Ciência em foco

Volume XIV

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Apresentação

A décima quarta edição da coletânea Ciência em Foco, traz uma coleção de artigos escritos por pesquisadores de diferentes áreas do conhecimento, que buscam apresentar e discutir temas relevantes para a compreensão da ciência e da sua relação com a sociedade. O objetivo da obra é estimular o debate e a reflexão sobre questões gerais da pesquisa científica. O livro é destinado a estudantes, professores, pesquisadores e interessados pela ciência e sua importância para o desenvolvimento humano. A pesquisa científica é essencial para o avanço do conhecimento, mas também para a solução de problemas práticos e para a promoção da cidadania. A interdisciplinariedade das várias áreas do conhecimento é uma forma de enriquecer as perspectivas e os métodos de investigação, bem como de ampliar o diálogo entre a ciência e outras formas de expressão cultural.

Ao longo dos capítulos são abordados os seguintes temas: saúde na escola: conscientização e prevenção da hipertensão arterial na educação básica; as origens gregas da fisiologia e dos estudos sobre circulação sanguínea; prática educativa sobre a prevenção e cuidados acerca do pé diabético no idoso: um relato de experiência; uso racional de medicamentos: um alerta aos estudantes da educação básica sobre os riscos da automedicação e das drogas ilícitas, e a implementação de uma metodologia para aplicações em sistemas de inteligência artificia que utilizam aprendizado de máquina.

Aos autores dos capítulos, pela dedicação e esforços, que possibilitaram a esta obra retratar os recentes avanços científicos e tecnológicos nas áreas pesquisadas, os agradecimentos dos Organizadores e da Pantanal Editora.

Por fim, esperamos que este ebook possa colaborar e instigar mais estudantes e pesquisadores na constante busca de novas tecnologias e avanços nas ciências, garantindo a difusão de conhecimento acessível para a sociedade.

Os organizadores

Sumário

Capítulo V

Ensemble Learning based on Analytic Hierarchy Process Voting

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Bruno Rodrigues de Oliveira

INTRODUÇÃO

In Machine Learning (ML) problems the induction algorithms use different strategies to learn the patterns from an environment, such as: parameters initialization, optimization methods, stop criteria, datasets subsampling, among others (Hansen and Salamonn, 1990; Polikar, 2006). Thus, each machine may learn differently even if it implements the same algorithm and uses the same data. In everyday life, it is known that multiple experts achieve better results than a single expert, and this is true for many situations. Therefore, in order to combine the predictions of multiple different machines into a single one, it is necessary to use an ensemble learning scheme in a divide and conquer spirit. One of these schemes is the voting, which returns the general output given by the individual machine outputs. Such learning scheme works if there is diversity with respect to the induced models, i.e., if the machines make wrong predictions for different instances (Polikar, 2006).

Since each machine has its own importance for the general predicted output, it is proposed in this paper a novel rule for weighted voting strategy to determine the weights for these machines, employing the Analytic Hierarchy Process (AHP) on performance measures varying from 0 to 1.

BACKGROUND

Ensemble Learning

Let $T = \{(x_n; y_n)\}_{n=1}^{N}$ be a training dataset with N instances (patterns) extracted from some environment, where $x_n \in \mathbb{R}^P$ is the n-th pattern and $y_n \in \{0,1,2,\dots,R\}$ discriminates the classes of these patterns. In order to learn these patterns, i.e., to obtain an association between class and pattern, ML algorithms are induced using T. The q-th ML algorithm provides a model $\hat{h}_q(\mathbf{x},\delta) = \hat{y}$, $q = \{1,2,\dots,Q\}$, which is an estimation of the real model h. For an unknown pattern $\mathbf{x}$ the model $\hat{h}$ predicts the output $\hat{y}$, given the parameters δ, estimated in training phase. Taking a test dataset $T' = \{(x'_n; y_n)\}_{n=1}^{N'}$ and the learned models $\hat{h}_q$, predictions errors are computed by

$$E(T', \hat{h}_q) = \sum_{n=1}^{N'} \begin{cases} 0, \text{if } y_n = \hat{y}_n \\ 1, \text{otherwise} \end{cases} \tag{1}$$

Different errors are expected for distinct models $\hat{h}_q$, since de ML algorithms learn differently, according to the reasons mentioned in the introduction. To use the knowledge of each ML algorithm simultaneously, an ensemble learning is employed, where the individual outputs are combined into a single output. Weighted voting is a classical scheme for ensemble learning, supported by a characteristic function (Raschka, 2018):

$$\Theta_{\mathrm{y}}(\mathbf{x}) = \sum_{q=1}^{Q} \omega_q \begin{cases} 1, & \text{if } \tau_q(\mathbf{x}) = y \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

that returns the number of correct predictions for class y considering Q machines, where $y \in \{0,1,2,\ldots,R\}$, $\tau_q(\mathbf{x})$ is the q-th machine prediction for unknown instance $\mathbf{x}$ and ω_q is q-th ML algorithm weight, such that $\sum \omega_q = 1$. Therefore, ensemble output for pattern $\mathbf{x}$ is given by (Raschka, 2018):

$$\hat{y_e} = \underset{y}{\operatorname{argmax}}\{\Theta_{\mathrm{y}}(\mathbf{x})\} \tag{3}$$

Analytic Hierarchy Process

Analytic Hierarchy Process (AHP) was proposed by Saaty (Saaty, 1987) for decision making problems. At the top and the bottom in the hierarchy model there are put a goal and the alternatives, respectively. In the middle there are fixed the criteria over which alternatives are compared, resulting in a real square pairwise matrix $A = \left(a_{ij}\right)_{n\times n}$, whose the main diagonal elements are equal to one and the others are reciprocal, i.e., $a_{ij} = 1/a_{ji}$, where $a_{ij} = w_i = w_j$ is the judgment value of alternative i over alternative j considering some criterion, and n is the amount of alternatives. These values (importance) are obtained by converting verbal judgment to numerical, according to the Saaty's scale described in the Table 1.

Table 1. Saaty's scale.

Verbal judgment	Importance value
Equal importance	1
Somewhat more importance	3
Much more important	5
Very much more important	7
Absolutely more important	9
Intermediate value (weaker)	2, 4, 6, 8

The local importance is given by the eigenvector $\mathbf{w} = [w_1, w_2, \ldots, w_n]^T$ related to the higher eigenvalue $\lambda_{\max}$ obtained from eigendecomposition of $\mathbf{A}$, where each w_i is the i-th alternative or local priority criterion and $w_i \geq 0$ for all i. The global priority over all alternatives, taking into account all judgments, is obtained by vector $\mathbf{v} = [v_1, v_2, \ldots, v_n]^T$, whose p-th element is the weighted sum:

$$v_p = \sum_{l=1}^{o} s_l t_{pl} \tag{4}$$

where $p = \{1, 2, \ldots, n\}$, t_{pl} is the local priority of alternative p in relation to the l-th criterion and s_l is the l-th criterion weight. For practical purposes this vector is normalized as $\mathbf{v}_{norm} = \mathbf{v}/\sum v_r$.

A NOVEL ENSEMBLE LEARNING

Let $C_1, C_2, \ldots, C_K \in [0,1]$ be the performance measures and $M_1, M_2, \ldots, M_Q$ be the machines induced over some dataset. Then, the M_i machine provides the performance Ω_{C_k,M_i} for the k-th measure. The machine M_i is better than M_j, with respect to C_k measure, if and only if $\Omega_{C_k,M_i} > \Omega_{C_k,M_j}$, where $i \neq j$. Therefore, a higher weight must be attributed to M_i, in the weighted ensemble learning approach. In order to obtain this weight, it is proposed the algorithm described from steps 1 to 4, which is performed on training dataset. In the context of AHP, our goal is to get the machine weights (alternatives) taking into account the criteria (performance measures).

1) Calculate the difference, Equation (5), between performance measures and multiply it by a constant $\varphi \in \mathbb{R}_+^*$. This constant increases the sensibility of the difference $d_{k,ij}$, when the machines M_i and M_j have close performances.

$$d_{k,ij} = (\Omega_{C_k,M_i} - \Omega_{C_k,M_j})\varphi \tag{5}$$

2) Mapping the difference $d_{k,ij}$ to the fundamental Saaty's scale through conversion formulas (6), (7) and (8). A version from formula (6) was firstly proposed by Oliveira et al (2019) to select the best machine.

$$\delta_{k,ij}(d_{k,ij}) = \begin{cases} 1, \text{if } |d_{k,ij}| < 1 \\ 9, \text{if } |d_{k,ij}| > 9 \\ \lceil |d_{k,ij}| \rceil, otherwise \end{cases} \tag{6}$$

$$\Delta_{k,ij}^{\mathcal{L}}(\delta_{k,ij}, d_{k,ij}) = \begin{cases} 1/\delta_{k,ij}, if \;\; d_{k,ij} < 0 \\ \delta_{k,ij}, otherwise \end{cases} \tag{7}$$

$$\Delta_{k,ij}^{\mathcal{Q}}(\delta_{k,ij}, d_{k,ij}) = \begin{cases} 1/\delta_{k,ij}^2, if \, d_{k,ij} < 0 \\ \delta_{k,ij}^2, otherwise \end{cases} \tag{8}$$

where $\lceil\cdot\rceil$ is the ceiling function. Equations (7) and (8) are referring to linear ($\mathcal{L}$) and quadratic ($\mathcal{Q}$) scales (Harker and Vargas, 1987), respectively.

3) From all $\Delta_{k,ij}$, $k = 1,2, \ldots, K$, build the pairwise comparison matrices:

$$\boldsymbol{A}_k = \begin{bmatrix} \Delta_{k,11} & \Delta_{k,12} & \cdots & \Delta_{k,1Q} \\ \Delta_{k,21} & \Delta_{k,22} & \cdots & \Delta_{k,2Q} \\ \vdots & \vdots & \ddots & \vdots \\ \Delta_{k,Q1} & \Delta_{k,Q2} & \cdots & \Delta_{k,QQ} \end{bmatrix} \tag{9}$$

4) Compute the global priority vector, using Equation (4), and the matrices on step 3, which provide the machines weights.

Finally, the machines weights ω_q are put in Equations (2) and (3), resulting in a weighted voting strategy that simulates distinct experts with different voting importance. This approach is named here as AHP weighted voting (AHP-WV).

To understand AHP-WV behavior, consider the following didactic example: It is desired to recognize four instances, named $(\mathbf{x}_1, 0), (\mathbf{x}_2, 1), (\mathbf{x}_3, 1)$ and $(\mathbf{x}_4, 0)$. Suppose three machines M_1, M_2 and M_3 that classifies these instances as $M_1 \leftarrow [1,1,0,1]$, $M_2 \leftarrow [0,1,0,0]$ and $M_3 \leftarrow [0,0,0,1]$, where the left and right sides of the symbol "←", mean a machine and its predictions for instances $\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3$ and $\mathbf{x}_4$, respectively. Machine M_2 produced two correct predictions, whereas M_1 and M_3 produced only one. In order to assess machine performances, three measures are used: C_1 (accuracy), C_2 (precision) and C_3 (recall). At the first level of AHP we assign the same priority for these measures, so $\mathbf{s} = [0.33, 0.33, 0.33]^T$. Judging alternatives M_1, M_2 and M_3 with respect to criteria C_1, C_2 and C_3, results in the pairwise matrices A_1, A_2 and A_3, respectively, taking $\varphi = 20$ and measures in Table 2.

$$A_1 = \begin{bmatrix} 1 & 1/9 & 1 \\ 9 & 1 & 9 \\ 1 & 1/9 & 1 \end{bmatrix} \qquad A_2 = \begin{bmatrix} 1 & 1 & 9 \\ 1 & 1 & 9 \\ 1/9 & 1/9 & 1 \end{bmatrix} \qquad A_3 = \begin{bmatrix} 1 & 1/9 & 7 \\ 9 & 1 & 9 \\ 1/7 & 1/9 & 1 \end{bmatrix}$$

Table 2. Measures of the didactic example.

Measure	Machine		
	M_1	M_2	M_3
C_1	0.25	0.75	0.25
C_2	0.33	1.00	0.0
C_3	0.50	0.50	0.0

Applying the AHP methodology on these matrices, using eigendecomposition, we get the local priority vectors: $\mathbf{t}_1 = [0.09, 0.81, 0.09]$, $\mathbf{t}_2 = [0.16, 0.78, 0.04]$ and $\mathbf{t}_3 = [0.47, 0.47, 0.05]$. The global priority vector $\mathbf{v}$ is given by $\mathbf{s}$, $\mathbf{t}_1$, $\mathbf{t}_2$ and $\mathbf{t}_3$ linear combination, according to Equation (4). Thus, $\mathbf{v} = [0.24, 0.69, 0.06$. Therefore, the machines M_1, M_2 and M_3 are associated to the weights $0.24, 0.69$ and 0.06, respectively. Note that, although M_1 and M_3 are wrong three times, whereas $\Omega_{C_j,M_1} > \Omega_{C_j,M_3}$, for $j = 2, 3$, M_1 was greater importance than M_3, since they err for different classes, and performance measures distinguish between positive and negative class. It is worth noting that if other measures are used the importance may change.

Finally, in the case where all weights are equal, then the weighted voting and the majority voting (without weight) have the same result. To avoid this fact, φ may be adjusted.

RESULTS AND DISCUSSIONS

In order to verify the ability of the proposed AHP-WV, some experiments on classical database available in Pedregosa et al. (2011) were conducted. Results are compared with majority voting. Three classical performance measures are used: accuracy (A_{cc}), precision (P_r) and recall (R_e).

Table 3 shows the results for the k-nearest neighbors (KNN), for $k = 1, 2, \ldots, 10$; Perceptron implemented with different regularization constants and Decision Tree using random initialization parameters. Therefore, it is intended to obtain some diversity in order to construct an ensemble learning with good generalization. Columns AHP-WV and Voting exhibit the performance calculated from Equations (2) and (3) with and without[7] the weights ω_q, respectively. For AHP-WV the linear and quadratic scales are considered, labeled as AHP-WV($\mathcal{L}$) and AHP-WV($\mathcal{Q}$), respectively. The sensibility parameter was experimentally chosen as $\varphi = 500$ and priority of measures (criteria) are the same as in didactic example from last section.

Table 3. Results employing majority voting and AHP-WV using $\varphi = 500$ for three ML algorithms and database.

Database	Voting (%)			AHP-WV($\mathcal{L}$) (%)			AHP-WV($\mathcal{Q}$) (%)		
	A_{cc}	P_r	R_e	A_{cc}	P_r	R_e	A_{cc}	P_r	R_e
KNN machines									
Cancer	93.00	92.27	92.89	94.40	94.00	94.00	95.80	95.86	92.89
Digits	97.77	97.91	97.83	98.66	98.74	98.67	99.11	99.14	99.13
Wine	71.11	62.45	62.89	75.55	70.57	71.23	77.77	74.33	75.39
Perceptron machines									
Cancer	62.93	31.46	50.00	92.30	93.18	90.39	92.30	93.13	90.39
Digits	26.88	15.77	24.73	89.33	90.95	89.50	89.33	90.95	89.50
Wine	46.66	15.55	33.33	60.00	70.62	63.29	53.33	75.86	63.69
Decision tree machines									
Cancer	86.71	85.74	87.89	90.90	89.89	92.00	91.60	90.58	92.55
Digits	86.44	87.76	86.49	86.44	87.00	86.48	86.66	87.08	86.70
Wine	91.11	90.89	92.65	93.33	93.26	94.24	95.55	94.70	96.32

Results presented in Table 3 point out that AHP-WV($\mathcal{L}$) and AHP-WV($\mathcal{Q}$) are better than majority voting, for all dataset and ML algorithms, except for Decision Trees performed on Digits database, regarding P_r measure. The higher difference between approaches is achieved when Perceptron machines are implemented. In this case, proposed approach has performed 62% higher than majority voting regarding A_{cc} measure. Unlike Perceptron, performance on the same database and evaluation measure by using Decision Trees remains almost unchanged.

[7] It means that the weigths have the same values.

The results described are related to the diversity about ML algorithms parameters. Another way to achieve diversity is dataset subsampling (Polikar, 2006). Table 4 shows the results for fixed ML algorithm and database, namely KNN with three neighbors and Cancer database, but with variations of the dataset size and instances used for training and test.

Table 4. Results employing majority voting and AHP-WV using $\varphi = 500$ for KNN and Cancer database. Std means standard deviation.

	Voting (%)			AHP-WV(L) (%)		
	A_{cc}	P_r	R_e	A_{cc}	P_r	R_e
	93.33	93.77	92.13	94.17	94.98	92.80
	96.67	96.30	96.30	96.67	96.30	96.30
	96.67	96.3	96.30	95.83	95.62	95.08
	92.50	92.69	91.76	92.50	92.69	91.76
	97.50	97.53	97.03	97.50	97.53	97.03
	96.67	96.55	96.55	95.83	95.57	95.85
	91.67	92.01	91.16	90.00	91.11	89.07
	94.17	94.44	93.40	93.33	93.36	92.71
	95.00	95.53	94.29	95.83	96.67	95.00
	92.50	92.45	90.93	93.33	94.44	91.03
	91.67	92.01	91.16	91.67	92.01	91.16
	92.50	92.20	92.43	94.17	94.12	93.86
	96.67	96.55	96.55	96.67	96.88	96.23
	97.50	97.86	97.17	96.67	97.18	96.23
	95.83	95.75	95.33	95.83	95.75	95.33
	94.17	94.12	93.86	94.17	94.12	93.86
	93.33	93.76	92.00	93.33	93.76	92.00
	94.17	93.96	93.56	94.17	93.96	93.56
	94.17	93.75	94.07	95.83	95.8	95.44
	93.33	93.75	92.76	94.17	94.44	93.72
Mean	94.50	94.56	93.94	94.58	94.82	93.90
Std	1.89	1.81	2.09	1.85	1.69	2.09

We can see in Table 4 that Voting and AHP-WV($\mathcal{L}$) approaches have the same general performance, since, for a particular subset, one is better than the other, but taking the standard deviations there are practically no differences.

CONCLUDING REMARKS

In this work it was proposed a new method to obtain the machine weights based on recognition of the machine importance for the general prediction, using the Analytic Hierarchy Process called AHP-WV. AHP-WV is a suitable method to obtain the machines weights in order to implement the voting strategy. However, when the diversity is achieved using subsampling datasets its advantage is not ensured, so a simple majority voting is preferable. Despite the goal of this work was the proposition of a scheme to obtain the weights for weighted voting scheme, AHP-WV is a useful tool for model selection too, since it yields numerical importance from the induced models.

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