

# Hybrid Machine Learning for Matchmaking in Digital Business Ecosystems



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## INTRODUCTION

Digital Business Ecosystems (DBE) is an up-to-date topic which encompasses traditional Business-to-business (B2B) and Business-to-Customer (B2C) relationships. This concept describes the situation of business transactions or exchange of products between different actors in order to exchange their products, services, or information within a market. The term ecosystem was inspired from nature as the ecosystem term comes from “ecological system” and includes “all the plants and living creatures in a particular area considered in relation to their physical environment” (OxfordLearnersDictionaries.Com, n.d.).

Like for a B2B network representing graph structure in which different nodes presented by companies are linked to each other by specific threads presented by relationships between them (Hvaakansson & Ford, 2002; Janke & Prídavok, 2012), DBE is composed in the same manner but can also include final customers. This kind of organization helps businesses communicate and collaborate more easily. Compared to the traditional B2B vision, DBE, developed later, enhances the communication and collaboration within a network by introducing collective learning and knowledge flow between different business actors (Janke & Prídavok, 2012; van Egeraat & Curran, 2010).

DBE can have several aspects such as: a) Transaction-based: In the case of a single company that establishes a transactional method common to all these major customers and suppliers for doing business with them. b) Process-Based: When two companies establish a common business process that enables them to conduct business effectively and efficiently with each other. c) Strategic relationships-based: Two or more companies establishing a strategic partnership relationship based on all major interactions between organizations. This includes transactions, processes and any other collaboration between the two organizations (Kumar & Raheja, 2012).

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An essential part of any digital DBE and the corresponding platform is the matchmaking process (Alpar, 2010). Matchmaking is the process of matching entities according to different criteria; it “allows one agent with some objective to learn the name of another agent that could take on that objective” (Decker et al., 1996). It is also “the process of searching the space of possible matches between demand and supplies” (Noia et al., 2004). Matchmaking is then essential for suppliers’ proposals and customers’ requirements to be connected (Alpar, 2010).

The matchmaking process attempts to assess the interest profiles of market players, with the aim of matching agents in the supply chain who have the least conflicting interests, thus supposed to have better profits from the arbitrage phases and subsequent execution (Medjahed et al., 2003). In a DBE environment, the use of an intermediary player who collects data and information on different market players, assists potential customers and suppliers in finding business partners and improves the efficiency of the matchmaking process (Ouksel et al., 2004) as in the financial and commodity digitized trading systems. In the same DBE environment, the authors have an opportunity to use the knowledge of the arbitration policy of the negotiation phase during the matchmaking phase, which strengthens the capacity of the matchmaker (Ouksel et al., 2004).

In this manner, the context of the DBE paradigm is not simple. It must indeed have multiple facets, such as the development of more and more entrepreneurship strategies to bring about the emergence of businesses and the extension of capacity building services for businesses in order to support them in their growth. However, seldom the growth of DBE has been primarily challenged due to non-availability of appropriate data towards precise matchmaking process.

In addition, matchmaking is complicated by incomplete data mainly because companies don’t want to share private data. Missing data affects data analysis in a wide range of domains including matchmaking within DBEs. It has been observed that there are a few hybrid models proposed in DBE-related paradigms to address the missing data frames (Jerez et al., 2010). However, most of the business information system model incorporates that the missing values are imputed using association rules by comparing the known attribute values of missing observations and the antecedent part of association rules (Jerez et al., 2010; Lakshminarayan et al., 1999). In the case, when there is no rule present or fired (i.e. no attributes relationship exists in the training data) against the missing value.

This rule-based system seldom becomes ineffective, especially where the business rules for the youngest firms may not be available in database either or due to confidentiality of business data. Hence, the static data and association rule could not be an acceptable solution for the purpose of DBE matchmaking. Thus, the decision support engine for matchmaking often demonstrates vague results while disappointing end-users. The authors investigate that recently deep latent variable models like DLVMs (Kingma & Welling, 2013; Rezende et al., 2014) have been applied to missing data problems in business and statistical domains with an unsupervised setting (Ipsen et al., 2020; Ivanov et al., 2018; Ma, Gong, et al., 2018; Ma, Tschitschek, et al., 2018; Mattei & Frellsen, 2018, 2019; Nazabal et al., 2020; Rezende et al., 2014; Yoon et al., 2018), while the supervised setting has not seen the same recent attention (Ipsen et al., 2020; Yoon et al., 2018).

The progress of unsupervised learning centers on inference and imputation. This provides more precision in the results than when learning with missing values of a criminalizing model. However, this approach does not necessarily minimize the prediction error (Cole, 2008).

Considering the random and ever-changing DBE context, it is worthy to apply certain bi-focal algorithms which could resolve the missing data features to some extent latently. Following that, the authors use a semi-supervised algorithm to deal with business matchmaking to recommend and infer about

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