Towards Explainability for Interaction Network Analysis

Maria Malek

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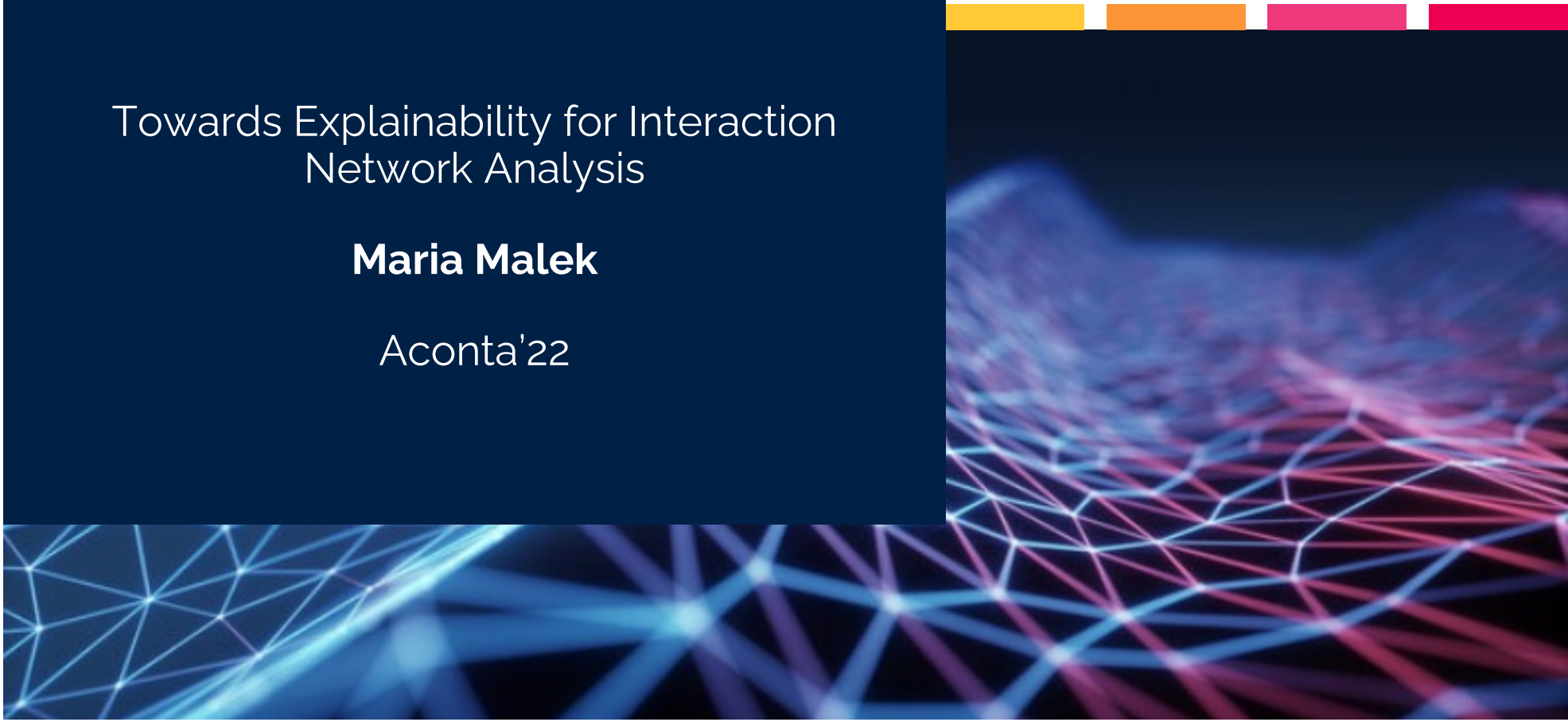
Aconta'22



ETIS
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Part 1
Explainability & Netwok analysis

- **Explainable AI (XIA)**
- **Explainability & Network Analysis**
  - Leveraging nodal and topological information
- **Network Embedding**
- **Graph Neural Network (GNN)**
- **Explainabililty for GNN**

Part 2
Sentiment Analysis Application

- **Explainable sentiment analysis**
- **Our approach for Detecting opinion change**
  - **Form ego Networks to Propagation network**
  - **Dataset: topological and textual information**
  - **Machine Learning and explainability**

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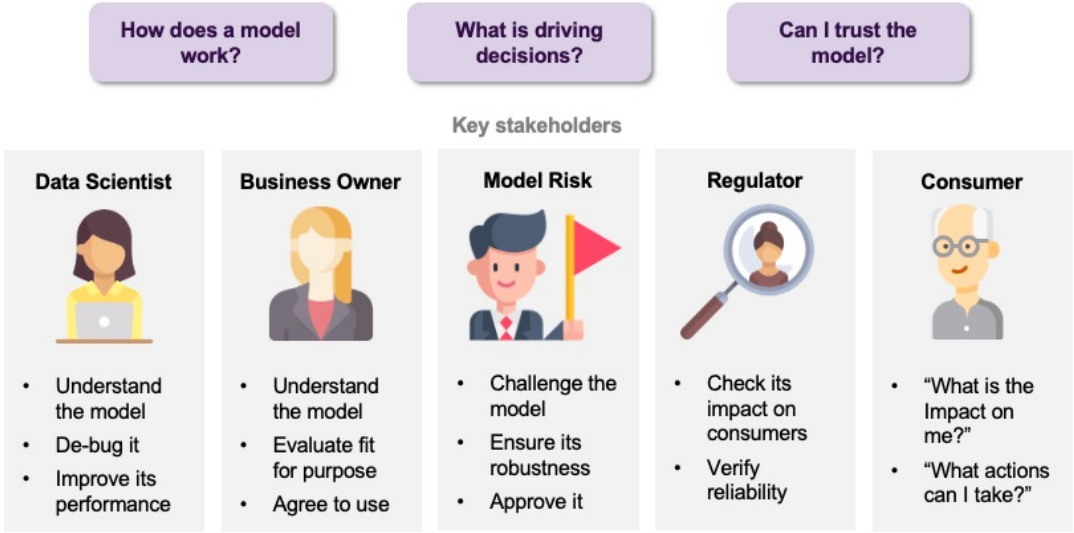
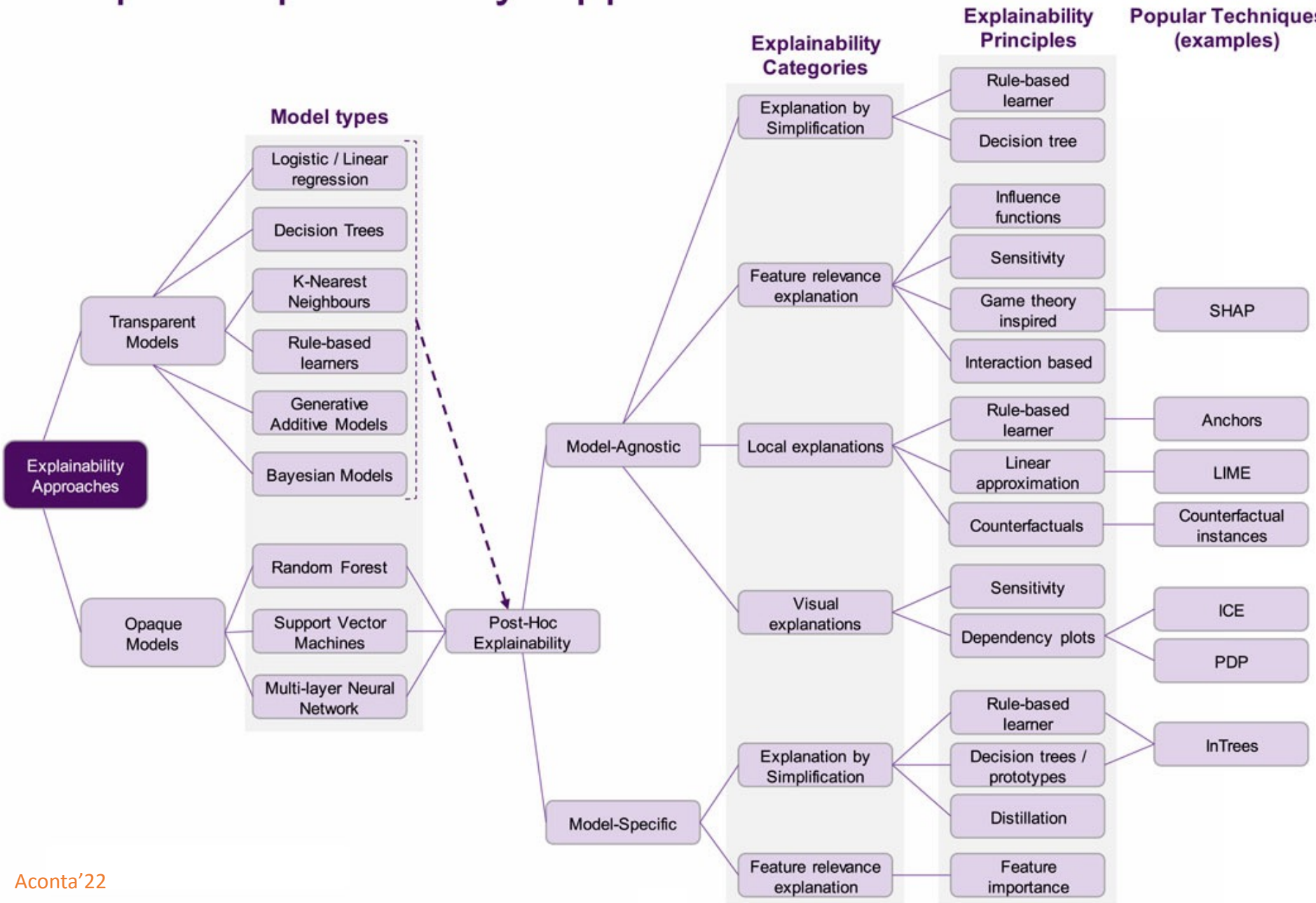
Explainable AI (XAI)

- Machine Learning methods reach today high level of performance to solve increasingly complex task.
- An emerging need to understand how decisions are rendered by AI methods
  - when the decisions of such systems affect the lives of human.
- The paradigm underlying this problem is the so-called Explainable AI (XIA) domain



V Belle, I Papantonis , Principles and practice of explainable machine learning, - Frontiers in big Data, 2021

Map of Explainability Approaches



Transparent versus Opaque methods

Transparent

Statistical framework with **clear interpretation**

High explainability

Example **Logistic regression**

$$\text{logit}(\pi_i) = \beta_0 + \beta_1 income_i + \varepsilon_i$$

After estimating a logistic regression, $\boldsymbol{\beta_1}$ **will tell you the impact of income** on the probability of default

Transparent models with many features **can become opaque**

Opaque

Statistical framework with **complex interpretation**

High performance

Example **Random forest**

Cannot comprehend all interactions that happen across decision trees in a random forest (decision via majority voting)

Post-hoc methods can help us understand opaque models

V Belle, I Papantonis , Principles and practice of explainable machine learning, - Frontiers in big Data, 2021

Explainability Categories

Explanation	Advantages	Disadvantages
Local explanations	Explains the model's behaviour in a local area of interest. Operates on instance-level explanations.	Explanations do not generalize on a global scale. Small perturbations might result in very different explanations. Not easy to define locality. Some approaches face stability issues.
Examples	Representative examples provide insights about the model's internal reasoning. Some of the algorithms uncover the most influential training data points that led the model to its predictions.	Examples require human inspection. They do not explicitly state what parts of the example influence the model.
Feature relevance	They operate on an instance level, calculating the importance of each feature in the model's decision. A number of the proposed approaches come with appealing theoretical guarantees.	They are sensitive in cases where the features are highly correlated. In many cases the exact solutions are approximated, leading to undesirable side effects, such as the ordering affecting the outcome.
Simplification	Simple surrogate models explain the opaque ones. Resulting explanations, such as rules, are easy to understand.	Surrogate models may not approximate the original models well. Surrogate models come with their own limitations.
Visualizations	Easier to communicate to non technical audience. Most of the approaches are intuitive and not hard to implement.	There is an upper bound on how many features we can consider at once. Humans need to inspect the resulting plots in order to produce explanations.

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Explainability & Network analysis

- Extend the explainability approaches to the domain of complex network analysis
  - produce emergent explanations from topological information:
    - global topological measures (density, clustering coefficient, diameter)
    - local measures as the different types of centralities: degree, betweenness, pageRank, etc.
- Necessary when complex network analysis is part of a decision system to performa task:
  - recommender systems, sentiment analysis or link prediction.
- Useful for understanding the community structures detected in the network.

Spyroula Masiala and Martin Atzmueller (2018) First Perspectives on Explanation in Complex Network Analysis. In: Proc. Benelux Conference on Artificial Intelligence (BNAIC), Jheronimus Academy of Data Science (JADS), 's-Hertogenbosch, The Netherlands

Explainability & Network analysis

- Machine learning: entities processed in interpretability method are related to
  - features (attributes), data, extracted prototypes
  - simple extracted knowledge often in the form of rules or decision trees.

- Interaction networks: new entities must be taken into consideration:
  - nature of the links in the graph (social link, collaboration or interaction link, etc.),
  - the topological information extracted from the graph.
  - To propose complete explanatory actions which integrate topological and semantic information.

Idea 1: Apply explainble ML to interaction networks
Network embedding and explainable GNN

Idea 2: Define an explainability approaches for graph (network) algorithms

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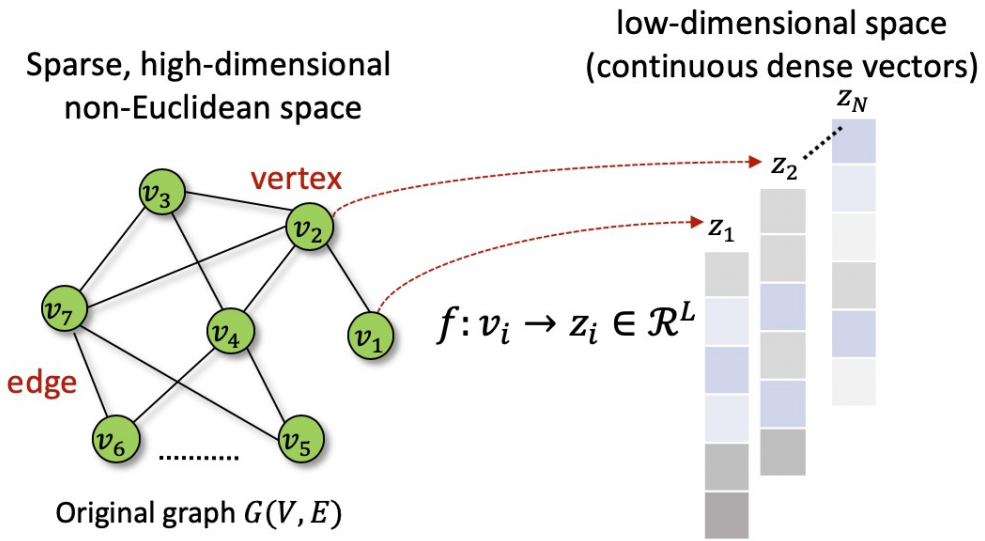
Network Embedding

- Industrial systems: graphs with over 50 million nodes and over a billion edges
  - Need of low computational complexity algorithms.
- Network embedding: learning latent low-dimensional feature representations for the nodes or links in a network.
- Learn encodings for the nodes in the network such that
  - the similarity in the embedding space reflects the similarity in the network.



Xu, Mengjia, Understanding Graph Embedding Methods and Their Applications}, SIAM Review, Vol. 63, No.44, pp. 825-853, 2021

Network Embedding

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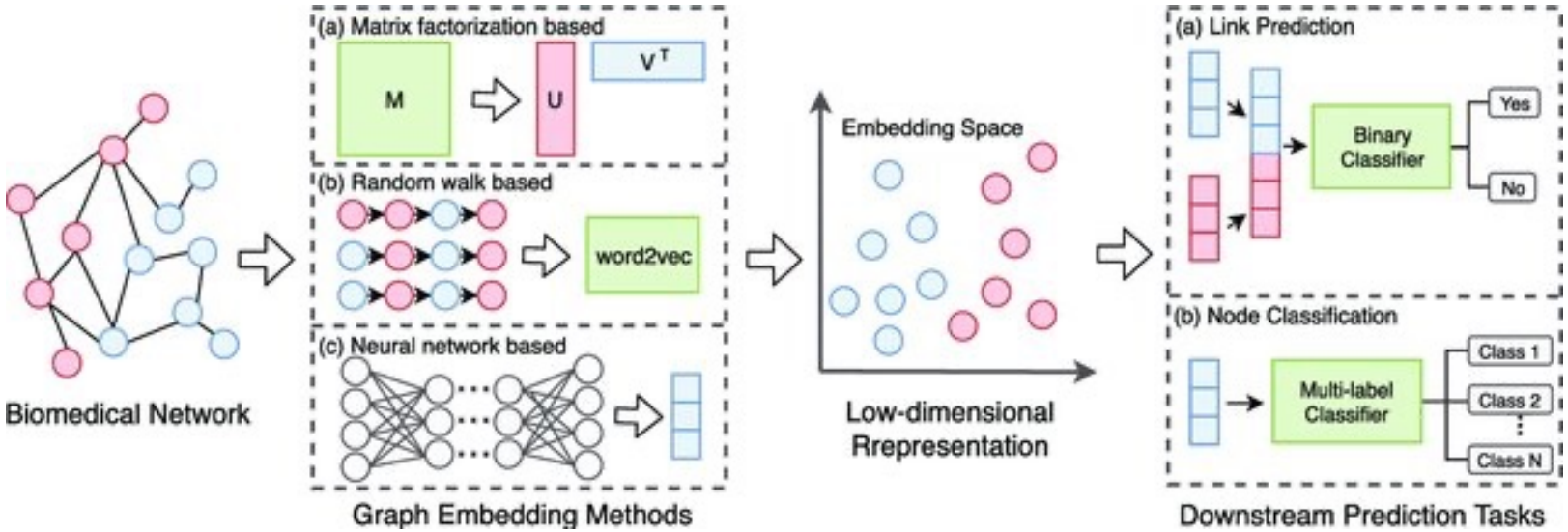
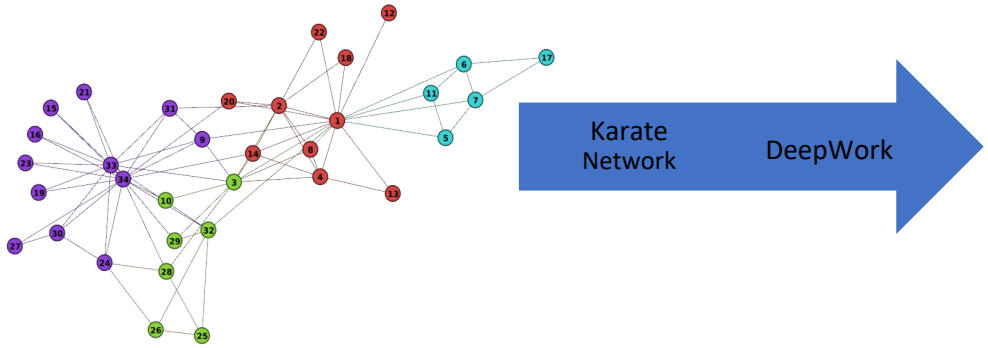


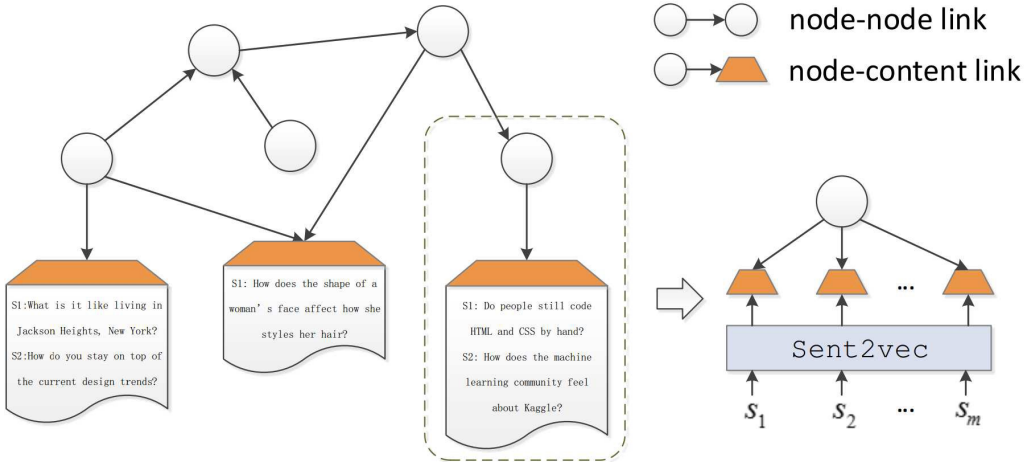
Xiang Yue, Zhen Wang, Jingong Huang, Srinivasan Parthasarathy, Soheil Moosavinasab, Yungui Huang, Simon M Lin, Wen Zhang, Ping Zhang, Huan Sun, Graph embedding on biomedical networks: methods, applications and evaluations, *Bioinformatics*, Volume 36, Issue 4, 15 February 2020, Pages 1241–1251, https://doi.org/10.1093/bioinformatics/btz718

- Support noisy datasets across different application domains:
  - social networks, citation networks, language networks, and biological networks

Network Embedding



Bryan Perozzi and Rami Al-Rfou and Steven Skiena, DeepWalk,
Proceedings of the 20th ACM, SIGKDD, international conference on Knowledge discovery and data mining, 2014



Sun, X.; Guo, J.; Ding, X.; and Liu, T.,
A general framework for content-enhanced network representation learning. arXiv preprint arXiv:1610.02906, 2016

Network Embedding

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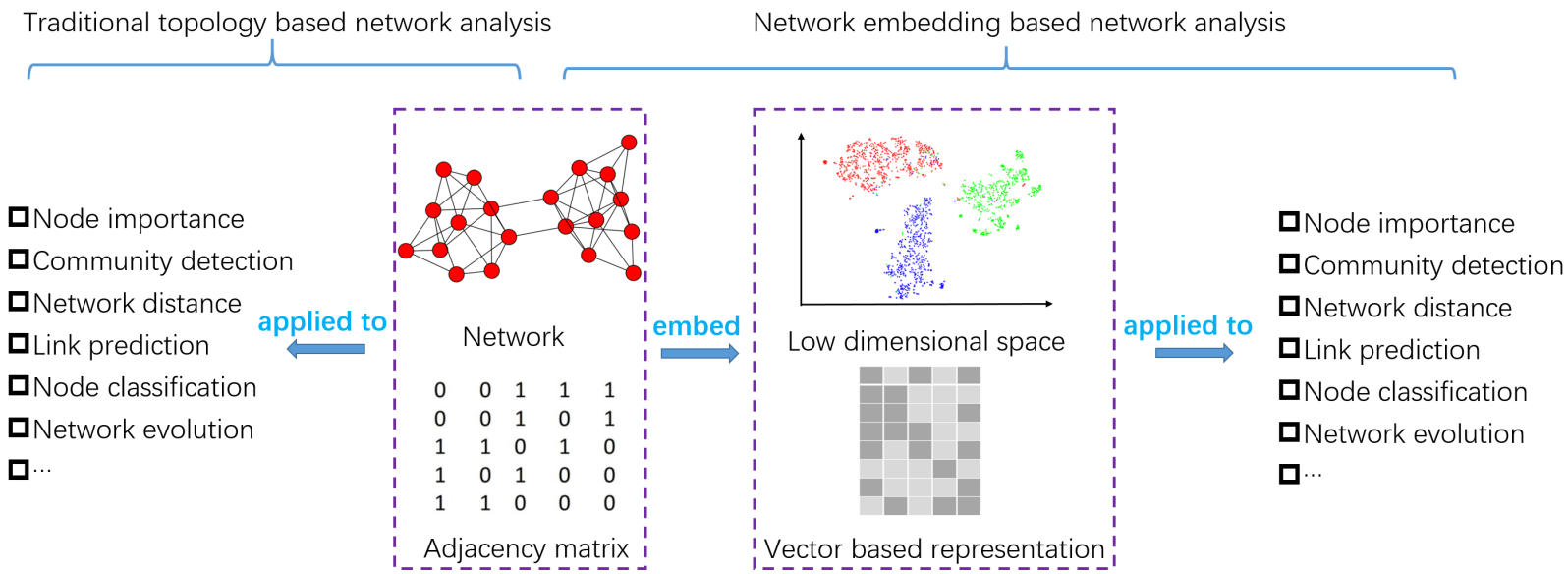

P. Cui, X. Wang, J. Pei and W. Zhu, "A Survey on Network Embedding, *IEEE Transactions on Knowledge and Data Engineering*, vol. 31, no. 5, pp. 833-852, 1 May 2019,

Despite the superior performances, one fundamental limitation of them is the lack of interpretability (Liu N.et al., 2018). Different dimensions in the embedding space usually have no specific meaning, thus it is difficult to comprehend the underlying factors that have been preserved in the latent space.

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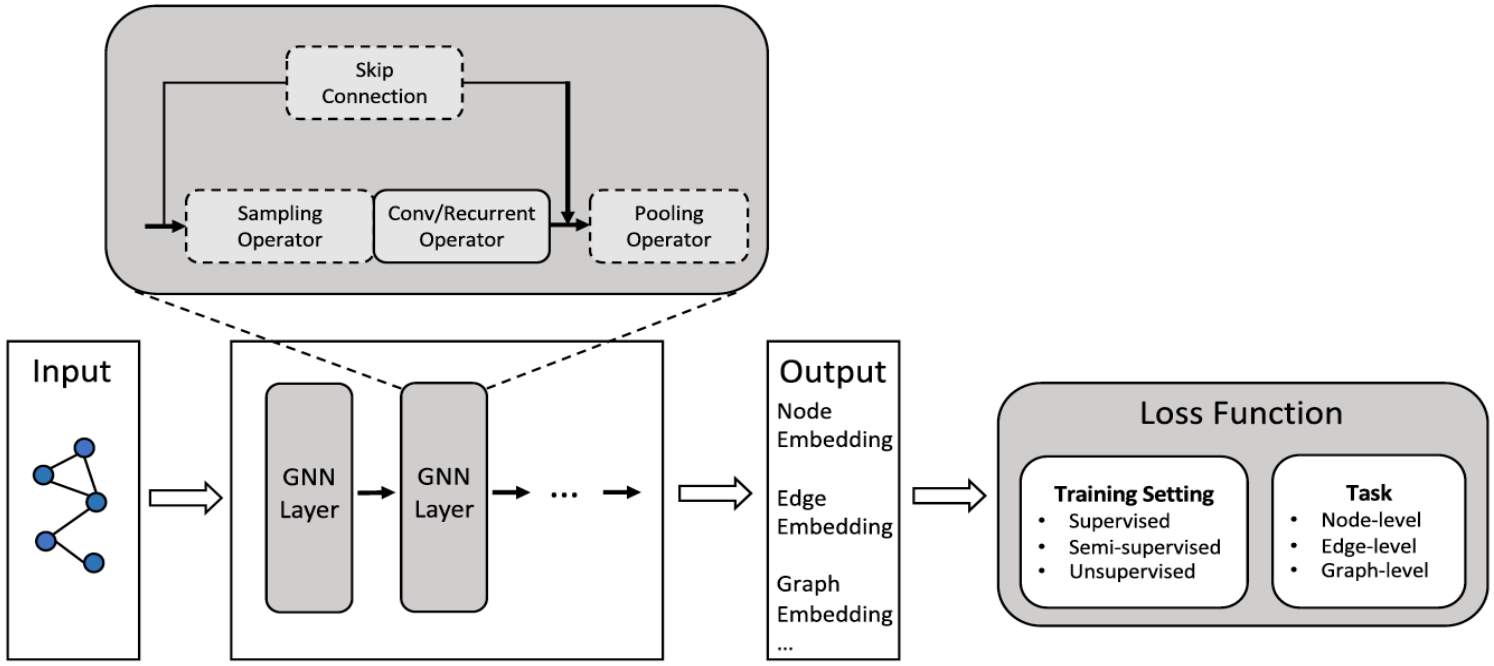
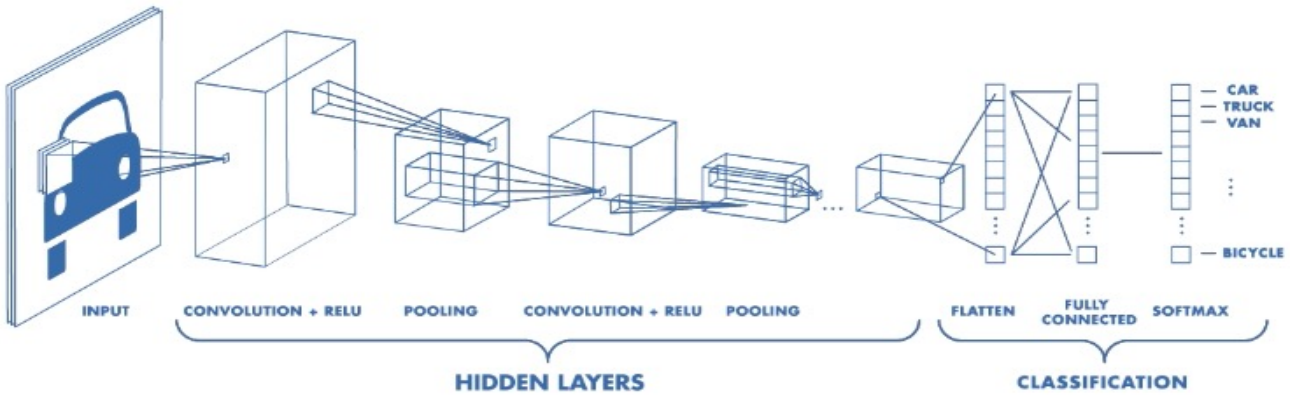
Graph Neural Networks (GNN)



- Graph neural networks (GNNs) are deep learning-based methods that operate on graph domain
- Applications: Citation networks, Bio-chemical Graphs, Social networks, Knowledge graphs

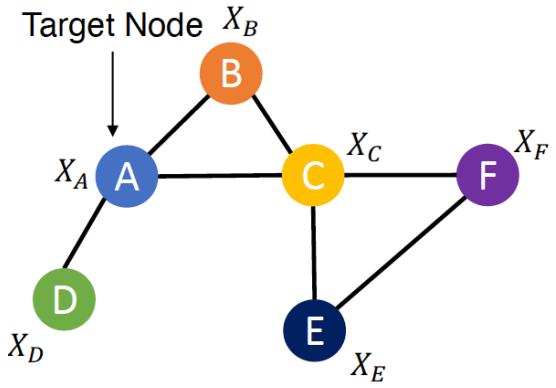
Jie Zhou, Ganqu Cui, Shengding Hu, Zhengyan Zhang, Cheng Yang, Zhiyuan Liu, Lifeng Wang, Changcheng Li, Maosong Sun, **Graph Neural Networks: A Review of Methods and Applications,** AI Open, 2021

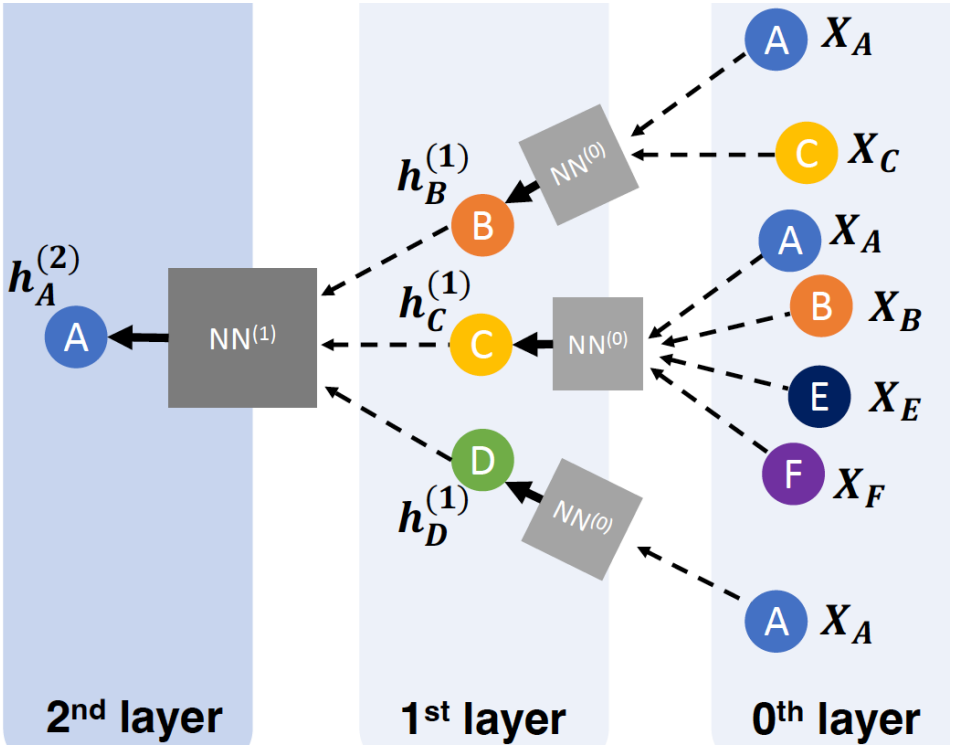
Deep Learning : exemple CNN



- Deep neural networks, especially convolutional neural networks (CNNs) (LeCun et al., 1998)
  - CNNs have the ability to extract multi-scale localized spatial features
  - compose them to construct highly expressive representations,
  - led to in almost all machine learning areas (LeCun et al., 2015).
- The keys of CNNs are local connection, shared weights and the use of multiple layers
- CNNs operate on regular Euclidean data like images (2D grids) and texts (1D sequences)

Latent representation of nodes





1. Aggregate messages

$$m_v^{(l)} = \frac{1}{|\mathcal{N}(v)+1|} \sum_{u \in \mathcal{N}(v) \cup \{v\}} h_u^{(l)}$$

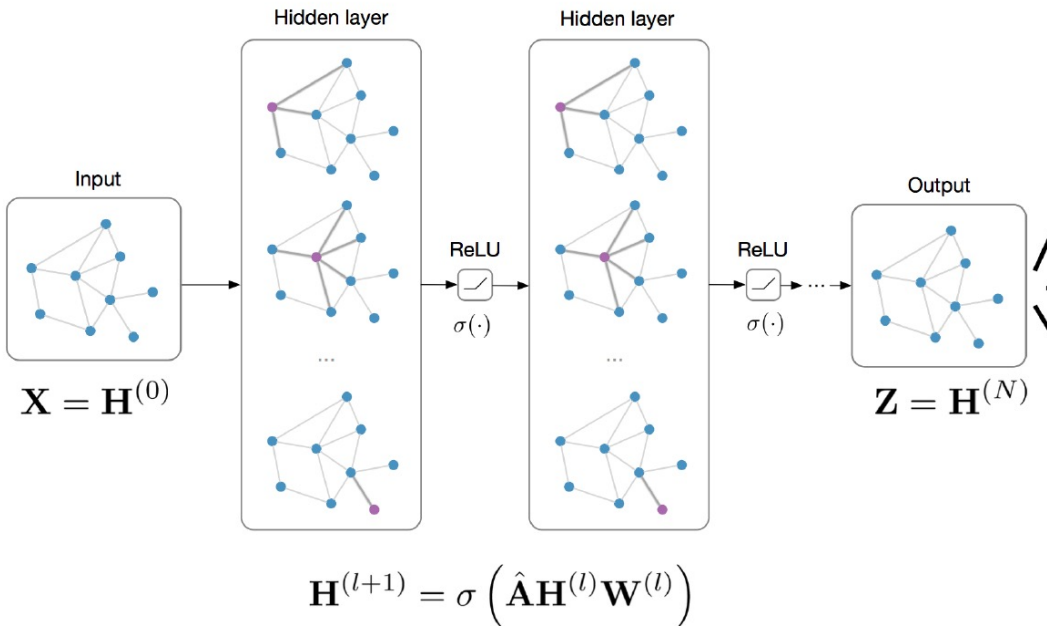
2. Transform messages

$$h_v^{(l+1)} = \boldsymbol{W}^{(l)} \circ m_v^{(l)}$$

Minji Yoon (CMU) - Guest lecture at 10707: Introduction to Deep Learning

GNN: Pass message and agglomerate

Input: Feature matrix $\mathbf{X} \in \mathbb{R}^{N \times E}$, preprocessed adjacency matrix $\hat{\mathbf{A}}$



Node classification:

$\mathrm{softmax}(\mathbf{z_n})$

e.g. Kipf & Welling (ICLR 2017)

Graph classification:

$\mathrm{softmax}(\sum_n \mathbf{z_n})$

e.g. Duvenaud et al. (NIPS 2015)

Link prediction:

$p(A_{ij}) = \sigma(\mathbf{z_i^T z_j})$

Kipf & Welling (NIPS BDL 2016)

"Graph Auto-Encoders"

Thomas Kipf, University of Amsterdam

GNN Applications : Node classification

Dataset	Type	Nodes	Edges	Classes	Features	Label rate
Citeseer	Citation network	3,327	4,732	6	3,703	0.036
Cora	Citation network	2,708	5,429	7	1,433	0.052
Pubmed	Citation network	19,717	44,338	3	500	0.003
NELL	Knowledge graph	65,755	266,144	210	5,414	0.001

Method	Citeseer	Cora	Pubmed	NELL
ManiReg [3]	60.1	59.5	70.7	21.8
SemiEmb [28]	59.6	59.0	71.1	26.7
LP [32]	45.3	68.0	63.0	26.5
DeepWalk [22]	43.2	67.2	65.3	58.1
ICA [18]	69.1	75.1	73.9	23.1
Planetoid* [29]	64.7 (26s)	75.7 (13s)	77.2 (25s)	61.9 (185s)
GCN (this paper)	**70.3** (7s)	**81.5** (4s)	**79.0** (38s)	**66.0** (48s)
GCN (rand. splits)	67.9 ± 0.5	80.1 ± 0.5	78.9 ± 0.7	58.4 ± 1.7

Summary of results in terms of classification accuracy (in %)

Kipf, Thomas N., and Max Welling,
Semi-supervised classification with graph convolutional networks, arXivpreprint arXiv:1609.02907, (2016)

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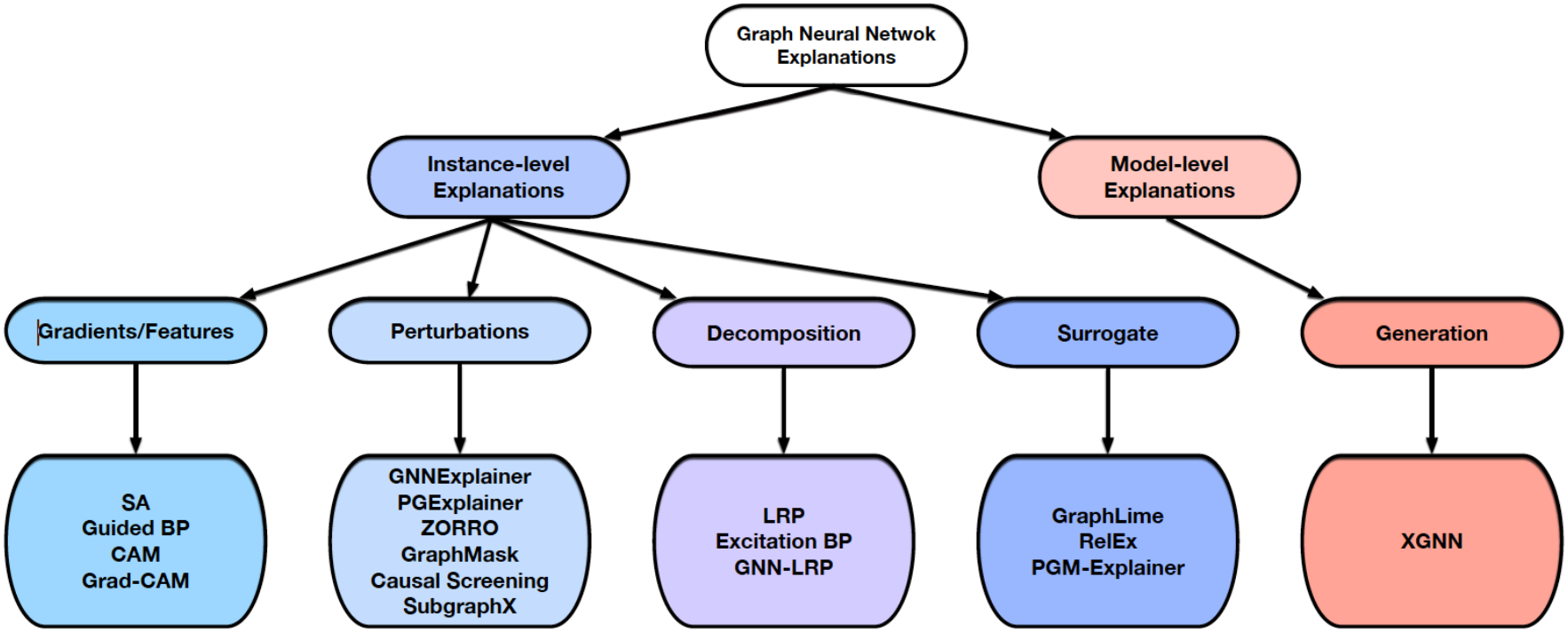
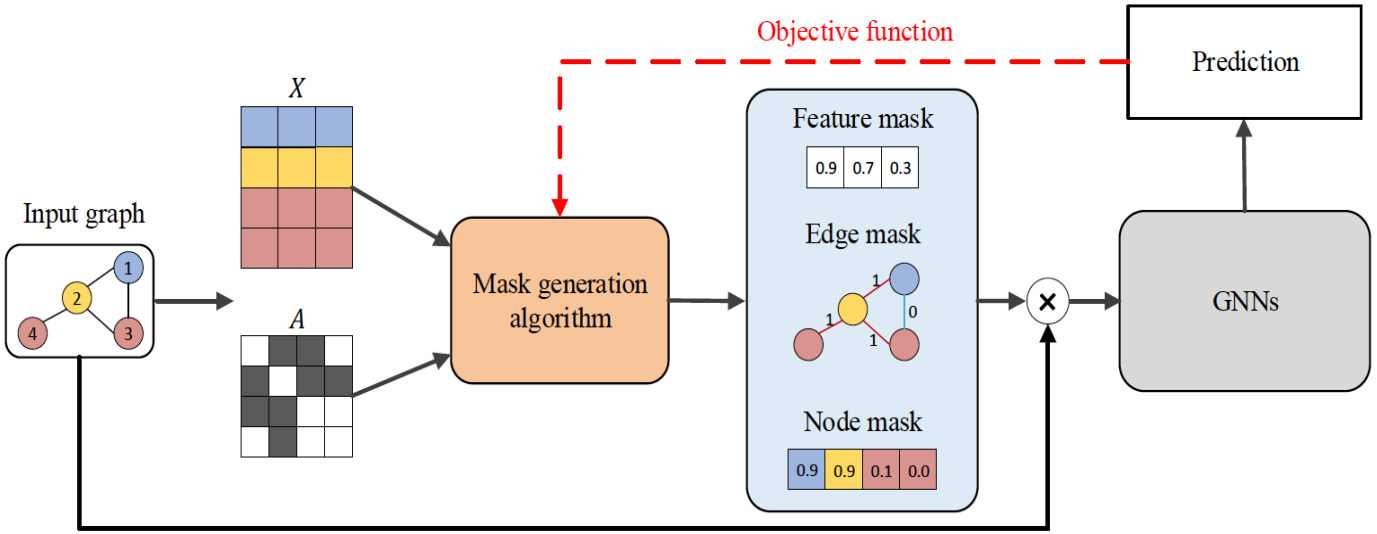
Explainability in GNN: approcahes



Yuan, Hao and Yu, Haiyang and Gui, Shurui and Ji, Shuiwang, Explainability in Graph Neural Networks: A Taxonomic Survey, arXiv, 2020,

Perturbation-based methods: general pipeline



- Mask generation algorithms to obtain different types of masks.
- The mask is combined with the input graph to capture important input information.
- The trained GNNs evaluate whether the new prediction is similar to the original prediction
  - can provide guidance for improving the mask generation algorithms.

Intuitively,
when important input information is retained, the predictions should be similar to the original predictions.

Explainability in GNN: evaluation metrics

- Fidelity+ : the difference of accuracy (or predicted probability) between the original predictions and the new predictions after masking out important input features (nodes/edges/ node feature)

- Explanations should be sparse, they should capture the most important input features and ignore the irrelevant ones.
- The metric Sparsity measures such a property.
  - measures the fraction of features selected as important by explanation methods

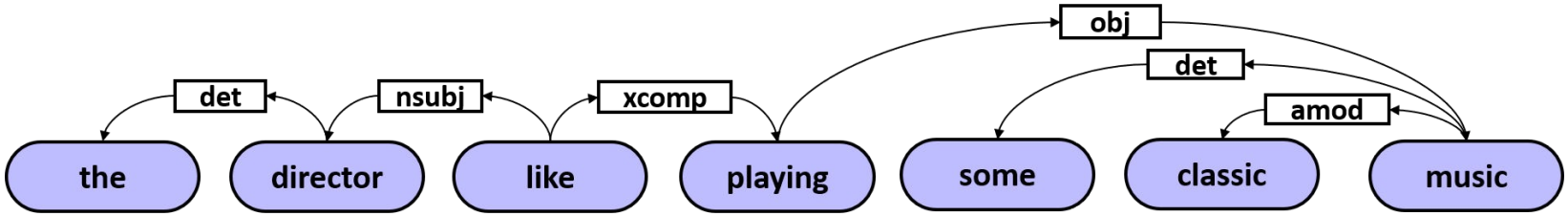
Accuracy related to ground truth (F1 score, AUC)
In addition, good explanations should be stable.

Stability: when small changes are applied to the input without affecting the predictions, the explanations should remain similar.

Explainability in GNN: Experiments

- 3 sentiment graph datasets based on text sentiment analysis data : SST2, SST5, and Twitter,
- Molecule data : BBBP
- Synthetic data sets: BA-shapes, BA-2motifs

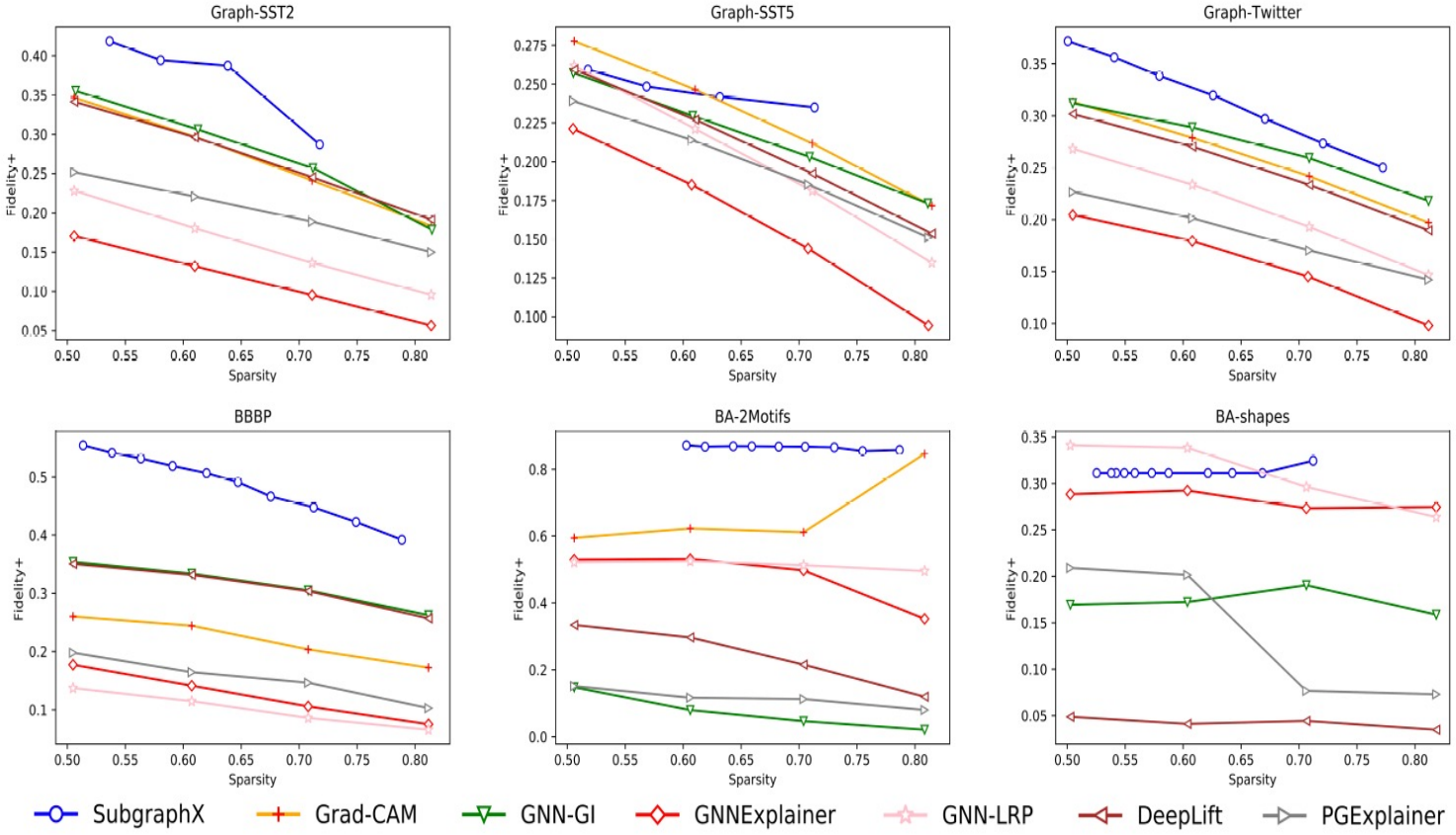
Dataset	Graph-SST2	Graph-SST5	Graph-Twitter
# of classes	2	5	3
# of features	768	768	768
Avg. # of nodes	10.199	19.849	21.103
# of train graphs	67,349	8,544	4,998
# of val. graphs	872	1,101	1,250
# of test graphs	1,821	2,210	692
GCN accuracy	0.892	0.443	0.614



- The Fidelity+ metric studies the prediction change by removing important nodes/edges/node features.
- the metric Fidelity- studies prediction change by keeping important input features and removing unimportant features.

Yuan, Hao and Yu, Haiyang and Gui, Shurui and Ji, Shuiwang, Explainability in Graph Neural Networks: A Taxonomic Survey, arXiv, 2020,

Explainability in GNN: experiments wt Fidelity+



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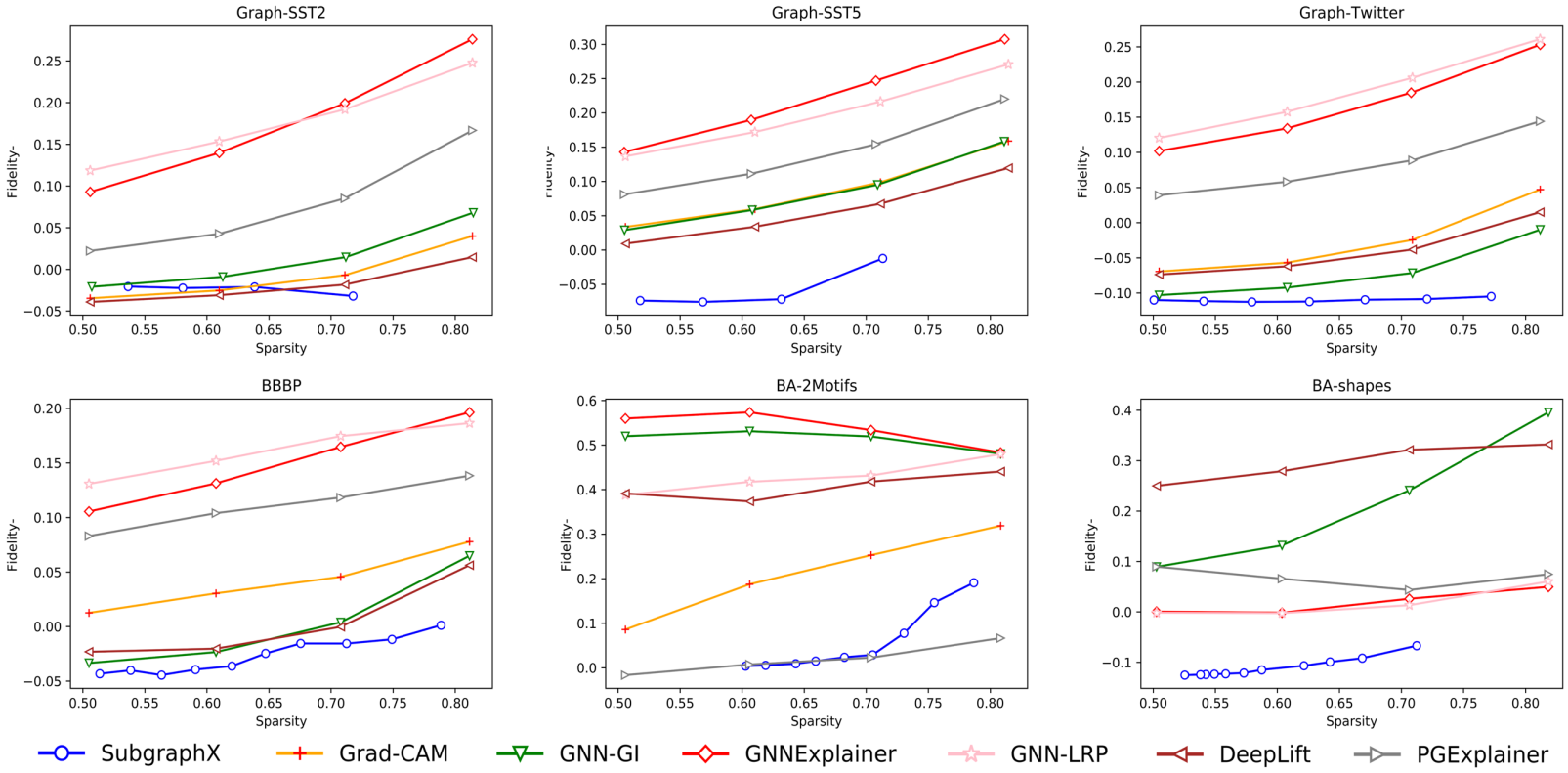

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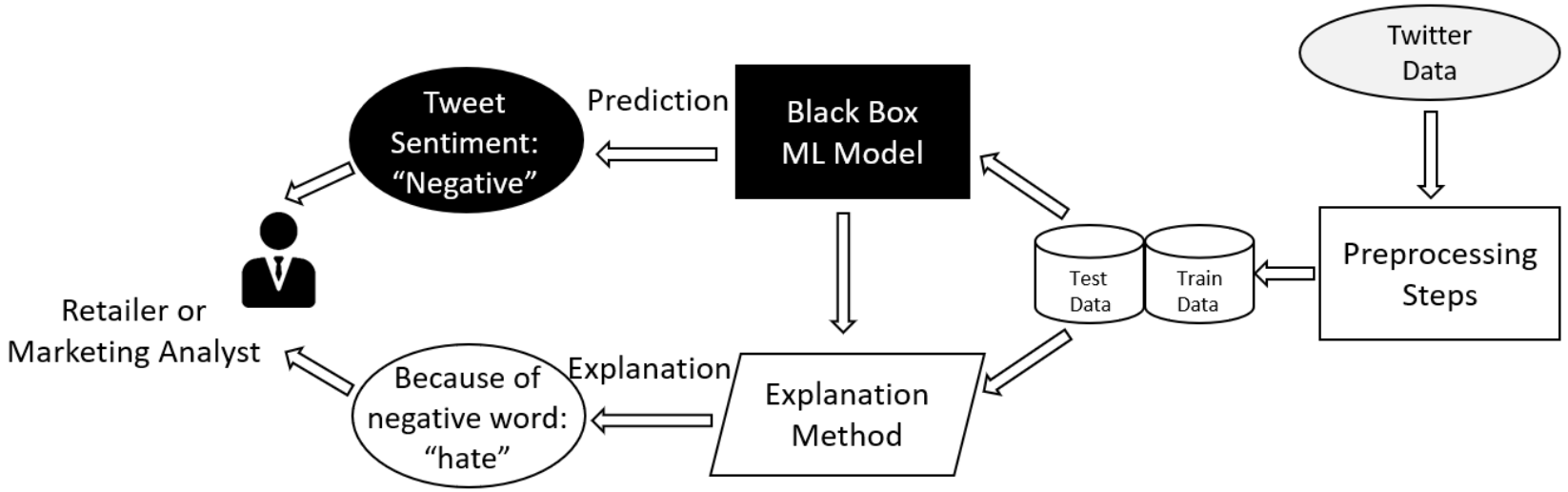
Explainable Sentiment Analysis



- Dataset of tweets discussing electronics products
- 375 positive and 1092 negative tweets,
- a total of 1467 instances.

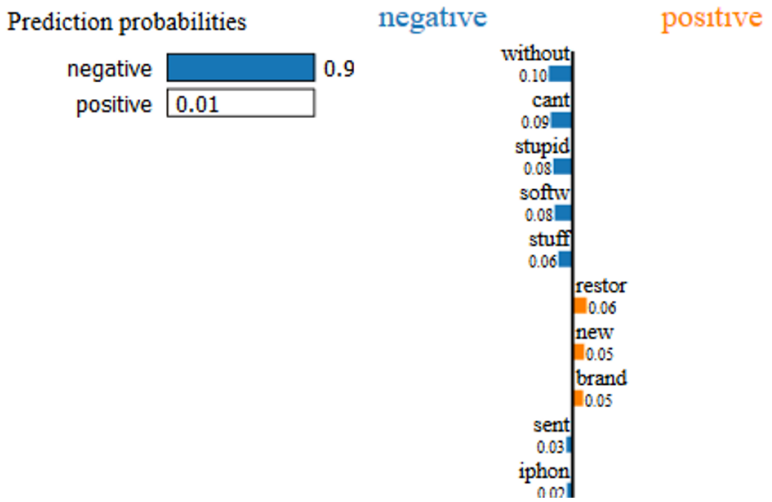
ML Model	Average F1 Score
SVM	0.75
RF	0.74
XGBoost	0.79
MLP	0.81

Cirqueira, Douglas et al. Explainable Sentiment Analysis Application for Social Media Crisis Management in Retail. *CHIRA* (2020).

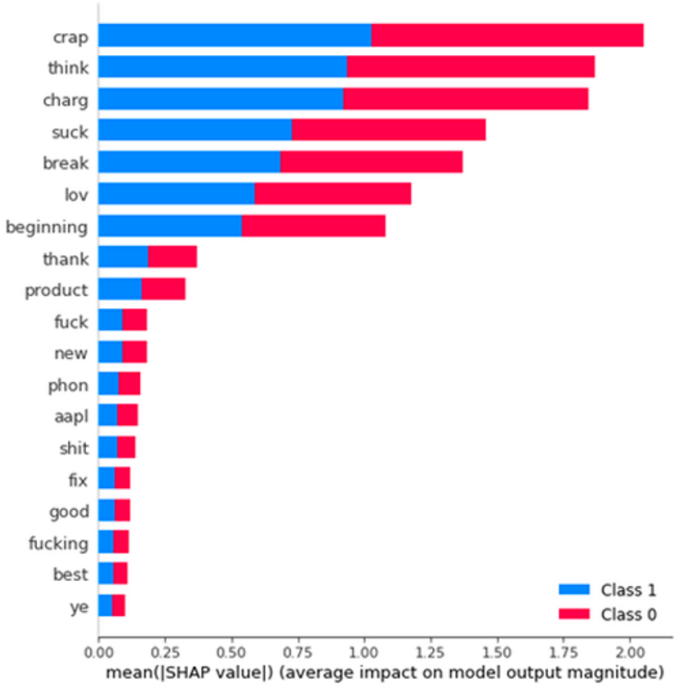
Explainable Sentiment Analysis

Tweet: "strik somewhat stupid sent brand new iphon without latest softw cant restor old stuff"

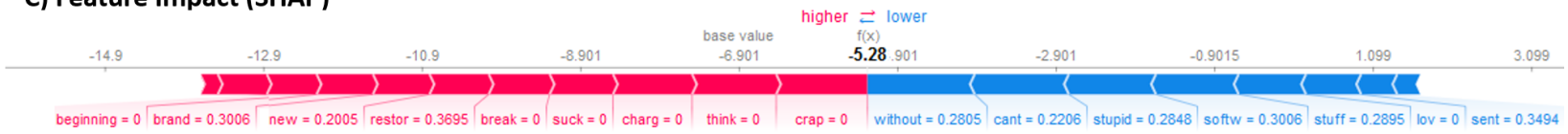
A) Local Feature Importance (LIME)



B) Global Feature Importance (SHAP)



C) Feature Impact (SHAP)



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Study of the interaction between two opposite ego networks

- Study the interaction between two ego networks around two influencers having opposite opinion on a given topic
  - its impact on opinion change and propagation within these two interconnected ego networks.

- Goal: explore the combination of sentiment analysis with complex networks analysis

- Proposition: Explainable Method for detecting opinion modification in relation to several nodal and topological measures: users' centralities, the opinion of the community to which belongs the users, as well as textual information extracted from tweets.

Folly, K., Malek, M., & Kotzinos, D. **Social networks analysis for opinion model extraction.**
In *Networks 2021: first combined meeting of the International Network for Social Network Analysis (Sunbelt XLI), and the Network Science Society (NetSci 2021)*, Indiana, United States, July 2021.

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Study of the interaction between two opposite ego netwoks: methodology

1. Data collection from twitter: retrieve tweets related the chosen topic

2. Find two opposite influencers
   - metrics: popularity, range the propagation, likeness scores, users' profiles

3. Construction of the propagation directed network
   - nodes: common repliers extracted from both influencers' egocentric networks at levels 1 and 2
   - edges: the actions of reply.

4. Study of the network characteristics :
   - centralities, community detection: Louvain algorithm

5. Sentiment Analysis
   - polarity and subjectivity computing for: users, ego networks, communities

6. (Explainabale) Machine Learning for detecting opinion change of users

Study of the interaction between two opposite ego networks: Machine Learning

- Machine Learning for detecting opinion change of users
  - Dataset: an entry is related to a link of the propagation network
  - nodal and topological features for both the original tweet and the reply author nodes
  - textual features are extracted with the TF-IDF method

1. Detecting opinion change over time
   - ✓ the target variable indicates if the replier has changed his opinion polarity over Time
2. Detecting opinion modification via the action of reply
   - ✓ the target variable indicates if the opinion is modi ed via the action of reply

- Find the best ML method for both

ML for detecting opinion modification: Features

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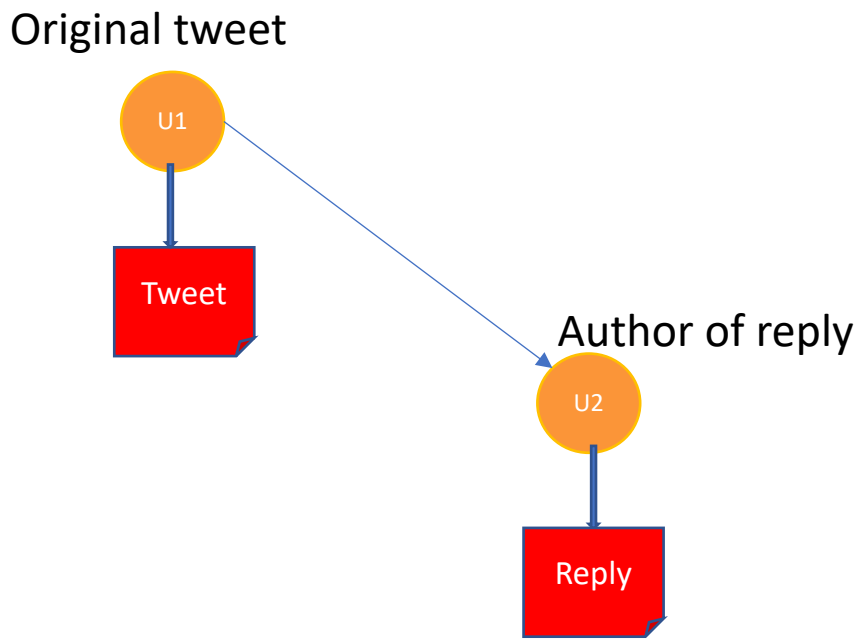
Features nature	Features
Topological features	Betweenness_centrality, Out_centrality, In_centrality, Pagerank, (for original tweet user) community_original_tweet_user, community_author, community_mean_subjectivity_original_tweet_user, community_mean_polarity_original_tweet_user, in_same_community
Nodal features	mean_polarity_original_tweet_user, mean_subjectivity_original_tweet_user, subjectivity_original_tweet_text
Tweet features	tweet_stopwords_ratio, reply_stopwords_ratio (low, medium, high, very high), length_reply_high (low, medium, high, very high), length_tweet (low, medium, high, very high)

Without textual features



Study of the interaction between two opposite ego networks: experiments

- The chosen topic Covid vaccination
- Period for retrieved tweets : October 1, 2021 to December 14, 2021.
- The query returned approximately 65.000 tweets.
- The found influencers were
  - Florian Philippot, politician against vaccination
  - Olivier Véran, for vaccination.

Nodes #	edges #	Outdegree	Indegree	Betwenness	pagerank	Communities #
21075	84441	[0.05,0.18]	[0.001,0.003]	[0.002,0.007]	[0.00004,0.0005]	36

Propagation network: characteristics (top 10)

- Out-degree centrality have significant values
  - detect influencing users that contribute to the propagation of opinions

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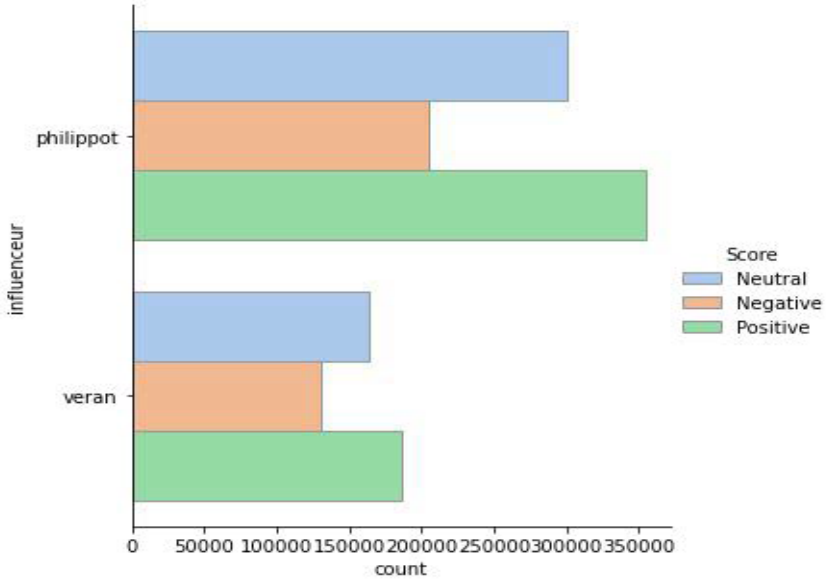
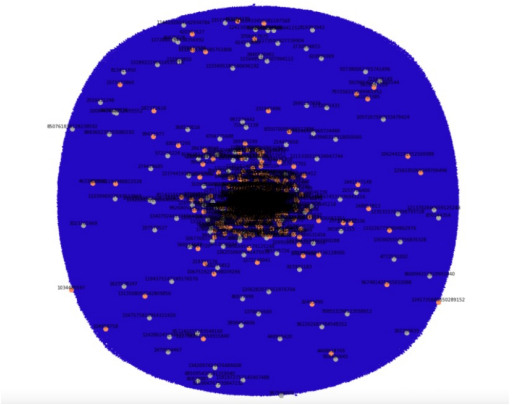
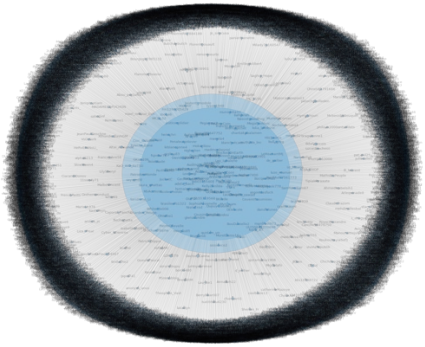
Study of the interaction between two opposite ego networks: opinion propagation



Opinion propagation in both egocentric networks



Propagation network



Retweet network

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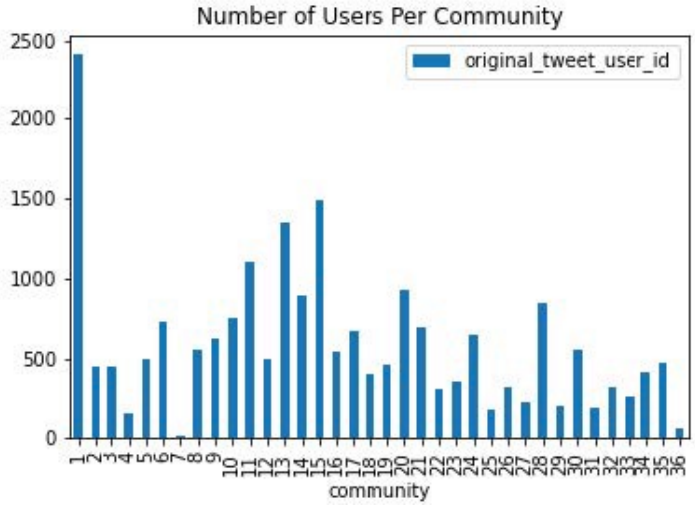
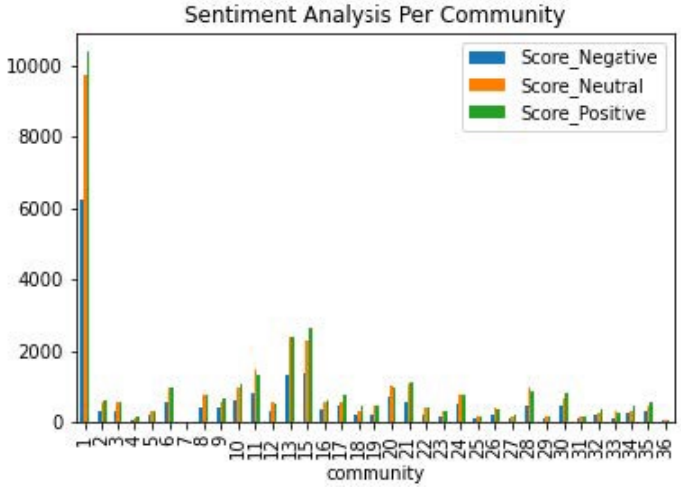
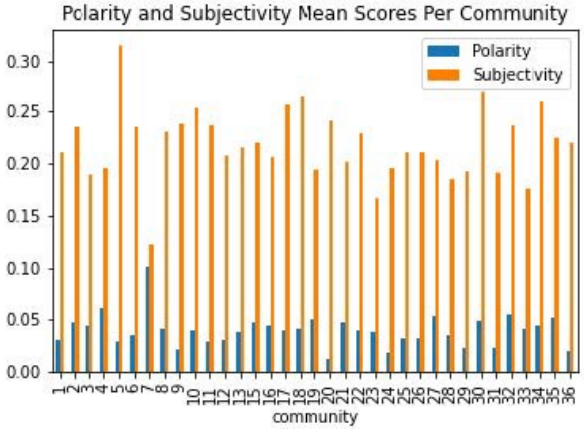
Study of the interaction between two opposite ego networks: community analysis







- ✓ Polarities are mixed and almost neutral within communities
- ✓ No opinion polarization within this configuration.

ML for detecting user opinion change

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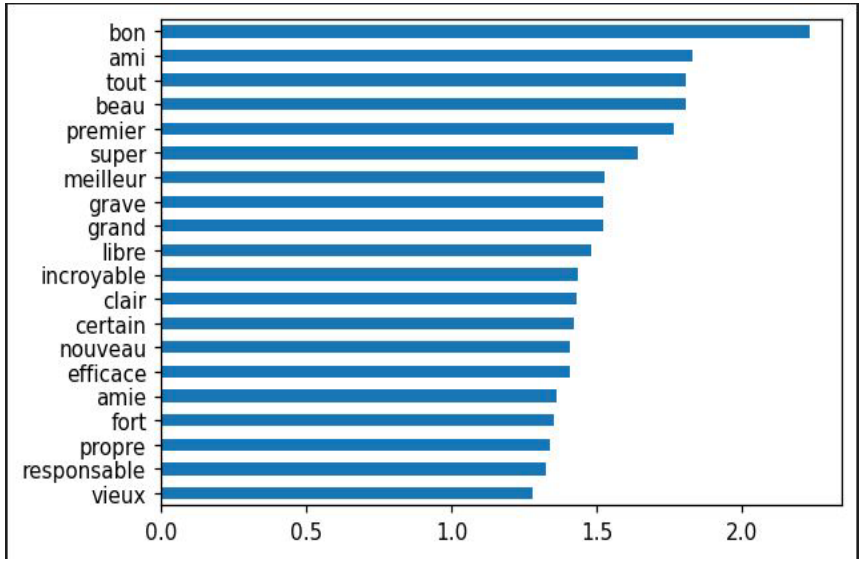
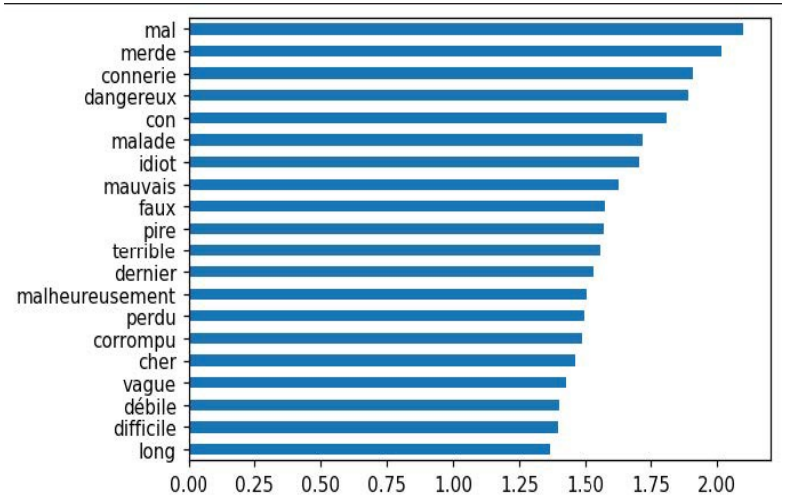
- Machine Learning for detecting user opinion change over time
  - Dataset: an entry is related to a link of the propagation network
  - nodal and topological features for both the original tweet and the reply author nodes
  - textual features are extracted with the TF-IDF method

  ✓ the target variable indicates if the replier has changed his opinion polarity over time

Performance for the 3 class values					
	Precision	*Recall*	*F1_score*	Accuracy	Support
TF-IDF				0.58	20062
Increased	0.67	0.64	0.65		8249
Decreased	0.56	0.63	0.59		8144
Static	0.44	0.36	0.38		3669

Ridge Classifier





Ridge model coefficients for the increased (left) and decreased (right) class values : textuel coefficients.

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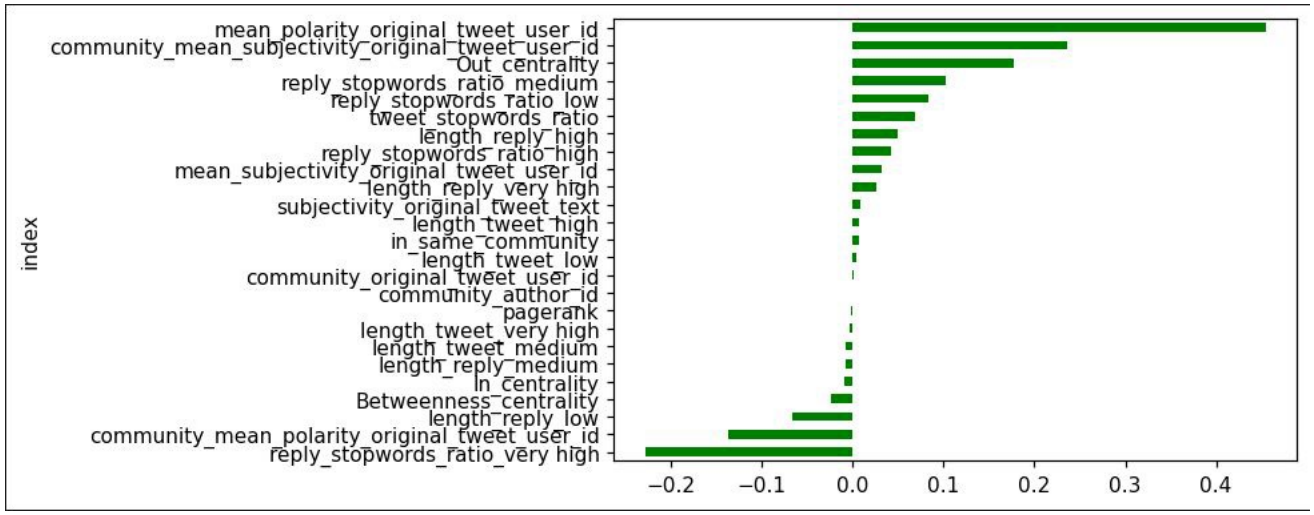
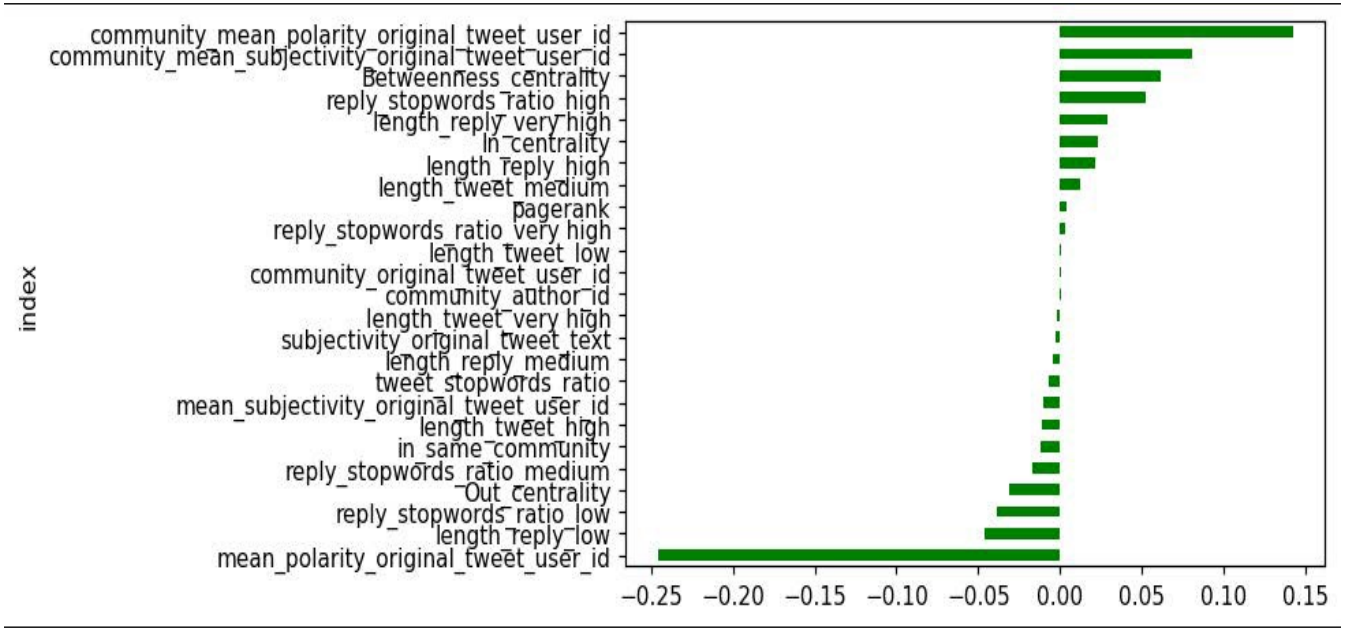
Explaining the increased value



Ridge model coefficients for the increased class value expect textual coefficients

the fact that the origin user has a high polarity in comparison to the polarity of its community, a high out-degree centrality and a low betweenness one, will contribute to the increase of the polarity of the replier.

Explaining the decreased value



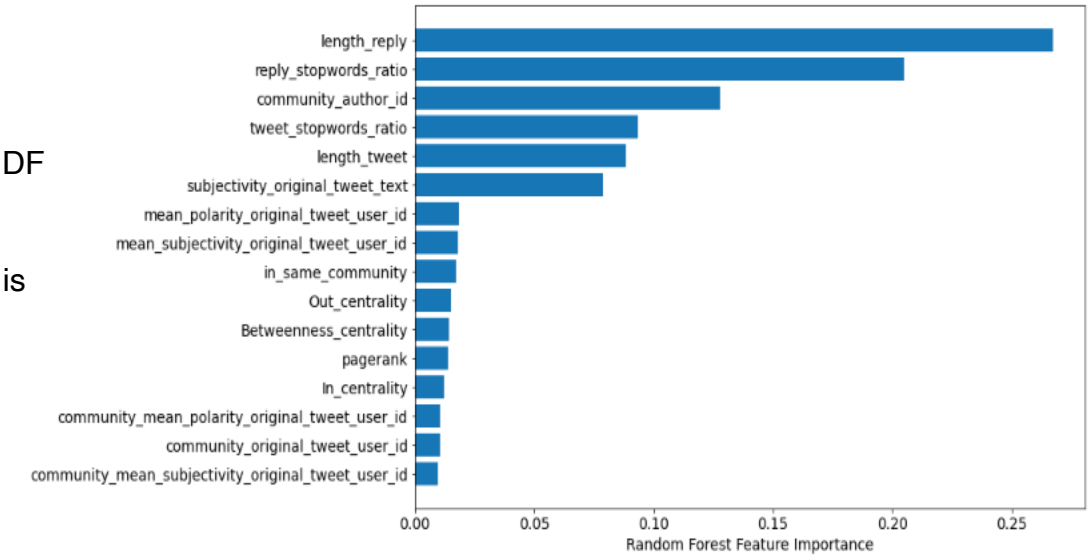
Ridge model coefficients for the decreased class value expect textual coefficients

ML for detecting user opinion modification

Équipes Traitement de l'Information et Systèmes

- Machine Learning for detecting user opinion modification via the action of reply
  - Dataset: an entry is related to a link of the propagation network
  - nodal and topological features for both the original tweet and the reply author nodes
  - textual features are extracted with the TF-IDF method

  ✓ the target variable indicates if the opinion is modified via the action of reply.



Retained (best) Model : Random Forest					
	Precision	*Recall*	*F1_score*	Accuracy	Support
				0.59	20062
True	0.62	0.68	0.65		11294
False	0.53	0.47	0.50		8768

- Some variables concerning the form of the reply text have an important role in the detection of the opinion modification
- the community of the author (replier) seems to have also certain importance.

Conclusion aand Perspectives

- Study the impact of the inuluencers ego networks' level (currently 2) on the polarisation of detected communities and the performances of opinion changedetection
- Study of the opinion formation in the propagation network models.
- Applying overlapping community detection algorithms
  - could help use to detect users that have role of moderators when spreading the information in the network.

Jean-Philippe Attal, Maria Malek, Marc Zolghadri. Overlapping community detection using core label propagation algorithm and belonging functions. Applied Intelligence, 51(11), 8067-8087, Springer,2021.

Explainability for interaction network analysis: discussion

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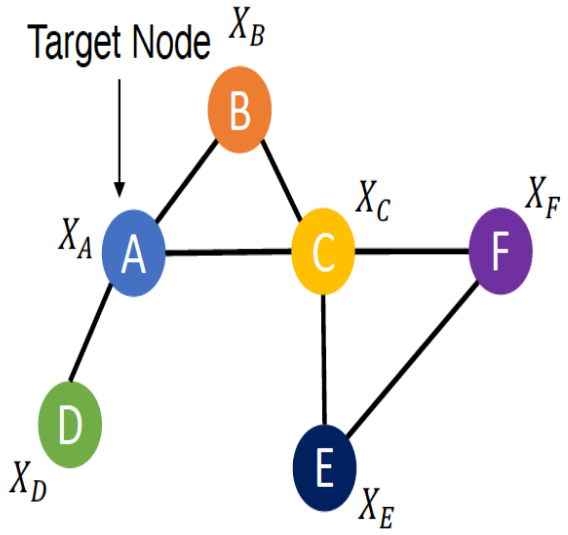
Explainability for interaction network algorithm ?

- Related Tasks: link prediction, node classification or searching, community detection, multilayer exploration, etc.
- Graph nature : similarity graph, interactions, social, etc.
- Can we distinguish transparent models and opaque models?
- Can we classify the model Types?

depth first research, breadth first research, random walk, shortest path, label propagation, heuristic optimization, etc.

- Can we define explainability categories? local, visual, by simplification, etc.
- Explainability principles? incidents links, neighbor nodes, attribute nodes, centrality measures, replay last steps of graph exploration, etc ..



Explainability for interaction network analysis: discussion

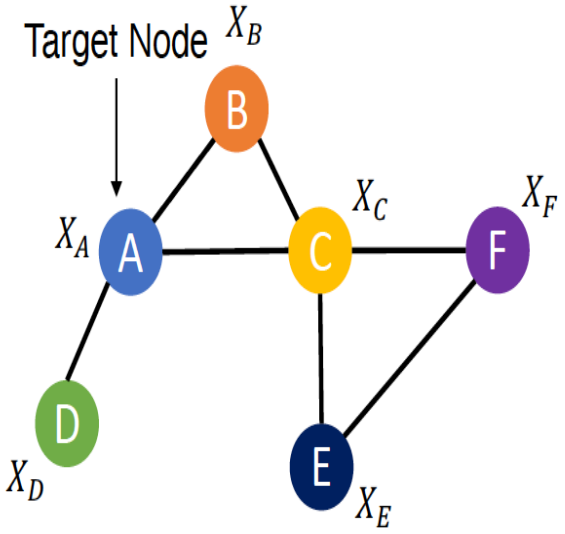
Examples (Use cases)

- Opinion formation:

$$x_i(t+1) = x_i(t) + \frac{\mu}{N_i} \sum [x_j(t) - x_i(t)]$$

- Recommendation:
  - Recommend an item or user: exploring a part of the graph
  - Recommend node because a given threshold is reached and explored edges have ”height weights”, heuristic is optimized, etc.

- How to explain?
  - Node attributes and centrality measures
  - Weight of incident links
  - Information about neighbors (attributes + centrality measures)
  - Replay last steps



Dalia Sulieman, **Maria Malek**, Hubert Kadima, Dominique Laurent:
Toward Social-Semantic Recommender Systems. Int. J. Inf. Syst. Soc. Chang. 7(1): 1-30 (2016)

Amir Mohammadinejad. Consensus opinion model in online social networks based on the impact of influential users. PhD thesis, Telecom & Management SudParis, Evry, France, 2018.

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