# Genericity and explicability in recommender systems.

**Location**: Paris-Dauphine University, LAMSADE, France

**Supervisor**: Elsa Negre, MCF HDR (elsa.negre@dauphine.fr)

**Keywords**: Recommender systems, Machine learning, Information systems.

**Funding**: This topic is a priority for a Ministry Scholarship application.

**Applications**: Interested candidates are invited to send a cover letter, a CV, their (Bachelor + Master) results and their rank, as soon as possible, before March 30, 2019. A second selection will then be made by the doctoral school and the laboratory on the basis of an audition in May 2019. Speaking French would be a plus.

**Context**:
Recommendation can be summarized by the problem of estimating scores for entities that have not yet been viewed/evaluated by a user. Indeed, the number of entities as well as the number of users of the system can be very important; it is therefore difficult for each user to see all the entities or for each entity to be evaluated by all the users. It is thus necessary to estimate the scores for the entities not yet evaluated. This assessment is usually based on scores given by a user to other entities. When it is possible to estimate scores for entities not yet evaluated, entities with the highest scores may be recommended to the user.

Recommender systems are used in many fields, whether for commercial, industrial or academic applications. In fact, among the best-known recommender systems, we can cite those used in e-commerce: Amazon.com for product recommendation and Netflix for movie recommendation. But nowadays, many systems that we use every day offer recommendations to their users (working groups or individuals in LinkedIn, friends on Facebook, music for last.fm or news for Forbes.com). Existing recommender systems therefore differ in scope, application context and the data they handle. But they also have many things in common: (i) the need: help decision-making; (ii) the objective: recommend items/users; (iii) the formalization: the famous utility matrix; (iv) the algorithm: predict scores. Yet, despite their similarities, existing recommender systems are application-specific and are developed/implemented through ad hoc frameworks.

However, recommender systems, like any computerized system, are governed by the principles of software engineering and quality. Software engineering is based on seven principles: Rigor and Formality, separation of Concerns, modularity, abstraction, anticipation of change, generality/genericity (according to which a reusable/adaptable system is much more valuable than a dedicated system) and incrementality. In addition, the ISO 9126 norm defines six groups of software quality indicators: Functionality, reliability, usability, efficiency, portability, maintainability, and portability. Currently, recommender systems are defined for specific use cases. It limits their adaptability, reusability and genericity. Thus, recommender system specialization goes against the principle of genericity and the ones of software engineering and quality. Therefore, tend towards recommender system genericity, i.e. a recommender system that works whatever the use case in order to have an adaptive system, with an abstraction level, favouring, among other things, interoperability and reusability is an important issue. To the best of our knowledge, there is no such recommender system.

In addition, interactions between the recommender system and the user are important. In general, users want to have control over the recommendations and to be able to indicate if a recommendation is not appropriate. This approach is part of the search for more user-centred systems. In addition, giving the user a personalized explanation can also help us gain confidence. In fact, being able to indicate why a recommendation is offered to the user can help to improve the confidence he has in the system, but also, if the user can interact with the recommender system, improve the system himself, even by matching the reasons for such a recommendation with the reasons for the user's agreement or refusal. Research works have already focused on explaining the recommendations. However, many of them limit themselves to displaying digital values or to giving an explanation like "Those who bought A also bought B". Being able to explain the recommendation raises issues such as explaining how the recommender system works, allowing users to tell the system that the recommendation is inappropriate, convincing users to follow the recommendation, improving the ease of use. An explanation like "This book belongs to your favourite genre: Thriller, it got an average score of 4/5 from other users and is available at the bookstore in your neighbourhood" could be a better explanation. To the best of our knowledge, there is no such recommender system.

The main objective of this thesis is to study the diversity of ***recommender systems***, their common points and differences (from an algorithmic but also an application point of view) in a context of ***large and constantly changing data mass***, as well as understand such systems in their context. The next step is to move towards a generic recommender system model that can explain to the user why such a recommendation is returned.

**Remarks:**
One possible way would be, for example to incorporate complementary information from social media analysis (among others), as it is done in cross-domain recommender systems. Indeed, the proliferation of e-commerce sites, social media, ... has allowed users to provide comments, express their preferences/interests and to maintain user profiles in multiple systems, reflecting the variety of their tastes/interests. Taking advantage of all this information available in different systems and related to different fields may be beneficial for generating more complete user profiles and better recommendations, for example by mitigating cold-start or low-density problems in a field target or by providing cross-personalized recommendations for different field items. Cross-domain recommender systems aim to generate or improve recommendations for a particular field by exploiting user profiles (or any other data/information) from other fields.

**Implications:**
This work can be based on Zahra Vahidi Ferdousi’s PhD work (context-aware recommender systems), on the work of the supervisor and on the participation of and the involvement of some LAMSADE members (e.g. “Data Science” team members).

**Publications of the supervisor related to the subject:**


- Zahra Vahidi Ferdousi, Dario Colazzo, Elsa Negre. *CBPF: Leveraging Context and Content Information for Better Recommendations*. ADMA 2018: 381-391
- Elsa Negre, Franck Ravat, Olivier Teste. *OLAP Queries Context-Aware Recommender System*. DEXA (2) 2018: 127-137
- Imène Brigui-Chtioui, Philippe Caillou, Elsa Negre. *Intelligent Digital Learning: Agent-Based Recommender System*. ICMLC 2017: 71-76
- Elsa Negre. *Systèmes de recommandation : généricité, évaluation et améliorations* Habilitation à Diriger des Recherches, Université de Toulouse, Novembre 2017.
- Ning Wang, Marie-Hélène Abel, Jean-Paul A. Barthès, Elsa Negre. *An answerer recommender system exploiting collaboration in CQA services*. CSCWD 2016: 198-203
- Elsa Negre. *Recommender Systems – Introduction.* Livre - WILEY, 2016.
- Elsa Negre. *Towards a Knowledge (Experience)-Based Recommender System for Crisis Management*. 3PGCIC 2013: 713-718