

## Chapter 2

# The Impact of Deep Learning on the Semantic Machine Learning Representation

**Abdul Kader Saiod**

*Nelson Mandela University (NMU), South Africa*

**Darelle van Greunen**

*Nelson Mandela University (NMU), South Africa*

### ABSTRACT

*Deep learning (DL) is one of the core subsets of the semantic machine learning representations (SMLR) that impact on discovering multiple processing layers of non-linear big data (BD) transformations with high levels of abstraction concepts. The SMLR can unravel the concealed explanation characteristics and modifications of the heterogeneous data sources that are intertwined for further artificial intelligence (AI) implementations. Deep learning impacts high-level abstractions in data by deploying hierarchical architectures. It is practically challenging to model big data representations, which impacts on data and knowledge-based representations. Encouraged by deep learning, the formal knowledge representation has the potential to influence the SMLR process. Deep learning architecture is capable of modelling efficient big data representations for further artificial intelligence and SMLR tasks. This chapter focuses on how deep learning impacts on defining deep transfer learning, category, and works based on the techniques used on semantic machine learning representations.*

### INTRODUCTION

Semantic Machine Learning and Deep Learning share the goal of composing artificial intelligence that simulates human possibilities such as indexing, validating, prognosticating and reasoning. Both fields have been impacting data and knowledge analysis considerably as well as their associated abstract representations (Dagmar *et al.* 2019). Deep Learning is an essential part of the Semantic Machine Learning Representations that perceives to experience high-level abstractions in big data by implementing

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hierarchical frameworks. Therefore, Deep Learning discovers an intricate Big Data structure using the backpropagation algorithm to specify internal logic to manipulate each computational model of the operation. Artificial Intelligence domains are challenging the traditional approaches to exploit structured knowledge to improve potential decision-making process performances. Deep Learning is an emerging approach and has been widely implemented in semantic artificial intelligence (Bordes *et al.* 2012) as well as in knowledge transfer (Yue-ting *et al.* 2017), linguistic data processing (Gemma 2020), computer visualisation (Alejandra *et al.* 2019) and many more. Artificial Intelligence is frequently aimed at representing the high-level human cognitive capabilities, such as making decisions, inferences and validations. On the other hand, knowledge-based representations facilitate logic reapplication and the sharing of inappropriate subsist semantic resources. Deep Learning is implemented to integrate big data representations, that transformations with multi-layer data processing algorithms. Today, such algorithms are well considered in the field of machine learning, where they have been successfully implemented to numerous real-world issues. With the challenges outlined, how can Deep Learning be implemented to address some important aspects such as semantic indexing, data tagging, searching, extracting complex patterns from Big Data, fast information retrieval and simplifying discriminative tasks in the SMLR process? Deep learning with semantic knowledge-based representation enhances the reapplication and sharing of knowledge in appropriate subsisting existing ontologies, which are divided into two nodes: decreasing the domain workload to reducing the processing time and enabling interoperability to provide a comprehensive process with other similar systems.

## **CONTEXT**

The aim of Deep Learning is to builds a persuasive instance for vindicating potential relationship between ontological linguistics and connectionism. This chapter will investigate further arguments and impacts extending them to the Semantic Machine Learning Representations in terms of improving data quality issues. The predominant features of DL in some of its breakthroughs in linguistic value processing have come from incorporating appropriation and terminologies from SMLR. Unfortunately, linguistic semantics has, to date, been much less influenced by DL research (Christopher *et al.* 2018). According to Lewis (1970), “To say what a meaning IS, we may first ask what a meaning DOES, and then find something that does that”. Machine learning is based on learning functions and classifiers to assemble and accumulate data, so the data quality standard that is implemented should be comprehensive. DL and Semantic terminologies share the motivation of implementing artificial intelligence that simulates our capabilities such as indexing, validating, formalising, defining, establishing and acquiring. Both terminologies have been concluding information and knowledge-based exploration considerably the related abstract affirmation to improve the Data Quality (DQ) issue. “All progress is born of inquiry. Doubt is often better than overconfidence, for it leads to inquiry and inquiry leads to the invention” is a famous Hudson Maxim in the context of which the significance of research can well be understood. This inquisitiveness is the mother of all knowledge and the method, which man employs for obtaining the knowledge of whatever the unknown, can be termed as research (Kothari 2004). Collected data were subjected to descriptive statistical and inferential statistical analysis, measurement modelling and structural equation modelling to provide the objectives formulated by this study. Matching is a process of finding alignment between sets of correspondences with a semantic verification output of the matching process (Hiba *et al.* 2020). This merging is a process of creating a new set of possibly overlapping data. How-

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