Skyline Modeling and Computing over Trust RDF Data

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Abstract: Resource Description Framework (RDF) data come from various sources whose reliability is sometimes questionable. Therefore, several researchers enriched the basic RDF data model with trust information. New methods to represent and reason with trust RDF data are introduced. In this paper, we are interested in querying trust RDF data. We particularly tackle the skyline problem, which consists in extracting the most interesting trusted resources according to user-defined criteria. To this end, we first redefined the dominance relationship in the context of trust RDF data. Then, we proposed an appropriate semantics of the *trust-skyline*; the set of most interesting resources in a trust RDF dataset. Efficient methods to compute the trust-skyline are provided and compared to some existing approaches as well. Experiments led on the algorithms' implementations showed promising results.

1 INTRODUCTION

The large adoption of Semantic Web in research and industry has led to the development of a large amount of Resource Description Framework (RDF) data on the Web (Berners-Lee et al., 1998; Frauenfelder, 2009; Antoniou and vanHarmelen, 2004). However, due to te openness of the web and variety of sources in internet, the reliability of collected data is questioned. To control information trustworthiness, new metrics were introduced in RDF representation to express intention of information provider about information trust (Hartig, 2009a; Tomaszuk et al., 2012; Fionda and Greco, 2015).

To reason in presence of trust information, we need new methods to query RDF data. In this paper, we are interested in preference-based queries (Chomicki, 2002; Kiessling, 2002; Chomicki, 2011; Chomicki et al., 2013) that show motivating results to personalize and filter the massive amount of information contained in data. Skyline operator, introduced in (Börzsönyi et al., 2001) is an important kind of preference queries that returns the most interesting objects according to user-defined criteria based on the Pareto dominance operator.

The aim of this paper is to adapt the skyline operator to trust weighted RDF data. First of all, we define the dominance between such data. While this operator produces a binary result in case of certain data, in the context of trust RDF data, it produces a degree of dominance rather than a boolean (true/false) result. Then, we provide a semantics for the trust-skyline, i.e., the set of resources that are dominated by no other resource with a degree exceeding a user-defined threshold denoted α. Up to our knowledge the only work proposed in the literature to extend skyline queries over RDF data to filter the massive amount of resources among the web is the proposal of (Chen et al., 2011). However, this method does not consider trust measures and is based on the basic definition of the RDF data.

To compute the trust-skyline, we proposed a new algorithm TRDF-Skyline. This algorithm is based on properties we checked and proved over the new redefined dominance relationship. We compared the proposed method to the naive solution for computing the trust-skyline, and also with an SQL query where data were assumed to be stored in a relational table of quadruples. The experiments showed interesting results.

The rest of the paper is organized as follows: In the second section, we present our background material. In the third section we review the related work in the literature. In section 4, we introduce our new

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model, the Trust-Skyline and we show how it operates over uncertain RDF data. Then, in section 5, we illustrate our experimental study. Finally, we conclude and present some perspectives in section 6.

2 BACKGROUND MATERIAL

2.1 Trust RDF Data

RDF is a W3C framework to represent information in the Web in a meaningful (semantic) way. An RDF statement is a triple $< s,p,o >$ where s, p, and o stand for *subject*, *property* and *object* respectively. RDF describes Web resources (subject) related/characterized (property) to other resources/literals (object).

A set of RDF statements is a graph for representing Meta-Data and describing the semantics of information in a machine-accessible way. Therefore, RDF data can be thought in terms of a decentralized directed labelled graph. The edges' labels are the as "properties", also called "predicates" or "attributes". The RDF data are stored as a set of `Subject(Node)-Property(Edge)-Object(Node)` triples, often called SPO triples $< s,p,o >$ and represented graphically as illustrated in figure 1. This later is an example of a simplified RDF graph that describes relation (co-writing) between the resource "Information retrieval book" on the one hand, and "Smith Jones" and "Scott King" on the other hand. To rate the trustworthiness of an RDF information,

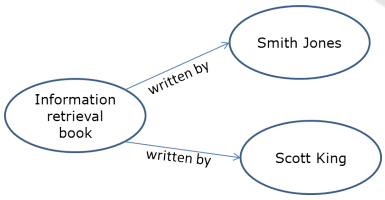


Figure 1: RDF Graph example.

Olaf Hartig introduced the trust model of RDF data in (Hartig, 2009a). He introduces the trust measure that quantifies the subjective belief/disbelief of an RDF information. Belief (disbelief) of an RDF triple is the degree of confidence in the truth (untruth) of the information. The trust RDF model was developed in several works such as (Hartig, 2009b; Tomaszuk et al., 2012; Fionda and Greco, 2015).

As mentioned above, trustworthiness of an RDF triple is represented by a trust degree. This measure, denoted t, is either unknown or a value in the interval $[-1,1]$ as shown in figure 2. If $t = 1$, the user is absolutely sure about the truth of the triple. A positive value less than 1 still represents belief in the information truth. A negative value expresses a disbelief, while $t = -1$ represents a certitude in the information untruth.

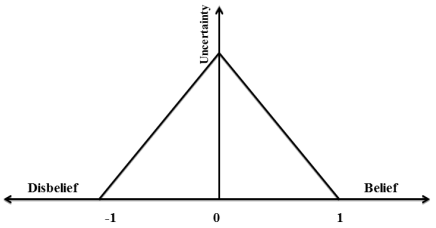


Figure 2: Meaning of trust values.

In the trust RDF model the triple $< s,p,o >$ is extended to a quadruple $< s,p,o,t >$ where the value t represents the trust degree of the triple $< s,p,o >$. We call the quadruple a "SPOT".

Definition 1. ***RDF SPOT.*** *An RDF SPOT X is a quadruple $< s,p,o,t >$, where o is a value of a predicate p related to a subject s, with a trust t. The triple $< s,p,o >$ is denoted by X^*.*

A SPOT describes a unique property of a subject. However, to compare two resources, we should consider all common properties. That is why we introduce the notion of *point* which is the set of SPOTs related to a unique resource (subject). In a multi-dimensional space, a point is characterized by several dimensions, as well as RDF resources, characterized by several properties.

Definition 2. ***Trust RDF Point.*** *A trust RDF tuple P_s is the set of SPOTs related to a unique subject s that has n properties p_i, having the values o_i and the trusts t_i with $1 \leq i \leq n$. P_s^* denotes the set of SPOs related to the subject s, i.e., without considering the trust measures.*

Example 1. *Consider the RDF data set in table 1. Four hotels are considered, each one has two properties that are "HasPrice" and "HasDistance". The quadruple $< h_1, HasPrice, 20, 0.8 >$ is a SPOT. We denote it X. Consequently, X^* is the SPO $< h_1, HasPrice, 20 >$. Let the pattern matching P be the set of SPOTs related to h_1. $P = \{< h_1, HasPrice, 20, 0.8 >, < h_1, HasDistance, 100, 0.9 >\}$. P^* is the set of SPOs related to h_1:*
$P^* = \{< h_1, HasPrice, 20 >, < h_1, HasDistance, 100 >\}$.

2.2 The Skyline Operator

The skyline operator is based on the Pareto dominance. In a set of database objects denoted by S, the

Table 1: Example of trust RDF data.

Subject	Predicate	Object	Trust
h_1	HasPrice	20	0.8
h_1	HasDistance	100	0.9
h_2	HasPrice	30	0.5
h_2	HasDistance	110	0.2
h_3	HasPrice	20	0.2
h_3	HasDistance	120	0.7
h_4	HasPrice	30	0.8
h_4	HasDistance	60	0.3

skyline consists of the objects dominated by no other object. The skyline copes with applications that involve multi-criteria decision making. It consists in finding the most interesting objects according to user-defined criteria.

Definition 3. ***Pareto Dominance.***
Let P and Q be two points in a set of points denoted O with n attributes. A point Q dominates a point P denoted by $Q \succ P$, if $\forall i \in [1, n]\ q_i \geq p_i \wedge \exists j, q_j > p_j$. The logical dominance concept between two points is modeled as follows:

$$Q \succ P = \bigwedge\Big(\bigwedge_{1 \leq i \leq n} q_i \geq p_i,\ \bigvee_{1 \leq i \leq n} q_i > p_i\Big)$$

The skyline is the set of points that are dominated by no other points. It is defined as follows:

Definition 4. ***Skyline.***
Let O be a set of points having n attributes. The skyline of O denoted by S is defined as:

$$S = \{P \in O / \nexists Q \in O, Q \succ P\}$$

Example 2. *We illustrate the well known example presented in (Börzsönyi et al., 2001). Given a list of hotels with the attributes* price *and* distance *(to the beach), we aim to find the cheapest and nearest hotels to the sea. Figure 3 illustrates the set of all hotels where each point is characterized by a price and a distance. Points in the curve represent the skyline, i.e., the set of hotels dominated by no other one according to the above-mentioned criteria (minimum distance and price).*

3 RELATED WORK

Up to our knowledge, there is no earlier work about computing skyline queries over trust RDF data. We present in this section 2 kind of works that cope at most with our concern: (1) modeling and managing uncertain RDF data, and (2) modeling and computing skyline queries over RDF data.

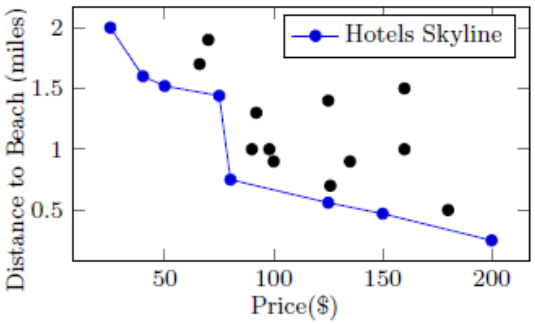


Figure 3: Hotels' prices and distances to beach (Börzsönyi et al., 2001).

Uncertainty can result from either imprecision/inaccuracy of sources or from inconsistency between them. The last two decades have witnessed a profusion of research works on this topic. There is an urgent need of a uniform way to manage uncertainty of the Web data and standardized mechanisms to evaluate data trustworthiness. (Richardson et al., 2003; Golbeck, 2006) introduced the web of trust. In (Richardson et al., 2003), authors estimate user believes in statements supplied by any other user and define properties for combination functions for merging trusts. The work of (Golbeck, 2006) copes with social networks for which authors present an approach to integrate trust, provenance and annotations in semantic web systems. Other works are based on ontologies such as (Golbeck et al., 2003) where authors investigate the applicability of social network analysis to the semantic web. They discuss the multi-dimensional networks evolving from ontological trust specifications. Olaf Hartig in (Hartig, 2009a) advocated the need of a uniform way to rate the trustworthiness of RDF Data. The author introduced a trust model that associates RDF statements with trust values. He also extended the semantics of SPARQL (the RDF query language) to manage trustworthiness of RDF data. The trust RDF model was then developed in several works such as (Hartig, 2009b; Tomaszuk et al., 2012; Fionda and Greco, 2015). In (Fionda and Greco, 2015), authors tackled the properties of the trust model related to semantic and complexity issues. Finally, in (Huang and Liu, 2009; Lian and Chen, 2011; Yuan et al., 2014) authors proposed to model uncertainty over RDF data using the probability theory.

On the other hand, the only existing work about extending skyline queries over RDF data is the proposal of (Chen et al., 2011). The authors introduced a skyline model over RDF data stored in a multiple relations way. They proposed an earlier filtering of the skyline candidate subjects using a new mechanism called the *Header Point*. The objective of the

Header Point is to maintain a concise summary of the already visited regions of the data space, and to prune a great number of subject without checking them with the whole of subjects in the RDF data set.
Although absence of works on skyline queries over uncertain RDF data, the literature is abundant on works about skyline queries over uncertain relational data, such as (Jiang et al., 2012), (Bosc et al., 2011), (Zhang et al., 2013). The extension of skyline queries over uncertain RDF has not been advocated in literature, in this paper we fill the gap.

4 TRUST-SKYLINE MODEL

In this section, we propose to extend the classic model of skyline queries to cope with the trust RDF model. We introduce the *Trust-Skyline* in which we extract the set of resources that are dominated by no other resource according to user-defined properties. As the skyline query is based on the Pareto dominance operator, we start by defining the dominance operator in the context of trust RDF data.

4.1 Trust Dominance

The dominance operator is based on comparison between the properties' values (see definition 3). In the context of certain data, the comparison between two values produces a binary result; 0 if false, and 1 if true. However, when data are uncertain, comparison is not binary. The comparison is rather quantified with a degree. For example, assume we have two SPOTs, $p_1 = (h_1,'distance',20,0.4)$ and $p_2 = (h_2,'distance',15,0.3)$. That means distance that separates hotels h_1 and h_2 from the beach are 20 with the trust 0.4, and 15 with the trust 0.3, respectively. We cannot conclude that $h_1.distance$ is greater than $h_2.distance$. We just quantify the trustworthiness of that comparison as shown in definition 5.

Definition 5. ***Comparison Trust.*** *Let a and b be two properties' values, having the trusts $Trust(a)$ and $Trust(b)$. Let λ be an arbitrary value such that $\lambda \leq -1$. Trust degree of the comparison between a and b, denoted by* ***Trust(a ϕ b)****, where the operator $\phi \in \{\leq, <, \geq, >, =, \neq\}$, is defined as follows:*

$$\textbf{\textit{Trust(a } } \phi \textbf{\textit{ b)}} = \begin{cases} min(Trust(a), Trust(b)) & if\ a \phi b = true \\ \lambda & else \end{cases}$$

In the rest of the paper, λ is arbitrary fixed to λ=-1.

We need now to define the dominance between two RDF triples. To consider the uncertain nature of the data, we adapt the Pareto dominance shown in definition 3. The logical connectors $\bigwedge$ and $\bigvee$, that represents the conjunction and disjunction of two binary comparisons, are changed to the minimum and maximum functions, respectively, to deal with the uncertain context.

Definition 6. ***Trust Dominance Degree.*** *Let P and Q be two subjects having n properties p_i and q_i, respectively with $1 \leq i \leq n$. The degree of dominance between P and Q, denoted by $d(Q \succ P)$ is defined as follows*[1]*:*

$$d(Q \succ P) = min(\min_{1 \leq i \leq n} Trust(q_i \leq p_i), \max_{1 \leq i \leq n} Trust(q_i < p_i))$$

Example 3. *We illustrate an example of two hotels h_1 and h_2, having the properties price and distance. We take four cases in order to test all scenarios between h_1 and h_2 as shown in the table2.*

Table 2: Example of hotels properties.

Hotels	case 1		case 2		case 3		case 4	
	price	distance	price	distance	price	distance	price	distance
h_1	20(0.2)	100(0.4)	20(0.6)	80(0.7)	20(0.3)	100(0.5)	20(0.3)	70(0.5)
h_2	30(0.3)	110(0.5)	25(0.3)	70(0.1)	20(0.4)	100(0.6)	25(0.4)	70(0.5)

We proceed on computing the Trust-Skyline over those cases:

- *case 1:*
  $d(h_1 \succ h_2)$= *min(min(0.2,0.4), max(0.2,0.4))=0.2*
- *case 2:*
  $d(h_1 \succ h_2)$= *min(min(0.3,-1), max(0.3,-1))=-1*
- *case 3:*
  $d(h_1 \succ h_2)$= *min(min(0.3,0.5), max(-1,-1))=-1*
- *case 4:*
  $d(h_1 \succ h_2)$= *min(min(0.3,0.5), max(0.3,-1))=0.3*

To simplify the computation of dominance degree between two triples, we introduce the concept of *trust of point*.

Definition 7. ***Trust of a Point.*** *Given an RDF point P with n properties p_i such that $1 \leq i \leq n$. Each property is associated with a trust value t_i. The trust of a point, denoted by $P.t^-$ is the minimum trust degree among all its properties.*

$$P.t^- = \min_{1 \leq i \leq n} (p_i.t)$$

The notion of *point trust* simplifies the computation of the trust dominance as presented in the following proposition.

Proposition 1. *Given two points P and Q having the trusts $Q.t^-$ and $P.t^-$.*

$$d(Q \succ P) = \begin{cases} min(Q.t^-, P.t^-) & if\ Q* \succ P* \\ -1 & else \end{cases}$$

[1]We assume in this paper, that the smaller value, the more preferable

Proof 1. *For two RDF points P and Q, $d(Q \succ P)$ is the minimum between two measures;* $\min_{1\leq i\leq n} Trust(q_i \leq p_i)$, *and* $\max_{1\leq i\leq n} Trust(q_i < p_i)$.

For the first measure($\min_{1\leq i\leq n} Trust(q_i \leq p_i)$*), we have two scenarios:*

- *if there exists any property i where $q_i \leq p_i$ is false, then the measure is equal to -1.*
- *if for each property i, $q_i \leq p_i$ is true, then the measure is equal to the smallest trust among all properties of P and Q. It is equal to $min(Q.t^-, P.t^-)$*

For the second measure($\max_{1\leq i\leq n} Trust(q_i < p_i)$*), we have two scenarios:*

- *if there exists at least one property i such that $q_i < p_i$, then the measure is equal to the greatest value between the trusts of all comparisons $q_i < p_i$ that return true.*
- *if there is no property i such that $q_i \leq p_i$ is true, then the measure is equal to -1.*

The scenarios above are combined in the table 3. The only case that returns a value different from λ *occurs when $\forall i, q_i \leq p_i$ and $\exists i, q_i < p_i$. In this case, we return:*
$min(\min_{1\leq i\leq n} Trust(q_i \leq p_i), \max_{1\leq i\leq n} Trust(q_i < p_i))$.
We are sure that $\min_{1\leq i\leq n} Trust(q_i \leq p_i)$ *is less or equal than* $\max_{1\leq i\leq n} Trust(q_i < p_i)$.
Hence, the measure $\min_{1\leq i\leq n} Trust(q_i \leq p_i)$ *returns the minimal trust among all properties' values of P and Q (see definition 5), that is simply $min(P.t^-, Q.t^-)$. The case where $\forall i, q_i \leq p_i$ and $\exists i, q_i < p_i$, corresponds in fact to $Q^* \succ P^*$. In this case, $d(Q \succ P)$ is equal to the smallest trust among all properties' trusts of P and Q (see definitions 6 and 7), which is the minimum value between $Q.t^-$ and $P.t^-$.*

Table 3: Dominance degree function.

	$\exists i, q_i < p_i$	$\nexists i, q_i < p_i$
$\forall i, q_i \leq p_i$	$min(\min_{1\leq i\leq n} Trust(q_i \leq p_i), \max_{1\leq i\leq n} Trust(q_i < p_i))$	-1
$\exists i, q_i > p_i$	-1	-1

Example 4. *If we take the same cases shown in example 3 using proposition 1, we obtain:*

- *case 1: $h_1^* \succ h_2^*$ then $d(h_1 \succ h_2) = min(Q.t^-, P.t^-) = min(0.2, 0.3) = 0.2$*
- *case 2: $h_1^* \not\succ h_2^*$ then $d(h_1 \succ h_2)$=-1*
- *case 3: $h_1^* \not\succ h_2^*$ then $d(h_1 \succ h_2)$=-1*
- *case 4: $h_1^* \succ h_2^*$ then $d(h_1 \succ h_2) = min(Q.t^-, P.t^-) = min(0.3, 0.4) = 0.3$*

Note that we obtain same results of example 3.

Proposition 2. *The trust dominance is transitive. Given two RDF triples P and Q, and a threshold* $\alpha \in [-1, 1]$

$$if\ d(R \succ Q) > \alpha\ and\ d(Q \succ P) > \alpha; - \longrightarrow d(R \succ P) > \alpha$$

Proof 2. *$d(R \succ Q) > \alpha$ and $d(Q \succ P) > \alpha$ (1)*
$d(R \succ Q) = min(R.t^-, Q.t^-)$ and $d(Q \succ P) = min(Q.t^-, P.t^-)$ (2)
(1) and (2) imply $min(R.t^-, Q.t^-) > \alpha$ and $min(Q.t^-, P.t^-) > \alpha$ (3)
(3) implies $min(R.t^-, Q.t^-, P.t^-) > \alpha$ (4)
(4) implies $d(R \succ P) > \alpha$

Proposition 3. *The trust dominance is asymmetric. Given two RDF triples P and Q, and a threshold* $\alpha \in [-1, 1]$
$d(Q \succ P) > \alpha$ Then $d(P \succ Q) = -1$

Proof 3. *$d(Q \succ P) > \alpha \longrightarrow Q^* \succ P^*$*
$Q^* \succ P^* \longrightarrow P^* \not\succ Q^*$
$P^* \not\succ Q^* \longrightarrow d(P \succ Q) = -1$

4.2 Trust-Skyline Model

In (Börzsönyi et al., 2001), skyline is defined as the set of database objects dominated by no other object. In such perfect context, dominance is binary. However, in context of trust RDF data (Hartig, 2009a), dominance has a degree in [-1, 1]. Thus, skyline is defined as the set of points dominated by no other point according to a trust threshold α.

Definition 8. ***Trust-Skyline.*** *The T-Skyline of a data set D, denoted by $T - Sky^\alpha$, contains each point P in D such there is no point Q that dominates P with a trust degree greater than a user defined threshold* $\alpha \in [-1, 1]$.

$$T - sky^\alpha = \{P \in D / \nexists Q \in D, d(Q \succ P) \geq \alpha\}$$

Example 5. *We illustrate the example of five hotels, with two properties each one (Price and Distance). For each property we specify a trust degree to describe the data trustworthiness.*

Table 4: Example of hotels candidate list of T-Sky.

Hotel	Price	Distance
h_1	23 (0.5)	5 (0.3)
h_2	50 (0.2)	4 (0.6)
h_3	50 (0.7)	3 (0.5)
h_4	40 (0.1)	1 (0.3)
h_5	50 (0.6)	2 (0.4)

We want to compute the T-Skyline of the above RDF data set when α is fixed to 0.1.

- *h_1 dominates h_2 with a degree equal to 0.2 ($\geq \alpha$). As the trust-dominance is asymetric h_2 does not dominate h_1. We conclude that h_2 could not integrate the skyline. We prune it.*
- *$d(h_1 \succ h_3) = 0.3$, thus h_3 is also pruned.*

- $d(h_1 \succ h_4) = -1$ *and* $d(h_4 \succ h_1) = -1$. *We make no pruning.*
- $d(h_1 \succ h_5) = 0.3$. h_5 *is pruned.*

We conclude that the Trust-Skyline list includes h_1 *and* h_4 *which are dominated by no other point.*

Remark in example 5 that some points could enter the trust-Skyline directly without comparing them with other ones. Indeed, if the trust of a point P (see definition 7) is less than the trust threshold α, then we conclude directly that P is in the skyline because we are sure there is no other point Q able to dominate it with a degree greater than α, even if $Q^* \succ P^*$.

Proposition 4. . *Given a data set D and its T-Skyline* $T - Sky^{\alpha}$ *and a point* $P \in D$. *If* $P.t^- < \alpha$ *then* $P \in T - Sky^{\alpha}$.

Proof 4. . *If* $P.t^- < \alpha$, *then we are sure there exists no point* $Q \in D$ *such that* $d(Q \succ P) \geq \alpha$ *since* $d(Q \succ P) is equal to min(Q.t^-, P.t^-) or -1$. *In this case, (there is no* $Q \in D$ *such that* $d(Q \succ P) \geq \alpha$*), we are sure that* $P \in T - Sky^{\alpha}$.

4.3 Trust-Skyline Computation

In order to compute the Trust-Skyline, we introduced two algorithms; the Naive T-Skyline algorithm and the TRDF-Skyline algorithm. In addition, for an evaluation matter, we present a non-native solution that consists in representing trust-RDF data in relational table and then extract the trust-Skyline using SQL.

In the next subsection, we show how the Trust-Skyline can be implemented on a relational database using an SQL query. We illustrate in table 5 the stored functions used in the query.

4.3.1 Extracting Trust-Skyline through SQL

Trust RDF data could be stored in a relational table as quadruplets (table 1 is an example). To implement our SQL method, we created a table named T_{RDF} with four attributes; s for Subject, p for Predicate, o for Object and t for Trust (SPOT). As the comparison between objects is not binary, we implemented two specific comparison operators to deal with the uncertain context; the *less* and *lessorequal* functions which return a degree between -1 and 1. The two functions are described in table5.

Below is the SQL query that returns the trust-skyline of the table T_{RDF} according to the threshold α. This latter selects each subject A such there is no subject B dominating A. B dominates A if two conditions are satisfied. First, there exists no predicate whose value for A is better or equal than its value for B. And second, it exists at least one

Table 5: Used functions Meaning.

less(v_1,v_2)	returns the least trust degree between two points $v1$ and $v2$ if $v1 < v2$
lessorequal(v_1,v_2)	returns the least trust degree between two points $v1$ and $v2$ if $v1 \leq v2$

predicate whose value for A is strictly better than its value for B. We recall here that the smaller values, the more preferable are, hence the use of functions *less* and *lessorequal*.

```
SELECT DISTINCT s FROM T_RDF A WHERE NOT EXISTS(
  SELECT * FROM T_RDF B WHERE B.s= A.s AND NOT EXISTS(
   SELECT * FROM T_RDF C WHERE C.s= A.s AND NOT EXISTS(
    SELECT * FROM T_RDF D WHERE D.s= B.s AND C.p= D.p
              AND lessorequal(D.o, D.t, C.o, C.t)>=&α))
  AND EXISTS
   (SELECT * FROM T_RDF E WHERE E.s=A.s AND EXISTS(
    SELECT * FROM T_RDF F WHERE F.s=B.s AND F.p= E.p
              AND less( F.o, F.t, E .o, E.t)>=&α)));
```

We present below the SQL code of the functions **less** and **lessorequal**.

```
    CREATE OR REPLACE FUNCTION less(v1 IN NUMBER, t1
NUMBER, v2 IN NUMBER, t2 NUMBER) RETURN NUMBER IS
    inferior NUMBER := -1;
    BEGIN
        IF (v1<v2) THEN
            inferior := least(t1,t2);
        END IF;
        RETURN inferior;
    END;
```

```
CREATE OR REPLACE FUNCTION lessorequal(v1 IN NUMBER, t1
NUMBER, v2 IN NUMBER, t2 NUMBER) RETURN NUMBER IS
    inferior NUMBER := -1;
    BEGIN
        IF (v1<=v2) THEN
            inferior := least(t1,t2);
        END IF;
        RETURN inferior;
    END;
```

4.3.2 Naive T-Skyline Algorithm

A naive approach to solve the problem of extracting the trust skyline, is to compare each pair of points. When a point is dominated, it is rejected. Only points that are dominated by no other points in the data set are kept in the trust skyline.

Based on proposition 4, we optimized the naive method by adding directly all points which trusts are less or equal to the threshold α. These points could not be dominated with a degree greater than α. Note that Complexity of this method is $O(n^2)$.

Based on the same example presented on the table 4 we proceed on modifying α to check its influence on the Skyline resulting list. If we choose α = 0.1,

each point that could be a part of the T-Skyline should be dominated by no other point with a degree greater than 0.1. The T-Skyline result list is $\{h_1,h_4\}$. If we increase α, points with trust measure inferior than α are in the Skyline because no other point could dominate them over this degree. The trust degree α has a big influence on computing the T-Skyline resulting list. Therefore, we used this measure in our Naive T-Skyline algorithm to make an earlier filtering of the candidate list.

Algorithm 1: The Naive T-Skyline Algorithm.

```
1: INPUT: n RDF triples.
2: OUTPUT: TSky Trust-Skyline points.
3: for each point P ∈ DB P do
4:       SKY= true;
5:       if P.t⁻ < α then
6:       Add P to TSky
7:       else
8:       for each point Q ∈ DB such that Q ≠ P do
9:         if (dominates(Q,P)=> α) then /*Using function
   dominates*/
10:            SKY=false;
11:            Break;
12:          end if
13:       end for
14:       if(SKY=true) then
15:          Add P to TSky
16:       end if
17: end for
```

4.3.3 TRDF-Skyline Algorithm

TRDF-Skyline is a new algorithm that uses, in addition to the optimization (based on property 4) in the naive T-Skyline method, a second optimization based on the transitivity property (proposition 2). Indeed, we are not obliged to compare all the pairs of points. If a point U dominates a point W, then W is eliminated and U is added to the trust skyline. Then, when we find that a point Z dominates U, then U is eliminated and Z is added to the skyline. Here the comparison between Z and W in useless because W cannot dominate U. We even know that Z dominates W thanks to the transitivity property ($U \succ W$ and $Z \succ U$ implies $Z \succ W$).

Even if the complexity of this method is $O(n^2)$, we are sure we pruned useless points thanks to the transitivity property. Algorithm of the TRDF-Skyline method is presented below.

Algorithm 2: The TRDF-Skyline Algorithm.

```
1: NPUT: n RDF triples.
2: OUTPUT: TSky Trust-Skyline points.
3: for each point P ∈ DB do
4:       if P.t⁻ < α then
5:        Add P to TSky
6:       else
7:        inSKY=true;
8:        for each point Q ∈ TSky, Q ≠ P do
9:         if (dominates(P,Q)=> α) then
10:          Remove (Q) from TSky
11:        else if (dominates(Q,P)=> α) then
12:          inSKY=false;
13:          Break;
14:        end if
15:       end for
16:       if (inSKY=true) then
17:        Add P to TSky
18:       end if
19: end for
```

5 EXPERIMENTAL EVALUATION

In this section, we evaluate the methods introduced in subsection 4.3, which are exact methods. That's why evaluation doesn't cope with the output quality. Indeed, the produced skyline is exactly the same regardless of the used method. Consequently, the experiments we led were about (1) the performance of the methods (time execution), and (2) the size of the skyline (readability of the result). For each measure, we varied (1) the trust threshold, (2) the size of the database and (3) the number of properties in the skyline query. The idea is to understand the effects of these parameters on the execution time and the resulted skyline.

5.1 Experimental Setup

Due to the lack of trust RDF databases, we generated synthetic data sets according to the parameters in table 6. For each experiment, we vary one parameter and set the others to the default values ()referred in the above-mentioned table). Note that data are generated following the uniform law. We used the triple storage approach (Sakr and Al-Naymat, 2009), extended to a quadruple format to deal with the trust measure. The data generator and the algorithms 2 and 1 were implemented in Java. The SQL query were implemented under Oracle 11g. Stored functions were implemented using PL/SQL. All experiments were conducted under Windows 7 on a 2.10 GHz Intel Core Duo processor computer with 4GB of RAM.

Table 6: Parameters under investigation.

Symbol	Parameter	Default
P	Number of properties	6
D	Number of quadruples	300 K
T	Size of T-Skyline data	-
α	Trust measure	0.2
X	Time execution (ms)	-

5.2 Impact of the Trust Threshold Variation

As we presented previously in this paper, we defined the Trust-Skyline as the set of points dominated by no other point according to a trust threshold α. In this experiment, we varied α in order to measure its impact on the execution time and on the trust skyline, as shown in figure 4.

When α has a great value, the two methods perform quickly (figure 4(a)). This is due to the fact that points' trusts are more probably less than α, and thus enter directly to the skyline without processing. In this case, thanks to proposition 4, the search space is considerably pruned. Size of the trust skyline (figure 4(b)) is important, because it is rare to check a dominance between two points, according to a threshold whose value is important. If there is rare dominance between points, then we obtain a great number of skyline points.

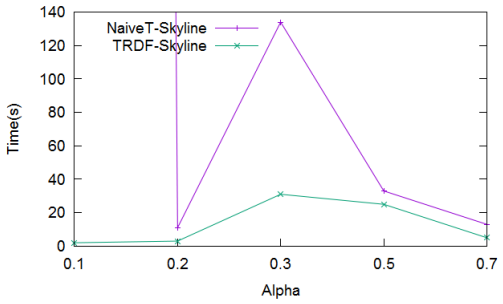
On the other hand, when α has a small value, several points are dominated and so do not enter to the skyline. That is why skyline size is small in this case. The Naive T-Skyline do not benefit from the proposition 4 pruning method, and execution time is very important. However, for TRDF-skyline, execution time is very acceptable, since pruning based on the transitivity property is always efficient and doesn't depend from α.

For the SQL query, with a database of 6k tuples the execution time exceeds 12.10^3 ms. SQL query is logically costly since we do not use a native environment, and we don't optimize computation as in the other methods. The SQL query compare all the points' pairs in the database.

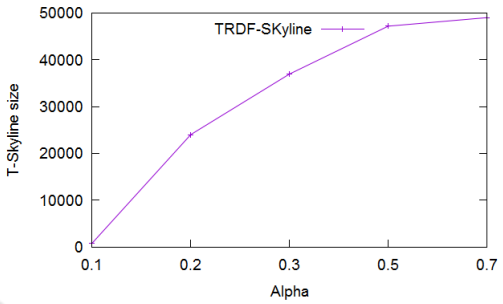
5.3 Size of the Data Set

In this experiment, we study the impact of the data size on the performance and size of the trust skyline. We varied the input data size from 100k, to 500k tuples as shown in figure 5. Figure 5 depicts a comparison between our two algorithms. As in the previous experiment, TRDF-Skyline algorithm performs better than the Naive Trust-Skyline algorithm. When the data size reaches 300k, the execution time of the Naive T-Skyline becomes exponential. At 500k it exceeded 223s, for the TRDF-Skyline it does not exceed 50s. The execution time of the SQL query is the worst, it is very high over a size greater than 12K.

When data set are very huge, we think that distributed methods are recommended. Since Pareto dominance is transitive, data set could be divided, extraction of trust-Skyline is computed in parallel, and then a smart fusion of the results is operated. An interesting perspective of this work is to model and implement distributed methods to extract trust-Skyline.



(a) Effect on time execution



(b) Effect on skyline size

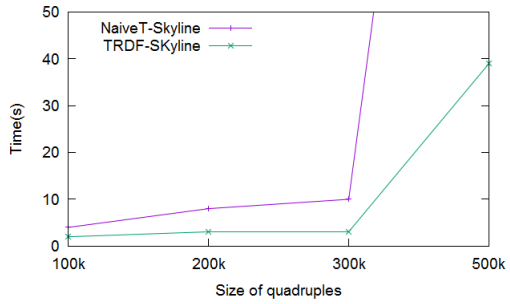
Figure 4: Effect of α on skyline computation.

5.4 Number of Properties in the Skyline Query

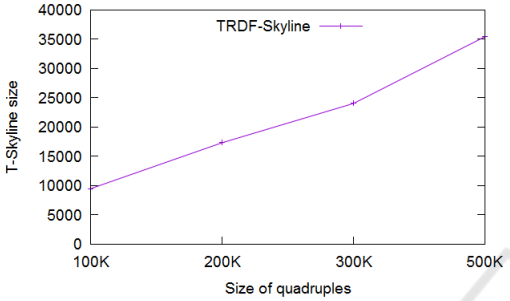
In this experiment, we study the effect of properties (criteria) number in the skyline query over the result computation. For this purpose, we increased the number of skyline query's properties as shown in figure 6. The trust skyline size increased with the increase of P (see figure 6(b)), because a subject has more chance to be not dominated when comparison copes with a high number of criteria. Figure 6(a) shows again the performance of the TRDF-Skyline that takes advantage from the transitivity property. The naive algorithm, even worst, outperforms the SQL query which compares all pairs of points, without pruning using the property 4.

6 CONCLUSION

In this paper, we proposed an extension of the skyline to the context of trust RDF data. A new variant of the skyline, called the trust-Skyline is introduced. To this end, semantics of Pareto dominance relationship and (traditional) skyline were redefined.

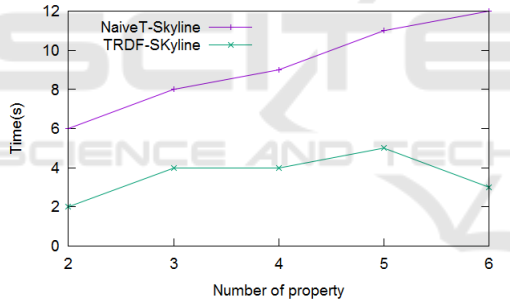


(a) Effect on time execution

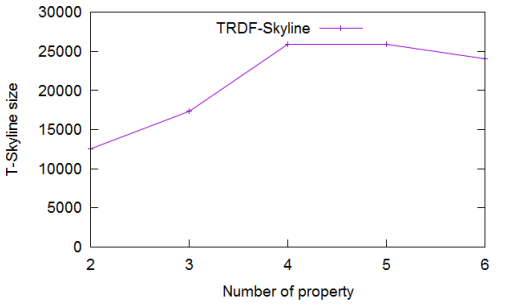


(b) Effect on skyline size

Figure 5: Effect of data size on skyline computation.



(a) Effect on time execution



(b) Effect on skyline size

Figure 6: Effect of criteria number on skyline computation.

To compute the trust-Skyline, we implemented two algorithms that take into account the trust measures to compute the trust-Skyline set. The Naive T-Skyline algorithm that uses points' trust degrees to make an early filtering of data. And the TRDF-Skyline algorithm that is optimized based on the transitivity property of the trust dominance operator. We also presented an SQL query to show how Trust-Skyline can be implemented on a relational database system.

Our experiments showed the efficiency of the TRDF-Skyline algorithm. The naive T-Skyline method is acceptable if the input data size is not huge and if the trust threshold is medium or high. However, the SQL query showed very limited performance.

As future work, two points attracted our attention. First, performance of all methods decreases when data set are voluminous. We think that distributed methods could perform better in this case. The transitivity property of the dominance operator encourage such solution. Second, when the trust threshold has an important value, the trust-Skyline size increases considerably. If the skyline is huge, our objective of filtering the initial data set to present only the most interesting points is not reached. In this case, we need a second analysis to refine the initial result (skyline). A top-k trust skyline query could be a promising solution.

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