Curriculum Vitae

Daniele Malitesta

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Current Position

Since November 1, 2020 Ph.D. Student at Polytechnic University of Bari. [**Ph.D. Graduation Period: Autumn 2023**]

Previous Positions

Jan 2020 - Oct 2020 Research Assistant at Polytechnic University of Bari.

1 Education

Visiting post-graduate research student at the University of Edinburgh.

Period: May 2023 - June 2023

Supervisor: Dr. Pasquale Minervini (`Google Scholar`)

Topic: *Implementation and evaluation of link-prediction approaches for recommendation.*

Ph.D. in Electrical and Information Engineering, Polytechnic University of Bari.

Graduation period: Autumn 2023.

Topic: *Graph Neural Networks for Recommendation leveraging Multimodal Content Side Information.*

Supervisor: Prof. Tommaso Di Noia (`Google Scholar`)

Master's Degree in Computer Science Engineering, Polytechnic University of Bari.

Graduation period: October 2019.

Thesis title: *Novel Approaches to Image Compression via Deep Learning.*

Supervisor: Prof. Tommaso Di Noia (`Google Scholar`)

Final score: Full marks with honors.

Bachelor's Degree in Computer Science and Automation Engineering, Polytechnic University of Bari.

Graduation period: September 2017.

Thesis title: *Performance Evaluation of Data-Centric Networks based upon Semantic-Naming Algorithms.*

Supervisor: Prof. Luigi Alfredo Grieco (`Google Scholar`)

Final score: Full marks with honors.

2 Research Interests

My research path started in the end of 2019 when I graduated at Polytechnic University of Bari (Italy) under the supervision of Prof. Tommaso Di Noia (SisInfLab). My initial research topic dealt with representation learning strategies to compress high-resolution images, since I was more interested in the computer vision domain. Soon after graduation, I was offered a position as research assistant at SisInfLab, and I started collaborating and working with other researchers from the same lab on a similar research topic, i.e., adversarial attacks against multimedia-seeking recommendation systems. In November 2020, when I decided to take up the PhD career, I was proposed to partially re-use the expertise acquired over the previous months to address a hot and quite challenging research topic, i.e., graph learning techniques for explainable multimedia recommender systems. They have been two years since I started studying and implementing recommendation systems based upon graph convolutional networks (GCNs), and I am very fascinated and motivated by this novel research field. I am especially curious about understanding the theoretical reasons why such models provide superior performance in recommendation, and, on such a basis, I would propose novel solutions leveraging GCNs (you may refer to Edge Graph Collaborative Filtering, see later).

2.1 Description of PhD Dissertation

Recommender systems (RSs) mitigate the overwhelming magnitude of information available on online platforms (e.g., e-commerce) by pointing users to a small subset of most relevant items from a huge catalogue, based on historical users' activity. Collaborative filtering (CF), one of the most prominent recommendation paradigms in recent years, promotes the intuition of similar users interacting with similar items. CF-based models usually map users and items to embeddings in the latent space and learn to predict future user-item interactions by optimizing an objective function calculated on the recorded user-item pairs. Despite such methods have long shown superior recommendation accuracy, at least two shortcomings arise.

First, traditional CF approaches tend to disregard a wealth of information encoded in the item descriptive attributes/features, along with users' fine-grained preferences towards each of them. Specifically, we refer to highly popular domains such as fashion, social networks, media-content delivery, and e-commerce. Under this assumption, multimedia recommender systems (MMRSs) have emerged as a sub-class of RSs combining low-level media processing and deep learning techniques to provide a more descriptive

representation of media items that would enrich (and quite likely facilitate) the recommendation task.

Second, existing CF techniques fail to explicitly embed the information conveyed by user-item interactions into the representation of users' and items' profiles. However, this is counter-intuitive to the above definition of the CF paradigm. Recently, the increasing success of graph convolutional networks (GCNs) has suggested that similar architectures could be applied to recommendation. Indeed, by modelling users and items as nodes with latent representations and their interaction as edges, the data can be naturally represented as a user-item bipartite graph. The iterative aggregation of contributions from neighborhoods (i.e., message-passing) updates nodes' initial representations thus effectively distilling the collaborative signal.

The two outlined shortcomings pave the way to the two parallel research directions followed over the first two PhD years, namely explainable multimedia recommendation, and graph collaborative filtering.

Explaining recommendation outcomes has become of the uttermost importance to foster users trust and loyalty to the system. For instance, in domains such as fashion, it would be interesting to understand if a customer bought a t-shirt because she liked its colour, shape/texture, or simply because it is a t-shirt. In this respect, I proposed a recommendation framework based upon users' fashion tastes towards colours, textures, and item categories. Moreover, in multimedia recommendation, items' representation is often multi-modal. For example, videos involve a visual, an audio, and a textual signal represented by subtitles and/or tags (or descriptions). Despite the plethora of approaches for multimedia recommendation, the literature lacks a formalization of the recommendation task under the lens of multi-modality. To this aim, I am working on the formalization a shared and unified framework for multimedia recommendation which explores and re-adapts the concept of multi-modality (as observed in other fields of machine learning) to personalized item recommendation.

Notwithstanding the most popular architectures in graph collaborative filtering, it should be noted that there exist two main recurrent strategy patterns (i.e., regarding neighborhood exploration and node representation) which may suit most of the existing works. Driven by such a model taxonomy, I assessed the influence of each of these strategies on the recommendation trade-off among accuracy, novelty, diversity, bias, and fairness. Moreover, following up the investigation on the message-passing schema, I also formally show the existence of a node error representation caused by the indiscriminate aggregation of neighborhood information and demonstrate that state-of-the-art weighting procedures for graph edges may alleviate the issue at the expense of limited explored neighborhoods. To this end, I proposed a novel approach, Edge Graph Collaborative Filtering (EGCF), which uses users' generated reviews to weight the importance of graph edges without giving up the exploration depth.

I am devoting the third PhD year to merge the ideas from the two research paths described above. First, I will deepen the formal reasons behind the recommendation performance of different graph CF approaches. Then, such outcomes will build the basis to a novel explainable graph CF technique which disentangles the intents underlying user-item interactions by describing users and items through their multi-modal aspects derived from textual reviews or side knowledge-based information.

3 GitHub Projects

The updated list of repositories related to my research activities is available at: `https://github.com/danielemalitesta`. Please note that all the repositories have been forked from the SisInfLab GitHub account, the official GitHub account of the research lab where I currently work.

Over the last two years, I have been taking part to the development of **Elliot**, an **open-source library** for reproducible recommender systems evaluation. Specifically, I gave my main contribution to implementing all visual-based and graph-based recommender systems, for a total of 27 models (i.e., 25 from the state-of-the-art and 2 novel proposed approaches). I also worked on the image data pipeline (implemented in TensorFlow) currently adopted for the visual-based recommender systems. Elliot's official repository is available at: `https://github.com/sisinflab/elliot`.

4 Programming Experience

Working on a wide range of ML model families, e.g., convolutional neural networks, autoencoders, graph neural networks, latent factors-based recommender systems, I have gained a strong experience in `Python` programming, `TensorFlow` and `PyTorch`.
For the research topics I am currently working on (i.e., graph-based recommender systems), I have specifically gained a strong experience in `PyTorch-Geometric`, developing a deep knowledge on operations involving dense and sparse tensors. Additionally, working with ML models which may benefit from GPU computation to speed-up the training/inference phases, I have gained strong experience with `TensorFlow` and `PyTorch` versions powered with `CUDA` technologies, as well as `Docker` containers equipped with such frameworks/technologies (we presented a poster about `V-Elliot` at NVIDIA GTC 2022).
During my university and research career, I have also worked with `Java`, `C/C++`, `C#`, and `JavaScript`, and popular tools, e.g., `Docker` and `Kubernetes`.

5 Teaching Activities

Algorithms and Data Structures in Java. Starting from 2020, I have been working as teaching assistant for the bachelor degree course: *Algorithms and Data Structures in Java*.

6 Ph.D. Publications

For some publications, authors follow the alphabetical order. The * stands for corresponding author(s).

[1] Vito Walter Anelli*, Alejandro Bellogín, Antonio Ferrara, Daniele Malitesta, Felice Antonio Merra, Claudio Pomo*, Francesco Maria Donini, and Tommaso Di Noia. Elliot: A comprehensive and rigorous framework for reproducible recommender systems evaluation. In *SIGIR*, pages 2405–2414. ACM, 2021.

[2] Vito Walter Anelli, Alejandro Bellogín, Antonio Ferrara, Daniele Malitesta, Felice Antonio Merra, Claudio Pomo, Francesco Maria Donini, and Tommaso Di Noia. V-elliot: Design, evaluate and tune visual recommender systems. In *RecSys*, pages 768–771. ACM, 2021.

[3] Vito Walter Anelli, Yashar Deldjoo, Tommaso Di Noia, Daniele Malitesta*, and Felice Antonio Merra*. A study of defensive methods to protect visual recommendation against adversarial manipulation of images. In *SIGIR*, pages 1094–1103. ACM, 2021.

[4] Vito Walter Anelli, Yashar Deldjoo, Tommaso Di Noia, Daniele Malitesta*, Vincenzo Paparella, and Claudio Pomo*. Auditing consumer- and producer-fairness

in graph collaborative filtering. In *ECIR (1)*, volume 13980 of *Lecture Notes in Computer Science*, pages 33–48. Springer, 2023.

[5] Vito Walter Anelli, Yashar Deldjoo, Tommaso Di Noia, Eugenio Di Sciascio, Antonio Ferrara, Daniele Malitesta*, and Claudio Pomo*. How neighborhood exploration influences novelty and diversity in graph collaborative filtering. In *MORS@RecSys*, volume 3268 of *CEUR Workshop Proceedings*. CEUR-WS.org, 2022.

[6] Vito Walter Anelli, Yashar Deldjoo, Tommaso Di Noia, Eugenio Di Sciascio, Antonio Ferrara, Daniele Malitesta*, and Claudio Pomo*. Reshaping graph recommendation with edge graph collaborative filtering and customer reviews. In *DL4SR@CIKM*, volume 3317 of *CEUR Workshop Proceedings*. CEUR-WS.org, 2022.

[7] Vito Walter Anelli*, Daniele Malitesta*, Claudio Pomo*, Alejandro Bellogín, Tommaso Di Noia, and Eugenio Di Sciascio. Challenging the myth of graph collaborative filtering: a reasoned and reproducibility-driven analysis. *To Appear in Proceedings of the 17th ACM Conference on Recommender Systems*, 10.1145/3604915.3609489, 2023.

[8] Vito Walter Anelli, Tommaso Di Noia, Daniele Malitesta*, and Felice Antonio Merra*. Assessing perceptual and recommendation mutation of adversarially-poisoned visual recommenders (short paper). In *DP@AI*IA*, volume 2776 of *CEUR Workshop Proceedings*, pages 49–56. CEUR-WS.org, 2020.

[9] Yashar Deldjoo, Tommaso Di Noia, Daniele Malitesta*, and Felice Antonio Merra. A study on the relative importance of convolutional neural networks in visually-aware recommender systems. In *CVPR Workshops*, pages 3961–3967. Computer Vision Foundation / IEEE, 2021.

[10] Yashar Deldjoo, Tommaso Di Noia, Daniele Malitesta*, and Felice Antonio Merra. Leveraging content-style item representation for visual recommendation. In *ECIR (2)*, volume 13186 of *Lecture Notes in Computer Science*, pages 84–92. Springer, 2022.

[11] Daniele Malitesta*, Giandomenico Cornacchia*, Claudio Pomo, and Tommaso Di Noia. Disentangling the performance puzzle of multimodal-aware recommender systems. In *EvalRS@KDD*, volume 3450 of *CEUR Workshop Proceedings*. CEUR-WS.org, 2023.

[12] Daniele Malitesta*, Giandomenico Cornacchia*, Claudio Pomo, and Tommaso Di Noia. On popularity bias of multimodal-aware recommender systems: A modalities-driven analysis. *To Appear in Proceedings of the 1st International Workshop on Deep Multimodal Learning for Information Retrieval co-located with the 31st ACM International Conference on Multimedia*, 10.1145/3606040.3617441, 2023.

[13] Daniele Malitesta*, Giuseppe Gassi*, Claudio Pomo, and Tommaso Di Noia. Ducho: A unified framework for the extraction of multimodal features in recommendation. *To Appear in Proceedings of the 31st ACM International Conference on Multimedia*, 10.1145/3581783.3613458, 2023.

[14] Daniele Malitesta*, Claudio Pomo*, Vito Walter Anelli, Alberto Carlo Maria Mancino, and Eugenio Di Sciascio Tommaso Di Noia. A topology-aware analysis of graph collaborative filtering. *CoRR*, abs/2308.10778, 2023.

[15] Daniele Malitesta*, Claudio Pomo*, Vito Walter Anelli, Tommaso Di Noia, and Antonio Ferrara. An out-of-the-box application for reproducible graph collaborative filtering extending the elliot framework. In *UMAP (Adjunct Publication)*, pages 12–15. ACM, 2023.

[16] Alberto Carlo Maria Mancino*, Antonio Ferrara*, Salvatore Bufi*, Daniele Malitesta, Tommaso Di Noia, and Eugenio Di Sciascio. Kgtore: Tailored recommendations through knowledge-aware gnn models. *To Appear in Proceedings of the 17th ACM Conference on Recommender Systems*, 10.1145/3604915.3608804, 2023.

[17] Felice Antonio Merra*, Vito Walter Anelli, Tommaso Di Noia, Daniele Malitesta, and Alberto Carlo Maria Mancino. Denoise to protect: A method to robustify visual recommenders from adversaries. In *SIGIR*, pages 1924–1928. ACM, 2023.

[18] Tommaso Di Noia, Daniele Malitesta, and Felice Antonio Merra. Taamr: Targeted adversarial attack against multimedia recommender systems. In *DSN Workshops*, pages 1–8. IEEE, 2020.

Bari, September 30, 2023

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