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Local Ontology Algorithm Using Local Spectral Method

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***Abstract*—**Ontology is an important topic in computer science. It has many applications in various fields. Ontology similarity computation plays a critical role in practical implementations. In some applications, however, ontology graphs that arise have certain local regions of interest, and the traditional spectral method will typically fail to provide information fine-tuned to every local region. In this paper, we use the locally-biased spectral method for ontology similarity computation and ontology mapping. The new ontology algorithm is given by Localspectral Optimization Program. At last, two experiments results show that the proposed algorithm has high accuracy and efficiency for similarity calculation and ontology mapping.

***Index Terms*—**ontology, computer network, information retrieval, search extension, spectral graph, local spectral algorithm, Laplacian matrix

I. INTRODUCTION

In information retrieval, ontology has been used to compute semantic similarity (see [1]) and search extensions for concepts. Every vertex on an ontology graph represents a concept; a user searches for a concept A, will return similarities concepts of A as search extensions. Let G be a graph corresponding to ontology O, the goal of ontology similarity measure is to approach a similarity function which maps each pair of vertices to a real number. Choose the parameter $M \in \mathbb{R}^+$, the concepts A and B have high similarity if Sim(A,B)>M. Choose the parameter $M \in \mathbb{R}^+$, let A,B be two concepts on ontology and Sim(A,B)>M, then return B as retrieval expand when search concept A. Therefore, the quality of similarity functions plays an important role in such applications. Moreover, ontology is also used in image retrieval (see [2-5]) in networks. Some effective methods for ontology similarity measure can be found in [6-11].

Let graphs G_1, G_2, …, G_k corresponding to ontologies O_1, O_2,…, O_k, respectively, and $G=G_1+G_2+\ldots+G_k$. For every vertex $v \in V(G_i)$, where $1 \le i \le k$, the goal of ontology mapping is finding similarity vertices from G-G_i. So, the ontology mapping problem is also ontology similarity measure problem. Choose the parameter $M \in [0,1]$, let A,B are two concepts on ontology and Sim(A,B)>M, then return B as retrieval expand when search concept A. So, the ontology mapping problem is also ontology similarity measure problem. Thus, the key trick for ontology similarity measure and ontology mapping is to find the best similarity function f: $V \times V \to \mathbb{R}^+ \cup \{0\}$, which maps each pair of vertices to a non-negative real number.

The common methods to design similarity functions for ontology applications are from the structure feature of ontology graph.

Example. Let $0 < \alpha, \beta, \gamma, \chi < 1$ be real numbers and $\alpha + \beta + \gamma + \chi = 1$. The similarity function can be represented as the weighting sum of their name similarity, structure similarity, instance similarly and attribute similarity:

$$Sim(A,B) = \alpha\, Sim_{\text{name}}(A,B) + \beta\, Sim_{\text{structe}}(A,B) + \gamma\, Sim_{\text{instance}}(A,B) + \chi\, Sim_{\text{attribute}}(A,B),$$

where each part of partial similarity is measured by name set, structure feature of ontology graph, instance set and attribute set of two vertices, respectively. Thus, each partial similarity function may have complex formula and expression. Such methods have high computation complex and there are lots of parameters need to be chosen.

In recent years, the ontology problem has gained attention in machine learning. In such ontology algorithm, one learns a real-valued function that assigns scores to instances. What is important is the relative list of vertices induced by those scores. One method is to use the second eigenvalue of the Laplacian matrix and its associated eigenvector are fundamental features of an ontology graph (see [12] and [13]).

An obvious potential drawback for using the second eigenvalue and its associated eigenvector is that they are natural global ontology concern, and thus they may not be responding to ontology subgraph with local information. Thus, relay on domain knowledge we might have specific target region information in the ontology subgraph, in which case we only interested in finding clusters near such pre-specified local region for ontology subgraph; but

this local ontology region might be naturally invisible to a trick that uses only global eigenvectors. For such reasons, standard global spectral techniques can have substantial difficulties in local ontology applications, where the goal is to learn more about a locally-biased target region of the ontology graph.

In [14], Mahoney et. al., provided a methodology to construct a locally-biased analogue of the second eigenvalue and its associated eigenvector, and demonstrated both theoretically and empirically that this localized vector inherits many of the good properties of the global second eigenvector.

In this paper, we propose the local ontology algorithm for ontology similarity measure and ontology mapping. Via the Localspectral Optimization Algorithm, the ontology graph is mapped into a line consists of real numbers. The similarity between two concepts then can be measured by comparing the difference between their corresponding real numbers. Two experimental results show that the proposed algorithm has high accuracy and efficiency both on ontology similarity calculation and ontology mapping.

II. SETTING

Let $G=(V,E,w)$ be a otology graph with $|V| = n$ vertices and $|E| = m$ edges. Each edge v_iv_j has weight w_{ij}. Let $A_G \in \mathbb{R}^{V\times V}$ be the adjacency matrix of ontology graph G, and $D_G \in \mathbb{R}^{V\times V}$ denoted as the diagonal degree matrix of G, i.e., $D_G(i,i)=d_i=\sum_{\{i,j\}\in E} w_{ij}$, the weighted degree of vertex i. The Laplacian of ontology graph G is stated as $L_G = D_G - A_G$.

Clearly, L_G is a symmetric matrix with standard quadratic form

$$x^T L_G x = \frac{1}{2}\sum_{ij\in E} w_{ij}(x_i - x_j)^2 ,$$

for each $x \in \mathbb{R}^V$. This implies that L_G is positive semi-definite matrix and $\mathbf{1} \in \mathbb{R}^V$ is the eigenvector corresponding to the smallest eigenvalue 0. Moreover, for a given matrix A, we use A^+ to denote its uniquely defined Moore-Penrose pseudo-inverse.

The degree-weighted inner product for any two vectors $x, y \in \mathbb{R}^n$ defined as

$$x^T D_G y = \sum_{i=1}^{n} x_i y_i d_i .$$

For a fixed subset of vertices $S \subseteq V$, $\mathbf{1}_S$ is denoted as the indicator vector of S in $\mathbb{R}^V$ and by 1 the vector in $\mathbb{R}^V$ having all entries set equal to 1.

I. THE LOCALSPECTRAL OPTIMIZATION PROGRAM

The local spectral optimization algorithm LocalSpectral(G,s,k) as a strengthening of the standard global spectral algorithm Spectral(G) was raised by Mahoney [14].

The standard second eigenvalue $\lambda_2(G)$ of the Laplacian L_G can be regarded as the optimum of the standard optimization problem Spectral(G) which can be described as follows:

$$\begin{aligned} \min \quad & x^T L_G x \\ \text{s.t.} \quad & x^T D_G x = 1 \\ & (x^T D_G \mathbf{1})^2 = 0 \\ & x \in \mathbb{R}^V \end{aligned}$$

In matrix notation, the corresponding optimal solution v_2 is a generalized eigenvector of L_G with respect to D_G. In order to consider the geometric meaning of this optimization formulation, suppose that we are dealing with in a vector space $\mathbb{R}^V$, where the ith dimension is stretched by a factor of d_i and the natural identity operator is D_G, the inner product between two vectors x and y is given by $\sum_{i\in V} d_i x_i y_i = x^T D_G y$. In this setting, Spectral(G) is seeking for vector $x \in \mathbb{R}^V$ which is orthogonal to the vector **1**, lies on the unit sphere, and minimizes the standard Laplacian quadratic form.

Mahoney et. al. [14] modified Spectral(G) to incorporate a bias towards a target region which we assume is given to us as an input vector s. In the following paper, we refer to s as the seed vector and to κ as the correlation parameter for a given LocalSpectral(G, s, κ) optimization problem. Moreover, we denote the objective value of the program LocalSpectral(G, s, κ) by the $\lambda(G,s,\kappa)$. It can be used in ontology application. W.l.o.g., assume s is properly orthogonalized and normalized such that $x^T D_G \mathbf{1} = 0$ and $x^T D_G s = 1$. While s is regarded as the indicator vector of vertices for certain sub-graph of ontology graph, which corresponding to the target region of the ontology graph. By [14], we obtain $\lambda(G,s,\kappa)$ from Spectral(G) by requiring that a feasible solution also have a sufficiently large correlation with the vector s. It is obtained by the addition of the constraint $(x^T D_G s)^2 \geq \kappa$, which implies the absolute value of projection of x onto the direction s is at least $\sqrt{\kappa}$, where the parameter $\kappa \in [0,1]$ is also an input parameter. Therefore, the solution is well-connected with or to lie near the seed vector s. Conclusion, the local optimization problem $\lambda(G,s,\kappa)$ can be described as follows:

$$\begin{aligned} \min \quad & x^T L_G x \\ \text{s.t.} \quad & x^T D_G x = 1 \\ & (x^T D_G \mathbf{1})^2 = 0 \\ & (x^T D_G s)^2 \geq \kappa \\ & x \in \mathbb{R}^V \end{aligned}$$

III THEORETIC SUPPORT

In this section, we show two theorems gave by [14], which are theoretic support for ontology application.

First result states that solutions to LocalSpectral can be showed as the solution to a system of linear equations which has a natural interpretation. This is a characterization of the optimal solutions of it.

Theorem 1 (Solution Characterization) [14] *Let* $s \in \mathbb{R}^V$ *be a seed vector such that* $s^T D_G 1=0$, $s^T D_G s = 1$, *and* $s^T D_G v_2 \neq 0$, *where* v_2 *is the second generalized eigenvector of* L_G *with respect to* D_G. *In addition, let* $1 > \kappa \geq 0$ *be a correlation parameter, and let* $x^\star$ *be an optimal solution to* LocalSpectral(G, s, κ). *Then, there exists some* $\gamma \in (-\infty, \lambda_2(G)$ *and a* $c \in [0, \infty]$ *such that*

$x^\star = c(L_G - \gamma D_G)^+ D_G s$.

Note: in Theorem 1, there are several parameters, such as s, κ, g, and c. [14] stated their relationship as follows: s and κ are the program parameters; c is a normalization factor that rescales the norm of the solution vector to be **1**; and g is implicitly defined by κ, G, and s. The correct setting of γ satisfies $(s^T D_G x^*)^2 = \kappa$, i.e., $x^\star$ is found exactly on the boundary of the feasible ontology region. From this point of view, the behavior of $x^\star$ and γ as κ changes.

$\lim_{\kappa \to 1} \gamma \to -\infty$,

$\lim_{\kappa \to 1} x^* \to s$,

$\lim_{\kappa \to 0} \gamma \to \lambda_2(G)$,

$\lim_{\kappa \to 0} x^* \to v_2$.

For a given choice of the parameters G, s, and κ. On how to compute an optimal solution for $\lambda(G, s, \kappa)$ efficiently, the theorem stated as follows:

Theorem 2 (Solution Computation) [14] *For any* $\varepsilon > 0$, *a solution to* LocalSpectral(G, s, κ) *of value at most* $(1+\varepsilon)\lambda(G, s, \kappa)$ *can be computed in time* $\tilde{O}(m/\sqrt{\lambda_2(G)} \cdot \log(1/\varepsilon))$ *using the Conjugate Gradient Method (Golub and Loan, [15]). Alternatively, such a solution can be computed in time* $\tilde{O}(m \log(1/\varepsilon))$ *using the Spielman-Teng linear-equation solver (Spielman and Teng, [16]).*

IV. ALGORITHM DESIGN

A. Ontology Similarity Measure Design

The new learning algorithm can be used in ontology concept similarity measure. The based idea is that: Via the ontology learning algorithm, the ontology graph is mapped into a line consisting of real numbers. The similarity between two concepts then can be measured by comparing the difference between their corresponding real numbers.

For $v \in V(G)$. We use the one of following methods to obtain the similarity vertices and return the outcome to the users.

Method 1：Choose parameter M, return set $\{u \in V(G), |f(u) - f(v)| \leq M\}$.

Method 2： Choose integer N, return the closest N concepts on the ranking list in $V(G)$.

Clearly, method 1 looks like more fair and method 2 can control the number of vertices that return to the users.

B. Ontology Mapping Design

For $v \in V(G_i)$, where $1 \leq i \leq k$. We use the one of following methods to obtain the similarity vertices and return the outcome to the users.

Method 1：Choose parameter M, return set $\{u \in V(G-G_i), |f(u) - f(v)| \leq M\}$.

Method 2： Choose integer N, return the closest N concepts on the ranking list in $V(G- G_i)$.

Also, method 1 looks like more fair and method 2 can control the number of vertices that return to the users.

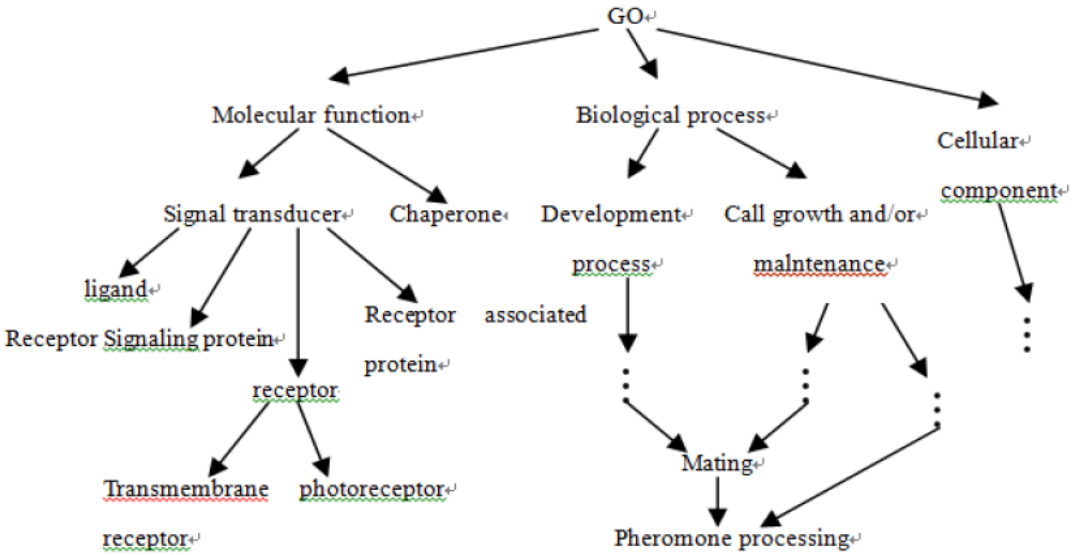

Fig. 1. "GO" ontology

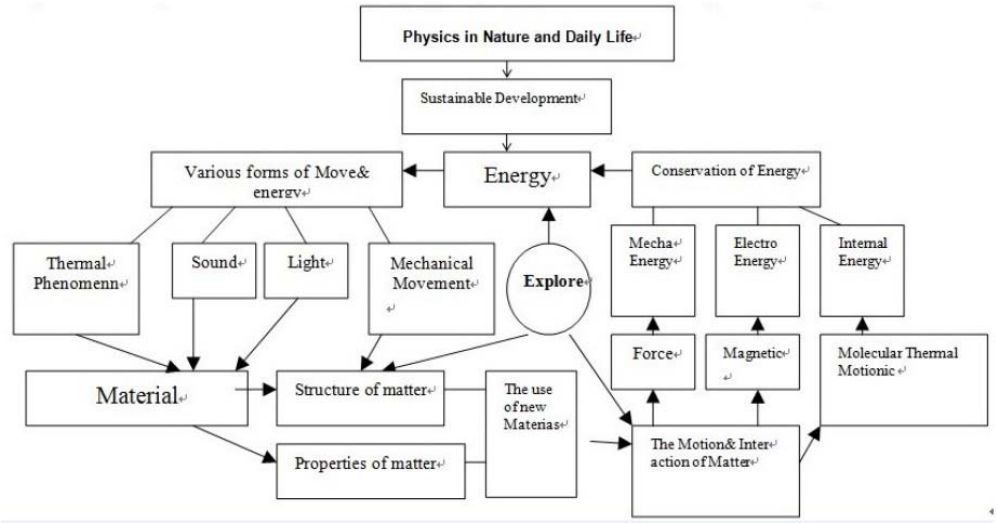

Fig.2. Physics education Ontology *O*

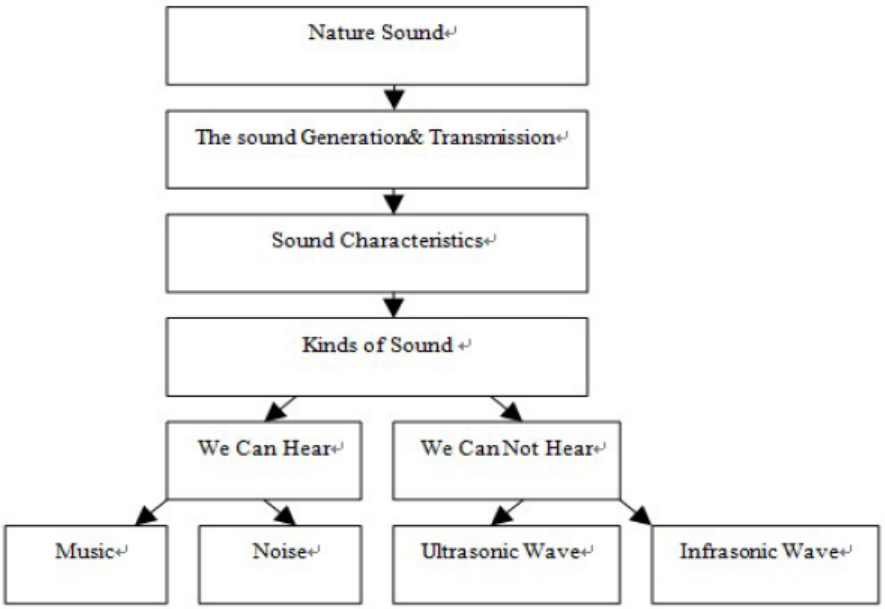

Fig.3. Physics education Ontology O_2

V. EXPERIMENTS

Two experiments concern ontology measure and ontology mapping are desired follow.

To connect ontology to this ontology algorithm, we should use a vector to express the vertex of information. This vector contains the information of name, instance, attribute and structure of vertex, where the instance of vertex is the set of its reachable vertex in the directed ontology graph.

For an ontology graph G, $W_{ij}>0$ if there exist an edge between vertex i and vertex j, where the value of W_{ij} is the value of edge; otherwise, $W_{ij}=0$. Note that one of method to computer the value of W_{ij} is using the Heat kernel:

$$W_{ij}=e^{-\frac{\|v_i-v_j\|^2}{t}}$$

where parameter $t\in\mathbb{R}$. Or, inverse multiquadric kernel:

$$W_{ij}=(c^2+\|v_i-v_j\|^2)^{-\alpha}$$

where c and α are positive parameters.

The first experiment concerns ontology similarity measurement is described as follows. In this experiment, we use computer ontology O_1 which was constructed in [17], Fig. 1 show O_1. We use *P@ N* (Precision Ratiosee [18]) to measure the equality of the experiment. First, the expert gives the first N concepts for every vertex on the ontology graph, and then we obtain the first N concepts for every vertex on ontology graph by the algorithm and compute the precision ratio

	P@3 average precision ratio	*P*@5 average precision ratio	*P*@10 average precision ratio	*P*@20 average precision ratio
Algorithm in our paper	59.60%	64.37%	73.59%	82.44%
Algorithm in [19]	52.78%	59.63%	72.14%	79.39%
Algorithm in [20]	53.48%	57.31%	62.56%	71.93%
Algorithm in [21]	57.34%	63.74%	69.17%	73.68%

Table 1. The experiment results

From the experiment result display above, we can see that our algorithm is more efficiently than algorithms raised in [19], [20] and [21] especially when N is lager. Therefore, thus the algorithm is of high efficiency.

For the second experiment, we use another Physics Education Ontologies O_2 and O_3 which constructed in [22], as Fig. 2 shows O_2 and Fig. 3 shows O_3. The goal of this experiment is given ontology mapping between O_2 and O_3. We also use *P@ N* Precision Ratio to measure the equality of experiment.

	P@3 average precision ratio	*P*@5 average precision ratio	*P*@10 average precision ratio	*P*@20 average precision ratio
Algorithm in our paper	40.61%	49.88%	57.37%	60.03%
Algorithm in [19]	39.45%	44.38%	52.56%	59.61%
Algorithm in [20]	31.33%	38.74%	46.16%	55.58%
Algorithm in [21]	32.69%	41.19%	49.87%	57.63%

Table 2. The experiment results

From the experiment result display above, we can see that our algorithm is more efficiently than algorithms raised in [19], [20] and [21] especially when N is lager. Therefore, thus the algorithm is of high efficiency.

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