

Suicidal Ideationn Detection In Online Social Content

Shaoxiong Ji, Aalto University

Photo by Dan Meyers on Unsplash

Mental Health & Suicide

1/4 suffering from mental disorder

3/4 people not receive treatment

900,000 committing suicide every year

Early detection !



source: deccanchronicle.com

[World Health Organization, Mental health action plan 2013 - 2020]

Tasks and Solutions

- Benchmarking for Suicidal Ideation Detection (SID)
 - feature engineering: TF-IDF, POS tags, linguistic, etc.
 - word embedding and neural networks.
- Leverage external indictors with relation networks
 - indicators include sentiment and topics;
 - relation network with self attention mechanism.
- Knowledge transferring in private communities
 - knowledge transferring via model aggregation;
 - average difference decent for federated transferring.



Source: hackernoon.com

Benchmarking for Suicidal Ideation Detection

- Input: title, text body
- Features: Statistics, POS, LIWC, TF-IDF, and Topics
- Classifier: SVM, ensemble methods, neural networks



FIGURE 2: Visualisation of extracted features using PCA.

Attentive Relation Networks

- Difference in emotions

 (pos/neg, anxiety, sadness)
 and topics (family, friends, work, money)
- Incorporating sentiment and topic information
- Relation networks with attention mechanism

$$RN(\mathcal{O}) = f_{\phi}\left(\sum_{i,j} g_{\theta}(o_{i}, o_{j})\right) \qquad \alpha = \operatorname{softmax}([r_{1}, r_{2}, ..., r_{l}]W^{T} + b)$$

$$r_{i} = \operatorname{MLP}(h_{i}, s_{i})$$

Knowledge Transferring via Model Aggregation

- Data scarcity in isolated private chatting rooms
- Trade-off between accuracy and data protection
- Collecting only aggregated information
- Knowledge sharing and transferring

✤ Local model training:

 $y_i = f_k(x_i; \theta_k)$ on local data $T_k = \{(x_i, y_i)\}_1^m$

✤ Global model ensemble:

$$F_{glob} = f(\theta_1, ..., \theta_n)$$

 1) Train an optimal local model,
 2) Train a global knowledge-shared model Optimize:

$$\hat{F}_{k} = \underset{F_{k}}{\arg\min \mathbb{E}_{x,y}[L(y, F_{k}(x))]}$$
$$\min_{\theta} \mathbb{E}_{k}[\frac{1}{2}D(\theta, \theta_{k})^{2}]$$

Summary

- Benchmarking and knowledge discovery
 - Comprehensive content analysis to discover knowledge from suicide-related text;
 - Benchmarking on binary classification using feature extraction and deep neural networks.
- Leverage external indictors with relation networks
 - Consider sentimental clues and topics in people's posts;
 - Reason the relations between risk factors and posts with attention relation networks;
 - Fine-grained suicidal ideation detection.
- Knowledge transferring in private communities
 - Another scenario of suicidal ideation detection in private chatting;
 - Knowledge transferring framework to train a global model for knowledge sharing with distributed agents.

Knowledge Graphs

A Survey on Knowledge Graphs: Representation, Acquisition and Applications. Shaoxiong Ji, Shirui Pan, Erik Cambria, Pekka Marttinen, and Philip S Yu. arXiv preprint arXiv:2002.00388, 2020.



- Suicidal Ideation Detection in Online Social Content. Shaoxiong Ji. Master of Philosophy, The University of Queensland. 2020.
- Suicidal Ideation Detection: A Review of Machine Learning Methods and Applications. *Shaoxiong Ji, Shirui Pan, Xue Li, Erik Cambria, Guodong Long, and Zi Huang*. <u>arXiv preprint</u> <u>arXiv:1910.12611</u>, 2020.
- Suicidal Ideation and Mental Disorder Detection with Attentive Relation Networks. *Shaoxiong Ji, Xue Li, Zi Huang, and Erik Cambria.* <u>arXiv preprint arXiv:2004.07601</u>, 2020.
- Detecting Suicidal Ideation with Data Protection in Online Communities. *Shaoxiong Ji, Guodong Long, Shirui Pan, Tianqing Zhu, Jing Jiang, and Sen Wang*. <u>24th International Conference on</u> Database Systems for Advanced Applications (DASFAA), 2019.
- Supervised Learning for Suicidal Ideation Detection in Online User Content. *Shaoxiong Ji, Celina Ping Yu, Sai-Fu Fung, Shirui Pan, and Guodong Long*. <u>Complexity</u>, 2018.

Thank you!



Call For Papers!

- Neurocomputing Special Issue on Knowledge Graph Representation & Reasoing
- https://sentic.net/kgrr.pdf

NEUCOM Special Issue on Knowledge Graph Representation & Reasoning

Recent years have witnessed the release of many open-source and enterprise-driven knowledge graphs with a dramatic increase of applications of knowledge representation and reasoning in fields such as natural language processing, computer vision, and bioinformatics. With those large-scale knowledge graphs, recent research tends to incorporate human knowledge and imitate human's ability of relational reasoning. Factual knowledge stored in knowledge bases or knowledge graphs can be utilized as a source for logical reasoning and, hence, be integrated to improve real-world applications.

Emerging embedding-based methods for knowledge graph representation have shown their ability to capture relational facts and model different scenarios with heterogenous information. By combining symbolic reasoning methods or Bayesian models, deep representation learning techniques on knowledge graphs attempt to handle complex reasoning with relational path and symbolic logic and capture the uncertainty with probabilistic inference. Furthermore, efficient representation learning and reasoning can be one of the paths towards the emulation of high-level cognition and human-level intelligence. Knowledge graphs can also be seen as a means to tackle the problem of explainability in Al. These trends naturally facilitate relevant downstream applications which inject structural knowledge into wide-applied neural architectures such as attention-based transformers and graph neural networks.

This special issue focuses on emerging techniques and trendy applications of knowledge graph representation learning and reasoning in fields such as natural language processing, computer vision, bioinformatics, and more.

Topics of Interests

The topics of this special issues include but not limited to:

- Representation learning on knowledge graphs
- Representation learning on text data
- Logical rule mining and symbolic reasoning
- Knowledge graph completion and link prediction
- Relation extraction
- Community embeddings
- Knowledge representation and reasoning over large-scale knowledge graphs
- Hybrid methods with symbolic and non-symbolic representation and reasoning
- Automatic knowledge graph construction
- Domain-specific knowledge graphs, e.g., medical knowledge graphs
- Knowledge dynamics of temporal knowledge graphs
- Time-evolving knowledge representation learning
- Question answering and dialogue systems with knowledge graphs
- Knowledge-injected sentiment analysis
- Commonsense knowledge representation and reasoning
- Knowledge graphs for neural machine translation
- Knowledge-aware recommendation systems
- Knowledge graphs for digital health, e.g., healthcare and medical diagnosis
- Few-shot relational learning on knowledge graphs
- Federated learning with multi-source graphs in decentralized settings
- Graph representation learning for structured data
- Explainable artificial intelligence with knowledge-aware models

Composition and Review Procedures

The Special Issue will consist of papers on novel methods and techniques that further develop and apply knowledge graph representation and reasoning for the development of intelligent tools, techniques, and applications. Some papers may survey various aspects of the topic. The balance between these will be adjusted to maximize the issue's impact. Paper submissions for the special issue should follow the submission format and guidelines for regular papers and submitted at https://ees.elsevier.com/neucom. All the papers will be peer-reviewed following NEUCOM reviewing procedures. Guest editors will make an initial assessment of the suitability and scope of all submissions. Papers will be evaluated based on their originality, presentation, relevance and contributions, as well as their suitability to the special issue. Papers that either lack originality, clarity in presentation or fall outside the scope of the special issue will not be sent for review. Authors should select "SI: KGRR" when they reach the "Article Type" step in the submission process. The submitted papers must propose original research that has not been published nor currently under review in other venues. Previously published conference papers should be clearly identified by the authors at the submission stage and an explanation should be provided about how such papers have been extended. Such contributions must have at least 50% difference from the research work they stem from.

Important Dates

Paper submission: 31 August 2020 Initial review feedback: 31 October 2020 Revision: 15 January 2021 Publication date: March 2021

Guest Editors

Erik Cambria, Nanyang Technological University, Singapore Shaoxiong Ji, Aalto University, Finland Shirui Pan, Monash University, Australia Philip S. Yu, University of Illinois at Chicago, USA