PAKDD 2023 Tutorial: **Multi-Aspect Learning – Issues, Algorithms and Applications**

Date & Time: 25 May 2023

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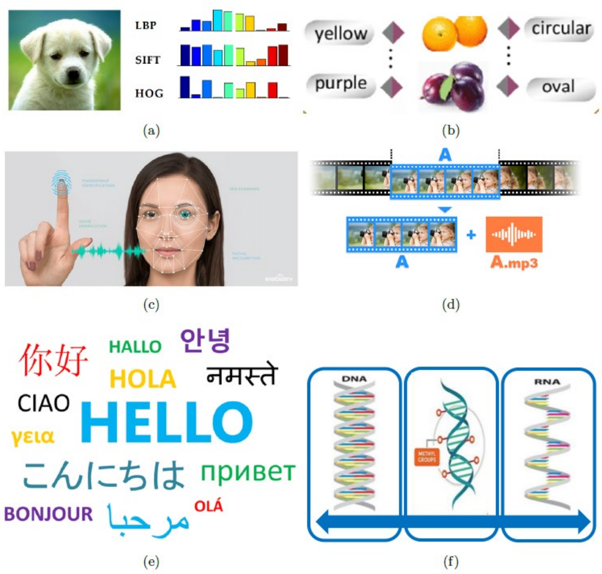
Description: Multi-aspect data, which consists of information from multiple perspectives or modalities, has become increasingly prevalent and significant in various domains. The main advantage of multi-aspect data is its ability to capture rich and diverse information that can facilitate machine learning algorithms to discover multiple patterns and types inherent in the data and produce informative outcomes for different learning tasks, whether supervised or unsupervised. However, multi-aspect data also poses several challenges to machine learning due to its natural complexity and heterogeneity. Therefore, it is essential to pay meticulous attention to the characteristics and properties of multi-aspect data and develop appropriate methods and techniques for effective machine learning on this type of data.

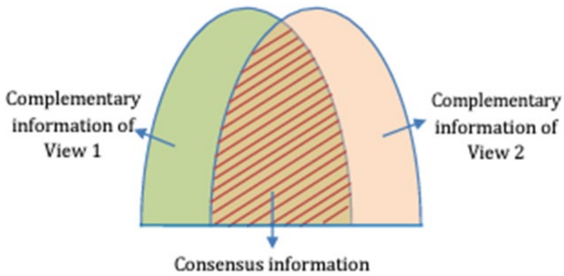
In this tutorial, we provide a comprehensive overview of an emerging research topic in machine learning, namely *multi-aspect learning*. We first introduce the different types and characteristics of multi-aspect data and discuss the challenges and opportunities that they present for machine learning tasks. We then review the state-of-the-art machine learning methods that can effectively exploit the underlying structures and relationships in multi-aspect data and achieve improved performance over traditional methods that ignore the multi-aspect nature of the data. More specifically, we will demonstrate how factorization and deep learning methods can generate an efficient joint feature space for the downstream machine learning task to be applied to multi-aspect data. Finally, we highlight current research gaps and open questions in this field and suggest possible directions for future research.

Keywords: machine learning, multi-view learning, multi-modal models, factorization and deep learning, joint feature space, multi-aspect learning applications



Background: In recent years, there has been an increasing interest in multi-aspect data learning for various machine learning tasks such as classification and clustering. Multi-aspect data represents information about the entities (i.e. objects such as customers, events etc) from multiple perspectives such as expressing multiple types of relationships or multiple types of features. The dataset that contains multiple types of data modalities (i.e. data format such as image, text and tabular) to represent distinct perspectives of the information is called Multi-modal data. The dataset that represents different perspectives of the information used in the same modality is called multi-view data. Examples of multi-modal data are a tweet collection containing textual and visual modalities or a movie clip containing audio and video modalities. Examples of multi-view data are a news story collection containing stories sourced from BBC, Yahoo and many others, or a multilingual dataset where each language type presents a view. Multi-aspect learning has many real-world applications such as recommender systems, sentiment analysis, bioinformatics, social network analysis, natural language processing, computer vision, topic modelling etc. *Knowledge of different types and characteristics of multi-aspect data, that lead to choosing the most effective machine learning method, is essential.*

Different modalities or views can provide rich complementary information to the same event/entity resulting in improved performance for supervised and unsupervised tasks. However, the multi-aspect data often suffer from feature-level bias due to the presence of varied feature dynamics and different noise topologies present in multiple modalities and views. Multi-aspect data is deemed to contain consensus (i.e. inter-aspect) and complementary (i.e. intra-aspect) information for learning a (meaningful and informative) joint feature space. The consensus information is expressed in the way different data views/modalities embed a compatible (or correlated) latent structure within the data. The complementary information is expressed in the way each view/modality provides a diverse (or distinct) characteristic within the data. It will be useful for an algorithm to focus on learning the common content of news among the views/modalities, i.e., the consensus information, by avoiding any ambiguity or conflict. At the same time, it will be useful to learn the distinct characteristics of each source to improve accuracy using complementary information. Learning a joint feature representation to perform different machine-learning tasks is challenging. Therefore, knowledge of various data issues that must be solved to learn a joint feature space is essential.



Machine learning methods that are designed for traditional data, where the data sample has one type of modality or a single view, need to be modified. The multi-aspect data learning methods that are customized for the data problems above should accurately discover and identify the hidden features and their relationships and extract more valuable and relevant knowledge for downstream machine learning. A myriad of multi-modal and multi-view methods have been developed based on the concepts of nonnegative matrix factorization (NMF) and deep learning. These approaches can identify the underlying structures in the multi-aspect data and show improved performance compared to traditional methods. Each method has associated strengths and shortcomings to deal with the problems faced with multi-aspect data. *Knowledge of these learning methods, which exploit the latent relatedness between samples and different features in multi-aspect data, is essential.*

<u>Tutorial Content</u>:

Part 1: Introduction

- Background and Motivation of multi-aspect data learning.
- Main characteristics, challenges, and opportunities of multi-aspect data: Heterogeneity, Complementarity, Consistency, Redundancy, Incompleteness, Feature level bias, Exhibition of different noise patterns, and Variations in feature dynamics.
- Applications of machine learning for multi-aspect data.

Part 2: Multi-modal Deep Learning Methods

- Why do traditional deep neural network methods fail to exploit the rich information contained in multi-modal data?
- How to align, fuse, and integrate multimodal data from different sources and domains? How to measure the similarity and diversity of multimodal data?
- Various data fusion methods, such as early, late, intermediate, and multi-stage, generating accurate joint feature representation or balance the intra- and inter-modal information at different abstract levels of deep neural networks. How to handle the missing, noisy, or imbalanced data in different modalities?
- Addressing the feature-level bias issue by designing better learning algorithms such as based on uncertainty-guidance, multi-task learning and gradient modulation.

Part 3: Multi-view Factorization Methods

- Why do traditional factorization methods fail to exploit the rich information contained in multi-view data?
- State-of-the-art models (i.e. objective functions) learning complementary and concise information to capture latent factors across multiple views.
- Incorporating regularization terms or robust loss functions to deal with various data problems.
- Multi-view deep factorization methods to learn non-linear features present in the data and generate accurate joint feature representations for downstream tasks.

Part 4: Real-World Application Scenarios

- Diverse real-world applications such as generating text (e.g., product reviews)), images (e.g., face images), bioinformatics (e.g., gene expression) and social networks (e.g., user profiles) data.
- State-of-the-art methods and techniques used in these applications.
- Designing more interpretable and trustworthy models for sensitive domains such as healthcare or finance; creating realistic benchmarks and evaluation metrics for multi-aspect tasks; fostering interdisciplinary collaboration among researchers from different fields such as natural language processing, computer vision, graph mining etc.

Part 5: Summary, Open Issues, and Future Directions

- Current limitations and challenges of existing methods.
- Identify emerging trends and hot topics in this field, such as self-supervised learning for multi-aspect representation learning; multi-aspect fusion with transformers; multi-aspect explainability; multi-aspect adversarial learning; multi-aspect meta-learning; multi-aspect reinforcement learning; etc.

Target audience: This tutorial is targeted at anyone interested in machine learning, multi-view learning, multi-modal models, factorization and deep learning from researchers to practitioners from the industry. We do not assume prerequisite knowledge from the audience and would explain the basic concepts necessary such as data representation problems, factorization process, deep learning models and various application-specific concepts. However, a basic knowledge of linear algebra and machine learning will be helpful.

Presenters

The team has a long-standing record of research and presentation in the field of machine learning, deep learning, factorization and multi-aspect learning.

Richi Nayak is a Professor at the School of Computer Science and Deputy Director of the Centre for Data Science, Faculty of Science, Queensland University of Technology (QUT), Brisbane, Australia. She is an internationally recognized expert in machine learning, data mining and text mining. Currently, her focus is on developing multi-view and multi-model machine learning methods for various applications. She consults several private, public and government agencies in machine learning projects and many of her research projects have been commercialised.

Md Abul Bashar is a Data Science Research Fellow at QUT's School of Computer Science and an Associate Investigator at the University Centre for Data Science. He is a leading researcher in abuse detection with extensive experience in applied data science. He has participated in successful industrial projects with the government, corporations, and the Australian Research Council. He has recognised expertise in deep learning, machine learning, and AI. His innovative concepts, such as progressive transfer learning, have produced successful outcomes.

Duoyi Zhang is a PhD student at the School of Computer Science, Faculty of Science, Queensland University of Technology, Brisbane, Australia. Her PhD thesis is about multimodal representation learning. In her PhD project, she has developed deep learning models to address the feature-level bias issue in multi-modal learning. She has presented her works on multi-modal at many conferences such as ICDM and AuSDM.