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Soft Integration of Geo-Tagged Data Sets in J-CO-QL$^+$

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Abstract: The possibility offered by the current technology to collect and store data sets regarding public places located on the Earth globe is posing new challenges, as far as the integration of these data sets is concerned. Analysts usually need to perform such an integration from scratch, without performing complex and long preprocessing or data-cleaning tasks, as well as without performing training activities that require tedious and long labeling of data; furthermore, analysts now have to deal with the popular *JSON* format and with data sets stored within *JSON* document stores. This paper demonstrates that a methodology based on soft integration (i.e., data integration performed through soft computing and fuzzy sets) can now be effectively applied from scratch, through the *J-CO* Framework, which is a stand-alone tool devised to process *JSON* data sets stored within *JSON* document stores, possibly by performing soft querying on data sets. Specifically, the paper provides the following contributions: (1) It presents a soft-computing technique for integrating data sets describing public places, without any preliminary pre-processing, cleaning and training, which can be applied from scratch; (2) it presents current capabilities for soft integration of *JSON* data sets, provided by the *J-CO* Framework; (3) it demonstrates the effectiveness of the soft integration technique; (4) it shows how a stand-alone tool able to support soft computing (as the *J-CO* Framework) can be effective and efficient in performing data-integration tasks from scratch.

Keywords: off-line integration of geo-tagged data sets; data sets about public places; soft integration methodology; effective soft integration through a stand-along tool

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1. Introduction

Integrating geo-spatial information has become a crucial task in the current world. In fact, in the era of Open Data and Big Data, a plethora of sources can provide both authoritative and non-authoritative data sets concerning places. The situation is further complicated by the fact that social media provide people with tools for describing places in a non-controlled way. For example, *Facebook* provides its users with the functionality to define a "page"; a specific category of the page describes a "public place", such as restaurants, pubs, air dressers, universities, parks and so on; through its API (Application Programming Interface), pages could be queried, on the basis of their category, location, coordinates, and so on. Another interesting service is called *Google Places*: it is a sub-service of *Google Maps*; *Google Places* API can be used to query its corpus to find places of interest, on the basis of category, location, and so on; this corpus is built by *Google Maps* by integrating both authoritative and non-authoritative data, these latter ones given by users through the social interface provided by *Google Maps*.

In the current scenario, it is very easy to collect data sets from multiple sources, such that these data sets provide geo-tagged information about public places. Since current APIs of social media and Open-Data portals provide data as (possibly) geo-tagged *JSON* documents (*JSON* stands for JavaScript Object Notation, see [1]), *JSON* document stores are the natural storage where to save such data sets. Consequently, integrating geo-tagged data sets describing public places asks for suitable tools, which are able to work on *JSON* document stores. This is the reason why at University of Bergamo (Italy), we are devising [2–5] an innovative tool, called *J-CO* Framework, to perform the complex integration and querying of (possibly geo-tagged) *JSON* data sets.

Nevertheless, integrating geo-tagged data sets describing public places is not a novel problem; in general, traditional approaches rely on machine-learning techniques that require a preliminary training phase. In [6], the problem was addressed in a different way, because the context of "online" aggregation was considered; a fuzzy relation was defined, which provides an easy-to-compute metric that is suitable for online integration of data about public places; the experiments demonstrated that the approach is effective and comparable, in terms of effectiveness, with off-line classification techniques. However, the technique presented in [6] was hard-coded within the software prototype; this fact made us able to include some pre-processing steps on strings that were performed on the fly, immediately after place descriptors were acquired. However, the approach seems to be general and could be applied for integrating data sets in an off-line way too, with data sets stored within *JSON* stores. Paradoxically, this apparently small change of context constitutes a significant challenge: in fact, the straightforward solution could be to still hard-code the technique into a software tool, but this approach is not coherent with the world of *JSON* document stores. We think that exploiting a stand-alone tool able to query *JSON* stores is preferable, since it is transparent and comprehensible for analysts; however, a stand-alone tool for processing *JSON* data sets is necessarily less flexible than a programming language. Thus, the challenge is the following: is it possible to identify a stand-alone tool and adapt the integration technique presented in [6] to the case of off-line integration of geo-tagged *JSON* data sets from *JSON* stores?

The current evolution of *J-CO-QL*$^+$, the query language of the *J-CO* Framework, provides constructs for evaluating membership of *JSON* documents to fuzzy sets [7–9]. Thus, the straightforward idea of checking the current capability of *J-CO-QL*$^+$ for integrating *JSON* data sets describing public places has come out: specifically, since *J-CO-QL*$^+$ is able to deal with complex soft querying of *JSON* data sets and the technique presented in [6] for online integration of data sets concerning public places is based on fuzzy relations, we had the intuition of mixing the two approaches. In other words, given two sets of place descriptors represented as *JSON* documents and stored within a *JSON* document store, in this paper, we experiment with the application of the fuzzy technique presented in [6] (to be precise, a slightly evolved version of it) by means of the *J-CO* Framework, in an off-line manner. The goal is to verify that this approach is suitable in an off-line context, without previous training activities and intervention by humans to label data sets for driving the learning phase (typical of classification techniques). Definitely, we want to demonstrate that the availability of a stand-alone tool such as the *J-CO* Framework, which is able to process *JSON* data sets by applying soft computing and fuzzy sets, indeed provides analysts with a powerful tool to address a problem faced by data analysts, in an effective and (possibly) efficient way.

Summarizing, the contribution of the paper is manifold: (1) Presenting a soft-computing technique for integrating data sets describing public places, without any preliminary pre-processing, cleaning and training, which can be applied from scratch; (2) presenting current capabilities for soft integration of *JSON* data sets, as they are provided by *J-CO-QL*$^+$; (3) demonstrating the effectiveness of the soft integration technique in a harder context than that considered in [6]; (4) showing how a stand-alone tool able to support soft computing (as *J-CO-QL*$^+$) can be effective and efficient in performing data-integration tasks from scratch.

The paper is organized as follows. Section 2 presents relevant related work concerned with the paper. Section 3 provides a brief introduction to relevant concepts concerning fuzzy-set theory. Section 4 introduces the main features of the *J-CO* Framework. Section 5 precisely explains the addressed problem and introduces the methodology we follow, which relies on the concept of fuzzy relation. Section 6 presents and discusses the script written by means of *J-CO-QL*$^+$, which practically applies the methodology presented in Section 5; each single instruction is explained, in order to illustrate how it behaves and its contribution within the script. Section 7 reports the results of an experimental evaluation, in which we evaluated effectiveness and, marginally, execution times. Finally, Section 8 draws the conclusions and possible future work.

2. Related Work

This paper embraces two different research lines: soft querying on databases in general and on *JSON* document stores in particular (Section 2.1), as well as the integration of data sets describing public places (Section 2.2).

2.1. Soft Querying on Databases

Providing data users with capabilities for flexibly querying databases is an old challenge. In particular, when selection conditions can rely on vague predicates, queries become "soft", meaning that they are tolerant to thresholds (e.g., given a Boolean predicate `price <=` 30 to select cheap products, a product whose price is 30.45 is not selected, while instead it could be of interest) and selected items could be ranked on the basis of their relevance to the selection condition. Fuzzy sets appeared as the formal framework to specify soft selection conditions [10]. Since relational-database technology dominated the panorama of database technology, many works were conducted to propose an extension of SQL (the standard query language for relational databases) towards soft querying based on fuzzy sets. Some popular proposals are *SQLf* [11,12] (for which we can mention an attempt to implement it [13]) and its extension named *SQLf3* (which copes with constructs introduced in *SQL3*), as well as *FQUERY for Access* [14,15] (designed to operate on databases managed by Microsoft Access). Among all these proposals, *SoftSQL* [16–18] provided users with a statement to define non-trivial "linguistic predicates", to be used in the extended `SELECT` statement to select table rows through linguistic predicates. The interested reader can find various surveys on the topic [19,20]; in particular, the work [21] is a very large handbook that summarizes all research work on this topic.

The advent of *NoSQL* (Not only SQL) databases [22], i.e., databases that do not rely on the classical relational model, has started a novel era in data management. In particular, the popularity obtained by the *JSON* (JavaScript Object Notation) format to represent any kind of complex data is facing the data engineer with the novel (with respect to relational databases) concept of "*JSON* document store", i.e., a database which stores *JSON* documents in a native way. The most famous *JSON* document store is *MongoDB* [23], but many others are available (such as *CouchDB* [24], exploited within the block-chain platform called HyperLedger Fabric [25]). As a result, this novel scenario is revamping the topic of soft querying on databases, this time on *NoSQL* databases in general and on *JSON* document stores in particular.

An extension of MQL, the *MongoDB* query language, is proposed in [26]; in this extension, called "fMQL", "fuzzy labels" can be used to query *JSON* documents, since they are equivalent to linguistic predicates; unfortunately, the work [26] does not provide any indication about how to define fuzzy labels. A further limitation of the proposal is that, for each single *JSON* document, only one membership degree is implicitly evaluated (in contrast, *J-CO-QL*$^+$ allows for dealing with many membership degrees for each single document).

Finally, the work [27] proposes an approach for soft querying *JSON* documents: the corpus of *JSON* documents is preliminarily translated into fuzzy RDF triples [28]; then, the query is translated into *fSPARQL* [29], a fuzzy extension of *SPARQL* [30]. In our opinion, this approach is not suitable for processing *JSON* documents, because it does not work on the original documents, but on an alternative representation of them.

2.2. Integrating Data Sets Describing Public Places

The topic of aggregating information about public places coming from internet sources has been investigated in the last decade. Many different approaches have been followed.

For example, the work [31] adopts the *DAS* technique to integrate data about public places uniquely by exploiting string similarity on names, in particular by comparing the two strings without and with tokenization.

The work [32] compares different string-similarity metrics with various machine learning methods, to solve the problem of toponym matching. The results demonstrate that machine learning methods (in particular, classifiers) perform better than string-similarity metrics. Obviously, they cannot be applied from scratch, without preliminary labeling and training activities. Similarly, the work [33] exploits a neural network to perform "toponym matching", i.e., pairing strings that represent the same location.

The work [34] addresses the problem of "geo-spatial data conflation" (the general name of the problem addressed in this paper) by adopting an entropy-based technique: the key idea is to use phonetic transcriptions, to compensate mistakes in writing names.

Another work that can be considered as related to this paper is [35], in which "semantic aligning" of heterogeneous geo-spatial data sets (GDs) is addressed. Specifically, it proposed an efficient similarity matching technique, which integrates various category systems simultaneously.

Finally, the closest work to this paper is [6]: this work could be considered the natural evolution of it. Specifically, a complex fuzzy relation is defined to perform public-place conflation in an online way. A comparison with a famous classification technique (i.e., "Random-Forest" classifiers) was performed, showing that the fuzzy approach is effective in a comparable way. Here, the definition of the fuzzy relation is improved to cope with not-cleaned names and addresses, as well as it is applied within the context of the *J-CO* Framework for the off-line integration of *JSON* data sets.

3. Basic Notions on Fuzzy Sets

In [36], Zadeh introduced the Fuzzy-Set Theory. It was rapidly clear that it had (and still has) an enormous potentiality to be successfully applied to many areas of computer science, such as decision making, control theory, expert systems, artificial intelligence, natural-language processing, and so on. Here, we report some basic concepts, which constitute the basis to understand the main contribution of this paper.

Definition 1. ***Fuzzy Set.*** *Consider a "universe set" U. A fuzzy set (or type-1 fuzzy set) A in U ($A \subseteq U$) is a mapping $A : U \rightarrow [0,1]$. The value $A(x)$ is referred to as the* membership degree *of the element x to the fuzzy set A. Alternatively, the notation $\mu_A(x) \in [0,1]$ can be used.*

Clearly, given an item $x \in U$, if $A(x) = 0$, this means that x does not belong at all to A; an intermediate value $0 < A(x) < 1$ means that x partially belongs to A (the greater the value, the higher its degree of membership); if $A(x) = 1$, this means that the item x fully belongs to A.

Consequently, a fuzzy set is "empty" if and only if its membership function is identically zero for each $x \in U$.

Furthermore, given two fuzzy sets A in U and B in U, they are "equal" (denoted as $A = B$), if and only if $A(x) = B(x)$ (alternatively, $\mu_A(x) = \mu_B(x)$) for all $x \in U$.

Operators on fuzzy sets can be easily defined, by extending the classical operators on traditional sets.

Definition 2. ***Union, Intersection and Complement.*** *Consider a universe U and two fuzzy sets A in U and B in U.*

The union *of two fuzzy sets A and B, denoted as $S = A \cup B$, generates a novel fuzzy set S whose membership function is $S(x) = max(A(x), B(x))$, for each $x \in U$ (alternatively, $\mu_S(x) = max(\mu_A(x), \mu_B(x))$).*

The Intersection *of two fuzzy sets A and B, denoted as $I = A \cap B$, generates a novel fuzzy set S whose membership function is $I(x) = min(A(x), B(x))$, for each $x \in U$ (alternatively, $\mu_I(x) = min(\mu_A(x), \mu_B(x))$).*

The Complement *of a fuzzy set A, denoted as $C = \overline{A}$, generates a novel fuzzy set C whose membership function is $C(x) = 1 - A(x)$, for each $x \in U$ (alternatively, $\mu_C(x) = 1 - \mu_A(x)$).*

Classical logical operators are mapped onto operators on fuzzy sets: the `OR` operator is mapped onto the union; the `AND` operator is mapped onto the intersection; the `NOT` operator is mapped onto the complement.

Fuzzy sets are useful to represent vague concepts, which characterize many real-life application contexts. For example, if the universe is the set of people, we could think to divide them into "young" and "old". However, is a person whose age is 40 actually young or old? He/she is a little bit young and a little bit old, neither fully young nor fully old.

Various other operators on fuzzy sets can be defined. In the following definition, we introduce the "weighted aggregation" operator.

Definition 3. ***Weighted Aggregation.*** *Given a universe U and two fuzzy sets A in U and B in U, the* weighted aggregation *operator $W = wag_\beta(A, B)$ (with $\beta \in [0, 1]$) generates a new fuzzy set W whose membership function is defined as $W(x) = \beta \times A(x) + (1 - \beta) \times B(x)$ (alternatively, $\mu_W(x) = \beta \times \mu_A(x) + (1 - \beta) \times \mu_B(x)$).*

Example 1. *Through the membership degree, it is possible to denote partial membership of an item $x \in U$ to A; this way, vague linguistic concepts can be modeled. For example, given a public place p, its membership to the $PopularPlaces$ fuzzy set could be partial, denoting a place that is not so popular; thus, the membership degree measures its degree of popularity, for example on the basis of the number of likes obtained on social media.*

Suppose that on the same universe of public places, we conceive the $CheapRestaurants$ fuzzy set, whose membership degree denotes the perception that a public place is cheap (this perception could be induced by analyzing menus published on social media).

We now illustrate how to aggregate the $PopularPlaces$ and the $CheapRestaurants$ fuzzy sets to obtain interesting places.

- *If we are looking for "popular* ***and*** *cheap restaurants", we could formulate the search as "$PopularPlaces$ `AND` $CheapRestaurants$" (in terms of fuzzy sets, it is $I = PopularPlaces \cap CheapRestaurants$). Clearly, the lower membership degree determines the actual relevance of a place p.*
- *If we are looking for "popular* ***or*** *cheap restaurants", we could formulate the search as "$PopularPlaces$ `OR` $CheapRestaurants$" (in terms of fuzzy sets, it is $S = PopularPlaces \cup CheapRestaurants$). Clearly, the higher membership degree determines the actual relevance of a place p (a place could be not popular, but highly cheap).*
- *If we are looking for "popular* ***and possibly*** *cheap restaurants", we could formulate the search as "70% $PopularPlaces$ `AND` 30% $CheapRestaurants$" (in terms of fuzzy sets, it is $W = wag_{0.7}(PopularPlaces, CheapRestaurants)$). Clearly, the final membership degree is dominated by the degree of popularity, but a popular place that is also a cheap restaurant has a higher membership degree than a popular place that is not at all a cheap restaurant.*

The three above-mentioned searches are examples of "soft queries", where selection conditions are expressed in a vague way; the resulting membership degree denotes the "relevance" of an item to the soft query.

Furthermore, notice that when the names given to fuzzy sets linguistically characterize items in a proper way, these names can be used in soft conditions to linguistically express them.

Definition 4. ***Fuzzy Relation.*** *Consider two universes U_1 and U_2. A* fuzzy relation *R on U_1 and U_2, is defined as $R : U_1 \times U_2 \to [0, 1]$. $R(x_1, x_2) \in [0, 1]$, with $x_1 \in U_1$ and $x_2 \in U_2$, is the membership degree of the relation between x_1 and x_2; the meaning of the relation is linguistically expressed by the name of the relation.*

Through the concept of fuzzy relation, it is possible to model the strength of a relation between two items $x_1 \in U_1$ and $x_2 \in U_2$. Nevertheless, notice that a fuzzy relation is a particular case of fuzzy set in the universe $U = U_1 \times U_2$. Thus, we can reformulate the relation as $R : U \to [0, 1]$, where $x = \langle x_1, x_2 \rangle \in U$; consequently, we can write, in an equivalent way, either $R(x_1, x_2)$ or $R(\langle x_1, x_2 \rangle)$.

In this paper, we work on the universe of *JSON* documents. So, given a document $d \in U$, the focus will be on the evaluation of its membership degrees to one or more fuzzy sets.

4. The *J-CO* Framework

The *J-CO* Framework is a suit of software tools able to process *JSON* data sets, in a way that is independent of the data source. In fact, it is able to obtain data sets both from *JSON* document stores (such as *MongoDB*) and from web sources. It is built around the *J-CO-QL*$^+$ language and it contains various tools, as illustrated in Figure 1.

- The *J-CO-QL*$^+$ *Engine* actually processes *J-CO-QL*$^+$ queries. It obtains data to process from *JSON* document stores and from web sources; it is able to store results again into *JSON* document stores.
- *J-CO-DS* is a simplified *JSON* document store [37]: it is designed to provide users with the capability of storing large single *JSON* documents (usually, popular *JSON* document stores are not able to deal with very-large single *JSON* documents). *J-CO-DS* does not provide any internal computational capability, i.e., it does not provide a query language: in fact, it is part of the *J-CO* Framework, in which the component that provides computational capabilities is the *J-CO-QL*$^+$ *Engine*.
- *J-CO-UI* is the user interface of the framework. It provides users with a graphical interface to interactively write *J-CO-QL*$^+$ queries in a step-by-step way; users can also inspect intermediate results.

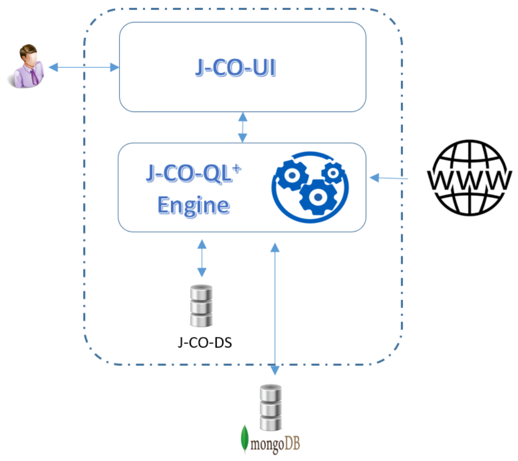


Figure 1. The *J-CO* Framework.

4.1. The Query Language

J-CO-QL$^+$ is the current evolution of the original *J-CO-QL* (see [3–5]): as its predecessor, it is designed to provide high-level and declarative statements, which does not require programming skills to be used; by means of them, it is possible to specify complex procedures (scripts) that are able to retrieve, integrate, transform and save *JSON* data sets. With respect to its predecessor, *J-CO-QL*$^+$ maintains the same approach, but revises syntax and semantics of statements, to improve their usability and effectiveness. Hereafter, we present its data model and its execution model.

4.1.1. Data Model

Here, we present the data model on which *J-CO-QL*$^+$ relies.

- The basic item to process is a *JSON* document. A document is represented within a pair of braces "`{`" and "`}`"; it is a sequence of fields separated by commas.
  A field is a "name: value" pair, where "name" is the field name, while "value" is the value of the field; the name is always enclosed within double quotes (e.g., `"name"`); the value can be a number, a string (enclosed either within double quotes or single quotes), a Boolean value, a nested sub-document (enclosed within a pair of braces "`{`" and "`}`") or an array (enclosed within square brackets "`[`" and "`]`", whose items can be any kind of *JSON* value, separated by commas).
- *J-CO-QL*$^+$ gives a special meaning to root-level fields whose name becomes with "`~`"; these names are compliant with *JSON* naming rules, but *J-CO-QL*$^+$ considers some of them in a special way, as illustrated hereafter.
  - The root-level `~fuzzysets` field is used to represent membership degrees of a d document to fuzzy sets. It works as a "key-value" map: given a field within `~fuzzysets`, the field name is the name of the fuzzy set to which the membership degree has been evaluated; the value is a real number in the range $[0, 1]$, which denotes the membership degree. This way, given a d document, it is possible to represent its membership to many fuzzy sets.
  - The root-level `~geometry` field represents geometries (also called "geo-tagging") of spatial entities represented as *JSON* documents. In this paper, we do not make use of geometries (the interested reader can refer to [5]).
- A "collection" is an unordered multi-set of heterogeneous documents, i.e., it can contain multiple copies of the same document.

4.1.2. Execution Model

The execution model is the same presented in previous publications [5,7]. Hereafter, we briefly summarize it.

- A "query" $q = (i_1, i_2, \ldots, i_n)$ is a sequence of instructions i_j, with $1 \leq j \leq n$. A query is a "pipe of instructions".
- Each instruction i_j receives an input "query-process state" s_{j-1} and generates a new query-process state s_j.
- A "query-process state" s_j (with $0 \leq j \leq n$) is a tuple $s_j = \langle tc, IR, DBS, FO, JSF \rangle$.
  - tc is called "temporary collection", since it is a collection of *JSON* documents that passes through the pipe of instructions, that contains temporary results of the query process.
  - IR is the "Intermediate-Results databaase", i.e., a database that is exclusive for the query process, to store intermediate results to be used later.
  - DBS is the set of "database descriptors", used to handle connections with external *JSON* document stores.
  - FO is the set of "Fuzzy Operators" defined within the query; they allows for evaluating membership degrees to fuzzy sets (see Section 6.2).
  - JSF is the set of user-defined "JavaScript Functions"; they are defined throughout the query to complete computational capabilities of the query language (see [38]).
- The initial query-process state is $s_0 = \langle tc : \emptyset, IR : \emptyset, DBS : \emptyset, FO : \emptyset, JSF : \emptyset \rangle$. Each instruction possibly modifies one member of the query-process state.

5. Problem and Methodology

In this section, we discuss the premises from which the paper has originated and introduce the problem we addressed as a case study (Section 5.1). Then, we present the methodological framework, which this work relies on (Section 5.2).

5.1. Premises and Problem

In [6], a fuzzy method for the online aggregation of POIs (Points of Interest) is presented. The problem addressed in that paper can be summarized as follows: if a web application has to integrate descriptors of public places (or POIs) caught on the fly from external services, the decision whether two descriptors actually describe the same public place or not must be taken in real time: techniques that require off-line work cannot be used.

In [6], it was proved that the technique can obtain very high levels of accuracy, absolutely comparable with off-line techniques; consequently, here, we argue that the same technique could be effectively adopted to integrate two data sets describing public places, in an off-line way. In particular, the novel support for soft querying [7] provided by *J-CO-QL*$^+$ (the query language of the *J-CO* Framework) has modified the scenario: in fact, the *J-CO* Framework is a stand-alone tool designed for manipulating and querying collections of *JSON* data sets. Consequently, it is straightforward to explore the possibility to exploit it for applying the fuzzy technique presented in [6] for integrating two collections of public-place descriptors coming from two different sources, by adopting a database approach (querying data by means of a query language) instead of hard coding the methodology with a programming language.

Hereafter, we present the problem. Then, Section 5.2 presents an improved formulation of the fuzzy technique presented in [6] that will be applied in *J-CO-QL*$^+$ scripts (discussed in Section 6).

Problem 1. *Consider two collections of descriptors D_1 and D_2. A* descriptor *d (such that either $d \in D_1$ or $d \in D_2$) describes a public place; we assume that d is a tuple whose minimal shape is $d = \langle name, address, lat, lon \rangle$, where $d.name$ is the name of the public place, $d.address$ is the raw address (i.e., as it is provided by the data source, without any pre-processing or cleaning) of the public place, while $d.lat$ and $d.lon$ are, respectively, the latitude and longitude of the public place. Depending on the source, these fields could be missing (either null value or zero-length string).*

Supposing that descriptors in D_1 and D_2 are related to the same municipality, we want to build the collection $SP = \{p_1, p_2, \dots\}$ of pairs of descriptors $p_i : \langle d_{1,h}, d_{2,k} \rangle$ (with $d_{1,h} \in D_1$ and $d_{2,k} \in D_2$) such that it is very likely that $d_{1,h}$ and $d_{2,k}$ actually describe the same public place.

5.2. Fuzzy Relation for Matching Public Places

The key contribution of [6] is a fuzzy relation called $MatchingPlaces$. Given two descriptors d_1 and d_2, it is written as $MatchingPlaces(d_1, d_2)$. Its membership degree denotes the possibility that d_1 and d_2 describe the same place. If we consider the universe $P = D_1 \times D_2$ of pairs $p_i : \langle d_{1,h}, d_{2,k} \rangle$, through the $MatchingPlaces$ fuzzy relation we want to build the fuzzy set PRP in P of Possibly-Relevant Pairs for which the membership degree of p_i is $PRP(p_i) > 0$.

To actually decide whether descriptors in a p_i pair actually describe the same public place, a minimum threshold $\alpha \in [0, 1]$ is used to focus on Relevant Pairs $RP \subseteq PRP$, where $RP(p_i) \geq \alpha$.

However, given a descriptor $d_{1,h} \in D_1$, it could appear several times in RP, because there might be many relevant pairs in which it is involved. For each $d_{1,h} \in D_1$, the subset $\overline{RP}_{1,h} \subseteq RP$ is the set of pairs $p_i \in RP$ such that $p_1.d_1 = d_{1,h}$; if $\overline{RP}_{1,h}$ is not empty, the pair $p_{1,h} \in \overline{RP}_{1,h}$ such that $\overline{RP}_{1,h}(p_{1,h}) \geq \overline{RP}_{1,h}(p_i)$, for all $p_i \in \overline{RP}_{1,h}$, appears in SP (because the two paired descriptors are actually supposed to describe the same place).

In the remainder of this section, we introduce the complete formal framework.

5.2.1. Basic Functions and Relations

The $MatchingPlaces$ fuzzy relation is defined by means of some basic functions and fuzzy relations.

Given two pairs of coordinates, i.e., lat_1, lon_1 and lat_2, lon_2 (denoting latitude and longitude of two points on the earth globe), the $Distance$ function computes the "Geodesic Distance" [39] between the two points in km; it is denoted as $Distance(lat_1, lon_1, lat_2, lon_2)$. On this basis, it is possible to define the $Close$ membership function that, given a distance $dist$ (in km) determines whether the distance denotes that two points are close; it is denoted as $Close(dist)$; an example of a typical membership function for this concept (the same exploited in [6]) is depicted in Figure 2: notice that, on the basis of the geodesic distance between the two points, the membership degree is 1 when the distance is between 0 and 50 m; then, it linearly decreases from 50 up to 1000 m. In Section 6.2, we will define a more sophisticated membership function.

The $Close$ membership function can be used as the basis for defining the $ClosePlaces$ fuzzy relation: given two place descriptors d_1 and d_2, $ClosePlaces(d_1, d_2) = Close(Distance(d_1.lat, d_1.lon, d_2.lat, d_2.lon))$.

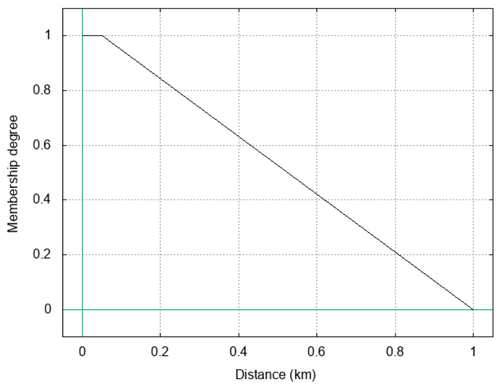


Figure 2. Sample $Close$ membership function taken from [6].

Given two strings s_1 and s_2, the $Similar$ fuzzy relation is denoted as $Similar(s_1, s_2)$. As a membership function, any string-similarity metric whose value is in the range $[0, 1]$ could be used; in [6], the Jaro-Winkler similarity metric [40–43] was used; here, we still use it, but in a more sophisticated way (see Section 6.2).

Based on the $Similar$ relation, which is defined on the universe of strings, it is possible to define two derived relations that are defined on the universe of descriptor pairs $P = D_1 \times D_2$.

The $SimilarAddress$ fuzzy relation denotes the extent to which the $address$ fields of the two descriptors are similar; it is defined as $SimilarAddress(d_1, d_2) = Similar(d_1.address, d_2.address)$.

The $SimilarName$ fuzzy relation denotes the extent to which the $name$ fields of the two descriptors are similar; it is defined as $SimilarName(d_1, d_2) = Similar(d_1.name, d_2.name)$.

5.2.2. The *SameLocation* Relation

The $MatchingPlaces$ relation is obtained by previously evaluating the $SameLocation$ fuzzy relation. It is denoted as $SameLocation(d_1, d_2)$. Its membership function changes, depending on the fact that fields concerning geographical aspects (i.e., address and coordinates) in d_1 and d_2 are missing or not. Hereafter, we provide three different definitions of the $SameLocation$ relation, one for each sub-case to deal with.

- **Case A: missing address(es).** If $d_1.address$ is missing, or $d_2.address$ is missing or both, but the two pairs of coordinates are available, only these latter ones can be used to evaluate the $SameLocation$ relation.

- **Case B: missing coordinate(s).** When one or more coordinates in d_1 and d_2 are missing, but both addresses $d_1.address$ and $d_2.address$ are available, only these latter ones can be used to evaluate the *SameLocation* relation.
- **Case C: addresses and coordinates are all available.** When in d_1 and d_2 all geographical fields (i.e., address and coordinates) are available, they all contribute to the evaluation of the *SameLocation* relation.

Once the three cases of interest have been identified, it is possible to define the *SameLocation* relation.

Definition 5. ***Case A.*** *Given two descriptors d_1 and d_2, for which either d_1.address or d_2.address or both are missing, while the lat and lon fields are not null in both d_1 and d_2, the SameLocation relation is defined as follows:*

$$SameLocation(d_1, d_2) = ClosePlaces(d_1, d_2)$$

i.e., the membership degree of the SameLocation relation coincides with the membership degree of the ClosePlaces relation.

Definition 6. ***Case B.*** *Given two descriptors d_1 and d_2 for which at least one among d_1.lat, d_1.lon, d_2.lat and d_2.lon is null, while both d_1.address and d_2.address are available, the SameLocation relation is defined as follows:*

$$SameLocation(d_1, d_2) = SimilarAddress(d_1, d_2)$$

i.e., the membership degree of the SameLocation relation coincides with the membership degree of the SimilarAddress relation.

Definition 7. ***Case C.*** *Given two descriptors d_1 and d_2, for which all the fields d_1.address, d_1.lat, d_1.lon, d_2.address, d_2.lat and d_2.lon are available, the SameLocation relation is defined as follows:*

$$SameLocation(d_1, d_2) = wag_{\beta_{geo}}(SimilarAddress(d_1, d_2), ClosePlaces(d_1, d_2))$$

i.e., the membership degree of the SameLocation relation is the weighted aggregation of the Similar Address relation and of the ClosePlaces relation; $\beta_{geo} \in [0, 1]$ is the weight of the first term (the similarity between addresses).

In Section 6.3, we use $\beta_{geo} = 0.55$: this way, the similarity between addresses slightly prevails over closeness; indeed, if two addresses are very similar, their similarity contributes more than coordinates; this way, the effect of erroneous coordinates that give rise to high distances is mitigated.

5.2.3. Global *MatchingPlaces* Relation

At this point, we can define the global *MatchingPlaces* relation.

Definition 8. *Given two descriptors d_1 and d_2, for which both fields d_1.name and d_2.name are available, and for which the SameLocation relation is defined and $SameLocation(d_1, d_2) \geq \alpha_{geo}$ (with $\alpha_{geo} \in [0, 1]$), the MatchingPlaces relation is defined as follows:*

$$MatchingPlaces(d_1, d_2) = wag_{\beta_{name}}(SimilarName(d_1, d_2), SameLocation(d_1, d_2))$$

i.e., the membership degree of the MatchingPlaces relation is obtained by aggregating the membership degrees of the SimilarName relation and of the SameLocation relation, by means of the weighted aggregator with weight β_{name} for similarity of names.

In Section 6.4, we set $\beta_{name} = 0.6$: this way, the similarity between names prevails over the membership degree of the *SameLocation* relation. The rationale is the following: given two similar names, they contribute only for the 60%; the remaining 40% is given by the geographical contribution. However, in order to avoid the two descriptors whose geographical contribution is not significant, the α_{geo} threshold is introduced: if the membership degree of the *SameLocation* fuzzy relation is less than α_{geo}, d_1 and d_2 are no longer considered eligible to be the same place: two places can have very similar names (even identical—imagine two restaurants of the same chain), but if there is the doubt that they are reasonably close, they could be a wrong pair. In Section 6.3, we set this threshold as $\alpha_{geo} = 0.4$.

The membership degree of the *MatchingPlaces* fuzzy relation is used to determine whether a pair actually belongs to the *RP* set of relevant pairs, i.e., $RP(p_i) \geq \alpha$ means $MatchingPlaces\ (p_1.d_1, p_1.d_2) \geq \alpha$. In Section 6.4, we set this threshold as $\alpha = 0.8$, because in our experiments (see Section 7.1), we found this is the threshold that gives the best effectiveness.

6. Presenting the Script

In this section, we provide the technical contribution of the paper. Specifically, we demonstrate how the current version of *J-CO-QL*$^+$ is able to perform the soft integration of two collections containing *JSON* documents that describe public places, obtained from two different data sources.

6.1. Data Set

A *MongoDB* database called `ijgiDb` contains two collections of *JSON* documents: the first one is called `FacebookDescriptors` and its documents are descriptors of pages that present public places mostly located in the area of Manchester (UK); the second collection is called `GoogleDescriptors` and its documents are descriptors of places mostly located in the area of Manchester (UK) as well, obtained from *Google Places*. The `FacebookDescriptors` collection contains 5738 documents, while the `GoogleDesciptors` collection contains 5214 documents. Figure 3a shows a sample document in the `FacebookDescriptors` collection, while Figure 3b reports a sample document in the `GoogleDescriptors` collection. The reader can notice that *Facebook* descriptors clearly distinguish the address (in the `fbStreet` field) from the city name (in the `fbCity` field) from the ZIP code (in the `fbZip` field). In contrast, within a *Google Places* descriptor, the content of the `gAddress` field is less clean, because it contains the city name too. This also demonstrates that we are working on names and addresses as they are provided by *Facebook* and *Google Places*, without any pre-processing or cleaning (in [6], addresses were cleaned from numbers and urban designations, such as "street"). Consequently, here, we are addressing a less favorable situation.

```
{
  "id"          : 266,
  "idLink"      : "1761andLilysBar"
  "fbName"      : "1761 & Lily's Bar",
  "fbCity"      : "Manchester",
  "fbCountry"   : "United Kingdom",
  "fbLatitude"  : 53.4802297,
  "fbLongitude" : -2.2435781,
  "fbStreet"    : "2 Booth Street",
  "fbZip"       : "M2 4AT",
}
```

(**a**)

```
{
  "gId"         : "ChIJ--wWob6xe0gRBF_8…",
  "gName"       : "Hope Studios"
  "gAddress"    : "52 Newton Street, Ma…",
  "gCity"       : "Manchester",
  "gLatitude"   : 53.4821537,
  "gLongitude"  : -2.2322586,
}
```

(**b**)

Figure 3. Examples of documents representing place descriptors. (**a**) Example of document in the `FacebookDescriptors` collection. (**b**) Example of document in the `GoogleDescriptors` collection.

6.2. Defining Fuzzy Operators

We start presenting the *J-CO-QL*$^+$ script. The first part of the script is reported in Listing 1.

The key concept provided by *J-CO-QL*$^+$ to evaluate membership degrees of *JSON* documents is the concept of "fuzzy operator". Such an operator is called within soft conditions: given some actual parameters (expressions based on document fields), the operator returns a membership degree. This degree will be used to evaluate the overall membership degree of a document to a specific fuzzy set.

Listing 1. *J-CO-QL*$^+$ script: fuzzy operators.

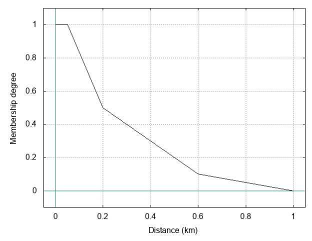
```
1. CREATE FUZZY OPERATOR Close
     PARAMETERS
       distance TYPE Float
     PRECONDITION
         distance >= 0
     EVALUATE
         distance
     POLYLINE
       [ (0.00, 1.00), (0.05, 1.00), (0.20, 0.50), (0.60, 0.10), (1.00, 0.00)  ];

2. CREATE FUZZY OPERATOR Similar
     PARAMETERS
       st1 TYPE String,
       st2 TYPE String
     EVALUATE
         JARO_WINKLER_SIMILARITY(st1, st2)
     POLYLINE
       [ (0.00, 0.00), (0.60, 0.40), (0.70, 0.80), (0.80, 1.00), (1.00, 1.00)  ];

3. CREATE FUZZY OPERATOR WeightedAggregationBeta
     PARAMETERS
       f1   TYPE Float,
       f2   TYPE Float,
       beta TYPE Float
     PRECONDITION
       f1   IN_RANGE [0, 1] AND
       f2   IN_RANGE [0, 1] AND
       beta IN_RANGE [0, 1]
     EVALUATE
       f1*beta + f2*(1-beta)
     POLYLINE
       [ (0.00, 0.00), (1.00, 1.00)  ];
```

6.2.1. The `Close` Fuzzy Operator

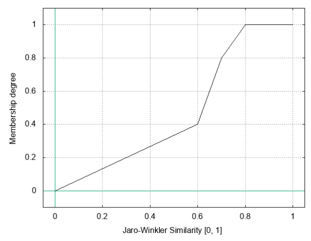
The instruction on line 1 of the *J-CO-QL*$^+$ script in Listing 1 defines the `Close` fuzzy operator: it evaluates the degree of closeness of two places, on the basis of the distance between them. Hereafter, we describe the instruction in details.

- The `PARAMETERS` clause defines the formal parameters of the operator. Specifically, only the `distance` parameter is defined.
- The `PRECONDITION` clause defines a condition on the parameters: if the condition is not satisfied, the evaluation of the fuzzy operator stops and an error signal is raised. Specifically, the precondition says that the distance must be no less than 0.
- The `EVALUATE` clause specifies a mathematical expression on the parameters, whose value is used as x-axis coordinate against the membership function defined by the subsequent `POLYLINE` clause. In the `Close` fuzzy operator, the expression simply takes the value of the `distance` parameter.
- The `POLYLINE` clause specifies the membership function actually used to compute the membership value. The function is defined as a polyline, by a sequence of pairs (x_i, y_i), where x_i can be any real value, while $y_i \in [0, 1]$; given two consecutive points (x_i, y_i) and (x_{i+1}, y_{i+1}), it must be $x_i < x_{i+1}$. Each pair of consecutive points defines a segment. Given an x value, if it is between x_1 and x_n (in the case of n points), the corresponding y value is considered as a membership degree; if $x < x_1$, the membership degree is y_1; if $x > x_n$, the membership degree is y_n.

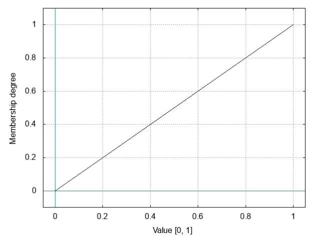
Figure 4a reports the polyline defined for the `Close` fuzzy operator. Notice that it is not the same defined in [6] (reported in Figure 2): in fact, we opted for a function that immediately penalizes distances that are between 50 m and 600 m, because two places in the same neighborhood are not perceived as very close when their distance becomes greater than 100 m.



(**a**)



(**b**)



(**c**)

Figure 4. Membership functions for the fuzzy operators in Listing 1. (**a**) `Close`; (**b**) `Similar`; (**c**) `WeightedAggregationBeta`.

6.2.2. The `Similar` Fuzzy Operator

The instruction on line 2 of the *J-CO-QL*$^+$ script in Listing 1 creates the `Similar` fuzzy operator. Its goal is to evaluate a membership degree on the basis of the similarity degree of two strings. The operator is described in detail hereafter.

- The operator receives two parameters, called `st1` and `st2`; they are the two strings to compare.
- No precondition is specified: in the case of empty or null strings, the operator returns 0 as membership degree, because the similarity degree is 0.
- The `EVALUATE` clause calls the built-in (i.e., provided by *J-CO-QL*$^+$) function named `JARO_WINKLER_SIMILARITY`, to obtain the similarity degree of the two strings. The similarity degree is a value in the range $[0, 1]$. In the case of null or zero-length strings, the returned similarity degree is 0.
- The `POLYLINE` clause defines the membership function depicted in Figure 4b. Notice that it penalizes similarity degrees that are less than 0.7, while membership degrees that are greater than 0.8 are rewarded: this is due to the sometimes bizarre behavior of the Jaro-Winkler similarity, that returns high similarity degrees even when strings only shares some characters, but are not actually similar; furthermore, for strings such as “`The Gray Horse`” and “`GrayHorse`”, the similarity degree is around 0.7, although they clearly have to be considered very similar. With this shape, we try to compensate the behavior of the Jaro-Winkler similarity, so as to deal with raw addresses and names (i.e., not cleaned from articles, numbers, punctuation, and so on).

6.2.3. The `WeightedAggregationBeta` Fuzzy Operator

The instruction on line 3 of the *J-CO-QL*$^+$ script in Listing 1 defines the third fuzzy operator. This is called `WeightedAggregationBeta` and its goal is to perform the “weighted aggregation” wag_β (see Definition 3). In fact, *J-CO-QL*$^+$ does not provide such an operator in its language; through the `WeightedAggregationBeta` fuzzy operator, we show how to introduce novel fuzzy concepts. The fuzzy operator is described in detail hereafter.

- The operator receives three parameters: `f1` and `f2` are the two values in the range $[0, 1]$ to aggregate, while `beta` is the aggregation weight (in the range $[0, 1]$ too) of `f1` with respect to `f2`.
- The `PRECONDITION` clause ensures that the actual values of the three parameters are in the range $[0, 1]$ (notice the `IN_RANGE` predicate).
- The `EVALUATE` clause actually performs the weighted aggregation.
- The `POLYLINE` clause defines a very simple membership function, which is reported in Figure 4c: it is a straight segment from the point $(0, 0)$ to the point $(1, 1)$; this way, the value computed by the `EVALUATE` clause is returned, as it is, as membership degree.

6.3. Retrieving and Pairing Descriptors

Once the three fuzzy operators are defined, it is time to start working on the data set. This is conducted by the second part of the *J-CO-QL*$^+$ script, which is reported in Listing 2.

Listing 2. *J-CO-QL*$^+$ script: retrieving and joining collections.

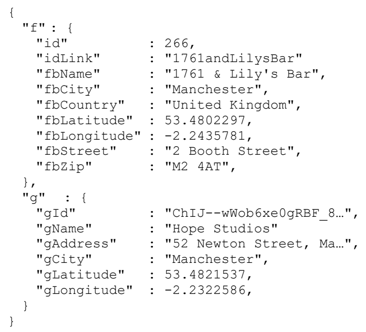
```
4. USE DB ijgiDb
      ON SERVER MongoDB 'http://127.0.0.1:27017';

5. JOIN OF COLLECTIONS
      FacebookDescriptors@ijgiDb AS f, GoogleDescriptors@ijgiDb AS g
    CASE
      // Case A: missing address(es)
      WHERE( FIELD  .f.fbStreet IS NULL  OR
             FIELD  .g.gAddress IS NULL  OR
                    .f.fbStreet = ""     OR
                    .g.gAddress = ""   )     AND
           FIELD .f.fbLatitude  IS NOT NULL AND
           FIELD .f.fbLongitude IS NOT NULL AND
           FIELD .g.gLatitude   IS NOT NULL AND
           FIELD .g.gLongitude  IS NOT NULL
        GENERATE
          CHECK FOR
           FUZZY SET ClosePlaces   USING
                     Close ( GEODESIC_DISTANCE(  .f.fbLatitude, .f.fbLongitude,
                                                 .g.gLatitude,   .g.gLongitude ) ),
           FUZZY SET SameLocation  USING ClosePlaces
          ALPHACUT 0.4 ON SameLocation

      // Case B: missing coordinate(s)
      WHERE  FIELD  .f.fbStreet     IS NOT NULL AND
             FIELD  .g.gAddress     IS NOT NULL AND
                    .f.fbStreet     != ""       AND
                    .g.gAddress     != ""       AND
             ( FIELD .f.fbLatitude  IS NULL  OR
               FIELD .f.fbLongitude IS NULL  OR
               FIELD .g.gLatitude   IS NULL  OR
               FIELD .g.gLongitude  IS NULL  )
          GENERATE
            CHECK FOR
              FUZZY SET SimilarAddress  USING Similar (.f.fbStreet, .g.gAddress),
              FUZZY SET SameLocation    USING SimilarAddress
            ALPHACUT 0.4 ON SameLocation

      // Case C: addresses and coordinates all available
      WHERE  FIELD .f.fbStreet    IS NOT NULL AND
             FIELD .g.gAddress    IS NOT NULL AND
                    .f.fbStreet     != ""       AND
                    .g.gAddress     != ""       AND
             FIELD .f.fbLatitude  IS NOT NULL AND
             FIELD .f.fbLongitude IS NOT NULL AND
             FIELD .g.gLatitude   IS NOT NULL AND
             FIELD .g.gLongitude  IS NOT NULL
        GENERATE
          CHECK FOR
            FUZZY SET SimilarAddress  USING Similar ( .f.fbStreet, .g.gAddress ),
            FUZZY SET ClosePlaces     USING
                      Close ( GEODESIC_DISTANCE(  .f.fbLatitude, .f.fbLongitude,
                                                  .g.gLatitude,   .g.gLongitude ) ),
            FUZZY SET SameLocation    USING
                        WeightedAggregationBeta(  MEMBERSHIP_OF(SimilarAddress),
                                                  MEMBERSHIP_OF(ClosePlaces), 0.55 )
          ALPHACUT 0.4 ON SameLocation;
```

The instruction on line 4 connects the query process to the database. After this instruction, it will be possible to access the `ijgiDb` database to retrieve and store collections.

The `JOIN OF COLLECTIONS` instruction on line 5 retrieves the two source collections (called `FacebookDescriptors` and `GoogleDescriptors`) and creates all possible pairs of documents contained in the two collections. Then, the subsequent `CASE` clause evaluates a pool of conditions on these pairs to possibly evaluate fuzzy sets on the actually-interesting pairs and discards the others. The instruction is explained in detail hereafter.

- The instruction retrieves the `FacebookDescriptors` collection from the `ijgiDb` database and aliases it as `f`; similarly, it retrieves the `GoogleDescriptors` collection from the same database and aliases it as `g`.
  For each *f* document from the `f` collection and for each *g* document from the `g` collection, a new *d* document is created. This document contains two fields: the first one is called `f` and its value is the source *f* document; the second one is called `g` and its value is the source *g* document. The *d* document is further processed by the subsequent `CASE` clause.

Figure 5 reports an example of d document, which is obtained by joining the two sample documents reported in Figure 3; notice the names of the root-level fields.



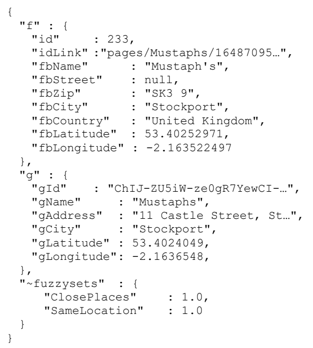
```
{
  "f" : {
    "id"          : 266,
    "idLink"      : "1761andLilysBar"
    "fbName"      : "1761 & Lily's Bar",
    "fbCity"      : "Manchester",
    "fbCountry"   : "United Kingdom",
    "fbLatitude"  : 53.4802297,
    "fbLongitude" : -2.2435781,
    "fbStreet"    : "2 Booth Street",
    "fbZip"       : "M2 4AT",
  },
  "g"  : {
    "gId"         : "ChIJ--wWob6xe0gRBF_8…",
    "gName"       : "Hope Studios"
    "gAddress"    : "52 Newton Street, Ma…",
    "gCity"       : "Manchester",
    "gLatitude"   : 53.4821537,
    "gLongitude"  : -2.2322586,
  }
}
```

Figure 5. Example of document generated by the `JOIN OF COLLECTIONS` instruction on line 5 of the *J-CO-QL*$^+$ script, before the `CASE clause`.

- The `CASE` clause evaluates a pool of selection conditions expressed within a `WHERE` clause; if a d document is selected by a condition, it is processed according to the subsequent sub-clauses. Many `WHERE` branches are possible: a d document is processed by the branch associated with the first `WHERE` condition that it satisfies; if no condition is satisfied, d is discarded (it will not appear in the output temporary collection).
  Specifically, the `CASE` clause in the instruction on line 5 in Listing 2 contains three `WHERE` branches: each of them deals with one of the three situations considered for defining the $SameLocation$ relation by Definitions 5–7. Hereafter, we separately discuss the behavior of the three branches.
  - The first `WHERE` branch deals with the case A of the $SameLocation$ fuzzy relation, defined in Definition 5. The condition is true if either the value for the `fbStreet` field is missing or the value for the `gAddress` field is missing or both are missing, and all coordinates are available. If a d document meets the condition, the `GENERATE` block further processes d through the `CHECK FOR` clause, whose goal is to evaluate the membership degrees of d to fuzzy sets.
    Specifically, two `FUZZY SET` branches are present: the former evaluates the `ClosePlaces` fuzzy set, the latter evaluates the `SameLocation` fuzzy set.
    The membership degree to the `ClosePlaces` fuzzy set is obtained by the associated `USING` clause: this is a "soft condition", in which fuzzy operators (such as those defined in Section 6.2) and fuzzy-set names can be composed by the usual (fuzzy) logical operators `AND`, `OR` and `NOT`; the resulting membership degree is the membership degree to the evaluated fuzzy set. If this is the first membership degree evaluated for d, then d does not have the special `~fuzzysets` field: in this case, the field is added and within it only one single field is present, having the same name of the evaluated fuzzy set, whose value is the computed membership degree. In contrast, if the `~fuzzysets` field is already present, it is extended with one extra internal field, describing the membership degree to the new evaluated fuzzy set.
    Specifically, the first branch evaluates the membership degree to the `ClosePlaces` fuzzy set, by means of the `Close` fuzzy operator (see Listing 1), which is called passing the geodesic distance computed by the `GEODESIC_DISTANCE` built-in function.
    The second `FUZZY SET` branch evaluates the membership degree to the `SameLocation` fuzzy set, by assuming that it coincides with the `ClosePlaces` fuzzy set (see Definition 5). Finally, the `ALPHACUT` clause discards the d document from the output temporary collection if its membership degree to the `SameLocation` fuzzy set is less than 0.4; remember that this is the α_{geo} threshold mentioned within Definition 8. Figure 6a reports a sample document generated

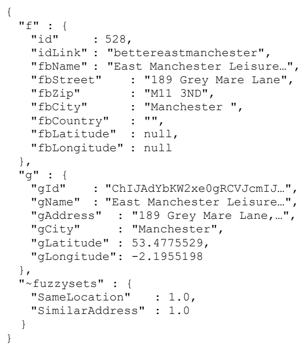
by the first WHERE branch; notice the presence of the ~fuzzysets field and its inner fields.

- The second WHERE branch deals with case *B* of the *SameLocation* relation (see Definition 6), i.e., at least one coordinate is null but both addresses are present. In this case (see Definition 6), the membership degree to the SimilarAddress fuzzy set is evaluated by means of the Similar fuzzy operator, which evaluates the fuzzy similarity relation between two strings (in this case, the two addresses). Then, as defined by Definition 6, the second FUZZY SET branch tells that the SameLocation fuzzy set coincides with the SimilarAddress fuzzy set. Again, the ALPHACUT clause puts the d document into the output temporary collection if the membership degree to the SameLocation fuzzy set is no less than 0.4 (the α_{geo} threshold in Definition 8). Figure 6b shows a sample document generated by the second WHERE branch.
- The third WHERE branch deals with case C of the *SameLocation* fuzzy relation (see Definition 7), i.e., both all addresses and all coordinates are available. Consequently, the membership degrees to three different fuzzy sets are evaluated: the first one is the SimilarAddress fuzzy set, by means of the Similar fuzzy operator applied to addresses; the second one is the ClosePlaces fuzzy set, by means of the Close fuzzy operator applied to the geodesic distance between the two points.
  The third FUZZY SET branch evaluates the membership degree to the fuzzy set named SameLocation: according to Definition 7, it is obtained by calling the WeightedAggregationBeta fuzzy operator, whose goal is to perform the weighted aggregation: it receives the two values (in the range $[0, 1]$) to aggregate and the β weight.
  The USING soft condition calls the WeightedAggregationBeta fuzzy operator, passing the membership values to the SimilarAddress fuzzy set and to the ClosePlaces fuzzy set, which are obtained by means of the MEMBERSHIP_OF built-in function (that extracts the membership degree from within the ~fuzzysets field). The third parameter is the constant value 0.55: thisis the β_{geo} weight presented and discussed in Definition 7. The ALPHACUT clause discards the evaluated document if its membership degree to the SameLocation fuzzy set is less than 0.4 (the α_{geo} threshold mentioned in Definition 8).
  Figure 6c reports a sample document generated by the third branch; notice that the ~fuzzysets field has three inner fields.



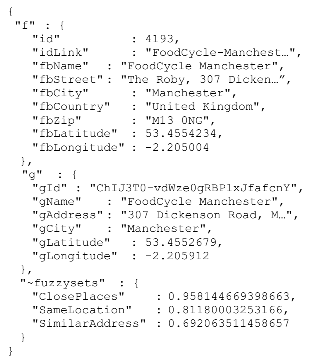
```
{
  "f" : {
    "id"     : 233,
    "idLink" :"pages/Mustaphs/16487095…",
    "fbName"      : "Mustaph's",
    "fbStreet"    : null,
    "fbZip"       : "SK3 9",
    "fbCity"      : "Stockport",
    "fbCountry"   : "United Kingdom",
    "fbLatitude"  : 53.40252971,
    "fbLongitude" : -2.163522497
  },
  "g" : {
    "gId"    : "ChIJ-ZU5iW-ze0gR7YewCI-…",
    "gName"     : "Mustaphs",
    "gAddress"  : "11 Castle Street, St…",
    "gCity"     : "Stockport",
    "gLatitude" : 53.4024049,
    "gLongitude": -2.1636548,
  },
  "~fuzzysets"  : {
      "ClosePlaces"    : 1.0,
      "SameLocation"   : 1.0
  }
}
```

(**a**)



```
{
  "f" : {
    "id"     : 528,
    "idLink" : "bettereastmanchester",
    "fbName" : "East Manchester Leisure…",
    "fbStreet"    : "189 Grey Mare Lane",
    "fbZip"       : "M11 3ND",
    "fbCity"      : "Manchester ",
    "fbCountry"   : "",
    "fbLatitude"  : null,
    "fbLongitude" : null
  },
  "g" : {
    "gId"    : "ChIJAdYbKW2xe0gRCVJcmIJ…",
    "gName"  : "East Manchester Leisure…",
    "gAddress"  : "189 Grey Mare Lane,…",
    "gCity"     : "Manchester",
    "gLatitude" : 53.4775529,
    "gLongitude": -2.1955198
  },
  "~fuzzysets" : {
    "SameLocation"   : 1.0,
    "SimilarAddress" : 1.0
   }
}
```

(**b**)



```
{
 "f" : {
    "id"            : 4193,
    "idLink"        : "FoodCycle-Manchest…",
    "fbName"   : "FoodCycle Manchester",
    "fbStreet": "The Roby, 307 Dicken…",
    "fbCity"        : "Manchester",
    "fbCountry"     : "United Kingdom",
    "fbZip"         : "M13 0NG",
    "fbLatitude"    : 53.4554234,
    "fbLongitude" : -2.205004
  },
  "g"  : {
    "gId" : "ChIJ3T0-vdWze0gRBPlxJfafcnY",
    "gName"    : "FoodCycle Manchester",
    "gAddress": "307 Dickenson Road, M…",
    "gCity"    : "Manchester",
    "gLatitude"   : 53.4552679,
    "gLongitude"  : -2.205912
  },
  "~fuzzysets"  : {
    "ClosePlaces"    : 0.958144669398663,
    "SameLocation"   : 0.81180003253166,
    "SimilarAddress" : 0.692063511458657
  }
}
```

(**c**)

Figure 6. Examples of documents generated by the JOIN OF COLLECTIONS instruction on line 5. (**a**) Example for Case A. (**b**) Example for Case B. (**c**) Example for Case C.

The temporary collection produced by the instruction on line 5 of Listing 2 contains heterogeneous documents, as far as the structure of the ~fuzzysets field is concerned, but all have the inner SameLocation field, denoting the membership degree to the SameLocation fuzzy set; it will be used in the next instruction, to evaluate the membership degree to the `MatchingPlaces` fuzzy set.

Furthermore, notice that `SameLocation`, `ClosePlaces` and `SimilarAddresses` are called "fuzzy sets", while they were defined in Section 5 as "fuzzy relations": this is not a mistake, but the consequence of the fact that *JSON* documents represent pairs of descriptors; consequently, fuzzy relation on pairs are translated into fuzzy sets on *JSON* documents.

6.4. Relevant Pairs

All documents contained in the temporary collection produced by the instruction on line 5 (Listing 2) have the membership degree to the `SameLocation` fuzzy set no less than $\alpha_{geo} = 0.4$, as required by Definition 8. The `FILTER` instruction on line 6 in Listing 3 actually evaluates the membership degree to the `MatchingPlaces` fuzzy set, which corresponds to the *MatchingPlces* relation defined in Definition 8. The `FILTER` instruction on line 6 is described in detail hereafter.

- The `FILTER` statement takes the temporary collection as input and generates a new temporary collection by applying a `CASE` clause. The behavior of this clause is the same as in the `JOIN OF COLLECTIONS` statement.
- On line 6, only one `WHERE` branch is present: if a document does not meet the selection condition, it is discarded from the output temporary collection.
  Specifically, the selection condition selects those documents having both the names in the two paired descriptors, so as to evaluate the membership degree to the `SimilarName` fuzzy set.
- The first `FUZZY SET` branch in the `CHECK FOR` clause evaluates the membership degree to the `SimilarName` fuzzy set; again, in the `USING` soft condition, the `Similar` fuzzy operator (see Listing 1) is called, this time passing names (instead of addresses).
- The second `FUZZY SET` branch can finally evaluate the membership degree to the `MatchingPlaces` fuzzy set, corresponding to the *MatchingPlaces* fuzzy relation defined by Definition 8. Remember that the fuzzy relations named *SameLocation* and *SimilarName* are aggregated by means of the weighted aggregation operator. In Listing 1, we defined the `WeightedAggregationBeta` fuzzy operator, which here is used to aggregate the `SimilarName` fuzzy set and the `SameLocation` fuzzy set; the `SimilarName` fuzzy set weights for the 60% of the final membership degree (this is the β_{name} weight mentioned in Definition 8), so that similarity between names moderately prevails over geographical similarity (whose goal is to cofirm that two places having similar or identical names are actually the same place). The resulting membership degree becomes the membership degree to the `MatchingPlaces` fuzzy set.
  The three sample documents reported in Figure 6 become as reported in Figure 7; notice the presence of the `MatchingPlaces` inner field within the `~fuzzysets` field.

Listing 3. *J-CO-QL*$^{+}$ script: matching places.

```
6. FILTER
     CASE
       WHERE  WITH .f.fbName, .g.gName  AND
              KNOWN FUZZY SETS SameLocation
         GENERATE
           CHECK FOR
             FUZZY SET SimilarName     USING Similar( .f.fbName, .g.gName ),
             FUZZY SET MatchingPlaces  USING
               WeightedAggregationBeta ( MEMBERSHIP_OF (SimilarName),
                                         MEMBERSHIP_OF (SameLocation),  0.60)
           ALPHACUT 0.8 ON MatchingPlaces
           BUILD{
             .f   : .f,
             .g   : .g,
             .rank: MEMBERSHIP_OF(MatchingPlaces)  }
           DEFUZZIFY;

7. SAVE AS RelevantPairs@ijgiDb;
```

```
{
  "f" : {
    "id"     : 233,
    "idLink" :"pages/Mustaphs/16487095…",
    "fbName"      : "Mustaph's",
    "fbStreet"    : null,
    "fbZip"       : "SK3 9",
    "fbCity"      : "Stockport",
    "fbCountry"   : "United Kingdom",
    "fbLatitude"  : 53.40252971,
    "fbLongitude" : -2.163522497
  },
  "g" : {
    "gId"    : "ChIJ-ZU5iW-ze0gR7YewCI-…",
    "gName"  : "Mustaphs",
    "gAddress"  : "11 Castle Street, St…",
    "gCity"     : "Stockport",
    "gLatitude" : 53.4024049,
    "gLongitude": -2.1636548,
  },
  "~fuzzysets"  : {
      "ClosePlaces"    : 1.0,
      "MatchingPlaces" : 1.0,
      "SameLocation"   : 1.0,
      "SimilarName"    : 1.0
  }
}
```

(**a**)

```
{
  "f" : {
    "id"     : 528,
    "idLink" : "bettereastmanchester",
    "fbName" : "East Manchester Leisure…",
    "fbStreet"    : "189 Grey Mare Lane",
    "fbZip"       : "M11 3ND",
    "fbCity"      : "Manchester ",
    "fbCountry"   : "",
    "fbLatitude"  : null,
    "fbLongitude" : null
  },
  "g" : {
    "gId"    : "ChIJAdYbKW2xe0gRCVJcmIJ…",
    "gName"  : "East Manchester Leisure…",
    "gAddress"  : "189 Grey Mare Lane,…",
    "gCity"     : "Manchester",
    "gLatitude" : 53.4775529,
    "gLongitude": -2.1955198
  },
  "~fuzzysets" : {
    "MatchingPlaces" : 1.0,
    "SameLocation"   : 1.0,
    "SimilarAddress" : 1.0,
    "SimilarName"    : 1.0
  }
}
```

(**b**)

```
{
 "f" : {
   "id"          : 4193,
   "idLink"      : "FoodCycle-Manchest…",
   "fbName"   : "FoodCycle Manchester",
   "fbStreet": "The Roby, 307 Dicken…",
   "fbCity"      : "Manchester",
   "fbCountry"   : "United Kingdom",
   "fbZip"       : "M13 0NG",
   "fbLatitude"  : 53.4554234,
   "fbLongitude" : -2.205004
  },
  "g"  : {
   "gId" : "ChIJ3T0-vdWze0gRBPlxJfafcnY",
   "gName"    : "FoodCycle Manchester",
   "gAddress": "307 Dickenson Road, M…",
   "gCity"    : "Manchester",
   "gLatitude"   : 53.4552679,
   "gLongitude"  : -2.205912
  },
  "~fuzzysets"  : {
   "ClosePlaces"    : 0.958144669398663,
   "MatchingPlaces" : 0.924720013012664,
   "SameLocation"   : 0.81180003253166,
   "SimilarAddress" : 0.692063511458657,
   "SimilarName"    : 1.0
  }
}
```

(**c**)

Figure 7. Examples of documents transformed by the `FILTER` instruction on line 6 before the `BUILD` section. (**a**) Example for Case A. (**b**) Example for Case B. (**c**) Example for Case C.

- At this point, only relevant pairs must be kept, i.e., those pairs whose membership degree to the `MatchingPlaces` fuzzy set is no less than $\alpha = 0.8$. The `ALPHACUT` clause does that.
- The final `BUILD` section (which is optional, this is why it was not present in the `JOIN OF COLLECTIONS` instruction on line 5 in Listing 2) restructures all survived documents. Specifically, a novel `rank` field is added, whose value is the membership degree to the `MatchingPlaces` fuzzy set. This field is necessary, because the subsequent `DEFUZZIFY` option discards the `~fuzzysets` field (as a consequence, documents are "defuzzified"). Figure 8 reports the final state of the three sample documents reported in Figure 7. Notice the presence of the `rank` field, whose value is the membership degree of the `MatchingPlaces` fuzzy set.

```
{
  "f"    : {
    "id"     : 233,
    "idLink" :"pages/Mustaphs/16487095…",
    "fbName"      : "Mustaph's",
    "fbStreet"    : null,
    "fbZip"       : "SK3 9",
    "fbCity"      : "Stockport",
    "fbCountry"   : "United Kingdom",
    "fbLatitude"  : 53.40252971,
    "fbLongitude" : -2.163522497
  },
  "g"    : {
    "gId"    : "ChIJ-ZU5iW-ze0gR7YewCI-…",
    "gName"  : "Mustaphs",
    "gAddress"  : "11 Castle Street, St…",
    "gCity"     : "Stockport",
    "gLatitude" : 53.4024049,
    "gLongitude": -2.1636548,
  },
  "rank" : 1.0,
}
```

(**a**)

```
{
  "f"    : {
    "id"     : 528,
    "idLink" : "bettereastmanchester",
    "fbName" : "East Manchester Leisure…",
    "fbStreet"    : "189 Grey Mare Lane",
    "fbZip"       : "M11 3ND",
    "fbCity"      : "Manchester ",
    "fbCountry"   : "",
    "fbLatitude"  : null,
    "fbLongitude" : null
  },
  "g"    : {
    "gId"    : "ChIJAdYbKW2xe0gRCVJcmIJ…",
    "gName"  : "East Manchester Leisure…",
    "gAddress"  : "189 Grey Mare Lane,…",
    "gCity"     : "Manchester",
    "gLatitude" : 53.4775529,
    "gLongitude": -2.1955198
  },
  "rank" : 1.0,
}
```

(**b**)

```
{
 "f"    : {
   "id"          : 4193,
   "idLink"      : "FoodCycle-Manchest…",
   "fbName"   : "FoodCycle Manchester",
   "fbStreet": "The Roby, 307 Dicken…",
   "fbCity"      : "Manchester",
   "fbCountry"   : "United Kingdom",
   "fbZip"       : "M13 0NG",
   "fbLatitude"  : 53.4554234,
   "fbLongitude" : -2.205004
  },
  "g"    : {
   "gId" : "ChIJ3T0-vdWze0gRBPlxJfafcnY",
   "gName"    : "FoodCycle Manchester",
   "gAddress": "307 Dickenson Road, M…",
   "gCity"    : "Manchester",
   "gLatitude"   : 53.4552679,
   "gLongitude"  : -2.205912
  },
  "rank" : 0.924720013012664
}
```

(**c**)

Figure 8. Examples of documents generated by the `FILTER` instruction on line 6. (**a**) Example for Case A. (**b**) Example for Case B. (**c**) Example for Case C.

The instruction on line 7 in Listing 3 saves the temporary collection into the `ijgiDb` database, with name `RelevantPairs`. Its documents contain the most promising pairs of descriptors (remember the *RP* set mentioned in Section 5.2), but it could happen that, e.g., the same *Google Places* descriptor is associated with more than one *Facebook* descriptor. Clearly, it is the case to choose the pair having the highest rank (i.e., building the final *SP* set mentioned in Section 5.2). This is discussed in Section 6.5.

6.5. Choosing the Best Pairs

The last part of the *J-CO-QL*$^+$ script is reported in Listing 4. It actually chooses the best pairs that involves each single *Google Places* descriptor obtained by line 6 in Listing 3. Indeed, the original *J-CO-QL* language (from which *J-CO-QL*$^+$ derives) was designed to cope with this kind of task too (see [3,4]). Hereafter, we briefly describe this last part of the script.

- The `GET COLLECTION` instruction on line 8 again obtains the `RelevantPairs` collection from the database, again making it the temporary collection.
- The `GROUP` instruction on line 9 groups documents in the temporary collection, on the basis of the `gId` field, which is the identifier of *Google Places* descriptors. For each group, a novel document is generated into the output collection, such that it has the `gId` field and an array called `gGroup`, in which all grouped documents are reported. This array is sorted in reverse order of value of the `rank` field within grouped documents. Figure 9a reports an example of the grouped document.
- The `EXPAND` instruction on line 10 unnests again all grouped documents. For each output document, the `gPair` field is added to the global ones (apart from the expanded array); this new field contains two inner fields: the `item` field contains the unnested document; the `position` field denotes the position occupied by the unnested item in the `gGroup` array.
  As a result, the temporary collection generated by line 10 contains as many documents in the `RankedPairs` collection, but now they are tagged with the relative order for *Google Places* descriptors on the basis of the `rank` field. Figure 9b reports an example of an unnested document.
- The `FILTER` instruction on line 11 actually selects only documents that previously occupied the first position in their group (based on the reverse order of `rank`, they are the ones with the highest rank). The `BUILD` section builds the same structure again, as in the `RelevantPairs` collection. Figure 9c reports an example of resulting document.
- Finally (on line 12) the last temporary collection is saved into the `ijgiDb` database with name `SamePlaces`, which is the desired output of the process.

```
{
  "g" : {
    "gId" : "ChIJH7MYbLKze0gRVIeX3GGlHFQ"
  },
  "gGroup" : [
    {
      "rank" : 1.0,
      "f" : {
        "id"          : 1773,
        "idLink"      : "TheFootparlour",
        "fbName"      : "The Footparlour",
        "fbCity"      : "Manchester",
        "fbCountry"   : "United Kingdom",
        "fbStreet"    : "448 Burnage Lane",
        "fbZip"       : "M19 1LH",
        "fbLatitude"  : 53.42517,
        "fbLongitude" : -2.20296
      },
      "g" : {
        "gId":"ChIJH7MYbLKze0gRVIeX3GGlHFQ",
        "gName"       : "The Foot Parlour",
        "gAddress"    : "448 Burnage Lan…",
        "gCity"       : "Manchester",
        "gLatitude"   : 53.4252831,
        "gLongitude"  : -2.2031884
      }
    },
    {
      "rank" : 0.810648074150466,
      "f" : {
        "id"          : 1996,
        "idLink"      : "burnageM19",
        "fbName"      : "The Food Box",
        "fbCity"      : "Manchester",
        "fbCountry"   : "United Kingdom",
        "fbStreet"    : "227 Burnage Lane",
        "fbZip"       : "M19 1FN",
        "fbLatitude"  : 53.43231411,
        "fbLongitude" : -2.200215987
      },
      "g" : {
        "gId":"ChIJH7MYbLKze0gRVIeX3GGlHFQ",
        "gName"       : "The Foot Parlour",
        "gAddress"    : "448 Burnage Lan…",
        "gCity"       : "Manchester",
        "gLatitude"   : 53.4252831,
        "gLongitude"  : -2.2031884
      }
    }
  ]
}
```

(**a**)

```
{
  "g"     : {
    "gId"  : "ChIJH7MYbLKze0gRVIeX3GGlHFQ"
  },
  "gPair"  : {
    "position": 1,
    "item"    : {
      "rank" : 1.0,
      "f"    : {
        "id"          : 1773,
        "idLink"      : "TheFootparlour",
        "fbName"      : "The Footparlour",
        "fbCity"      : "Manchester",
        "fbCountry"   : "United Kingdom",
        "fbStreet"    : "448 Burnage Lane",
        "fbZip"       : "M19 1LH",
        "fbLatitude"  : 53.42517,
        "fbLongitude" : -2.20296
      },
      "g"    : {
        "gId": "ChIJH7MYbLKze0gRVIeX3GGlHFQ",
        "gName"       : "The Foot Parlour",
        "gAddress"    : "448 Burnage Lane…",
        "gCity"       : "Manchester",
        "gLatitude"   : 53.4252831,
        "gLongitude"  : -2.2031884
      }
    }
  }
}
```

(**b**)

```
{
  "rank" : 1.0,
  "f"    : {
  "id"          : 1773,
    "idLink"      : "TheFootparlour",
    "fbName"      : "The Footparlour",
    "fbCity"      : "Manchester",
    "fbCountry"   : "United Kingdom",
    "fbStreet"    : "448 Burnage Lane",
    "fbZip"       : "M19 1LH",
    "fbLatitude"  : 53.42517,
    "fbLongitude" : -2.20296
  },
  "g"    : {
    "gId": "ChIJH7MYbLKze0gRVIeX3GGlHFQ",
    "gName"       : "The Foot Parlour",
    "gAddress"    : "448 Burnage Lane, Ma…",
    "gCity"       : "Manchester",
    "gLatitude"   : 53.4252831,
    "gLongitude"  : -2.2031884
  }
}
```

(**c**)

Figure 9. Examples of documents during selection of `BestPairs` in Listing 4. (**a**) Example of document after `GROUP` instruction on line 9. (**b**) Example of document during `EXPAND` instruction on line 10 before the `BUILD` clause. (**c**) Example of document after `EXPAND` instruction on line 10.

Listing 4. *J-CO-QL*$^+$ script: Selecting the best pairs.

```
8. GET COLLECTION RelevantPairs@ijgiDb;

9. GROUP
    PARTITION WITH .g.gId
      BY    .g.gId
      INTO .gGroup
        ORDER BY .rank TYPE NUMERIC DESC;

10. EXPAND
      UNPACK WITH .gGroup
        ARRAY  .gGroup
        TO     .gPair;

11. FILTER
      CASE WHERE WITH .gPair AND
                  .gPair.position = 1
        GENERATE
          BUILD {
            .f     : .gPair.item.f,
            .g     : .gPair.item.g,
            .rank  : .gPair.item.rank };

12. SAVE AS SamePlaces@ijgiDb;
```

7. Experimental Evaluation

In this section, we report a brief evaluation of the results that can be obtained by the *J-CO-QL*$^+$ script. We exploited the same data set adopted in [6], related with the city of Manchester (UK). Remember, from Section 6.1, that the `FacebookDescriptors` collection contains 5738 descriptors, while the `GoogleDescriptors` collection contains 5214 descriptors. Both collections contain descriptors about a variety of different public places, such as restaurants, pubs, hairdressers, universities, parks and so on.

7.1. Effectiveness

In order to evaluate the effectiveness of the method, we performed a sensitivity analysis by varying the value of the α threshold from 0.5 to 0.99.

We used the same test set again, which was used in the work [6]: it contained a total of 400 pairs, selected among the 5738×5214 total pairs, evaluated by a human as *Good* or *Bad*. We randomly selected 300 pairs from the starting 400 pairs, and from each pair we extracted the related 300 *Google Places* descriptors and 300 *Facebook* descriptors; among all possible pairs, 103 pairs were labeled as *Good* pairs (and obviously the remaining 197 were labeled as *Bad*).

Then, we run the script on these two reduced collections of descriptors. Table 1 reports the results of our experiments. Specifically, the first colum reports the single values for the alpha-cut α; the second and third columns report the number of relevant pairs saved by line 7 of the *J-CO-QL*$^+$ script (Listing 3) into the `RelevantPairs` collection and the number of pairs generated by line 12 of the script (Listing 4) and saved into the `SamePlaces` collection, respectively. The, columns from 4 to 7 reports the number TP of true positive pairs, the number TN of negative pairs, the number FP of false positive pairs and the number FN of false negative pairs, respectively. Finally, the last three columns reports "Precision" (defined as $TP/(TP+FP)$), "Recall" (defined as $TP/(TP+FN)$) and "Accuracy" (defined as $(TP+TN)/(TP+TN+FP+FN)$), respectively. These three latter values are depicted in Figure 10: the x-axis reports the values of the alpha-cut α parameter; precision is depicted by the blue line, recall is depicted by the red line and accuracy is depicted by the black line.

Analyzing Table 1 and Figure 10, it is possible to see that the best combination of values for precision, recall and accuracy were obtained for $\alpha = 0.8$: precision is 0.962, recall is 0.981 and accuracy is 0.980. Indeed, this value for α appears to be the best compromise between the need to keep as many pairs as possible and the fact that those pairs actually describe the same place, even though names, addresses and coordinates are different. The reader can further notice that higher values of α give rise to a precision of 1 with poor recall, while lower values for α give rise to a recall of 1 with poor precision. To conclude this analysis, notice that with $\alpha = 0.85$, the accuracy is the same as the one obtained for $\alpha = 0.8$; it could be considered as a valid alternative choice, with better precision but low recall.

Table 1. Sensitivity analysis.

Alpha Cut	Relevant Pairs	Same Places	TP	TN	FP	FN	Precision	Recall	Accuracy
0.50	253	163	103	137	60	0	0.632	1.000	0.800
0.55	178	139	103	161	36	0	0.741	1.000	0.880
0.60	140	124	103	176	21	0	0.831	1.000	0.930
0.65	119	112	103	188	9	0	0.920	1.000	0.970
0.70	110	108	101	190	7	2	0.935	0.981	0.970
0.75	109	107	101	191	6	2	0.944	0.981	0.973
0.80	106	105	101	193	4	2	0.962	0.981	0.980
0.85	98	97	97	197	0	6	1.000	0.942	0.980
0.90	90	90	90	197	0	13	1.000	0.874	0.957
0.95	80	80	80	197	0	23	1.000	0.777	0.923
0.99	71	71	71	197	0	32	1.000	0.689	0.893

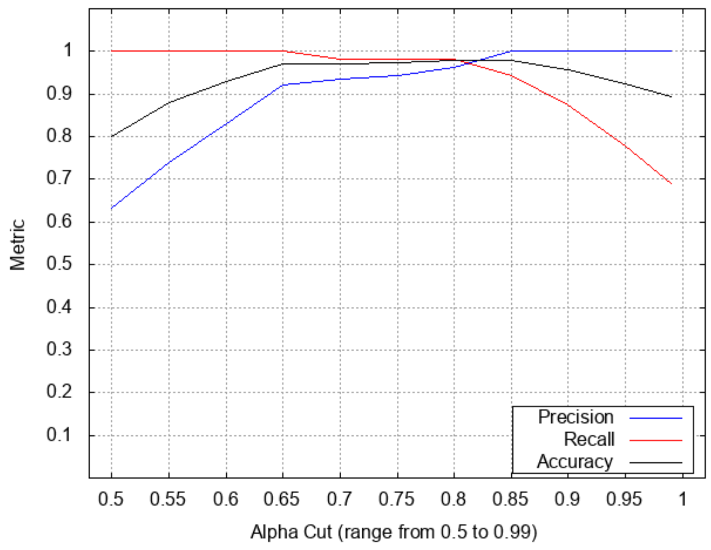


Figure 10. Sensitivity analysis of precision, recall and accuracy.

Thus, we can state that the novel formulation for the *MatchingPklaces* relation and the complex membership functions adopted for the `Similar` fuzzy operator and for the `Close` fuzzy operator are effective, provided that $\alpha = 0.8$.

We can consider the results reported in [6] as a baseline for further evaluating the effectiveness of the novel formulation of the technique.

Remember that the version presented in [6] (for online aggregation) performed pre-processing tasks on names and addresses, so as to clean them from urban designations and numbers. In contrast, the present version does not. The main reason is that such a kind of pre-processing and cleaning is not easy to do within *J-CO-QL*$^+$ scripts; however, the flexibility of the `CREATE FUZZY OPERATOR` statement as far as the possibility to define complex shapes for membership functions seems to be effective. Consequently, the proper baseline to consider is the best result presented in [6]. There, a comparison with a machine-learning technique, namely "Random Forest" classification, was performed, by applying it on the same data set. Results are reported in Table 2: for the three considered techniques, precision, recall and F1-score (defined as $2 \times (precision \times recall)/(precision + recall)$) are reported. Notice that in [6], the proposed technique was as effective as random-forest classifiers; the current version outperform them, even though names and addresses are neither pre-processed nor cleaned. Observe that the old version of the fuzzy technique and the Random-Forest technique, applied on the data set describing public places in Manchester (UK), obtain the same identical effectiveness; this is why [6] states that the two techniques are comparable.

Table 2. Comparison with experimental results presented in [6].

Technique	Precision	Recall	F1-Score
Current version	0.962	0.981	0.971
Best of [6]	0.931	0.931	0.931
Random Forest (from [6])	0.931	0.931	0.931

Consequently, we can say that the current version improves the old one and is suitable to be executed as a *J-CO-QL*$^+$ script. Furthermore, it still maintains the advantage provided by the old version in comparison with classification techniques, i.e., it can be applied from scratch, without knowing the data set; in contrast, classification techniques ask for a training step on previously labeled training sets, which is a time-consuming and critical activity.

7.2. About Execution Times

Before concluding this work, we report some considerations about execution times.

Usually, this aspect is not considered in the literature about integration of geographical data sets: authors were focused on the effectiveness of the proposed techniques, but did not consider efficiency. However, in our opinion, this is not a negligible aspect for the practical use of integration techniques, in particular with large data sets to integrate.

In this paper, the goal is neither to provide the most efficient technique, nor to evaluate execution times of a plethora of techniques proposed in the literature. Here, the goal is to observe "what to expect" while running the *J-CO-QL*$^+$ script on a real data set, such as the one we used for our experiments.

We decided to consider a working environment that could be a common situation: analysts are equipped with stand-alone PCs, on which they perform their daily activities. On these PCs, they might have a running instance of *MongoDB*, which stores their data sets about geographical places, as well as an installation of the *J-CO* Framework; indeed, not necessarily analysts are equipped with super-computers. Consequently, we run experiments on a laptop PC powered by an Intel quad-Core i7-8550-U processor, running at 1.80 GHz, equipped with 16 GB RAM and 250 GB Solid-State Drive and running the Java Virtual Machine version 1.8.0_251 (the *J-CO-QL*$^+$ *Engine* is written in the Java programming language).

Table 3 reports the execution times of the script discussed in this paper. We used the full data set reporting descriptors of public places located in Manchester (UK). Remember that it contains 5738 *Facebook* descriptors and 5214 *Google* descriptors.

Table 3 reports the execution times observed for each single instruction in the script; the right-most column reports the cumulative execution time after each instruction. Clearly, the overall execution time is dominated by the `JOIN OF COLLECTIONS` instruction, which actually builds $5738 \times 5214 = 29,917,932$ pairs of descriptors; it takes 216.61 s. Looking at the other instructions they contribute only less than 4 s, so that the overall execution time is 220.804 s, i.e., about 3.6 min.

In terms of user perception, waiting for about 3 min is acceptable in this context, in which near-real time performances are not expected. Furthermore, we want to remark that once the two data sets to integrate are available, the *J-CO-QL*$^+$ script can be applied from scratch, and a few minutes later the integrated data set is obtained. This is an incredible advantage if compared with the adoption of classification techniques, because there is no need to build training sets labeled by humans; this activity can take from several hours to several days (depending on the size of the training set) and is prone to errors and misunderstanding, as well as its effectiveness depends on the way the training sets are built before labeling.

Table 3. Execution times of the *J-CO-QL*$^+$ script.

N.	Instruction	Instruction Time (s)	Incremental Time (s)
1	`CREATE FUZZY OPERATOR`	0.000	0.000
2	`CREATE FUZZY OPERATOR`	0.000	0.000
3	`CREATE FUZZY OPERATOR`	0.000	0.000
4	`USE DB`	0.003	0.003
5	`JOIN OF COLLECTIONS`	216.661	216.664
6	`FILTER`	1.262	217.926
7	`SAVE AS`	0.529	218.455
8	`GET COLLECTION`	0.106	0.106
9	`GROUP`	0.035	0.141
10	`EXPAND`	1.910	2.051
11	`FILTER`	0.091	2.142
12	`SAVE AS`	0.207	2.349
Total Time (s)			220.804

8. Conclusions and Future Work

To conclude, it is time to summarize and discuss the contribution of the paper, as well as to sketch future developments.

8.1. Conclusions

This paper addresses the problem of soft integrating data sets describing public places, when these data sets are represented as *JSON* documents and are stored within a *JSON* document store. Specifically, fuzzy-set theory provides the formal framework for the integration methodology presented in the paper: the *MatchingPlaces* fuzzy relation is the core of the proposed methodology. Then, the soft integration method is applied in a practical way by means of the *J-CO* Framework: a script (or query) written in *J-CO-QL*$^+$ (the query language of the *J-CO* Framework) is written, which implements the soft integration method, by exploiting its fuzzy capabilities. This is the main contribution of the paper: showing that a novel stand-alone tool (the *J-CO* Framework), suitable for performing the soft integration of geo-tagged *JSON* data sets stored within *JSON* document stores, is now available for analysts and spatial-data engineers.

Hereafter, we would like to perform some considerations.

- The effectiveness that the script obtains is very interesting: with the value of the α threshold set to $\alpha = 0.8$, it is possible to obtain the best balance between precision and recall, which are slightly less than 100%.
- Execution times are good too: less than 4 min to perform the soft integration is absolutely acceptable (the reader can notice that writing the full script from scratch takes longer).
- The complex membership functions that it is possible to specify in fuzzy operators (see Section 6.2) were exploited to deal with bizarre behavior of the Jaro-Winkler string-similarity metric. In fact, it returns high similarity values for strings that appears to be very different (in the sense that they do not denote similar names or similar addresses). However, we experienced also the opposite behavior, i.e., two strings that were actually very similar obtained not-so-high similarity degree. The complex membership function that we defined for the `Similar` fuzzy operator allowed us to compensate this behavior.

8.2. Future Work

As future works, many activities are planned along the development of the *J-CO* Framework and its application to data integration problems.

- First of all, we are going to complete the extension of all *J-CO-QL*$^+$ statements with support for fuzzy concepts. In particular, we are going to address the problem of defining "soft aggregators" that can be applied on arrays of *JSON* documents; we will adopt the same approach followed for defining fuzzy operators.
- Various types of fuzzy sets have been proposed in the literature (for example, Intuitionistic Fuzzy Sets [44,45] and Type-2 Fuzzy Sets [46–48]. In our perspective evolution, we plan to extend *J-CO-QL*$^+$ to support multiple types of fuzzy sets simultaneously.
- Many challenges concerning integration and processing of geo-tagged data sets are arising. For example, the *GeoJSON* format [49] represents a geographical information layer as a unique, giant, *JSON* document. We conceived the idea of defining a domain-specific language for querying features within *GeoJSON* documents [50], which is translated into *J-CO-QL*$^+$ scripts. We plan to further explore this idea, by identifying other application domains and defining novel domain-specific languages to translate into *J-CO-QL*$^+$. Indeed, the idea of devising the *J-CO* Framework came out while working on an international project [51,52], in which Big Data concerning mobility had to be collected and processed.

The *J-CO* Framework is available on a public GitHub repository (https://github.com/JcoProjectTeam/JcoProjectPage, accessed on 1 September 2022).

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