

Fuzzy Support Vector Machine Method for Evaluating Innovation Sources in Service Firms

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doi: 10.4156/jcit.vol5.issue7.25

Abstract

The traditional evaluating methods can not deal with the evaluation problem of innovation sources in service firms with fuzzy information, authors have constructed fuzzy support vector machine based on support vector machine and fuzzy chance constrained programming, and applied this new method to evaluating innovation sources in service firms. In basis of related literature reviewing, authors have summarized 7 indicators of innovation sources in service firms which are internal R&D, staff quality, customers, suppliers and so on. By selecting the data of 80 service firms of Zhejiang Province in China as samples and 60 firms being as training samples, we obtain the model of evaluating innovation sources of service firms. Simultaneously the other 20 firms being as testing samples, the results show higher accuracy rate (90%) and lower error rate (average error is 0.038). Therefore fuzzy support vector machine method for innovation sources in service firms provides a new way in the process of selecting innovation sources.

Key words: Fuzzy support vector machine, Service innovation, Innovation sources, Evaluation

1. Introduction

By 2007, the service sector accounted for over 60 percent of GDP in all OECD countries. In the same year, the service sector accounted for 40.2 percent of GDP in China^①. At this stage, the manufacturing sectors all over the world are competing fiercely, the industry structure in China shows a new trend that being from manufacturing type to service type. Innovation is the fundamental driving force of economic development^[1], it is surprising that innovation in services has not received much attention until recently. In part this may be because of the traditional tendency to view services as relatively low-tech and non-innovation when compared with the manufacturing sector, which is bound to affect the understanding of service innovation. However the intangible nature of service output and the fact that service firms are less likely to engage in traditional R&D activities than manufacturing sector, does not mean that service firm are not innovative. Now the consensus in the literature is that service firms do innovate, but in the form of innovation performance and innovation sources may not do so in quite the same way as manufacturing^[2-4]. Among the literature, Coombs and Miles(2000) propose the synthesis approach^[3] which is an integrative approach and service, organizational and technological innovations should all be accounted for equally, the present research is in the spirit of synthesis approach. In addition, Tether(2005) shows that service innovation often depends on “soft technology”, not only relying on internal resources such as R&D activity and abilities of their workforce, but on cooperation with outside organizations such as suppliers, customers, competitors and so on^[5]. The internal and external resources promoting the firms’ innovation can be called innovation sources in literature^[6], therefore the firm’s innovation sources will have important impact on the innovation performance, and how to evaluation and select the firm’ current innovation sources properly is particularly important to the development of the service firms.

Support vector machines (SVMs) proposed by Vapnik, is a novel method for machine learning^[7-8]. Due to its excellent learning capability, it has become a hot spot of the machine learning field and applied successfully to many application fields. But as an immature novel technique, it still needs further improvements. For example, in the evaluation of service innovation sources we need to determine the

^① The data is from OECD website and Blue Book of Chinese Academy of Social Sciences in 2007.

innovation performance, but this innovation performance itself is a fuzzy concept, simply to use “good” or “bad” to measure is not accurate, we describe the degree of belonging to “good” or “bad” which is more objective. So fuzzy support vector machine is constructed based on support vector machine and fuzzy chance constrained programming, and applied this new method to evaluating innovation sources in service firms in order to provide scientific and objective basis for selecting proper innovation sources.

2. Fuzzy Support Vector Classification

We define a training point which is positive class membership grade^[7-8] or negative class membership grade as δ^+ or δ^- ($\delta^+, \delta^- \in [0.5, 1]$), and we introduce $\delta \in [-1, -0.5] \cup [0.5, 1]$ for short, which $\delta^+ = \delta$, $\delta^- = -\delta$. Therefore A kind of special triangle fuzzy number is introduced as an extension of positive class symbol 1 or negative class symbol -1, when the input of a training point is positive class membership grade δ^+ ($0.5 \leq \delta^+ \leq 1$) or negative class membership grade δ^- ($0.5 \leq \delta^- \leq 1$), we define the corresponding output as the following triangle fuzzy number^[9-10].

$$\tilde{y} = (r_1, r_2, r_3) = \begin{cases} (\frac{2\delta^2 + \delta - 2}{\delta}, 2\delta - 1, \frac{2\delta^2 - 3\delta + 2}{\delta}), 0.5 \leq \delta \leq 1 \\ (\frac{2\delta^2 + 3\delta + 2}{\delta}, 2\delta + 1, \frac{2\delta^2 - \delta - 2}{\delta}), -1 \leq \delta \leq -0.5 \end{cases} \quad (1)$$

Given the training set of classification is

$$S = \{(x_1, \tilde{y}_1), \dots, (x_p, \tilde{y}_p), (x_{p+1}, \tilde{y}_{p+1}), \dots, (x_l, \tilde{y}_l)\}, \quad (2)$$

where $x_j \in R^n$ is an usual input, \tilde{y}_j ($j = 1, \dots, l$) is a triangle fuzzy number as shown in (1), $j = 1, \dots, l$, (x_t, \tilde{y}_t) are fuzzy positive points ($t = 1, \dots, p$), (x_i, \tilde{y}_i) are fuzzy negative points ($i = p + 1, \dots, l$).

Under the confidence level λ ($0 < \lambda \leq 1$), fuzzy linearly separability problem of the fuzzy training set as shown in (2), can be transformed to fuzzy chance constrained programming with decision variable $(w, b)^T$:

$$\begin{cases} \min_{w, b} \frac{1}{2} \|w\|^2 \\ s.t. Pos\{\tilde{y}_j((w \cdot x_j) + b) \geq 1\} \geq \lambda, j = 1, \dots, l \end{cases}, \quad (3)$$

Where $Pos\{\cdot\}$ is a feasibility estimate of the fuzzy event $\{\cdot\}$.

The certain equivalence programming common programming equivalent to(3) of the fuzzy chance constrained programming (3) is the quadratic programming^[11]:

$$\begin{cases} \min_{w, b} \frac{1}{2} \|w\|^2 \\ s.t. ((1-\lambda)r_{t3} + \lambda r_{t2})(w \cdot x_t) + b \geq 1, t = 1, \dots, p \\ ((1-\lambda)r_{i1} + \lambda r_{i2})(w \cdot x_i) + b \geq 1, i = p + 1, \dots, l \end{cases}. \quad (4)$$

The duality programming of quadratic programming (9) is quadratic programming with decision variable $(\beta, \alpha)^T$:

$$\begin{cases} \min_{\beta, \alpha} \frac{1}{2} (A + 2B + D) - (\sum_{t=1}^p \beta_t + \sum_{i=p+1}^l \alpha_i) \\ s.t. \sum_{t=1}^p \beta_t ((1-\lambda)r_{t3} + \lambda r_{t2}) + \sum_{i=p+1}^l \alpha_i ((1-\lambda)r_{i1} + \lambda r_{i2}) = 0 \\ \beta_t \geq 0, t = 1, \dots, p \\ \alpha_i \geq 0, i = p + 1, \dots, l \end{cases}, \quad (5)$$

Where $(\beta, \alpha)^T$ is decision variable,

$$A = \sum_{t=1}^p \sum_{s=1}^p \beta_t \beta_s ((1-\lambda)r_{t3} + \lambda r_{t2}) ((1-\lambda)r_{s3} + \lambda r_{s2}) (x_t \cdot x_s),$$

$$B = \sum_{t=1}^p \sum_{i=p+1}^l \beta_t \alpha_i ((1-\lambda)r_{t3} + \lambda r_{t2}) ((1-\lambda)r_{i1} + \lambda r_{i2}) (x_t \cdot x_i),$$

$$D = \sum_{i=p+1}^l \sum_{q=p+1}^l \alpha_i \alpha_q ((1-\lambda)r_{i1} + \lambda r_{i2}) ((1-\lambda)r_{q1} + \lambda r_{q2}) (x_i \cdot x_q),$$

$$\beta = (\beta_1, \dots, \beta_p)^T \in \mathbb{R}_+^p, \quad \alpha = (\alpha_{p+1}, \dots, \alpha_l)^T \in \mathbb{R}_+^{l-p}.$$

Programming (5) is a convex quadratic programming. After getting its optimal solution $(\beta^*, \alpha^*)^T = (\beta_1^*, \dots, \beta_p^*, \alpha_{p+1}^*, \dots, \alpha_l^*)^T$, we can get the certain optimal classification hyperplane^[8]:

$$(w^* \cdot x) + b^* = 0, x \in \mathbb{R}^n, \quad (6)$$

where

$$w^* = \sum_{t=1}^p \beta_t^* ((1-\lambda)r_{t3} + \lambda r_{t2}) x_t + \sum_{i=p+1}^l \alpha_i^* ((1-\lambda)r_{i1} + \lambda r_{i2}) x_i,$$

$$b^* = ((1-\lambda)r_{s3} + \lambda r_{s2}) - \left(\sum_{t=1}^p \beta_t^* ((1-\lambda)r_{t3} + \lambda r_{t2}) (x_t \cdot x_s) + \sum_{i=p+1}^l \alpha_i^* ((1-\lambda)r_{i1} + \lambda r_{i2}) (x_i \cdot x_s) \right),$$

$$s \in \{s \mid \beta_s^* > 0\},$$

or

$$b^* = ((1-\lambda)r_{q1} + \lambda r_{q2}) - \left(\sum_{t=1}^p \beta_t^* ((1-\lambda)r_{t3} + \lambda r_{t2}) (x_t \cdot x_q) + \sum_{i=p+1}^l \alpha_i^* ((1-\lambda)r_{i1} + \lambda r_{i2}) (x_i \cdot x_q) \right),$$

$$q \in \{q \mid \alpha_q^* > 0\}.$$

Through $g(x) = (w^* \cdot x) + b^*$ we obtain a fuzzy optimal classification function^[12]:

$$\delta = \delta(u) = \begin{cases} \varphi_+(u), & 0 < u \leq \varphi_+^{-1}(1), \\ 1, & u > \varphi_+^{-1}(1), \\ -\varphi_-(u), & \varphi_-^{-1}(1) \leq u < 0, \\ -1, & u < \varphi_-^{-1}(1), \end{cases} \quad (7)$$

where $u = g(x)$, $\varphi_+(u)$ are regression functions (monotonous increasing function on u) obtained from the ε -support vector regression^[8]. And ε -support vector regression is constructed by the following method:

(i) Build up the Construct training set of the regression problem

$$\{(g(x_1), \delta_1), \dots, (g(x_p), \delta_p)\}. \quad (8)$$

(ii) Use (8) as training set, and select appropriate $\varepsilon > 0$, penalty parameter $C > 0$, choose a linear kernel as the kernel function, thus to construct ε -support vector regression.

Similarly, $\varphi_-(u)$ is a regression function (monotonous decreasing function on u) obtained from the ε -support vector regression which is constructed with the same method.

From the above discussion, we can achieve the following algorithm:

(i) Given a fuzzy training set (2), and select an appropriate confidence level $\lambda (\sigma \leq \lambda \leq 1)$, $C > 0$ and a kernel function $K(x, x')$, then construct quadratic programming:

$$\left\{ \begin{array}{l} \min_{\beta, \alpha} \frac{1}{2} (A_K + 2B_K + D_K) - \left(\sum_{t=1}^p \beta_t + \sum_{i=p+1}^l \alpha_i \right) \\ \text{s.t.} \sum_{t=1}^p \beta_t ((1-\lambda)r_{t3} + \lambda r_{t2}) + \sum_{i=p+1}^l \alpha_i ((1-\lambda)r_{i1} + \lambda r_{i2}) = 0 \\ 0 \leq \beta_t \leq C, t = 1, \dots, p \\ 0 \leq \alpha_i \leq C, i = p+1, \dots, l \end{array} \right. \quad (9)$$

where $A_K = \sum_{t=1}^p \sum_{s=1}^p \beta_t \beta_s ((1-\lambda)r_{t3} + \lambda r_{t2}) ((1-\lambda)r_{s3} + \lambda r_{s2}) K(x_t, x_s)$,

$$B_K = \sum_{t=1}^p \sum_{i=p+1}^l \beta_t \alpha_i ((1-\lambda)r_{t3} + \lambda r_{t2}) ((1-\lambda)r_{i1} + \lambda r_{i2}) K(x_t, x_i),$$

$$D_K = \sum_{i=p+1}^l \sum_{q=p+1}^l \alpha_i \alpha_q ((1-\lambda)r_{i1} + \lambda r_{i2}) ((1-\lambda)r_{q1} + \lambda r_{q2}) K(x_i, x_q),$$

$\beta = (\beta_1, \dots, \beta_p)^T \in R_+^p$, $\alpha = (\alpha_{p+1}, \dots, \alpha_l)^T \in R_+^{l-p}$, $(\beta, \alpha)^T$ is a decision variable.

(ii) Solve quadratic programming(9), get optimal solution $(\beta^*, \alpha^*)^T = (\beta_1^*, \dots, \beta_p^*, \alpha_{p+1}^*, \dots, \alpha_l^*)^T$.

(iii) Select the positive component $\beta_s^* \in (0, C)$ of β^* , or $\alpha_q^* \in (0, C)$ of α^* , then compute

$$b^* = ((1-\lambda)r_{s3} + \lambda r_{s2}) - \left(\sum_{t=1}^p \beta_t^* ((1-\lambda)r_{t3} + \lambda r_{t2}) K(x_t, x_s) + \sum_{i=p+1}^l \alpha_i^* ((1-\lambda)r_{i1} + \lambda r_{i2}) K(x_i, x_s) \right)$$

or $b^* = ((1-\lambda)r_{q1} + \lambda r_{q2}) - \left(\sum_{t=1}^p \beta_t^* ((1-\lambda)r_{t3} + \lambda r_{t2}) K(x_t, x_q) + \sum_{i=p+1}^l \alpha_i^* ((1-\lambda)r_{i1} + \lambda r_{i2}) K(x_i, x_q) \right)$.

(iv) Construct function :

$$g(x) = \sum_{t=1}^p \beta_t^* ((1-\lambda)r_{t3} + \lambda r_{t2}) K(x_t, x_s) + \sum_{i=p+1}^l \alpha_i^* ((1-\lambda)r_{i1} + \lambda r_{i2}) K(x_i, x_s).$$

(v) Consider $\{(g(x_1), \delta_1), \dots, (g(x_p), \delta_p)\}$ and $\{(g(x_{p+1}), -\delta_{p+1}), \dots, (g(x_l), -\delta_l)\}$ as training set respectively, construct ε -support vector regression (select appropriate $\varepsilon > 0$, penalty parameter $C > 0$, choose a linear kernel as the kernel function), then obtain regression functions $\varphi_+(u)$ and $\varphi_-(u)$.

(vi) Construct fuzzy optimal classification function (7).

Note: In the optimal solution $(\beta_1^*, \dots, \beta_p^*, \alpha_{p+1}^*, \dots, \alpha_l^*)^T$ in quadratic programming (9) only some β_t^* and α_i^* are not zero, the corresponding inputs of fuzzy training points are fuzzy support vectors, the other inputs are non-fuzzy support vectors. Only fuzzy support vectors can work in the fuzzy optimal classification function, but non-fuzzy support vectors do not. So $g(x)$ in fuzzy optimal classification function (7) is

$$g(x) = \left(\sum_{(FSV)^+} \beta_t^* [(1-\lambda)r_{t3} + \lambda r_{t2}] (x_t \cdot x) + \sum_{(FSV)^-} \alpha_i^* [(1-\lambda)r_{i1} + \lambda r_{i2}] (x_i \cdot x) \right) + b^*,$$

where $(FSV)^+$ is the set including all fuzzy support vectors in the fuzzy positive points, and $(FSV)^-$ is the set including all fuzzy support vectors in the fuzzy negative points.

3. Fuzzy Support Vector Machine Method for Evaluating Innovation Sources in Service Firms

3.1 Identifying Indicators

NO matter manufacturing or service, much research on R&D and its role on innovation has been conducted^[13-15]. Previous research has shown that firms which conduct internal R&D activity are better able to use externally information^[16], have better absorptive capacity relevant when the addition of external linkages by innovation will be discussed. In addition, the educational level of employees is

an important factor, having qualified workforce is suggested to aid in firm's innovation efforts^[5].

Innovation cannot be regarded purely as an internal matter as firms' external linkages may also play an important role^[17]. The external linkages may help by stimulating creativity, reducing risk, accelerating or upgrading the quality of the innovation made^[18]. In a comparison of the innovation process of manufacturing and service firms, Tether (2005) finds that while manufacturers are more likely to innovate through internal R&D and collaborations with universities and research institutes, service firms are more likely to make use of collaborations with customers, suppliers and so on^[5]. Leiponen (2005) finds support for this view. In a survey of Finnish service firms, she finds that external sourcing of knowledge, especially from customers and competitors, positively affected both the probability and extent of innovation.

We select strategic alliances, suppliers, customers, external consultants and competitor as external innovation sources of service firms. Each of these has to some extent received attention in the academic literature.

A firm's participation in strategic alliances has been a widely researched topic. Strategic alliances include activities such as R&D partnerships, collaborative manufacturing and co-marketing arrangements. The most common rationales offered for corporate partnering and external collaboration involve some combination of risk sharing, obtaining access to new markets and technologies, speeding products to market and pooling complementary skills^[19-20]. Additionally, firms use external relations, such as collaborations, as a temporary mechanism to compensate for capabilities a firm has not mastered^[18]. Linnarsson and Werr (2004) find some of challenges of radical innovation could be reduced by engaging in alliances for innovation^[21].

Suppliers and their role in the value-added chain regarding innovation is also an important topic, particularly so due to the close relationship existing between firm and supplier. The relationship allows for both formal and informal interaction, possibly a hotbed for originating innovative ideas and suggestions^[5, 16].

Existing customers can be an excellent source of information to service firms. Customer's involvement in a firm's innovation process, either formal or informal, has been the subject of considerable research^[5, 13, 16], with a general consensus that, where it exists, such input is generally favorable to service innovation.

With respect to the role of consultancy firms, it is suggested that the development of client-consultancy relations requires to be viewed as an interactive process, with both partners playing an equally important role. Where this is the case, the use of consultancy firms has been shown to be another positive source for innovation^[22], especially where firm is considering moving into completely new areas of service.

Closely monitoring the competition is an obvious tactic for many firms, and can be an important source of idea for new and improved products. For example, Hipp (2002) found a positive effect in knowledge-intensive business services which utilize competitors as an external innovation source, and Leiponen (2005) found that completely new services are most often introduced by firms that engage in external knowledge sourcing particularly from customers and competitors.

According to the content above, the establishment of indicators of evaluating the innovation sources of service firm is completed (Table 1).

Table 1. Indicators of evaluating the innovation sources of service firm

Objective	Indicator X	Quantitative of Indicator
To select Proper innovation sources	internal R&D X_1	percentage of R&D fund in firm's sales
	quality of workforce X_2	percentage of employees with at least a bachelor's degree
	strategic alliance X_3	taking value(0-1)
	supplier X_4	taking value(0-1)
	customer X_5	taking value(0-1)
	consultancy firm X_6	taking value(0-1)
	competitor X_7	taking value(0-1)

Note: The data above is collected from the questionnaires which were mailed to service firms of Zhejiang Province in China in 2009. We select 80 in the usable obtained questionnaires which are mainly from technology service (32 percent), business service (20 percent), culture service (8 percent) and other service (40 percent). The quantitative of indicators of external innovation sources is taken value (0-1) according to frequency which firms contact with external resources, where 1 is the highest score.

3.2 Selecting Training Points

Of the 80 selected questionnaires, we select 60 firms before Number 60 (including Number60) as training samples, and the other 20 as testing samples (Table 2).

Table 2 Descriptive statistics of service firms of Zhejiang Province in China

Firm	X_1	X_2	X_3	X_4	X_5	X_6	X_7	Positive class membership grade δ^+
1	0.023	0.43	0.75	0.82	0.93	0.65	0.70	0.91
2	0.021	0.49	0.69	0.76	0.90	0.68	0.78	0.83
3	0.011	0.41	0.52	0.79	0.92	0.42	0.62	0.69
4	0.031	0.73	0.53	0.83	0.95	0.68	0.81	1.00
5	0.019	0.42	0.49	0.83	0.85	0.56	0.71	0.88
6	0.016	0.31	0.43	0.82	0.89	0.31	0.79	0.73
7	0.034	0.48	0.42	0.72	0.69	0.58	0.81	0.75
8	0.027	0.38	0.45	0.68	0.66	0.56	0.79	0.68
9	0.029	0.39	0.49	0.70	0.68	0.61	0.79	0.7
10	0.018	0.35	0.52	0.79	0.83	0.33	0.65	0.67
11	0.015	0.31	0.51	0.73	0.78	0.32	0.61	0.64
12	0.025	0.49	0.61	0.81	0.83	0.59	0.82	0.95
13	0.026	0.46	0.58	0.77	0.77	0.60	0.81	0.93
14	0.009	0.21	0.48	0.70	0.76	0.32	0.56	0.61
15	0.01	0.23	0.49	0.72	0.79	0.46	0.58	0.63
16	0.022	0.4	0.73	0.79	0.89	0.64	0.68	0.88
17	0.020	0.46	0.67	0.73	0.86	0.67	0.76	0.8
18	0.018	0.36	0.7	0.75	0.85	0.56	0.59	0.78
19	0.016	0.42	0.64	0.69	0.82	0.59	0.67	0.70
20	0.006	0.34	0.47	0.72	0.84	0.33	0.51	0.56
21	0.026	0.66	0.48	0.76	0.87	0.59	0.70	0.87
22	0.014	0.35	0.44	0.76	0.77	0.47	0.60	0.75
23	0.011	0.24	0.38	0.75	0.81	0.22	0.68	0.60
24	0.029	0.41	0.37	0.65	0.61	0.49	0.70	0.62
25	0.022	0.31	0.40	0.61	0.58	0.47	0.68	0.55
26	0.013	0.28	0.47	0.72	0.75	0.24	0.54	0.54
27	0.010	0.24	0.46	0.66	0.70	0.23	0.5	0.53
28	0.020	0.42	0.56	0.74	0.75	0.50	0.71	0.82
29	0.021	0.39	0.53	0.70	0.69	0.51	0.70	0.80
30	0.005	0.16	0.44	0.65	0.71	0.37	0.47	0.52
31	0.017	0.33	0.68	0.72	0.81	0.55	0.57	0.75
32	0.015	0.39	0.62	0.66	0.78	0.58	0.65	0.67
33	0.012	0.31	0.63	0.67	0.76	0.52	0.50	0.67
34	0.010	0.37	0.57	0.61	0.73	0.55	0.58	0.59
35	0.020	0.61	0.41	0.68	0.78	0.55	0.61	0.76
36	0.008	0.30	0.37	0.68	0.68	0.43	0.51	0.64
37	0.014	0.37	0.49	0.66	0.66	0.46	0.62	0.71
38	0.015	0.34	0.46	0.62	0.6	0.47	0.61	0.69
39	0.009	0.28	0.61	0.64	0.72	0.51	0.48	0.64
40	0.009	0.34	0.55	0.58	0.69	0.54	0.56	0.56
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	Negative class membership grade δ^-
41	0.011	0.23	0.41	0.68	0.61	0.21	0.53	0.57
42	0.010	0.19	0.38	0.51	0.58	0.21	0.39	0.64
43	0.014	0.22	0.34	0.43	0.41	0.42	0.48	0.58
44	0.004	0.1	0.16	0.21	0.23	0.12	0.22	1.00
45	0.008	0.22	0.43	0.64	0.70	0.22	0.48	0.53
46	0.004	0.14	0.43	0.63	0.68	0.23	0.45	0.52
47	0.006	0.29	0.4	0.64	0.75	0.29	0.42	0.55

48	0.005	0.19	0.31	0.67	0.72	0.18	0.59	0.51
49	0.023	0.36	0.30	0.57	0.52	0.45	0.61	0.53
50	0.016	0.26	0.33	0.53	0.49	0.43	0.59	0.56
51	0.018	0.27	0.37	0.55	0.51	0.48	0.59	0.54
52	0.005	0.20	0.39	0.63	0.64	0.18	0.43	0.59
53	0.007	0.23	0.40	0.64	0.66	0.20	0.45	0.57
54	0.002	0.17	0.36	0.56	0.61	0.18	0.39	0.61
55	0.004	0.19	0.39	0.58	0.61	0.19	0.41	0.60
56	0.004	0.09	0.36	0.55	0.59	0.19	0.36	0.63
57	0.005	0.11	0.37	0.57	0.62	0.33	0.38	0.61
58	0.016	0.22	0.32	0.45	0.40	0.36	0.49	0.66
59	0.003	0.15	0.34	0.53	0.53	0.06	0.33	0.71
60	0.005	0.18	0.35	0.54	0.55	0.08	0.35	0.69
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	Positive class membership grade δ^+
61	0.020	0.42	0.55	0.71	0.71	0.50	0.68	0.76
62	0.021	0.39	0.52	0.67	0.65	0.51	0.67	0.74
63	0.015	0.33	0.67	0.69	0.77	0.55	0.54	0.69
64	0.015	0.39	0.61	0.63	0.74	0.58	0.62	0.61
65	0.029	0.36	0.44	0.64	0.61	0.57	0.77	0.65
66	0.016	0.29	0.46	0.72	0.74	0.27	0.61	0.60
67	0.018	0.32	0.47	0.73	0.76	0.29	0.63	0.62
68	0.043	0.56	0.43	0.85	0.81	0.27	0.77	0.98
69	0.015	0.28	0.46	0.67	0.71	0.28	0.59	0.59
70	0.025	0.46	0.56	0.75	0.76	0.55	0.80	0.90
71	0.026	0.43	0.53	0.71	0.70	0.56	0.79	0.88
72	0.010	0.20	0.44	0.66	0.72	0.42	0.56	0.58
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	Negative class membership grade δ^-
73	0.011	0.25	0.45	0.68	0.69	0.22	0.49	0.54
74	0.013	0.28	0.46	0.69	0.71	0.24	0.51	0.52
75	0.008	0.22	0.42	0.61	0.66	0.22	0.45	0.56
76	0.010	0.24	0.45	0.63	0.66	0.23	0.47	0.55
77	0.009	0.12	0.32	0.51	0.54	0.23	0.32	0.65
78	0.011	0.16	0.43	0.62	0.67	0.37	0.44	0.58
79	0.017	0.35	0.41	0.42	0.59	0.42	0.57	0.57
80	0.009	0.15	0.33	0.44	0.49	0.28	0.44	0.64

Note: ①The data above is collected from the questionnaires, membership grades represent the innovation performance of service firms, which is taken value (0.5-1) according to the situation of service, organizational and technological innovations by experts, where 1 is the highest score. ② δ^+ represents positive class membership grade (Innovation performance is good), δ^- represents negative class membership grade (Innovation performance is poor).

3.3 Defining Fuzzy Training Set

$$S = \{(x_1, \tilde{y}_1), \dots, (x_{40}, \tilde{y}_{40}), (x_{41}, \tilde{y}_{41}), \dots, (x_{60}, \tilde{y}_{60})\}$$

Where $x_1 = (0.023, 0.43, 0.75, 0.82, 0.93, 0.65, 0.70)^T$,

$$x_{40} = (0.009, 0.34, 0.55, 0.58, 0.69, 0.54, 0.56)^T,$$

$$x_{41} = (0.011, 0.23, 0.41, 0.68, 0.61, 0.21, 0.53)^T, \dots,$$

$$x_{60} = (0.005, 0.18, 0.35, 0.54, 0.55, 0.08, 0.35)^T;$$

$$\tilde{y}_1 = (0.62, 0.82, 1.02), \dots, \tilde{y}_{40} = (-1.45, 0.12, 1.69),$$

$$\tilde{y}_{41} = (-1.65, -0.14, 1.37), \dots, \tilde{y}_{60} = (-1.28, -0.38, 0.52).$$

$\tilde{y}_j (j=1, \dots, 60)$ are triangle fuzzy number into which the membership grades in Table 2 are converted by (1).

3.4 Training and Testing

Use S as fuzzy training set, under the algorithm (fuzzy support vector machine), the fuzzy training points are trained on (choose Gauss kernel as the kernel function $K(x, x') = \exp(-\|x - x'\|^2 / \sigma^2)$, penalty parameter $C = 10$, confidence level $\lambda = 0.95$). With the help of MATLAB, fuzzy support vectors are obtained:

$$x_{26} = (0.013, 0.28, 0.47, 0.72, 0.75, 0.24, 0.54)^T.$$

$$x_{27} = (0.01, 0.24, 0.46, 0.66, 0.7, 0.23, 0.5)^T.$$

$$x_{30} = (0.005, 0.16, 0.44, 0.65, 0.71, 0.37, 0.47)^T.$$

$$x_{34} = (0.01, 0.37, 0.57, 0.61, 0.73, 0.55, 0.58)^T.$$

$$x_{46} = (0.004, 0.14, 0.43, 0.63, 0.68, 0.23, 0.45)^T.$$

$$x_{48} = (0.005, 0.19, 0.31, 0.67, 0.72, 0.18, 0.59)^T.$$

$$x_{49} = (0.023, 0.36, 0.3, 0.57, 0.52, 0.45, 0.61)^T.$$

$$x_{50} = (0.016, 0.26, 0.33, 0.53, 0.49, 0.43, 0.59)^T.$$

Then use the data of $X_1 - X_7$ (Number 61-80) in Table 2 as inputs of testing, the testing results are obtained through MATLAB:

$$\begin{aligned} \delta(g(x_{61})) &= 0.74, & \delta(g(x_{62})) &= 0.72, & \delta(g(x_{63})) &= 0.71, & \delta(g(x_{64})) &= 0.63, & \delta(g(x_{65})) &= 0.65, \\ \delta(g(x_{66})) &= 0.62, & \delta(g(x_{67})) &= 0.51, & \delta(g(x_{68})) &= 1.00, & \delta(g(x_{69})) &= 0.60, & \delta(g(x_{70})) &= 0.95, \\ \delta(g(x_{71})) &= 0.91, & \delta(g(x_{72})) &= 0.55, & \delta(g(x_{73})) &= -0.59, & \delta(g(x_{74})) &= -0.55, & \delta(g(x_{75})) &= -0.61, \\ \delta(g(x_{76})) &= -0.57, & \delta(g(x_{77})) &= -0.71, & \delta(g(x_{78})) &= -0.62, & \delta(g(x_{79})) &= -0.53, & \delta(g(x_{80})) &= -0.52. \end{aligned}$$

3.5 Evaluating the testing results

Each testing result $\hat{\delta}$ is compared with the original result δ .

The testing results are listed: 0.74, 0.72, 0.71, 0.63, 0.65, 0.62, 0.51, 1.00, 0.60, 0.95, 0.91, 0.55; -0.59, -0.55, -0.61, -0.57, -0.71, -0.62, -0.53, -0.52. According to $\delta^+ = \delta, \delta^- = -\delta$, the original results (membership grade δ^+, δ^-) are written as : 0.76, 0.74, 0.69, 0.61, 0.65, 0.60, 0.62, 0.98, 0.59, 0.90, 0.88, 0.58; -0.54, -0.52, -0.56, -0.55, -0.65, -0.58, -0.57, -0.64. Compare the two sets of data, calculate the testing errors $|\hat{\delta} - \delta|$ of every testing point.

Here we take two approaches to evaluate:

(i) Define a real number $\varepsilon (0 \leq \varepsilon \leq 1)$.

For every testing point, if the testing error $|\hat{\delta} - \delta| \leq \varepsilon$, the testing of the testing point is considered correct; And otherwise, the testing is considered wrong. And the testing accuracy is percentage of quantity of correct testing points accounted for the total number.

Here we define $\varepsilon = 0.1$, and evaluate the testing results of 20 testing points. Of the 20 testing number, it is clear that $|\hat{\delta} - \delta| > \varepsilon$ for Number 7 and Number 20, so the testing is considered wrong; For other 18 testing points, $|\hat{\delta} - \delta| \leq \varepsilon$, and the testing is considered correct. So the testing accuracy is 90 percent.

Generally in the evaluation of testing results in fuzzy support vector machine, define $0 \leq \varepsilon \leq 1$, and the smaller ε is, the more stringent is the evaluation criteria. And otherwise, the broader is the evaluation criteria. $\varepsilon = 0.1$ shows this evaluation criteria more stringent. In the criteria the testing accuracy which is 90 percent shows good effect.

(ii) Add each testing error $|\hat{\delta} - \delta|$ together, then obtain a total error(positive real number). Total error divided by the total number of testing points is average error. And it is clear that the smaller average error is, the more accurate is the testing. Otherwise, the rougher is the testing. We hope that the

average error is as small as possible. Through calculating the total error of 20 testing points is 0.76, and average error is 0.038.

According to the knowledge of fuzzy math^[9-12], if the difference of membership grades of two points belonging to one category is 0.038, then the membership grades have little difference. In this section the average error of testing points being 0.038 shows good effect.

4. Conclusion

Authors have constructed fuzzy support vector machine based on support vector machine and fuzzy chance constrained programming, and applied this new method to evaluating innovation sources in service firms. In basis of related literature reviewing, authors have summarized 7 indicators of innovation sources in service firms which are internal R&D, staff quality, customers, suppliers and so on. The training and testing samples are selected, the testing results show higher accuracy rate (90%) and lower error rate (average error is 0.038). Therefore fuzzy support vector machine method for innovation sources in service firms provides a new way in the process of selecting innovation sources.

5. References

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