American Journal of Circuits, Systems and Signal Processing
Vol. 1, No. 1, 2015, pp. 14-19
http://www.aiscience.org/journal/ajcssp

Ontology Similarity Measuring and Ontology Mapping Algorithms Based on Fused Lasso Signal Approximator

Yun Gao[1], Wei Gao[2, *]

[1]Department of Editorial, Yunnan Normal University, Kunming, China
[2]School of Information Science and Technology, Yunnan Normal University, Kunming, China

Abstract

Ontology similarity calculation is important research topics in information retrieval and widely used in science and engineering. By analyzing the technology of fused lasso signal approximator, we propose the new algorithm for ontology similarity measure and ontology mapping. Via the ontology sparse vector learning, 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. The experiment results show that the proposed new algorithm has high accuracy and efficiency on ontology similarity calculation and ontology mapping.

Keywords

Ontology, Similarity Measure, Ontology Mapping, Sparse Vector, Fused Lasso Signal Approximator

Received: April 2, 2015 / Accepted: April 17, 2015 / Published online: May 8, 2015

1. Introduction

As a conceptual shared and knowledge representation model, ontology has been used in knowledge management, image retrieval and information retrieval search extension. Furthermore, acted as an effective concept semantic model, ontology is employed in other fields except computer science, including medical science, social science, pharmacology science, geography science and biology science (see Przydzial et al., [1], Koehler et al., [2], Ivanovic and Budimac [3], Hristoskova et al., [4], and Kabir et al., [5] for more detail).

The ontology model is a graph $G = (V,E)$ such that each vertex v expresses a concept and each directed edge $e=v_iv_j$ denote a relationship between concepts v_i and v_j. The aim of ontology similarity measure is to get a similarity function Sim: $V\times V \rightarrow \mathbb{R}^+ \cup \{0\}$ such that each pair of vertices is mapped to a non-negative real number. Moreover, the aim of ontology mapping is to obtain the link between two or more ontologies. In more applications, the key of ontology mapping is to get a similarity function S to determine the similarity between vertices from different ontologies.

In recent years, ontology similarity-based technologies were employed in many applications. By virtue of technology for stable semantic measurement, a graph derivation representation based trick for stable semantic measurement is presented by Ma et al., [6]. Li et al., [7] determined an ontology representation method which can be used in online shopping customer knowledge with enterprise information. A creative ontology matching system is proposed by Santodomingo et al., [8] such that the complex correspondences are deduced by processing expert knowledge with external domain ontologies and in view of novel matching technologies. The main features of the food ontology and several examples of application for traceability aims were reported by Pizzuti et al., [9]. Lasierra et al., [10] pointed out that ontologies can be employed in designing an architecture for taking care of patients at home. More ontology

* Corresponding author
E-mail address: gaowei@ynnu.edu.cn (Wei Gao)

learning algorithms can refer to [11-22].

In this paper, we present the new ontology similarity computation and ontology mapping algorithms relied on sparse vector learning and fused lasso signal approximator. In terms of the sparse vector, the ontology graph is mapped into a real line and vertices are mapped into real numbers. Then the similarity between vertices is measured by the difference between their corresponding real numbers.

2. Basic Idea

Let V be a instance space. For any vertex in ontology graph G, its information (including its attribute, instance, structure, name and semantic information of the concept which is corresponding to the vertex and that is contained in its vector) is denoted by a vector with p dimension. Let $v=\{v_1,\cdots,v_p\}$ be a vector which is corresponding to a vertex v. For facilitating the expression, we slightly confuse the notations and denote v both the ontology vertex and its corresponding vector. The purpose of ontology learning algorithms is to get an optimal ontology function f: $V\rightarrow\mathbb{R}$, then the similarity between two vertices is determined by the difference between two real numbers which they correspond to. The essence of such algorithm is dimensionality reduction, that is to say, use one dimension vector to represent p dimension vector. From this point of view, an ontology function f can be regarded as a dimensionality reduction map f: $\mathbb{R}^p\rightarrow\mathbb{R}$.

In the real implement, the sparse ontology function can be denoted as

$$f_\beta(v)=\sum_{i=1}^{p}v_i\beta_i\,, \tag{1}$$

where $\boldsymbol{\beta}=(\beta_1,\cdots,\beta_p)$ is a sparse vector. For determining the ontology function f, we should get the sparse vector $\boldsymbol{\beta}$ first.

3. Main Ontology Algorithms

In this section, we present our main ontology sparse vector learning algorithms for ontology similarity measuring and ontology mapping by virtue of fused lasso signal approximator.

The one-dimensional fussed lasso signal approximator is defined by

$$\min_\beta Y_\beta=l(y,\beta)+\lambda_1\sum_{i=1}^{p}|\beta_i| +\lambda_2\sum_{i=2}^{p}|\beta_i-\beta_{i-1}|\,, \tag{2}$$

where $l(y,\beta)=\sum_{i=1}^{p}l_i(y,\beta)$. By introducing the auxiliary variables θ_i, $i=2,\ldots,p$, the following linearly constrained problem is trivially equivalent to (2),

$$\min_{\beta,\theta} g(\beta,\theta)=\sum_{i=1}^{p}l_i(y,\beta)+\lambda_1\sum_{i=1}^{p}|\beta_i|+\lambda_2\sum_{i=2}^{p}|\theta_i|\,,$$

$$\text{s. t. } \theta_i=\beta_i-\beta_{i-1}\,,\ i=2,\ldots,p.$$

Set $c>0$, the augmented Lagrangian is defined by

$$L_c(\beta,\theta,x)=g(\beta,\theta)+\sum_{i=2}^{p}x_i(\theta_i-\beta_i+\beta_{i-1}) +\frac{c}{2}\sum_{i=2}^{p}(\theta_i-\beta_i+\beta_{i-1})^2\,,$$

where $x=(x_2,\cdots,x_p)$ is the Lagrange multiplier.

Considering the following saddle-point problem,

Search β^*,θ^*,x^*,

$$\text{s. t. } L_c(\beta^*,\theta^*,x)\le L_c(\beta^*,\theta^*,x^*)\le L_c(\beta,\theta,x^*),\ \forall\beta,\theta,x\,. \tag{3}$$

By the duality theory, β^* is a solution of (2) if and only if (β^*,θ^*,x^*) is a solution of (3) for some θ^* and x^*.

The popular algorithm for searching the saddle point is described as follows:

Initialize x^0, arbitrarily.

For k=1,2,…

$$(\beta^k,\theta^k)=\arg\min_{\beta,\theta}L_c(\beta,\theta,x^{k-1})$$

$$x_i^k=x_i^{k-1}+c(\theta_i^k-\beta_i^k+\beta_{i-1}^k)\,,\ i=2,\ldots,\ p.$$

In general, it is difficult to minimize $L_c(\beta,\theta,x^k)$ over β and θ simultaneously, but it might be easier to minimize over β when fixing θ and vice versa. In this case, we can alternate these two steps until convergence. It turns out that we can update β and θ just once when the other is fixed, resulting in the following algorithm (raised by [23])

Initialize x^0 and θ^0, arbitrarily.

For k=1, 2,…

$$\beta^k=\arg\min_\beta L_c(\beta,\theta^{k-1},x^{k-1})\,,$$

$$\theta^k=\arg\min_\theta L_c(\beta^k,\theta,x^{k-1})\,,$$

$$x_i^k = x_i^{k-1} + c(\theta_i^k - \beta_i^k + \beta_{i-1}^k),\ i=2,\ldots,\ p.$$

For example, apply the second algorithm to (2) with quadratic loss, the augmented Lagrangian is given by

$$L_c(\beta,\theta,x) = \|y - V\beta\|_2^2 + \lambda_1 \sum_{i=1}^{p} |\beta_i|$$

$$+ \lambda_2 \sum_{i=2}^{p} |\theta_i| + \sum_{i=2}^{p} x_i(\theta_i - \beta_i - \beta_{i-1})$$

$$+ \frac{c}{2} \sum_{i=2}^{p} (\theta_i - \beta_i - \beta_{i-1})^2 .$$

If λ_1=0, fixed θ^{k-1} and x^{k-1}, the minimization over β is a quadratic problem and all components of β can be found simultaneously by solving a linear system $B\beta = b$.

For $\lambda_1 > 0$, it is more difficult to update β directly. Fortunately, for quadratic loss, solution for FLSA with $\lambda_1 > 0$ can be obtained by thresholding the solution for FLSA with $\lambda_1 = 0$, and thus we only consider $\lambda_1 = 0$.

With $\beta = \beta^k$ and $x = x^{k-1}$ fixed, the minimization over θ is a lasso regression with orthogonal design and thus we have the simple component-wise soft thresholding updating rule

$$\theta_i^k = sign(\hat{\theta}_i)(|\hat{\theta}_i| - \frac{\lambda_2}{2})_+ , \tag{4}$$

where $\hat{\theta}_i = \beta_i^k - \beta_{i-1}^k - \frac{x_i^{k-1}}{c}$ and $(a)_+$ expresses the positive part of a.

For quadratic loss, the example shows that both update for β and for θ can be computed efficiently for $\lambda_1 = 0$. However, for more general loss for $\lambda_1 > 0$, it is difficult to update β directly and thus in ontology implementation we do not use the first and the second Algorithms. By introducing another set of auxiliary variables γ_i, i=1,…,p, the optimizing problem (2) can be expressed as

$$\min_{\gamma,\beta,\theta} g(\gamma,\beta,\theta) = \sum_{i=1}^{p} l_i(y_i,\gamma_i) + \lambda_1 \sum_{i=1}^{p} |\gamma_i| \ + \lambda_2 \sum_{i=2}^{p} |\theta_i| ,$$

$$\text{s. t. } \gamma_i = \beta_i,\ i=1,\ldots,p.$$

$$\theta_j = \beta_j - \beta_{j-1},\ j=2,\ldots,p.$$

The corresponding (doubly) augmented Lagrangian is

$$L_c(\gamma,\beta,\theta,\mu,x) = g(\gamma,\beta,\theta) + \sum_{i=1}^{p} \mu_i(\gamma_i - \beta_i) + \frac{c}{2}\sum_{i=1}^{p}(\gamma_i - \beta_i)^2 + \sum_{i=2}^{p} x_i(\theta_i - \beta_i + \beta_{i-1}) + \frac{c}{2}\sum_{i=2}^{p}(\theta_i - \beta_i + \beta_{i-1})^2 . \tag{5}$$

With the newly defined Lagrangian in (5), it can similarly modify the saddle-point problem (3) in an obvious way and it can be shown that the saddle-point problem is the same as the original FLSA problem (2). Accordingly, the following algorithms for finding the saddle point which directly extends the first Algorithm and the second Algorithm respectively (raised by [23]).

Initialize x^0, arbitrarily.

For k=1, 2,…

$$(\gamma^k, \beta^k, \theta^k) = \arg\min_{\gamma,\beta,\theta} L_c(\gamma,\beta,\mu^{k-1},x^{k-1})$$

$$x_i^k = x_i^{k-1} + c(\theta_i^k - \beta_i^k + \beta_{i-1}^k),\ i=2,\ldots,\ p,$$

$$\mu_i^k = \mu_i^{k-1} + c(\gamma_i^k - \beta_i^k),\ i=1,\ldots,\ p.$$

Initialize x^0, β^0 and θ^0, arbitrarily.

For k=1, 2,…

$$\gamma^k = \arg\min_{\gamma} L_c(\gamma,\beta^{k-1},\theta^{k-1},\mu^{k-1},x^{k-1})$$

$$\beta^k = \arg\min_{\beta} L_c(\gamma^k,\beta,\theta^{k-1},\mu^{k-1},x^{k-1}),$$

$$\theta^k = \arg\min_{\theta} L_c(\gamma^k.\beta^k,\theta,\mu^{k-1},x^{k-1}),$$

$$x_i^k = x_i^{k-1} + c(\theta_i^k - \beta_i^k + \beta_{i-1}^k),\ i=2,\ldots,\ p,$$

$$\mu_i^k = \mu_i^{k-1} + c(\gamma_i^k - \beta_i^k),\ i=1,\ldots,\ p.$$

4. Experiments

Two simulation experiments on ontology similarity measure and ontology mapping are designed in this section. For detail implement, we first obtain the optimal sparse vector using the algorithm raised in our paper, and then the ontology function is yielded by (1).

4.1. Experiment on Biology Data

The "Go" ontology O_1 was constructed by http: //www. geneontology. org. (Fig. 1 presents the graph structure of O_1). We use $P@N$ (defined by Craswell and Hawking [24]) to determine the equality of the experiment result.

Beside our ontology algorithm, ontology algorithms in Huang et al., [12], Gao and Liang [13] and Gao and Gao [14] are also acted to “Go” ontology. Then, we compare the precision ratio which we have deduced from the four tricks. Some parts of experiment results can be seen in Table 1.

Table 1. The experiment data for ontology similarity measure

	P@3 average precision ratio	*P*@5 average precision ratio	*P*@10 average precision ratio	*P*@20 average precision ratio
Our Algorithm	47.18%	54.48%	64.81%	84.98%
Algorithm in [12]	46.38%	53.48%	62.34%	74.59%
Algorithm in [13]	43.56%	49.38%	56.47%	71.94%
Algorithm in [14]	42.13%	51.83%	60.19%	72.39%

As we can see in the Table 1, when N= 3, 5, 10 or 20, the precision ratio in view of our algorithm is higher than that got by tricks which has been determined in Huang et al., [12], Gao and Liang [13] and Gao and Gao [14].

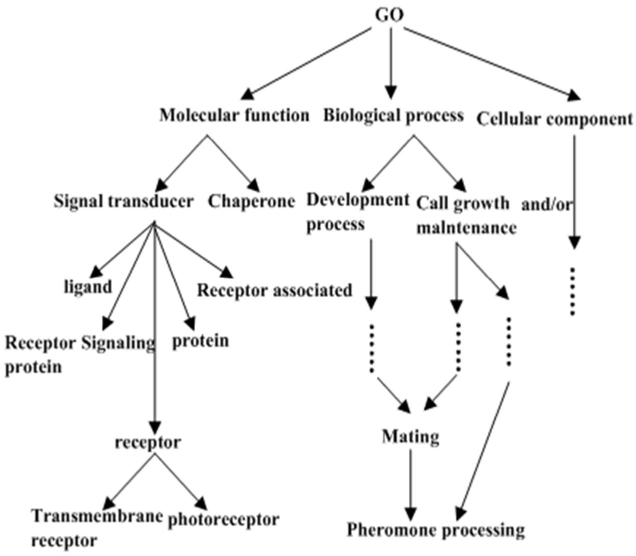

Figure 1. “Go” ontology

4.2. Experiment on Physical Education Data

For our second experiment, we use physical education ontologies O_2 and O_3 (the graph structures of O_2 and O_3 are raised in Fig. 2 and Fig. 3 respectively). The purpose of this experiment is to construct the ontology mapping between O_2 and O_3. Again, *P@N* criterion is applied to measure the equality of the experiment results.

Furthermore, ontology technologies in Huang et al., [12], Gao and Liang [13] and Gao et al., [16] are employed to “physical education” ontology. At last, we compare the precision ratio that we have obtained from four tricks. Table 2 present several results for this experiment.

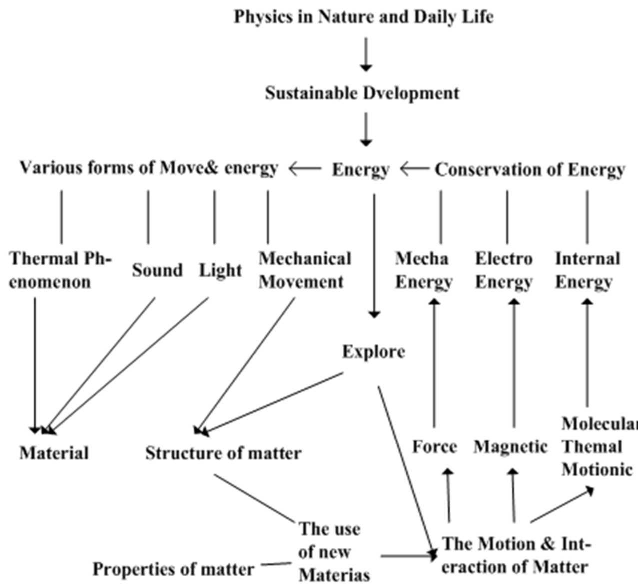

Figure 2. “Physical Education” Ontology O_2

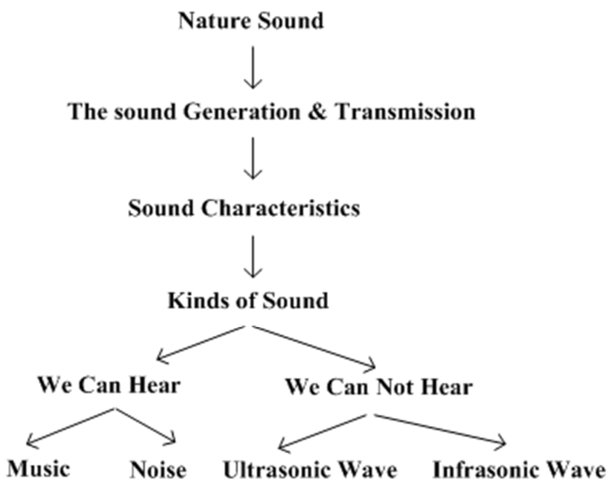

Figure 3. “Physical Education” Ontology O_3.

Table 2. The experiment data for ontology mapping

	P@1 average precision ratio	*P*@3 average precision ratio	*P*@5 average precision ratio
Our Algorithm	67.74%	78.49%	90.32%
Algorithm in [12]	61.29%	73.12%	79.35%
Algorithm in [13]	69.13%	75.56%	84.52%
Algorithm in [16]	67.74%	77.42%	89.68%

From what we have obtained in Table 2, we find it more efficient to use our Algorithm than algorithms determined by Huang et al., [12], Gao and Liang [13] and Gao et al., [16], especially where *N* is sufficiently large.

5. Conclusions

In our article, a new algorithm for ontology similarity measure and ontology mapping application is presented by virtue of fused lasso signal approximator. Furthermore, experiment results reveal that our new algorithm has high efficiency in both biology and physics education. The ontology algorithm presented in our paper illustrates the promising application prospects for ontology use.

Acknowledgment

We thank the reviewers for their constructive comments in improving the quality of this paper. The research is financed by: NSFC (No.11401519), and the PhD initial funding of the second author.

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