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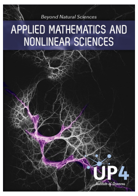

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Affine Transformation Based Ontology Sparse Vector Learning Algorithm

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Abstract

In information science and other engineering applications, ontology plays an irreplaceable role to find the intrinsic semantic link between concepts and to determine the similarity score returned to the user. Ontology mapping aims to excavate the intrinsic semantic relationship between concepts from different ontologies, and the essence of these applications is similarity computation. In this article, we propose the new ontology sparse vector approximation algorithms based on the affine transformation tricks. By means of these techniques, we study the equivalent form of ontology dual problem and determine its feasible set. The simulation experiments imply that our new proposed ontology algorithm has high efficiency and accuracy in ontology similarity computation and ontology mapping in biology, chemical and related fields.

Keywords: Ontology, Similarity measure, Ontology mapping, Sparse vector, Affine transformation
AMS 2010 codes: 14L17

1 Introduction

As a kind of information representation and shared model, ontology is introduced in nearly all fields of computer science. Acting as a concept semantic framework, ontology works high effectiveness and is widely employed in other engineering applications such as biology science, medical science, pharmaceutical science, material science, mechanical science and chemical science (for instance, see Coronnello et al. [2], Vishnu et

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al. [3], Roantree et al. [4], Kim and Park [5], Hinkelmann et al. [6], Pesaranghader et al. [7], Daly et al. [8], Agapito et al. [9], Umadevi et al. [10] and Cohen [11]).

The model of ontology can be regarded as a graph $G = (V, E)$, in which each vertex v expresses a concept and each edge $e = v_i v_j$ represents a directly contact between two concepts v_i and v_j. The aim of ontology similarity calculating is to learn a similarity function $Sim : V \times V \to \mathbb{R}^+ \cup \{0\}$ which maps each pair of vertices to a score real number. Moreover, the purpose of ontology mapping is to bridge the link between two or more different ontologies based on the similarity between their concepts. Using two graphs G_1 and G_2 to express two ontologies O_1 and O_2, respectively. The target is to determine a set $S_v \subseteq V(G_2)$ for each $v \in G_1$ where the vertices in S_v are semantically high similarity to the concept corresponding to v. Hence, it may compute the similarity $S(v, v_j)$ for each $v_j \in V(G_2)$ and select a parameter $0 < M < 1$ for each $v \in G_1$. S_v is set for vertex v and its element meets $S(v, v_j) \geq M$. From this perspective, the essence of ontology mapping is to yield a similarity function S and to determine a suitable parameter M according to detailed applications.

There are several effective learning tricks in ontology similarity measure and ontology mapping. Gao and Zhu [12] studied the gradient learning algorithms for ontology similarity computing and ontology mapping. Gao and Xu [13] obtained the stability analysis for ontology learning algorithms. Gao et al. [14] manifested an ontology sparse vector learning approach for ontology similarity measuring and ontology mapping based on ADAL trick. Gao et al. [15] researched an ontology optimization tactics according to distance calculating techniques. More theoretical analysis of ontology learning algorithm can be referred to Gao et al. [16].

In this paper, we propose a new ontology learning trick based on affine transformation. Furthermore, we present the efficiency of the algorithm in the biology and chemical applications via experiments.

2 Setting

Let V be an instance space. We use p dimension vector to express the semantics information of each vertex in ontology graph. Specifically, let $v = \{v_1, \cdots, v_p\}$ be a vector corresponding to a vertex v. To facilitate the representation, we slightly confused the notations and v is used to represent both the ontology vertex and its corresponding vector.In the learning setting, the aim of ontology algorithms is to yield an vertices can be determined according to the difference between their corresponding real numbers. Obviously, the ontology function can be regarded as a dimensionality reduction operator $f : \mathbb{R}^p \to \mathbb{R}$.

In recent years, the application of ontology algorithm faces many challenges. When it comes to the field of chemical and biology, the situation may become very complex since we need to deal with high dimensional data or big data. Under this background, sparse vector learning algorithms are introduced in biology and chemical ontology computation (see Afzali et al. [17], Khormuji, and Bazrafkan [18], Ciaramella and Borzi [19], Lorincz et al. [20], Saadat et al. [21], Yamamoto et al. [22], Lorintiu et al. [23], Mesnil and Ruzzene [24], Gopi et al. [25], and Dowell and Pinson [26] for more details). For example, if we aim to find what kind of genes causes a certain genetic disease, there are millions of genes in human's bodies and the computation task is complex and tough. However, in fact, only a few classes of genes cause this kind of genetic disease. The sparse vector learning algorithm can effectively help scientists pinpoint genes in the mass disease genes.

One computational method of ontology function via sparse vector is expressed by

$$f_{\mathbf{w}}(v) = \sum_{i=1}^{p} v_i w_i + \delta, \tag{1}$$

where $\mathbf{w} = \{w_1, \cdots, w_p\}$ is a sparse vector which is used to shrink irrelevant component to zero and δ is a noise term. Using this model, the key to determine the ontology function f is to learn the optimal sparse vector $\mathbf{w}$.

For example, the standard framework with the penalize term via the l_1-norm of the unknown sparse vector $\mathbf{w} \in \mathbb{R}^p$ can be stated as:

$$Y_{\mathbf{w}} = l(\mathbf{w}) + \lambda \|\mathbf{w}\|_1, \tag{2}$$

where $\lambda > 0$ is a balance parameter and l is the principal function to measure the error of $\mathbf{w}$. The balance term $\lambda\|\mathbf{w}\|_1$ is used to measure the sparsity of sparse vector $\mathbf{w}$.

3 Algorithm description

Let $\mathbf{D}$ be a $(p-1)\times p$ matrix which is denoted as

$$\mathbf{D} = \begin{pmatrix} 1 & -1 & 0 & \cdots & 0 & 0 \\ 0 & 1 & -1 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & -1 & 0 \\ 0 & 0 & \cdots & 0 & 1 & -1 \end{pmatrix} \tag{3}$$

One general ontology sparse vector learning framework can be stated as

$$\min_{\mathbf{w}\in\mathbb{R}^p} \frac{1}{2}\|\mathbf{y}-\mathbf{V}\mathbf{w}\| + \frac{\rho}{2}\|\mathbf{w}\|^2 + \lambda\|\mathbf{D}\mathbf{w}\|_1, \tag{4}$$

where $\rho \geq 0$ is also a balance parameter. Let $\tilde{\mathbf{V}} = \binom{\mathbf{V}}{\sqrt{\rho}\mathbf{I}}$ and $\tilde{\mathbf{y}} = \binom{\mathbf{y}}{0}$. Then ontology sparse vector learning problem (4) can be expressed as

$$\min_{\mathbf{w}\in\mathbb{R}^p} \frac{1}{2}\|\tilde{\mathbf{y}}-\tilde{\mathbf{V}}\mathbf{w}\|_2^2 + \lambda\|\mathbf{D}\mathbf{w}\|_1. \tag{5}$$

An effective method to get the solution is to set variables $\beta = \mathbf{D}\mathbf{w}$, then it becomes

$$\min_{\mathbf{w}\in\mathbb{R}^p,\beta\in\mathbb{R}^{p-1}} = \frac{1}{2}\|\tilde{\mathbf{y}}-\tilde{\mathbf{V}}\mathbf{w}\|_2^2 + \lambda\|\beta\|_1,$$

$$\beta = \mathbf{D}\mathbf{w}.$$

By derivation, the Lagrange dual problem of above ontology problem is formulated as

$$\min_{u\in\mathbb{R}^{p-1}} \frac{1}{2}(\tilde{\mathbf{V}}^T\tilde{\mathbf{y}}-\mathbf{D}^T\mathbf{u})^T(\tilde{\mathbf{V}}^T\tilde{\mathbf{V}})^{\dagger}(\tilde{\mathbf{V}}^T\tilde{\mathbf{y}}-\mathbf{D}^T\mathbf{u}),$$

$$\|u\|_\infty \leq \lambda, \mathbf{D}^T\mathbf{u} \in \mathrm{span}(\tilde{\mathbf{V}}^T).$$

The other version of ontology framework can be simply expressed as

$$\min_{\mathbf{w}} \frac{1}{2}\|\mathbf{y}-\mathbf{V}\mathbf{w}\| + \lambda\|\mathbf{w}\|_1. \tag{6}$$

And, the ontology dual problem of (6) can be written as

$$\sup_{\theta} \frac{1}{2}\|\mathbf{y}\|_2^2 - \frac{\lambda^2}{2}\|\frac{\mathbf{y}}{\lambda}-\theta\|^2, \tag{7}$$

$$\text{s.t.} \quad |v_i^T\theta| \leq 1$$

for any $i \in \{1,2,\cdots,p\}$. Moreover, ontology problem (7) is equal to the following problem:

$$\min_{\theta} \frac{1}{2}\|\frac{\mathbf{y}}{\lambda}-\theta\|^2, \tag{8}$$

$$\text{s.t.} \quad |v_i^T\theta| \leq 1$$

for any $i \in \{1,2,\cdots,p\}$.

Set $\mathscr{D} = \{\theta : |v_i^T\theta| \leq 1, i \in \{1,2,\cdots,p\}\}$ as the feasible set of ontology problem (8). Obviously, $\mathscr{D}$ can be regarded as the intersection of a collection of closed half spaces which is a closed convex set, and $\mathscr{D} \neq \emptyset$ since $0 \in \mathscr{D}$. By means of (8), the projection of $\frac{\mathbf{y}}{\lambda}$ onto $\mathscr{D}$ is the dual optimal solution θ^* which is stated as $\theta^* = \mathbb{P}_{\mathscr{D}}\frac{\mathbf{y}}{\lambda}$.

Next, we present our dual framework of ontology problem which can be formulated as a problem of projection. Set

$$\beta = \tilde{\mathbf{y}} - \tilde{\mathbf{V}}\mathbf{w}, \tag{9}$$

then the ontology problem (5) becomes

$$\min_{w\in\mathbb{R}^p,\beta\in\mathbb{R}^n} \frac{1}{2}||\beta||^2 + \lambda||\mathbf{D}\mathbf{w}||_1,$$

$$\text{s.t.} \quad \beta = \tilde{\mathbf{y}} - \tilde{\mathbf{V}}\mathbf{w}.$$

Set $\lambda\theta \in \mathbb{R}^N$ as the Lagrangian multipliers. Hence, the Lagrangian of ontology problem (5) can be expressed as

$$\begin{aligned} L(\mathbf{w},\beta;\theta) &= \frac{1}{2}||\beta||^2 + \lambda||\mathbf{D}\mathbf{w}||_1 + \lambda < \theta, \tilde{\mathbf{y}} - \tilde{\mathbf{V}}\mathbf{w} - \beta > \\ &= \frac{1}{2}||\beta||^2 - \lambda < \theta,\beta > +\lambda||\mathbf{D}\mathbf{w}||_1 - \lambda < \theta,\tilde{\mathbf{V}}\mathbf{w} > +\lambda < \theta,\tilde{\mathbf{y}} > . \end{aligned}$$

Set $g_1(\beta) = \frac{1}{2}||\beta||^2 - \lambda < \theta,\beta >$ and $g_2(\mathbf{w}) = \lambda||\mathbf{D}\mathbf{w}||_1 - \lambda < \theta,\tilde{\mathbf{V}}\mathbf{w} >$. Since $g_1(\beta)$ is a quadratic, we deduce

$$\bigtriangledown g_1(\beta) = 0 \to \lambda\theta = \beta \to \min_{\beta} g_1(\beta) = -\frac{\lambda^2}{2}||\theta||^2. \tag{10}$$

Furthermore, we infer

$$0 \in \partial g_2(\mathbf{w}) \to \min_{\mathbf{w}} g_2(\mathbf{w}) = 0. \tag{11}$$

In terms of (10) and (11), we get the following equal ontology optimization version:

$$\min_{w\in\mathbb{R}^p,\beta\in\mathbb{R}^n} L(\mathbf{w},\beta;\theta) = -\frac{\lambda^2}{2}||\theta||^2 + \lambda < \theta,\tilde{\mathbf{y}} >= \frac{1}{2}||\tilde{\mathbf{y}}||^2 - \frac{\lambda^2}{2}||\frac{\tilde{\mathbf{y}}}{\lambda} - \theta||^2. \tag{12}$$

Now, we discuss the deep ontology optimization model in view of affine transformation. Set $\Theta_1 \in \mathbb{R}^{p\times p}$ as

$$\Theta_1 = \begin{pmatrix} 1 & 1 & 1 & \cdots & 1 \\ 0 & 1 & 1 & \cdots & 1 \\ 0 & 0 & 1 & \cdots & 1 \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \end{pmatrix} \tag{13}$$

and $\overline{\mathbf{V}} = (\overline{\mathbf{v}}_1,\cdots,\overline{\mathbf{v}}_p) = \tilde{\mathbf{V}}\Theta_1$. Then, we obtain $\overline{\mathbf{v}}_i = \sum_{k=1}^{i}\tilde{v}_k$ for any $i \in \{1,\cdots,p\}$. Thus, the dual problem of the ontology sparse vector problem (5) becomes

$$\max_{\theta\in\mathbb{R}^n} = \frac{1}{2}||\tilde{\mathbf{y}}||^2 - \frac{\lambda^2}{2}||\frac{\tilde{\mathbf{y}}}{\lambda} - \theta||^2, \tag{14}$$

$$\text{s.t.} \quad |\overline{\mathbf{v}}_i^T\theta| \leq 1, \quad ,i \in \{1,\cdots,p-1\},$$

$$\overline{\mathbf{v}}_p^T\theta = 0.$$

In addition, the ontology problem (14) has the equal solution with the following ontology optimization problem

$$\min_{\theta\in\mathbb{R}^n} = \frac{1}{2}\|\frac{\tilde{\mathbf{y}}}{\lambda}-\theta\|^2 \tag{15}$$

$$\text{s.t.} \quad |\overline{\mathbf{v}}_i^T\theta| \le 1, \quad ,i\in\{1,\cdots,p-1\},$$

$$\overline{\mathbf{v}}_p^T\theta = 0.$$

Set $\overline{\mathscr{H}}$ as the feasible set of ontology problem (15), we yield

$$\overline{\mathscr{H}} = \{\theta : |\overline{\mathbf{v}}_i^T\theta| \le 1, \quad ,i\in\{1,\cdots,p-1\}, \overline{\mathbf{v}}_p^T\theta = 0\}. \tag{16}$$

It is not hard to check that the dual optimal solution of ontology problem is the projection of $\frac{\tilde{\mathbf{y}}}{\lambda}$ onto $\overline{\mathscr{H}}$.

In the following contexts, we show the equivalent optimization model of our ontology sparse vector problem. Our discussion can be divided into two cases according to whether the value of $\overline{\mathbf{v}}_p$ equals to zero or not.

If $\overline{\mathbf{v}}_p = 0$, then we can skip the condition $\overline{\mathbf{v}}_p^T\theta = 0$ and the ontology framework can be reduced to

$$\min_{\theta\in\mathbb{R}^n} = \frac{1}{2}\|\frac{\tilde{\mathbf{y}}}{\lambda}-\theta\|^2 \tag{17}$$

$$\text{s.t.} \quad |\overline{\mathbf{v}}_i^T\theta| \le 1, \quad ,i\in\{1,\cdots,p-1\}.$$

If $\overline{\mathbf{v}}_p \ne 0$, we set $\mathscr{U} = \{\alpha\overline{\mathbf{v}}_p : \alpha\in\mathbb{R}\}$, $\mathscr{V} = \{\mathbf{x} : \mathbf{x}^T\overline{\mathbf{x}}_p = 0\}$, $\Theta_2 = \mathbf{I} - \frac{\overline{\mathbf{v}}_p\overline{\mathbf{v}}_p^T}{\|\overline{\mathbf{v}}_p\|^2}$, $\tilde{\mathbf{y}}^\perp = \Theta_2\tilde{\mathbf{y}} = \tilde{\mathbf{y}} - \frac{\overline{\mathbf{v}}_p^T\tilde{\mathbf{y}}}{\|\overline{\mathbf{v}}_p\|^2}$, $\overline{\mathbf{v}}_i^\perp = \Theta_2\overline{\mathbf{v}}_i = \overline{\mathbf{v}}_i - \frac{\overline{\mathbf{v}}_p^T\overline{\mathbf{v}}_i}{\|\overline{\mathbf{v}}_p\|^2}$ for $i\in\{1,\cdots,p-1\}$. We get $<\tilde{\mathbf{y}}^\perp,\overline{\mathbf{v}}_p> = 0$ and $<\theta,\overline{\mathbf{v}}_p> = 0$ for any $\theta\in\mathscr{H}$ according to the fact that Θ_2 is a projection operator onto the linear subspace $\mathscr{V}$ which is the orthogonal complement subspace of $\mathscr{U}$. Therefore, for any $\theta\in\mathscr{H}$, we yield $<\frac{\tilde{\mathbf{y}}^\perp}{\lambda}-\theta,\overline{\mathbf{v}}_p> = 0$ and further $\|\frac{\tilde{\mathbf{y}}}{\lambda}-\theta\|^2 = \|\frac{\tilde{\mathbf{y}}^\perp}{\lambda}-\theta\|^2 + \frac{(\overline{\mathbf{v}}_p^T\tilde{\mathbf{y}})^2}{\lambda^2\|\overline{\mathbf{v}}_p\|^2}$.

Therefore, our ontology problem (15) can be expressed as

$$\min_{\theta\in\mathbb{R}^n} = \frac{1}{2}\|\frac{\tilde{\mathbf{y}}^\perp}{\lambda}-\theta\|^2 + \frac{1}{2}\frac{(\overline{\mathbf{v}}_p^T\tilde{\mathbf{y}})^2}{\lambda^2\|\overline{\mathbf{v}}_p\|^2} \tag{18}$$

$$\text{s.t.} \quad |\overline{\mathbf{v}}_i^T\theta| \le 1, \quad ,i\in\{1,\cdots,p-1\},$$

$$\overline{\mathbf{v}}_p^T\theta = 0.$$

Note that the second term in (18) doesn't rely on θ, the ontology problem (18) can be determined by

$$\min_{\theta\in\mathbb{R}^n} = \frac{1}{2}\|\frac{\tilde{\mathbf{y}}^\perp}{\lambda}-\theta\|^2, \tag{19}$$

$$\text{s.t.} \quad |\overline{\mathbf{v}}_i^T\theta| \le 1, \quad ,i\in\{1,\cdots,p-1\},$$

$$\overline{\mathbf{v}}_p^T\theta = 0.$$

Let $\mathscr{H}^\perp = \{\theta : |<\overline{\mathbf{v}}_i^\perp,\theta>| \le 1, i\in\{1,\cdots,p-1\}, \overline{\mathbf{v}}_p^T\theta = 0\}$. We can derive that $\mathscr{H} = \mathscr{H}^\perp$. Thus, the ontology problem (19) can be further stated as

$$\min_{\theta\in\mathbb{R}^n} = \frac{1}{2}\|\frac{\tilde{\mathbf{y}}^\perp}{\lambda}-\theta\|^2, \tag{20}$$

$$\text{s.t.} \quad |<\overline{\mathbf{v}}_i^\perp,\theta>| \le 1, \quad ,i\in\{1,\cdots,p-1\},$$

$$\overline{\mathbf{v}}_p^T\theta = 0.$$

It implies that the dual optimal solution of ontology problem is the projection of $\frac{\tilde{\mathbf{y}}^{\perp}}{\lambda}$ onto the feasible set $\mathscr{H}^{\perp}$. Finally, we have the final version of ontology sparse vector learning problem which has the same optimal solution with ontology problem (20):

$$\min_{\theta\in\mathbb{R}^n} = \frac{1}{2}\|\frac{\tilde{\mathbf{y}}^{\perp}}{\lambda} - \theta\|^2, \tag{21}$$

$$\text{s.t.} \quad |<\overline{\mathbf{v}}_i^{\perp}, \theta>| \leq 1, \quad ,i \in \{1,\cdots,p-1\}.$$

The feasible set of ontology problem (21) is stated as

$$\widehat{\mathscr{H}} = \{\theta : |<\overline{\mathbf{v}}_i^{\perp}, \theta>| \leq 1, \quad ,i \in \{1,\cdots,p-1\}\}.$$

4 Experiments

In this section, we test the feasibility of our new algorithm via the following four simulation experiments related to ontology similarity measure and ontology mapping below. After obtaining the sparse vector **w**, the ontology function is given by $f_{\mathbf{w}}(v) = \sum_{i=1}^{p} v_i w_i$ in which we ignore the noise term.

4.1 Ontology similarity measure experiment on biology data

In biology science, "GO" ontology (denoted by O_1 which was constructed in http: //www. geneontology. org, and Fig. 1 presents the basic structure of O_1) is a widely used database for gene researchers. Now, we apply this data set for our first experiment. We use $P@N$ (Precision Ratio, see Craswell and Hawking [27] for more details) to measure the effectiveness of the experiment. In the first step, the closest N concepts (have highest similarity) for each vertex was deduced by the expert. Then, in the second step, the first N concepts for each vertex on ontology graph are determined by the algorithm and the precision ratios are obtained. In addition to our ontology learning algorithm, programming from Huang et al. [29], Gao and Liang [30] and Gao et al. [16] are employed to "GO" ontology, and the precision ratios which we inferred from these tricks are compared. Partial experiment results can be referred to Tab. 1.

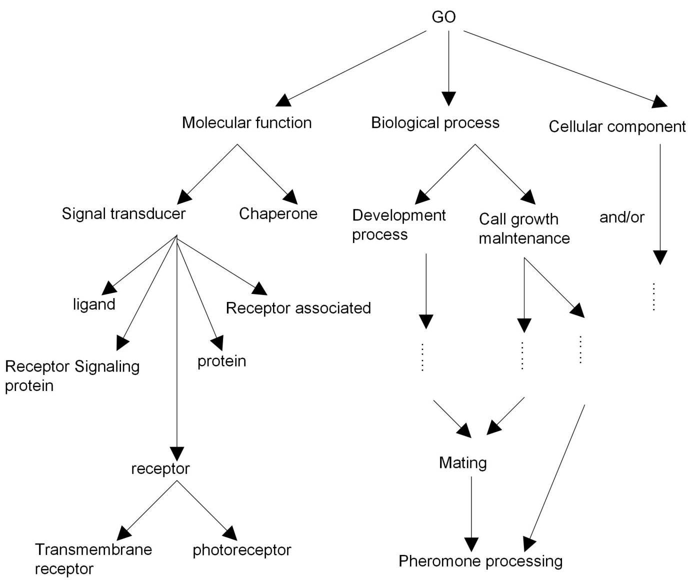

Fig. 1 The Structure of "GO" Ontology.

	$P@3$ average precision ratio	$P@5$ average precision ratio	$P@10$ average precision ratio	$P@20$ average precision ratio
Algorithm in our paper	0.4762	0.5504	0.6731	0.7918
Algorithm in Huang et al. [29]	0.4638	0.5348	0.6234	0.7459
Algorithm in Gao and Liang [30]	0.4356	0.4938	0.5647	0.7194
Algorithm in Gao et al. [16]	0.4213	0.5183	0.6019	0.7239

Table 1. The experiment results of ontology similarity measure

From Fig. 1, take $N = 3, 5, 10$ or 20, the precision ratio in terms of our sparse vector ontology learning algorithm is higher than the precision ratio computed by algorithms by Huang et al. [29], Gao and Liang [30] and Gao et al. [16]. Specially, such precision ratios apparently increase as N increases. Thus, one result can be concluded that the ontology learning algorithm described in our paper is superior to that proposed by Huang et al. [29], Gao and Liang [30] and Gao et al. [16].

4.2 Ontology mapping experiment on physical data

Physical ontologies O_2 and O_3 (the structures of O_2 and O_3 can refer to Fig. 2 and Fig. 3, respectively) are used for our second experiment which aims to test the utility of ontology mapping. The ontology mapping between O_2 and O_3 are determined by means of our new ontology learning algorithm and $P@N$ criterion is applied as well to test the equality of the experiment. Huang et al. [29], Gao and Liang [30] and Gao et al. [31] also employed ontology algorithms to "Physical" ontology, and we made a comparison among the precision ratios which we get from four methods. Several experiment results can be referred to Tab. 2.

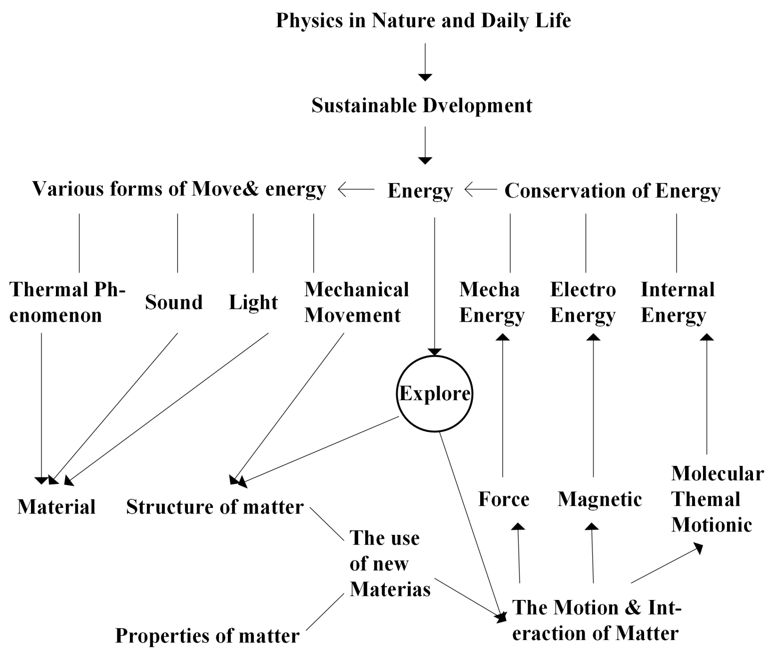

Fig. 2 "Physical" ontology O_2

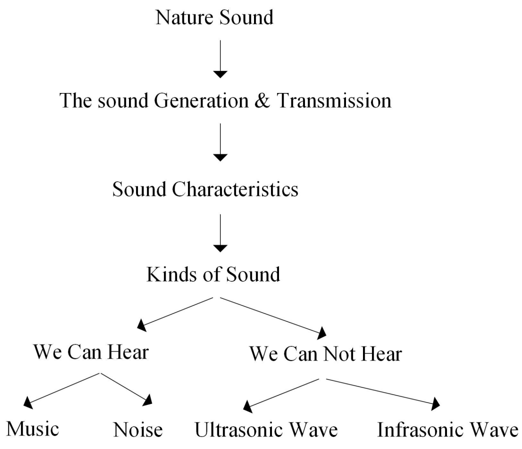

Fig. 3 "Physical" ontology O_3

	$P@1$ average precision ratio	$P@3$ average precision ratio	$P@5$ average precision ratio
Algorithm in our paper	0.6913	0.7742	0.9161
Algorithm in Huang et al. [29]	0.6129	0.7312	0.7935
Algorithm in Gao and Liang [30]	0.6913	0.7556	0.8452
Algorithm in Gao et al. [31]	0.6774	0.7742	0.8968

Table 2. The experiment results of ontology mapping

It can be seen that our algorithm is more efficient than ontology learning algorithms raised in Huang et al. [29], Gao and Liang [30] and Gao et al. [31] in particular when N is sufficiently large.

4.3 Ontology similarity measure experiment on plant data

In this part, "PO" ontology O_4 (which was constructed in http: //www.plantontology.org. Fig. 4 shows the basic structure of O_4) is used to test the efficiency of our new ontology learning algorithm for ontology similarity calculating. This ontology is famous in plant science which can be used as a dictionary for scientists to learn and search concepts and botanical features. $P@N$ standard is used again for this experiment. Furthermore, ontology learning approaches in Wang et al. [28], Huang et al. [29] and Gao and Liang [30] are borrowed to the "PO" ontology in our experiment for comparison requirements. The accuracy by these ontology learning algorithms are computed and parts of the results are compared and presented in Tab. 3.

	$P@3$ average precision ratio	$P@5$ average precision ratio	$P@10$ average precision ratio
Algorithm in our paper	0.4865	0.6052	0.7393
Algorithm in Wang et al. [28]	0.4549	0.5117	0.5859
Algorithm in Huang et al. [29]	0.4282	0.4849	0.5632
Algorithm in Gao and Liang [30]	0.4831	0.5635	0.6871

Table 3. The experiment results of ontology similarity measure

It's revealed in the Tab. 3 that the precision ratio in view of our ontology sparse vector learning algorithm is higher than the precision ratio proposed by ontology learning algorithms that Wang et al. [28], Huang et al. [29] and Gao and Liang [30] when N=3, 5 or 10. Furthermore, such precision ratios are increasing apparently as N increases. Therefore, we can conclude that the ontology sparse vector learning algorithm described in our paper is superior to the trick recommended in Wang et al. [28], Huang et al. [29] and Gao and Liang [30].

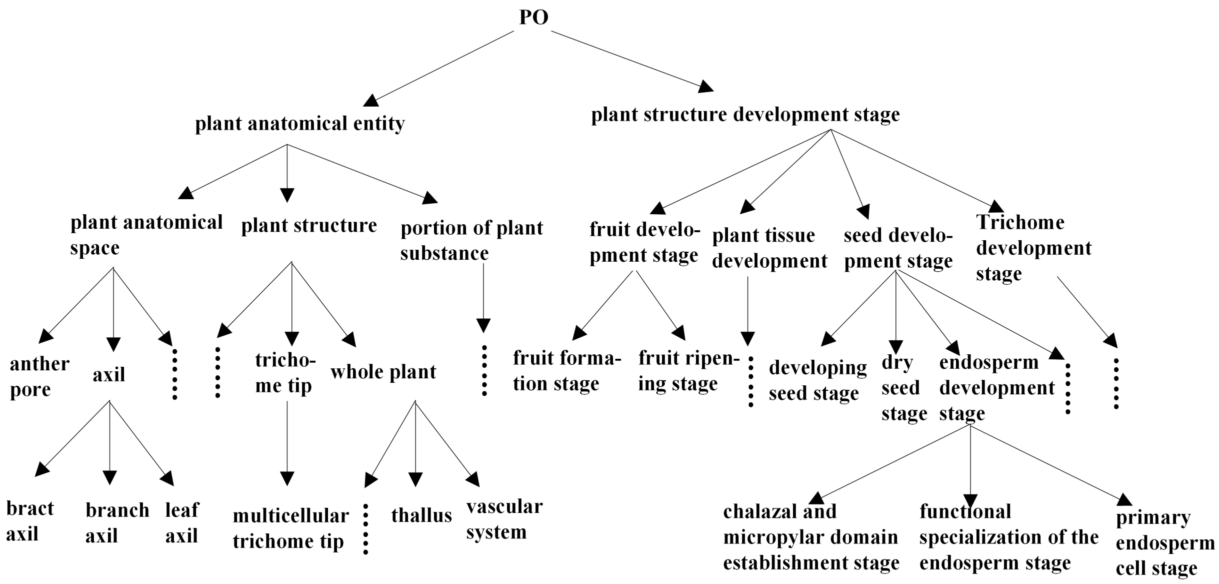

Fig. 4 The Structure of "PO" Ontology.

4.4 Ontology mapping experiment on humanoid robotics data

Humanoid robotics ontologies (denoted by O_5 and O_6, constructed by Gao and Zhu [12], and the structures of O_5 and O_6 can refer to in Fig. 5 and Fig. 6 respectively) are employed for our last experiment. Humanoid robotics ontologies are used to orderly and clearly express the humanoid robotics, and this experiment aims to determine ontology mapping between O_5 and O_6. Again, we use $P@N$ criterion to measure the accuracy of data gotten in the experiment. Beside our ontology learning algorithm, ontology algorithms raised in Gao and Lan [32], Gao and Liang [30] and Gao et al. [31] are also applied on humanoid robotics ontologies, and the precision ratios which are obtained from four ontology learning algorithms are compared. Partial experiment results can refer to Tab. 4.

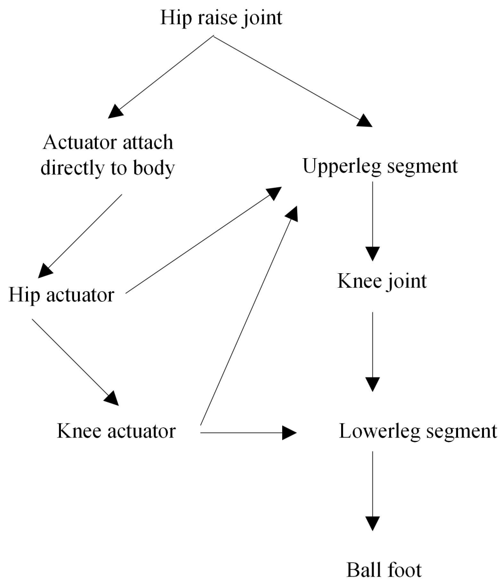

Fig. 5 "Humanoid Robotics"ontology O_5

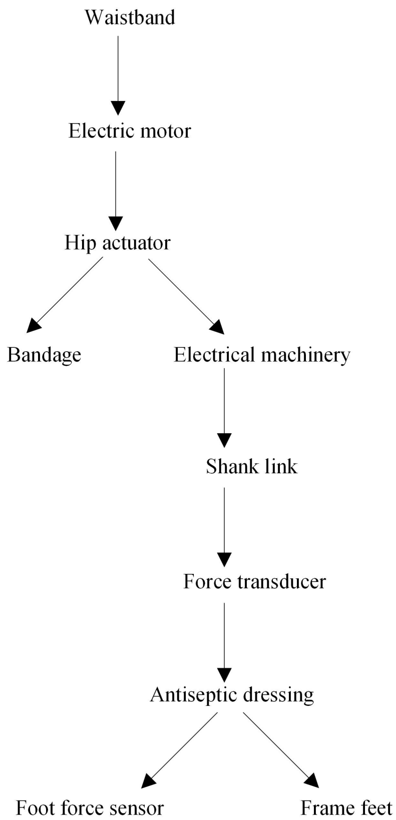

Fig. 6 "Humanoid Robotics " ontology O_6

	P@1 average precision ratio	P@3 average precision ratio	P@5 average precision ratio
Algorithm in our paper	0.2778	0.5000	0.6556
Algorithm in Gao and Lan [32]	0.2778	0.4815	0.5444
Algorithm in Gao and Liang [30]	0.2222	0.4074	0.4889
Algorithm in Gao et al. [31]	0.2778	0.4630	0.5333

Table 4. The experiment results of ontology mapping

The experiment results presented in Table 4 imply that our ontology sparse vector learning algorithm works with more efficiency than other ontology learning algorithms obtained in Gao and Lan [32], Gao and Liang [30] and Gao et al. [31] especially when N is sufficiently large.

5 Conclusion

In our paper, an affine transformation based computation technology is considered and presented to the readers. This ontology technology is suitable for biological and chemical ontology engineering applications because of its similarity measure and ontology mapping. The main approach is based on affine transformation and its theoretical derivation. At last, simulation data show that our ontology scheming has high efficiency in biology, physics, plant and humanoid robotics fields. The ontology sparse vector learning algorithm raised in our paper illustrates the promising application prospects in multiple disciplines.

6 Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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