Deep adaptation network for cross-domain sitting posture recognition using pressure sensor arrays

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ABSTRACT

Accurate and timely detection of improper sitting postures is essential for mitigating potential health risks. Numerous studies have explored the use of pressure sensing to monitor sitting postures, but few have systematically evaluated intra-subject and inter-subject variations in designing a practical sitting posture recognizer. To address this gap, we propose a cross-domain sitting posture recognition framework based on the transfer learning paradigm, aimed at reducing the distribution discrepancy between source-domain and target-domain pressure sensor data. The proposed framework incorporates an adaptation neural network to automatically extract discriminant features and minimize both marginal and conditional distribution discrepancies between domains in the learned latent feature space. To assess the effectiveness of the framework, comparative experiments are conducted against five traditional transfer learning algorithms and one deep transfer learning model. Performance metrics, including accuracy and F1 score, are evaluated on the collected experimental data under two typical cross-domain scenarios (i.e., *cross-subject* and *cross-time*). The results indicate that cross-domain sitting posture recognition is significantly impacted by degraded accuracy and that transfer learning helps mitigate the issue. Among the evaluated methods, the end-to-end deep transfer learning techniques generally outperform traditional transfer learning techniques, demonstrating superior cross-domain performance.

Keywords: sitting posture, pressure sensing, cross-domain, adaptation network

1. INTRODUCTION

Recent studies indicate that modern adults spend a significant amount of time in seated positions, with improper sitting postures leading to uneven spinal pressure and potentially causing musculoskeletal disorders such as cervical spondylosis, chronic back pain, spinal misalignment, joint and muscle discomfort, and intervertebral disc damage. Furthermore, improper sitting postures adversely affect both physical and mental well-being, imposing substantial economic burdens on healthcare system. A practical solution to mitigating these issues involves recognizing ongoing sitting postures and providing timely feedback [1]. However, the recognition of sitting postures presents challenges due to environmental changes and posture variations across individuals. Sitting postures exhibit characteristics such as *similarity*, *intra-subject variation*, and *inter-subject variation*. For instance, individuals may perform the same posture differently across time and locations (intra-subject variation), while variations also occur between different individuals performing the same posture (inter-subject variation). These complexities make accurate sitting posture recognition a challenging yet significant research topic [2].

To achieve better performance and adaptability in complex scenarios, researchers have developed various methods for sitting posture recognition and timely feedback. Based on the sensing units used, these methods can be broadly categorized into vision-based, wearable sensor-based, environmental sensor-based, and pressure sensor-based approaches [3]. Vision-based methods use one or more depth cameras to capture images of sitting postures. Machine learning algorithms are then utilized to train posture recognizers, which predicts ongoing postures [4]. While effective, these methods are susceptible to occlusion, interference, and privacy issues, limiting their practical applications. Wearable sensor-based methods involve attaching sensors to specific body parts (e.g., back, neck, and legs) to collect and annotate posture data for training a recognizer. Commonly used sensors include, but not limited to, accelerometers, gyroscopes, and strain sensors. For instance, Ma et al. collected triaxial accelerometer data and applied support vector machines and K-means to classify postures such as *normal*, *forward-leaning*, *backward-leaning*, *studying/writing*, and *crossed-leg* sitting postures [5]. Despite their portability and low cost, wearable sensor-based approaches can disrupt users, leading to poor adherence. Environmental sensor-based approaches utilize technologies like WiFi, RFID, millimeter-wave, or infrared sensors to

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detect and classify sitting postures. For example, Li et al. employed RFID technology and extracted discriminant features from phase sequences to differentiate five sitting postures [6]. Although less invasive, these methods are highly sensitive to external factors such as humidity, temperature, occlusion, interference, and lighting. As a result, maintaining these systems is often labor-intensive and time-consuming.

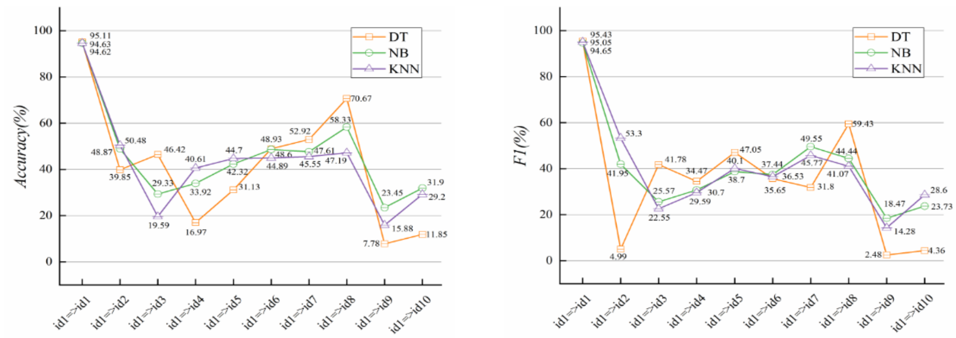
Compared with the previously discussed methods, pressure sensor-based approaches offer advantages such as lower cost, non-invasiveness, and enhanced privacy protection [7]. These methods typically involve installing pressure sensors on the seat pan and backrest of a chair to capture distributed pressure data for various sitting postures. The annotated data are then used to train a recognizer, which subsequently detects and classifies sitting postures. Key components of this approach include the placement of pressure sensors, the extraction of discriminant features, and the selection of suitable models. For instance, Jeong et al. combined force-sensitive resistors and infrared distance sensors embedded in an office chair and evaluated its effectiveness in detecting eleven sitting postures. Their experiments demonstrated accuracies of 59.00%, 82.00%, and 92.00% for the use of pressure sensors, distance sensors, and the combination of both, respectively [8]. In addition to traditional machine learning models, recent studies have explored end-to-end deep learning techniques to enhance accuracy and automate feature extraction. For instance, Fan et al. utilized convolutional neural networks (CNNs) to analyze pressure distribution at the hip interface and predict different sitting postures. Their system achieved accuracy of 99.82%, demonstrating the potential of deep learning techniques [9].

Although existing studies have achieved satisfactory recognition accuracy, few have systematically addressed the cross-domain challenge, where a recognizer may suffer from accuracy degradation when applied to different subjects (i.e., *cross-subject* recognition) or the same individual at different time points (i.e., *cross-time* recognition) due to the factors such as sensor calibration differences, individual behavior change, or environmental conditions. Specifically, in the cross-subject scenario, a recognizer optimized using sensor data from subject A is used to infer sitting postures for subject B. In the cross-time scenario, a recognizer trained on sensor data from a subject during time period T_a is employed to predict the subject's sitting postures during a different time period T_b. The primary cause of accuracy degradation is the distribution discrepancy between domains, such as variations across subjects or time points. A straightforward solution to this problem is to detect and annotate pressure sensor data for each new subject or new time period. However, this approach is time-consuming and often impractical. A more feasible alternative is to reuse knowledge or data from existing domains. For pressure sensor-based sitting posture recognition, the critical challenge lies in handling time-series sensor data to bridge the gap between source and target domains. To address this issue, we propose a cross-domain sitting recognition framework aimed at reducing the distribution discrepancy between source-domain and target-domain pressure sensor data. The main contributions of our study are summarized as follows. (1) Systematic evaluation of cross-domain sitting posture recognition. We systematically investigate and experimentally evaluate cross-subject and cross-time sitting posture recognition. Results reveal that sitting posture recognizers are highly susceptible to accuracy degradation in cross-domain scenarios, highlighting the importance of considering these challenges in future research. (2) Proposed framework with deep transfer learning. We introduce a sitting posture recognition framework based on the transfer learning paradigm, incorporating a deep transfer learning model to minimize marginal and conditional distribution differences between domains in the latent feature space. This alignment improves the semantic consistency between source and target domains. (3) Extensive comparative experiments. Comprehensive experiments are conducted, comparing our framework against five traditional transfer learning algorithms and one deep transfer learning model under both cross-subject and cross-time settings. Results demonstrate the effectiveness of transfer learning in improving cross-domain accuracy.

2. THE PROPOSED SITTING POSTURE RECOGNITION MODEL

From the machine learning perspective, the sitting posture recognition chain (SPRC) primarily consists of two phases: the training stage and the prediction stage. In the training stage, pressure sensor data are collected and annotated to construct a sitting posture recognizer. This recognizer is subsequently applied to detect sitting postures as new pressure sensor data are received. A fundamental assumption underlying this process is that the training and test data are independent and identically distributed (i.e., the i.i.d. assumption). However, when this assumption is violated, the performance of the sitting posture recognizer degrades significantly. For example, Figure 1 illustrates the accuracy (*acc*) and F1 of a sitting posture recognizer for three classification models: decision tree (DT), naïve Bayes (NB), k-nearest-neighbor (KNN), where "A => B" denotes that sensor data from user A are used to train a recognizer and sensor data from user B are used for evaluation. Taking subject id1 as an example, we observe accuracy degradation due to inter-subject variation. When the decision tree is used, the accuracy for id1=>id1 (i.e., training and testing on the same subject) reaches 95.11%. However, the accuracy drops dramatically when the recognizer is tested on other subjects: 39.85% (id1=>id2), 46.42% (id1=>id3), 16.97% (id1=>id4), 31.13% (id1=>id5), 48.93% (id1=>id6), 52.92% (id1=>id7), 70.67% (id1=>id8), 7.78% (id1=>id9) and 11.85%

(id1=>id10). These results highlight the significant impact of inter-subject variation. The observed performance degradation underscores the limitations of directly applying a recognizer across different users, emphasizing the need for methods that can address cross-domain challenges in this context.



(a) Accuracy

(b) F1

Figure 1. Results of subject-dependent and cross-subject sitting recognition. (a) accuracy; (b) F1.

2.1 The proposed cross-domain sitting posture recognition framework

In practice, the i.i.d. assumption is often violated when building a practical sitting posture recognition system. This is primarily due to variable circumstances such as diverse sitting habits, changes in users' body shapes, and sensor reading drift. These factors lead to distribution discrepancies between different domains (e.g., across subjects or time periods). While collecting sensor data and training a new recognizer for each domain is an option, it is labor-intensive and impractical. A more feasible solution is to leverage source-domain knowledge in the target domain [10]. Inspired by the ability of transfer learning to reduce distribution discrepancies and its success in advancing various research fields, we propose a transfer learning-based sitting posture recognition framework, illustrated in Figure 2.

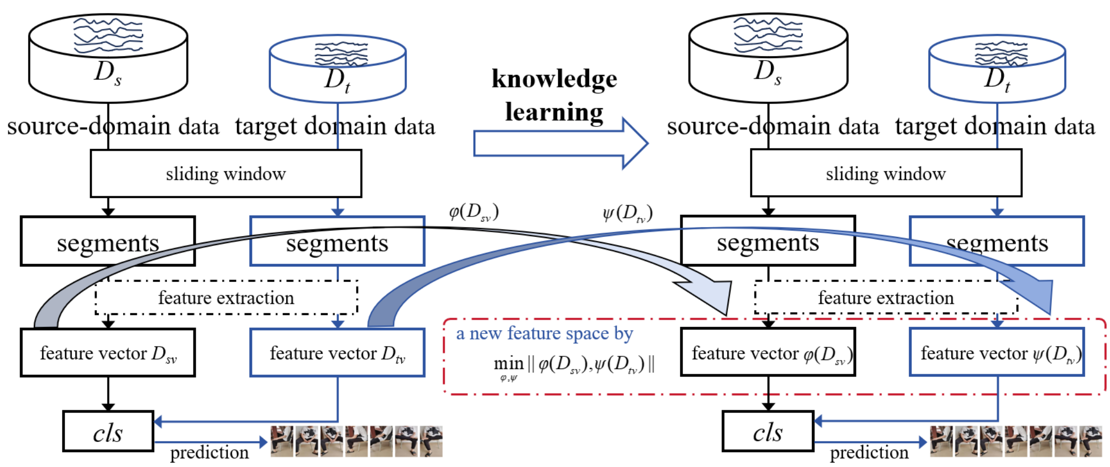


Figure 2. Cross-domain sitting posture recognition framework.

Formally, given a training dataset D_s (*source domain*), our goal is to develop a sitting posture recognizer that can make predictions on cross-domain pressure sensor data D_t (*target domain*). Instead of directly training a recognizer on D_s and applying it on D_t, we first map D_s and D_t to a latent space, ensuring their distribution discrepancy is limited. Subsequently, we train a sitting posture recognizer *cls* on the mapped source domain data $\varphi(D_s)$ and apply *cls* on the mapped target domain data $\psi(D_t)$. Specifically, given D_s consisting of labeled pressure sensor readings and D_t containing unlabeled sensor data, we first segment the data using a sliding window. Next, the segments are encoded into feature vectors, denoted as D_{sv} and D_{tv}. Particularly, for traditional transfer learning models, feature engineering techniques are utilized to extract handcrafted features from the segments; for deep learning models, feature extraction can be omitted. Afterwards, we minimize the distribution difference between D_{sv} and D_{tv}. Finally, a recognizer is trained on the projected source domain data and used to predict sitting postures on the projected target domain data.

To automate feature extraction and jointly optimize feature learning and model training, we incorporate the Dynamic Adversarial Adaptation Network (DAAN) into the framework to balance both marginal distribution and conditional distribution while learning latent features from raw sensor data [11]. Although DAAN has been successfully applied in tasks such as image recognition, hyperspectral image classification, and rotating machinery fault detection, its potential for pressure sensor-based posture recognition remains underexplored. By integrating DAAN into the framework, we aim to address cross-domain challenges and advance the state of sitting posture recognition. DAAN primarily consists of four components [11]: (a) Feature Extractor G_f. It extracts features from the input data. (b) Label Classifier G_y. G_y predicts the label of a source domain sample with an associated loss function. (c) Global Domain Discriminator G_d. G_d aims to distinguish the source domain from target domain. (d) Local Domain Discriminator G_d^c associated with class c.

3. EXPERIMENTAL SETUP AND RESULTS

3.1 Experimental setup

Ten volunteers (seven males and three females) are recruited for our study. The male participants have an average height of 169.4 ± 3.05 cm and an average weight 64.0 ± 8.12 kg, while the female participants have average height 157.7 ± 4.04 cm and an average weight 55.0 ± 5.0 kg. For the sitting posture sensing units, we place four pressure sensors on the seat pan and one on the backrest to collect sensor signals corresponding to seven sitting postures (i.e., *upright*, *leaning left*, *leaning right*, *leaning forward*, *leaning backward*, *right leg crossed*, *left leg crossed*) [3]. Figure 2 provides an illustration of these sitting postures. To ensure natural behavior and minimize interference, we do not impose any restrictions on how participants perform the sitting postures. Additionally, a camera is used for annotating the sensor data. During the experiments, each participant's pressure sensor data is recorded for a total duration of 12 minutes. We use the hardware system to collect sensor data and apply signal processing techniques to obtain high-quality data [4]. To evaluate the effectiveness of the proposed model, we compare its performance against three non-transfer learning approaches (i.e., NB, KNN, and DT), five traditional transfer learning algorithms, and one deep transfer learning model. Recent studies unravel that deep neural network can learn transferable features which generalize well for domain adaptation tasks and deep adaptation networks (DAN) efficiently reduces the dataset bias and better align the feature representations of the two domains, which remains the priority. The five commonly used transfer learning models used in our study are transfer component analysis (TCA), joint distribution adaptation (JDA), balanced distribution adaptation (BDA), geodesic flow kernel (GFK), and stratified transfer learning (STL). For the five traditional transfer learning approaches, feature engineering is required to extract meaningful features from the raw sensor signals. Specifically, we segment the streaming sensor data using a 1s sliding window with 75% overlap between adjacent windows. Subsequently, we extract time-domain features such as mean, variance, standard deviation, minimum, maximum, zero-crossing number, mode, and the difference between maximum and minimum values. We also apply the Fast Fourier Transform to transform the time domain signal into frequency domain and extract features such as DC components, amplitude features, and shape features. In contrast, the deep transfer learning model (i.e., DAN and DAAN) directly take as input the segmented raw sensor data. Both DAN and DAAN adopt Resnet50 as the backbone network. The Adam optimizer is used for model training, with the following hyperparameter settings: an initial learning rate of 0.01, weight decay of 5e-4, and a batch size of 16. The Xavier initializer is utilized and the networks are trained from scratch using PyTorch for ten epochs. The training procedure for DAN is conducted in similar manner.

To ensure the independence of the training and test sets, a ten-fold cross-validation is employed, with each of the ten folds serving as the test set and the remaining nine folds as the training set. This process is repeated ten times, and the results are averaged to evaluate performance in terms of accuracy and $F1$.

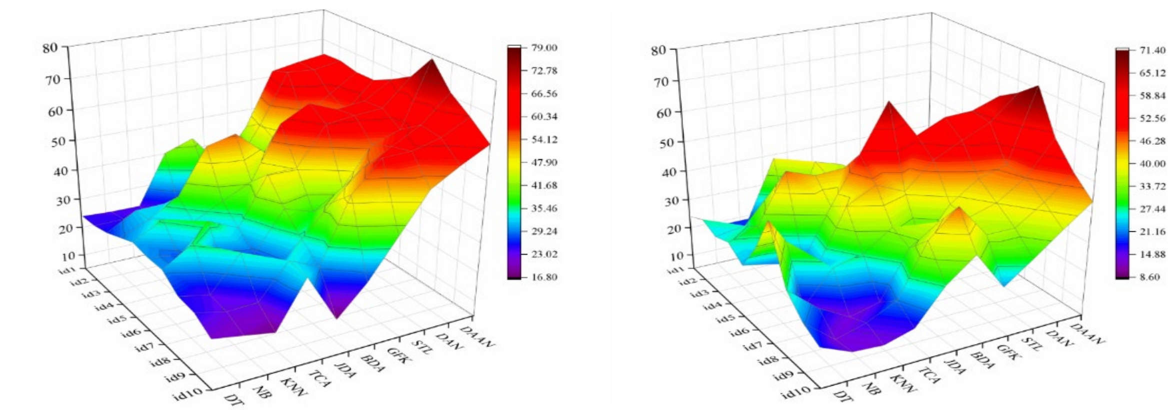
3.2 Cross-subject sitting posture recognition

In this subsection, we evaluate the cross-subject sitting posture recognition setting, where the training data and test data are from different subjects. Table 1 presents the experimental results using various transfer learning methods. The notation *A=>B* in the first column denotes that sensor data from user *A* are used as the training data and data from user *B* are used as the test data. Due to limited space, we only present results for id1, id2, and id3. The best result for each cross-subject experiment is highlighted in bold. Particularly, the last row summarized the average performance across all ten participants. From Table 1, we observe that DAAN generally obtains better accuracy than its competitors. For example, the average accuracy of DAAN is 65.45%, compared to the 35.83%, 35.49%, 38.16%, 51.41%, 52.91%, 58.22% for TCA, JDA, BDA, GFK, STL, and DAN, respectively.

Figure 3 presents the average cross-subject accuracy and F1 for the ten volunteers using different sitting posture recognizers, where the X-axis indicates ten individuals, Y-axis refers to different recognizers, and Z-axis shows accuracy and $F1$. For example, the result for id1 is calculated by averaging the performance of a recognizer trained on id1 and tested on the other nine individuals. From Figure 3, we can observe that deep transfer learning models generally improve cross-subject sitting posture recognition compared with traditional transfer learning models. Additionally, the results reveal that volunteers with similar demographic characteristics (i.e., gender, age, height, and weight) tend to obtain higher accuracy. For example, for id2 (25-year-old male, 170cm height, and 70kg weight) and id3 (25-year-old male, 174cm height, 73kg weight), DAAN achieves 75.13% and 77.30% accuracies for id2=>id3 and id3=>id2, respectively. This partially indicates that demographic similarity between subjects contributes to reducing data distribution discrepancies, thereby improving recognition accuracy.

Table 1. Results of cross-subject sitting posture recognition using transfer learning.

	TCA		**JDA**		**BDA**		**GFK**		**STL**		**DAN**		**DAAN**	
	Acc	F1	Acc	F1	Acc	F1	Acc	F1	Acc	F1	Acc	F1	Acc	F1
id1 => id2	37.76	38.21	41.79	40.93	42.65	41.21	47.20	46.05	50.16	46.03	47.25	46.44	**52.20**	51.40
id2 => id1	22.67	20.96	20.89	19.58	21.55	21.38	45.35	46.11	47.85	48.13	56.55	47.89	**57.74**	48.00
id1 => id3	22.18	22.68	21.02	21.16	23.74	23.04	33.47	38.11	34.82	37.07	46.63	34.35	**56.99**	49.74
id3 => id1	21.36	21.63	10.72	12.87	16.41	19.33	42.96	40.60	39.14	38.08	**77.98**	73.57	70.24	65.31
id2 => id3	29.84	26.21	26.38	23.68	27.88	24.42	34.30	36.24	32.44	34.53	67.36	64.43	**75.13**	71.94
id3 => id2	31.28	34.56	22.03	21.45	25.02	24.01	41.49	45.77	44.35	47.21	43.41	45.68	**77.30**	71.15
Average	35.83	33.69	35.49	32.22	38.16	35.30	51.41	51.70	52.91	52.33	58.22	54.49	**65.45**	61.41



(a) Accuracy (b) F1

Figure 3. Results of cross-subject sitting posture recognition of different models. (a) Accuracy; (b) F1.

3.3 Cross-time sitting posture recognition

In this section, we evaluate the performance of a sitting posture recognizer in the cross-time setting. We first present the experimental results without using transfer learning, followed by the results using transfer learning. Table 2 presents the cross-time recognition results, where $A(t_a{=}{>}t_b)$ means that we train a recognizer on the sensor data collected during a period of time t_a from subject A and use the recognizer to predict sitting postures for subject A with the sensor data collected during a period of time t_b. From Figure 1 and Table 2, we can observe that the recognizer suffers from degraded accuracy. The main reason is that sensor data have experienced a drift over time, which leads to data distribution difference between t_a and t_b. This highlights the necessity of updating the recognizer even for the same individual. Table 3 presents the results of cross-time sitting posture recognition experiments using transfer learning. From Table 3, we observe that DAAN and DAN perform better in the majority of cases. For example, on id1(t_a=>t_b), DAAN and DAN achieve the accuracies of 85.12% and 81.55%, respectively. From Tables 2 and 3, we observe that transfer learning generally obtains better accuracy. This improvement can be attributed to the ability of deep neural networks to extract and leverage high-level latent features. Furthermore, DAAN generally outperforms DAN, indicating that the dynamic adversarial network more effectively aligns the feature spaces of the source and target domains.

4. CONCLUSION

In this paper, we propose a cross-domain sitting posture recognition framework based on the transfer learning paradigm. Specifically, to achieve semantic alignment between domains, we incorporate the dynamic adversarial adaptation network into the framework. Comparative experiments are conducted against five traditional transfer learning algorithms and one deep transfer learning model under two representative cross-domain scenarios. Results demonstrate that end-to-end deep transfer learning techniques achieve superior cross-domain accuracy. Since there are other factor such as cross-device variations that lead to degraded accuracy, we would apply the proposed model to handle other cross-domain issues for future work.

Table 2. Results of cross-time sitting posture recognition without transfer learning.

	DT		NB		KNN	
	Acc	F1	Acc	F1	Acc	F1
id1(t_a=>t_b)	70.43	54.37	54.37	52.09	56.11	52.24
id1(t_b=>t_a)	51.91	50.24	50.24	46.34	50.00	45.47
id2(t_a=>t_b)	57.81	63.23	63.23	53.30	39.98	38.16
id2(t_b=>t_a)	62.35	54.12	54.12	54.52	42.59	38.53
id3(t_a=>t_b)	42.70	58.16	58.16	45.77	44.43	38.60
id3(t_b=>t_a)	28.70	45.08	45.08	44.34	29.53	30.44
AVE	52.32	54.20	54.20	49.39	43.77	40.57

Table 3. Results of cross-time sitting posture recognition using transfer learning.

	TCA		JDA		BDA		GFK		STL		DAN		DAAN	
	Acc	F1	Acc	F1	Acc	F1	Acc	F1	Acc	F1	Acc	F1	Acc	F1
id1(t_a=>t_b)	43.66	40.93	49.87	46.25	50.24	46.99	66.59	62.43	67.40	64.64	81.55	80.61	**85.12**	82.48
id1(t_b=>t_a)	45.35	44.41	50.91	48.40	50.08	47.71	70.76	72.25	**77.80**	77.07	63.95	63.09	55.81	48.88
id2(t_a=>t_b)	36.21	38.19	44.46	44.62	43.79	43.97	61.68	62.52	67.33	67.07	54.95	52.73	**68.68**	66.08
id2(t_b=>t_a)	28.10	26.74	36.62	37.80	39.70	40.78	50.27	55.99	53.46	58.03	70.17	72.09	**73.48**	74.36
id3(t_a=>t_b)	40.00	40.84	49.30	47.31	46.00	45.01	38.16	40.59	42.92	44.13	**57.51**	46.72	57.51	45.94
id3(t_b=>t_a)	30.47	27.14	31.91	27.72	32.97	29.23	30.05	33.30	30.67	32.56	63.78	60.60	**69.19**	70.15
AVE	37.30	36.38	43.85	42.02	43.80	42.28	52.92	54.51	56.60	57.25	65.32	62.64	**68.30**	64.65

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