# NoSym: Non-Symbolic Databases for Data Decoupling

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## 1. INTRODUCTION

Under the Unique Name Assumption (UNA), users need to have shared agreements on signifiers to use in schema or data, e.g. to use "genre" and not "type" to refer to a movie's category. Agreements are difficult in open environments such as datasets on the web, open data, and crowd-sourced databases, thus this assumption can be invalid. Schema matching and data integration can be limited in responding to this problem [2] as: (1) schemas might not be available a priori with schema-less data sources and queries becoming more common; (2) dataset-level schema/data mappings limit a user's ability to provide a contextual interpretation of a signifier suitable for a specific query-data matching task; and (3) data integration typically has an overhead which hinders the availability and low latency of databases.

## 2. THE PRINCIPLE OF DECOUPLING

Lack of shared agreements, or "decoupling", can be good. In Message-Oriented Middleware (MOM) it has been leveraged to achieve scalability as parties do not have to: know each others' addresses (space decoupling), be active at the same time (time decoupling), or block each other (synchronization decoupling) [1]. We call the lack of shared agreements on the entities and schema dimension "data decoupling". From a semiotics perspective, the shared agreements needed on data are on a mapping between signifiers (schema labels or data values), and signifieds (what the labels and values mean). In databases, there is a very little distinction between these two worlds which makes the problem intractable.

## 3. NON-SYMBOLIC DATABASES

We propose, as shown in Figure 1, a new paradigm which consists of three components:

(1) *Symbolic Encoder*: it translates data and queries from their symbolic form, e.g. English, into a non-symbolic representation. Deep learning models for example are trained on large corpora, e.g. Wikipedia, and can map a single word into a vector or tensor of hundreds of dimensions [5]. Such a vector or tensor is called a distributed representation of the word and can approximate its signified. User can provide contextual data such as tags to tailor the encoding [3].

(2) *Non-Symbolic Database Management System*: it stores the tensors representations, index them, and process encoded queries against stored encoded data.

(3) *Symbolic Decoder*: it translates a query result into a symbolic form that the user can readily work with, e.g. English data rows.

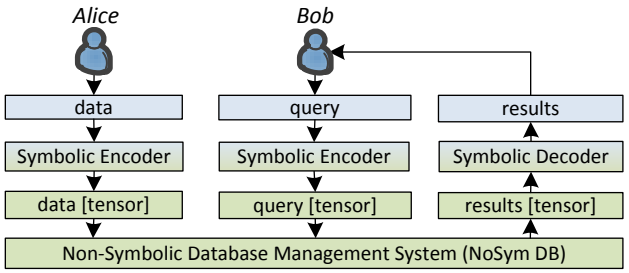


**Figure 1: System components.**

## 4. CHALLENGES

Tensors are numeric and can be larger than the original symbols. We need formal and efficient models to store, index, and query them, e.g. TensorDB [4], and such models need to take into account the peculiarity that these tensors represent schema labels and data values. Besides, non-symbolic tensors form a metric space where distance is defined with a topology that reflects the relatedness between the original values, e.g. "genre" and "type". This topology can be used for efficient storage and retrieval.

Encoders and decoders can become heterogeneous due to decoupling. However, as the NoSym database has native support for distances, it can natively catch similar or related signifiers. Besides, building agreements on encoders/decoders and their background corpora is not fine-grained, as with ontologies, and thus is more achievable. Furthermore, establishing a few anchor points between two metric spaces can lead to more points being automatically linked.

## 5. REFERENCES

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