Graph Machine Learning with Missing Multimodal Information

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Abstract

Graph data with multimodal information is ubiquitous, from users posting content on social networks and customers buying products on e-commerce platforms to patients interconnected with diseases and drugs in electronic health records (EHRs). For these reasons, graph machine learning has gradually shifted from a unimodal to a multimodal paradigm over the past few years. Despite their effectiveness, these approaches may be greatly limited if such multimodal information is noisy or (even worse) missing—a quite common situation in real-world scenarios. This tutorial intends to provide one of the first formal and practical outlooks on established and recent techniques to impute missing multimodal information in graph machine learning. By first introducing traditional graph approaches to tackle missing information in unimodal settings, it then presents the current literature on imputation for multimodal data in graph machine learning. Moreover, the tutorial offers an overview on popular applicative scenarios where the missing information issue occurs, such as the recommendation and healthcare domains, highlighting how graphs can be the source of missingness (the former) or the tools to address the missingness of multimodal information (the latter). The applicative scenarios are further explored during a hands-on session, which presents and tests the complete experimental pipeline of two recent solutions. The tutorial website is accessible at: https://log-centralesupelec.github.io/missing-multimod-gml-log2025/.

1 Learning objectives

This tutorial will provide technical and practical notions about graph machine learning with missing multimodal information. First, attendees will learn which sources of missing information might exist in graph machine learning and the common solutions categorized in the literature [1–3]. Then, the audience will learn how graph machine learning approaches can generally operate with multimodal graph data [4–6], by considering some notable applications related to personalized recommendation and healthcare. On such basis, the attendees will be taught which are the main paradigms for addressing missing information in or through multimodal graph learning [7], with a specific focus on the practical case of recommendation [8] and healthcare [9, 10]. To provide a practical perspective, a hands-on session will follow on the two considered applicative scenarios, where the attendees will deep dive into the complete experimental pipelines of two recent solutions [8, 9]. Finally, the tutorial will indicate current challenges in the field, summarized into the following questions: (i) which is the best imputation/learning paradigm? (ii) how to design comprehensive evaluation protocols? (iii) can we make these models interpretable, especially in specific domains (e.g., healthcare)? (iv) are there other recent strategies that can be leveraged?. Then, the tutorial will suggest possible avenues for future research into the field, such as exploiting diffusion models [11–13] for imputing missing multimodal information on graphs [14].

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2 Tutorial schedule

Date: December 12, 2025 (11:30 - 14:00 MST)

Duration: 150 minutes

Tutorial's type: lecture style + hands-on

- **Introduction and background** (15 min)
  - Introduction and motivations of the tutorial (5 min)
  - Basic concepts of imputation in machine learning (7 min)
  - Tutorial's overview (3 min)
- **Graph machine learning with missing multimodal information** (65 min)
  - Missing information in unimodal graph machine learning (15 min)
    - Sources of missing information: node attributes, node features, edges
    - Models' taxonomy: impute on or through graph, robustness vs. imputation
    - Main existing techniques
  - Multimodal graph learning (20 min)
    - Integrating multimodal information in the graph learning pipeline
    - Notable applications: recommendation and healthcare
  - Missing information in multimodal graph machine learning (30 min)
    - How to define missing multimodal information on graphs
    - Models' taxonomy: impute on or through graphs, robustness vs. imputation, node similarity vs bipartite graphs
    - Dealing with missing modalities in multimodal recommendation
    - Handling missing multimodal information in healthcare
- **Break** (5 min)
- **Hands-on session: tackling missing multimodal information in personalized recommendation and healthcare** (45 min)
  - An imputation pipeline for missing multimodal information in recommendation (25 min)
  - Multimodal processing and training with missing information in healthcare (20 min)
- **Closing remarks, current challenges, and future directions** (10 min)
- **Q&A session** (10 min)

3 Relevance to LoG

The tutorial covers highly-related topics to the ones of LoG, as evidenced in works regarding missing information in graph learning [2, 15] and multimodal graph learning [16] presented in previous editions of the conference. Moreover, unlike similar tutorials (see below), this tutorial brings graph and multimodal learning together, by depicting common and established techniques to handle missing multimodal information, and tailoring the discussion to applicative scenarios where graph machine learning represents a fundamental paradigm, such as personalized recommendation and healthcare.

4 Previous related tutorials

We retrieved all tutorials presented at top-tier venues within the time range 2020-2025, whose main topics referred to (some or all) the following keywords: "graph", "missing", "incomplete", "data", "multimodal". The considered conferences are: LoG, NeurIPS, ICML, AAAI, CVPR, ICCV, IJCAI, KDD, The Web Conference, CIKM, and WSDM. The selected tutorials were categorized into most related tutorials (Table 1) and other related tutorials (see below). As a general trend, we observed that none of the selected tutorials covered, at the same time, all the main topics and applicative scenarios we plan to address with this tutorial.

Then, among the most related tutorials, we highlight that [17] is the closest to ours in the intention to outline data challenges in graph machine learning (which also involves missing information), while

Table 1: Most related tutorials from 2020-2025.

Title	Venue	Website	Slides	Video
Synthetic Healthcare Data Generation and Assessment: Challenges, Methods, and Impact on Machine Learning	ICML 2021	✗	link	link
Multimodal Pre-training and Generation for Recommendation [18]	WWW 2024	✗	link	✗
Data Quality-Aware Graph Machine Learning [17]	CIKM 2024	link	✗	✗
Multimodal Artificial Intelligence in Healthcare	AAAI 2025	link	link	✗

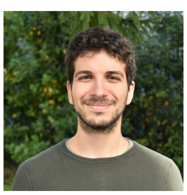
the other discuss multimodal learning and generation in healthcare and recommendation, our two applicative scenarios.

Other related tutorials. Building trustworthy ML: The role of label quality and availability (AAAI 2025); Tutorial on MultiModal Machine Learning (ICML 2023, CVPR 2022); Learning and Mining with Noisy Labels (CIKM 2022); Advances in Mining Heterogeneous Healthcare Data (KDD 2021); Data Quality for Machine Learning Tasks (KDD 2021); Learning with Small Data (WSDM 2020).

5 Useful materials

All useful materials are available at the tutorial's website: https://log-centralesupelec.github.io/missing-multimod-gml-log2025/.

6 Tutorial speakers



Daniele Malitesta (website: https://danielemalitesta.github.io) is a Postdoctoral researcher at Université Paris-Saclay. During his PhD at Politecnico di Bari (Italy) he mainly focused on graph-based multimodal recommendation, while now he is currently interested in missing multimodal information in graph learning and fair graph generative models. He has published at top-tier conferences, such as ECML-PKDD, The Web Conference, SIGIR, and RecSys. Daniele has actively contributed to LoG, serving as a reviewer for all editions (outstanding reviewer at LoG 2024), hosting a tutorial at LoG 2023, co-organizing the 2024 Paris LoG meetup, and co-organizing LoG 2025. Since 2024, he has been invited to give talks and lectures regarding his past and recent research. He has recently co-hosted a tutorial on "Data processing in recommendation" at RecSys 2025.

Fragkiskos D. Malliaros (website: https://fragkiskosm.github.io/) is a Professor at Université Paris-Saclay, CentraleSupélec, Inria. Previously, he was a postdoctoral researcher at UC San Diego (2016-17) and Ecole Polytechnique (2015-16). He received his Ph.D. in Computer Science from École Polytechnique (2015) and his M.Sc. degree (2011) from the University of Patras, Greece. He is the recipient of the 2012 Google European Doctoral Fellowship in Graph Mining, the 2015 Thesis Prize by École Polytechnique, and best paper awards at TextGraphs-NAACL 2018 and AAAI ICWSM 2020 (honorable mention). He is currently an associate editor of Big Data Research and a guest editor in Applied Network Science and the Data Mining and Knowledge Discovery journals. In the past, he has presented 12 tutorials in various data science venues (e.g., The Web Conference, CIKM, ECML-PKDD, WSDM). His current research interests focus on graph machine learning and applications.

7 Intended audience and level

The proposed tutorial deals with intermediate and advanced theoretical/practical topics related to imputation in machine learning and (multimodal) graph learning. While the tutorial will mostly cover specific scenarios in the recommendation and healthcare domains, we believe that the presented topics might apply to several other domains and tasks in multimodal graph learning, being of interest to a wide range of researchers and practitioners in the field. Programming knowledge of Python and PyTorch (with a specific focus on PyTorch Geometric) would be a good-to-have skill, even though the tutorial will guide the attendees step-by-step, especially during the hands-on sessions. We do not set a strong requirement for the maximum number of participants (which we estimate to be around 100). For the technical support, the tutorial will require basic streaming tools for slides presentation.

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