Complex Networks and Machine Learning

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Data Science: Machine Learning

In a wide range of domains:

• In automatic manner

• Data structure and features

generate models apt to organize the existing knowledge or mimic the behaviour of experts
Complex system

In a wide range of domains:

• In automatic manner

• Objects relationships/networking

extract a knowledge from the way objects are structured and evolve, and if and how they are connected
Why combine them

In a wide range of domains:

• Objects relationships/networking

• (Objects’s) data structure and features

extract a knowledge from the way objects are structured and if and how they are connected generate models apt to organize the extracted knowledge or mimic the behaviour of experts
Related Work: ML in CN

• development of new machine learning techniques based on complex networks:
  
  • unsupervised learning technique based on particle competition in complex networks;
  
  • supervised learning extension of the particle competition model for classification tasks
  
  • semi-supervised learning with combination of low (physical) and high (patterns identification) level classifiers

Thiago Christiano Silva
*Machine learning in complex networks: modeling, analysis, and applications*
PhD dissertation (2012)
Related Work: ML meets CN

- characterization of the large variety of real network structures, which are originating from the Big Data

- network geometry for understanding their complex network structures by revealing their hidden metric:
  - intelligent machines for unsupervised recognition and visualization of similarities in big data can be reconducted to hyperbolic model
  - on such hyperbolic model we can apply complex networks theory to discover the hidden metric

Alessandro Muscoloni, Josephine Maria Thomas, Sara Ciucci, Ginestra Bianconi & Carlo Vittorio Cannistraci
*Machine learning meets complex networks via coalescent embedding in the hyperbolic space*
Nature Communications volume 8, Article number: 1615 (2017)
CN to empower ML

- characterization of the large variety of real network structures, which are originating from the Big Data

- understand their complex network structures

- build on top of such structure some “layered” machine learning solution:
  - tradeoff between dynamics control and performance
  - possibility to take into consideration some metrics
  - possibility to have multiple scales

Garg Kamini, Arnaboldi Valerio, Giordano Silvia
“A Novel Approach to Predict Retweets and Replies Based on Privacy and Complexity-Aware Feature Planes”
Complex Networks 2016, 30th Nov. - 2nd Dec. 2016, Milano, Italy

Luceri Luca, Torsten Braun, and Giordano Silvia.
"Social Influence (Deep) Learning for Human Behavior Prediction."
Twitter prediction

- Predict the likelihood to retweet and reply by using different feature planes based on:
  - Complexity to acquire
  - Privacy intrusiveness.
- Predicts the likelihood of tweets received from friends and/or others as well.

Garg Kamini, Arnaboldi Valerio, Giordano Silvia
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Twitter prediction: features classification

Tweet Features: Time of tweet, retweet count, length of the tweet, # urls, #hashtag
Twitter prediction: machine learning

• Utilized Gradient boosting method: XGBoost Model

• Tested model on two different samples of dataset based on different time-intervals with 673,858 and 1,031,116 tweets respectively.

• Model accuracy was tested for each plane starting from Profile plane to Global plane.
Twitter prediction: results

Dataset 1

Dataset 2
Twitter prediction

Profile

Social

Activity

Sentiment

Global
Twitter prediction

- Predicted the single step diffusion in social networks based on different feature planes (multiple network topologies).

- Our model enables retweet and reply prediction for tweets received from friends and/or others as well.

- Activity plane performs the best. Adding more information does not improve prediction.

- Move toward cascade prediction
Twitter prediction

Complex Networks and Machine Learning
Event participation prediction

Study the social influence

\[ p_{u_i}(S_{u_i},a) : \text{probability that subject } u_i \text{ is} \]
\[
\text{influenced by the active friends } S_{u_i,a} \]

\[ p_{u_i}(S_{u_i},a) = 1 - \prod_{u_j \in S_{u_i},a} (1 - p_{u_j,u_i}) \]

where \( p_{u_j,u_i} \in [0, 1] \) is the influence probability of \( u_j \) on \( u_i \)

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Event participation prediction

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Event participation prediction

Deep Neural Network (DNN)
Event participation prediction: CN+ML

- Monolithic DNN
- Local-DNN (L-DNN)
- Community-based DNN (C-DNN)
Event participation prediction

Monolithic DNN

Complex Networks and Machine Learning
Event participation prediction

N Local-DNN (L-DNN)
Event participation prediction

L Community-based DNN (C-DNN)
### Event participation prediction: results

<table>
<thead>
<tr>
<th></th>
<th>DNN</th>
<th>L-DNN</th>
<th>C-DNN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>85%</td>
<td>80%</td>
<td>82%</td>
</tr>
<tr>
<td># of DNNs</td>
<td>1</td>
<td>N</td>
<td>1&lt;L&lt;N</td>
</tr>
</tbody>
</table>
Event participation prediction

- C-DNN much “understandable” and robust
- C-DNN performance just slightly below M-DNN
- We want to study C-DNN with more types of communities:
  - physical
  - social
  - interest