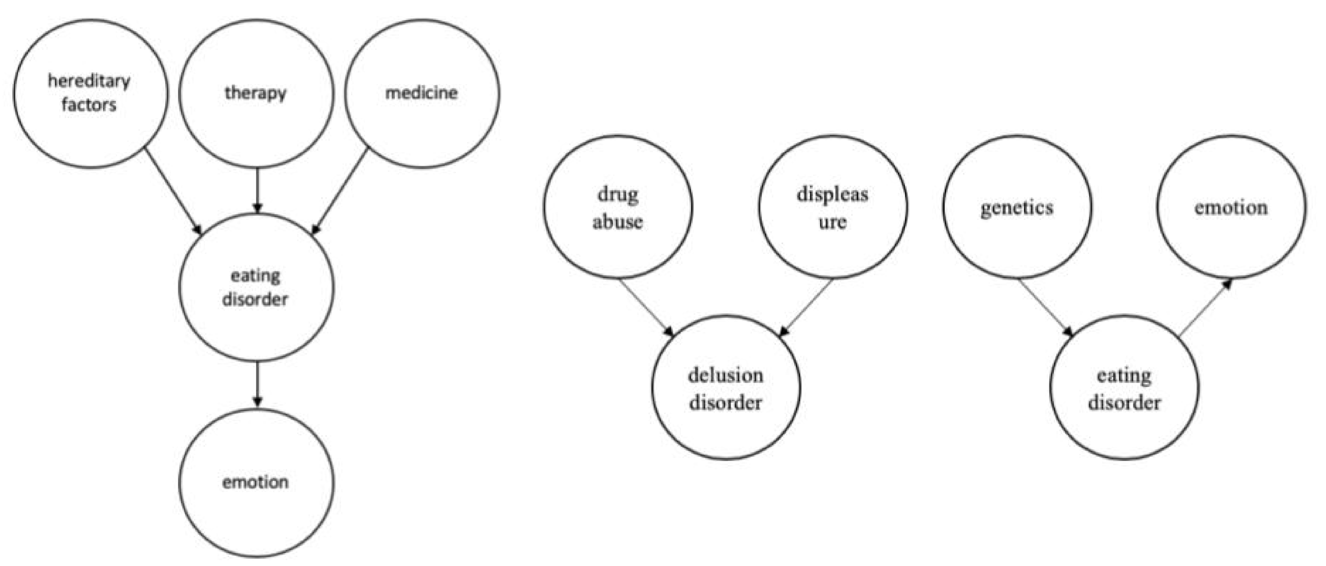
Learning Causal Bayesian Networks from Text

Farhad Moghimifar, Afshin Rahimi, Mahsa Baktashmotlagh, Xue Li

The University of Queensland
AUSTRALIA
CREATE CHANGE

Introduction

Causal relationships form the basis for reasoning and decision-making in Artificial Intelligence systems. Causation is a powerful psychological tool for human to choreograph his surrounding environment into a mental model, and use it for reasoning and decision-making. Extraction of causal relations from text is necessity in many NLP tasks such as question answering and textual inference, and has attracted a considerable research in recent years.



Takeaways

- We focus on identifying causal relation between concepts (e.g. *physical activity* and *health*).
- We propose a novel method to represent the extracted causal knowledge in the form of a Causal Bayesian Network, enabling easy incorporation of this invaluable knowledge into downstream NLP tasks.
- We release PsyCaus dataset which can be used to evaluate causal relation extraction models in the domain of psychology.

Our Approach

Given the input, in form of human written language, we aim to extract the causal relation between concepts and represent the output in form of a Causal Bayesian Network. We split this task into three sub-tasks: extracting linguistic variables and values, identifying causality between extracted variables, and creating conditional probability table for each variable.

Our Approach

A *linguistic variable* is a variable which values are words in natural language. In order to create a Bayesian Network (BN) from text, we leverage a probabilistic method to extract all possible *IsA* relations from corpus. Using Formal Concept Analysis, we represent the extracted hypernym-hyponym relations in form of a hierarchy. For example, consider *(Fluoxetine, IsA, medication)*, *(Fluoxetine, IsA, selective serotonin reuptake inhibitors(SSRI))*, and *(selective serotonin reuptake inhibitors (SSRI, IsA, medication)*, creating the following hierarchy with these three concepts, avoids redundancy. $Fluoxetine \xrightarrow{\text{IsA}} SSRI \xrightarrow{\text{IsA}} medication$ Using both discourse and verb makers of causality, we create a database of cause-effect (Γ) from given sentences. Each of the input sentences are split into simpler version, using dependency parser, and once any of causality markers are identified in a sentence, the stopwords from cause and effect parts are eliminated and the remaining words are stemmed. Having the constructed cause-effect database (Γ), the causal relation between two concepts is defined as:

$$\mathrm{CR}(V_m, V_n) = \frac{\sum_{i=1}^{|V_m|}\sum_{j=1}^{|V_n|} \mathbb{1}[(v_m^i, v_n^j) \in \Gamma]\vec{v}_m^i \cdot \vec{V}_m}{\sum_{i=1}^{|V_m|} \vec{v}_m^i \cdot \vec{V}_m} - \frac{\sum_{j=1}^{|V_n|}\sum_{i=1}^{|V_m|} \mathbb{1}[(v_n^j, v_m^i) \in \Gamma]\vec{v}_n^j \cdot \vec{V}_n}{\sum_{j=1}^{|V_n|} \vec{v}_n^j \cdot \vec{V}_n} \quad (1)$$

$$r(a,b) = \begin{cases} 1 & if(a,b) \in \Gamma \\ 0 & if(a,b) \notin \Gamma \end{cases} \quad (2)$$

$$w(a,b) = 1 - S_c(a,b) = 1 - sim(a,b) \quad (3)$$

The output of CR can be categorised as follow:

$$\mathrm{CR(A,B)} \in \begin{cases} (\mu, 1] & \text{A cause; B effect} \\ [-\mu, \mu] & \text{no causal relationship (4)} \\ [-1, -\mu) & \text{B cause; A effect} \end{cases}$$

In order to extend the implementation of CPD for sets of linguistic variables we use *Normalized Pointwise Mutual Information (PMI)* score to calculate the probability distribution.

$$i_n(x,y) = (ln\frac{p(x,y)}{p(x)p(y)})/ - ln(p(x,y)) \quad (5)$$

Experimental Results